



Green Urban Scenarios: A Framework for Digital Twin Representation and Simulation for Urban Forests and Their Impact Analysis

By Bulent Ozel and Marko Petrovic

Abstract. Background: Trees are a critical part of urban infrastructure. Cities worldwide are pledging afforestation objectives due to net-zero targets; however, their realisation requires a comprehensive framework that combines science, policy, and practice. Methods: The paper presents the Green Urban Scenarios (GUS) framework for designing and monitoring green infrastructures. GUS considers weather, maintenance, tree species, diseases, and spatial distributions of trees to forecast their impacts. The framework uses agent-based modelling (ABM) and simulation paradigm to integrate green infrastructure into a city's ecological, spatial, economic, and social context. ABM enables the creation of digital twins for urban ecosystems at any level of granularity, including individual trees, to accurately predict their future trajectories. Digital representation of trees is created using a combination of datasets such as earth observations from space, street view images, field surveys, and qualitative descriptions of typologies within existing and future projects. Machine learning and statistical models calibrate biomass growth patterns and carbon release schemes. Results: The paper examines various green area typologies, simulating several hypothetical scenarios based on Glasgow's urban forests. It exhibits the emergence of heterogeneity features of the forests due to interactions among trees. The growth trajectory of trees has a non-linear transition phase toward stable growth in its maturity. Reduced maintenance deteriorates the health of trees leading to lower survival rate and increased CO₂ emissions, while the stormwater alleviation capacity may differ among species. Conclusions: The paper demonstrates how GUS can facilitate policies and maintenance of urban forests with environmental, social, and economic benefits.

Keywords. Agent-Based Modelling; Digital Twins; Nature-Based Solutions; Scenario Analysis; Urban Forest.

INTRODUCTION

Trees are a critical part of urban infrastructure alongside bridges, roads, and rails, yet the lack of understanding around the ecosystem benefits they provide stands in the way of them being conceived and implemented as such. Even though cities are pledging challenging targets—Prague has made a commitment to plant 1 million trees (Dimitrova 2021), Sydney to plant 5 million trees by 2030 (New South Wales Government 2020)—the realisation of such targets is questionable given the current practices, tools, and methodologies.

Models and software tools evaluating the ecosystem benefits of trees fall short because they are too general: they fail to include location and species-specific data (Zhang and DeAngelis 2020; Grueters et al. 2021). In addition, they lack modularity and extensibility and cannot be fully interrogated as they lack sufficient transparency to be adopted by other practitioners and

researchers. Besides, in the growth process of an urban forest, trees are not the sole actors. Other actors, such as the built environment and humans, through their policies and interventions, can all affect the growth of an urban forest. The scale of the problem requires approaching practices of planning and maintaining urban forests as well as estimating their impacts through a complex systems lens (Zhang and DeAngelis 2020).

The work presented in this paper takes a holistic approach combining science, policy, and technology. It proposes a theoretical and computational framework that other researchers and practitioners can adopt and extend. It contributes to the state of the art in a number of complementary ways. On the scientific side, it adopts and extends previous work on agent-based forest growth models. On the policy side, it adopts the Cynefin framework (Snowden

2000), a conceptual framework for decision-making. On the technical side, it creates an end-to-end open-source and documented software framework. A detailed discussion of previous work and the gap in the state of the art is provided below.

The overall objective is to enable cities to monitor, (re)design, and forecast green infrastructure portfolios and their long-term impacts under varying weather conditions, maintenance regimes, species compositions, spatial distributions and their exposure to diseases. This paper presents a Green Urban Scenarios (GUS) framework and its application under a set of simplified urban forest planning schemes. For more complex and granular use cases, as well as to enable replicability, integration with other tools and models, and further extensions by other practitioners and researchers, a detailed model specification and code documentation is provided at its public source code distribution channel as a live document (Ozel and Petrovic 2022).

This manuscript discusses relevant works within the field on complex systems, presenting the novelties introduced in this work; outlines the methodology for applications of the framework; provides key model specifications and the current calibration of its parameters; demonstrates an exemplary geo-localised scenario design set-up that would enable a policymaker or a project owner to gain insights into planning, monitoring, and measuring the impacts of green infrastructure, presenting the results from the simulations; and discusses the modelling approach and points to potential use cases and extensions of the framework.

BACKGROUND

In this study, an urban forest is considered as a complex system with 4 underlying characteristics, adopted from Newman (2011). Figure 1 depicts the complex systems features relevant to urban forests. First, each urban forest is located at a physical location where the density of its trees, exposure to the sun, access to water, and other location-specific conditions can vary drastically, comparing one city to another and within the same city. Capturing such location-specific conditions is referred to as a *specificity* characteristic. Second, each urban forest may have different species composition. Even 2 trees within the same species often have different shapes and physiology and hence, may respond to the same environment differently (Bittebiere et al. 2012). Such *heterogeneity* is an

inherent feature of complex systems (Newman 2011). Third, a tree constantly interacts with its environment and other trees (Coates et al. 2003). Due to specificity and heterogeneity, its growth process is dynamic, depending on its size, age, and reach to resources such as light, soil, water, or other factors (Berger and Hildenbrandt 2000). The collection of individual tree-level interactions leads to the *emergence* of a forest-level growth pattern that might differ from an individual tree. This characteristic is highlighted in Figure 1, comparing the growth trajectory of a tree's trunk size during its life cycle versus the growth trajectory of the whole tree population, where individual tree versus forest growth generally exhibits varying patterns (Dale et al. 1985). Last, an urban forest is an open system and is exposed to external shocks such as invasive insects, fires, and frequent human interventions. Such *externalities* are essential and integral to the analysis of complex systems.

An agent-based paradigm is adopted to model an urban forest as a complex system with its components and interactions within a geophysical context. An agent is an abstraction for an autonomous, reactive, and proactive information-processing entity (Epstein and Axtell 1996). Thus, trees and other entities such as birds, bees, insects, or sensors that collect data on soil health could all be construed as autonomous agents. The physical system can then be mimicked digitally by configuring agents and their interactions within the surrounding ecosystem to capture the context and conduct very granular computational experiments.

The agent-based modelling (ABM) approach of the framework provides a complex systems design and analysis methodology, a modelling paradigm, a software programming style, and a simulation framework (Savaglio et al. 2020). There are many purposes for using simulation modelling (Epstein 2008). Simulations can serve as decision-support tools to create would-be worlds, explore alternative counterfactuals, and perform what-if scenarios. As a prime example of this method, the Decision Theatre at Arizona State University uses wall-sized 260° screens and surround sound to create an immersive experience, helping participants make informed policy decisions. In addition, Dubbelboer et al. (2017) employ ABM to simulate the dynamical evolution of flood risk and economic vulnerability to facilitate London's more informed insurance mechanism. Other common uses of simulation include using it for new theory formation (Schelling

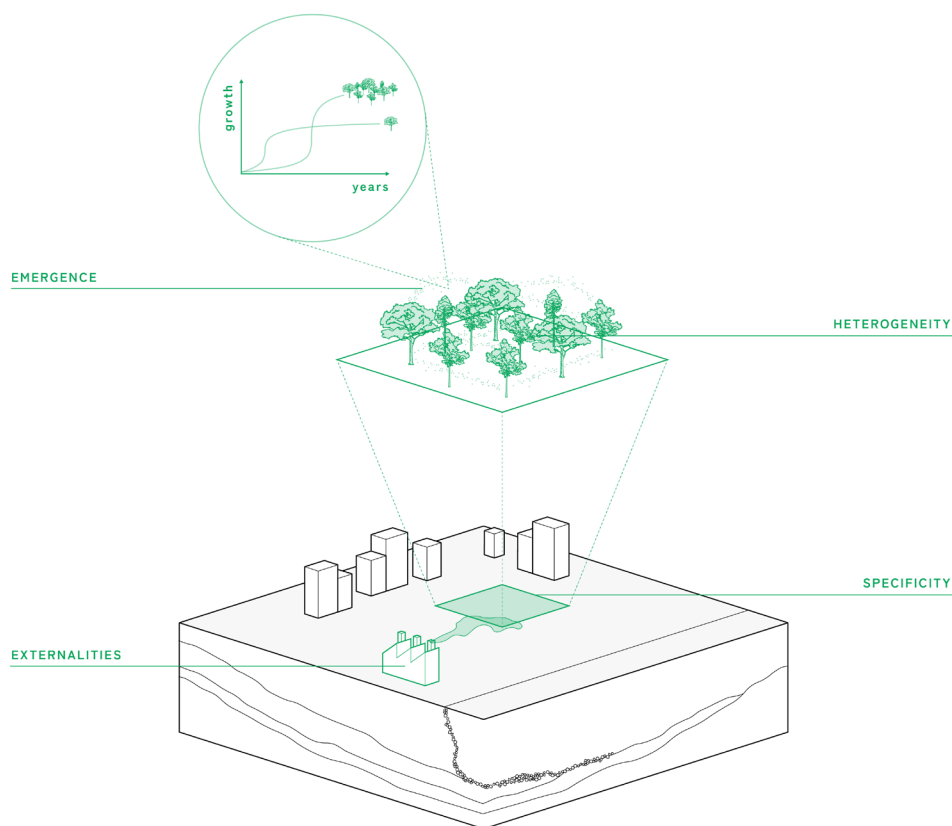


Figure 1. Modelling features of the Green Urban Scenarios (GUS) framework representing an urban forest as a complex system. Adopted from a complex systems science perspective (Newman 2011). The figure highlights the role of location-specific conditions on the growth of trees, the impact of externalities such as pollutants from neighbouring industries, the heterogeneity among trees, and the variance in growth trajectories of an individual tree versus the tree population as a whole.

