



Original article

Performance-driven optimization of nature-based solutions for advancing urban canyon shading

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ABSTRACT

Climate change is affecting environmental quality, especially at the urban canyon level, leading to hazards such as heat stress, and intensified heatwaves. To enhance urban resilience and mitigate rising temperatures, systemic solutions are required. Nature-Based Solutions (NBS) are recognized as promising strategies, yet their implementation often lacks proper planning and quantification of performance. Existing simulation tools remain limited by high computational demands. This study applies Machine Learning (ML) to reduce reliance on simulations, streamline workflows, all while optimizing NBS performance, specifically urban street trees. A comprehensive dataset was developed, integrating urban canyons geometries and trees characteristics representative of typical urban conditions and plant species commonly used in design. A validated real time tool for computational simulations was used to investigate correlations between site morphology and street trees shading performance, which were then generalized across the Italian territory through Machine Learning (ML) approaches. Across more than 300'000 simulated canyon-tree configurations, latitude emerged as the dominant predictor of shading performance, while wider canyons and larger crown radii consistently achieved high scores (TOPSIS Scores > 0.9), identifying single- and double-row layouts as the most effective solutions. This methodology demonstrates that urban trees shading effectiveness can be predicted and generalized thanks to the representativeness of the dataset. These findings support the integration of NBS into early-stage design, providing a scalable framework for improving microclimate regulation in cities.

1. Introduction

Urban areas are currently characterized by several challenges due to anthropic activities and the worldwide increase in cities size (United Nations, 2018). Factors such as land use (Zhou and Chen, 2018), greenhouse gases emissions (“Greenhouse Gas Emissions from Energy Use in Buildings in Europe” 2023), and urban morphology (Zhang et al. 2023) and related reduction of vegetation (Tan et al. 2021), are among the most relevant features affecting urban liveability (Waite and Knobel, 2018), and driving anthropogenic climate change (Ahmadi et al. 2022). Although the recognized effects of climate change on urban and natural ecosystems are multiple, the increase in urban temperatures and heatwaves are among the most challenging (Thompson et al. 2023; European Commission. Directorate General for Climate Action, 2023), due to their impact on ecological functions (Singh et al. 2020a) and citizens health (Heaviside et al. 2017; Singh et al. 2020b). Nature-based Solutions (NBS), defined as solutions inspired or supported by natural processes

(Castellar et al. 2021), are increasingly recognized as promising strategies to enhancing urban canyon quality, particularly with regard to microclimatic conditions, due to their ability to deliver ecosystem services (Babí Almenar et al. 2021; Pedersen Zari, 2015). By reintroducing vegetation across multiple spatial scales, especially at the urban canyon one, NBS can mitigate the effects of heatwaves and regulate microclimates through shading - which lowers local mean radiant temperatures - and evapotranspiration processes (Jones, 2013; Gu and Goto, 2024; Sun et al., 2025). However, efficient planning and implementation strategies for leveraging NBS to mitigate climate change effects are still lacking. In particular, such solutions are rarely deployed in urban canyons with adequate quantification and prediction of their site-specific performance (Mosca, 2024). A comprehensive understanding of the performance of NBS in locally mitigating the Urban Heat Island (UHI) effect is essential for effective urban planning and design (Albert et al. 2021). Yet, this understanding is often constrained by the complex and context-dependent nature of NBS effectiveness (UNDRR, 2024). Each

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urban context presents unique characteristics, such as climatic conditions (Gulyás et al., 2006), land use patterns (Zhou and Chen, 2018), topography, and built environment morphology (Allen-Dumas et al., 2020), that significantly influence how NBS perform in reducing local temperatures. Consequently, site-specific simulations and analyses are typically required for each project to accurately assess the potential benefits and limitations of proposed interventions (Peters and Peters, 2018).

In this context, the performance of various NBS is typically assessed through computational simulations, conducted on a case-by-case basis. This approach enables designers and planners to assess the effectiveness of alternative design configurations for a given site, and several tools have been developed over the past decades to support this process. Nonetheless, significant limitations persist. Simulations often require substantial computational resources (Peters and Peters, 2018), as well as ad-hoc models of both the study area and the NBS configurations for each project. Moreover, iterative design processes involving NBS can be particularly challenging to implement within typical design workflows (Canepa et al. 2022; Mosca et al. 2025).

A promising perspective to support the decision-making for urban planning and design is constituted by the implementation of Machine Learning (ML) methods. ML systems can extract patterns from training data and applying them to predict outcomes for unseen cases, offering both high accuracy and strong adaptability (Koutra and Ioakimidis, 2022). Their strength lies in supporting decisions in complex, data-rich environments such as cities, particularly as the current environmental crisis increases the unpredictability of urban conditions (Li et al. 2022; Koutra and Ioakimidis, 2022). In this study, Machine Learning (ML) methodologies can help define more efficient strategies and tools for designers to improve urban climate resilience. ML techniques can reduce the need for ad hoc simulations by learning from datasets that describe urban contexts with specific characteristics and the corresponding most effective solution relative to specific research questions or urban challenges. Specifically, these approaches allow bypassing the preliminary simulations to compare different solutions and select the best performing one at early design stage. From an operational perspective, ML techniques have been increasingly applied in recent years to study climate change-related phenomena (Miniandi et al. 2025; Ghorbany et al. 2024). However, their use in supporting the optimization of NBS performance remains largely unexplored (Gutiérrez Caloir et al. 2023; Zou et al. 2025).

1.1. Research objectives

Building upon the current state of the art, the complexity of the urban conditions described above, and the identified gaps in NBS planning and implementation, this study aims to develop and test a methodology to support designers and planners in implementing NBS in urban canyons, with particular focus on urban street trees to increase shaded areas during the summer period. By integrating Machine Learning techniques, the research seeks to reduce the need for extensive microclimatic simulations in the early design stages when identifying the most effective NBS configurations for shading. Detailed microclimatic assessments of the selected solutions can thus be deferred to the final design phase, optimizing time and computational resources while maintaining environmental performance accuracy.

More in detail, the following research objectives of this research are proposed:

1. Generate a comprehensive training dataset by developing a flexible and adaptable methodology to analyse urban canyons in terms of microclimatic and shading conditions and related urban trees performance using computational simulations.
2. Identify recurring best-performing solutions by integrating a multi-criteria decision-making (MCDM) approach to rank the simulated solutions and identify optimal trees configurations (including tree

species) depending on climatic and geographical conditions across different urban canyon geometries and assess the influence of latitude and urban canyon geometry on urban street trees shading performance.

3. Predict the most effective urban street trees configuration for any latitude within the thresholds of the training set and urban canyon configuration and demonstrate the results through a selected case study with machine learning (ML) algorithms.
4. Validate and test the methodology's effectiveness and applicability across diverse geographical locations.

