

A KPI-based model for smart management of urban green infrastructure and ecosystem services

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Abstract

Urban areas face increasing challenges, including air and water pollution, rising temperatures, and natural resource depletion. The effective management of green infrastructure has the potential to mitigate urban heat, reduce air pollutants, and enhance economic benefits. This study aims to develop a conceptual decision-support model for urban green infrastructure management based on KPI evaluation and smart technologies. The model was demonstrated through a pilot case study for Tsar Simeon Garden in Plovdiv using secondary environmental data (temperature, humidity, $PM_{2.5}$ and PM_{10} concentrations, and NDVI) and proxy-based estimates of KPIs. Key performance indicators were derived and evaluated using an AHP–TOPSIS framework. In addition, a scenario-based simulation was conducted to assess the potential effect of alternative management strategies, including vegetation enhancement, smart irrigation, and integrated interventions. The proposed framework supports more efficient management of urban green infrastructure, improving cooling, vegetation health, and resource use. The results indicate that KPI-based, data-informed evaluation can enhance decision-making for urban green infrastructure, particularly under data-constrained conditions.

Key words: artificial intelligence, decision-making, ecosystem services, IoT, KPI, sustainable development.

Introduction

Urbanisation and climate change intensify challenges such as air pollution, rising temperatures, and resource depletion. These pressures require a rethinking of how cities are planned and managed. Urban green infrastructure has emerged as a key approach to improving environmen-

tal quality and supporting more sustainable urban environments (Sharifi 2021, Andreev et al. 2023).

Green infrastructure provides key ecological and social benefits, including microclimate regulation, improved air quality, and enhanced biodiversity (Ramyar et al. 2021, Vannucchi et al. 2021, Viecco et al. 2021, Hajam et al. 2023).

The growing importance of these benefits highlights the need for effective tools to manage green systems in cities. Smart technologies can support these processes. The Internet of Things (IoT) can be used to monitor the state of the environment in real-time and to create 'smart cities' (Chen et al. 2023). GIS can be used to analyse environmental conditions, monitor them remotely, and evaluate social vulnerabilities (Czyza and Kowalczyk 2024). Artificial intelligence contributes through automation, predictive modelling and the ability to analyse large datasets, helping cities adapt to climate-related pressures (Georgieva and Vasilev 2024, Shaamala et al. 2024).

Although significant technological advancements have been made, existing studies rarely integrate environmental key performance indicators (KPIs), IoT, GIS, and AI into a decision support system. This creates a gap in the ability to evaluate and manage green infrastructure using consistent and comparable indicators.

This study aims to develop a conceptual decision-support model for urban green infrastructure management, integrating IoT sensor networks, GIS-based spatial analysis, and AI algorithms. The framework is further illustrated through a pilot case study and scenario-based simulation, demonstrating the generation and comparative evaluation of KPI values under alternative management interventions.

Materials and Methods

In the proposed conceptual model, a systematic approach is applied, based on a thematic literature review, synthesis of technological solutions, and the derivation of environmental KPIs.

Literature analysis procedure

A literature search was conducted in the electronic databases Google Scholar and ResearchGate in December 2025. In order to ensure the relevance of the technological developments, the search covered the last five years.

Synthesis and selection of smart technologies

The chosen technologies, namely IoT, GIS, and AI, were assessed in terms of the following three criteria: (i) the capacity of the technologies to supply relevant information on the environment, (ii) the technologies' interoperability with each other on a single digital platform, and (iii) the technologies' proven applicability in the context of smart city development and sustainability (Chen et al. 2023, Czyza and Kowalczyk 2024).

Derivation of KPIs

The scientific literature on the subject matter was systematically reviewed to determine the most appropriate environmental performance indicators for the assessment of urban green infrastructure. Current research in relation to ecosystem services and the management of urban green infrastructure commonly emphasizes five fundamental functional aspects: vegetation provisioning, microclimate modulation, carbon fixation, biodiversity maintenance, and air quality improvement (Ramyar et al. 2021, Vannucchi et al. 2021, Viecco et al. 2021, Hajam et al. 2023). Thus, KPIs selected for the proposed model are as follows:

- Green Coverage Index (GCI) (green area per inhabitant);
- Urban Cooling Index (UCI) (cooling effect);

- CO₂ Sequestration;
- Biodiversity Index;
- Air-Quality Improvement.

These indicators represent key quantitative measures for evaluating environ-

mental performance in relation to defined sustainability goals. Their associated ecosystem functions and potential management applications are summarised in Table 1.

Table 1. Key indicators and associated ecosystem functions of urban green infrastructure.

Indicator	Ecosystem function	Management application
Urban Cooling Index	Microclimate regulation	Heat stress mitigation
Green Coverage Index	Vegetation provision	Green-space planning
CO ₂ Sequestration	Carbon capture	Climate mitigation planning
Biodiversity Index	Ecological sustainability	Habitat protection
Air-Quality Improvement	Pollution reduction	Air-quality management

Normalisation and quantitative integration into the model

To ensure comparability, the five selected KPIs were normalised to a 0–1 scale using reference-based normalisation. This facilitated the integration of the indicators into the multi-criteria evaluation process without the influence of differing units and magnitudes. Each KPI was associated to a specific ecosystem function and was incorporated into the Analytic Hierarchy Process (AHP) – Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) technique based on the weight it was assigned.

The reliability of KPIs was assessed by means of two methods: (i) cross-validation against reference values reported in the scientific literature, and (ii) internal consistency checks of the IoT data, GIS-derived spatial indicators, and remote sensing data. This approach ensured that the KPI values used in the model reflect realistic ecological conditions and maintain methodological robustness.