1978), for testing new market mechanisms (Gode and Sunder 1993), for the role of green housing (Raberto et al. 2019), or as a purely pedagogical device (Kirman 1993).

This paper develops a simulator to explore aspects such as the emergence of forest growth patterns at the site and city scale through event-based scenarios, leading to more efficient design and implementation of green infrastructures. This approach has been used in urban planning. For example, Karnouskos and de Holanda (2009) created an agent-based environment to simulate a smart city where different smart objects could act autonomously, collaborate and dynamically use or produce energy. In addition, ABMs have also been employed in scientific research in ecology. Berger and Hildenbrandt (2000) discuss the need for spatially explicit modelling of forest dynamics, looking into the growth of individual trees and their competition for space and other resources. Bittebiere et al. (2012) used an agent-based approach to look deeper

into the role of competition on the growth of plants, while Grimm et al. (2017) argue that ABM is the best fit to study biodiversity in ecosystems. Zhang and DeAngelis (2020) provide an in-depth literature review on the use of ABM in plant biology and ecology.

This paper advances existing works on ecosystem growth models (e.g., Canham et al. 1994; Berger and Hildenbrandt 2000; Bittebiere et al. 2012; Zhang and DeAngelis 2020; Grueters et al. 2021), by introducing a generic and modular framework that can be applied to various urban forests at different levels of granularity as well as further extended and integrated with other tools in the literature. It explicitly shares the position of Grueters et al. (2021) that growth models should pay attention to spatial aspects and move from mean-field models to the granularity of individual trees. However, unlike Grueters et al. (2021), which is specifically designed to study the growth dynamics of Mangrove forests, the model presented in this work can be used for any forest type with single or

multiple tree species. This novelty is introduced by its computational model, where species-specific allometric equations and their location-specific parameters are dynamically loaded during the initialisation phase of the simulations. This computational modularity is further extended to capture location-specific weather and landscape conditions. Ozel and Petrovic (2022) provide detailed documentation for adopting the model to study urban or non-urban forest growth dynamics.

JABOWA, a software with proprietary and closed-source code (Botkin 1993), can be regarded as one of the pioneering software applications where the growth of individual trees serves as the foundation for simulating forest growth, while SORTIE (Coates et al. 2003) is a computational model that predicts forest dynamics by simulating changes in tree populations over time. In a similar vein, GUS considers interactions among nearby individual trees, much like SORTIE. However, SORTIE is specifically designed to offer growth predictions for individual trees in multi-species forests. On the other hand, mesoFON (Grueters et al. 2019), a newly developed agent-based model, focuses on mangrove forest dynamics and aims to identify forest management scenarios that maximise timber yield. GUS encompasses modelling features found in both SORTIE and mesoFON, and it adopts a generic and modular framework that is applicable to urban forests. Its modular nature allows for integration with other tools, including iTree (Nowak 2020), a widely used software for assessing the value of ecosystem services provided by urban forests.

In addition to combining existing computational and scientific features in a modular and interoperable manner, the current version extends the state-of-the-art studies by implementing a dynamic carbon release process as part of the growth dynamics. For details, see the Methodology section. Individual tree growth dynamics not only consider competition between neighbouring trees (Coates et al. 2003) but also the current health of a tree and the health of other surrounding trees. This, in turn, enables GUS to study disease contagion without a need to develop a contagion model from scratch (see the Discussion section for details).

Lastly, as presented in the subsequent section, the forest growth model and simulator are designed and implemented as an integral component of an urban policy-making scheme and a novel decision-making methodology.

METHODOLOGY

The methodology is inspired by the Cynefin framework (Snowden 2000), a framework for decision-making. The Cynefin framework initially proposes context-aware decision-making schemes. This work adopts the set of actions that the Cynefin framework proposes for complex systems, where actions to make a qualitative change in the system are based on probation and making sense of alternative pathways.

While working in complexity, Snowden (2000) proposes to start with invoking new experiments or collecting information on emergent features (probe) by a careful reflection to make sense of how the system reacts to new experiments (sense), followed by calibrated actions that may lead to a new state (respond). Figure 2 depicts the adoption of the Cynefin framework as an overarching methodology, and Figure 3 presents technical infrastructure on how the methodology is implemented as software and data processing components. The adoption aims to make a systemic change by combining policy intervention, planning, impact forecasting and monitoring.

Urban forests are in constant interaction with their environments; therefore, GUS requires a continuous and iterative process in monitoring, sense-making, and interventions with feedback loops. Figure 2 visualises how a linear probe-sense-respond process is made iterative with feedback loops.

As the figure suggests, a typical process starts with data curation and processing to create a digital representation of urban forests at the desired level of granularity and fidelity. The upper and lower panels are contrasted in the figure to point out potential simplifications while moving from real physical trees into their digital twin representations. For this paper, the database from the iTree survey on tree canopy in Glasgow (Rumble et al. 2015) is used to create a simplified and generic representation of tree populations in Glasgow. However, an automated monitoring component is being developed within ReTreevAlable Project (2022) where remote sensing data is used to detect and recognise individual trees while creating their digital twin representations.

Figure 3 details the overall architecture, presenting how the methodology is implemented. It depicts continuous feedback loops between 3 main pillars: policy interventions (module 1); scenario analysis, including inputs and scenario design (module 2); population initialisation (module 3); population dynamics (module 4);

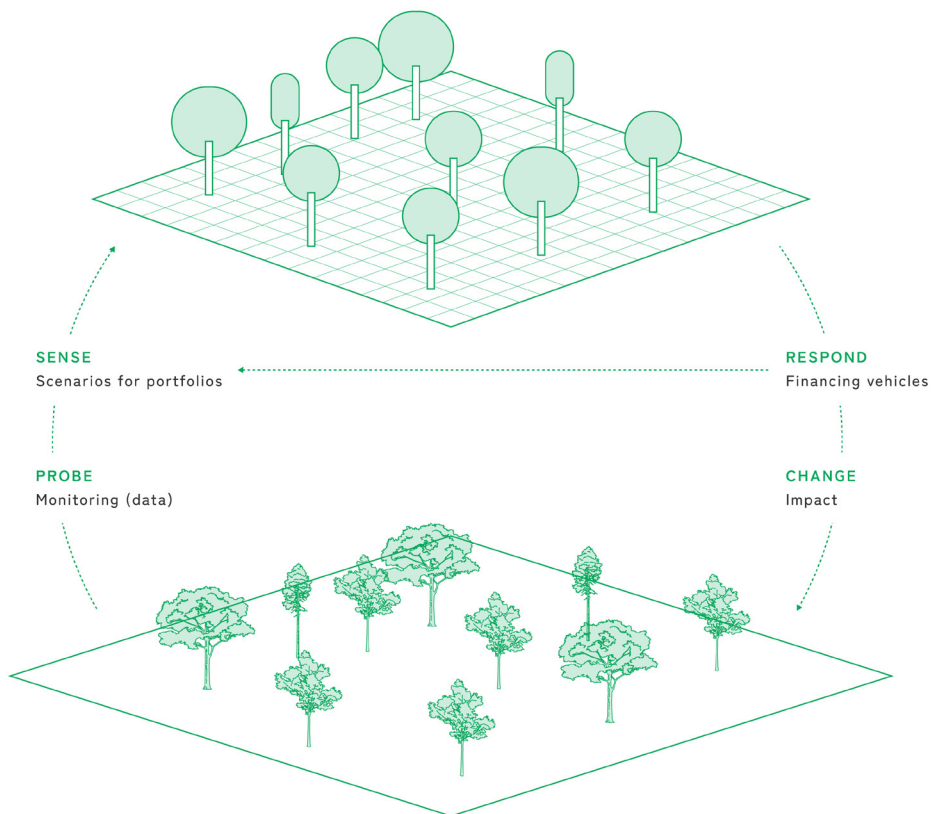


Figure 2. Change model in complexity that combines science, practice, and policy adopted from Cynefin framework (Snowden 2000) as an overarching methodology for Green Urban Scenarios framework. The figure depicts how data collection is connected to digital twin representation and scenario analysis with designated parameters, which in return may inform practitioners or policymakers to allocate financial and other resources for creating and maintaining urban forests.

