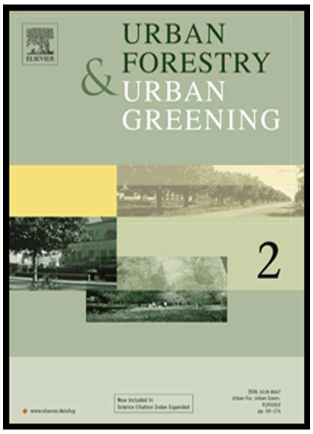

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Supporting Decision-makers in Estimating Irrigation Demand for Urban Street Trees

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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 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.

Keywords: Urban green, irrigation water demand, water budgeting, linear time series, green space management, sustainable cities

1. Introduction

The World Health Organization (WHO) defines urban green spaces (UGS) as “all urban land covered by vegetation of any kind” [1]. 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 [2].

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 [3]. 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 [4]. Similarly, some regions in northern Italy, Portugal, and Spain also announced emergency measures and requested their residents to economise their water usage [5, 6]. Mandatory water restrictions targeting the irrigation of both public and private open spaces are also frequently observed in Canberra, Sydney, and Melbourne in Australia [7].

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 [8, 9].

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 [10, 11, 12]. 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 [13]. Existing models for urban conditions, such as [14, 15, 16], 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 [17, 18].

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

1.1. Models for agricultural areas

Different studies have presented irrigation scheduling approaches for the agricultural sector [19, 20]. 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 [21]. Similarly, AquaCrop model was developed for single, and uniform crop fields applications [22]. Delgoda et al. [23] 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 [24].

The limitation of the aforementioned irrigation scheduling models is their total focus on crops and crop yield, which also applies to the respective submodels. 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. [23], 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 [13]. 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 [25]. 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 [26]. Therefore, the stress factor for urban trees is usually high and leads to a lower survival rate than in rural areas [27, 18]. 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 [13, 28]. The majority of existing research focuses on either residential irrigation demand [29, 30], urban vegetation evapotranspiration (ET) [31, 20], or turf grass water demand [32, 33] with a goal of reducing demand. Vico et al. [14] 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 [34] by further quantifying nutrients retention in soil. On a greater spatial scale, Volo et al. [15] 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. [35] 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 [36]. 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 [37]. 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 [38]. 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. [13] 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 [39].

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 1: Comparative analysis of available irrigation models and apporaches.

Study	Year	ET measurement	Soil moisture change	Agriculture	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		✓			✓	✓		✓	✓	✓			✓	✓

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 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 [40], 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 [41]. 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 $\mathrm{K_L}$ to account for the landscape characteristics as shown in Equation 2 [42]. $\mathrm{K_L}$ itself is composed of a species factor ($\mathrm{K_s}$), a density factor for UGS ($\mathrm{K_d}$), and a microclimate factor ($\mathrm{K_{mc}}$), 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 [43].

$$ET_\mathrm{L} = K_\mathrm{L} \times ET_0 \tag{2}$$

$$K_\mathrm{L} = K_\mathrm{s} \times K_\mathrm{d} \times K_\mathrm{mc} \tag{3}$$

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 ($\mathrm{P_{eff}}$). $\mathrm{P_{eff}}$

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, ground-cover, 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

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 [44]. 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 [45, 46, 47].

$$P_{\text{eff}} = (1 - c_{\text{inc}}) \times P \tag{4}$$

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. [24], Revelli and Porporato [34], and Vico et al. [14] 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 $\mathrm{P_{eff}}$ after the infiltration ($\mathrm{P_{inf}}$) has taken place. The maximum amount of water that can enter a particular soil in a time unit is represented using the infiltration rate ($\mathrm{c_{inf}}$). The intensity of $\mathrm{P_{eff}}$ is determined as $\mathrm{P_{eff}}$/h, where h describes the duration of the precipitation event in hours. As shown in Equation 5, RO will occur whenever the intensity of $\mathrm{P_{eff}}$ exceeds the $\mathrm{c_{inf}}$ 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 [48]. 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.

$$RO = \begin{cases} 0, & \text{if } c_{\text{inf}} \geq P_{\text{eff}}/h \\ P_{\text{eff}} - (c_{\text{inf}} \times h) & \text{else} \end{cases} \tag{5}$$

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 [49]. The FAO provides a range of TAW values for undisturbed soil types [50]. 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 [51]. The root depth for this system is defined as 0.5m (broad), 1m (oblique), 2m (deep) [52]. 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.

