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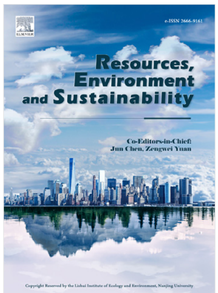

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Prioritizing Urban Green Spaces in Resource Constrained Scenarios

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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

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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.

Keywords: Urban green, green space management, resource allocation, goal programming, sustainable cities, decision support

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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 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

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for scarce resources [55]. 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 [78]. This challenge is compounded by the involvement of various stakeholders from departments of garden, road, forestry, waste and civic society groups [35, 23]. 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 [53]. 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 [88]. 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 [88]. Providing universal access to green and public spaces is part of the United Nations Sustainable Development Goal target 11.7 as well [83]. 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 [67]. 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 [75]. 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 [41]. 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 [64]. 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 [63], water allocation [77], urban sustainability [27], facility management [39], and reservoir control [86]. 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 [11], machine learning-based techniques for the optimal allocation of UGS [50], crowd-sourcing-based participatory management [53, 80], GIS-based methods for prioritizing tree planting sites based on criteria for need and suitability [49], and organizational-based strategies like the place-keeping process [26, 11]. While existing literature, such as [49], [58], and [59], 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.

2. Literature Review

2.1. MCDM approaches

MCDM is an effective tool for solving decision-making problems with conflicting objectives [28]. 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)) [41]. 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 [46]. 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 [58]. For instance, [48] utilized a multi-objective programming method to determine the required quantity of UGS for achieving a specified level of carbon offset. Meanwhile, [46] implemented spatial optimization for UGS layout planning, considering equitable distribution and conversion costs as decision criteria. [33] devised a regression-based optimization strategy for UGS planning, focusing on accessibility and quality as primary targets. Using an LP approach, [57] determined the optimal distribution of green spaces at the district level, considering spatial conditions. Similarly, [58] 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 [59]. However, these studies primarily concentrated on benefits maximization and didn't 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 haven't 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, [61] integrated MCDM with GIS for participatory renovation of urban areas, [19] used a Markov decision process for a communication system, [69] implemented a fish swarm algorithm to distribute cloud resources, and [70], [10] 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 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.

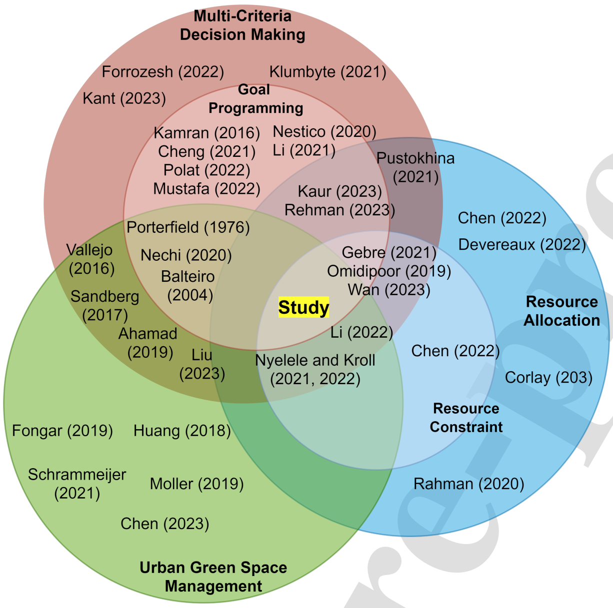


Figure 1: Classification of relevant literature with current study focus is highlighted.

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 [62]. 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 [56]. 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. [9] pioneered GP, which was later expanded upon by [43], [8], [34], [76], and [79]. 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 [42], healthcare [52, 74], software development [38], water use [4], and reservoir operation [47].

