Data-Enabled Decision Support System for Sustainable Urban Development: A Case of Urban Green Space Management

Zur Erlangung des akademischen Grades eines
Doktors der Ingenieurwissenschaften (Dr.-Ing.)

von der KIT-Fakultät für Wirtschaftswissenschaften
des Karlsruher Instituts für Technologie (KIT)

genehmigte

DISSERTATION

von

M.Sc. **Mihir Jitendra Rambhia**

Tag der mündlichen Prüfung:	12. Dezember 2024
Referent:	Prof. Dr. Frank Schultmann
Korreferent:	Prof. Dr. Anupam Kumar Singh

Abstract

Cities, considered important centers of socio-economic activity and growth, currently confront adverse impacts from climate change. Efforts have been made to leverage modern technologies to make cities smarter. However, implementing them for the efficient management of the urban environment can help cities simultaneously grow smart and sustainable. Urban green spaces (UGS) offer substantial social, environmental, and economic benefits, making their preservation and enhancement a key priority for city administrators. Nevertheless, with changing climatic conditions and intensifying resource constraint conditions, such as water scarcity, labor shortage, and limited funding, decision-makers need to prioritize the allocation of limited resources. However, decision-makers struggle to find the right balance between conflicting objectives and subsequently make informed decisions. Therefore, to achieve effective UGS management, a multidimensional, evidence-based approach is necessary to balance diverse objectives. Accordingly, this thesis, through four interconnected studies, presents a data-enabled decision support system based on utilitarian principles that aims to maximize UGS benefits at minimum costs. This is achieved by systematically incorporating both the total costs of sustaining UGS and the benefits they provide to city residents.

The first study provides the initial component of the decision support system by estimating the management demands associated with sustaining UGS, also referred to as costs. In this, a novel linear time series model, based on soil water balance principles and the Water Use Classifications of Landscape Species approach, was developed. The model provides estimates for the weekly irrigation demand of urban street trees, considering tree characteristics, current and forecasted weather conditions, and soil properties. The second study further adds to the decision support system by estimating the attainable benefits from UGS. Through a novel GIS-based approach, accessibility and quality benefits are calculated using publicly available data on UGS spatial distribution, space size, noise map, remote sensing data, crime statistics, and population distribution in the city. Building upon the foundation laid by the initial two studies, the third study develops a Goal programming-based decision-making model that integrates multiple objectives, including conserving stored carbon, increasing attainable quality and accessibility, and addressing constraints on available resources such as water and personnel. The developed model allows making prioritization decisions to allocate resources efficiently and maximize benefits gained. The final study addresses a critical aspect of data-enabled system: assessing and enhancing the input data quality. By developing a comprehensive quality assessment framework based on total data quality management principles and

implementing data filling techniques, the framework improves the reliability and utility of digital tree inventories, thereby enabling informed decision-making in cities with limited data availability.

The findings demonstrate that the proposed decision support system can improve the attainable benefits from UGS in case of resource-constraint scenarios. It presents three prioritization approaches: based on demands, based on benefits, and then by integrating both the demands and benefits. Moreover, through novel approaches developed to quantify social benefits, such as accessibility and quality, and key management inputs like irrigation demand, it showcases the wide applications of available public datasets for urban resource management applications. Also, the significance of data quality and challenges related to low-quality public datasets are addressed through a systematic quality assessment framework. Therefore, it has the potential to significantly contribute to supporting decision-makers in making informed choices for managing UGS.

Declaration of Authorship

I, Mihir Jitendra Rambhia, declare that this thesis titled, 'Data-Enabled Decision Support System for Sustainable Urban Development: A Case of Urban Green Space Management' and the work presented in it are my own. I confirm that:

- The thesis comprises only my original work towards the Doctor of Philosophy (PhD) except where indicated;
- due acknowledgement has been made in the text to all other material used; and
- the thesis is fewer than 100,000 word limit in length, exclusive of tables, maps, bibliographies and appendices as approved by the Research Higher Degrees Committee.

Signed: Mihir Jitendra Rambhia

Date: October 2025

Preface

This PhD thesis is a thesis with publications. It solely consists of the original contributions of the author, with proper citations to external sources wherever necessary. All co-authors have consented to include material from the specified publications into the author's thesis, acknowledging that the author's contribution exceeds 50% of the content and is the primary contributing author. The research outcomes, comprising publications and conference presentations derived from this dissertation, are enumerated below. Currently, these include two studies published in Q1 peer-reviewed journals, with another study ready for submission to a Q1 peer-reviewed journal. Moreover, as part of scientific outreach, presentations were made at two renowned international conferences, from which one has been published as part of the proceedings, and the other has been invited for submission to the Science Talks journal, where submission will be made in April 2024.

Journal publications:

1. **Rambhia, M.**, Volk, R., Rismanchi, B., Winter, S., & Schultmann, F. (2023). Supporting decision-makers in estimating irrigation demand for urban street trees. Urban Forestry & Urban Greening, 82, 127868–127868. https://doi.org/10.1016/j.ufug.2023.127868 [Published] - Thesis chapter 5.

2. **Rambhia, M.**, Volk, R., Rismanchi, B., Winter, S., & Schultmann, F. (2022). Prioritising urban green spaces using accessibility and quality as criteria. IOP Conference Series: Earth and Environmental Science, 1101(2), 022043–022043. https://doi.org/10.1088/1755-1315/1101/2/022043 [Published] - Thesis chapter 6.

3. **Rambhia, M.**, Volk, R., Rismanchi, B., Winter, S., & Schultmann, F. (2023). Prioritizing urban green spaces in resource constrained scenarios. Resources, Environment and Sustainability, 82, 127868–127868. https://doi.org/10.1016/j.resenv.2024.100150 [Published] - Thesis chapter 7.

4. **Rambhia, M.**, Volk, R., Rismanchi, B., Winter, S., & Schultmann, F. (2024). Data Quality Challenges for Decision-Making in Urban Green Space Management. [To be submitted in April 2024] - Thesis chapter 8.

Conference presentations:

1. **Rambhia, M.**, Volk, R., Rismanchi, B., Winter, S., & Schultmann, F. (2022). Prioritising urban green spaces using accessibility and quality as criteria. CIB World Building Congress 2022, Melbourne, Australia. [Abstract and Presentation]

2. **Rambhia, M.**, Rismanchi, B., Volk, R., Winter, S., & Schultmann, F. (2022). Comparative analysis of machine learning-based methods for decision-making under resource constraint scenarios. EcoSummit 2023, Gold Coast, Australia. [Abstract and Presentation, Invited for submission to Science Talks]

In addition to studies done as a primary author, there was a joint study in co-authorship with fellow researchers from the institute on the available tools for urban resource management. This study included a separate section pertaining to the tools and frameworks available for management of green space that was solely contributed by the author, and therefore, only that particular section has been included in this thesis.

Co-author publication:

1. Volk, Rebekka, **Rambhia, Mihir**, Naber, Elias and Schultmann, Frank. (2022). Urban Resource Assessment, Management, and Planning Tools for Land, Ecosystems, Urban Climate, Water, and Materials—A Review. Sustainability 14, no. 12: 7203. https://doi.org/10.3390/su14127203. [Published] - Thesis chapter 2.

The research activities were made possible with the support of the following scholarships, which covered university fees, living stipends, and travel expenses for attending academic conferences:

1. Graduate School for Climate and Environment (GRACE) Scholarship, Karlsruhe Institute of Technology (March 2020 to December 2023).

2. Melbourne Research Scholarship - Fee offset, The University of Melbourne (April 2020 to April 2024).

3. Engineering and IT Conference Travel Scholarship, The University of Melbourne (2023).

A city without trees is like a world without poetry and music. Tree-lined streets are more than shaded passageways linking buildings. They give us a chance to bring nature into the heart of our communities while linking us to our past.

Henry Arnold, Planning for Trees (1992)

Acknowledgements

This Ph.D. thesis is carried out at the Institute for Industrial Production (IIP), Karlsruhe Institute of Technology (KIT), Germany, and the Department of Infrastructure Engineering (IE), The University of Melbourne (UoM), Australia, as a joint research endeavor. I am deeply grateful to both universities for entrusting me with this opportunity and for their faith in my abilities. I take this opportunity to acknowledge and pay my respects to the traditional custodians of the land on which the UoM and the City of Melbourne are located, and to their elders, past and present.

I extend my sincere gratitude to all my supervisors: **Dr. Behzad Rismanchi**, Senior Lecturer in Building Energy, IE, UoM; **Prof. Dr.-Ing. Stephan Winter**, Professor, IE, UoM; **Prof. Dr. rer. pol. Frank Schultmann**, Chair of Business Administration, Production, and Operations Management, IIP, KIT, for their unwavering support and guidance. I am indebted to them for sharing their valuable time, knowledge, and expertise. Also, I would like to acknowledge the immense contribution of **Dr.-Ing. Rebekka Volk**, Head of Resource Management of the built environment research group, IIP, KIT, in providing constant feedback and guidance which has helped steer this work in the right direction. I would also like to express my gratitude to **Prof. Dr. Dongryeol Ryu**, Professor, IE, UoM, for chairing the advisory committee and providing valuable feedback and suggestions to fulfill my research objectives.

I also wish to acknowledge the valuable support of the Graduate School for Climate and Environment (GRACE) for financially supporting my research through a scholarship. **Dr.-Ing. Andreas Schenk**, Scientific Coordinator at GRACE, for his support in coordinating the scholarship process. Additionally, I extend my heartfelt thanks to the entire administrative staff of IIP (KIT) and the Department of Infrastructure Engineering (UoM) for their overwhelming assistance during my enrollment. Their cordiality and receptiveness made me feel like an intrinsic part of the organization.

Furthermore, I extend my gratitude to **Dr. Stefan Lossow** (Disy Informationssysteme), **Dr. Christian Feilcke** (Technical University of Munich), **Prof. Dr.-Ing. Markus Disse** (Technical University of Munich), **Dr. David Wüpper** (ETH Zurich), **Dr. Philipp Mennig** (Technical University of Munich), **Dr. Aloke Mathur** (Ex-Indian Space Research Organization), **Dr. Shweta Sharma** (Indian Space Research Organization), **Dr. Alpana Shukla** (M.G. Science Institute), **Dr. Tejas Thaker** (Pandit Deendayal Energy University), and **Gautam Dadhich** (Food and Agricultural Organization) for their constant support and encouragement throughout my academic and professional journey.

Although no words would be enough, I would like to thank the ever-generous God, my lovely family (Mom and Dad, Sona, Akash, Rupa, Palak, and Cousins), and friends (Meet, Kartik, Daksh, Abhijeet, Hardik, Vastav, Shivang, Dream Green and MAD) for everything they do for me. Finally, I would like to thank my dearest Jainy for patiently bearing with me and being there as a rock-solid support throughout. Thank you, everyone.

Contents

List of Figures

List of Tables

List of Abbreviations

CBD Convention on Biological Diversity.

ET Evapotranspiration.

GHG Greenhouse Gas.

GP Goal Programming.

ICT Information and Communication Technology.

MCDM Multi-Criteria Decision-Making.

MLR Multiple Linear Regression.

NDVI Normalized Difference Vegetation Index.

OSM OpenStreetMap.

RF Random Forest.

SDG Sustainable Development Goals.

SLIDE Simplified Landscape Irrigation Demand Estimation.

SLR Simple Linear Regression.

UGS Urban Green Spaces.

UN United Nations.

WHO World Health Organization.

WUCOLS Water Use Classification of Landscape Species.

Chapter 1

Introduction and Motivation

1.1 Background

Global studies have observed substantial urban expansion, especially in North America and East Asia over the last few decades (Wang et al., 2012). Zhong et al. (2023) observed that the impervious surface area, an indicator of urban development, grew annually by more than 2000 km^2 in the United States and China and by 1423 km^2 in Europe from 1985 to 2018. According to estimates from United Nations (2018), in 2015, around 54% of the world's population lived in cities, up from only 33% in 1960, and is further expected to increase to 68% by 2050. Cities enable the development of culture, education, research, and business clusters, which reduce production and transport costs, increase market access, create jobs, and foster innovation (Duranton, 2015; Concilio et al., 2019). Therefore, agglomeration effects in cities play a central role in efficiently sustaining the majority of the population. However, cities are also the biggest consumers of energy and raw materials (Hoornweg, 2010). Consequently, cities are significant contributors to Greenhouse Gas (GHG) emissions. Inefficient and unplanned cities exacerbate energy demand and intensify the issues of climate change (Rashed, 2023). Furthermore, urbanization damages natural habitats and has a detrimental impact on local biodiversity (Zang et al., 2010; Thebo et al., 2014).

Therefore, cities must undergo a timely and sustainable transition to achieve holistic sustainability. However, this necessitates a substantial transformation in the way cities are currently planned, built, and managed. To guide this indispensable change in the right direction, the United Nations (UN) has laid out various forward-looking goals for global growth in Agenda 2030 for Sustainable Development. The 17 interlinked Sustainable Development Goals (SDG) are aimed at achieving a better and sustainable future for everyone (United Nations, 2020). In this, the SDG 11 is particularly focused on urban development and affirms to make cities and human settlements inclusive, safe, resilient, and sustainable.

Exponentially growing population, demographic variations, economic disparity, diverse culture, and many other aspects bring challenges to city administrators (Cohen, 2006). This has pushed city administrators to look for newer technologies to provide a better quality of life to citizens. Technology, when rightly implemented, could act as a powerful catalyst to accelerate change. Information and Communication Technology (ICT) such as low-cost sensor networks, Internet of Things, artificial intelligence, big data analytics, geolocation, and geospatial technology are at the forefront of transformation into so-called 'smart cities' (Silva et al., 2018; Maksimovic, 2017; Liu, 2018; Bibri, 2018). For instance, Barcelona, a frontrunner in the smart city movement, has created a digital platform, *Decidim*, where citizens can voice their opinions and participate in the democratic decision-making process (Gascó-Hernandez, 2018). Another example is the City of Nice in France, considered the first European smart city, which has implemented an extensive sensor network to monitor critical environmental data such as air quality, noise level, energy consumption, and air humidity (Silva et al., 2018).

Shared mobility, decentralized energy production and distribution, real-time air and water quality monitoring, and open governance systems are just a few examples of the emerging areas that interlink technological innovation with sustainability transformation (Bibri and Krogstie, 2017; Cabrera and Woda, 2018; Chui et al., 2018; Pereira et al., 2018). This presents a novel opportunity for cities to implement advancing smart city technologies to achieve their sustainability goals. In this context, several researchers have investigated the role of smart city technologies in enabling sustainable urban development, usually referred to as smart and sustainable cities (Bibri and Krogstie, 2018; Fakhimi et al., 2021; Maksimovic, 2017; Bibri and Krogstie, 2018; Nitoslawski et al., 2019). However, every city is a complex system of interdependent physical, social, economic, and environmental components such as housing, retail, transportation networks, waste and water infrastructure, and the natural environment. As the management of each component requires a targeted, need-based approach, the scope of this dissertation study is limited to the green spaces existing within cities.

1.1.1 Urban green spaces

The World Health Organization (2017) defines the Urban Green Spaces (UGS) as "Public or private land within city covered by vegetation of any kind irrespective of its size and function". UGS are a crucial part of cities as they support a large number of functions (Building and Nuclear Safety (BMUB), 2018). They are distinguished for their many advantages to city residents and the environment. Studies have shown their essential role in protecting and enhancing local biodiversity (Aronson et al., 2017), carbon sequestration (Ariluoma et al., 2021), increased water retention (Alexander et al., 2019), improved social cohesion (Wan et al., 2021), and boosting physical and mental well-being (Kondo et al., 2018). During the recent COVID-19 pandemic, Geng et al. (2021) clearly noted a significant increase in the utilization of UGS, reaching up to 350%. These UGS not only assisted individuals in adapting to stringent lockdown measures but also served as a natural means to ensure sufficient social distancing. Moreover, they provide indirect benefits such as livelihood (Knuth, 2006), aesthetic joy (Sabbion, 2018), and an increase in property and land values (Crompton, 2001). Accordingly, high-quality and sufficient green spaces are significant components for achieving sustainable, livable, resilient, and viable cities.

Considering the significant advantages offered by UGS, the UN SDG goal related to cities established target 11.7 with the aim of ensuring "universal access to safe, inclusive and accessible, green and public spaces for everyone" (United Nations, 2020). Additionally, the World Health Organization (WHO) advocates for the provision of "access to at least 0.5-1 ha of green space within 300 meters' linear distance" to all urban residents (World Health Organization, 2017). Moreover, several German federal ministries collaborated in 2015 and integrated UGS into sustainable urban planning (Building and Nuclear Safety (BMUB), 2018). Similarly, the Convention on Biological Diversity (CBD) in Germany has also suggested a goal to offer "publicly accessible UGS with a variety of qualities and functions within walking distance of every urban household" (Federal Ministry for the Environment, 2007). These policies reflect the growing importance of preserving and improving UGS. Consequently, the conservation of UGS is of paramount interest for city administrators. Moreover, a city should aim for a tree distribution that spreads over different ages and diverse species to ensure its healthy survival over longer periods. It is essential to emphasize that, since trees reap substantially higher benefits as they mature, it is significantly vital to preserve existing vegetation rather than greening newer areas (Barrell, 2017; O'Neil-Dunne and Safavi, 2020). Accordingly, UGS should be planned, designed, and evaluated incorporating local needs to maximize the benefits for city residents.

1.1.2 Challenges in UGS management

Despite clearly acknowledging its importance, UGS programs often lack the required post-planting maintenance and management support. The shortage of staff, inadequate funding, and lack of expertise largely contribute to this inefficacy (Haaland and van den Bosch, 2015; Feltynowski et al., 2018). Additionally, city managers struggle to find the right balance between conflicting objectives and making decisions to maximize possible gains. For instance, many cities experience stress between a desire for more UGS and the increased use of limited water to maintain them. Similarly, in cities, grass lawns are regularly mowed, trees and shrubs pruned, and non-native plant species introduced to meet the aesthetic and safety requirements of the city's residents. In 2016, the Parks department of Berlin cut off 14 large trees, citing them as being 'improper street trees' and 'wild trees that threatened pedestrian safety' (Springer, 2019). In contrast, wild grass and native trees are considered essential for preserving biodiversity. When transformed into meadows, lawns comprise diverse plant species and provide habitat for a large number of birds, insects, and animals (Aronson et al., 2017). Moreover, currently, the decision to cut down a tree is based on forest tree models that unduly prioritize timber production over other ecosystem services, resulting in a 75% loss of potential ecosystem benefits (Barrell, 2017).

Furthermore, existing management practices rely on limited field observations, physical inspections, and individual experience. Due to the absence of real-time data, many planning decisions are made without considering field conditions. Thus, not only is management carried out in a subjective manner, but it is also restricted to formal UGS covered under statutory authority. Overall, the existing practice is highly cost-intensive, has a limited spatial and temporal scale, and provides insufficient decision support to administrators. As a result, efficient and effective management of UGS is an enormous challenge for municipalities.

1.1.3 Smart and sustainable cities context

The current urban management scenario can be significantly transformed through the adoption of smart city technologies, which enable the recording and analysis of real-time data. For example, under a smart initiative in Barcelona, the city administration installed a network of environmental sensors to monitor temperature, humidity, pressure, wind, and rainfall in various parks. This sensor data is further used to control electro-valves to deliver the required water for the city parks (Adler, 2016). The implementation of this process enabled the city to reduce its water consumption by 25%, resulting in approximately 500,000 Euros in annual savings, due to the reduced expenses associated with importing water via ships. Similarly, the national-level environmental institute of the Netherlands has created a nationwide map of the coverage and height of all vegetation. Subsequently, this public dataset is combined with an open-source OpenStreetMap (OSM) dataset to quantify the average greenness per street and neighborhood level (Steinberg, 2020). In another example, a tree canopy assessment done for Boston, USA, revealed the scarcity of tree coverage in high-density urban areas, followed by an increased urban heat island effect (O'Neil-Dunne and Safavi, 2020). Likewise, real-time information about tree counting can be obtained using computer vision on satellite images and the proportion of vegetation from the Google Street view images (Liu et al., 2023). Thus, informed decisions can be made by analyzing varied data sources generated through smart and innovative technologies, leading to a better and greener city. In summary, evidence obtained through data and science is critical for government agencies to make informed decisions in advance.

1.2 Research approach

As previously mentioned, preserving existing UGS holds greater significance than planting new trees in order to maximize the benefits of ecosystem services. Moreover, similar to industrial sectors, cities also frequently encounter the dilemma of distributing resources when demand exceeds supply capacities. These constrained scenarios necessitate that decision-makers allocate resources to units in order of significance, requiring prioritization decision-making. Presently, such decisions often rely on subjective assessments or personal expertise. Consequently, there is a research gap for a structured approach to tackle resource allocation challenges. In the context of smart cities, data availability is constantly improving, enabling novel data-enabled approaches to decision-making. In this regard, an approach based on the utilitarian principle is developed to enhance UGS management. Therefore, the method prioritizes resource allocation to those existing UGS from which maximum benefits are derived while taking into account the associated input costs with the management of each unit.

Accordingly, the research methodology is divided into four parts. The first part quantifies the total management demand needed for sustaining the existing UGS. In the second part, the total benefits derived from each UGS unit are quantified as a score. Then, in the third part, a decision-making model is developed utilizing the quantified cost and benefit, available resources, and decision-makers' preferences for allocating resources based on prioritization. The final part addresses the data quality challenges in the existing tree inventory datasets, providing decision support to cities with limited or low-quality data. Four studies with a building block approach are undertaken to comprehensively achieve the research aim.

1.3 Research contributions

The research in this thesis presents a multi-dimensional approach for optimizing UGS management in resource-constrained environments, with a focus on maximizing social benefits. The major contributions of this research to the current state of knowledge are in developing four novel methodologies for UGS: (i) benefit estimation, (ii) demand estimation, (iii) decision-making, and (iv) a data quality framework.

First, as the integration between benefit estimation and decision-making was lacking, a novel GIS-based method was developed that quantifies the UGS benefits using public datasets and assigns a prioritization score using which management decisions could be made. This is critical because during resource-constrained scenarios, without knowing the most beneficial UGS, resource allocation could be sub-optimal, leading to reduced UGS benefits for city residents.

Second, the existing methods were not sufficient to quantify the irrigation demand of urban street trees at a weekly timescale that corresponds to current management practices. Therefore, a linear time series model was developed, utilizing soil water balance and the Water Use Classification of Landscape Species (WUCOLS) approach, to estimate weekly irrigation demand for UGS. Leveraging publicly available data on trees, soil, and weather forecasts, this model provides decision-makers with valuable insights for assessing irrigation demand for existing trees and budgeting water for new plantations. This is valuable because by incorporating field data and conditions, the appropriate amount of irrigation water could be supplied, helping the city conserve water as well as prevent trees from deteriorating due to under or over watering.

Third, to address resource constraints effectively, a Goal Programming (GP) based model was formulated to prioritize UGS. This is critical because making decisions solely based on attainable benefits and without incorporating the associated management need of each UGS, the allocation of resources could be inefficient. Moreover, the allocation was analyzed considering district and sub-district scales to investigate different management conditions. Through this approach, the research demonstrated a significant increase in total benefits compared to baseline scenarios.

Additionally, a quality assessment and enhancement framework, based on total quality management principles, was developed to evaluate the quality of existing tree inventory datasets. Furthermore, a data enhancement approach was demonstrated by filling missing tree height values using Simple Linear Regression (SLR), Multiple Linear Regression (MLR), and Random Forest (RF)-based regression models. This enables cities with limited data to evaluate the suitability of their datasets for application models and provides a structured process to enhance their quality by imputing missing data using machine-learning methods. The impact of missing data on decision-making applications, such as estimating water demand and carbon sequestration potential, was also assessed.

Therefore, by introducing the concept of prioritization in UGS decision-making processes, the study enables decision-makers to make informed decisions. Collectively, these findings contribute to the advancement of UGS management strategies, providing decision-makers with practical tools and methodologies to optimize resource allocation and maximize green space benefits in urban environments.

1.4 Thesis outline

This thesis consists of ten chapters. The summary of the outline is described below:

In Chapter 2, a detailed review of the literature describing the benefits of UGS, management needs of UGS, and the current state of available tools, technologies, and frameworks for UGS management is presented. Chapter 3 introduces the research question and outlines the aims and objectives aimed at addressing it. In Chapter 4, the overall methodological approach and framework for the thesis are presented. It also describes the interlinks between different research objectives and their methodologies. Chapters 5 to 8 each cover the detailed methodological approach taken to address each of the research objectives, respectively.

In Chapter 5, a linear time-series based approach is developed for estimating the irrigation water demand of street trees on a weekly time scale. In Chapter 6, a benefit quantification model for UGS is developed, consisting of accessibility and quality criteria, and is subsequently used for prioritization decision-making. In Chapter 7, a GP based Multi-Criteria Decision-Making (MCDM) model is developed that integrates quantified demands and benefits and prioritizes UGS under resource constraint scenarios. Then, in Chapter 8, a quality assessment framework is proposed for ascertaining and enhancing the quality of public UGS data for decision-making in cities with limited data.

In Chapter 9, the overall results regarding the proposed research questions, comparison to the existing status quo, application, and implications of the key findings for research, policy, and decision-makers, as well as limitations of the work, are discussed. Finally, Chapter 10 describes the key findings and conclusions of this thesis and provides an outlook and suggestions for future research.

Bibliography

Adler, L. (2016). How smart city barcelona brought the internet of things to life.

Alexander, K., Hettiarachchi, S., Ou, Y., and Sharma, A. (2019). Can integrated green spaces and storage facilities absorb the increased risk of flooding due to climate change in developed urban environments? *Journal of Hydrology*, 579:124201.

Ariluoma, M., Ottelin, J., Hautamäki, R., Tuhkanen, E.-M., and Mänttäri, M. (2021). Carbon sequestration and storage potential of urban green in residential yards: A case study from helsinki. *Urban Forestry & Urban Greening*, 57:126939.

Aronson, M. F., Lepczyk, C. A., Evans, K. L., Goddard, M. A., Lerman, S. B., MacIvor, J. S., Nilon, C. H., and Vargo, T. (2017). Biodiversity in the city: key challenges for urban green space management. *Frontiers in Ecology and the Environment*, 15(4):189–196.

Barrell, J. (2017). Tree benefits; the missing part of the street tree cost benefit analysis equation.

Bibri, S. E. (2018). A foundational framework for smart sustainable city development: Theoretical, disciplinary, and discursive dimensions and their synergies. *Sustainable Cities and Society*, 38(December 2017):758–794.

Bibri, S. E. and Krogstie, J. (2017). Smart sustainable cities of the future: An extensive interdisciplinary literature review. *Sustainable Cities and Society*, 31(March):183–212.

Bibri, S. E. and Krogstie, J. (2018). The big data deluge for transforming the knowledge of smart sustainable cities: A data mining framework for urban analytics. In *Proceedings of the 3rd International Conference on Smart City Applications*, SCA '18, New York, NY, USA. Association for Computing Machinery.

Building and Nuclear Safety (BMUB) (2018). White paper: Green spaces in the city.

Cabrera, L. T. B. and Woda, A. M. (2018). How smart are smart cities?: How can big data influence the planning of sustainable urban mobility? *Digitala Vetenskapliga Arkivet.*

Chui, K. T., Lytras, M. D., and Visvizi, A. (2018). Energy sustainability in smart cities: Artificial intelligence, smart monitoring, and optimization of energy consumption. *Energies*, 11(11):1–20.

Cohen, B. (2006). Urbanization in developing countries: Current trends, future projections, and key challenges for sustainability. *Technology in Society*, 28(1):63–80. Sustainable Cities.

Concilio, G., Li, C., Rausell, P., and Tosoni, I. (2019). *Cities as Enablers of Innovation*, pages 43–60. Springer International Publishing, Cham.

Crompton, J. L. (2001). The impact of parks on property values: A review of the empirical evidence. *Journal of Leisure Research*, 33(1):1–31.

Duranton, G. (2015). Growing through cities in developing countries. *The World Bank Research Observer*, 30(1):39–73.

Fakhimi, A. H., Khani, A. H., and Sardroud, J. M. (2021). 2 - smart-city infrastructure components. In Vacca, J. R., editor, *Solving Urban Infrastructure Problems Using Smart City Technologies*, pages 17–54. Elsevier.

Federal Ministry for the Environment (2007). National strategy on biological diversity.

Feltynowski, M., Kronenberg, J., Bergier, T., Kabisch, N., Łaszkiewicz, E., and Strohbach, M. W. (2018). Challenges of urban green space management in the face of using inadequate data. *Urban Forestry & Urban Greening*, 31:56–66.

Gascó-Hernandez, M. (2018). Building a smart city: lessons from barcelona. *Commun. ACM*, 61(4):50–57.

Geng, D. C., Innes, J., Wu, W., and Wang, G. (2021). Impacts of COVID-19 pandemic on urban park visitation: a global analysis. *Journal of Forestry Research*, 32(2):553–567.

Haaland, C. and van den Bosch, C. K. (2015). Challenges and strategies for urban green-space planning in cities undergoing densification: A review. *Urban Forestry & Urban Greening*, 14(4):760–771.

Hoornweg, D. (2010). Cities and climate change: An urgent agenda. *World Bank*.

Knuth, L. (2006). Greening cities for improving urban livelihoods. *Rome, FAO*.

Kondo, M. C., Fluehr, J. M., McKeon, T., and Branas, C. C. (2018). Urban green space and its impact on human health. *International Journal of Environmental Research and Public Health*, 15(3).

Liu, D., Jiang, Y., Wang, R., and Lu, Y. (2023). Establishing a citywide street tree inventory with street view images and computer vision techniques. *Computers, Environment and Urban Systems*, 100:101924.

Liu, L. (2018). IoT and a sustainable city. *Energy Procedia*, 153:342–346.

Maksimovic, M. (2017). The Role of Green Internet of Things (G-IoT) and Big Data in Making Cities Smarter, Safer and More Sustainable. *International Journal of Computing and Digital Systemss*, 6(4):175–184.

Nitoslawski, S. A., Galle, N. J., van den Bosc, C. K., and Steenberg, J. W. (2019). Smarter ecosystems for smarter cities? A review of trends, technologies, and turning points for smart urban forestry. *Sustainable Cities and Society*, 51(August).

O'Neil-Dunne, J. and Safavi, N. (2020). Tree Canopy Assessment for Boston, MA. Technical report, Boston Parks and Recreation Department.

Pereira, G. V., Parycek, P., Falco, E., and Kleinhans, R. (2018). Smart governance in the context of smart cities: A literature review. *Information polity*, 23:143–162.

Rashed, A. H. (2023). The impacts of unsustainable urbanization on the environment. In Almusaed, A. and Almssad, A., editors, *Sustainable Regional Planning*, chapter 6. IntechOpen, Rijeka.

Sabbion, P. (2018). Chapter 4.3 - green streets social and aesthetic aspects. In Pérez, G. and Perini, K., editors, *Nature Based Strategies for Urban and Building Sustainability*, pages 283–290. Butterworth-Heinemann.

Silva, B. N., Khan, M., and Han, K. (2018). Towards sustainable smart cities: A review of trends, architectures, components, and open challenges in smart cities. *Sustainable Cities and Society*, 38:697–713.

Springer, A.-S. (2019). *The word for world is still forest.* K. Verlag.

Steinberg, L. (2020). Quantifying urban greenness in the netherlands.

Thebo, A., Drechsel, P., and Lambin, E. (2014). Global assessment of urban and peri-urban agriculture: irrigated and rainfed croplands. *Environmental research letters*, 9:114002–114002.

United Nations (2018). 2018 revision of world urbanization prospects.

United Nations (2020). Goal 11.

Wan, C., Shen, G. Q., and Choi, S. (2021). Underlying relationships between public urban green spaces and social cohesion: A systematic literature review. *City, Culture and Society*, 24:100383.

Wang, H., He, Q., Liu, X., Zhuang, Y., and Hong, S. (2012). Global urbanization research from 1991 to 2009: A systematic research review. *Landscape and Urban Planning*, 104(3):299–309.

World Health Organization (2017). Urban green spaces: A brief for action. *Regional Office For Europe*, page 24.

Zang, S., Wu, C., Liu, H., and Na, X. (2010). Impact of urbanization on natural ecosystem service values: a comparative study. *Environmental Monitoring and Assessment*, 179:575–588.

Zhong, C., Guo, H., Swan, I., Gao, P., Yao, Q., and Li, H. (2023). Evaluating trends, profits, and risks of global cities in recent urban expansion for advancing sustainable development. *Habitat International*, 138:102869.

Chapter 2

State of the art and practice

The present thesis focuses on improving prioritization decision-making in UGS management. The conceptualization of the thesis is based on the utilitarian principle, aiming to maximize benefits for users (in this case, city residents) with available resources. Therefore, it is necessary to understand the current state of knowledge in three aspects. First, identifying the varied benefits provided by UGS to the city is essential to understand which parameters should be considered while prioritizing UGS to maximize the benefits obtained from them. Second, identifying the management needs that must be fulfilled for the sustenance of UGS is crucial to determine if the city has sufficient resources to manage its UGS. Third, identifying the existing tools and frameworks available for UGS management is significant for making prioritization decisions regarding resource allocation to UGS during future constrained scenarios.

2.1 Benefits of UGS

Whether in parks, along streets, or in any other form, UGS provide multifaceted benefits, ranging from environmental, social, and economic aspects. An extensive literature review is presented in the subsequent paragraphs, summarising the available scientific evidence regarding the benefits derived from UGS.

2.1.1 Environmental benefits

The natural habitat of flora and fauna is destroyed as cities continue to expand. This was highlighted in a study on Australia, where plant species in cities were found to be significantly more threatened than comparable non-urban areas (Ives et al., 2016). Moreover, Aronson et al. (2017) also found the species density to be lower in urban than in non-urban areas. UGS could reduce this distress by providing a secure environment for indigenous animals and plants. A study conducted in Melbourne, Australia, observed an increase of 30-120% in occupancy of birds and insects when under-storey cover and native vegetation were increased from 10% to 30%, supporting the case for the positive impact of UGS on biodiversity Threlfall et al. (2017). While the positive role of UGS in conserving biodiversity is evident from the literature, its role in enhancing biodiversity is uncertain.

Cities experience the phenomenon of the urban heat island effect, where the temperature inside cities is usually higher than its surrounding (Bolund and Hunhammar, 1999). This effect is primarily associated with an interaction between solar radiation and a large number of heat-absorbing surfaces present on buildings and roads. The absorbed heat is later released back to the environment, causing the temperature to rise. A study conducted in a city in Northern Greece observed a higher temperature by up to 4-5°C during summer, resulting in increased energy needs for surrounding buildings (Dimoudi et al., 2013). UGS can possibly lower this effect by blocking the incoming solar radiation from directly striking the surfaces. In addition to that, a part of the solar energy is lost in vaporising the water transpired from trees. This further reduces the heat energy available to increase the air temperature. A study on small UGS found a reduction of air temperature between 1.0-3.5°C depending on the size and structure of space (Park et al., 2017). Another study observed the highest reduction of 1-2°C for large parks, which were greater than 10ha in size (Aram et al., 2019). (Reis and Lopes, 2019) calculated the total cooling potential of UGS in Lisbon, Portugal and concluded that an area of $50m^2$ vegetation could reduce the air temperature by 1°C. However, further research is required on the impact of different categories of UGS such as street trees, parks, and rooftops on the cooling potential.

Cities usually observe higher levels of air pollutants like carbon monoxide and nitrogen oxides because of their traffic, industries, and power plants (Mayer, 1999). The airflow that passes through trees undergoes a dry deposition process wherein the particulate matter (PM) from the air gets deposited on the tree surface. As a result, the atmospheric concentration of PM reduces. Studies have shown that higher trees and shrub coverage in a city reduce the amount of pollutants and improve the air quality (Nowak et al., 2006; Moradpour and Hosseini, 2020). Trees restoration was also identified as a more cost-effective solution in abating ground-level O_3 and NO_2 pollution compared to other conventional technological options by Kroeger et al. (2014).

Noise pollution is another issue where UGS are found to have a positive impact. Vegetation belts can absorb, deflect, refract, and mask the sound waves and thus be an effective barrier against noise from high-traffic roads. In a study done by Tyagi et al. (2013) on three cities of India, an average noise attenuation of 15-20dB was observed depending on the frequency. Similarly, Ow and Ghosh (2017) reported an average reduction of 9-11dB in traffic noise due to roadside trees and suggested a minimum of 5m as the depth of an effective barrier. The analysis further identified that the presence of shrubs nearly as tall as a car along with a few large trees had the highest effect. Additionally, trees also reduce the chance of flooding by intercepting a portion of rainwater and through increased infiltration occurring in the root zone.

2.1.2 Social benefits

The positive effect of UGS on human health is well-investigated. An early study conducted on patients undergoing surgeries between 1972-1981 at a suburban hospital in Pennsylvania found that assigning a room with a sight of a natural scene accelerated the recovery time, reduced the need for pain medications, and improved satisfaction (Ulrich, 1984). Nutsford et al. (2013) confirmed the lesser need for anxiety and mood disorder treatments in residents within a 3km distance of UGS. The use of public parks and playgrounds as a recreation choice can also alleviate physical and mental stress. This would be especially important for low-income communities which cannot afford other paid means of recreation. Tamosiunas et al. (2014) also highlighted the importance of parks to promote a healthy lifestyle and minimize health risks among the public. Although park users were found to have lower health risks, obesity, and prevalence of diabetes compared to non-park users, no statistically significant association between access or presence of UGS and cardiovascular risk factors was observed. Therefore, closer access to the parks might help encourage higher physical activity among the citizens.

Apart from recreation and physical fitness, UGS offer an opportunity for social connectivity. The residents get a chance to meet and interact with people of different ages, cultures, and economic classes. It creates a possibility to participate in various public events. Overall, this improves social cohesion among the city community. However, a study by Bertram and Rehdanz (2015) highlights a limit on the benefits that can be derived. It focused on the marginal utility of UGS and found a non-linear, inverted U-shape effect on human well-being. This indicates that life satisfaction among urban residents, although initially increases with an increase in UGS, then decreases, possibly due to lack of sufficient infrastructure facilities. The findings suggested 36ha or 11.5% as the optimal UGS within the 1km buffer area.

2.1.3 Economic benefits

UGS provides an excellent opportunity for eco-tourism, creating synergy between 'preserving the environment' and 'supporting the local economy'. Besides tourism, the construction and maintenance of UGS and the allied infrastructure also provide direct and indirect employment. The land and housing properties adjacent to green areas usually witness higher appreciation in their value than other areas. A study by the Urban Land Institute on American real estate projects also noted an increase in profits when greenscape and landscaping were integrated into development (Urban Land Institute, 1996). Similarly, the National Association of Home Builders estimated that schemes with trees sold on average 20-30% higher than those without trees. A survey conducted by them revealed that 77% of consumers considered natural open space as an essential feature for their new home (National Association of Home Builders, 1996). Therefore, an increased willingness to pay for housing is noticeable. On the contrary, increased housing prices commonly lead to gentrification, wherein local inhabitants are replaced by wealthier people getting attracted to the respective area.

As described earlier, higher temperatures in cities eventually lead to higher building energy consumption, especially for cooling in summers. Urban green, through its cooling effect, can contribute to lowering this energy demand. Zhang et al. (2012) calculated the savings in indoor air cooling demand at 60% due to 16,577 ha of UGS in Beijing, China. This not only resulted in substantial economic savings but also saved 243 thousand tons of CO_2 emissions going into the environment. Moreover, lower temperatures also increase labor productivity and reduce sickness caused by the hot climate.

2.1.4 Summary of UGS benefits

Various studies discussed in preceding sections covering the UGS benefit aspects are summarized in Table 2.1. The summary of key findings and their implications from this literature review are summarized in Table 2.2.

Table 2.1: Summary of studies investigating benefits of UGS.

	Benefit	Literature	Key Point of Literature
Environmental	Less air pollution	Mayer (1999), Nowak et al. (2006), Moradpour and Hosseini (2020)	Significant removal of O3, SO2, and PM10; urban greens contribute to air purification in cities
	Biodiversity	Lin and Fuller (2013), Ives et al. (2016), Threlfall et al. (2017), Aronson et al. (2017)	Support regional biodiversity and threatened species
	Noise reduction	González-Oreja et al. (2010), Tyagi et al. (2013), Dzhambov and Dimitrova (2015), Ow and Ghosh (2017)	Vegetation belts reduce noise level; UGS reduce noise sensitivity
	Temperature reduction	Oke (1973), Bolund and Hunhammar (1999), Dimoudi et al. (2013), Park et al. (2017), Aram et al. (2019)	Help reduce urban heat island effect and urban temperature
	Soil	De Baets et al. (2006), Francini et al. (2018), Mills et al. (2020)	Vegetated soil reduces flooding risk and hosts diverse microbiota
Economic	Energy Savings	Zhang et al. (2014), Kong et al. (2016)	Mitigates heat island effect; reduces cooling energy
	Water runoff	Xiao et al. (2000), Pataki et al. (2011), Song et al. (2017)	Trees and soil reduce rainwater runoff
	Property Value	McMahon (1996), Camargo (2016), Liebelt et al. (2019)	Positive relationship between distance to UGS and house prices
Social	Recreation and Wellbeing	Maas et al. (2006), Bertram and Rehdanz (2015), Madureira et al. (2015)	Positive impact on life satisfaction; depends on size and distance
	Human Health	Ulrich (1984), Takano et al. (2002), Nutsford et al. (2013), Tamosiunas et al. (2014)	Active users have better health; less air pollution and noise
	Tourism and Employment	Gibson et al. (2003), Ties (2016)	Attracts urban ecotourism; enhances social interaction

Table 2.2: Summary of key findings and implications from the review of UGS benefits.

No.	Finding	Implication
1	Benefits obtained from a particular UGS depend on several characteristics such as size, type, age, species, species diversity, aesthetics, and local needs.	A city needs all types of UGS due to the heterogeneous features and functioning of different UGS.
2	Native tree species are an extremely important part.	It is essential to prioritize native species over non-native.
3	Trade-offs between benefits are inevitable in certain cases.	Decision-makers need to select the priority benefit criteria considering the city's needs.

2.2 Management demands of UGS

In the second part of the literature review, the focus is on ascertaining the management demands of UGS. The management of UGS is a complex and expensive process that encounters several challenges. First of all, the management of UGS involves multiple stakeholders with different roles and responsibilities. For instance, the gardening division takes care of parks and lawns, whereas the forestry division manages urban forests. In some cities, the road authority is responsible for managing street trees. Moreover, the water department controls the irrigation plans, and the waste department handles the cleaning of foliage. Baycan-Levent and Nijkamp (2009), in their study on European cities, observed that cities where an integrated approach is followed for UGS planning and management perform better than those with distributed responsibilities among multiple administrations. Despite that, most cities lack central coordination at the city scale, leading to a fragmented approach towards managing UGS (Feltynowski et al., 2018).

As highlighted in the preceding section, UGS provide numerous benefits. As a result, decision-makers struggle with making management decisions considering the trade-offs between environmental, economic, social, and cultural factors (Mwendwa and Giliba, 2012). Therefore, the second key challenge in UGS management is to balance the disparity between ecological requirements and the aspirations of city residents (Aronson et al., 2017). Threlfall et al. (2016) observed that green spaces in Melbourne, Australia, preserved in their native vegetation structure, exhibited a higher diversity of birds and bats. Nevertheless, native species are often cut down and replaced with alternatives that better suit the expectations. Politi Bertoncini et al. (2012) also observed this in a study on Paris, France, where natural lawns exhibited significantly higher biodiversity than pesticide-treated lawns. This was further highlighted in a study by Aronson et al. (2017), which ascertained that high biodiversity areas such as Remnant were correlated with limited human use. This highlights the trade-offs often encountered while addressing the varied needs of the city population and the natural environment.

Another challenge involves minimizing the unintended consequences of UGS. This includes an increase in the prices of nearby housing property, making them unaffordable, forcing the low-income community to migrate, referred to as gentrification (Wolch et al., 2014). Furthermore, inefficient management practices could instead have a counterproductive effect on climate change mitigation. For example, managing ornamental lawns by means of fertilizer and mowing can emit up to four times more carbon than is stored in them (Kumari et al., 2022). UGS could also potentially intensify water stress in cities because of irrigation, if applied, or because of their consumption of groundwater. Nouri et al. (2019), in their study on the City of Adelaide, found that UGS depend between 49% (in October) to 67% (in March) on blue water resources for their consumption. Considering this, World Health Organization (2017) highlighted the need for multidimensional evaluation of UGS interventions to help municipalities make evidence-based decisions. Lastly, in order to fulfill regulatory requirements, local governments are constrained to select the lowest bidder for managing UGS. In many cases, this encourages the contractor to replace larger trees, which have higher maintenance costs, with smaller tree species. It is crucial to emphasize here that trees older than 50 years produce substantially higher ecosystem benefits than younger trees (Barrell, 2017). Figure 2.1 demonstrates the benefit curve principle for an exemplary tree. Therefore, while the majority of the benefits are received from a tree after the age of 25, less than 50% of urban trees survive more than 10 years (Roman and Scatena, 2011; Hilbert et al., 2019).

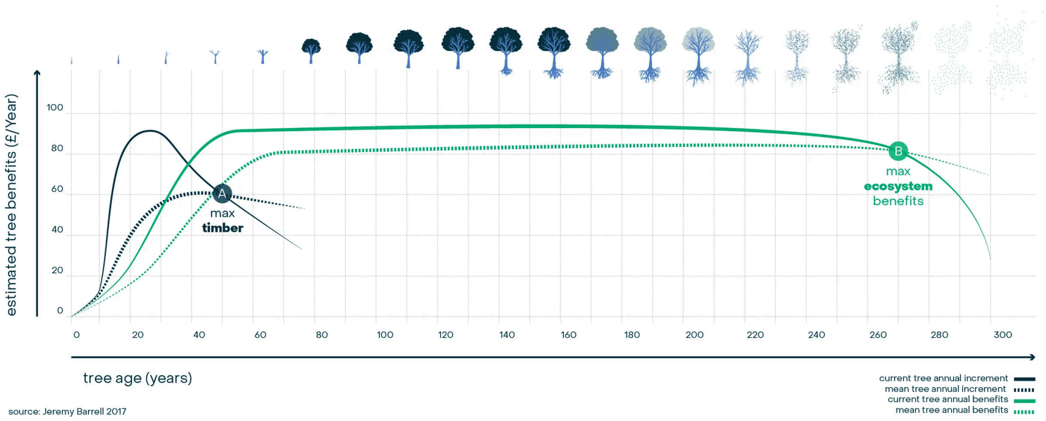


FIGURE 2.1: Estimated tree ecosystem service benefits (GBP/year) over the life of an exemplary tree. (Source: Barrell (2017), Image Courtesy: Dark Matter (2020))

2.2.1 Summary of management demands

The key findings and their implications from this literature review are summarized in Table 2.3.

TABLE 2.3: Summary of key findings and implications from the review of UGS management needs.

No.	Finding	Implication
1	A major portion of the ecosystem service benefits from a tree is received after the age of 30-50 years.	It is crucial to preserve existing tree species over greening newer areas.
2	Direct, indirect, and unintended impacts of UGS on city components.	There is a need for multidimensional evaluation of UGS interventions.
3	UGS management faces resource constraints and is expected to further exacerbate with climate change.	Decision-makers need to optimize resource allocation.

2.3 Available tools and frameworks for UGS management

In the third part[1] of the literature review, a study was conducted to identify the relevant tools, frameworks and guidelines currently available for monitoring, planning, and managing UGS. Numerous tools are available to estimate the benefits obtained from UGS and/or to estimate the management needs for UGS maintenance (Well and Ludwig, 2020). With the substantial number of tools, there are also various themes that the tools are somewhat connected with. Monitoring is an integral part of the management of UGS, and with the focus on the benefits of UGS to urban quality of life, aspects such as usage, experiences, and accessibility are also considered. In the following section, the reviewed tools are described in detail.

Collect Earth (FAO, 2021) is a satellite image viewing tool and interpretation system developed by SERVIR Global (NASA and USAID initiative) and FAO that enables users to analyze land use/land cover (LULC) change from high and very high resolution satellite imagery sourced from Google Earth and Bing Maps (Patterson, M. S. and Mccallum, Kimberly, 2022). Resource Watch is another such monitoring tool (WRI, 2022). However, it is a tool that operates at a macroscopic level. It features hundreds of datasets that help users visualize the state of the planet's resources and people. Similarly, The U.S. Community Protocol for Accounting and Reporting of Greenhouse Gas Emissions is also a potential resource for the monitoring of UGS (ICLEI – Local Governments for Sustainability USA, 2019). However, rather than directly aiding in the process of monitoring, it instead offers the advanced methodologies and the best practices to assist local governments in measuring and reporting area emissions. This tool is particularly useful to assess the effects of UGS in a localized region. Kommunaler Flächenrechner 2.0 is a national and regional tool for the depiction of current land use designation and for a top-down derivation of a communal land use budget to meet national goals (Gutsche and Grimski, 2021; Umwelt Bundesamt, 2021). Siedlungsflächenmonitoring NRW is a web-GIS tool that focuses on regional and communal land use monitoring and management by depicting land reserves per use categories in the land development plan and redesigned areas (ILS - Institut für Landes- und Stadtentwicklungsforschung, 2015). Mapping tools such as Treetect or remote sensing products are mapping UGS from satellite data, for example, via machine learning/neuronal nets; however, they do not yet quantify other parameters such as species type, canopy size, or leaf area, which are relevant for urban climate modeling (Green City Watch, 2020). Other monitoring tools also include Urban Tree Canopy Assessment, which can measure the extent of the tree canopy and help communities understand their total tree and forest resources and establish tree canopy goals as part of broader urban greening and sustainability initiatives (U. S. Department of Agriculture, 2019).

Various tools offer similar advisory utilities, such as the Green Infrastructure Toolkit (Georgetown Climate Center, 2016), which highlights the common approaches taken in cities across the world to integrate green infrastructure and spaces to manage storm-water

[1] This section is based on the following published journal article: Volk, Rebekka, **Rambhia, Mihir**, Naber, Elias and Schultmann, Frank. (2022). "Urban Resource Assessment, Management, and Planning Tools for Land, Ecosystems, Urban Climate, Water, and Materials—A Review". Sustainability 14, no. 12: 7203. https://doi.org/10.3390/su14127203.
The entire content of this particular section in the article (Section 3.2.1. Land Use, Surface Use, and Urban Green Tools) was contributed solely by the author. The published manuscript can be found in the appendix.

runoff, thus aiding local governments to compare and analyze the best-suited option according to their requirements. Tools can also have a more direct contribution to the planning of UGS, such as the Urban Forest Management Plan Toolkit by the Inland Urban Forest Council that outlines a structured plan for designing and implementing an urban forest management plan (Inland Urban Forest Council, 2016). Likewise, the Urban Forestry Toolkit also provides a step-by-step guide to planning and implementing an urban forestry project (U. S. Forest Service, 2021). On the other hand, tools such as i-Tree Eco are more user-driven in their approach (USDA Forest Service, 2024). i-Tree has five core tools that are used to analyze and assess urban and rural forestry. i-Tree Eco is their flagship tool, and it utilizes data collected in the field from either single trees, complete inventories, or randomly located plots to quantify forest structure, environmental effects, and the value to communities (USDA Forest Service, 2024). Healthy Trees, Healthy Cities also undertakes a similar user-driven approach, as it enables users to undertake the sampling and data collection process of individual trees to create an inventory of urban trees and their health indices (Nature Conservancy, 2016). Treeplotter (PlanIT Geo, 2021) is another tool that creates urban tree inventories and helps in the management of urban forests but is instead dependent on GIS for data rather than on the users. Tree Canopy (Google, 2021) analyzes aerial data together with other public data (e.g., 3D digital surface models and socio-economic data) to map a city's tree coverage, the average land surface temperature, and population density.

The collection of data from users can be an integral part of UGS management, and tools are not just capable of utilizing such data but can also organize community efforts. The Toolkit for Community Participation in Pocket Parks helps in the design, execution, and development of small-scale urban 'pocket parks' with the help of community participation (Trust for Public Land, 2020). The Stewardship Mapping and Assessment Project (STEW-MAP) by the USDA Forest Service is capable of studying how civic groups are working towards the fostering of stewardship in cities (USDA Forest Service, 2023). Upon the analysis of 28 criteria, The Community Assessment and Goal-Setting Tool can assess the community for the development and management of UGS (U. S. Forest Service, 2017). Such tools can be indispensable for administration and are designed to aid decision-makers. Social Values for Ecosystem Services (SolVES) is a tool that is capable of assessing, mapping, and quantifying the perceived social values of ecosystem services, thus helping administrators to make informed decisions while implementing UGS measures (Geosciences and Environmental Change Science Center, 2021). Likewise, the United Nations Development Programme's Learning for Nature initiative serves as a platform for encouraging collaboration between biodiversity policymakers, advocates, and experts in the field to advance biodiversity conservation efforts and support the attainment of the UN SDG (United Nations Development Programme, 2024). The tool GREEN-AREA is a commercial service that assesses the potentials of urban greening measures on building roofs and impervious soil surfaces (Klärle et al., 2017). The viewer-based service allows for georeferenced individual plot assessments of their technical potential and simplified greening impact for green roofs and unsealing ground (Universitätsstadt Marburg, 2015; Stadt Hanau Vermessungsamt, 2015).

The utility of tools for administrators in UGS is not limited to the domain of community management. WaterWorld and Co$ting Nature are two analysis tools to explore ecosystem services using spatial data as well as models of biophysical and social systems. Co$ting Nature can help cities understand the value of forests at multiple scales since users can try alternative scenarios based on different policy options (Mulligan, 2015). Similarly, Global Forest Watch can analyze forests and forest trends, which can be useful in realizing appropriate conditions for maintaining UGS (WRI, 2014). Restoration Opportunities Assessment Methodology (ROAM) (Maginnis et al., 2014) can also be used as a reference for the development of UGS, as it provides a framework for building a forest restoration program from the ground up.

Particular tools can also assist in the integration of UGS into urban settings. Complete Streets is a global transportation design and policy approach that ensures safer, convenient, and accessible transport and fosters the introduction of trees on urban streets, thereby contributing to the growth of UGS (Smart Growth America and National Complete Streets Coalition, 2023). InVEST (Integrated Valuation of Ecosystem Services and Tradeoffs), developed by the Stanford University National Capital Project, helps map and quantify the natural resources and services that sustain human life and ecosystem health (Natural Capital Project, 2019). The Atlas serves as an additional resource, empowering decision-makers through an online community designed for local government leaders. It facilitates the exploration of case studies, enables the tracking of relevant topics, and encourages the sharing and exchange of ideas and advice through crowdsourcing (The Atlas, 2024). The Review of Municipal Codes and Ordinances Worksheet assists in evaluating the environmental impact of policies and regulations by recommending suitable tree coverage that is optimized, taking into account factors such as public safety, visibility, accessibility, and economic significance (Center for Watershed Protection, 2018).

Finally, MeinGrün App is a web-based tool available for the German cities Heidelberg and Dresden that helps citizens find UGS with particular points of interest and furnishings or that are most suitable for leisure (Leibniz-Institut für ökologische Raumentwicklung, 2021). It includes multiple characteristics such as grass, trees, water, animals, slope, size, shade, quietness, fitness equipment, sport facilities, benches, or waste bins.

2.3.1 Summary of UGS management tools

It is essential to understand the design requirements of UGS to ensure the maximization of health, social, and environmental benefits. In summary, a total of 35 tools and frameworks were identified that address different aspects of UGS management. This includes models that can quantify benefits from UGS and monitor and manage certain activities of UGS management. Some models solely quantify the varied benefits from UGS. Moreover, few tools address the requirements of UGS management, but most focus only on part of the problems. However, there is limited research on integrating these benefits with urban planning and management. Some ongoing research projects also aim to solve this challenge. For instance, under a European Union-funded research project, Life UrbanGreen, research partners are developing a platform, R3Trees, intended to make UGS management efficient and responsible (R3 GIS, 2018). Nevertheless, tools that integrate the assessed benefits with the planning and management activities are not available. As a result, an integrated approach towards holistic management is largely missing. This highlights the need for further research on integrating the outcomes of benefit analysis with management decisions.

Bibliography

Aram, F., Higueras García, E., Solgi, E., and Mansournia, S. (2019). Urban green space cooling effect in cities.

Aronson, M. F., Lepczyk, C. A., Evans, K. L., Goddard, M. A., Lerman, S. B., MacIvor, J. S., Nilon, C. H., and Vargo, T. (2017). Biodiversity in the city: key challenges for urban green space management. *Frontiers in Ecology and the Environment*, 15(4):189–196.

Barrell, J. (2017). Tree benefits; the missing part of the street tree cost benefit analysis equation.

Baycan-Levent, T. and Nijkamp, P. (2009). Planning and management of urban green spaces in europe: Comparative analysis. *Journal of urban planning and development*, 135:1–12.

Bertram, C. and Rehdanz, K. (2015). The role of urban green space for human well-being. *Ecological Economics*, 120:139–152.

Bolund, P. and Hunhammar, S. (1999). Ecosystem services in urban areas. *Ecological Economics*, 29(2):293–301.

Camargo, R. (2016). The effects of urban green spaces on house prices.

Center for Watershed Protection (2018). Making your community forest-friendly: A worksheet for review of municipal codes and ordinances.

Dark Matter (2020). Trees as infrastructure - dark matter laboratories.

De Baets, S., Poesen, J., Gyssels, G., and Knapen, A. (2006). Effects of grass roots on the erodibility of topsoils during concentrated flow. *Geomorphology*, 76(1-2):54–67.

Dimoudi, A., Kantzioura, A., Zoras, S., Pallas, C., and Kosmopoulos, P. (2013). Investigation of urban microclimate parameters in an urban center. *Energy and Buildings*, 64:1–9.

Dzhambov, A. M. and Dimitrova, D. D. (2015). Green spaces and environmental noise perception. *Urban Forestry and Urban Greening*, 14(4):1000–1008.

FAO (2021). Collect earth online home - collect earth online.

Feltynowski, M., Kronenberg, J., Bergier, T., Kabisch, N., Łaszkiewicz, E., and Strohbach, M. W. (2018). Challenges of urban green space management in the face of using inadequate data. *Urban Forestry & Urban Greening*, 31:56–66.

Francini, G., Hui, N., Jumpponen, A., Kotze, D. J., Romantschuk, M., Allen, J. A., and Setälä, H. (2018). Soil biota in boreal urban greenspace: Responses to plant type and age. *Soil Biology and Biochemistry*, 118:145–155.

Georgetown Climate Center (2016). Green infrastructure toolkit.

Geosciences and Environmental Change Science Center (2021). Social values for ecosystem services (solves) 4.1.

Gibson, A., Dodds, R., Joppe, M., and Jamieson, B. (2003). Ecotourism in the city? Toronto's Green Tourism Association. *International Journal of Contemporary Hospitality Management*, 15(6):324–327.

González-Oreja, J. A., Bonache-Regidor, C., and De La Fuente-Díaz-Ordaz, A. A. (2010). Far from the noisy world? Modelling the relationships between park size, tree cover and noise levels in urban green spaces of the city of Puebla, Mexico. *Interciencia*, 35(7):486–492.

Google (2021). Tree canopy lab.

Green City Watch (2020). Treetect.

Gutsche, J.-M. and Grimski, D. (2021). Mit mengenbegrenzungen die flächenneuinanspruchnahme planen: Flächenrechner 2.0. In *Flächennutzungsmonitoring XIII: Flächenpolitik - Konzepte - Analysen - Tools*, volume 79 of *IÖR Schriften*, pages 257–264. Rhombos-Verlag, Berlin.

Hilbert, D. R., Roman, L. A., Koeser, A. K., Vogt, J., and van Doorn, N. S. (2019). Urban tree mortality: A literature review. *Arboriculture & Urban Forestry (AUF)*, 45(5):167–200.

ICLEI – Local Governments for Sustainability USA (2019). U.s. community protocol for accounting and reporting of greenhouse gas emissions.

ILS - Institut für Landes- und Stadtentwicklungsforschung (2015). Siedlungsflächenmonitoring nordrhein-westfalen.

Inland Urban Forest Council (2016). Urban forest management plan toolkit.

Ives, C. D., Lentini, P. E., Threlfall, C. G., Ikin, K., Shanahan, D. F., Garrard, G. E., Bekessy, S. A., Fuller, R. A., Mumaw, L., Rayner, L., Rowe, R., Valentine, L. E., and Kendal, D. (2016). Cities are hotspots for threatened species. *Global Ecology and Biogeography*, 25(1):117–126.

Klärle, M., Langendörfer, U., Lanig, S., and Popp, F. (2017). Green-area – intelligentes gründachkataster auf der basis von gis-daten. *ZfV - Zeitschrift für Geodäsie, Geoinformation und Landmanagement*.

Kong, F., Sun, C., Liu, F., Yin, H., Jiang, F., Pu, Y., Cavan, G., Skelhorn, C., Middel, A., and Dronova, I. (2016). Energy saving potential of fragmented green spaces due to their temperature regulating ecosystem services in the summer. *Applied Energy*, 183:1428–1440.

Kroeger, T., Escobedo, F. J., Hernandez, J. L., Varela, S., Delphin, S., Fisher, J. R., and Waldron, J. (2014). Reforestation as a novel abatement and compliance measure for ground-level ozone. *Proceedings of the National Academy of Sciences of the United States of America*, 111(40):E4204–e4213.

Kumari, S., Patel, M., Choudhury, A. G., and Kumari, A. (2022). *Adverse Effect of Lawn on Carbon Sequestration Vis-a-Vis Climate Change and Mitigation Strategies*, pages 2229–2254. Springer Nature Singapore, Singapore.

Leibniz-Institut für ökologische Raumentwicklung (2021). meingrün app.

Liebelt, V., Bartke, S., and Schwarz, N. (2019). Urban Green Spaces and Housing Prices: An Alternative Perspective. *Sustainability*, 11(13):3707.

Lin, B. B. and Fuller, R. A. (2013). FORUM: Sharing or sparing? How should we grow the world's cities? *Journal of Applied Ecology*, 50(5):1161–1168.

Maas, J., Verheij, R. A., Groenewegen, P. P., De Vries, S., and Spreeuwenberg, P. (2006). Green space, urbanity, and health: How strong is the relation? *Journal of Epidemiology and Community Health*, 60(7):587–592.

Madureira, H., Nunes, F., Oliveira, J. V., Cormier, L., and Madureira, T. (2015). Urban residents' beliefs concerning green space benefits in four cities in France and Portugal. *Urban Forestry and Urban Greening*, 14(1):56–64.

Maginnis, S., Laestadius, L., Verdone, M., DeWitt, S., Saint-Laurent, C., Rietbergen-McCracken, J., and Shaw, D. M. P. (2014). Restoration opportunities assessment methodology (roam).

Mayer, H. (1999). Air pollution in cities. In *Atmospheric Environment*, number 24-25 in 33, pages 4029–4037. Pergamon.

McMahon, E. T. (1996). Green enhances growth. *Planning Commissioners Journal*, 22:4–5.

Mills, J. G., Bissett, A., Gellie, N. J. C., Lowe, A. J., Selway, C. A., Thomas, T., Weinstein, P., Weyrich, L. S., and Breed, M. F. (2020). Revegetation of urban green space rewilds soil microbiotas with implications for human health and urban design. *Restoration Ecology*, 28(S4):S322–s334.

Moradpour, M. and Hosseini, V. (2020). An investigation into the effects of green space on air quality of an urban area using CFD modeling. *Urban Climate*, 34:100686.

Mulligan, M. (2015). Waterworld and co$ting nature: Web-based policy support systems. In *American Association for the Advancement of Science*.

Mwendwa, P. and Giliba, R. A. (2012). Benefits and challenges of urban green spaces. *Chinese Journal of Population Resources and Environment*, 10(1):73–79.

National Association of Home Builders (1996). Building greener neighborhoods.

Natural Capital Project (2019). Urban invest.

Nature Conservancy (2016). Healthy trees, healthy cities app.

Nouri, H., Chavoshi Borujeni, S., and Hoekstra, A. Y. (2019). The blue water footprint of urban green spaces: An example for adelaide, australia. *Landscape and Urban Planning*, 190:103613.

Nowak, D. J., Crane, D. E., and Stevens, J. C. (2006). Air pollution removal by urban trees and shrubs in the United States. *Urban Forestry and Urban Greening*, 4(3-4):115–123.

Nutsford, D., Pearson, A. L., and Kingham, S. (2013). An ecological study investigating the association between access to urban green space and mental health. *Public Health*, 127(11):1005–1011.

Oke, T. R. (1973). City size and the urban heat island. *Atmospheric Environment (1967)*, 7(8):769–779.

Ow, L. F. and Ghosh, S. (2017). Urban cities and road traffic noise: Reduction through vegetation. *Applied Acoustics*, 120:15–20.

Park, J., Kim, J. H., Lee, D. K., Park, C. Y., and Jeong, S. G. (2017). The influence of small green space type and structure at the street level on urban heat island mitigation. *Urban Forestry and Urban Greening*, 21:203–212.

Pataki, D. E., Carreiro, M. M., Cherrier, J., Grulke, N. E., Jennings, V., Pincetl, S., Pouyat, R. V., Whitlow, T. H., and Zipperer, W. C. (2011). Coupling biogeochemical cycles in urban environments: ecosystem services, green solutions, and misconceptions. *Frontiers in Ecology and the Environment*, 9(1):27–36.

Patterson, M. S. and Mccallum, Kimberly (2022). Collect earth – open foris.

PlanIT Geo (2021). Treeplotter software suite.

Politi Bertoncini, A., Machon, N., Pavoine, S., and Muratet, A. (2012). Local gardening practices shape urban lawn floristic communities. *Landscape and Urban Planning*, 105(1-2):53–61.

R3 GIS (2018). LIFE 3.0 Project.

Reis, C. and Lopes, A. (2019). Evaluating the Cooling Potential of Urban Green Spaces to Tackle Urban Climate Change in Lisbon. *Sustainability*, 11(9):2480.

Roman, L. A. and Scatena, F. N. (2011). Street tree survival rates: Meta-analysis of previous studies and application to a field survey in philadelphia, pa, usa. *Urban Forestry & Urban Greening*, 10(4):269–274.

Smart Growth America and National Complete Streets Coalition (2023). Elements of a complete streets policy.

Song, X., Ping, ., Tan, P., Yok, ., Edwards, P. ., and Richards, D. (2017). The economic benefits and costs of trees in urban forest stewardship: A systematic review ETH Library. *Urban Forestry & Urban Greening*, 29:162–170.

Stadt Hanau Vermessungsamt (2015). Gründach- und entsiegelungskataster hanau.

Takano, T., Nakamura, K., and Watanabe, M. (2002). Urban residential environments and senior citizens' longevity in megacity areas: The importance of walkable green spaces. *Journal of Epidemiology and Community Health*, 56(12):913–918.

Tamosiunas, A., Grazuleviciene, R., Luksiene, D., Dedele, A., Reklaitiene, R., Baceviciene, M., Vencloviene, J., Bernotiene, G., Radisauskas, R., Malinauskiene, V., Milinaviciene, E., Bobak, M., Peasey, A., and Nieuwenhuijsen, M. J. (2014). Accessibility and use of urban green spaces, and cardiovascular health: Findings from a Kaunas cohort study. *Environmental Health: A Global Access Science Source*, 13(1):20.

The Atlas (2024). Local government case studies.

Threlfall, C. G., Mata, L., Mackie, J. A., Hahs, A. K., Stork, N. E., Williams, N. S. G., and Livesley, S. J. (2017). Increasing biodiversity in urban green spaces through simple vegetation interventions. *Journal of Applied Ecology*, 54(6):1874–1883.

Threlfall, C. G., Williams, N. S., Hahs, A. K., and Livesley, S. J. (2016). Approaches to urban vegetation management and the impacts on urban bird and bat assemblages. *Landscape and Urban Planning*, 153:28–39.

Ties (2016). What is Ecotourism? | The International Ecotourism Society.

Trust for Public Land (2020). Pocket park toolkit.

Tyagi, V., Kumar, K., and Jain, V. K. (2013). Road traffic noise attenuation by vegetation belts at some sites in the tarai region of India. *Archives of Acoustics*, 38(3):389–395.

U. S. Department of Agriculture (2019). Urban tree canopy assessment:a community's path to understanding and managing the urban forest.

U. S. Forest Service (2017). Community assessment & goal-setting tool.

U. S. Forest Service (2021). Urban forestry toolkit.

Ulrich, R. S. (1984). View through a window may influence recovery from surgery. *Science*, 224(4647):420–421.

Umwelt Bundesamt (2021). Flächenrechner 2.0.

United Nations Development Programme (2024). Learning for nature.

Universitätsstadt Marburg (2015). Gründachkataster marburg.

Urban Land Institute (1996). Value by design: Landscaping, site planning and amenities.

USDA Forest Service (2023). The stewardship mapping project (stew-map).

USDA Forest Service (2024). i-tree eco.

Well, F. and Ludwig, F. (2020). Blue–green architecture: A case study analysis considering the synergetic effects of water and vegetation. *Frontiers of Architectural Research*, 9(1):191–202.

Wolch, J. R., Byrne, J., and Newell, J. P. (2014). Urban green space, public health, and environmental justice: The challenge of making cities 'just green enough'. *Landscape and Urban Planning*, 125:234–244.

World Health Organization (2017). Urban green spaces: A brief for action. *Regional Office For Europe*, page 24.

WRI (2014). Global forest watch.

WRI (2022). Resource watch.

Xiao, Q., McPherson, E. G., Ustin, S. L., and Grismer, M. E. (2000). A new approach to modeling tree rainfall interception. *Journal of Geophysical Research: Atmospheres*, 105(D23):29173–29188.

Zhang, B., di Xie, G., xi Gao, J., and Yang, Y. (2014). The cooling effect of urban green spaces as a contribution to energy-saving and emission-reduction: A case study in Beijing, China. *Building and Environment*, 76:37–43.

Zhang, B., Xie, G., Zhang, C., and Zhang, J. (2012). The economic benefits of rainwater-runoff reduction by urban green spaces: A case study in Beijing, China. *Journal of Environmental Management*, 100:65–71.

Chapter 3

Research objectives

To achieve the goal of sustainable cities, providing sufficient management input is essential to protect and sustain existing UGS (Jabbar et al., 2021; Vidal et al., 2020). The management of UGS typically includes three phases: *Monitoring*, *Managing*, and *Greening*. *Monitoring* involves understanding the current status of the UGS. This is mainly carried out through routine field surveys performed by arborists or urban foresters. During this phase, important tree characteristics such as species type, diameter size, canopy size and shape, planting date, and health condition are recorded. Modern technology-based solutions like drones, aerial imagery, and remote sensing have also been implemented for detecting trees and their health conditions (Irene Capecchi and Bernetti, 2023; Kulhandjian et al., 2024; Gupta et al., 2024). Then, the *managing* phase focuses on management of the existing UGS. This involves numerous activities such as watering, application of fertilizer and pesticides, pruning of trees, cutting, lawn mowing, tree stability inspection, leaf-litter cleaning, and maintenance of recreational facilities. Finally, the *greening* phase deals with planning additional trees and greening of new areas to increase total coverage and subsequently receive higher benefits.

As highlighted in the chapter 2, current methods and tools have focused on the need to identify existing UGS and for optimal spatial planning of newer green areas. Moreover, for existing UGS, the focus is either on estimating the total benefits derived from UGS or on estimating its management needs independently. However, the integration between both the cost and benefits with the decision-making process is currently lacking. As underscored by Gosling and Arnell (2013) and Yáñez-Arancibia et al. (2013), resource constraints are anticipated to escalate, particularly in water, soil, and personnel, across numerous regions globally due to climate change and evolving socio-economic structures. Consequently, prioritization becomes increasingly imperative for allocating limited resources. In the absence of a systematic, objective approach, inefficient resource allocation may occur, potentially resulting in reduced or inequitable distribution of UGS benefits among city residents. Additionally, with the evolution of smart cities, an abundance of data becomes accessible through digital administrative records, satellite and drone imagery, sensor observations, social media, and crowd-sourced data (Sarker, 2022). These diverse datasets, when amalgamated, have the potential to assist decision-makers in assessing urban conditions and making informed management decisions (Bibri and Krogstie, 2020). Therefore, a data-enabled decision support system is conceptualized in this thesis to aid decision-makers in making well-informed choices.

Accordingly, the research must first address the following research question:

RQ1: Can state-of-the-art technological solutions be integrated to support UGS management?

This primary question was addressed by conducting an extensive literature review of the existing tools and frameworks available for UGS management. Subsequently, following the identification of research gaps in the existing solutions, the need arises to investigate the following second research question:

RQ2: How can the benefits of UGS be maximized with minimum costs in different resource-constrained scenarios?

3.1 Research aim

Considering the above, the present research aims to investigate how a data-enabled approach could support decision-makers responsible for UGS management. Accordingly, it aims to address two main challenges concerning the management of UGS: first, making informed decisions to manage the existing UGS, and second, maximizing the benefits from UGS at minimum costs.

3.2 Objectives

. To accomplish this goal, the research work is divided into the following objectives:

1. Develop a cost model to estimate the input management demand required to maintain UGS.
2. Develop a benefit model to estimate the benefits attainable from UGS for city residents.
3. Develop a multi-criteria decision support system to prioritize resource allocation under resource-constrained scenarios.
4. Develop a framework to assess and enhance the quality of input data for decision-making in cities with limited data availability.

3.3 Scope and limitations

However, to provide comprehensive decision support for UGS management within a feasible time-frame and with available data and resources, the scope of the current research design is limited to the following:

1. Sustainability is a broad concept comprising social, economic, and environmental sustainability. However, the present research solely aims at enhancing environmental sustainability, and economic and social sustainability are not explicitly incorporated as targets.

2. As described in subsection 1.1.1, all vegetation, whether individual or in groups, located within city boundaries, is part of UGS. Therefore, all types of green areas located in urban and peri-urban public areas are included in the scope of this project. However, for simplicity of reference, UGS is sub-grouped into street trees, which include individual trees, parks that include groups of trees and landscapes, including farmland, meadows, urban forests, golf parks, picnic sites, and zoos.

3. As described in section 2.1, UGS offer diverse benefits. However, considering the existing WHO policy guidelines and SDG targets, the research is currently focused on quantifying the social benefits of UGS (represented as accessibility to city residents). Similarly, for individual street trees, carbon sequestration was used as an exemplary benefit criterion.

4. The management demand of UGS consists of physical human intervention or various input resources required for its sustenance. Nevertheless, the scope of this research primarily aimed at estimating the watering demand of UGS as it is the most significant component with higher implications. While for the demand need of other activities, it was estimated as the aggregated personnel demand in the total number of hours required for the management of UGS.

5. UGS on private land are excluded from the analysis as these are mostly managed by individual homeowners and not city administration.

3.4 Research outline

A decision support system planned for the optimum management of existing UGS is presented in Figure 3.1. The overall research methodology, consisting of four integrated research objectives, is aimed at providing decision support, particularly for making prioritization decisions during resource constraint scenarios.

To make the methodology suitable for a wide range of cities, the focus is placed on utilizing public datasets. This especially includes tree inventory and meteorological datasets, along with input from decision-makers regarding their criteria and preferences, which are used for quantifying input parameters. These parameters include tree characteristics such as tree height, diameter, and species type, climate characteristics such as Evapotranspiration (ET) and precipitation, as well as socio-economic characteristics such as population distribution. For optimal decision-making, conducting a cost-benefit analysis of UGS is essential. Therefore, using these parameters as input, a demand model developed in the first objective estimates the management input required by the UGS for its sustenance, while the benefit model developed in the second objective estimates the benefits derived from each UGS.

Next, criteria are derived from city strategy and planning, largely based on international and national policy guidelines. Subsequently, resource constraints are established based on resource availability in the city. Taking into account the outcomes of both the demand and benefit models, along with the obtained criteria and constraints, a decision-making model developed in the third objective is implemented to prioritize decisions. This prioritization outcome could assist decision-makers in making resource allocation decisions. Following the implementation of these decisions on the field, the city administrators should also monitor and assess the status of the UGS, and subsequently, the dataset should be updated. In the final step, in order to confirm that the data being used for decision-making applications is of sufficient quality and quantity, a quality assessment framework developed in the fourth objective is implemented. This will further address the challenge for cities with limited data or low-quality datasets. In summary, the research is based on utilizing existing public datasets to provide a data-enabled decision support system for UGS management.

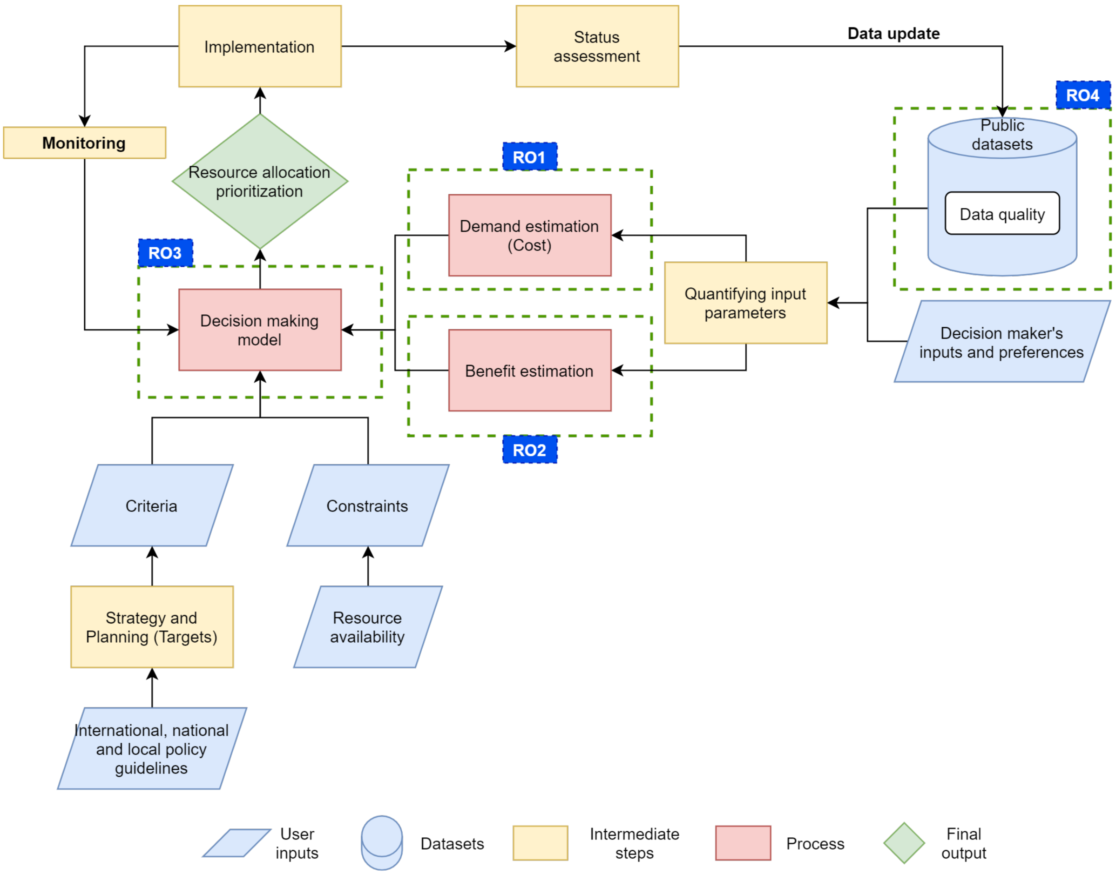


FIGURE 3.1: Research outline illustrating the integration among research objectives.

Bibliography

Bibri, S. E. and Krogstie, J. (2020). The emerging data–driven smart city and its innovative applied solutions for sustainability: the cases of london and barcelona. *Energy Informatics*, 3.

Gosling, S. N. and Arnell, N. W. (2013). A global assessment of the impact of climate change on water scarcity. *Climatic Change*, 134:371–385.

Gupta, A., Mora, S., Zhang, F., Rutten, M., Venkatesha Prasad, R., and Ratti, C. (2024). Greenscan: Toward large-scale terrestrial monitoring the health of urban trees using mobile sensing. *IEEE Sensors Journal*, 24(13):21286–21299.

Irene Capecchi, T. B. and Bernetti, I. (2023). Automated urban tree survey using remote sensing data, google street view images, and plant species recognition apps. *European Journal of Remote Sensing*, 56(1):2162441.

Jabbar, M., Yusoff, M. M., and Shafie, A. (2021). Assessing the role of urban green spaces for human well-being: a systematic review. *GeoJournal*, 87.

Kulhandjian, H., Irineo, B., Sales, J., and Kulhandjian, M. (2024). Low-cost tree health categorization and localization using drones and machine learning. In *2024 International Conference on Computing, Networking and Communications (ICNC)*, pages 296–300.

Sarker, I. H. (2022). Smart city data science: Towards data-driven smart cities with open research issues. *Internet of Things*, 19:100528.

Vidal, D. G., Barros, N., and Maia, R. L. (2020). *Public and Green Spaces in the Context of Sustainable Development*, pages 479–487. Springer International Publishing, Cham.

Yáñez-Arancibia, A., Day, J., Hall, C., and Reyes, E. (2013). Diminished resources, energy scarcity and climate change: unsustainable future development. *WIT Transactions on State-of-the-art in Science and Engineering*, 64.

Chapter 4

Methodology

The primary contribution of this thesis lies in the introduction of a data-enabled multi-criteria decision support system. Additionally, the research methodology is interdisciplinary, blending engineering technology with techniques drawn from Operations Research. It aims to facilitate the management of UGS under resource-constrained scenarios. This is achieved using a prioritization approach, wherein only those UGS prioritized will receive the necessary management inputs required for their sustenance. The overall methodology is based on the utilitarian approach, which aims to maximize the UGS benefits attainable for city residents while minimizing input management demand.

As outlined in the previous chapter, to achieve the research aim, the methodology was subdivided into four parts. Accordingly, four studies, denoted as Study A, B, C, and D in this thesis, were undertaken to comprehensively address the research questions. Table 4.1 summarizes the contributions of the study to the cross-study research objectives. The studies were executed using a building block approach, progressively targeting research objectives.

First, Study A focused on estimating the management demand of UGS, specifically quantifying irrigation water for street trees. Prioritization based solely on resource demand was implemented accordingly. Second, Study B concentrated on estimating the benefits provided by UGS, determining accessibility and quality benefits. Consequently, prioritization based solely on attainable benefits was implemented. Third, Study C combined the demand model of Study A and the benefit model of Study B, further enhancing both by additionally including the estimation of personnel demand and carbon sequestration benefit, respectively. Then, using a MCDM approach, prioritization was derived considering both costs and benefits, taking into account available resources and decision-makers' preferences. The final fourth Study D proposed a data quality assessment and enhancement framework for implementing decision support systems in cities with limited data. Subsequent sections elaborate on the structure of each of these studies, the methods used, the key inputs and outcomes of the study, their impact, and their integration in the context of the overall research aim.