$$D = \begin{cases} 0, & \text{if } P_{\text{inf}} \leq TAW \\ P_{\text{inf}} - TAW & \text{else} \end{cases} \tag{6}$$

$$RAW = r \cdot TAW \tag{7}$$

where, r= root zone depth (m)

$$RAW = \begin{cases} c_{\text{s}} \cdot P_{\text{inf}} & \text{if } P_{\text{inf}} \geq RAW \\ P_{\text{inf}} & \text{else} \end{cases} \tag{8}$$

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 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 Figure 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.

$$I_{\mathrm{t}} = \sum ET_{\mathrm{L,t}} - ET_{\mathrm{L,t\text{-}1}} + I_{\mathrm{t\text{-}1}} + (c_{\mathrm{s,t}} \cdot P_{\mathrm{inf,t}}) - (c_{\mathrm{s,t+1}} \cdot P_{\mathrm{inf,t+1}}) \tag{9}$$

such that,

$$ET_{\mathrm{L,t}} = \sum_{s \forall S} (K_{\mathrm{L,s}} \cdot ET_{0,\mathrm{t}}) \tag{10}$$

$$P_{\mathrm{eff,t}} = (1 - c_{\mathrm{inc}}) \cdot P_{\mathrm{t}} \tag{11}$$

$$P_{\mathrm{inf,t}} = \begin{cases} P_{\mathrm{eff,t}}, & if c_{\mathrm{inf}} \geq P_{\mathrm{eff,t}}/h \\ c_{\mathrm{inf}} \cdot h, & \text{else} \end{cases} \tag{12}$$

$$RAW_{\mathrm{t}} = \sum_{s \forall S} r_{\mathrm{s}} \cdot TAW \tag{13}$$

$$c_{\mathrm{s,t}} = \begin{cases} RAW/P_{\mathrm{inf,t}}, & if P_{\mathrm{inf,t}} > RAW \\ 1, & \text{else} \end{cases} \tag{14}$$

$$\tag{15}$$

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).

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 [54] 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,

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 [48]
r	I	Depth of roots	0.5m/1m/2m depending on root system
TAW	I	Total available water	Newman [51]
ET_0	I	Reference ET	Weather data [53]
ET_L	C	Landscape ET	Using WUCOLS database [43]
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

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 [43].

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 [45, 47], while for the remaining species for which data was unavailable, it was set to 0.227 as the default [46]. In Step 8,

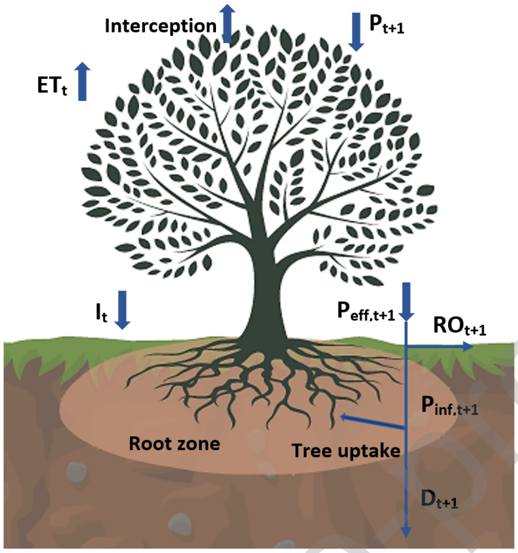


Figure 1: The parameters in the water balance approach considered in the time series model.

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 [48]. 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 [55]. 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.

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 [56].

4.1. Data used and Inputs

In Germany, the German weather service DWD offers data from 5,980 meteorological stations spread across the whole country [53]. 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 $\mathrm{ET_0}$, as well as past and future precipitation data. For the calculation of $\mathrm{ET_L}$, the WUCOLS dataset provided by the University of California is used [43]. 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 [57]. Information regarding the soil type in Berlin was obtained from the Federal Institute for Geosciences and Natural Resources [58]. Using this, sandy loam soil was selected for Berlin. Subsequently, the default value for $\mathrm{c_{inf}}$ 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 [51].

For a more precise irrigation recommendation, the forecast for precipitation and $\mathrm{ET_0}$ is necessary. The DWD [53] makes predictions about future rain events, but $\mathrm{ET_0}$ forecasts are not available. Hence, in this case, the average $\mathrm{ET_0}$ of the prior week is used as a forecast, considering that the $\mathrm{ET_0}$ 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 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.