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 [37], fleet management [85, 71, 32], urban regeneration [56], logistics [45, 12], energy strategies [2], and more. Several researchers have also used GP to address challenges pertaining to UGS management. For instance, [55] utilized GP to determine a sustainable development pathway, with a central focus on accommodating decision-makers' preferences. [68] presented a GP-based model for the optimal selection of a tree improvement program. Similarly, [22] 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 [36]. 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 (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.

$$\min d = \sum_{g=0}^{n} d_g^+ + d_g^- \tag{1}$$

$$f_g(x) + d_g^+ - d_g^- = t_g \ , \ g = 1, ...G \ , \ x \in F \tag{2}$$

$$d_g^+, d_g^- \geq 0 \ , \quad g = 1, ...G \tag{3}$$

Table 1: Major Goal Programming variants (Source: [36])

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.

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

Figure 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 [87], 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.

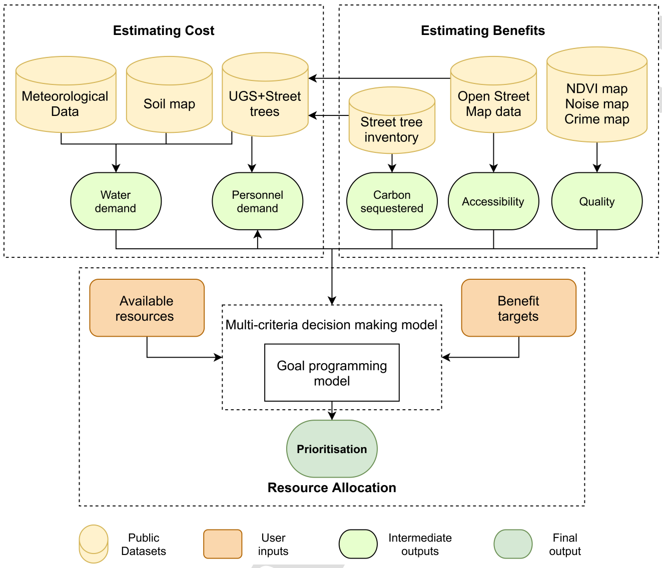


Figure 2: Modeling framework for prioritizing UGS in resource constrained scenarios.

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 [25, 7]. In their research, [87] 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 [73].

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 [1]. 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 [30], [31], [20], and [44]. 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 hours annually in Germany and 1707 hours annually in Australia [60]. 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 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

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 ($\mathrm{S_C}$) and the essentiality score ($\mathrm{S_E}$). The first component, $\mathrm{S_C}$, measures the number of residences that benefit from a specific park. The second component, $\mathrm{S_E}$, 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 ($\mathrm{S_{Q,A}}$), greenness ($\mathrm{S_{Q,G}}$), noise ($\mathrm{S_{Q,N}}$), and safety ($\mathrm{S_{Q,S}}$). 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 [72]. Since there is a positive correlation between the size of the tree and the amount of carbon captured by the tree [81, 51], the sequestered carbon for each street tree is calculated from its species type and diameter size according to the method in [84].

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 equation (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

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

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 (5)–(7) drives the model to attain the expected level of benefit targets (B^{carbon},B^{access},$B^{quality}$). The hard constraints given in equations (8) and (9) ensure that the resource demand does not exceed the available resources during the constraint scenario. Lastly, the equations (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

$$D = \sum_{l \epsilon L} \left(\sum_{i \epsilon s_p} w_1 * \frac{d1_{l,i}}{B^{carbon}} + \sum_{i \epsilon g_p} w_2 * \frac{d2_{l,i}}{B^{access}} + w_3 * \frac{d3_{l,i}}{B^{quality}} \right) \tag{4}$$

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):

$$\sum_{l \epsilon L} \sum_{i \epsilon s_p} b_{l,i}^{carbon} + d1 = B^{carbon} \tag{5}$$

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.

$$\sum_{l \epsilon L} \sum_{i \epsilon g_p} b_{l,i}^{access} + d2 = B^{access} \tag{6}$$

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.

$$\sum_{l \epsilon L} \sum_{i \epsilon g_p} b_{l,i}^{quality} + d3 = B^{quality} \tag{7}$$

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):

$$\sum_{i \epsilon s_p} w_i^{demand} + \sum_{i \epsilon g_p} w_i^{demand} \leq W^{available} \tag{8}$$