Table 4.1: Overview of the studies and their contribution to the cross-study research objectives

Research objective	Study A	Study B	Study C	Study D
Estimating management demand of UGS	X		X	X
Estimating benefit provided by UGS		X	X	X
Decision-making of prioritization for resource allocation	X	X	X	
Data quality assessment and enhancement				X

4.1 Demand estimation

With the introduction of UN SDG, city administrations have given considerable attention to 'greening the cities' as a means to enhance urban sustainability (Nouri et al., 2019a). However, a challenging dilemma emerges for city administrators: striking a balance between expanding UGS and managing finite water resources essential for their sustenance. According to Young (2011), practitioners often struggle with ensuring an adequate water supply to maintain urban trees. Moreover, the situation is expected to worsen across various regions due to prolonged dry spells resulting from climate change (Cook et al., 2018). This underscores the critical need to optimize water usage within UGS based on climatic conditions and species-specific water requirements.

Many existing irrigation scheduling models primarily cater to the agricultural sector. However, urban environments present unique challenges such as localized micro-climates, compacted soil, shading, and human disturbances, rendering agriculture-focused irrigation models unsuitable for cities (Nouri et al., 2013). Although models by Vico et al. (2013), Volo et al. (2014), and Nouri et al. (2019b) address urban conditions, they lack in estimating irrigation demands at individual tree or park levels. Moreover, in some instances, estimates are only provided on monthly or yearly scales, inadequate for practical irrigation management application (Wessolek and Kluge, 2021; Sjöman and Busse Nielsen, 2010). This underscores the need for further research in estimating UGS irrigation demands.

Consequently, Study A focused on specifically estimating water demand for urban street trees. To address this, a linear time-series model based on the soil water balance approach was developed, estimating the irrigation demand of any tree species by utilizing public datasets containing tree inventory and meteorological data, soil type, and the impact of urban characteristics using a Water Use Classification of Landscape Species (WUCOLS) dataset. The model is based on assessing the amount of water accessible for tree absorption, derived from the infiltrated precipitation that remains after factors such as canopy interception, drainage, ET, and runoff have been taken into account. Additionally, the future expected precipitation is subtracted from the irrigation demand to avoid overwatering. The model is then compared against the existing alternative method Simplified Landscape Irrigation Demand Estimation (SLIDE) and a soil-moisture based model currently implemented in the Berlin city.

The developed model provides species-wise as well as city-wide weekly irrigation demand for street trees. Estimating the irrigation demand of UGS can help decision-makers in implementing watering schedules for existing trees and planning water budgets for new greening areas. This can also distinguish the water-intensive tree species and parks, allowing for informed decisions in case of the need for prioritization. Additionally, through optimizing the irrigation network, cities can simultaneously fulfill the objectives outlined in the EU Strategy on Adaptation to Climate Change (EU Commission, 2023) as well as the EU Water Framework Directive (EU Commission, 2024). Moreover, by adapting the input data, scenario analysis is conducted to assess the impact of future climatic conditions, such as reduced rainfall, on the irrigation demand of UGS. Table 4.2 presents an overview of Study A, describing the inputs, methods used, outcomes, and its impact on current management practices.

Table 4.2: Summary of the irrigation demand estimation study

Item	**Description**
Inputs	Public tree inventory, WUCOLS dataset, reference ET, past and future precipitation, soil map, literature values
Methods	Soil water balance, linear time series modeling, scenario analysis, SLIDE method, critical literature review, case study
Outcomes	- Species-wise weekly/daily irrigation demand. - City-wide total water consumption of all street trees. - Seasonal water demand trends.
Impact	- Supports decision-makers in determining the irrigation schedule for the city at a weekly time scale. - Enables scenario analysis, such as an increase in trees or decrease in rainfall, to prepare for future climate change conditions.
Contribution to	RO1, RO3 - Chapter 5

4.2 Benefit estimation

Access to high-quality UGS is vital for promoting healthy living conditions in urban areas. Therefore, it is crucial to ensure that public UGS are evenly distributed throughout cities and accessible to all demographic groups from various socio-economic backgrounds. Thus, evaluating the physical accessibility of existing UGS is imperative. While previous studies, such as those by Wüstemann et al. (2016) and Poelman (2018), have analyzed the quantity of UGS access, there remains a notable gap in the literature regarding the distribution of UGS quality. Despite the subjectivity surrounding UGS quality, certain defining characteristics are likely significant for its assessment. These include proximity to residents, size, species diversity, public access, tranquility, recreational facilities, and safety (Daniels et al., 2018; Stessens et al., 2020). Moreover, in the context of UGS management, it is essential to measure not only the associated input costs but also the attainable benefits. This is necessary as certain UGS, although highly resource-intensive, could be critical for the city, particularly if located in densely populated regions with limited UGS availability. Therefore, optimizing resource allocation during constrained scenarios necessitates measuring the benefits provided by these UGS units.

Addressing this gap, Study B focused on estimating the benefits provided by UGS and subsequently utilizing them for decision-making. The benefits are measured using UGS accessibility and quality as indicators, while the decision to be made concerns prioritization. The model employs open datasets in an automated manner to estimate the residents impacted by the lack of UGS accessibility and display the distribution of UGS quality in the city. The accessibility methodology is based on WHO and EURO guidelines, recommending a minimum of 0.5 hectares of UGS within a 300-meter radius for all city residents (World Health Organization, 2017). Furthermore, for quality measurement, a composite quality indicator was developed, assigning weights to each criterion. Subsequently, each quality parameter was quantified using publicly available datasets. For instance, the Normalized Difference Vegetation Index (NDVI) was computed using Sentinel-2 satellite imagery to measure vegetation intensity, referred to here as 'greenness'. Subsequently, the accessibility and quality scores were plotted on a scatter plot to visually depict their distribution among different UGS. City administrators can then establish the minimum target for prioritization order when selecting which UGS to prioritize. This involves selecting UGS based on the prioritization order calculated by combining their scores with their corresponding weights.

For the first time, the developed method has implemented the UGS benefit criteria to inform decision-making in UGS management. This integrated framework highlights the contribution and criticalness of each UGS in maintaining the required level of accessibility according to WHO recommendations through prioritization order. Local authorities in park and forest departments can utilize this approach to efficiently allocate limited resources in constrained scenarios, maximizing benefits. Additionally, the method categorizes UGS into four groups based on their accessibility and quality levels using a scatter plot. This categorization enables the formulation of precise management plans for each type of UGS. Furthermore, the method analyzes the quality aspect of UGS accessibility, bridging a crucial gap in current approaches. Table 4.3 presents an overview of Study B, describing the inputs, methods used, outcomes, and its impact on current management practices.

4.3 Decision-making under resource constraint

In a resource-constrained scenario, it might not be possible to provide complete management support to all the UGS in the city. In such cases, it becomes indispensable to prioritize those UGS to which resources should be allocated. The prioritization should be done such that benefits are maximized, costs are minimized, and resource constraints are satisfied. Some possible resource-constraint scenarios include a limited budget, a number of equipment to supply water, staff, minimum access to the public, and scarce water quantity available. Moreover, a comprehensive data-driven framework can help reduce subjectivity and enhance decision-making reliability (Matheus et al., 2020; Bibri, 2021; Osman et al., 2022).

Addressing this gap, Study C focused on maximizing the total benefit of UGS by efficiently allocating the resources to those UGS that are providing maximum benefits with minimum input management demands. For efficient decision-making in resource-constrained scenarios, a Goal Programming (GP)-based model is developed. GP is a

Table 4.3: Summary of the benefit estimation study

Item	Description
Inputs	OSM datasets, sentinel-2 imagery, crime statistics, noise map, policy recommendations
Methods	Parameter definition, mathematical formulation, geospatial analysis, remote sensing, case study
Outcomes	- Introduces a novel GIS-based approach to prioritize UGS based on the WHO recommended accessibility indicator. - Considers the quality of UGS, measured using size, greenness, quietness, and safety, when assigning the priority score to each UGS.
Impact	- Provides a unique way of integrating benefit criteria for making informed UGS management decisions. - Highlights the contribution and criticalness of each UGS in maintaining the required level of accessibility in the city. - Offers visual insights into the distribution of UGS quality and identifies areas lacking sufficient UGS.
Contribution to	RO2, RO3 - Chapter 6

Multi-Criteria Decision-Making (MCDM) method for solving multiple goal problems, especially when all the defined goals are not in a common unit. It can derive the best possible satisfactory strategy by minimizing the underachievement of each goal with the help of deviation variables. Currently, two benefits, accessibility to the public and quality of the UGS, are considered for parks, and for street trees, carbon sequestrations are considered while maximizing the benefits. Goals are set by defining the minimum accessibility that needs to be maintained and the quantity of high-quality UGS that needs to be protected. Constraints are set by defining the maximum available water and personnel capacity. The model produces a prioritization order as the outcome based on which the resource should be allocated. Subsequently, the resource allocation performance is evaluated based on various benefit metrics, such as allocated resource units, resources consumed, and goals achieved.

Moreover, conventional decision-making approaches are limited in handling the varied spatial scales required for large-scale urban applications. Therefore, the GP-based model is extended to also analyze resource allocation decisions and desired goals at varying spatial scales. The study demonstrates analyzes the cases with targets set at both district and city scales, while resource allocation decisions are made at the district and sub-district scale. Therefore, decision-makers can choose whether they would prefer a resource-efficiency-oriented prioritization or a goal-oriented prioritization.

The proposed GP-based method represents the first attempt to tackle the challenge of allocating resources for UGS during periods of resource constraints. The proposed method assists decision-makers in maximizing total benefits while effectively balancing conflicting goals and constraints. Moreover, it facilitates the integration of the city's preferences and priorities into the decision-making process. Therefore, by incorporating these goals into decision-making, the method enables cities to fulfill UN SDG targets and WHO guidelines even under resource-constrained conditions. Additionally, it provides decision-makers with the opportunity to evaluate how modifying the order of priority for goals and their corresponding weights influences the prioritization decision. Table 4.4 presents an overview of Study C, describing the inputs, methods used, outcomes, and its impact on current management practices.

Table 4.4: Summary of the decision support system study

Item	**Description**
Inputs	Benefit model, demand model, city targets and priorities, available resources, public tree inventory, and weather datasets
Methods	MCDM, GP, spatial analysis, critical literature review, case study
Outcomes	- Presents a decision-making approach for UGS management incorporating multiple benefit objectives (such as accessibility, quality, and carbon sequestration) and addressing resource constraints (including water and personnel). - Enables prioritization decision-making at district and sub-district scales with benefit targets set at city and district levels.
Impact	- Supports decision-makers in making prioritization decisions under resource constraint scenarios. - Analyzes the impact of modifying the priority order or goals on the prioritization decision.
Contribution to	RO1, RO2, RO3 - Chapter 7

4.4 Decision-making under limited data

Effective planning and maintenance of UGS requires a comprehensive dataset detailing the distribution and feature characteristics of diverse UGS. Nevertheless, these datasets vary significantly in terms of their temporal and spatial scopes, definitions, data sources, and methodologies. A study conducted in Lodz, Poland, by Feltynowski et al. (2018) highlighted the issue of data quality and observed a substantial 48.4% difference in UGS area between public statistics data and a national land surveying dataset. This disparity was consistently observed across all 17 cities examined in the study, underscoring the challenges cities encounter in obtaining accurate and consistent data for UGS planning and management. Furthermore, the current version of the decision-making model developed in Study C requires a substantial amount of public UGS data for comprehensive analysis. However, due to the lack of necessary input data for many cities, either in terms of quality or quantity, implementation of a data-enabled approach is not feasible.

To address this gap, Study D focuses on assessing input data quality and quantity to determine the suitability of available public datasets for subsequent usage in management applications. In this study, tree inventory datasets were analyzed on five standard quality dimensions derived from total data quality management principles: completeness, uniqueness, accuracy, timeliness, and reliability. Statistical tests were utilized to check against the set threshold limits to assess the performance of the dataset on each of these dimensions. Subsequently, based on the assessment, the dataset was classified as high/low quality and high/low quantity. This was followed by data pre-processing through a combination of data cleaning and data-filling techniques. The framework was applied to tree inventories from ten cities in Germany, and their results were compared. The impact of the missing values on the desired management application was analyzed to check the sensitivity of the parameter. Finally, the enhanced dataset was made available for subsequent usage as an input in various management applications.

The implementation of the proposed framework allows identifying the quality gaps in existing tree inventory datasets. It also highlights the high impact of missing data on the management outcomes, signifying the importance of acquiring accurate UGS datasets. Through a regression-based approach, the potential of data enhancement was also demonstrated. Accordingly, this enables decision-making in cities with limited data availability. Table 4.5 presents an overview of Study D, describing the inputs, methods used, outcomes, and its impact on current management practices.

Table 4.5: Summary of the tree inventory dataset quality management study

Item	**Description**
Inputs	Public tree inventories dataset, application model, quality thresholds
Methods	Total data quality management principles, simple linear regression, multiple linear regression, random forest, statistical evaluation
Outcomes	- Presents a quality assessment and enhancement framework for the tree inventory dataset. - Conducts quality assessment of tree inventory datasets from ten German cities.
Impact	- Enables data-enabled decision-making in cities with insufficient quantity or quality of input data. - Provides a framework to deal with the data quality challenges in UGS management.
Contribution to	RO4 - Chapter 8

Bibliography

Bibri, S. E. (2021). A novel model for data-driven smart sustainable cities of the future: the institutional transformations required for balancing and advancing the three goals of sustainability. *Energy Informatics*, 4.

Cook, B. I., Mankin, J. S., and Anchukaitis, K. J. (2018). Climate change and drought: From past to future. *Current climate change reports*, 4:164–179.

Daniels, B., Zaunbrecher, B. S., Paas, B., Ottermanns, R., Ziefle, M., and Roß-Nickoll, M. (2018). Assessment of urban green space structures and their quality from a multidimensional perspective. *Science of The Total Environment*, 615:1364–1378.

EU Commission (2023). Eu adaptation strategy.

EU Commission (2024). Water framework directive.

Feltynowski, M., Kronenberg, J., Bergier, T., Kabisch, N., Łaszkiewicz, E., and Strohbach, M. W. (2018). Challenges of urban green space management in the face of using inadequate data. *Urban Forestry & Urban Greening*, 31:56–66.

Matheus, R., Janssen, M., and Maheshwari, D. (2020). Data science empowering the public: Data-driven dashboards for transparent and accountable decision-making in smart cities. *Government Information Quarterly*, 37(3):101284.

Nouri, H., Beecham, S., Kazemi, F., and Hassanli, A. (2013). A review of ET measurement techniques for estimating the water requirements of urban landscape vegetation. *Urban Water Journal*, 10(4):247–259.

Nouri, H., Chavoshi Borujeni, S., and Hoekstra, A. Y. (2019a). The blue water footprint of urban green spaces: An example for adelaide, australia. *Landscape and Urban Planning*, 190:103613.

Nouri, H., Chavoshi Borujeni, S., and Hoekstra, A. Y. (2019b). The blue water footprint of urban green spaces: An example for Adelaide, Australia. *Landscape and Urban Planning*, 190:103613.

Osman, A. M. S., Elragal, A. A., and Ståhlbröst, A. (2022). Data-driven decisions in smart cities: A digital transformation case study. *Applied Sciences*, 12(3).

Poelman, H. (2018). A walk to the park? assessing access to green areas in europe's cities.

Sjöman, H. and Busse Nielsen, A. (2010). Selecting trees for urban paved sites in scandinavia – a review of information on stress tolerance and its relation to the requirements of tree planners. *Urban Forestry & Urban Greening*, 9:281–293.

Stessens, P., Canters, F., Huysmans, M., and Khan, A. Z. (2020). Urban green space qualities: An integrated approach towards gis-based assessment reflecting user perception. *Land Use Policy*, 91:104319.

Vico, G., Revelli, R., and Porporato, A. (2013). Ecohydrology of street trees: design and irrigation requirements for sustainable water use. *Ecohydrology*, 7:508–523.

Volo, T. J., Vivoni, E. R., Martin, C. A., Earl, S., and Ruddell, B. L. (2014). Modelling soil moisture, water partitioning, and plant water stress under irrigated conditions in desert urban areas. *Ecohydrology*.

Wessolek, G. and Kluge, B. (2021). Predicting water supply and evapotranspiration of street trees using hydro-pedo-transfer functions (hptfs). *Forests*, 12:1010.

World Health Organization (2017). Urban green spaces: A brief for action. *Regional Office For Europe*, page 24.

Wüstemann, H., Kalisch, D., and Kolbe, J. (2016). Towards a national indicator for urban green space provision and environmental inequalities in Germany: Method and findings Towards a national indicator for urban green space provision and environmental inequalities in Germay: Method and findings 1. *Economic Risk*.

Young, R. F. (2011). Planting the living city: Best practices in planning green infrastructure - Results from major U.S. cities. *Journal of the American Planning Association*, 77(4):368–381.

Chapter 5

Demand estimation

5.1 Prelims

This chapter[1] contributes to the first research objective (RO1): "develop a cost model to estimate the input management demand required to maintain UGS". Therefore, Study A focused on quantifying the management needs of UGS. These inputs are considered costs in decision support, as they are limited by available physical resources, personnel, or funding. Since water is the most significant and essential component of UGS management, the scope of the research was limited to the irrigation water demand of the UGS in this study.

The chapter structure is outlined as follows: initially, the background and introduction to the research gap are provided in section 5.4. Subsequently, existing models available for water demand estimation in agricultural and urban areas are examined in subsection 5.4.1 and subsection 5.4.2, respectively. The discussion then delves into the soil water balance approach for a single street tree under urban conditions in section 5.5. Addressing identified limitations in current approaches, a novel linear time series model is introduced, integrating ET estimation and the WUCOLS approach, as detailed in section 5.6. Following this, the implementation of the proposed model in the case study city of Berlin, Germany, is introduced in section 5.7. The outcomes of this case study are subsequently presented in subsection 5.7.2. Finally, a thorough discussion comparing the obtained results with those of the existing soil moisture-based approach is presented in section 5.8. Concluding remarks and suggestions for future research directions are then provided in section 5.9.

[1] This chapter is based on a published article:
Rambhia, M., Volk, R., Rismanchi, B., Winter, S., & Schultmann, F. (2023). "Supporting decision-makers in estimating irrigation demand for urban street trees". Urban Forestry & Urban Greening, 82, 127868–127868. https://doi.org/10.1016/j.ufug.2023.127868
The paper presented in section 5.2 is reformatted for consistency within the thesis, including the numbering of figures and tables, as well as the referencing style. The research presented in this article was carried out by the author while other co-authors have been supervisors and provided feedback throughout the process. The published manuscript can be found in the appendix.

Study A: Supporting decision-makers in estimating irrigation demand for urban street trees

5.2 Abstract

Greening cities is of considerable significance to creating sustainable cities. Cost-benefit analyses have shown that urban green is not only ecologically and socially desirable but also economically advantageous. However, maintaining this urban green is becoming challenging due to changing climatic conditions. With frequent heat-waves, droughts and increasing water scarcity in many regions, it is crucial to establish systematic approaches to economise the available water used for irrigation. Currently, cities rely on rough approximations to assess irrigation demand. To address this gap, a linear time series model was developed based on soil water balance and Water Use Classifications of Landscape Species (WUCOLS) approach. The model uses publicly available data regarding trees, soil, and current and forecasted weather to estimate the irrigation demand of urban street trees on a weekly time scale. The developed model is applied in a case study of a metropolis in a moderate continental climate. The results show more distributed irrigation demand than the currently implemented soil moisture based model of the case study city. Accordingly, the model can support the decision-makers to not only assess the irrigation demand of existing trees but also help in water budgeting of new plantation under varying climatic conditions.

5.3 Highlights

- Using public datasets to estimate weekly irrigation demand for urban street trees.
- Integrating WUCOLS and soil water balance approach for the estimation.
- Distributed demand than currently implemented soil moisture based model.
- Supporting decision-makers for budgeting water under varying climatic conditions.

5.4 Introduction

The World Health Organization (WHO) defines urban green spaces (UGS) as "all urban land covered by vegetation of any kind" (World Health Organization, 2016). This includes trees along streets, parks, play grounds, private gardens, urban forests, green roofs or walls, and farms within city boundaries. Access to sufficient UGS provides exposure to nature and enhances the quality of living in cities, as acknowledged by the United Nations' Sustainable Development Goals Target 11.7, which aims to provide access to safe green spaces for everyone living in cities by 2030 (United Nations, 2020).

In response, city administrators have formulated goals for the conservation and development of new UGS. However, increasing green spaces also introduces competing interests with the use of scarce water resources and limited budgets to maintain them. While UGS contribute positively to water storage through reduced runoff and increased infiltration, supplementary irrigation needs are likely to increase the pressure on limited water resources in cities. Practitioners have often cited the availability of water supply as one of the significant challenges in maintaining urban trees (Young, 2011). The problem is expected to further exacerbate due to more frequent and extended drier periods with increasing effects of climate change. For example, in summer 2022 some districts in California had to declare a water emergency state, allowing outer watering only once a week (Patel and Samenow, 2022). Similarly, some regions in northern Italy, Portugal, and Spain also announced emergency measures and requested their residents to economise their water usage (France-Presse Agence, 2022; Deutsche Welle, 2022). Mandatory water restrictions targeting the irrigation of both public and private open spaces are also frequently observed in Canberra, Sydney, and Melbourne in Australia (Fam et al., 2008).

The type of tree species and local micro-climatic conditions are the factors that can significantly affect irrigation demand. This stipulates the need to optimise the watering supply to the UGS such that, water is solely supplied when and where it is actually required and in a judicious quantity. However, the current practice of watering through tankers or watering bags lacks the flexibility to consider these factors. Nevertheless, these parameters have been included in this study, expecting the implementation of smart drip irrigation or water network systems in future. Thus, by optimising the operational management of an irrigation system for UGS, cities can simultaneously meet the objectives of the EU Strategy on Adaptation to Climate Change as well as the EU Water Framework Directive, which aims to prepare cities for the challenges associated with climate change such as urban heat island and droughts (European Commission, 2021, 2000).

However, predicting the dynamic water demand of trees is an arduous task. Water consumption by trees can be divided into two categories: The *blue* water from irrigation or groundwater, and the *green* water from rainwater. Accordingly, the focus of this study is to estimate the required quantity of blue water to be supplied externally for managing UGS in optimal conditions, after accounting for the green water available through the rain. Most of the existing irrigation scheduling models are developed for the agricultural sector because of the higher economic implications (Adeyemi et al., 2018; Khan et al., 2017, 2020). These are further discussed in subsection 5.4.1. However, distinct conditions in cities, such as local micro-climatic conditions, sealed and compacted soil, shading, and anthropogenic disturbances, make the irrigation models developed for rural conditions inapplicable for urban areas (Nouri et al., 2013d). Existing models for urban conditions, such as (Vico et al., 2013; Volo et al., 2014; Nouri et al., 2019), are limited in estimating the irrigation demand at a single tree or park level. Additionally, in some studies the estimates are generated at monthly or annual time scales, which is not enough for operational irrigation management (Wessolek and Kluge, 2021; Sjöman and Busse Nielsen, 2010).

This demands further research on estimating irrigation demand for UGS. As described earlier, UGS includes a variety of green spaces, however, the scope of this research is focused on estimating the irrigation needs of urban street trees. Moreover, since for street trees weekly watering by tankers is the commonly applied method, the current study adopts a weekly time scale for the estimation to support practical usage. Unlike existing models that focus on a smaller spatial scale, this work is focused on city level and therefore, includes trees from a variety of species. Furthermore, with the increasing availability of data under open data initiatives of various cities, our approach particularly uses available public datasets without relying on sensors or remote sensing data, which might not be accessible to every municipality. Accordingly, this study aims to address the following two research questions:

- Can the irrigation demand of street trees be determined on a weekly time scale using available public datasets?
- Can the future water demand for new street tree plantations be assessed under varying climatic conditions?

Accordingly, the scope of the research includes (1) identifying a suitable approach for estimating irrigation demand in urban context; (2) considering the necessary adaptations required for applying it at street tree level; (3) identifying the relevant public datasets and assimilation procedures to obtain the required model parameters; (4) comparing the model performance with the existing models; and (5) evaluating the change in irrigation demand under varied scenario conditions.

The research approach is based on identifying the suitable method for irrigation demand estimation based on the comprehensiveness, adaptability, and feasibility of the method. Accordingly, the proposed model is an implementation of the water-balance model wherein the individual parameters are derived from different published datasets or values reported in the literature. This model is further compared with an existing Plant Factors (PF) based method used for irrigating urban landscapes as well as the model currently adopted by the city chosen in our case study. In summary, the research aims for two outcomes: First, a model that estimates weekly irrigation demand for street trees that is easily adaptable for changes in input parameters depending on the availability of data, that uses nominal quantity of data without requiring special field measurements, that takes into account current and forecasted weather data, and that is applicable under varying climatic conditions. The second outcome includes insights for city administrators to make informed decisions regarding water budgeting of existing and new plantations of street trees.

The paper is organised as follows: first, a literature review describes the state-of-the-art irrigation models for agricultural and urban applications and the research gap. Based on this, a water balance model is selected as the basis and its parameters are detailed in the background section, followed by the modeling approach section discussing its implementation in a python-based model. In the case-study section, the results from applying the model to data from Berlin city are discussed. The final two sections present the discussion and conclusions.

List of abbreviations
UGS Urban Green Spaces
WUCOLS Water Use Classifications of Landscape Species
SLIDE Simplified Landscape Irrigation Demand Estimation
List of Symbols

CR capillary rise
D Deep percolation
ET evapotranspiration
ET_0 reference evapotranspiration
I irrigation
P precipitation
PF plant factor
r root depth
RAW readily available water
RO runoff
ΔS soil moisture change
TAW total available water

5.4.1 Models for agricultural areas

Different studies have presented irrigation scheduling approaches for the agricultural sector (George et al., 2000; Contreras et al., 2011). In addition, the Food and Agriculture Organization of the United Nations (FAO) also offers two models based on soil water balance approach: CropWat and AquaCrop. CropWat provides an irrigation schedule for crops using daily or monthly, weather, crop and soil data (FAO, 2021b). Similarly, AquaCrop model was developed for single, and uniform crop fields applications (FAO, 2021a). Delgoda et al. (2016b) used the AquaCrop model to test an irrigation control model that estimates root zone soil moisture deficits to determine irrigation demand. However, the approach was tested only for crops and not for urban environments. The authors also presented an approach based on model predictive control that aims to achieve the desired soil moisture level while considering limitations on available water (Delgoda et al., 2016a).

The limitation of the aforementioned irrigation scheduling models is their total focus on crops and crop yield, which also applies to the respective sub-models. Hence, it is difficult to directly apply them to the urban vegetation with its peculiar characteristics. In addition, literature regarding the necessary adjustments required for applying these models to UGS is missing. Other shortcomings of the presented models include the missing dynamics of parameters D and RO in the model of Delgoda et al. (2016b), and the granularity of data in the FAO models that uses average monthly climatic data.

5.4.2 Models for urban areas

UGS is quite diverse in its configuration compared to agricultural fields. It is planted in various species combinations, with spatial distributions and densities that are in high contrast to organised, uniform crop lines on a field (Nouri et al., 2013d). Especially for street trees, the micro-climate effects due to nearby buildings, road and other sealed surfaces, as well as compacted and restricted tree trenches, significantly affects their water demand (Dimoudi and Nikolopoulou, 2003). In addition, UGS is also highly influenced by human activities such as construction works causing root damage or soil compaction, pollutant emission from traffic or heating, or urine and salt contamination (Nouri et al., 2013b). Therefore, the stress factor for urban trees is usually high and leads to a lower survival rate than in rural areas (Koeser et al., 2013; Sjöman and Busse Nielsen, 2010). Besides, it is also more challenging to gather field data in the urban environment due to large variations within a city. When focusing on one particular crop field, it is relatively easy to deploy low-cost sensor networks or measuring devices such as lysimeters for direct measurements. However, cities would require the installation and calibration of large numbers of such measuring devices. Thus, verifying the quality of irrigation models for UGS is more complicated than for the agricultural sector. Hence, for most of the models discussed in this section for UGS, there exist no substantial performance evaluations.

Until now, most research on UGS irrigation needs has relied on the soil water balance or remote sensing approach (Nouri et al., 2013d; Shi et al., 2018). The majority of existing research focuses on either residential irrigation demand (Hilaire et al., 2008; Domene and Saurí, 2006), urban vegetation evapotranspiration (ET) (Allen et al., 2011; Contreras et al., 2011), or turf grass water demand (Huang and Fry, 2000; Pooya et al., 2013) with a goal of reducing demand. Vico et al. (2013) present a method for determining and reducing the daily irrigation demand of isolated street trees using soil, plant, and climate data. The authors propose a probabilistic model that takes into account the species, tree size, tree trench design, rainfall patterns, and irrigation systems used. They limit their model to circular tree trenches and ignore the possibility of capillary rise (CR).

This model was further enhanced by Revelli and Porporato (2018) by further quantifying nutrients retention in soil. On a greater spatial scale, Volo et al. (2014) investigate the irrigation demand and optimal irrigation schedule for mesic conditions and xeric conditions in Phoenix, USA. They provide recommendations for optimal daily irrigation scheduling based on the targeted level of plant stress after calibrating the model with soil moisture data from two sensors and past meteorological information. Because their model is limited to two types of neighborhoods and is based on sensor data, it cannot be easily adapted to more diverse districts or entire city areas. Orusa et al. (2020) calculated ET values using a remote sensing dataset from MODIS to derive ET values, but at a coarse spatial resolution of 500m.

The Simplified Landscape Irrigation Demand Estimation (SLIDE) provides an estimation method for the irrigation requirement of urban landscapes (Kjelgren et al., 2016). Based on adjusted literature values, it defines a plant factor (PF) for five different combinations of UGS type (turf/woody/desert) and climate (cool/warm/dry/humid). To calculate the water demand, the PF value is multiplied with reference ET (ET_0) and transpiring leaf/landscape area. Hereby, the authors assert that in a mixed zone, the water demand should be coordinated with the plant type yielding the highest PF. However, SLIDE does not consider precipitation events or soil properties, therefore it is only suitable to determine the ET of UGS but not the irrigation demand.

Finally, some cities offer examples for estimating the irrigation demand for street trees. For example, the Department for Plant Protection in Berlin estimates the need for irrigation based on the available soil moisture calculated for one tree species (Tilia cordata) located on the street Tempelhofer Weg in Berlin-Neukölln (Pflanzenschutzamt Berlin, 2021a). The soil moisture is defined relative to the total available water (TAW), and is categorised in a colour coded system, with green indicating above 50% moisture, yellow indicating below 50%, and red indicating below 30%. Whenever moisture reaches the red zone on the chart, the department recommends applying irrigation to all the street trees. On one side, this approach is easy to understand, includes current and predicted weather data, and also includes an irrigation forecast for the following week. But on the other side, the calculations are only valid for a single tree at one location, and are extended to the entire city without any adaptations. Moreover, while the method provides information about irrigation timing, it does not give any details on how much water quantity should be irrigated for different species. In South Australia, the water provider SA Water collaborated with the local councils to improve the irrigation of the public parks (SA Water, 2021). However, their approach requires the installation of numerous sensors which might not be feasible for all the municipalities. Moreover, since the algorithm to generate irrigation schedule is proprietary it is not available for scientific review.

Table 5.1 presents a comparative analysis made between the aforementioned approaches based on the estimation method, scope of application, spatial and temporal scale, and the input data. Most of these methods cover limited spatial scale such as grass, parks or single trees. Few of the studies are based on the soil moisture approach in which irrigation demand gets concentrated during summer months, increasing the water scarcity risk. In some studies, methodology is data intensive requiring extensive field measurements or deployment of large number of sensors.

The review indicates a lack of ET-based models for estimating the irrigation demand for urban street trees at daily or weekly time scale using public datasets. Nouri et al. (2013d) reviewed various techniques available to determine the ET demand for urban landscapes including lysimeter, Sap flow, WUCOLS, Eddy covariance, and remote sensing, and concluded that WUCOLS is the most suitable approach to implement for practical applications. Since other studies on urban landscapes also came to the same conclusion, this method was also used for this study (Nouri et al., 2013a).

The existing literature covers the irrigation models for crops and agricultural land extensively but it has only been implemented for limited cases for UGS so far. So, the proposed model of this paper aims to fill the gap and to be practically implementable by the cities for estimating the weekly irrigation demand using the available open datasets. The proposed methodology extends the current literature by suggesting the necessary adaptations required for implementing the water balance approach on the street trees on city level. Moreover, the methodology accounts for the tree's ET demand, incoming water from rainfall, and available water in the soil.

Table 5.1: Comparative analysis of available irrigation models and apporaches.

Study	Year	ET measurement	Soil moisture change	Agri culture	Urban	Tree	Park	City	Daily/ Weekly	Monthly/ Annual	Sensors/ Field measurements	Remote Sensing	Other Public datasets	Rainfall
Gober et al.	2010						✓			✓				
Contreras et al.	2011			✓						✓		✓		✓
Vico et al.	2014		✓		✓	✓			✓				✓	✓
Volo et al. (a)	2014		✓		✓		✓							
Delgoda et al.	2016	✓		✓					✓		✓		✓	
Kjelgren et al. (SLIDE)	2016	✓			✓	✓	✓	✓	✓				✓	
Shi et al.	2017				✓		✓	✓		✓			✓	✓
Adeyemi et al.	2018		✓	✓		✓			✓				✓	
Revelli & Porporato	2018		✓		✓			✓		✓				
Nouri et al.	2019	✓			✓		✓			✓	✓		✓	✓
Reyes-Paecke et al.	2019				✓		✓							
Khan et al.	2020			✓		✓			✓		✓	✓	✓	✓
Henrich et al.	2021	✓			✓	✓			✓				✓	✓
Wessolek & Kluge	2021	✓			✓	✓				✓	✓		✓	✓
Berlin City	2021		✓		✓	✓			✓				✓	✓
AquaCrop, FAO		✓		✓		✓								
CropWat, FAO		✓		✓		✓								
Karlsruhe City		-	-						-					-
SA Water		?	?		✓		✓		✓		✓			✓
Time Series Model		✓			✓	✓		✓	✓	✓			✓	✓

5.5 Background

Overall, the aim of efficient irrigation systems is to deliver the minimum amount of water that is required to ensure the survival, functioning and aesthetically pleasing appearance of the UGS. A large number of existing models are based on the soil water balance approach (see Equation 5.1). The approach is based on a closed water cycle system, where at any moment the outflow should be equal to the inflow.

The inflow consists of the sum of precipitation (P), irrigation (I) and capillary rise (CR). The outflow is composed of Evapotranspiration (ET), Runoff (RO), drainage or deep percolation (D), and change in soil moisture (ΔS). As any errors in measuring or estimating the individual parameter values add up to the cumulative error, the soil water balance approach is generally less accurate than direct measurements. However, it is still useful for practical applications as direct measurements are quite expensive and, hence, generally lacking.

$$P + I + CR = ET + RO + D + \Delta S \tag{5.1}$$

In the subsequent paragraphs, an approach for determining individual parameters of soil water balance (see Equation 5.1) followed by the steps to design a computational model are presented.

5.5.1 Estimating Evapotranspiration (ET)

One of the critical parameters that highly influences the irrigation demand is ET. ET depends on vegetation characteristics such as species type, canopy size, age, root type, and micro-climatic conditions. For canopy size, usually the bigger the canopy size, the higher is the ET and the water demand. This is due to a greater number of leaves leading to higher water demand for photosynthesis as well as higher loss of water through stomata. However, in case of age, usually, the demand for external irrigation reduces as the tree matures. This is because of the development of root systems that makes the tree self-reliant. Depending on the depth and spread of the root system, a tree can access the available water in the soil layers and groundwater. Lastly, climatic conditions like temperature, humidity, wind, precipitation, and solar radiation will affect the ET demand of the trees. This is further influenced by local anthropogenic conditions such as presence of buildings and roads nearby that can either directly influence through shading or indirectly by altering the micro-climate. Hence, the location and immediate neighbourhood of the UGS are of considerable importance while calculating the ET.

For the purpose of this study, the Penman-Monteith equation is used to theoretically estimate the potential ET, based on hydrometeorological parameters (FAO, 2021c), since we assume no sensor data from the field. This method is also a recommended approach by the FAO for ET estimation. However, the derived potential ET is based on grass of uniform height, and therefore, it requires adaption for street trees. The WUCOLS approach estimates the water requirements of UGS to meet acceptable aesthetic expectations, health and reasonable growth for all available tree species (Costello and Jones, 2014). As this provides the desired quantity for irrigation, it is best suited for scarce water resource conditions.

The WUCOLS method uses a landscape vegetation coefficient K_L to account for the landscape characteristics as shown in Equation 5.2 (Costello L. R., 2014). K_L itself is composed of a species factor (K_s), a density factor for UGS (K_d), and a microclimate factor (K_{mc}), as shown in Equation 5.3. The values of these coefficients are chosen according to the categories shown in Table 5.2 based on prevailing conditions. WUCOLS also provides an extensive database that categorises the tree water demand into high, medium, low, and very low according to species type and the climatic region. The database includes 778 types of tree species and covers six different climatic regions of the State of California (UC Davis, 2021).

$$ET_{\mathrm{L}} = K_{\mathrm{L}} \times ET_0 \tag{5.2}$$

$$K_{\mathrm{L}} = K_{\mathrm{s}} \times K_{\mathrm{d}} \times K_{\mathrm{mc}} \tag{5.3}$$

Table 5.2: Coefficients for WUCOLS approach (Costello et al.)

Coefficient	Categories	Value	Group
Species Factor (K_s)	Very low Low Medium High	<10 % of ET_0 10-30 % of ET_0 40-60 % of ET_0 70-90 % of ET_0	Based on species type such as bamboo, bulb, grass, ground-cover, perennial, palm and cycad, shrub, succulent, tree, vine, natives
Density factor (K_d)	Low	0.5 - 0.9	Immature and sparsely populated vegetation
	Average	1	Single vegetation type
	High	1.1 - 1.3	Mixed vegetation with trees, shrubs, and ground cover
Microclimate factor (K_{mc})	Low	0.5 -0.9	Vegetation under building overhangs or shade
	Average	1	Open area and not influenced by urban features
	High	1.1 - 1.4	In the vicinity of buildings or sealed area

5.5.2 Estimating Effective Precipitation (P_{eff})

To improve the accuracy of the irrigation demand estimation and to avoid over-watering the trees during a rain event, it is essential to account for the actual and expected precipitation during the time period. Precipitation data is often available through weather departments at the state or national level. In Germany, for example, the German Weather Service (DWD) operates weather stations throughout the country and provides weather and climate data, including the precipitation at daily time scale. However, for the purpose of irrigation, it needs to be converted into effective precipitation (P_{eff}). P_{eff} is defined as the fraction of the rainwater that is not intercepted by vegetation. The fraction is represented as the interception coefficient (c_{inc}).Rainfall (amount, intensity, direction, consecutive rain days) and other meteorological conditions such as wind speed and direction all have an impact on interception (Gerrits et al., 2007). However, there is no standard approach available for its depiction, and hence, it requires field experiments for its adjustment. As field experiments involve high personnel and equipment costs, they might not be feasible for smaller cities. Therefore, for this study, P_{eff} is determined according to Equation 5.4. Because c_{inc} varies depending on the species, literature values are required for implementation (Llorens and Domingo, 2007; Nytch et al., 2018; Yang et al., 2019).

$$P_{\text{eff}} = (1 - c_{\text{inc}}) \times P \tag{5.4}$$

where, c_{inc} is the interception coefficient.

5.5.3 Estimating Capillary Rise (CR)

Capillary Rise (CR) describes the water made available to vegetation by the movement of groundwater from the groundwater table into the root zone. It depends on the groundwater table, the type of soil, and its characteristics. However, as the ET derived with the WUCOLS approach is only suitable in situations without CR as a water source, for this study it is assumed that there is no CR in the root zone. This is possible when the groundwater table is low enough to disable CR. Previous studies by Delgoda et al. (2016a), Revelli and Porporato (2018), and Vico et al. (2013) used the same reasoning. This assumption should be reasonable in the context of street trees, as the compact tree trench and highly dense soil in cities would restrict the growth of the root system, making them unable to access the groundwater.

5.5.4 Estimating Runoff (RO)

The accurate way of determining the Runoff (RO) would be by conducting field experiments. However, in the absence of field data, RO can be indirectly calculated through the infiltration rate. The RO is then defined as the remaining water from P_{eff} after the infiltration (P_{inf}) has taken place. The maximum amount of water that can enter a particular soil in a time unit is represented using the infiltration rate (c_{inf}). The intensity of P_{eff} is determined as P_{eff}/h, where h describes the duration of the precipitation event in hours. As shown in Equation 5.5, RO will occur whenever the intensity of P_{eff} exceeds the c_{inf} of the soil. The infiltration rates for different types of soil are available in published literature. The Minnesota Stormwater Manual, for example, specifies infiltration rates for gravel to clay (Minnesota Pollution Control Agency, 2013). Depending on the soil type of the region, a suitable rate can be used. Additionally, the manual recommends using a reduced rate by one level in the case of compacted soils in urban areas.

$$RO = \begin{cases} 0, & \text{if } c_{\text{inf}} \geq P_{\text{eff}}/h \\ P_{\text{eff}} - (c_{\text{inf}} \times h) & \text{else} \end{cases} \tag{5.5}$$

where, h= duration of precipitation event (hours)

5.5.5 Estimating Drainage (D) and the Soil Moisture Change (Δ S)

Drainage refers to the quantity of water that directly percolates below the root zone and, hence, is unavailable for the trees to use. It depends on soil characteristics, rainfall intensity and duration, and the distribution of roots. Accordingly, this parameter can be calculated as the difference between the amount of infiltrated water and the water holding capacity of the soil, as shown in Equation 5.6. To calculate this, first, total available water (TAW) is calculated as the difference between field capacity and the wilting point of the soil (FAO, 1990). The FAO provides a range of TAW values for undisturbed soil types (Brouwer et al., 1985). However, with vegetation, TAW will increase as root systems hold more water in the root zone. The Department of Primary Industries and Regional Development of the Western Australian government provides information about TAW for different soils (Newman, 2012). The root depth for this system is defined as 0.5m (broad), 1m (oblique), 2m (deep) (Dobson, 1995). After the determination of TAW, the effective root depth is multiplied with the TAW value, resulting in readily available water (RAW) (see Equation 5.7). A coefficient c_s is defined as the portion of the infiltrated water available for trees. If P_{inf} is higher, c_s equals RAW/P_{inf} because, after drainage, only RAW will be available for the tree. Second, if both values are equal or if P_{inf} is smaller than RAW, there will be no deep percolation and c_s will be one.

$$D = \begin{cases} 0, & \text{if } P_{\text{inf}} \leq TAW \\ P_{\text{inf}} - TAW & \text{else} \end{cases} \tag{5.6}$$

$$RAW = r \cdot TAW \tag{5.7}$$

where, r= root zone depth (m)

$$RAW = \begin{cases} c_{\text{s}} \cdot P_{\text{inf}} & \text{if } P_{\text{inf}} \geq RAW \\ P_{\text{inf}} & \text{else} \end{cases} \tag{5.8}$$

5.6 Modeling approach

5.6.1 Time-series model

Based on the theoretical approach described in the previous section, a novel time series model for estimating the weekly irrigation demand of urban street trees is developed as given in Equation 5.9. It calculates the water available for the tree uptake as a portion of infiltrated precipitation remaining after canopy interception, drainage, and runoff. Table 5.3 describes the list of parameters used in the model along with the respective data source used for the subsequent case study (see section 5.7). The interaction between the parameters is illustrated for a single tree in Figure 5.1. The Equation 5.10 calculates the total ET_L demand for all the tree species, as explained in subsection 5.5.1. In the Equation 5.11, water reaching the soil surface is determined by reducing the water lost through interception, as explained in subsection 5.5.2. The Equation 5.12 is used to compute the amount of water that penetrates into the soil, depending on whether the rainfall intensity is lower than c_{inf} as explained in subsection 5.5.4. Lastly, Equation 5.13 and Equation 5.14 calculate the portion of the infiltrated water that is available to the tree depending on the soil type and root depth, as explained in subsection 5.5.5.

$$I_{\text{t}} = \sum ET_{\text{L,t}} - ET_{\text{L,t-1}} + I_{\text{t-1}} + (c_{\text{s,t}} \cdot P_{\text{inf,t}}) - (c_{\text{s,t+1}} \cdot P_{\text{inf,t+1}}) \tag{5.9}$$

such that,

$$ET_{\text{L,t}} = \sum_{s\forall S}(K_{\text{L,s}} \cdot ET_{0,\text{t}}) \tag{5.10}$$

$$P_{\text{eff,t}} = (1 - c_{\text{inc}}) \cdot P_{\text{t}} \tag{5.11}$$

$$P_{\text{inf,t}} = \begin{cases} P_{\text{eff,t}}, & if c_{\text{inf}} \geq P_{\text{eff,t}}/h \\ c_{\text{inf}} \cdot h, & \text{else} \end{cases} \tag{5.12}$$

$$RAW_{\text{t}} = \sum_{s\forall S} r_{\text{s}} \cdot TAW \tag{5.13}$$

$$c_{\text{s,t}} = \begin{cases} RAW/P_{\text{inf,t}}, & if P_{\text{inf,t}} > RAW \\ 1, & \text{else} \end{cases} \tag{5.14}$$

$$\tag{5.15}$$

where subscript, s = tree species (s ∈ S), t = unit time (daily/weekly).

Table 5.3: Summary of parameters defined in the python corresponding to the designed model

Symbol	Type[a]	**Description**	**Data Source**
s	I	Name of the species	Latin name
c_{inc}	I	Interception coefficient	Literature values (0.17/0.227/0.3058)
c_{inf}	I	Infiltration rate	Minnesota Pollution Control Agency (2013)
r	I	Depth of roots	0.5m/1m/2m depending on root system
TAW	I	Total available water	Newman (2012)
ET_0	I	Reference ET	Weather data (Deutscher Wetterdienst, 2021)
ET_L	C	Landscape ET	Using WUCOLS database (UC Davis, 2021)
P_{eff}	C	Effective precipitation	Difference of Precipitation and Interception
P_{inf}	C	Infiltration amount	Depending on soil type and compactness
RAW	C	Available water	Depending on TAW and rootdepth
I_t	C	Irrigation demand	According to Equation 5.9

[a]Type: I = Input, C = Calculated

The computational steps followed by the model are as follows: In Step 1, the sum of the precipitation for the past week is calculated from the precipitation data source (daily). In Step 2, the sum of the precipitation forecast for next week is calculated from the precipitation forecast data source (daily). In Step 3, the sum of the ET_0 is calculated, according to the FAO method, for the prior week from the reference ET data source (daily).

In Step 4, using the tree species information from the tree inventory, ET_L is calculated for each tree by matching its botanical name (in Latin) with the WUCOLS dataset. Due to certain differences in spellings of species in tree inventories and the WUCOLS database, a fuzzy matching algorithm (Cohen, 2020) is used to identify the highest matching keywords based on the botanical name. Therefore, if a specific species type is missing from the WUCOLS database, the most similar tree name from the same botanic family will be assigned to it. If no match is found, a medium water demand value is assumed by default. Since WUCOLS was originally composed for California, the region type with the most similar climate to the study area needs to be selected.

The description of the six available climatic zones is published on the WUCOLS and the Sunset website (UC Davis, 2021).

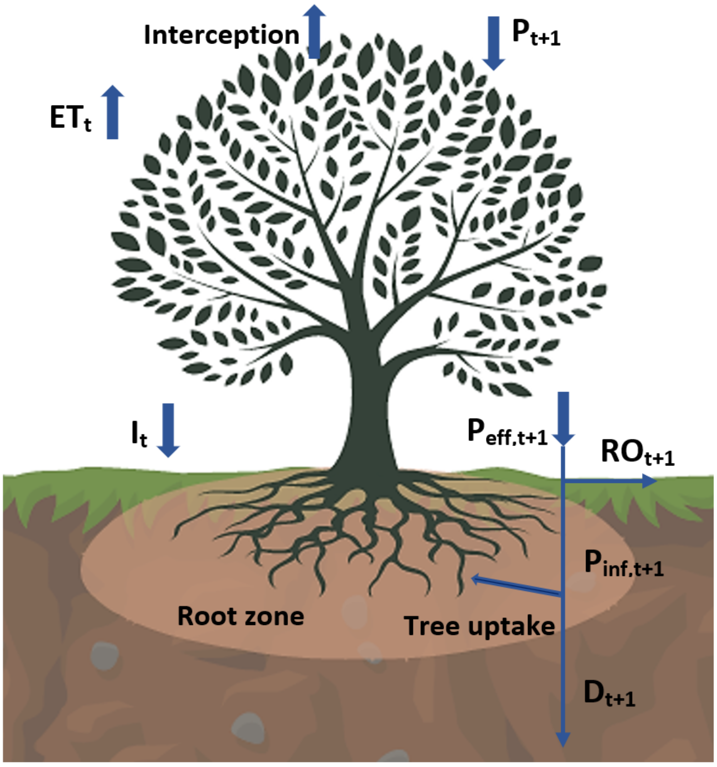


Figure 5.1: The parameters in the water balance approach considered in the time series model.

In Step 5, a species factor (K_s) is defined according to Table 5.2. By default, the factor is set to the middle of the given range (see Table 5.2). However, a user can modify the value within the respective range. A similar procedure is applied to select the density factor (K_d) and the micro-climate factor (K_{mc}) according to the category obtained in Step 4. Again, the default value is set at the middle of the range; however, the user can manually adjust the values in the case, for example, of newly planted trees or completely shaded areas. Then, a landscape factor (K_L) is calculated by multiplying all three factors as per Equation 5.3.

In Step 6, the weekly ET_0 obtained in Step 3 is multiplied with K_L to obtain the weekly ET_L. This is further multiplied with the species-wise tree count to obtain the ET_L demand for each species (Equation 5.10). In Step 7, to determine P_{eff} according to Equation 5.11. Based on the available data from the literature, c_{inc} for *Quercus* and *Aesculus* trees was set as 0.17 and 0.3058, respectively (Llorens and Domingo, 2007; Yang et al., 2019), while for the remaining species for which data was unavailable, it was set to 0.227 as the default (Nytch et al., 2018). In Step 8, the amount of water infiltrating into the soil is calculated using infiltration rate c_{inf} according to Equation 5.12. If there are no field data, the Minnesota Pollution Control Agency provides design infiltration rates for different soil types in the Minnesota Stormwater Manual (Minnesota Pollution Control Agency, 2013). In Step 9, the available RAW is calculated by multiplying the root depth given in Table 5.3. In Step 10, weekly irrigation demand I_t is calculated as the difference of ET_L and the available infiltrated water in the root zone according to Equation 5.9.

The aforementioned model was implemented in Python language (version 3.10) using the Google Colab service (Google, 2021). The program initialises by downloading and storing all of the listed datasets from their respective servers, using the requests library. Additionally, the matplot library was used for the purpose of plotting. The total run-time with a tree inventory of around 0.5 million trees is about 15 minutes.

5.7 Case study: Berlin city

The described model is applied to a case study on the City of Berlin. Berlin is the capital and largest city of Germany, with around 3.6 million inhabitants and a city area of 891 km^2. The mean population density in the city is about 4200 residents/km^2 which is considered as high-density cluster according to the degree of urbanisation classification of Eurostat. The city is mainly flat in topography and located on the Spree River, surrounded by numerous lakes and woodlands. Berlin has an average of around 80 trees per kilometre of the city's streets, totalling about 431,000 trees in the entire city. They consist of trees from over 50 different species. The most common tree genus include lime (Tilia), maple (Acer), oak (Quercus), plane (Platanus), and chestnut (Aesculus), which account for over 75% of the total number of street trees. Currently, the city spends around 37 million euros/year on the maintenance of existing street trees and around 2500 euros/tree to take care of newly planted trees for the first three years (Pflanzenschutzamt Berlin, 2021b).

5.7.1 Data used and inputs

In Germany, the German weather service DWD offers data from 5,980 meteorological stations spread across the whole country (Deutscher Wetterdienst, 2021). From this set of meteorological stations, 11 are located in the Berlin city region. As a result, meteorological data from all 11 stations is averaged to obtain a mean value for different parameters. The dataset includes the ET_0, as well as past and future precipitation data. For the calculation of ET_L, the WUCOLS dataset provided by the University of California is used (UC Davis, 2021). For Berlin, climate region two was the appropriate choice, which was used to determine the relevant coefficients from Table 5.2. The city tree inventory available from the open-data initiative of Berlin was used for obtaining tree specific information such as type of tree, species type, and distribution (Berlin City, 2021). Information regarding the soil type in Berlin was obtained from the Federal Institute for Geosciences and Natural Resources (Bundesanstalt für Geowissenschaften und Rohstoffe, 2007). Using this, sandy loam soil was selected for Berlin. Subsequently, the default value for c_{inf} should be 20.3 mm/h for normal soil, but for the case of street trees, it is set one level below at 11.4 mm/h due to compacted soils near the tree trench. Additionally, the default TAW value for sandy loam soil was used at 70 mm based on the literature (Newman, 2012).

For a more precise irrigation recommendation, the forecast for precipitation and ET_0 is necessary. The DWD (Deutscher Wetterdienst, 2021) makes predictions about future rain events, but ET_0 forecasts are not available. Hence, in this case, the average ET_0 of the prior week is used as a forecast, considering that the ET_0 should not change substantially in the short run. Moreover, the available soil moisture from the previous seven days is taken into account as the available water.

Figure 5.2 presents a snapshot of the tree inventory dataset of the City of Berlin, wherein the colour of the marker indicates the species type. This dataset includes information on the tree's location, botanical name, and species family. Moreover, for a share of trees (75%) it also includes year of plantation, crown size, trunk size, and tree height information. Although this additional tree maturity information was not considered in the current study, it should be further investigated to improve the estimations.

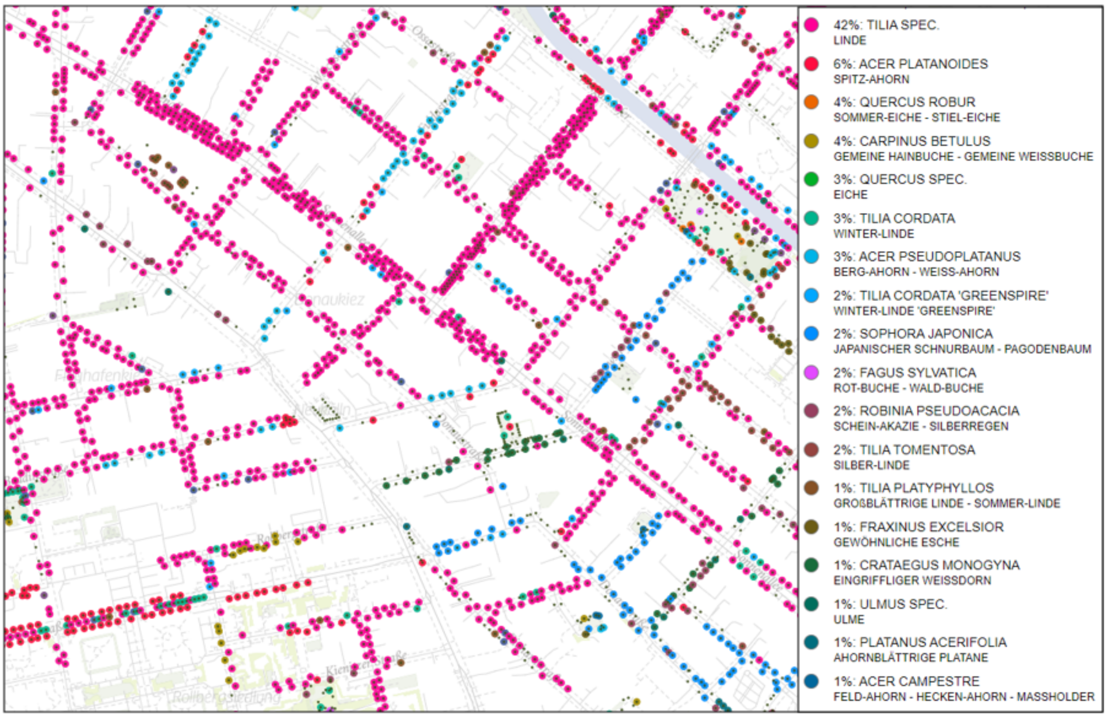
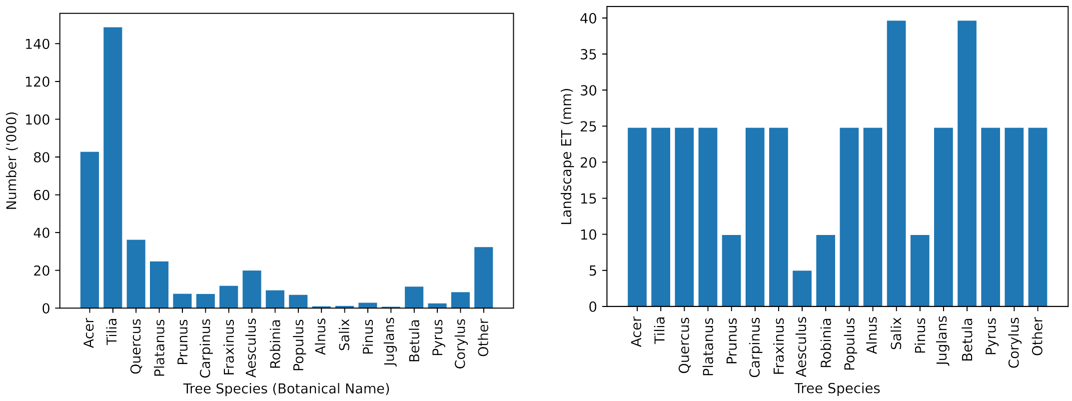


FIGURE 5.2: Snapshot of the street trees in Berlin with the colour of the marker indicating the species type (Source: http://opentrees.org/).

5.7.2 Results for the street trees in Berlin

Figure 5.3a presents the species-wise distribution of trees in Berlin. It can be observed that Tilia (Lime) is the most dominant species, followed by Acer (Maple) and Quercus (Oak). First, an analysis was performed for a single week of 2021 (41st week). Figure 5.3b presents the species-wise ET_L demand for street trees in Berlin for this particular week. It can also be observed that Salix (Willows) and Betula (Birch) have the highest ET_L demand whereas Aesculus (Chestnut horse) has the lowest ET_L demand, of all tree species in Berlin. In the following step, irrigation is recommended if the precipitation forecast for the next seven days is lower than the sum of the current irrigation demand and the forecasted ET_L for the next seven days. Depending on the irrigation system, municipalities might also be interested in applying additional water to meet future irrigation demands. In such a case, the maximum demand is supplied according to the assessed irrigation demand for the next seven days. The bar plots in Figure 5.4a and Figure 5.4b depict the species-wise current and maximum irrigation recommendation (mm) for a single tree. This information can be further used by the decision-makers to assess the future increase in water demand in the case of new plantations of trees. Although several factors such as nativity, climate resilience, full-grown canopy size, aesthetics, and cost need to be considered while selecting the species type for a new plantation, watering demand can be a significant determining factor, especially, for drought-prone cities. Furthermore, Figure 5.4c and Figure 5.4d show the species-wise total current and maximum irrigation recommendation for all the city's street trees. Again, Tilia has the highest total irrigation demand, followed by Acer and Quercus. Since the chosen week occurs during the peak of the summer season in Berlin, the irrigation demand observed in this case was particularly high.



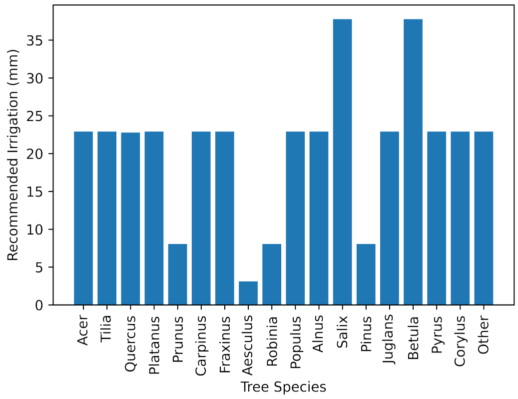
(A) (B)

FIGURE 5.3: Bar plots showing (a) Species-wise distribution of street trees in Berlin. (b) Species-wise Landscape ET demand (mm) of street trees in Berlin.

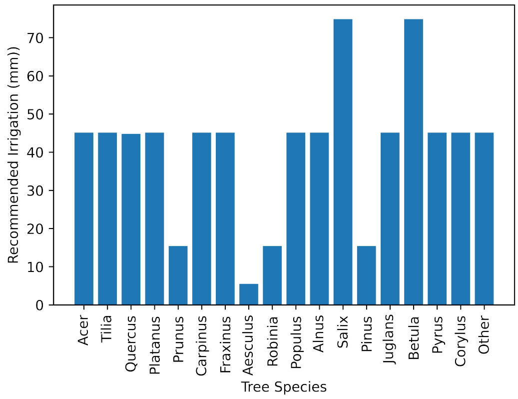
Based on this, the total irrigation requirement for this particular week is computed for all the street trees and is presented in Figure 5.5. If the watering is done through drip irrigation, the water height figures in mm should be converted into m^3 or liters by multiplying the height with the tree area (taken as 6 m^2 in this study) to calculate the volume of water to be supplied. However, in the case of watering tankers, the estimates in water height should be used directly for uniformly applying it over the tree trench.

Next, the time series model is run for all the weeks of 2021 to obtain the weekly irrigation demand. Figure 5.6 (left) presents the species-wise weekly irrigation demand of the most commonly found tree species in Berlin. This is particularly useful for the road and garden department's day-to-day operations of supplying the water only in the required quantity. The total irrigation demand for all the street trees in the cities is given in Figure 5.6 (right). This is particularly useful for the city administrators to make long-term plans in terms of water budgeting for existing and newly planted trees. The seasonal variations are quite evident in the result, wherein during the winter weeks the irrigation demand is significantly lower in comparison to the summer months. This further reinforces the need for applying such a model in practice so that cities can plan and prepare their water budgets in advance. Furthermore, besides watering schedules, city administrators can also use this to make management decisions regarding the required water storage capacity, rainwater collection, irrigation scheduling, logistics, and the feasible amount of new trees that can be supported in the future.

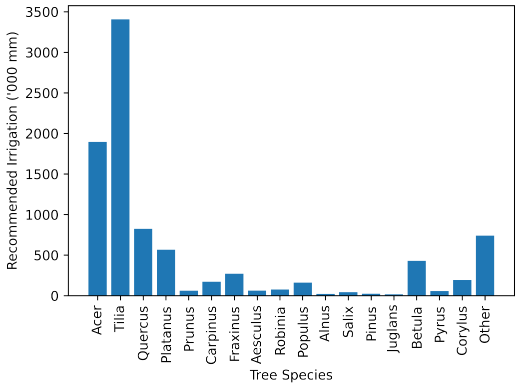
To illustrate an application for scenario analysis, the irrigation demand considering a drought scenario is computed. For this, the model was run with the input precipitation data reduced by 50%, while keeping all other parameters identical to the baseline scenario. This resulted in an increase of around 8.5 % in the external irrigation demand.



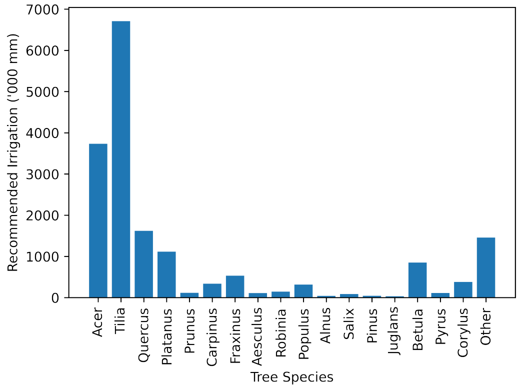
(A)



(B)



(C)



(D)

FIGURE 5.4: Bar plots showing species-wise current (a) and maximal (b) irrigation demand for a single tree, and species-wise current (c) and maximal (d) irrigation demand for all street trees (in mm) in Berlin.

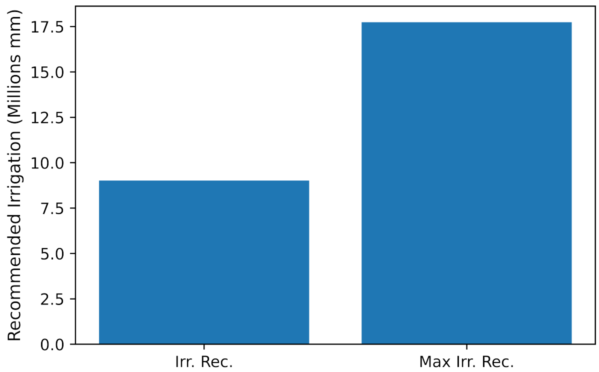


FIGURE 5.5: A bar plot showing the total current (Irr. Rec.) and maximum (Max. Irr. Rec.) irrigation recommendations (mm) for all street trees in Berlin during one week (41st week of 2021).

Figure 5.7 presents the weekly increment in water demand in this case. Here, too, the effect is stronger during the summer weeks compared to winter. In actual conditions, this

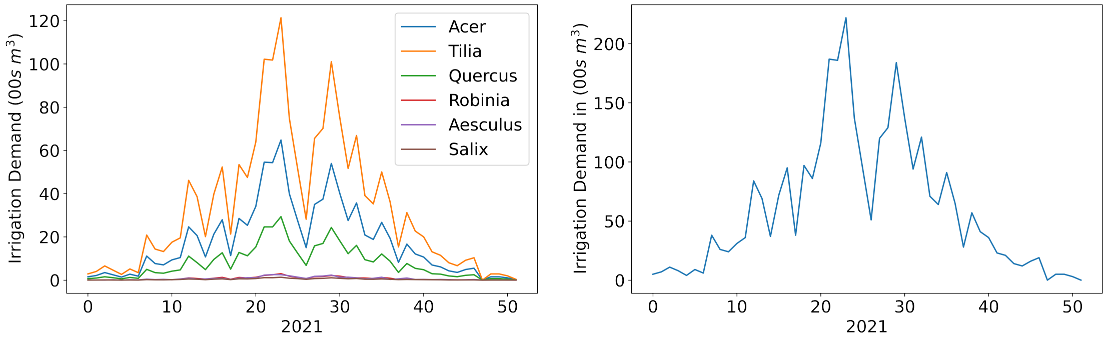


FIGURE 5.6: A plot showing estimation of weekly irrigation demand (in m^3) for the most commonly found street tree species (on left) and for all the street trees in Berlin combined (on right).

impact is likely to be even higher, since the reduced rainfall will also cause the depletion of groundwater resources.

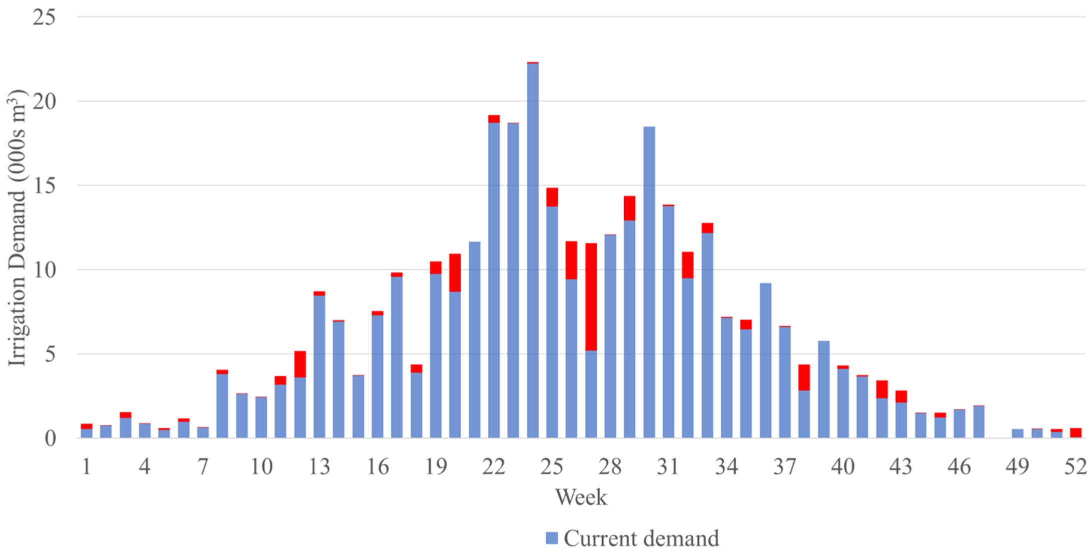


FIGURE 5.7: A plot showing the change in irrigation demand in case only 50 % of rainfall occurs.

We also compared our model with the existing SLIDE method, which is based on assigning PF values to adjust the ET_0 based on urban context. Street trees can be classified under woody plants, so a PF value of 0.5 was applied here. Accordingly, only the coefficient $(K_s \cdot K_d \cdot K_{mc})$ of Equation 5.10 was replaced by PF, while everything else remained the same. The calculated irrigation demand by both methods is presented in Figure 5.8. As visible, the SLIDE approach estimates a lower demand compared to our model. Overall, a 19 % reduction in the total annual irrigation demand was seen. This can be potentially attributed to the comprehensiveness of the WUCOLS approach, which includes three separate coefficients to incorporate the impact of urban conditions, therefore leading to higher ET_L demand and, subsequently, recommending higher irrigation.

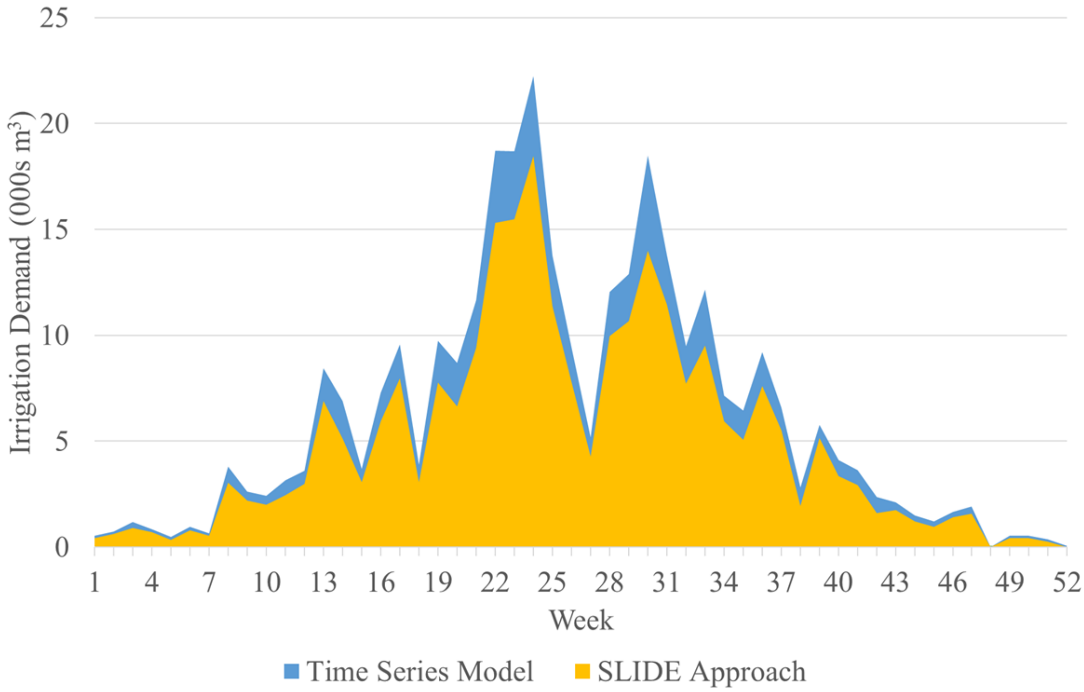


FIGURE 5.8: A plot showing estimated irrigation demand (m^3) for the Berlin city in 2021 by the time series and SLIDE model.

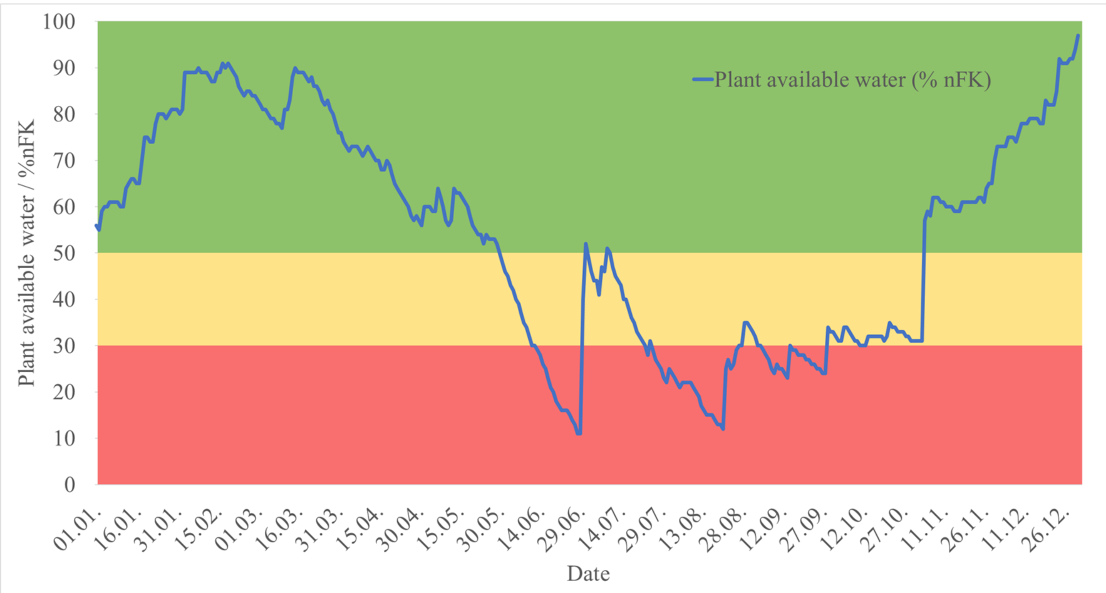


FIGURE 5.9: A plot showing estimated soil moisture available to plants at the example site Tempelhofer Weg in Berlin-Neukölln for the year 2021 (data source: (Pflanzenschutzamt Berlin, 2021a)).

Moreover, Figure 5.9 presents a plot from the currently implemented model in Berlin that estimates the soil moisture available to plants for a single tree (Tilia cordata) at the Tempelhofer Weg in Berlin-Neukölln for the year 2021. According to this system, irrigation will only take place when the plant's available water in the soil falls below 30%. So, in this case, this would be from the beginning of June to the end of September. This is distinctly different than in the time series model, where irrigation is recommended almost throughout the year.

5.8 Discussion

The developed time series model is suitable for estimating an irrigation schedule for all street trees in a city on daily or weekly time scales. Since it is based on the soil water balance principle and incorporates the WUCOLS approach for the estimation of ET demand, it can adapt irrigation recommendations according to urban conditions. Moreover, it is not dependent on any sensor data to measure soil moisture change. However, if field measurements are available, they can be integrated into the same model for greater accuracy.

The estimations from the developed time series model suggest an improvement over the currently implemented forecasting model in Berlin. The currently applied model extends the calculation made for one tree species to the entire city without any adjustments. Furthermore, a high concentration of irrigation demand during the summer months can aggravate already stressed water systems during droughts or drier summers. Additionally, the soil moisture approach informs about the necessity to irrigate but does not provide any information on the quantity of water to be irrigated. These limitations are addressed by the time series model, which uses an ET-based approach for estimating the irrigation demand.

Furthermore, to obtain the irrigation demand estimation, the time series approach should be preferred when compared to available alternative approaches such as SLIDE, which basically assumes one average PF for all tree plantings and therefore ignores the species type or density as an important driver of the ET_L. In addition to that, in the SLIDE method, the forecasted rainfall is not incorporated within the estimation and, therefore, is missing out on the potential water savings. WUCOLS, on the other hand, considers more aspects of the study site through its species, density and micro-climate factor. Nouri et al. (2013c), in their study of Adelaide, also found that WUCOLS leads to more realistic results than the PF approach. As WUCOLS offers more scope for adaptation according to the site peculiarities, it was the chosen method for calculating ET_L in this time series model. Comparative analysis shows a lower irrigation demand with the SLIDE approach than with the time series model. Due to the lack of other data sources concerning the ET and the irrigation demand, only a qualitative comparison of the two approaches is possible.

The accuracy of the proposed model can be further improved by calibrating it using field data and including the uncertainty in the weather data. The limitations of the model include obtaining the infiltration coefficients and root depths from literature, since in reality, those actually depend on the individual tree and site-specific characteristics. Nevertheless, in the future, when accurate data is available, e.g., via sensors or field data regarding the interception or infiltration rates, it could be easily incorporated into the proposed model to incorporate the localisation and thus improve model performance. Additionally, the impact of omitting CR from the model needs further investigation, especially, for the cities with high groundwater tables. For the calculation of the annual irrigation demand, the climatic data on a daily time scale has been used. For ET_0 this time resolution is suitable; however, for the precipitation, a higher temporal resolution would be ideal. Since the infiltration rate is used to determine the actual water quantity from effective precipitation percolating into the root zone, detailed information about the intensity of the rain event would lead to more precise estimations. Furthermore, the weather data originated from the DWD stations, which are spread around the entire city, and were averaged to obtain the input data. However, depending on the placement of the measuring instruments, the data might not have incorporated the full effect of the urban conditions on the weather data. Also, rain could have fallen erratically over the investigated area. The model, however, assumes regular or constant rainfall in the investigated region. Considering the above factors and the uncertainties involved with the estimation, the final results should be used as a guideline for the administrators on a relative scale rather than at an absolute level. Moreover, in this study, the results are calculated for the year 2021. Historic data are not used yet but could be used for computing the potential variability of irrigation demand due to changing weather and long-term climate change effects.

5.9 Conclusion and future research

In order to safeguard the benefits attainable from UGS, it is crucial that the city trees survive dry and hot periods, receive enough water to fulfill the ET demand, moderate the climate, and remain aesthetically pleasing. Hence, quantifiable information about the irrigation demand of UGS is of high interest to municipalities.

The proposed time series model based on soil water balance and the WUCOLS approach present a unique solution for determining an irrigation schedule for city street trees at a finer (daily or weekly) temporal resolution. The model requires limited input data that is readily available from open-access datasets, and no additional installation of sensors is required. The proposed model provides a feasible solution for a large number of cities, especially in developing regions where access to reliable data is limited. With more frequent and extreme weather events caused by global warming and the resulting water scarcity, the time series model can provide reasonable accuracy for the water demand of street trees, allowing the garden and forestry departments to avoid relying on historic or speculative values.

However, it is crucial to understand the drivers of the input parameters and the approach adopted for their estimation. Furthermore, the input data and conditions can be varied to generate irrigation estimations for different scenarios, such as an increase in trees, longer and drier summers, or the depletion of groundwater. The results from this model can be further combined with the benefit estimation of each UGS to make an informed decision regarding the future planning of newer green areas and efficient resource management. For instance, depending on the availability of stored water resources and the UGS' specific water demand, an evidence based decision regarding the allocation of the available water can be made. Likewise, if the water deficit is known in advance, the necessary rainwater collection and storage systems can be designed accordingly.

To increase the model's applicability, performance should be evaluated through controlled experiments or field trials. Furthermore, the model can be improved by integrating forecast uncertainties as well as higher spatial and temporal resolutions of the relevant input data and design parameters. For instance, precise hourly rainfall intensity and the actual ET at sub-city spatial scale could improve the irrigation schedule estimation.

Bibliography

Adeyemi, O., Grove, I., Peets, S., Domun, Y., and Norton, T. (2018). Dynamic neural network modelling of soil moisture content for predictive irrigation scheduling. *Sensors (Switzerland)*, 18(10).

Allen, R. G., Pereira, L. S., Howell, T. A., and Jensen, M. E. (2011). Evapotranspiration information reporting: I. Factors governing measurement accuracy. *Agricultural Water Management*, 98:899–920.

Berlin City (2021). Open Data Berlin.

Brouwer, C., Goffeau, A., and Heibloem, M. (1985). Irrigation water management: Training manual no. 1.

Bundesanstalt für Geowissenschaften und Rohstoffe (2007). Bodenübersichtskarte von Deutschland 1:3000000.

Cohen, A. (2020). fuzzywuzzy: Fuzzy string matching in python.

Contreras, S., Jobbágy, E. G., Villagra, P. E., Nosetto, M. D., and Puigdefábregas, J. (2011). Remote sensing estimates of supplementary water consumption by arid ecosystems of central Argentina. *Journal of Hydrology*, 397:10–22.

Costello, L. and Jones, K. (2014). WUCOLS IV: Water use classification of landscape species.

Costello L. R., J. K. S. (2014). (Water Use Classification of Landscape Species).

Delgoda, D., Malano, H., Saleem, S. K., and Halgamuge, M. N. (2016a). Irrigation control based on model predictive control (mpc): Formulation of theory and validation using weather forecast data and aquacrop model. *Environmental Modelling & Software*, 78:40–53.

Delgoda, D., Saleem, S. K., Malano, H., and Halgamuge, M. N. (2016b). Root zone soil moisture prediction models based on system identification: Formulation of the theory and validation using field and aquacrop data. *Agricultural Water Management*, 163:344–353.

Deutsche Welle (2022). Water scarcity: EU countries forced to restrict drinking water access.

Deutscher Wetterdienst (2021). DWD open data.

Dimoudi, A. and Nikolopoulou, M. (2003). Vegetation in the urban environment: microclimatic analysis and benefits. *Energy and Buildings*, 35:69–76.

Dobson, M. (1995). Tree root systems.

Domene, E. and Saurí, D. (2006). Urbanisation and water consumption: Influencing factors in the metropolitan region of barcelona. *Urban Studies*, 43:1605–1623.

European Commission (2000). Establishing a framework for community action in the field of water policy.

European Commission (2021). Forging a climate-resilient Europe - the new EU strategy on adaptation to climate change.

Fam, D., Mosley, E., Lopes, A., Mathieson, L., Morison, J., and Connellan, G. (2008). Irrigation of urban green spaces: a review of the environmental, social and economic benefits.

FAO (1990). Chapter 8 - etc under soil water stress conditions.

FAO (2021a). Aquacrop.

FAO (2021b). Cropwat.

FAO (2021c). Penman-Monteith equation.

France-Presse Agence (2022). Italy declares state of emergency in drought-hit northern regions.

George, B., Shende, S., and Raghuwanshi, N. (2000). Development and testing of an irrigation scheduling model. *Agricultural Water Management*, 46:121–136.

Gerrits, A. M. J., Savenije, H. H. G., Hoffmann, L., and Pfister, L. (2007). New technique to measure forest floor interception – an application in a beech forest in luxembourg. *Hydrology and Earth System Sciences*, 11:695–701.

