

Article

Data-Driven Optimization of Urban Green Infrastructure Through Parametric Design: Environmental Performance and Plant Selection

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Abstract

Urban green infrastructure design faces growing challenges posed by climate change and urbanization, necessitating precise, site-specific plant selection. Existing approaches rely on general guidelines and lack integration of environmental data with reproducible decision-making methods. This study proposes a data-driven parametric framework combining Grasshopper with environmental analysis plugins (Ladybug, Honeybee, Gismo) and a custom rule-based plant suitability model. A botanical database of over 100 species was developed to encode environmental requirements, growth characteristics, and maintenance parameters. The system processes site-specific solar radiation, soil conditions, microclimate, and water availability to evaluate plant–environment compatibility and generate spatially explicit planting configurations. The framework was validated in an urban case study, demonstrating improved alignment between plant requirements and site conditions and reduced selection time compared to conventional approaches. Integrating environmental data with parametric tools supports more transparent and reproducible decision-making in climate-responsive urban vegetation design.

Keywords: urban green infrastructure; parametric design; plant selection; environmental analysis; climate-responsive design; urban vegetation planning

1. Introduction

Architectural programming has undergone significant transformations driven by advances in digital technologies and the growing emphasis on sustainable design [1]. In this context, optimization techniques and artificial intelligence (AI) are increasingly employed to address complex design challenges with improved precision and efficiency [2]. Among these challenges, integrating greenery into architectural and urban design has become particularly important. Vegetation is now recognized not only for its aesthetic and ecological value, but also for its influence on microclimatic conditions [3], user comfort, and building performance [4]. The effective incorporation of green infrastructure requires a multi-scalar, interdisciplinary approach that combines knowledge of plant-specific environmental requirements with architectural and functional constraints [5]. Although numerous studies highlight the environmental benefits of urban vegetation, existing approaches to plant selection are often based on generalized guidelines and lack integration

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with site-specific environmental data and computational decision-support systems. As a result, plant selection remains inconsistent, difficult to reproduce, and insufficiently adapted to local microclimatic conditions [6].

This study addresses this gap by proposing a data-driven parametric framework that integrates environmental analysis with an automated plant selection system. The main innovation of this research lies in combining a structured botanical database, site-specific environmental data processing, and algorithmic evaluation of plant–environment compatibility within a unified parametric workflow. Parametric design tools enable architects to develop environmentally responsive and adaptive design solutions [7]. At the same time, architectural factors such as building orientation, materiality, and programmatic requirements significantly influence vegetation performance and spatial integration [8]. By systematically linking these variables, computational approaches can support more informed and consistent design decisions [9].

Recent studies highlight the growing role of algorithms in architectural practice, particularly in spatial optimization, environmental analysis, and generative design [10]. These approaches frame environmental constraints as drivers of design processes rather than limitations [11]. Building on this perspective, the present study integrates machine-readable plant data into a parametric system that enables dynamic plant selection based on site-specific microclimatic conditions. Existing computational approaches to vegetation planning can be broadly grouped into three categories: (i) rule-based expert systems that encode horticultural heuristics but lack explicit environmental data coupling; (ii) generic planting guidelines and species lists that are not calibrated to site-specific microclimatic conditions; and (iii) emerging AI-assisted greening tools that optimize spatial layout but rarely formalize plant–environment compatibility as a reproducible, quantifiable function. Each of these approaches lacks at least one of the two properties this study targets simultaneously: environmental data specificity and algorithmic reproducibility. This gap motivated the proposed framework. The proposed framework is based on an extensive dataset of plant species and environmental parameters. The database includes information on solar exposure, soil conditions, moisture levels, growth behavior, and maintenance requirements [12,13]. These data are structured to enable algorithmic processing and precise matching between plant characteristics and environmental conditions [5,14].

Optimization methods play a key role in evaluating multiple variables, such as solar exposure, soil properties, and temperature ranges, while balancing ecological and architectural requirements [15]. The system is implemented in a parametric design environment, enabling real-time interaction between environmental data and spatial configuration [16,17]. Environmental analyses, including microclimatic conditions, climatic variation, and energy performance, further support the decision-making process [3,9,18]. Urban challenges, such as the Urban Heat Island effect, highlight the need for more effective, data-driven greening strategies [19,20]. Vegetation has been shown to reduce urban temperatures through shading and evapotranspiration [4,21], improve air quality, and support biodiversity [4,21]. However, the effectiveness of these interventions depends strongly on appropriate species selection and placement, which remain insufficiently supported by existing methods [6].

To address this, the framework incorporates environmental analysis tools and multi-criteria decision-making methods to improve the accuracy and transparency of plant selection processes [22]. By translating qualitative plant characteristics into measurable parameters, such as solar exposure, soil pH, and growth conditions, the system enables precise evaluation of plant–environment compatibility [15,23]. This approach aligns with performance-oriented design principles, where environmental factors actively inform design decisions [1]. In this context, vegetation is treated not as a passive element but as an active component of architectural systems, contributing to environmental performance, user

well-being, and urban resilience [2,4,7]. The framework also allows for the inclusion of user-defined criteria, supporting flexible, context-sensitive design processes [24]. Extensive research has confirmed the environmental, social, and economic benefits of urban greenery, including improved mental health [25,26], enhanced learning environments [27], and increased property values [28]. Additional benefits include noise reduction, improved thermal insulation, and improved stormwater management through green roofs and vegetated systems [29,30]. These findings further underscore the need for systematic, data-driven approaches to vegetation design in urban environments.

