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A 3D Target-Driven Optimisation Tool for Tree Planting Location Using Temporal Tree Crown Geometry Development

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Abstract

The effectiveness of urban green infrastructure depends on selecting optimal tree planting locations, as local conditions influence tree growth and their ability to provide key ecosystem services such as cooling and shading. This study presents a novel 3D target-driven optimization tool for tree placement in urban environments, focusing on optimizing tree locations based on 3D target canopy shapes and planting areas. This optimization model uniquely incorporates complex 3D tree crown geometries and their interactions with surrounding structures. By simulating tree canopy development over time, the model enhances long-term urban forest planning, providing a more accurate method for achieving environmental objectives like canopy coverage and microclimate regulation. Results from sample case studies using *Platanus x hispanica* and *Tilia cordata* trees showed varying optimization outcomes depending on the tree species and target conditions. The tool achieved various scores and optimal planting locations with different settings for the number of trees and target age. This experiment shows the applicability and feasibility of the tool in tree planting location optimisation. However, limitations include high computational demands, the exclusion of below-ground factors, and the validation of the crown growth model is restricted to Munich. Despite these constraints, the model's integration of spatial and temporal dynamics represents a significant advancement in urban tree placement optimization. Future research can improve computational efficiency and expand the model to diverse urban environments and species.

Keywords: tree planting, tree location optimization, Hill-climbing algorithm, crown development

Introduction

With increasing urbanisation and the effects of climate change, urban green infrastructure (UGI) has become increasingly important for improving human health and well-being in cities [1]. Being a vital component of UGI trees require in-depth study and research to fully understand and optimise their benefits. Since trees undergo dynamic growth throughout their lifecycles, effective UGI depends on proper design and management practices that support the long-term development of trees to enhance Ecosystem Services (ESS). ESS encompasses all the benefits that urban green infrastructures provide for human well-being. In urban forestry, ESS is assessed for each tree based on attributes like diameter at breast height, age, and crown shape. Local environmental conditions influence tree growth [2, 3], which affects ESS outcomes such as shading and cooling [4].

Previous research has emphasised the importance of optimising urban tree locations, arrangement and configuration by assessing various target indicators, such as thermal comfort, safety, mobility, etc. These studies employ specific prioritised classification methods or geographic information system (GIS) models to achieve their goals [5–7]. Additionally, some have employed a design model approach to modify the spatial relationship between urban trees and roadways to enhance habitat comfort [8, 9]. Nonetheless, the potential drawbacks of improperly planting urban trees—such as reduced ecological value, environmental issues, and potential risks—have often been overlooked [10].

Studies have shown that the radiative cooling effect of trees is impacted by both the location and the structural characteristics of a tree [11]. The location includes aspects such as the configuration of trees in the context of surrounding objects, as well as their distance from each other and from buildings [3]. The structural characteristics of trees include aspects like canopy area, diameter in breast height (DBH), crown diameter (CD), and leaf area index (LAI) [11–13]. Yang et al. [14] examined how the distance of a tree to a neighboring building influences the thermal condition of semi-outdoor spaces. Their findings highlight that tree location affects the ESS in open spaces. Furthermore, the location of a tree significantly affects the geometry of the canopy and, thus, also the ESS (e.g., shading) [3, 15].

Previous studies evaluated different scenarios and variables for improving the planting locations of trees. Zhao et al. [16] emphasized that optimal tree planting should avoid canopy overlap and ensure that trees do not block wind corridors to maintain effective ventilation. Liu et al. [17] provide evidence-based guidelines for landscape designers to optimize tree planting locations, considering the physical characteristics of the trees as well as the surrounding urban context. Although dense shade is beneficial, the findings underscore that greater cooling effects are achieved when the shaded area is maximized through the even distribution of the trees and the orientation of the

planting. Lachapelle et al. [18] suggest e.g. planting trees on the north side of east-west streets and the east side of north-south streets since then they are most effective during hot afternoon periods. Moreover, street orientations that allow for maximum exposure to direct sunlight during the hottest periods of the day benefit most from tree planting. Ouyang et al. [19] emphasize that trees should be strategically planted in areas with high solar exposure and open street canyons to maximize their cooling potential. For example, in deep and narrow street canyons, trees may not be as effective, and other cooling strategies should be considered. However, for wider streets, combining trees with other UGI strategies, such as green roofs and green walls, is recommended to achieve optimal cooling.

In addition to such strategy-oriented studies, there are a few tools to optimize the planting location of trees that are suggested based on the local environment and different targets such as shading, transpiration, and wind. Zhao et al. [20] utilised a greedy-adding algorithm [21] with a combination of the brute-force method [22] in a GIS platform. It aims to maximize tree shade coverage on building facades and open structures while minimizing shade on rooftops to preserve solar panel efficiency. The model considers tree characteristics such as height, crown diameter, and trunk height, focusing on a typical desert tree. Serdar et al. [23] utilized a Quadtree algorithm [24] for their optimisation model. The targets of the optimisation model were to analyze and improve the micro-climatic conditions and human behaviours in urban open spaces by optimising the location. The features of the trees used in the model included their tree species, numbers, approximate locations, sizes, and ecological and social functions such as shadowing and bordering.

Stojakovic et al. [25] employed the Galapagos Solver algorithm [26] for their optimisation model. The objective of the optimisation model is to mitigate building insolation in urban green spaces by optimizing the location of trees to maximize shading and reduce heat exposure. The model considers tree characteristics such as crown shape, crown size, and trunk height, using simplified geometries like spheres, ellipsoids, and cones to represent the trees in the simulations. Estacio et al. [27] utilize a Genetic Algorithm (GA) [28] for their optimisation model. The target of the optimisation model is to maximize walking frequency in urban environments by optimizing the location of trees. The model considers tree characteristics such as spacing between trees, the direction of neighbouring buildings, and Building Shadow Exposure (BSE). Hao et al. [29] employed a Genetic Algorithm (GA) [28] for the optimisation model. The objectives of the optimisation model were to decrease the heat stress for human in urban parks by strategically locating trees to maximize their cooling by trees through shading and evapotranspiration. The model incorporates features such as tree height, canopy width, leaf area index, albedo, leaf emissivity, and leaf transmittance.

Ghods et al. [30] employed an Ant Colony Optimisation (ACO) [31] algorithm for their optimisation model. The targets of the optimisation model are to maximise tree shade coverage on the façades and opening components of buildings while minimising shading on rooftops to preserve solar panel efficiency. Tree characteristics in the model include height, crown radius, and the ability to provide shading. Wallenberg et al. [32] employed a hill-climbing algorithm [33] for the optimisation model. The objectives of the optimisation model are to mitigate outdoor radiant load and reduce human

heat stress in urban areas by optimising the placement of trees to provide maximum shading. The model considers tree characteristics such as height, canopy diameter, and trunk zone height, focusing on their shading potential.