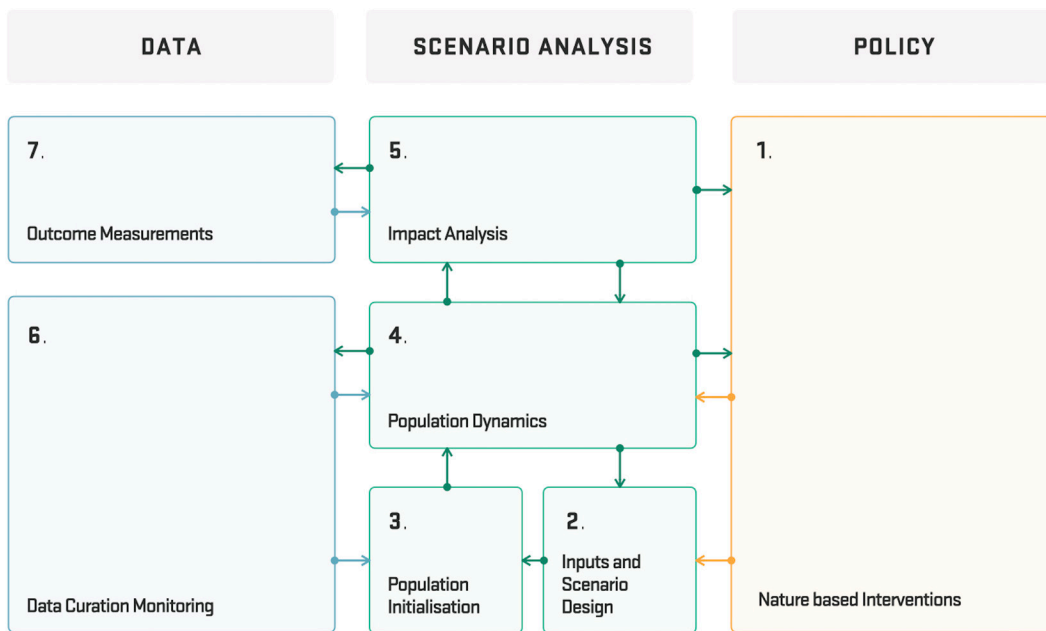


Figure 3. Green Urban Scenarios (GUS) framework architecture diagram.

impact analysis (module 5), and data curation and monitoring (modules 6 and 7). Each of these elements is designed as an independent module; when combined, they form the GUS framework. A typical use case starts by proposing policy intervention (module 1), for example, building a new urban park in a city. Different park typologies and scenarios are created for examination using the experiment setup (module 2). Typologies can differ according to the species composition, tree distribution, different maintenance strategies, etc. Once determined, scenarios are passed to the population initialisation module (3), where hypothetical tree populations are created for each scenario. Each hypothetical population is then forwarded to module 4 (population dynamics) to simulate the population growth and development over N years. The simulation results can be either sent back to module 2 for a redesign of the scenario, sent back to the policy-makers, stored in the data curation module (6), or forwarded to module 5 to calculate ecosystem services (carbon sequestration, water retention, and air pollution removal) over N years in the future. Each of these modules is further explained in the following sections.

Policy Intervention

Analysis in the GUS starts by entering the description of a nature-based solutions (NbS) project. The description is given in terms of input parameters to the model describing the population's size and characteristics (e.g., the number of trees, species, typology, density), planting/maintaining activities, etc. If the typology already exists, the population is initialised based on actual observations; otherwise, the population is initialised using the rest of the input parameters given in the NbS description.

Scenario Analysis

The second pillar, scenario analysis, includes 4 modules: inputs, population initialisation, population dynamics, and impact analysis.

Input Data Types

The framework is flexible and applicable to any forest typology at any location. It divides the inputs into 4 different segments: (i) site configuration, (ii) population configuration, (iii) allometric equations, and (iv) experiment configuration, where the user can provide an independent (stand-alone) database for each segment. All databases are easily expandable, allowing users to improve the quality of the description

of the existing data or to enter information about new sites, species, allometric equations, and experiments.

The site configuration is a database with non-exhaustive information about specific sites. For instance, it stores the data about the exact location of a site, its boundaries, the total area of the site, the data about the surface, and any other relevant data that may describe a specific location. The list of variables is expandable; therefore, users may use the database to improve the quality of descriptions of the existing sites or enter information about new sites. This paper creates a hypothetical site that matches species and climate conditions in Glasgow for demonstration purposes. For this purpose, an i-Tree survey on the urban area is used (Rumble et al. 2015).

The population configuration is a database describing the tree population at a specific location. It can consist of the existing trees at a given location, the planned tree population, or any hypothetical tree population that could be studied at a particular site. The granularity of the data in the database is flexible, meaning that one can describe each tree in the population using a non-exhaustive list of variables in detail. The current paper employs a hypothetical tree population of newly planted young trees at the site using the following variables to describe it: species, diameter at breast height (DBH), tree height, canopy height, canopy width, leaf area index (LAI), bark area index (BAI), plant area index (PAI), tree dieback ratio, tree age, canopy overlap, and the exact coordinate of each tree in the site.

On the other hand, if a real tree population is under study and some data points are missing, one can use less granular data, such as more generic species information or DBH and other tree size measures drawn from a particular distribution. If missing, some of the variables can also be estimated, such as tree height, canopy height, canopy width, LAI, and BAI. Other variables, such as tree dieback ratio, tree age, canopy overlap, and coordinates, can be assumed.

The allometric database consists of allometric equations for specific species at specific locations. Each species at each site is described with an allometric equation. If some allometric equations are missing, the researcher can define a representative or mean allometric for the specific area, considering a more generic family of species. In the most generic case, there is one mean allometric for deciduous and one for conifers at the specific location. This work considers 2 species: European ash (*Fraxinus excelsior*) and Port

Orford cedar (*Chamaecyparis lawsoniana*). Thus, species-specific allometric equations to calculate biomass, tree height, grown height, and crown are identified from Nowak (2020).

The experiment configuration database describes the experiments to be performed on the particular tree population at the given location. For now, experiments are available related to the different maintenance strategies. This paper uses three levels ($M0$, $M1$, $M2$) of tree maintenance which is related to planting, removal and disposal, and tree replacement. Maintaining level $M0$ disregards any maintenance activities, while the activities increase with maintaining levels $M1$ and $M2$.

Population Initialisation

Based on inputs (described in the previous section), the model initialises the digital ecosystem, creating a digital representation of each tree in the population. Each tree can be described by a list of variables such as DBH, tree height, canopy height, canopy width, tree health, and percentage crown loss from the population configuration database. In addition, each tree is assigned an allometric equation from the allometric database based on species and location. The digital trees are then distributed on a digital grid. The model uses a special configuration method that creates a digital site based on the site configuration database. It allocates each digital tree on a grid, where each tree has its own x and y coordinate. Therefore, each tree has a unique place in the digital site, surrounded by neighbouring trees. The spatial configuration translates all other site characteristics from the actual site into digital space, such as site size, the distance among trees, and the sun exposure. The initialised tree population, including all parameters and weather data, is passed to the core simulation engine in module 4 (Figure 3), where the tree population growth is simulated over N years.

Population Dynamics

The main component of the population dynamics component is a flexible agent-based model that simulates a spectrum of interactions among the trees. Each simulation consists of N iterations (steps), where each iteration represents a period of one year. Within each iteration, each agent performs tasks, imitating what a real agent (e.g., a tree) would do during one year. For instance, trees would be exposed to the weather conditions that would trigger their growth. They would be competing with other trees for sun exposure,

which influences their growth. They would be exposed to various diseases which can affect their diebacks and probability of dying. If a tree dies, humans can proceed with site maintaining actions which could result in removing or replacing the dead tree or could result in no action. One simulation of GUS over N years provides one unique realisation of the world. Nevertheless, by repeating the simulation process, one can obtain another possible/unique outcome. By simulating the model M times over N years, GUS provides the outputs and M unique possible realisations. Hence, the outputs can be analysed either by observing each unique realisation (so-called “run”, “simulation”, or “seed”), or by aggregating the outputs and looking at the average outcome and its variance over M seeds, which allows the researchers to measure the confidence interval and the risk of the estimation.

Data Curation and Monitoring

The data on population growth and ecosystem services can be stored in the data curation module and reutilised at any time during the simulations. Finally, monitoring collects the data from the field, real data, during the project time span. The methodology developed in this paper has fully or semi-automated components for data collection, curation, integration, and generation processes. The use of actual data spans the phases from model calibration and validation to verification of the outcomes.

MODEL SPECIFICATION AND CALIBRATION

The tree growth occurs within each iteration/simulation step, mimicking a calendar year. At each step, the growth model predicts DBH, height, crown width, and crown height growths taking into account environmental and tree health conditions (Figure 4). It also calculates tree biomass and net carbon sequestration (NCS). NCS is a difference between gross carbon sequestration (GCS) and decomposition. GCS represents the amount of sequestered carbon dioxide in one year, while decomposition denotes the emission/release of carbon dioxide due to the tree decomposition process (Nowak et al. 2002; Nowak et al. 2008). In the following section, each segment of the tree growth process is presented.

