Environmental Data Science (2024), 3: e37, 1–15
doi:10.1017/eds.2024.55

APPLICATION PAPER

Adaptive decision-making: Bayesian Network Modeling for blue–green infrastructure selection in dynamic climate and land use context

Dima Seker and Nur H. Orak

Environmental Engineering, Marmara University, Istanbul, Türkiye
Corresponding author: Nur H. Orak; Email: nur.orak@marmara.edu.tr

Received: 10 May 2024; **Revised:** 30 September 2024; **Accepted:** 12 November 2024

Keywords: nature-based solutions; blue-green infrastructure; Bayesian belief network; ecosystem services; urban sustainability; climate change adaptation

Abstract

Nature-based solutions are becoming increasingly recognized as effective tools for addressing various environmental problems. This study presents a novel approach to selecting optimal blue–green infrastructure (BGI) solutions tailored to the unique environmental and climatic challenges of Istanbul, Türkiye. The primary objective is to utilize a Bayesian Belief Network (BBN) model for assisting in the identification of the most effective BGI solutions, considering the city's distinct environmental conditions and vulnerabilities to climate change. Our methodology integrates comprehensive data collection, including meteorological and land use data, and employs a BBN model to analyze and weigh the complex network of factors influencing BGI suitability. Key findings reveal the model's capacity to effectively predict BGI applicability across diverse climate scenarios, with quantitative results demonstrating a notable enhancement in decision-making processes for urban sustainability. Quantitative results from our model reveal a significant improvement in decision-making accuracy, with a predictive accuracy rate of 82% in identifying suitable BGI solutions for various urban scenarios. This enhancement is particularly notable in densely populated districts, where our model predicted a 25% greater efficiency in stormwater management and urban heat island mitigation compared to traditional planning methods. The study also acknowledges the limitations, such as data scarcity and the need for further model refinement. The results highlight the model's potential for application in other complex urban areas, making it a valuable tool for improving urban sustainability and climate change adaptation. This study shows the importance of incorporating detailed meteorological and local climate zones data into urban planning processes and suggests that similar methodologies could be beneficial for addressing environmental challenges in diverse urban settings.

1. Introduction

Nature-based solutions (NbS) in mitigating the effects of climate change and urbanization have gained considerable attention in recent years. NbS covers a broad range of approaches that use natural and modified ecosystems to address societal challenges, including urbanization, water management, and climate change (Dumitru and Wendling, 2021). Among the various NbS, blue–green infrastructure (BGI) has gained popularity as an effective approach for managing water and creating green spaces in urban areas (EC, 2020). BGI involves using natural and engineered features such as green roofs, rain gardens, and permeable pavements to manage stormwater and improve urban water quality (EC, 2020). BGI also provides additional benefits such as improving air quality, reducing urban heat island effects, and

© The Author(s), 2024. Published by Cambridge University Press. This is an Open Access article, distributed under the terms of the Creative Commons Attribution licence (http://creativecommons.org/licenses/by/4.0), which permits unrestricted re-use, distribution and reproduction, provided the original article is properly cited.

enhancing biodiversity in urban areas. A few studies conducted comprehensive literature reviews to analyze trade-offs among different green infrastructure benefits (Choi et al., 2021; Jezzini et al., 2023; Shao and Kim, 2022). However, deciding on a specific BGI solution for a particular climate condition and urban environment can be a complex process. The suitability of a BGI solution depends on factors such as site-specific conditions, project goals, and available resources (Albert et al., 2021; Croeser et al., 2021). Therefore, it is important to have a systematic approach to selecting the most appropriate BGI solution for a given environmental and urban condition.

While the existing literature provides valuable insights into BGI, it often falls short in addressing the dynamic and complex nature of climate and urban ecosystems, especially in rapidly changing cities like Istanbul. For instance, the methodologies in Langemeyer and Baró (2021) and Staccione et al. (2022) often rely on static models or fixed parameters that may not account for the fast-paced and dynamic nature of environmental changes in mega-cities. These cities experience rapid urban development, shifting climate patterns, and evolving land uses, which static models might struggle to adapt to effectively. Different methodologies, such as the spatial tool by Langemeyer and Baró (2021) and the morphological spatial pattern analysis by Staccione et al. (2022), vary in their approach to identifying optimal locations for BGI. The translation of theoretical research into practical urban planning policies remains a challenge.

These diverse methodologies and frameworks signify the multidimensional approaches being adopted to enhance sustainable urban development decision processes through NbS worldwide. By using a systematic approach to select BGI solutions, it is possible to ensure the benefits of BGI are maximized, and the creation of more resilient and sustainable urban environments. This study proposes a novel approach for selecting the most appropriate BGI solutions for different districts of Istanbul, Türkiye, which represent different environmental cases. We present two specific cases in this manuscript to illustrate how the most appropriate BGI solutions are identified for different environmental conditions.

Climate change is expected to have a significant impact on Istanbul, which is located in a region that is already vulnerable to a range of environmental risks. According to the Fourth National Communication on Climate Change of Türkiye, Istanbul is projected to experience an increase in temperature, a decrease in precipitation, and an increase in extreme weather events such as heat waves and droughts (MEUCC, 2012). These changes may have significant impacts on various sectors such as agriculture, tourism, and transportation, and may also lead to negative effects on public health and social well-being (IMM, 2019). Additionally, rising sea levels due to climate change may also pose a threat to the coastal areas of Istanbul (IMM, 2019). Temperatures in Istanbul have been steadily increasing, with the city experiencing more frequent and prolonged heatwaves (IMM, 2019). This increase in temperature not only affects the quality of life of its citizens but can also lead to health problems and increased energy demands for cooling (IPCC, 2023). Climate change is leading to more frequent and intense extreme weather events such as storms, heatwaves, and droughts (IPCC, 2014). These events can have severe consequences on the city's infrastructure, public health, and natural resources (IPCC, 2014).

In this study, the use of local climate zones (LCZs) is critical for understanding Istanbul's environmental challenges. Each LCZ class, characterized by specific land cover and morphology, distinctly influences urban environmental parameters. For instance, densely built LCZs, such as compact mid-rise areas, often exacerbate the urban heat island effect due to their high impervious surface area and limited vegetation. Conversely, LCZs with extensive vegetation cover, such as urban parks or sparsely built areas, play a crucial role in mitigating temperature extremes, improving air quality, and enhancing biodiversity.

