GroTree – A Novel Toolbox for Simulating and Managing Urban Tree Canopy Growth

Hadi Yazdi[1], Qiguan Shu[1], Xi Chen[1], Thomas Rötzer[2], Ferdinand Ludwig[1]

[1]School of Engineering and Design, Technical University of Munich/Germany · hadi.yazdi@tum.de
[2]School of Life Sciences, Technical University of Munich/Germany

Abstract: Urban trees provide cities with critical Ecosystem Services (ESS) through their large biomass and specific canopy geometry, making them a fundamental component of Urban Green Infrastructure (UGI). Following the concept of target-driven tree planting and maintenance, we outline here a comprehensive toolbox embedded in Rhino Grasshopper that integrates three models already developed and three models currently under development by the authors. The three existing models are 1) CityTree for estimating tree growth, ecosystem services, and plant physiology, 2) TreeML for predicting tree canopy geometry growth, and 3) PrunML for growth prediction under pruning. The three other tools currently under development will be integrated into the toolbox in the next version. These are 4.) TLV-Generator for generating Target Leaf Voxel (TLV), 5.) TreeML-Planter for optimizing the tree planting location, and 6.) PrunML-Manager for making tree canopy manipulation decisions. The final toolbox aims to assist designers, planners, gardeners, and other professionals in enhancing the ESS of trees in the next generation of UGI. We conclude by discussing the chances and potential limitations of the individual tools and the overall approach and frame open questions and potential next research steps.

Keywords: Urban tree, grasshopper plug-in, urban green infrastructure, ecosystem services, computational design

1 Introduction

Urban trees, a significant element within UGI, function as nature-based solutions to alleviate the severity of heat islands, enhance the overall city climate (OKE et al. 1997), and provide various health benefits (TZOULAS et al. 2007, WOLF et al. 2020). Individual tree canopies play a crucial role in providing these services, with their size and shape being particularly important. Therefore, appropriate design and management of urban trees can increase ESS for cities.

To increase ESS in UGI through urban trees, YAZDI, SHU & LUDWIG (2023) introduced a conceptual workflow for a target-driven tree planting and maintenance strategy. In this novel approach, the optimization of tree planting locations and branch pruning follows the TLV approach (YAZDI, SHU & LUDWIG 2023), following criteria to improve ESS outcomes.

Based on this approach, we outline here a comprehensive planned toolbox that integrates three models already developed and three models currently under development by the authors. The toolbox aims to facilitate the practical implementation of the target-driven tree planting and maintenance concept developed by YAZDI, SHU & LUDWIG (2023) and is intended to be a valuable resource to designers, urban planners, gardeners, and other experts involved in urban tree management. The GroTree V1.0 will include a set of Grasshopper plug-ins that display the results in real-time through the Rhino interface.

In recent years, a range of tools has been developed to assist designers and decision-makers in the early stages of urban tree planning, facilitating the evaluation of ESS offered by indi-

Journal of Digital Landscape Architecture, 9-2024, pp. 815-825. © Wichmann Verlag, VDE VERLAG GMBH · Berlin · Offenbach. ISBN 978-3-87907-752-6, ISSN 2367-4253, e-ISSN 2511-624X, doi:10.14627/537752076.

vidual trees within the Rhino Grasshopper environment. Table 1 provides a summary of current tools and workflows compared to the planned functions of our toolbox.

Table 1: A summary of existing tools and workflows and their functions in Rhino and Grasshopper, compared to the planned functions of the GroTree toolbox version 1.0. (Green: included and Orange: not included)

Tools in Rhino and Grasshopper (www.food4rhino.com)	**Functions**									
	Tree growth in size	Tree growth in LAI and CPA	Carbon fixation	Respiration and NNP	Water Balance (WB)	Shading	Cooling by evapotranspiration	Cooling by shading	Crown geometry growth	Resprouting in relation to pruning
LANDS DESIGN (by Albert Rodríguez)	Green	Orange	Orange	Orange	Orange	Orange	Orange	Orange	Orange	Orange
CO2 Absorption Calculator (by Alfonso Melero)	Orange	Orange	Green	Orange	Orange	Orange	Orange	Orange	Orange	Orange
Surface Temperature (by VerenaV)	Orange	Orange	Orange	Orange	Orange	Green	Orange	Green	Orange	Orange
Solar Radiation (by VerenaV)	Orange	Orange	Orange	Orange	Orange	Orange	Orange	Green	Orange	Orange
PANDO (by Ata Chokhachian)	Green	Orange	Green	Orange	Green	Orange	Green	Orange	Orange	Orange
GroTree V1.0 (Our Toolbox)	Green	Green	Green	Green	Green	Green	Green	Green	Green	Green