At the initial state, $t = 0$, the entire digital ecosystem is initialised, all trees' variables are set to their initial values, and the system is ready to be simulated. When the simulation runs from time $t = 0$ to time $t = 1$

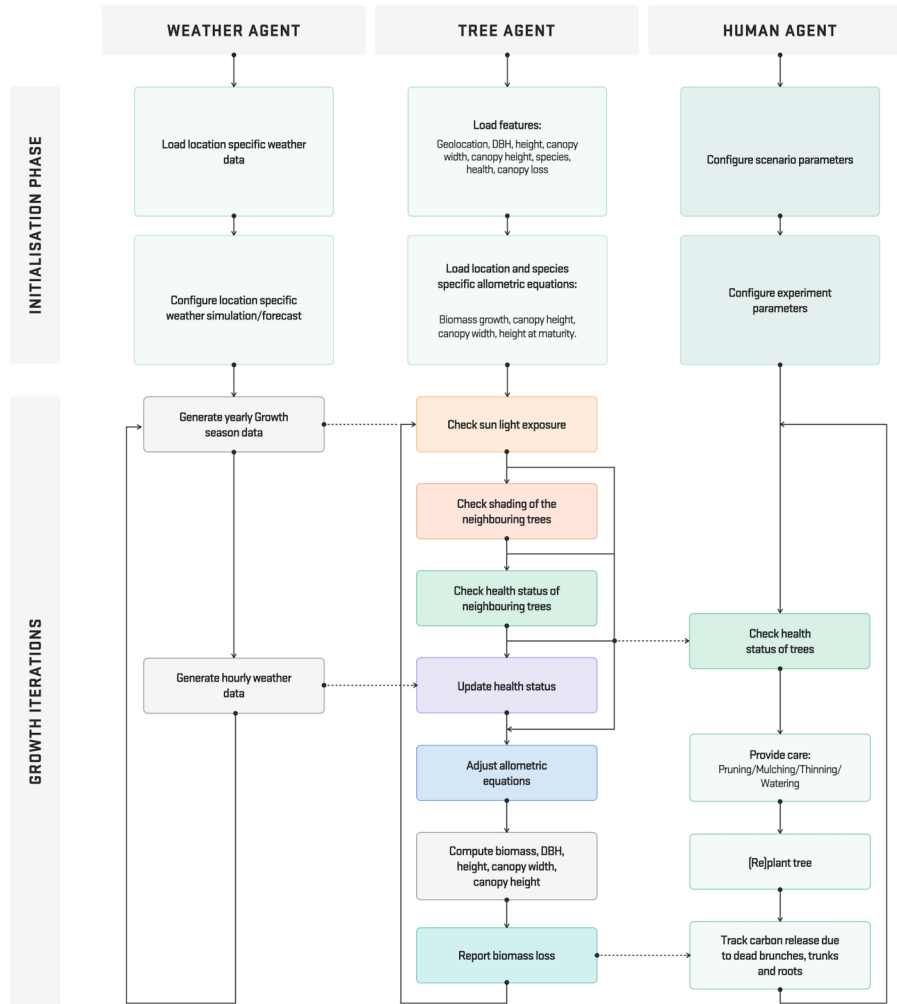


Figure 4. ABM diagram: the state graph showing the agents' interactions, decision-making, and adaptation processes.

(i.e., one iteration takes place), trees perform the following tasks.

Each tree reads information about weather conditions for the current year. In particular, each tree gets the information about frost-free days $ffd(t)$ at year t . Each tree at each iteration also checks the state of its neighbouring trees and determines its current crown light exposure (CLE). Trees compute the crown overlap at time t concerning their neighbours:

$$overlap_{ij} = \max(0, 0.5 \times [crown\ width_i + crown\ width_j - bark\ distance_{ij}])(m) \quad (1)$$

where index j denotes a neighbouring tree, while index i stands for the reference tree. Note that index t is omitted for the sake of better readability. Therefore, $bark\ distance_{ij}$ is the distance between tree i and its neighbouring tree j , while $overlap_{ij}$ is the crown

overlap in meters between trees i and j rescaled for a multiplier of 0.5 to correct for the square-shaped assumption of the tree crown. Based on the crown overlap size, the overlap ratio is calculated as:

$$overlap\ ratio_{ij} = 0.25 \times \min\left(1, \frac{overlap_{ij}}{crown\ width_i}\right) \quad (2)$$

where 0.25 multiplier accounts for 1 of the 4 sides of the grid cell. In addition, the crown overlap ratio is adjusted for the neighbouring relative height, assuming that a taller tree creates more shading. Thus, the adjusted crown overlap ratio is given as:

$$\overline{overlap\ ratio}_i = \sum_{j=1}^k overlap\ ratio_{ij} : \quad (3) \\ \times \frac{height_j}{height_j + height_i}$$

where k is the number of neighbours, while $height(i)$ and $height(j)$ are the heights of the reference and neighbouring trees, respectively. The crown light exposure is then calculated for each tree i at time t as:

$$cle_i = \max\left(0, 1 - \text{light loss multiplier} \times \frac{1}{\text{overlap ratio}_i}\right) \quad (4)$$

where the *light loss multiplier* is a constant set to 0.75.

Dieback

The dieback ratio indicates the percentage of the tree that is dying, and/or it indicates the health condition of trees. For instance: dieback < 0.01 \Rightarrow excellent condition; $0.01 \leq$ dieback \leq 0.1 \Rightarrow good condition; $0.1 <$ dieback \leq 0.25 \Rightarrow fair condition; $0.25 <$ dieback \leq 0.5 \Rightarrow poor condition; $0.5 <$ dieback \leq 0.75 \Rightarrow critical condition; $0.75 <$ dieback \leq 0.99 \Rightarrow dying condition; dieback = 1 \Rightarrow dead tree. The modelled dieback ratio depends on (i) the latest condition of the tree, (ii) the age via DBH, and (iii) the health of neighbouring trees. The health of neighbouring trees determines the contagion risk, which is calculated as:

$$\text{contagion risk}_i = 0.9 \times \sum_{j=1}^k \frac{\sum_{r=1}^j k^{r-1} \times \text{dieback}_r}{k^j} \quad (5)$$

where k is the total number of neighbours, j , and 0.9 is an adjustment parameter. The new dieback rate is drawn from a uniform distribution between the healing range and dying range, calculated as

$$\text{healing range}_i = -1 \times (1 - \text{contagion risk}_i) \times \frac{\sqrt{dbh}}{M} \times \text{healing rate}_i \quad (6)$$

where M is a parameter indicating maintenance scope, such that $M(M0) = 5$, $M(M1) = 4$ and $M(M2) = 1$; while *healing rate*(i) is a parameter set to 0.005. Furthermore, the dying range is calculated as:

$$\text{dying range}_i = \frac{\text{risk rate}_i \times M}{(1 - \text{contagion risk}_i) \times \sqrt{dbh}} \quad (7)$$

where risk rate is a parameter set to 0.005. Therefore, the new dieback of tree i at time t is calculated as:

$$\text{dieback}_{it} = \text{dieback}_{i,t-1} + U \sim (\text{healing range}_{it}, \text{dying range}_{it}) \quad (8)$$

At every period t , there is a probability that a tree dies. It is modelled as a step function, and it is

increasing in dieback ratio (i.e., the worse the condition, the higher the probability of dying), as well as the function is decreasing in maintenance scope (i.g., the higher the maintenance scope, the lower the probability of dying).

Another component of the core module is the tree growth model developed following the work of Smith and Shifley (1984), Nowak (1994), and Nowak (2020). These growth models are extended by considering the health of a tree and the health of its neighbours, as well as exposure to light. The resilience of a tree against crown loss or diseases is heterogeneous and correlates with its current age or DBH. Combining the input data on tree species, site configuration, allometric equations, and experiments (e.g., maintaining activities), the core module simulates the tree population's growth and development. In particular, the model calculates DBH growth (cm) as:

$$\Delta dbh_{it} = \text{diameter growth}_{it} \times \text{growth adjustment}_{it} \quad (9)$$

where diameter growth (cm) is given as:

$$\text{diameter growth}_{it} = \text{standard growth}_t \times \frac{ffd_t}{ffd} \times cle \times (1 - \text{dieback}_{it}) \quad (10)$$

Standard growth is a location-species specific parameter which is provided in the allometric database for each species and location, and it is constant during the simulation. If missing, the moderate annual growth rate of 0.8382 cm is applied (see the literature on diameter growth for details, e.g., Smith and Shifley 1984; DeVries 1987; Lorimer et al. 1992; Nowak 1994; Nowak 2020). ffd_t is the number of frost-free days in the year t , while ffd is the average number of frost-free days at the given location. The growth adjustment is a parameter calculated as a ratio of tree height to tree height at maturity (Ozel and Petrovic 2022). In addition, *tree height*, *crown height*, and *crown width* are calculated as functions of DBH using the species-specific and location-specific equations provided in the allometric database.

Based on the predicted tree growth, the model estimates the biomass, carbon stock, yearly sequestration, and CO₂ release for each tree in the population over N years. The descriptions of all calculations can be found in the model specification (Ozel and Petrovic 2022).

Decomposition

Decomposition is a process of carbon dioxide release from dead or alive trees. If a tree is still alive, decomposition may occur on its dead branches due to die-backs or crown loss. The amount of carbon to be released due to dead branches of alive trees is calculated as:

$$CO_2 \text{ release alive}_{it} = \text{crown to trunk ratio}_i \times \text{dieback}_{it} \times \text{carbon storage}_{it} \quad (11)$$

where *crown to trunk ratio*(*i*) is a parameter set to 0.05.