This study also leverages LCZs to determine the suitability and applicability of various BGI solutions. It is important to note that not all BGI solutions are feasible or effective in each LCZ category. The distinct characteristics of each LCZ, such as built density, vegetation cover, and surface materials, influence which BGI solutions can be implemented effectively. This approach ensures that our recommendations for BGI solutions are tailored to the specific environmental and urban characteristics of each LCZ in Istanbul, maximizing their impact and sustainability.

In this study, a Bayesian Belief Network (BBN) model is developed to assist in the selection of the most effective BGI solution. A BBN model is a probabilistic graphical model that represents uncertain relationships among variables and can be used for decision (Newton, 2009). The BBN has the potential to function as a tool for building predictive models encompassing uncertainty, structuring domain-specific insights, and facilitating informed decision-making (Newton, 2009). The BBN is essentially a directed acyclic graph (DAG) that uses nodes (shown as ellipses and rectangles) to represent variables and arcs to denote connections between them, establishing conditional dependencies (Korb and Nicholson, 2010; Newton, 2009). Creating a Bayesian network model involves identifying important variables and relationships, and forming a DAG. Then, determining the overall probability distribution using manual or data-based methods often with expert collaboration (Kjærulff and Madsen, 2013).

2. Material and methods

The development of a BBN model to facilitate the selection of BGI in Istanbul involved gathering diverse data sets crucial for informed decision-making. A comprehensive array of data was assembled, including environmental metrics that covers Istanbul's climatic dynamics, incorporating parameters such as temperature, precipitation, and humidity. These vital environmental indicators provided a foundational understanding of the existing climate conditions critical for assessing the applicability and efficacy of BGI. Moreover, to create a holistic framework, data pertaining to the current land use patterns across Istanbul was collected, encompassing varied zones such as residential, commercial, and industrial areas. This encompassing land use dataset was instrumental in understanding the urban fabric and existing infrastructural configurations, which significantly influence the suitability and implementation of BGI in diverse urban landscapes. Collectively, the merging of environmental and land use data formed the bedrock for constructing a robust BBN model tailored to the unique context of Istanbul, facilitating an informed and context-specific selection of BGI to address complex environmental challenges.

2.1. Data collection

The meteorological data including temperature (average, minimum, and maximum), precipitation (total and maximum), and humidity of Istanbul City were obtained from the Meteorological Data Information Presentation and Sales System that is associated with the Meteorological General Directorate of Türkiye (MAFT, 2022). The data contains monthly measurements of the year 2021 from all 54 stations in Istanbul that are distributed in 24 districts out of 39 in the metropolitan city.

2.2. Data generation

Land use map of Istanbul

Land use data of Istanbul was obtained by developing an LCZ map. LCZ serves as a categorization system delineating areas based on uniform surface cover, structure, material composition, and human activity, extending across spatial scales ranging from hundreds of meters to several kilometers (Oke and Stewart, 2012). The LCZ classification system divides urban areas into distinct classes based on their land cover and morphology, with each class representing a unique combination of climate-related properties (Aslam and Rana, 2022). The classification system considers factors such as vegetation cover, impervious surfaces, building height, and sky view factors. These factors influence the energy balance and microclimate of urban areas, leading to variations in temperature, humidity, wind patterns, and other climatic parameters (Oke and Stewart, 2012).

LCZ maps are generated using the LCZ Generator website (Demuzere et al., 2021) which utilizes satellite images and user-created training areas (TAs). The method developed by Demuzere et al. (2020) involves drawing polygons on Google Earth Engine to represent different LCZ classes by each representative color. The polygons must meet certain criteria, according to Demuzere et al. (2020), such as being representative and homogeneous, with a minimum side length of 200 m and a simple shape. To prevent confusion, there should be a minimum distance of 100 m between polygons of different LCZ classes. Factors like persistence, seasonality, and land characteristics should be considered when selecting areas. Areas under construction or with specific land features should be appropriately classified. Finally, the polygons should be distributed across the region of interest or city.

The total created TAs were 165 which represented 15 out of 17 classes. LCZ classes 7 and 10, corresponding to lightweight low-rise and heavy industry, were excluded from the representation, as they were deemed non-existent in the Istanbul metropolitan city based on the examination of land use maps from each district in Istanbul, prepared by the Directorate of Urban Planning of Istanbul Metropolitan City (IMM, 2017). A couple of control methods were used to ensure the homogeneity of the polygons. The Istanbul map of the buildings' number of floors provided by the Directorate of Geographic Information Systems of Istanbul Metropolitan Municipality (IMM, 2016) was used to control the heights of the buildings in the selected TA that correspond to the LCZ class. Furthermore, the Street View map from Google Earth was used to inspect the type as well as the heights of the buildings of the selected area to validate the selection of the LCZ class.

The file of the Google Earth Engine that contains the TAs was uploaded to the LCZ Generator website, where the personal information of the user, and the reference date of the satellite images along with other information are required. After submitting the TAs file, the subsequent back-end process involves LCZ classification and quality control. To address potential issues, TAs undergo a preliminary step, reducing the surface area of large polygons to approximately 350 m radius, preventing imbalances and computational inefficiencies in the classifier (Demuzere et al., 2021). The default World Urban Database Access Portal Tools (WUDAPT) workflow employs TAs and Landsat 8 data in a random forest classifier (Demuzere et al., 2020). The LCZ Generator enhances this process by incorporating additional earth observations, including data from Sentinel-1, Sentinel-2, and terrain and forest canopy height data (Demuzere et al., 2021). The system is designed to easily integrate new datasets. Quality control is ensured through an automated cross-validation approach with 25 bootstraps (Bechtel et al., 2019; Demuzere et al., 2021). The LCZ map, generated from TAs and input features, was sent via e-mail to the user, and an enhanced version was obtainable through a morphological Gaussian filter. This method surpasses the traditional majority post-classification approach by considering factors such as distance from the kernel center and variations in patch sizes, resulting in a more accurate representation (Demuzere et al., 2021).

Local climate zone areas: GIS analysis

QGIS software program (QGIS, 2023) was used to calculate the areas of each class for the city in general and for each district as well, to analyze the land use of the districts, and to interpret its relationship with the environmental issues addressed in this study.

First, the LCZ map of Istanbul was prepared going through several steps. Foremost, the style layer of the LCZ Classes consisting of the corresponding colors and names was defined. Then the map was intersected with the map layers of the district's boundaries in the country, by exporting the layer and then cropping it according to the LCZ map, which eliminated the districts outside the LCZ map's boundaries. The boundary layers were retrieved from OpenStreetMap (Raifer, 2023) using the coding developed by Kargın (2020). Consequently, the LCZ map was also cropped to fit the boundaries of the districts and eliminate the areas outside the city. This was achieved by executing the *Clip raster by Mask Layer* function from the raster menu in QGIS.