Despite the development of tree planting optimisation tools, previous tools have two major limitations. First, they generally aim to optimize tree locations for specific, narrow objectives, such as providing shade for pedestrians or buildings, mitigating wind, or influencing human behaviour and walking patterns. However, no tool currently employs a comprehensive, target-driven method capable of integrating multifaceted requirements. Yazdi et al. [34] proposed a target-driven tree-planting approach utilizing 3D voxels, referred to as Target Leaf Voxels (TLVs), to reconcile the need for larger tree canopy volumes and space for other human uses, such as traffic and open space, as well as functions like sun exposure and ventilation. By excluding forbidden voxels that impede other functions and prioritising beneficial voxels critical for achieving target ESS, a collection of TLVs is set spatially explicit to represent the desired canopy location and shape in a 3D format.

Second, they fail to account for the complexity of 3D tree crown shapes and how crown geometry evolves over time in urban environments. The dynamic nature of trees—particularly the effects of time and growth—remains largely overlooked.

The tree location optimization tool developed in this study addresses the limitations and gaps in current tree location optimization tools. The primary focus of this study is the development, improvement, and evaluation of an innovative planting optimization tool to achieve the Target Leaf Voxel (TLV) conceptual framework, assuming that ecosystem services and microclimate factors are already embedded in the generated TLV. In light of this primary objective, the limitations identified in previous studies lead to the following research questions:

1. Is it possible to optimise tree locations using a 3D target-driven approach, such as TLV [34] (Q1)?
2. How can the complex geometry of tree crowns and their dependence on the local environment be considered in a tree planting optimisation tool (Q2)?
3. How can the aspects of time and tree growth models be incorporated into a tree planting optimisation tool (Q3)?

Methods

This study introduces a target-driven tree location optimisation tool focused on tree crown geometry growth over time. It builds on the conceptual framework proposed by Yazdi et al. [34] and Yazdi et al. [35], which outlined a comprehensive 3D voxel target model. The tool utilises the TreeML model [3], a machine learning-based prediction model for urban tree crown growth in competitive urban environments, to predict crown shapes. Additionally, it employs the hill-climbing algorithm [33], whose efficiency in tree location optimisation was demonstrated by Wallenberg et al. [32]. The proposed tool for tree planting location optimisation is called TreeML-Planter, which is developed as an open-source tool on the Rhino and Grasshopper platform (www.rhino3d.com). Its primary goal is to maximize the achievement of TLV.

TreeML-Planter involves several steps and functions, as illustrated in Figure 1, which outlines the methodological framework of the optimisation tool. This framework is divided into three sections: input variables (green), optimisation functions (red), and output values (blue). Each function and variable are explained in detail in the following subsections. To test the tool's applicability and visualise results with different input variables, we applied TreeML-Planter to a sample case study. This case study involves an open space in Munich, featuring a randomly selected planting area and 3D target voxels, detailed in the next subsection. Although TLV is defined as a fixed target voxel in this case study, Shu [36] treats target leaf voxels as flexible design inputs that define a desired spatial distribution of foliage rather than as fixed outcomes. While the implemented experiments use static target voxel configurations within individual simulations, the framework conceptually allows these targets to be adjusted for each planning scenario, enabling time-dependent adaptation of canopy design objectives.

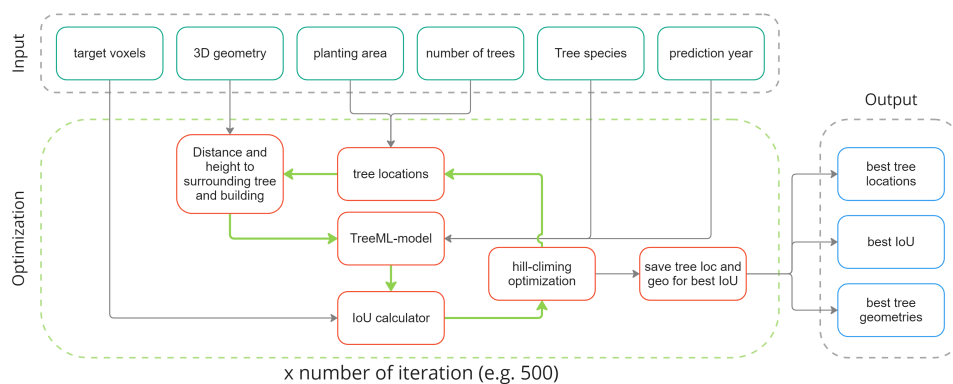


Fig. 1 The methodological framework of the optimisation mode. It is divided into three sections: input variables (green), optimisation functions (red), and output values (blue). The green arrows show the loop functions inside the optimisation algorithm.

Case study

To investigate the functionality of the TreeML-Planter model, we chose a square in Alfons-Goppel-Straße, 80539 Munich, closely surrounded by buildings for the case study (Figure 2, a,b). The square is bordered by a road on its east side and by historical buildings of about 4 stories in height on the other three sides. Very few infrastructures are placed on the square, including mainly a fountain in the middle of the southern part of the square, which allows a large area to be considered for planting trees.

The contextual information of the site was obtained from the online dataset OPENDATA Bayern (www.geodaten.bayern.de/opengeodata/), offered by the Bavarian State Office for Survey and Geoinformation. The 3D building model in LoD2 is based on the building floor plans from ALKIS® and

the roofs from airborne laser scanning data, ALKIS®-3D building surveys (www.ldbv.bayern.de/produkte/kataster/alkis.html), and the aerial photograph-based digital surface model. The point clouds with the label “object point” were initially filtered out by CloudCompare (www.danielgm.net/cc/) to eliminate the building and ground points. Figure 2 shows the plan and perspective view of the case study in addition to a sample planting area and target voxels (see section [Input data](#)) inside the square.

This case study is selected to test the applicability and feasibility of the TreeML-Planter. We applied the tool to a sample planting area and target voxels (see Figure 2). Based on the available computational power, the number of iterations was set to 100, with each optimization round taking approximately 24 hours. We selected two common tree species, *Tilia cordata*, and *Platanus × hispanica*, for testing the tool. For each species, the TreeML-Planter was run using three different tree number settings ($n = 5, 7, 9$) and three target ages (age = 20, 40, 60), resulting in nine simulation runs per species and a total of 18 model runs. The following subsections provide a step-by-step explanation of the TreeML-Planter tool and its components. Section [Results](#) presents the results obtained from testing the TreeML-Planter tool on the selected case study.