2 Tools

The GroTree toolbox outlined in this paper will consist of six tools (Fig. 1): (1) CityTree, a physiologically based growth and ESS simulation tool for individual urban trees; (2) TreeML, which predicts crown geometry growth of trees based on their surrounding environment; (3) PrunML, a tool for growth prediction under pruning, (4) TLV-Generator, a TLV generation tool by considering human comfort and ESS factors, (5) TreeML-Planter, a target-driven optimization tool for tree planting; (6) PrunML-Manager, which makes manipulation decisions towards a targeted canopy geometry on a Markov chain. The first version of the GroTree toolbox which contains the tools (1) to (3) will be released with this paper while the other three functional tools are under development and will be released by the later versions.

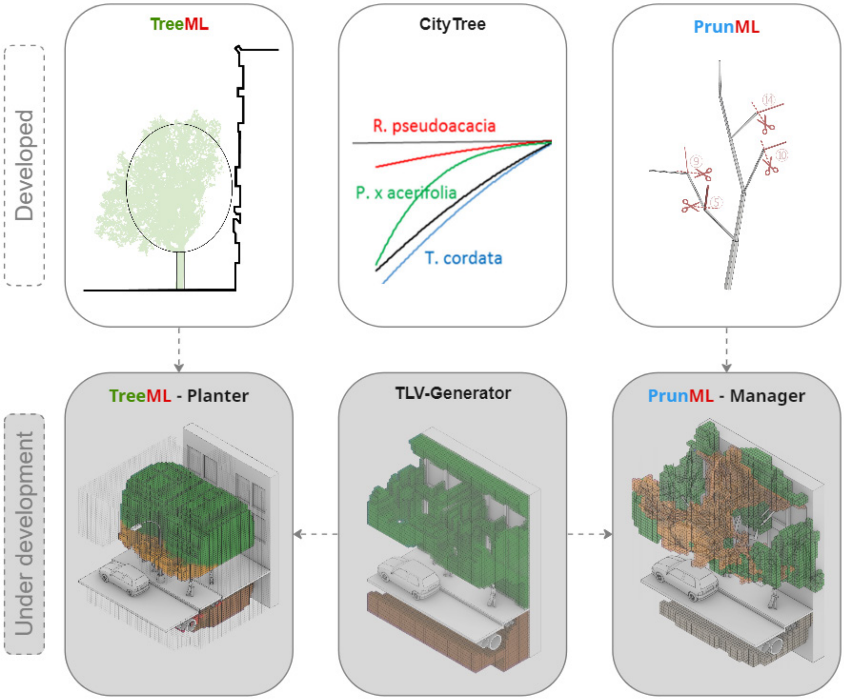

Fig. 1: A visualization of the tools and their connection in different sections of the toolbox. These tools are divided into two developed (CityTree, TreeML, and PrunML) and under-development (TLV-Generator, TreeML-Planter, and PrunML-Manager) sections. The outputs of the TLV-Generator will define the target voxels for the TreeML-Planter and PrunML-Manager.

2.1 CityTree

The CityTree model stands out as one of the rare models capable of simulating tree growth in urban settings while simultaneously projecting future tree growth and ecosystem services. It operates on a process-based approach, focusing on individual trees, where the primary calculations for tree growth are derived from physical, chemical and physiological equations. This unique feature allows calculating biomass increment based on various environmental factors. Consequently, the model's uniqueness lies in its ability to simulate tree growth driven by climate and water balance, accommodating minor and substantial environmental variations. Furthermore, the model distinguishes itself by its connection between tree growth and ecosystem services, including aspects like water consumption, carbon sequestration, and cooling through transpiration and shading. The simulation and analysis of tree growth and ecosystem services have been conducted for Central European cities, encompassing both current climate conditions and future climate scenarios, as reported by RÖTZER et al., (2019, 2021).