2. Methods

To achieve the research objective (RO) outlined in the previous section, different methodological steps were defined and implemented (Fig. 1). To translate the urban morphology into a geometric model that can be shaped and scaled to reproduce different possible configurations, the scientific model of the urban canyon was used (Yola, 2020). This model is widely used in studies investigating urban microclimatic behaviour and the dispersion of air pollutants and fine particulate matter (Gong, 2025 De Quadros et al., 2024). It enables the complexity of the urban environment to be reduced to a set of key geometric and physical parameters, allowing its behaviour to be analysed in terms of fluid dynamics and shadow generation.

Based on this assumption, the methodology of the study has been structured as follows:

1. Identify key urban canyon and urban trees features, define evaluation criteria, and define the operative workflow to perform computational simulations of urban canyon configurations to generate the training set; (*obj 1*)
2. Implement the selected MCDM methodology to identify the best-performing urban trees configuration for given sites and urban canyons in terms of shading; (*obj 2*)
3. Identify the most suitable ML Identify the most suitable ML method by comparing the results obtained on the training set, and implement the selected algorithm to enable the prediction of urban trees performances for a given site and urban canyon through a case study analysis; (*obj 3*)
4. Validate the ML predictions and the overall workflow against computational simulations for canyon/urban trees combinations not included in the training dataset to assess effectiveness and applicability across different geographical locations. (*obj 4*)

2.1. Training set definition and simulation settings

In the context of this research, ML models are trained on datasets containing spatial and urban parameters. Through training, the model learns relationships between inputs (such as urban canyon features and design criteria) and outputs (such as NBS features). Once trained, it can predict outcomes for new scenarios, supporting rapid evaluation of design choices without the need for full simulations.

The first step of the study focuses on the definition of a set of variables for the characterization of urban areas and NBS. Specifically, the urban canyon model has been selected due to its wide application in urban studies, as a simplified but exhaustive representation of urban environments (Zhong et al. 2023; Evola et al. 2020; Lobaccaro and Acero, 2015). These variables, defined as "input variables", are particularly relevant as they allow the simulation of different urban canyon morphologies and derive an exhaustive dataset of correlations between urban configurations and NBS performance (Muniz-Gaal et al., 2020). The most relevant urban canyon and NBS variables have been defined, and the related thresholds identified, as shown in Tables 1 and 2. With regard to the canyon variables, the study considers only geometric and geographic characteristics, excluding other relevant parameters such as

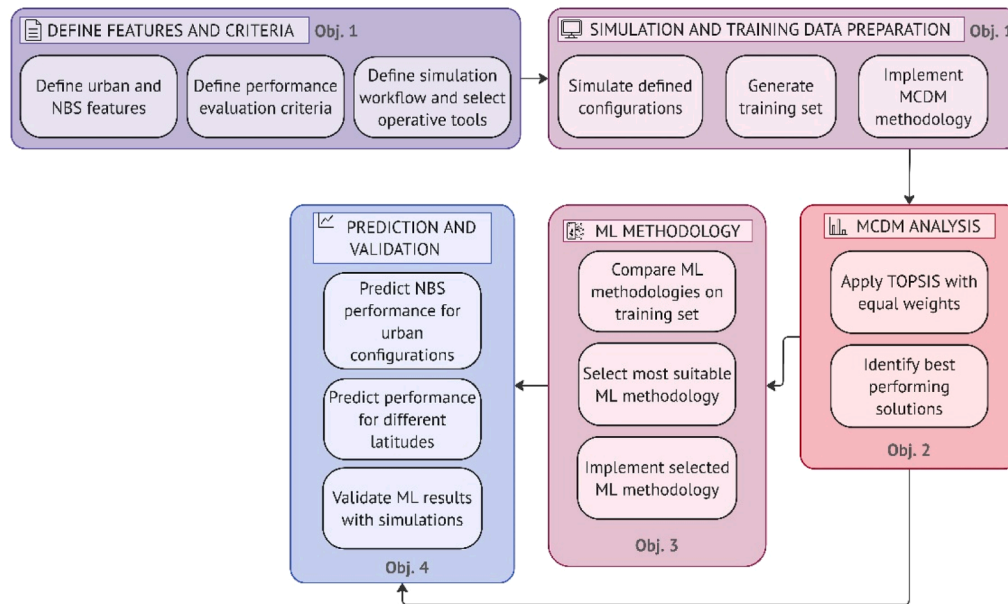


Fig. 1. Overview of the methodological steps of the study.

Table 1

List of input variables for urban canyon features and related thresholds for simulations.

Variables canyon	Values	Unit
Building distance	10	m
	25	
	40	
Building length	40	m
	10	
Building height	25	m
	40	
	10	
Orientation	0	° (degrees from North)
	90	
	1.5	
Grid size	1.5	m
Latitude (Turin, Genoa, Rome, Palermo)	45°04'13" N,	°
	44°25'35" N	
	41°53'30" N	
	38°07'55" N	

the thermal properties of building envelopes and surface materials. This choice reflects the objective of the methodology, which is to streamline decision-making in the early design stages by focusing on shading performance rather than on detailed microclimatic dynamics.

Concerning NBS variables, these have been defined according to the literature on the geometrical configuration of trees (Jucker et al., 2022), allowing for a final reconnection of the best performing configurations with specific tree species that could be introduced in urban canyons to reach the predetermined microclimatic performance.

Once the input variables for the training set were defined, the output parameters (i.e., the optimization criteria) were established. These criteria were selected according to the primary objective of improving the microclimatic and shading conditions of urban areas, as well as operational goals such as reducing the maintenance requirements of NBS and other green urban spaces (Mosca et al. 2025). In addition, the selection of the criteria has been guided by the need to balance computational effort with the accuracy of results. For example, concerning the shading capacity of trees, the performance has been calculated in terms of solar radiation reduction, as key parameter for microclimate regulation, instead of simulating Mean Radiant Temperature (MRT) which is more time and energy consuming (Alexandri & Jones, 2008; Alzahrani and Gadi, 2024; Acero and Herranz-Pascual,

Table 2

List of input variables for NBS features and related thresholds for simulations (* trees features corresponding to average values for *Abies alba*; Jucker et al., 2022).

Variables NBS	Values	Unit
Trunk radius	0.05	m
	0.15*	
	0.30	
Crown radius	0.5	m
	3*	
	5	
NBS height	2	m
	10	
	20*	
Crown height	1/4 h*	m (fractions of NBS height – h)
	2/4 h	
	3/4 h	
NBS type	Single tree	-
	Single row	
	Double row	
NBS shape	Sphere	-
	Cylinder	
	Cone	
Number of trees	Reverse cone*	-
	Low (1/8 possible locations)	
	Medium (1/4 possible locations)	
	High (1/2 possible locations)	

2015; Aghamolaei et al. 2022; Liu et al. 2022). This choice has been driven by the necessity to balance the computational power needs for the definition of the training set, but also by the aim of considering the shading capacity of trees from a geometrical perspective (i.e. by the shading provided depending on the solar angle).