Input data

The TreeML-Planter tool needs nine inputs to optimize the tree planting location. These inputs are iteration numbers, the number of trees, tree species, planting age, prediction year, 3D geometry of surrounding objects, planting area, target 3D voxels, and saved models of TreeML. These inputs and their data format are explained below.

Iteration Number: The iteration number specifies how many times the optimisation model will run from scratch with new random tree locations. During each iteration, the model begins with random potential planting locations for the trees. It then employs the hill-climbing algorithm (section [Hill-climbing algorithm](#)) to determine the optimal locations.

Number of Trees and Tree Species: Two other key input variables are the number of trees and the tree species. There is no restriction on the number of trees apart from computational power and planting area constraints. The tree species must be compatible with the TreeML model, which has been validated for 12 common central European species [3]. However, the initial version of TreeML-Planter utilises only five main species due to the limited availability of age-to-DBH equations (section [Age-to-DBH conversion](#)). These species are *Tilia cordata*, *Acer platanoides*, *Platanus x hispanica*, *Robinia pseudoacacia*, and *Aesculus hippocastanum*.

Planting Age and Prediction Year: The next input variables are planting age and prediction year. Although the TreeML model predicts crown geometry based on DBH, we used age-to-DBH equations (section [Age-to-DBH conversion](#)) to integrate prediction time into the optimisation model. Planting age refers to the age of the trees at the time of planting, and prediction year indicates the number of years after planting. Thus, the final age of the tree is calculated as: final tree age = planting age + prediction year.

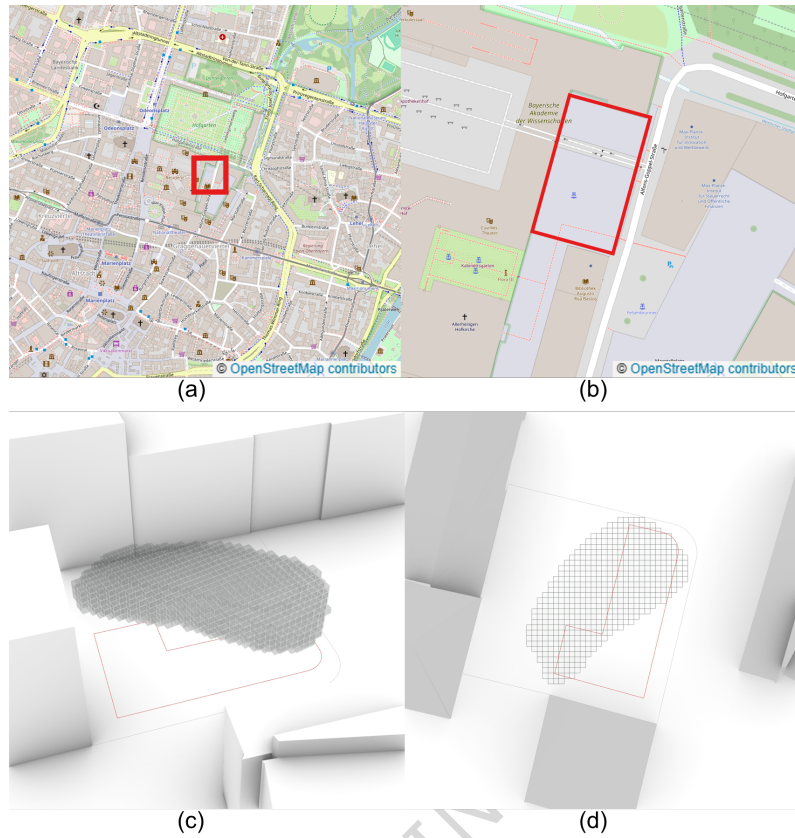


Fig. 2 A case study of a square in the old town of Munich. Figures a and b visualize the location of the case study on the Map (©OpenStreetMap contributors). Figures c and d show the perspective and plan view of the planting area (red lines, see subsection [Input data](#)) and the target 3D voxels (gray color 3D voxels, see subsection [Input data](#)) in Rhino 8 (Rhinoceros 3D, Robert McNeel & Associates).

3D Geometry: The 3D geometry input encompasses the geometry of surrounding objects near the planting area (Figure 2, c,d). This is divided into two inputs: surrounding buildings and surrounding trees. These inputs are crucial for the TreeML model (section [TreeML model](#)) to accurately predict crown geometry shapes considering the surrounding objects.

Planting Area: This input data format is a closed union bounding box (Figure 2, c,d). The planting area is a set of grid points on the ground surface where tree trunks can be placed. It is defined by two inputs: the coordinates of the grid's starting point and a table of Boolean values indicating whether the current grid point is inside the planting area boundary line or not. The grid size is fixed at 1 meter in this study as a sample. However, it is adjustable in the open-source code. The grid is entirely contained within the union bounding box of all boundaries. The Boolean values are defined by testing if each grid point is inside or outside the boundaries.

Target 3D Voxels: This input data is a set of 3D voxels above the ground that shows the target tree canopy location and shape. Similar to the definition of the planting area, the target voxels are also defined by a system of units and a set of Boolean values to represent whether the unit is selected. The voxel system is described by two parameters: the bottom-left corner of the initial voxel and the count of the voxels in the X, Y, and Z dimensions. In order to reduce the computational load, the voxel size is fixed to 1 meter in this study. However, it is adjustable in the open-source code.

Trained Models: TreeML is a machine learning-based prediction model trained on a specific dataset [37]. Consequently, TreeML-Planter requires the trained model as an input to predict crown shapes during the optimisation process. The input files are in "joblib" format, and the Joblib library (joblib.readthedocs.io) is used to save and import these trained models into TreeML-Planter.

Hill-climbing algorithm

The hill-climbing algorithm [33] is a heuristic search method used for mathematical optimisation problems, where the goal is to find the peak (maximum) or valley (minimum) of a function by iteratively making small adjustments to the input values. It begins with an initial solution and evaluates neighbouring solutions by making incremental changes. If a neighbouring solution offers a better value for the objective function, the algorithm moves to this new solution and repeats the process. The algorithm stops when no better-neighbouring solutions are found, which can result in convergence to the local optima rather than the global optimum. Hill-climbing is a simple and computationally efficient approach, making it suitable for many optimisation problems; however, it is prone to becoming trapped in local optima or flat regions of the search space, which can prevent it from identifying the global optimum [38].