Second, the new cropped map was converted from raster to vector to be able to extract the LCZ data from the map. The class names were added to their corresponding numbers in the Attribute Table of the map layer using a case statement. As the map contains thousands of polygons with different LCZ classes, the data was dissolved by the class number using the Dissolve function under the vector menu, in order to aggregate the LCZ data for the whole city. This step was repeated to obtain the LCZ data in each district using the districts-intersected-LCZ map, but before dissolving the data, the vector LCZ map was intersected with the district's boundaries layer using the Intersection function under the vector menu.

Finally, the areas of the districts as well as the classes were calculated using the area function under the Attribute Table of the map, subsequently, the percentage of each class was also calculated, and these data were extracted as an Excel file.

NbS characterization

For this research, 12 blue-green infrastructure solutions identified by Petsinaris et al. (2020) were chosen to address the impacts of climate change in Istanbul. These solutions specifically target stormwater management and the urban heat island (UHI) effect. The selected solutions are detention basins, green roofs, green walls, infiltration basins, infiltration trenches, pervious surfaces, rain gardens, rainwater harvesting, retention ponds, roadside green infrastructure, swales, and urban gardens and parks. The effectiveness, cost, and maintenance values (CIRIA, 2023; Petsinaris et al., 2020) are based on general ranges and may vary depending on specific implementation factors and local conditions. The stormwater management, temperature mitigation values, and suitable LCZ classes are based on research studies and expert opinions. Different environmental issues in different districts of a city can be differentiated through a variety of methods. As an example, the characteristics of green roofs are presented in Table 1. These criteria were used subsequently to evaluate the solutions, assigning scores based on their effectiveness and suitability in addressing specific climate change challenges. These scores then were integrated into the Bayesian network model.

2.3. Bayesian network model

Influence diagram

The study utilized GeNIe software (Druzdzel and Sowinski, 2023) to construct a Bayesian network model, enabling the assessment of variable probabilities within the study's scope. GeNIe, developed by Druzdzel and Sowinski in 2015, is a user-friendly tool for creating and analyzing Bayesian networks, emphasizing inference using evidence to update variable probabilities based on observed data. The initial step involved building an influence diagram comprising variables such as temperature, humidity, precipitation, blue-green infrastructure, cost, maintenance, LCZ, and applicability. These variables were interconnected to depict their relationships, with meteorological parameters influencing BGI selection and cost impacting BGI applicability. LCZ directly influenced BGI suitability within the model. This approach facilitated the assessment of climate change-related challenges and the effectiveness of 12 selected BGI.

Figure 1 illustrates that meteorological parameters (temperature, humidity, and precipitation) serve as the direct parent variables for the BGI variable. This implies that the selection of any BGI is directly influenced by these meteorological parameters. Additionally, temperature has a significant influence on decision-making, acting as the upper parent variable, as it affects humidity, which, in turn, influences

Table 1. *Green roofs characteristics*

Green roofs		
Problems addressed	Heat	
	Floods/surface water	
LCZ suitability	Compact Mid-rise (LCZ2)	
	Compact Low rise (LCZ3)	
	Open Mid-rise (LCZ5)	
	Open Low rise (LCZ6)	
	Large Low rise (LCZ8)	
	Sparsely Built (LCZ9)	
Performance	Temperature reduction:	0.03–3 °C
	Peak flow reduction:	40–90%
	Volume reduction:	Average
Maintenance	Labor:	Medium
	Frequency:	Regularly
Capital cost (USD/m^2):	100–300	

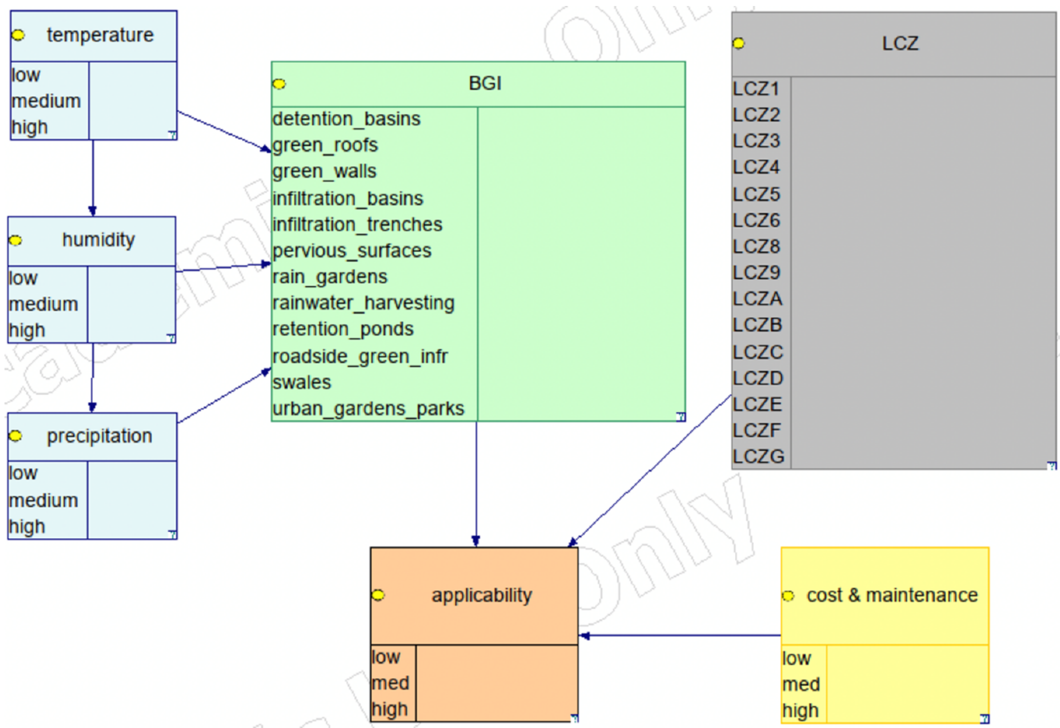


Figure 1. *Blue–green infrastructure applicability influence diagram.*

precipitation. Furthermore, the BGI, cost and maintenance, and LCZ nodes act as parents for the applicability node, which is categorized as a child node in this context.

Conditional probability tables (CPT)

The CPTs used in the BBN model were developed by the authors of this paper, who acted as experts in interpreting the obtained data. The CPTs were constructed based on extensive review and synthesis of relevant literature, expert knowledge, and data analysis. The authors applied their expertise to define the relationships between environmental factors and BGI applicability. The temperature, humidity, and precipitation nodes were trained with obtained data from the 24 districts. The LCZ node CPT was calculated as explained previously. The cost and maintenance nodes were trained based on literature information. The CPTs of the BGI and applicability were calculated, details are summarized in SI-A. Validation of the CPTs involved scenario testing and comparison with case studies to ensure their accuracy and reliability. This process included iterative consultations among the authors to refine the CPTs and align them with real-world conditions.