The model comprises eight distinct sub-modules, including climate, plant development, water balance (WB), photosynthesis, respiration, allocation, shading, and cooling (RÖTZER et al. 2019). These sub-models are accessible as separate, individual components within the

CityTree tool. Currently, they are designed to function with 12 prominent Central European tree species, namely *Tilia cordata, Robinia pseudoacacia, Platanus x hispanica, Aesculus hippocastanum, Acer platanoides, Acer pseudoplatanus, Fraxinus excelsior, Betula pendula, Fagus sylvatica, Populus nigra 'Italica', Quercus robur, Carpinus betulus* (Fig. 2). In addition, efforts are ongoing to expand the compatibility of the CityTree tool to more tree species.

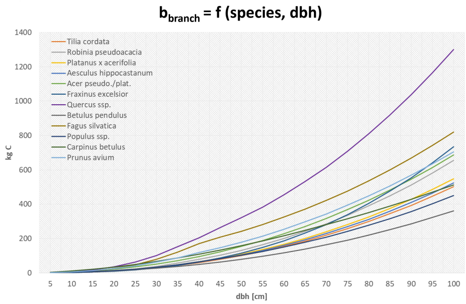

Fig. 2:
Simulated total biomass increments for 12 tree species by the CityTree branch biomass sub-model depending on DBH. CityTree is a process base simulation model for tree growth base on tree structure data and climate info and all details are explained by RÖTZER et al. (2019, 2021).

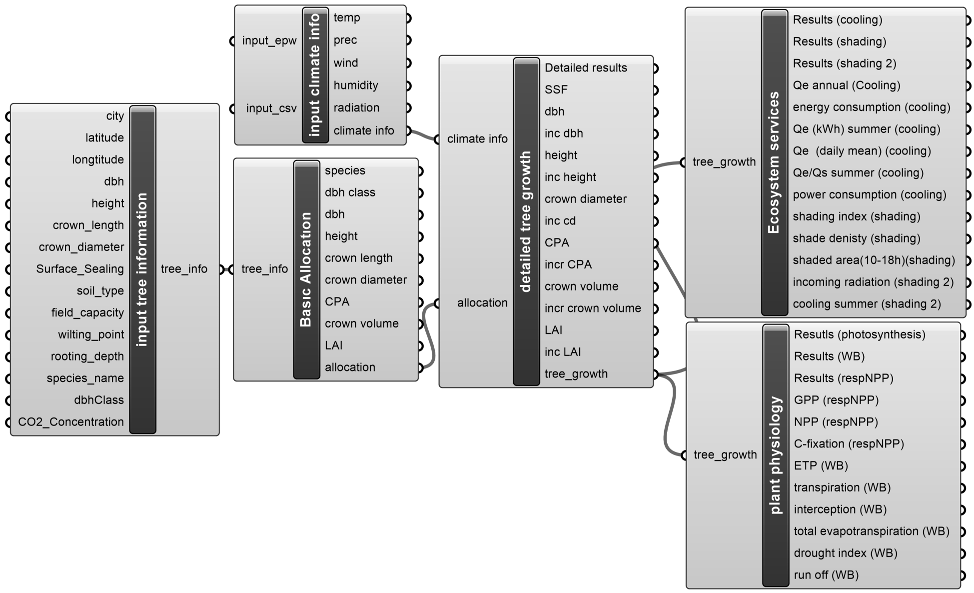

Fig. 3: A visualization of the CityTree Grasshopper batteries in the GroTree toolbox. It contains two input batteries for getting the tree and climate data and four separate batteries for calculating tree growth, plant physiology, and ecosystem services.

The grasshopper batteries and connections of the CityTree tool are visualized in Figure 3. This tool contains two input batteries: tree info and climate info. This info can be provided by the user or from internal saved data for 12 species. The tool contains four batteries for calculating tree growth (basic allocation and detailed tree growth), plant physiology, and ecosystem services.

2.2 TreeML

In the context of tree growth models like CityTree, it is well understood that local environmental conditions exert a significant influence. However, the precise quantitative impact of these factors on the evolution of a tree's canopy remains a subject of ongoing evaluation. Notably, aspects such as nearby buildings and trees can induce changes in canopy shape, but these variations are not yet accurately accounted for in these tree growth models. A planning approach that neglects to assess these impacts is bound to fall short of achieving the desired ESS objectives.