TreeML-Planter uses a hill-climbing algorithm to optimise tree locations. In each iteration, the optimisation model assigns random locations to the trees within the planting area. These initial random locations must be unique for each tree, and no tree can be placed in the neighbouring locations of another tree. The neighbouring locations are defined as the eight neighbouring positions surrounding a specific location within the gridded planting area. Once the initial random locations are set, the algorithm iteratively adjusts the position of each tree to one of its neighbouring locations, checking if the new position improves the target score. The target score is quantified by an Intersection over Union (IoU) score (see Section [IoU calculator](#)), which the optimisation model aims to maximise. The objective of the target score is to maximise the 3D coverage of the target voxels by the tree crowns and minimize the presence of the tree crowns in the areas outside the target voxels.

During each iteration, the algorithm relocates a tree to a neighbouring location and calculates the IoU score for this new configuration. If the IoU score improves, the new location is retained; otherwise, the algorithm reverts to the previous location. Figure 3 illustrates the pseudocode of the optimisation algorithm used in TreeML-Planter to find the best planting locations. This pseudocode provides a concise, abstract overview of the TreeML-Planter algorithm, combining programming concepts with natural language for clarity.

```

1  inputs = [num_iterations, num_trees, botanical_name, planting_age, prediction_year,
2            target_voxels, planting_area, surr_Buildings, surr_Trees, savedModel_filepath] (Section 2.2)
3  iteration_IoU = 0
4  for i in num_iterations:
5
6      tree_locations = initial random locations
7      distances = measure distance and height of surrounding buildings and trees (Section 2.4)
8      dbh = age_to_DBH conversion (Section 2.5)
9      tree_crown_geometry = use TreeML-model for generating the initial tree crown variables (Section 2.6)
10     tree_to_mesh = generating tree crown meshes from the TreeML output
11     initial_IoU = using IoU calculator for defining the initial IoU of the start positions (Section 2.7)
12
13     improvement = True
14     while improvement = True:
15         improvement = False
16         best_IoU = initial_IoU
17
18         for each tree:
19             best_location = tree_location for the current tree
20             neighbours = get neighbouring locations for the current tree location within planting_area
21
22             for neighbour in neighbours:
23                 If the neighbour is not in current tree_locations or in neighbours of other tree_locations:
24                     new_location = neighbour
25                     distances = measure distance and height with updated location (Section 2.4)
26                     tree_crown_geometry = use TreeML-model with updated input data (Section 2.6)
27                     tree_to_mesh = Update tree meshes with new tree locations and TreeML results
28                     new_IoU = using IoU calculator to calculate new IoU for updated tree locations (Section 2.7)
29
30                     if new_IoU > best_IoU:
31                         best_IoU = new_IoU
32                         best_location = new_location
33                         improvement = True
34             update tree_location to best_location
35         if best_IoU > iteration_IoU:
36             iteration_IoU = best_IoU
37             final_locations = tree_locations
38             tree_meshes = final tree_to_mesh values
39
40     return iteration_IoU, final_locations, and tree_meshes

```

Fig. 3 Pseudocode of the tree location optimisation algorithm in the TreeML-Planter.

Surrounding objects' distance and height measurement

The calculation of the distance to surrounding objects and their heights is a step of translating the input of 3D geometries into numerical values that can describe the relationships between the tree location and the competitive surrounding environment. The result will be fed into the TreeML model to predict the growth of the tree crown in eight different directions, starting from the east and going counterclockwise with an interval of 45 degrees to the southern east. Accordingly, the data translation follows the structure of eight directions and differentiates the impacts of buildings and trees. Four variables are calculated for each direction: the distance from the tree location to

Table 1 List of equations between the age and dbh of 5 main species based on the previous studies. dbh = diameter at breast height (cm); h = tree height (m).

Species	Equation	Variables	References
<i>T. cordata</i>	$\text{age [yrs]} = -a + e^{(b+c \times \text{dbh}/100+d \times h)}$	$a=264.073, b=5.5834, c=0.3397, d=0.0026$	[39]
	$\ln(h) = a + b \times \ln(\text{dbh})$	$a=0.89751, b=0.51497$	[3]
<i>R. pseudoacacia</i>	$\text{age [yrs]} = 0.996 \times \text{dbh}$	–	[40]
<i>P. × hispanica</i>	$\text{age [yrs]} = 1.01 \times \text{dbh}$	–	[41]
<i>A. hippocastanum</i>	$\text{age [yrs]} = -a + e^{(b+c \times \text{dbh}/100+d \times h)}$	$a=54.2714, b=4.0709, c=0.7988, d=0.0209$	[39]
	$\ln(h) = a + b \times \ln(\text{dbh})$	$a=0.8242, b=0.47354$	[3]
<i>A. platanoides</i>	$\text{age [yrs]} = 5.4256 + 1.5741 \times \text{dbh}$	–	[42]

the nearest building and to the nearest surrounding tree, as well as the height of the nearest building and of the nearest tree.

The distance to and the height of a surrounding object are both determined based on the vertical plane that originates from the tree location and extends in one of the eight directions. The intersection tests are conducted between each plane and the two sets of geometry input. As illustrated in Figure 4a, the test results are the intersecting polylines with surrounding buildings (red) and with trees (green). To obtain the horizontal distance to the object and its height above the tree location, the bounding box of each polyline is generated on each plane (see Figure 4b). By going through all the polylines and comparing the smallest X coordinate of the bounding boxes, the distance from the tree location to the nearest building or tree, along with its height in this particular direction, can be calculated. The smallest distance and the largest height are initialised at 100 meters and 0 meters, respectively. Therefore, when no tree or building is found in a certain direction, as the situation illustrated on the right side of Figure 4b, the output remains the default.

Age-to-DBH conversion

The TreeML model, as described in Section TreeML model, is based on the diameter at breast height (DBH) of trees. In the TreeML-planter, we developed an Age-to-DBH conversion function that transforms the input age of a tree into its corresponding DBH, enabling the use of the TreeML model for predicting canopy geometry. Table 1 presents equations from previous studies that describe the relationship between DBH and tree age for five target species. For certain species, such as *Tilia cordata* and *Aesculus hippocastanum*, the relationship between DBH and age requires tree height (h , in meters) as an additional input. Therefore, for these species, we utilised a second set of equations from other studies to estimate both DBH and tree height.