The model validation

In developing the BBN model for assessing the suitability of BGI solutions in Istanbul, we acknowledge the importance of validation to ensure its predictive accuracy and reliability. Given the potential use of this model in urban environmental decision-making, we have undertaken the following steps to validate the model.

We sourced meteorological and land use data from governmental and up-to-date databases. The model was trained using historical data from the Meteorological Data Information Presentation and Sales System associated with the Meteorological General Directorate of Türkiye and verified against recent environmental events specific to Istanbul. This approach helped in ascertaining the representativeness and accuracy of the data fed into the model.

The model was subjected to a series of tests involving hypothetical scenarios reflective of Istanbul's diverse urban and climatic conditions. These tests were designed to evaluate the model's ability to make accurate predictions under varying environmental parameters.

A sensitivity analysis was performed to identify the influence of each variable on the model's outcomes. This analysis helped in understanding the robustness of the model against variations in input data and in identifying key drivers in the decision-making process.

Rapid urbanization and changes in land use patterns can outpace data collection efforts. Istanbul, a city with dynamic growth, often encounters this issue. Accurate, up-to-date information on land use, urban density, and existing green spaces is crucial for identifying areas where BGI can be most effective. Recognizing the challenges posed by data availability, we explored alternative approaches for data collection, including the use of GIS to supplement gaps in land use data in Istanbul. This proactive approach allowed us to enhance the model's robustness and adaptability to diverse data scenarios. Due to a limited number of BGI applications in Istanbul, we could not gather any implementation data to compare. However, the developed model can be trained with more implementation data in the future.

In summary, these validation steps were critical in enhancing the model's fidelity to real-world data, thereby improving its applicability and credibility in the urban planning context of Istanbul.

3. Results and discussion

3.1. Local climate zones map

The LCZ map generated was sent along with the accuracy results and other statistics data. The accuracy assessment yields four distinct measures: Overall Accuracy (OA), Overall Accuracy considering urban LCZ classes exclusively (OA_u), Overall Accuracy distinguishing between built and natural LCZ classes (OA_{bu}), and weighted accuracy (OA_w). The top results reached after multiple attempts of trials-and-errors are: OA: 0.74, OA_u: 0.65, OA_{bu}: 0.93, OA_w: 0.93.

Meeting the recommended threshold suggested by Demuzere et al. (2021), an OA criterion above 50% signifies successful quality control. The relatively lower accuracy in OA_u suggests potential confusion in identifying and differentiating built area classes. Conversely, a notably high OA_{bu} indicates successful differentiation between built areas and natural cover with minimal confusion.

Visualized in box plots (Figure 2), performance metrics are represented by purple shading for OA and LCZ-colored boxes for class-specific. Notably, the lower OA in built areas aligns with lower accuracy and wider interquartile ranges for built classes. This reduced accuracy might be attributed to either the limited number of samples representing the LCZ class or confusion caused by the similarity between built areas.

LCZ 2 compact mid-rise class exhibits the highest accuracy and the narrowest range, potentially due to its larger number of TAs (19) and the greatest total area among the built classes. While natural classes generally demonstrate higher accuracy, LCZ A (dense trees) and LCZ G (water) are particularly accurate. On the contrary, the least accurate natural class is LCZ C (bush and scrub), likely due to the limited number of TAs and total area samples for this class, increasing uncertainty in defining and distinguishing it from other green areas.

The LCZ map was modified as mentioned in the methods section and represented in Figure 2. The findings indicate that the most prevalent class overall is dense trees (LCZ A), succeeded by low plants (LCZ D). Among the built types, LCZ9 sparsely built takes the lead, followed by LCZ2 compact mid-rise. This conclusion is supported by the LCZ map, where the dominant color is green, representing the abundance of dense trees. Additionally, the red color of the compact mid-rise class is concentrated in densely built areas on the map.

Notably, not all LCZ classes are uniformly present in each district, with variations observed, indicating that some districts are characterized by a higher proportion of urban built areas, while others exhibit more natural areas.