The final set of criteria and their corresponding optimization directions, according to the literature, includes maximizing the percentage of shaded street area (Sanusi et al., 2016), the percentage of shaded building area (Berry et al., 2013), and tree crown volume (m³) (Berry et al., 2013), while minimizing trunk volume (m³) and the number of trees (Scarmana and McDougall 2023).

Then, the operative pipeline for the simulation of the different configurations has been defined. Given the parametric nature of this study, Rhinoceros 3D (McNeel, 2025), coupled with the parametric plug-in

Grasshopper (GH), has been selected. For the implementation of the workflow, two plug-ins have been selected and included: Ladybug Tools (<https://www.ladybug.tools/>) and Colibri (<https://www.food4rhino.com/en/app/tt-toolbox>). The former is a suite of validated environmental design and analysis tools (Nicholson et al., 2024), simulating and visualizing environmental factors at early design stages such as sunlight, airflow, and microclimate conditions (Sadeghipour Roudsari et al., 2013). The latter automates simulation loops by generating and recording all the combinations defined. For the calculation of the shading capacity of different street trees, weather data have been derived from georeferenced.epw files for a typical summer condition (21st June, 2 PM) and used for all the simulation scenarios. The pipeline consists of recreating all different canyon-city-trees scenarios, guided by physical constraints and design rules (e.g., limiting trees that can be positioned in a street given their crown size, or positioning trees in specific rows), computing the criteria necessary for assessing the performance of each scenario. Based on the selected input variables (Tables 1, 2), the simulations have been grouped in different scenarios as follows:

Total number of scenarios = 6 cities x 3 NBS types x 4 tree types = 72 scenarios

Results from the simulated scenarios were then saved as.csv files to apply the MCDM approach and define the training set for the implementation of the ML methodology.

2.2. Multi-criteria decision-making analysis

The simulation results were subsequently used to identify the best-performing configurations for a given urban canyon condition. To do so, the most appropriate MCDM methodology has been selected according to the requirements of this study, the strength of the approach, and its wide applicability according to literature (Pandey et al. 2023). The TOPSIS (Technique for Order of Preference by Similarity to Ideal Solution) is a multicriteria decision-making method that ranks alternatives by measuring their relative closeness to an ideal solution. The best alternative is the one closest to the positive ideal (maximizing benefits and minimizing costs) and farthest from the negative ideal (the worst values across criteria (Celik and Ogun Binatli, 2018)). The process involves normalizing data, applying weights to criteria, calculating distances from the ideal solutions, and deriving a closeness index to rank the options. In this study, entropy weights have been applied to the different criteria, to define the best-performing solutions for given sites and urban canyons avoiding unbalanced results (Chen, 2021).

2.3. Machine learning implementation

We selected different ML regression models from the literature by varying grades of algorithmic complexity, considering Linear Regression (LR), Kernel Ridge Regression (KRR), Random Forest (RF), Support Vector Regression (SVR), and Multi-Layer Perceptron Regression (MLP) (Demir & Sahin, 2024; Oukhouya, El Himdi, 2023). We used the sklearn implementation of each (Pedregosa et al., 2011), with two notes. Firstly, we run a grid-search cross-validation for optimizing hyperparameters of all models but LR. Additionally, due to the relatively small training set size, we introduced the Repeated K-fold method in the grid-search to improve the optimization (Lumumba et al., 2024). Secondly, SVR, normally fitted for scalar regression, was converted for multi-output prediction to be usable in this application (Wang et al., 2024). The training data corresponded to 70% of the total amount of best simulations, leaving 15% for validation and 15% for testing. After training, R^2 scores are used to select the most accurate and reliable model to predict NBS performance for different urban and geographical conditions. The selected model is then tested to illustrate its functionality.

2.4. Case studies selection and validation

To analyse the performance of the different urban street trees configurations, six Italian cities with different latitude (from 38°13' to 45°07') have been selected to serve as representative case studies. In relation to Research Objective 2, focused on the identification of the best-performing solution for a given urban site and canyon configuration, a subset of configurations from the training are selected. For each city, 18 canyon combinations with different height and width of the canyon (10, 25, and 40 m), and two orientations (0, and 90°) have been examined. This analysis provided a detailed understanding of how canyon geometry and orientation influenced the effectiveness of NBS strategies in a real urban context. Research Objective 3 is carried out quantitatively by confronting R^2 and Mean Squared Error (MSE) scores, and qualitatively by assessing the distribution of predicted data over an array of interpolated values ranging from the maximum to the minimum possible values for canyon geometries and latitudes.

Finally, the testing of the ML results (Research Objective 4) is carried out using the testing set, corresponding to 15% of the total amount of best simulations. Random sampling is used to assess the predictive quality of the model against the true simulated values. To test the robustness of the methodology, specifically in the optimization process, the validation includes a sensitivity analysis of the MCDM algorithm by comparing the results obtained with TOPSIS with VIKOR, an equally frequently adopted MCDM method in optimization tasks, paralleling all the processes done with TOPSIS and comparing the scores by mean of the difference of standard deviations (Stević et al., 2022).

3. Results and discussion

3.1. Performance simulation, ranking and ML algorithm selection

A total of 314'928 simulations were generated across 72 scenarios, differentiated by city latitude, tree shape and type. Analysis of the simulated scenarios revealed clear trends in NBS performance across different geographical locations and urban canyon configurations (Fig. 2). Across the 18 combined city-NBS scenarios, most configurations displayed similar performance patterns per city (rows) and NBS type (columns), indicating that latitude and context geometry plays a significant role in determining the effectiveness of NBS. Significantly, there is no scenario where a solution with very high TOPSIS score (>0.9) cannot be determined, indicating that all scenarios can be satisfied with context-specific optimal NBS according to our criteria. In addition, the simulation results align with literature on the shading performance of trees in urban environments as a function of geographical location and latitude (Del Campo-Hitschfeld et al. 2023; Kumakura et al. 2011; Palme et al., 2020), thereby supporting the validity of the initial conditions used in the learning approach.