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.

$$\sum_{i \epsilon s_p} p_i^{demand} + \sum_{i \epsilon g_p} p_i^{demand} \leq P^{available} \tag{9}$$

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

$$s_p = r_{a,i} * S \;\; \forall\; i \;\epsilon\; I \tag{10}$$

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.

$$g_p = r_{a,i} * G \;\; \forall\; i \;\epsilon\; I \tag{11}$$

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.

$$r_{a,i} \;\epsilon\; (0,1) \;\; \forall\; i \;\epsilon\; I \tag{12}$$

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 [29]. 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 [65]. 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 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 [24]. 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 [66]. In spite of spending heavily on maintenance, the city has witnessed a reduction in the number of total trees over last 5 years. Figure 3a 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 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$ [16]. 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 [14]. 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 4a 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.

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 [21] and the Bureau of Meteorology Victoria [6] to estimate the water demand of street trees and parks. Furthermore, the WUCOLS dataset [82], as well as the soil maps from the Federal Institute for Geosciences and Natural Resources [5] and the City of Melbourne [17], 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 [3] and Melbourne [18] 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 [83].

The results for the three cases of Berlin are presented in the Figure 3. In the first case (see Figure 3b), 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 3c), resource allocation is at the sub-district scale with city-scale goals. The third case (see Figure 3d) 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.

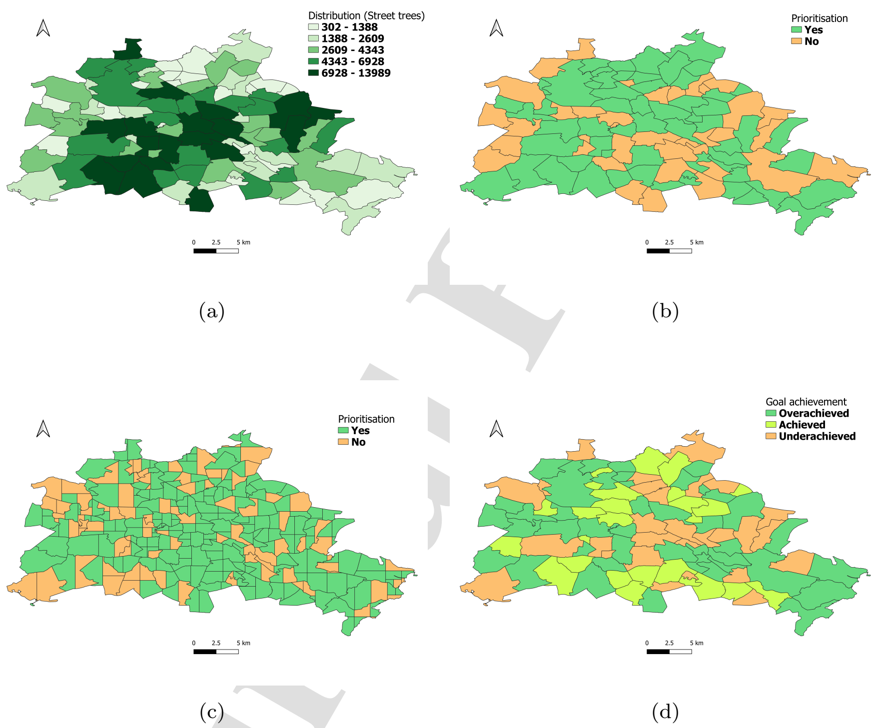
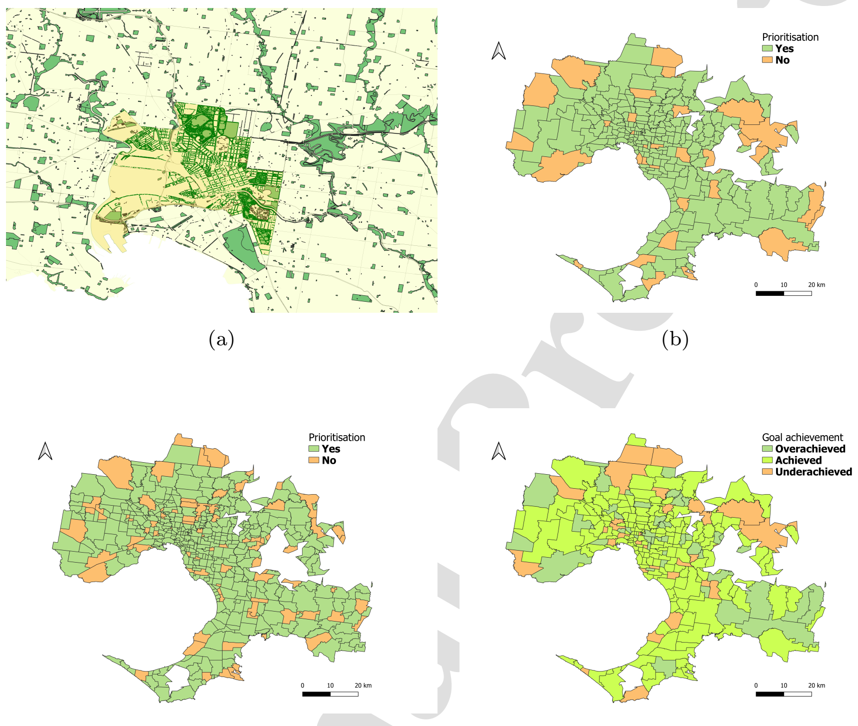