TreeML is a machine-learning prediction model for tree crown growth based on local environmental factors. This model is trained on an extensive dataset with Munich street trees (YAZDI et al. 2023) comprising information about urban trees and their immediate surroundings, including parameters such as proximity to buildings or other trees, as well as the height of adjacent buildings or trees. Its purpose is to anticipate how alterations in the tree crown's geometry may manifest when there are nearby structures or trees. The initial version of the TreeML model focuses on six commonly found tree species in central Europe, specifically *Tilia cordata, Acer platanoides, Platanus × hispanica, Robinia pseudoacacia, Populus nigra var. italica, Aesculus hippocastanum* (Fig. 4). The prediction model of tree height achieved the R2-score of 0.83, And the crown radius models in 8 different directions achieved between 0.67-0.71. Furthermore, the prediction model of the trees' max crown diameter, crown projection area, and total woody volume achieved R2-score respectively, 0.81, 0.78, and 0.7 (YAZDI et al. 2024).

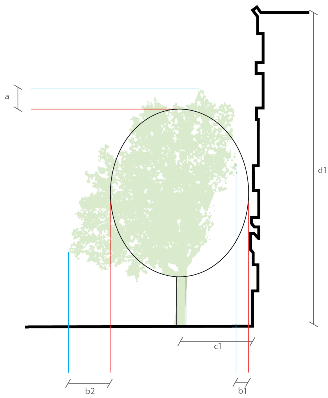

Fig. 4:
TreeML model is a machine learning prediction model for tree crown geometry growth. It predicts the accurate crown geometry based on species, DBH, and surrounding objects' geometry. Surrounding objects contain the neighbor buildings and trees. The details of the model and methodology are explained by HADI YAZDI et al. (2024).

The Grasshopper batteries related to the TreeML tool and their connections together are illustrated in the Figure 5. The two main input data for running the TreeML tool are the tree data and the surrounding object geometries. Based on these inputs, TreeML can predict the tree crown geometry. By changing the DBH input, TreeML can calculate and visualize the tree crown growth based on the surrounding objects in the Rhino interface.

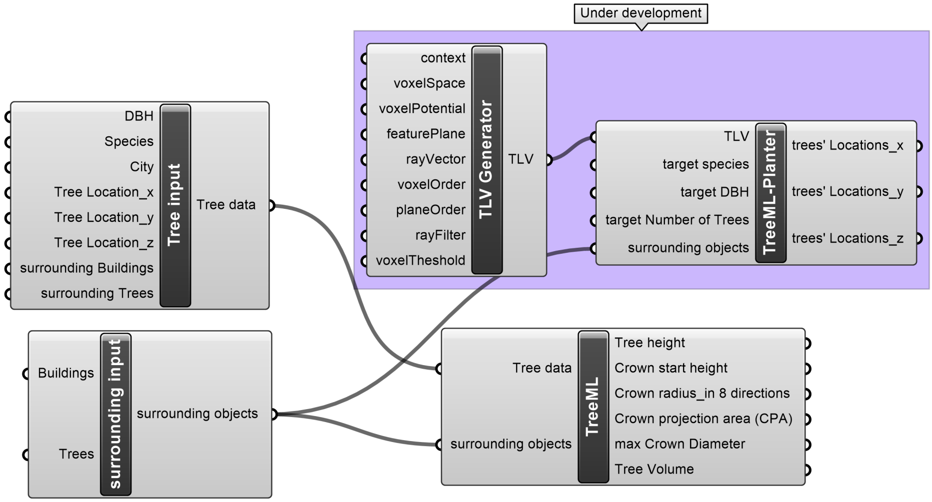

Fig. 5: A conceptual visualization of the TreeML battery (developed), TreeML-Planter and TLV-Generator (under development) in Grasshopper interface regarding their input, output, and connections

2.3 PrunML

Resprouting is a common strategy for trees to respond to branch loss: new shoots emerge from specific dormant buds to replace the previous ones. Understanding the pattern behind this phenomenon is the key to predicting the changes in trees after a natural or artificial intervention such as branch pruning. PrunML is a tool to forecast the positions of new shoots based on the positions of pruning on a tree structure described by a quantitative structural model (QSM, see RAUMONEN et al. 2013). These structural data about trees can be obtained through point clouds by LiDAR or photogrammetry surveys. The first version of the PrunML tool supports the prediction of *Platanus x hispanica*. It was trained with 28 annual pruned table-topped plane trees at Bruns Nursery in the north of Germany by classical machine learning models (SHU et al. 2023). The training dataset consists of 34245 cylinders from QSM of these trees reconstructed from point cloud by terrestrial LiDAR scanning (Fig. 6).