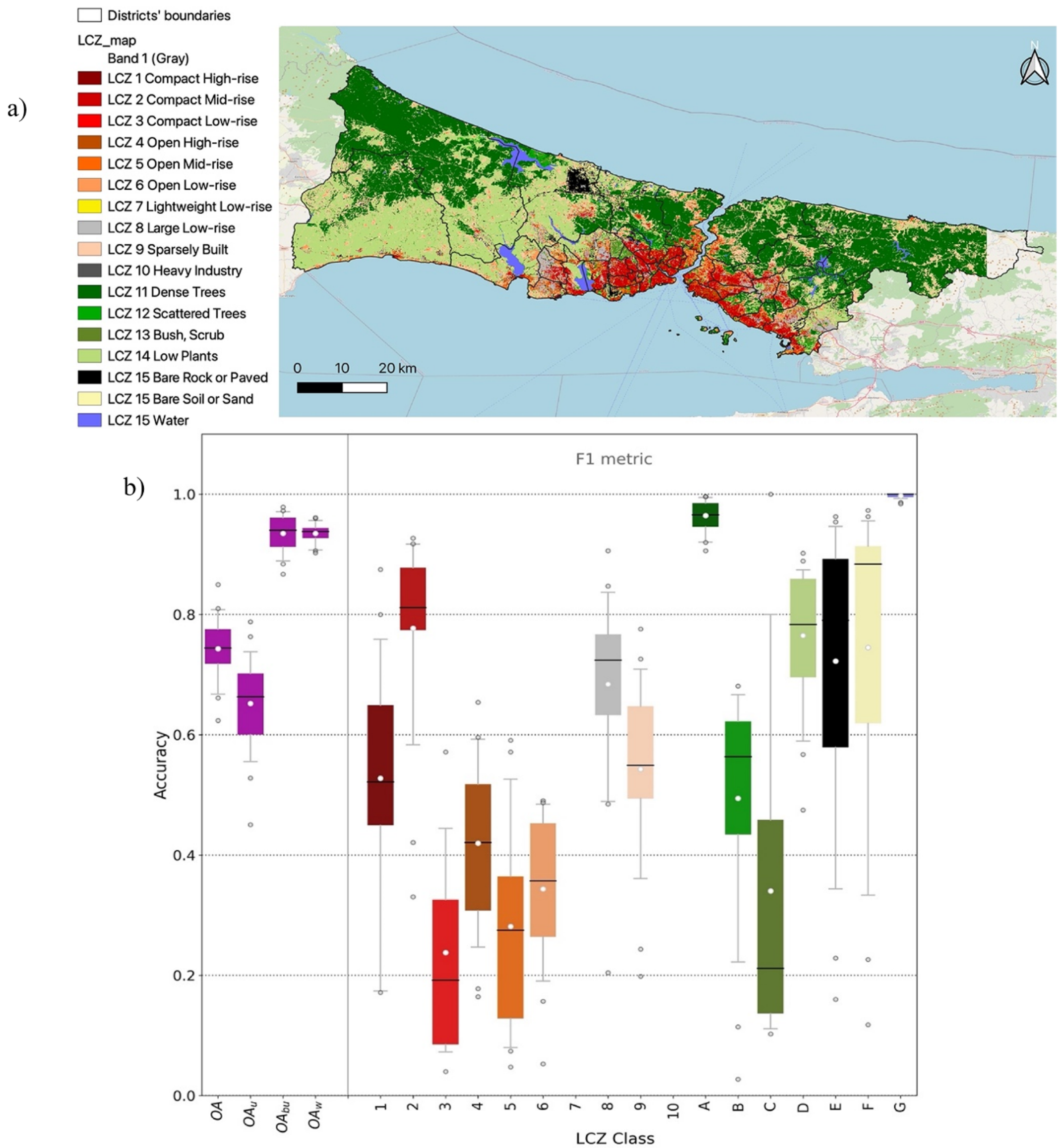


Figure 2. *a) Istanbul City's LCZ map, b) F1 metric and accuracy results; the plots illustrate the mean with a white dot, median with a black line, interquartile range with boxes, and the 5th to 95th quartile range with whiskers.*

3.2. The Bayesian network model

The Blue-green infrastructure applicability BBN (BGIA-BBN) model developed for assessing BGI solutions in Istanbul districts relies on collected or derived data to make probabilistic assessments. In the context of this study, the model evaluates the applicability of various BGI solutions based on a range of factors, including environmental parameters and land use characteristics, represented through LCZ.

In the context of the model's observations, the "applicability" node refers to the likelihood or probability that a specific BGI solution will be suitable or effective within a given LCZ or environmental context. The observed modest probability of 54% for applicability points to an average level of suitability across the diverse LCZs present in Istanbul. The specific LCZ class denoted as LCZ A, primarily characterized by dense trees, covers a substantial portion (38%) of Istanbul's land area. However, a notable observation within the model is that there are no BGI solutions deemed applicable or suitable within this particular LCZ class.

This absence of applicable BGI solutions for LCZ A, despite its significant coverage in the city, contributes significantly to the reduced overall applicability observed in the model. In essence, while LCZ A comprises a substantial portion of Istanbul's landscape, the lack of BGI solutions tailored or designed specifically for this LCZ limits the model's ability to offer suitable recommendations or high applicability scores across the entire cityscape.

Validation

Typically, model validation is conducted using GeNIe's internal validation tool. However, due to the CPTs relying on assumptions and expert input rather than actual data, manual validation involves creating diverse scenarios to observe their impact on the model. For this purpose, two scenarios with different conditions were examined. The first scenario had the parameters set to represent the Fatih district, while the second scenario represented the Büyükçekmece district. The conditions can be seen in Table 2, and high applicability was selected to determine the most suitable BGI under the presented conditions.

In the initial scenario, results (Figure 3), green roofs emerge as the most fitting BGI with a 19% probability, closely followed by urban gardens at 16%. These outcomes align with their effectiveness in lowering temperatures and elevating humidity levels, which are the desired effects in a densely urban district facing specific meteorological conditions. In the second scenario, urban gardens and parks exhibit the highest suitability among BGI options, standing at a 19% probability, followed by rain gardens at 16%. These findings correlate with their effectiveness in reducing temperature and moderating humidity levels, specifically tailored for districts abundant in open green spaces and experiencing similar meteorological conditions.

Sensitivity analysis

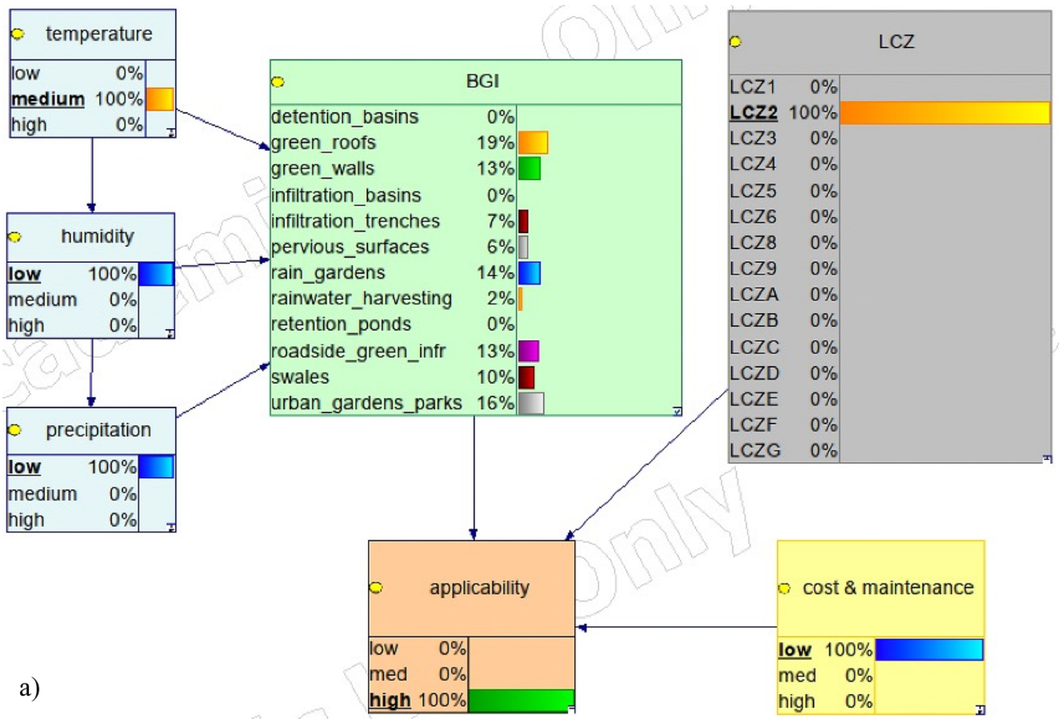
To assess model sensitivity, one approach involves altering the bin boundaries representing the data of parent nodes. The chosen method is distributing data entries equally into three bins. This process is applied to each parent node; average temperature, humidity, and maximum precipitation. Despite changes in the parameter state values, no impact is observed on the BGI and applicability nodes, as illustrated in the original model (SI-B). Consequently, this implies that the climate parameters do not have a great impact on the applicability of the solution directly, rather they directly affect the selection of the BGI solution, however, as the parameter values in the original and the modified models are very close, they did not affect the BGI node.