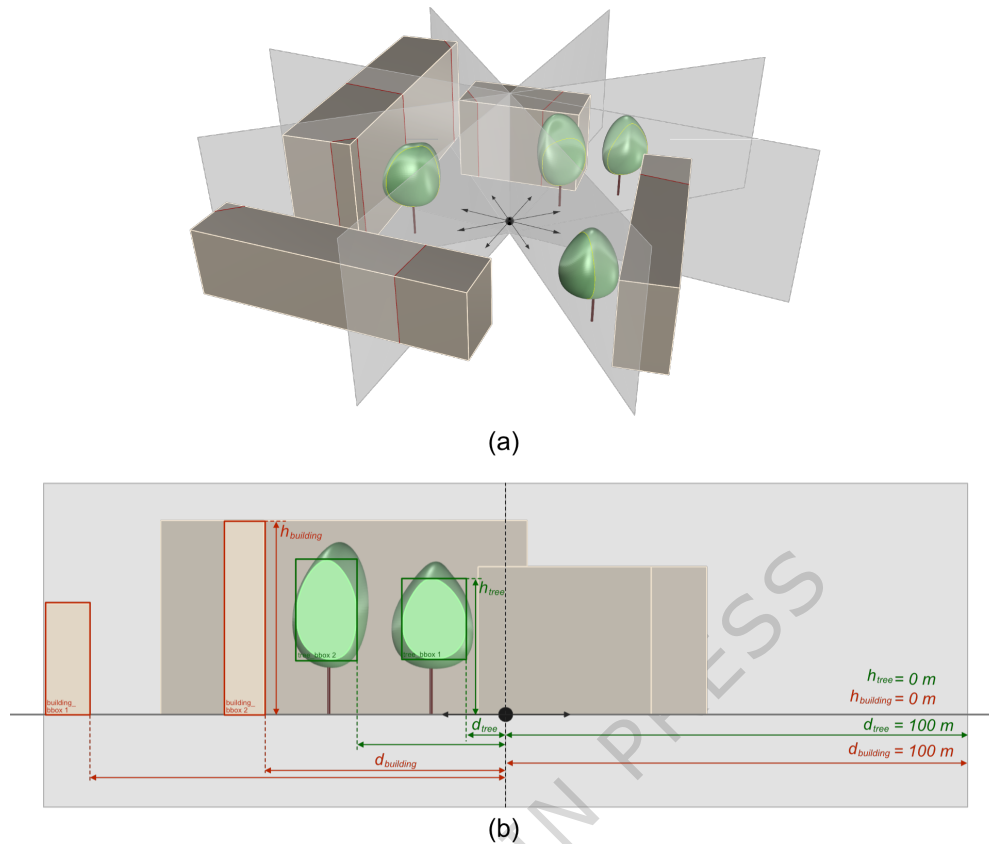


Fig. 4 The calculation of the distance to the closest building and tree and their heights in eight directions. The intersection tests are conducted between the surrounding objects and the eight vertical planes (a). The distance to the nearest building or tree and its height are calculated by generating the bounding boxes of the intersecting polylines and comparing their smallest X coordinates (b-left). The output remains the default value when no objects are intersected by the plane in a certain direction (b-right).

TreeML model

To predict the crown geometry of trees over several years, we employed the TreeML model [3]. This advanced machine learning framework is specifically designed to model and predict various attributes of tree crown geometry in urban environments, where interactions with surrounding buildings and objects are critical. TreeML utilises a machine learning model to predict key tree crown parameters, including total tree height, crown start height, and crown radius in eight geographical directions. By integrating these multiple predictions, the model can provide a detailed and 3-dimensional forecast of the tree's crown growth. This enables TreeML not only to predict the size and shape of a tree's crown but also to offer a rough visualization of how the tree's canopy will interact with nearby objects, such as buildings or other vegetation. The

model is trained using the TreeML-Data dataset [37], which comprises an extensive collection of tree structure data, including high-resolution point clouds captured from urban environments. This dataset is crucial for the model's accuracy, as it allows for the inclusion of real-world variability in tree growth patterns and the unique challenges posed by urban spaces.

In addition to intrinsic tree attributes such as diameter at breast height (DBH), TreeML incorporates spatial information on the surrounding environment, including the distance, height, and distribution of neighboring trees and nearby buildings. These features allow the model to account for competition for space and light, which is a major driver of asymmetric crown development in urban settings. As a result, TreeML can produce directional crown predictions that better reflect observed urban tree growth than models based only on tree-internal variables.

TreeML employs a Hist Gradient Boosting Regressor due to its strong performance in modeling non-linear relationships and its computational efficiency. Model transparency is supported through SHapley Additive exPlanations (SHAP), which quantify the influence of individual input features on crown predictions. In this study, TreeML is used as a data-driven growth prediction tool to simulate crown geometry over multiple years under constant environmental conditions, providing an empirically grounded approach for forecasting individual-tree crown development without explicitly modeling physiological growth processes.

IoU calculator

Intersection over Union (IoU), also known as the Jaccard Index, is a widely used metric in computer vision for assessing the similarity between two sets or areas, particularly in object detection and image segmentation tasks. It quantifies how well the predicted region, such as a bounding box or segmentation mask, aligns with the ground truth. IoU is calculated by dividing the area of overlap (the intersection of the predicted and actual regions) by the area covered by both regions combined (the union). A higher IoU value indicates a greater overlap and, thus, better model accuracy [43]. For datasets A and B, IoU is generally defined as:

$$IoU = \frac{|A \cap B|}{|A \cup B|} = \frac{|A \cap B|}{|A| + |B| - |A \cap B|} \quad (1)$$

As the last step of each iteration, the IoU calculator is used to evaluate how much the predicted tree crowns at the current locations fulfil the pre-established target. However, the two datasets are not directly comparable due to their different form of data: the prediction results from the TreeML-model are numerical values describing the dimensions of crown geometries along certain axes, while a voxel system and a set of voxel states define the target tree crowns. To bridge the gap with high computation efficiency, the IoU is calculated on a voxel basis:

$$IoU_{\text{voxel}} = \frac{\text{Intersection voxels}}{\text{Union voxels}} = \frac{\text{Fulfilled target voxels}}{\text{Target voxels} + \text{Predicted voxels outside target range}} \quad (2)$$

Table 2 The IoU scores for various runs of *Tilia cordata* and *Platanus × hispanica* were analyzed using the TreeML-Planter, which optimized tree planting locations in the case study. The model was run with three different tree number settings (n = 5, 7, 9) and three target ages (age = 20, 40, 60). The highest IoU score for each configuration is highlighted in bold.