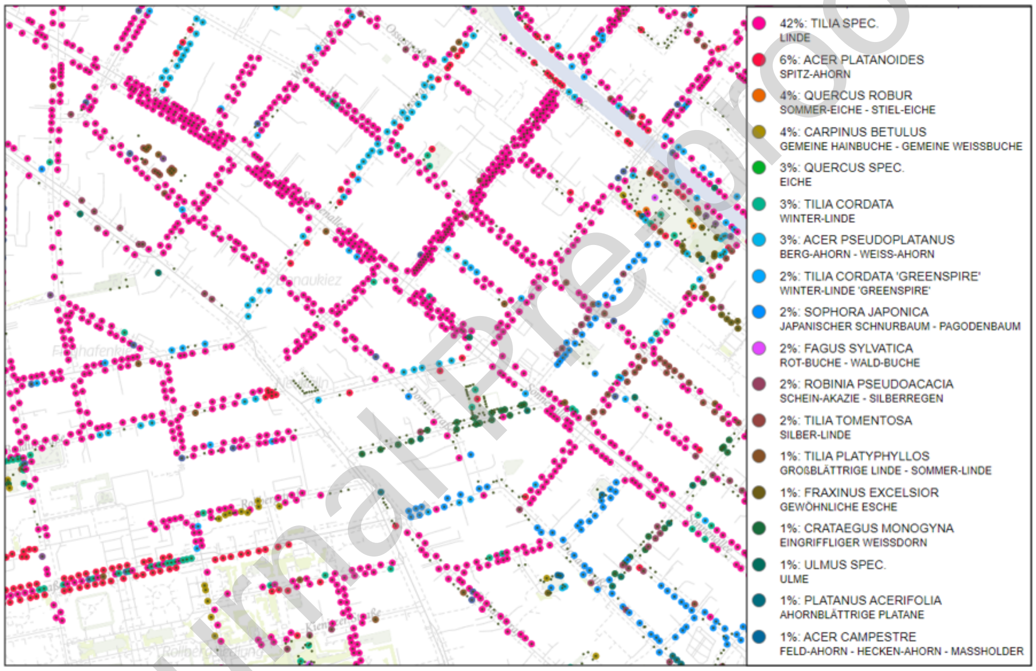
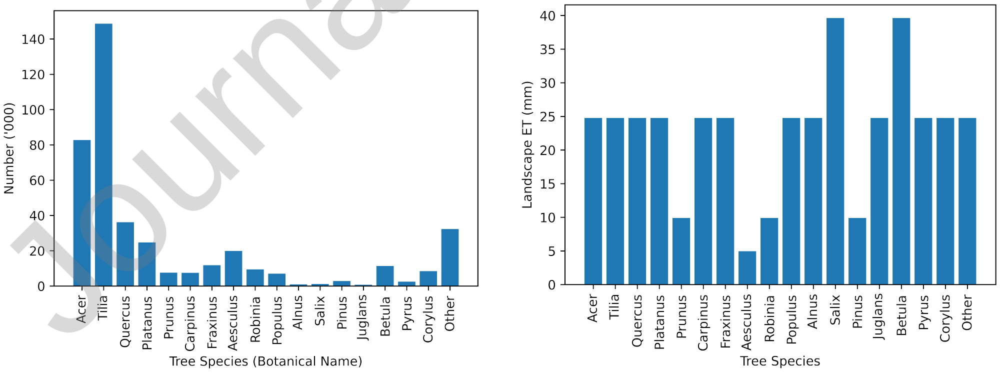


Figure 2: Snapshot of the street trees in Berlin with the colour of the marker indicating the species type (Source: http://opentrees.org/).

4.2. Results for the street trees in Berlin

Figure 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 (41$^{\text{st}}$ week). Figure 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 4a and Figure 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 4c and Figure 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.