The decomposition rate of dead branches depends mainly on human actions, such as maintenance activities. For now, the model distinguishes 2 scenarios: (i) if the dead branches are mulched and left to be decomposed in nature, or (ii) if the dead branches are immediately decomposed (e.g., burnt). The first scenario happens with 90% probability, and in this case, the decomposition rate is given as:

$$\text{decomposition rate}_{i,t-\tau} = \frac{1}{k \times e^{\frac{t-\tau}{k}}} \quad (12)$$

where parameter *k* determines the speed of the decomposition. It is set to 2 for mulched dead branches, indicating the fast decomposition observed elsewhere (Nowak and Crane 2002), where it is seen that in the first 3 years, around 60% of carbon is released, corresponding to empirical findings for mulched biomass above ground. The index τ indicates the year when the branches died. The release profile is then given as:

$$CO_2 \text{ release profile}_{i,t-\tau} = \text{decomposition rate}_{i,t-\tau} \times CO_2 \text{ release alive}_{it} \quad (13)$$

When the dead branches are burnt, the amount of CO_2 release alive is immediately released. When a tree dies, the entire sequestered carbon dioxide is released in the years ahead. The decomposition of the tree's root and the biomass above ground are considered separately since the decomposition of the root is independent of human actions. Therefore, the CO_2 release from the 2 parts is given as:

$$CO_2 \text{ release root}_{it} = \text{root to shoot ratio}_i \times \text{carbon storage}_{it} \quad (14)$$

and

$$(1 - \text{root to shoot ratio}_i) \times \text{carbon storage}_{it} \quad (15)$$

where *root to shoot ratio*(*i*) is a percentage of a tree's biomass under the ground. There is a 50% probability that a dead tree will be removed from the site.

Given that it is removed, there is a 70% probability that it will be burnt, in which case the release of CO_2 is immediate and given as:

$$CO_2 \text{ release profile}_{it} = 0.7 \times CO_2 \text{ release above ground}_{it} \quad (16)$$

The remaining 30% is assumed to be converted into sustainable products. If the tree is not removed from the site, there is a 40% chance that it will stay untouched (standing) and a 60% probability that it will be mulched. In the first case, the slow decomposition rate is applied (Equation 12) for both root and above-ground biomass, with parameter $k = 5$; while in the second case, the root is still decomposed by the slow rate, while the biomass above ground is decomposed by the fast rate setting parameter $k = 2$. Therefore, the CO_2 release profile of a standing tree is computed as:

$$CO_2 \text{ release profile}_{i,t-\tau} = \text{decomposition rate}_{i,t-\tau}^{\text{slow}} \times \text{carbon storage}_{it} \quad (17)$$

$$CO_2 \text{ release profile}_{i,t-\tau} = \text{decomposition rate}_{i,t-\tau}^{\text{slow}} \times CO_2 \text{ release root}_{it} + \text{decomposition rate}_{i,t-\tau}^{\text{fast}} \times CO_2 \text{ release above ground}_{it} \quad (18)$$

The dead tree can also be replaced with a new tree which is planted at the location where the tree is dead. The replacement will depend on the maintenance project in place. For instance, if the maintenance scope is *M0*, there will not be any replacement; if it is *M1* the tree is replaced with 30% probability, and in the case of maintenance scope *M2*, any dead tree will be replaced.

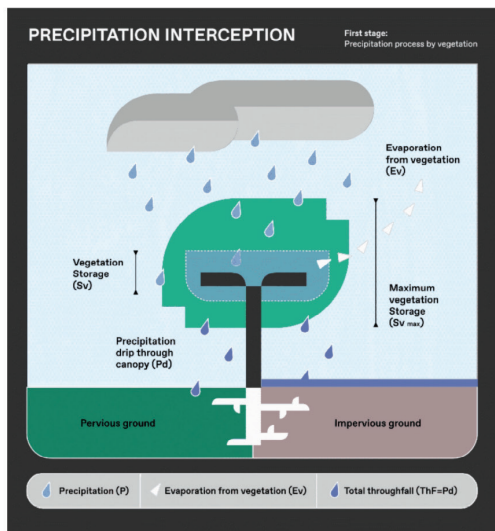
Water Retention

The population dynamic module provides growth projection data as output, which are passed to the impact analysis module (Figure 3) along with the hourly weather data to estimate the ecosystem services. Currently, the module incorporates computations based on existing literature to address water retention, carbon sequestration, and air pollution removal (Wang et al. 2008; Hirabayashi 2013; Castro and Maidment

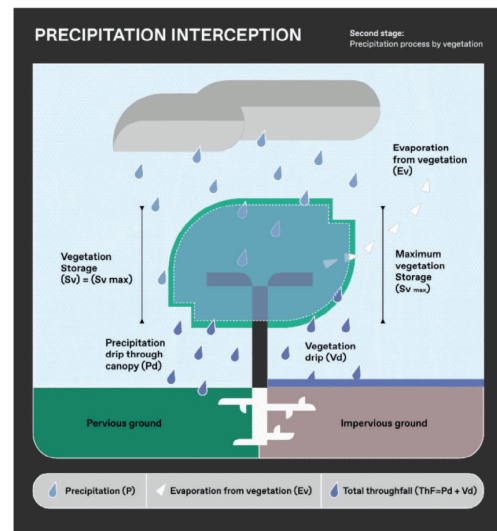
2020; Lin et al. 2020) as well as i-Tree models such as i-Tree Eco, and i-Tree Hydro (United States Department of Agriculture Forest Service, Washington DC, USA)(Ozel and Petrovic 2022). The output from the impact analysis modules on ecosystem services can be further used to update population data and/or NbS design and rerun simulations and recalculate the ecosystem services. Since the nature of the model is stochastic, the simulation can be performed M times over N years, considering different weather

conditions and different probabilities of agents' interaction. The results are then aggregated over 2 dimensions, time and simulation runs, and presented coherently.

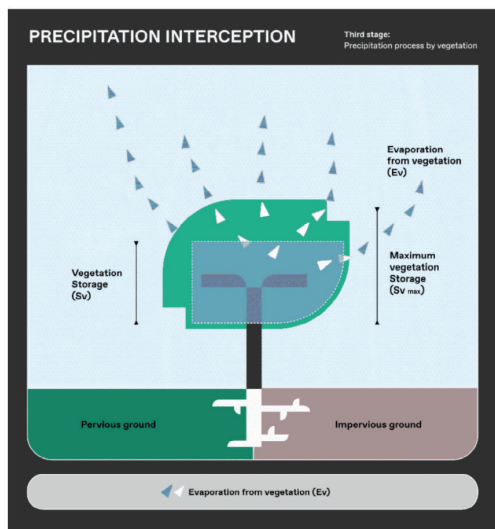
Figure 5 summarises the 3 stages of water retention through panels 5a to 5c. Figure 5a presents the first stage, where the precipitation starts and the tree canopy (vegetation storage [S_v]) still has the capacity to retain the water. A part of the water from the canopy evaporates (E_v) while a small part of the



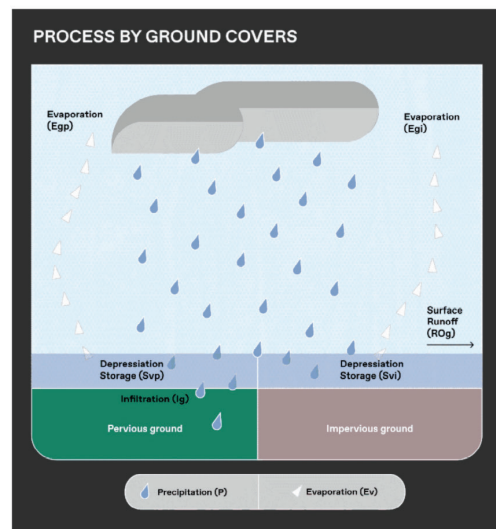
(a) First stage precipitation-evaporation.



(b) Second stage precipitation-evaporation.



(c) Third stage precipitation-evaporation.



(d) Hypothetical scenario.

Figure 5. Precipitation-evaporation dynamic. Panels (a) to (c) depict stages, and panel (d) presents a hypothetical baseline on the process of water run-off in the absence of trees.

precipitation reaches the previous and/or impervious ground under the canopy due to precipitation drip through the canopy (P_d). Figure 5b presents the second stage, where the vegetation storage reaches its maximum capacity $S_v = S_v(\max)$, and the entire precipitation hits the ground. If the rain hits the previous cover, it infiltrates the ground; if it hits the impervious cover, it is considered runoff. The evaporation from the canopy (E_v) continues. Figure 5c shows the third stage when the precipitation stops, and the evaporation from vegetation (E_v) continues until the canopy dries up (vegetation storage $S_v = 0$) or until new precipitation begins.

Figure 5d represents the hypothetical case of the considered site without trees. To trace out the additionality of trees, the following equation calculates the stormwater retention and runoffs for the hypothetical case without trees, along with the regular scenario under the study and calculates the water-related benefits of trees as

$$\text{improvement in water retention} = \text{water retention} - \text{water retention}(\text{hypothetical}) \quad (19)$$

and

$$\text{avoided runoff} = \text{runoff}(\text{hypothetical}) - \text{runoff} \quad (20)$$

Where *improvement in water retention* and *avoided runoff* are net water-related benefits of the trees under the study. The detailed procedure to calculate water retention and runoff are given in (Ozel and Petrovic 2022).

APPLICATION

Scenario Design

This section develops several controlled experiments demonstrating how different portfolios of urban forests can aid long-term flood risk management. The objective of this section is twofold: to present the granularity and flexibility of GUS through several simplified experiments, and to point out how controlled computational experiments within a geo-context can lead to efficient and informed decision-making.

The model is calibrated to match the geo-context of a hypothetical site in the City of Glasgow. Therefore, using the Glasgow weather data over the last 15 years, data on tree species that are native or common, and urban forest typologies observable or applicable in the area, this paper examines the role of species, maintenance scopes, and urban forest typology in the provision of ecosystem services.