		<i>Tilia cordata</i>			<i>Platanus × hispanica</i>		
		Age of the trees after the prediction years					
		20	40	60	20	40	60
Number of the planting trees	Five	0.04	0.37	0.45	0.26	0.42	0.32
	Seven	0.06	0.48	0.45	0.35	0.37	0.32
	Nine	0.07	0.56	0.46	0.44	0.37	0.29

The predicted parameters of each tree are first utilized to generate a closed Brep geometry based on the formula of NURBS modelling in Rhino. The Breps are subsequently voxelised using the identical voxel system of the target voxels by ascertaining whether the centre of each voxel unit lies within the boundaries of the Brep. By simultaneously checking if each “inside” voxel is also a target voxel, a total is computed for the number of intersection voxels and the “unexpected” voxels that are predicted to be reached by the trees but not targeted in the first place. Following the voxelisation process, the IoU score can be calculated by dividing the number of intersection voxels by that of the union voxels, whereby the union voxels comprise both the target voxels and the “unexpected” voxels. The IoU of the current iteration is compared with the best score saved after the previous iterations and serves as the indicator for determining whether the location should be shifted and the best IoU should be updated.

Results

Feasibility Analysis of the Optimization Model

To evaluate the applicability and feasibility of the TreeML-Planter, we applied the tool to a case study in Munich with different settings (see Section Case study). Table 2 presents the IoU scores for these settings. For *Tilia cordata*, the highest IoU score (0.56) was achieved with 9 trees and a target age of 40 (n = 9, age = 40), while the lowest score (0.04) was observed with 5 trees and a target age of 20 (n = 5, age = 20). For *Platanus × hispanica*, the best IoU score (0.44) was recorded with 9 trees and a target age of 20 (n = 9, age = 20). The lowest score (0.26) occurred with 5 trees and a target age of 20 (n = 5, age = 20). Notably, the setting of 5 trees and a target age of 40 (n = 5, age = 40) for *Platanus × hispanica* produced a close IoU score (0.42), just 0.02 below the highest value. Overall, the IoU scores for most settings with *Tilia cordata* were higher than those for *Platanus × hispanica*, except in the settings with a 20-year age prediction, where *Platanus × hispanica* achieved higher scores.

In addition to the IoU score, which is the primary output of the optimization model, the TreeML-Planter also provides the optimized tree locations and predicted crown shapes for these locations. Figures 5 and 6 illustrate these outputs (IoU score, optimized locations, and predicted crown shape) for the nine different settings (n = 5,

7, 9 / age = 20, 40, 60) in both plan and perspective views within the Rhino platform. These figures demonstrate how the crown geometries adapt to the target voxels to achieve the highest IoU scores, such as in the setting ($n = 9$, age = 40) for *Tilia cordata* and ($n = 9$, age = 20) for *Platanus × hispanica*.

Discussion

Unlike tree planning tools that consider broader aspects like species selection, planting area design, or ecological factors, the TreeML-Planter is dedicated to spatial optimization aimed at achieving specific objectives. The TreeML-Planter is a unique tree-planting location optimization tool that differs from conventional tree-planting tools by focusing solely on optimizing tree locations based on specific 2D targets. The primary innovation of this tool is the ability to account for the complex geometry of tree crowns within dynamic 3D environments and provide a more accurate and realistic method for optimizing tree placement, particularly in dense urban areas. By incorporating the spatial dynamics of tree crowns and their interactions with nearby built structures, the model enhances tree placement decisions to maximize a 3D target leaf voxel (TLV) achievement [34].

In this study, we limited the optimization tool's running on the case study because of the limited computational power. However, even based on these settings, there should be an optimized point for these two settings, which are tree number and target age. First, the comparison between Figures 5 and 6 shows that the *Platanus × hispanica* trees can achieve their maximum IOU scores (0.44) in a shorter period ($n = 9$, age = 20) compared to the *Tilia cordata* trees, which took 40 years ($n = 9$, age = 40) to achieve 0.56 IOU score. Second, For the *Tilia cordata* simulation, the IOU score increases as much as the number of trees increases. However, in *Platanus × hispanica* simulations, the optimization model usually shows a higher IOU score in the lower tree number. This contrast is highlighted especially in the settings of 5 trees in 40 years ($n = 5$, age = 40) for *Platanus × hispanica*, where the IOU score is 0.42, just 0.02 less than the highest IOU score. It shows that the optimum settings for the number of trees and the target age is not always the maximum number of these settings. The results of this experiment on the case study demonstrate the tool's functionality in supporting users during the planning and decision-making phase. It enables manual balancing of various factors, such as tree species, the number of trees to plant, planting age, and the target age of the trees. Then, based on these factors, the TreeML-Planter tool optimizes the best planting location for achieving the 3D Target Leaf Voxel (TLV).

Existing tree location optimization tools, such as tools developed by Wallenberg et al. [32] and Ghods et al. [30], typically focus on optimizing tree locations for narrow, specific objectives. Our tool, in contrast, employs a 3D Target Leaf Voxel (TLV) method, which was developed by Yazdi et al. [34] and can simultaneously consider multiple objectives. This TLV approach allows for a more nuanced and effective urban forest planning strategy that balances various environmental, social, and economic factors [34]. Additionally, a significant limitation of current existing tools is their failure to account for the complexity of 3D tree crown shapes and their evolution over time in urban environments. Our model explicitly incorporates these crucial aspects of 3D