Google (2021). Google colaboratory.

Hilaire, R., Arnold, M., Wilkerson, D., Devitt, D., Hurd, B., Lesikar, B., Lohr, V., Martin, C., McDonald, G., Morris, R., Pittenger, D., Shaw, D., and Zoldoske, D. (2008). Efficient water use in residential urban landscapes. *HortScience horts*, 43(7):2081 – 2092.

Huang, B. and Fry, J. D. (2000). Turfgrass evapotranspiration. *Journal of Crop Production*, 2:317–333.

Khan, M. A., Islam, M. Z., and Hafeez, M. (2020). Data Pre-Processing and Evaluating the Performance of Several Data Mining Methods for Predicting Irrigation Water Requirement. *arXiv*, 2011:1–13.

Khan, M. S., Woo, M., Nam, K., and Chathoth, P. K. (2017). Smart city and smart tourism: A case of Dubai. *Sustainability (Switzerland)*, 9(12).

Kjelgren, R., Beeson, R., Pittenger, Jr., D., and Montague, T. (2016). Simplified landscape irrigation demand estimation: Slide rules. *Applied Engineering in Agriculture*, 32:363–378.

Koeser, A., Hauer, R., Norris, K., and Krouse, R. (2013). Factors influencing long-term street tree survival in milwaukee, wi, usa. *Urban Forestry & Urban Greening*, 12:562–568.

Llorens, P. and Domingo, F. (2007). Rainfall partitioning by vegetation under mediterranean conditions. a review of studies in europe. *Journal of Hydrology*, 335:37–54.

Minnesota Pollution Control Agency (2013). Minnesota stormwater manual.

Newman, H. (2012). Calculating readily available water.

Nouri, H., Anderson, S., Beecham, S., and Bruce, D. (2013a). Estimation of Urban Evapotranspiration through Vegetation Indices Using WorldView2 Satellite Remote Sensing Images. *Conference: Sustainable Agriculture through ICT Innovation*, pages 24–27.

Nouri, H., Beecham, S., Hassanli, A., and Ingleton, G. (2013b). Variability of drainage and solute leaching in heterogeneous urban vegetation environs. *Hydrology and Earth System Sciences*, 17(11):4339–4347.

Nouri, H., Beecham, S., Hassanli, A. M., and Kazemi, F. (2013c). Water requirements of urban landscape plants: A comparison of three factor-based approaches. *Ecological Engineering*, 57:276–284.

Nouri, H., Beecham, S., Kazemi, F., and Hassanli, A. (2013d). A review of ET measurement techniques for estimating the water requirements of urban landscape vegetation. *Urban Water Journal*, 10(4):247–259.

Nouri, H., Chavoshi Borujeni, S., and Hoekstra, A. Y. (2019). The blue water footprint of urban green spaces: An example for Adelaide, Australia. *Landscape and Urban Planning*, 190(June 2018).

Nytch, C., Meléndez-Ackerman, E., Pérez, M.-E., and Ortiz-Zayas, J. (2018). Rainfall interception by six urban trees in san juan, puerto rico. *Urban Ecosystems*, 22:103–115.

Orusa, T., Orusa, R., Viani, A., Carella, E., and Borgogno Mondino, E. (2020). Geomatics and eo data to support wildlife diseases assessment at landscape level: A pilot experience to map infectious keratoconjunctivitis in chamois and phenological trends in aosta valley (nw italy). *Remote Sensing*, 12(21).

Patel, K. and Samenow, J. (2022). California declares historic water emergency measures amid drought. *Washington Post*.

Pflanzenschutzamt Berlin (2021a). Bewässerungsempfehlung für Stadtbäume.

Pflanzenschutzamt Berlin (2021b). Stadtbäume.

Pooya, E., Tehranifar, A., Shoor, M., Selahvarzi, Y., and Ansari, H. (2013). The use of native turf mixtures to approach sustainable lawn in urban landscapes. *Urban Forestry & Urban Greening*, 12:532–536.

Revelli, R. and Porporato, A. (2018). Ecohydrological model for the quantification of ecosystem services provided by urban street trees. *Urban Ecosystems*, 21:489–504.

SA Water (2021). Cooling the community.

Shi, Y., Yang, G., Du, Y., Ren, Y., Lu, Y., Fan, L., Chang, J., Ge, Y., and Bao, Z. (2018). Estimating irrigation water demand for green spaces in humid areas: seeking a sustainable water management strategy. *Urban Water Journal*, 15(1):16–22.

Sjöman, H. and Busse Nielsen, A. (2010). Selecting trees for urban paved sites in scandinavia – a review of information on stress tolerance and its relation to the requirements of tree planners. *Urban Forestry & Urban Greening*, 9:281–293.

UC Davis (2021). WUCOLS plant search database.

United Nations (2020). Goal 11.

Vico, G., Revelli, R., and Porporato, A. (2013). Ecohydrology of street trees: design and irrigation requirements for sustainable water use. *Ecohydrology*, 7:508–523.

Volo, T. J., Vivoni, E. R., Martin, C. A., Earl, S., and Ruddell, B. L. (2014). Modelling soil moisture, water partitioning, and plant water stress under irrigated conditions in desert urban areas. *Ecohydrology*.

Wessolek, G. and Kluge, B. (2021). Predicting water supply and evapotranspiration of street trees using hydro-pedo-transfer functions (hptfs). *Forests*, 12:1010.

World Health Organization (2016). Urban green spaces and health - a review of evidence.

Yang, B., Lee, D. K., Heo, H. K., and Biging, G. (2019). The effects of tree characteristics on rainfall interception in urban areas. *Landscape and Ecological Engineering*, 15:289–296.

Young, R. F. (2011). Planting the living city: Best practices in planning green infrastructure - Results from major U.S. cities. *Journal of the American Planning Association*, 77(4):368–381.

Chapter 6

Benefit estimation

6.1 Prelims

This chapter[1] contributes to the second research objective (RO2): "develop a benefit model that estimates the benefits obtained from UGS for the city residents". Accordingly, based on the WHO indicator, the Study B focused on estimating the social benefits provided by each UGS unit. It utilizes a composite score calculated by including the contribution of the UGS in providing accessibility to city residents and its performance on selected quality parameters.

It should be noted that since this study was submitted for review to an Australian-based review committee, British English was adhered to, in contrast to American English, for the rest of the publications. Therefore, spellings for certain words such as prioritizing (prioritising), prioritization (prioritisation), maximizing (maximising), and analyzing (analysing) are used as per British English in this chapter.

The chapter structure is outlined as follows: initially, the background and introduction to the research gap are provided in section 6.3. Subsequently, section 6.4 describes the methodology for identifying available green space (subsection 6.4.1), calculating accessibility score (subsection 6.4.2), calculating quality score (subsection 6.4.3), and subsequently deriving prioritization (subsection 6.4.4). Following this, the implementation of the proposed method in the case study city of Berlin, Germany, is introduced in section 5.7. The outcomes of this case study are subsequently presented in section 6.5. Next, a thorough discussion covering the implications and limitations of the approach is presented in section 6.6. Concluding remarks and suggestions for future research directions are then provided in section 6.7.

[1] This chapter is based on a published article:
Rambhia, M., Volk, R., Rismanchi, B., Winter, S., & Schultmann, F. (2022). "Prioritising urban green spaces using accessibility and quality as criteria". IOP Conference Series: Earth and Environmental Science, 1101(2), 022043–022043. https://doi.org/10.1088/1755-1315/1101/2/022043
The paper presented in section 6.2 is reformatted for consistency within the thesis, including the numbering of figures and tables, as well as the referencing style. The research presented in this article was carried out by the author while other co-authors have been supervisors and provided feedback throughout the process. The published manuscript can be found in the appendix.

Study B: Prioritising urban green spaces using accessibility and quality as criteria

6.2 Abstract

Urban green spaces are a critical component of cities, providing environmental, social, cultural, and economic benefits. To support smart(er) decisions by city planners and managers, this study aims to investigate how open data sources could be integrated into urban green space management. Specifically, it proposes a novel GIS-based method to prioritise urban green space in a resource-constraint scenario so that social benefits are maximised. To quantify the social benefits, the methodology is based on the WHO indicator, which recommends access to at least 0.5-1 ha of green space within 300 metres' linear distance to all the city residents. The approach assigns each urban green space an 'accessibility score' based on its significance in the city, and a 'quality score' based on its performance on different quality parameters (size, greenness, quietness, and safety). Urban green spaces are ranked with respect to these two scores, enabling to prioritise spaces under resource constraints such as water shortage, limited staff, or budget. This approach is demonstrated through a case study on a mid-size German city and is transferable to other cities worldwide with varying weightage factors.

6.3 Introduction

Whether in parks, along streets, inside forests, or in any other form, the green spaces in an urban area provide multifaceted benefits, including environmental, social, and economic (Poelman, 2018). The World Health Organisation (WHO), defines Urban Green Spaces (UGS) as the collection of "all kinds of vegetation present on public or private land within a city, irrespective of its size and function" (WHO, 2017). Studies have shown the beneficial role of UGS in protecting and enhancing local biodiversity, increasing water retention, improving social cohesion, and carbon sequestration as well as regulating local micro-climate (Middel et al., 2015; WHO, 2016; Threlfall et al., 2016; Moradpour and Hosseini, 2020). Regular exposure to an UGS is found to boost physical and mental well-being (Nutsford et al., 2013; Tamosiunas et al., 2014). It also provides an opportunity for recreation, especially in highly congested and densely populated neighbourhoods and for low-economic communities that cannot frequently afford other means of recreation. The significance was evident during the recent COVID-19 pandemic when researchers observed a rise of up to 350% in the usage of public parks (Geng et al., 2021). UGS helped people to recreate even under strict lockdown measures while maintaining adequate social distance.

Taking into account the enormous benefits obtained from UGS, the United Nations in its Sustainable Development Goals set a target 11.7 that aims to provide universal access to safe, inclusive and accessible, green and public spaces for everyone. WHO as well recommends 'access to at least 0.5-1 ha of green space within 300 metres' linear distance to all the city residents' (WHO, 2017). Moreover, the Convention on Biological Diversity (CBD) in Germany set a target to provide publicly accessible UGS with a diverse range of qualities and functions within walking distance to every urban household (Federal Ministry for the Environment, 2007). Therefore, to provide sufficient UGS accessibility, city governments need to plan newer greening areas in addition to protecting existing UGS. This, however, encounters dual challenge from urbanisation. First, as the urban population increases, the higher housing demand puts constant pressure to colonise the open and green spaces. Second, as the population density rises, the per capita UGS availability deteriorates. This commonly leads to crowding and occasionally uneven distribution of UGS, especially affecting low-income communities that are highly dependent on public parks and playgrounds for affordable recreation. Therefore, it is critical to monitor the status of UGS accessibility and take required steps to maintain and enhance it.

Furthermore, constant management is required to maintain the UGS in healthy conditions. This involves watering, application of fertiliser and pesticides, pruning of trees, cutting, lawn mowing, tree stability inspection, cleaning leaf litter, and maintenance of recreational facilities. However, it might not be possible to provide ample management support to all the UGS in the case of limited/constrained resources such as water, budget, staff or equipment. For example, in case of water shortage due to droughts or as experienced recently, limited personnel during pandemic. In such cases, it becomes indispensable to prioritise the UGS that need to be preserved. The prioritisation should be done so that either benefits are maximised, costs are minimised, or resource constraints are satisfied or all together, depending on the decision-makers' preference.

This study proposes a novel GIS-based method to prioritise the UGS management under resource constraint scenarios. The main objective is to prioritise in a manner that the total benefits from UGS are maximised. However, to simplify the case, the present study solely incorporates public accessibility as a single parameter measuring social benefit. Previous studies such as Wüstemann et al. (2016) and Poelman (2018) have analysed the amount of UGS accessible by city residents, but the distribution in terms of quality is largely missing in the existing literature. Although, both WHO and CBD only refer to 'quantity' access of UGS in their targets, the model endeavours for a greater ambition of ensuring that this access is also of 'high-quality'. Moreover, establishing a linkage between the analysis of field data and management decisions such as prioritisation is mostly absent in the literature until now. Therefore, the study aims to investigate how open-data sources can be integrated into the decision-making of UGS management. This is the major contribution of this study at hand. In the following sections, the methodology is described, followed by the results, the discussion, and conclusions.

6.4 Methodology

The methodology aims to assign a prioritisation index to each UGS based on two criteria: its significance in providing social benefit measured in terms of public accessibility, and, its performance on various quality parameters. Each of these criteria is assessed with a score; namely, *Accessibility Score* (S_A) and *Quality Score* (S_Q), measured by means of defined parameters. In all cases, a normalised score value between 0 to 10 is derived by applying a feature re-scaling on individual parameters. In the case of positive scaling, the highest score was equated to the highest parameter value while in the case of negative scaling it was the opposite. The overall score is then derived by combining the two subscores by user-defined weight. Consequently, the UGS are ranked in priority according to their score, where a higher score value gets a greater/higher priority. The methodology comprises of four parts. The first part focuses on identifying the available UGS in the cities. The second and third part include quantifying the above-mentioned two scores, S_A and S_Q. The last part include determining the prioritisation index for informed decision-making.

6.4.1 Green space availability

A free and open-source Geographic Information System, QGIS, was used to perform the spatial analysis to determine the UGS accessibility of a city's population. Initially, a vector layer designating the city's administrative boundary was imported. This is based on the premise that city governments are usually responsible for managing UGS within their administrative jurisdiction. Subsequently, an OpenStreetMap (OSM) dataset for the city is introduced (OpenStreetMap contributors, 2021), which comprises numerous layers delineating various features within a city. For this study, the feature layers consisting of buildings, roads, water, land-use, natural, places, and points of interest (POIs) were used. Each of these layers is reprojected into a common co-ordinate referencing system (CRS) and is spatially clipped by the extent of the city boundary.

Subsequently, UGS are identified from the imported OSM layers using tag values listed in Table 6.1. A filter operation is applied to match the key field of the layer with the tag values and only the matching polygon features are retained. Next, the filtered polygons are merged into a single layer that will delineate all the UGS in the city. In this process, an UGS might get repeated or overlapped in some instances due to repeated tagging in different OSM layers. Moreover, in a few instances, an UGS is identified as a group of adjoining polygons instead of one large polygon. Therefore, to reduce data redundancy, such mini-polygons are combined into single elements by using the dissolve function. Furthermore, all UGS smaller than 50 m^2 are eliminated from the dataset. Thus, street trees and tiny UGS are not considered further in this study. All the remaining UGS are suitable for the public usage and henceforth referred to as *Available Green Spaces*.

6.4.2 Accessibility score

In this part, proximity analysis is done to evaluate the UGS accessibility in the city. It should be highlighted that accessibility is defined here in terms of 'walking accessibility', which implies the possibility of reaching UGS by foot using permanent pathways. To simplify the computation, circular buffer approach is used to check the accessibility in

Table 6.1: Different labels used in Open Street Map for tagging UGS.

Key	Label
landuse	allotments, cemetery, farm, forest, grass, heath, meadow, orchard, park, recreation ground, scrub, vineyard
natural	tree
places	farm
POIs	dog park, golf course, graveyard, park, picnic site, zoo, playground

linear distance. To concur with the WHO recommendation, circular buffers with 300 m radius are created with each building unit as a punctiform centre to obtain the buffered building area layer. Subsequently, the sum of all UGS areas that overlap with this buffer represents the quantity of UGS area accessible by particular buildings' residents. Accordingly, the buildings with less than the minimum recommended 0.5 ha of UGS in their buffer are classified as buildings without sufficient UGS accessibility. To find the number of city residents that do not have access to sufficient UGS, a population density map containing residents/ha is used. The population density layer is intersected with the buildings layer and multiplied with its area value to obtain the number of residents living in a particular building. The summation of population is done for the buildings without access to sufficient UGS which gives us the percent of population that is impacted by the deficit.

In the next step, the contribution of each UGS $\rightarrow i$ in maintaining the accessibility is quantified with an *Accessibility Score* (S_{A}). The score is defined as the equally weighted aggregation of two components: *Building coverage score* (S_{C}) and *Essentiality score* (S_{E}) (see Equation 6.6). The first component, $\mathrm{S_C}$, measures the number of residential buildings that benefit from a particular UGS. The second component, $\mathrm{S_E}$, quantifies the criticality of a particular green space in maintaining accessibility. Throughout the text, a variable symbol implies the total score for all UGS, whereas, variable with a subscript i is used to describe the computation for a single UGS 'i'. The calculation of the scores is elaborated in the next paragraphs.

Once again, circular buffers with a 300 m radius are created, but this time with each UGS as a polygon-shaped centre. All UGS and their respective buffer area will represent the total city area benefiting from UGS. This buffered UGS layer is then spatially intersected with the building vector dataset. Now, the summation of building area for those buildings elements that are in conjunction with a buffered UGS area is referred as *Building Area Covered* (A_{BC}) by UGS $i \in [1, g]$, and is computed by Equation 6.1, where g represents the total number of available UGS (above the threshold size). Accordingly, the residents living within area $\mathrm{A_{BC}}$ will have access to sufficient UGS within walking distance. Next, a log transformation is applied on $A_{\mathrm{BC_i}}$ to reduce the skewness of the size values between very small and very large UGS. Furthermore, logged $A_{\mathrm{BC_i}}$ values are positively re-scaled using Equation 6.2 to derive the associated *Building Coverage score* ($S_{\mathrm{C_i}}$). Those UGS that are accessible by a higher quantity of building area will score higher on $\mathrm{S_C}$.

For $i \in \mathbb{N}\ :\ i \in [1, g]$, g $= Total\ Available\ Green\ Spaces$

$$A_{\mathrm{BC_i}} = (Green\ Space\ Area_{\mathrm{i}} + Buffer\ Area_{\mathrm{i}}) \cap Building\ Area \tag{6.1}$$

$$S_{\mathrm{C_i}} = \frac{10 \times (log_{10}\ A_{\mathrm{BC_i}} - max(log_{10}\ A_{\mathrm{BC_i}}))}{max(log_{10}\ A_{\mathrm{BC_i}}) - min(log_{10}\ A_{\mathrm{BC_i}}))} + 10 \tag{6.2}$$

In the next step, the *Essentiality score* (S_{E}) is computed. For this, the buffered building area layer is spatially intersected with the green space vector dataset. As calculated in the earlier step, those UGS elements that have at least some overlap with the buffered building area can be considered as accessible by that building and its residents. The total count of such intersecting elements yields number of *Green Spaces Accessible* (G_{A}) (Equation 6.3), where b represents the total number of buildings in a city. The buildings with a G_{A} value greater than 0 have access to atleast 1 UGS within walking distance. As the $\mathrm{G_A}$ values are in a narrow range, they are directly re-scaled using Equation 6.4 to derive the associated score $S_{\mathrm{E_j}}$. Here, negative re-scaling is applied to take into account the inverse relation between $G_{\mathrm{A_j}}$ and $S_{\mathrm{E_j}}$. Accordingly, buildings having access to merely a singular UGS will score highest on $S_{\mathrm{E_i}}$. In contrast, buildings with several UGS within 300 m will score lower. In the subsequent step, $S_{\mathrm{E_i}}$ for each UGS is calculated as the mean $\mathrm{S_{E_j}}$ of all the buildings that are located within the buffer zone around the UGS determined by Equation 6.1.

For $j \in \mathbb{N}\ :\ j \in [1, b]$ and $i \in \mathbb{N}\ :\ i \in [1, g]$, b $=$ *Total buildings*

$$G_{\mathrm{A_j}} = count((Building\ Centroid_{\mathrm{j}} + Buffer\ Area) \cap Green\ Space\ Area) \tag{6.3}$$

$$S_{\mathrm{E_j}} = \frac{10 \times (\ G_{\mathrm{A_j}} - min(\ G_{\mathrm{A_j}}))}{min(\ G_{\mathrm{A_j}}) - max(\ G_{\mathrm{A_j}})} + 10 \tag{6.4}$$

$$S_{\mathrm{E_i}} = \overline{S_{\mathrm{E_j}}}\ ,\ \forall\ (j \cap Building\ Area\ Covered_{\mathrm{i}}) \tag{6.5}$$

Lastly, the *Accessibility Score* (S_{A}) is calculated by averaging $\mathrm{S_C}$ and $\mathrm{S_E}$ with equal weightage (Equation 6.6). The score characterises the impact of any UGS in providing UGS accessibility to city residents. Therefore, UGS with greater $\mathrm{S_A}$ reflects its prominence in providing higher social benefits and thus should be prioritised higher.

$$S_{\mathrm{A_i}} = 0.5 \times (S_{\mathrm{C_i}}\ +\ S_{\mathrm{E_i}}) \tag{6.6}$$

6.4.3 Quality score

The second part of the methodology focuses on the quality aspect of UGS described by the *Quality Score* (S_{Q}). The quality of an UGS is a subjective issue that depends on several characteristics for its depiction. It includes the proximity to residents, size, diversity of species, free public access, quietness, recreational facilities, and safety (Herzele and Wiedemann, 2003). In the context of this study, the quality of UGS is defined as its cumulative performance on selected quality parameters, namely size ($\mathrm{S_{Q,A}}$), greenness ($\mathrm{S_{Q,G}}$), quietness ($\mathrm{S_{Q,N}}$), and safety ($\mathrm{S_{Q,S}}$) (as in Equation 6.11). In the case of evaluating the size, the area of the particular UGS was directly used to assign a score. Since a larger area will provide higher ecosystem services, the UGS with the biggest area was assigned a maximum score. Moreover, the skewness in the area distribution of UGS due to a few disproportionately large UGS was reduced by log transformation. Subsequently, the values were positively feature-scaled to derive a corresponding score $\mathrm{S_{Q_i,A_i}}$ according to Equation 6.7. Further, to assess the greenness, the mean Normalised difference vegetation index (NDVI) value was computed for each UGS from Sentinel-2 satellite data. NDVI is an effective indicator to identify green vegetation based on the spectral reflectance of plants. It is derived by spectrally contrasting surface reflectance measurements in the near-infrared (NIR) and red spectral bands, calculated as (NIR - Red) / (NIR + Red). This is because healthy and dense vegetation has high reflectance in the NIR band and strong absorption in the red band due to the presence of chlorophyll. Accordingly, the UGS with a greater NDVI value will likely have a high density of trees and therefore provide higher ecosystem benefits. So, the NDVI values were positively feature-scaled, such that UGS with the highest NDVI value will obtain the maximum score. This operation to derive $\mathrm{S}_{\mathrm{Q_i,G_i}}$ is given in Equation 6.8. To evaluate the quietness in the UGS, the average noise level (dB) for each UGS is obtained from the available Noise Map. Following this, the score $\mathrm{S}_{\mathrm{Q_i,N_i}}$ for noise is derived by negatively feature-scaling the mean noise values such that UGS with a higher noise value obtain a lower score. This is shown in Equation 6.9 below. Similarly, the score $\mathrm{S}_{\mathrm{Q_i,S_i}}$ for safety is derived by negatively feature-scaling the number of criminal offences recorded in the particular district. This is shown in Equation 6.10 below.

For $i \,\epsilon\, \mathbb{N} \;:\; i \,\epsilon\, [1, g]$,

$$S_{\mathrm{Q_i,A_i}} = \frac{10 \times (log_{10}Green\ Space\ Area_{\mathrm{i}} - max(log_{10}Green\ Space\ Area_{\mathrm{i}}))}{max(log_{10}Green\ Space\ Area_{\mathrm{i}}) - min(log_{10}Green\ Space\ Area_{\mathrm{i}})} + 10 \quad (6.7)$$

$$S_{\mathrm{Q_i,G_i}} = \frac{10 \times (\overline{NDVI} - max(\overline{NDVI}))}{max(\overline{NDVI}) - min(\overline{NDVI})} + 10 \quad (6.8)$$

$$S_{\mathrm{Q_i,N_i}} = \frac{10 \times (\overline{Noise} - min(\overline{Noise}))}{min(\overline{Noise}) - max(\overline{Noise})} + 10 \quad (6.9)$$

$$S_{\mathrm{Q_i,S_i}} = \frac{10 \times (Crime - min(Crime))}{min(Crime) - max(Crime)} + 10 \quad (6.10)$$

Finally, the overall *Quality Score* ($S_{\mathrm{Q_i}}$) is calculated by combining the individual scores obtained on all quality parameters by respective weights (Equation 6.11). The model allows to adapt the weights according to the preferences of residents and decision makers' priorities. For example, a survey done in the City of Karlsruhe identified lower noise and pollution as extremely important criteria for UGS usage among the residents (Stadt Karlsruhe, 2015). So a higher w3 value should be considered for that city. However, for the purpose of this case study, all the quality parameters are weighted equally and therefore all weights are set to 0.25. Accordingly, the UGS that are bigger in size, consist of dense and mature trees, have a quiet neighbourhood, and are located in districts with lower crime rates, will classify as a high-quality UGS. Overall, the score characterises the ability of UGS to provide higher ecosystem benefits and satisfy the user's needs. Therefore, UGS with greater $\mathrm{S_Q}$ should be prioritised higher.

$$S_{\mathrm{Q_i}} = w1 \times (S_{\mathrm{Q_i,A_i}}) + w2 \times (S_{\mathrm{Q_i,G_i}}) + w3 \times (S_{\mathrm{Q_i,N_i}}) + w4 \times (S_{\mathrm{Q_i,S_i}}) \quad (6.11)$$

6.4.4 Prioritisation

In the last part, a prioritisation order is obtained by averaging the *Accessibility Score* (S_{A}) and *Quality Score* (S_{Q}) with desired weightage factors that might vary between decision-makers. Depending on the weightage values, the significance of the quality of accessibility will change against the quantity. This is given in Equation 6.12.

$$Prioritisation_{\mathrm{i}} = w1 \ \times \ (S_{\mathrm{A_i}}) + \ w2 \ \times \ (S_{\mathrm{Q_i}}) \tag{6.12}$$

6.5 Results

The described method is applied to a case study on the City of Berlin and results are presented in this section. Berlin is the capital and largest city of Germany with around 3.6 million inhabitants and a city area of 89100 ha. The mean population density in the city is about 130 residents/ha. The city is mainly flat in topography and is located on the Spree river, surrounded by numerous lakes and woodlands. To analyse the UGS accessibility in Berlin, the OSM dataset was accessed from the Geofabrik GmbH portal. Later, all the input datasets were reprojected into a common CRS, ETRS89 / LCC Germany (E-N), and imported into the QGIS software. After combining the relevant tagged elements, a layer containing all UGS was obtained. A snapshot of this step is presented in Figure 6.1. Almost one-third of the city's area comprises of green spaces such as parks, forests, rivers, and lakes. In total, 12,486 UGS elements were identified using the OSM dataset. The UGS included in the analysis range from 50m^2 to 30.57 km^2 of area. In total, 47,473 residents were found to have less than the minimum 0.5 ha of UGS area accessible.

Subsequently, the available UGS are analysed together with the buildings layer to derive the *Accessibility Score* (S_{A}). A map presenting the performance of UGS on $\mathrm{S_A}$ is given in Figure 6.2. It is visible that $\mathrm{S_A}$ for the UGS in the shown section range between 6-10 and the majority of them have a score higher than 8. Furthermore, the available UGS are analysed together with secondary data sources to derive the *Quality Score* (S_{Q}). To determine the greenness, we used the median NDVI values from cloud-free Sentinel-2 image with 10 m spatial resolution for the Year 2020. The Strategic Noise Map 2017 (Environmental Atlas, 2017) which provides total noise values from traffic sources, was used to determine the mean noise levels in UGS. Figure 6.3 presents an example from the study area to demonstrate the impact of noise levels on the $\mathrm{S_{Q,N}}$. In the figure, the mean noise level at any point is indicated by the intensity of the grey colour. It can be observed that UGS surrounded by streets/highways with higher noise levels obtain lower $\mathrm{S_{Q,N}}$. Additionally, the Crime Atlas 2020 published by police crime statistics of Berlin (Polizeiliche Kriminalstatistik, 2020) was used to determine the number of criminal offences that occur in various city districts. A map presenting the total performance of UGS on $\mathrm{S_Q}$ is given in Figure 6.4. Despite the high accessibility of UGS in most parts of the study area, we find that in particular, the inner-city UGS have a medium or low *Quality Score*.

The performance of UGS in Berlin on the two scores, S_{A} and S_{Q} is described in Table 6.2. It is evident from the mean and median scoring that overall UGS perform considerably better on accessibility criteria than on quality. This can be attributed to complementary

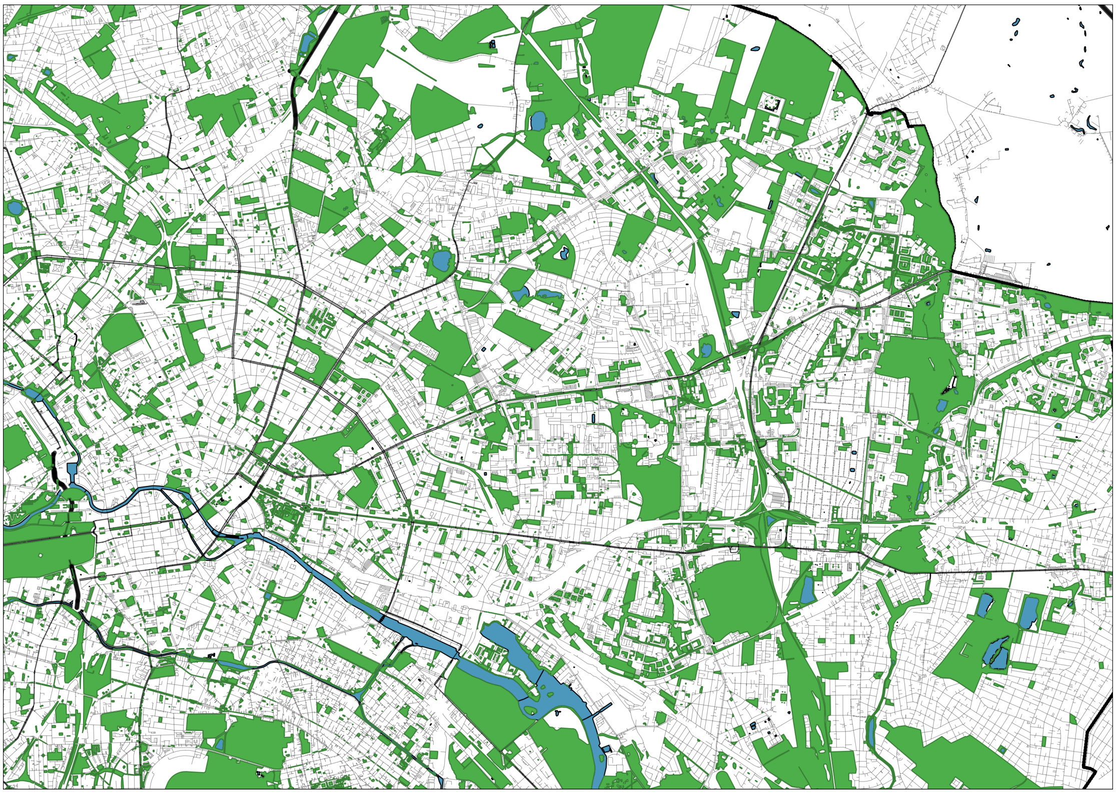


FIGURE 6.1: Illustration of *Available Green Spaces* in the City of Berlin; section of city centre and Eastern Berlin.

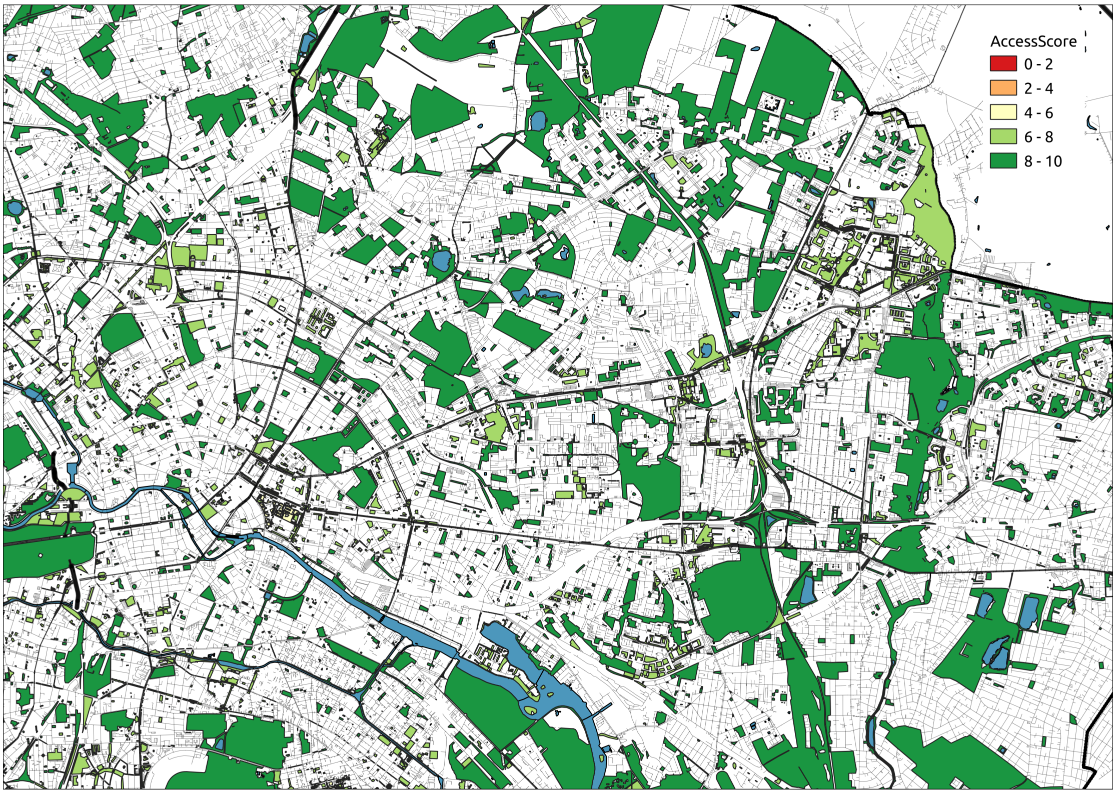


FIGURE 6.2: Map of the UGS indicating the *Accessibility Score* (S_{A}).

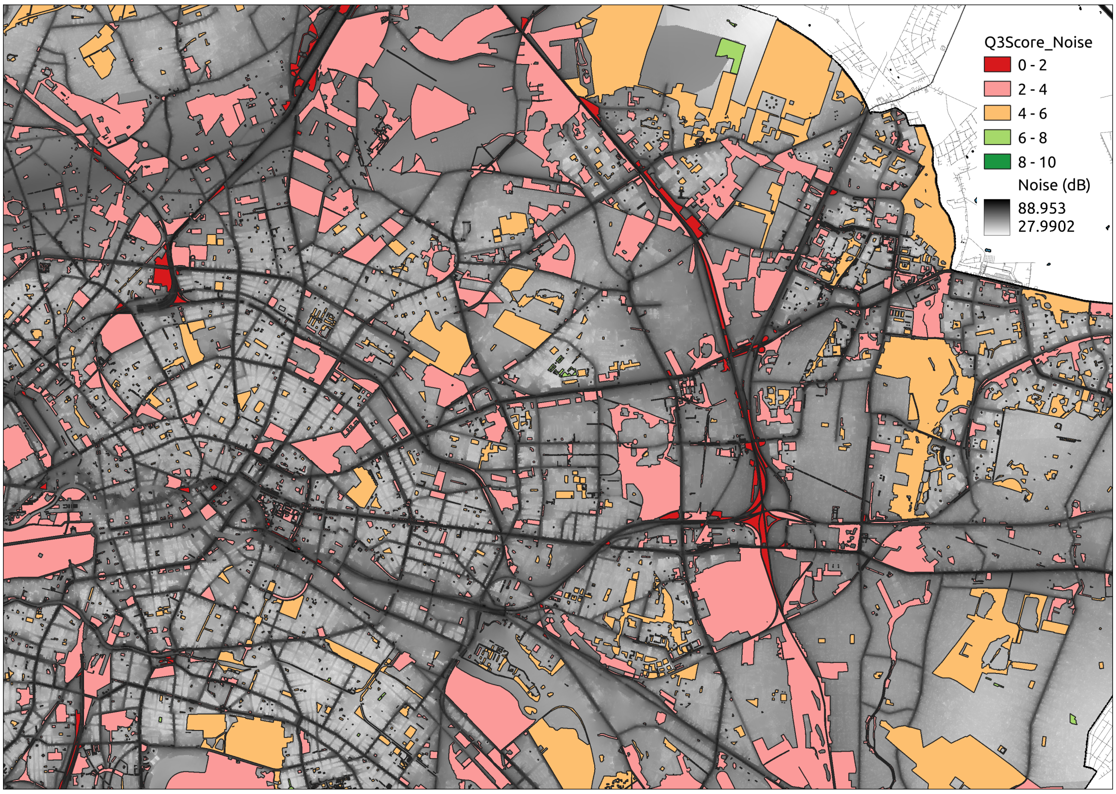


FIGURE 6.3: Map of the UGS indicating the Quality Score for Noise (S_{Q_i,N_i}).

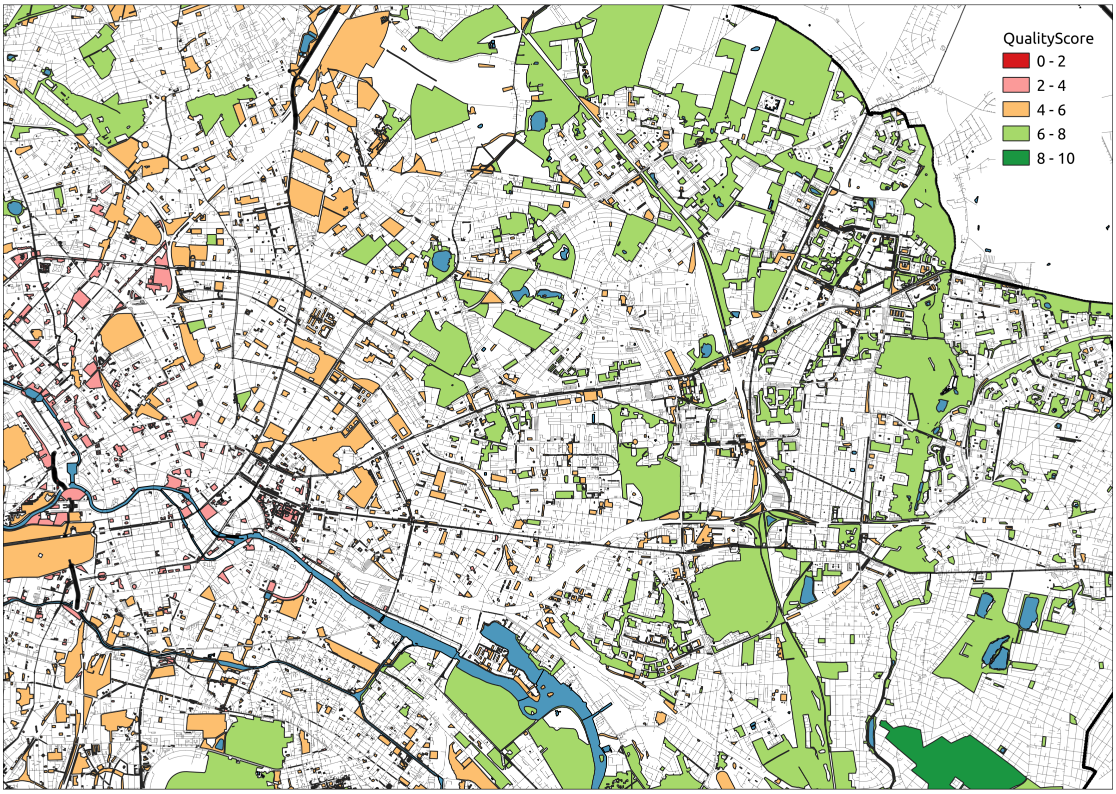


FIGURE 6.4: Map of the UGS indicating the overall *Quality Score* (S_Q).

Table 6.2: Performance of UGS in Berlin on defined *Accessibility Score* (S_A) and *Quality Score* (S_Q).

	Minimum	Maximum	Mean	Median	Standard deviation	Coefficient of Variation
S_A	0	9.8	8.2	8.4	0.82	0.1
S_Q	0.9	8.8	4.7	4.8	1.24	0.26

behaviour observed in the components of S_A. The UGS located on the fringes of the city usually had lower S_C due to the fewer number of houses in the vicinity. At the same time, the houses in that region were as well dependent on a single UGS available nearby, therefore, giving it a higher S_E score. As a result, lower S_C were compensated by higher S_E and vice versa. On the contrary, a higher coefficient of variation in S_Q reflects the large variability among the UGS in performance on quality parameters.

Finally, the obtained S_A and S_Q are plotted on a scatter plot to visualise the distribution of scores among the UGS. This is presented in Figure 6.5. According to this, the UGS to be prioritised are selected using the prioritisation order calculated by aggregating both the scores with their corresponding weights. At present the values of $w1$ and $w2$ required for Equation 6.11 are fixed at 0.75 and 0.25, respectively, to simulate the present priorities that emphasises on providing the 'quantity' access to UGS. Then, the decision-makers in city departments can select the minimum target of prioritisation order for prioritising the UGS. In this example, the target was chosen as 6. Therefore, all the UGS having an aggregated total score greater than 6 will be highlighted as a priority. These are marked with green colour in Figure 6.5. So, in the case of resource-constrained scenarios, the management of these UGS needs to be prioritised. Moreover, the scatter plot categorises the UGS into 4 groups with high/low accessibility in pair with high/low quality. Using this information a precise management plan can be devised for each type of UGS. For example, measures should be taken to improve the quality in UGS type (high accessibility, low quality) as it will benefit many residents.

6.6 Discussion

The methodology described in the previous section illustrates an approach to take management decisions such as prioritisation based on the field data. This is done using two criteria; namely, accessibility and quality. As only the open datasets are used in this study, the results are reproducible for any part of/cities in the world based on the availability of the data. However, there also exists a possibility of missing data in this case. The method used to create an UGS layer based on the tagged information from the OSM data might have introduced errors depending on the accuracy of the data. Also note that a circular buffer approach, as used here for proximity analysis is a simplistic determination of linear access between two points. Unlike the network analysis approach or Manhattan metric, the chosen approach does not incorporate the aspect of actual physical access through public roads and pathways. Hence, it might underestimate the actual distance between a residential building and nearby UGS. However, this method has the advantage of faster computing time and therefore allows for multiple iterations required for continual decision-making and management. Moreover, all types of buildings are included in the buildings layer, which also include commercial buildings, and

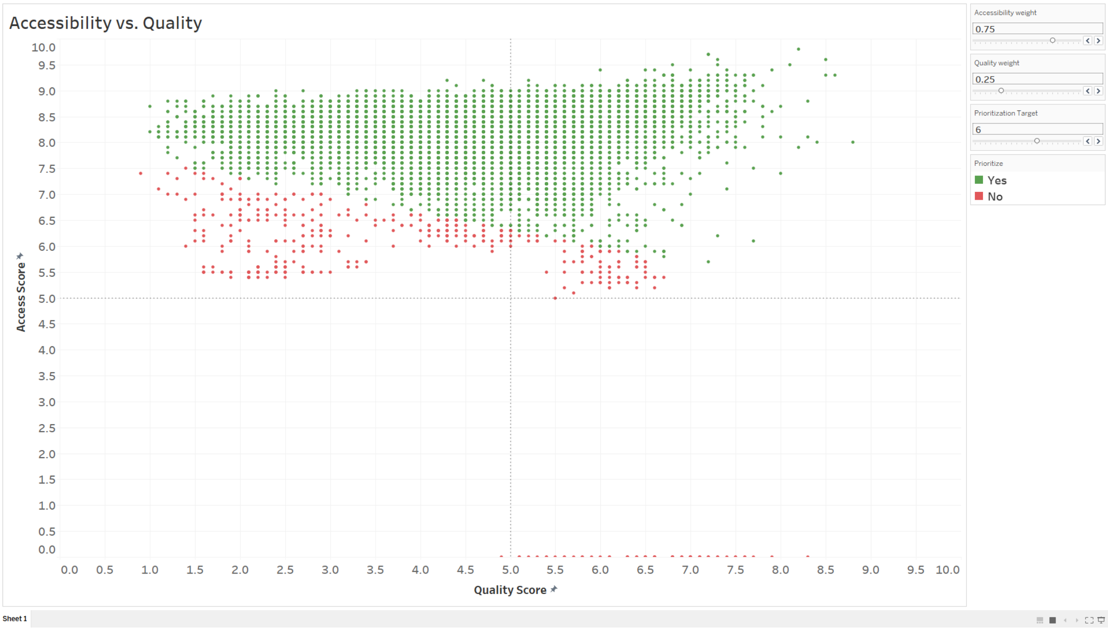


FIGURE 6.5: A scatter plot showing performance of UGS on S_A vs S_Q for prioritising UGS with a minimum total score of 6.

industrial estates. So in a likely case, an area with lack of UGS can be a storage warehouse and therefore, not actually affecting any residents' accessibility. Additionally, no differentiation between public and a private UGS have been made. As some of the UGS such as golf park, private gardens, farms, might be only available to private communities, the actual accessibility is likely to be lower than the current estimates. Moreover, the quality of an UGS depends on numerous factors. Taking this complexity into account, this study takes a representative sample of criteria, and develops a numerical quality score for UGS. Nevertheless, the method is open to integrate further criteria as they may emerge in different contexts or different cities. Furthermore, it can be observed that higher weightage is assumed for the accessibility criteria (0.75) in comparison with the quality (0.25). This is done on the basis of the current expectations set by the German government policy as well as WHO recommendation, where the focus is exclusively on providing the access to a sufficient quantity of UGS without any targets with respect to the UGS quality. Though, this can be easily adapted in the model according to city's needs and priorities. Also note that the scope of current analysis was limited to the benefit side of the UGS while the cost part was not included. As a result, a UGS is prioritised solely on the basis of derived benefits without considering the input costs/resource requirements. This might lead to inefficient allocation of resources if the UGS with greater cost per unit of benefit (resource efficiency) is prioritised higher than the one with lower.

6.7 Conclusions and further research

The developed method has for the first time, implemented the UGS benefit criteria for informed decision making in UGS management. The benefit is measured using UGS accessibility and quality as an indicators, while the decision to be made is of prioritisation.

The model uses open datasets in an automated way to estimate the residents impacted by the lack of UGS accessibility and show the distribution of UGS quality in the city. Moreover, through prioritisation order, it highlights the contribution and criticalness of each UGS in maintaining the required level of accessibility according to WHO recommendations. This can support local authorities in park/forest departments to efficiently allocate the limited resources in constrained scenarios and maximise the benefits. Thus, it provides an integrated framework to evaluate the UGS benefits and subsequently use it for decision making. However, the method needs further elaboration with respect to differentiation of buildings by type (residential/non-residential), segregation of UGS by type (public/private), with respect to the integration of further benefit criteria (environmental and economic), and the extension of factors within existing criteria e.g. UGS quality can be further enhanced by adding parameters like biodiversity and availability of leisure/sport equipment. Furthermore, the variation of score weights and their impacts on decision-making require further research. In the future course of work, varying combinations of different weightage factors will be evaluated through a sensitivity analysis. Moreover, along with estimating the benefits derived from UGS, the resources required to maintain a UGS will be calculated for a more comprehensive evaluation.

Bibliography

Environmental Atlas (2017). Grid map lden - sum of all traffic sources.

Federal Ministry for the Environment (2007). National strategy on biological diversity.

Geng, D. C., Innes, J., Wu, W., and Wang, G. (2021). Impacts of COVID-19 pandemic on urban park visitation: a global analysis. *Journal of Forestry Research*, 32(2):553–567.

Herzele, A. and Wiedemann, T. (2003). A monitoring tool for the provision of accessible and attractive urban green spaces. *Landscape and Urban Planning*, pages 109–126.

Middel, A., Chhetri, N., and Quay, R. (2015). Urban forestry and cool roofs: Assessment of heat mitigation strategies in phoenix residential neighborhoods. *Urban Forestry and Urban Greening*, 14(1):178–186.

Moradpour, M. and Hosseini, V. (2020). An investigation into the effects of green space on air quality of an urban area using CFD modeling. *Urban Climate*, 34:100686.

Nutsford, D., Pearson, A. L., and Kingham, S. (2013). An ecological study investigating the association between access to urban green space and mental health. *Public Health*, 127(11):1005–1011.

OpenStreetMap contributors (2021). Openstreetmap.

Poelman, H. (2018). A walk to the park? Assessing access to green areas in Europe's cities. Update using completed Copernicus Urban Atlas data. *European Commision Regional and Urban Policy*, page 13.

Polizeiliche Kriminalstatistik (2020). Kriminalitätsatlas berlin bezirksregion.

Stadt Karlsruhe (2015). Bürgerumfrage 2015 grün in der stadt.

Tamosiunas, A., Grazuleviciene, R., Luksiene, D., Dedele, A., Reklaitiene, R., Baceviciene, M., Vencloviene, J., Bernotiene, G., Radisauskas, R., Malinauskiene, V., Milinaviciene, E., Bobak, M., Peasey, A., and Nieuwenhuijsen, M. J. (2014). Accessibility and use of urban green spaces, and cardiovascular health: Findings from a Kaunas cohort study. *Environmental Health: A Global Access Science Source*, 13(1):20.

Threlfall, C. G., Williams, N. S., Hahs, A. K., and Livesley, S. J. (2016). Approaches to urban vegetation management and the impacts on urban bird and bat assemblages. *Landscape and Urban Planning*, 153:28–39.

WHO (2016). Urban green spaces and health.

WHO (2017). Urban green spaces: a brief for action.

Wüstemann, H., Kalisch, D., and Kolbe, J. (2016). SFB 649 Discussion Paper 2016-022 Towards a national indicator provision and environmental inequalities in Germany : Method and findings. *Landscape and Urban Planning*, 164(January):124–131.

Chapter 7

Decision making under resource constraint

7.1 Prelims

This chapter[1] contributes to the third research objective (RO3): "develop a multi-criteria decision support system to prioritize resource allocation under resource-constrained scenarios". Therefore, Study C focused on determining prioritization using a multi-criteria decision-making model that incorporates costs estimated in Study B, benefits estimated in Study B, and decision-makers' input regarding the availability of resources in the city and the priority of goals. This was achieved using a GP-based approach that maximizes the achievement of benefits in the city while considering the available resources as constraints. Moreover, the prioritization analysis was carried out at different spatial scales to enable decision-makers to consider various scenarios.

The chapter structure is as follows: first, the motivation, background, and introduction to the research gap are provided in section 7.4. Subsequently, section 7.5 presents a literature review on various available MCDM approaches (subsection 7.5.1) and their application to resource allocation problems (subsection 7.5.2), followed by an overview of the goal programming approach (subsection 7.5.3). The section 7.6 includes the methodology that details the modeling framework (subsubsection 7.6.1.1) and its components: estimating demand parameters, estimating benefit parameters, spatial analysis, and finally, the prioritization model. Moreover, it describes the case study area in subsection 7.6.2 and the data used in subsection 7.6.3. In subsection 7.6.2, the proposed methodology is then demonstrated through a case study on two cities with distinct characteristics, Berlin in Germany, and Melbourne in Australia. The section 7.7 presents the performance results of prioritization on different spatial scales on various benefit metrics. Finally, a thorough discussion analyzing the obtained results and the limitations of the approach

[1] This chapter is based on a published article:
Rambhia, M., Volk, R., Rismanchi, B., Winter, S., & Schultmann, F. (2023). "Prioritizing urban green spaces in resource constrained scenarios. Resources, Environment and Sustainability", 82, 127868–127868. https://doi.org/10.1016/j.resenv.2024.100150
The paper presented in section 7.2 is reformatted for consistency within the thesis, including the numbering of figures and tables, as well as the referencing style. The research presented in this article was carried out by the author while other co-authors have been supervisors and provided feedback throughout the process. The published manuscript can be found in the appendix.

is presented in section 7.8. Concluding remarks and suggestions for future research directions are then provided in section 7.9.

Study C: Prioritizing urban green spaces in resource constrained scenarios

7.2 Abstract

Urban Green Space management requires a multi-dimensional, evidence-based approach to effectively balance social, environmental, and economic objectives. City administrators currently lack a data-driven framework for allocating resources during constraint scenarios, leading to subjective decisions. Existing literature lacks objective solutions for managing city-scale green spaces, each with its distinct characteristics. Another challenge is handling varied spatial scales required for urban applications. This study proposes a novel goal programming-based model for urban green space management wherein multiple benefit objectives, such as conserving sequestered carbon in trees and enhancing quality and accessibility of parks, as well as handling demand constraints on available resources like water and personnel, are included. The proposed method was demonstrated in two cities with diverse conditions, Berlin and Melbourne, and evaluated on various benefit metrics, such as allocated green space units, resources consumed, and goals achieved. The model was analyzed with resource allocation decisions and goals at different spatial scales. The highest benefit achievement and resource allocation were observed when resources were allocated at the sub-district scale with a city-level target. Alternatively, setting targets at the district level provided a more even resource distribution; however, at the cost of reduced overall benefits. Results show that the proposed method increased the total benefits gained while effectively balancing conflicting goals and constraints. Additionally, it allows incorporating the city's preferences and priorities, offering a scalable solution for informed decision-making in varied urban applications. Depending on data availability, this approach can be scaled to other cities, including additional benefits and resource constraints as required.

7.3 Highlights

- Multi-criteria decision making framework for urban green spaces prioritization.
- Extending goal programming approach for varying spatial scale application.
- Integrating management demand and potential benefits into decision making.
- Increased total benefits gained while effectively balancing the conflicting goals.

- Supporting decision-makers for budgeting resources under constraint scenarios.

7.4 Introduction

Cities often face challenges related to resource constraints. Critical project resources such as personnel, commodities, equipment, and funding are limited and in competition with other uses or projects. Consequently, decision-makers must prioritize resource allocation to fulfil the distinct needs of the city and its residents. For example, a city dealing with a budget constraint might need to allocate limited funds between essential services like infrastructure development and welfare schemes for the needy. Prioritizing one theme, such as offering free entry to public recreational spaces for encouraging its usage, could lead to decreased funding for maintaining or developing new spaces, conflicting with the broader goal of ensuring its universal access in the long run. City administrators deal with this difficulty of prioritizing spending decisions and making trade-offs between competing demands for scarce resources (Nechi et al., 2019). Similar to cities, the management of Urban Green Space (UGS) also encounters the challenge of resource allocation with multiple, often conflicting, objectives, such as increasing green spaces while developing compact cities (Rößler, 2017). This challenge is compounded by the involvement of various stakeholders from departments of garden, road, forestry, waste and civic society groups (Jim, 2004; Eisenman et al., 2021). Moreover, the increasing pressure on resource availability, such as funding cuts, personnel shortages, and reduced water supply due to expected droughts from climate change, will further exacerbate this problem. Current decision-making processes often rely on limited data, physical inspections, and subjective assumptions, excluding the comprehensive assessment of trade-offs and the resulting impact on costs and benefits of the decision.

Reliable field data is critical for UGS planning, management, and decision-making (Moller et al., 2019). The World Health Organisation (WHO) also highlighted the need for a multi-dimensional evaluation of UGS interventions to assist municipalities in making evidence-based decisions (World Health Organization, 2017). Moreover, WHO guidelines suggest that public UGS of at least 0.5-1 ha should be accessible within a 300-metre distance to all city residents (World Health Organization, 2017). Providing universal access to green and public spaces is part of the United Nations Sustainable Development Goal target 11.7 as well (United Nations, 2020). As a result, access to green spaces becomes an important indicator for the management. However, expansion of newer UGS spaces to meet the increased demand might not always be possible due to resource constraints. For instance, in a survey conducted in 2020 across 12 cities in the United States, 83% of the cities reported an increase in visitation to natural areas, while 72% experienced decreased capacity to manage them due to severe shortages of seasonal staff (Plitt et al., 2021). Similarly, increasing the number of trees and UGS areas to meet a city's greening targets will further strain water sources, especially in drought-prone regions (Ricciardi et al., 2022). Consequently, taking into account the costs and benefits associated with a particular resource allocation strategy and its impact on the city's UGS and the resource conditions, becomes crucial before its implementation.

Multi-criteria decision-making (MCDM) methods have been extensively used to assist decision-makers in situations involving multiple stakeholders, criteria, and conflicting objectives (Kumar et al., 2017). These methods first derive feasible alternatives under given constraints that meet the preferences of decision-makers. Subsequently, the performance of all alternatives is evaluated to generate a decision that fulfills conditions and maximizes objectives (Pavan and Todeschini, 2009). In certain approaches, the alternatives are predefined by the user, and maximization is achieved for the given options. MCDM has been applied for decision-making in a large spectrum of domains, such as disaster management (Pankaj Kant and Natha, 2023), water allocation (Roozbahani et al., 2014), urban sustainability (Foroozesh et al., 2022), facility management (Klumbytė et al., 2021), and reservoir control (Wan et al., 2023). However, existing multi-criteria approaches have limitations in addressing urban challenges, especially in handling trade-offs and conflicts among various criteria (both quantitative and qualitative), as well as dealing with large-scale problems with numerous constraints and criteria.

Different types of approaches have been proposed to improve the management of UGS. For example, optimization-based methods for location allocation (Chen et al., 2023), machine learning-based techniques for the optimal allocation of UGS (M. Vallejo and Vargas, 2017), crowd-sourcing-based participatory management (Moller et al., 2019; Schrammeijer et al., 2021), GIS-based methods for prioritizing tree planting sites based on criteria for need and suitability (Locke et al., 2010), and organizational-based strategies like the place-keeping process (Fongar et al., 2019; Chen et al., 2023). While existing literature, such as Locke et al. (2010), Nyelele and Kroll (2021), and Nyelele et al. (2022), has used MCDM to address the challenge of prioritizing new tree plantations, the prioritization of existing UGS has not been studied. Furthermore, while benefit parameters have been included, resource constraints, such as water and personnel, are also not covered.

As a result, the research study aims to answer the following research question:
Can the resource allocation decisions for managing UGS in constrained scenarios be optimized using an MCDM approach?

The research scope includes (1) identifying a suitable MCDM approach for optimizing urban resource allocation in constrained scenarios; (2) considering the necessary adaptations for its application to UGS management; (3) identifying the required model parameters and relevant public datasets for its quantification; (4) implementing the optimization model for decision-making on prioritization; (5) assessing the model's performance on various benefit metrics; and (6) evaluating the impact of different scenario conditions on decision-making.

The research approach includes identifying the appropriate method for optimizing resource allocation decisions, considering factors such as complexity, adaptability, and the ability to handle trade-offs and uncertainties. Accordingly, the proposed model is an extension of the goal programming (GP) model that can support varying inputs, constraints, and targets at different spatial scales. The model was tested in two case-study cities, and its performance under various constraints was evaluated and compared with a baseline reference scenario.

This research achieves two main outcomes. The first outcome is the development of a model that optimizes the decision-making of prioritization under different constraint scenarios. The model is scalable to handle city-scale datasets, capable of addressing trade-offs and conflicts, and incorporates decision-makers' preferences. It is also adaptable to various cost-benefit parameters to address the resource allocation problem in varying spatial conditions. The second outcome is the provision of insights to aid city administrators in making informed decisions regarding resource allocation and budgeting, especially under constraint scenarios. Additionally, the findings will assist in planning and maintaining both existing and new street trees and parks.

The paper is organized as follows: First, a literature review describes the various MCDM methodologies and research gaps in the context of UGS management applications. Based on this, GP is chosen as the basis of the methodology. This is followed by the modelling approach section, which discusses the model parameters and its implementation in a Python-based model. In the case study section, the results of applying the model to data from Berlin and Melbourne are discussed. The final two sections present the discussion and conclusions.

7.5 Literature review

7.5.1 MCDM approaches

MCDM is an effective tool for solving decision-making problems with conflicting objectives (Gebre et al., 2021). Numerous optimization methods based on mathematical models, expert judgments, and heuristics have been developed to solve MCDM problems. These methods can be categorized based on whether the decision-maker implicitly provides plausible solutions (Multi-Attribute Decision Making (MADM)) and whether their preferences are taken into account during the decision-making process (Multi-Objective Decision Making (MODM)) (Kumar et al., 2017). MCDM methods have been used to address varied types of problems, such as prioritization, selection, allocation, optimization, scheduling, routing, and management. The commonly used MCDM methods include linear programming (LP), non-linear programming, integer programming, dynamic programming, goal programming (GP), weighted product model (WPM), Analytical Hierarchy Process (AHP), Multi-Attribute Utility Theory (MAUT), and Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS). These methods can be further classified as analytical methods if they are quantitative and based on mathematical models or as interactive methods if they constantly involve human judgment and preferences. The selection of the suitable MCDM method for the UGS management application is done based on the requirements of the problem. Since, in UGS management, the problem involves multiple resource constraints, a desired benefits target to be achieved, decision-maker's preference, and there are no preset solutions available. Therefore, the chosen method should be of the MODM type to ensure that the solution is considered from a continuous space.

Several studies have implemented MCDM approaches to address various aspects of UGS planning and management, including location, layout, design, function, and size of UGS (Li et al., 2022). This has been done with respect to varied objectives such as public accessibility, UGS quality, heat island mitigation, runoff regulation, carbon offset, and enhancing biodiversity (Nyelele and Kroll, 2021). For instance, Liu et al. (2023) utilized a multi-objective programming method to determine the required quantity of UGS for achieving a specified level of carbon offset. Meanwhile, Li et al. (2022) implemented spatial optimization for UGS layout planning, considering equitable distribution and conversion costs as decision criteria. Huang et al. (2018) devised a regression-based optimization strategy for UGS planning, focusing on accessibility and quality as primary targets. Using an LP approach, Neuenschwander et al. (2011) determined the optimal distribution of green spaces at the district level, considering spatial conditions. Similarly, Nyelele and Kroll (2021) utilized an LP model to pinpoint optimal locations for maximizing overall benefits derived from urban greening. Later, they proposed a multi-objective optimization framework to prioritize tree planting scenarios based on current and future ecosystem services (Nyelele et al., 2022). However, these studies primarily concentrated on benefits maximization and did not consider associated management costs in decision-making. Furthermore, as evident, their scope was limited to new plantations, and the planning and management of existing UGS have not been considered by any of the studies.

7.5.2 Resource allocation problem

In resource allocation problems, the aim is to distribute the available resources and maximize the achievement of the desired objectives. A large number of optimization algorithms have been developed and applied to obtain optimal resource allocation. For example, (Omidipoor et al., 2019) integrated MCDM with GIS for participatory renovation of urban areas, (Corlay and Sibel, 2023) used a Markov decision process for a communication system, (Pustokhina and Pustokhin, 2021) implemented a fish swarm algorithm to distribute cloud resources, and (Rahman and Sharma, 2020), (Chen et al., 2022) proposed a game theoretic approach to allocate defense resources. All of the referred studies were based on the utilitarian principle, focusing on benefit maximization. Accordingly, that objective has been adopted for this study as well.

Figure 7.1 presents a summary of relevant literature, classified based on study methodology and application. It can be observed that a larger number of studies use MCDM methods to obtain an optimal resource allocation strategy. However, the application of these techniques in UGS management has been scarce. Furthermore, even for UGS, most studies have focused solely on planting strategies. No studies were discovered that apply these methods to manage existing UGS, especially in resource-constrained conditions.

Nevertheless, each of these existing methods has certain limitations. Most of these optimization approaches aim for feasible solutions. However, in resource-constrained scenarios, achieving a feasible solution might not always be possible. Additionally, strictly adhering to the objective function may result in no solution or inferior utilization of available resources. Since both LP and GP provide solutions over continuous space and can incorporate resource constraint conditions, those two were considered as prospective approaches. LP has the limitation of optimizing a single objective function with numerous linear constraints. However, in real-life problems, multiple conflicting objectives are often present, making LP inadequate for such applications. Unlike LP, where a decision-maker can only have one objective function, GP can handle multiple goals simultaneously (Orumie and Ebong, 2014). Furthermore, while LP allows for a fixed goal, in GP, the goal is considered only as the initial target. This allows flexibility for the decision-maker to compromise on the solution in case of competing goals (Nestıcò et al., 2020). Therefore, GP was a suitable option for addressing the described problem.

7.5.3 Goal programming

GP is an MCDM approach based on determining a satisfactory solution to multi-goal decision-making problems. Charnes et al. (1968) pioneered GP, which was later expanded

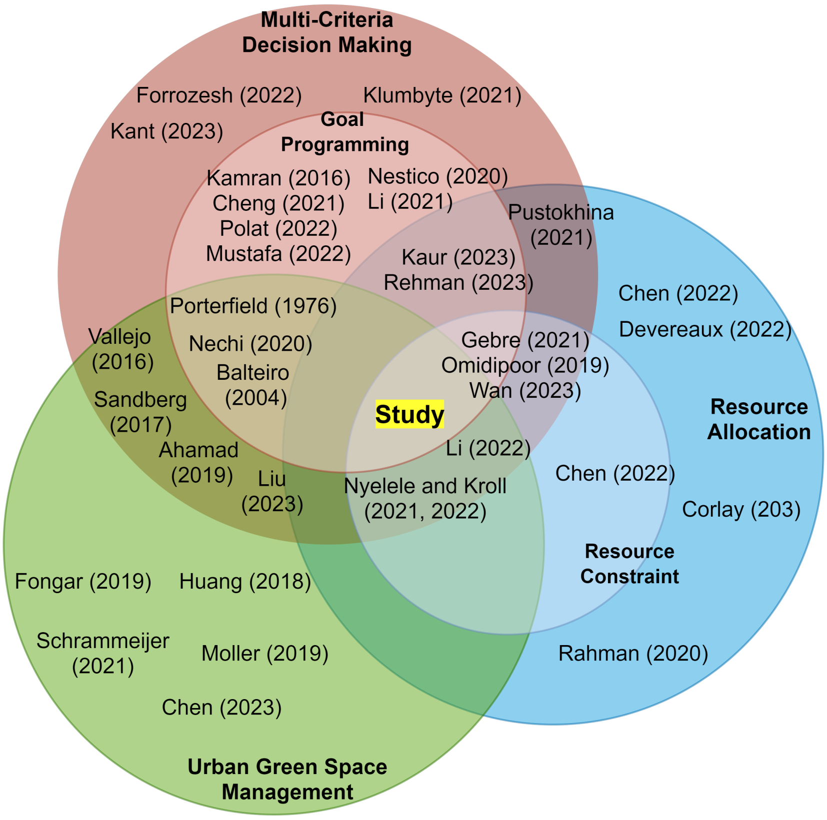


FIGURE 7.1: Classification of relevant literature with current study focus is highlighted.

upon by Lee and Clayton (1972), Charnes and Cooper (1977), Ignizio (1978), Romero (1985), and Schniederjans (2012). Researchers have developed various GP variants for a variety of problem types and use-case applications. The major variations are listed in Table 7.1 to showcase the applicability of existing variants. From these variants, each basic variant could be used in conjunction with a special case. GP has been extensively applied in different planning and operational applications such as finance (Lashkari et al., 2018), healthcare (Mishra et al., 2018; Rehman et al., 2023), software development (Kaur et al., 2023), water use (Bravo and Gonzalez, 2009), and reservoir operation (Li et al., 2017).

Due to its capability to efficiently find feasible solutions, flexibility in managing multiple competing goals, and ease of use, GP has found extensive application in addressing resource allocation challenges as well. Resource-allocation focused studies also cover diverse domains such as healthcare (Kamran et al., 2016), fleet management (Valcárcel-Aguiar and Fernández, 2018; Rajendran, 2021; Hamurcu and Eren, 2022), urban regeneration (Nestıcò et al., 2020), logistics (Li et al., 2021; Cheng et al., 2021), energy strategies (Bakhtavar et al., 2020), and more. Several researchers have also used GP to address challenges pertaining to UGS management. For instance, Nechi et al. (2019) utilized GP to determine a sustainable development pathway, with a central focus on accommodating decision-makers' preferences. Porterfield (1976) presented a GP-based model for the optimal selection of a tree improvement program. Similarly, Diiaz-Balteiro and Romero (2004) developed a GP model for evaluating forest plans, considering multiple spatial scales from a regional level down to a stand level through aggregation. The ability of

GP to adapt and be flexible makes it a valuable tool for managing different types of resources.

GP is based on the principle of getting as close to the decision makers' goals as possible. Accordingly, it aims to minimize the underachievement of each goal using deviation variables. The primary distinction between GP and other MCDM approaches is that it seeks to satisfy rather than optimize the objective (Jones and Tamiz, 2010). Therefore, GP is especially suitable for handling trade-offs between multiple conflicting goals. Moreover, the priority order for the goals can be established by either weighing or ranking them. The GP model includes two types of constraints: system and goal constraints. Systems, or hard constraints, describe actual capabilities and are therefore limiting, whereas goals, or soft constraints, indicate desired aims to be accomplished and are thus flexible. The basic formulation of the GP model is presented in equations (7.1) to (7.3). Overachievement is represented by the positive deviation variable d^{+}, whereas underachievement is represented by the negative d^{-}. The model allows for G goals, indexed as g = 1,2,..G, and x is the decision variable that belongs to the feasible region F, consisting of points that satisfy all the constraints. The decision maker sets an achievable target, t_g, for each goal, and the achieved value of the goal is represented by f(x). Finally, the objective function minimizes the sum of deviations to maximize goal achievement.

$$\min d = \sum_{g=0}^{n} d_g^{+} + d_g^{-} \tag{7.1}$$

$$f_g(x) + d_g^{+} - d_g^{-} = t_g \ , \ g = 1,...G \ , \ x \in F \tag{7.2}$$

$$d_g^{+}, d_g^{-} \geq 0 \ , \quad g = 1,...G \tag{7.3}$$

TABLE 7.1: Major Goal Programming variants (Source: Jones and Tamiz (2010))

Variant	Application
Normal	Based on minimizing the sum of all deviations
Lexicographic	Pre-defined priority levels (When no trade-off comparisons)
Weighted	Assigned weights to the goals (Trade-offs)
Chebyshev	Based on maximal deviation from any goal
Special Cases	
Fuzzy	For uncertainty in goal weights or target values.
Integer	Restricted to take only discrete values
Fractional	One or more goal of the form a/b
Non-standard Preference	Non-linear penalty function
Objective bounds	One or more constraints are rigid
Interval	A range of target to be satisfied

However, the current variants of GP do not have the capability to accommodate varying input characteristics. Each UGS is unique in terms of its demands and the benefits it provides. This is different from industrial or financial sectors, where the inputs required for the production of each unit and the corresponding value of the output produced are relatively constant. Additionally, there is a significant gap in incorporating spatial and temporal variations in the constraints and goals. While the availability of immobile resources required to meet the demand could differ among city districts, the benefits of public infrastructure should be evenly available to everyone in the city. Therefore, in urban management, it is necessary to have the flexibility to set goals or constraints for each neighborhood or district. Moreover, as mentioned earlier, research on the application of GP for resource allocation in cities has been inadequate and completely absent for UGS. Therefore, an extended GP variant is necessary to effectively address the requirements of urban applications, especially UGS management.

7.6 Methodology

The methodology aims to develop a multi-criteria decision support system for determining UGS prioritization under resource constraint conditions. It implements a utilitarian-based approach to prioritize UGS based on maximizing benefit achievement. The following subsections describe each component of the system and its implementation in more detail.

7.6.1 Modeling framework

Figure 7.2 presents the overall framework of the decision-making model. The model comprises three modules: E*stimating cost*, *estimating benefits* and *resource allocation*. The outputs of the first two modules are used to make prioritization decision in the third module. It is to be noted that while the cities consist of a variety of UGS (Wirtz et al., 2021), for this study, they are grouped into two major categories. First, *street trees* consisting of all trees alongside roads, and second, *parks* consisting of trees and the area in public parks, playgrounds, urban forests, and farms within city boundaries.

7.6.1.1 Estimating demand parameters

The literature highlights the importance of supplying necessary water resources and emphasizes the critical role that local management play in maintaining the performance of UGS (Fam et al., 2008; CABE, 2010). In their research, Wirtz et al. (2021) emphasize that experienced urban forestry staff are critical for the successful governance of UGS. Accordingly, two input demands were chosen to demonstrate the integration of management needs as a cost factor into the resource allocation decision-making framework: *water* and *personnel*. In the context of a street tree, water demand refers to the total amount of water (in mm) required annually to sustain an individual tree, while for a park, it refers to the sum of water demand for trees and the landscape area. Similarly, personnel demand refers to the total amount of physical work (in hours) required annually to carry out maintenance tasks, such as watering, cutting, pruning, litter cleaning, and the application of fertilizers. Estimates for street trees are made at the tree scale, while in the case of parks, it is the aggregated total of all the trees in the park as well as the total landscape area. To estimate species-wise annual water demand, a linear time-series-based model was used. The model, based on soil water balance and the Water Use Classifications of Landscape Species (WUCOLS) approach, estimates weekly water demand using publicly available data on tree species, soil type, and current/future weather conditions. The detailed methodology of the aforementioned water estimation model is described in (Rambhia et al., 2023).

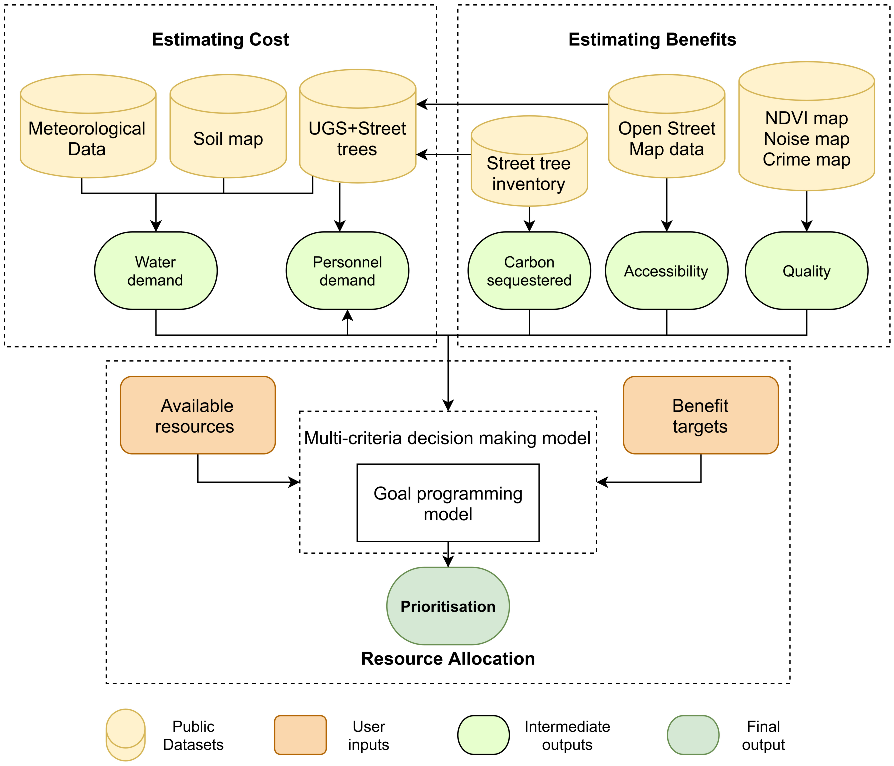


FIGURE 7.2: Modeling framework for prioritizing UGS in resource constrained scenarios.

The most common types of laborers needed for UGS management are cleaners, gardeners (for pruning, pest management, and fertilizer application), and truck drivers (to transport the leaf litter). In the absence of primary datasets related to the personnel management of UGS, reliance on secondary sources becomes imperative. This approach is deemed suitable since deriving the required staff from the existing actual staff might not be accurate. Typically, cities recruit staff based on factors such as the city's population or the availability of funds (American Public Works Association, 2015). To estimate the necessary personnel demand, we considered two parameters: the estimated time required for each activity and the desired frequency of these activities based on established best practices guidelines. These activities are discussed in more detail by Greening, Landscape and Tree Management Section Development Bureau (2014), Greening, Landscape and Tree Management Section Development Bureau (2020), Davies et al. (2017), and LI et al. (2022). Accordingly, the estimations used for the personnel required to maintain a single street tree or a 0.01 ha area are shown in Table 7.2. A single personnel works for 1349 hours annually in Germany and 1707 hours annually in Australia (OECD, 2023). As a result, one personnel staff in Germany may handle around 415 street trees or a 4.15 ha park area, while in Australia, they may handle around 525 street trees or a 5.25 ha park area. Moreover, the decision-makers could vary this input based on management preference and local needs.

Table 7.2: Estimating personnel demand for UGS management for a single street tree or 0.01 ha of park area

	Input (hours/week)	Frequency (week/year)	Total demand (hours/year)
Cleaner	0.05	13	0.65
Gardener	0.1	13	1.3
Driver	0.025	52	1.3
			3.25 hours/year

7.6.1.2 Estimating benefit parameters

While various environmental, social, and economic advantages are associated with UGS, three have been selected to illustrate the inclusion of benefits as a factor in a resource allocation decision-making framework: *accessibility*, *quality*, and *carbon sequestration*. Accessibility and quality benefits are estimated for all parks, as the trees in parks collectively provide not only environmental benefits but also high social benefits. In contrast, carbon sequestration is derived as a benefit from street trees since they act individually, with the primary focus on environmental benefits.

Accessibility is a custom-built indicator that quantifies a specific park's role in providing urban residents with access to green space, as recommended by the WHO. It is calculated as a weighted average of the building coverage score (S_C) and the essentiality score (S_E). The first component, S_C, measures the number of residences that benefit from a specific park. The second component, S_E, measures the significance of a specific park in ensuring accessibility to nearby residences. Similarly, the quality of UGS is defined as its cumulative performance on area size ($S_{Q,A}$), greenness ($S_{Q,G}$), noise ($S_{Q,N}$), and safety ($S_{Q,S}$). Accordingly, parks with a larger area, a higher density of trees located in districts with lower average noise levels, and fewer reported crime events are typically rated high in quality scores. Both accessibility and quality are derived as scores between 0 to 10 using min-max normalization (re-scaling) of the underlying features. The detailed approach for calculating benefit parameters for parks is outlined in Rambhia et al. (2022). Since there is a positive correlation between the size of the tree and the amount of carbon captured by the tree (Stephenson et al., 2014; Mildrexler et al., 2020), the sequestered carbon for each street tree is calculated from its species type and diameter size according to the method in US Department of Energy (1998).

7.6.1.3 Spatial analysis

Given that management decisions cannot be practically implemented at an individual tree level, it is necessary to group trees and parks into larger units. To assess the influence of spatial resolution on decision-making, the analysis is conducted in three different configurations. The first case involves allocating resources at the district level while establishing targets at the city level. The second case involves allocating resources at the sub-district (or cluster) level with city-level targets. Finally, the third case involves allocating resources at the sub-district level while establishing targets at the district level.

7.6.1.4 Prioritization model

The objective of the GP model is to prioritize resource allocation to street trees and UGS to maximize total benefits with available resources. As a result, the criteria are to maximize carbon sequestration in street trees, overall accessibility attained by the UGS, and UGS quality.

TABLE 7.3: Notation of sets, parameters, and variables used in the optimization model.

Sets	
G	Set of urban parks ($g \in G$)
G_p	Set of prioritized urban parks ($G_p \subseteq G$)
S	Set of street trees ($s \in S$)
S_p	Set of prioritized street trees ($S_p \subseteq S$)
L	Set of Spatial locations ($l \in L$)
Parameters	
w_i^{demand}	Water demand of unit i
p_i^{demand}	Personnel demand of unit i
$W^{available}$	Total water available for irrigation
$P^{available}$	Total personnel available for management
b_i^{carbon}	Carbon sequestration benefit of unit i
b_i^{access}	Accessibility benefit of unit i
$b_i^{quality}$	Quality benefit of unit i
B^{carbon}	Target carbon sequestration benefit
B^{access}	Target accessibility benefit
$B^{quality}$	Target quality benefit
Variables	
ra_i	Resource allocation decision for unit i
$d1$	Deviation from carbon sequestration goal
$d2$	Deviation from accessibility goal
$d3$	Deviation from quality goal
D	Total deviation for all goals

The sets, parameters, and variables utilized in the optimization model are listed in Table 7.3. The sets feature a complete and prioritized collection of park and street trees and a set of districts and sub-districts. The parameters include four components: *cost*, *benefit*, *available resources*, and *targets*. The value of the cost and benefit parameters are derived using various public datasets and for available resources and target can be obtained from the decision maker's inputs. The variables stores the deviation and decision variables as model's intermediate and final results, respectively.

The objective function of the model is given in equation (7.4) where the purpose is to minimize the weighted sum of all deviation variables at a given spatial scale. This objective function is subject to soft and hard constraints. As can be seen, both the optimization function and constraints utilize two summation functions. The first summation function aggregates the individual prioritized units (street tree or park) with varying input characteristics, including water demand, personnel demand, access benefit, quality benefit, and carbon sequestration benefit. The second summation function aggregates all the prioritized units within a selected spatial location, either a sub-district or district. The soft constraints given in equations (7.5) to (7.7) drives the model to attain the expected level of benefit targets (B^{carbon},B^{access},$B^{quality}$). The hard constraints given in equations (7.8) and (7.9) ensure that the resource demand does not exceed the available resources during the constraint scenario. Lastly, the equations (7.10) to (7.12) define the prioritized sets and the feasible values for the decision variable. Accordingly, the resource allocation decision ($r_{a,i}$) is binary in nature and the choice of allocating resources is solely made for complete allocation. As a result, a partial allocation at a unit level is not allowed in the model. Moreover, if a park spreads across multiple districts or sub-districts, then it is included in the region with the highest overlap of area.