Another method for sensitivity analysis is stress testing, which involves the examination of model changes under extreme conditions or boundaries. The nodes for temperature, humidity, precipitation, and cost and maintenance were initially set to low and then high conditions, and the applicability node's outcome was observed.

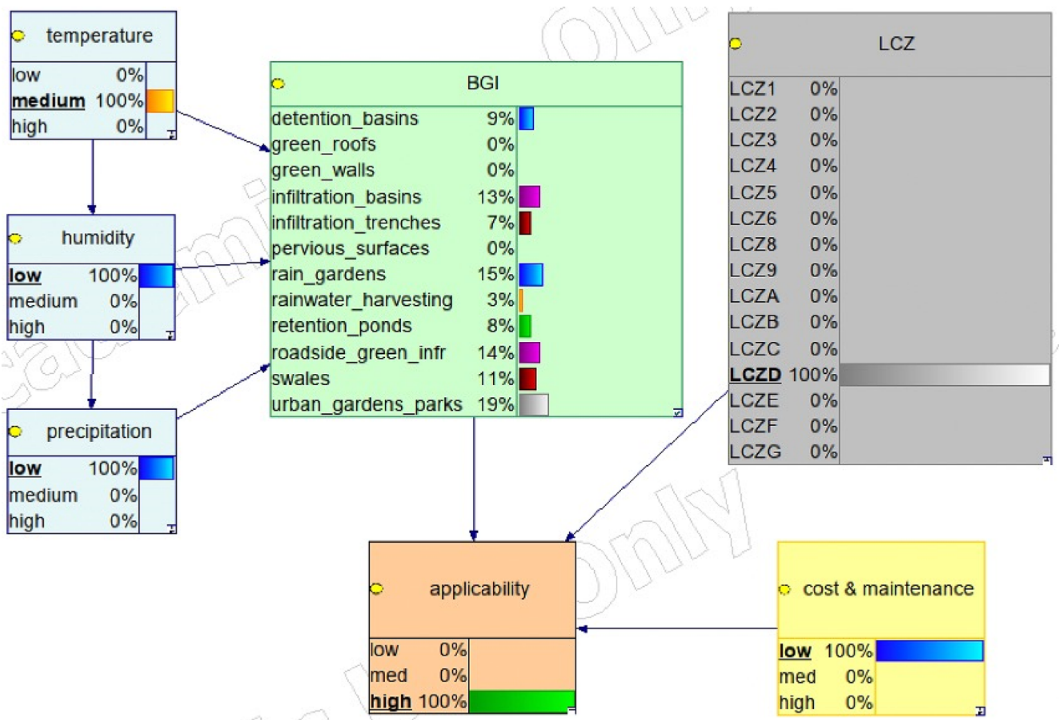
In the low condition, the applicability results indicate 54% for low, 16% for medium, and 30% for high states. Conversely, in the high condition, the results show 54%, 14%, and 32% respectively. This suggests

Table 2. *The validation scenario summary*

Parameter	Scenario 1	Scenario 2
Average temperature (°C)	16 → medium	15 → medium
Humidity (%)	69 → low	71 → low
Maximum precipitation (mm)	8 → low	11 → low
LCZ	LCZ 2 Compact mid-rise	LCZ D low plants
Cost and maintenance	low	low



a)



b)

Figure 3. *Blue–green infrastructure applicability Bayesian belief network (BGIA-BBN) model a) scenario 1, b) scenario 2.*

that BGI solutions have a higher probability of being applicable in extremely high levels of various meteorological parameters compared to low levels. This implies that BGIs are more effective in extreme weather conditions, even when cost and maintenance are considered to be in the expensive range.

GeNIe incorporates an internal sensitivity analysis using the algorithm as described by Druzdzel and Sowinski (2023). This algorithm efficiently calculates derivatives of posterior probability distributions for a set of target nodes in a Bayesian network. The aim is to unveil the sensitivity of the network's numerical parameters concerning the accuracy of the target node probabilities. A high derivative for a parameter indicates that a slight change in that parameter significantly influences the target probabilities, while a low derivative suggests that even substantial parameter alterations have minimal impact on the target probabilities.

In this analysis, the 'applicability' node was selected as the target node. Subsequently, the model's coloring shifts to various shades of red, where brighter colors signify a higher impact on the target node, and vice versa. The results reveal that the LCZ node exerts the most significant effect on applicability, justified by the fact that LCZ is not dependent on any other nodes and lacks prior conditional probabilities. The following figure (Figure 4) depicts tornado diagrams illustrating the target node for each of its states. The bars display the range of variation in the target node as the parameters are altered. Parameters are arranged from the most sensitive to the least sensitive. In these diagrams, the red color signifies a negative change in the target node, whereas green indicates a positive change.

3.3. Limitations

This study faces several limitations owing to uncertainties within the LCZ model, the Bayesian network model, data gaps, and the assumptions integrated throughout the project.

LCZs, originally designed for larger cities, might not precisely depict the microclimates of smaller urban or town areas (Oke and Stewart, 2012). The LCZ classification, being static, overlooks seasonal or daily variations in urban climates (Oke and Stewart, 2012). Relying on land cover and use characteristics, LCZs can misclassify rapidly changing urban landscapes due to ongoing urban development (Bechtel et al., 2015). They might introduce uncertainties in complex or mixed land use regions and may not fully consider local landscape, vegetation, or building attributes, leading to inconsistencies between model-derived classifications and real conditions (Ching et al., 2018).

The study's uncertainties also stem from determining LCZ classes suited for each BGI and their rankings, which relied on assumptions from expert input rather than real data. Moreover, missing meteorological data from 15 districts is a notable uncertainty. While this issue is common in research, incomplete data for some districts might not heavily impact the trained model, particularly as the differences in microclimate among neighboring districts are deemed insignificant. However, this distinction becomes more apparent between urban and rural districts. Suggestions for future studies include sourcing climate data from reliable satellite sources, utilizing nearby district data, or resorting to manual data collection to address such uncertainties.