Hourly meteorological data from several official weather stations are combined to create controlled weather projections for long-term impact analysis. The weather data is also used to characterise the length of a stochastic tree growth season and to tune the parameters of the evapotranspiration mechanisms.

i-Tree survey Rumble et al. (2015) has provided the tree canopy, species composition and the city-scale tree inventory used in the analysis. High-resolution satellite images are used to identify flood risk zones and potentially effective locations for green infrastructures.

To understand the role of species in providing ecosystem services, 2 species are selected: European ash (*Fraxinus excelsior*) and Port Orford cedar (*Chamaecyparis lawsoniana*). Ash is Glasgow's most common deciduous tree, while cedar is the most common evergreen tree. Following the urban tree categorisation guidelines (Nowak 1996), Woodland, Street, and Park typologies are examined. Each typology is characterised by the density of trees and the percentage of impervious and pervious ground cover. In addition, 3 tiers of maintenance and care for each scenario are investigated. At maintenance Scope-0, there is no human care, while at maintenance Scope-2, state-of-art maintenance is assumed.

Each scenario is identified by maintenance, typology, and species compositions. Nevertheless, the complexity and variability are further reduced to compare the impact of each experiment parameter. In the reported experiments for this paper, the initial hypothetical population of trees are composed of young trees of the same species; they have the same girth (DBH) size and are in good health condition. Besides, within a given typology, trees are planted at equal distances from each other, and they all have the same initial sun and weather exposure. There is no shading due to buildings, hills, or other taller trees. However, one should note that these assumptions can be relaxed to match the heterogeneity and specificity features of a more complex and realistic green infrastructure within the GUS framework. Due to dynamic interactions between trees and their exposure to externalities, initially, homogeneous tree populations gain heterogeneity throughout their life cycle. They compete for canopy space and sun exposure (Coates et al. 2003). Each tree's dieback rate and recovery from a poor or critical health condition depend on its unique history and location.

The configuration described above translates into an experiment set-up composed of 18 different scenarios:

2 (*species*) × 3 (*typology*) × 3 (*maintenance*). Since GUS is a stochastic framework that captures the probabilistic nature of weather and the interaction of trees with each other and the environment, each scenario is run multiple times. Probabilistic variables, such as the recovery chance of a dying tree, are drawn from the underlying probability distribution according to the Monte Carlo method (Metropolis and Ulam 1949), using different seeds for random number generators.

Each tree has a unique identifier and designated spatial coordination depending on its host typology. This hypothetical experiment set-up has 6 different initial tree populations: 2 (*species*) × 3 (*typology*). However, one should note that each scenario and its tree population can be created using a physical site. Then each unique tree in the digital space can be created using monitored features such as girth, height, canopy dimension, health condition, and exact geolocation. In such cases, the population initialisation module of the GUS framework (Figure 3) would enable a practitioner to create a one-to-one representation of an actual site and its digital twin version.

In the following section, this paper presents a demonstrative subset of results from the experiment set-ups relevant to growth patterns, carbon sequestration and release, water retention capacity, and avoided water runoff.

Growth and Impacts

As Figure 3 above suggests, a typical analysis cycle comprises multiple phases. A project planning or policy intervention initiates a scenario design with relevant intervention or control parameters. For instance, as laid out previously, maintenance as an intervention instrument is parameterised with 3 distinctive scopes, while street trees, woodland, and parks characterise types of green infrastructures. A combination of design parameters leads to the identification of a scenario. Then, an initial tree population and site-specific configuration files are then prepared and linked for each scenario. As part of this initialisation process, each tree agent automatically fetches its locality and species-specific base biomass and canopy growth functions from a respective database. In the current version of the model, an individual tree agent holds and keeps track of information on its state of health, girth, canopy height, crown size, the ratio of its crown dieback, rate of recovery from the latest dieback, distance and position from neighbouring trees, its exposure to

light, and the under-canopy ground surface type. Next, each scenario is simulated 100 times. This number can be reduced or increased depending on the variability and required size of data points for statistical analysis. Finally, the data generated through scenario simulation are fed into impact models. Figures 6 and 7 below present exemplary outputs relevant to carbon sequestration and flood avoidance ecosystem services.

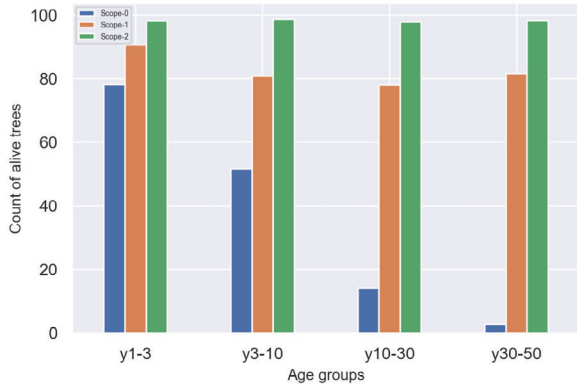
The plots in Figure 8 illustrate how the GUS model demonstrates an urban forest's growth and emergence features at the individual tree agent and population level, revealing the characteristics of a complex system.

Result 1. Heterogeneity Features of the Urban Forest as a Complex System

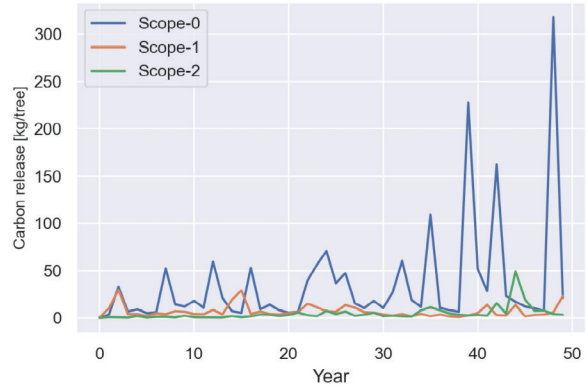
The size distribution plot in Figure 8a is a tree population at year 50 from one selected simulation run out of 100 runs. The histogram gives distribution in tree diameters measured at breast height, typically 1.35 m from the ground. Each of the 100 runs starts with the same population. However, each initially identical population evolves into a distinct urban forest over time. At the very inception of each project (i.e., each run), they all start with a composition of identical trees: a healthy young ash (*Fraxinus* spp.) tree with a diameter of 4.77 cm. The initial uniform distribution transforms its shape over the lifetime of the forest. The size distribution by the end of year 50 reveals the emergence of heterogeneity features of the urban forest as a complex system.

Result 2. The Validity of the Observed Growth Trajectory Over 100 Runs

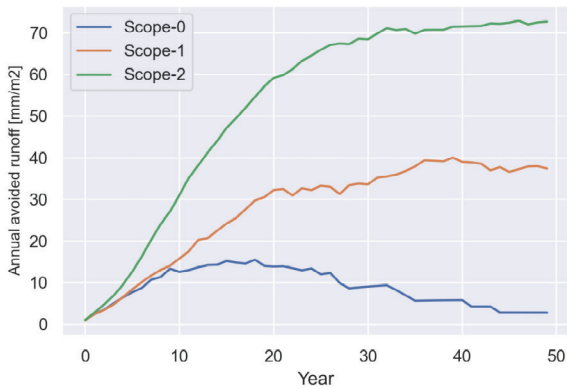
Figure 8b displays the mean net sequestration of 100 runs and the variance. The validity of the observed growth trajectory is examined by running statistical tests in R version 0.1.3 (Marwick and Krishnamoorthy 2019). For instance, in the scenario in Figure 8, a woodland of ash trees with Scope-2 maintenance, the average coefficient of variation (CV) of the sequestration is 5.4% for 50 years; it is 4.1% for the first 10 years and 6.8% for the last 10 years. The solid line is the average sequestration over the total number of planted trees, while the grey band around the line shows its variance over 100 Monte Carlo simulations. Halfway through the simulated time, a healthy part of the tree population reaches maturity and keeps per-tree sequestration performance stable, even though young and under-performing trees are added to populations to replace the dead ones.



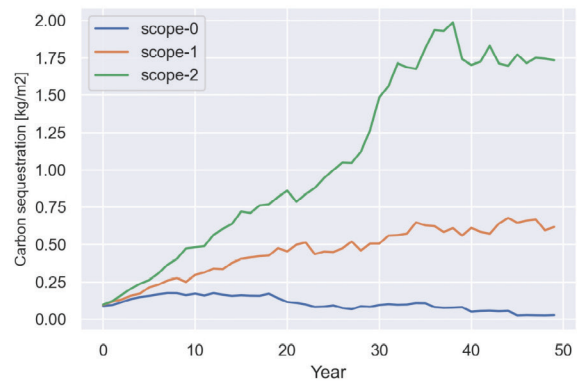
(a) Forest health by maintenance scope.



(b) Carbon release by maintenance scope.

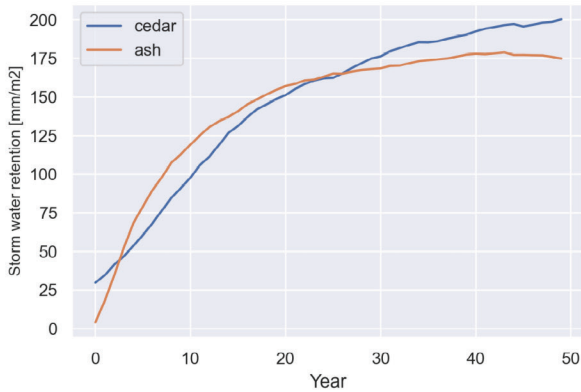


(c) Avoided runoff by maintenance scope.