Figure 3: (a) Snapshot of the street trees in Berlin with the intensity of colour indicating the tree density in the district (Source: [3]) (b) Case-1 Berlin: Resource allocation decision at district spatial scale with city-level goals. (c) Case-2 Berlin: Resource allocation decision at sub-district spatial scale with city-level goals. (d) Case-3 Berlin: Goal achievement in each district with district-level goals.

Similar to the Berlin case, the green-marked city districts in Figure 4



(a) (b) (c) (d)

Figure 4: (a) Snapshot of the parks in Greater Melbourne and street trees in the inner city (Source: [18]) (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.

represent the districts in Melbourne where all UGS are prioritized for allocating resources. Figure 4b 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 4c 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. Figure 4d 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 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.

Table 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 *qual-*

ity 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 3d and Figure 4d, 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's 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 [54]. 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 [15] and Open Space for Everyone Strategy [13]. 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 [40]. 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.

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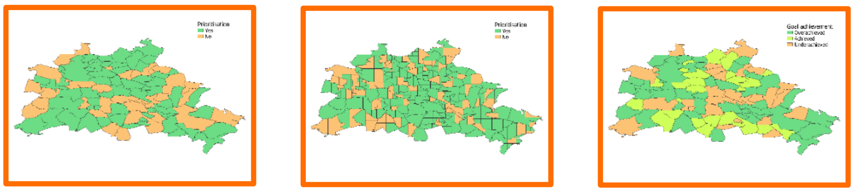
Highlights

- Multi-criteria decision making framework for urban green spaces prioritisation.
- 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.

Prioritising Urban Green Spaces in Resource Constrained Scenarios

A goal-programming based multi-criteria decision making method to allocate limited water and personnel resources while maximizing the benefits obtained from urban green spaces .



Increasing spatial resolution (left to right) led to improved resource allocation and goal attainment for the case-study city Berlin, with district-scale targets yielding more consistent resource allocation than city-scale ones.

The proposed approach can help increase the total benefits gained while effectively balancing the conflicting goals and constraints while considering city's preferences and priorities.

Journal Pre-proof

CRediT authorship contribution statement

Mihir Rambhia: Conceptualisation, Methodology, Software, Formal analysis, Investigation, Data curation, Visualisation, Writing Draft, 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 interests

☒ 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.

☐ The author is an Editorial Board Member/Editor-in-Chief/Associate Editor/Guest Editor for [Journal name] and was not involved in the editorial review or the decision to publish this article.

☐ The authors declare the following financial interests/personal relationships which may be considered as potential competing interests:

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.