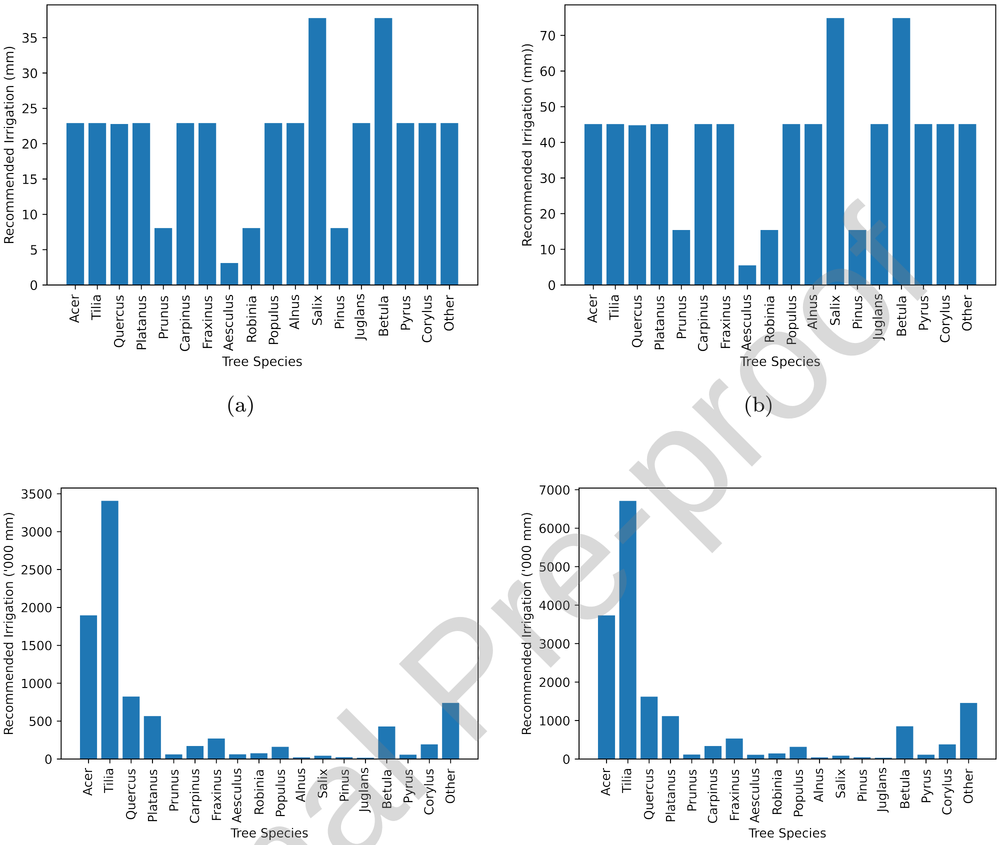


(a)

(b)

Figure 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



(a)

(b)

(c)

(d)

Figure 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.

is computed for all the street trees and is presented in Figure 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 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 op-

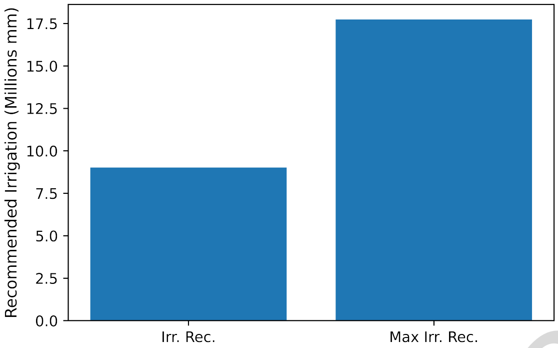


Figure 5: A bar plot showing the one week (41st week of 2021) total current and maximum irrigation recommendation (in mm) for all street trees in Berlin.

erations 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 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. Figure 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 was

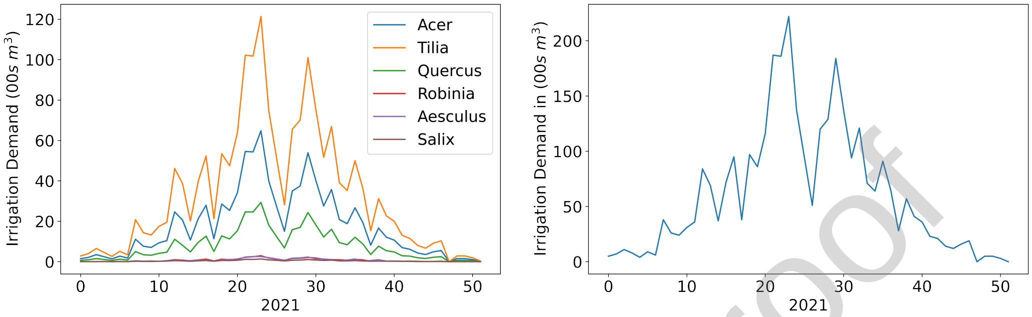


Figure 6: A plot showing estimation of weekly irrigation demand (in m^3) for the most commonly found street tree species (on left) and for all the street trees in Berlin combined (on right).