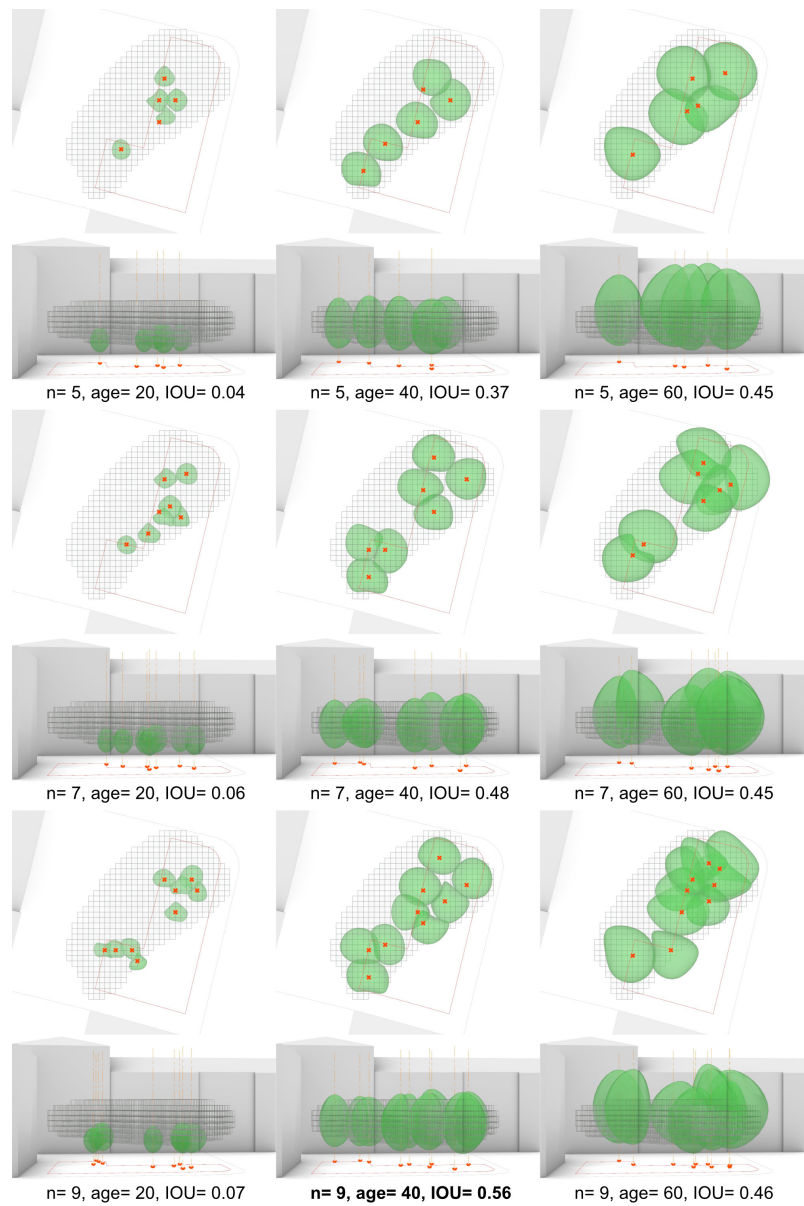


Fig. 5 In our case study, the optimized planting locations for *Tilia cordata* were identified using the TreeML-Planter across three different tree number settings ($n = 5, 7, 9$) and three target ages (age = 20, 40, 60). Among these configurations, the setting with 9 trees and a target age of 40 ($n = 9$, age = 40) yielded the highest Intersection Over Union (IOU).

crown geometry, which is essential for accurately predicting. By simulating tree growth over time, we can optimize placement not just for immediate benefits but for long-term urban forest performance. This temporal consideration is crucial for sustainable

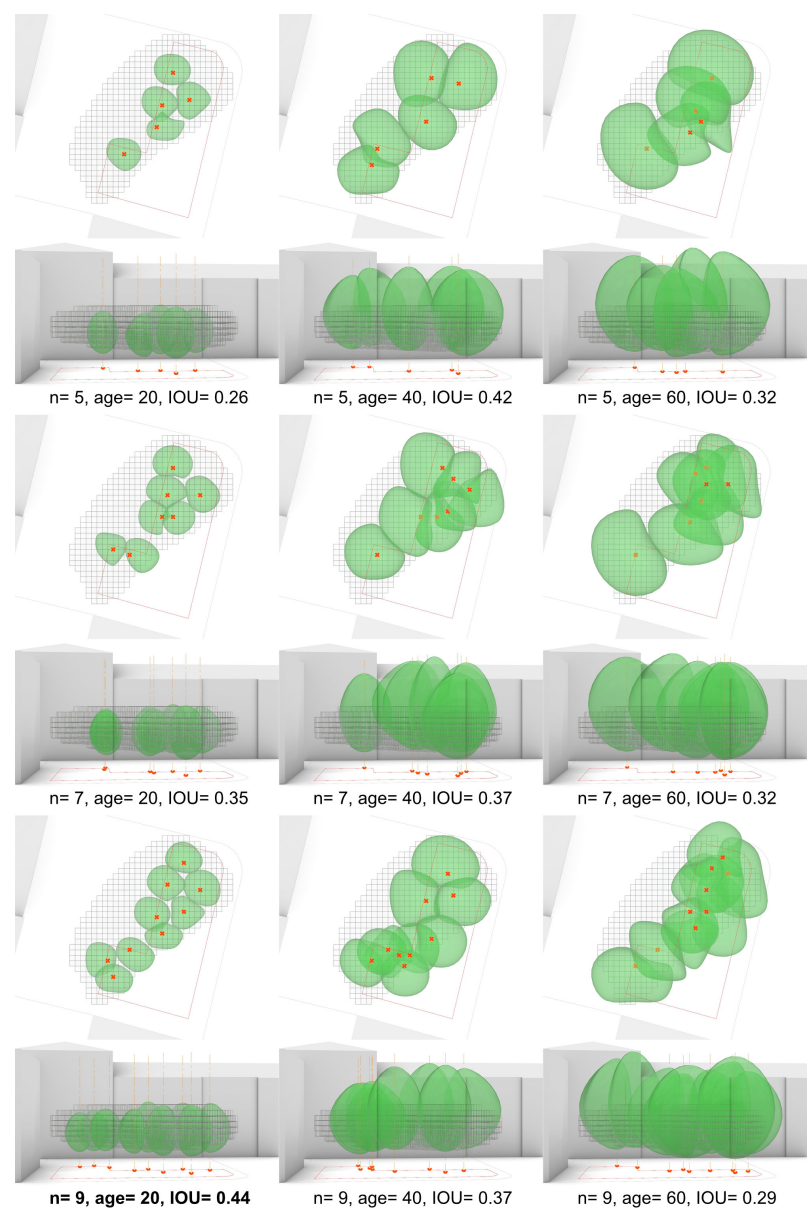


Fig. 6 In our case study, the optimized planting locations for *Platanus x hispanica* were identified using the TreeML-Planter across three different tree number settings ($n = 5, 7, 9$) and three target ages (age = 20, 40, 60). Among these configurations, the setting with 9 trees and a target age of 20 ($n = 9$, age = 20) yielded the highest Intersection Over Union (IOU).

urban planning and ensures that the benefits of urban trees are maximized throughout their lifecycle.