This study is guided by one primary and one secondary objective. The primary objective is to develop and validate a reproducible, data-driven algorithm for site-specific plant selection that integrates a structured botanical database with environmental simulation. The secondary objective is to assess the microclimatic performance of the resulting vegetation configuration in a real case study. Accordingly, the study addresses two research questions: (1) can environmental and botanical data be systematically encoded to support reproducible, site-specific plant selection; and (2) does the resulting vegetation configuration produce measurable microclimatic benefits at the case-study scale?

2. Materials and Methods

2.1. Research Objective and Workflow Overview

The primary objective of this study was to develop and evaluate a computational tool implemented as a McNeel Rhinoceros 3D (ver. 8.6) plug-in that enables automated selection of plant species based on site-specific environmental conditions. A secondary objective was to assess the microclimatic impact of the selected vegetation (Figure 1).

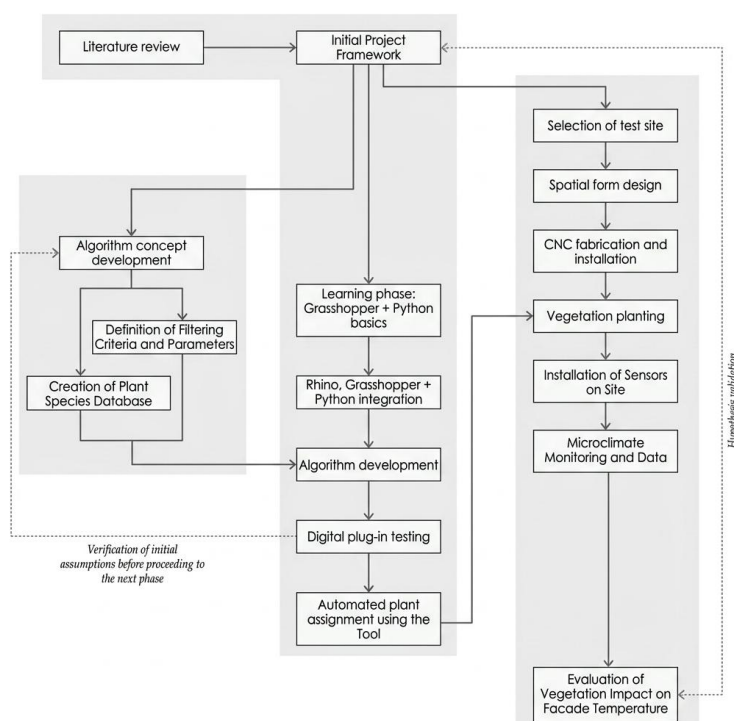


Figure 1. Workflow of the proposed methodology.

The methodological framework consists of four sequential stages. The initial stage involved a comprehensive literature review to establish the current state of knowledge on vegetation-microclimate interactions in urban environments. Based on this review, a conceptual model of the plug-in was defined, including key classification criteria for plant

species, such as light requirements, soil moisture tolerance, resilience to anthropogenic stressors, and adaptability to urban conditions. This was followed by the development of a dedicated plant species database that compiled detailed information on plant characteristics and habitat preferences. The database forms the basis for algorithmic selection. The plug-in was implemented in the Grasshopper visual programming environment, with Python (ver. 3.12) scripts used to manage conditional logic and selection procedures. A core component of the system is dynamic solar radiation analysis, which generates a high-resolution spatial distribution of solar exposure across the design surface. Based on the resulting solar zones, plant species are matched to localized environmental conditions. Subsequently, the tool was applied to a case study site, where a spatial structure was developed and populated with vegetation generated by the algorithm.

In the final stage, the feasibility of the proposed solution was verified through physical implementation and empirical measurements. The final plant list was manually filtered based on market availability to enable implementation. The site was instrumented with environmental sensors to monitor key microclimatic variables, including air temperature and relative humidity near the vegetation.

2.2. Environmental Data Collection and Plant Database

The integration of greenery into architectural design requires a structured, multi-layered process of environmental data collection and analysis to ensure ecological viability under site-specific conditions. The initial phase involved acquiring meteorological and climatic data, including mean and extreme air temperatures, solar radiation, humidity patterns, and soil pH. These data were obtained from national meteorological institutes, global climate databases, and local weather stations to ensure both accuracy and geographic relevance. Soil analysis constituted an additional layer of evaluation. Site-specific data on soil composition, pH, texture, nutrient content, and drainage capacity were collected to determine species compatibility. These parameters were cross-referenced with plant-specific soil preferences stored in the database.

The plant species database includes a wide range of biological, ecological, and morphological attributes, such as mature height, canopy spread, growth habit, leaf and flower characteristics, phenology, light and water requirements, toxicity, allergenic potential, and root system architecture. These parameters define a multi-criteria decision space used by the selection algorithm. Plant selection is based on the compatibility between environmental conditions and species requirements. For each species, suitability is evaluated using a weighted matching approach, in which environmental parameters (e.g., solar exposure, soil conditions, humidity) are compared with species-specific thresholds and preferences. Species that satisfy the most criteria or achieve the highest compatibility score are prioritized. For example, shade-tolerant and moisture-adapted species are assigned to low-light, high-humidity zones, whereas drought-resistant and heliophilic species are allocated to areas with high solar exposure. A key validation mechanism in the selection process is climatic suitability analysis, which is based on the assumption that species with a history of successful cultivation in a given region are more likely to survive in the long term.