Studying the feature influences over the TOPSIS-based performance revealed nuanced patterns (Fig. 3). Several continuous features display clear directional effects, such as Building Distance and Crown Radius that both transition from strongly negative Z-Scores (defined as $Z_i = (x_i - \mu)/\sigma$, where x_i is the observed value, μ is the mean, and σ is the standard deviation, expressing each feature in units of standard deviations from the mean) at low values (-1.14 and -1.09 respectively) to distinctly positive values near +0.75 to +0.87 at their upper range, indicating that larger distances and crown radii consistently improve performance. Building Height and Crown Height show the opposite trend, with high values associated with Z-Scores near -0.9 to -1.0, suggesting diminishing performance as height increases. City Latitude exhibits the widest spread, ranging from +1.59 to -1.05, highlighting substantial sensitivity to geographic location. Among categorical variables, Tree Shape shows the strongest contrast, with "Sphere" outperforming "Cone Reversed" by more than two standard deviations, and Row declining sharply from the first to the third row. These patterns indicate that geometric and spatial configuration variables exert the strongest

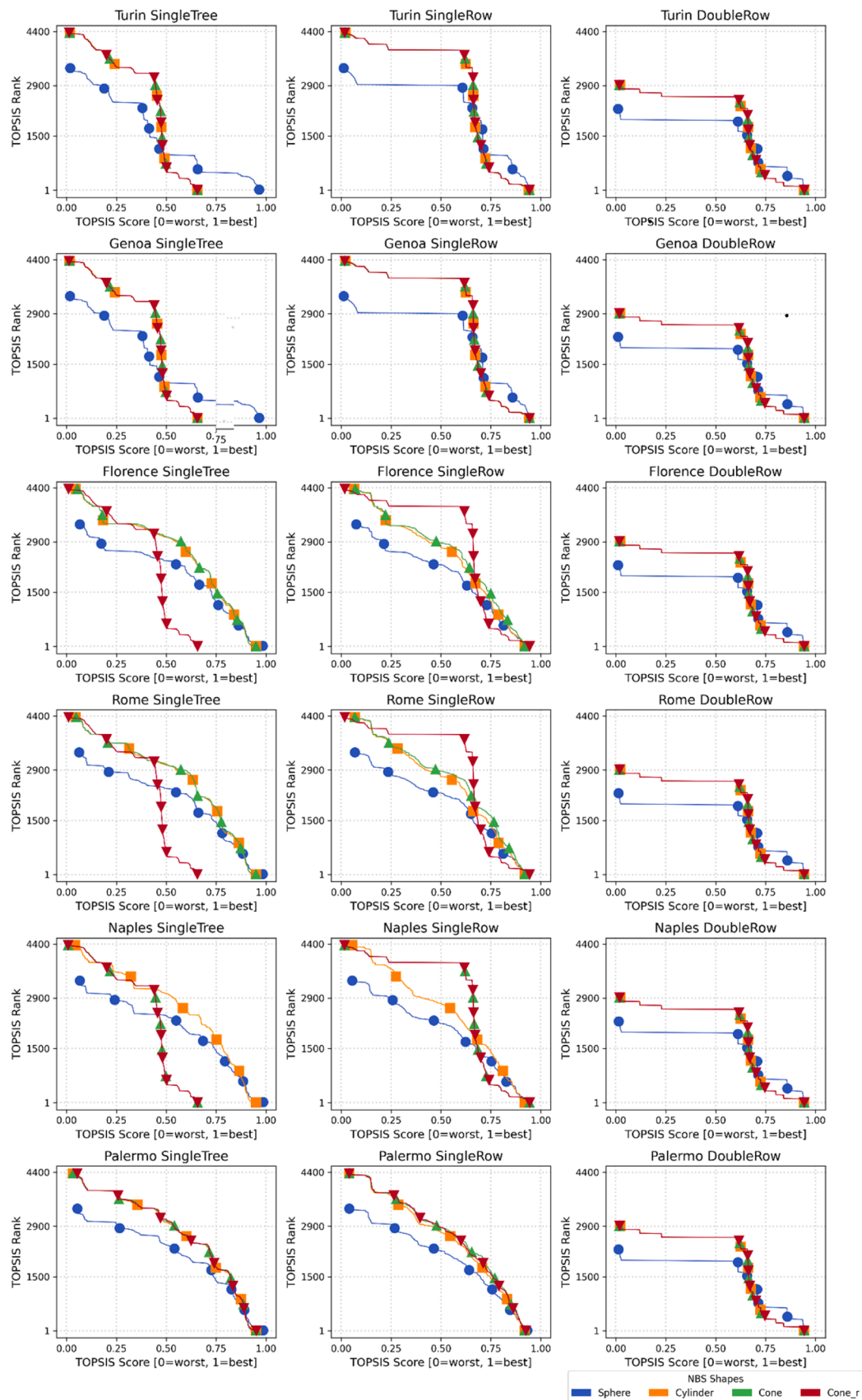


Fig. 2. NBS simulated data, divided in 72 scenarios of different city, trees Shape (Sphere, Cylinder, Cone, Reversed cone), and trees Type (Single Tree, Single Row, Double Row). A TOPSIS Score of “1” is equal to the ideal solution, and a Rank of “1” is the highest ranking.