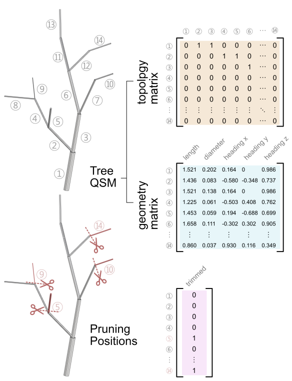

Fig. 6:
PrunML is a machine learning based model for predicting the location and number of the new shoots based on the QSM data of trees and their pruning position. It is trained on *Platanus x hispanica* species in a controlled nursery area. The model details and methodology are explained by SHU et al. (2023).

All grasshopper batteries related to the PrunML tool, and their connections are shown in Figure 7. To start the tool, a QSM and its pruning positions can either be read from a CSV file or manually fed in from the grasshopper panel. Based on these two inputs, PrunML predicts wether there will be new shoot on each cylinder or not. The balanced accuracy of PrunML model was 80.3% on the test dataset mentioned above (SHU et al. 2023).

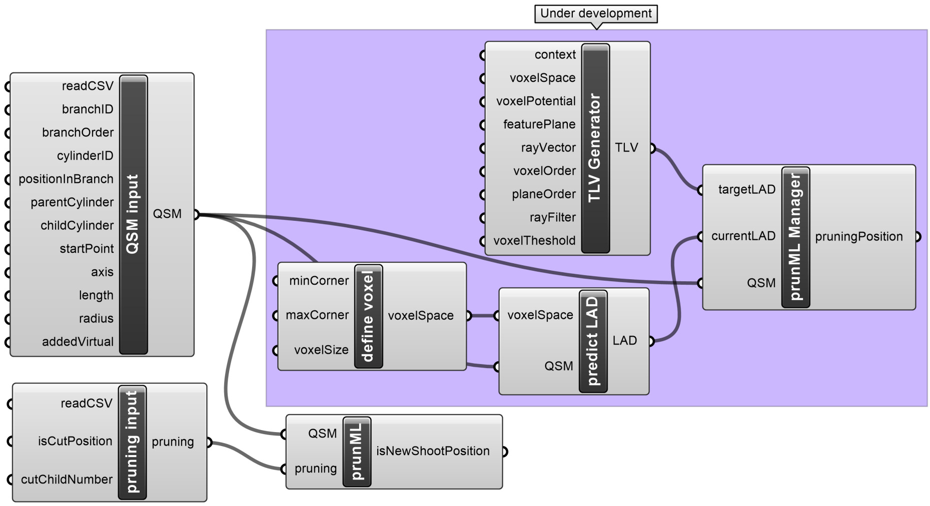

Fig. 7: A conceptual visualization of the PrunML (developed) and PrunML-Manager and TLV-Generator (under development) in Grasshopper interface regarding their input, output, and connections

2.4 TLV-Generator

Generating TLV (Yazdi, Shu & Ludwig, 2023) is essential for optimizing tree planting and maintenance. It contains not only occupancy data but also key properties related to biomass and ESS, including Leaf Area Density (LAD). In order to propose targets at different stages of urban tree design, we are developing a performance-oriented design tool called TLV-Generator. It uses a generative algorithm tailored to specific design objectives to produce TLV results within the bounds of the voxelized potential canopy space. As the fundamental step of this workflow, potential leaf voxels are defined based on site boundaries, excluding space allocated for grey infrastructure (e. g. buildings) and human use (e. g. traffic). For the generative process, we proposed that the first TLV-Generator tool will focus on voxel occupancy and addresses specific human needs that are modeled through a ray tracing method. It addresses thermal and visual comfort by tracing sun rays and line-of-sight. Occupancy results for TLV are generated by the components in this tool according to defined goals, such as shielding against intense summer radiation or ensuring favorable window views for building occupants. In the future, we intend to develop further tool version to generate TLV results incorporating LAD properties (Fig. 8).