Accordingly, the current version of the database is limited to species native to or well-adapted to temperate-transitional climate zones, consistent with the study's geographical context. The current database comprises 112 species, each characterized by 14 parameters spanning light, soil, moisture, morphological, allergenic, and maintenance attributes. Future development will incorporate automated climate filtering based on geolocation, enabling the system to exclude species incompatible with specific global climate zones. The algorithm supports filtering based not only on environmental parameters but also on user-defined design criteria, including maintenance requirements, aesthetic objectives, and bi-

odiversity targets. In its current form, the maintenance parameter includes pruning frequency, irrigation needs, susceptibility to pests and disease, and expected lifespan under urban stress conditions, stored per species alongside the environmental compatibility attributes described above, rather than treated as a secondary post hoc filter. Given the dynamic nature of botanical knowledge and the continuous introduction of new cultivars, the database is currently updated manually using verified sources. While this ensures high data reliability, it limits scalability. To address this limitation, future development will incorporate an AI-assisted data expansion mechanism. A natural language processing (NLP) model will be used to extract structured information from digital plant databases, scientific literature, and nursery catalogs. In addition, image recognition techniques can be applied to derive aesthetic attributes from visual data directly. This approach enables continuous database expansion and improves the system's long-term adaptability without requiring constant expert input. By integrating empirical environmental data, structured botanical knowledge, and computational filtering, the tool supports a systematic and context-aware approach to vegetation design.

Beyond biophysical compatibility, species selection can also be informed by ecosystem-service provisioning capacity, for example, pollinator support, carbon sequestration potential, or stormwater retention. Incorporating such functional criteria, as demonstrated in recent ecosystem-assessment frameworks applied to land-use planning [31], represents a natural extension of the present database structure and is discussed further in Section 4.

2.3. Optimization Algorithm and System Architecture

The developed optimization algorithm supports architects and urban designers in selecting appropriate plant species and determining their spatial distribution within architectural and urban environments. The system follows a data-driven approach that enables context-sensitive and ecologically consistent vegetation integration based on environmental and spatial parameters. The algorithm's architecture is modular, combining environmental filtering, spatial analysis, user-defined constraints, and real-time visual feedback. Each module performs a discrete set of tasks while contributing to the overarching goal of optimizing vegetation placement from both ecological and design perspectives.

The Environmental Filtering and Species Selection Module (Figure 2) performs the environmental filtering process. This module evaluates solar radiation across the site using dynamic simulation. Each spatial unit is classified according to solar exposure (e.g., full sun, partial shade, full shade), and this classification is matched with species-specific light requirements stored in the plant database. As a result, heliophilic species are assigned to high-exposure zones, while shade-tolerant species are allocated to areas with limited light.

In parallel, the algorithm evaluates soil conditions, with particular emphasis on pH levels. User-defined thresholds, introduced via the interface, are compared with species-specific tolerance ranges. This ensures compatibility between selected vegetation and site conditions. The spatial allocation process is based on plant morphology and growth parameters. Using data such as mature height, canopy spread, and root depth, species are classified into functional groups (e.g., trees, shrubs, herbaceous plants). The Space Definition Module determines the maximum number of plants that can be placed within a given area. This is achieved by applying buffer zones derived from plant dimensions and growth behavior, thereby preventing overcrowding and minimizing interspecies competition.

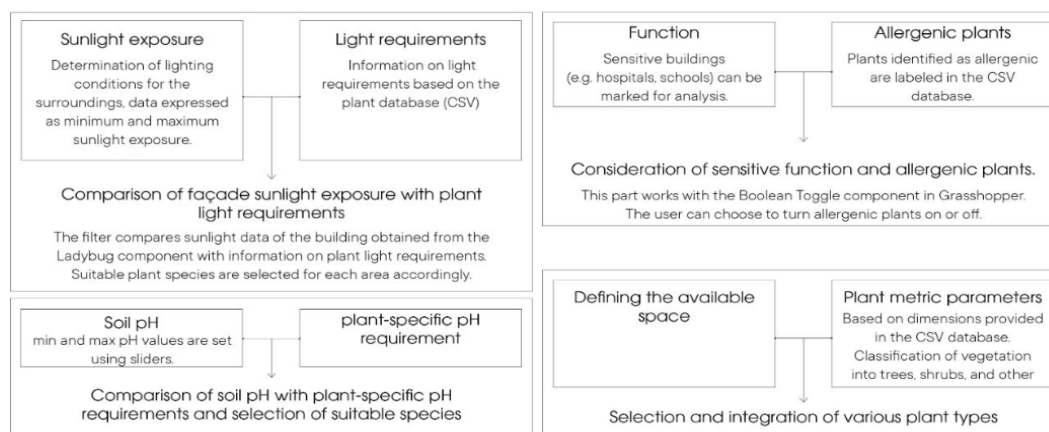


Figure 2. Environmental filtering and species selection module.

Health-related constraints are incorporated through an Allergenic Risk Filter. The system identifies sensitive zones (e.g., schools, hospitals, residential areas) and compares them with a predefined list of allergenic species. Depending on project requirements, designers can include or exclude such species from the selection process. To support interpretation of the results, the system includes a visualization module that translates environmental and biological data into simplified graphical representations. Plant species are represented using geometric primitives (e.g., spheres and cylinders) corresponding to their mature form and spatial footprint. This abstraction enables rapid assessment of spatial relationships and potential conflicts.