Minimize

$$D = \sum_{l \epsilon L} \left(\sum_{i \epsilon s_p} w_1 * \frac{d1_{l,i}}{B^{carbon}} + \sum_{i \epsilon g_p} w_2 * \frac{d2_{l,i}}{B^{access}} + w_3 * \frac{d3_{l,i}}{B^{quality}} \right) \tag{7.4}$$

The optimization function aims to minimize D, the weighted sum of deviation variables $d1$, $d2$, and $d3$. Since all the deviations are in different units, they are normalized using their respective benefit targets before summing them up. The weights $w1$, $w2$, and $w3$ are used to prioritize carbon sequestration, access, and quality goals and depend on the city's preference. Soft constraints (goals/benefits):

$$\sum_{l \epsilon L} \sum_{i \epsilon s_p} b_{l,i}^{carbon} + d1 = B^{carbon} \tag{7.5}$$

The achieved carbon sequestration benefits are the sum of the sequestered carbon by all the prioritized trees in all the prioritized spatial sections of the city. Given that B^{carbon} represents the target, d1 indicates any underachievement from this carbon storage target.

$$\sum_{l \epsilon L} \sum_{i \epsilon g_p} b_{l,i}^{access} + d2 = B^{access} \tag{7.6}$$

The achieved access benefits result from the sum of access score provided by individual parks in all prioritized spatial sections of the city. Given that B^{access} is the target, d2 represents any underachievement in access reached compared to the target.

$$\sum_{l \epsilon L} \sum_{i \epsilon g_p} b_{l,i}^{quality} + d3 = B^{quality} \tag{7.7}$$

Similarly, the achieved quality benefits result from the sum of the quality scores of individual parks in all prioritized spatial sections of the city. Given that $B^{quality}$ is the target, d3 represents any underachievement in quality attained compared to the target

Hard constraints (resource constraints/costs):

$$\sum_{i \epsilon s_p} w_i^{demand} + \sum_{i \epsilon g_p} w_i^{demand} \leq W^{available} \tag{7.8}$$

Due to restrictions on the availability of water in any city, the fulfilled water demand should not exceed the budget allocated for green space irrigation. Therefore, the sum of water demand from prioritized trees and prioritized parks should be less than the available water.

$$\sum_{i \epsilon s_p} p_i^{demand} + \sum_{i \epsilon g_p} p_i^{demand} \leq P^{available} \tag{7.9}$$

Similarly, the availability of personnel for management activities is also limited. Therefore, the sum of personnel demand from prioritized trees and prioritized parks should be less than the available personnel

$$s_p = r_{a,i} * S \ \ \forall \ i \ \epsilon \ I \tag{7.10}$$

s_p denotes the set of prioritized street trees, and S represents the entire set of street trees in the city. The binary decision variable $r_{a,i}$ indicates whether a specific street tree is prioritized.

$$g_p = r_{a,i} * G \ \ \forall \ i \ \epsilon \ I \tag{7.11}$$

Similarly, g_p denotes the set of prioritized parks, and G represents the entire set of parks in the city. The binary decision variable $r_{a,i}$ indicates whether a specific park is prioritized.

$$r_{a,i} \ \epsilon \ (0,1) \ \ \forall \ i \ \epsilon \ I \tag{7.12}$$

As mentioned earlier, the binary decision variable $r_{a,i}$ takes the value of 0 to indicate that a particular unit is not prioritized, and 1 to signify prioritization with allocated resources.The solution of the model will yield an array of (0,1), indicating whether a particular UGS should be prioritized or not.

The aforementioned model has been implemented in Python language (Version 3.10) using a web-based interactive computing service, Google Colab (Google, 2022). The CP-SAT solver from OR-Tools v9.5, an open-source library developed by Google, was used to implement and solve the optimization model in Python (Perron and Furnon, 2022). Additionally, QGIS, an open-source GIS software, was used for the purpose of analysing and plotting the allocation result. The program initializes by importing the cost and benefit data, which is estimated as described in 7.6.1.1 and 7.6.1.2, respectively, or using the data provided by the user. The demand and benefit data is then aggregated at district or sub-district level depending on the scale of analysis.

7.6.2 Study area

The described model has been applied to case studies in Berlin, Germany, and Greater Melbourne, Australia, to showcase its applicability under diverse conditions. The selection of the two cities was guided by several factors, including the availability of open data, diversity in city conditions, familiarity with the geographical locations and social conditions, access to garden authorities, and consideration of the challenges faced by the cities. While Berlin has an evenly distributed population and UGS throughout the city, Melbourne has a dense population within its city boundary and a varying distribution of UGS. Moreover, inner Melbourne mostly consists of street trees and small parks, whereas the suburban region has large parks and urban forests. Additionally, the quality of data availability varies between the two regions. In Greater Melbourne, tree inventory data is maintained by individual councils for each district and is not entirely published under open data initiatives. Similarly, the noise map of Melbourne is also not available as open data. Accordingly, case studies from two diverse geographical and on-field conditions will illustrate the handling of different urban situations.

7.6.2.1 Berlin city

Berlin, the largest and capital city of Germany, spans an area of 891 km^2 and has a population of 3.6 million people. It is recognized as a high-density city with an average population density of about 4200 residents per square kilometer Eurostat (2011). Situated along the Spree river, Berlin has a temperate seasonal climate. In terms of green space, the city boasts an impressive number of trees, approximately 80 per kilometer, totaling around 431,000 trees throughout the city. These trees encompass more than 50 different species, with lime, maple, oak, plane, and chestnut being the most prevalent genera, accounting for over 75% of the total street trees. The city allocates an annual budget of approximately 37 million Euros for the maintenance of existing street trees, with an expenditure of around 2,500 Euros for planting a new tree and maintaining it for the first three years (Pflanzenschutzamt Berlin, 2021). In spite of spending heavily on maintenance, the city has witnessed a reduction in the number of total trees over last 5 years. Figure 7.3 presents a snapshot of the tree distribution in the City of Berlin, where the color intensity represents the tree density per district. The tree inventory dataset includes details such as tree location, year of plantation, age, crown size, tree height, diameter, and species information. As the methodology adopted for the estimation of tree-sequestered carbon requires the diameter size of the trees, only those trees ($\sim$75%) for which this information was available were included in the analysis.

7.6.2.2 Melbourne city

Melbourne is the capital of the state of Victoria and the second-most populous city in Australia, with around 5 million inhabitants and a city area of 9,993 km^2. The mean population density in the city is about 503 residents/km^2. Greater Melbourne is an urban agglomeration consisting of Melbourne (inner city of around 37 km^2) and 30 local municipalities (outer city). The city extends along the Yarra River and experiences a temperate climate known for its abrupt changes. Melbourne has more than 80,000 trees in the inner city region, valued at around 800 million$ (City of Melbourne, 2023). The city also maintains a register of exceptional trees (currently 279 trees) that are on private land but need protection due to their natural or heritage significance (City of Melbourne, 2019). Additionally, more than 3000 trees are planted annually to enhance the canopy cover and improve the diversity among tree species. As street tree data is limited for the rest of Greater Melbourne, both street trees and parks were included for the inner city, but only parks were included as UGS for the outer city. The most common tree genera in the city include Eucalyptus, Acacia, Ulmus, Platanus, and Corymbia. The tree inventory dataset includes tree location, scientific and common name, year of plantation, tree maturity, and diameter. Figure 7.7 presents a snapshot of the park distribution in Greater Melbourne and the street trees in inner Melbourne considered in this analysis. Similar to Berlin, only trees with available diameter information ($\sim$40%) were included.

7.6.3 Data and other inputs

The meteorological dataset, which includes data on evapotranspiration and past and future precipitation, was obtained from the German weather service DWD (Deutscher Wetterdienst, 2021) and the Bureau of Meteorology Victoria (Bureau of Meteorology,

2023) to estimate the water demand of street trees and parks. Furthermore, the WUCOLS dataset (UC Davis, 2021), as well as the soil maps from the Federal Institute for Geosciences and Natural Resources (Bundesanstalt für Geowissenschaften und Rohstoffe, 2021) and the City of Melbourne (City of Melbourne Open Data Team, 2014), were used as input data for the time series model employed for water demand estimation. To obtain tree-specific information such as tree type, species, diameter, and distribution, the city tree inventory available through the open-data initiatives of Berlin (Berlin City, 2021) and Melbourne (City of Melbourne Open Data Team, 2023) was used.

7.7 Results

In scenarios of sufficient resource availability, the resource demands of all trees could be met. However, in resource-constrained situations, prioritization becomes crucial to determine which trees and parks should be allocated resources. The results demonstrate how the prioritization of various districts or sub-districts occurs using the proposed goal-programming based model under a given resource constraint scenario. The green-marked regions in the city denote regions where all UGS should be prioritized for resource allocation, while the orange-marked region signifies those not prioritized. A resource constraint scenario of 20% reduction in the available resources is analyzed for both the case-study cities. For this particular analysis, the access and quality targets are set at the mean score of 8 and 6, respectively. Higher targets are set for access since the existing targets of WHO and UN SDG focus exclusively on providing higher access to a sufficient quantity of UGS without any specific targets related to the quality of those spaces or for carbon sequestration (United Nations, 2020).

The results for the three cases of Berlin are presented here. In the first case (see Figure 7.4), resources are allocated at the district scale with city-scale goals. Here, 59 out of 96 districts received allocations, fulfilling the resource demand in the green-marked districts. In the second case (see Figure 7.5), resource allocation is at the sub-district scale with city-scale goals. The third case (see Figure 7.6) illustrates each district's performance in goal achievement when resources are allocated at the sub-district scale with district-scale targets. Since in this case each district has an individual goal, the model aims to minimize the deviation for each district. Consequently, resources are allocated to each district. However, due to insufficient resources to meet the entire demand of all districts, some districts will still experience underachievement of their goals. Unlike the binary response obtained in the previous two cases, resource allocation is done in each district to maximize goal achievement. For this case, districts are categorized as achieved if the goal is met, underachieved if the goal achievement is below the target, and overachieved if it exceeds the target. It can be observed that some districts experience overachievement, especially when large parks within those districts are fully prioritized, potentially surpassing the predefined or expected targets, set at a score of 8 for access and 6 for quality.

Similar to the Berlin case, the green-marked city districts represent the districts in Melbourne where all UGS are prioritized for allocating resources. Figure 7.8 presents the first case wherein resources are allocated at the district scale (divided according to localities) with goals set at the city scale. In this case, 231 out of 266 districts were prioritized. Figure 7.9 presents the second case wherein resource allocation is done at the sub-district scale (divided according to zip codes) with goals set at the city scale. In this case, 440

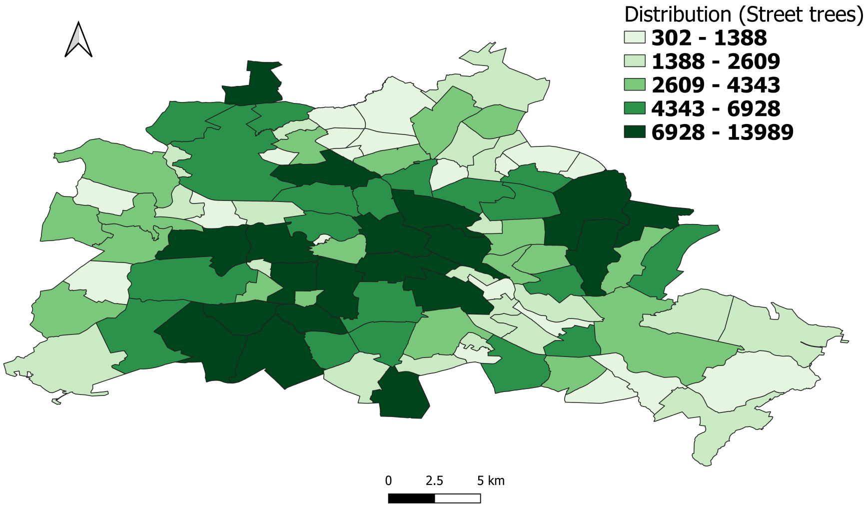


FIGURE 7.3: Snapshot of the street trees in Berlin with the intensity of colour indicating the tree density in the district (Source: (Berlin City, 2021)).

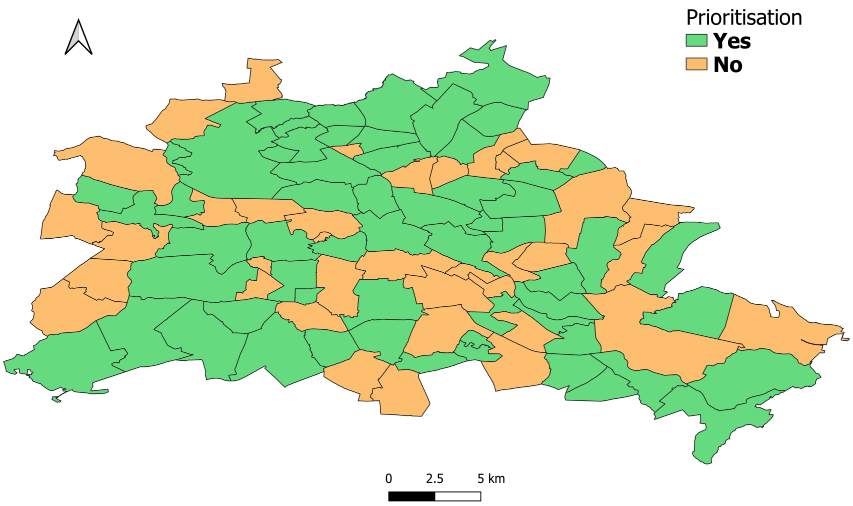


FIGURE 7.4: Case-1 Berlin: Resource allocation decision at district spatial scale with city-level goals.

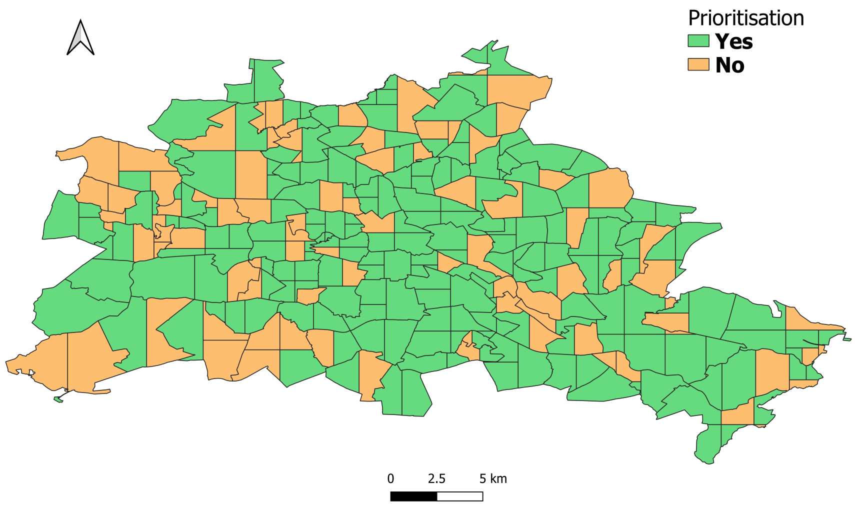


FIGURE 7.5: Case-2 Berlin: Resource allocation decision at sub-district spatial scale with city-level goals.

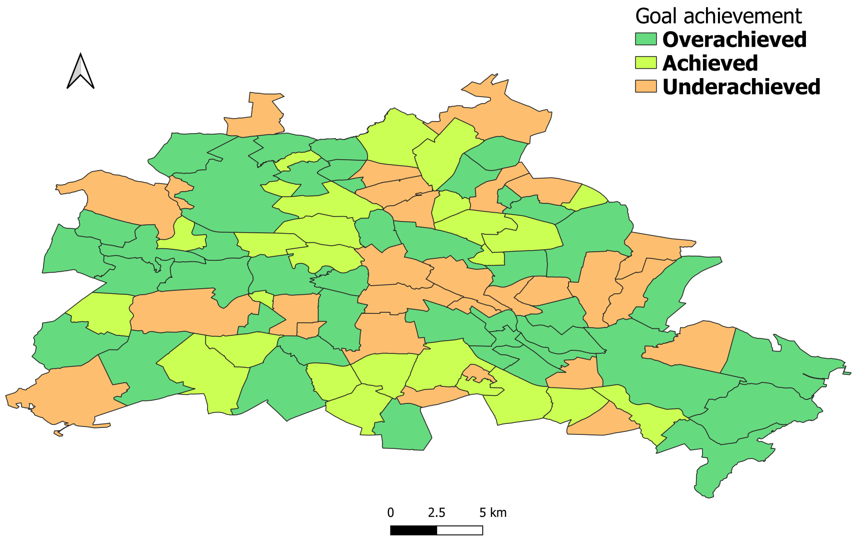


FIGURE 7.6: Case-3 Berlin: Goal achievement in each district with district-level goals.

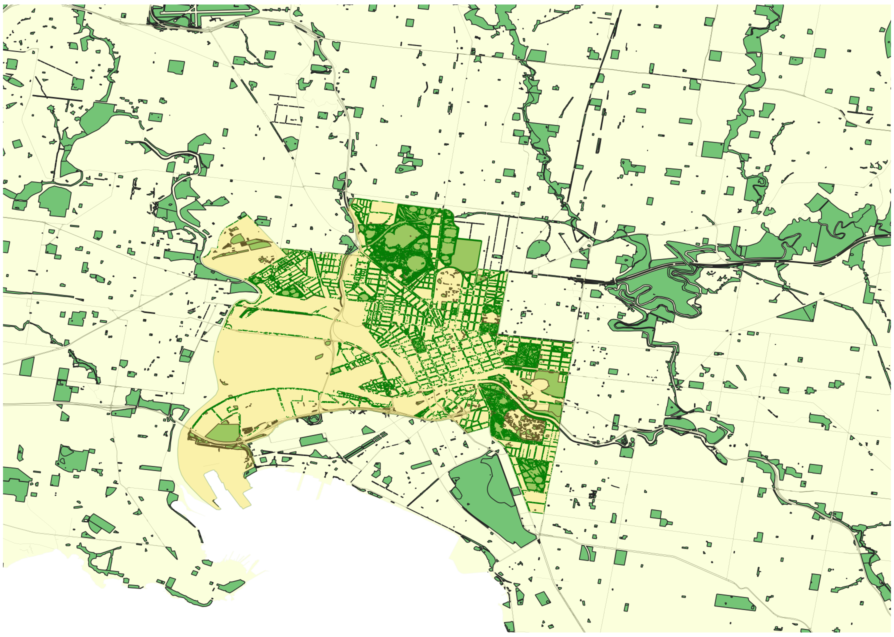


FIGURE 7.7: Snapshot of the parks in Greater Melbourne and street trees in the inner city (Source: (City of Melbourne Open Data Team, 2023)).

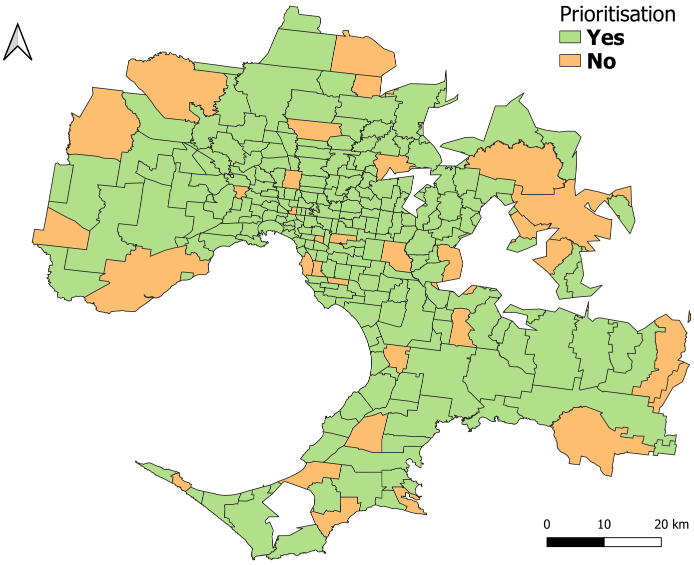


FIGURE 7.8: Case-1 Melbourne: Resource allocation decision at district spatial scale with city-level goals.

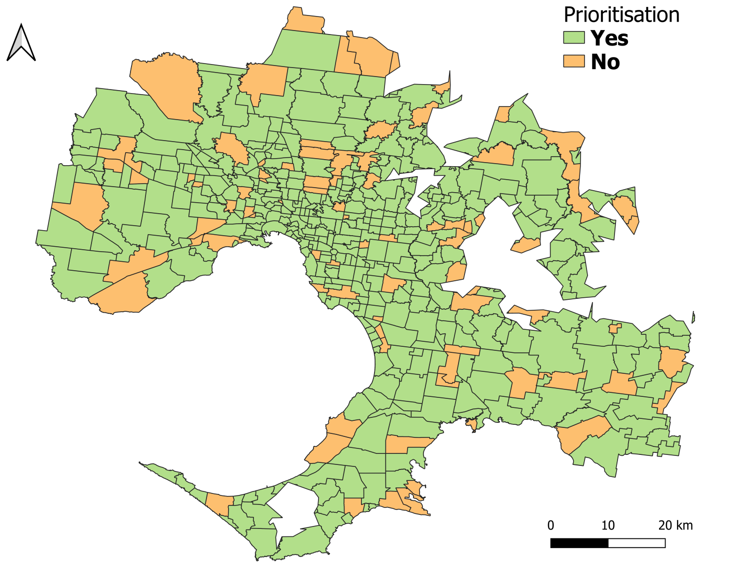


FIGURE 7.9: Case-2 Melbourne: Resource allocation decision at sub-district spatial scale with city-level goals.

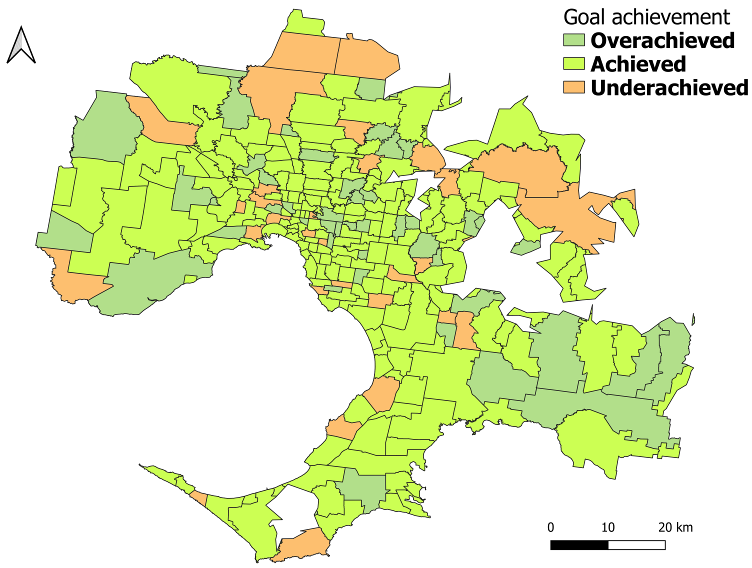


FIGURE 7.10: Case-3 Melbourne: Goal achievement in each district with district-level goals.

out of 527 sub-districts were prioritized. Figure 7.10 presents the third case wherein resource allocation is done at the sub-district scale, but the targets are set at the district scale instead of the city scale. As a result, resources are allocated to each district, but the achievement of goals varies depending on the allocation and the resource availability. As explained in subsubsection 7.6.1.2, the access score is determined by the number of people benefiting from a particular UGS. Consequently, UGS located on the outskirts of the city generally exhibit lower access scores compared to those situated in areas with a higher population density. While this is partially mitigated by the higher quality of UGS on the periphery compared to inner-city UGS, the overall prioritization still favors inner-city UGS. This preference is evident in the results from Melbourne, where several districts on the periphery did not receive prioritization. This contrasted with Berlin, where the relatively even distribution of the population resulted in a different prioritization pattern.

Water demand and personnel demand are costs associated with the management of each UGS, so it is critical to evaluate how much cost is involved in implementing a particular strategy. Similarly, street trees allocated and parks allocated are indirect benefits that will determine the direct benefits desired by a decision-maker, i.e., achieved accessibility, achieved quality, and retained sequestered carbon upon implementing a particular strategy. Based on this principle, several benefits metrics were calculated and Table 7.4 provides a performance summary of resource allocation strategies across various benefit metrics.

TABLE 7.4: Performance on various benefit metrics under given constraints.

		Berlin			Melbourne		
No	Parameter	City-level target		District-level target	City-level target		District-level target
		Districts	Cluster	Cluster	Districts	Cluster	Cluster
		(Case-1)	(Case-2)	(Case-3)	(Case-1)	(Case-2)	(Case-3)
1	Water consumed (%)	94.28	97.35	95.17	96.56	98.72	97.3
2	Personnel consumed (%)	91.69	93.86	90.84	95.85	98.22	96.44
3	Street trees allocated (%)	84.15	92.23	81.22	89.6	94.37	87.7
4	Parks allocated (%)	92.46	89.74	94.59	90.12	88.46	92.28
5	Access score achieved	7.9	8.3	7.8	8.1	8.7	8
6	Quality score achieved	7.3	7.7	7.1	8.8	8.9	8.8
7	Carbon sequestered (%)	86.94	93.29	87.70	91.5	97.35	90.20
8	Heritage trees allocated (%)	-	-	-	95.8	95.8	97.1
8	Model run time (mins)	35	50	80	30	40	65

The metrics *water consumed* and *personnel consumed* describe the resources used from the total available. They are calculated as the percentage of water allocated to the prioritized UGS from the available 80% water during the resource constraint scenario, and similarly for personnel allocation. *Street trees allocated* and *parks allocated* represent the resources receiving the required management inputs for sustenance. These metrics are calculated as the percentage of street trees and parks that received management support from the total considered in the analysis. *Access achieved* and *quality achieved* describe the achievement of access and quality targets. These metrics are measured as the mean accessibility score or quality score of the prioritized or allocated parks. As previously mentioned, each of these scores falls within a range from 0 to 10, with 10 representing the highest score. *Carbon sequestered* presents the percentage of stored carbon that will continue to remain stored due to the allocated street trees. This is calculated as the percentage of carbon stored in the prioritized trees against the carbon stored in all trees. *Heritage trees allocated* is the percentage of heritage (exceptional) trees that will remain conserved under the given prioritization from the total heritage trees in the city. Lastly, *model run time* represents the total time taken to run the entire model, including the three sub-modules described earlier.

Benefit metrics provide several insights into the prioritization recommended by the model. In Case-1, for Berlin, more parks received allocation than street trees, whereas, for Melbourne, the allocation was quite similar for both. This difference is likely due to the distribution of street trees throughout the entire city in Berlin, whereas, in the case of Melbourne, they are concentrated only in the inner city. Nevertheless, as observed, up to 8.31% (mean = 5.40%) of resources are left undistributed. The minimum resource required for each non-priority district is higher than the remaining resources; therefore, they cannot be allocated any resource. Consequently, all street trees and parks in those districts will remain without any resources, despite some resources being left in the city. Since the benefit target for access was set higher than for quality, parks will have higher priority. However, in Case-2, street trees received a higher allocation because, at a higher spatial resolution, resources are distributed among a greater number of regions, leaving fewer resources for each sub-district. Additionally, since each unit of parks requires more resources, this will favor street trees. As a result, an improvement in resource utilization can also be observed for both cities. In this case, only up to 6.14% (mean = 2.96%) of resources are left undistributed. With the increase in resource allocation, the total UGS allocation also improved in Case-2 compared to Case-1.

The overall benefits show improvement when goals are established at the district level instead of the city level (Case 3). In this case, as the benefit target aimed at maximizing access and quality achievement for each district, the prioritization highly favored the parks. As seen in Figure 7.6 and Figure 7.10, each district receives a portion of resources, and therefore, no region remains unmanaged. While this improves the uniformity in distribution, the allocation to trees reduced in this case, as some resources also went into managing previously not prioritized districts. In cases with a higher allocation of resources to parks, the mean access and quality scores are observed to be lower. This occurs because prioritizing a larger number of parks will also include parks that perform lower on these scores. As expected, higher carbon sequestration is observed in cases with a higher allocation of resources to street trees. Especially in Melbourne, where all street trees are concentrated in the inner city and most of those districts got prioritized, the street trees allocation and achievement of the carbon target are relatively much higher than in Berlin. The heritage trees metric was calculated only for Melbourne since the city has a special focus on preserving these trees. Lastly, the model run time increased as we increased the spatial resolution of the analysis and the number of constraints.

7.8 Discussion

The proposed extended GP model addresses the need for methods that can prioritize UGS while managing multiple resource constraints, such as water resources and personnel limitations. It leads to solutions that are not only feasible but also balance the achievement of multiple goals. In both the cases of Berlin and Melbourne, it can be observed that the benefit metrics improve when resource allocation is done at a sub-district spatial scale (Case-2) compared to when it is done at the district scale (Case-1). This is likely due to the criterion of absolute allocation. When optimization is done at a lower spatial resolution, the total number of street trees and UGS is much higher in a single unit. As a result, the cumulative management demands of each unit are comparatively higher, and the optimal or near-optimal result suffers from this aggregation. Therefore, under a resource constraint scenario, the number of district units that can be allocated resources is relatively lower. Moreover, when the allocation pattern is analyzed in comparison to the tree distribution in the city, many of the non-allocated sub-districts lie in the high tree density areas. It is critical to emphasize that since partial allocation is not considered, some of the resources are left unused. Therefore, the gained benefits can likely be further improved by including partial allocation.

While case-1 bounds the prioritization by a lower spatial scale, case-3 forces goal fulfillment in each district. Therefore, decision-makers aiming for a resource-efficiency-oriented distribution should opt for allocation at the sub-district level since, among all three, it offers the highest model flexibility to choose the UGS for prioritization. While case-3 is better suited for a goal-oriented prioritization approach, as the focus is higher on the achievement of goals across the city than on benefit maximization. The benefits gained increase as the spatial resolution increases. For the decision-maker, this implies that the distribution of resources using smaller hubs is better. In such cases, a smaller group of resource-intensive UGS can be targeted. However, if the decision is made at a district level to allocate resources to all UGS within the district, it would cover UGS with a varied range of demands and benefits. Nevertheless, higher spatial resolution not only exponentially increases the computation efforts for the model but also raises implementation complexity in the field, requiring different management applications for each region. It might be feasible to apply in the future using an IoT-based micro-irrigation system. Secondly, the district-level target approach is more appropriate since it does not leave any district completely disadvantaged and provides a more uniform resource allocation across the city. Therefore, this is suitable for cities like Berlin, where the population distribution is more uniform.

Moreover, to assess improvements in goal achievement, a comparison is conducted with a baseline scenario. In the absence of a prioritization standard or framework available for the cities, decision-makers are unable to distinguish between higher and lower beneficial trees or parks and higher or lower resource-intensive tree species. Consequently, a symmetrical distribution of resources must be made, considering all trees and parks in all districts equally based on the availability of resources. In the event of a 20% reduction in available resources, the resources will be sufficient to meet the annual management demands of 80% of the total UGS. In such a case, over the large iterations, the benefits achieved will be proportionate as well.

However, with GP model-based prioritization, the allocation surpasses 80% in all three scenarios for both street trees and parks. This is achieved by the model favoring UGS with lower resource demands per unit of benefits provided. As a result, resource-intensive UGS receive reduced management support. This prioritization strategy enables cities to attain greater benefits even under constrained scenarios. It is crucial to note that these results are based on available public data. Since the open tree inventory lacked essential data for some trees, updating the missing data could potentially alter management requirements, recommendations, and GP-based decision-making. Consequently, future research should focus on addressing these data gaps.

The review of the existing city plans also indicated a critical gap in the urban greening strategies of both cities. The city of Berlin has developed a Landscape Program to ensure sufficient availability of recreational areas for people and the needs of wild animals and plants in the future (Naturschutz, Landschaftsplanung, 2023). This initiative involves the creation of new green spaces and a network of connecting paths. Although the program has effectively integrated environmental goals into planning procedures, it lacks strategies to address challenges in the event of resource constraints. Similarly, the City of Melbourne recognizes the importance of UGS and has developed a Green Our City Strategic Action Plan (City of Melbourne, 2020) and Open Space for Everyone Strategy (City of Melbourne, 2012). However, the primary focus remains on increasing new green spaces to meet the growing demand, enhancing the diversity of tree species, and improving vegetation health. While acknowledging the extended drought and subsequent water shortage, a recommendation has been made to plant drought-resistant tree species and implement stormwater harvesting. Nevertheless, no consideration has been given to prioritizing existing UGS based on the benefits obtained.

7.9 Conclusion and future research

The proposed GP model allocates limited resources to maximize the social and environmental benefits obtained from UGS. The reduced availability of demand parameters, water, and personnel is included to demonstrate the constraint scenario. However, these parameters can be extended by adding additional demand parameters, such as the quantity of fertilizer, the number of trucks, or the available budget. The benefit parameter is calculated using the custom-built accessibility and quality indicators for parks and the sequestered carbon indicator for street trees. Nevertheless, these parameters can be easily replaced or extended with other benefit parameters, such as biodiversity, air pollution reduction, or heat mitigation (cooling), depending on the needs of the city and availability of the accurate data.

The novelty of the study lies in its implementation of a MCDM approach to address the resource allocation challenge for existing UGS. It introduces a utilitarian principle-based prioritization using a multi-objective GP model. The proposed model can accommodate diverse UGS, including parks and street trees, with varying characteristics, and allows analysis at different spatial scales. Moreover, it uniquely incorporates accessibility as a goal, enabling cities to meet UN SDG targets even under resource constraint conditions. Additionally, the framework is scalable, allowing the inclusion of additional cost and benefit parameters. Lastly, the model was tested in two cities with diverse conditions regarding data availability, green space density, population distribution, and local climatic conditions.

It is important to note that the GP-based method, instead of optimizing, derives a solution that satisfies the goals. Consequently, some resources may remain unused in the final solution. Additionally, the current approach is limited to spatial planning of resource allocation and can be extended by considering temporal aspects. For instance, different temporal goals or constraints at various spatial scales could be incorporated. In addition, currently, constraints are considered at the city level, which can be further extended to different spatial scales, as was done for the goals in this study. Similarly, the current model adopts a single-choice goal, allowing the decision-maker to set fixed target values for each benefit. This approach can be expanded to a multi-choice goal, where a range of benefit targets can be specified, as demonstrated by Kouaissah and Hocine (2020). As mentioned earlier, more benefits and management demands can be included to create more realistic trade-off scenarios. Furthermore, it is important to note that the analysis included only around 75% of street trees for Berlin and 40% for Melbourne, for which diameter information was available in the tree inventory dataset to calculate the sequestered carbon. As a result, the actual management demand and benefits obtained from street trees would likely be proportionately higher than the estimated values. Therefore, further research is needed to address such data gaps in urban datasets. Moreover, due to a lack of information on personnel in the public domain, certain assumptions were made in estimating the personnel demand. However, following the process of the demonstration, these assumptions can be replaced with factual city data to obtain more accurate results.

The developed model is a novel approach for UGS management, serving as an example for urban resource allocation applications. Decision-makers can utilize this model to make prioritization decisions at various spatial scales under constraint scenarios. The model is adaptable to include additional demand and benefit parameters based on the availability of relevant datasets. Moreover, it allows decision-makers to observe the impact of modifying the priority order of goals and their respective weights on the prioritization decision.

Bibliography

American Public Works Association (2015). Urban forestry best management practices for public works managers - staffing.

Bakhtavar, E., Prabatha, T., Karunathilake, H., Sadiq, R., and Hewage, K. (2020). Assessment of renewable energy-based strategies for net-zero energy communities: A planning model using multi-objective goal programming. *Journal of Cleaner Production*, 272:122886–122886.

Berlin City (2021). Open data berlin.

Bravo, M. and Gonzalez, I. (2009). Applying stochastic goal programming: A case study on water use planning. *European Journal of Operational Research*, 196(3):1123–1129.

Bundesanstalt für Geowissenschaften und Rohstoffe (2021). Bodenübersichtskarte von Deutschland 1:3000000.

Bureau of Meteorology (2023). Victoria daily evapotranspiration.

CABE (2010). Managing green spaces - seven ingredients for success.

Charnes, A. and Cooper, W. (1977). Goal programming and multiple objective optimizations. *European Journal of Operational Research*, 1:39–54.

Charnes, A., Cooper, W. W., Devoe, J. K., Learner, D. B., and Reinecke, W. (1968). A Goal Programming Model for Media Planning. *Management Science*, 14(8):B–423–B–430.

Chen, S., Zhao, X., Chen, Z., Hou, B., and Wu, Y. (2022). A game-theoretic method to optimize allocation of defensive resource to protect urban water treatment plants against physical attacks. *International Journal of Critical Infrastructure Protection*, 36:100494–100494.

Chen, Y., Men, H., and Ke, X. (2023). Optimizing urban green space patterns to improve spatial equity using location-allocation model: A case study in wuhan. *Urban Forestry and Urban Greening*, 84:127922–127922.

Cheng, J., Feng, X., and Bai, X. (2021). Modeling equitable and effective distribution problem in humanitarian relief logistics by robust goal programming. *Computers & Industrial Engineering*, 155:107183–107183.

City of Melbourne (2012). Open space strategy.

City of Melbourne (2019). Exceptional tree register.

City of Melbourne (2020). Green our city strategic action plan.

City of Melbourne (2023). Urban forest.

City of Melbourne Open Data Team (2014). Soil types by area (urban forest).

City of Melbourne Open Data Team (2023). Trees, with species and dimensions (urban forest).

Corlay, V. and Sibel, J.-C. (2023). An mdp approach for radio resource allocation in urban future railway mobile communication system (frmcs) scenarios.

Davies, H., Doick, K. J., Hudson, M. D., and Schreckenberg, K. (2017). Challenges for tree officers to enhance the provision of regulating ecosystem services from urban forests. *Environmental Research*, 156:97–107.

Deutscher Wetterdienst (2021). DWD open data.

Diiaz-Balteiro, L. and Romero, C. (2004). Sustainability of forest management plans: a discrete goal programming approach. *Journal of Environmental Management*, 71:351–359.

Eisenman, T. S., Chang, S., and Laurian, L. (2021). Stewarding street trees for a global urban future. *Springer eBooks*, pages 1–18.

Eurostat (2011). Degree of urbanisation classification - 2011 revision.

Fam, D., Mosley, E., Lopes, A., Mathieson, L., Morison, J., and Connellan, G. (2008). Irrigation of urban green spaces: a review of the environmental, social and economic benefi ts.

Fongar, C., Randrup, T. B., Wiström, B., and Solfjeld, I. (2019). Public urban green space management in norwegian municipalities: A managers' perspective on place-keeping. *Urban Forestry and Urban Greening*, 44:126438–126438.

Foroozesh, F., Monavari, S. M., Salmanmahiny, A., Robati, M., and Rahimi, R. (2022). Assessment of sustainable urban development based on a hybrid decision-making approach: Group fuzzy bwm, ahp, and topsis–gis. *Sustainable Cities and Society*, 76:103402–103402.

Gebre, S. L., Cattrysse, D., and Van Orshoven, J. (2021). Multi-criteria decision-making methods to address water allocation problems: A systematic review. *Water (Switzerland)*, 13(2):1–28.

Google (2022). Google colaboratory.

Greening, Landscape and Tree Management Section Development Bureau (2014). Management guidelines for mature trees.

Greening, Landscape and Tree Management Section Development Bureau (2020). Guidelines on tree pruning.

Hamurcu, M. and Eren, T. (2022). Multicriteria decision making and goal programming for determination of electric automobile aimed at sustainable green environment: a case study. *Environment Systems and Decisions*, 43:211–231.

Huang, C., Huang, P. S., Wang, X., and Zhou, Z. (2018). Assessment and optimization of green space for urban transformation in resources-based city – a case study of lengshuijiang city, china. *Urban Forestry and Urban Greening*, 30:295–306.

Ignizio, J. P. (1978). A review of goal programming: A tool for multiobjective analysis. *Journal of the Operational Research Society*, 29(11):1109–1119.

Jim, C. Y. (2004). Green-space preservation and allocation for sustainable greening of compact cities. *Cities*, 21:311–320.

Jones, D. and Tamiz, M. (2010). *Practical Goal Programming.* Springer.

Kamran, M. A., Karimi, B., Bakhtiari, H., and Masoumzadeh, S. (2016). A resource allocation model in a healthcare emergency center using goal programming. *Journal of Engineering Research*, 4.

Kaur, J., Singh, O., Anand, A., and Agarwal, M. (2023). A goal programming approach for agile-based software development resource allocation. *Decision Analytics Journal*, 6:100146–100146.

Klumbytė, E., Bliūdžius, R., Medineckienė, M., and Fokaides, P. A. (2021). An mcdm model for sustainable decision-making in municipal residential buildings facilities management. *Sustainability*, 13(5).

Kouaissah, N. and Hocine, A. (2020). Optimizing sustainable and renewable energy portfolios using a fuzzy interval goal programming approach. *Computers and Industrial Engineering*, 144:106448–106448.

Kumar, A., Sah, B., Singh, A. R., Deng, Y., He, X., Kumar, P., and Bansal, R. C. (2017). A review of multi criteria decision making (MCDM) towards sustainable renewable energy development. *Renewable and Sustainable Energy Reviews*, 69(November 2016):596–609.

Lashkari, M., Yazdi-Feyzabadi, V., Mohammadi, M., Saberi, H., and Mehrolhassani, M. (2018). Designing a financial resource allocation model using goal programming approach: A case study of a hospital in iran.

Lee, S. M. and Clayton, E. R. (1972). A Goal Programming Model for Academic Resource Allocation. *Management Science*, 18(8).

LI, I., Zhang, W., and Yang, P. (2022). Estimating management demands and cost for urban green spaces (ugs) in melbourne.

Li, S., Liang, Y., Wang, Z., and Zhang, D. (2021). An optimization model of a sustainable city logistics network design based on goal programming. *Sustainability*, 13:7418–7418.

Li, X., Li, X., and Ma, X. (2022). Spatial optimization for urban green space (ugs) planning support using a heuristic approach. *Applied Geography*, 138:102622–102622.

Li, Y., Cui, Q., Li, C., Wang, X., Cai, Y., Cui, G., and Yang, Z. (2017). An improved multi-objective optimization model for supporting reservoir operation of china's south-to-north water diversion project. *Science of The Total Environment*, 575:970–981.

Liu, Y., Xia, C., Ou, X., Lv, Y., Ai, X., Pan, R., Zhang, Y., Shi, M., and Zheng, X. (2023). Quantitative structure and spatial pattern optimization of urban green space from the perspective of carbon balance: A case study in beijing, china. *Ecological Indicators*, 148:110034–110034.

Locke, D., Grove, M., Lu, J., Troy, A., O'Neil-Dunne, J., and Beck, B. (2010). Prioritizing preferable locations for increasing urban tree canopy in new york city. *Cities and the Environment (CATE)*, 3.

M. Vallejo, D. C. and Vargas, P. (2017). Online/offline evolutionary algorithms for dynamic urban green space allocation problems. *Journal of Experimental & Theoretical Artificial Intelligence*, 29(4):843–867.

Mildrexler, D. J., Berner, L. T., Law, B. E., Birdsey, R. A., and Moomaw, W. R. (2020). Large trees dominate carbon storage in forests east of the cascade crest in the united states pacific northwest. *Frontiers in forests and global change*, 3.

Mishra, V., Som, T., Samuel, C., and Sharma, S. (2018). Fuzzy goal programming approach for resource allocation in an ngo operation. *Springer proceedings in mathematics & statistics*, pages 373–385.

Moller, M. S., Olafsson, A. S., Vierikko, K., Sehested, K., Elands, B., Buijs, A., and Konijnendijk, C. C. (2019). Participation through place-based e-tools: A valuable resource for urban green infrastructure governance? *Urban Forestry and Urban Greening*, 40:245–253.

Naturschutz, Landschaftsplanung (2023). Landschaftsprogramm einschließlich artenschutzprogramm (lapro).

Nechi, S., Aouni, B., and Mrabet, Z. (2019). Managing sustainable development through goal programming model and satisfaction functions. *Annals of Operations Research*, 293:747–766.

Nestıcò, A., Elizabeth, C., and Naddeo, V. (2020). Sustainability of urban regeneration projects: Novel selection model based on analytic network process and zero-one goal programming. *Land Use Policy*, 99:104831–104831.

Neuenschwander, N., Wissen Hayek, U., and Grêt-Regamey, A. (2011). Gis-based 3d urban modeling framework integrating constraints and benefits of ecosystems for participatory optimization of urban green space patterns. *Proceedings of REAL CORP 2011*.

Nyelele, C. and Kroll, C. N. (2021). A multi-objective decision support framework to prioritize tree planting locations in urban areas. *Landscape and Urban Planning*, 214:104172–104172.

Nyelele, C., Kroll, C. N., and Nowak, D. J. (2022). A comparison of tree planting prioritization frameworks: i-tree landscape versus spatial decision support tool. *Urban Forestry and Urban Greening*, 75:127703–127703.

OECD (2023). Hours worked (indicator).

Omidipoor, M., Jelokhani-Niaraki, M., Moeinmehr, A., Sadeghi-Niaraki, A., and Choi, S.-M. (2019). A gis-based decision support system for facilitating participatory urban renewal process. *Land Use Policy*, 88:104150–104150.

Orumie, U. C. and Ebong, D. (2014). A glorious literature on linear goal programming algorithms. *American Journal of Operations Research*, 04:59–71.

Pankaj Kant, P. K. M. and Natha, A. R. (2023). Evaluation of decision support system for disaster management using multi-criteria decision techniques: a case study of alappuzha, kerala. *Urban, Planning and Transport Research*, 11(1):2262546.

Pavan, M. and Todeschini, R. (2009). Multicriteria decision-making methods. *Elsevier eBooks*, pages 591–629.

Perron, L. and Furnon, V. (2022). Or-tools.

Pflanzenschutzamt Berlin (2021). Stadtbäume.

Plitt, S., Pregitzer, C. C., and Charlop-Powers, S. (2021). Brief research report: Case study on the early impacts of covid-19 on urban natural areas across 12 american cities. *Frontiers in Sustainable Cities*, 3.

Porterfield, R. L. (1976). A goal programming model to guide and evaluate tree improvement programs. *Forest Science*, 22:417–430.

Pustokhina, I. V. and Pustokhin, D. A. (2021). *An Intelligent Multi-Objective Optimal Resource Allocation via Modified Fish Swarm for Sustainable Smart Cities*, pages 71–85. Springer International Publishing, Cham.

Rahman, M. F. and Sharma, N. (2020). Reinforcement learning based approach for urban resource allocation and path planning problems. In *2020 International Conference on Intelligent Data Science Technologies and Applications (IDSTA)*, pages 115–118.

Rajendran, S. (2021). Real-time dispatching of air taxis in metropolitan cities using a hybrid simulation goal programming algorithm. *Expert Systems with Applications*, 178:115056–115056.

Rambhia, M., Volk, R., Rismanchi, B., Winter, S., and Schultmann, F. (2022). Prioritising urban green spaces using accessibility and quality as criteria. *IOP Conference Series: Earth and Environmental Science*, 1101:022043.

Rambhia, M., Volk, R., Rismanchi, B., Winter, S., and Schultmann, F. (2023). Supporting decision-makers in estimating irrigation demand for urban street trees. *Urban Forestry and Urban Greening*, page 127868.

Rehman, A. U., Usmani, Y. S., Mian, S. H., Abidi, M. H., and Alkhalefah, H. (2023). Simulation and goal programming approach to improve public hospital emergency department resource allocation. *Systems*, 11:467–467.

Ricciardi, L., D'Odorico, P., Galli, N., Chiarelli, D. D., and Rulli, M. C. (2022). Hydrological implications of large-scale afforestation in tropical biomes for climate change mitigation. *Philosophical Transactions of the Royal Society B: Biological Sciences*, 377(1857):20210391.

Romero, C. (1985). Naive weighting in non-preemptive goal programming. *Journal of the Operational Research Society*, 36(7):647–648.

Roozbahani, R., Abbasi, B., Schreider, S., and Ardakani, A. (2014). A multi-objective approach for transboundary river water allocation. *Water Resources Management*, 28:5447–5463.

Rößler, S. (2017). Demands, opportunities and constraints of green space development for future urban development under demographic and climate change. *Springer eBooks*, pages 87–98.

Schniederjans, M. (2012). *Goal Programming: Methodology and Applications: Methodology and Applications*. books.google.com.

Schrammeijer, E. A., , B., and Verburg, P. H. (2021). Whose park? crowdsourcing citizen's urban green space preferences to inform needs-based management decisions. *Sustainable Cities and Society*, 74:103249–103249.

Stephenson, N. L., Das, A. J., and Condit, R. (2014). Rate of tree carbon accumulation increases continuously with tree size. *Nature*, 507:90–93.

UC Davis (2021). WUCOLS plant search database.

United Nations (2020). Goal 11.

US Department of Energy (1998). Method for calculating carbon sequestration by trees in urban and suburban settings — urban forestry south.

Valcárcel-Aguiar, B. and Fernández, P. M. (2018). Evaluation and management of urban liveability: A goal programming based composite indicator. *Social Indicators Research*, 142:689–712.

Wan, X., Xue, Y., Hua, L., and Wu, Q. (2023). Multi-objective collaborative decision-making for flood resource utilization in a reservoir. *Stochastic Environmental Research and Risk Assessment*.

Wirtz, Z., Hagerman, S., Hauer, R. J., and Konijnendijk, C. C. (2021). What makes urban forest governance successful? – a study among canadian experts. *Urban Forestry and Urban Greening*, 58:126901–126901.

World Health Organization (2017). Urban green spaces: a brief for action.

Chapter 8

Decision making under limited data

8.1 Prelims

This chapter[1] contributes to the fourth research objective (RO4): “develop a framework to assess and enhance the quality of input data for decision-making in cities with limited data availability". Accordingly, Study D focused on developing a quality assessment and enhancement framework for UGS data, particularly tree inventory datasets. It provides a systematic method to verify the appropriateness of the existing data for integration into management application models. Each dataset is categorized as high or low quality and quantity using dimensions derived from total data quality management principles. Furthermore, data enhancement techniques are applied based on the performance against set thresholds before further utilization of the dataset.

The chapter structure is as follows: first, the motivation, background, and introduction to the research gap are provided in section 8.3. Then, in section 8.4, a literature review covering two parts is presented: methods available for data quality assessment (subsection 8.4.1) and data quality enhancement (subsection 8.4.2). Next, the proposed framework for UGS management application is presented in section 8.5. The methodology section consists of five steps: data evaluation (subsection 8.5.1), data classification (subsection 8.5.2), data preprocessing (subsection 8.5.3), data filling (subsection 8.5.4), and model evaluation (subsection 8.5.5). Subsequently, the proposed framework is applied to tree inventory datasets from ten German cities, and its results are included in section 8.6. Finally, a thorough discussion analyzing the obtained results and the limitations of the approach is presented in section 8.7. Concluding remarks and suggestions for future research directions are then provided in section 8.8.

[1] This chapter is based on a article:
Rambhia, M., Volk, R., Rismanchi, B., Winter, S., & Schultmann, F. (2024). “Data Quality Challenges for Decision-Making in Urban Green Space Management". [To be submitted]
The paper presented in section 8.2 is reformatted for consistency within the thesis, including the numbering of figures and tables, as well as the referencing style. The published manuscript from the journal is attached in the Appendix.

Study D: Data quality challenges for decision-making in urban green space management

8.2 Abstract

In the era of smart and sustainable cities, the increasing availability of urban data in the public domain has become a primary focus for cities worldwide. This trend has resulted in the development of numerous models that utilize public datasets to support decision-making in urban management. However, the quantity and quality of these input datasets require thorough evaluation before being used as model inputs, as their application without proper assessment may lead to inaccurate results and interpretations, impacting decision-making. In cases where data quality is insufficient, additional preprocessing interventions are necessary to enhance it before applying it to various applications. Digital tree inventories, in particular, are critical inputs for decision-making in urban green space management, but their public availability varies significantly. The current literature lacks a systematic approach to particularly assess the quality of these datasets, analyze its impact on decision-making applications, and enhance their quality. To address these gaps, we developed a quality assessment and enhancement framework based on total data quality management principles. Additionally, a random forest-based regression model was implemented to address data quantity challenges. The proposed framework was used to evaluate tree inventories in ten cities in Germany and subsequently applied to one of these dataset to enhance it by filling in missing tree height values. Accordingly, this methodology could enable informed decision-making in cities, even where required input data are available with insufficient quantity or quality.

8.3 Introduction

The total digital data volume of the world is projected to reach 175 Zettabytes by 2025 (Reinsel et al., 2018). Additionally, every day, 1000 petabytes of new data are generated globally, and this trend is on a sharp upward trajectory (Bartley, 2020). Consequently, the value of data in every application has increased immensely, earning it the designation of the new era gold (Ditfurth and Aholt, 2018). In recent times, the focus has also increased on analyzing this large amount of data, commonly referred to as Big Data, to generate practical and actionable insights for various applications. As a result, researchers and industries have developed several approaches to process and utilize this data for quantifying performance indicators, analyzing trends, and making future predictions (Kaluarachchi, 2022). In the domain of Operations Research, the focus has been on developing decision-making models to improve operational efficiency and assist decision-makers in improving the objectivity of their decisions. This is especially useful for achieving the desired objective optimally while balancing multiple conflicting criteria and constraints.

Simultaneously, the push towards a smarter world has led to cities incorporating digitalization across a wide range of departments. Accordingly, several governments have recognized the importance of providing public access to data and have framed regulations, guidelines, and plans for its advancement. This has led to several open data initiatives wherein cities publish a large number of urban datasets publicly, and this trend is continuously rising worldwide (Lämmerhirt et al., 2017). This generally includes datasets such as city plans, infrastructure networks like roads and railways, public institutions' availability, weather data, and environment. Researchers have used such public datasets to advance diverse areas like city planning, infrastructure planning, traffic, waste, public health, disaster management, and security (Domingo et al., 2013).

Nevertheless, such applications require extensive data for a comprehensive and accurate analysis. Most urban applications-oriented decision-making models depend on the availability of public datasets for this. However, challenges arise in many cities due to the insufficient availability of data in the desired quality for analysis. Brandusescu et al. (2017) reported that public data published by the government is "typically incomplete, out of date, of low quality, and fragmented." While the push from national governments is gradually improving the availability of public data, as observed by the Open Data Census, the quality of these datasets is not known to the user (Lämmerhirt et al., 2017). Along with the sufficient availability of data, good quality is also critical for its effective usage in various applications. Poor-quality data leads to inaccurate analysis, interpretation, and subsequently reduced utility of data (Wang and Strong, 1996). Accordingly, it is crucial to define what constitutes good data and to quantify the quality of existing datasets. Moreover, how the current quality will influence the decision-making outcome needs to be investigated.

In addition, with the adoption of Sustainable Development Goals, cities have begun to identify the use cases of urban data to further enhance their sustainability. Accordingly, the Park and Garden departments have also begun recording, maintaining, and publishing digital tree registers, also referred to as tree inventories, typically including information on the number and geographical location of trees in cities. Moreover, some cities also record details on tree species type, genus name, common and scientific name, diameter or circumference, tree height, and date of plantation or age. These information act as a critical input for making Urban Green Space (UGS) management decisions. For instance, to ensure fairness of access to UGS, it should be uniformly provided to all city residents. Therefore, identifying new areas for planting trees could be based on the distribution of existing trees and parks as well as the population density data. Similarly, street tree inventories could be used to assess diversity within tree species, genera, and families to determine the resilience of the urban environment (Galle et al., 2021) and to estimate ecosystem service benefits provided by urban trees (Scholz et al., 2018).

While Shankaranarayanan and Zhu (2021) have found that data quality metadata improves decision performance, Møller et al. (2019) have highlighted the need for reliable field data for effective planning, management, and decision-making of UGS. Accordingly, the current study focuses on data quality issues of tree inventories and how they can be assessed. This serves as a basis for deriving the necessary attributes a high-quality dataset must possess and methods for quantifying it. Moreover, in cities where sufficient data is not available, it is necessary to improve the quality of data before utilizing it for further applications.

Therefore, the present study aims to address the research question: Can the quality of public datasets be methodically ascertained and enhanced for decision-making in UGS management?

The research scope includes (1) identifying a suitable framework for the data quality assessment of public datasets, (2) assessing the impact of missing data on decision-making, (3) analyzing the quality of existing data of various exemplary cities, (4) implementing a suitable method for enhancing data quality, and (5) investigating how enhanced datasets influence decision-making processes.

The research approach includes reviewing available quality assessment frameworks in literature. Next, examine its suitability for assessing the data quality and quantity of a tree inventory dataset, considering its subsequent use as an input in decision-making for UGS management. Accordingly, the proposed framework is based on the total data quality management approach and includes five key quality dimensions. The proposed framework is tested on data from ten German cities, and the dataset is categorized into four quality categories. Then the impact of the poor quality data, in terms of missing data is evaluated on UGS application. Then a random forest based regression model is used to fill the missing values and subsequently the impact of data quality is evaluated and compared with a baseline reference scenario.

This research achieves three main outcomes: first, the development of a quality assessment framework to evaluate the suitability of tree inventory datasets for decision-making in UGS management; second, the improvement of dataset quality using a combination of data-cleaning and data-filling techniques; and third, the demonstration of an approach to assess the impact of data quality and enhancement on UGS management applications.

The research paper is organized as follows: First, a literature review introduces and compares various frameworks available for determining the quality of public datasets and techniques for quality enhancement. Based on this, a framework is proposed in the context of UGS management applications in the methodology section. Subsequently, a model for enhancing data by filling missing values is presented. The results section discusses the quality of tree inventory datasets for ten German cities and the impact of missing data in the Berlin dataset on decision-making. The paper concludes with discussion and conclusions sections.

8.4 Literature review

The literature review comprises two parts: the first part describes the available frameworks for assessing the quality of existing public datasets, and the second part discusses the available methodologies for enhancing the quality of the datasets.

8.4.1 Data quality assessment

In the era of open data initiatives, a large number of public datasets have become accessible. However, many of these datasets often come with a common challenge: insufficient or poor-quality data (Brandusescu et al., 2017). Several researchers have highlighted the shortcomings related to data quality in urban datasets (Vetrò et al., 2016). Poor-quality data can seriously impact the utility of these datasets for models dependent on them for informed decision-making and city planning (Madnick et al., 2009; Vetrò et al., 2016). Observations by Ryu et al. (2006) and Haug et al. (2011) indicate that poor-quality data can significantly negatively affect organizational efficiency and performance. Moreover, the agencies publishing the data do not disclose sufficient information on the quality of the data being published. Therefore, it becomes critical to first evaluate the quality of the dataset before using it further.

Data quality assessment methods can be divided into two types: subjective assessment and objective assessment. Subjective assessment is based on expert knowledge and experience, while quantification of parameters is performed for an objective assessment (Nie et al., 2014). While several assessment methods have been proposed, depending on the characteristics of the dataset, a suitable assessment method needs to be selected for an accurate assessment of data quality. A variety of methods have been proposed depending on the type of data, such as numerical records, time series, remote sensing (Nie et al., 2014) and images (Wang et al., 2004). For instance, Tute et al. (2021) focused on a data quality assessment framework for healthcare data taking into account the requirements for a particular task and domain. Moreover, several studies have focused on data quality assessment (Zhu and Wu, 2010; Zheng et al., 2011; Heinrich and Klier, 2011; Närman et al., 2011; Zhu and Wu, 2011) and data quality for decision support. The present study focuses on determining a suitable framework to assess the data quality of the tree inventories dataset considering UGS management application.

8.4.1.1 Data quality definition

As summarized by Xiao et al. (2014), progress in data quality research began with identifying data quality issues and defining definitions and attributes of data quality. This was later followed by methodologies to assess and improve data quality. In practice, there is no single standard definition for data quality attributes and dimensions, as it is application-specific (Chen et al., 2014b). The assessment of data quality begins by defining the concept of data quality. Many existing approaches related to data quality have focused on the overall characteristics of the published data, such as availability on the web, machine-readable format, usage of open standards, free usage for users, and the use of non-proprietary formats. However, the scope of this study concentrates on the inherent quality of the dataset rather than on the quality of its provision. While data quality has been defined in various ways depending on perspectives, “fit for use in the context of data users" is a common principle (Chen et al., 2014a). Wang and Strong (1996) categorized data quality into intrinsic, contextual, representation, and accessibility. Since the dataset considered is a public tree inventory, consistency in representation of the data and its accessibility is inherent. Therefore, the scope of this study aims at ascertaining intrinsic quality that mainly refers to the accuracy within the dataset and contextual data quality that pertains to the dataset’s suitability for a particular application. It is important to emphasize that achieving perfect data isn’t necessary; instead, the focus should be on attaining optimum data quality that meets requirements within reasonable efforts and costs (Haug et al., 2011).

8.4.1.2 Methods for assessing data quality

The three key foundational frameworks considered for data quality assessment are: the Total Data Quality Management method (TDQM) (Wang et al., 1995), the Data Quality Assessment Framework (DQAF) (International Monetary Fund, 2003), and the Data Quality Maturity Model (DQMM) (Ryu et al., 2006).

The TDQM framework, developed by Wang et al. (1995), was designed to identify and address data quality challenges within organizations. Based on the iterative Plan, Do, Check, Act framework (Deming, 1986), this framework consists of Define, Measure, Analyze, and Improve steps. Definition outlines data quality dimensions and requirements; Measurement establishes metrics; Analysis identifies potential root causes of quality problems; and Improvement implements suggestions for enhancement (Wijnhoven et al., 2007).

The DQAF, developed by the International Monetary Fund (International Monetary Fund, 2003), is a structured approach supporting data quality requirements for financial statistics reporting. It includes prerequisite criteria followed by five quality dimensions: Assurances of integrity, methodological soundness, accuracy and reliability, serviceability, and accessibility. Constituent elements are identified for each dimension, followed by quantifying indicators for each respective element. Finally, focal issues and key points are tailored depending on the needs of different types of datasets. The framework primarily compares existing data and systems with international best practices, concentrating on developing improvement measures with a focus on goal-oriented evaluation of analysis results.

The DQMM, developed by Ryu et al. (2006), addresses data quality issues related to data structure. Primarily aimed at improving the level of data quality management in businesses, it consists of four steps: Initial, involving an initial dataset assessment; Defined, setting dimensions and uniform standards; Managed, implementing data quality measurement; and Optimization, improving identified errors and incorporating continuous monitoring (Kumar, 2006). Unlike the other two, the DQMM framework is less focused on pinpointing anomalies in specific dimensions; rather, it comprehensively examines the process by taking a broader view of the entire system and its processes. However, specific error sources may be overlooked due to the potentially extensive dataset.

Overall, the methods structurally resemble each other. Initially, dimensions are established, based on which analyses are conducted through specific methods. Subsequently, a solution for improving quality is implemented. However, the three approaches pursue distinct primary objectives related to data quality. Since the TDQM framework systematically examines quality attributes, establishes dimensions, and utilizes metrics to identify errors, it is most suitable for a thorough analysis of error detection within an individual dataset. Accordingly, TDQM framework principles were adopted for the present study.

Determining quality dimensions is the key step for implementing the TDQM framework. Wang and Strong (1996) determined a list of important data quality attributes based on a survey conducted among data consumers. The most commonly observed attributes include completeness, accuracy, and timeliness. Another approach by Wang emphasizes four main dimensions: availability, interpretability, relevance, and accuracy. In a review of 39 publications, it was observed that the most commonly used attributes were completeness, accuracy, and timeliness (Chen et al., 2014b). Similarly, Weiskopf and Weng (2013) conducted a systematic review of literature to determine the quality of electronic health records and identified completeness, correctness, concordance, plausibility, and currency as the five key dimensions. (Vetrò et al., 2016) proposed a quality framework based on metrics such as Completeness, Accuracy, Traceability, Currentness, Expiration, Compliance, and Understandability. Batini and Scannapieco (2016) also observed that the number of data quality dimensions varies significantly across different frameworks and depending on the data type and application.

Additionally, several frameworks have been proposed that describe various attributes covering different dimensions of data quality (Chen et al., 2014a). Vaziri et al. (2016) also proposed a task-based data quality method for improving the operations in organizations.

8.4.2 Data quality enhancement

Several researchers have attempted various methods like sampling techniques, data cleaning, data mining, and quality controls to enhance data quality through a structured and systematic approach (Farrell and Abreu, 2012; Feng et al., 2018; Ünal, 2020; Shankaranarayanan and Zhu, 2021). Traditional statistical methods have been used for data imputation, but they are often deemed inefficient, particularly for small temporal and spatial scales. Consequently, more advanced techniques, including machine learning (ML), have been employed to improve data quality.

ML techniques can recognize patterns and relationships within available data, using supervised, unsupervised, and semi-supervised learning approaches. These patterns can predict and fill in missing values, ultimately enhancing the completeness and quality of urban datasets, crucial for informed decision-making. Consequently, numerous ML-based approaches have been proposed for data filling in urban datasets. Specifically, K-nearest neighbors (KNN), Artificial Neural Networks (ANN), Support Vector Machines (SVM), Decision Trees (DT), Naive Bayes (NB), Random Forests (RF), and Reinforcement Learning (RL) have shown promising performance in modeling nonlinear problems (Dong et al., 2014; Zhang et al., 2018). Each ML method presents a trade-off between simplicity, interpretability, and predictive power. In the subsequent subsection, we compare different available approaches with the aim of identifying the most suitable ML-based method for filling missing values in UGS datasets.

8.4.3 Comparison of ML-based methods for data filling

Recent studies have highlighted the potential of machine learning methods in improving the quality of urban datasets. Haldorai et al. (2019) and Du et al. (2020) both emphasize the role of machine learning in enhancing urban planning processes and spatial data handling, respectively. Recent research has proposed several innovative methods for filling missing data in datasets. For instance, Bischof et al. (2017) proposed an Open City Data pipeline to automatically integrate data from multiple sources, enrich the data, and provide access to users through a web-based interface. They also implemented various regression-based techniques such as KNN, MLR, and RF to predict missing values with different distributions and measured the accuracy using the normalized root mean squared error method. Huang (2021) also suggested a two-step approach, using linear interpolation for short-term missing data and LightGBM for long-term missing data. Sharifyanov and Latypova (2023) introduced a modified method based on the KNN method and filled up to 25% missing data in biological datasets. Mostafa (2019) presented an imputation algorithm, cumulative linear regression, which incorporates imputed variables into the linear regression equation. Dubey and Rasool (2019) provided an overview of current imputation methods, emphasizing the use of local or global correlation within the dataset. In summary, these studies have demonstrated promising solutions for handling missing data in datasets.

Each of these methods has its individual strengths and weaknesses, and the applicability of each will depend on the type of data, objectives, and computational resources available. KNN offers simplicity, requiring no model training and serving both regression and classification tasks. However, its sensitivity to the choice of distance metric and computational intensity on large datasets are significant limitations (Zhang, 2016). ANNs can capture spatial patterns without the need for extensive data preprocessing and have demonstrated impressive predictive accuracy. While ANNs excel in modeling complex relationships, particularly in tasks involving image and text data, their susceptibility to overfitting, resource-intensive nature, and lack of interpretability are common drawbacks (Ray, 2019). SVM is effective in capturing linear and nonlinear relationships, accommodating high-dimensional data, and resisting overfitting (Zhang, 2012). Nevertheless, parameter tuning is a challenge, and its performance may degrade on exceptionally large datasets. DT provides a simple and interpretable approach for handling both numerical and categorical data. However, their susceptibility to overfitting and the potential creation of complex trees can limit their effectiveness in certain scenarios (Song and Lu, 2015). NB is acknowledged for its simplicity and quick training and prediction, proving effective in text classification tasks (Yang, 2018). However, its reliance on the assumption of feature independence may not hold in real-world data. RF, renowned for its robustness and resistance to overfitting, performs well in regression and classification tasks but may face challenges with datasets containing a high number of features (Wang et al., 2018). RL, effective for sequential decision-making tasks, is complex and resource-intensive, making it less suitable for straightforward data filling tasks (Li, 2018).

In summary, the selection of the most suitable ML-based method for imputing missing urban data hinges on the specific dataset's characteristics, the nature of the missing data, and available computational resources. Each method represents a trade-off between simplicity, interpretability, and predictive power. Depending on the characteristics of these methods, Table 8.1 summarizes their suitability for various applications in UGS decision-making.

8.5 Methodology

The initial process in working with any public dataset is to evaluate its existing features and verify that both a sufficient quantity and good quality of data are available to obtain accurate output from the applied model. As described in the preceding section, several researchers have proposed quality assessment frameworks for different kinds of datasets.

Table 8.1: Suitability of various ML-based approaches for decision-making in UGS management.

Method	Resource constraint	Feedback	Handling Missing Data	Filling Missing Data
DT	Low	No	High	Yes
RF	Low	No	High	Yes
SVM	Low	No	Medium	No
ANN	Medium	Yes	Medium	Yes
NB	Low	No	High	No
KNN	Low	No	Medium	Yes
RL	High	Yes	Medium	No

Accordingly, considering the requirements of tree inventory datasets, a quality assessment framework is presented in this section.

The methodology aims to analyze how the quality of public tree inventory datasets could affect the applied models for decision-making in UGS management. The four-step approach of this study is outlined in Figure 8.1. In the first step, *data evaluation*, assessment is done using a framework comprising five key dimensions: Completeness, Uniqueness, Accuracy, Timeliness, and Reliability. In the second step, *data classification*, the reviewed dataset is categorized according to the performance on assessed quality criteria using standard statistical tests. In the third step, depending on the requirement, the dataset is *pre-processed* using available cleaning or filling techniques to enhance data quality. Finally, *model evaluation* is conducted by using the original dataset and the enhanced dataset in an applied model and comparing the model's performance with the baseline scenario.

8.5.1 Data evaluation

As discussed in the preceding section, there is no fixed definition of attributes by which data quality can be measured. Data quality depends on relevant dimensions, and its measurement is relative. A comprehensive understanding of data quality necessitates defining various characteristics that can quantify it. Therefore, for this study, seven key essential dimensions—Accessibility, Granularity, Completeness, Uniqueness, Accuracy, Timeliness, and Reliability—are identified, drawing inspiration from previous works such as Girres and Touya (2010), Jayawardene et al. (2015), Batini and Scannapieco (2016), and Picard et al. (2020).

Since the study is aimed only at public datasets, accessibility is an implied condition. Accordingly, data must be available as open-access and free for all users. Moreover, as the scope particularly focuses on tree inventories in the context of UGS management, granularity is fixed at a unit tree level. Therefore, the proposed framework covers the remaining five key quality dimensions, including Completeness and Uniqueness specifically for data quantity evaluation, whereas Accuracy, Timeliness, and Reliability cover data quality needs. As observed, both data quantity and quality are assessed in this.

Completeness ensures that the data are complete, meaning no relevant data is missing for the given use case. This requirement is categorized into three levels: mandatory attributes requiring a value, optional attributes that may have a value, and inapplicable

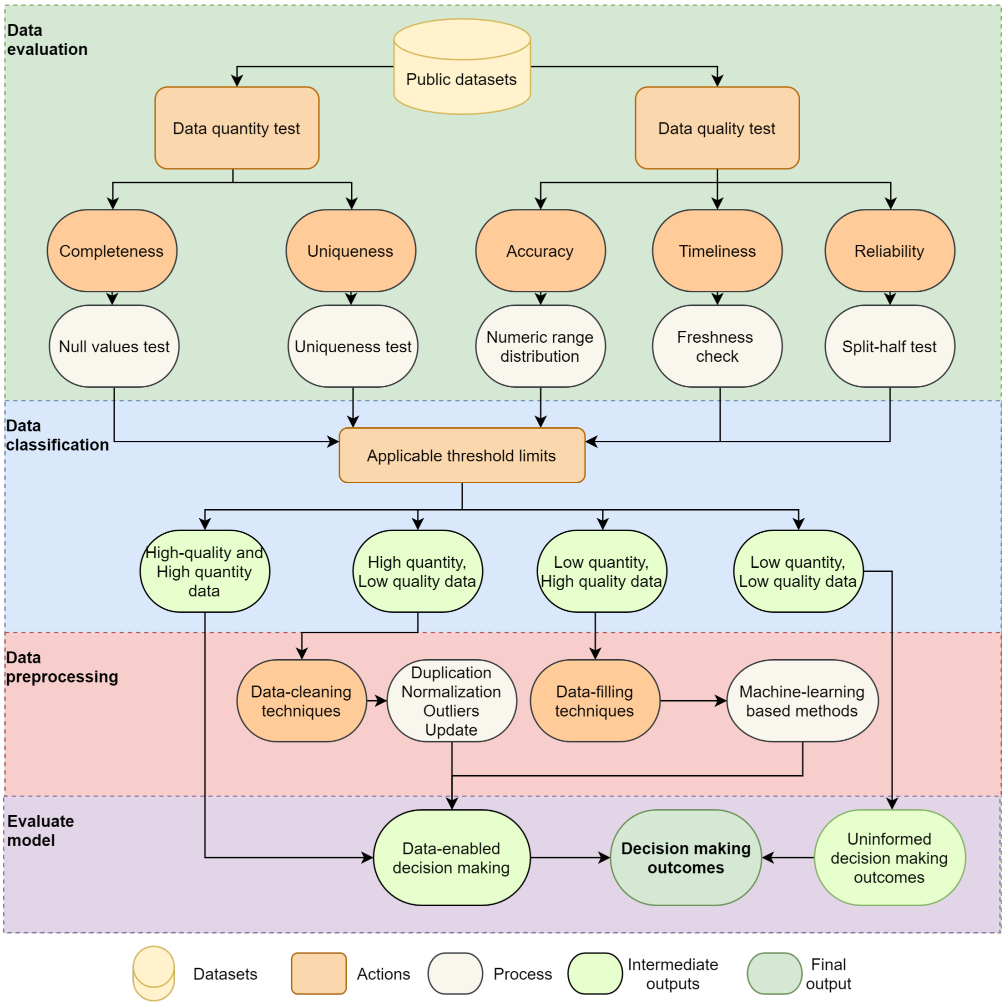


FIGURE 8.1: Proposed quality assessment framework for UGS datasets.

attributes that may not have a value. It is important to emphasize that if the necessary data required for a particular application is present while having missing data for other features, a complete dataset can be assumed. Moreover, completeness only focuses on the missing values within the dataset, and any missing records due to a lack of coverage are not included here. For example, if a city has ten thousand trees and nine thousand trees are recorded in the dataset, the missing thousand trees are currently not part of the scope of the work. So, missing mandatory attributes will be quantified from the recorded nine thousand trees.

Second, Uniqueness aims to ensure that the dataset is unique, with no duplicate entries or repetitions, maintaining data clarity and avoiding redundancies. This is done to avoid erroneous records made for the same tree multiple times. Third, Accuracy involves identifying errors when compared to a reference dataset of a similar nature or reality. Types of errors include geometric, attribute, and semantic errors. This includes examining whether the data is correctly written and categorized. Fourth, Timeliness focuses on ensuring datasets are up-to-date, and information is available in a timely manner, considering the frequency of updates. Fifth, the Reliability attribute refers to the extent to which the correctness of information is verifiable or provable in the context of a particular activity.

Additional quality attributes that could have been considered for this selection include consistency, validity, interpretability, objectivity, and availability. However, the most relevant dimensions are selected based on the applications of UGS management. Assessing data quality involves considering the suitability of available data for a specific purpose, determining whether the intended outcome can be achieved with them. Merely stating that data form a good basis for any application is insufficient for the objective evaluation and comparison of datasets. Therefore, in the next step, these selected dimensions need to be quantified.

Standard metrics and measurement methods referred to in the literature are used to quantitatively assess the attributes. For Completeness, a null values test is incorporated to check the number of missing values of any parameter. The approach to ensuring Completeness involves a null-values test, although the coverage aspect remains unaddressed. For Uniqueness, this can be checked using a uniqueness test that verifies unique data values. For Accuracy, a numerical range distribution test can be done to identify significant outliers within the data and find discrepancies in the dataset. For Timeliness, using a freshness test, the age of the most recently added records in the data is checked. For Reliability, a split-half test can be done to check the reliability of data by splitting the dataset into two randomly created sub-parts and then evaluating them separately for an identical objective. The similarity of the output could confirm the reliability of the dataset. The accuracy of the dataset represents the measure of coherence between the data and the actual values.

8.5.2 Data classification

The current status of the dataset quality could be ascertained by its performance on various quality characteristics in comparison to the applicable thresholds. However, the threshold limits are dependent on the application, and defining that could be a complex task. Once the thresholds are set, they are used to classify the datasets into high-quality and high-quantity, high-quality and low-quantity, low-quality and high-quantity, and low-quality and low-quantity categories.

8.5.3 Data preprocessing

Subsequently, depending on the classification made in the preceding section, the required preprocessing is executed. If the dataset is of high quality and high quantity, it does not need any additional preprocessing and therefore can be directly used for the applied decision-making model. If the dataset has a high quantity of data but low quality, it needs some data cleaning techniques to filter and eliminate erroneous records. This includes various techniques like removal of duplication, filtering out outliers, normalization of data, and updating the recorded data with new field collection. Upon removal of the low-quality records from the dataset, the overall quality of the dataset will improve, making it suitable for the application. In case the dataset has a low quantity of data but the available data is of high quality, it needs data filling techniques. This is required to fill the missing values so that the quantity of the available data could be increased. In certain cases, both data-cleaning and data-filling techniques might be required in a phased manner. Finally, the dataset with low quantity and low-quality data is not considered suitable for further applications in decision-making models as it might lead to incorrect analysis and outcomes. Therefore, such situations would require conventional decision-making approaches involving experienced subject experts or field observations.

8.5.4 Data filling

In the case of high-quality data but low-quantity data, certain features may lack sufficient data for subsequent usage in an application model. To enhance the usability of the dataset, the missing values need to be filled using available data. Three approaches have been selected to fill the missing values in the tree inventory dataset: Simple Linear Regression (SLR), Multiple Linear Regression (MLR), and Random Forest (RF). The SLR and MLR are conventional regression techniques used to model the linear relationship between two variables, while RF is a non-parametric ML approach that requires fewer assumptions regarding the distribution of data. All three methods follow quite similar processing steps: cleaning and normalizing data, implementing regression models, splitting train-test data, training models, evaluating models, filling missing values on test data, assessing performance, adjusting parameters, and filling missing values on actual data. In the case of RF, data normalization is not required as it is not sensitive to the scale of the features.

Notation	**Description**
H_i	Tree height of the i-th observation
C_i	Trunk circumference of the i-th observation
A_i	Tree age of the i-th observation
D_i	Crown diameter of the i-th observation
S_i	Species type of the i-th observation
β_0	Intercept term
ε_i	Error term for the i-th observation

TABLE 8.2: Scientific notations used in the model

For modeling, first, relevant features from the dataset, denoted as X, are identified. From the available dataset, this mainly includes trunk circumference (C), tree age (A), crown diameter (D), and species type (S). Then, the rows with missing values in features other than the tree height variable are filtered. Next, to incorporate the categorical features like tree species type, they need to be encoded. Therefore, label and frequency encoding methods have been used to convert the categorical data into numerical. Then, depending on the regression model type, features are selected to predict tree height (H). Finally, to train the model, the dataset is split into training and testing sets ($X_{\text{train}}, X_{\text{test}}, H_{\text{train}}, H_{\text{test}}$). For this study, a 0.2 split was used to divide the available data into an 80-20 ratio of train and test data, which is consistent with the standard practice.

1. **Simple Linear Regression**

   In this case, a simple linear regression based model is used to predict the missing H values using C as a predictor variable. This model considers a linear relationship between C and H. Accordingly, the model is described in Equation 8.1.

$$H_i = \beta_0 + \beta_1 C_i + \varepsilon_i \tag{8.1}$$

where H_i represents the tree height of the i-th observation, C_i denotes the trunk circumference of the i-th observation, β_0 is the intercept term, β_1 is the coefficient associated with trunk circumference, and ε_i represents the error term for the i-th observation.

2. **Multiple Linear Regression**

   In this case, a multiple linear regression based model is used to predict the missing H values using A, C, and D as predictor variables. This model considers a linear relationship between independent variables A, C, and D with the dependent variable H. Accordingly, the model is described in Equation 8.2.

$$H_i = \beta_0 + \beta_1 X_{1i} + \beta_2 X_{2i} + \beta_3 X_{3i} + \varepsilon_i \tag{8.2}$$

   where H_i represents the tree height of the i-th observation, X_{1i}, X_{2i}, and X_{3i} denote the normalized tree age, trunk circumference, and crown diameter of the i-th observation, respectively. β_0 is the intercept term, and β_1, β_2, and β_3 are the coefficients associated with tree age, trunk circumference, and crown diameter, respectively. ε_i represents the error term for the i-th observation.

3. **Random Forest Regression**

   In this case, an RF-based regression model is used to predict the missing H values using A, C, and S as predictor variables. Therefore, the model considers the combined effect of all three independent variables A, C, and S in predicting the dependent variable H. Accordingly, the function $f(\cdot)$ described in Equation 8.3 represents the RF model.

$$H_i = f(C_i, A_i, S_i) + \varepsilon_i \tag{8.3}$$

   where H_i represents the tree height of the i-th observation, C_i, A_i, and S_i denote the trunk circumference, tree age, and species type of the i-th observation, respectively. ε_i represents the error term for the i-th observation.

After training the respective models, the trained model is then used to predict missing tree height values in X_{missing}. The performance of the filled values on the test dataset is evaluated by comparing them to the actual tree heights, using metrics like Root Mean Squared Error (RMSE) (Equation 8.4), Mean Absolute Error (MAE) (Equation 8.5), and R-squared (R^2) (Equation 8.6). Moreover, visualizations are used for assessing the accuracy and range distribution. Finally, the trained model is used to update the missing values in the original dataset.

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(H_i - \hat{H}_i)^2}{n}} \tag{8.4}$$

$$MAE = \frac{\sum_{i=1}^{n}|H_i - \hat{H}_i|}{n} \tag{8.5}$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(H_i - \hat{H}_i)^2}{\sum_{i=1}^{n}(H_i - \bar{H})^2} \tag{8.6}$$

8.5.5 Evaluate model

Once the data quality has been enhanced, as described earlier, it can be used for various management application models developed by the community of users, researchers, and organizations. To evaluate the impact of data quality on decision-making, two application models have been selected. Since for any effective decision-making, the essential criteria are the cost and benefits involved with the management decision, one model is selected to quantify the associated costs with managing street trees, while another model quantifies the associated benefits obtainable from the street trees. The first model is a linear time-series-based water demand estimation model that can be used to determine the irrigation requirements of street trees (Rambhia et al., 2023). The second model estimates the carbon sequestration potential of street trees using tree characteristics (Shadman et al., 2022). As described in Figure 8.1, evaluation is first done using the raw data with the missing values to quantify the associated costs and benefits, and then the process is repeated with the enhanced dataset. The variance in the outcome is then reported as the impact of data quality on decision-making.

8.5.6 Data and other inputs

The methodology for assessing data quality is demonstrated using tree inventories from ten cities in Germany. The selection of these cities was based on the number of trees, with a threshold set at 15,000 trees, and the availability of the tree inventories in the public domain. Accordingly, this included datasets from Berlin (2024); Bonn (2020); Chemnitz (2023); Cologne (2020); Constance (2022); Frankfurt (2023); Hamburg (2023); Karlsruhe (2021); Leipzig (2023); Rostock (2024). Most of these tree inventory datasets included tree characteristics such as the geographical location, year of plantation or age, crown size, tree height, trunk diameter or circumference, and species information, encompassing both common and scientific names of species and their genus. Moreover, additional datasets for water demand estimation models are detailed in Rambhia et al. (2023). This mainly includes the tree-species wise water demand classification from the WUCOLS dataset (UC Davis, 2021) and meteorological data from the German Weather Service (Deutscher Wetterdienst, 2021), consisting of Evapotranspiration, as well as past and future precipitation data.