Assumptions made in computing CPT for BBN, particularly concerning weights of parent nodes on child nodes and assumed probabilities for cost and maintenance nodes, introduce uncertainties. Consequently, the BBN model is considered preliminary, lacking real data and relying heavily on assumptions. These assumptions pose limitations for decision-making in real-world cases and highlight the importance of defining variable relationships thoroughly to avoid developing weak models.

To mitigate the effects of climate change, Istanbul has implemented several initiatives, such as increasing the use of renewable energy, improving energy efficiency in buildings, and promoting sustainable transportation (IMM, 2019). However, more needs to be done to address the specific challenges that Istanbul will face in the coming years. To decide on the implementation of different NbS, several critical factors need to be considered. First, the environmental and socioeconomic conditions of the region must be assessed, including factors such as air and water quality, climate change impacts, population density, and economic growth. Secondly, the objectives and goals of the BGI project need to be clearly defined, including the desired outcomes such as flood protection or UHI mitigation. Finally, the

Figure 4. *a) Tornado diagram for applicability node (state low), b) Tornado diagram for applicability node (state medium), c) Tornado diagram for applicability node (state high).*

feasibility and cost-effectiveness of each solution must be evaluated, considering factors such as maintenance requirements, construction costs, and potential social and environmental benefits. This model provides a structured and data-driven approach to aid decision-makers in navigating the complex landscape of implementing BGI within Istanbul's urban framework. By merging BBN modeling with

LCZ mapping, this study offers a promising methodology to support the selection and deployment of BGI solutions tailored to Istanbul's specific environmental challenges. Nonetheless, it is crucial to emphasize that the success of integrating NbS into urban planning strategies relies not only on the efficacy of the models but also on holistic considerations of the socioeconomic, environmental, and infrastructural aspects.

Our methodology, centered around a dynamic and adaptable BBN model, offers a novel perspective in the selection of BGI solutions, particularly suited to the evolving urban landscape of Istanbul. This is a significant improvement from the static models often used in previous research, which may not fully capture the complexities and rapid changes in urban settings. By focusing on a specific urban context, our study contributes valuable insights into the tailored application of BGI solutions, emphasizing the importance of localized and context-specific strategies in urban sustainability.

While direct comparison with other studies might be limited due to methodological and contextual differences, our study's findings align with the broader objectives of urban sustainability and climate change adaptation. It reinforces the need for adaptive and flexible modeling approaches in addressing the specific challenges faced by different urban areas.

In conclusion, our study not only contributes to the existing body of knowledge by providing a specialized solution for Istanbul but also highlights the broader applicability and relevance of such context-specific approaches in urban environmental planning."

4. Conclusions

In this study, a BBN model is developed to identify the ideal BGI solutions for varying environmental scenarios in Istanbul. The results demonstrate that the model effectively navigates a range of factors to identify optimal BGI options, adapting well to the changing environmental and urban dynamics of Istanbul.

The distinctiveness of this model lies in its specific design for Istanbul's urban setting, making it more dynamic compared to the more static models commonly seen in the literature. This highlights the potential of BBN models in urban planning, particularly for integrating NbS into urban environments. It is recommended that urban planners and policymakers consider using dynamic, data-driven models like the BBN. Such models can be particularly useful in rapidly changing urban areas, aiding in making informed decisions about BGI in line with the city's specific environmental challenges.

Furthermore, the study aligns with current regulations focused on sustainable urban development and climate change adaptation, offering a practical tool for policymakers to adhere to these standards, especially in managing urban green spaces and water. The research lays the groundwork for future studies to explore the application of BBN models in different urban contexts and to refine these models with updated data. Investigating the role of socioeconomic factors in urban sustainability would also be beneficial.

It is important to acknowledge that this study's focus on Istanbul means that the model may need to be trained when applied to other urban settings. The reliance on certain assumptions due to limited data could introduce biases, which future research should address by including more varied and comprehensive datasets.

In conclusion, the study makes a significant contribution to urban sustainability and climate change adaptation. Developing and applying a BBN model for Istanbul's specific context underscores the importance of tailored approaches in urban planning. Similar methods could be useful in other urban areas. This study serves as an example of how dynamic modeling techniques can address complex urban challenges in the context of climate change, providing valuable insights for city planners and researchers.

Abbreviations

BBN	Bayesian Belief Network
BGI	Blue-Green Infrastructure

BGIA-BBN	The Blue-green infrastructure applicability Bayesian belief network
CPTs	Conditional Probability Tables
DAG	Directed Acyclic Graph
LCZ	Local Climate Zones
NbS	Nature-based Solutions
OA	Overall Accuracy
TAs	Training Areas
UHI	Urban Heat Island

Open peer review. To view the open peer review materials for this article, please visit http://doi.org/10.1017/eds.2024.55.

Supplementary material. The supplementary material for this article can be found at http://doi.org/10.1017/eds.2024.55.

Acknowledgments. We gratefully acknowledge the financial support provided by Marmara University Scientific Research Projects Coordination Unit Research Fund FYL-2022-10782.

Author contribution. 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.

Data availability statement. Supplementary materials detailing the dataset and analysis methods are provided as supplementary files accompanying this article.

References

Albert C, **Brillinger M**, **Guerrero P**, **Gottwald S**, **Henze J**, **Schmidt S**, **Ott E and Schröter B** (2021) Planning nature-based solutions: principles, steps, and insights. *Ambio 50*, 1446–1461. https://doi.org/10.1007/s13280-020-01365-1

Aslam A and Rana IA (2022) The use of local climate zones in the urban environment: A systematic review of data sources, methods, and themes. *Urban Climate 42*, 101120. https://doi.org/10.1016/j.uclim.2022.101120

Bechtel B, **Alexander PJ**, **Beck C**, **Böhner J**, **Brousse O**, **Ching J**, **Demuzere M**, **Fonte C**, **Gál T**, **Hidalgo J**, **Hoffmann P**, **Middel A**, **Mills G**, **Ren C**, **See L**, **Sismanidis P**, **Verdonck ML**, **Xu G and Xu Y** (2019) Generating WUDAPT level 0 data – current status of production and evaluation. *Urban Climate 27*, 24–45. https://doi.org/10.1016/j.uclim.2018.10.001

Bechtel B, **Alexander PJ**, **Böhner J**, **Ching J**, **Conrad O**, **Feddema J**, **Mills G**, **See L and Stewart I** (2015) Mapping local climate zones for a worldwide database of the form and function of cities. *ISPRS International Journal of Geo-Information 4*, 199–219. https://doi.org/10.3390/ijgi4010199