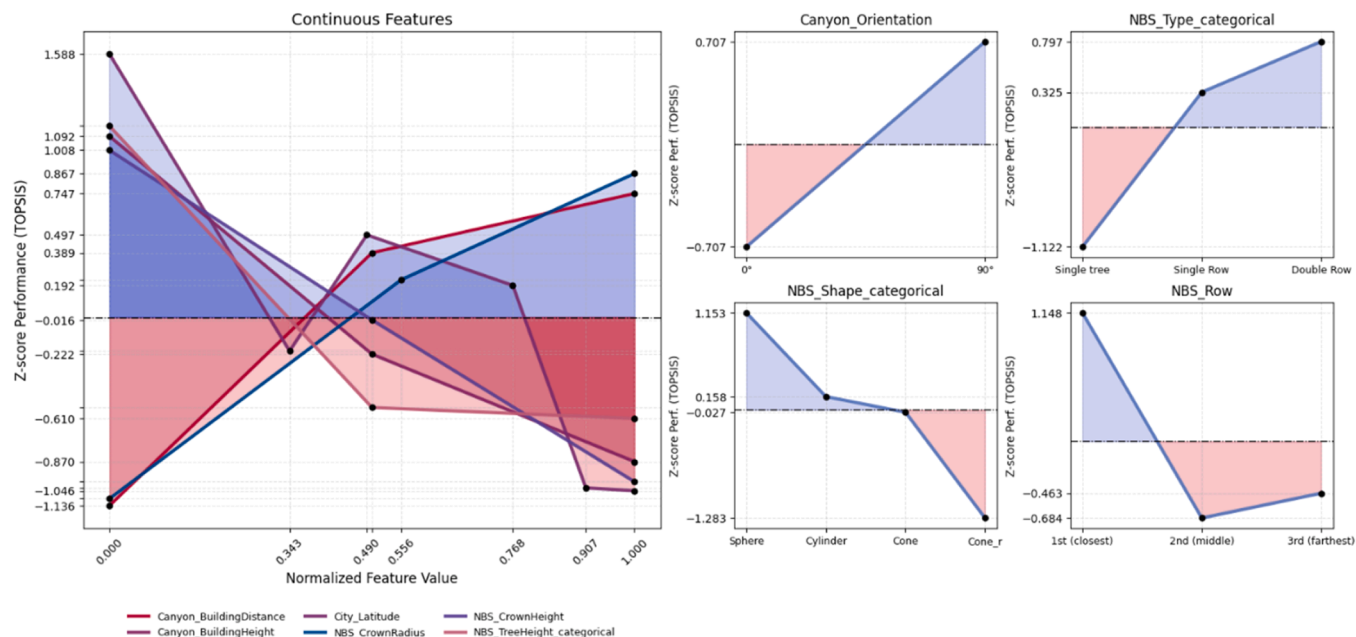


Fig. 3. Influencing factors trends over TOPSIS-based standardized performance using the Z-Score. A Z-Score of 0 indicates average performance, while values around +1 or -1 reflect substantially better- or worse-than-average behaviour, respectively.

influence on the TOPSIS distance to the ideal solution. When contrasted with the VIKOR results (Annex A) the TOPSIS curves appear sharper and more polarized, reflecting TOPSIS’s emphasis on consistent proximity to the ideal solution rather than compromise across criteria.

Correlation analysis between the variables and optimization criteria (Spearman’s ρ , Fig. 4) highlighted several notable patterns. Number of Trees and Tree Trunk Volume exhibited high correlations ($\rho = +0.62$), indicating that optimizing for these criteria relies on the same variables. Specifically, Number of Trees and Trunk Volume are highly correlated to the Trees Type ($\rho = +0.88$ and $\rho = +0.36$) and Tree Quantity ($\rho = +0.79$ for both). While Tree Crown Volume generally followed the same collinearity pattern as Number of Trees and Trunk Volume, it diverged in relation to Crown Radius ($\rho = +0.67$). Increasing Crown Radius enlarged individual canopies but limited the number of trees and total green cover, highlighting a trade-off between canopy size and overall Trees coverage. These findings are aligned with studies in the field of

ecology which demonstrate the correlations between Crown Radius and Trunk Volume (O’Brien et al. 1995; Pretzsch and Dieler, 2012; Zhu et al. 2021), strengthening the relevance of the selected parameters for Trees modelling and performance quantification.

Shading on Building and Street Surfaces showed medium-to-high correlations ($\rho = +0.39$ and $+0.69$ respectively), with Building Distance identified as the primary influencing factor. The analysis of correlation is consistent with similar studies, although the Canyon Ratio is widely considered (Takebayashi and Moriyama 2012; Andreou, 2014). Street shading was also affected by Building Height ($\rho = -0.51$), whereas Building Shading showed no correlation with Height, likely due to the fixed solar radiation calculations, which made building-to-building shading uniform and left NBS as the main source of variation.

Finally, the relationship between location and canyon characteristics was examined by selecting the highest-scoring NBS for each city across

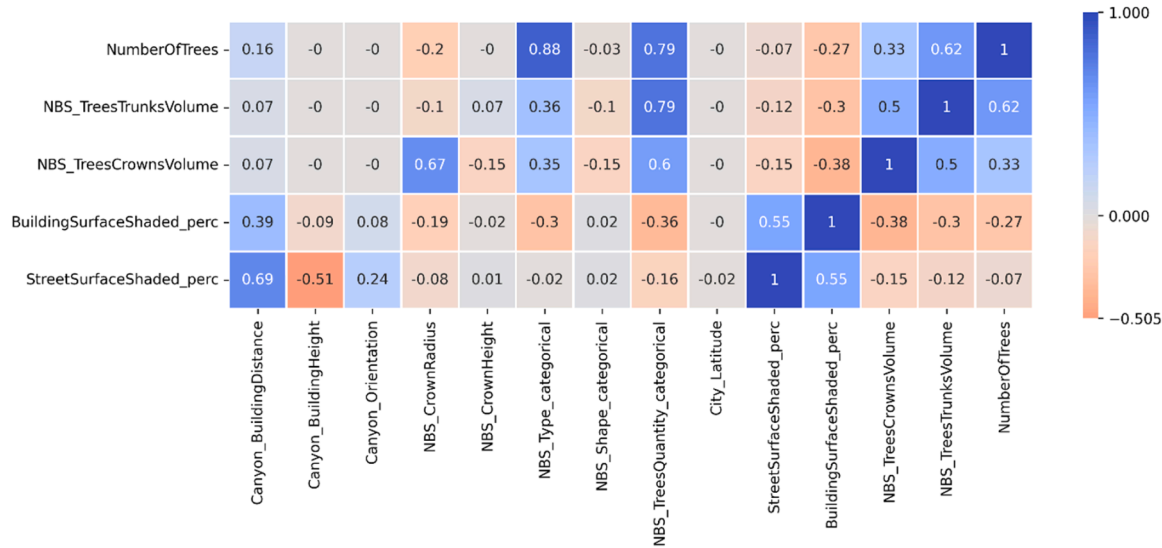


Fig. 4. Correlation analysis using Spearman’s ρ between simulation variables and optimization criteria. Scores of “1” equal to a perfect positive correlation, while scores of “-1” equal to perfect negative correlation.

eighteen simulated canyon Height–Depth–Orientation configurations (Fig. 5). This approach revealed how optimal trees performance varies with both geographic context and urban canyon geometry.

Through this analysis, we deduce that all canyons for Turin, Genoa, Florence, Rome, and Naples have at least one NBS that scores higher than TOPSIS Score > 0.9 . Additionally, canyons with $W=40$ generally tend to have the highest scores, enabling the highest performing NBS overall (scores > 0.97) in both orientations. The performance of NBS gradually degrades by lowering latitude for 0° canyons, with Palermo being the overall lowest, especially in canyons with $W=10$. The behaviour is similar in 90° canyon, albeit showing that lower latitudes have higher performances in worst canyons ($W=10$) and in the best canyons ($W=40$). Regarding the lowest latitude considered in the study (Palermo, 38.13°N), the TOPSIS Score results lower due to the higher latitude gap compared to the other selected cities, that has a direct correlation with the solar angle. Indeed, as already demonstrated in literature (Kopp, 2023), geographical coordinates as well as the time-frame considered for the quantification, have a strong impact on solar radiation calculation.

In a second phase, a more detailed analysis of the best-performing trees configurations for a selected site (Genoa) and the different canyon configurations have been performed (Fig. 5).