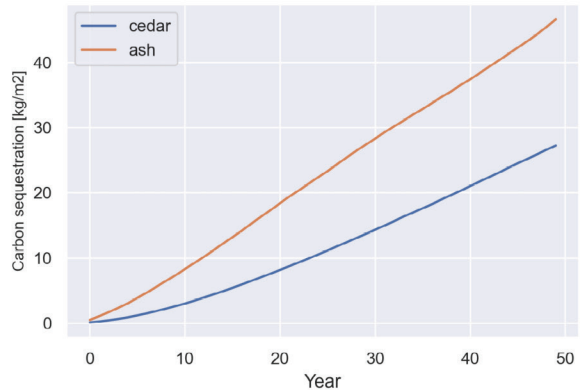


(d) Carbon sequestration maintenance scope.

Figure 6. Results from maintenance scenarios.



(a) Species comparison as of storm water retention.



(b) Species comparison as of carbon sequestration.

Figure 7. Results from species-related experiments.

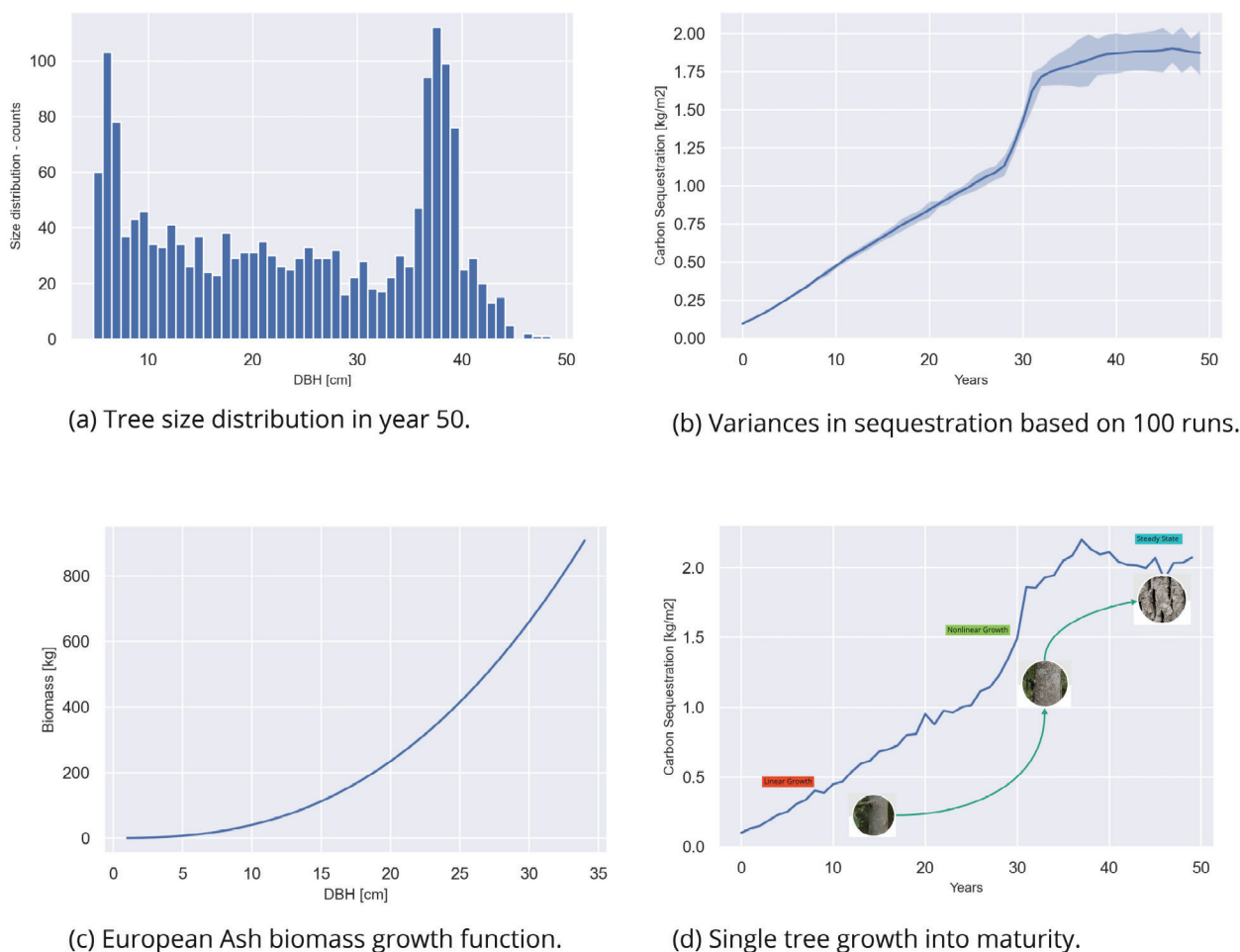


Figure 8. Model dynamics and emergence.

Result 3. The Biomass Function of a Single Ash Tree

The biomass function of a single ash tree in the model, plotted in Figure 8c, is exponential.

Result 4. Growth Trajectory of European Ash Within an Urban Park Has a Non-Linear Transition Phase Toward a Stable Growth in Its Maturity

Figure 8d shows a typical growth trajectory of ash trees within an urban park that has grown into maturity and stayed healthy. The growth pattern, observed through its biomass within the simulations, expresses a linear growth during its youth, followed by an exponential-like transition into steady-state sequestration during its maturity. Empirical studies confirm this non-linear growth pattern of trees (Muukkonen and Mäkipää 2006).

The water-related ecosystem services are calculated hourly and derived from the tree population and weather conditions. In particular, stormwater retention, improvement in stormwater retention, and avoided runoff are calculated for different typologies of European ash and Port Orford cedar based on the 50 years of forecasted weather conditions in Glasgow.

Figure 6 displays several representative analyses where the role of maintenance on the health of the urban forests and their water-related ecosystem services is explored.

Result 5. Good Maintenance Improves Carbon Sequestration and Prevents Storm-Water Run-Off

Figure 6a compares the number of live trees per year under different maintenance scopes. Lower or no maintenance scope leads to a decrease in the number of surviving trees and an increase in the likelihood of

the release of stored carbon stocks. Figures 6b, 6c, and 6d highlight the difference good maintenance can make in avoiding carbon release, improving carbon sequestration, and preventing storm-water run-off.

The current version of GUS estimates carbon release at an individual tree and site level. The model tracks the time-dependent carbon release process taking into account differing release trajectories of dead roots, standing dead trees, mulched parts, and parts that are removed from the site immediately.

Result 6. Poorly Maintained Trees Release Significant Amounts of Carbon Back into the Atmosphere

Controlled experiments show that poorly maintained trees or immediately removed dead tree trunks and roots release significant amounts of carbon back into the atmosphere. Although some of this carbon release is inevitable and necessary for soil regeneration and biodiversity, good maintenance practices can avoid a significant amount of unnecessary release, as shown in plot b of Figure 6.

Result 7. As Cedar Trees Reach Maturity, They Surpass European Ash in Their Ability to Alleviate Stormwater, Proving More Effective after a Span of 25 Years

Figure 7 compares the role of tree species on ecosystem services. The figure shows that European ash, a deciduous tree, can capture more carbon than cedar, an evergreen tree. However, as a cedar tree grows into maturity in the longer term, it becomes more effective in stormwater alleviation. In short, this subset of controlled experiments indicates that species composition significantly impacts the outcomes of ecosystem services. Therefore, the results suggest that given the location and urgency, the decision-makers should consider the species composition of urban forests as a design parameter to optimise their impact.

Good practices in complex system design and analysis require conducting systematic internal and external validation exercises. The internal validation examines how the model responds to changes in weather conditions and other model parameters. For instance, an increase in solar radiation and/or vapour pressure deficit raises the potential evapotranspiration. In addition, the external validation compares results with the outputs of other models in the literature. Table 1 summarises water-related outcomes from the i-Tree report on Glasgow and the results from GUS considering the same set of trees. Columns in the

light background show i-Tree reported data, while columns in the dark background indicate the results from the computational experiments of GUS. This validation exercise selects the most common species in Glasgow, European ash (*Fraxinus excelsior*), and calculates (i) under canopy area using the crown width, (ii) leaf area index (LAI) dividing leaf area (LA) by under-canopy area, (iii) bark area (BA) using trees' diameter at breast height (DBH), and (iv) plant area index (PAI) taking into account leaf-off and leaf-on seasons (Wang et al. 2008). The tree population sample is matched with hourly weather data from Glasgow and potential evapotranspiration is calculated for each tree in each hour. Finally, the yearly potential evapotranspiration (PET) for each tree is provided in the last column of the table, showing that the results match the outputs of i-Tree in the penultimate column.

For certain ecosystem services, such as flood prevention or heat island reduction, the location-specific effect of urban forests can be optimised further by combining insights from GUS with additional geospatial data analysis.

The following section discusses current limitations, ongoing development efforts, and future pathways.

DISCUSSION

The work presented in this paper aims to serve as a framework and a tool for the research community, and as a software product for practitioners both in the public and private sectors. Given its overarching objective, its development process follows good science and software engineering practices.