Additionally, plant types are color-coded to improve readability and facilitate the evaluation of spatial distribution and biodiversity. The visualization operates within a grid-based spatial framework, supporting consistent placement logic and facilitating implementation. The visual representation is designed to enhance usability by reducing cognitive load through simplified geometry, standardized color schemes, and structured spatial organization. This approach improves user comprehension and supports efficient decision-making during the design process.

2.4. Spatial Optimization and Selection Algorithm Formulation

The proposed optimization algorithm discretizes the design region into a uniform grid of cells and evaluates plant suitability for each spatial unit based on environmental constraints. The analyzed region is defined as a bounded domain $A \subseteq \mathbb{R}^2$, which represents the spatial extent of the project area.

Let $P = \{P_1, P_2, \dots, P_n\}$ denote the set of available plant species. Each P_i describes one species:

$$p_i = (l_i, s_i, h_i, a_i, \dots)$$

where l_i represents light requirements, s_i represents soil pH tolerance, h_i represents moisture/edaphic preferences, and a_i represents allergenicity level.

The objective of the algorithm is to determine a subset $S \subseteq P$ and assign spatial positions $B = \{B_1, B_2, \dots, B_{|S|}\}$, where each $B_i \in A$. Each selected species is mapped to a spatial location that satisfies its environmental compatibility constraints.

For each grid cell $c \in A$, environmental parameters are evaluated using simulation-based inputs. Solar radiation is computed using Ladybug sun-vector analysis, while soil and allergenicity constraints are applied as filtering conditions. A species p_i is considered feasible for cell c if the following condition is satisfied:

$$f(p_i, E_c) = 1$$

where E_c denotes the environmental state of cell c , and f is a binary compatibility function based on threshold matching of environmental variables.

The final selection set S is obtained by aggregating all species satisfying local conditions across the discretized domain, and spatial allocation B is derived accordingly.

The computational complexity of the algorithm depends on the number of species n , the spatial domain area A , and the grid resolution r . Assuming uniform discretization, the number of evaluated cells scales as A/r^2 , resulting in the following time complexity:

$$O\left(n \cdot \frac{A}{r^2}\right)$$

In the present implementation, the compatibility function f applies a weighted-threshold scheme in which each environmental variable (solar exposure, soil pH, moisture) contributes a binary pass/fail score against species-specific tolerance ranges; a species is only retained for a cell if it satisfies all hard constraints (light and soil pH) and at least 70% of soft constraints (moisture, allergenicity, maintenance). This threshold value was set empirically during system calibration and is exposed as a user-adjustable parameter. This formulation reflects the interaction between dataset size and spatial resolution. It is assumed that environmental preprocessing steps, such as solar radiation simulation, are performed before the selection algorithm is executed and are therefore excluded from runtime estimation.

2.5. Computational Implementation in Grasshopper

The theoretical model was implemented as a parametric tool using Grasshopper for Rhino 3D. Grasshopper provides a node-based visual programming environment that enables real-time processing of geometric and environmental data, making it suitable for integrating simulation outputs with spatial design logic (Figure 3). The implementation integrates environmental datasets, plant information, and spatial geometry within a unified computational workflow. Plant species data are stored in a structured CSV database containing key parameters, including light requirements, soil pH tolerance, mature size (height and canopy spread), and allergenic potential. This dataset serves as the input for the selection algorithm described in Section 2.4. Spatial and contextual data are generated using the Gismo plugin, which enables geolocation of the site via coordinates or shapefiles and allows import of urban context data from OpenStreetMap. Environmental analysis is further supported by Ladybug Tools, which processes EPW climate data to compute solar exposure using sun-path and direct-sun-hour simulations. In addition, Honeybee is used to generate surface temperature maps for assessing urban heat island (UHI) effects.

The core selection logic was implemented in Python using the GhPython component. The script receives input data, including boundary geometry, grid resolution, solar radiation values, soil pH constraints, and the plant database. The design region is discretized into a uniform grid, and each cell is evaluated against species-specific environmental requirements. For each cell, a filtering operation is applied to identify all plant species that satisfy local conditions. If multiple species meet the same criteria, a stochastic selection function is applied to introduce variability and improve biodiversity distribution.

The algorithm's output is a spatial map of selected plant species, represented in the Grasshopper environment as geometric primitives. Vegetation is visualized using simplified forms: spheres represent canopy extent, while vertical cylinders approximate plant height. A categorical color-coding system distinguishes plant types (trees, shrubs, and groundcover species), and textual labels provide species-specific information. This visualization framework enables designers to interpret spatial patterns and ecological distributions without direct interaction with raw numerical datasets, supporting an intuitive design workflow.