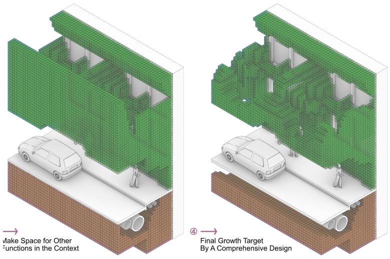

Fig. 8:
TLV-Generator is a performance-oriented design tool which uses a generative algorithm tailored to specific design objectives to produce TLV results within the bounds of the voxelized potential canopy space.

The TLV-Generator batteries and their connections in the GroTree toolbox are shown in Figure 9. This tool contains three input batteries for establishing the geometries of potential voxels, human living space, and tracing rays. With these inputs, along with necessary context settings, the TLV-Generator battery is empowered to compute the performance of each voxel and determine the TLV.

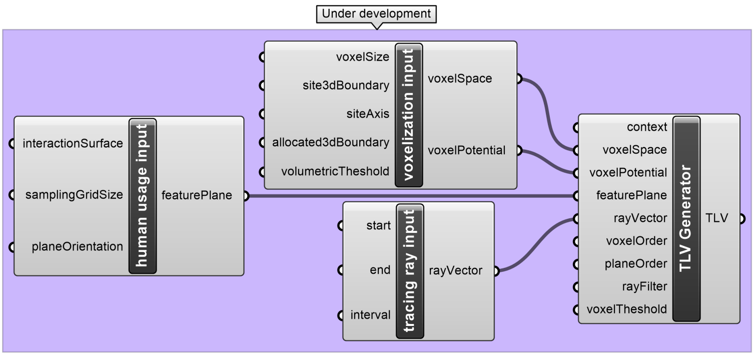

Fig. 9: A conceptual visualization of the TLV-Generator batteries (under development) in the GroTree toolbox, which contain three input batteries for establishing the geometries of potential voxels, human living space, and tracing rays.

2.5 TreeML-Planter

Current design approaches often fall short in achieving the best possible ESS. Building on the assumption, the prevailing standardized practice of linear tree planting at equal spacing and uniform age distribution results in lower ESS achievement, high maintenance costs, and encroachment into restricted zones, including human spaces, transit areas, and underground infrastructure.

A tree planting design model is a specialized tree location optimization model that takes into account the unique characteristics of the local urban environment during the design and planning stages. While several tree location optimization models exist (e. g. ESTACIO et al. 2022, GHODS et al. 2023, HAO et al. 2022, WALLENBERG et al. 2022), none of these models consider trees as dynamic, semi-natural growing entities within urban areas. They primarily represent tree geometry as a 3D sphere and focus on optimizing individual indicators, such as shading or radiant temperature, using a 2D surface model.

To address this limitation, there is a need to develop a tree optimization model that targets multiple 3D aspects, such as TLV (YAZDI, SHU & LUDWIG 2023). We are developing this model (TreeML-Planter) that is based on the TreeML model. Based on the current research, TreeML-Planter can optimize the trees' locations for increasing the chance of TLV achievement by using the TreeML model as a crown geometry growth model. Therefore, TreeML-Planter can suggest the optimum planting location by iterating the growth simulation several times to achieve the best optimum accuracy (Fig. 10). TreeML-Planter is proposed to use five inputs to be able to suggest the best locations. These inputs are 1) TLV, 2) species, 3) target DBH, 4) number of trees, and 5) surrounding geometries (see Fig. 5).

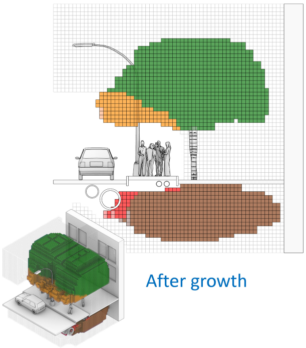

Fig. 10:
TreeML-Planter is an under-development model which optimizes the best location of tree planting to increase the chance of TLV achievement. It uses the TreeML model to estimate the crown geometry shape in time. Next, it calculates the percentage of the target achievement. Then, the optimization model will iterate these growth prediction and calculation until the best result will achieve.