8.6 Results

The proposed quality assessment framework is applied to selected tree inventory datasets. This includes quantification of the quality dimensions for each dataset and subsequently classifying the dataset. Then, a sensitivity analysis is performed to determine the impact of missing data on the selected application or objective. Finally, depending on the dataset classification, a data-cleaning or data-filling approach is implemented to enhance the dataset quality. After filling the missing parameters, the dataset is then utilized for the management application. The three-step process is outlined in Figure 8.2.

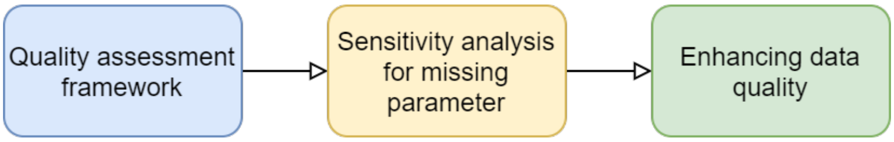


FIGURE 8.2: Outline of the process for the application case

8.6.1 Quality assessment

Table 8.3 summarizes the status of existing tree inventory datasets for ten cities in Germany. The dataset publication years range from 2020 to 2024. Moreover, there is a wide range in the number of trees in each city, ranging from around sixteen thousand trees in Constance to over eight hundred thousand trees in Berlin. This difference is mainly due to three factors: the size of the city (55 km^2 for Constance to 892 km^2 for Berlin), tree density, and whether only street trees are recorded or all the trees within the city boundary. For instance, the City of Berlin includes both street trees (Straßenbäume) and trees planted in public green spaces (Anlagenbäume). All of the datasets, except for Cologne, have complete records for location and species type information. This is likely due to digitizing the tree register being of the highest priority and being less labor-intensive compared to measuring other parameters. The other features are either completely or partially missing in most datasets, except for Frankfurt, which has less than 1% missing values in the entire dataset. It is noteworthy that the figures for missing values were observed to increase by up to 3.5% (median = 0.9) when outliers (3 * IQR) were further removed from the datasets.

TABLE 8.3: Observed missing/unreported values in the published datasets. All values except Year and Records are in percent (%). ✓and × represent that data is fully complete and absent, respectively.

No	City	Year	Records	Location	Species	Age	Height	Diameter	Crown
1	Berlin	2024	8,39,693	✓	0.12	17.37	18.51	0.88	41.29
2	Bonn	2020	65,669	✓	0.13	0.2	×	×	×
3	Chemnitz	2023	47,584	✓	0.02	9.33	×	×	×
4	Cologne	2020	1,53,094	✓	28.48	86.26	31.75	32.96	31.9
5	Constance	2022	15,936	✓	0.03	×	0.22	0.24	0.27
6	Frankfurt	2023	1,61,819	✓	✓	✓	0.03	0.92	0.01
7	Hamburg	2023	2,28,628	✓	0.68	2.64	×	0.71	0.78
8	Karlsruhe	2021	87,413	✓	✓	×	×	×	×
9	Leipzig	2023	60,623	✓	✓	✓	×	×	×
10	Rostock	2024	70,680	✓	✓	×	2.85	3.09	2.98

Subsequently, using the quality assessment framework, the existing quality and quantity of the tree inventory datasets are quantified. Table 8.4 presents a summary of the performance of the Berlin tree inventory dataset on the selected quality dimensions. The thresholds need to be set according to the needs of the application. In this case, since the irrigation water demand estimation model requires species type as a mandatory input, the parameter is included as the threshold requirement. Therefore, when assessed for water demand application, the Berlin dataset is classified as high-quality and high-quantity dataset as the missing data is about 0.12%. However, if the same dataset is considered for carbon sequestration estimation, then along with species type information, the diameter, height, and age of the tree are also essential to quantify the significance of a tree in providing ecosystem service benefits to the city. Therefore, concerning the application of carbon sequestration estimation, the dataset will be classified as high-quality but low-quantity. Consequently, it will need additional preprocessing, like filling missing data before it could be directly used for that management application.

TABLE 8.4: Quality assessment for the Berlin tree inventory dataset.

Dimension	Performance	Assessment
Accessibility	Public	High
Granularity	Unit level	High
Completeness	Species type (0.12%), age (17.37%),	Water demand - High
	diameter (0.88%)	Carbon sequestration - Low
Uniqueness	No duplication	High
Accuracy	Outlier <0.5%	High
Timeliness	2023	High
Reliability	Split-half correlated	High

Similarly, all ten datasets have been evaluated concerning the application of carbon sequestration estimation. The results are presented on the Data Quality vs Data Quantity chart in Figure 8.3. As can be observed, three cities (Frankfurt, Constance, and Rostock) have high-quality and high-quantity datasets, one city (Hamburg) has low-quality and high-quantity datasets, five cities (Berlin, Chemnitz, Bonn, Karlsruhe, and Leipzig) have high-quality and low-quantity datasets, whereas one city (Cologne) has a low-quality and low-quantity dataset. Accordingly, the datasets need to be handled for further application.

8.6.2 Impact of missing values

In order to demonstrate how various missing values affect the subsequent decision-making process, an analysis is conducted for Berlin city. For this, a decision-making model proposed by Rambhia et al. (2023), which estimates the irrigation water demand for street trees using a public tree inventories dataset, is used as an application model. One of the key inputs for determining the irrigation demand for any tree is the species type. Depending on the water demand of a particular species type, it could be classified into very low, low, medium, and high water requirement plant species (UC Davis, 2021). Therefore, the impact of missing species type information on irrigation water demand estimation is assessed.

To perform this analysis, the irrigation demand model is first run with tree species information available for all the trees (case-1). This provides the baseline scenario of the estimation without any missing data. In practice, when data is not available, a common approach is to consider the tree as a species of the most dominating tree species in the city. This is done based on the probability that the tree belongs to the dominant species type considering geographic, climatic, and planting conditions. Another option is to consider it as the most water-demanding tree species wherever the data is not available. This precaution ensures that no tree receives less water than its actual demand. Both of

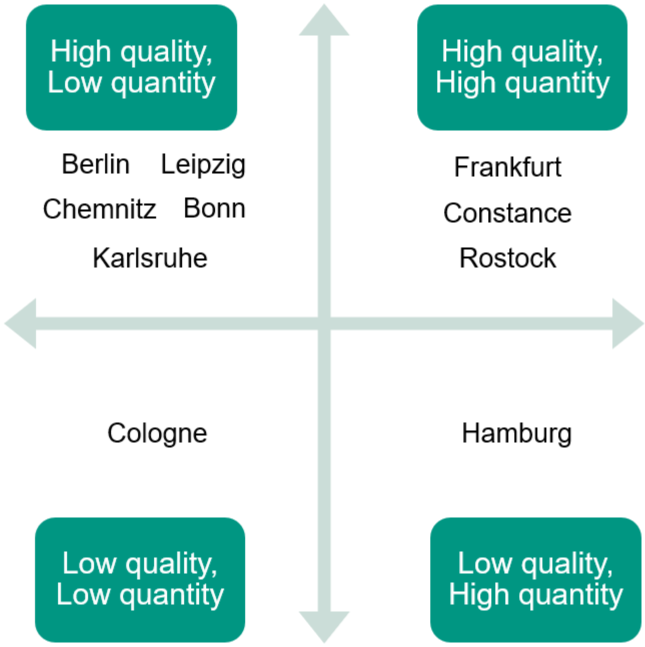


FIGURE 8.3: Assessment of data quality and quantity performance across ten German cities.

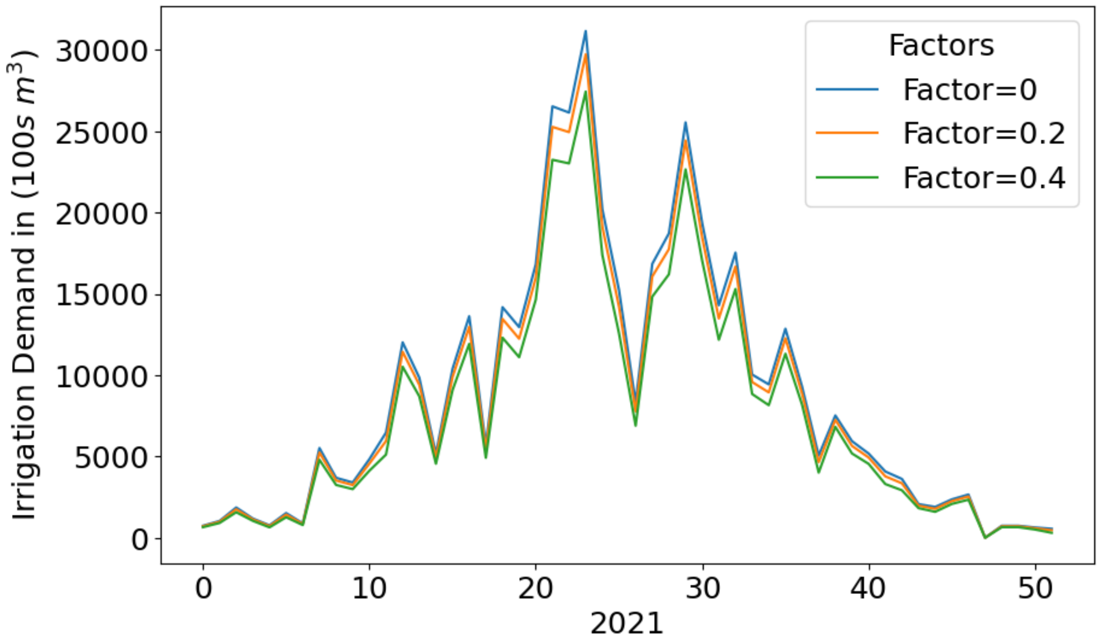
these scenarios are considered accordingly. In the next step, a randomized selection of trees from the entire Berlin dataset is performed, omitting the tree species data for 20% and 40% of the total trees for case 2 and case 3, respectively.

Figure 8.4b illustrates the observed impact of missing tree species values on irrigation demand estimation when replaced with dominant species, while Figure 8.4a depicts the observed impact when replaced with expensive species. The proportion of missing data is represented using factor values, where 0 and 1 represent 0 to 100% missing values, respectively. It was observed that in cases where the missing data is filled with the dominant species, annual water demand increases by 2% to 4%, and when the missing data is filled with the most expensive species type, annual water demand was found to be 16% to 42% higher. While the impact is relatively less when the data is filled with the dominant species type, it puts some of the tree units at risk of receiving lower irrigation water than needed.

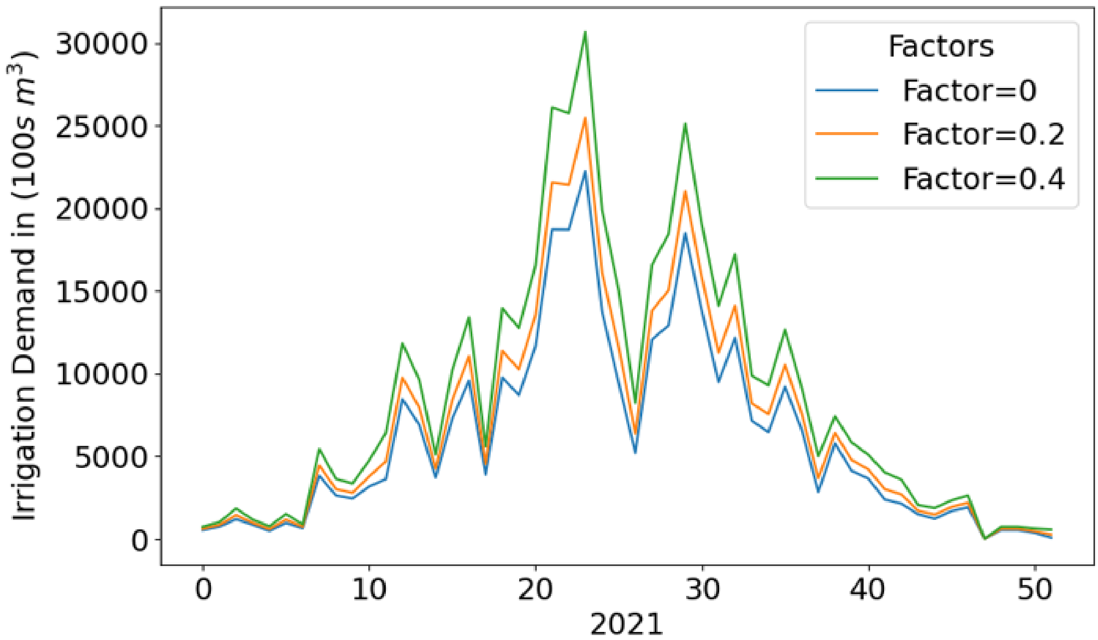
8.6.3 Data enhancement

For the carbon sequestration potential estimation benefit model, the Berlin tree inventory dataset is classified as a low-quantity, high-quality dataset. Therefore, data filling technique needs to be implemented to make it suitable before using it for this application model. The parameters essential for quantifying the carbon sequestration include tree diameter and tree height. Since the tree diameter has fewer than 1% missing values, tree height is the feature that particularly needs enhancement. Consequently, the aforementioned three approaches have been used to fill the missing tree height values.

In the case of MLR, Figure 8.5 presents the proportional effect with confidence intervals of normalized tree age, circumference, and crown diameter values on tree height. The



(a)



(b)

Figure 8.4: Impact of missing tree species values on irrigation demand estimation replaced with (a) Dominant species (b) Expensive species.

Table 8.5: Comparative analysis of regression models on performance metrics.

Performance Metric	SLR	MLR	RF
RMSE	4.04	3.73	2.92
MAE	3.05	2.84	2.02
R^2	0.51	0.57	0.73

statistics are also numerically presented in Table 8.6. The coefficients obtained from the MLR denote the change in tree height for a one standard deviation increase in each respective independent variable, keeping other variables constant. For instance, the coefficient for normalized tree age indicates the change in tree height for a one standard deviation increase in tree age, while keeping the trunk circumference and crown diameter constant. The confidence intervals represent the range of values within which the true population parameters are likely to lie with a 95% level of confidence. Since all the coefficients are greater than zero, they represent a positive correlation of all three parameters with tree height. Accordingly, the relative importance and directionality of the relationship between different features can be observed.

Figure 8.6a presents the box-plot distribution of actual vs. predicted tree height values against trunk circumference for the case of RF. The variability in the predicted tree height values is lower in trees with smaller trunk size than in those with larger trunk size. This could likely be attributed to the higher number of trees with smaller trunk size available in the dataset for training the model compared to those with larger trunk size. Moreover, Figure 8.6b presents the histogram of tree height values in the original dataset compared to the enhanced dataset, which includes the filled missing values. As expected, the frequency distribution of tree height follows a normal distribution, with the majority of trees lying between 5 to 15 meters in height. Consequently, the number of missing values was highest in this range, which required data filling.

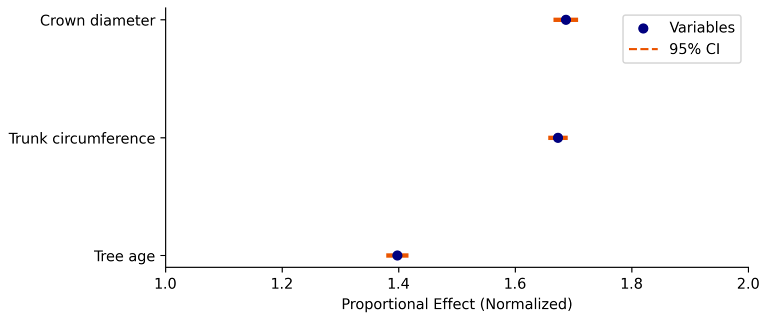


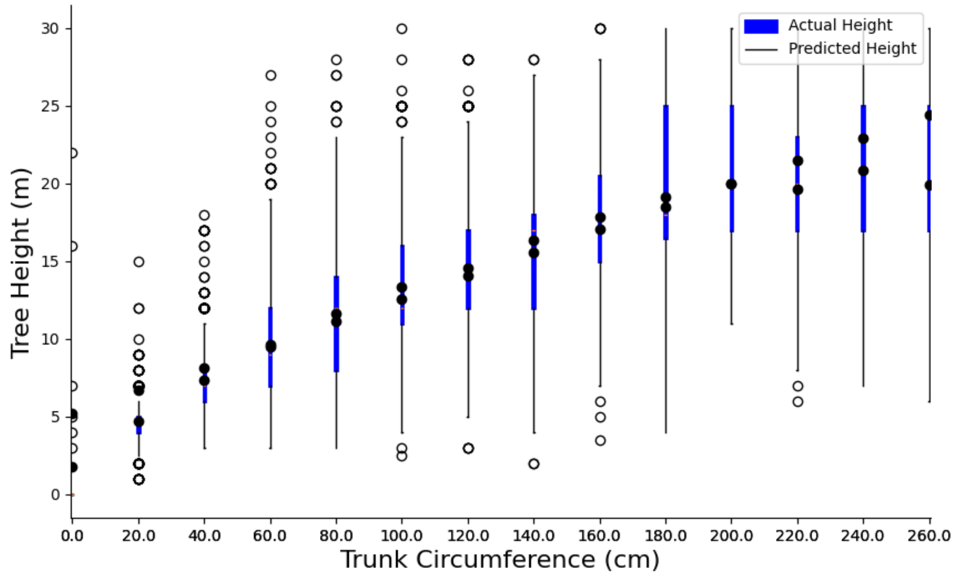
Figure 8.5: Proportional effects of normalized Tree age, Trunk circumference, and Crown diameter on Tree height in MLR.

Table 8.6: Regression coefficients and confidence intervals for normalized features.

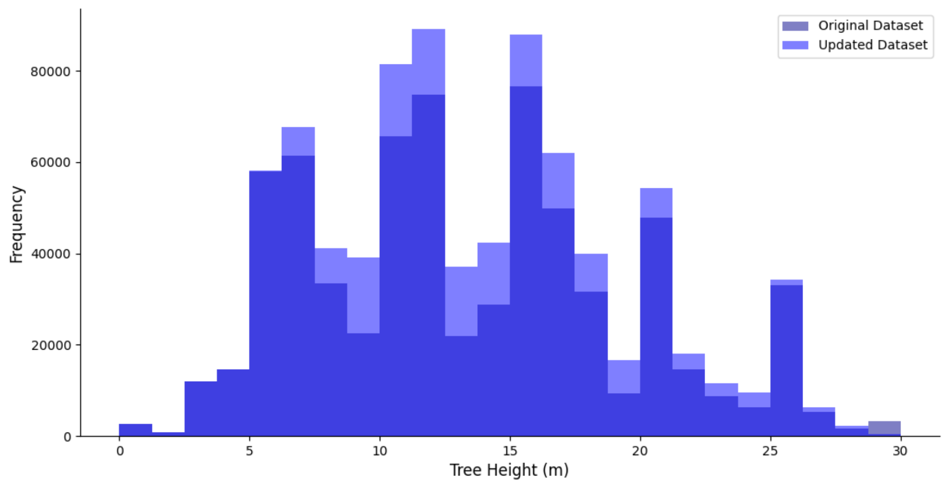
Normalized Feature	Coefficient	Lower CI	Upper CI	Unit
Tree Age	1.3977	1.3787	1.4166	Years
Trunk Circumference	1.6734	1.6567	1.6901	Centimeters
Crown Diameter	1.6868	1.6656	1.708	Meters

8.7 Discussion

The presented quality assessment framework offers a systematic approach for evaluating public tree inventory datasets, emphasizing their relevance to UGS management



(A)



(B)

FIGURE 8.6: (a) Actual vs. Predicted height and (b) Distribution of tree height in Original vs. Updated dataset with RF regression.

decision-making. The methodology covers data evaluation, classification, preprocessing, enhancement, and model evaluation. In the case of data quality assessment, key quality dimensions including Completeness, Uniqueness, Accuracy, Timeliness, and Reliability are assessed to determine the dataset quality. It was observed that currently, the majority of cities have a low quantity but high-quality dataset category. This is because most cities in Germany have achieved a significant level of success in collecting and publishing high-quality datasets with relatively fewer erroneous records. However, many cities still lack critical tree features such as tree height and trunk circumference, which could be crucial for effective UGS management. While manual measurement of these features could be quite expensive, especially for smaller towns with limited budgets and personnel, advanced technologies such as aerial imagery and lidar could help significantly reduce the cost and time of collection. Moreover, through the evaluation of an irrigation water demand estimation model, the practical impact of missing tree inventory data on decision-making outcomes was demonstrated.

As observed through performance metrics, the RF model outperforms both SLR and MLR in predicting missing tree height values. This could likely be attributed to the correlation between predictor variables, such as the size of the tree trunk and crown, where multicollinearity has a lesser impact on the training of the random forest model. In all three cases, out of the total 152,949 missing values, 149,346 were filled. 3,603 tree height rows remain unfilled as they were filtered out due to outliers (higher than 1.5 times the interquartile range) observed in one of the predictor variables. While this improves the quality of the model prediction, it could also lead to the removal of some true values from the dataset and cause the underestimation of the prediction of some trees. However, the number of such trees is quite low, as observed in the frequency distribution.

The RF model, which was the best-performing among the selected three, demonstrated an R-squared value of 0.73. This indicates that the standard deviation of the errors is around 50% of the standard deviation of the target variable, in this case, tree height (Nau, 2020). While there is no specific threshold above which the model is considered good, a value closer to one is generally deemed better. Moreover, currently, only the data from the same city have been used to train the model for filling the missing values. However, a dataset consisting of data from multiple cities with similar climatic conditions could also be explored further.

The study's application to tree inventories from ten cities in Germany underscores the framework's practical relevance and the need for tailored quality assessment criteria. Despite the comprehensive approach, challenges persist, including the evolving nature of open data sources and the need for advanced data filling techniques. In conclusion, the proposed framework contributes to advancing UGS management for cities with limited data by addressing challenges associated with dataset quality, heterogeneity, and application-specific requirements. The insights gained from this study lay the groundwork for further research and the development of practical tools for decision-makers to effectively manage UGS.

8.8 Conclusion and future research

Sufficient quantity and quality of data are essential for making accurate analyses. Therefore, this study implements a novel quality assessment framework based on total data quality management principles on tree inventory datasets to ascertain its suitability for UGS management applications. Moreover, it applies regression techniques to enhance the dataset by filling in missing tree height values. Currently, tree characteristics such as tree circumference, tree age, crown size, and species type have been included. However, these parameters could be extended by adding additional feature parameters such as climatic conditions, tree decomposition, shading from buildings, or planting distance. Three methods, SLR, MLR, and RF, were tested, with RF outperforming the other two methods in filling the missing tree height values. However, depending on the application and feature requirements, other ML-based methods such as DT or GB also seem to have high potential for filling the missing data and enhancing the dataset quality.

The study contributes in three distinct ways. First, a quality assessment framework has been developed, especially focused on ascertaining the quality of public tree inventory datasets. The framework was applied to ten cities, and their results were compared. Second, it implements two statistical and one ML-based approach to enhance the data quality by filling missing values. Third, it uniquely evaluates the impact of data quality on decision-making models in UGS by using one cost (water demand) estimation and another benefit (carbon sequestration potential) estimation model, which was lacking in the existing literature. The study demonstrates the significance of high-quality data to subsequently use it for various application models.

While three regression methods were tested, with one ML-based approach, to demonstrate the data quality enhancement, additional methods could be explored further for data filling. Moreover, only public tree inventories were considered, and no private trees were included in the scope. Furthermore, for the evaluation of data quality, a demand estimation and a benefit estimation model were considered. It is to be emphasized that the evaluation strongly depends on the chosen areas of application.

The developed framework is a novel approach for ascertaining and enhancing the quality of the existing tree inventory dataset. Depending on the needs of the city, decision-makers can evaluate their datasets and accordingly prioritize the collection or digitalization of missing/additional tree records. For instance, a city interested in applying the resource allocation model in their city will likely require the tree diameter along with tree location and species type for its accurate analysis. The framework is adaptable to include additional quality dimensions and custom thresholds based on the dataset requirements.

Bibliography

Bartley, K. (2020). Big data statistics: How much data is there in the world?

Batini, C. and Scannapieco, M. (2016). *Data and Information Quality*. Springer International.

Berlin, O. D. (2024). Baumbestand berlin - [wms] | offene daten berlin.

Bischof, S., Kämpgen, B., Harth, A., Polleres, A., and Schneider, P. (2017). Open city data pipeline. *Vienna University of Economics and Business*.

Bonn, O. D. (2020). Baumkataster bonn.

Brandusescu, A., Iglesias, C., and Robinson, K. (2017). Open data barometer - 4th edition.

Chemnitz, S. (2023). Baumkataster chemnitz.

Chen, H., Hailey, D., Ning, W., and Yu, P. (2014a). A review of data quality assessment methods for public health information systems. *International Journal of Environmental Research and Public Health*, 11:5170–5207.

Chen, H., Hailey, D., Wang, N., and Yu, P. (2014b). A review of data quality assessment methods for public health information systems. *International Journal of Environmental Research and Public Health*, 11(5):5170–5207.

Cologne, O. D. (2020). Baumkataster koeln.

Constance, O. D. (2022). Baumkataster konstanz | offene daten konstanz.

Deming, W. E. (1986). *Out of the Crisis*. MIT-CAES.

Deutscher Wetterdienst (2021). DWD open data.

Ditfurth, J. v. and Aholt, H. (2018). Data is the new gold.

Domingo, A., Bellalta, B., Palacin, M., Oliver, M., and Almirall, E. (2013). Public open sensor data: Revolutionizing smart cities. *IEEE Technology and Society Magazine*, 32:50–56.

Dong, L., Li, X., and Xie, G. (2014). Nonlinear methodologies for identifying seismic event and nuclear explosion using random forest, support vector machine, and naive bayes classification. *Abstract and applied analysis*, 2014:1–8.

Du, P., Bai, X., Tan, K., Xue, Z., Samat, A., Xia, J., Li, E., Su, H., and Liu, W. (2020). Advances of four machine learning methods for spatial data handling: a review. *Journal of Geovisualization and Spatial Analysis*, 4.

Dubey, A. and Rasool, A. (2019). Data mining based handling missing data. In *2019 Third International conference on I-SMAC (IoT in Social, Mobile, Analytics and Cloud) (I-SMAC)*, pages 483–489.

Farrell, M. B. and Abreu, S. H. (2012). A practical guide to quality improvement in nuclear medicine. *Journal of Nuclear Medicine Technology*.

Feng, F.-j., Yao, J., and Li, X. (2018). Research on the technology of data cleaning in big data. *Destech Transactions on Computer Science and Engineering*.

Frankfurt, O. D. (2023). Baumkataster frankfurt.

Galle, N. J., Halpern, D., Nitoslawski, S., Duarte, F., Ratti, C., and Pilla, F. (2021). Mapping the diversity of street tree inventories across eight cities internationally using open data. *Urban Forestry & Urban Greening*, 61:127099.

Girres, J.-F. and Touya, G. (2010). Quality assessment of the french openstreetmap dataset. *Transactions in GIS*, 14:435–459.

Haldorai, A., Ramu, A., and Murugan, S. (2019). Artificial intelligence and machine learning for future urban development. *Urban computing*, pages 91–113.

Hamburg, B. (2023). Baumkataster hamburg.

Haug, A., Zachariassen, F., and van Liempd, D. (2011). The costs of poor data quality. *Journal of Industrial Engineering and Management (JIEM)*, 4(2):168–193.

Heinrich, B. and Klier, M. (2011). Assessing data currency — a probabilistic approach. *Journal of Information Science*, 37(1):86–100.

Huang, G. (2021). Missing data filling method based on linear interpolation and lightgbm. *Journal of Physics: Conference Series*, 1754(1):012187.

International Monetary Fund (2003). Fifth review of the fund's data standards initiatives – data quality assessment framework and data quality program.

Jayawardene, V., Sadiq, S., and Indulska, M. (2015). An analysis of data quality dimensions.

Kaluarachchi, Y. (2022). Implementing data-driven smart city applications for future cities. *Smart cities*, 5:455–474.

Karlsruhe, S. (2021). Fachpläne - baumkataster.

Kumar, S. (2006). *Total Quality Management*. Laxmi Publications Pvt Limited.

Leipzig, O. D. (2023). Baumkataster leipzig.

Li, Y. (2018). Deep reinforcement learning: An overview.

Lämmerhirt, D., Rubinstein, M., and Montiel, O. (2017). The state of open government data in 2017.

Madnick, S. E., Wang, R. Y., Lee, Y. W., and Zhu, H. (2009). Overview and framework for data and information quality research. *J. Data and Information Quality*, 1(1).

Mostafa, S. M. (2019). Imputing missing values using cumulative linear regression. *CAAI Transactions on Intelligence Technology*, 4(3):182–200.

Møller, M. S., Olafsson, A. S., Vierikko, K., Sehested, K., Elands, B., Buijs, A., and van den Bosch, C. K. (2019). Participation through place-based e-tools: A valuable resource for urban green infrastructure governance? *Urban Forestry & Urban Greening*, 40:245–253. Urban green infrastructure – connecting people and nature for sustainable cities.

Nau, R. (2020). Statistical forecasting: notes on regression and time series analysis.

Nie, S., Wang, C., Li, G., Pan, F., Xi, X., and Luo, S. (2014). Signal-to-noise ratio–based quality assessment method for ICESat/GLAS waveform data. *Optical Engineering*, 53(10):103104.

Närman, P., Holm, H., Johnson, P., König, J., Chenine, M., and Ekstedt, M. (2011). Data accuracy assessment using enterprise architecture. *Enterprise Information Systems*, 5(1):37–58.

Picard, S., Chapdelaine, C., Cappi, C., Gardes, L., Jenn, E., Lefevre, B., and Soumarmon, T. (2020). Ensuring dataset quality for machine learning certification. In *2020 IEEE International Symposium on Software Reliability Engineering Workshops (ISSREW)*, pages 275–282.

Rambhia, M., Volk, R., Rismanchi, B., Winter, S., and Schultmann, F. (2023). Supporting decision-makers in estimating irrigation demand for urban street trees. *Urban Forestry and Urban Greening*, page 127868.

Ray, S. (2019). A quick review of machine learning algorithms. In *2019 International Conference on Machine Learning, Big Data, Cloud and Parallel Computing (COMIT-Con)*, pages 35–39.

Reinsel, D., Gantz, J., and Rydning, J. (2018). The digitization of the world.

Rostock, A. f. S. N. u. F. (2024). Bäume - rostock.

Ryu, K.-S., Park, J.-S., and Park, J.-H. (2006). A data quality management maturity model. *ETRI Journal*, 28(2):191–204.

Scholz, T., Hof, A., and Schmitt, T. (2018). Cooling effects and regulating ecosystem services provided by urban trees—novel analysis approaches using urban tree cadastre data. *Sustainability*, 10(3).

Shadman, S., Ahanaf Khalid, P., Hanafiah, M. M., Koyande, A. K., Islam, M. A., Bhuiyan, S. A., Sin Woon, K., and Show, P.-L. (2022). The carbon sequestration potential of urban public parks of densely populated cities to improve environmental sustainability. *Sustainable Energy Technologies and Assessments*, 52:102064.

Shankaranarayanan, G. and Zhu, B. (2021). Enhancing decision-making with data quality metadata. *Journal of Systems and Information Technology*.

Sharifyanov, N. and Latypova, V. (2023). A method of filling missing values in data using data mining. In *2023 IX International Conference on Information Technology and Nanotechnology (ITNT)*, pages 1–5.

Song, Y.-Y. and Lu, Y. (2015). Decision tree methods: applications for classification and prediction. *Shanghai archives of psychiatry*, 27:130–5.

Tute, E., Scheffner, I., and Marschollek, M. (2021). A method for interoperable knowledge-based data quality assessment. *BMC Medical Informatics and Decision Making*, 21.

UC Davis (2021). WUCOLS plant search database.

Vaziri, R., Mohsenzadeh, M., and Habibi, J. (2016). Tbdq: A pragmatic task-based method to data quality assessment and improvement. *PLOS ONE*, 11:e0154508–e0154508.

Vetrò, A., Canova, L., Torchiano, M., Minotas, C. O., Iemma, R., and Morando, F. (2016). Open data quality measurement framework: Definition and application to open government data. *Government Information Quarterly*, 33:325–337.

Wang, R. Y., Storey, V. C., and Firth, C. P. (1995). A framework for analysis of data quality research. *IEEE Transactions on Knowledge & Data Engineering*, 7(04):623–640.

Wang, R. Y. and Strong, D. M. (1996). Beyond accuracy: What data quality means to data consumers. *Journal of Management Information Systems*, 12(4):5–33.

Wang, Z., Bovik, A., Sheikh, H., and Simoncelli, E. (2004). Image quality assessment: from error visibility to structural similarity. *IEEE Transactions on Image Processing*, 13(4):600–612.

Wang, Z., Wang, Y., Zeng, R., Srinivasan, R. S., and Ahrentzen, S. (2018). Random forest based hourly building energy prediction. *Energy and Buildings*, 171:11–25.

Weiskopf, N. G. and Weng, C. (2013). Methods and dimensions of electronic health record data quality assessment: enabling reuse for clinical research. *Journal of the American Medical Informatics Association*, 20(1):144–151.

Wijnhoven, F., Boelens, R., Middel, R., and Louissen, K. (2007). Total data quality management: A study of bridging rigor and relevance. In *European Conference on Information Systems*.

Xiao, Y., Lu, L. Y., Liu, J. S., and Zhou, Z. (2014). Knowledge diffusion path analysis of data quality literature: A main path analysis. *Journal of Informetrics*, 8(3):594–605.

Yang, F.-J. (2018). An implementation of naive bayes classifier. In *2018 International Conference on Computational Science and Computational Intelligence (CSCI)*, pages 301–306.

Zhang, Y. (2012). Support vector machine classification algorithm and its application. In Liu, C., Wang, L., and Yang, A., editors, *Information Computing and Applications*, pages 179–186, Berlin, Heidelberg. Springer Berlin Heidelberg.

Zhang, Y., Wei, S., Zhang, L., and Liu, C. (2018). Comparing the performance of random forest, svm and their variants for ecg quality assessment combined with nonlinear features. *Journal of medical and biological engineering*, 39:381–392.

Zhang, Z. (2016). Introduction to machine learning: k-nearest neighbors. *Annals of translational medicine*, 4:218–218.

Zheng, H., Wu, K., and Meng, F. (2011). A provenance-aware data quality assessment system. In Yu, Y., Yu, Z., and Zhao, J., editors, *Computer Science for Environmental Engineering and EcoInformatics*, pages 265–269, Berlin, Heidelberg. Springer Berlin Heidelberg.

Zhu, H. and Wu, H. (2010). Assessing quality of data standards: Framework and illustration using xbrl gaap taxonomy. In Sánchez-Alonso, S. and Athanasiadis, I. N., editors, *Metadata and Semantic Research*, pages 288–299, Berlin, Heidelberg. Springer Berlin Heidelberg.

Zhu, H. and Wu, H. (2011). Quality of data standards: framework and illustration using xbrl taxonomy and instances. *Electronic Markets*, 21:129–139.

Ünal, F. (2020). Data mining for student performance prediction in education. In Birant, D., editor, *Data Mining*, chapter 9. IntechOpen, Rijeka.

Chapter 9

Discussion

After presenting the four individual studies and their findings, this chapter discusses the key findings of the overall research and their implications for both research and policy.

9.1 Implications

For achieving the research aim, the first research question that needs to be investigated is:

RQ1: Can state-of-the-art technological solutions be integrated to support UGS management?

The thesis critically evaluates the existing literature in three areas: UGS benefits, UGS management needs, and available tools and frameworks for UGS management. The literature presents sufficient evidence on the multifaceted benefits available from UGS, including social, environmental, and economic aspects. However, these benefits are contingent on UGS characteristics such as size, type, age, species diversity, and composition. Consequently, trade-offs between benefits become inevitable. For instance, trees with larger canopies are preferred for increased shading and higher heat mitigation benefits, while open grass is favored for sufficient ventilation (Choi et al., 2021). As highlighted by Barrell (2017), trees yield significant ecosystem service benefits as they grow older; however, fewer than half of urban trees manage to survive beyond a decade (Galle, 2020). Mullaney et al. (2015) observe that this is due to challenging growing conditions faced by street trees. Moreover, Erlwein and Pauleit (2021) conclude that conserving existing trees is currently the most effective and cost-efficient strategy for climate change adaptation. However, the current success metrics are highly inclined towards planting new trees and less towards protecting existing trees.

Moreover, management decisions also face trade-off scenarios. For instance, having a UGS close to major roads and public transport hubs improves accessibility for users; however, the increased noise levels due to frequent vehicle movements impact the quality of benefits derived by the user. Similarly, pruning of trees is important for street trees along roads for pedestrian and vehicle safety; however, it leads to reduced shading and higher surface temperatures. Therefore, decision-makers need to set the priority goals considering the needs of the city and its residents. Furthermore, management challenges are expected to exacerbate with changing climatic conditions. As the frequency of droughts increases and rainfall patterns become erratic, it will lead to reduced water availability in cities. For instance, the city of Melbourne experienced drought conditions from 1997 to 2010, which led to serious deterioration of its urban forest health (City of Melbourne, 2012b). Similarly, many countries, particularly Australia, Canada, and the United States, face labor shortages, especially in labor-intensive jobs, leading to limited personnel available for regular maintenance (Causa et al., 2022). Accordingly, resources available for urban management are expected to become further constrained. As a result, prioritization is expected to become a critical decision in the future. Existing literature lacks the approaches for prioritizing UGS. As a result, city administrators have to rely on subjective assumptions or arbitrary allocation of resources. This might lead to degradation of attainable UGS benefits for city residents. For instance, a single park in the city could take over a disproportionate portion of the resources without providing substantial benefits to the larger population of the city. As a result, quantification of benefits of each UGS unit is required. Furthermore, quantification of benefits is also essential to create a viable economic case for UGS conservation.

Based on the findings from the literature review, two research gaps were identified. First, the tools and frameworks that integrate the outcome of benefit analysis with management decisions are currently lacking. Moreover, while resources are expected to be constrained in the future, there are no existing methods to support decision-makers in making UGS prioritization decisions during resource-constrained scenarios. Subsequently, given these identified gaps in current solutions, there arose a need to further investigate the following research question:

RQ2: How can the benefits of UGS be maximized with minimum costs in different resource-constrained scenarios?

For investigating this research question, the research outline was designed considering the UGS decision-makers as the target users. This could include park managers, the garden department, environmental authority, or the executive committee of the city depending on the organizational structure in the city. The decision-maker is responsible for all three phases: monitoring, managing, and greening and has the ability and authority to regulate the provision of resources for UGS management.

Study A:

Through the irrigation demand estimation for Berlin city, the high-water-intensive species are Salix (Willows) and Betula (Birch), while Aesculus (Chestnut horse) is the least-water-intensive species. However, since the number of Tilia trees in the city is highest, followed by Acer (Maple), the total water demand of Tilia (Lime) is highest in the city. Moreover, the seasonal trends reveal significantly higher irrigation demand in summer months than in winter months. However, multiple dips are observed throughout the year, representing the major inflow through precipitation and thus reducing the external irrigation demand. When compared with the currently implemented soil moisture-based approach in Berlin city, the distribution of irrigation demand is found to be much more uniform throughout the year in the time series model. While this increases the management efforts for the application of water, it significantly reduces the burden on water resources during summer months. Moreover, the model addresses the urban context more comprehensively by including species type and density factor, in addition to the planting factor being used in the SLIDE approach that likely underestimates the irrigation demand.

Additionally, the scenario analysis carried out for reduced rainfall conditions observes an 8.5% increase in irrigation demand for a 50% reduction in precipitation. Similarly, different scenario analyses can be performed, such as increased temperature, a greater number of trees, and a different tree species composition. This is significantly useful for decision-makers so that they can not only plan irrigation schedules for existing trees but can also budget appropriate water quantity for future needs. It is also to be noted that while estimates could be made at an improved timescale, since current management practices rely on manual interventions, daily watering of trees is not currently feasible. Therefore, weekly, bi-weekly, or monthly scales are currently preferred choices for cities.

Study B:

The UGS accessibility and quality analysis show that although most of the UGS in the inner zone of the city are critical for providing accessibility to nearby city residents, they mostly score lower on quality due to their relatively small size, high noise in the neighborhood, and lower tree density. In contrast, the UGS in the outer zone perform quite well on quality parameters, but they have a significantly lower contribution to providing accessibility to city residents. This could be mitigated by allowing more residential communities in the suburban area. However, urban sprawling has its own environmental consequences (Johnson, 2001). Another solution could be providing reliable public transport connectivity to these UGS so that even residents from the inner zone can easily access these spaces. However, this might not be a feasible solution for children and the elderly community. Moreover, due to a lack of physical proximity, it can only provide limited benefits to the citizens.

The prioritization order obtained by integrating accessibility and quality as indicators highlights the UGS with the highest contribution in fulfilling the WHO recommendation. Furthermore, scenario analysis is performed to check the sensitivity of the findings towards the two essential criteria in the WHO guideline: a minimum area of 0.5 ha and a maximum distance of 300 m. It is observed that results are susceptible to the distance criteria but not significantly impacted by the area criteria. This is potentially attributed to the high urban density, wherein UGS could not be provided to everyone at a distance closer than 300 m. The scatter plot that categorizes the UGS into high/low accessibility paired with high/low quality could give a clear visualization of the distribution of UGS in each type, and management plans can be designed accordingly. Initially, decision-makers should prioritize addressing the UGS characterized by high accessibility but low quality. Improving these areas is crucial since many city residents depend on them to reap the benefits they offer.

Study C:

Integrating both cost and benefit considerations along with decision-makers' preferences allows for optimal resource allocation to maximize benefits at minimum costs. The spatial analysis shows that establishing targets at the district level rather than the city level increases the uniformity of resource distribution. However, this improvement comes with the drawback of less optimal resource allocation. Conversely, setting targets at the city scale and implementing them at the sub-district level results in the most optimal allocation. Nevertheless, as the scale increases, implementing this strategy in the field becomes more challenging. While analysis at the single tree unit level is possible, current management practices lack the necessary infrastructure to support such estimations. However, this limitation could potentially be addressed in the future by implementing a controlled or sensor-based irrigation system for all urban trees. Consequently, the sub-district or district scale is currently chosen for analysis.

In summary, in order to achieve resource-efficiency-oriented prioritization, the allocation should be done at the sub-district scale with goals set at the city level. However, if the preference is for higher goal achievement, then the allocation should be done at the sub-district scale with goals set at the district level. Moreover, the resource allocation between street trees and parks will be influenced by the goal priorities set by the decision-makers. In case of equally weighted goals, at higher spatial resolution, street trees will be favored over parks as fewer resources are available for each sub-district and each unit of park requires substantially more resources. It is to be emphasized that while both the case-study cities, the City of Berlin (Naturschutz, Landschaftsplanung, 2023) and the City of Melbourne (City of Melbourne, 2012a, 2020), have developed strategic plans to increase and enhance UGS in their cities, no contingency plan has been made for UGS management in case of resource-constrained situations.

Study D:

The data quality assessment of tree inventories from ten German cities shows that while the availability of datasets is improving, many critical feature data are still partially or completely missing. This especially includes features such as tree height, diameter, and crown size, which are more labor-intensive and expensive to measure. Moreover, the quality of a dataset predominantly depends on the application model for which it is used as input. For instance, in the case of irrigation demand estimation for a tree, tree-species information is critical to determine the reference water demand of the tree. Therefore, even if the diameter data is absent, it would not affect its use for the application. However, if the parameter is crucial in the decision-making model and is only partially available in the data, it could potentially have a large impact on the decision. For example, in the case of water demand estimation, a 20% missing value of tree species could lead to a 2% to 16% difference in the estimation, depending on the imputation technique used.

Therefore, city administrators should also assess the quality of the collected data and aim to obtain high-quality datasets with fewer erroneous records through regular data updates. Additionally, in case of a high-quality but low-quantity dataset, data imputation techniques like Random Forest, which demonstrate lower mean error, could be used to predict the missing values. This could be further enhanced by integrating multiple data sources such as remote sensing, LiDAR, and aerial imagery.

In addition to study specific implications, the relevant observations for effective UGS management are presented below:

Moreover, promoting citizen education about the benefits of various types of UGS is crucial. For example, many individuals perceive lawns as the preferred form of urban nature (Ignatieva and Hedblom, 2018). Consequently, city administrators often feel compelled to frequently mow lawns. For instance, in Sweden, 52% of UGS consists of lawns (Hedblom et al., 2017). However, increased biodiversity is observed in wild lawns. Therefore, through citizen education programs, people could be informed about the advantages of wild grasses as well. In Germany, there is growing acceptance of the concept of alternative wild lawns. This pilot program has been implemented in Gleisdreieck Park and Südgelände Nature Park (Ignatieva and Hedblom, 2018). Furthermore, citizen initiatives for UGS management should be encouraged. This yields dual benefits: First, it reduces the cost burden on the city and eases the pressure on its limited resources. Second, it strengthens the connection between citizens and UGS. Additionally, with larger citizen groups, a higher temporal scale could be achieved, and localized care for vulnerable trees could be provided more quickly.

Lepri et al. (2017) has also highlighted the shortcomings of data-driven approaches and recommended providing transparency, accountability, and civic participation to mitigate them. Therefore, while implementing such approaches, decision-makers should follow the fundamental principles of equity and fairness so that benefits are uniformly distributed among city residents.

9.2 Limitations and criticism

The limitations and criticisms of the existing approach are discussed in the subsequent paragraphs.

Prioritization is a challenging, often arguable, but at the same time necessary requirement in case of resource-constrained scenarios. In real-life scenarios, this could be akin to choosing who gets to live. A difficult yet valid analogy is drawn from the medical field, where administrators are often faced with the challenging task of choosing between providing treatment to a young patient with a higher likelihood of complete recovery and associated higher economic potential, versus an older patient who likely requires more extensive and prolonged intervention and associated lower economic potential (Guindo et al., 2012). This dilemma was observed in several countries across the world during the COVID-19 pandemic where the demand for resources far exceeded the supply (Karahda et al., 2020; Huseynov et al., 2020).

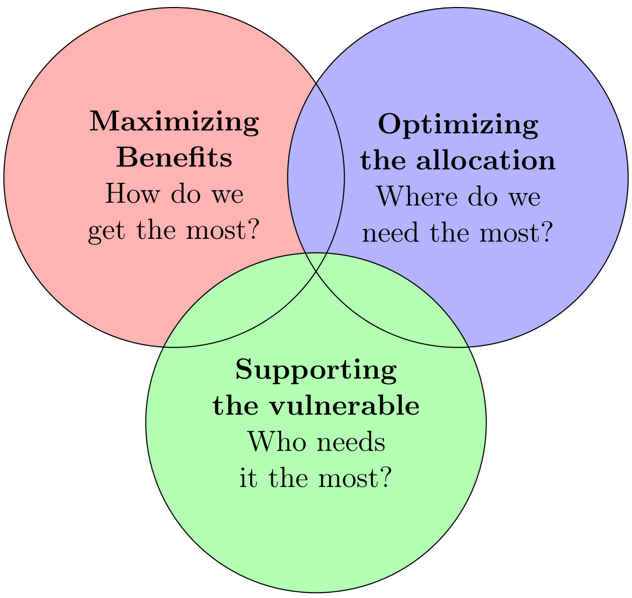


Figure 9.1: Basis for resource allocation.

Figure 9.1 presents three approaches for resource allocation with different ethical considerations. First, the red circle indicates the Utilitarianism approach aimed at extracting the maximum total benefits from the UGS. Moreover, since the city residents are kept at the central focus, only those UGS prioritized that provide maximum benefits to the city residents. The blue circle indicates the Consequentialism approach aimed at allocating resources such that the consequential benefits are achieved as per the city target. For instance, if a certain part of the city faces a higher urban heat island impact, then the UGS of that part of the city are always prioritized higher. Lastly, the green circle represents the Altruism approach that keeps the UGS at the center of decision-making instead of city residents. Accordingly, the most vulnerable UGS are identified, and the necessary management support is provided to them irrespective of their contribution to the overall benefits or the associated costs.

The current design of the approach is based on the utilitarian principle as it offers the advantage of higher resource allocation efficiency compared to the other two approaches. However, this could lead to the neglect of younger trees (due to lower ecosystem service benefits) or certain tree species (such as those with high water consumption), suburban areas (due to a smaller beneficial population), and unintended consequences. These challenges could be overcome by incorporating additional criteria, such as always prioritizing trees younger than particular age or setting targets at the sub-district scale instead of the city scale, which would encourage a more uniform distribution of resources, as demonstrated in chapter 7.

As discussed in chapter 2, UGS offers a broad range of benefits. However, only UGS accessibility was included as the key benefit indicator for parks. For the quantification of other environmental and economic benefits of UGS, they were indirectly estimated under the UGS quality, which includes factors such as greenness, size, quietness, and safety. The higher quality of the UGS is likely to be proportional to the other benefits, especially in the case of higher tree density and larger size. However, for more accurate estimations of each benefit, each attainable benefit should be quantified using benefit-specific models developed by researchers and organizations. There are benefit models available that could be integrated into the proposed model for incorporating a broad range of UGS benefits. Nevertheless, this was not included in the existing approach considering the existing policy guidelines focusing solely on providing UGS accessibility to city residents. Although some cities have adopted UGS as a nature-based solution to tackle local problems such as the urban heat island or to improve biodiversity, these are not currently explicitly set as the policy targets at the national and international scales. Similarly, since street trees are individual units and have an area less than 0.5 ha, they could not be considered as contributing to accessibility for city residents. As a result, carbon sequestration was used as its benefit indicator, which is considered the most valuable benefit from an individual tree. Including more benefit criteria could provide more evidence for management decisions; however, this could also increase the complexity of trade-offs between different benefits. Therefore, it is recommended that city administrators include the benefit criteria depending on the city's needs and priorities.

Moreover, in all four studies, only public UGS have been included and analyzed. This was done for multiple reasons. First, private UGS are not accessible to everyone, so it is logical that they are not available for consumption by other city residents. Second, most of these UGS are managed by individual homeowners or resident associations. Since the city administration has only limited responsibilities for private UGS, such as ensuring they are pest-free, not prone to failure, and do not hinder movement on the street, they are not part of the regular management responsibilities of decision-makers. Third, most of these UGS are not recorded in the existing tree inventory datasets. However, private UGS also contribute significantly to benefits, as demonstrated by Naber et al. (2022) and Dewaelheyns et al. (2014). In some cities, the amount of private UGS may even exceed the amount of public UGS, as shown by Pristeri et al. (2021). Therefore, not including private UGS could lead to an underestimation of both demand and benefits.

Thirdly, the thesis mainly focused on managing existing UGS and did not explicitly incorporate planning for new plantations. This choice was made, as discussed in section 2.2, considering the substantially higher benefits obtained from established trees aged 25-30 years or older. Consequently, sustaining existing UGS was given much higher priority in the management approach than planning for new areas. Moreover, in the demand module, UGS are considered as costs within the city's balance sheet. While this is consistent with current accounting practices, some practitioners have criticized this approach and have recommended instead to include them as assets (Dark Matter, 2020). Furthermore, when investigating the data quality of existing tree inventory datasets, the coverage of the data was not considered. The quality and quantity of the data were analyzed only within the dataset. Since this provides only partial information on missing data, remote sensing and aerial imagery-based methods could be further used to assess the actual UGS covered by the current data.

Finally, the current version of the decision-making model offers interaction only at the input level. As a result, it does not consider the decision-maker's feedback after the prioritization decision is made. There is also some subjectivity in the weighting criteria. For instance, in the determination of the benefit score of UGS, accessibility benefits were assigned a weightage of 0.75, whereas quality benefits were assigned a weightage of 0.25. Again, this decision was made based on current policy goals that emphasize mainly on providing access to UGS.

Bibliography

Barrell, J. (2017). Tree benefits; the missing part of the street tree cost benefit analysis equation.

Causa, O., Abendschein, M., Luu, N., Soldani, E., and Soriolo, C. (2022). The post-covid-19 rise in labour shortages. *OECD Economics Department Working Papers*, 1721(1721).

Choi, C., Berry, P., and Smith, A. (2021). The climate benefits, co-benefits, and trade-offs of green infrastructure: A systematic literature review. *Journal of Environmental Management*, 291:112583.

City of Melbourne (2012a). Open space strategy.

City of Melbourne (2012b). Urban forest strategy.

City of Melbourne (2020). Green our city strategic action plan.

Dark Matter (2020). Trees as infrastructure - dark matter laboratories.

Dewaelheyns, V., Rogge, E., and Gulinck, H. (2014). Putting domestic gardens on the agenda using empirical spatial data: The case of flanders. *Applied Geography*, 50:132–143.

Erlwein, S. and Pauleit, S. (2021). Trade-offs between urban green space and densification: Balancing outdoor thermal comfort, mobility, and housing demand. *Urban Planning*, 6(1):5–19.

Galle, N. (2020). Urban deforestation and what we can do about it.

Guindo, L. A., Wagner, M., Baltussen, R., Rindress, D., van Til, J., Kind, P., and Goetghebeur, M. M. (2012). From efficacy to equity: Literature review of decision criteria for resource allocation and healthcare decisionmaking. *Cost Effectiveness and Resource Allocation*, 10.

Hedblom, M., Lindberg, F., Vogel, E., Wissman, J., and Ahrné, K. (2017). Estimating urban lawn cover in space and time: Case studies in three swedish cities. *Urban Ecosystems*, 20:1109–1119.

Huseynov, S., Palma, M. A., and Nayga, R. M. (2020). General public preferences for allocating scarce medical resources during covid-19. *Frontiers in Public Health*, 8.

Ignatieva, M. and Hedblom, M. (2018). An alternative urban green carpet. *Science*, 362(6411):148–149.

Johnson, M. P. (2001). Environmental impacts of urban sprawl: A survey of the literature and proposed research agenda. *Environment and Planning A: Economy and Space*, 33(4):717–735.

Karahda, A., Sethi, S., and Prasad, S. K. (2020). Effect of healthcare burden and resource reallocation on elderly during covid-19 pandemic. *Journal of Geriatric Care and Research*, 7(2):89–92.

Lepri, B., Staiano, J., Sangokoya, D., Letouzé, E. F., and Oliver, N. (2017). The tyranny of data? the bright and dark sides of data-driven decision-making for social good. *Studies in big data*, pages 3–24.

Mullaney, J., Lucke, T., and Trueman, S. J. (2015). A review of benefits and challenges in growing street trees in paved urban environments. *Landscape and Urban Planning*, 134:157–166.

Naber, E., Volk, R., Mörmann, K., Boehnke, D., Lützkendorf, T., and Schultmann, F. (2022). Namares—a surface inventory and intervention assessment model for urban resource management. *Sustainability*, 14(14).

Naturschutz, Landschaftsplanung (2023). Landschaftsprogramm einschließlich artenschutzprogramm (lapro).

Pristeri, G., Peroni, F., Pappalardo, S. E., Codato, D., Masi, A., and De Marchi, M. (2021). Whose urban green? mapping and classifying public and private green spaces in padua for spatial planning policies. *ISPRS International Journal of Geo-Information*, 10(8).

Chapter 10

Conclusions

This chapter provides a comprehensive summary of the research study's findings, key contributions to the current state of knowledge, and their implications. Additionally, the outlook section proposes prospective research approaches for the future.

10.1 Summary

The thesis contributes to the current state of knowledge with four studies aimed at supporting decision-makers in addressing various aspects of UGS management, with the primary goal of benefiting city residents. Consequently, through a data-enabled approach, valuable insights are provided to decision-makers to make informed decisions regarding the allocation of limited resources to UGS using a prioritization approach.

The first research objective (RO1) aimed to develop a cost model to estimate the management demand necessary for the sustenance of existing UGS. As sufficient water is essential for the healthy growth of trees, Study A focused on developing a linear time-series model based on a soil water balance approach. Additionally, personnel demand estimation was also conducted in Study C to estimate the required hours for cleaners, gardeners for pruning, pest management, fertilizer application, and drivers to transport leaf litter. The watering model is capable of estimating the irrigation water demand of individual street trees. The proposed model enhances existing methods by providing estimates at a weekly time scale, consistent with current watering application practices. Furthermore, as it integrates the WUCOLS approach for ET demand estimation of trees, it also incorporates the effect of urban characteristics on the ET demand. Additionally, by including factors such as tree species information, soil conditions, weather data (temperature, humidity, reference ET), and past and future rainfall, the method precisely estimates the demand, aiding in water conservation. Moreover, as the methodology relies entirely on public datasets, it allows broad usage among users. Through a case study on the city of Berlin, it was demonstrated how city administrators can use this method not only to estimate water demand for existing trees but also to project future climatic conditions, such as reduced rainfall and shifting rainfall patterns. Furthermore, additional water demand required for new planting programs could also be estimated according to the tree species types.

The second research objective (RO2) aimed to develop a benefit model to estimate the benefits received from UGS for city residents. Considering the WHO guidelines, Study B proposed a novel GIS-based approach to quantify the social benefits of UGS. In addition, carbon sequestration benefit was estimated in Study C to quantify the potential benefits from tree species depending on their diameter. The *Building Coverage Score* measures the number of residents benefiting from a particular UGS, while the *Essentiality Score* measures its criticalness in maintaining green space accessibility for dependent residents. Additionally, a composite quality indicator is derived using the performance of UGS on size, greenness, quietness, and safety criteria. The proposed model enhances existing methods by providing a comprehensive assessment of benefits from UGS as measured according to current policy guidelines. Moreover, the methodology uses publicly available OSM datasets, enabling users to replicate the methods for other cities. Also, for the first time, a unique integration of benefits with management decision-making for existing UGS was made. This was also demonstrated through a case study in the city of Berlin, where the benefits of UGS were quantified and subsequently used for prioritization. This method could support local park management authorities in gaining insights into the existing state of UGS and accordingly planning management activities. For instance, a UGS with a higher access score but a lower quality score should be further improved by adding more trees (to enhance density) or adding sufficient lighting (to reduce crimes), as a higher number of residents depend on its benefits.

The third research objective (RO3) aimed to develop a multi-criteria decision support system to prioritize resource allocation under resource-constrained scenarios. The model proposed in Study C addresses the research gap by providing a suitable method for resource allocation during constrained scenarios for UGS management. This GP-based method builds upon the outcomes from the cost model developed in Study A and the benefit model developed in Study B, along with resource availability and city targets, to make prioritization decisions. Since this method incorporates both cost and benefit in decision-making, it provides a more resource-efficient solution compared to Study B. Furthermore, the model can handle various UGS types, such as parks and street trees, and allows decisions to be made at different spatial scales. Additionally, by incorporating UGS accessibility as a goal, the model enables cities to pursue SDG targets even during resource-constrained conditions. Moreover, the framework's scalability allows for the integration of additional cost and benefit parameters. The applicability of the model was demonstrated through case studies in two cities, Berlin and Melbourne, each presenting distinct conditions regarding data availability, green space density, population distribution, and local climate. Decision-makers can use this model in practice to make informed decisions regarding the allocation of the available resources and maximize the benefits for city residents.

The fourth objective (RO4) aimed to develop a framework to assess and enhance the quality of input data for decision-making in cities with limited data availability. In this regard, Study D based on the total data quality management principles, extends the existing knowledge through three contributions. First, it devises a framework dedicated to evaluating the quality of public tree inventory datasets. This has been demonstrated through a comparative quality analysis study of tree inventories from ten German cities. Second, it implements three approaches—two statistical and one machine learning-based—to enhance data quality by filling missing tree height values. Third, it investigated the impact of data quality on UGS decision-making models, by utilizing both a cost estimation model (focused on water demand) and a benefit estimation model (for carbon sequestration potential). Accordingly, it identifies the data quality challenges in UGS management. The study concluded that the availability of high-quality and quantity data can significantly enhance subsequent usage in diverse application models. Decision-makers can apply this framework to evaluate the existing state of datasets and a structured approach to address quality issues. In addition, From SLR, MLR, and RF, the best data enhancement was obtained in case of RF (RMSE=2.92) reflecting the high potential of advanced machine learning approaches to address data quality issues. Moreover, it enables informed decision-making in cities, even where required input data are available with insufficient quantity or quality.

10.2 Outlook

The methodological framework established in this thesis offers a pathway for further research and innovation in the management of UGS. By addressing current limitations, future research can enhance decision-making. Firstly, the current approach solely considers applications in UGS management, neglecting trade-off scenarios between different sectors. Therefore, in the future, multiple models designed for various urban sectors should be combined to effectively manage city-wide resources. Secondly, within UGS assessment, expanding the cost estimation model to include additional management demand parameters could provide extensive insight into the resources required for UGS management and associated costs.

Similarly, expanding the benefit estimation model to include additional social, economic, or environmental benefits could provide more realistic trade-off scenarios. Therefore, integrating multiple benefit models that quantify UGS benefits would be beneficial. An alternative approach could be to quantify each benefit individually in terms of a financial metric or currency and subsequently maximize it.

Moreover, the current methodology heavily relies on public data, which is advantageous in many cities where data is available in sufficient quantity but poses a challenge in cities where data is scarce. Implementing a data quality enhancement framework could address this issue for cities with limited data quality, while investigating advanced remote-sensing or aerial imagery-based approaches could further improve existing dataset coverage.

In the future, evaluating research approaches based on consequentialism or altruism, and analyzing the differences in outcomes compared to the proposed utilitarian-based approach, will be valuable. Additionally, considering a mechanism to incorporate decision-makers' feedback into the decision-making model could further support them in achieving desired outcomes for city residents. For example, if a heritage tree is not prioritized by the model, incorporating this feedback into the next iteration could improve results. Furthermore, emerging sensor network-based monitoring of UGS could provide additional real-time data on soil moisture, temperature, humidity, and park visitation numbers. Therefore, investigating the integration of such novel data sources within decision support systems is crucial. Moreover, it is essential to consider integrating management practices by facilitating communication among diverse citizen science initiatives, community-based solutions, and decision support systems using interoperable principles.

Appendix A

Published papers

sustainability

MDPI

Review

Urban Resource Assessment, Management, and Planning Tools for Land, Ecosystems, Urban Climate, Water, and Materials—A Review

Rebekka Volk *, **Mihir Rambhia**, **Elias Naber** and **Frank Schultmann**

Institute for Industrial Production (IIP), Karlsruhe Institute of Technology (KIT), 76187 Karlsruhe, Germany; mihir.rambhia@partner.kit.edu (M.R.); elias.naber@kit.edu (E.N.); frank.schultmann@kit.edu (F.S.)
* Correspondence: rebekka.volk@kit.edu

Abstract: Increasing awareness of global and local climate change and the limited resources of land, surface, water, raw materials, urban green spaces, and biodiversity alter the exigencies of urban development. Already perceivable local climate changes such as heavy rains, droughts, and urban heat islands urge planners to take action. Particularly in densely populated areas, conflicting interests are pre-programmed, and decision making has to include multiple impacts, mutual competition, and interaction with respect to investments into provisioning services. Urban planners and municipal enterprises increasingly work with digital tools for urban planning and management to improve the processes of identifying social or urbanistic problems and redevelopment strategies. For this, they use 2D/3D city models, land survey registers, land use and re-/development plans or other official data. Moreover, they increasingly request data-based planning tools to identify and face said challenges and to assess potential interventions holistically. Thus, this contribution provides a review of 51 current tools. Simple informational tools, such as visualizations or GIS viewers, are widely available. However, databases and tools for explicit and data-based urban resource management are sparse. Only a few focus on integrated assessment, decision, and planning support with respect to impact and cost assessments, real-time dashboards, forecasts, scenario analyses, and comparisons of alternative options.

Keywords: urban resource management; software; web tools; urban green spaces; land use; water; material/waste; urban climate; review

check for updates

Citation: Volk, R.; Rambhia, M.; Naber, E.; Schultmann, F. Urban Resource Assessment, Management, and Planning Tools for Land, Ecosystems, Urban Climate, Water, and Materials—A Review. *Sustainability* **2022**, *14*, 7203. https://doi.org/10.3390/su14127203

Academic Editor: Maria Rosa Trovato

Received: 30 March 2022
Accepted: 8 June 2022
Published: 12 June 2022

1. Introduction

Cities are facing multiple challenges with respect to climate change adaption, land, surface and space use, water supply and use, material and waste management, urban green spaces, and biodiversity, just to name a few. Furthermore, continuous urbanization, a high demand for residential areas, and the densification of cities are further driving forces for urban transformation. The UN Sustainable Development Goals (SDG) and energy and mobility transitions as well as the associated attention of the public (COP26 and Friday for Future) lead to further demands and complexity with respect to urban planning [1]. A multitude of methods and tools are available for analyzing urban processes and activities. However, urban policymakers tend to use best management practices rather than quantitative data to support policy decisions [2,3].

Nature-based solutions (NBS) or blue-green infrastructures (BGI) are seen as key aspects to make urban areas more sustainable, e.g., healthier, more biodiverse, and attractive, and to make cities more resilient with respect to urban heat island effects, extreme weather, and climate change [4,5]. These challenges need to be addressed and systematically worked on in urban planning. The main tasks are to formulate goals and to derive operational targets, projects, and milestone plans for the demanded urban transformation in different fields. However, cities also experience major challenges with climate adaptation measures:

resource availability, a lack of expertise, institutional settings, and collaborative governance and planning [6]. Furthermore, urban transformation is not limited to climate adaptation challenges but requires integrated urban development strategies and operational approaches considering multiple challenges at once [6].

Geographical data are changing how cities and urban districts are planned, monitored, and managed [7]. More and more cities provide open data on their built environment, development plans, local climate and heat islands, CO_2-emissions, many other pollutants, biodiversity, urban green infrastructure and water bodies, and others. Moreover, other service providers provide data on cities, such as 3D models from federal/state agencies, satellite and ortho images, local weather data, and semantic and labelled maps, that give further information on urban areas. Furthermore, standardized data models, exchange formats, and processes are under development and are used for efficient urban planning (e.g., XÖV and XPlanung; XPlanung is a standard for urban land use planning in Germany. Since 2018, it is obligatory for communities, with a 5-year transition period. XÖV is a standardized XML format for public administration in Germany). Moreover, atlases or apps show the most important points and services of general interest [8,9], social and urban planning problems or solar potentials (solare-stadt.de), monitor urban development [10,11] (e.g., KomMonitor is an interactive GEO-based tool focusing on the monitoring of the demography and social structure; it allows for statistical analysis and time series and shows points, lines, and areas of interest [10]), and help search for affordable housing or enable digital citizen participation [12]. Geoportals offer many open data on cities, e.g., on noise [13,14], public tree inventories [13], standard ground values [15], water infrastructure [16], energy, water, and greenhouse gas performance [17], and air quality or demographics. Others also show improvement potentials, e.g., concerning solar heat or power generation, related potential CO_2 savings, and the exhaustion level of the full potential [18–20] or potential for green roofs and unsealing ground [21], with examples in [22,23]. However, the information availability and granularity of urban data differ, and only a limited number of studies include spatially explicit data to inform planning practitioners [24]. Some cities offer information on contaminated sites and individual plot geometries/polygons (e.g., [25]), while others do not share such data (classified due to data protection). Some extend to the surrounding regions up to the state level (e.g., [26]), while others are restricted to the urban or metropolitan areas.

Furthermore, urban data and, in particular, the monitoring and performance evaluation of concepts and measures are crucial to manage and measure urban transition [27]. GIS-based planning, monitoring, and management tools for a more sustainable urban resource management and development have to consider a multitude of factors and their complex interplay. They should be able to consider local conditions (e.g., ecosystems) and to pursue the realization of communal goals. Moreover, such tools can help to share information, to improve planning processes, and to enable quantification, resource monitoring, and management in (almost) real time. Tool addressees are researchers, municipalities, and their administrations as well as urban planners and consultancies. These tools are not solely for analysis and administration purposes; they also facilitate the public display of urban data and maps, which could contribute to citizen engagement, e.g., data collection and feedback on current developments. Specific and integrated urban planning and decision making could also be supported by tools that allow for the identification of suitable locations of additional NBS (potentials); the quantification of services, disservices, and cost (see e.g., [5]); the consideration of interactions with water/materials, ecosystems, and other aspects; or the inclusion of NBS in inter-/trans-sectoral urban planning and governance strategies/funding programs. "A large variety of tools have been developed worldwide to support the mainstreaming and uptake of NBSs in cities, ranging from methodologies, software, catalogues, repositories and e-platforms, to guidelines and handbooks. [. . .] Tools can, for example, inform and aid the planning processes by selecting and evaluating NBSs, simulating NBS implementation, calculating the costs and benefits of NBSs, supporting stakeholder involvement and facilitating collaborative processes" [6].

However, in the literature only a few papers are available that collect and review the existing tools [5,6,28]. Saikia et al. stated "an increasing demand for innovative tools and guidance to apply water resilience concept in practice" [29]. Din Dar et al. found "a major gap in performance evaluation of different BGI technologies" that they attempted to close by discussing the available modeling tools [5]. Despite their extensive review, the authors of [6] focused on how existing tools can meet the implementation/use challenges instead of assessing their capabilities and quality in detail. In addition, important academic and commercial tools are lacking, such as PALM4U and ENVI-met. Ataman and Tuncer performed a systematic review on urban interventions and participation tools [28]. They found that more studies on urban data, tool development, and stakeholder involvement are required. Frantzeskaki et al. elaborated on advances in planning, knowledge coproduction, indicators, big data, and novel financing models to mainstream NBS [4]. Thus, existing and developing tools require a classification, characterization, and review of their capabilities, e.g., with respect to the precision of simulations/forecasts and cost estimations. To face these challenges with suitable tools, an overview on the available tools as well as an assessment/review of their field of application, capabilities, technology readiness level (TRL) status, and availability is provided in this study and complements the mentioned reviews. In contrast to [6] and other reviews, this study focuses on software instead of methodologies, catalogues, repositories, e-platforms, guidelines, or handbooks, which are increasingly available. Furthermore, this review focuses not only on NBS but also on technological solutions and water and materials. In addition, we include tools developed and used outside Europe.

This study aims to answer the following research question: Which urban planning tools are spatially explicit, quantitative, and capable of supporting the multi-disciplinary urban planning fields of land use, water, materials, and urban ecosystems? Further sub-questions that arise naturally are also addressed:

- Which application areas can be distinguished, or do overlaps exist?
- Which are the primary tool capabilities that can be distinguished?
- What technology readiness levels do the tools have?
- Which tools are freely available, and which are commercially available?
- At which scale does the tool assess, operate, and plan?
- Do the tools allow for monodirectional or bidirectional communication with stakeholders?

The remainder of the study is organized as follows. First, we will elaborate on the approach and review method (Section 2). Then, we will present the developed classification and subcategories as well as the classification results (Section 3). This is followed by a review of each application area of the most relevant tools. The study closes with a discussion (Section 4) and a conclusion section (Section 5). The target group is urban planners.

2. Materials and Methods

In this study, we conducted a comprehensive search, collection, and analysis for communal resource planning, monitoring, and management tools. For this, we researched German and English literature as well as national and international online platforms. First, we searched within scientific databases (Sciencedirect and Scopus). A search with the keywords "urban management tool" and "urban resource management tool" at Sciencedirect and Scopus (within the title, abstract, and keywords) led to several thousand entries (see Table 1). However, by scanning the first pages of the search results, only a few suitable studies could be identified and added to the collection of reviewed tools. The suitability of a contribution or tool for this review was determined by whether it has a spatial and/or georeferenced database, a quantitative approach, and a model- or software-like applicability in the urban planning process. From expert interviews, we learned that these properties are seen as very helpful for urban planners to support a district assessment, a potential analysis, and political decision making.

Table 1. Search results by database and keywords (Status: 16 November 2021).

Keywords	Sciencedirect	Scopus
urban management tool	141,317	11,431
urban land use tool	66,234	2230
urban water management tool	79,426	3158
urban green management tool	48,760	789
urban materials management tool	83,452	669
urban ecology management tool	23,703	468
urban resource management tool	64,376	2674

Due to manifold contributions and analyses existing on communal energy planning (e.g., [30–39]) and transportation/mobility (e.g., [40–44]), such tools were explicitly excluded from this review. Similarly, tools with their main focus on stakeholder participation, such as those reviewed by Ataman and Tuncer [28], are not the focus of this review.

It became clear that most of the found studies (particularly in the scientific databases) host scientific concepts rather than applicable or applied models, tools, or software applications for said purposes. Thus, we supplemented the retrieved results from the scientific databases with an extensive and explorative search mode including EU, US, and other national project websites, national funding programs, reputable institutions' websites, city websites (geoportals), and other platforms. The main sources of the listed tools below were the Cities4forest toolbox, the German Federal Ministry of Education and Research (BMBF) funding programs RES:Z on "Ressourceneffiziente Stadtquartiere" (Resource efficient urban districts), and "Stadtklima im Wandel" (Urban Climate under Change) as well as their inherent research projects (e.g., [45,46]) and other national and international projects. This search was followed by a snowball system that was less controlled and more random than a structured database request from scientific databases since no review or structured overview on the available tools were available.

Then, we classified the found tools to answer the following questions: In which application areas can tools be divided? What are the major capabilities that can be distinguished? What technology readiness level do the tools have? We identified gaps and development needs in the fields of application and other identified categories relevant for urban planners (Section 3.1) and reviewed them (Sections 3.2 and 3.3).

3. Results

3.1. Classification

Based on the collected tools, we developed a classification scheme to classify the tools into different fields of application, type, availability, scale, and dimensionality (directionality). Within the categories we found different subcategories (see Table 2). Due to the broad fields and challenges of urban planning, we focused on tools addressing land use, water, urban green spaces (UGS), materials, and their nexuses, e.g., with urban climate. We classified the found tools accordingly (see Table 3). Then, we differentiated the tools' capabilities with respect to static assessment and viewers (e.g., geoportals), the dynamic monitoring and management of existing resources (e.g., dashboard), and the planning of new resources or changes/transition (area/UGS and items). Considerable other capabilities (e.g., routing) were not included in the review. Next, we classified the tools according to their technology readiness levels (TRL) as scientific concepts (TRL3), scientific codes (TRL4), standalone software or web-based or app-based tools (TRL5 to TRL7), or as qualified tools (TRL8 to TRL9). Furthermore, we identified whether the tool is available freely (open-source) or commercially or if it is unavailable for use or further development. Then, we differentiated the scale addressed by the tool. This ranged from the building scale or lower (single UGS or partial surfaces) to the city block scale, district scale that includes multiple building blocks and UGS, city scale, and whole metropolitan areas. The national scale was used for some kinds of key performance indicators or management purposes (e.g., SDG reporting), but it was outside of the scope of this study. Finally, we assessed the directionality of the tool, which describes if a tool is providing information from one stakeholder or a stakeholder group only (one-directional) or if it allows for communication/interaction (bi-directional) between different stakeholders. For example, geo-portals could either provide administrative information to the citizens (one-directional), e.g., [13,25,47,48], or they can also ask for data or feedback from citizens (bi-directional), e.g., 3D Public Survey [49–52], DIPAS [53,54], or CITY_CODE [55,56], which could improve citizens' participation, governmental processes, and actions. We excluded simple information web tools from the subsequent review and focused on assessment, monitoring/management, and planning tools.

Table 2. Classification scheme for urban resource management tools.

Application	Capability	Technology Readiness Level (TRL)	Availability	Scale	Directionality
• Land use • UGS • Urban climate • Water • Materials	• Static assessment, viewers • Dynamic monitoring/management • Planning	• Scientific concept (TRL3) • Scientific code (TRL4) • Standalone software, app, or website (TRL5-7) • Qualified tool (TRL8-9)	• None • Open-Source • Commercial	• Building • City block • District • City	• One-directional • Bi-directional

Table 3. List of identified and reviewed tools for urban resource monitoring, planning, and/or management.

Tool (Source, Developer/Operator)	Application					Capability			Type				Availability			Scale				Dir.
	Land/surface/space use	Urban Green Space	Urban climate	Water	Materials/Waste	Assessment/Viewer	Monitoring/Management	Planning/Simulation	TRL3/4: Scientific concept/code	TRL5/7: Standalone software	TRL5/7: Web-based tool/app	TRL8/9: Qualified tool	None	Open source	Commercial use	Building	City block	District	City	One or two
namares [57,58]	x	(x)	(x)	x	x	x	x	x	x	-	x	-	x	-	-	x	x	x	x	1
PALM4U [59,60]	x	x	x	x	x	-	-	x	x	x	-	x	-	x	-	(x)	x	x	x	1
ENVI-met ** [61]	x	x	x	(x)	-	-	-	x	-	x	-	x	-	-	x	(x)	x	x	x	1
INKAS [62]	-	(x)	x	(x)	-	-	-	-	-	-	x	-	-	x	-	-	x	x	x	1
MeinGrün App [63]	-	x		(x)	-	x	-	-	-	-	x	-	-	x	-	-	-	-	x	1
Kommunaler Flächenrechner 2.0 [64,65]	x	-	-	-	-	x	x	x	-	-	x	?	-	x	-	-	-	-	x	1
GREEN-AREA [21]	x	x	-	-	-	x	-	x	-	-	x	x	-	-	x	x	x	x	x	1
Labs: Tree Canopy [66,67]	-	x	-	-	-	x	(x)	-	-	-	x	-	-	x	-	-	x	x	x	1
HydroWebView/STORM [68]	x	-	-	x	-	-	x	x	-	x	-	-	-	-	x	-	?	?	?	1
WABILA-Expert [69]	-	x	x	x	(x *)	-	-	x	-	x	-	?	-	-	x	-	x	x	x	1
Storm Water Management Model [70,71]	-	-	-	x	-	-	-	x	-	x	-	?	-	x	-	-	x	x	x	1
SWMM-UrbanEVA [72]	-	x	x	x	-	-	-	x	x	-	-	-	-	x	-	-	x	x	-	1
Versickerungs-Expert [73]	-	-	-	x	-	-	-	x	-	x	-	?	-	-	x	-	x	-	-	1

Table 3. *Cont.*

Tool (Source, Developer/Operator)	Application					Capability			Type				Availability			Scale				Dir.
	Land/surface/space use	Urban Green Space	Urban climate	Water	Materials/Waste	Assessment/Viewer	Monitoring/Management	Planning/Simulation	TRL3/4: Scientific concept/code	TRL5/7: Standalone software	TRL5/7: Web-based tool/app	TRL8/9: Qualified tool	None	Open source	Commercial use	Building	City block	District	City	One or two
Planungshilfe Abfluss-Steuerung (PASST) [74]	-	-	-	x	-	-	x	x	x	-	-	?	-	x	-	-	x	x	x	1
SAmpSONS2 [75]	-	-	-	x	x	-	-	x	-	x	-	?	-	x	-	-	x	-	-	1
TransMiT WebViewer [76]	-	-	-	x	-	x	-	x	x	-	x	-	-	x	-	-	x	x	-	1
Greenscenario [77]	-	x	x	x	-	-	-	x	-	-	x	-	-	-	x	?	x	x	-	1
ECOPLAN Tools ** [78,79]	x	x	x	x	x	x	(x)	x	x	-	-	-	x	-	-	?	x	x	?	1
CityCode/ DATA4CITY [55,56]	-	-	-	-	-	x	-	-	-	-	x	-	-	-	x	-	-	-	-	2
City Water Resilience Framework (CWRF) [29]	-	-	-	x	-	x	-	x	x	-	-	-	x	-	-	-	-	-	x	1
Siedlungsflächenmonitor web GIS [11]	x	-	-	-	-	x	x	-	-	-	x	?	(x) [1]	-	-	-	-	-	x	1
Collect Earth [80]	x	x	-	-	-	x	x	-	-	x	x	-	-	x	-	-	x	x	x	1
Green Infrastructure Toolkit [81]	x	x	-	x	-	x	x	x	-	x	x	x	-	x	-	-	-	x	x	1
Urban Forest Management Plan Toolkit [82]	x	x	-	-	-	-	-	x	x	-	-	-	-	x	-	-	-	x	x	1
i-Tree Eco [83]	x	x	x	x	-	x	x	x	-	x	-	x	-	x	-	x	x	x	x	2
Healthy Trees, Healthy Cities [84]	-	x	-	-	-	x	x		-	-	x	?	x		-	x	x	x	x	2
Treeplotter [85]	-	x	-	-	-	x	x	x	-	-	x	?	-	-	x	x	x	x	x	2
Urban Tree Canopy Assessment [86]	x	x	-	-	-	x	x		x	-	-	-	x	-	-	-	-	x	x	1
Toolkit for Community Participation in Pocket Parks [87]	-	x	-	-	-	-	x	x	x	-	-	-	-	x	-	x	x	-	-	2
Community Assessment & Goal-Setting Tool [88]	-	x	-	-	-	x	-	x	x	-	x	-	-	x	-	-	-	x	x	1
SolVES [89]	x	x	-	x	-	x	-	x	-	x	-	x	-	x	-	-	-	x	x	1
Learning for Nature [90]	x	x	x	x	-	-	x	x	x	-	-	-	-	x	-	-	-	-	x	1
Aqueduct Global Flood Analyzer [91]	-	-	-	x	-	-	x	x	-	-	x	x	-	x	-	-	-	x	x	1
Green-Gray Assessment Guide [92]	-	x	-	x	-	x	-	x	x	-	-	-	-	x	-	-	-	-	x	1
WaterWorld [93]	x	-	-	x	-	-	x	x	-	-	x	?	-	x	-	-	-	-	x	1
Co$ting Nature [94]	x	x	-	-	-	-	x	x	-	-	x	?	-	x	-	-	-	-	x	2
Water Funds Toolbox [95]	x	-	-	x	-	-	x	x	x	-	-	?	-	x	-	-	-	-	x	1

Table 3. *Cont.*

Tool (Source, Developer/Operator)	Application					Capability			Type				Availability			Scale				Dir.
	Land/surface/space use	Urban Green Space	Urban climate	Water	Materials/Waste	Assessment/Viewer	Monitoring/Management	Planning/Simulation	TRL3/4: Scientific concept/code	TRL5/7: Standalone software	TRL5/7: Web-based tool/app	TRL8/9: Qualified tool	None	Open source	Commercial use	Building	City block	District	City	One or two
i-Tree Hydro Plus [96]	x	x	-	x	-	x	x	x	-	x	-	x	-	x	-	-	-	x	x	2
Biodiversity A-Z [97]	x	-	-	-	-	-	-	-	x	-	-	-	-	x	-	-	-	-	x	1
Global Forest Watch [98]	x	x	-	-	-	x	x	-	-	x	x	-	-	x	-	-	-	-	x	1
Complete Streets [99]	-	x	-	-	-	-	-	x	x	-	-	-	-	x	-	-	-	x	x	1
InVEST [100]	x	x	x	x	-	x	x	x	-	x	-	?	-	x	-	-	x	x	x	2
The Atlas [101]	x	x	x	x	x	-	x	x	x	-	-	-	-	x	-	-	x	x	x	1
ROAM [102]	x	x	-	-	-	x	-	-	x	-	-	-	x	-	-	-	-	-	x	1
Stewardship Mapping and Assessment Project (STEW-MAP) [103]	x	-	-	-	-	x	-	-	x	-	-	-	x	-	-	-	-	x	x	1
GI Valuation Tool Kit (GI-Val) [104,105]	x	x	-	-	-	x	-	-	x	x	-	-	-	x	-	(x)	x	x	x	1
Forecast reference evapotranspiration tool (FRET) [106,107]	x	-	-	x	-	-	-	x	x	x	-	?	-	x	-	-	-	x	x	1
Worksheet for Review of Municipal Codes and Ordinances [108]	x	x	-	-	-	-	x	x	x	-	-	-	-	x	-	-	-	-	x	1
Integrated Urban Metabolism Analysis Tool (IUMAT) [3,109,110]	x	-	-	-	x	x	-	x	x	-	-	-	x	-	-	x	x	x	x	1
Smart Urban Metabolism (SUM) [111]	-	-	-	-	x	x	-	-	x	-	-	-	x	-	-	x	x	x	-	1
Greenpass [112,113]	-	-	x	-	-	x	-	-	-	x	-	(x)	-	-	x	x	x	x	-	1

x: category applies; (x): category partly applies; -: category does not apply; ?: unclear/insufficient information; *: pollution; **: incl. energy aspects; [1] restricted access; Dir. = directionality.