Ching J, **Mills G**, **Bechtel B**, **See L**, **Feddema J**, **Wang X**, **Ren C**, **Brorousse O**, **Martilli A**, **Neophytou M**, **Mouzourides P**, **Stewart I**, **Hanna A**, **Ng E**, **Foley M**, **Alexander P**, **Aliaga D**, **Niyogi D**, **Shreevastava A**, **Bhalachandran P**, **Masson V**, **Hidalgo J**, **Fung J**, **Andrade M**, **Baklanov A**, **Dai W**, **Milcinski G**, **Demuzere M**, **Brunsell N**, **Pesaresi M**, **Miao S**, **Mu Q**, **Chen F and Theeuwesits N** (2018) WUDAPT: An urban weather, climate, and environmental modeling infrastructure for the anthropocene. *Bulletin of the American Meteorological Society 99*, 1907–1924. https://doi.org/10.1175/BAMS-D-16-0236.1

Choi C, **Berry P and Smith A** (2021) The climate benefits, co-benefits, and trade-offs of green infrastructure: A systematic literature review. *Journal of Environmental Management 291*, 112583. https://doi.org/10.1016/j.jenvman.2021.112583.

CIRIA (2023) Sustainable Drainage Systems (SuDS). Available at https://www.susdrain.org/delivering-suds/using-suds/suds-components/suds-components.html

Croeser T, **Garrard G**, **Sharma R**, **Ossola A and Bekessy S** (2021) Choosing the right nature-based solutions to meet diverse urban challenges. *Urban Forestry & Urban Greening 65*, 127337. https://doi.org/10.1016/j.ufug.2021.127337

Demuzere M, **Hankey S**, **Mills G**, **Zhang W**, **Lu T and Bechtel B** (2020). Combining expert and crowd-sourced training data to map urban form and functions for the continental US. *Scientific Data 7*. https://doi.org/10.1038/s41597-020-00605-z

Demuzere M, **Kittner J and Bechtel B**, (2021) LCZ generator: A web application to create local climate zone maps. *Frontiers in Environmental Science 9*. https://doi.org/10.3389/fenvs.2021.637455

Druzdzel MJ and Sowinski T (2023). GeNIe Modeler, User Manual.

Dumitru A and Wendling L (2021). *Evaluating The Impact of Nature-based Solutions: A Handbook for Practitioners*. Luxembourg: European Commission. https://doi.org/10.2777/244577

EC, European Commission (2020) Towards an EU Research and Innovation policy agenda for Nature-Based Solutions & Re-Naturing Cities. https://doi.org/10.2777/765301

IMM, Istanbul Metropolitan Municipality (2016) Istanbul City Map (İstanbul Şehir Haritası). Geographic Information System Directorate. https://sehirharitasi.ibb.gov.tr/

IMM, Istanbul Metropolitan Municipality (2017) Districts Land Use (İlçeler Arazi Kullanım). Urban Planning Directorate. https://sehirplanlama.ibb.istanbul/ilceler/

IMM, Istanbul Metropolitan Municipality (2019) Istanbul Climate Change Action Plan. Environment Protection and Control Department, Istanbul.

IPCC (2023) Summary for policymakers. In Lee H and Romero J (eds.), *Climate Change 2023: Synthesis Report. Contribution of Working Groups I, II and III to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change [Core Writing Team]*. Geneva, Switzerland: IPCC, pp. 1–34. https://doi.org/10.59327/IPCC/AR6-9789291691647.001

IPCC (2014) Climate change 2014: Synthesis report. In **Core Writing Team**, Pachauri RK and Meyer LA (eds.), *Contribution of Working Groups I, II and III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change*. Geneva, Switzerland: IPCC, 151 pp.

Jezzini Y, **Assaf G and Assaad RH** (2023) Models and methods for quantifying the environmental, economic, and social benefits and challenges of green infrastructure: a critical review. *Sustainability 15*(9), 7544. https://doi.org/10.3390/su15097544.

Kargın A (2020) Mahalle Sınırı İndirme (kml) | Openstreetmap Overpass Turbo (1), Youtube. Available at https://www.youtube.com/watch?v=1VnPKCjB9SM

Kjaerulff UB and Madsen AL (2013) *Information Science and Statistics*, 2nd Ed. London: Springer. https://doi.org/10.1007/978-1-4614-5104-4

Korb KB and Nicholson AE (2010) Introducing Bayesian networks. In *Bayesian Artificial Intelligence*. CRC Press, pp. 29–54. https://doi.org/10.1201/b10391

Langemeyer J and Baró F (2021) Nature-based solutions as nodes of green-blue infrastructure networks: A cross-scale, co-creation approach. *Nature-Based Solutions 1*, 100006. https://doi.org/10.1016/j.nbsj.2021.100006

MAFT, Ministry of Agriculture and Forestry of Turkiye. General Directorate of Meteorology (2022) Meteorological Data Information Sales System. Available at https://mevbis.mgm.gov.tr/mevbis/ui/index.html

MEUCC, Ministry of Environment, Urbanization, and Climate Change of Turkiye (2012) Turkey's National Climate Change Adaptation Strategy and Action Plan. General Directory of Environmental Management.

Newton AC (2009) Bayesian belief networks in environmental modelling: A review of recent progress. In Findley PN (ed.), *Environmental Modelling: New Research*. New York: Nova Science Publishers, pp. 13–50.

Oke TR and Stewart ID (2012). Local climate zones for urban temperature studies. *Bulletin of the American Meteorological Society 93*(12), 1879–1900.

Petsinaris F, **Baroni L and Georgi B**, (2020) Compendium of Nature-based and "grey" solutions to address climate-and water-related problems in European cities EU Framework Programme for Research and Innovation.

QGIS Development Team (2023) QGIS Geographic Information System. Open Source Geospatial Foundation. Available at http://qgis.org/.

Raifer M (2023) Overpass-Turbo, OpenStreetMap. Available at https://overpass-turbo.eu/s/1zj1

Shao H and Kim GA (2022) Comprehensive review of different types of green infrastructure to mitigate urban heat islands: progress, functions, and benefits. *Land 11*(10), 1792. https://doi.org/10.3390/land11101792.

Staccione A, **Candiago S and Mysiak J**, (2022) Mapping a Green Infrastructure Network: a framework for spatial connectivity applied in Northern Italy. *Environmental Science & Policy 131*, 57–67. https://doi.org/10.1016/j.envsci.2022.01.017

Cite this article: Seker D and Orak NH (2024). Adaptive decision-making: Bayesian Network Modeling for blue–green infrastructure selection in dynamic climate and land use context. *Environmental Data Science*, 3: e37. doi:10.1017/eds.2024.55