It is worth noting that, as illustrated in Fig. 6, the “optimal” urban street trees configuration varies across canyon types, ranging from a single tree (particularly effective in narrow canyons) to single or double rows of trees. Furthermore, in terms of tree shape, the optimal configurations include spherical, conical, and reverse-conical geometries. The results underline the critical role of crown surface in enhancing shading and improving microclimatic conditions within urban canyons, in line with the results from Sharmin et al. 2023; Kuuluvainen and Pukkala,

1987; Franceschi et al. 2022, who highlighted the strong relationship between tree shapes, especially in terms of crown distribution and volume, and the capacity to locally regulate microclimate. Notably, regardless of canyon dimensions, orientation, NBS type, or tree shape, the optimal crown radius consistently measures 5 m, being the maximum value included in the training dataset. An analysis of the variation in urban street trees types based on different optimization objectives reveals the adaptability of the proposed methodology. It can be tailored to meet specific goals or constraints, demonstrating the flexibility of the approach and the versatility of street trees in addressing diverse design and environmental criteria. A more detailed analysis of the results shown in Fig. 5 shows that:

- 1) The number of trees changes significantly depending on the canyon orientation. This confirms that the influence of building shadow has a relevant impact on the canyon's shading conditions.
- 2) In both orientations, under the condition of low buildings and wide canyons, we expected that, given the building shading, the number of trees would be higher, contrary to what was observed. This outcome may depend on the fact that the optimization process considers several parameters, not only those directly related to shading (tree crown and tree trunk volume, and number of trees).

This result demonstrates that boundary conditions are decisive. The explanation can be found in the behaviour of the optimization algorithm, particularly regarding the association of each input variable with the optimization criteria. For shading-related variables, the correlation study revealed a relationship with both canyon parameters (boundary) and NBS parameters; for non-shading variables, a correlation was found only with the characteristics of the NBS. Therefore, in order to satisfy all

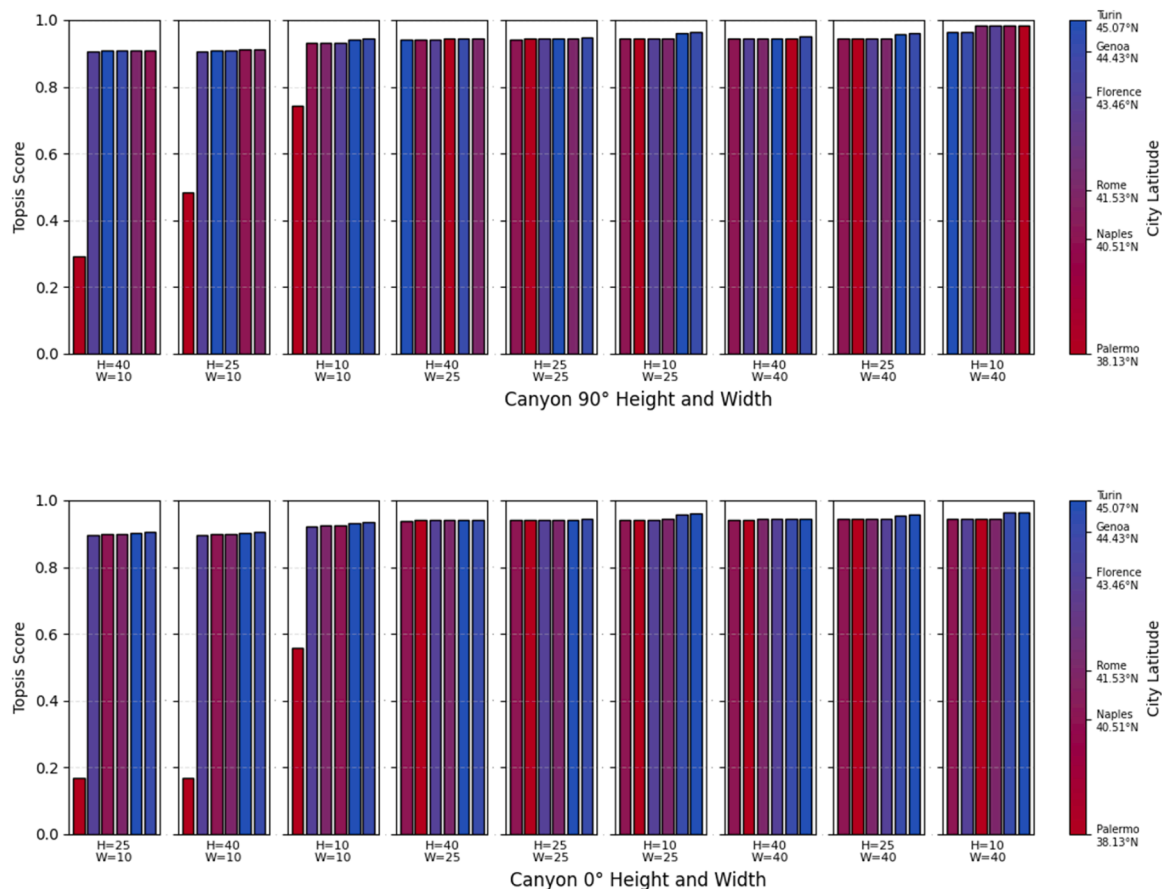


Fig. 5. Bar graph of the best trees configuration from each canyon configuration data for each city, Fig. 4a (top) refers to canyons with 90° orientation, Fig. 4b (bottom) refers to canyons with 0° orientation.

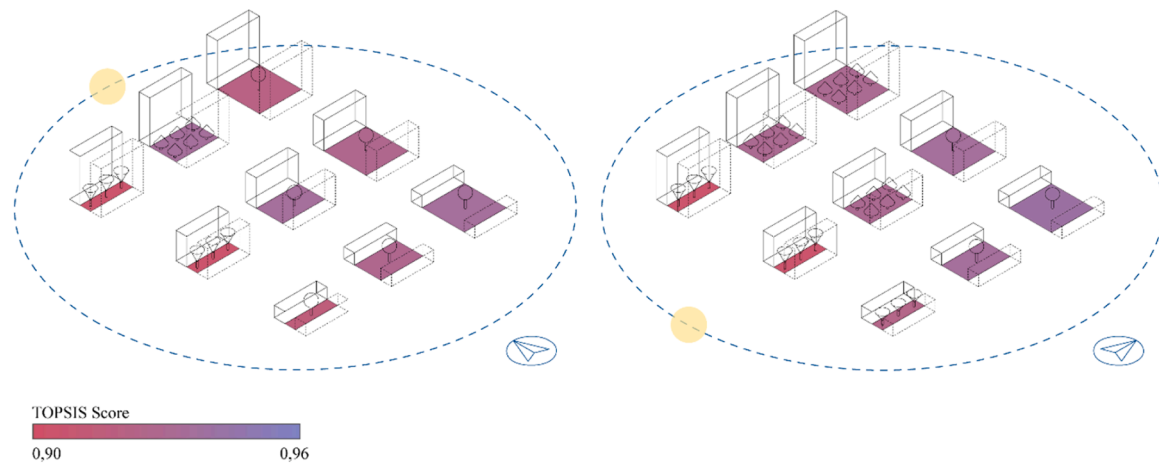


Fig. 6. Best performing street trees in Genoa for the nine types of urban canyon considered at 0° (left) and 90° (right), with equal weights assigned to all the optimization criteria.

optimization criteria, the algorithm is more constrained by non-shading characteristics, since they rely on fewer input variables that take precedence (Fig. 4). Consequently, shading is mainly addressed through canyon variables. Future developments should further explore how to reduce the weight of boundary conditions in the selection of optimal solutions.