3.2. Review of Each Field of Application

3.2.1. Land Use, Surface Use, and Urban Green Tools

Tools for planning land and surface (roofs and facades) use in urban areas are manifold. Numerous tools are available to estimate the benefits obtained from urban green spaces and/or to figure out the management needs for UGS maintenance [5]. With the substantial number of tools, there are also various themes that the tools are somewhat connected with. Monitoring is an integral part of the management of UGS, and with the focus on the benefits of green spaces to urban quality of life, aspects such as usage, experiences, and accessibility are also considered. Overlaps exist, mainly with water and urban climate tools. In the following section, the reviewed tools are described in detail.

Collect Earth [80] is a satellite image viewing tool and interpretation system developed by SERVIR Global (NASA and USAID initiative) and FAO that enables users to analyze land use/land cover (LULC) change from high and very high resolution satellite imagery sourced from Google Earth, Bing Maps, etc. [114]. It can help identify and monitor urban green spaces and their implementation progress in an efficient manner. **Resource Watch** is another such monitoring tool. However, it is a tool that operates at a macroscopic level [115]. It features hundreds of datasets that help users visualize the state of the planet's resources and people. Using this, benefits from the implementation of urban green spaces can be estimated at a regional scale with the help of Collect Earth. Similarly, The U.S. **Community Protocol for Accounting and Reporting of Greenhouse Gas Emissions** is also a potential resource for the monitoring of urban green spaces [116]. However, rather than directly aiding in the process of monitoring, it instead offers the advanced methodologies and the best practices to assist local governments in measuring and reporting area emissions. This tool is particularly useful to assess the effects of urban green spaces in a localized region. **Kommunaler Flächenrechner 2.0** is a national and regional tool for the depiction of current land use designation and for a top-down derivation of a communal land use budget to meet national goals [64,65]. **Siedlungsflächenmonitoring NRW** [11] is a web-GIS tool that focuses on regional and communal land use monitoring and management by depicting land reserves per use categories in the land development plan and redesigned areas. Mapping tools such as **Treetect [117]** or remote sensing products are mapping urban green spaces from satellite data, e.g., via machine learning/neuronal nets (except a few difficult cases); however, they do not yet quantify other parameters such as species type, canopy size or leaf area, which are relevant for urban climate modeling. Other monitoring tools also include **Urban Tree Canopy Assessment** [86], which can measure the extent of the tree canopy and help communities understand their total tree and forest resources and establish tree canopy goals as part of broader urban greening and sustainability initiatives.

Various tools offer similar advisory utilities, such as the **Green Infrastructure Toolkit [81]**, which highlights the common approaches taken in cities across the world to integrate green infrastructure and spaces to manage stormwater runoff, thus aiding local governments to compare and analyze the best-suited option according to their requirements. Tools can also have a more direct contribution to the planning of urban green spaces, such as the **Urban Forest Management Plan Toolkit** [82] by the Inland Urban Forest Council that outlines a structured plan for designing and implementing an urban forest management plan. Likewise, the **Urban Forestry Toolkit** also provides a step-by-step guide to planning and implementing an urban forestry project. On the other hand, tools such as **i-Tree Eco** are more user-driven in their approach. i-Tree has five core tools that are used to analyze and assess urban and rural forestry. **i-Tree Eco** is their flagship tool, and it utilizes data collected in the field from either single trees, complete inventories, or randomly located plots to quantify forest structure, environmental effects, and the value to communities [83]. **Healthy Trees, Healthy Cities** also undertakes a similar user-driven approach, as it enables users to undertake the sampling and data collection process of individual trees to create an inventory of urban trees and their health indices [84]. **Treeplotter** is another tool that creates urban tree inventories and helps in the management of urban forests but is instead dependent on GIS for data rather than on the users [85]. **Tree Canopy** [66,67] analyzes aerial data together with other public data (e.g., 3D digital surface models and socio-economic data) to map a city's tree coverage, the average land surface temperature, and population density.

The collection of data from users can be an integral part of urban green space management, and tools are not just capable of utilizing such data but can also organize community efforts. The Toolkit for Community Participation in **Pocket Parks** helps in the design, execution, and development of small-scale urban 'pocket parks' with the help of community participation [87]. The Stewardship Mapping and Assessment Project (**STEW-MAP**) by the USDA Forest Service is capable of studying how civic groups are working towards the fostering of stewardship in cities [103]. Upon the analysis of 28 criteria, **The Community Assessment and Goal-Setting Tool** [88] can assess the community for the development and management of urban green spaces. Such tools can be indispensable for administration, and tools such as SolVES are designed to aid decision makers. **Social Values for Ecosystem**

Services (SolVES) is a tool that is capable of assessing, mapping, and quantifying the perceived social values of ecosystem services, thus helping administrators to make informed decisions while implementing urban green space measures [89]. Similarly, **Learning for Nature** by the UNDP [90] connects biodiversity policymakers, change makers, and on-the-ground subject matter experts to promote biodiversity conservation and facilitate the achievement of the Sustainable Development Goals. The tool **GREEN-AREA** is a commercial service that assesses the potential of urban greening measures on building roofs and impervious soil surfaces [21,118,119]. The viewer-based service allows for georeferenced individual plot assessments of their technical potential and simplified greening impact for green roofs and unsealing ground (for examples see [22,23]).

The utility of tools for administrators in urban green spaces is not just limited to the domain of community management. **WaterWorld** and **Co$ting Nature** are two analysis tools to explore ecosystem services using spatial data as well as models of biophysical and social systems. Co$ting Nature can help cities understand the value of forests at multiple scales since users can try alternative scenarios based on different policy options [94]. For other tools of water such as **WaterWorld** [93], **Aqueduct Global Flood Analyzer** [91], the **Green-Gray Assessment Guide [92]**, the **Water Funds Toolbox** [95] or **i-Tree HydroPlus [96]**, see Section 3.2.2.

Although not directly relevant to urban green spaces, tools such as **Biodiversity A–Z** [97] can assist in the maintenance of urban green spaces. The database website provides information about regional biodiversity and biodiversity conservation. Similarly, **Global Forest Watch** [98] can analyze forests and forest trends, which can be useful in realizing appropriate conditions for maintaining urban green spaces. **Restoration Opportunities Assessment Methodology (ROAM)** can also be used as a reference for the development of urban green spaces, as it provides a framework for building a forest restoration program from the ground up [102].

Particular tools can also help in the integration of green spaces into urban settings. **Complete Streets [99]** is a global transportation design and policy approach that ensures safer, convenient, and accessible transport and fosters the introduction of trees on urban streets, thereby contributing to the growth of urban green spaces. **InVEST** (Integrated Valuation of Ecosystem Services and Tradeoffs), developed by the Stanford University National Capital Project, helps map and quantify the natural resources and services that help sustain human life and the health of the ecosystem [100]. **The Atlas** [101] is another tool that can support decision makers, as it provides an online community for local government leaders to browse case studies, follow topics, and crowdsource ideas and advice. The **Worksheet for Review of Municipal Codes and Ordinances** similarly helps to assess the environmental friendliness of policies and regulations. It seeks to provide guidance to maximize tree cover while considering public safety, visibility, access, and economic value [108].

MeinGrün App is a web-based tool available for the German cities Heidelberg and Dresden that helps citizens to find urban green spaces with particular points of interest and furnishing/equipment or that are most suitable for their leisure [63]. It includes multiple characteristics such as grass, trees, water, animals, slope, size, shade, quietness, fitness equipment, sport facilities, benches, or waste bins.

3.2.2. Water Tools

Water-related planning tools range from groundwater simulations to rainwater and dirt water runoff and treatment systems (incl. pollutant extraction), infiltration systems, evapotranspiration, and urban water inventories. Thus, it has overlaps with land use regarding the imperviousness and infiltration of surfaces, with urban green and blue-green infrastructure (BGI), local urban climate models (evapotranspiration), and with material flows.

WABILA-Expert is a water balance model to realistically depict the local water supply and inventory and to support rainwater management [69,120]. It can also compare different alternative options of rainwater usages that are in accordance with local conditions. The **Storm Water Management Model (SWMM)** is a dynamic rainfall–runoff–subsurface runoff simulation model with extensive functionalities for single event to continuous simulation that can plan and size components and retention devices of the drainage system for flood protection in urban areas [70,71] (Further useful models from the EPA in particular on stormwater but also on watershed management, ecosystems, and green infrastructure can be found here: https://www.epa.gov/water-research/green-infrastructure-modeling-toolkit (accessed on 16 March 2022). Furthermore, it maps potential flooding areas of natural canal systems and includes pollution, controls property runoff, and evaluates best practices to reduce pollution during rains. **SWMM-UrbanEVA** is a fully integrated extension of SWMM with improved simulations for shading and evapotranspiration of urban vegetation [72]. **Versickerungs-Expert** is a tool to plan, construct, and operate systems for the infiltration of rainwater, including area infiltration; infiltration basins; trench, pipe trench, and hollow-trench infiltration; shaft infiltration; edge, pointed, and hollow channels; and the dimensioning of drainage channels. Furthermore, it can import KOSTRA rain data from Deutscher Wetterdienst (DWD). **Planungshilfe Abfluss-Steuerung (PASST)** is a rather simple checklist and evaluation table to improve and make the rainwater and dirty water runoff more flexible [74]. Flood warning system **HydroWebView** software (including rainfall–runoff modeling with STORM.Design, STORM.Sim, and STORM.Pro) is a comprehensive planning tool for the planning of sustainable rainwater management, general drainage planning, and aspects of water ecology and flood protection with a graphical user interface and GIS interface, import and export functions, and automated reporting. It provides simplified flooding evidence according to the German standard DIN 1986-100 and the preparation of water balances [68]. **SAmpSONS2** is a simulator to visualize material flows in resource-optimized sanitary systems and can consider up to eight trace elements/micropollutants as well as technologies for nutrient recovery [121]. As a result, it produces Sankey diagrams but no dynamic simulations of the sewage systems [75,121]. The **TransMiT WebViewer** shows a surface model of an urban district with a simulation of potential flooding, surface roughness, and emergency water runoff paths on the surface [76]. The **Forecast Reference Evapotranspiration Tool** (**FRET**) provides evapotranspiration forecasts at a 2.5 km grid resolution for the U.S. [106]. Based on FRET, Hamouda et al. assess forecasts for evapotranspiration to enable prospective irrigation scheduling for different microclimate regions. However, this focuses on crops rather than on urban vegetation [107]. Vystavna et al. developed a tool for urban groundwater resource management with respect to contaminants, tracing sewage leakages to groundwater [122]. The **City Water Resilience Framework (CWRF)** is a governance-based water resilience planning tool that enables cities to collectively assess and plan for strengthening urban water resilience [29]. The **Aqueduct Global Flood Analyzer** [91] assesses the current and future risks of flooding and monitors the effects of climate change. The tool can help users understand and estimate the effectiveness of UGS in mitigating floods in flood-prone cities. The **Green-Gray Assessment Guide** by the World Resources Institute [92] can be used for investigating and valuing the costs and benefits of integrating green (or natural) infrastructure into existing water supply systems to improve their performance. **WaterWorld** allows the user to test out alternative management strategies and understand how these decisions would impact the ecosystem services provided by water resources [93,123]. The **Water Funds Toolbox** helps in implementing the Water Funds model that unites public, private, and civil stakeholders for the mutual aim of water security through natural solutions and by managing watersheds in a sustainable way [95]. The **i-Tree HydroPlus** tool allows for the comparative analyses of different land cover scenarios and their hydrological impacts at various scales [96]. The **GI Valuation Tool Kit** (GI-Val) evaluates the social and environmental benefits of BGI [104,105,124].

Further tools on BGI and, in particular, on hydrological impacts (in urban areas), sewer overflow, stormwater pollution control and vegetative filters, water quality, and the estimation of surface water runoff and runoff reduction such as **VFSMOD** or **Long-Term**

Hydrologic Impact Assessment (L-THIA) for its impact on soil, land use, and long-term precipitation can be found in [5,125]. Other models and tools focus on the energy and water nexus, such as SIMGRO and SUEWS, e.g., see [126–128]. These tools are not further considered here.

3.2.3. Material/Waste Tools

The tools simulating material and waste can range from the pollution of single chemical elements (trace elements), micropollutants, and chemical compounds or gases (particles and aerosols) to larger mass flows in the air, water, and soil (eluate and waste). Furthermore, it can include construction material stocks (urban mines) and flows as well as waste stocks and flows. "Urban metabolism (UM) is fundamentally an accounting framework whose goal is to quantify the inflows, outflows, and accumulation of resources (such as materials and energy) in a city." [129] This includes the macro material/waste stocks and flows that supply a city with demanded goods (incl. energy and water) and relieves it of waste but also micro stocks/flows such as greenhouse gas emissions or pollutants (e.g., see [130]). This field has overlaps with some overarching tools that include trace elements, aerosols, and particle simulations (e.g., ENVI-met and PALM). A similar concept comprises the urban industrial symbiosis [131], which is based on material flow analysis and energy balancing. However, other aspects, such as urban land use, urban climate, or urban green spaces, are often excluded from the urban metabolism or the urban industrial symbiosis concepts as well as spatially explicit modeling. Furthermore, the data availability of urban metabolism models is an issue, so most studies focus on a limited set of resources—materials (particularly metals), energy, water, and nutrients—and a single time period [129].

Mostafavi et al. developed an **Integrated Urban Metabolism Analysis Tool (IUMAT)** [3,109,110], which provides a quantitative approach to assessing the sustainability indicators in a city. The IUMAT covers land use/cover, transportation, and energy/water/resource use as well as the inter-dependencies between them. Zhu et al. [132] analyzed how geographical information systems can support urban mining assessment. Badach et al. [133] developed a QGIS-based urban planning tool for air quality management zones, including ventilation potential and human exposure to pollution. However, the simulations use a grid size of 200m x 200m and thus have quite a low resolution and are not further considered here.

The **BRIDGE** project [134] developed a GIS-based decision support on urban metabolism to assess urban planning alternatives but empathized the need for a local focus [125,128]. Their **Smart Urban Metabolism (SUM) model** can provide real-time feedback on energy and material flows from the household to the urban district level [111]. However, none of these models seem to be readily available for urban planners and decision makers. Otero Peña et al. [24] provided a GIS-based resource efficiency analysis and urban metabolism study on the city scale of Mexico City. However, its spatial granularity is relatively low.

Further academic models on material flow accounting models include, e.g., the urban metabolism analyst (UMAn) [135], urban industrial symbiosis [131], and urban material or waste flow analysis [136–141] in respective case studies that are not necessarily spatially explicit and are not further assessed here.

3.3. Overarching Tools

PALM4U is a capable urban climate model for the simulation of urban atmospheric boundary layers and to support practical city planning related to the urban microclimate and climate change [59]. Currently, it includes seven modules of urban surfaces, chemistry, technical solutions, radiation, impact, vegetation, and soil. It has turbulence simulations, domain size definition, energy balance solvers, wall material and heat transfer models, indoor climate, radiative transfer, reflections and canopy shading, chemistry transport and reactions, roots, soil temperature and moisture, and a multi-agent system of urban residents as well as analysis tools and a GUI. The model is not limited to urban areas. However, this academic model is not easy to handle and does not work on administrative/governance levels such as individual buildings or plots. The model is based on PALM version 5.0 and is modelled in FORTRAN code [142]. Further information (handbook, etc.) can be found in [60,142,143].

ENVI-met is a leading software in analyzing the effects of architecture and urban planning [61] in an urban microclimate model. It includes a solar analysis with long- and short-wave radiation, shading and reflections, evapotranspiration and plant water demand, the temperature of surfaces, green façades and roofs, wind flows and patterns in complex environments, comfort, and the emission and transport of particles/aerosols and NO, NO_2, and O_3 as well as biometeorological indices that can be calculated. Furthermore, plant growing conditions, wind stress, tree damage, and a simulation of their water demand are included, and built density and urban morphology can be assessed [144]. Moreover, it is coupled with a multi-criteria decision analysis for different interventions in case study districts, e.g., [145]. The commercial tool can visualize data and can be connected with Python code.

The **namares** tool is dedicated to assessing land use, water, ecosystem services, material aspects, and intervention (improvement) measures on the district level down to individual buildings and plots as well as their partial surfaces [57,58]. The tool enables technical, economic, and environmental assessments of the surface inventories and of the potential of different sustainable development interventions within a city. For example, it quantifies the actual degree of land sealing and the required area for cars and waste bins per plot. With this information, it calculates predefined resource enhancement potentials and the efficiency of improvement interventions such as the de-sealing of soil, the installation of green roofs and facades, photovoltaic (PV) and solar thermal installations, or a combination of PV and green roofs. The calculated indicators per intervention and building, plot, or partial surface are, among others, the sealing degree of the soil; the number of private trees; the ecoscore; evapotranspiration; cooling; biodiversity gain/loss; CO_2 fixation; the effects on fine dust; NO_2 (nitrogen dioxide), SO_2 (sulfur dioxide), and O_3 (ozone) levels; induced mass flows of materials; and cost (incl. investments and funding). The tool is applied to a case study in Germany but is under development and not yet available.

The simulation software **Greenscenario** is an integrated planning method for concepts of water-sensible and climate-adapted urban redevelopment that visualizes the impact of single measures quickly and comprehensibly. It allows a comparative assessment and the identification of optimization potentials [77]. However, it only includes the assessment of BGI and requires data acquisition and entry. In addition, it seems that it is not working with existing urban data (3D models) but requires prior modeling. Reference projects in larger European cities range from 1–95 ha.

The **Greenpass** [112] assessment toolbox allows a rough evaluation of the climate resilience of buildings, urban districts, and open spaces via five indicators and based on machine learning and database requests. It works with LOD 0 (2D floor plans and building height) and can be applied both to existing and new districts. Greenpass calculates the thermal exhaust air stream, thermal comfort, run-off coefficient, CO_2 fixation, and thermal storage capacity based on a simulation database powered by ENVI-met and urban standard typologies [113]. Moreover, the initiative offers a pre-certification and certification with up to 28 indicators, but it is limited to a district size of ca. 4 ha and cannot simulate the actual project situation.

ECOPLAN tools aim to fulfill different urban planning requirements and have several modules for monitoring, trade-off, participation, or simulation [78]. They follow a classical planning procedure: First, a principal decision is required with respect to a certain objective, e.g., regional development or ecological objectives. Then, alternative options, in particular on land cover, land-use change, and the integration of ecosystem services, are developed, compared, and evaluated, followed by decision making and implementation. The tools include an ecosystems services interaction database as well as a scenario evaluator as a QGIS plugin [79]. The web viewer version seems to consist of different layers but was not accessible at the time of research.

INKAS and INKAS-NRW are climate adaptation tools of DWD that provide information, district consulting services, and planning support for urban planners and citizens to develop urban climate adaptation measures and heat-adapted districts [62,146]. The tools analyze different urban fabrics and the effects of urban heat island reduction measures for each urban fabric type. Furthermore, INKAS provides information on the degree of sealing and the average building height. However, the INKAS tool is not spatially explicit but a general information tool, while INKAS-NRW (Fachinformationssystem Klimaanpassung) is a map-based geoinformation portal with climate adaptation information, e.g., on climate impact (today and expected), building densities, green roof cadasters and potentials, human health, and the soil moisture applied to North-Rhine-Westphalia (NRW), Germany [147]. However, not all intended categories are coved with data yet (e.g., drought, biodiversity, flooding, agriculture, and forestry).

CityCode assesses the "urban quality index" with urban city monitoring and hyperlocal questionnaires comprising the fields of attractiveness, cleanliness, safety, service, and environment [55,56]. Furthermore, it allows for crowd geo-mapping and commenting by citizens. This is transferred to a georeferenced forum to collect, exchange, and evaluate ideas in a participative co-design process with citizens to improve city life and conditions in succeeding (construction) projects. It is implemented in a native app (IOS and Android) and City cockpit with APIs for sensors or other platforms. However, this tool does not use any climate, building, or infrastructure stock data.

4. Discussion

4.1. Communal Assessment and Information Viewer (Web) Tools

Publicly accessible communal assessment tools often comprise land use cadasters and maps showing potentials for change and interventions on both the aggregated and disaggregated levels. However, this is not a detailed city inventory on the plot level but an aggregated depiction of the situation depending on the considered aspect as well as on data protection aspects. The underlying data/information are often not publicly revealed or can be extracted for further assessment, data merging, or use. Furthermore, most tools focus on specific fields or planning aspects but lack an integrated perspective that explicitly considers the interdependencies. Thus, newer approaches propose a systems approach [1] including multipurpose cadasters, open data, and collaborative participation interfaces (e.g., [148]).

Publicly accessible communal information web tools mainly have simple features based on a static assessment. Only a few accessible communal information web tools are integrated to their full extent. Web viewers are usually specialized in showing different layers or point features. Databases often only offer full datasets that are not converted, unified, or filtered. The information in publicly accessible communal information webtools is mostly static and historic. The timeliness of the data depends on data updates; (almost) real-time data are not shown in such systems. Analysis features contain mostly point, line, or area marking functions, distance and area measuring functions, or sometimes elevation profiles and similar functions. Only a few tools comprise a participation module where stakeholders can add data or suggest recommendations for action.

4.2. Communal Monitoring and Management (Web) Tools

Among the identified and reviewed tools, we did not find any real-time monitoring tools that map and assess the existing building and infrastructure stock with respect to its current resource use over a longer time period. The available static information on this is distributed in different GIS layers (solar, green roof, or tree cadasters) or other datasets (waste generation/collection, ground surface permeability, rainwater harvest, and runoff). Sensors are available that measure urban climate or traffic emissions in a higher or lower resolution depending on the sensor grid. However, these are often only installed at scarce locations and in neuralgic points, not covering whole city districts or cities, and their sensor information is not yet merged into a digital urban twin allowing for integrated modeling, planning, and decision-making support. Furthermore, a finer spatio-temporal resolution is recommended by [149] for monitoring energy and water flows in order to develop interventions to optimize resource flows.

Management approaches are restricted to tools that can compare different invention designs, investments, or decision-making options. Some include multi-criteria decision approaches. However, we did not find integrated management tools, e.g., that support the operationalization of city strategies (e.g., climate neutrality or resilience goals); the derivation of road maps, action plans, or concrete interventions; or supportive functions for an integrated project or intervention management (e.g., joint data management, contact data, collaboration support for city departments, reminders, and success indicators).

4.3. Communal Planning and Simulation (Web) Tools

Tools for land use, urban green spaces, water management, and flooding protection are extensive and available, including detailed planning. Newer tools include ecosystems and ecosystem services, but they are not covered extensively by any of the reviewed applications. Moreover, a few integrated or multi-purpose planning approaches or designs of multifunctional surfaces (e.g., [150]) are mentioned but not yet broadly supported by commercial digital planning tools.

The reviewed assessment, planning, and simulation tools focus on ground surfaces and roofs where spatial information can be captured easily from aerial or satellite data. Surfaces on facades are rarely considered in the reviewed tools. Only ENVI-met, namares, and PALM4U are considering building facades in their models. Simulation tools such as ENVI-met or PALM4U use simplified urban 3D models instead of actual and detailed urban 3D models (LOD3). The optimization of the interplay of the different application areas and fields of view are only rudimentarily recognizable in simulations by PALM4U, ENVI-met, namares, and GreenScenario, for example, via an intervention design or scenario comparison. However, according to the available information, GreenScenario seems to be a conceptual vision and not fit for action (in operation).

The existing planning and simulation tools mostly operate on a city block scale and not yet on the surface and plot scales (except for namares). However, only the latter detailed planning level allows for an actual plot- and stakeholder-specific information that can support decision making and change easier than voxel-wise or block-wise simulations and assessments.

4.4. Identified Research and Tool Development Gaps

The reviewed tools largely cover the fields of urban land use and water management as well as integrated urban climate modeling, while the fields of materials and material flows from buildings, infrastructures, and municipal, commercial, or industrial waste are underrepresented. Furthermore, the investigated tools mostly use official data (e.g., georeferenced data and statistics) or citizen information (open source, sentiments, and proposals) instead of sensor data (e.g., from smartphones, meters, or air, temperature, or weather sensors). Sensor data on urban climate are few since integrated and broad sensor networks are in installation in urban areas to provide information for smart city models. Moreover, tools mostly operate on the city (block) scale and not yet on the partial surfaces, building, and plot scales. However, only the latter detailed planning level allows for actual decision support in urban development processes.

Furthermore, our research experiences indicate that data from different city departments are often not shared or merged to enable the generation of data pools, digital twins, or other smart city models. It remains unclear why this is the case—a lack of staff, expertise, or willingness.

Public urban green space is often registered and inventoried, and its data are publicly available (e.g., tree inventories), while private urban green space is rarely mapped even though it constitutes a large share of urban green space in dense inner-city districts, e.g., ca. 50% in [151]. Additionally, the evapotranspiration of (street) trees should be integrated with their water demand and their potential cooling during the hot and dry seasons in existing models. In addition, a discussion on economic assessment or the appropriate monetization of urban ecosystem services is lacking, which could be included in a monitoring, planning, and decision support system that also covers the economic perspective.

Moreover, integrated and spatially explicit inventory assessment tools of urban districts are lacking that comprise more than a few indicators, that include the assessment of the economic impacts and social perspectives of interventions and improvement measures, have a multi-criteria decision support approach, include project/intervention management support, and use actual building stock data instead of urban fabrics or urban standard types. Moreover, optimization approaches to the interplay of the different application areas and fields of view are lacking. In addition, a joint database, for example, in a city information model or digital twin (see, e.g., [152]) and a joint modeling environment or interfaces between the sectoral tools, particularly from water, land use, climate, and ecosystems are required to combine the existing data and tools in an adequate and efficient way. Furthermore, many planning tools are available, but (real-time) monitoring or management tools that can quickly identify, organize, and realize maintenance and improvement projects are rare. Moreover, objective comparisons of the available tools' capabilities are missing with respect to spatial and temporal resolution, simulation precision, and uncertainty, e.g., on the same open dataset or case study.

Moreover, dynamic modeling and monitoring or assessments over several time periods should be considered to actually reflect and measure a system change and urban transformation, e.g., the impacts of urban interventions/improvement measures.

Furthermore, an overarching general framework of the calculated indicators or at least a minimum collection of "must-have" indicators (as an overview) provided by existing web-based tools and assessment methods is missing. Instead, every tool and every community are using their own data structure, data formats, and indicators, hampering standardization and comparison. Recently, respective typologies of indicators were published [153,154], and a standard (DIN SPEC 91468 [155]) is under development. However, these indicator catalogues or guidelines are not harmonized, scientifically published, or internationally agreed on.

4.5. Limitations

Although our study showed numerous results, it was also restricted. The limitations of our study were the exclusion of energy or mobility tools and tools focusing on citizen participation as well as models and tools covering other/neighboring fields, such as air emissions and clean air strategies/interventions, chemical distribution and monitoring, detailed urban climate modeling, and biodiversity monitoring (incl. faunistic aspects). Furthermore, tools and models used on a national level could have been included but were seen as outside of the scope of this study since the focus lay on urban districts. In addition, due to the investigative and explorative character of this review using the snowball method, the list of reviewed tools is not exhaustive (e.g., see [6]). Some tools might have been missed and were not covered in this study. Furthermore, the classification of tools could have been conducted differently, e.g., thematically through the target user group or the input data requirements.

In addition, urban datasets are structured in different ways. In Germany, a standard is under way (see introduction), but other countries might have different geospatial data structures, data protection and ownership rights, statistics, etc., which might influence the usability of the reviewed tools.

Despite the data management and assessment of buildings, districts, and cities being a useful decision support, urban data collection is effortful. In the case of biodiversity and habitat data, however, this will be often required since comprehensive data, particularly on private areas, are often not available. Furthermore, we learned that urban data are underused due to capacity challenges, data ownership issues, and privacy concerns within city administration [27].

5. Conclusions

Our work summarizes the status quo and research gaps in communal urban tools for assessment and information viewers, monitoring, and management as well as planning and simulation. We identified and reviewed 51 tools and classified their fields of application, their capabilities, their types and TRL levels, their availability for users, the scales they cover, and their directionality.

The remaining open challenges include (1) the localization of SDG fulfilment efforts in the form of concrete interventions, e.g., by using a data-based approach that facilitates localization [27]. For this, near-real-time information would be required to actually design the interventions appropriately and to allow the planning based on this information and the monitoring of the interventions to also be close to real-time. (2) Furthermore, data acquisition, updating, and validation approaches are associated with a high level of effort. Thus, efficient acquisition and updating methods need to be developed for the urban data that are required and used by (academic) urban tools but are not yet available or updated in all communities and cities. In addition, data sharing within city departments or with other authorities (e.g., from the region or federal state) and automated image or data processing could help to support this. (3) Methods and tools to facilitate data management and the maintenance of official urban data are required, e.g., via automation, which could relieve administrative staff so that they would have more capacities for project and intervention management, stakeholder communication, or participation processes. (4) To deal with data-based approaches, the enhancement of equipment, interdisciplinary skills, and involvement in localities/communities and their planning departments is required. In addition, a clarification of privacy issues and data ownership (e.g., between city departments) would be helpful to remove doubts. (5) More collaboration between science and practice would help to co-develop tools that address the problems and challenges of urban planners. This would lead to higher usability and practicability in urban planning and urban transformation processes, particularly with intersectoral functionality, project/intervention management support, and stakeholder participation. This should also include tool development from current static or single-period assessments to more dynamic and near-real-time dashboards/assessments and from aggregated input–output models or stock and flow models to spatially, explicitly, and highly resolved models on real urban data (see also [128]).

Author Contributions: Conceptualization, R.V.; methodology, R.V.; formal analysis, R.V., M.R. and E.N.; investigation, R.V., M.R. and E.N.; resources, R.V., M.R. and E.N.; data curation, R.V., M.R. and E.N.; writing—original draft preparation, R.V., M.R. and E.N.; writing—review and editing, R.V., M.R., E.N. and F.S.; visualization, R.V.; supervision, R.V. and F.S.; project administration, R.V.; funding acquisition, R.V. All authors have read and agreed to the published version of the manuscript.

Funding: We gratefully acknowledge the funding of the Federal Ministry of Education and Research (BMBF) of Germany in the course of the RESZ research project "NaMaRes–Bewertung der Ökologie, Wirtschaftlichkeit und sozialen Effekte von ressourcensteigernden Maßnahmen auf Quartiersebene–von der volkswirtschaftlichen zur akteursspezifischen Perspektive" (grant number: #033W111A). Furthermore, we gratefully acknowledge the funding from GRACE graduate School at Karlsruhe Institute of Technology (KIT) in cooperation with the University of Melbourne.

Acknowledgments: We thank Clemens Krug for his contributions to the tool research.

Conflicts of Interest: Despite being co-editor of the Special Issue "Resource Management in Urban Districts" in Sustainability, Rebekka Volk declares that she was not involved in the review process and did not decide on the publication of this manuscript. The other authors declare no conflict of interest. The funders had no role in the design of the study; in the collection, analyses, or interpretation of the data; in the writing of the manuscript; or in the decision to publish the results.

References

1. Bai, X.; Surveyer, A.; Elmqvist, T.; Gatzweiler, F.W.; Güneralp, B.; Parnell, S.; Prieur-Richard, A.H.; Shrivastava, P.; Siri, J.G.; Stafford-Smith, M.; et al. Defining and advancing a systems approach for sustainable cities. *Curr. Opin. Environ. Sustain.* **2016**, *23*, 69–78. [CrossRef]
2. Punter, J. Developing Urban Design as Public Policy: Best Practice Principles for Design Review and Development Management. *J. Urban Des.* **2007**, *12*, 167–202. [CrossRef]
3. Mostafavi, N.; Farzinmoghadam, M.; Hoque, S. A framework for integrated urban metabolism analysis tool (IUMAT). *Build. Environ.* **2014**, *82*, 702–712. [CrossRef]
4. Frantzeskaki, N.; McPhearson, T.; Collier, M.; Kendal, D.; Bulkeley, H.; Dumitru, A.; Walsh, C.; Noble, K.; Van Wyk, E.; Ordóñez, C.; et al. Nature-Based Solutions for Urban Climate Change Adaptation: Linking Science, Policy, and Practice Communities for Evidence-Based Decemberisation-Making. *BioScience* **2019**, *69*, 455–466. [CrossRef]
5. Dar, M.U.D.; Shah, A.I.; Bhat, S.A.; Kumar, R.; Huisingh, D.; Kaur, R. Blue Green infrastructure as a tool for sustainable urban development. *J. Clean. Prod.* **2021**, *318*, 128474. [CrossRef]
6. Voskamp, I.; de Luca, C.; Polo-Ballinas, M.B.; Hulsman, H.; Brolsma, R. Nature-Based Solutions Tools for Planning Urban Climate Adaptation: State of the Art. *Sustainability* **2021**, *13*, 6381. [CrossRef]
7. BBSR. Wie Geodaten und Digitale Tools die Raumplanung Verändern/How do Geographic Data and Digital Tools Change Urban Planning. 2020. Available online: https://www.bbsr.bund.de/BBSR/DE/startseite/topmeldungen/2020-izr-geoinformationen.html (accessed on 22 September 2021).
8. Barron, C. Ökologischer Planungsatlas, Stadt Mannheim, Fachbereich Geoinformation und Stadtplanung. 2022. Available online: https://www.mannheim.de/de/stadt-gestalten/planungskonzepte/oekologischer-planungsatlas (accessed on 10 February 2022).
9. Barron, C. Stadtklimaanalyse 2010, Stadt Mannheim, Fachbereich Geoinformation und Stadtplanung. 2022. Available online: https://www.mannheim.de/de/stadt-gestalten/planungskonzepte/stadtklimaatlas/stadtklimaanalyse-2010 (accessed on 10 February 2022).
10. KomMonitor. Kommunales Monitoring zur Raumentwicklung/Kommunal Monitoring for Urban Development. 2021. Available online: https://kommonitor.de/ (accessed on 16 November 2021).
11. NRW. Siedlungsflächenmonitoring Nordrhein-Westfalen—Ansatzpunkte für die Konzeptionelle Weiterentwicklung des Siedlungsflächenmonitorings Nordrhein-Westfalen, ILS—Institut für Landes- und Stadtentwicklungsforschung gGbmH. 2015. Available online: https://www.wirtschaft.nrw/sites/default/files/asset/document/20160621_sfm_nrw_-_abschlussbericht_weiterentwicklung.pdf (accessed on 16 November 2021).
12. Smarticipate. Opening Up the Smart City—Smarticipate Open to All. 2021. Available online: https://www.smarticipate.eu/ (accessed on 30 November 2021).
13. Geoportal Karlsruhe. Geoportal Karlsruhe. 2021. Available online: https://www.karlsruhe.de/b3/bauen/geodaten.de (accessed on 1 December 2021).
14. MULNV. Umgebungslärm in NRW, Ministerium für Umwelt, Landwirtschaft, Natur- und Verbraucherschutz (MULNV) des Landes Nordrhein-Westfalen. 2021. Available online: www.Umgebungslaerm-kartierung.nrw.de (accessed on 1 December 2021).
15. Boris.NRW. Aktuelle Informationen zum Immobilienmarkt in NRW. 2021. Available online: https://www.boris.nrw.de/borisplus/?lang=de (accessed on 1 December 2021).
16. ELWAS-WEB. Über ELWAS-WEB, Ministerium für Umwelt, Landwirtschaft, Natur- und Verbraucherschutz (MULNV) des Landes Nordrhein-Westfalen. 2021. Available online: https://www.elwasweb.nrw.de/elwas-web/index.xhtml;jsessionid=0161C9700D2DF6C7B6FB1093DE4B07A6?nested=false (accessed on 1 December 2021).
17. NYC. NYC Energy & Water Performance Map. 2021. Available online: https://energy.cusp.nyu.edu/#/ (accessed on 1 December 2021).
18. SolareStadt. Solarpotenzialkataster, Tetraeder.Solar. 2021. Available online: https://www.solare-stadt.de/home/Solarpotenzialkataster (accessed on 1 December 2021).
19. Geoportal Karlsruhe. Solarkataster Karlsruhe, Geoportal Karlsruhe, Stadt Karlsruhe, Karlsruher Energie- und Klimaagentur. 2021. Available online: https://geoportal.karlsruhe.de/solarkataster/ (accessed on 1 December 2021).
20. Solarpotential-KreisKa. Potenzial (Gemeindeebene). 2021. Available online: https://www.solarpotenzial-kreiska.de/ (accessed on 1 December 2021).
21. Klärle. Gründachkataster (GREEN-AREA), Umweltplanung. 2022. Available online: https://www.klaerle.de/leistungsbild/kommunalplanung/gruendachkataster/ (accessed on 8 March 2022).
22. Hanau. Gründach- und Entsiegelungskataster. 2021. Available online: https://www.gpm-webgis-13.de/geoapp/kataster/hanau/ (accessed on 19 November 2021).
23. Marburg. Gründachkataster Marburg. 2021. Available online: https://www.gpm-webgis-10.de/geoapp/gruendachkataster/marburg/ (accessed on 19 November 2021).
24. Otero Peña, D.; Perrotti, D.; Mohareb, E. Advancing urban metabolism studies through GIS data: Resource flows, open space networks, and vulnerable communities in Mexico City. *J. Ind. Ecol.* **2022**, *110*, 1–17. [CrossRef]
25. Geoportal Herne. Geoportal. 2021. Available online: https://www.herne.de/Stadt-und-Leben/Stadtfakten/Geoportal/index-2.html (accessed on 1 December 2021).

26. openGeodata.NRW. openGeodata.NRW, Ministerium für Information und Technik, Nordrhein-Westfalen. 2021. Available online: https://www.opengeodata.nrw.de/produkte/ (accessed on 1 December 2021).
27. Jain, G.; Espey, J. Lessons from nine urban areas using data to drive local sustainable development. *NPJ Urban Sustain.* **2022**, *2*, 7. [CrossRef]
28. Ataman, C.; Tuncer, B. Urban Interventions and Participation Tools in Urban Design Processes: A Systematic Review and Thematic Analysis (1995–2021). *Sustain. Cities Soc.* **2022**, *76*, 103462. [CrossRef]
29. Saikia, P.; Beane, G.; Garriga, R.G.; Avello, P.; Ellis, L.; Fisher, S.; Leten, J.; Ruiz-Apilánez, I.; Shouler, M.; Ward, R.; et al. City Water Resilience Framework: A governance based planning tool to enhance urban water resilience. *Sustain. Cities Soc.* **2021**, *77*, 103497. [CrossRef]
30. Herbert, A.; Arthur, S.; Chillingworth, G. Thermal modelling of large scale exploitation of ground source energy in urban aquifers as a resource management tool. *Appl. Energy* **2013**, *109*, 94–103. [CrossRef]
31. Mainzer, K.; Killinger, S.; McKenna, R.; Fichtner, W. Assessment of rooftop photovoltaic potentials at the urban level using publicly available geodata and image recognition techniques. *Sol. Energy* **2017**, *155*, 561–573. [CrossRef]
32. Oldenburg, O.; Murshed, S.M.; Kremers, E.; Mainzer, K.; Koch, A. Model-Based Analysis of Urban Energy Systems (On the Basis of a City's Energy Master Plan), Emergence: Complexity and Organization. 2015. Available online: https://www.researchgate.net/publication/298072977_Model-based_analysis_of_urban_energy_systems_On_the_basis_of_a_city%27s_energy_master_plan (accessed on 11 May 2022).
33. McKenna, R.; Bertsch, V.; Mainzer, K.; Fichtner, W. Combining local preferences with multi-criteria decision analysis and linear optimization to develop feasible energy concepts in small communities. *Eur. J. Oper. Res.* **2018**, *268*, 1092–1110. [CrossRef]
34. Mainzer, K.; McKenna, R.; Fichtner, W. Übertragbare Methoden zur Bestimmung und räumlichen Verortung des Wärmebedarfs von Wohngebäuden in Städten. In Proceedings of the BauSIM2018-7 Deutsch-Österreichische IBPSA-Konferenz: Tagungsband. Hrsg.: P. von Both, Karlsruhe, Germany, 26–28 September 2018; pp. 471–477. [CrossRef]
35. Mainzer, K.; Schlund, D.; Killinger, S.; McKenna, R.; Fichtner, W. Rooftop PV Potential Estimations: Automated Orthographic Satellite Image Recognition Based on Publicly Available Data. In Proceedings of the 32nd European Photovoltaic Solar Energy Conference and Exhibition (EU PVSEC), München, Germany, 20–24 June 2016.
36. Yan, X.; Abbes, D.; Francois, B. Development of a tool for urban microgrid optimal energy planning and management. *Simul. Model. Pr. Theory* **2018**, *89*, 64–81. [CrossRef]
37. Ferrari, S.; Zagarella, F.; Caputo, P.; Bonomolo, M. Assessment of tools for urban energy planning. *Energy* **2019**, *176*, 544–551. [CrossRef]
38. Akrofi, M.M.; Okitasari, M. Integrating solar energy considerations into urban planning for low carbon cities: A systematic review of the state-of-the-art. *Urban Gov.* **2022**, *in press*. [CrossRef]
39. Oregi, X.; Roth, E.; Alsema, E.; van Ginkel, M.; Struik, D. Use of ICT Tools for Integration of Energy in Urban Planning Projects. *Energy Procedia* **2015**, *83*, 157–166. [CrossRef]
40. Comi, A.; Schiraldi, M.M.; Buttarazzi, B. Smart urban freight transport: Tools for planning and optimising delivery operations. *Simul. Model. Pr. Theory* **2018**, *88*, 48–61. [CrossRef]
41. Boeing, G.; Higgs, C.; Liu, S.; Giles-Corti, B.; Sallis, J.F.; Cerin, E.; Lowe, M.; Adlakha, D.; Hinckson, E.; Moudon, A.V.; et al. Using open data and open-source software to develop spatial indicators of urban design and transport features for achieving healthy and sustainable cities. *Lancet Glob. Health* **2022**, *10*, e907–e918. [CrossRef]
42. Magalhães, I.; Santos, E. Evaluating the potential of mobility plans for achieving sustainable urban development. *Res. Transp. Bus. Manag.* **2022**, *43*, 100743. [CrossRef]
43. De Lotto, R.; Greco, A.; Moretti, M.; Pietra, C.; Venco, E.M. Collaborative Soft Mobility Planning for University Cities: The Case of Pavia. *Transp. Res. Procedia* **2022**, *60*, 472–479. [CrossRef]
44. Navarro-Ligero, M.L.; Valenzuela-Montes, L.M. A Tool for the Assessment of Urban Mobility Scenarios in Climate Change Mitigation: An Application to the Granada's LRT Project. *Transp. Res. Procedia* **2016**, *19*, 364–379. [CrossRef]
45. ProPolis. ProPolis. 2021. Available online: https://www.climate-service-center.de/science/projects/detail/084205/index.php.en (accessed on 23 December 2021).
46. ProPolis. ProPolis—Basics for the Operationalization of PALM-4U—Practicability and Continuation Strategy. 2021. Available online: https://uc2-propolis.de/index.php.en (accessed on 23 December 2021).
47. Bürgerportal Radolfzell. Metadaten Bürgerportal Stadt Radolfzell am Bodensee. 2022. Available online: https://metadaten.geoportal-bw.de/geonetwork/srv/eng/catalog.search#/metadata/c5deee40-5ccd-4fe7-c3f5-7b8f5d4c8981 (accessed on 5 January 2022).
48. Bürgerportal Radolfzell. Bürgerportal Stadt Radolfzell am Bodensee. 2022. Available online: https://radolfzell.aed-synergis.de/WebOffice_flex/synserver?project=Radolfzell_flex&client=flex (accessed on 5 January 2022).
49. ESRI/ArcGIS. 3D Public Survey—Bürgerbeteiligung in 3D. 2022. Available online: https://arcgis.esri.de/3d-public-survey-buergerbeteiligung-in-3d/ (accessed on 5 January 2022).
50. OpenDataBrandenburg. Open Data in Brandenburg—Suchen, Visualisieren, Herunterladen, Nutzen. 2022. Available online: https://brandenburg-smartgeohub.opendata.arcgis.com/ (accessed on 5 January 2022).
51. Demoanwendung. Demoanwendung—Unsere Stadt Wird Lebenswerter, ESRI Deutschland GmbH. 2022. Available online: https://survey123.arcgis.com/share/b4ba15fd1bc1452fa7bc3e9b5a1cf44f (accessed on 5 January 2022).

52. Demoanwendung. Demoanwendung—Bürgerbeteiligungs-Dashboard, ESRI Deutschland GmbH. 2022. Available online: https://www.arcgis.com/apps/opsdashboard/index.html#/5fed8207Decemberc4d27832ec2d80e987b90 (accessed on 5 January 2022).
53. DIPAS. Digitale Bürgerbeteiligung Weiter Denken—Das Erste Medienbruchfreie Digitale System zur Bürgerbeteiligung Online und vor Ort. 2022. Available online: https://www.dipas.org/ (accessed on 5 January 2022).
54. Geobranchen. Bürgerbeteiligung—Das Digitale Partizipationssystem DIPAS Wird Veröffentlicht: Hamburger Software Erweitert Möglichkeiten der Bürgerbeteiligung. 2022. Available online: https://www.geobranchen.de/mediathek/geonews/item/hamburger-software-erweitert-m%C3%B6glichkeiten-der-b%C3%BCrgerbeteiligung (accessed on 5 January 2022).
55. IÖB. CITY_CODE: Digitale Bürgerpartizipation & Co-Desig. 2022. Available online: https://www.ioeb-inNovemberationsplattform.at/challenges/detail/wien-gemeinsam-gestalten-instrumentenbox-fuer-partizipation/detailIdea/city-code-digitale-buergerpartizipation-co-design/ (accessed on 5 January 2022).
56. IÖB. CITY_CODE—Eine Instrumentenbox für Digitale Bürgerpartizipation & Co-Design in der Stadtentwicklung. 2022. Available online: https://www.ioeb-inNovemberationsplattform.at/fileadmin/user_upload/Media_Library/Uploads/Challenge/Idea/Documents/CITY_CODE.pdf (accessed on 5 January 2022).
57. Volk, R.; Naber, E.; Lützkendorf, T.; Böhnke, D.; Mörmann, K.; Schultmann, F.; Norra, S. Identifikation und Bewertung von Entsiegelungspotenzialen als Beitrag zur nachhaltigen Quartiersentwicklung—Zwischenergebnisse aus NaMaRes. In Proceedings of the Flächennutzungsmonitoring XIII: Flächenpolitik-Konzepte-Analysen Tools, Dresden, Germany, 28–29 June 2021; Volume 79, pp. 209–219. [CrossRef]
58. Naber, E.; Volk, R. Schultmann. Namares—A surface inventory and intervention assessment model for urban resource management. *Sustainability*, 2022; under review.
59. PALM. PALM-4U Components. 2021. Available online: https://palm.muk.uni-hanNovember.de/trac/wiki/palm4u (accessed on 19 November 2021).
60. PALM. The PALM Model System. 2021. Available online: https://palm.muk.uni-hanNovember.de/trac (accessed on 3 December 2021).
61. ENVI-met. ENVI-Met Software, Envi-Met GmbH. 2021. Available online: https://www.envi-met.com/de/software/ (accessed on 19 November 2021).
62. DWD. INKAS—Informationsportal KlimaAnpassung in Städten, Deutscher Wetterdienst. 2021. Available online: https://www.dwd.de/DE/forschung/klima_umwelt/klimawirk/stadtpl/inkas/inkas_node.html (accessed on 19 November 2021).
63. MeinGrün App. MeinGrün App. 2021. Available online: https://app.meingruen.org/#/ (accessed on 19 November 2021).
64. Raum&Energie. Bund-/Länder-Dialog Fläche: Flächenrechner 2.0—Wegweiser für Kommunen zum Ziel „30-Hektar-X". 2021. Available online: https://www.raum-energie.de/veranstaltungen/details/news/bund-laender-dialog-flaeche-flaechenrechner-20-wegweiser-fuer-kommunen-zum-ziel-30-hektar-x/ (accessed on 2 December 2021).
65. UBA. Kommunaler Flächenrechner, Umweltbundesamt, Germany. 2021. Available online: https://gis.uba.de/maps/resources/apps/flaechenrechner/index.html?lang=de (accessed on 2 December 2021).
66. Google. Labs: Tree Canopy—Explore Tree Canopy from City Scale to Street Level. 2021. Available online: https://insights.sustainability.google/labs/treecanopy (accessed on 1 December 2021).
67. Google. How 5 Cities Plan to Use Tree Canopy to Fight Climate Change. 2021. Available online: https://blog.google/products/maps/how-5-cities-plan-use-tree-canopy-fight-climate-change/ (accessed on 3 December 2021).
68. Sieker. Flood Warning System HydroWebView, Sieker the Stormwater Experts. 2021. Available online: https://www.sieker.de/en/software/software-gis/product/flood-warning-system-hydrowebview-46.html (accessed on 1 December 2021).
69. DWA. Wasserbilanz-Expert (WABILA)—Standortgerechte Regenwasserbewirtschaftung, Deutsche Vereinigung für Wasserwirtschaft, Abwasser und Abfall e. V. *(DWA)*. 2021. Available online: https://de.dwa.de/de/Wasserbilanz.html (accessed on 2 December 2021).
70. EPA. Storm Water Management Model—User's Manual Version 5.1, United States Environmental Protection Agency (EPA). 2015. Available online: https://www.epa.gov/sites/default/files/2019-02/documents/epaswmm5_1_manual_master_8-2-15.pdf (accessed on 2 December 2021).
71. EPA. Storm Water Management Model (SWMM), United States Environmental Protection Agency (EPA). 2021. Available online: https://www.epa.gov/water-research/storm-water-management-model-swmm (accessed on 2 December 2021).
72. Hörnschemeyer, B.; Henrichs, M.; Uhl, M. SWMM-UrbanEVA: A Model for the Evapotranspiration of Urban Vegetation. *Water* **2021**, *13*, 243. [CrossRef]
73. DWA. Versickerungs-Expert, Deutsche Vereinigung für Wasserwirtschaft, Abwasser und Abfall e. V. *(DWA)*. 2021. Available online: https://de.dwa.de/de/versickerungs-expert.html (accessed on 3 December 2021).
74. DWA. Planungshilfe Abfluss-Steuerung (PASST), Deutsche Vereinigung für Wasserwirtschaft, Abwasser und Abfall e. V. *(DWA)*. 2021. Available online: https://de.dwa.de/de/Planungshilfe_Abfluss-Steuerung.html (accessed on 2 December 2021).
75. IFAK. SAmpSONS2—Visualisierung und Nachhaltigkeitsbewertung von Ressourcen-Orientierten Sanitärsystemen, Ifak—Institut für Automation und Kommunikation e. V. 2021. Available online: https://www.ifak.eu/de/produkte/sampsons (accessed on 3 December 2021).
76. TransMIT. Webviewer—Oberflächige (Not-)Wasserwege. 2021. Available online: https://webmap.ikg.uni-hanNovember.de/TransMiTWebViewer/ (accessed on 3 December 2021).

77. Ramboll. GreenScenario. 2021. Available online: https://de.ramboll.com/-/media/eaac28970c9c40cc815ca60f920a9fba.pdf (accessed on 3 December 2021).
78. ECOPLAN. ECOPLAN Tools. *University of Antwerp*. 2021. Available online: https://www.uantwerpen.be/en/research-groups/ecoplan/ecoplan-tools/ (accessed on 3 December 2021).
79. ECOPLAN. ECOPLAN Scenario Evaluator—ECOPLAN Simulation Tool. University of Antwerp. 2021. Available online: https://www.uantwerpen.be/en/research-groups/ecoplan/ecoplan-tools/scenario-evaluator/ (accessed on 3 December 2021).
80. FAO. Collect Earth Online, FAO and SERVIR Global (NASA and USAID Initiative, Version: Prod-2021-12-2). 2022. Available online: https://collect.earth/ (accessed on 25 February 2022).
81. GCC. Green Infrastructure Toolkit, Georgetown Climate Center. 2022. Available online: https://www.georgetownclimate.org/adaptation/toolkits/green-infrastructure-toolkit/introduction.html?full (accessed on 25 February 2022).
82. IUFC. Urban Forest Management Plan Toolkit, Inland Urban Forest Council. 2022. Available online: https://ufmptoolkit.net/ (accessed on 8 March 2022).
83. USDA. I-Tree Eco, USDA Forest Service. 2022. Available online: https://www.itreetools.org/tools/i-tree-eco (accessed on 8 March 2022).
84. The Nature Conservancy. Healthy Trees, Healthy Cities. 2022. Available online: https://healthytreeshealthycitiesapp.org/ (accessed on 8 March 2022).
85. PlanIT GEO. Treeplotter TM Software Suite. 2022. Available online: https://planitgeo.com/treeplotter/ (accessed on 8 March 2022).
86. USDA. Urban Tree Canopy Assessment: A Community's Path to Understanding and Managing the Urban Forest, U.S. In *Department of Agriculture.*; 2022. Available online: https://www.fs.usda.gov/sites/default/files/fs_media/fs_document/Urban%20Tree%20Canopy%20paper.pdf (accessed on 8 March 2022).
87. WRI México.Toolkit for Community Participation in Pocket Parks. 2016. Available online: https://wriciudades.org/research/publication/toolkit-community-participation-pocket-parks (accessed on 8 March 2022).
88. Vibrant Cities Lab. Community Assessment & Goal-Setting Tool. 2022. Available online: https://www.vibrantcitieslab.com/assessment-tool/ (accessed on 25 February 2022).
89. USGS. Social Values for Ecosystem Services (SolVES), USGS Rocky Mountain Geographic Science Center & Colorado State University. 2018. Available online: https://www.usgs.gov/centers/geosciences-and-environmental-change-science-center/science/social-values-ecosystem (accessed on 14 March 2022).
90. UNDP. Learning for Nature, United Nations Development Programme. 2022. Available online: https://www.learningfornature.org/en/ (accessed on 14 March 2022).
91. WRI. Aqueduct Floods BETA (Aqueduct Global Flood Analyzer), World Resources Institute (WRI). 2022. Available online: http://floods.wri.org/ (accessed on 25 February 2022).
92. Gray, E.; Ozment, S.; Altamirano, J.C.; Feltran-Barbieri, R.; Morales, G. Green-Gray Assessment: How to Assess the Costs and Benefits of Green Infrastructure for Water Supply Systems, Working Paper, World Resources Institute (WRI). 2019. Available online: https://files.wri.org/d8/s3fs-public/green-gray-assessment.pdf (accessed on 25 February 2022).
93. King's College London. WaterWorld, King's College London & AmbioTEK. 2022. Available online: http://www.policysupport.org/waterworld (accessed on 14 March 2022).
94. King's College London. Co$ting Nature, King's College London & AmbioTEK & UNEP-WCMC. 2022. Available online: http://www.policysupport.org/costingnature (accessed on 14 March 2022).
95. The Nature Conservancy. Water Funds Toolbox, The Nature Conservancy. 2022. Available online: https://waterfundstoolbox.org/ (accessed on 14 March 2022).
96. USDA. I-Tree HydroPlus, USDA Forest Service. 2022. Available online: https://www.itreetools.org/tools/hydro (accessed on 15 March 2022).
97. UNEP. Biodiversity A–Z, UN Environment Programme World Conservation Monitoring Centre (UNEP-WCMC). 2022. Available online: https://www.biodiversitya-z.org/ (accessed on 25 February 2022).
98. WRI. Forest Monitoring Designed for Action, Global Forest Watch, World Resources Institute (WRI). 2022. Available online: https://globalforestwatch.org/ (accessed on 25 February 2022).
99. Complete Streets. Complete Streets Policy Implementation Resources, Smart Growth America—Improving Lives by Improving Communities, National Complete Streets Coalition. 2022. Available online: https://smartgrowthamerica.org/tag/complete-streets-policy-implementation-resources/ (accessed on 25 February 2022).
100. Stanford. InVEST (Integrated Valuation of Ecosystem Services and Tradeoffs), Stanford University. 2022. Available online: https://naturalcapitalproject.stanford.edu/software/invest (accessed on 15 March 2022).
101. The Atlas. The Atlas. 2022. Available online: https://the-atlas.com/ (accessed on 15 March 2022).
102. IUCM. Restoration Opportunities Assessment Methodology (ROAM), IUCN & World Resources Institute. 2016. Available online: https://www.iucn.org/resources/conservation-tools/more/restoration-opportunities-assessment-methodology (accessed on 15 March 2022).
103. USDA. Stewardship Mapping and Assessment Project (STEW-MAP). 2022. Available online: https://www.nrs.fs.fed.us/STEW-MAP/ (accessed on 16 March 2022).

104. The Mersey Forest. GI Valuation Tool Kit (GI-Val), The Mersey Forest More from Trees. 2022. Available online: https://www.merseyforest.org.uk/services/gi-val/ (accessed on 16 March 2022).
105. EKN. Green Infrastructure Valuation Toolkit (GI-Val), Ecosystems Knowledge Network. 2022. Available online: https://ecosystemsknowledge.net/green-infrastructure-valuation-toolkit-gi-val (accessed on 16 March 2022).
106. NWS. Forecast of Reference Crop Evapotranspiration (FRET) for Short Canopy Vegetation, National Weather Service (NWS), National Oceanic and Atmosphereric Administration. 2014. Available online: https://nws.weather.gov/products/viewItem.php?selrow=245 (accessed on 17 March 2022).
107. Hamouda, B.; Zaccaria, D.; Bali, K.; Snyder, R.L.; Ventura, F. Evaluation of Forecast Reference Evapotranspiration for Different Microclimate Regions in California to Enable Prospective Irrigation Scheduling. *J. Irrig. Drain. Eng.* **2022**, *148*, 04021061. [CrossRef]
108. CWP. Making Your Community Forest-Friendly: A Worksheet for Review of Municipal Codes and Ordinances, Center for Watershed Protection. 2018. Available online: https://owl.cwp.org/mdocs-posts/making-your-community-forest-friendly-a-worksheet-for-review-of-municipal-codes-and-ordinances/ (accessed on 15 March 2022).
109. Mostafavi, N.; Farzinmoghadam, M.; Hoque, S.; Weil, B. Integrated Urban Metabolism Analysis Tool (IUMAT). *Urban Policy Res.* **2013**, *32*, 53–69. [CrossRef]
110. Mostafavi, N.; Farzinmoghadam, M.; Hoque, S. Urban residential energy consumption modeling in the Integrated Urban Metabolism Analysis Tool (IUMAT). *Build. Environ.* **2017**, *114*, 429–444. [CrossRef]
111. Shahrokni, H.; Lazarevic, D.; Brandt, N. Smart Urban Metabolism: Towards a Real-Time Understanding of the Energy and Material Flows of a City and Its Citizens. *J. Urban Technol.* **2015**, *22*, 65–86. [CrossRef]
112. Greenpass. Greenpass Toolbox. 2021. Available online: https://greenpass.io/de/toolboxx/ (accessed on 10 December 2021).
113. Greenpass. Greenpass Product Book Assessment. 2022. Available online: https://greenpass.io/de/info-material-gpas/ (accessed on 5 January 2022).
114. Patterson, M.S.; Mccallum, K. Collect Earth, Openforis. 2020. Available online: https://openforis.org/tools/collect-earth/ (accessed on 1 August 2021).
115. WRI. Resource Watch, World Resources Institute. 2022. Available online: https://resourcewatch.org/data/explore (accessed on 16 March 2022).
116. ICLEI. U.S. Community Protocol for Accounting and Reporting of Greenhouse Gas Emissions. 2022. Available online: https://icleiusa.org/us-community-protocol/ (accessed on 16 March 2022).
117. Treetect. Treetect. 2022. Available online: https://github.com/krakchris/TreeTect (accessed on 16 March 2022).
118. Klärle, M.; Langendörfer, U.; Lanig, S.; Popp, F. GREEN-AREA—Intelligentes Gründachkataster auf der Basis von GIS-Daten. *ZfV-Z. Geodäsie Geoinf. Landmanag.* **2017**, 146–150. [CrossRef]
119. Klärle, M.; Langendörfer, U.; GREEN-AREA—Intelligentes Gründachkataster auf der Basis von GIS-Daten. Transforming Cities 3/2018, pp. 74–77. 2018. Available online: https://www.transforming-cities.de/ausgabe-3-2018-urbane-raeume-und-flaechen/ (accessed on 17 March 2022).
120. DWA. DWA-Software—Wasserbilanz-Expert—Handbuch, Deutsche Vereinigung für Wasserwirtschaft, Abwasser und Abfall e. V. *(DWA)*. 2021. Available online: https://de.dwa.de/files/_media/content/05_PUBLIKATIONEN/Software/WABILA-Expert/WasserbilanzExpert_Handbuch_2018_11_01.pdf (accessed on 2 December 2021).
121. DWA. Simulator zur Visualisierung von Stoffströmen, Deutsche Vereinigung für Wasserwirtschaft, Abwasser und Abfall e. V. *(DWA)*. 2021. Available online: https://de.dwa.de/de/sampsons2.html (accessed on 2 December 2021).
122. Vystavna, Y.; Schmidt, S.; Diadin, D.; Rossi, P.M.; Vergeles, Y.; Erostate, M.; Yermakovych, I.; Yakovlev, V.; Knöller, K.; Vadillo, I. Multi-tracing of recharge seasonality and contamination in groundwater: A tool for urban water resource management. *Water Res.* **2019**, *161*, 413–422. [CrossRef]
123. Mulligan, M. WaterWorld: A self-parameterising, physically based model for application in data-poor but problem-rich environments globally. *Hydrol. Res.* **2013**, *44*, 748–769. [CrossRef]
124. Montalto, F.A.; Bartrand, T.A.; Waldman, A.M.; Travaline, K.A.; Loomis, C.H.; McAfee, C.; Geldi, J.M.; Riggall, G.J.; Boles, L.M. Decentralised green infrastructure: The importance of stakeholder behaviour in determining spatial and temporal outcomes. *Struct. Infrastruct. Eng.* **2013**, *9*, 1187–1205. [CrossRef]
125. Muñoz-Carpena, R.; Ritter, A.; Fox, G. Comparison of empirical and mechanistic equations for vegetative filter strip pesticide mitigation in long-term environmental exposure assessments. *Water Res.* **2019**, *165*, 114983. [CrossRef] [PubMed]
126. Chrysoulakis, N. The BRIDGE approach. In *Understanding Urban Metabolism*, 1st ed.; Chrysoulakis, N., Anselmo de Castro, E., Moors, E.J., Eds.; Routledge: London, UK, 2014; 9p.
127. Hodges, N.; González, A.; Mitraka, Z. Decemberisation support tools for urban planning. In *Understanding Urban Metabolism*, 1st ed.; Chrysoulakis, N., Anselmo de Castro, E., Moors, E.J., Eds.; Routledge: London, UK, 2014; 5p. [CrossRef]
128. Moors, E.J.; Grimmond, C.S.B.; Veldhuizen, A.; Järvi, L.; van der Bolt, F. Urban water balance and hydrology models to support sustainable urban planning. In *Understanding Urban Metabolism*, 1st ed.; Chrysoulakis, N., Anselmo de Castro, E., Moors, E.J., Eds.; Routledge: London, UK, 2014; 11p.
129. Derrible, S.; Cheah, L.; Arora, M.; Yeow, L.W. Urban Metabolism. In *Urban Informatics*; Shi, W., Goodchild, M.F., Batty, M., Kwan, M.-P., Zhang, A., Eds.; Springer: Berlin/Heidelberg, Germany, 2021.

130. Chrysoulakis, N.; Anselmo de Castro, E.; Moors, E.J. (Eds.) *Understanding Urban Metabolism—A Tool for Urban Planning*, 1st ed.; Routledge: London, UK, 2014.
131. Sun, L.; Li, H.; Dong, L.; Fang, K.; Ren, J.; Geng, Y.; Fujii, M.; Zhang, W.; Zhang, N.; Liu, Z. Eco-benefits assessment on urban industrial symbiosis based on material flows analysis and emergy evaluation approach: A case of Liuzhou city, China. *Resour. Conserv. Recycl.* **2017**, *119*, 78–88. [CrossRef]
132. Zhu, X. GIS and Urban Mining, Special Issue Wealth from Waste: Urban Metal Resources and Industrial Ecology. *Resources* **2014**, *3*, 235–247. [CrossRef]
133. Badach, J.; Voordeckers, D.; Nyka, L.; Van Acker, M. A framework for Air Quality Management Zones - Useful GIS-based tool for urban planning: Case studies in Antwerp and Gdańsk. *Build. Environ.* **2020**, *174*, 106743. [CrossRef]
134. BRIDGE. About BRIDGE Project. 2011. Available online: https://www.bridge-fp7.eu/ (accessed on 17 March 2017).
135. Rosado, L.; Niza, S.; Ferrao, P. A Material Flow Accounting Case Study of the Lisbon Metropolitan Area using the Urban Metabolism Analyst Model. *J. Ind. Ecol.* **2014**, *18*, 84–101. [CrossRef]
136. Hu, D.; You, F.; Zhao, Y.; Yuan, Y.; Liu, T.; Cao, A.; Wang, Z.; Zhang, J. Input, stocks and output flows of urban residential building system in Beijing city, China from 1949 to 2008. *Resour. Conserv. Recycl.* **2010**, *54*, 1177–1188. [CrossRef]
137. Alfonso Piña, W.H.A.; Pardo Martínez, C.I. Urban material flow analysis: An approach for Bogotá, Colombia. *Ecol. Indic.* **2014**, *42*, 32–42. [CrossRef]
138. Guo, Z.; Hu, D.; Zhang, F.; Huang, G.; Xiao, Q. An integrated material metabolism model for stocks of urban road system in Beijing, China. *Sci. Total Environ.* **2014**, *470-471*, 883–894. [CrossRef]
139. Li, Y.; Beeton, R.; Halog, A.; Sigler, T. Evaluating urban sustainability potential based on material flow analysis of inputs and outputs: A case study in Jinchang City, China. *Resour. Conserv. Recycl.* **2016**, *110*, 87–98. [CrossRef]
140. Yang, P.P.-J.; Wiedenback, A.; Tobey, M.; Wu, Y.; Quan, S.J.; Chauhan, Y.; Wu, J. Material Based Urban Modeling: An Approach to Integrate Smart Materials in a Near-Zero Community Design. *Energy Procedia* **2017**, *105*, 3765–3771. [CrossRef]
141. Zeller, V.; Towa, E.; Degrez, M.; Achten, W.M. Urban waste flows and their potential for a circular economy model at city-region level. *Waste Manag.* **2018**, *83*, 83–94. [CrossRef] [PubMed]
142. DWD. Stadtklimamodell PALM-4U, Deutscher Wetterdienst. 2021. Available online: https://www.dwd.de/DE/leistungen/palm4u/palm4u.html (accessed on 19 November 2021).
143. MOSAIK2. MOSAIK-2—Second Phase of The Project "Model-based city planning and application in climate change". 2021. Available online: https://palm.muk.uni-hanNovember.de/mosaik/ (accessed on 3 December 2021).
144. Gusson, C.D.S.; Duarte, D.H. Effects of Built Density and Urban Morphology on Urban Microclimate—Calibration of the Model ENVI-met V4 for the Subtropical Sao Paulo, Brazil. *Procedia Eng.* **2016**, *169*, 2–10. [CrossRef]
145. Epelde, L.; Mendizabal, M.; Gutiérrez, L.; Artetxe, A.; Garbisu, C.; Feliu, E. Quantification of the environmental effectiveness of nature-based solutions for increasing the resilience of cities under climate change. *Urban For. Urban Green.* **2022**, *67*, 127433. [CrossRef]
146. DWD. INKAS-NRW—Wirkungsanalyse, Deutscher Wetterdienst. 2022. Available online: https://www.dwd.de/DE/leistungen/inkas/inkas_nrw_wirkungsanalyse.html (accessed on 17 March 2022).
147. LANUV. Fachinformationssystem Klimaanpassung, Landesamt für Natur, Umwelt und Verbraucherschutz, Nordrhein-Westphalen. 2022. Available online: https://www.klimaanpassung-karte.nrw.de/ (accessed on 17 March 2022).
148. Da Silva, A.O.; Souza Fernandes, R.A. Smart governance based on multipurpose territorial cadastre and geographic information system: An analysis of geoinformation, transparency and collaborative participation for Brazilian capitals. *Land Use Policy* **2020**, *97*, 104752. [CrossRef]
149. Voskamp, I.M.; Spiller, M.; Stremke, S.; Bregt, A.K.; Vreugdenhil, C.; Rijnaarts, H.H. Space-time information analysis for resource-conscious urban planning and design: A stakeholder based identification of urban metabolism data gaps. *Resour. Conserv. Recycl.* **2018**, *128*, 516–525. [CrossRef]
150. Teng, M.; Wu, C.; Zhou, Z.; Lord, E.; Zheng, Z. Multipurpose greenway planning for changing cities: A framework integrating priorities and a least-cost path model. *Landsc. Urban Plan.* **2011**, *103*, 1–14. [CrossRef]
151. Böhnke, D.; Volk, R.; Lützkendorf, T.; Naber, E.; Krehl, A.; Becker, R.; Norra, S. Grünbestände in privaten Innenhöfen und deren Ökosystemleistungen im Stadtquartier—Erkenntnisse einer quartiersweiten Erhebung in Karlsruhe. In Proceedings of the Flächennutzungsmonitoring XIII: Flächenpolitik-Konzepte-Analysen Tools, Dresden, Germany, 28–29 June 2021. [CrossRef]
152. Dembski, F.; Wössner, U.; Letzgus, M.; Ruddat, M.; Yamu, C. Urban Digital Twins for Smart Cities and Citizens: The Case Study of Herrenberg, Germany. *Sustainability* **2020**, *12*, 2307. [CrossRef]
153. Schebek, L.; Lützkendorf, T.; Uhl, M. Handreichung zur Typologie von Indikatoren Sowie Ihrer Anwendung in Planungsprozessen und Projekten zur Nachhaltigen Quartiersentwicklung, Bundesministerium für Bildung und Forschung (BMBF), FONA. 2022. Available online: https://ressourceneffiziente-stadtquartiere.de/wp-content/uploads/2022/02/Handreichung_Indikatorik_01-2022_final.pdf (accessed on 23 March 2022).
154. Schinkel, U.; Becker, N.; Trapp, M.; Speck, M. Assessing the Contribution of Innovative Technologies to Sustainable Development for Planning and Decision-Making Processes: A Set of Indicators to Describe the Performance of Sustainable Urban Infrastructures (ISI). *Sustainability* **2022**, *14*, 1966. [CrossRef]
155. DIN SPEC 91468 „Leitfaden für ressourceneffiziente Stadtquartiere"/Guideline for Resource-Efficient Urban Districts. Available online: https://www.din.de/de/forschung-und-inNovemberation/din-spec/alle-geschaeftsplaene/wdc-beuth:din21:346552454 (accessed on 23 March 2022).

Urban Forestry & Urban Greening 82 (2023) 127868

Contents lists available at ScienceDirect

Urban Forestry & Urban Greening

journal homepage: www.elsevier.com/locate/ufug

Supporting decision-makers in estimating irrigation demand for urban street trees

Mihir Rambhia [a,b], Rebekka Volk [a], Behzad Rismanchi [b,*], Stephan Winter [b], Frank Schultmann [a]

[a] Institute for Industrial Production, Karlsruhe Institute of Technology, Karlsruhe 76187, Germany
[b] Department of Infrastructure Engineering, The University of Melbourne, Melbourne 3010, Australia

ARTICLE INFO

Keywords:
Urban green
Irrigation water demand
Water budgeting
Linear time series
Green space management
Sustainable cities

ABSTRACT

Greening cities is of considerable significance to creating sustainable cities. Cost-benefit analyses have shown that urban green is not only ecologically and socially desirable but also economically advantageous. However, maintaining this urban green is becoming challenging due to changing climatic conditions. With frequent heatwaves, droughts and increasing water scarcity in many regions, it is crucial to establish systematic approaches to economise the available water used for irrigation. Currently, cities rely on rough approximations to assess irrigation demand. To address this gap, a linear time series model was developed based on soil water balance and Water Use Classifications of Landscape Species approach. The model uses publicly available data regarding trees, soil, and current and forecasted weather to estimate the irrigation demand of urban street trees on a weekly time scale. The developed model is applied in a case study of a metropolis in a moderate continental climate. The results show more distributed irrigation demand than the currently implemented soil moisture based model of the case study city. Accordingly, the model can support the decision-makers to not only assess the irrigation demand of existing trees but also help in water budgeting of new plantation under varying climatic conditions.

1. Introduction

The World Health Organization (WHO) defines urban green spaces (UGS) as "all urban land covered by vegetation of any kind" (World Health Organization, 2016). This includes trees along streets, parks, play grounds, private gardens, urban forests, green roofs or walls, and farms within city boundaries. Access to sufficient UGS provides exposure to nature and enhances the quality of living in cities, as acknowledged by the United Nations' Sustainable Development Goals Target 11.7, which aims to provide access to safe green spaces for everyone living in cities by 2030 (United Nations, 2020).

In response, city administrators have formulated goals for the conservation and development of new UGS. However, increasing green spaces also introduces competing interests with the use of scarce water resources and limited budgets to maintain them. While UGS contribute positively to water storage through reduced runoff and increased infiltration, supplementary irrigation needs are likely to increase the pressure on limited water resources in cities. Practitioners have often cited the availability of water supply as one of the significant challenges in maintaining urban trees (Young, 2011). The problem is expected to further exacerbate due to more frequent and extended drier periods with increasing effects of climate change. For example, in summer 2022 some districts in California had to declare a water emergency state, allowing outer watering only once a week (Patel and Samenow, 2022). Similarly, some regions in northern Italy, Portugal, and Spain also announced emergency measures and requested their residents to economise their water usage (France-Presse Agence, 2022; Deutsche Welle, 2022). Mandatory water restrictions targeting the irrigation of both public and private open spaces are also frequently observed in Canberra, Sydney, and Melbourne in Australia (Fam et al., 2008).

The type of tree species and local micro-climatic conditions are the factors that can significantly affect irrigation demand. This stipulates the need to optimise the watering supply to the UGS such that, water is solely supplied when and where it is actually required and in a judicious quantity. However, the current practice of watering through tankers or watering bags lacks the flexibility to consider these factors. Nevertheless, these parameters have been included in this study, expecting the implementation of smart drip irrigation or water network systems in future. Thus, by optimising the operational management of an irrigation system for UGS, cities can simultaneously meet the objectives of the EU Strategy on Adaptation to Climate Change as well as the EU Water Framework Directive, which aims to prepare cities for the challenges associated with climate change such as urban heat island and droughts

* Corresponding author.
E-mail address: brismanchi@unimelb.edu.au (B. Rismanchi).

https://doi.org/10.1016/j.ufug.2023.127868
Received 16 October 2022; Received in revised form 1 February 2023; Accepted 7 February 2023
Available online 13 February 2023

Nomenclature

UGS	Urban Green Spaces.
WUCOLS	Water Use Classifications of Landscape Species.
SLIDE	Simplified Landscape Irrigation Demand Estimation.

List of Symbols

CR	capillary rise.
D	Deep percolation.
ET	evapotranspiration.
ET_0	reference evapotranspiration.
I	irrigation.
P	precipitation.
PF	plant factor.
r	root depth.
RAW	readily available water.
RO	runoff.
ΔS	soil moisture change.
TAW	total available water.

(European Commission, 2021,2000).

However, predicting the dynamic water demand of trees is an arduous task. Water consumption by trees can be divided into two categories: The *blue* water from irrigation or groundwater, and the *green* water from rainwater. Accordingly, the focus of this study is to estimate the required quantity of blue water to be supplied externally for managing UGS in optimal conditions, after accounting for the green water available through the rain. Most of the existing irrigation scheduling models are developed for the agricultural sector because of the higher economic implications (Adeyemi et al., 2018; Khan et al., 2017,2020). These are further discussed in subsection 1.1. However, distinct conditions in cities, such as local micro-climatic conditions, sealed and compacted soil, shading, and anthropogenic disturbances, make the irrigation models developed for rural conditions inapplicable for urban areas (Nouri et al., 2013a). Existing models for urban conditions, such as Vico et al. (2013), Volo et al. (2014), Nouri et al. (2019), are limited in estimating the irrigation demand at a single tree or park level. Additionally, in some studies the estimates are generated at monthly or annual time scales, which is not enough for operational irrigation management (Wessolek and Kluge, 2021; Sjöman and Busse Nielsen, 2010).

This demands further research on estimating irrigation demand for UGS. As described earlier, UGS includes a variety of green spaces, however, the scope of this research is focused on estimating the irrigation needs of urban street trees. Moreover, since for street trees weekly watering by tankers is the commonly applied method, the current study adopts a weekly time scale for the estimation to support practical usage. Unlike existing models that focus on a smaller spatial scale, this work is focused on city level and therefore, includes trees from a variety of species. Furthermore, with the increasing availability of data under open data initiatives of various cities, our approach particularly uses available public datasets without relying on sensors or remote sensing data, which might not be accessible to every municipality.

Accordingly, this study aims to address the following two research questions: .

- Can the irrigation demand of street trees be determined on a weekly time scale using available public datasets?
- Can the future water demand for new street tree plantations be assessed under varying climatic conditions?

Accordingly, the scope of the research includes (1) identifying a suitable approach for estimating irrigation demand in urban context; (2) considering the necessary adaptations required for applying it at street tree level; (3) identifying the relevant public datasets and assimilation procedures to obtain the required model parameters; (4) comparing the model performance with the existing models; and (5) evaluating the change in irrigation demand under varied scenario conditions.

The research approach is based on identifying the suitable method for irrigation demand estimation based on the comprehensiveness, adaptability, and feasibility of the method. Accordingly, the proposed model is an implementation of the water-balance model wherein the individual parameters are derived from different published datasets or values reported in the literature. This model is further compared with an existing Plant Factors (PF) based method used for irrigating urban landscapes as well as the model currently adopted by the city chosen in our case study. In summary, the research aims for two outcomes: First, a model that estimates weekly irrigation demand for street trees that is easily adaptable for changes in input parameters depending on the availability of data, that uses nominal quantity of data without requiring special field measurements, that takes into account current and forecasted weather data, and that is applicable under varying climatic conditions. The second outcome includes insights for city administrators to make informed decisions regarding water budgeting of existing and new plantations of street trees.

The paper is organised as follows: first, a literature review describes the state-of-the-art irrigation models for agricultural and urban applications and the research gap. Based on this, a water balance model is selected as the basis and its parameters are detailed in the background section, followed by the modeling approach section discussing its implementation in a python-based model. In the case-study section, the results from applying the model to data from Berlin city are discussed. The final two sections present the discussion and conclusions.

1.1. Models for agricultural areas

Different studies have presented irrigation scheduling approaches for the agricultural sector (George et al., 2000; Contreras et al., 2011). In addition, the Food and Agriculture Organization of the United Nations (FAO) also offers two models based on soil water balance approach: CropWat and AquaCrop. CropWat provides an irrigation schedule for crops using daily or monthly, weather, crop and soil data (FAO, 2021b). Similarly, AquaCrop model was developed for single, and uniform crop fields applications (FAO, 2021c). Delgoda et al. (2016a) used the AquaCrop model to test an irrigation control model that estimates root zone soil moisture deficits to determine irrigation demand. However, the approach was tested only for crops and not for urban environments. The authors also presented an approach based on model predictive control that aims to achieve the desired soil moisture level while considering limitations on available water (Delgoda et al., 2016b).

The limitation of the aforementioned irrigation scheduling models is their total focus on crops and crop yield, which also applies to the respective sub-models. Hence, it is difficult to directly apply them to the urban vegetation with its peculiar characteristics. In addition, literature regarding the necessary adjustments required for applying these models to UGS is missing. Other shortcomings of the presented models include the missing dynamics of parameters D and RO in the model of Delgoda et al. (2016a), and the granularity of data in the FAO models that uses average monthly climatic data.

1.2. Models for urban areas

UGS is quite diverse in its configuration compared to agricultural fields. It is planted in various species combinations, with spatial distributions and densities that are in high contrast to organised, uniform crop lines on a field (Nouri et al., 2013a). Especially for street trees, the micro-climate effects due to nearby buildings, road and other sealed surfaces, as well as compacted and restricted tree trenches, significantly affects their water demand (Dimoudi and Nikolopoulou, 2003). In addition, UGS is also highly influenced by human activities such as construction works causing root damage or soil compaction, pollutant emission from traffic or heating, or urine and salt contamination (Nouri et al., 2013b). Therefore, the stress factor for urban trees is usually high and leads to a lower survival rate than in rural areas (Koeser et al., 2013; Sjöman and Busse Nielsen, 2010). Besides, it is also more challenging to gather field data in the urban environment due to large variations within a city. When focusing on one particular crop field, it is relatively easy to deploy low-cost sensor networks or measuring devices such as lysimeters for direct measurements. However, cities would require the installation and calibration of large numbers of such measuring devices. Thus, verifying the quality of irrigation models for UGS is more complicated than for the agricultural sector. Hence, for most of the models discussed in this section for UGS, there exist no substantial performance evaluations.

Until now, most research on UGS irrigation needs has relied on the soil water balance or remote sensing approach (Nouri et al., 2013a; Shi and Yang, 2018). The majority of existing research focuses on either residential irrigation demand (Hilaire et al., 2008; Domene and Saurí, 2006), urban vegetation evapotranspiration (ET) (Allen et al., 2011; Contreras et al., 2011), or turf grass water demand (Huang and Fry, 2000; Pooya et al., 2013) with a goal of reducing demand. Vico et al. (2013) present a method for determining and reducing the daily irrigation demand of isolated street trees using soil, plant, and climate data. The authors propose a probabilistic model that takes into account the species, tree size, tree trench design, rainfall patterns, and irrigation systems used. They limit their model to circular tree trenches and ignore the possibility of capillary rise (CR).