This study demonstrated that utilizing a crown geometry prediction model, such as the TreeML model [3], allows for the optimization of tree planting locations using a 3D Target Leaf Voxel (TLV) approach (Q1). Moreover, the underlying TreeML model [3] accounts for the complex geometries of tree crowns based on their species in competitive urban environments (Q2) and considers tree growth over time (Q3). However, several limitations persist:

- One major challenge was the high computational demand due to the model's complexity, as running the models can be time-consuming and require significant computational power.
- This model is limited in simulating the dynamics of the nature of urban environments, including rapid changes in cities like new constructions and changes in green spaces, such as the removal or plantation of trees.
- The underlying TreeML [3] model focuses solely on above-ground environmental factors, yet tree growth is also influenced by below-ground conditions, which are complicated by a dense collection of various underground infrastructure, including building foundations, roadbeds and clusters of pipes and cables. Although tree root system development is subject to genetic control, i.e., tap root system for many urban tree species, it is more largely affected by the presence of these underground constructions both through the physical restriction of the available soil volume and through soil compaction due to engineering standards [44]. These constraints often lead to an uneven distribution of root biomass, consequently contributing to the asymmetry of crown growth (Wang et al., 2025) [45]. These factors, currently not integrated into the model's calculations, can significantly impact the aboveground tree crown development and overall tree health.
- The model relies on generalized age-to-DBH equations, which may not accurately capture tree growth variations based on location, soil conditions, and environmental stressors. Individual trees in urban environments often experience highly variable growing conditions, leading to growth rates that can deviate significantly from these generalized predictions.
- The current validation of the underlying TreeML model [3] is specific to Munich, Germany. As such, the model's applicability and accuracy in other urban contexts with different climatic, environmental, and urban design characteristics remain to be established. Further validation studies in diverse urban settings are necessary to confirm the model's broader applicability.
- The main focus of this study is to examine how planting location affects the likelihood of achieving the final target voxel configuration. However, the final outcome can be further improved through pruning interventions applied during the growth process and after the target configuration has been reached. In particular, pruning can be used when tree growth extends into forbidden voxels, thereby reducing conflicts with restricted spaces and increasing the IoU.

Despite these limitations, the comprehensive nature of our 3D model, its ability to account for tree growth over time, and its multi-target optimization capabilities represent a significant advancement in urban forest tree location optimization tools. Several promising advancements for future work can enhance the accuracy, efficiency

and applicability of this tool in urban environments. Future studies can focus on integrating machine learning-based 3D optimization tools to speed up calculations. Expanding the model to include a wider variety of tree species, age variations, and locations would improve its adaptability. This expansion would require extensive data collection and validation studies in various urban environments, potentially leading to a more robust and universally applicable tool for urban forest planning. Additionally, future research can also explore the development of 3D target voxel generation models that are based on specific urban goals, such as maximizing shadow coverage or minimizing surface temperatures to offer more target solutions for urban planners and policymakers.

A promising application of our tool lies in coupling our voxel-based approach with advanced microclimatic numerical simulation models. This integration would enable the development of sophisticated radiative transfer models that accurately capture the complex interactions between urban vegetation and the local environment. Our voxel-based optimization of urban vegetation allows for detailed, spatially explicit modelling of vegetation structure and its effects on radiative transfer, airflow, and thermal dynamics within the urban canopy. By incorporating the dynamic growth patterns of the urban canopy over time, this coupled model could quantify how changes in urban forest composition and structure affect the local microclimate. Such a model could account for seasonal variations, climate change projections, and various urban development scenarios, providing a powerful, data-driven tool for urban planners and decision-makers.

Conclusions

Our research demonstrates that optimizing tree locations using a 3D target-driven approach, such as the Target Leaf Voxel (TLV) method, is feasible and effective. By incorporating the complexity of tree crown geometry and its interaction with the local environment, the tool can account for species-specific growth patterns and spatial constraints. Additionally, integrating time and dynamic tree growth models enhances the ability to predict long-term changes in tree structure and optimize planting strategies accordingly.

One of the key contributions of this model is its ability to integrate spatial and temporal considerations into the tree placement process. This stands in contrast to existing tools that often focus on immediate outcomes without factoring in the long-term evolution of tree growth or the impact of urban structures. The model's dynamic approach enables urban planners to optimize not just for the present but also for future urban environments, making it a valuable tool for sustainable urban planning.

Moreover, the inclusion of target-based optimization goals, such as improving canopy coverage or reducing urban heat islands, offers urban planners and policymakers' new ways to prioritize urban vegetation based on specific ecological or social objectives. The voxel-based approach combined with potential future integration into advanced microclimatic models could revolutionize how urban forests are designed, ensuring that tree placement contributes effectively to local climate control, air quality improvement, and overall urban well-being.

While the model has demonstrated strong potential, limitations related to computational power, the exclusion of below-ground factors, and generalizations in age-to-DBH relationships highlight areas for future refinement. Expanding the model's applicability to other urban environments, integrating additional tree species, and addressing below-ground dynamics would significantly enhance the tool's robustness and accuracy. Future development could also explore the integration of machine learning techniques to further optimize computational efficiency and improve predictive capabilities.

Code Availability

The source code and necessary input material for the optimization model are provided as a Grasshopper file (.gh), a Python file (.py), and a Rhino 3D model (.3dm) included in the TreeML-Planter GitHub repository (<https://github.com/hadi-yazdi/TreeML-planter>).

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CRedit authorship contribution statement

Hadi Yazdi: Conceptualization, Formal analysis, Investigation, Methodology, Software, Validation, Visualization, Data curation, Writing – original draft, Writing – review & editing. **Xi Chen:** Formal analysis, Methodology, Software, Visualization, Data curation, Writing – original draft. **Thomas Rötzer:** Supervision, Writing – review & editing. **Leila Parhizgar:** Writing – original draft, Writing – review & editing. **Nayanesh Pattnaik:** Writing – original draft, Writing – review & editing. **Ferdinand Ludwig:** Conceptualization, Methodology, Supervision, Writing – review & editing.

Data Availability

TreeML-Data is used for developing the TreeML model. For accessing the dataset, codes and descriptor article, please use the links below:

TreeML-Dara Github repository: <https://github.com/hadi-yazdi/TreeML-Data>

TreeML-Data paper: <https://doi.org/10.1038/s41597-023-02873-x>

TreeML-Data dataset repository: <https://doi.org/10.6084/m9.figshare.c.6788358>

The TreeML model was developed based on TreeML-Data, and its code is available in this GitHub repository:

<https://github.com/hadi-yazdi/TreeML>

And for the codes, 3D model, and input material related to TreeML-Planter, please check the TreeML-Planter GitHub repository:

<https://github.com/hadi-yazdi/TreeML-planter>

Declaration of competing interests

The authors declare no competing interests.

Declaration of generative AI in scientific writing

While preparing this work, the authors used ChatGPT 4 to improve the language and quality of the text. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the publication's content.

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