Finally, this methodology also enables the future quantification and optimization of additional environmental benefits associated with urban tree integration, particularly those linked to biomass. For instance, it can support the assessment of the capacity of urban trees to sequester and store carbon (Jin et al. 2023), enhance air quality through particulate matter absorption (Haq et al. 2024), and promote local biodiversity by providing nutrients and nesting areas for insects, birds, and other living organisms (Atkins, 2018). It is worth highlighting that in the optimization process and later in the learning process, NBS features such as height and crown radius are not directly correlated. Therefore, the selection of the species can be made at the end of the process once the shape of the best performing NBS and related dimension features are defined.

Finally, across the five ML algorithm tested and compared using the selected scores, SVR was chosen due to its best performance ($R^2 = 0.630$, $MSE = 0.197$), also considering its smoother predictions for unobserved data (Annex A).

3.2. Case study and validation

The internal validation with the 15% of the data yielded fluctuating R^2 results. Notably, R^2 scores obtained in the grid-search optimization were generally higher than scores obtained by predicting the validation set. While this could be attributed to small dataset effects, a more probable reason could be a mild optimism bias in the grid-search, because in the grid-search models are evaluated multiple times while the internal validation is a single split. If this split happens to be harder (e.g., contains outliers or unusual patterns) then the R^2 will look worse (Arlot and Celisse, 2010). All cases for the five considered machine learning models, including a sensitivity analysis of the MCDM optimization, are provided in the supplementary material (Annex A).

The results were then tested by comparing the data predicted by the implemented ML methodology with the simulated data generated using the pipeline developed for the training set. Specifically, the testing process is focused on the prediction of NBS on different latitudes (within the minimum and maximum values considered in the definition of the training set) as it is one of the most influencing parameters in relation to the solar elevation angle and solar radiation. Here, we present four urban canyons, sampled from the testing set, highlighting the

differences in NBS design configurations (Table 3). These results indicate that the methodology is overall consistent, with only minor discrepancies in NBS parameters such as tree height, where the prediction tended to underestimate compared to the simulated outcomes. The approach appeared more robust when we expanded the training set from four to six cities, with the addition of Florence and Naples, which led to greater stability in the outcomes. Nonetheless, at specific latitudes such as Palermo, performance deteriorates likely due to the influence of solar irradiation angle (Kopp, 2023) suggesting that further enriching the training set would enhance the robustness of the predictions. This could be done either by adding more cities, therefore adding consistency, or by changing the time for the solar irradiation simulations, thus changing the angle.

Regarding the sensitivity analysis of the MCDM algorithms, the difference of standard deviation scores showed a very low difference between the two algorithms scoring. In both cases, while comparing results from seen and unseen datasets, TOPSIS showed as slightly lower (-0.011 and -0.020) than VIKOR (-0.012 and -0.022). This suggests that, although the differences are marginal, TOPSIS demonstrates a slightly more consistent performance across sets, indicating a modest advantage in terms of stability.

Finally, in addition to the definition of reliable methods for NBS selection, this paper presents an operative methodology that can be replicated in different geographical contexts to support the improvement of microclimate conditions of urban sites towards climate adaptation through planning and design actions. Fig. 7 summarizes the key steps of the operative workflow for its application, highlighting phases (2) and (3) as the key contribution of this research. The process starts with the identification of the urban site along with its geographical and climatic conditions (1), that can be select according to site-specific needs, e.g. urban regeneration initiatives, or based on the application of methodologies aimed at defining areas with high risks for citizens in relation to the UHI effect (Sidiqui et al., 2022; Assaf and Assaad, 2024).

Based on the selected site, the most suitable urban canyon is identified and its geometric features (width, height, orientation) are derived (2). Building on the characteristics defined in Phase 2, the machine learning (ML) pipeline is then applied to identify the best-performing NBS and to evaluate their associated performances (3). Finally, based on the NBS features obtained (e.g., tree height and crown diameter), the design process can proceed with the selection of the most suitable tree species (4), taking into account the environmental and ecological conditions of the site, as shown by Calbi et al. (2024) and Mosca et al. (2025). This operative workflow highlights the novelty of the proposed methodology in addressing existing gaps in the optimization of planning and implementation of NBS for urban climate adaptation.

Table 3

List of input variables for urban canyon features and related thresholds for simulations. The prediction set is obtained by sampling from the testing set random combinations of urban canyon designs. For each prediction, a typical tree species with the same characteristic is associated.

Location	Canyon variables			Prediction set		Testing set	
	Width	Height	Orientation	NBS	TOPSIS score	NBS	TOPSIS score
Florence	40 m	25 m	0°	Double row (1st and 3rd row, 6 trees) Cone 5 m crown radius 20 m tree height 1/4 h crown height (e.g. <i>Abies alba</i>)	0.944	Double row (1st and 3rd row, 6 trees) Cone 5 m crown radius 10 m tree height 1/4 h crown height	0.954
Rome	25 m	25 m	0°	Double row (2nd and 3rd row, 6 trees) Cone 5 m crown radius 2 m tree height 1/4 h crown height (e.g. <i>Salix Arbutifolia</i>)	0.942	Double row (1st and 3rd row, 6 trees) Cone 5 m crown radius 10 m tree height 1/4 h crown height	0.958
Naples	25 m	10 m	0°	Double row (2nd and 3rd row, 6 trees) Cone 5 m crown radius 20 m tree height 1/4 h crown height (e.g. <i>Platanus Hispanica</i>)	0.942	Double row (2nd and 3rd row, 6 trees) Cone 5 m crown radius 20 m tree height 1/4 h crown height	0.942
Palermo	10 m	25 m	0°	Single row (2nd row, 3 trees) Cone reversed 5 m crown radius 2 m tree height 1/4 h crown height (e.g. <i>Populus alba</i>)	0.169	Single row (2nd row, 3 trees) Cone reversed 5 m crown radius 10 m tree height 1/4 h crown height	0.179