2.6 PrunML-Manager

The PrunML model predicts the immediate reactions of trees (resprouting) after branch pruning, However, this model alone does not specify operations on trees. The great value of managing trees lies in an iterative process combining branch pruning and shoot regrowth, guiding the tree canopy toward desired shapes and functions (Yazdi, Shu & Ludwig 2023). This iterative process takes a relatively long time (several years to daces). To provide specific instructions on how to prune (and potentially bend) tree branches in a time sequence to approach certain TLVs, we are developing a tool named PrunML-Manager (see Fig.7). The inputs are (1) TLV, defining where the canopy should or should not develop (see section 2.4), (2) current leaf area density distributed in the space (this can be derived from the QSM), and (3) current tree structures described in QSM. The model then calculates iterative steps of growths of the trees in the framework of a Markov chain model. By relating this forecast to the TLV an optimized management-path leading to the target leaf voxels is generated, makes specific suggestions when to prune which branches. In a vision, suggestions about when to bend which branches towards which directions could possibly be added.

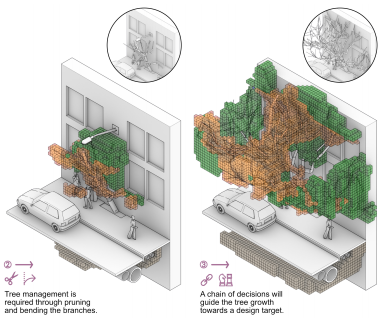

Fig. 11:
PrunML-Manager is an under-development model which calculates iterative steps of growth of the trees after pruning in the framework of a Markov chain model. It works based on the PrunML model that predicts the position of the new shoots.

3 Discussion and Conclusion

The GroTree toolbox V1.0 has been outlined to compile practical tools relevant to urban trees, aiming to assist designers, planners, gardeners, and other professionals in decision-making for design and maintenance throughout the life-cycle of trees. By growth prediction and the coupled target-driven processeson individual trees, GroTree will enhance the likelihood of achieving ESS by urban forest. For instance, it can give designers guidance toa tree crown that is well integrated into the building envelope, similar to the Tree-Façade (HÖPFL et al. 2022).

However, it is important to note limitations in the initial development stage of these tools. First of all, only three tools are developed yet, we cannot evaluate the full utilization of the proposed toolset yet, especially their impacts to practical works of landscape design and urban planning. Secondly, the embedded models in the developed tools are research based, therefore, the predictions are limited to their experimental settings. In other words, these tools can be site-specific, only validated under contingent environmental conditions, using given tree species, form, and e. g. the timing of pruning. Some specific limitations for each embedded model are listed below:

1) CityTree is parameterized for the 12 most common urban tree species based on measurements of over 6000 tree individuals in more than 20 cities in Central Europe. This means that the model can be applied to any city due to the process-based approach, but is limited to 12 tree species.

2) TreeML is developed with just six main urban tree species and tested on twelve species in Munich. However, the test results on the same trees in other cities such as Hamburg and Essen indicated larger deviations. Therefore, the first version of the toolbox is limited to these common species in Munich.

3) PrunML is developed and validated with table-topped *Platanus x hispanica* of the same size in Bruns Nursery in northern Germany, featuring these specific tree shape and size. Therefore, it is limited for predicting the resprouting of plane trees in the same growing conditions as the investigated trees in the first version.

The ongoing effort involves analysing a more extensive dataset of tree data in different cities to broaden the applicability of the tools to a greater variety of species and urban contexts. Furthermore, we plan to evaluate the complete set of tools once established in a follow-up research project.

References

ESTACIO, I., HADFI, R., BLANCO, A., ITO, T. & BABAAN, J. (2022), Optimization of tree positioning to maximize walking in urban outdoor spaces: A modeling and simulation framework. Sustainable Cities and Society, 86, 104105. doi:10.1016/j.scs.2022.104105.

GHODS, M., AGHAMOHAMMADI ZANJIRABAD, H., VAFAEINEJAD, A., BEHZADI, S. & GHARAGOZLO, A. (2023), Optimizing the shade coverage of trees on a block of residential buildings using GIS and ACO (case study: Semnan, Iran). International Journal of Environmental Science and Technology, 20 (1), 489-502. doi:10.1007/s13762-022-04537-6.