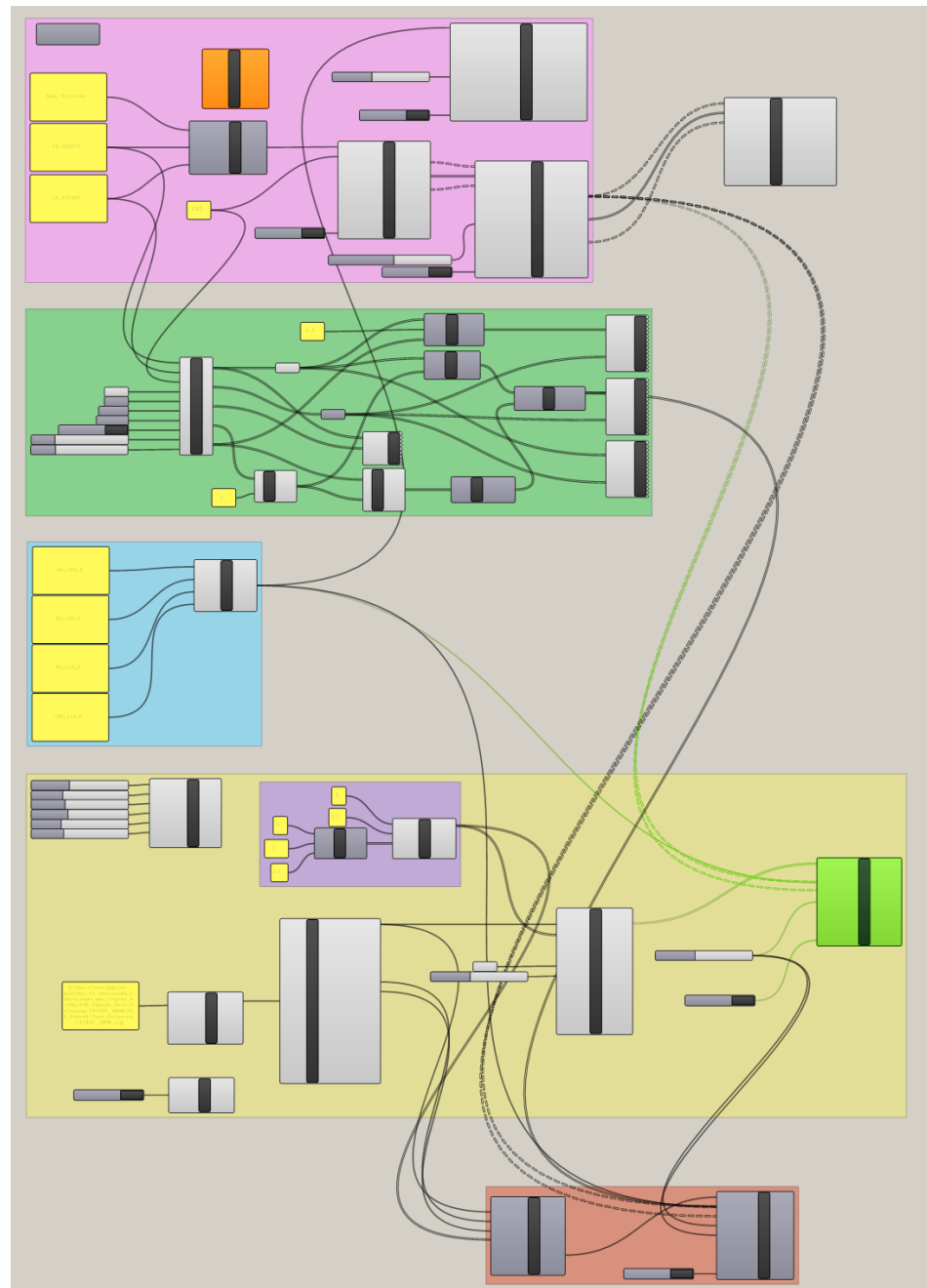


Figure 3. Grasshopper implementation of the optimization algorithm.

2.6. Case Study and System Validation

The developed plugin was evaluated at a selected site on the campus of Gdańsk University of Technology, in a courtyard adjacent to the Faculty of Architecture (Figure 4). The site is characterized by heterogeneous solar exposure due to surrounding building massing, providing a suitable test environment for assessing the algorithm's spatial differentiation capabilities. This site was selected as it is representative of the dense, mid-rise urban courtyard typologies common across European campus and residential blocks, which are characterized by partial building enclosure and mixed solar exposure gradients. Validation was conducted at a single site and therefore constitutes an exploratory rather than a generalizable benchmark; extension to additional urban typologies is identified as a priority for future work. The system successfully assigned plant species to spatial zones based on calculated solar radiation levels, confirming the proper operation of the environmental filtering mechanism and the algorithm's ability to adapt to site-specific conditions.

To further assess environmental performance, thermal simulations were conducted using the Honeybee plugin. The initial results indicated a mean surface temperature reduction of 1.8 °C with a range of 0.8 to 4.0 °C in areas shaded by the proposed vegetation compared to unshaded reference zones (Figure 5), suggesting that implementing data-driven planting strategies can help mitigate Urban Heat Island (UHI) effects at the microclimatic scale.