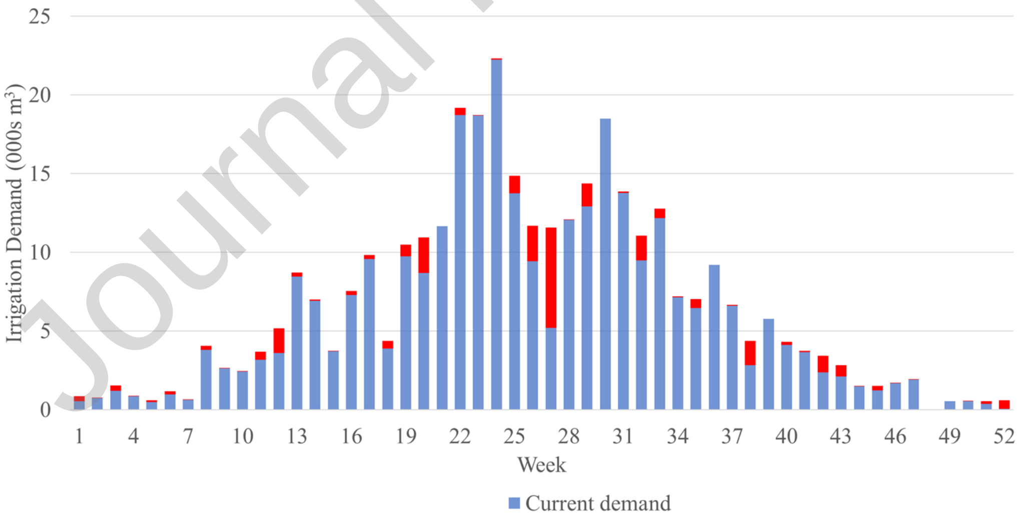


Figure 7: A plot showing the change in irrigation demand in case only 50 % of rainfall occurs.

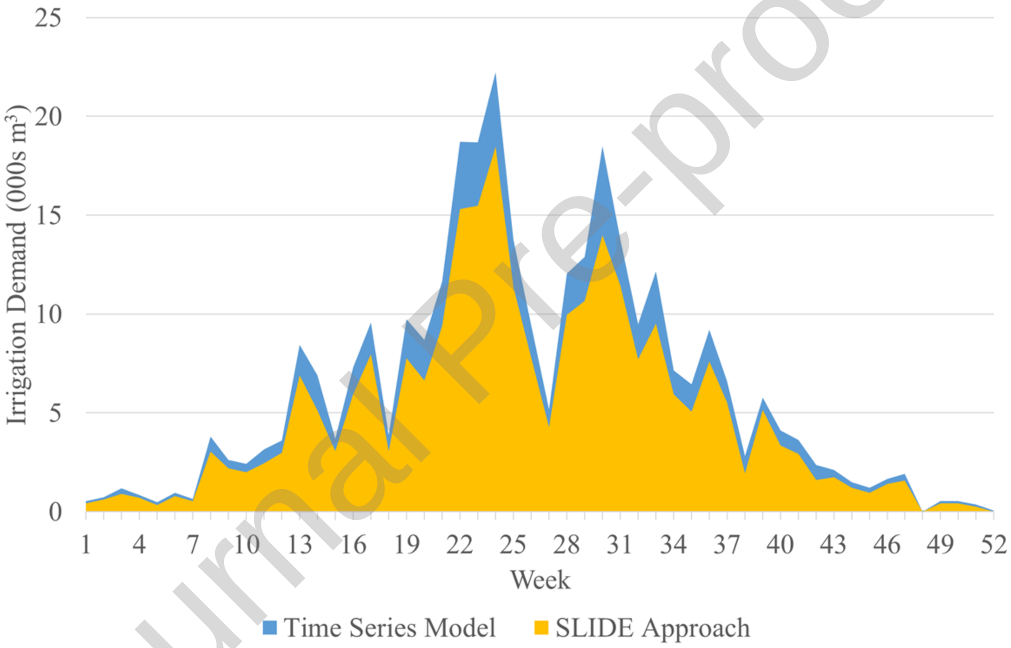


Figure 8: A plot showing estimated irrigation demand (m^3) for the Berlin city in 2021 by the time series and SLIDE model.