Validation and Reusability

The model development process follows a recursive cycle of verification, validation, and calibration steps (Law and Kelton 1991). Model verification should assure that the programming implementation of the conceptual model is correct. This process follows typical software debugging and testing exercises. Model validation checks whether the simulation model can accurately mimic real-world tree growth patterns. Model calibration is an iterative process that adjusts model parameters to match the location and scenario-specific requirements.

Biomass growth, carbon release, sequestration, leaf and bulk area estimation, evapotranspiration, and other impact assessment models are based on peer-reviewed scientific literature. The source code and model

Table 1. Validation: water impact of European ash (*Fraxinus excelsior*). The table shows the output for several selected trees, while the entire table includes 109 trees provided by the i-Tree report. In addition, $\Delta(\text{PET})_i = \text{PET}(\text{i-Tree})_i - \text{PET}(\text{GUS})_i$ is calculated, taking into account all 109 trees, and the following results are obtained: $\Delta(\text{PET})_{\text{mean}} = -0.195$, $\Delta(\text{PET})_{\text{median}} = 0.181$, along with t -test statistics = -1.301 and P -value = 0.196 , not rejecting the null hypothesis $\Delta(\text{PET}) = 0$. PET (potential evapotranspiration); DBH (diameter at breast height); BAI (bark area index); LAI (leaf area index); PAI (plant area index).

Plot	ID	Leaf area (m ²)	DBH (cm)	Height (m)	Crown width (m)	Under-canopy area (m ²)	BAI	LAI	PAI	PET (m ³ /yr) – i-Tree	PET (m ³ /yr) – GUS
131	36	2.4	8.5	10.0	1.0	0.8	2.7	3.1	5.8	0.1	0.1
198	26	2.0	7.0	11.5	1.0	0.8	2.4	2.5	4.9	0.1	0.1
37	1	9.1	7.5	6.0	2.0	3.1	0.2	2.9	3.0	0.3	0.4
...
...
198	20	131.8	19.5	14.0	6.0	28.3	0.1	4.7	4.8	4.1	4.0
131	74	12.2	8.8	10.0	2.0	3.1	0.4	3.9	4.2	0.4	0.4
11	3	116.4	16.6	10.0	6.0	28.3	0.1	4.1	4.2	3.7	3.7

specification documents are made open to enable transparency, replicability of the analysis, and ease of adoption of the framework.

The GUS framework modules are architected to complement or extend the functionality of existing tools, such as the i-Tree species tool. When the data from a granular tree detection and recognition facility feeds GUS, it functions as a digital twin version of the actual site. In such a use case, GUS serves as a virtual laboratory.

Uncertainty and Transparency

Limitations and errors are inherent to any modelling exercise on complex systems, which mandate

transparency about these sources of uncertainty and how they affect measurements. Figure 9 depicts potential sources of errors in the design, calibration, and interpretation of modelling outputs. These uncertainties have further implications on outcome-driven valuations and financing strategies in planning and maintaining green infrastructures. There are 3 potential sources of divergence from actuality:

Modelling: The models diverge from reality. As discussed earlier in this paper, continuity in verification, validation, and calibration cycles may reduce the divergence or help make the divergence explicit and quantifiable.

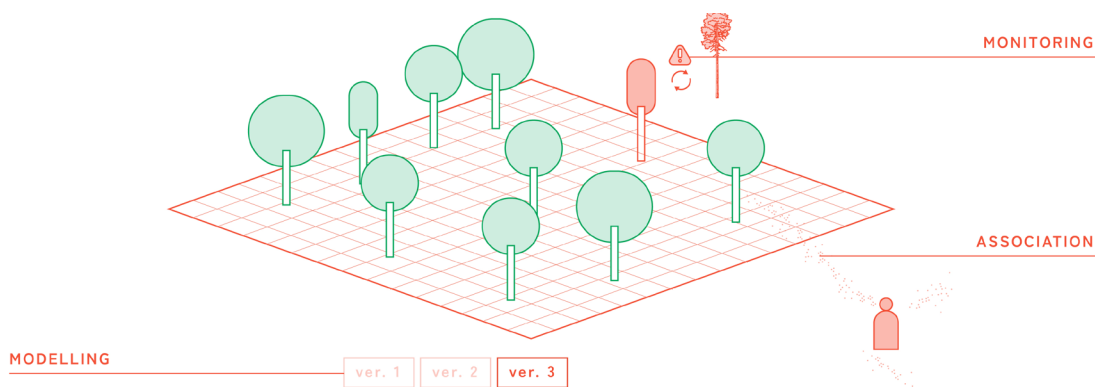


Figure 9. Potential sources of errors or uncertainties.

Monitoring: The data points may not represent reality accurately enough. For example, human monitoring can have lower accuracy than a remote sensor. In some cases, remote sensor devices fail to capture accurate enough estimates or inject additional errors. Recurrent data validation practices need to be integrated into impact assessment processes.

Association: An urban forest's contribution to removing carbon dioxide from the atmosphere can be fully quantified. However, its contribution to other outcome types, such as mental health, may not be effectively isolated from other socio-economic factors. For instance, to what extent fewer mental health cases can be only associated with residential proximity to the parks? In this case, decoupling the additionality of urban forests from the contribution of other underlying sociodemographic factors requires extensive and detailed empirical studies. Future extensions of GUS aim to reduce this gap by serving as a computational laboratory to experiment and observe other sociodemographic effects. Its underlying agent-based paradigm enables it to scale its complexity by adding human agents, considering mobility and housing choices concerning their sociodemographic profiles.

The model implementation is open-sourced, along with detailed model specifications (Ozel and Petrovic 2022) and code documentation. It enables interrogation and replicability by other practitioners and researchers and hence, continuous improvement in calibration and interpretation, which in return, closes the gap between the model and the reality.

Further Directions

Further extension of the GUS framework will maintain its modular architecture while adding new components and features. Modularity provides flexibility in turning system components on and off depending on the context and its required level of granularity and complexity.

A generic contagion model of infectious tree diseases is under development. Once validated, it will be activated and calibrated for the urban forests where there is a likelihood of ash dieback cases, a fungal disease of ash trees in Europe characterised by leaf loss and crown dieback in infected trees (Musolin et al. 2017). This feature should help tree officers to gain insight into contagion patterns and restore spatial compositions of urban trees with more resistant species.

In addition to carbon and water-related modules that are presented in this paper, impact estimation and prediction models on the other ecosystem services will be made available as application programming interface (API) endpoints. The access will enable other researchers and practitioners to configure or monitor location-specific urban forest typologies and gain insights into their effect on air pollution removal, heat island reduction, energy-saving, and mental health improvements.

Future extensions of GUS will keep following theoretical and practical guidelines of the augmented collective intelligence (ACI) that have been developed elsewhere for civic initiatives (Ozel and van der Hoog 2020). ACI accommodates trees, humans, and other non-human actors and their interactions using artificial intelligence (AI). As containers of AI, agent-based models explore counterfactual scenarios, taking data from the physical environment to simulate potential outcomes, which can be used to help decision-making in the real world. Thus, augmented collective intelligence emerges from interacting with people, technology, and nature in the physical world and the digital environment.

CONCLUSION

This paper presented GUS, an innovative and practical scenario analysis framework for green infrastructures. The paper analyses several urban forest typologies within Glasgow's context, examining how different maintenance strategies may affect tree population dynamics as well as the provision of ecosystem services.

The results show emergent behaviours can be discovered without explicitly being coded into the simulation. The analysis confirms that building and using agent-based models is an essential tool for understanding complex systems aspects of biological, ecological, and urban planning issues.

A subset of the computational experiments provided in the paper shows that poorly maintained trees or immediately removed dead tree trunks and roots release significant amounts of captured carbon. Although some of this carbon release is inevitable and is necessary for soil regeneration and biodiversity, a large part of unnecessary release can be avoided by improving maintenance practices. Another subset of the computational experiments indicates that species composition significantly impacts the outcomes

of ecosystem services and that impact measurements for each species need to be considered. For example, as cedar trees reach maturity, they have been found to surpass European ash in their ability to alleviate stormwater, proving more effective after a span of 25 years. Depending on the location and the urgency of particular ecosystem services, this paper suggests that decision-makers should consider the species composition of urban forests as a design parameter.

Using the current version of GUS, practitioners can carefully design a new urban forest or explore the impact of an existing one. The urban forest can encompass various typologies, comprising a diverse range of species, while its growth and benefits can be simulated over any desired timeframe. The growth of the urban forest considers the health of individual trees and their influence on neighbouring trees, resulting in population growth through interactions between them. Practitioners can delve into each ecosystem service, tailoring the level of granularity and complexity on a project-by-project basis. Additionally, the modular nature of the framework facilitates expansion of ecosystem services and integration with other existing tools in the field.

The science-based scenario design and impact analysis models presented in this paper can also be extended as an open-source software toolset for researchers, practitioners, and policymakers. Its use also puts forth an economic case where the benefits of urban forests far exceed the costs, making a compelling argument for maintaining a green infrastructure with carbon, water, health, energy, and economic and social benefits as a basis for co-investments.

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Bulent Ozel (corresponding author)
Lucidminds AI
Amsterdam, Netherlands
bulent@lucidminds.ai

Marko Petrovic
Lucidminds AI
Amsterdam, Netherlands
Department of Economic Analysis
University of Valencia
Valencia, Spain
marko@lucidminds.ai

Conflicts of Interest:

The authors reported no conflicts of interest.