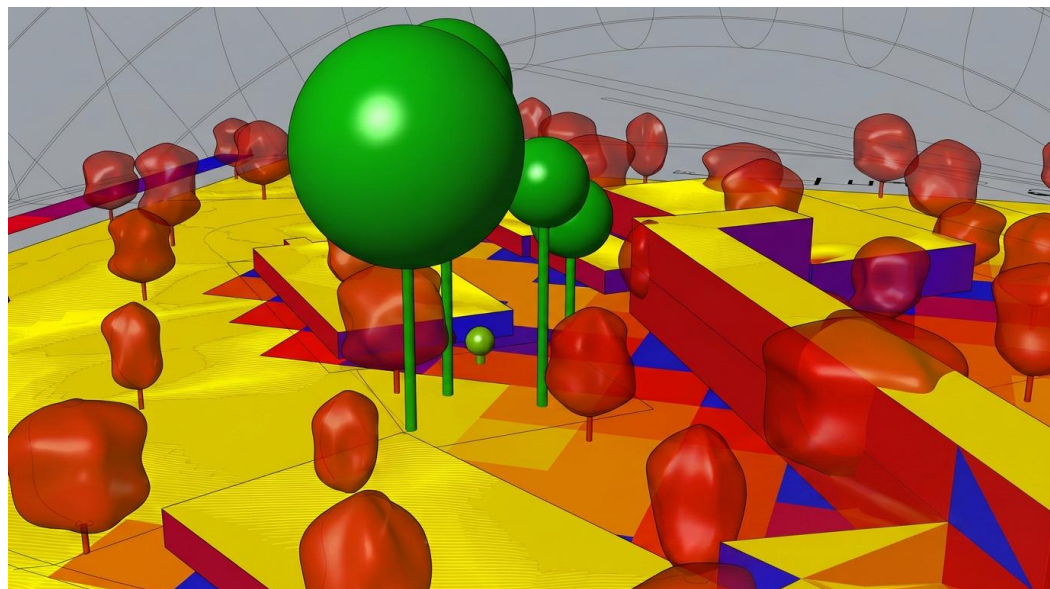


Figure 4. Case study site at the campus of Gdańsk University of Technology.

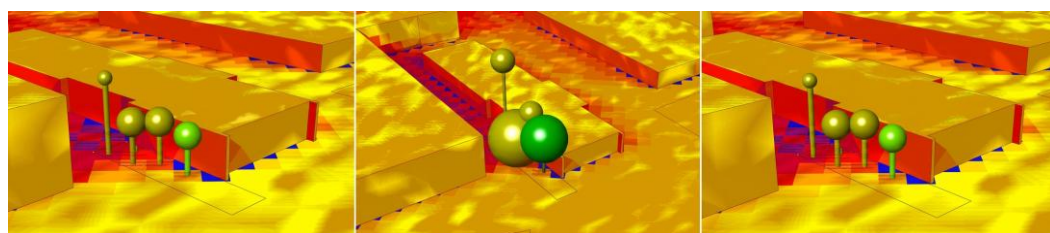


Figure 5. Thermal simulation results showing surface temperature distribution with proposed vegetation.

2.7. Design Evaluation and System Performance

The developed plugin was evaluated using a combination of simulation-based testing and scenario analysis to assess its robustness under varying environmental and design conditions. The evaluation was conducted within Rhino 3D using integrated environmental simulation tools, ensuring consistency with the computational workflow described in the previous sections. The system's performance was tested across multiple environmental scenarios, including variations in solar exposure, seasonal changes in the sun's path, building orientation, and urban density configurations. For each scenario, the algorithm dynamically recalculated plant selection and spatial allocation, allowing for assessment of its adaptability to changing site conditions. To further evaluate system stability, sensitivity analysis was conducted to identify the most influential input parameters affecting plant selection outcomes. These included solar radiation thresholds, soil pH thresholds, and spatial density constraints. The analysis enabled quantification of how variations in input parameters affect the consistency of species assignment and spatial distribution patterns.

In addition, a validation procedure was performed to verify the reliability of the computational model. This included comparing algorithm outputs under controlled environmental conditions with expected ecological constraints derived from plant database re-

quirements. The goal of this step was to ensure logical consistency between environmental inputs and species selection outputs. To support evaluation under realistic conditions, simulation tools integrated with Rhino 3D (Rhinoceros) were used to visualize system behavior in a spatial context. These simulations enabled assessment of whether generated plant distributions remain feasible under changing geometric and environmental constraints. The prototype scenario was developed to test system behavior across the complete design pipeline, from environmental inputs to spatial plant allocation. The results of this scenario confirmed that the system maintains functional consistency across different scales and levels of environmental complexity, supporting its applicability in early-stage parametric landscape design workflows.

3. Results

The developed prototype system was tested in a real-world urban scenario to evaluate its performance in generating site-specific plant selection strategies for building façades. The input parameters included solar radiation data, façade orientation, available planting zones, and microclimatic conditions derived from environmental analysis tools. The algorithm successfully processed these multidimensional inputs and generated spatially explicit vegetation proposals tailored to individual façade zones. A key observed outcome of the system was its ability to differentiate between façade areas with varying degrees of environmental exposure clearly. High-solar-exposure zones were consistently assigned heliophilic and drought-tolerant species, while species with lower light requirements and higher humidity tolerance populated shaded or partially shaded zones. This spatial differentiation emerged directly from the environmental filtering logic embedded in the algorithm, demonstrating its sensitivity to microclimatic variability within a single architectural object. The optimization process generated multiple alternative vegetation configurations for each analyzed site condition. These configurations were automatically ranked using a multi-criteria evaluation scheme that considered shading efficiency, spatial feasibility, ecological compatibility, and alignment with architectural constraints. Although no external weighting system was imposed, the algorithm internally balanced environmental constraints with geometric limitations of façade surfaces, leading to solutions that were both ecologically appropriate and spatially realistic.