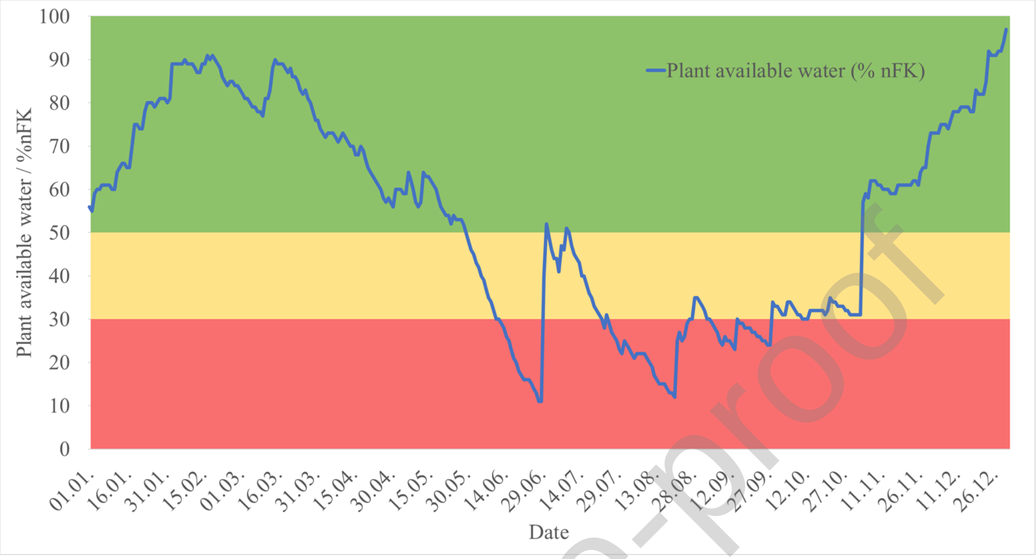


Figure 9: A plot showing estimated soil moisture available to plants at the example site Tempelhofer Weg in Berlin-Neukölln for the year 2021 (data source: [37]).

applied here. Accordingly, only the coefficient $(K_{\mathrm{s}} \cdot K_{\mathrm{d}} \cdot K_{\mathrm{mc}})$ of Equation 10 was replaced by PF, while everything else remained the same. The calculated irrigation demand by both methods is presented in Figure 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 $\mathrm{ET_L}$ demand and, subsequently, recommending higher irrigation.

Moreover, Figure 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. 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 $\mathrm{ET_L}$. 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. [59], 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 $\mathrm{ET_L}$ 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.

References

[1] World Health Organization, Urban green spaces and health - a review of evidence, 2016.

[2] United Nations, Goal 11, 2020. URL: `https://sdgs.un.org/goals/goal11`.

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

[4] K. Patel, J. Samenow, California declares historic water emergency measures amid drought, Washington Post (2022).

[5] France-Presse Agence, Italy declares state of emergency in drought-hit northern regions, 2022. URL: `https://www.theguardian.com/world/2022/jul/05/italy-declares-state-emergency-drought-hit-northern-regions`.

[6] Deutsche Welle, Water scarcity: EU countries forced to restrict drinking water access, 2022. URL: `https://www.dw.com/en/water-scarcity-eu-countries-forced-to-restrict-drinking-water-access/a-62363819`.

[7] 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.

[8] European Commission, Forging a climate-resilient Europe - the new EU strategy on adaptation to climate change, 2021.

[9] European Commission, Establishing a framework for community action in the field of water policy, 2000.

[10] O. Adeyemi, I. Grove, S. Peets, Y. Domun, T. Norton, Dynamic neural network modelling of soil moisture content for predictive irrigation scheduling, Sensors (Switzerland) 18 (2018). doi:`10.3390/s18103408`.

[11] M. S. Khan, M. Woo, K. Nam, P. K. Chathoth, Smart city and smart tourism: A case of Dubai, Sustainability (Switzerland) 9 (2017). doi:`10.3390/su9122279`.

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

[13] H. Nouri, S. Beecham, F. Kazemi, A. Hassanli, A review of ET measurement techniques for estimating the water requirements of urban landscape vegetation, Urban Water Journal 10 (2013) 247–259. doi:`10.1080/1573062X.2012.726360`.

[14] G. Vico, R. Revelli, A. Porporato, Ecohydrology of street trees: design and irrigation requirements for sustainable water use, Ecohydrology 7 (2013) 508–523. doi:`10.1002/eco.1369`.

[15] 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). doi:`10.1002/eco.1457`.

[16] H. Nouri, S. Chavoshi Borujeni, A. Y. Hoekstra, The blue water footprint of urban green spaces: An example for Adelaide, Australia, Landscape and Urban Planning 190 (2019). doi:`10.1016/j.landurbplan.2019.103613`.