This model was further enhanced by Revelli and Porporato (2018) by further quantifying nutrients retention in soil. On a greater spatial scale, Volo et al. (2014) investigate the irrigation demand and optimal irrigation schedule for mesic conditions and xeric conditions in Phoenix, USA. They provide recommendations for optimal daily irrigation scheduling based on the targeted level of plant stress after calibrating the model with soil moisture data from two sensors and past meteorological information. Because their model is limited to two types of neighborhoods and is based on sensor data, it cannot be easily adapted to more diverse districts or entire city areas. Orusa et al. (2020) calculated ET values using a remote sensing dataset from MODIS to derive ET values, but at a coarse spatial resolution of 500 m.

The Simplified Landscape Irrigation Demand Estimation (SLIDE) provides an estimation method for the irrigation requirement of urban landscapes (Kjelgren et al., 2016). Based on adjusted literature values, it defines a plant factor (PF) for five different combinations of UGS type (turf/woody/desert) and climate (cool/warm/dry/humid). To calculate the water demand, the PF value is multiplied with reference ET (ET_0) and transpiring leaf/landscape area. Hereby, the authors assert that in a mixed zone, the water demand should be coordinated with the plant type yielding the highest PF. However, SLIDE does not consider precipitation events or soil properties, therefore it is only suitable to determine the ET of UGS but not the irrigation demand.

Finally, some cities offer examples for estimating the irrigation demand for street trees. For example, the Department for Plant Protection in Berlin estimates the need for irrigation based on the available soil moisture calculated for one tree species (Tilia cordata) located on the street Tempelhofer Weg in Berlin-Neukölln (Pflanzenschutzamt Berlin, 2021a). The soil moisture is defined relative to the total available water (TAW), and is categorised in a colour coded system, with green indicating above 50% moisture, yellow indicating below 50%, and red indicating below 30%. Whenever moisture reaches the red zone on the chart, the department recommends applying irrigation to all the street trees. On one side, this approach is easy to understand, includes current and predicted weather data, and also includes an irrigation forecast for the following week. But on the other side, the calculations are only valid for a single tree at one location, and are extended to the entire city without any adaptations. Moreover, while the method provides information about irrigation timing, it does not give any details on how much water quantity should be irrigated for different species. In South Australia, the water provider SA Water collaborated with the local councils to improve the irrigation of the public parks (SA Water, 2021). However, their approach requires the installation of numerous sensors which might not be feasible for all the municipalities. Moreover, since the algorithm to generate irrigation schedule is proprietary it is not available for scientific review.

Table 1 presents a comparative analysis made between the aforementioned approaches based on the estimation method, scope of application, spatial and temporal scale, and the input data. Most of these methods cover limited spatial scale such as grass, parks or single trees. Few of the studies are based on the soil moisture approach in which irrigation demand gets concentrated during summer months, increasing the water scarcity risk. In some studies, methodology is data intensive requiring extensive field measurements or deployment of large number of sensors.

The review indicates a lack of ET-based models for estimating the irrigation demand for urban street trees at daily or weekly time scale using public datasets. Nouri et al. (2013a) reviewed various techniques available to determine the ET demand for urban landscapes including lysimeter, Sap flow, WUCOLS, Eddy covariance, and remote sensing, and concluded that WUCOLS is the most suitable approach to implement for practical applications. Since other studies on urban landscapes also came to the same conclusion, this method was also used for this study (Nouri et al., 2013d).

The existing literature covers the irrigation models for crops and agricultural land extensively but it has only been implemented for limited cases for UGS so far. So, the proposed model of this paper aims to fill the gap and to be practically implementable by the cities for estimating the weekly irrigation demand using the available open datasets. The proposed methodology extends the current literature by suggesting the necessary adaptations required for implementing the water balance approach on the street trees on city level. Moreover, the methodology accounts for the tree's ET demand, incoming water from rainfall, and available water in the soil.

2. Background

Overall, the aim of efficient irrigation systems is to deliver the minimum amount of water that is required to ensure the survival, functioning and aesthetically pleasing appearance of the UGS. A large number of existing models are based on the soil water balance approach (see Equation (1)). The approach is based on a closed water cycle system, where at any moment the outflow should be equal to the inflow.

The inflow consists of the sum of precipitation (P), irrigation (I) and capillary rise (CR). The outflow is composed of Evapotranspiration (ET), Runoff (RO), drainage or deep percolation (D), and change in soil moisture (ΔS). As any errors in measuring or estimating the individual parameter values add up to the cumulative error, the soil water balance approach is generally less accurate than direct measurements. However, it is still useful for practical applications as direct measurements are quite expensive and, hence, generally lacking.

$$P + I + CR = ET + RO + D + \Delta S \tag{1}$$

In the subsequent paragraphs, an approach for determining individual parameters of soil water balance (see Equation (1)) followed by the steps to design a computational model are presented.

2.1. Estimating evapotranspiration (ET)

One of the critical parameters that highly influences the irrigation demand is ET. ET depends on vegetation characteristics such as species type, canopy size, age, root type, and micro-climatic conditions. For canopy size, usually the bigger the canopy size, the higher is the ET and

Table 1
Comparative analysis of available irrigation models and approaches.

Study	Year	ET measurement	Soil moisture change	Agri culture	Urban	Tree	Park	City	Daily/ Weekly	Monthly/ Annual	Sensors/ Field measurements	Remote Sensing	Other Public datasets	Rainfall
Gober et al.	2010						✓			✓				
Contreras et al.	2011			✓						✓		✓		✓
Vico et al.	2014		✓		✓	✓			✓				✓	✓
Volo et al. (a)	2014		✓		✓		✓							
Delgoda et al.	2016	✓		✓					✓		✓		✓	
Kjelgren et al. (SLIDE)	2016	✓			✓	✓	✓	✓	✓				✓	
Shi et al.	2017				✓		✓	✓		✓			✓	✓
Adeyemi et al.	2018		✓	✓		✓			✓				✓	
Revelli & Porporato	2018		✓		✓			✓		✓				
Nouri et al.	2019	✓			✓		✓			✓	✓		✓	✓
Reyes-Paecke et al.	2019				✓		✓							
Khan et al.	2020			✓		✓			✓		✓	✓	✓	✓
Henrich et al.	2021	✓			✓	✓			✓				✓	✓
Wessolek & Kluge	2021	✓			✓	✓				✓	✓		✓	✓
Berlin City	2021		✓		✓	✓			✓				✓	✓
AquaCrop, FAO		✓		✓		✓								
CropWat, FAO		✓		✓		✓								
Karlsruhe City		-	-						-					-
SA Water		?	?		✓		✓		✓		✓			✓
Time Series Model		✓			✓	✓		✓	✓	✓			✓	✓

the water demand. This is due to a greater number of leaves leading to higher water demand for photosynthesis as well as higher loss of water through stomata. However, in case of age, usually, the demand for external irrigation reduces as the tree matures. This is because of the development of root systems that makes the tree self-reliant. Depending on the depth and spread of the root system, a tree can access the available water in the soil layers and groundwater. Lastly, climatic conditions like temperature, humidity, wind, precipitation, and solar radiation will affect the ET demand of the trees. This is further influenced by local anthropogenic conditions such as presence of buildings and roads nearby that can either directly influence through shading or indirectly by altering the micro-climate. Hence, the location and immediate neighbourhood of the UGS are of considerable importance while calculating the ET.

For the purpose of this study, the Penman-Monteith equation is used to theoretically estimate the potential ET, based on hydrometeorological parameters (FAO, 2021a), since we assume no sensor data from the field. This method is also a recommended approach by the FAO for ET estimation. However, the derived potential ET is based on grass of uniform height, and therefore, it requires adaption for street trees. The WUCOLS approach estimates the water requirements of UGS to meet acceptable aesthetic expectations, health and reasonable growth for all available tree species (Costello and Jones, 2014a). As this provides the desired quantity for irrigation, it is best suited for scarce water resource conditions.

The WUCOLS method uses a landscape vegetation coefficient K_L to account for the landscape characteristics as shown in Equation (2) (Costello and Jones, 2014b). K_L itself is composed of a species factor (K_s), a density factor for UGS (K_d), and a microclimate factor (K_{mc}), as shown in Equation (3). The values of these coefficients are chosen according to the categories shown in Table 2 based on prevailing conditions. WUCOLS also provides an extensive database that categorises the tree water demand into high, medium, low, and very low according to species type and the climatic region. The database includes 778 types of tree species and covers six different climatic regions of the State of California (UC Davis, 2021).

$$ET_L = K_L \times ET_0 \tag{2}$$

$$K_L = K_s \times K_d \times K_{mc} \tag{3}$$

Table 2
Coefficients for WUCOLS approach (Costello et al.).

Coefficient	Categories	Value	Group
Species Facor (K_s)	Very low	< 10% of ET_0	Based on species type such as bamboo, bulb, grass, groundcover, perennial, palm and cycad, shrub, succulent, tree, vine, natives
	Low	10–30% of ET_0	
	Medium	40–60% of ET_0	
	High	70–90% of ET_0	
Density factor (K_d)	Low	0.5–0.9	Immature and sparsely populated vegetation
	Average	1	Single vegetation type
	High	1.1–1.3	Mixed vegetation with trees, shrubs, and ground cover
Microclimate factor (K_{mc})	Low	0.5–0.9	Vegetation under building overhangs or shade
	Average	1	Open area and not influenced by urban features
	High	1.1–1.4	In the vicinity of buildings or sealed area

2.2. Estimating effective precipitation (P_{eff})

To improve the accuracy of the irrigation demand estimation and to avoid over-watering the trees during a rain event, it is essential to account for the actual and expected precipitation during the time period. Precipitation data is often available through weather departments at the state or national level. In Germany, for example, the German Weather Service (DWD) operates weather stations throughout the country and provides weather and climate data, including the precipitation at daily time scale. However, for the purpose of irrigation, it needs to be converted into effective precipitation (P_{eff}). P_{eff} is defined as the fraction of the rainwater that is not intercepted by vegetation. The fraction is represented as the interception coefficient (c_{inc}). Rainfall (amount, intensity, direction, consecutive rain days) and other meteorological conditions such as wind speed and direction all have an impact on interception (Gerrits et al., 2007). However, there is no standard approach available for its depiction, and hence, it requires field experiments for its adjustment. As field experiments involve high personnel and equipment costs, they might not be feasible for smaller cities. Therefore, for this study, P_{eff} is determined according to Equation (4). Because c_{inc} varies depending on the species, literature values are required for implementation (Llorens and Domingo, 2007; Nytch et al., 2018; Yang et al., 2019).

$$P_{\text{eff}} = (1 - c_{\text{inc}}) \times P \tag{4}$$

where, c_{inc} is the interception coefficient.

2.3. Estimating capillary rise (CR)

Capillary Rise (CR) describes the water made available to vegetation by the movement of groundwater from the groundwater table into the root zone. It depends on the groundwater table, the type of soil, and its characteristics. However, as the ET derived with the WUCOLS approach is only suitable in situations without CR as a water source, for this study it is assumed that there is no CR in the root zone. This is possible when the groundwater table is low enough to disable CR. Previous studies by Delgoda et al. (2016b), Revelli and Porporato (2018), and Vico et al. (2013) used the same reasoning. This assumption should be reasonable in the context of street trees, as the compact tree trench and highly dense soil in cities would restrict the growth of the root system, making them unable to access the groundwater.

2.4. Estimating runoff (RO)

The accurate way of determining the Runoff (RO) would be by conducting field experiments. However, in the absence of field data, RO can be indirectly calculated through the infiltration rate. The RO is then defined as the remaining water from P_{eff} after the infiltration (P_{inf}) has taken place. The maximum amount of water that can enter a particular soil in a time unit is represented using the infiltration rate (c_{inf}). The intensity of P_{eff} is determined as P_{eff}/h, where h describes the duration of the precipitation event in hours. As shown in Equation (5), RO will occur whenever the intensity of P_{eff} exceeds the c_{inf} of the soil. The infiltration rates for different types of soil are available in published literature. The Minnesota Stormwater Manual, for example, specifies infiltration rates for gravel to clay (Minnesota Pollution Control Agency, 2013). Depending on the soil type of the region, a suitable rate can be used. Additionally, the manual recommends using a reduced rate by one level in the case of compacted soils in urban areas.

$$RO = \left\{ \begin{array}{ll} 0, & \text{if } c_{\text{inf}} \geq P_{\text{eff}}/h \\ P_{\text{eff}} - (c_{\text{inf}} \times h) & \text{else} \end{array} \right\} \tag{5}$$

where, h = duration of precipitation event (hours).

2.5. Estimating drainage (D) and the soil moisture change (Δ S)

Drainage refers to the quantity of water that directly percolates below the root zone and, hence, is unavailable for the trees to use. It depends on soil characteristics, rainfall intensity and duration, and the distribution of roots. Accordingly, this parameter can be calculated as the difference between the amount of infiltrated water and the water holding capacity of the soil, as shown in Equation (6). To calculate this, first, total available water (TAW) is calculated as the difference between field capacity and the wilting point of the soil (FAO, 1990). The FAO provides a range of TAW values for undisturbed soil types (Brouwer et al., 1985). However, with vegetation, TAW will increase as root systems hold more water in the root zone. The Department of Primary Industries and Regional Development of the Western Australian government provides information about TAW for different soils (Newman, 2012). The root depth for this system is defined as 0.5 m (broad), 1 m (oblique), 2 m (deep) (Dobson, 1995). After the determination of TAW, the effective root depth is multiplied with the TAW value, resulting in readily available water (RAW) (see Equation (7)). A coefficient c_s is defined as the portion of the infiltrated water available for trees. If P_{inf} is higher, c_s equals RAW/P_{inf} because, after drainage, only RAW will be available for the tree. Second, if both values are equal or if P_{inf} is smaller than RAW, there will be no deep percolation and c_s will be one.

$$D = \left\{ \begin{array}{ll} 0, & \text{if } P_{\text{inf}} \leq TAW \\ P_{\text{inf}} - TAW & \text{else} \end{array} \right\} \tag{6}$$

$$RAW = r \cdot TAW \tag{7}$$

where, r = root zone depth (m)

$$RAW = \left\{ \begin{array}{ll} c_s \cdot P_{\text{inf}} & \text{if } P_{\text{inf}} \geq RAW \\ P_{\text{inf}} & \text{else} \end{array} \right\} \tag{8}$$

3. Modeling approach

3.1. Time-series model

Based on the theoretical approach described in the previous section, a novel time series model for estimating the weekly irrigation demand of urban street trees is developed as given in Equation (9). It calculates the water available for the tree uptake as a portion of infiltrated precipitation remaining after canopy interception, drainage, and runoff. Table 3

Table 3
Summary of parameters defined in the python corresponding to the designed model.

Symbol	Type[a]	Description	Data Source
s	I	Name of the species	Latin name
c_{inc}	I	Interception coefficient	Literature values (0.17/0.227/0.3058)
c_{inf}	I	Infiltration rate	Minnesota Pollution Control Agency (2013)
r	I	Depth of roots	0.5 m/1 m/2 m depending on root system
TAW	I	Total available water	Newman (2012)
ET_0	I	Reference ET	Weather data (Deutscher Wetterdienst, 2021)
ET_L	C	Landscape ET	Using WUCOLS database (UC Davis, 2021)
P_{eff}	C	Effective precipitation	Difference of Precipitation and Interception
P_{inf}	C	Infiltration amount	Depending on soil type and compactness
RAW	C	Available water	Depending on TAW and rootdepth
I_t	C	Irrigation demand	According to Equation (9)

[a]Type: I = Input, C = Calculated

describes the list of parameters used in the model along with the respective data source used for the subsequent case study (see section 4). The interaction between the parameters is illustrated for a single tree in Fig. 1. The Equation (10) calculates the total ET_L demand for all the tree species, as explained in subsection 2.1. In the Equation (11), water reaching the soil surface is determined by reducing the water lost through interception, as explained in subsection 2.2. The Equation (12) is used to compute the amount of water that penetrates into the soil, depending on whether the rainfall intensity is lower than c_{inf} as explained in subsection 2.4. Lastly, Equation (13) and Equation (14) calculate the portion of the infiltrated water that is available to the tree depending on the soil type and root depth, as explained in subsection 2.5.

$$I_t = \sum ET_{L,t} - ET_{L,t-1} + I_{t-1} + (c_{s,t} \cdot P_{inf,t}) - (c_{s,t+1} \cdot P_{inf,t+1}) \tag{9}$$

such that,

$$ET_{L,t} = \sum_{s \forall S} (K_{L,s} \cdot ET_{0,t}) \tag{10}$$

$$P_{eff,t} = (1 - c_{inc}) \cdot P_t \tag{11}$$

$$P_{inf,t} = \begin{Bmatrix} P_{eff,t}, & \text{if } c_{inf} \geq P_{eff,t}/h \\ c_{inf} \cdot h, & \text{else} \end{Bmatrix} \tag{12}$$

$$RAW_t = \sum_{s \forall S} r_s \cdot TAW \tag{13}$$

$$c_{s,t} = \begin{Bmatrix} RAW/P_{inf,t}, & \text{if } P_{inf,t} > RAW \\ 1, & \text{else} \end{Bmatrix} \tag{14}$$

where subscript, s = tree species (s ∈ S), t = unit time (daily/weekly).

The computational steps followed by the model are as follows: In Step 1, the sum of the precipitation for the past week is calculated from the precipitation data source (daily). In Step 2, the sum of the precipitation forecast for next week is calculated from the precipitation forecast data source (daily). In Step 3, the sum of the ET_0 is calculated, according to the FAO method, for the prior week from the reference ET data source (daily).

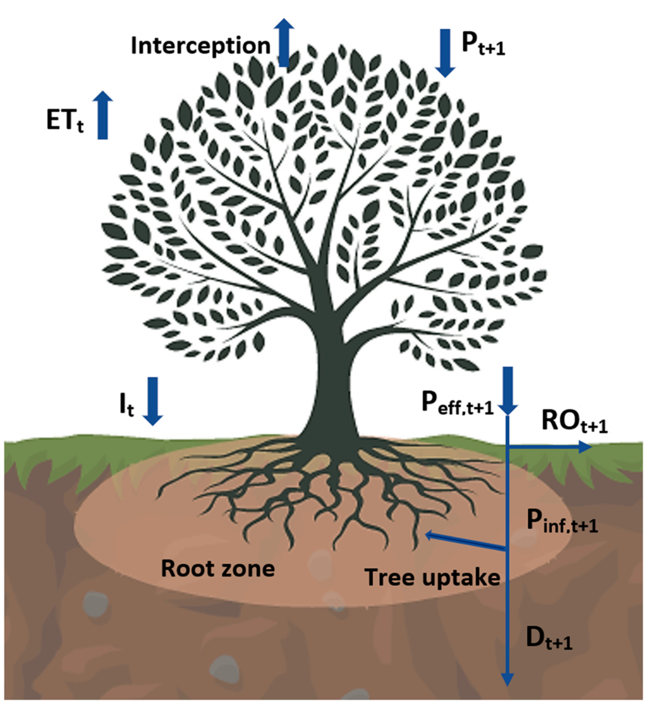


Fig. 1. The parameters in the water balance approach considered in the time series model.

In Step 4, using the tree species information from the tree inventory, ET_L is calculated for each tree by matching its botanical name (in Latin) with the WUCOLS dataset. Due to certain differences in spellings of species in tree inventories and the WUCOLS database, a fuzzy matching algorithm (Cohen, 2020) is used to identify the highest matching keywords based on the botanical name. Therefore, if a specific species type is missing from the WUCOLS database, the most similar tree name from the same botanic family will be assigned to it. If no match is found, a medium water demand value is assumed by default. Since WUCOLS was originally composed for California, the region type with the most similar climate to the study area needs to be selected. The description of the six available climatic zones is published on the WUCOLS and the Sunset website (UC Davis, 2021).

In Step 5, a species factor (K_s) is defined according to Table 2. By default, the factor is set to the middle of the given range (see Table 2). However, a user can modify the value within the respective range. A similar procedure is applied to select the density factor (K_d) and the micro-climate factor (K_{mc}) according to the category obtained in Step 4. Again, the default value is set at the middle of the range; however, the user can manually adjust the values in the case, for example, of newly planted trees or completely shaded areas. Then, a landscape factor (K_L) is calculated by multiplying all three factors as per Equation (3).

In Step 6, the weekly ET_0 obtained in Step 3 is multiplied with K_L to obtain the weekly ET_L. This is further multiplied with the species-wise tree count to obtain the ET_L demand for each species (Equation (10)). In Step 7, to determine P_{eff} according to Equation (11). Based on the available data from the literature, c_{inc} for *Quercus* and *Aesculus* trees was set as 0.17 and 0.3058, respectively (Llorens and Domingo, 2007; Yang et al., 2019), while for the remaining species for which data was unavailable, it was set to 0.227 as the default (Nytch et al., 2018). In Step 8, the amount of water infiltrating into the soil is calculated using infiltration rate c_{inf} according to Equation (12). If there are no field data, the Minnesota Pollution Control Agency provides design infiltration rates for different soil types in the Minnesota Stormwater Manual (Minnesota Pollution Control Agency, 2013). In Step 9, the available RAW is calculated by multiplying the root depth given in Table 3. In Step 10, weekly irrigation demand I_t is calculated as the difference of ET_L and the available infiltrated water in the root zone according to Equation (9).

The aforementioned model was implemented in Python language (version 3.10) using the Google Colab service (Google, 2021). The program initialises by downloading and storing all of the listed datasets from their respective servers, using the requests library. Additionally, the matplot library was used for the purpose of plotting. The total run-time with a tree inventory of around 0.5 million trees is about 15 min.

4. Case study: Berlin City

The described model is applied to a case study on the City of Berlin. Berlin is the capital and largest city of Germany, with around 3.6 million inhabitants and a city area of 891 km^2. The mean population density in the city is about 4200 residents/km^2 which is considered as high-density cluster according to the degree of urbanisation classification of Eurostat. The city is mainly flat in topography and located on the Spree River, surrounded by numerous lakes and woodlands. Berlin has an average of around 80 trees per kilometre of the city's streets, totalling about 431,000 trees in the entire city. They consist of trees from over 50 different species. The most common tree genus include lime (Tilia), maple (Acer), oak (Quercus), plane (Platanus), and chestnut (Aesculus), which account for over 75% of the total number of street trees. Currently, the city spends around 37 million euros/year on the maintenance of existing street trees and around 2500 euros/tree to take care of newly planted trees for the first three years (Pflanzenschutzamt Berlin, 2021b).

4.1. Data used and inputs

In Germany, the German weather service DWD offers data from 5980 meteorological stations spread across the whole country (Deutscher Wetterdienst, 2021). From this set of meteorological stations, 11 are located in the Berlin city region. As a result, meteorological data from all 11 stations is averaged to obtain a mean value for different parameters. The dataset includes the ET_0, as well as past and future precipitation data. For the calculation of ET_L, the WUCOLS dataset provided by the University of California is used (UC Davis, 2021). For Berlin, climate region two was the appropriate choice, which was used to determine the relevant coefficients from Table 2. The city tree inventory available from the open-data initiative of Berlin was used for obtaining tree specific information such as type of tree, species type, and distribution (Berlin City, 2021). Information regarding the soil type in Berlin was obtained from the Federal Institute for Geosciences and Natural Resources (Bundesanstalt für Geowissenschaften und Rohstoffe, 2007). Using this, sandy loam soil was selected for Berlin. Subsequently, the default value for c_{inf} should be 20.3 mm/h for normal soil, but for the case of street trees, it is set one level below at 11.4 mm/h due to compacted soils near the tree trench. Additionally, the default TAW value for sandy loam soil was used at 70 mm based on the literature (Newman, 2012).

For a more precise irrigation recommendation, the forecast for precipitation and ET_0 is necessary. The DWD (Deutscher Wetterdienst, 2021) makes predictions about future rain events, but ET_0 forecasts are not available. Hence, in this case, the average ET_0 of the prior week is used as a forecast, considering that the ET_0 should not change substantially in the short run. Moreover, the available soil moisture from the previous seven days is taken into account as the available water.

Fig. 2 presents a snapshot of the tree inventory dataset of the City of Berlin, wherein the colour of the marker indicates the species type. This dataset includes information on the tree's location, botanical name, and species family. Moreover, for a share of trees (75%) it also includes year of plantation, crown size, trunk size, and tree height information. Although this additional tree maturity information was not considered in the current study, it should be further investigated to improve the estimations.

4.2. Results for the street trees in Berlin

Fig. 3a presents the species-wise distribution of trees in Berlin. It can be observed that Tilia (Lime) is the most dominant species, followed by Acer (Maple) and Quercus (Oak). First, an analysis was performed for a single week of 2021 (41st week). Fig. 3b presents the species-wise ET_L demand for street trees in Berlin for this particular week. It can also be observed that Salix (Willows) and Betula (Birch) have the highest ET_L demand whereas Aesculus (Chestnut horse) has the lowest ET_L demand, of all tree species in Berlin. In the following step, irrigation is recommended if the precipitation forecast for the next seven days is lower than the sum of the current irrigation demand and the forecasted ET_L for the next seven days. Depending on the irrigation system, municipalities might also be interested in applying additional water to meet future irrigation demands. In such a case, the maximum demand is supplied according to the assessed irrigation demand for the next seven days. The bar plots in Fig. 4a and b depict the species-wise current and maximum irrigation recommendation (mm) for a single tree. This information can be further used by the decision-makers to assess the future increase in water demand in the case of new plantations of trees. Although several factors such as nativity, climate resilience, full-grown canopy size, aesthetics, and cost need to be considered while selecting the species type for a new plantation, watering demand can be a significant determining factor, especially, for drought-prone cities. Furthermore, Fig. 4c and d show the species-wise total current and maximum irrigation recommendation for all the city's street trees. Again, Tilia has the highest total

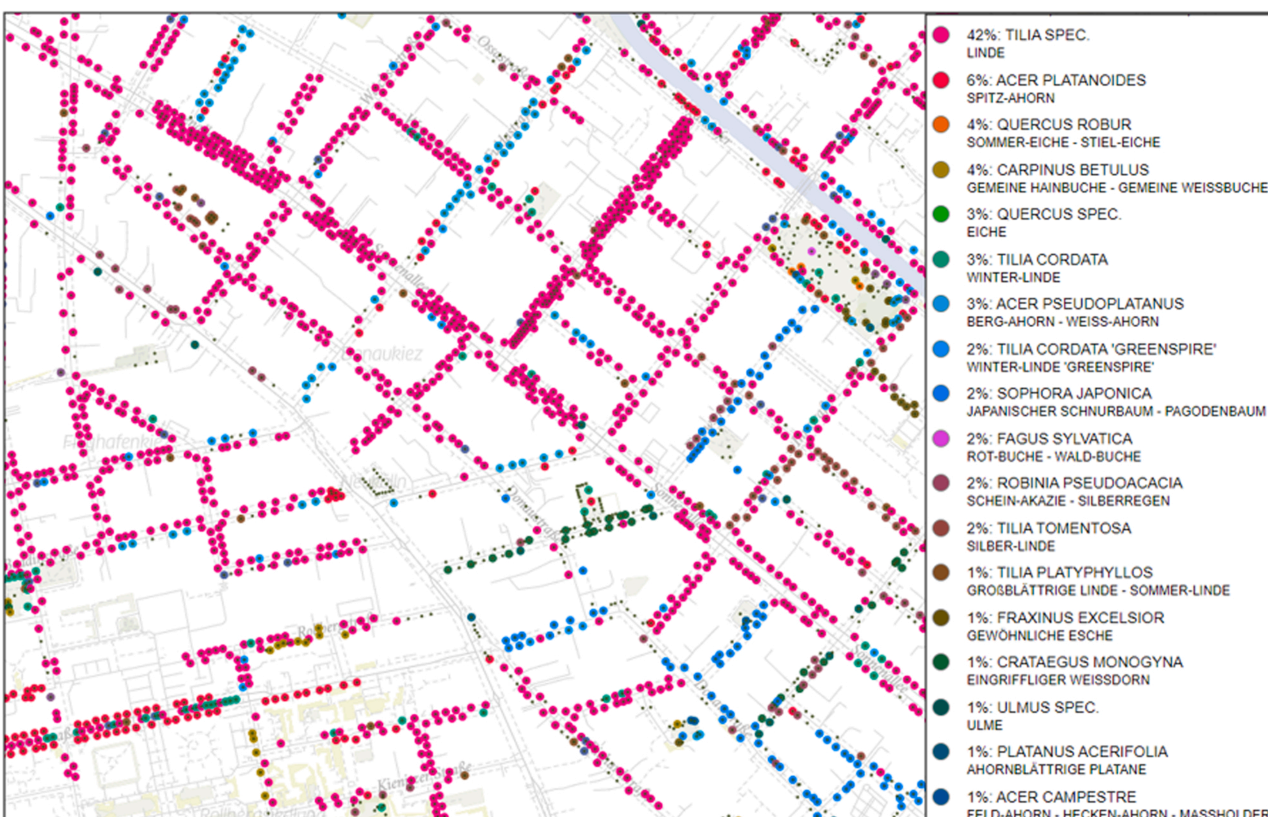


Fig. 2. Snapshot of the street trees in Berlin with the colour of the marker indicating the species type.
Source: http://opentrees.org/.

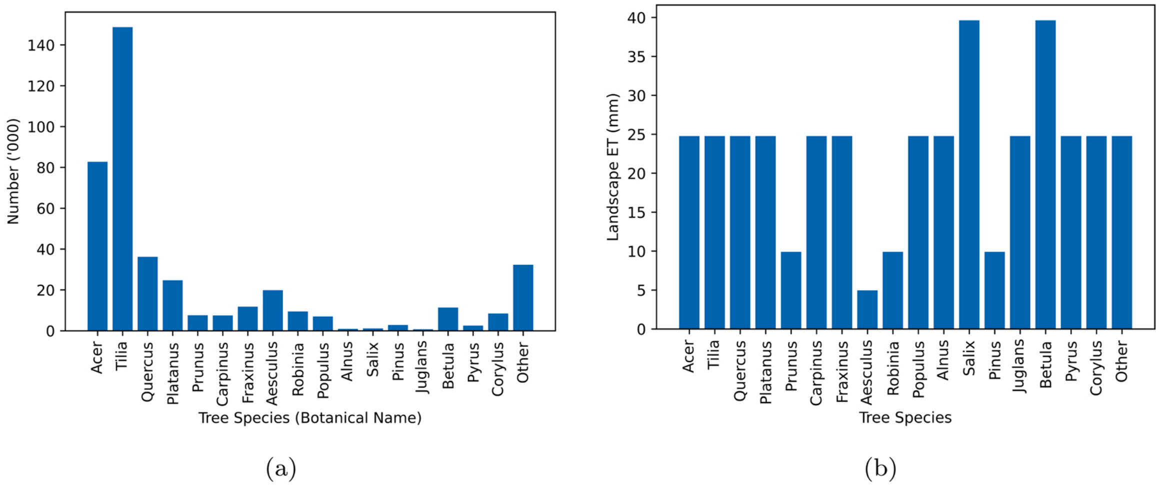


Fig. 3. Bar plots showing (a) Species-wise distribution of street trees in Berlin. (b) Species-wise Landscape ET demand (mm) of street trees in Berlin.

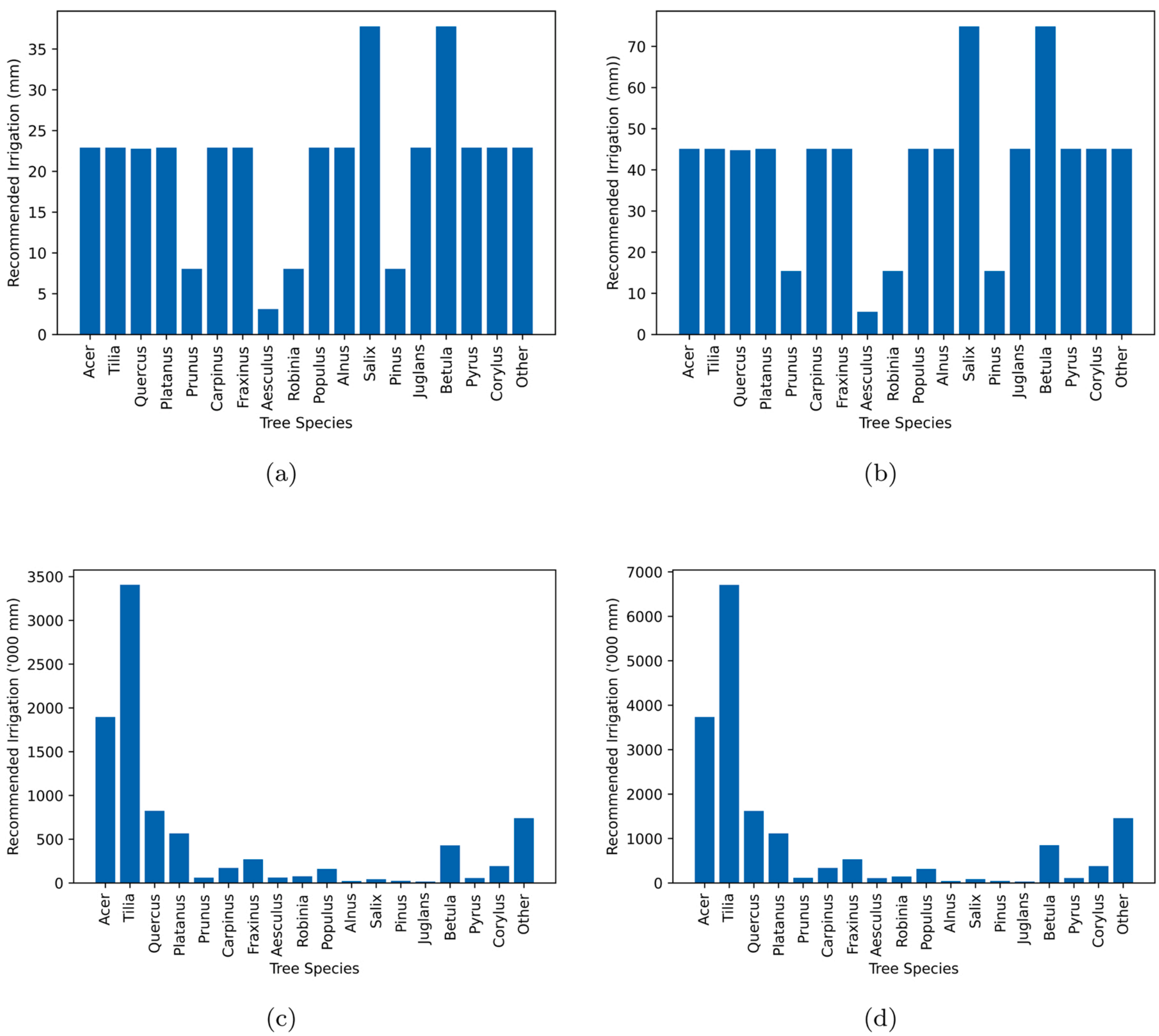


Fig. 4. Bar plots showing species-wise current (a) and maximal (b) irrigation demand for a single tree, and species-wise current (c) and maximal (d) irrigation demand for all street trees (in mm) in Berlin.

irrigation demand, followed by Acer and Quercus. Since the chosen week occurs during the peak of the summer season in Berlin, the irrigation demand observed in this case was particularly high.

Based on this, the total irrigation requirement for this particular week is computed for all the street trees and is presented in Fig. 5. If the watering is done through drip irrigation, the water height figures in mm should be converted into m^3 or liters by multiplying the height with the tree area (taken as 6 m^2 in this study) to calculate the volume of water to

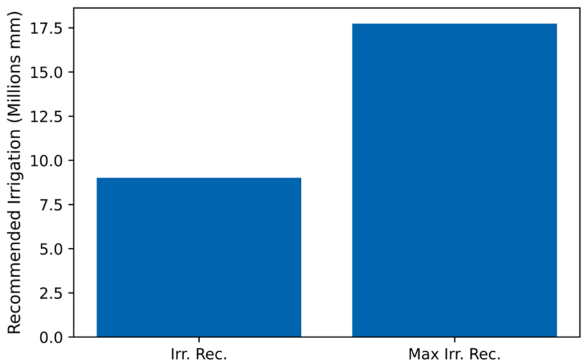


Fig. 5. A bar plot showing the one week (41st week of 2021) total current and maximum irrigation recommendation (in mm) for all street trees in Berlin.

be supplied. However, in the case of watering tankers, the estimates in water height should be used directly for uniformly applying it over the tree trench.

Next, the time series model is run for all the weeks of 2021 to obtain the weekly irrigation demand. Fig. 6 (left) presents the species-wise weekly irrigation demand of the most commonly found tree species in Berlin. This is particularly useful for the road and garden department's day-to-day operations of supplying the water only in the required quantity. The total irrigation demand for all the street trees in the cities is given in Fig. 6 (right). This is particularly useful for the city administrators to make long-term plans in terms of water budgeting for existing and newly planted trees. The seasonal variations are quite evident in the result, wherein during the winter weeks the irrigation demand is significantly lower in comparison to the summer months. This further reinforces the need for applying such a model in practice so that cities can plan and prepare their water budgets in advance. Furthermore, besides watering schedules, city administrators can also use this to make management decisions regarding the required water storage capacity, rainwater collection, irrigation scheduling, logistics, and the feasible amount of new trees that can be supported in the future.

To illustrate an application for scenario analysis, the irrigation demand considering a drought scenario is computed. For this, the model was run with the input precipitation data reduced by 50%, while keeping all other parameters identical to the baseline scenario. This resulted in an increase of around 8.5% in the external irrigation demand. Fig. 7 presents the weekly increment in water demand in this case. Here, too, the effect is stronger during the summer weeks compared to winter. In actual conditions, this impact is likely to be even higher, since the reduced rainfall will also cause the depletion of groundwater resources.

We also compared our model with the existing SLIDE method, which is based on assigning PF values to adjust the ET_0 based on urban context. Street trees can be classified under woody plants, so a PF value of 0.5

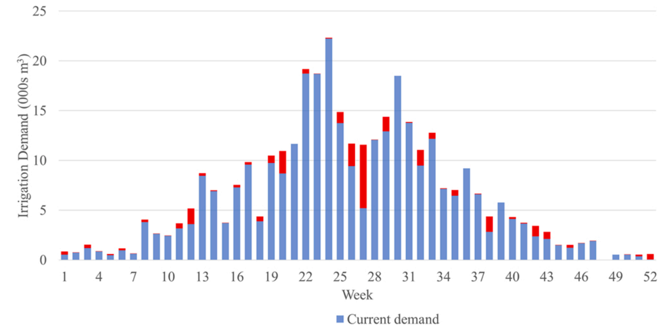


Fig. 7. A plot showing the change in irrigation demand in case only 50% of rainfall occurs.

was applied here. Accordingly, only the coefficient ($K_s \cdot K_d \cdot K_{mc}$) of Equation (10) was replaced by PF, while everything else remained the same. The calculated irrigation demand by both methods is presented in Fig. 8. As visible, the SLIDE approach estimates a lower demand compared to our model. Overall, a 19% reduction in the total annual irrigation demand was seen. This can be potentially attributed to the comprehensiveness of the WUCOLS approach, which includes three separate coefficients to incorporate the impact of urban conditions, therefore leading to higher ET_L demand and, subsequently, recommending higher irrigation.

Moreover, Fig. 9 presents a plot from the currently implemented model in Berlin that estimates the soil moisture available to plants for a single tree (Tilia cordata) at the Tempelhofer Weg in Berlin-Neukölln for the year 2021. According to this system, irrigation will only take place when the plant's available water in the soil falls below 30%. So, in this

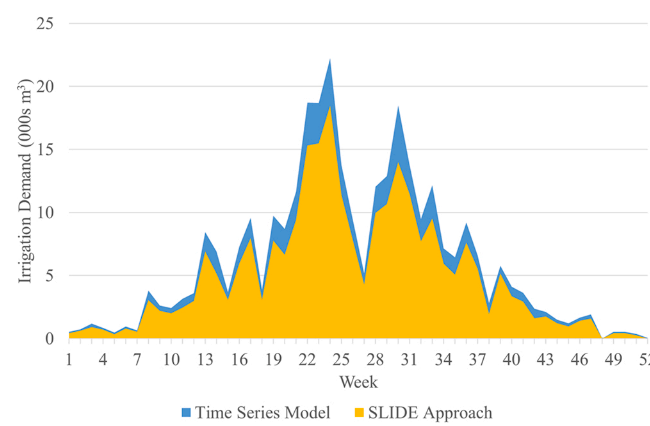


Fig. 8. A plot showing estimated irrigation demand (m^3) for the Berlin city in 2021 by the time series and SLIDE model.

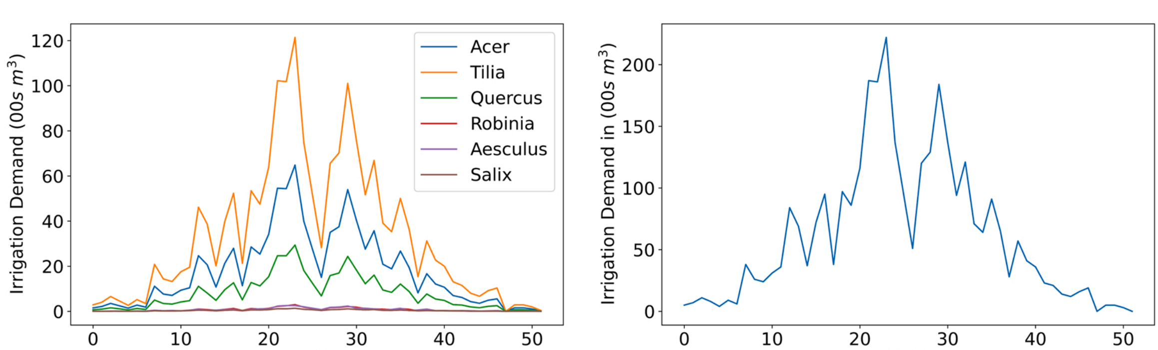


Fig. 6. A plot showing estimation of weekly irrigation demand (in m^3) for the most commonly found street tree species (on left) and for all the street trees in Berlin combined (on right).

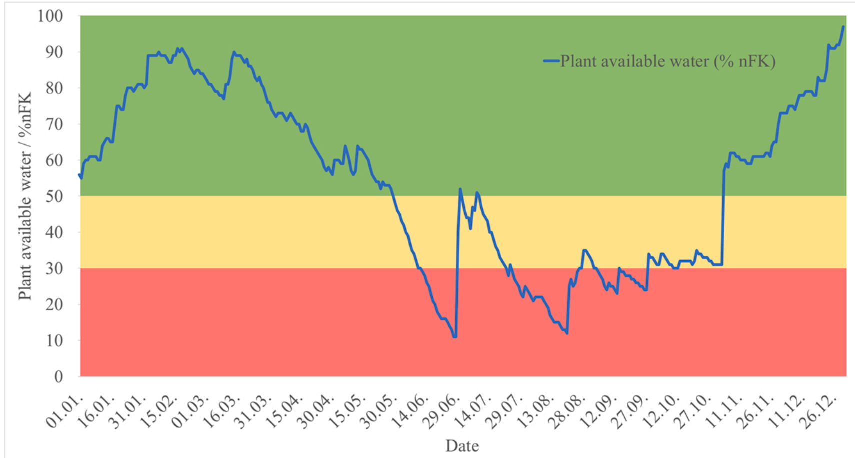


Fig. 9. A plot showing estimated soil moisture available to plants at the example site Tempelhofer Weg in Berlin-Neukölln for the year 2021.
Data Source: (Pflanzenschutzamt Berlin, 2021a).

case, this would be from the beginning of June to the end of September. This is distinctly different than in the time series model, where irrigation is recommended almost throughout the year.

5. Discussion

The developed time series model is suitable for estimating an irrigation schedule for all street trees in a city on daily or weekly time scales. Since it is based on the soil water balance principle and incorporates the WUCOLS approach for the estimation of ET demand, it can adapt irrigation recommendations according to urban conditions. Moreover, it is not dependent on any sensor data to measure soil moisture change. However, if field measurements are available, they can be integrated into the same model for greater accuracy.

The estimations from the developed time series model suggest an improvement over the currently implemented forecasting model in Berlin. The currently applied model extends the calculation made for one tree species to the entire city without any adjustments. Furthermore, a high concentration of irrigation demand during the summer months can aggravate already stressed water systems during droughts or drier summers. Additionally, the soil moisture approach informs about the necessity to irrigate but does not provide any information on the quantity of water to be irrigated. These limitations are addressed by the time series model, which uses an ET-based approach for estimating the irrigation demand.

Furthermore, to obtain the irrigation demand estimation, the time series approach should be preferred when compared to available alternative approaches such as SLIDE, which basically assumes one average PF for all tree plantings and therefore ignores the species type or density as an important driver of the ET_L. In addition to that, in the SLIDE method, the forecasted rainfall is not incorporated within the estimation and, therefore, is missing out on the potential water savings. WUCOLS, on the other hand, considers more aspects of the study site through its species, density and micro-climate factor. Nouri et al. (2013c), in their study of Adelaide, also found that WUCOLS leads to more realistic results than the PF approach. As WUCOLS offers more scope for adaptation according to the site peculiarities, it was the chosen method for calculating ET_L in this time series model. Comparative analysis shows a lower irrigation demand with the SLIDE approach than with the time series model. Due to the lack of other data sources concerning the ET and the irrigation demand, only a qualitative comparison of the two approaches is possible.

The accuracy of the proposed model can be further improved by calibrating it using field data and including the uncertainty in the weather data. The limitations of the model include obtaining the infiltration coefficients and root depths from literature, since in reality, those actually depend on the individual tree and site-specific characteristics. Nevertheless, in the future, when accurate data is available, e. g., via sensors or field data regarding the interception or infiltration rates, it could be easily incorporated into the proposed model to incorporate the localisation and thus improve model performance. Additionally, the impact of omitting CR from the model needs further investigation, especially, for the cities with high groundwater tables. For the calculation of the annual irrigation demand, the climatic data on a daily time scale has been used. For ET_0 this time resolution is suitable; however, for the precipitation, a higher temporal resolution would be ideal. Since the infiltration rate is used to determine the actual water quantity from effective precipitation percolating into the root zone, detailed information about the intensity of the rain event would lead to more precise estimations. Furthermore, the weather data originated from the DWD stations, which are spread around the entire city, and were averaged to obtain the input data. However, depending on the placement of the measuring instruments, the data might not have incorporated the full effect of the urban conditions on the weather data. Also, rain could have fallen erratically over the investigated area. The model, however, assumes regular or constant rainfall in the investigated region. Considering the above factors and the uncertainties involved with the estimation, the final results should be used as a guideline for the administrators on a relative scale rather than at an absolute level. Moreover, in this study, the results are calculated for the year 2021. Historic data are not used yet but could be used for computing the potential variability of irrigation demand due to changing weather and long-term climate change effects.

6. Conclusion and future research

In order to safeguard the benefits attainable from UGS, it is crucial that the city trees survive dry and hot periods, receive enough water to fulfill the ET demand, moderate the climate, and remain aesthetically pleasing. Hence, quantifiable information about the irrigation demand of UGS is of high interest to municipalities.

The proposed time series model based on soil water balance and the WUCOLS approach present a unique solution for determining an irrigation schedule for city street trees at a finer (daily or weekly) temporal resolution. The model requires limited input data that is readily available from open-access datasets, and no additional installation of sensors is required. The proposed model provides a feasible solution for a large number of cities, especially in developing regions where access to reliable data is limited. With more frequent and extreme weather events caused by global warming and the resulting water scarcity, the time series model can provide reasonable accuracy for the water demand of street trees, allowing the garden and forestry departments to avoid relying on historic or speculative values.

However, it is crucial to understand the drivers of the input parameters and the approach adopted for their estimation. Furthermore, the input data and conditions can be varied to generate irrigation estimations for different scenarios, such as an increase in trees, longer and drier summers, or the depletion of groundwater. The results from this model can be further combined with the benefit estimation of each UGS to make an informed decision regarding the future planning of newer green areas and efficient resource management. For instance, depending on the availability of stored water resources and the UGS' specific water demand, an evidence based decision regarding the allocation of the available water can be made. Likewise, if the water deficit is known in advance, the necessary rainwater collection and storage systems can be designed accordingly.

To increase the model's applicability, performance should be evaluated through controlled experiments or field trials. Furthermore, the model can be improved by integrating forecast uncertainties as well as higher spatial and temporal resolutions of the relevant input data and design parameters. For instance, precise hourly rainfall intensity and the actual ET at sub-city spatial scale could improve the irrigation schedule estimation.

CRediT authorship contribution statement

Mihir Rambhia: Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Data curation, Writing - original draft, Writing - review & editing, Visualisation. **Rebekka Volk**: Writing - review & editing, Project administration, Supervision. **Behzad Rismanchi**: Writing - review & editing, Supervision. **Stephan Winter**: Writing - review & editing, Supervision. **Frank Schultmann**: Writing - review & editing, Supervision, Funding acquisition.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgments

The first author sincerely thank Marlene Dickmann for her contributions to the development of software. The first author gratefully acknowledge the funding from Graduate School for Climate and Environment (GRACE) at Karlsruhe Institute of Technology (KIT), Germany in cooperation with the University of Melbourne, Australia to undertake this research.

References

Adeyemi, O., Grove, I., Peets, S., Domun, Y., Norton, T., 2018. Dynamic neural network modelling of soil moisture content for predictive irrigation scheduling. Sens. (Switz.) 18. https://doi.org/10.3390/s18103408.

Allen, R.G., Pereira, L.S., Howell, T.A., Jensen, M.E., 2011. Evapotranspiration information reporting: I. Factors governing measurement accuracy. Agric. Water Manag. 98, 899–920. https://doi.org/10.1016/j.agwat.2010.12.015.

Berlin City, Open Data Berlin, 2021.⟨https://daten.berlin.de/⟩.

C. Brouwer, A. Goffeau, M. Heibloem, Irrigation water management: Training manual no. 1, 1985.⟨https://www.fao.org/3/r4082e/r4082e00.htm⟩.

Bundesanstalt für Geowissenschaften und Rohstoffe, Bodenübersichtskarte von Deutschland 1:3000000, 2007.⟨https://www.bgr.bund.de/DE/Themen/Boden/Produkte/Karten/Downloads/BUEK3000.pdf⟩.

A. Cohen, fuzzywuzzy: Fuzzy string matching in python, 2020.⟨https://pypi.org/project/fuzzywuzzy/⟩.

Contreras, S., Jobbágy, E.G., Villagra, P.E., Nosetto, M.D., Puigdefábregas, J., 2011. Remote sensing estimates of supplementary water consumption by arid ecosystems of central Argentina. J. Hydrol. 397, 10–22. https://doi.org/10.1016/j.jhydrol.2010.11.014.

L. Costello, K. Jones WUCOLS IV: Water use classification of landscape species, 2014a.

L.R. Costello K.S. Jones(Water Use Classification of Landscape Species), 2014b.⟨https://ucanr.edu/sites/WUCOLS/files/183514.pdf⟩.

Delgoda, D., Saleem, S.K., Malano, H., Halgamuge, M.N., 2016a. Root zone soil moisture prediction models based on system identification: Formulation of the theory and validation using field and aquacrop data. Agric. Water Manag. 163, 344–353. https://doi.org/10.1016/j.agwat.2015.08.011.

Delgoda, D., Malano, H., Saleem, S.K., Halgamuge, M.N., 2016b. Irrigation control based on model predictive control (mpc): Formulation of theory and validation using weather forecast data and aquacrop model. Environ. Model. Softw. 78, 40–53. https://doi.org/10.1016/j.envsoft.2015.12.012.

Deutsche Welle, Water scarcity: EU countries forced to restrict drinking water access, 2022.⟨https://www.dw.com/en/water-scarcity-eu-countries-forced-to-restrict-drinking-water-access/a-62363819⟩.

Deutscher Wetterdienst, DWD open data, 2021.⟨https://www.dwd.de/⟩.

Dimoudi, A., Nikolopoulou, M., 2003. Vegetation in the urban environment: microclimatic analysis and benefits. Energy Build. 35, 69–76. https://doi.org/10.1016/s0378-7788(02)00081-6.

M. Dobson, Tree root systems, 1995.

Domene, E., Saurí, D., 2006. Urbanisation and water consumption: influencing factors in the metropolitan region of barcelona. Urban Stud. 43, 1605–1623. https://doi.org/10.1080/00420980600749969.

European Commission, Establishing a framework for community action in the field of water policy, 2000.

European Commission, Forging a climate-resilient Europe - the new EU strategy on adaptation to climate change, 2021.

D. Fam, E. Mosley, A. Lopes, L. Mathieson, J. Morison, G. Connellan, Irrigation of urban green spaces: a review of the environmental, social and economic benefits, 2008.

FAO, Chapter 8 - etc under soil water stress conditions, 1990.⟨https://www.fao.org/3/x0490e/x0490e0e.htm⟩.

FAO, Penman-Monteith equation, 2021a.⟨https://www.fao.org/3/x0490e/x0490e06.htm⟩.

FAO, Cropwat, 2021b.⟨https://www.fao.org/land-water/databases-and-software/cropwat/en⟩.

FAO, Aquacrop, 2021c.⟨https://www.fao.org/aquacrop⟩.

France-Presse Agence, Italy declares state of emergency in drought-hit northern regions, 2022.⟨https://www.theguardian.com/world/2022/jul/05/italy-declares-state-emergency-drought-hit-northern-regions⟩.

George, B., Shende, S., Raghuwanshi, N., 2000. Development and testing of an irrigation scheduling model. Agric. Water Manag. 46, 121–136. https://doi.org/10.1016/s0378-3774(00)00083-4.

Gerrits, A.M.J., Savenije, H.H.G., Hoffmann, L., Pfister, L., 2007. New technique to measure forest floor interception – an application in a beech forest in luxembourg. Hydrol. Earth Syst. Sci. 11, 695–701. https://doi.org/10.5194/hess-11-695-2007.

Google, Google colaboratory, 2021.⟨https://colab.research.google.com/⟩.

Hilaire, R., Arnold, M., Wilkerson, D., Devitt, D., Hurd, B., Lesikar, B., Lohr, V., Martin, C., McDonald, G., Morris, R., Pittenger, D., Shaw, D., Zoldoske, D., 2008. Efficient water use in residential urban landscapes. HortScience horts 43, 2081–2092. https://doi.org/10.21273/HORTSCI.43.7.2081.

Huang, B., Fry, J.D., 2000. Turfgrass evapotranspiration. J. Crop Prod. 2, 317–333. https://doi.org/10.1300/j144v02n02_14.

Khan, M.S., Woo, M., Nam, K., Chathoth, P.K., 2017. Smart city and smart tourism: a case of Dubai. Sustain. (Switz.) 9. https://doi.org/10.3390/su9122279.

Khan, M.A., Islam, M.Z., Hafeez, M., 2020. Data pre-processing and evaluating the performance of several data mining methods for predicting irrigation water requirement. arXiv 2011, 1–13.

Kjelgren, R., Beeson, R., Pittenger Jr., D., Montague, T., 2016. Simplified landscape irrigation demand estimation: Slide rules. Appl. Eng. Agric. 32, 363–378. https://doi.org/10.13031/aea.32.11307.

Koeser, A., Hauer, R., Norris, K., Krouse, R., 2013. Factors influencing long-term street tree survival in milwaukee, wi, usa. Urban For. Urban Green. 12, 562–568. https://doi.org/10.1016/j.ufug.2013.05.006.

Llorens, P., Domingo, F., 2007. Rainfall partitioning by vegetation under mediterranean conditions. a review of studies in europe. J. Hydrol. 335, 37–54. https://doi.org/10.1016/j.jhydrol.2006.10.032.

Minnesota Pollution Control Agency, Minnesota stormwater manual, 2013.⟨https://stormwater.pca.state.mn.us/index.php/Main_Page⟩.

H. Newman, Calculating readily available water, 2012.⟨https://www.agric.wa.gov.au/citrus/calculating-readily-available-water?page=0⟩.

Nouri, H., Beecham, S., Kazemi, F., Hassanli, A., 2013a. A review of ET measurement techniques for estimating the water requirements of urban landscape vegetation. Urban Water J. 10, 247–259. https://doi.org/10.1080/1573062X.2012.726360.

Nouri, H., Beecham, S., Hassanli, A., Ingleton, G., 2013b. Variability of drainage and solute leaching in heterogeneous urban vegetation environs. Hydrol. Earth Syst. Sci. 17, 4339–4347. https://doi.org/10.5194/hess-17-4339-2013.

Nouri, H., Beecham, S., Hassanli, A.M., Kazemi, F., 2013c. Water requirements of urban landscape plants: a comparison of three factor-based approaches. Ecol. Eng. 57, 276–284. https://doi.org/10.1016/j.ecoleng.2013.04.025.

H. Nouri, S. Anderson, S. Beecham, D. Bruce, Estimation of Urban Evapotranspiration through Vegetation Indices Using WorldView2 Satellite Remote Sensing Images, Conference: Sustainable Agriculture through ICT Innovation (2013d)24–27.

Nouri, H., ChavoshiBorujeni, S., Hoekstra, A.Y., 2019. The blue water footprint of urban green spaces: an example for Adelaide, Australia. Landsc. Urban Plan. 190 https://doi.org/10.1016/j.landurbplan.2019.103613.

Nytch, C., Meléndez-Ackerman, E., Pérez, M.-E., Ortiz-Zayas, J., 2018. Rainfall interception by six urban trees in San Juan, Puerto Rico. Urban Ecosyst. 22, 103–115. https://doi.org/10.1007/s11252-018-0768-4.

Orusa, T., Orusa, R., Viani, A., Carella, E., Borgogno Mondino, E., 2020. Geomatics and eo data to support wildlife diseases assessment at landscape level: a pilot experience to map infectious keratoconjunctivitis in chamois and phenological trends in aosta valley (nw italy). Remote Sens. 12.

Patel, K., Samenow, J., 2022. California declares historic water emergency measures amid drought. Wash. Post.

Pflanzenschutzamt Berlin, Bewässerungsempfehlung für Stadtbäume, 2021a.⟨https://www.berlin.de/pflanzenschutzamt/stadtgruen/beratung/bewaesserungsempfehlung-fuer-stadtbaeume/⟩.

Pflanzenschutzamt Berlin, Stadtbäume, 2021b.⟨https://www.berlin.de/sen/uvk/natur-und-gruen/stadtgruen/stadtbaeume/⟩.

Pooya, E., Tehranifar, A., Shoor, M., Selahvarzi, Y., Ansari, H., 2013. The use of native turf mixtures to approach sustainable lawn in urban landscapes. Urban For. Urban Green. 12, 532–536. https://doi.org/10.1016/j.ufug.2013.06.009.

Revelli, R., Porporato, A., 2018. Ecohydrological model for the quantification of ecosystem services provided by urban street trees. Urban Ecosyst. 21, 489–504. https://doi.org/10.1007/s11252-018-0741-2.

SA Water, Cooling the community, 2021.⟨https://www.sawater.com.au/education-and-community/community-and-events/cooling-the-community⟩.

Shi, Y., Yang, G., Du, Y., Ren, Y., Lu, Y., Fan, L., Chang, J., Ge, Y., Bao, Z., 2018. Estimating irrigation water demand for green spaces in humid areas: seeking a sustainable water management strategy. Urban Water J. 15, 16–22. https://doi.org/10.1080/1573062X.2017.1363255.

Sjöman, H., Busse Nielsen, A., 2010. Selecting trees for urban paved sites in scandinavia – a review of information on stress tolerance and its relation to the requirements of tree planners. Urban For. Urban Green. 9, 281–293. https://doi.org/10.1016/j.ufug.2010.04.001.

UC Davis, WUCOLS plant search database, 2021.⟨https://ucanr.edu/sites/WUCOLS/Plant_Search/⟩.

United Nations, Goal 11, 2020.⟨https://sdgs.un.org/goals/goal11⟩.

Vico, G., Revelli, R., Porporato, A., 2013. Ecohydrology of street trees: design and irrigation requirements for sustainable water use. Ecohydrology 7, 508–523. https://doi.org/10.1002/eco.1369.

T.J. Volo, E.R. Vivoni, C.A. Martin, S. Earl, B.L. Ruddell, Modelling soil moisture, water partitioning, and plant water stress under irrigated conditions in desert urban areas, Ecohydrology (2014). 10.1002/eco.1457.

Wessolek, G., Kluge, B., 2021. Predicting water supply and evapotranspiration of street trees using hydro-pedo-transfer functions (hptfs). Forests 12, 1010. https://doi.org/10.3390/f12081010.

World Health Organization, Urban green spaces and health - a review of evidence, 2016.

Yang, B., Lee, D.K., Heo, H.K., Biging, G., 2019. The effects of tree characteristics on rainfall interception in urban areas. Landsc. Ecol. Eng. 15, 289–296. https://doi.org/10.1007/s11355-019-00383-w.

Young, R.F., 2011. Planting the living city: best practices in planning green infrastructure - results from major U.S. cities. J. Am. Plan. Assoc. 77, 368–381.

IOP Conference Series: Earth and Environmental Science

PAPER • **OPEN ACCESS**

Prioritising urban green spaces using accessibility and quality as criteria

To cite this article: M Rambhia *et al* 2022 *IOP Conf. Ser.: Earth Environ. Sci.* **1101** 022043

Prioritising urban green spaces using accessibility and quality as criteria

M Rambhia[1], R Volk[1], B Rismanchi[2], S Winter[2] and F Schultmann[1]

[1] Karlsruhe Institute of Technology, Germany
[2] University of Melbourne, Australia

E-mail: `mihir.rambhia@partner.kit.edu`

Abstract. Urban green spaces are a critical component of cities, providing environmental, social, cultural, and economic benefits. To support smart(er) decisions by city planners and managers, this study aims to investigate how open data sources could be integrated into urban green space management. Specifically, it proposes a novel GIS-based method to prioritise urban green space in a resource-constraint scenario so that social benefits are maximised. To quantify the social benefits, the methodology is based on the WHO indicator, which recommends access to at least 0.5-1 ha of green space within 300 metres' linear distance to all the city residents. The approach assigns each urban green space an 'accessibility score' based on its significance in the city, and a 'quality score' based on its performance on different quality parameters (size, greenness, quietness, and safety). Urban green spaces are ranked with respect to these two scores, enabling to prioritise spaces under resource constraints such as water shortage, limited staff, or budget. This approach is demonstrated through a case study on a mid-size German city and is transferable to other cities worldwide with varying weightage factors.

1. Introduction

Whether in parks, along streets, inside forests, or in any other form, the green spaces in an urban area provide multifaceted benefits, including environmental, social, and economic [1]. The World Health Organisation (WHO), defines Urban Green Spaces (UGS) as the collection of all kinds of vegetation present on public or private land within a city, irrespective of its size and function [2]. Studies have shown the beneficial role of UGS in protecting and enhancing local biodiversity, increasing water retention, improving social cohesion, and carbon sequestration as well as regulating local micro-climate [3, 4, 5, 6]. Regular exposure to an UGS is found to boost physical and mental well-being [7, 8]. It also provides an opportunity for recreation, especially in highly congested and densely populated neighbourhoods and for low-economic communities that cannot frequently afford other means of recreation. The significance was evident during the recent COVID-19 pandemic when researchers observed a rise of up to 350% in the usage of public parks [9]. UGS helped people to recreate even under strict lockdown measures while maintaining adequate social distance.

Taking into account the enormous benefits obtained from UGS, the United Nations in its Sustainable Development Goals set a target 11.7 that aims to provide universal access to safe, inclusive and accessible, green and public spaces for everyone. WHO as well recommends 'access to at least 0.5-1 ha of green space within 300 metres' linear distance to all the city residents' [2]. Moreover, the Convention on Biological Diversity (CBD) in Germany set a target to provide publicly accessible UGS with a diverse range of qualities and functions within walking distance to every urban household [10]. Therefore, to provide sufficient UGS accessibility, city governments need to plan newer greening areas in addition to protecting existing UGS. This, however, encounters dual challenge from urbanisation. First, as the urban population increases, the higher housing demand puts constant pressure to colonise the open and green spaces. Second, as the population density rises, the per capita UGS availability deteriorates. This commonly leads to crowding and occasionally uneven distribution of UGS, especially affecting low-income communities that are highly dependent on public parks and playgrounds for affordable recreation. Therefore, it is critical to monitor the status of UGS accessibility and take required steps to maintain and enhance it.

Furthermore, constant management is required to maintain the UGS in healthy conditions. This involves watering, application of fertiliser and pesticides, pruning of trees, cutting, lawn mowing, tree stability inspection, cleaning leaf litter, and maintenance of recreational facilities. However, it might not be possible to provide ample management support to all the UGS in the case of limited/constrained resources such as water, budget, staff or equipment. For example, in case of water shortage due to droughts or as experienced recently, limited personnel during pandemic. In such cases, it becomes indispensable to prioritise the UGS that need to be preserved. The prioritisation should be done so that either benefits are maximised, costs are minimised, or resource constraints are satisfied or all together, depending on the decision-makers' preference.

This study proposes a novel GIS-based method to prioritise the UGS management under resource constraint scenarios. The main objective is to prioritise in a manner that the total benefits from UGS are maximised. However, to simplify the case, the present study solely incorporates public accessibility as a single parameter measuring social benefit. Previous studies such as [11] and [1] have analysed the amount of UGS accessible by city residents, but the distribution in terms of quality is largely missing in the existing literature. Although, both WHO and CBD only refer to 'quantity' access of UGS in their targets, the model endeavours for a greater ambition of ensuring that this access is also of 'high-quality'. Moreover, establishing a linkage between the analysis of field data and management decisions such as prioritisation is mostly absent in the literature until now. Therefore, the study aims to investigate how open-data sources can be integrated into the decision-making of UGS management. This is the major contribution of this study at hand. In the following sections, the methodology is described, followed by the results, the discussion, and conclusions.

2. Methodology

The methodology aims to assign a prioritisation index to each UGS based on two criteria: its significance in providing social benefit measured in terms of public accessibility, and, its performance on various quality parameters. Each of these criteria is assessed with a score; namely, *Accessibility Score* (S_A) and *Quality Score* (S_Q), measured by means of defined parameters. In all cases, a normalised score value between 0 to 10 is derived by applying a feature re-scaling on individual parameters. In the case of positive scaling, the highest score was equated to the highest parameter value while in the case of negative scaling it was the opposite. The overall score is then derived by combining the two subscores by user-defined weight. Consequently, the UGS are ranked in priority according to their score, where a higher score value gets a greater/higher priority. The methodology comprises of four parts. The first part focuses on identifying the available UGS in the cities. The second and third part include quantifying the above-mentioned two scores, S_A and S_Q. The last part include determining the prioritisation index for informed decision-making.

Table 1: Different labels used in Open Street Map for tagging UGS.

Key	Label
landuse	allotments, cemetery, farm, forest, grass, heath, meadow, orchard, park, recreation ground, scrub, vineyard
natural	tree
places	farm
POIs	dog park, golf course, graveyard, park, picnic site, zoo, playground

2.1. Green Space Availability

A free and open-source Geographic Information System, QGIS, was used to perform the spatial analysis to determine the UGS accessibility of a city's population. Initially, a vector layer designating the city's administrative boundary was imported. This is based on the premise that city governments are usually responsible for managing UGS within their administrative jurisdiction. Subsequently, an OpenStreetMap (OSM) dataset for the city is introduced [12], which comprises numerous layers delineating various features within a city. For this study, the feature layers consisting of buildings, roads, water, land-use, natural, places, and points of interest (POIs) were used. Each of these layers is reprojected into a common co-ordinate referencing system (CRS) and is spatially clipped by the extent of the city boundary.

Subsequently, UGS are identified from the imported OSM layers using tag values listed in Table 1. A filter operation is applied to match the key field of the layer with the tag values and only the matching polygon features are retained. Next, the filtered polygons are merged into a single layer that will delineate all the UGS in the city. In this process, an UGS might get repeated or overlapped in some instances due to repeated tagging in different OSM layers. Moreover, in a few instances, an UGS is identified as a group of adjoining polygons instead of one large polygon. Therefore, to reduce data redundancy, such mini-polygons are combined into single elements by using the dissolve function. Furthermore, all UGS smaller than 50 m^2 are eliminated from the dataset. Thus, street trees and tiny UGS are not considered further in this study. All the remaining UGS are suitable for the public usage and henceforth referred to as *Available Green Spaces*.

2.2. Accessibility Score

In this part, proximity analysis is done to evaluate the UGS accessibility in the city. It should be highlighted that accessibility is defined here in terms of 'walking accessibility', which implies the possibility of reaching UGS by foot using permanent pathways. To simplify the computation, circular buffer approach is used to check the accessibility in linear distance. To concur with the WHO recommendation, circular buffers with 300 m radius are created with each building unit as a punctiform centre to obtain the buffered building area layer. Subsequently, the sum of all UGS areas that overlap with this buffer represents the quantity of UGS area accessible by particular buildings' residents. Accordingly, the buildings with less than the minimum recommended 0.5 ha of UGS in their buffer are classified as buildings without sufficient UGS accessibility. To find the number of city residents that do not have access to sufficient UGS, a population density map containing residents/ha is used. The population density layer is intersected with the buildings layer and multiplied with its area value to obtain the number of residents living in a particular building. The summation of population is done for the buildings without access to sufficient UGS which gives us the percent of population that is impacted by the deficit.

In the next step, the contribution of each UGS $\rightarrow i$ in maintaining the accessibility is quantified with an *Accessibility Score* (S_{A}). The score is defined as the equally weighted aggregation of two components: *Building coverage score* (S_{C}) and *Essentiality score* (S_{E}) (see Equation 6). The first component, $\mathrm{S_C}$, measures the number of residential buildings that benefit from a particular UGS. The second component, $\mathrm{S_E}$, quantifies the criticality of a particular green space in maintaining accessibility. Throughout the text, a variable symbol implies the total score for all UGS, whereas, variable with a subscript i is used to describe the computation for a single UGS 'i'. The calculation of the scores is elaborated in the next paragraphs.

Once again, circular buffers with a 300 m radius are created, but this time with each UGS as a polygon-shaped centre. All UGS and their respective buffer area will represent the total city area benefiting from UGS. This buffered UGS layer is then spatially intersected with the building vector dataset. Now, the summation of building area for those buildings elements that are in conjunction with a buffered UGS area is referred as *Building Area Covered* (A_{BC}) by UGS $i \in [1, g]$, and is computed by Equation 1, where g represents the total number of available UGS (above the threshold size). Accordingly, the residents living within area $\mathrm{A_{BC}}$ will have access to sufficient UGS within walking distance. Next, a log transformation is applied on $A_{\mathrm{BC_i}}$ to reduce the skewness of the size values between very small and very large UGS. Furthermore, logged $A_{\mathrm{BC_i}}$ values are positively re-scaled using Equation 2 to derive the associated *Building Coverage score* ($S_{\mathrm{C_i}}$). Those UGS that are accessible by a higher quantity of building area will score higher on $\mathrm{S_C}$.

For $i \in \mathbb{N} \ : \ i \in [1, g]$, g = *Total Available Green Spaces*

$$A_{\mathrm{BC_i}} = (Green\ Space\ Area_{\mathrm{i}} + Buffer\ Area_{\mathrm{i}}) \cap Building\ Area \tag{1}$$

$$S_{\mathrm{C_i}} = \frac{10 \times (log_{10}\ A_{\mathrm{BC_i}} - max(log_{10}\ A_{\mathrm{BC_i}}))}{max(log_{10}\ A_{\mathrm{BC_i}}) - min(log_{10}\ A_{\mathrm{BC_i}}))} + 10 \tag{2}$$

In the next step, the *Essentiality score* (S_{E}) is computed. For this, the buffered building area layer is spatially intersected with the green space vector dataset. As calculated in the earlier step, those UGS elements that have at least some overlap with the buffered building area can be considered as accessible by that building and its residents. The total count of such intersecting elements yields number of *Green Spaces Accessible* (G_{A}) (Equation 3), where b represents the total number of buildings in a city. The buildings with a G_{A} value greater than 0 have access to atleast 1 UGS within walking distance. As the $\mathrm{G_A}$ values are in a narrow range, they are directly re-scaled using Equation 4 to derive the associated score $S_{\mathrm{E_j}}$. Here, negative re-scaling is applied to take into account the inverse relation between $G_{\mathrm{A_j}}$ and $S_{\mathrm{E_j}}$. Accordingly, buildings having access to merely a singular UGS will score highest on $S_{\mathrm{E_i}}$. In contrast, buildings with several UGS within 300 m will score lower. In the subsequent step, $S_{\mathrm{E_i}}$ for each UGS is calculated as the mean $\mathrm{S_{E_j}}$ of all the buildings that are located within the buffer zone around the UGS determined by Equation 1.

For $j \in \mathbb{N} \ : \ j \in [1, b]$ and $i \in \mathbb{N} \ : \ i \in [1, g]$, b = *Total buildings*

$$G_{\mathrm{A_j}} = count((Building\ Centroid_{\mathrm{j}} + Buffer\ Area) \cap Green\ Space\ Area) \tag{3}$$

$$S_{\mathrm{E_j}} = \frac{10 \times (\ G_{\mathrm{A_j}} - min(\ G_{\mathrm{A_j}}))}{min(\ G_{\mathrm{A_j}}) - max(\ G_{\mathrm{A_j}})} + 10 \tag{4}$$

$$S_{\mathrm{E_i}} = \overline{S_{\mathrm{E_j}}}\ ,\ \forall\ (j \cap Building\ Area\ Covered_{\mathrm{i}}) \tag{5}$$

Lastly, the *Accessibility Score* (S_{A}) is calculated by averaging $\mathrm{S_C}$ and $\mathrm{S_E}$ with equal weightage (Equation 6). The score characterises the impact of any UGS in providing UGS accessibility to city residents. Therefore, UGS with greater S_A reflects its prominence in providing higher social benefits and thus should be prioritised higher.

$$S_{A_i} = 0.5 \times (S_{C_i} + S_{E_i}) \tag{6}$$

2.3. Quality Score

The second part of the methodology focuses on the quality aspect of UGS described by the *Quality Score* (S_Q). The quality of an UGS is a subjective issue that depends on several characteristics for its depiction. It includes the proximity to residents, size, diversity of species, free public access, quietness, recreational facilities, and safety [13]. In the context of this study, the quality of UGS is defined as its cumulative performance on selected quality parameters, namely size ($S_{Q,A}$), greenness ($S_{Q,G}$), quietness ($S_{Q,N}$), and safety ($S_{Q,S}$) (as in Equation 11). In the case of evaluating the size, the area of the particular UGS was directly used to assign a score. Since a larger area will provide higher ecosystem services, the UGS with the biggest area was assigned a maximum score. Moreover, the skewness in the area distribution of UGS due to a few disproportionately large UGS was reduced by log transformation. Subsequently, the values were positively feature-scaled to derive a corresponding score S_{Q_i,A_i} according to Equation 7. Further, to assess the greenness, the mean Normalised difference vegetation index (NDVI) value was computed for each UGS from Sentinel-2 satellite data. NDVI is an effective indicator to identify green vegetation based on the spectral reflectance of plants. Accordingly, the UGS with a greater NDVI value will likely have a high density of trees and therefore provide higher ecosystem benefits. So, the NDVI values were positively feature-scaled, such that UGS with the highest NDVI value will obtain the maximum score. This operation to derive S_{Q_i,G_i} is given in Equation 8. To evaluate the quietness in the UGS, the average noise level (dB) for each UGS is obtained from the available Noise Map. Following this, the score S_{Q_i,N_i} for noise is derived by negatively feature-scaling the mean noise values such that UGS with a higher noise value obtain a lower score. This is shown in Equation 9 below. Similarly, the score S_{Q_i,S_i} for safety is derived by negatively feature-scaling the number of criminal offences recorded in the particular district. This is shown in Equation 10 below.

For $i \in \mathbb{N} \, : \, i \in [1, g]$,

$$S_{Q_i,A_i} = \frac{10 \times (log_{10}Green\ Space\ Area_i - max(log_{10}Green\ Space\ Area_i))}{max(log_{10}Green\ Space\ Area_i) - min(log_{10}Green\ Space\ Area_i)} + 10 \tag{7}$$

$$S_{Q_i,G_i} = \frac{10 \times (\overline{NDVI} - max(\overline{NDVI}))}{max(\overline{NDVI}) - min(\overline{NDVI})} + 10 \tag{8}$$

$$S_{Q_i,N_i} = \frac{10 \times (\overline{Noise} - min(\overline{Noise}))}{min(\overline{Noise}) - max(\overline{Noise})} + 10 \tag{9}$$

$$S_{Q_i,S_i} = \frac{10 \times (Crime - min(Crime))}{min(Crime) - max(Crime)} + 10 \tag{10}$$

Finally, the overall *Quality Score* (S_{Q_i}) is calculated by combining the individual scores obtained on all quality parameters by respective weights (Equation 11). The model allows to adapt the weights according to the preferences of residents and decision makers' priorities. For example, a survey done in the City of Karlsruhe identified lower noise and pollution as extremely important criteria for UGS usage among the residents [14]. So a higher w3 value should be considered for that city. However, for the purpose of this case study, all the quality parameters are weighted equally and therefore all weights are set to 0.25. Accordingly, the UGS that are bigger in size, consist of dense and mature trees, have a quiet neighbourhood, and are located in districts with lower crime rates, will classify as a high-quality UGS. Overall, the score characterises the ability of UGS to provide higher ecosystem benefits and satisfy the user's needs. Therefore, UGS with greater S_Q should be prioritised higher.

$$S_{Q_i} = w1 \times (S_{Q_i,A_i}) + w2 \times (S_{Q_i,G_i}) + w3 \times (S_{Q_i,N_i}) + w4 \times (S_{Q_i,S_i}) \tag{11}$$

2.4. Prioritisation
In the last part, a prioritisation order is obtained by averaging the *Accessibility Score* (S_A) and *Quality Score* (S_Q) with desired weightage factors that might vary between decision-makers. Depending on the weightage values, the significance of the quality of accessibility will change against the quantity. This is given in Equation 12.

$$Prioritisation_i = w1 \times (S_{A_i}) + w2 \times (S_{Q_i}) \tag{12}$$

3. Results
The described method is applied to a case study on the City of Berlin and results are presented in this section. Berlin is the capital and largest city of Germany with around 3.6 million inhabitants and a city area of 89100 ha. The mean population density in the city is about 130 residents/ha. The city is mainly flat in topography and is located on the Spree river, surrounded by numerous lakes and woodlands. To analyse the UGS accessibility in Berlin, the OSM dataset was accessed from the Geofabrik GmbH portal. Later, all the input datasets were reprojected into a common CRS, ETRS89 / LCC Germany (E-N), and imported into the QGIS software. After combining the relevant tagged elements, a layer containing all UGS was obtained. A snapshot of this step is presented in Figure 1a. Almost one-third of the city's area comprises of green spaces such as parks, forests, rivers, and lakes. In total, 12,486 UGS elements were identified using the OSM dataset. The UGS included in the analysis range from 50m^2 to 30.57 km^2 of area. In total, 47,473 residents were found to have less than the minimum 0.5 ha of UGS area accessible.

Subsequently, the available UGS are analysed together with the buildings layer to derive the *Accessibility Score* (S_A). A map presenting the performance of UGS on S_A is given in Figure 1b. It is visible that S_A for the UGS in the shown section range between 6-10 and the majority of them have a score higher than 8. Furthermore, the available UGS are analysed together with secondary data sources to derive the *Quality Score* (S_Q). To determine the greenness, we used the median NDVI values from cloud-free Sentinel-2 image with 10 m spatial resolution for the Year 2020. The Strategic Noise Map 2017 [15] which provides total noise values from traffic sources, was used to determine the mean noise levels in UGS. Figure 1c presents an example from the study area to demonstrate the impact of noise levels on the $S_{Q,N}$. In the figure, the mean noise level at any point is indicated by the intensity of the grey colour. It can be observed that UGS surrounded by streets/highways with higher noise levels obtain lower $S_{Q,N}$. Additionally, the Crime Atlas 2020 published by police crime statistics of Berlin [16] was used to determine the number of criminal offences that occur in various city districts. A map presenting the total performance of UGS on S_Q is given in Figure 1d. Despite the high accessibility of UGS in most parts of the study area, we find that in particular, the inner-city UGS have a medium or low *Quality Score*.

The performance of UGS in Berlin on the two scores, S_A and S_Q is described in Table 2. It is evident from the mean and median scoring that overall UGS perform considerably better on accessibility criteria than on quality. This can be attributed to complementary behaviour observed in the components of S_A. The UGS located on the fringes of the city usually had lower S_C due to the fewer number of houses in the vicinity. At the same time, the houses in that region were as well dependent on a single UGS available nearby, therefore, giving it a higher S_E score. As a result, lower S_C were compensated by higher S_E and vice versa. On the contrary, a

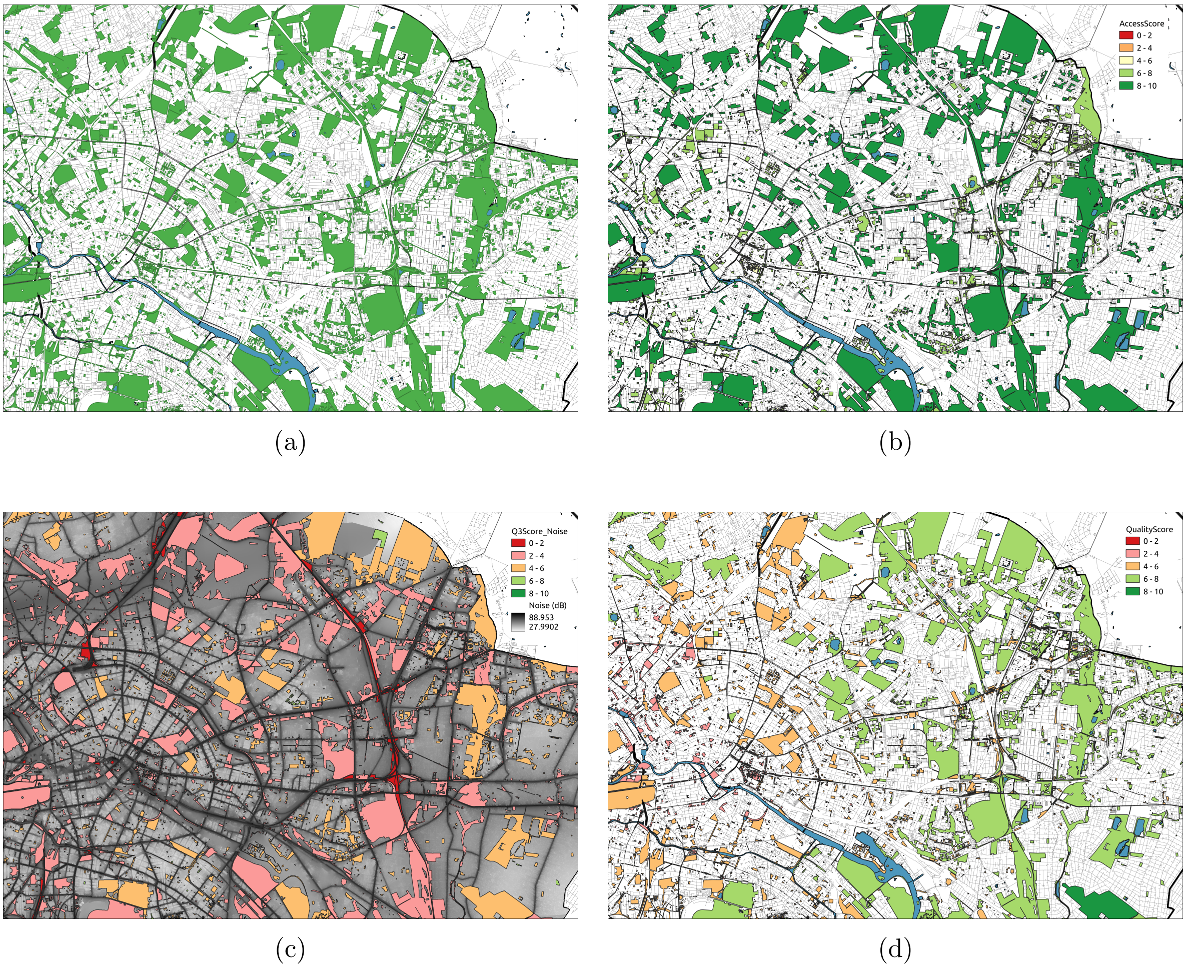


Figure 1: (a) Illustration of *Available Green Spaces* in the City of Berlin; section of city centre and Eastern Berlin. (b) Map of the UGS indicating the *Accessibility Score* (S_A) (c) Map of the UGS indicating the Quality Score for Noise (S_{Q_i,N_i}) (d) Map of the UGS indicating the overall *Quality Score* (S_Q)

Table 2: Performance of UGS in Berlin on defined *Accessibility Score* (S_A) and *Quality Score* (S_Q).