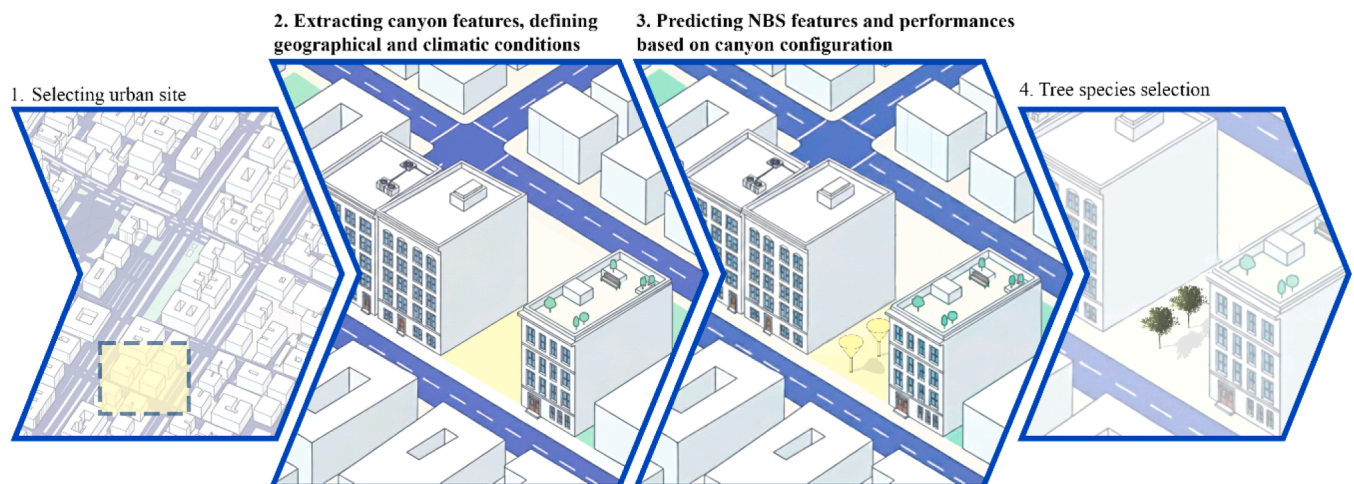


Fig. 7. Operative workflow for the application of the proposed methodology in real world applications.

3.3. Limitations of the study

The present study proposes a framework to support planners, designers, and researchers in identifying the best-performing NBS, specifically urban tree configurations, to optimize shading in urban canyons. However, several key limitations should be acknowledged and discussed.

First, the study focuses exclusively on NBS (specifically street trees), although other shading solutions could be effectively implemented. This choice is motivated by the wide range of co-benefits provided by NBS (Babí Almenar et al. 2021), which could be further integrated into the proposed methodology. Among the various NBS options, urban street trees were selected because several studies have demonstrated their superior shading potential compared to other NBS at the spatial scale considered in this research (Wei et al., 2025; Mosca et al., 2021). In addition to providing shade, urban trees contribute to local microclimate regulation through evapotranspiration and deliver multiple ecosystem services, such as pollutant removal and rainwater runoff

reduction. Nevertheless, the methodology could be further tested and extended to other NBS types, such as shrubs or vegetated barriers.

Additional limitations are related to computational constraints. The training dataset is characterized by a limited range of shading hours, simplified geometric configurations, and a restricted selection of case-study cities. Moreover, the current methodology relies on non-optimized GPU processing, and the calculation of Mean Radiant Temperature (MRT) is not integrated, despite its recognized relevance for microclimate regulation (Perini et al., 2017).

Finally, the study approaches the urban canyon primarily from an environmental and climatic perspective, consistent with its main objective of improving summer shading conditions. However, it does not incorporate other relevant aspects that may influence the selection of nature-based strategies, such as patterns of social use, functional characteristics of buildings, or the spatial dynamics of public open spaces within the urban canyon.

4. Conclusions and future developments

This study proposes a novel methodology to optimize and predict the performance of NBS in urban canyons for shading provision, as a key parameter for microclimate regulation, that can be easily applied in different geographical contexts. The presented work highlights the wide applicability of the proposed methodology and related potentials to support the transition of urban areas towards resilience. Indeed, it constitutes a starting point for further development to include a wider range of NBS performances such as carbon sequestration capacity, air quality improvement, or stormwater retention, aiming at optimizing the design of urban areas for climate change adaptation. Overall, concerning the analysis and optimization of NBS performance in terms of shading provision, the following conclusions can be drafted in relation to the study objectives:

- The study produced a comprehensive dataset that integrates detailed information on urban canyon geometries and NBS characteristics. It is representative of typical urban street conditions and common plant species used in urban design to ensure broad applicability across diverse contexts. Additionally, this dataset enables correlation to be drawn between urban morphology, geographical conditions, and NBS performance.
- Using a MCDM approach, optimal NBS configurations were identified across different canyon geometries and geographical locations. The methodology enables the selection of best-performing NBS tailored to site-specific requirements and objectives, including maximising street- and building-level outdoor shading.
- The selected ML algorithms demonstrated that NBS performance is strongly influenced by tree shape and canyon geometry, and latitude, whose plays the biggest role. The methodology provides a framework to simulate urban canyon conditions and learn from them to derive best-performing NBS types and related tree features and improve predictive accuracy.
- The methodology was tested across six different locations, confirming its usefulness for early-stage design analysis for planners, designers, and researchers, based on solar radiation as key parameter for outdoor shading conditions. However, predicting NBS performance remains complex, as reflected in R^2 and MSE values, and expanding the dataset in terms of latitudes and timeframes would improve reliability.

Future development could focus on the development of a methodology to select the sites at the urban scale for the introduction of NBS and scale down at the urban canyon level to streamline the application of the proposed methodology. In addition, other ecosystem services could be included in the NBS performance quantification, such as carbon sequestration, but also reduction of rainwater runoff in very dense urban areas. Finally, further works should aim at expanding the dataset (e.g., different hours of the day, as shown in Palermo TOPSIS results), explore alternative microclimatic indicators such as MRT, and adopt more advanced computational framework to enhance scalability and efficiency.

CRedit authorship contribution statement

Silvia Villa: Writing – review & editing, Methodology. **Francesca Mosca:** Writing – original draft, Visualization, Methodology, Conceptualization. **Katia Perini:** Writing – review & editing, Methodology, Funding acquisition, Conceptualization. **Gabriele Oneto:** Writing – review & editing, Visualization, Software, Methodology, Data curation.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence

the work reported in this paper.

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Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at [doi:10.1016/j.ufug.2026.129457](https://doi.org/10.1016/j.ufug.2026.129457).

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