One of the most important outcomes of the system was the ability to produce diverse yet consistent design alternatives. The generated solutions included combinations of climbing vegetation systems, modular green wall components, and container-based planting strategies. Each solution varied in density, vertical distribution, and plant typology, enabling flexible adaptation to diverse architectural contexts. Therefore, the system did not converge on a single optimal solution but instead produced a ranked set of feasible design scenarios. Thus, it can be interpreted as a design support tool rather than a deterministic solution generator. From a computational perspective, the system demonstrated stable performance across multiple iterations of environmental input changes. Adjustments in façade orientation, solar access, or spatial constraints consistently led to predictable changes in vegetation distribution. This indicates that the algorithm is robust to input variations and maintains logical consistency across varying design scenarios. Environmental performance was evaluated through simulation-based analysis using integrated thermal modeling tools (Honeybee). The simulations indicated that vegetation placement reduced surface temperature accumulation in high-solar-exposure zones. This cooling effect was primarily associated with shading provided by plant canopy structures and secondary evapotranspiration processes. Although the study does not quantify energy savings in absolute values, the spatial distribution of thermal reduction zones clearly corresponded with vegetation density and exposure levels.

The simulation outputs further revealed that cooling effects were not uniform across the façade but instead exhibited localized intensity depending on plant type and positioning. Climbing vegetation systems demonstrated stronger façade-adjacent cooling effects, while container-based systems contributed more to localized microclimatic moderation at the pedestrian level. This differentiation suggests that plant typology plays a significant role in the spatial distribution of environmental benefits. To support simulation results, limited in situ measurements were conducted using environmental sensors placed in vegetated and non-vegetated zones. These measurements recorded variations in air temperature and relative humidity over time. The observed trends were consistent with simulation outputs, particularly in identifying cooler microclimatic zones associated with vegetation. The initial monitoring campaign spanned over 14 consecutive days in three vegetated and three non-vegetated control zones. While this dataset is limited in temporal scope and site number, it provides supporting quantitative evidence for the validity of the algorithmic predictions and is presented as a proof-of-concept validation rather than a statistically generalizable result. An additional observed outcome of the system was the significant reduction in design iteration time. Compared to traditional manual plant selection workflows, the algorithm enabled near-instant generation of vegetation proposals once environmental inputs were defined. This reduction in processing time enabled rapid exploration of multiple design scenarios and improved decision-making efficiency in early-stage architectural design. Specifically, generating a complete planting configuration for the case-study site required approximately 3 min using the algorithm, compared to an estimated 2 h for manual selection performed by a project team member following conventional guideline-based methods, representing an approximate 75% reduction in processing time.

The system also demonstrated adaptability in line with its design intent. By adjusting input constraints such as maintenance level, allergenic sensitivity, or aesthetic preferences, users were able to influence the composition of plant selections without altering the core algorithm. This indicates that the system functions as a flexible decision-support tool rather than a fixed optimization engine, enabling integration with various design methodologies. From a spatial design perspective, the results confirm that computational plant selection can effectively operate within architectural constraints. The algorithm consistently avoided overcrowding by considering plant growth form, canopy spread, and root system characteristics. As a result, the generated planting schemes maintained spatial coherence and did not violate basic principles of architectural usability or façade integrity. This demonstrated the algorithm's ability to translate complex environmental datasets into structured and actionable vegetation design proposals. It successfully integrated ecological parameters, architectural constraints, and spatial logic into a unified computational workflow. The results indicate that this approach can support climate-responsive façade design by improving the efficiency and precision of vegetation planning in urban environments.

A dimension not yet fully integrated into the present algorithm is human maintenance and management. While the algorithm treats maintenance requirements as an optional filtering parameter (Section 2.2), the long-term viability of any generated planting scheme ultimately depends on sustained human management capacity, including irrigation scheduling, pruning, and pest control, which vary substantially across species. Even an environmentally optimal species-to-site match can fail without adequate institutional responsibility for upkeep. Future iterations of the framework should more explicitly integrate maintenance-cost estimation and management-capacity input as first-class optimization criteria, alongside participatory stakeholder input, to ensure that computationally optimal solutions remain practically sustainable.

4. Discussion

The results demonstrate that automated green infrastructure design tools can play a crucial role in addressing urban climate challenges, particularly in relation to overheating, biodiversity loss, and air quality degradation. The integration of computational optimization into urban planning workflows aligns with established approaches to green infrastructure as a key climate adaptation strategy in cities [32,33]. From a methodological perspective, the use of multi-scale digital modeling and AI-driven optimization reflects a broader shift in sustainable urban design towards data-intensive, algorithmic decision-making frameworks [34]. Such approaches enable the integration of heterogeneous environmental datasets and support more systematic spatial planning under complex urban conditions.

However, the effectiveness of such systems remains dependent on the quality and spatial resolution of ecological and environmental input data. Previous research highlights that multi-stage optimization frameworks are highly sensitive to long-term climatic variability and require robust environmental datasets to ensure reliability under changing conditions [35]. Similarly, stormwater and spatial functional zoning studies indicate that soil and hydrological parameters are critical constraints that must be explicitly incorporated into urban vegetation models [36]. Beyond environmental performance, urban green infrastructure also plays a significant role in shaping socio-ecological systems. Vegetation contributes to ecological awareness, community engagement, and urban stewardship practices, reinforcing its function as more than just a technical or aesthetic element [37]. In addition, empirical studies confirm that access to green spaces has measurable positive effects on mental health and well-being, including reduced stress and improved emotional stability [38,39].