	Minimum	Maximum	Mean	Median	Standard deviation	Coefficient of Variation
S_A	0	9.8	8.2	8.4	0.82	0.1
S_Q	0.9	8.8	4.7	4.8	1.24	0.26

higher coefficient of variation in S_Q reflects the large variability among the UGS in performance on quality parameters.

Finally, the obtained S_A and S_Q are plotted on a scatter plot to visualise the distribution of scores among the UGS. This is presented in Figure 2. According to this, the UGS to be prioritised are selected using the prioritisation order calculated by aggregating both the scores with their corresponding weights. At present the values of $w1$ and $w2$ required for Equation

11 are fixed at 0.75 and 0.25, respectively, to simulate the present priorities that emphasises on providing the 'quantity' access to UGS. Then, the decision-makers in city departments can select the minimum target of prioritisation order for prioritising the UGS. In this example, the target was chosen as 6. Therefore, all the UGS having an aggregated total score greater than 6 will be highlighted as a priority. These are marked with green colour in Figure 2. So, in the case of resource-constrained scenarios, the management of these UGS needs to be prioritised. Moreover, the scatter plot categorises the UGS into 4 groups with high/low accessibility in pair with high/low quality. Using this information a precise management plan can be devised for each type of UGS. For example, measures should be taken to improve the quality in UGS type (high accessibility, low quality) as it will benefit many residents.

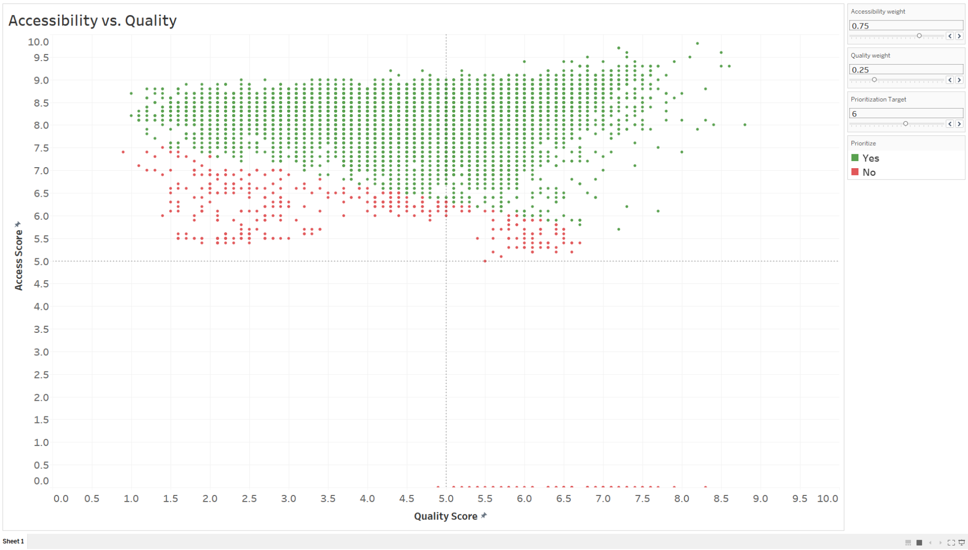


Figure 2: A scatter plot showing performance of UGS on S_A vs S_Q for prioritising UGS with a minimum total score of 6.

4. Discussion

The methodology described in the previous section illustrates an approach to take management decisions such as prioritisation based on the field data. This is done using two criteria; namely, accessibility and quality. As only the open datasets are used in this study, the results are reproducible for any part of/cities in the world based on the availability of the data. However, there also exists a possibility of missing data in this case. The method used to create an UGS layer based on the tagged information from the OSM data might have introduced errors depending on the accuracy of the data. Also note that a circular buffer approach, as used here for proximity analysis is a simplistic determination of linear access between two points. Unlike the network analysis approach or Manhattan metric, the chosen approach does not incorporate the aspect of actual physical access through public roads and pathways. Hence, it might underestimate the actual distance between a residential building and nearby UGS. However, this method has the advantage of faster computing time and therefore allows for multiple iterations required for continual decision-making and management. Moreover, all types of buildings are included in the buildings layer, which also include commercial buildings, and industrial estates. So in a likely case, an area with lack of UGS can be a storage warehouse and therefore, not actually affecting any residents' accessibility. Additionally, no differentiation between public and a private UGS have been made. As some of the UGS such as golf park, private gardens, farms, might be only available to private communities, the actual accessibility is likely to be lower than the current estimates. Moreover, the quality of an UGS depends on numerous factors. Taking this complexity into account, this study takes a representative sample of criteria, and develops a numerical quality score for UGS. Nevertheless, the method is open to integrate further criteria as they may emerge in different contexts or different cities. Furthermore, it can be observed that higher weightage is assumed for the accessibility criteria (0.75) in comparison with the quality (0.25). This is done on the basis of the current expectations set by the German government policy as well as WHO recommendation, where the focus is exclusively on providing the access to a sufficient quantity of UGS without any targets with respect to the UGS quality. Though, this can be easily adapted in the model according to city's needs and priorities. Also note that the scope of current analysis was limited to the benefit side of the UGS while the cost part was not included. As a result, a UGS is prioritised solely on the basis of derived benefits without considering the input costs/resource requirements. This might lead to inefficient allocation of resources if the UGS with greater cost per unit of benefit (resource efficiency) is prioritised higher than the one with lower.

5. Conclusions and Further Research

The developed method has for the first time, implemented the UGS benefit criteria for informed decision making in UGS management. The benefit is measured using UGS accessibility and quality as an indicators, while the decision to be made is of prioritisation. The model uses open datasets in an automated way to estimate the residents impacted by the lack of UGS accessibility and show the distribution of UGS quality in the city. Moreover, through prioritisation order, it highlights the contribution and criticalness of each UGS in maintaining the required level of accessibility according to WHO recommendations. This can support local authorities in park/forest departments to efficiently allocate the limited resources in constrained scenarios and maximise the benefits. Thus, it provides an integrated framework to evaluate the UGS benefits and subsequently use it for decision making. However, the method needs further elaboration with respect to differentiation of buildings by type (residential/non-residential), segregation of UGS by type (public/private), with respect to the integration of further benefit criteria (environmental and economic), and the extension of factors within existing criteria e.g. UGS quality can be further enhanced by adding parameters like biodiversity and availability of leisure/sport equipment. Furthermore, the variation of score weights and their impacts on decision-making require further research. In the future course of work, varying combinations of different weightage factors will be evaluated through a sensitivity analysis. Moreover, along with estimating the benefits derived from UGS, the resources required to maintain a UGS will be calculated for a more comprehensive evaluation.

References

[1] Poelman H 2018 *European Commision Regional and Urban Policy* 13
[2] WHO 2017 Urban green spaces: a brief for action
[3] Middel A, Chhetri N and Quay R 2015 *Urban Forestry & Urban Greening* **14** 178–186 ISSN 1618-8667
[4] WHO 2016 Urban green spaces and health
[5] Threlfall C G, Williams N S, Hahs A K and Livesley S J 2016 *Landscape and Urban Planning* **153** 28–39 ISSN 0169-2046
[6] Moradpour M and Hosseini V 2020 *Urban Climate* **34** 100686 ISSN 22120955
[7] Nutsford D, Pearson A L and Kingham S 2013 *Public Health* **127** 1005–1011 publisher: W.B. Saunders
[8] Tamosiunas A, Grazuleviciene R, Luksiene D, Dedele A, Reklaitiene R, Baceviciene M, Vencloviene J, Bernotiene G, Radisauskas R, Malinauskiene V, Milinaviciene E, Bobak M, Peasey A and Nieuwenhuijsen M J 2014 *Environmental Health: A Global Access Science Source* **13** 20–20
[9] Geng D C, Innes J, Wu W and Wang G 2021 *Journal of Forestry Research* **32** 553–567 ISSN 1993-0607
[10] Federal Ministry for the Environment 2007 National strategy on biological diversity

[11] Wüstemann H and Kalisch D 2016 Towards a national indicator for urban green space provision and environmental inequalities in germany: Method and findings SFB 649 Discussion Paper 2016-022
[12] OpenStreetMap contributors 2021 Openstreetmap URL https://www.openstreetmap.org
[13] Van Herzele A and Wiedemann T 2003 *Landscape and Urban Planning* **63** 109–126 ISSN 0169-2046
[14] Stadt Karlsruhe 2015 Bürgerumfrage 2015 grün in der stadt
[15] Environmental Atlas 2017 Grid map lden - sum of all traffic sources URL https://www.berlin.de/umweltatlas/en/traffic-noise/noise-pollution/
[16] Polizeiliche Kriminalstatistik 2020 Kriminalitätsatlas berlin bezirksregion URL https://www.kriminalitaetsatlas.berlin.de/K-Atlas/atlas.html

Resources, Environment and Sustainability 16 (2024) 100150

Contents lists available at ScienceDirect

Resources, Environment and Sustainability

journal homepage: www.elsevier.com/locate/resenv

Research article

Prioritizing urban green spaces in resource constrained scenarios

Mihir Rambhia [a,b,*], Rebekka Volk [a], Behzad Rismanchi [b], Stephan Winter [b], Frank Schultmann [a]

[a] Institute for Industrial Production, Karlsruhe Institute of Technology, Karlsruhe, 76187, Germany
[b] Department of Infrastructure Engineering, The University of Melbourne, Melbourne, 3010, Australia

ARTICLE INFO

Keywords:
Urban green
Green space management
Resource allocation
Goal programming
Sustainable cities
Decision support

ABSTRACT

Urban Green Space management requires a multi-dimensional, evidence-based approach to effectively balance social, environmental, and economic objectives. City administrators currently lack a data-driven framework for allocating resources during constraint scenarios, leading to subjective decisions. Existing literature lacks objective solutions for managing city-scale green spaces, each with its distinct characteristics. Another challenge is handling varied spatial scales required for urban applications. This study proposes a novel goal programming-based model for urban green space management wherein multiple benefit objectives, such as conserving sequestered carbon in trees and enhancing quality and accessibility of parks, as well as handling demand constraints on available resources like water and personnel, are included. The proposed method was demonstrated in two cities with diverse conditions, Berlin and Melbourne, and evaluated on various benefit metrics, such as allocated green space units, resources consumed, and goals achieved. The model was analyzed with resource allocation decisions and goals at different spatial scales. The highest benefit achievement and resource allocation were observed when resources were allocated at the sub-district scale with a city-level target. Alternatively, setting targets at the district level provided a more even resource distribution; however, at the cost of reduced overall benefits. Results show that the proposed method increased the total benefits gained while effectively balancing conflicting goals and constraints. Additionally, it allows incorporating the city's preferences and priorities, offering a scalable solution for informed decision-making in varied urban applications. Depending on data availability, this approach can be scaled to other cities, including additional benefits and resource constraints as required.

1. Introduction

Cities often face challenges related to resource constraints. Critical project resources such as personnel, commodities, equipment, and funding are limited and in competition with other uses or projects. Consequently, decision-makers must prioritize resource allocation to fulfill the distinct needs of the city and its residents. For example, a city dealing with a budget constraint might need to allocate limited funds between essential services like infrastructure development and welfare schemes for the needy. Prioritizing one theme, such as offering free entry to public recreational spaces for encouraging its usage, could lead to decreased funding for maintaining or developing new spaces, conflicting with the broader goal of ensuring its universal access in the long run. City administrators deal with this difficulty of prioritizing spending decisions and making trade-offs between competing demands for scarce resources (Nechi et al., 2019). Similar to cities, the management of Urban Green Space (UGS) also encounters the challenge of resource allocation with multiple, often conflicting, objectives, such as increasing green spaces while developing compact cities (Rößler, 2017). This challenge is compounded by the involvement of various stakeholders from departments of garden, road, forestry, waste and civic society groups (Jim, 2004; Eisenman et al., 2021). Moreover, the increasing pressure on resource availability, such as funding cuts, personnel shortages, and reduced water supply due to expected droughts from climate change, will further exacerbate this problem. Current decision-making processes often rely on limited data, physical inspections, and subjective assumptions, excluding the comprehensive assessment of trade-offs and the resulting impact on costs and benefits of the decision.

Reliable field data is critical for UGS planning, management, and decision-making (Moller et al., 2019). The World Health Organisation (WHO) also highlighted the need for a multi-dimensional evaluation of UGS interventions to assist municipalities in making evidence-based decisions (World Health Organization, 2017). Moreover, WHO guidelines suggest that public UGS of at least 0.5-1 ha should be accessible within a 300-metre distance to all city residents (World Health Organization, 2017). Providing universal access to green and public spaces is part of the United Nations Sustainable Development Goal target 11.7 as well (United Nations, 2020). As a result, access to green spaces becomes an important indicator for the management. However, expansion of

* Corresponding author at: Department of Infrastructure Engineering, The University of Melbourne, Melbourne, 3010, Australia.
E-mail address: mihir.rambhia@partner.kit.edu (M. Rambhia).

https://doi.org/10.1016/j.resenv.2024.100150
Received 19 September 2023; Received in revised form 7 January 2024; Accepted 27 January 2024
Available online 6 February 2024

newer UGS spaces to meet the increased demand might not always be possible due to resource constraints. For instance, in a survey conducted in 2020 across 12 cities in the United States, 83% of the cities reported an increase in visitation to natural areas, while 72% experienced decreased capacity to manage them due to severe shortages of seasonal staff (Plitt et al., 2021). Similarly, increasing the number of trees and UGS areas to meet a city's greening targets will further strain water sources, especially in drought-prone regions (Ricciardi et al., 2022). Consequently, taking into account the costs and benefits associated with a particular resource allocation strategy and its impact on the city's UGS and the resource conditions, becomes crucial before its implementation.

Multi-criteria decision-making (MCDM) methods have been extensively used to assist decision-makers in situations involving multiple stakeholders, criteria, and conflicting objectives (Kumar et al., 2017). These methods first derive feasible alternatives under given constraints that meet the preferences of decision-makers. Subsequently, the performance of all alternatives is evaluated to generate a decision that fulfills conditions and maximizes objectives (Pavan and Todeschini, 2009). In certain approaches, the alternatives are predefined by the user, and maximization is achieved for the given options. MCDM has been applied for decision-making in a large spectrum of domains, such as disaster management (Pankaj Kant and Natha, 2023), water allocation (Roozbahani et al., 2014), urban sustainability (Foroozesh et al., 2022), facility management (Klumbytė et al., 2021), and reservoir control (Wan et al., 2023). However, existing multi-criteria approaches have limitations in addressing urban challenges, especially in handling trade-offs and conflicts among various criteria (both quantitative and qualitative), as well as dealing with large-scale problems with numerous constraints and criteria.

Different types of approaches have been proposed to improve the management of UGS. For example, optimization-based methods for location allocation (Chen et al., 2023), machine learning-based techniques for the optimal allocation of UGS (M. Vallejo and Vargas, 2017), crowd-sourcing-based participatory management (Moller et al., 2019; Schrammeijer et al., 2021), GIS-based methods for prioritizing tree planting sites based on criteria for need and suitability (Locke et al., 2010), and organizational-based strategies like the place-keeping process (Fongar et al., 2019; Chen et al., 2023). While existing literature, such as Locke et al. (2010), Nyelele and Kroll (2021), and Nyelele et al. (2022), has used MCDM to address the challenge of prioritizing new tree plantations, the prioritization of existing UGS has not been studied. Furthermore, while benefit parameters have been included, resource constraints, such as water and personnel, are also not covered.

As a result, the research study aims to answer the following research question:

Can the resource allocation decisions for managing UGS in constrained scenarios be optimized using an MCDM approach?

The research scope includes (1) identifying a suitable MCDM approach for optimizing urban resource allocation in constrained scenarios; (2) considering the necessary adaptations for its application to UGS management; (3) identifying the required model parameters and relevant public datasets for its quantification; (4) implementing the optimization model for decision-making on prioritization; (5) assessing the model's performance on various benefit metrics; and (6) evaluating the impact of different scenario conditions on decision-making.

The research approach includes identifying the appropriate method for optimizing resource allocation decisions, considering factors such as complexity, adaptability, and the ability to handle trade-offs and uncertainties. Accordingly, the proposed model is an extension of the goal programming (GP) model that can support varying inputs, constraints, and targets at different spatial scales. The model was tested in two case-study cities, and its performance under various constraints was evaluated and compared with a baseline reference scenario.

This research achieves two main outcomes. The first outcome is the development of a model that optimizes the decision-making of prioritization under different constraint scenarios. The model is scalable to handle city-scale datasets, capable of addressing trade-offs and conflicts, and incorporates decision-makers' preferences. It is also adaptable to various cost-benefit parameters to address the resource allocation problem in varying spatial conditions. The second outcome is the provision of insights to aid city administrators in making informed decisions regarding resource allocation and budgeting, especially under constraint scenarios. Additionally, the findings will assist in planning and maintaining both existing and new street trees and parks.

The paper is organized as follows: First, a literature review describes the various MCDM methodologies and research gaps in the context of UGS management applications. Based on this, GP is chosen as the basis of the methodology. This is followed by the modeling approach section, which discusses the model parameters and its implementation in a Python-based model. In the case study section, the results of applying the model to data from Berlin and Melbourne are discussed. The final two sections present the discussion and conclusions.

2. Literature review

2.1. MCDM approaches

MCDM is an effective tool for solving decision-making problems with conflicting objectives (Gebre et al., 2021). Numerous optimization methods based on mathematical models, expert judgments, and heuristics have been developed to solve MCDM problems. These methods can be categorized based on whether the decision-maker implicitly provides plausible solutions (Multi-Attribute Decision Making (MADM)) and whether their preferences are taken into account during the decision-making process (Multi-Objective Decision Making (MODM)) (Kumar et al., 2017). MCDM methods have been used to address varied types of problems, such as prioritization, selection, allocation, optimization, scheduling, routing, and management. The commonly used MCDM methods include linear programming (LP), non-linear programming, integer programming, dynamic programming, goal programming (GP), weighted product model (WPM), Analytical Hierarchy Process (AHP), Multi-Attribute Utility Theory (MAUT), and Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS). These methods can be further classified as analytical methods if they are quantitative and based on mathematical models or as interactive methods if they constantly involve human judgment and preferences. The selection of the suitable MCDM method for the UGS management application is done based on the requirements of the problem. Since, in UGS management, the problem involves multiple resource constraints, a desired benefits target to be achieved, decision-maker's preference, and there are no preset solutions available. Therefore, the chosen method should be of the MODM type to ensure that the solution is considered from a continuous space.

Several studies have implemented MCDM approaches to address various aspects of UGS planning and management, including location, layout, design, function, and size of UGS (Li et al., 2022). This has been done with respect to varied objectives such as public accessibility, UGS quality, heat island mitigation, runoff regulation, carbon offset, and enhancing biodiversity (Nyelele and Kroll, 2021). For instance, Liu et al. (2023) utilized a multi-objective programming method to determine the required quantity of UGS for achieving a specified level of carbon offset. Meanwhile, Li et al. (2022) implemented spatial optimization for UGS layout planning, considering equitable distribution and conversion costs as decision criteria. Huang et al. (2018) devised a regression-based optimization strategy for UGS planning, focusing on accessibility and quality as primary targets. Using an LP approach, Neuenschwander et al. (2011) determined the optimal distribution of green spaces at the district level, considering spatial conditions. Similarly, Nyelele and Kroll (2021) utilized an LP model to pinpoint optimal locations for maximizing overall benefits derived from urban greening. Later, they proposed a multi-objective optimization

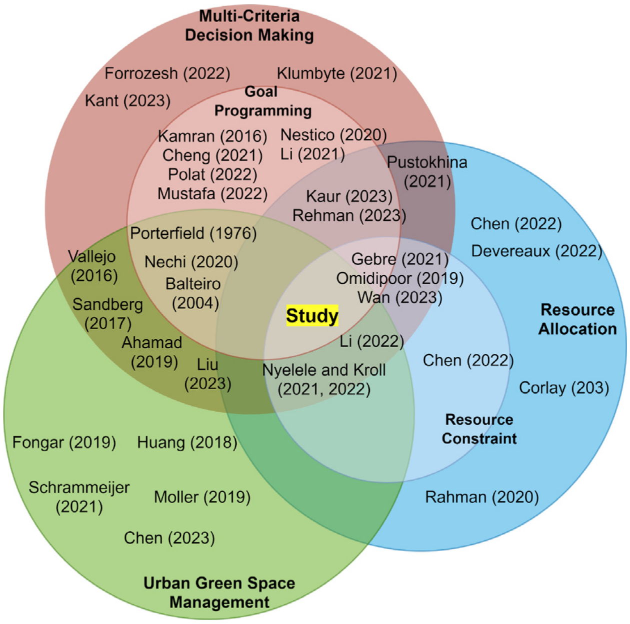


Fig. 1. Classification of relevant literature with current study focus is highlighted.

framework to prioritize tree planting scenarios based on current and future ecosystem services (Nyelele et al., 2022). However, these studies primarily concentrated on benefits maximization and did not consider associated management costs in decision-making. Furthermore, as evident, their scope was limited to new plantations, and the planning and management of existing UGS have not been considered by any of the studies.

2.2. Resource allocation problem

In resource allocation problems, the aim is to distribute the available resources and maximize the achievement of the desired objectives. A large number of optimization algorithms have been developed and applied to obtain optimal resource allocation. For example, (Omidipoor et al., 2019) integrated MCDM with GIS for participatory renovation of urban areas, (Corlay and Sibel, 2023) used a Markov decision process for a communication system, (Pustokhina and Pustokhin, 2021) implemented a fish swarm algorithm to distribute cloud resources, and Rahman and Sharma (2020), Chen et al. (2022) proposed a game theoretic approach to allocate defense resources. All of the referred studies were based on the utilitarian principle, focusing on benefit maximization. Accordingly, that objective has been adopted for this study as well.

Fig. 1 presents a summary of relevant literature, classified based on study methodology and application. It can be observed that a larger number of studies use MCDM methods to obtain an optimal resource allocation strategy. However, the application of these techniques in UGS management has been scarce. Furthermore, even for UGS, most studies have focused solely on planting strategies. No studies were discovered that apply these methods to manage existing UGS, especially in resource-constrained conditions.

Nevertheless, each of these existing methods has certain limitations. Most of these optimization approaches aim for feasible solutions. However, in resource-constrained scenarios, achieving a feasible solution might not always be possible. Additionally, strictly adhering to the objective function may result in no solution or inferior utilization of available resources. Since both LP and GP provide solutions over continuous space and can incorporate resource constraint conditions, those two were considered as prospective approaches. LP has the limitation of optimizing a single objective function with numerous linear constraints. However, in real-life problems, multiple conflicting objectives are often present, making LP inadequate for such applications. Unlike LP, where a decision-maker can only have one objective function, GP can handle multiple goals simultaneously (Orumie and Ebong, 2014). Furthermore, while LP allows for a fixed goal, in GP, the goal is considered only as the initial target. This allows flexibility for the decision-maker to compromise on the solution in case of competing goals (Nesticò et al., 2020). Therefore, GP was a suitable option for addressing the described problem.

2.3. Goal programming

GP is an MCDM approach based on determining a satisfactory solution to multi-goal decision-making problems. Charnes et al. (1968) pioneered GP, which was later expanded upon by Lee and Clayton (1972), Charnes and Cooper (1977), Ignizio (1978), Romero (1985), and Schniederjans (2012). Researchers have developed various GP variants for a variety of problem types and use-case applications. The major variations are listed in Table 1 to showcase the applicability of existing variants. From these variants, each basic variant could be used in conjunction with a special case. GP has been extensively applied in different planning and operational applications such as finance (Lashkari et al., 2018), healthcare (Mishra et al., 2018; Rehman et al., 2023), software development (Kaur et al., 2023), water use (Bravo and Gonzalez, 2009), and reservoir operation (Li et al., 2017).

Due to its capability to efficiently find feasible solutions, flexibility in managing multiple competing goals, and ease of use, GP has found extensive application in addressing resource allocation challenges as well. Resource-allocation focused studies also cover diverse domains such as healthcare (Kamran et al., 2016), fleet management (Valcárcel-Aguiar and Fernández, 2018; Rajendran, 2021; Hamurcu and Eren, 2022), urban regeneration (Nesticò et al., 2020), logistics (Li et al., 2021; Cheng et al., 2021), energy strategies (Bakhtavar et al., 2020), and more. Several researchers have also used GP to address challenges pertaining to UGS management. For instance, Nechi et al. (2019) utilized GP to determine a sustainable development pathway, with a central focus on accommodating decision-makers' preferences. Porterfield (1976) presented a GP-based model for the optimal selection of a tree improvement program. Similarly, Diiaz-Balteiro and Romero (2004) developed a GP model for evaluating forest plans, considering multiple spatial scales from a regional level down to a stand level through aggregation. The ability of GP to adapt and be flexible makes it a valuable tool for managing different types of resources.

GP is based on the principle of getting as close to the decision makers' goals as possible. Accordingly, it aims to minimize the underachievement of each goal using deviation variables. The primary distinction between GP and other MCDM approaches is that it seeks to satisfy rather than optimize the objective (Jones and Tamiz, 2010). Therefore, GP is especially suitable for handling trade-offs between multiple conflicting goals. Moreover, the priority order for the goals can be established by either weighing or ranking them. The GP model includes two types of constraints: system and goal constraints. Systems, or hard constraints, describe actual capabilities and are therefore limiting, whereas goals, or soft constraints, indicate desired aims to be accomplished and are thus flexible. The basic formulation of the GP model is presented in Eqs. (1)–(3). Overachievement is represented by the positive deviation variable d^+, whereas underachievement is represented by the negative d^-. The model allows for G goals, indexed as $g = 1, 2, ..G$, and x is the decision variable that belongs to the feasible region F, consisting of points that satisfy all the constraints. The decision maker sets an achievable target, t_g, for each goal, and the achieved value of the goal is represented by f(x). Finally, the objective function minimizes the sum of deviations to maximize goal achievement.

$$\min d = \sum_{g=0}^{n} d_g^+ + d_g^- \tag{1}$$

Table 1
Major goal programming variants.
Source: Jones and Tamiz (2010).

Variant	Application
Normal	Based on minimizing the sum of all deviations
Lexicographic	Pre-defined priority levels (When no trade-off comparisons)
Weighted	Assigned weights to the goals (Trade-offs)
Chebyshev	Based on maximal deviation from any goal
Special cases	
Fuzzy	For uncertainty in goal weights or target values.
Integer	Restricted to take only discrete values
Fractional	One or more goal of the form a/b
Non-standard preference	Non-linear penalty function
Objective bounds	One or more constraints are rigid
Interval	A range of target to be satisfied

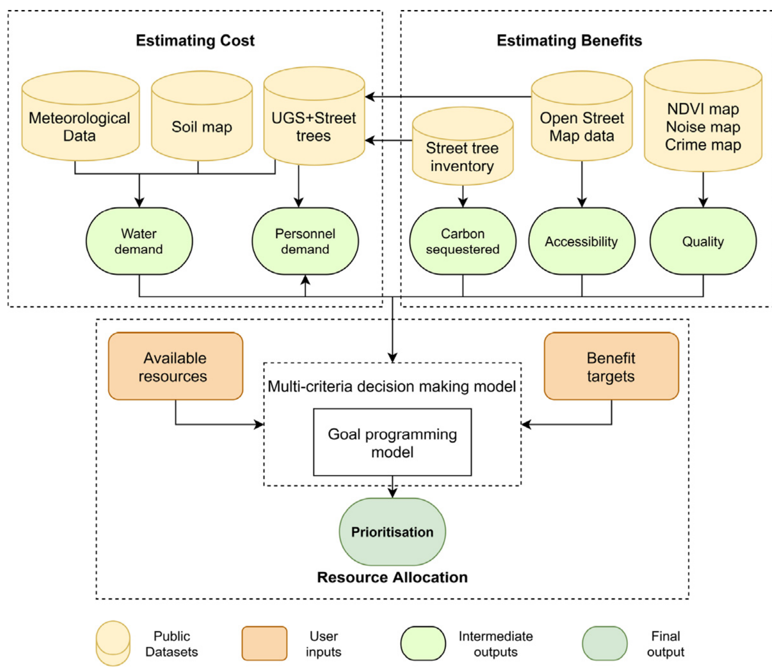


Fig. 2. Modeling framework for prioritizing UGS in resource constrained scenarios.

$$f_g(x) + d_g^+ - d_g^- = t_g \ , \ \ g = 1, \dots, G \ , \ \ x \in F \qquad (2)$$

$$d_g^+, d_g^- \geq 0 \ , \quad g = 1, \dots, G \qquad (3)$$

However, the current variants of GP do not have the capability to accommodate varying input characteristics. Each UGS is unique in terms of its demands and the benefits it provides. This is different from industrial or financial sectors, where the inputs required for the production of each unit and the corresponding value of the output produced are relatively constant. Additionally, there is a significant gap in incorporating spatial and temporal variations in the constraints and goals. While the availability of immobile resources required to meet the demand could differ among city districts, the benefits of public infrastructure should be evenly available to everyone in the city. Therefore, in urban management, it is necessary to have the flexibility to set goals or constraints for each neighborhood or district. Moreover, as mentioned earlier, research on the application of GP for resource allocation in cities has been inadequate and completely absent for UGS. Therefore, an extended GP variant is necessary to effectively address the requirements of urban applications, especially UGS management.

3. Methodology

The methodology aims to develop a multi-criteria decision support system for determining UGS prioritization under resource constraint conditions. It implements a utilitarian-based approach to prioritize UGS based on maximizing benefit achievement. The following subsections describe each component of the system and its implementation in more detail.

3.1. Modeling framework

Fig. 2 presents the overall framework of the decision-making model. The model comprises three modules: E*stimating cost*, *estimating benefits* and *resource allocation*. The outputs of the first two modules are used to make prioritization decision in the third module. It is to be noted that while the cities consist of a variety of UGS (Wirtz et al., 2021), for this study, they are grouped into two major categories. First, *street trees* consisting of all trees alongside roads, and second, *parks* consisting of trees and the area in public parks, playgrounds, urban forests, and farms within city boundaries.

3.1.1. Estimating demand parameters

The literature highlights the importance of supplying necessary water resources and emphasizes the critical role that local management play in maintaining the performance of UGS (Fam et al., 2008; CABE, 2010). In their research, Wirtz et al. (2021) emphasize that experienced urban forestry staff are critical for the successful governance of UGS. Accordingly, two input demands were chosen to demonstrate the integration of management needs as a cost factor into the resource

Table 2
Estimating personnel demand for UGS management for a single street tree or 0.01 ha of park area.

	Input (hours/week)	Frequency (week/year)	Total demand (hours/year)
Cleaner	0.05	13	0.65
Gardener	0.1	13	1.3
Driver	0.025	52	1.3
			3.25 hours/year

allocation decision-making framework: *water* and *personnel*. In the context of a street tree, water demand refers to the total amount of water (in mm) required annually to sustain an individual tree, while for a park, it refers to the sum of water demand for trees and the landscape area. Similarly, personnel demand refers to the total amount of physical work (in hours) required annually to carry out maintenance tasks, such as watering, cutting, pruning, litter cleaning, and the application of fertilizers. Estimates for street trees are made at the tree scale, while in the case of parks, it is the aggregated total of all the trees in the park as well as the total landscape area. To estimate species-wise annual water demand, a linear time-series-based model was used. The model, based on soil water balance and the Water Use Classifications of Landscape Species (WUCOLS) approach, estimates weekly water demand using publicly available data on tree species, soil type, and current/future weather conditions. The detailed methodology of the aforementioned water estimation model is described in Rambhia et al. (2023).

The most common types of laborers needed for UGS management are cleaners, gardeners (for pruning, pest management, and fertilizer application), and truck drivers (to transport the leaf litter). In the absence of primary datasets related to the personnel management of UGS, reliance on secondary sources becomes imperative. This approach is deemed suitable since deriving the required staff from the existing actual staff might not be accurate. Typically, cities recruit staff based on factors such as the city's population or the availability of funds (American Public Works Association, 2015). To estimate the necessary personnel demand, we considered two parameters: the estimated time required for each activity and the desired frequency of these activities based on established best practices guidelines. These activities are discussed in more detail by Greening, Landscape and Tree Management Section Development Bureau (2014), Greening, Landscape and Tree Management Section Development Bureau (2020), Davies et al. (2017), and LI et al. (2022). Accordingly, the estimations used for the personnel required to maintain a single street tree or a 0.01 ha area are shown in Table 2. A single personnel works for 1349 h annually in Germany and 1707 h annually in Australia (OECD, 2023). As a result, one personnel staff in Germany may handle around 415 street trees or a 4.15 ha park area, while in Australia, they may handle around 525 street trees or a 5.25 ha park area. Moreover, the decision-makers could vary this input based on management preference and local needs.

3.1.2. Estimating benefit parameters

While various environmental, social, and economic advantages are associated with UGS, three have been selected to illustrate the inclusion of benefits as a factor in a resource allocation decision-making framework: *accessibility*, *quality*, and *carbon sequestration*. Accessibility and quality benefits are estimated for all parks, as the trees in parks collectively provide not only environmental benefits but also high social benefits. In contrast, carbon sequestration is derived as a benefit from street trees since they act individually, with the primary focus on environmental benefits.

Accessibility is a custom-built indicator that quantifies a specific park's role in providing urban residents with access to green space, as recommended by the WHO. It is calculated as a weighted average of the building coverage score (S_C) and the essentiality score (S_E). The first component, S_C, measures the number of residences that benefit from a specific park. The second component, S_E, measures the significance of a specific park in ensuring accessibility to nearby residences. Similarly, the quality of UGS is defined as its cumulative performance on area size ($S_{Q,A}$), greenness ($S_{Q,G}$), noise ($S_{Q,N}$), and safety ($S_{Q,S}$). Accordingly, parks with a larger area, a higher density of trees located in districts with lower average noise levels, and fewer reported crime events are typically rated high in quality scores. Both accessibility and quality are derived as scores between 0 to 10 using min–max normalization (re-scaling) of the underlying features. The detailed approach for calculating benefit parameters for parks is outlined in Rambhia et al. (2022). Since there is a positive correlation between the size of the tree and the amount of carbon captured by the tree (Stephenson et al., 2014; Mildrexler et al., 2020), the sequestered carbon for each street tree is calculated from its species type and diameter size according to the method in US Department of Energy (1998).

Table 3
Notation of sets, parameters, and variables used in the optimization model.

Sets	
G	Set of urban parks ($g \in G$)
G_p	Set of prioritized urban parks ($G_p \subseteq G$)
S	Set of street trees ($s \in S$)
S_p	Set of prioritized street trees ($S_p \subseteq S$)
L	Set of Spatial locations ($l \in L$)
Parameters	
w_i^{demand}	Water demand of unit i
p_i^{demand}	Personnel demand of unit i
$W^{available}$	Total water available for irrigation
$P^{available}$	Total personnel available for management
b_i^{carbon}	Carbon sequestration benefit of unit i
b_i^{access}	Accessibility benefit of unit i
$b_i^{quality}$	Quality benefit of unit i
B^{carbon}	Target carbon sequestration benefit
B^{access}	Target accessibility benefit
$B^{quality}$	Target quality benefit
Variables	
ra_i	Resource allocation decision for unit i
$d1$	Deviation from carbon sequestration goal
$d2$	Deviation from accessibility goal
$d3$	Deviation from quality goal
D	Total deviation for all goals

3.1.3. Spatial analysis

Given that management decisions cannot be practically implemented at an individual tree level, it is necessary to group trees and parks into larger units. To assess the influence of spatial resolution on decision-making, the analysis is conducted in three different configurations. The first case involves allocating resources at the district level while establishing targets at the city level. The second case involves allocating resources at the sub-district (or cluster) level with city-level targets. Finally, the third case involves allocating resources at the sub-district level while establishing targets at the district level.

3.1.4. Prioritization model

The objective of the GP model is to prioritize resource allocation to street trees and UGS to maximize total benefits with available resources. As a result, the criteria are to maximize carbon sequestration in street trees, overall accessibility attained by the UGS, and UGS quality.

The sets, parameters, and variables utilized in the optimization model are listed in Table 3. The sets feature a complete and prioritized collection of park and street trees and a set of districts and sub-districts. The parameters include four components: *cost*, *benefit*, *available resources*, and *targets*. The value of the cost and benefit parameters are derived using various public datasets and for available resources and target can be obtained from the decision maker's inputs. The variables stores the deviation and decision variables as model's intermediate and final results, respectively.

The objective function of the model is given in Eq. (4) where the purpose is to minimize the weighted sum of all deviation variables at a given spatial scale. This objective function is subject to soft and hard constraints. As can be seen, both the optimization function and constraints utilize two summation functions. The first summation function aggregates the individual prioritized units (street tree or park) with varying input characteristics, including water demand, personnel demand, access benefit, quality benefit, and carbon sequestration benefit. The second summation function aggregates all the prioritized units within a selected spatial location, either a sub-district or district. The soft constraints given in Eqs. (5)–(7) drives the model to attain the expected level of benefit targets (B^{carbon}, B^{access}, $B^{quality}$). The hard constraints given in Eqs. (8) and (9) ensure that the resource demand does not exceed the available resources during the constraint scenario. Lastly, Eqs. (10)–(12) define the prioritized sets and the feasible values for the decision variable. Accordingly, the resource allocation decision ($r_{a,i}$) is binary in nature and the choice of allocating resources is solely made for complete allocation. As a result, a partial allocation at a unit level is not allowed in the model. Moreover, if a park spreads across multiple districts or sub-districts, then it is included in the region with the highest overlap of area.

Minimize

$$D = \sum_{l\epsilon L}(\sum_{i\epsilon s_p} w_1 * \frac{d1_{l,i}}{B^{carbon}} + \sum_{i\epsilon g_p} w_2 * \frac{d2_{l,i}}{B^{access}} + w_3 * \frac{d3_{l,i}}{B^{quality}}) \tag{4}$$

The optimization function aims to minimize D, the weighted sum of deviation variables $d1$, $d2$, and $d3$. Since all the deviations are in different units, they are normalized using their respective benefit targets before summing them up. The weights $w1$, $w2$, and $w3$ are used to prioritize carbon sequestration, access, and quality goals and depend on the city's preference. Soft constraints (goals/benefits):

$$\sum_{l\epsilon L}\sum_{i\epsilon s_p} b^{carbon}_{l,i} + d1 = B^{carbon} \tag{5}$$

The achieved carbon sequestration benefits are the sum of the sequestered carbon by all the prioritized trees in all the prioritized spatial sections of the city. Given that B^{carbon} represents the target, d1 indicates any underachievement from this carbon storage target.

$$\sum_{l\epsilon L}\sum_{i\epsilon g_p} b^{access}_{l,i} + d2 = B^{access} \tag{6}$$

The achieved access benefits result from the sum of access score provided by individual parks in all prioritized spatial sections of the city. Given that B^{access} is the target, d2 represents any underachievement in access reached compared to the target.

$$\sum_{l\epsilon L}\sum_{i\epsilon g_p} b^{quality}_{l,i} + d3 = B^{quality} \tag{7}$$

Similarly, the achieved quality benefits result from the sum of the quality scores of individual parks in all prioritized spatial sections of the city. Given that $B^{quality}$ is the target, d3 represents any underachievement in quality attained compared to the target

Hard constraints (resource constraints/costs):

$$\sum_{i\epsilon s_p} w^{demand}_i + \sum_{i\epsilon g_p} w^{demand}_i \leq W^{available} \tag{8}$$

Due to restrictions on the availability of water in any city, the fulfilled water demand should not exceed the budget allocated for green space irrigation. Therefore, the sum of water demand from prioritized trees and prioritized parks should be less than the available water.

$$\sum_{i\epsilon s_p} p^{demand}_i + \sum_{i\epsilon g_p} p^{demand}_i \leq P^{available} \tag{9}$$

Similarly, the availability of personnel for management activities is also limited. Therefore, the sum of personnel demand from prioritized trees and prioritized parks should be less than the available personnel

$$s_p = r_{a,i} * S \quad \forall\ i\ \epsilon\ I \tag{10}$$

s_p denotes the set of prioritized street trees, and S represents the entire set of street trees in the city. The binary decision variable $r_{a,i}$ indicates whether a specific street tree is prioritized.

$$g_p = r_{a,i} * G \quad \forall\ i\ \epsilon\ I \tag{11}$$

Similarly, g_p denotes the set of prioritized parks, and G represents the entire set of parks in the city. The binary decision variable $r_{a,i}$ indicates whether a specific park is prioritized.

$$r_{a,i}\ \epsilon\ (0,1) \quad \forall\ i\ \epsilon\ I \tag{12}$$

As mentioned earlier, the binary decision variable $r_{a,i}$ takes the value of 0 to indicate that a particular unit is not prioritized, and 1 to signify prioritization with allocated resources. The solution of the model will yield an array of (0, 1), indicating whether a particular UGS should be prioritized or not.

The aforementioned model has been implemented in Python language (Version 3.10) using a web-based interactive computing service, Google Colab (Google, 2022). The CP-SAT solver from OR-Tools v9.5, an open-source library developed by Google, was used to implement and solve the optimization model in Python (Perron and Furnon, 2022). Additionally, QGIS, an open-source GIS software, was used for the purpose of analyzing and plotting the allocation result. The program initializes by importing the cost and benefit data, which is estimated as described in 3.1.1 and 3.1.2, respectively, or using the data provided by the user. The demand and benefit data is then aggregated at district or sub-district level depending on the scale of analysis.

3.2. Study area

The described model has been applied to case studies in Berlin, Germany, and Greater Melbourne, Australia, to showcase its applicability under diverse conditions. The selection of the two cities was guided by several factors, including the availability of open data, diversity in city conditions, familiarity with the geographical locations and social conditions, access to garden authorities, and consideration of the challenges faced by the cities. While Berlin has an evenly distributed population and UGS throughout the city, Melbourne has a dense population within its city boundary and a varying distribution of UGS. Moreover, inner Melbourne mostly consists of street trees and small parks, whereas the suburban region has large parks and urban forests. Additionally, the quality of data availability varies between the two regions. In Greater Melbourne, tree inventory data is maintained by individual councils for each district and is not entirely published under open data initiatives. Similarly, the noise map of Melbourne is also not available as open data. Accordingly, case studies from two diverse geographical and on-field conditions will illustrate the handling of different urban situations.

3.2.1. Berlin city

Berlin, the largest and capital city of Germany, spans an area of 891 km^2 and has a population of 3.6 million people. It is recognized as a high-density city with an average population density of about 4200 residents per square kilometer (Eurostat, 2011). Situated along the Spree river, Berlin has a temperate seasonal climate. In terms of green space, the city boasts an impressive number of trees, approximately 80 per kilometer, totaling around 431,000 trees throughout the city. These trees encompass more than 50 different species, with lime, maple, oak, plane, and chestnut being the most prevalent genera, accounting for over 75% of the total street trees. The city allocates an annual budget of approximately 37 million Euros for the maintenance of existing street trees, with an expenditure of around 2500 Euros for planting a new tree and maintaining it for the first three years (Pflanzenschutzamt Berlin, 2021). In spite of spending heavily on maintenance, the city has witnessed a reduction in the number of total trees over last 5 years. Fig. 3(a) presents a snapshot of the tree distribution in the City of Berlin, where the color intensity represents the tree density per district.

The tree inventory dataset includes details such as tree location, year of plantation, age, crown size, tree height, diameter, and species information. As the methodology adopted for the estimation of tree-sequestered carbon requires the diameter size of the trees, only those trees (~75%) for which this information was available were included in the analysis.

3.2.2. Melbourne city

Melbourne is the capital of the state of Victoria and the second-most populous city in Australia, with around 5 million inhabitants and a city area of 9993 km^2. The mean population density in the city is about 503 residents/km^2. Greater Melbourne is an urban agglomeration consisting of Melbourne (inner city of around 37 km^2) and 30 local municipalities (outer city). The city extends along the Yarra River and experiences a temperate climate known for its abrupt changes. Melbourne has more than 80,000 trees in the inner city region, valued at around 800 million$ (City of Melbourne, 2023). The city also maintains a register of exceptional trees (currently 279 trees) that are on private land but need protection due to their natural or heritage significance (City of Melbourne, 2019). Additionally, more than 3000 trees are planted annually to enhance the canopy cover and improve the diversity among tree species. As street tree data is limited for the rest of Greater Melbourne, both street trees and parks were included for the inner city, but only parks were included as UGS for the outer city. The most common tree genera in the city include Eucalyptus, Acacia, Ulmus, Platanus, and Corymbia. The tree inventory dataset includes tree location, scientific and common name, year of plantation, tree maturity, and diameter. Fig. 4(a) presents a snapshot of the park distribution in Greater Melbourne and the street trees in inner Melbourne considered in this analysis. Similar to Berlin, only trees with available diameter information (~40%) were included.

3.3. Data and other inputs

The meteorological dataset, which includes data on evapotranspiration and past and future precipitation, was obtained from the German weather service DWD (Deutscher Wetterdienst, 2021) and the Bureau of Meteorology Victoria (Bureau of Meteorology, 2023) to estimate the water demand of street trees and parks. Furthermore, the WUCOLS dataset (UC Davis, 2021), as well as the soil maps from the Federal Institute for Geosciences and Natural Resources (Bundesanstalt für Geowissenschaften und Rohstoffe, 2021) and the City of Melbourne (City of Melbourne Open Data Team, 2014), were used as input data for the time series model employed for water demand estimation. To obtain tree-specific information such as tree type, species, diameter, and distribution, the city tree inventory available through the open-data initiatives of Berlin Berlin City (2021) and Melbourne (City of Melbourne Open Data Team, 2023) was used.

4. Results

In scenarios of sufficient resource availability, the resource demands of all trees could be met. However, in resource-constrained situations, prioritization becomes crucial to determine which trees and parks should be allocated resources. The results demonstrate how the prioritization of various districts or sub-districts occurs using the proposed goal-programming based model under a given resource constraint scenario. The green-marked regions in the city denote regions where all UGS should be prioritized for resource allocation, while the orange-marked region signifies those not prioritized. A resource constraint scenario of 20% reduction in the available resources is analyzed for both the case-study cities. For this particular analysis, the access and quality targets are set at the mean score of 8 and 6, respectively. Higher targets are set for access since the existing targets of WHO and UN SDG focus exclusively on providing higher access to a sufficient quantity of UGS without any specific targets related to the quality of those spaces or for carbon sequestration (United Nations, 2020).

The results for the three cases of Berlin are presented in Fig. 3. In the first case (see Fig. 3(b)), resources are allocated at the district scale with city-scale goals. Here, 59 out of 96 districts received allocations, fulfilling the resource demand in the green-marked districts. In the second case (see Fig. 3(c)), resource allocation is at the sub-district scale with city-scale goals. The third case (see Fig. 3(d)) illustrates each district's performance in goal achievement when resources are allocated at the sub-district scale with district-scale targets. Since in this case each district has an individual goal, the model aims to minimize the deviation for each district. Consequently, resources are allocated to each district. However, due to insufficient resources to meet the entire demand of all districts, some districts will still experience underachievement of their goals. Unlike the binary response obtained in the previous two cases, resource allocation is done in each district to maximize goal achievement. For this case, districts are categorized as achieved if the goal is met, underachieved if the goal achievement is below the target, and overachieved if it exceeds the target. It can be observed that some districts experience overachievement, especially when large parks within those districts are fully prioritized, potentially surpassing the predefined or expected targets, set at a score of 8 for access and 6 for quality.

Similar to the Berlin case, the green-marked city districts in Fig. 4 represent the districts in Melbourne where all UGS are prioritized for allocating resources. Fig. 4(b) presents the first case wherein resources are allocated at the district scale (divided according to localities) with goals set at the city scale. In this case, 231 out of 266 districts were prioritized. Fig. 4(c) presents the second case wherein resource allocation is done at the sub-district scale (divided according to zip codes) with goals set at the city scale. In this case, 440 out of 527 sub-districts were prioritized. Fig. 4(d) presents the third case wherein resource allocation is done at the sub-district scale, but the targets are set at the district scale instead of the city scale. As a result, resources are allocated to each district, but the achievement of goals varies depending on the allocation and the resource availability. As explained in Section 3.1.2, the access score is determined by the number of people benefiting from a particular UGS. Consequently, UGS located on the outskirts of the city generally exhibit lower access scores compared to those situated in areas with a higher population density. While this is partially mitigated by the higher quality of UGS on the periphery compared to inner-city UGS, the overall prioritization still favors inner-city UGS. This preference is evident in the results from Melbourne, where several districts on the periphery did not receive prioritization. This contrasted with Berlin, where the relatively even distribution of the population resulted in a different prioritization pattern.

Water demand and personnel demand are costs associated with the management of each UGS, so it is critical to evaluate how much cost is involved in implementing a particular strategy. Similarly, street trees allocated and parks allocated are indirect benefits that will determine the direct benefits desired by a decision-maker, i.e., achieved accessibility, achieved quality, and retained sequestered carbon upon implementing a particular strategy. Based on this principle, several benefits metrics were calculated and Table 4 provides a performance summary of resource allocation strategies across various benefit metrics.

The metrics *water consumed* and *personnel consumed* describe the resources used from the total available. They are calculated as the percentage of water allocated to the prioritized UGS from the available 80% water during the resource constraint scenario, and similarly for personnel allocation. *Street trees allocated* and *parks allocated* represent the resources receiving the required management inputs for sustenance. These metrics are calculated as the percentage of street trees and parks that received management support from the total considered in the analysis. *Access achieved* and *quality achieved* describe the achievement of access and quality targets. These metrics are measured as the mean accessibility score or quality score of the prioritized or allocated parks. As previously mentioned, each of these scores falls within a range from 0 to 10, with 10 representing the highest score. *Carbon*

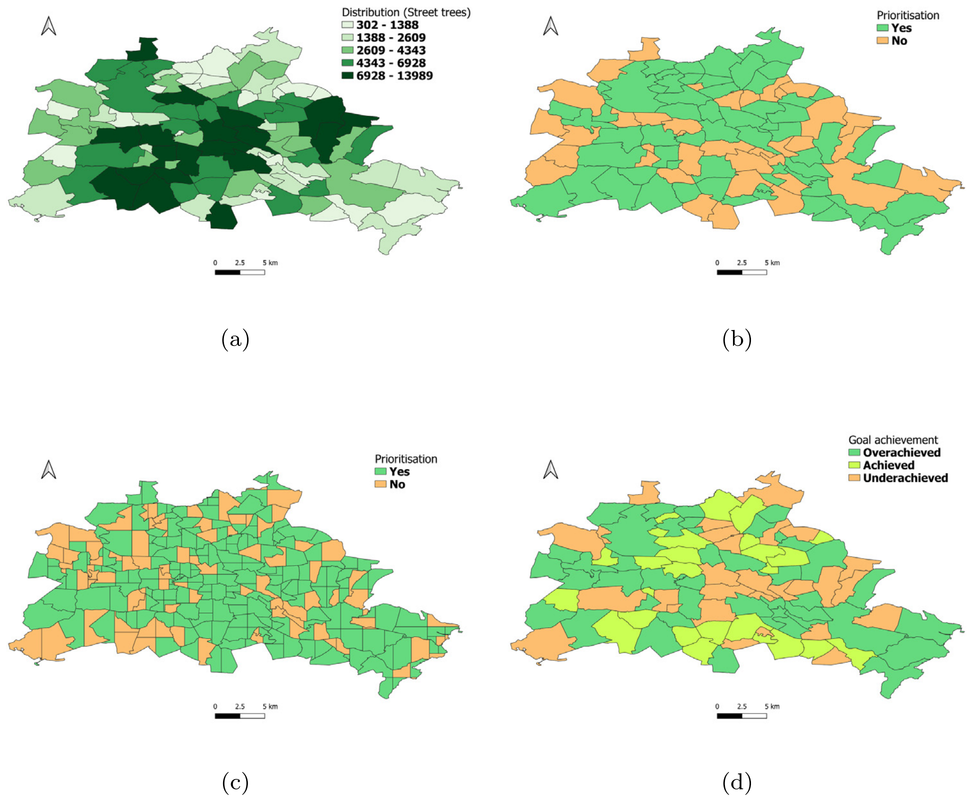


Fig. 3. (a) Snapshot of the street trees in Berlin with the intensity of color indicating the tree density in the district (b) Case-1 Berlin: Resource allocation decision at district spatial scale with city-level goals. (c) Case-2 Berlin: Resource allocation decision at sub-district spatial scale with city-level goals. (d) Case-3 Berlin: Goal achievement in each district with district-level goals.
Source: Berlin City (2021).

Table 4
Performance on various benefit metrics under given constraints.

No	Parameter	Berlin			Melbourne		
		City-level target		District-level target	City-level target		District-level target
		Districts	Cluster	Cluster	Districts	Cluster	Cluster
		(Case-1)	(Case-2)	(Case-3)	(Case-1)	(Case-2)	(Case-3)
1	Water consumed (%)	94.28	97.35	95.17	96.56	98.72	97.3
2	Personnel consumed (%)	91.69	93.86	90.84	95.85	98.22	96.44
3	Street trees allocated (%)	84.15	92.23	81.22	89.6	94.37	87.7
4	Parks allocated (%)	92.46	89.74	94.59	90.12	88.46	92.28
5	Access score achieved	7.9	8.3	7.8	8.1	8.7	8
6	Quality score achieved	7.3	7.7	7.1	8.8	8.9	8.8
7	Carbon sequestered (%)	86.94	93.29	87.70	91.5	97.35	90.20
8	Heritage trees allocated (%)	–	–	–	95.8	95.8	97.1
8	Model run time (mins)	35	50	80	30	40	65

sequestered presents the percentage of stored carbon that will continue to remain stored due to the allocated street trees. This is calculated as the percentage of carbon stored in the prioritized trees against the carbon stored in all trees. *Heritage trees allocated* is the percentage of heritage (exceptional) trees that will remain conserved under the given prioritization from the total heritage trees in the city. Lastly, *model run time* represents the total time taken to run the entire model, including the three sub-modules described earlier.

Benefit metrics provide several insights into the prioritization recommended by the model. In Case-1, for Berlin, more parks received allocation than street trees, whereas, for Melbourne, the allocation was quite similar for both. This difference is likely due to the distribution of street trees throughout the entire city in Berlin, whereas, in the case of Melbourne, they are concentrated only in the inner city. Nevertheless, as observed, up to 8.31% (mean = 5.40%) of resources are left undistributed. The minimum resource required for each non-priority district is higher than the remaining resources; therefore, they cannot be allocated any resource. Consequently, all street trees and parks in those districts will remain without any resources, despite some resources being left in the city. Since the benefit target for access was set higher than for quality, parks will have higher priority. However, in Case-2, street trees received a higher allocation because, at a higher spatial resolution, resources are distributed among a greater number of regions, leaving fewer resources for each sub-district. Additionally, since each unit of parks requires more resources, this will favor street trees. As a result, an improvement in resource utilization can also be observed for both cities. In this case, only up to 6.14% (mean = 2.96%) of resources are left undistributed. With the increase in resource allocation, the total UGS allocation also improved in Case-2 compared to Case-1.

The overall benefits show improvement when goals are established at the district level instead of the city level (Case 3). In this case, as the benefit target aimed at maximizing access and quality achievement for each district, the prioritization highly favored the parks. As seen

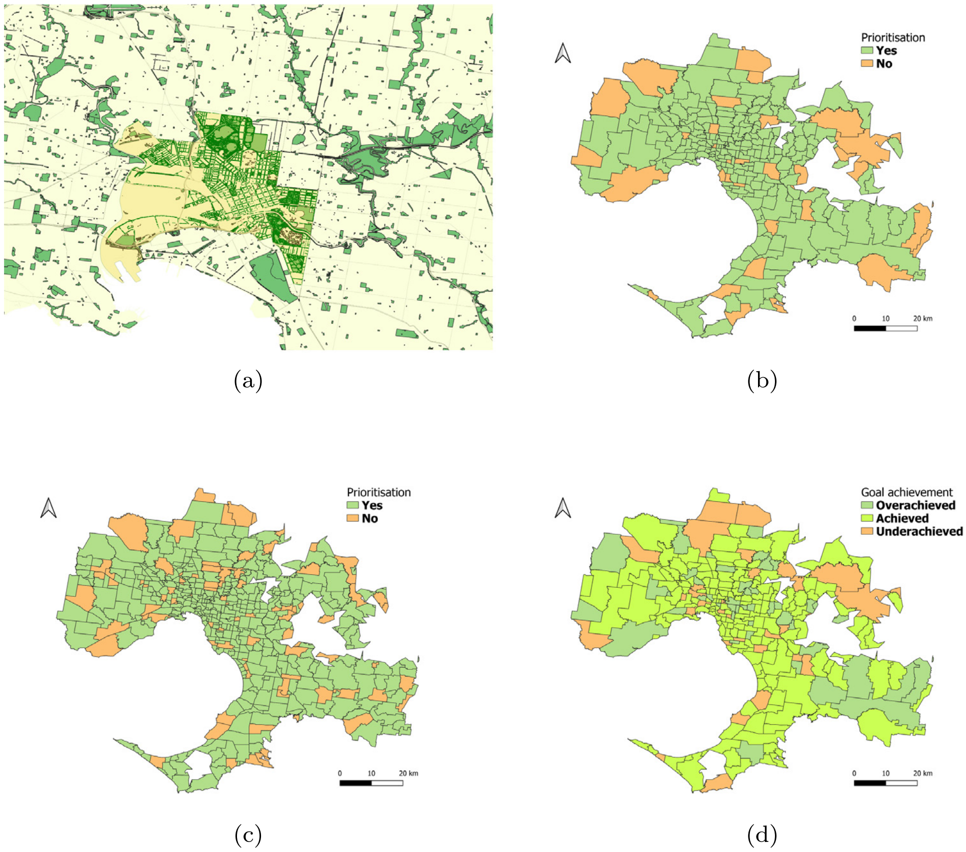


Fig. 4. (a) Snapshot of the parks in Greater Melbourne and street trees in the inner city (b) Case-1 Melbourne: Resource allocation decision at district spatial scale with city-level goals. (c) Case-2 Melbourne: Resource allocation decision at sub-district spatial scale with city-level goals. (d) Case-3 Melbourne: Goal achievement in each district with district-level goals.
Source: City of Melbourne Open Data Team (2023).

in Figs. 3(d) and 4(d), each district receives a portion of resources, and therefore, no region remains unmanaged. While this improves the uniformity in distribution, the allocation to trees reduced in this case, as some resources also went into managing previously not prioritized districts. In cases with a higher allocation of resources to parks, the mean access and quality scores are observed to be lower. This occurs because prioritizing a larger number of parks will also include parks that perform lower on these scores. As expected, higher carbon sequestration is observed in cases with a higher allocation of resources to street trees. Especially in Melbourne, where all street trees are concentrated in the inner city and most of those districts got prioritized, the street trees allocation and achievement of the carbon target are relatively much higher than in Berlin. The heritage trees metric was calculated only for Melbourne since the city has a special focus on preserving these trees. Lastly, the model run time increased as we increased the spatial resolution of the analysis and the number of constraints.

5. Discussion

The proposed extended GP model addresses the need for methods that can prioritize UGS while managing multiple resource constraints, such as water resources and personnel limitations. It leads to solutions that are not only feasible but also balance the achievement of multiple goals. In both the cases of Berlin and Melbourne, it can be observed that the benefit metrics improve when resource allocation is done at a sub-district spatial scale (Case-2) compared to when it is done at the district scale (Case-1). This is likely due to the criterion of absolute allocation. When optimization is done at a lower spatial resolution, the total number of street trees and UGS is much higher in a single unit. As a result, the cumulative management demands of each unit are comparatively higher, and the optimal or near-optimal result suffers from this aggregation. Therefore, under a resource constraint scenario, the number of district units that can be allocated resources is relatively lower. Moreover, when the allocation pattern is analyzed in comparison to the tree distribution in the city, many of the non-allocated sub-districts lie in the high tree density areas. It is critical to emphasize that since partial allocation is not considered, some of the resources are left unused. Therefore, the gained benefits can likely be further improved by including partial allocation.

While case-1 bounds the prioritization by a lower spatial scale, case-3 forces goal fulfillment in each district. Therefore, decision-makers aiming for a resource-efficiency-oriented distribution should opt for allocation at the sub-district level since, among all three, it offers the highest model flexibility to choose the UGS for prioritization. While case-3 is better suited for a goal-oriented prioritization approach, as the focus is higher on the achievement of goals across the city than on benefit maximization. The benefits gained increase as the spatial resolution increases. For the decision-maker, this implies that the distribution of resources using smaller hubs is better. In such cases, a smaller group of resource-intensive UGS can be targeted. However, if the decision is made at a district level to allocate resources to all UGS within the district, it would cover UGS with a varied range of demands and benefits. Nevertheless, higher spatial resolution not only exponentially increases the computation efforts for the model but also raises implementation complexity in the field, requiring different management applications for each region. It might be feasible to apply in the future using an IoT-based micro-irrigation system. Secondly, the district-level target approach is more appropriate since it does not leave any district completely disadvantaged and provides a more uniform resource allocation across the city. Therefore, this is suitable for cities like Berlin, where the population distribution is more uniform.

Moreover, to assess improvements in goal achievement, a comparison is conducted with a baseline scenario. In the absence of a prioritization standard or framework available for the cities, decision-makers are unable to distinguish between higher and lower beneficial trees or parks and higher or lower resource-intensive tree species. Consequently, a symmetrical distribution of resources must be made, considering all trees and parks in all districts equally based on the availability of resources. In the event of a 20% reduction in available resources, the resources will be sufficient to meet the annual management demands of 80% of the total UGS. In such a case, over the large iterations, the benefits achieved will be proportionate as well.

However, with GP model-based prioritization, the allocation surpasses 80% in all three scenarios for both street trees and parks. This is achieved by the model favoring UGS with lower resource demands per unit of benefits provided. As a result, resource-intensive UGS receive reduced management support. This prioritization strategy enables cities to attain greater benefits even under constrained scenarios. It is crucial to note that these results are based on available public data. Since the open tree inventory lacked essential data for some trees, updating the missing data could potentially alter management requirements, recommendations, and GP-based decision-making. Consequently, future research should focus on addressing these data gaps.

The review of the existing city plans also indicated a critical gap in the urban greening strategies of both cities. The city of Berlin has developed a Landscape Program to ensure sufficient availability of recreational areas for people and the needs of wild animals and plants in the future (Naturschutz, 2023). This initiative involves the creation of new green spaces and a network of connecting paths. Although the program has effectively integrated environmental goals into planning procedures, it lacks strategies to address challenges in the event of resource constraints. Similarly, the City of Melbourne recognizes the importance of UGS and has developed a Green Our City Strategic Action Plan (City of Melbourne, 2020) and Open Space for Everyone Strategy (City of Melbourne, 2012). However, the primary focus remains on increasing new green spaces to meet the growing demand, enhancing the diversity of tree species, and improving vegetation health. While acknowledging the extended drought and subsequent water shortage, a recommendation has been made to plant drought-resistant tree species and implement stormwater harvesting. Nevertheless, no consideration has been given to prioritizing existing UGS based on the benefits obtained.

6. Conclusion and future research

The proposed GP model allocates limited resources to maximize the social and environmental benefits obtained from UGS. The reduced availability of demand parameters, water, and personnel is included to demonstrate the constraint scenario. However, these parameters can be extended by adding additional demand parameters, such as the quantity of fertilizer, the number of trucks, or the available budget. The benefit parameter is calculated using the custom-built accessibility and quality indicators for parks and the sequestered carbon indicator for street trees. Nevertheless, these parameters can be easily replaced or extended with other benefit parameters, such as biodiversity, air pollution reduction, or heat mitigation (cooling), depending on the needs of the city and availability of the accurate data.

The novelty of the study lies in its implementation of a MCDM approach to address the resource allocation challenge for existing UGS. It introduces a utilitarian principle-based prioritization using a multi-objective GP model. The proposed model can accommodate diverse UGS, including parks and street trees, with varying characteristics, and allows analysis at different spatial scales. Moreover, it uniquely incorporates accessibility as a goal, enabling cities to meet UN SDG targets even under resource constraint conditions. Additionally, the framework is scalable, allowing the inclusion of additional cost and benefit parameters. Lastly, the model was tested in two cities with diverse conditions regarding data availability, green space density, population distribution, and local climatic conditions.

It is important to note that the GP-based method, instead of optimizing, derives a solution that satisfies the goals. Consequently, some resources may remain unused in the final solution. Additionally, the current approach is limited to spatial planning of resource allocation and can be extended by considering temporal aspects. For instance, different temporal goals or constraints at various spatial scales could be incorporated. In addition, currently, constraints are considered at the city level, which can be further extended to different spatial scales, as was done for the goals in this study. Similarly, the current model adopts a single-choice goal, allowing the decision-maker to set fixed target values for each benefit. This approach can be expanded to a multi-choice goal, where a range of benefit targets can be specified, as demonstrated by Kouaissah and Hocine (2020). As mentioned earlier, more benefits and management demands can be included to create more realistic trade-off scenarios. Furthermore, it is important to note that the analysis included only around 75% of street trees for Berlin and 40% for Melbourne, for which diameter information was available in the tree inventory dataset to calculate the sequestered carbon. As a result, the actual management demand and benefits obtained from street trees would likely be proportionately higher than the estimated values. Therefore, further research is needed to address such data gaps in urban datasets. Moreover, due to a lack of information on personnel in the public domain, certain assumptions were made in estimating the personnel demand. However, following the process of the demonstration, these assumptions can be replaced with factual city data to obtain more accurate results.

The developed model is a novel approach for UGS management, serving as an example for urban resource allocation applications. Decision-makers can utilize this model to make prioritization decisions at various spatial scales under constraint scenarios. The model is adaptable to include additional demand and benefit parameters based on the availability of relevant datasets. Moreover, it allows decision-makers to observe the impact of modifying the priority order of goals and their respective weights on the prioritization decision.

CRediT authorship contribution statement

Mihir Rambhia: Conceptualization, Methodology, Software, Formal analysis, Investigation, Data curation, Visualization, Writing – original draft, Writing – review & editing. **Rebekka Volk:** Review & editing, Project administration, Supervision. **Behzad Rismanchi:** Review & editing, Project administration, Supervision. **Stephan Winter:** Review & editing, Project administration, Supervision. **Frank Schultmann:** Review & editing, Supervision, Funding acquisition.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgments

The first author gratefully acknowledge the funding from Graduate School for Climate and Environment (GRACE) at Karlsruhe Institute of Technology (KIT), Germany in cooperation with the University of Melbourne, Australia to undertake this research.

References

American Public Works Association, 2015. Urban forestry best management practices for public works managers - staffing.

Bakhtavar, E., Prabatha, T., Karunathilake, H., Sadiq, R., Hewage, K., 2020. Assessment of renewable energy-based strategies for net-zero energy communities: A planning model using multi-objective goal programming. J. Clean. Prod. 272, 122886.

Berlin City, 2021. Open data berlin.

Bravo, M., Gonzalez, I., 2009. Applying stochastic goal programming: A case study on water use planning. European J. Oper. Res. 196 (3), 1123–1129.

Bundesanstalt für Geowissenschaften und Rohstoffe, 2021. Bodenübersichtskarte von Deutschland 1:3000000.

Bureau of Meteorology, 2023. Victoria Daily Evapotranspiration. Australian Government - Bureau of Meteorology.

CABE, 2010. Managing Green Spaces - Seven Ingredients for Success. Commision for Architecture and the Built Environment.

Charnes, A., Cooper, W., 1977. Goal programming and multiple objective optimizations. European J. Oper. Res. 1, 39–54.

Charnes, A., Cooper, W.W., Devoe, J.K., Learner, D.B., Reinecke, W., 1968. A goal programming model for media planning. Manage. Sci. 14 (8), B–423–B–430.

Chen, Y., Men, H., Ke, X., 2023. Optimizing urban green space patterns to improve spatial equity using location-allocation model: A case study in Wuhan. Urban Forest. Urban Greening 84, 127922.

Chen, S., Zhao, X., Chen, Z., Hou, B., Wu, Y., 2022. A game-theoretic method to optimize allocation of defensive resource to protect urban water treatment plants against physical attacks. Int. J. Crit. Infrastruct. Prot. 36, 100494.

Cheng, J., Feng, X., Bai, X., 2021. Modeling equitable and effective distribution problem in humanitarian relief logistics by robust goal programming. Comput. Ind. Eng. 155, 107183.

City of Melbourne, 2012. Open space strategy.

City of Melbourne, 2019. Exceptional Tree Register. Tree management.

City of Melbourne, 2020. Green our city strategic action plan.

City of Melbourne, 2023. Urban forest. Greening the city.

City of Melbourne Open Data Team, 2014. Soil types by area (urban forest). data.melbourne.vic.gov.au.

City of Melbourne Open Data Team, 2023. Trees, with species and dimensions (urban forest). data.melbourne.vic.gov.au.

Corlay, V., Sibel, J.-C., 2023. An MDP approach for radio resource allocation in urban future railway mobile communication system (FRMCS) scenarios. arXiv.org.

Davies, H., Doick, K.J., Hudson, M.D., Schreckenberg, K., 2017. Challenges for tree officers to enhance the provision of regulating ecosystem services from urban forests. Environ. Res. 156, 97–107.

Deutscher Wetterdienst, 2021. DWD open data.

Diiaz-Balteiro, L., Romero, C., 2004. Sustainability of forest management plans: A discrete goal programming approach. J. Environ. Manag. 71, 351–359.

Eisenman, T.S., Chang, S.-J., Laurian, L., 2021. Stewarding Street Trees for a Global Urban Future. Springer eBooks, pp. 1–18.

Eurostat, 2011. Degree of Urbanisation Classification - 2011 Revision. Eurostat.

Fam, D., Mosley, E., Lopes, A., Mathieson, L., Morison, J., Connellan, G., 2008. Irrigation of urban green spaces: A review of the environmental, social and economic benefi ts.

Fongar, C., Randrup, T.B., Wiström, B., Solfjeld, I., 2019. Public urban green space management in norwegian municipalities: A managers' perspective on place-keeping. Urban Forest. Urban Greening 44, 126438.

Foroozesh, F., Monavari, S.M., Salmanmahiny, A., Robati, M., Rahimi, R., 2022. Assessment of sustainable urban development based on a hybrid decision-making approach: Group fuzzy BWM, AHP, and TOPSIS–GIS. Sustainable Cities Soc. 76, 103402.

Gebre, S.L., Cattrysse, D., Van Orshoven, J., 2021. Multi-criteria decision-making methods to address water allocation problems: A systematic review. Water (Switzerland) 13 (2), 1–28.

Google, 2022. Google colaboratory.

Greening, Landscape and Tree Management Section Development Bureau, 2014. Management guidelines for mature trees.

Greening, Landscape and Tree Management Section Development Bureau, 2020. Guidelines on tree pruning.

Hamurcu, M., Eren, T., 2022. Multicriteria decision making and goal programming for determination of electric automobile aimed at sustainable green environment: A case study. Environ. Syst. Decis. 43, 211–231.

Huang, C., Huang, P.S., Wang, X., Zhou, Z., 2018. Assessment and optimization of green space for urban transformation in resources-based city – a case study of lengshuijiang city, China. Urban Forest. Urban Greening 30, 295–306.

Ignizio, J.P., 1978. A review of goal programming: A tool for multiobjective analysis. J. Oper. Res. Soc. 29 (11), 1109–1119.

Jim, C.Y., 2004. Green-space preservation and allocation for sustainable greening of compact cities. Cities 21, 311–320.

Jones, D., Tamiz, M., 2010. Practical Goal Programming. Springer.

Kamran, M.A., Karimi, B., Bakhtiari, H., Masoumzadeh, S., 2016. A resource allocation model in a healthcare emergency center using goal programming. J. Eng. Res. 4.

Kaur, J., Singh, O., Anand, A., Agarwal, M., 2023. A goal programming approach for agile-based software development resource allocation. Decis. Anal. J. 6, 100146.

Klumbytė, E., Bliūdžius, R., Medineckienė, M., Fokaides, P.A., 2021. An MCDM model for sustainable decision-making in municipal residential buildings facilities management. Sustainability 13 (5).

Kouaissah, N., Hocine, A., 2020. Optimizing sustainable and renewable energy portfolios using a fuzzy interval goal programming approach. Comput. Ind. Eng. 144, 106448.

Kumar, A., Sah, B., Singh, A.R., Deng, Y., He, X., Kumar, P., Bansal, R.C., 2017. A review of multi criteria decision making (MCDM) towards sustainable renewable energy development. Renew. Sustain. Energy Rev. 69 (November 2016), 596–609.

Lashkari, M., Yazdi-Feyzabadi, V., Mohammadi, M., Saberi, H., Mehrolhassani, M., 2018. Designing a financial resource allocation model using goal programming approach: A case study of a hospital in Iran. .

Lee, S.M., Clayton, E.R., 1972. A goal programming model for academic resource allocation. Manage. Sci. 18 (8).

Li, Y., Cui, Q., Li, C., Wang, X., Cai, Y., Cui, G., Yang, Z., 2017. An improved multi-objective optimization model for supporting reservoir operation of China's south-to-north water diversion project. Sci. Total Environ. 575, 970–981.

Li, X., Li, X., Ma, X., 2022. Spatial optimization for urban green space (UGS) planning support using a heuristic approach. Appl. Geogr. 138, 102622.

Li, S., Liang, Y., Wang, Z., Zhang, D., 2021. An optimization model of a sustainable city logistics network design based on goal programming. Sustainability 13, 7418.

LI, I., Zhang, W., Yang, P., 2022. Estimating Management Demands and Cost for Urban Green spaces (UGS) in Melbourne. Capstone Project Report.

Liu, Y., Xia, C., Ou, X.-Y., Lv, Y., Ai, X., Pan, R., Zhang, Y., Shi, M., Zheng, X., 2023. Quantitative structure and spatial pattern optimization of urban green space from the perspective of carbon balance: A case study in Beijing, China. Ecol. Indic. 148, 110034.

Locke, D., Grove, M., Lu, J., Troy, A., O'Neil-Dunne, J., Beck, B., 2010. Prioritizing preferable locations for increasing urban tree canopy in New York City. Cities Environ. (CATE) 3.

M. Vallejo, D.C., Vargas, P., 2017. Online/offline evolutionary algorithms for dynamic urban green space allocation problems. J. Exper. Theor. Artif. Intell. 29 (4), 843–867.

Mildrexler, D.J., Berner, L.T., Law, B.E., Birdsey, R.A., Moomaw, W.R., 2020. Large trees dominate carbon storage in forests east of the cascade crest in the United States Pacific northwest. Front. Forests Glob. Change 3.

Mishra, V., Som, T., Samuel, C., Sharma, S., 2018. Fuzzy goal programming approach for resource allocation in an NGO operation. Springer Proc. Math. Stat. 373–385.

Moller, M.S., Olafsson, A.S., Vierikko, K., Sehested, K., Elands, B., Buijs, A., Konijnendijk, C.C., 2019. Participation through place-based e-tools: A valuable resource for urban green infrastructure governance? Urban Forest. Urban Greening 40, 245–253.

Naturschutz, L., 2023. Landschaftsprogramm einschließlich artenschutzprogramm (lapro).

Nechi, S., Aouni, B., Mrabet, Z., 2019. Managing sustainable development through goal programming model and satisfaction functions. Ann. Oper. Res. 293, 747–766.

Nestıcò, A., Elizabeth, C., Naddeo, V., 2020. Sustainability of urban regeneration projects: Novel selection model based on analytic network process and zero-one goal programming. Land Use Policy 99, 104831.

Neuenschwander, N., Wissen Hayek, U., Grêt-Regamey, A., 2011. GIS-based 3D urban modeling framework integrating constraints and benefits of ecosystems for participatory optimization of urban green space patterns. In: Proceedings of REAL CORP 2011.

Nyelele, C., Kroll, C.N., 2021. A multi-objective decision support framework to prioritize tree planting locations in urban areas. Landsc. Urban Plan. 214, 104172.

Nyelele, C., Kroll, C.N., Nowak, D.J., 2022. A comparison of tree planting prioritization frameworks: i-tree landscape versus spatial decision support tool. Urban Forest. Urban Greening 75, 127703.

OECD, 2023. Hours worked (indicator). OECD Data.

Omidipoor, M., Jelokhani-Niaraki, M., Moeinmehr, A., Sadeghi-Niaraki, A., Choi, S.-M., 2019. A GIS-based decision support system for facilitating participatory urban renewal process. Land Use Policy 88, 104150.

Orumie, U.C., Ebong, D., 2014. A glorious literature on linear goal programming algorithms. Am. J. Oper. Res. 04, 59–71.

Pankaj Kant, P.K.M., Natha, A.R., 2023. Evaluation of decision support system for disaster management using multi-criteria decision techniques: A case study of Alappuzha, Kerala. Urban Plan. Transp. Res. 11 (1), 2262546.

Pavan, M., Todeschini, R., 2009. Multicriteria Decision-Making Methods. Elsevier eBooks, pp. 591–629.

Perron, L., Furnon, V., 2022. OR-Tools. Google.

Pflanzenschutzamt Berlin, 2021. Stadtbäume. www.berlin.de.

Plitt, S., Pregitzer, C.C., Charlop-Powers, S., 2021. Brief research report: Case study on the early impacts of COVID-19 on Urban Natural Areas across 12 American cities. Front. Sustain. Cities 3.

Porterfield, R.L., 1976. A goal programming model to guide and evaluate tree improvement programs. Forest Sci. 22, 417–430.

Pustokhina, I.V., Pustokhin, D.A., 2021. An intelligent multi-objective optimal resource allocation via modified fish swarm for sustainable smart cities. In: Artificial Intel-

ligence Applications for Smart Societies: Recent Advances. Springer International Publishing, Cham, pp. 71–85.
Rahman, M.F., Sharma, N., 2020. Reinforcement learning based approach for urban resource allocation and path planning problems. In: 2020 International Conference on Intelligent Data Science Technologies and Applications. IDSTA, pp. 115–118.
Rajendran, S., 2021. Real-time dispatching of air taxis in metropolitan cities using a hybrid simulation goal programming algorithm. Expert Syst. Appl. 178, 115056.
Rambhia, M., Volk, R., Rismanchi, B., Winter, S., Schultmann, F., 2022. Prioritising urban green spaces using accessibility and quality as criteria. IOP Conf. Ser.: Earth Environ. Sci. 1101, 022043.
Rambhia, M., Volk, R., Rismanchi, B., Winter, S., Schultmann, F., 2023. Supporting decision-makers in estimating irrigation demand for urban street trees. Urban Forest. Urban Greening 127868.
Rehman, A.U., Usmani, Y.S., Mian, S.H., Abidi, M.H., Alkhalefah, H., 2023. Simulation and goal programming approach to improve public hospital emergency department resource allocation. Systems 11, 467.
Ricciardi, L., D'Odorico, P., Galli, N., Chiarelli, D.D., Rulli, M.C., 2022. Hydrological implications of large-scale afforestation in tropical biomes for climate change mitigation. Philos. Trans. R. Soc. B 377 (1857), 20210391.
Romero, C., 1985. Naive weighting in non-preemptive goal programming. J. Oper. Res. Soc. 36 (7), 647–648.
Roozbahani, R., Abbasi, B., Schreider, S., Ardakani, A., 2014. A multi-objective approach for transboundary river water allocation. Water Res. Manag. 28, 5447–5463.
Rößler, S., 2017. Demands, Opportunities and Constraints of Green Space Development for Future Urban Development under Demographic and Climate Change. Springer eBooks, pp. 87–98.
Schniederjans, M., 2012. Goal Programming: Methodology and Applications: Methodology and Applications. books.google.com, pp. 1–23.
Schrammeijer, E.A., van Zanten, B.T., Verburg, P.H., 2021. Whose park? Crowdsourcing citizen's urban green space preferences to inform needs-based management decisions. Sustainable Cities Soc. 74, 103249.
Stephenson, N.L., Das, A.J., Condit, R., 2014. Rate of tree carbon accumulation increases continuously with tree size. Nature 507, 90–93.
UC Davis, 2021. WUCOLS plant search database. ucanr.edu.
United Nations, 2020. Goal 11. Department of Economic and Social Affairs, Sustainable Development.
US Department of Energy, 1998. Method for calculating carbon sequestration by trees in urban and suburban settings — Urban forestry south.
Valcárcel-Aguiar, B., Fernández, P.M., 2018. Evaluation and management of urban liveability: A goal programming based composite indicator. Soc. Ind. Res. 142, 689–712.
Wan, X., Xue, Y., Hua, L., Wu, Q., 2023. Multi-objective collaborative decision-making for flood resource utilization in a reservoir. Stochastic Environ. Res. Risk Assess..
Wirtz, Z., Hagerman, S., Hauer, R.J., Konijnendijk, C.C., 2021. What makes urban forest governance successful? – a study among Canadian experts. Urban Forest. Urban Greening 58, 126901.
World Health Organization, 2017. Urban Green Spaces: a Brief for Action. Regional Office for Europe.