[17] G. Wessolek, B. Kluge, Predicting water supply and evapotranspiration of street trees using hydro-pedo-transfer functions (hptfs), Forests 12 (2021) 1010. doi:`10.3390/f12081010`.

[18] H. Sjöman, A. Busse Nielsen, 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 (2010) 281–293. doi:`10.1016/j.ufug.2010.04.001`.

[19] B. George, S. Shende, N. Raghuwanshi, Development and testing of an irrigation scheduling model, Agricultural Water Management 46 (2000) 121–136. doi:`10.1016/s0378-3774(00)00083-4`.

[20] S. Contreras, E. G. Jobbágy, P. E. Villagra, M. D. Nosetto, J. Puigdefábregas, Remote sensing estimates of supplementary water consumption by arid ecosystems of central Argentina, Journal of Hydrology 397 (2011) 10–22. doi:`10.1016/j.jhydrol.2010.11.014`.

[21] FAO, Cropwat, 2021. URL: `https://www.fao.org/land-water/databases-and-software/cropwat/en`.

[22] FAO, Aquacrop, 2021. URL: `https://www.fao.org/aquacrop`.

[23] D. Delgoda, S. K. Saleem, H. Malano, M. N. Halgamuge, 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 (2016) 344–353. doi:`10.1016/j.agwat.2015.08.011`.

[24] D. Delgoda, H. Malano, S. K. Saleem, M. N. Halgamuge, Irrigation control based on model predictive control (mpc): Formulation of theory and validation using weather forecast data and aquacrop model, Environmental Modelling & Software 78 (2016) 40–53. doi:`10.1016/j.envsoft.2015.12.012`.

[25] A. Dimoudi, M. Nikolopoulou, Vegetation in the urban environment: microclimatic analysis and benefits, Energy and Buildings 35 (2003) 69–76. doi:`10.1016/s0378-7788(02)00081-6`.

[26] H. Nouri, S. Beecham, A. Hassanli, G. Ingleton, Variability of drainage and solute leaching in heterogeneous urban vegetation environs, Hydrology and Earth System Sciences 17 (2013) 4339–4347. doi:`10.5194/hess-17-4339-2013`.

[27] A. Koeser, R. Hauer, K. Norris, R. Krouse, Factors influencing long-term street tree survival in milwaukee, wi, usa, Urban Forestry & Urban Greening 12 (2013) 562–568. doi:`10.1016/j.ufug.2013.05.006`.

[28] Y. Shi, G. Yang, Y. Du, Y. Ren, Y. Lu, L. Fan, J. Chang, Y. Ge, Z. Bao, Estimating irrigation water demand for green spaces in humid areas: seeking a sustainable water management strategy, Urban Water Journal 15 (2018) 16–22. doi:`10.1080/1573062X.2017.1363255`.

[29] R. Hilaire, M. Arnold, D. Wilkerson, D. Devitt, B. Hurd, B. Lesikar, V. Lohr, C. Martin, G. McDonald, R. Morris, D. Pittenger, D. Shaw, D. Zoldoske, Efficient water use in residential urban landscapes, HortScience horts 43 (2008) 2081 – 2092. doi:`10.21273/HORTSCI.43.7.2081`.

[30] E. Domene, D. Saurí, Urbanisation and water consumption: Influencing factors in the metropolitan region of barcelona, Urban Studies 43 (2006) 1605–1623. doi:`10.1080/00420980600749969`.

[31] R. G. Allen, L. S. Pereira, T. A. Howell, M. E. Jensen, Evapotranspiration information reporting: I. Factors governing measurement accuracy, Agricultural Water Management 98 (2011) 899–920. doi:`10.1016/j.agwat.2010.12.015`.

[32] B. Huang, J. D. Fry, Turfgrass evapotranspiration, Journal of Crop Production 2 (2000) 317–333. doi:`10.1300/j144v02n02_14`.

[33] E. Pooya, A. Tehranifar, M. Shoor, Y. Selahvarzi, H. Ansari, The use of native turf mixtures to approach sustainable lawn in urban landscapes, Urban Forestry & Urban Greening 12 (2013) 532–536. doi:`10.1016/j.ufug.2013.06.009`.

[34] R. Revelli, A. Porporato, Ecohydrological model for the quantification of ecosystem services provided by urban street trees, Urban Ecosystems 21 (2018) 489–504. doi:`10.1007/s11252-018-0741-2`.