At the same time, green infrastructure has been shown to provide broader economic and environmental benefits, including increased property values and improved urban attractiveness [40]. These findings reinforce the importance of integrating ecological design with urban development strategies that consider both environmental and socio-economic dimensions. From a biophysical perspective, vegetation significantly influences urban microclimates through shading and evapotranspiration processes. Comparative studies of urban tree species demonstrate that these mechanisms can substantially reduce local heat stress and modify thermal comfort conditions in dense urban environments [41]. This supports the role of vegetation as an active climatic regulator within built environments.

The biophilic cities framework [42] extends this socio-ecological perspective by conceptualizing urban greenery as integral to human experience and psychological connection with nature, rather than as a purely technical or environmental intervention. Situating the present framework within this perspective suggests that future iterations should evaluate not only microclimatic performance but also experiential qualities such as visual accessibility, sensory diversity, and proximity to daily human activity.

Theoretical frameworks in urban ecology further emphasize the importance of experimental and adaptive approaches to designing with living systems. Designed experiments in urban ecosystems highlight the need for iterative, data-informed methodologies to understand complex ecological interactions in cities [9]. Similarly, projective ecological thinking conceptualizes landscapes as dynamic systems shaped by both environmental processes and design interventions [43]. In addition to ecological and climatic dimensions, the cultural and symbolic value of vegetation in architecture is being increasingly recognized. Recent research shows that integrating sensory and symbolic aesthetics into green infrastructure design can enhance social engagement and strengthen emotional connections to nature in urban environments [44]. This highlights the importance of considering not only functional but also experiential qualities in computational design systems. Broader environmental planning research confirms that urban green spaces contribute

significantly to ecosystem services and urban resilience, particularly in densely built environments [39]. These services include temperature regulation, air purification, and support for biodiversity, reinforcing the multifunctional role of vegetation in cities.

Furthermore, large-scale reviews of algorithmic and AI-based approaches in green infrastructure optimization indicate a growing convergence between computational design tools and climate-responsive urban planning strategies [33]. These developments suggest that digital tools are increasingly capable of supporting complex decision-making processes in sustainable landscape architecture. Multi-objective optimization frameworks applied to grey-green infrastructure systems demonstrate the importance of balancing ecological, spatial, and long-term climatic factors in urban planning [35]. This aligns with the present study, which combined parametric design and environmental modeling to support vegetation placement under multiple constraints. Overall, the findings confirm that integrating computational design tools with environmental datasets enables more precise and adaptive planning of urban vegetation systems. However, the long-term success of such systems depends on improving the resolution of ecological data, integrating hydrological and soil dynamics more explicitly, and incorporating socio-cultural dimensions into algorithmic frameworks, extending the model to ecosystem-service-based selection criteria, and incorporating maintenance and management-capacity constraints as explicit optimization variables. These directions align with current research on sustainable urban design and climate-responsive planning [32,34,36].

5. Conclusions

This study shows that combining optimization methods with environmental data analysis and computational design tools can establish a structured approach for integrating vegetation into architectural programming. Rather than treating greenery as an auxiliary element, the proposed framework enables it to be incorporated as a parameter within spatial decision-making processes, improving the consistency and evidence-based nature of urban design strategies. The developed system relies on a multi-stage workflow in which environmental conditions, including microclimate, soil properties, terrain characteristics, and building geometry, are processed in relation to plant-specific requirements. These datasets are evaluated using a rule-based selection logic that also allows for the inclusion of project-specific constraints. This enables the generation of planting configurations that remain sensitive to both ecological conditions and design intentions.

One of the main contributions of this work is the implementation of a prototype plugin that integrates parametric modeling with environmental simulation and automated species selection. The tool's principal technical contribution is the formalization of plant–environment compatibility as an explicit, reproducible weighted-threshold function (Section 2.4), enabling systematic and auditable species selection in place of ad hoc manual filtering. At the same time, it strengthens early design phases by allowing environmental and spatial factors to be assessed in parallel rather than sequentially. In terms of environmental performance, the approach demonstrates how vegetation placement can be aligned with exposure conditions to improve local thermal comfort. The system supports design strategies that respond more precisely to heat accumulation patterns, particularly in densely built urban areas where microclimatic variation is significant. Beyond environmental performance alone, the framework also contributes to improving spatial quality and supporting more diverse ecological outcomes in urban settings. The integration of biological and architectural criteria within a unified computational process allows for more coherent planning of green infrastructure.

Future work should concentrate on improving the resolution and regional specificity of ecological datasets, as well as increasing the system's ability to adapt to changing environmental conditions. Scalability to multiple urban typologies and climate zones, auto-

mated climate-based species filtering, and integration with municipal green-infrastructure planning and permitting frameworks are identified as key directions for extending the system's applicability from a design-support prototype toward operational deployment. Incorporating feedback-driven mechanisms and participatory input could also enhance its applicability in real-world planning contexts and strengthen its relevance for both designers and stakeholders. The findings indicate that computational approaches to vegetation planning can support more adaptive and resource-efficient design practices while also improving the integration of ecological thinking within architectural decision-making.

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Abbreviations

The following abbreviations are used in this manuscript:

AI	Artificial Intelligence
NLP	Natural Language Processing
UHI	Urban Heat Island
CSV	Comma-Separated Values
EPW	EnergyPlus Weather (file format)
GIS	Geographic Information System
3D	Three-Dimensional
pH	Potential of Hydrogen

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