HAO, T., ZHAO, Q. & HUANG, J. (2022, November 26), Optimization of Tree Locations to Reduce Human Heat Stress in an Urban Park. OSF Preprints. doi:10.31219/osf.io/t7ukq.

HÖPFL, L., PILLA, D., KÖHL, F., BURKHARD, C., LIENHARD, J. & LUDWIG, F. (2022), TREE-FAÇADES Integrating trees in the building envelope as a new form of Façade Greening, 192-213. doi:10.19229/978-88-5509-446-7/7112022.

OKE, T. R., CROWTHER, J. M., MCNAUGHTON, K. G., MONTEITH, J. L., GARDINER, B., JARVIS, P. G. et al. (1997), The micrometeorology of the urban forest. Philosophical Transactions of the Royal Society of London. B, Biological Sciences, 324 (1223), 335-349. Royal Society. doi:10.1098/rstb.1989.0051.

RAUMONEN, P., KAASALAINEN, M., ÅKERBLOM, M., KAASALAINEN, S., KAARTINEN, H., VASTARANTA, M. et al. (2013), Fast Automatic Precision Tree Models from Terrestrial Laser Scanner Data. Remote Sensing, 5 (2), 491-520. Multidisciplinary Digital Publishing Institute. doi:10.3390/rs5020491.

RÖTZER, T., MOSER-Reischl, A., RAHMAN, M. A., GROTE, R., PAULEIT, S. & PRETZSCH, H. (2021), Modelling Urban Tree Growth and Ecosystem Services: Review and Perspectives. In: F.M. CÁNOVAS, U. LÜTTGE, M.-C. RISUEÑO & PRETZSCH, H. (Eds.), Progress in Botany, 82, 405-464. Cham: Springer International Publishing. doi:10.1007/124_2020_46.

RÖTZER, T., RAHMAN, M. A., MOSER-REISCHL, A., PAULEIT, S. & PRETZSCH, H. (2019), Process based simulation of tree growth and ecosystem services of urban trees under present and future climate conditions. Science of The Total Environment, 676, 651-664. doi:10.1016/j.scitotenv.2019.04.235.

SHU, Q., YAZDI, H., RÖTZER, T. & LUDWIG, F. (2023, August 13), Predicting resprouting of Platanus × hispanica following branch pruning by means of machine learning. bioRxiv. doi:10.1101/2023.08.11.552927.

TZOULAS, K., KORPELA, K., VENN, S., YLI-PELKONEN, V., KAŹMIERCZAK, A., NIEMELA, J. et al. (2007), Promoting ecosystem and human health in urban areas using Green Infrastructure: A literature review. Landscape and Urban Planning, 81 (3), 167-178. doi:10.1016/j.landurbplan.2007.02.001.

WALLENBERG, N., LINDBERG, F. & RAYNER, D. (2022), Locating trees to mitigate outdoor radiant load of humans in urban areas using a metaheuristic hill-climbing algorithm – introducing TreePlanter v1.0. Geoscientific Model Development, 15 (3), 1107-1128. Copernicus GmbH. doi:10.5194/gmd-15-1107-2022.

WOLF, K. L., LAM, S. T., MCKEEN, J. K., RICHARDSON, G. R. A., VAN DEN BOSCH, M. & BARDEKJIAN, A. C. (2020), Urban Trees and Human Health: A Scoping Review. International Journal of Environmental Research and Public Health, 17 (12), 4371. Multidisciplinary Digital Publishing Institute. doi:10.3390/ijerph17124371.

YAZDI, H., MOSER-REISCHL, A., RÖTZER, T., PETZOLD, F. & LUDWIG, F. (2024), TreeML; a Crown Geometry Growth Prediction Model for Urban Trees in Competition with Surrounding Trees or Buildings (preprint version).

YAZDI, H., SHU, Q. & LUDWIG, F. (2023), A Target-driven Tree Planting and Maintenance Approach for Next Generation Urban Green Infrastructure (UGI). Journal of Digital Landscape Architecture, 8-2023, 178-185. doi:10.14627/537740019.

YAZDI, H., SHU, Q., RÖTZER, T., PETZOLD, F. & LUDWIG, F. (2023, September 15), TreeML-Data; a multidisciplinary and multilayer urban tree dataset. doi:10.21203/rs.3.rs-3358921/v1.