[35] T. Orusa, R. Orusa, A. Viani, E. Carella, E. Borgogno Mondino, 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 (2020).

[36] R. Kjelgren, R. Beeson, D. Pittenger, Jr., T. Montague, Simplified landscape irrigation demand estimation: Slide rules, Applied Engineering in Agriculture 32 (2016) 363–378. doi:`10.13031/aea.32.11307`.

[37] Pflanzenschutzamt Berlin, Bewässerungsempfehlung für Stadtbäume, 2021. URL: `https://www.berlin.de/pflanzenschutzamt/stadtgruen/beratung/bewaesserungsempfehlung-fuer-stadtbaeume/`.

[38] SA Water, Cooling the community, 2021. URL: `https://www.sawater.com.au/education-and-community/community-and-events/cooling-the-community`.

[39] 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 (2013) 24–27.

[40] FAO, Penman-Monteith equation, 2021. URL: `https://www.fao.org/3/x0490e/x0490e06.htm`.

[41] L. Costello, K. Jones, WUCOLS IV: Water use classification of landscape species, 2014.

[42] J. K. S. Costello L. R., (Water Use Classification of Landscape Species), 2014. URL: `https://ucanr.edu/sites/WUCOLS/files/183514.pdf`.

[43] UC Davis, WUCOLS plant search database, 2021. URL: `https://ucanr.edu/sites/WUCOLS/Plant_Search/`.

[44] A. M. J. Gerrits, H. H. G. Savenije, L. Hoffmann, L. Pfister, New technique to measure forest floor interception – an application in a beech forest in luxembourg, Hydrology and Earth System Sciences 11 (2007) 695–701. doi:`10.5194/hess-11-695-2007`.

[45] P. Llorens, F. Domingo, Rainfall partitioning by vegetation under mediterranean conditions. a review of studies in europe, Journal of Hydrology 335 (2007) 37–54. doi:`10.1016/j.jhydrol.2006.10.032`.

[46] C. Nytch, E. Meléndez-Ackerman, M.-E. Pérez, J. Ortiz-Zayas, Rainfall interception by six urban trees in san juan, puerto rico, Urban Ecosystems 22 (2018) 103–115. doi:`10.1007/s11252-018-0768-4`.

[47] B. Yang, D. K. Lee, H. K. Heo, G. Biging, The effects of tree characteristics on rainfall interception in urban areas, Landscape and Ecological Engineering 15 (2019) 289–296. doi:`10.1007/s11355-019-00383-w`.

[48] Minnesota Pollution Control Agency, Minnesota stormwater manual, 2013. URL: `https://stormwater.pca.state.mn.us/index.php/Main_Page`.

[49] FAO, Chapter 8 - etc under soil water stress conditions, 1990. URL: `https://www.fao.org/3/x0490e/x0490e0e.htm`.

[50] C. Brouwer, A. Goffeau, M. Heibloem, Irrigation water management: Training manual no. 1, 1985. URL: `https://www.fao.org/3/r4082e/r4082e00.htm`.

[51] H. Newman, Calculating readily available water, 2012. URL: `https://www.agric.wa.gov.au/citrus/calculating-readily-available-water?page=0%5C%2C1`.

[52] M. Dobson, Tree root systems, 1995.

[53] Deutscher Wetterdienst, DWD open data, 2021. URL: `https://www.dwd.de/`.

[54] A. Cohen, fuzzywuzzy: Fuzzy string matching in python, 2020. URL: `https://pypi.org/project/fuzzywuzzy/`.

[55] Google, Google colaboratory, 2021. URL: `https://colab.research.google.com/`.

[56] Pflanzenschutzamt Berlin, Stadtbäume, 2021. URL: `https://www.berlin.de/sen/uvk/natur-und-gruen/stadtgruen/stadtbaeume/`.

[57] Berlin City, Open Data Berlin, 2021. URL: `https://daten.berlin.de/`.

[58] Bundesanstalt für Geowissenschaften und Rohstoffe, Bodenübersichtskarte von Deutschland 1:3000000, 2007. URL: `https://www.bgr.bund.de/DE/Themen/Boden/Produkte/Karten/Downloads/BUEK3000.pdf`.

[59] H. Nouri, S. Beecham, A. M. Hassanli, F. Kazemi, Water requirements of urban landscape plants: A comparison of three factor-based approaches, Ecological Engineering 57 (2013) 276–284. doi:`10.1016/j.ecoleng.2013.04.025`.

CRediT authorship contribution statement

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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.

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