Reliability assessment of KPIs

Although the present research does not include direct field measurements from

an *in situ* sensor network, the framework was illustrated using secondary environmental data and literature-based proxy indicators. For instance, the urban vegetation cooling effect is typically reported to vary from 1–2 °C, soil moisture levels in managed urban parks vary from 20–30 % Volumetric Water Content (VWC), while the rates of CO₂ sequestration by mature urban trees are typically reported to exceed 6–8 t·ha⁻¹ (Strohbach and Haase 2012, Ziter et al. 2019, Zabret et al. 2023). The ranges of the KPIs identified in the scientific literature provide a sense of the applicability of the KPIs in the proposed conceptual model.

Model-based simulation of KPI scenarios

To ensure that the scenario analysis is based on real, datadriven computations rather than heuristic adjustments, a simulation module was developed using the observed environmental data for the period 10–16 July 2025. The baseline Normalized Difference Vegetation Index (NDVI) (0.43), mean Particulate Matter ≤ 10 µm (PM₁₀) concentration (19.4 µg·m⁻³), and literaturereported

cooling ranges (1–2 °C) were used to calibrate a simple, transparent model that generates KPI values under alternative management scenarios.

Cooling model

The UCI was modelled as a linear function of vegetation density, expressed by Equation (1):

$$UCI = a \cdot NDVI + b, \quad (1)$$

where: a is the coefficient that determines how strongly changes in NDVI influence the cooling index; b is the baseline offset representing the cooling effect when vegetation density is minimal.

Airquality model

Air-quality response was modelled as a function of the cooling effect, expressed by Equation (2):

$$PM_{10sim} = PM_{10base} - c \cdot UCI, \quad (2)$$

where: PM_{10sim} is the simulated PM_{10} concentration ($\mu g \cdot m^{-3}$), PM_{10base} is the baseline PM_{10} concentration ($\mu g \cdot m^{-3}$), and c is an empirical coefficient describing the relationship between cooling and particulate matter reduction.

The coefficient $c = 0.8 \mu g \cdot m^{-3}$ per °C reflects typical temperature–particulate interactions reported in the literature.

Air-Quality Improvement was computed using Equation (3):

$$AQI_{imp} = 1 - \frac{PM_{10sim}}{40}, \quad (3)$$

where: 40 $\mu g \cdot m^{-3}$ is the EU reference threshold.

Scenario simulation

Three scenarios were simulated by modifying NDVI values and propagating these changes through the calibrated model:

1. NDVI +10 %
2. NDVI +20 %
3. NDVI +20 % + 0.3 °C additional cooling.

Model calibration

The parameters of the cooling model were calibrated using literature-reported ranges of vegetation-induced cooling in urban parks. Numerous studies indicate that typical cooling effects range between 1–2 °C for areas with moderate vegetation density (Kong et al. 2014, Ziter et al. 2019). Given the observed NDVI value for the study area (0.43), the coefficients $a = 2.5$ and $b = 0.1$ were selected to ensure that the simulated baseline cooling effect (1.18 °C) falls within this empirically documented range. The resulting linear model is therefore consistent with published cooling responses while remaining sufficiently simple for scenario-based simulation.

This method establishes a relationship between intervention inputs and KPI outputs, which can be used to simulate the evaluation of various management approaches.

AHP–TOPSIS Methodology

The AHP procedure follows the standard pairwise comparison approach described by Saaty (1980). In this study, the selected KPIs function as evaluation criteria within the AHP hierarchy. A panel of five experts in urban forestry, ecology, and municipal green space management provided the pairwise judgments used to determine the relative importance of the criteria. Consistency ratios ($CR < 0.1$) were used to ensure the reliability of the expert evaluations. The final pairwise comparison matrix was obtained by aggregating the ex-

pert judgments using the geometric mean.

All KPIs were normalised to a 0–1 scale using reference-based normalisation to enable their integration into the multi-criteria framework. The AHP-derived weights were then used as inputs to the TOPSIS method, which was applied to support the aggregated evaluation of environmental performance based on the distance from an ideal and an anti-ideal solution (Hwang and Yoon 1981).

In the TOPSIS method, the normalised value of the KPI formed the decision matrix, which was then multiplied by the AHP weights to obtain the weighted matrix. The ideal and anti-ideal solutions were then computed for each criterion, followed by the computation of the Euclidean distances. Finally, the closeness coefficient was calculated. Higher values indicate better overall environmental performance. This process creates a reproducible framework for incorporating expert knowledge with quantified environmental measures.

Architecture of the conceptual model

The proposed conceptual model for sustainable management of urban green infrastructure using smart technologies is presented in Fig. 1.

The proposed model consists of three

subsystems or modules:

1. Input – IoT sensors (measuring temperature, humidity, pollutants), GIS (spatial data for properties and infrastructure) and mobile applications for city management. These data sources form the basis for calculating the environmental KPIs used in the model.

2. Processing – machine learning techniques (for detecting patterns and vegetation stress) and multi-criteria analysis (AHP–TOPSIS) – for supporting aggregated environmental evaluation and management decision-making. This subsystem integrates expert knowledge with quantitative environmental indicators.

3. Output – processing of big data allows the development of automated solutions related to green infrastructure management, including those related to irrigation, afforestation and maintenance. These outputs support operational and strategic management of urban green spaces.

Table 2 summarises the three layers of the model and their main functions.

Smart technologies, including IoT sensors, GIS analysis, and remote sensing imagery, are integrated at all levels of the model. Overall, these technologies provide real-time information on the environment, spatial information, and vegetation

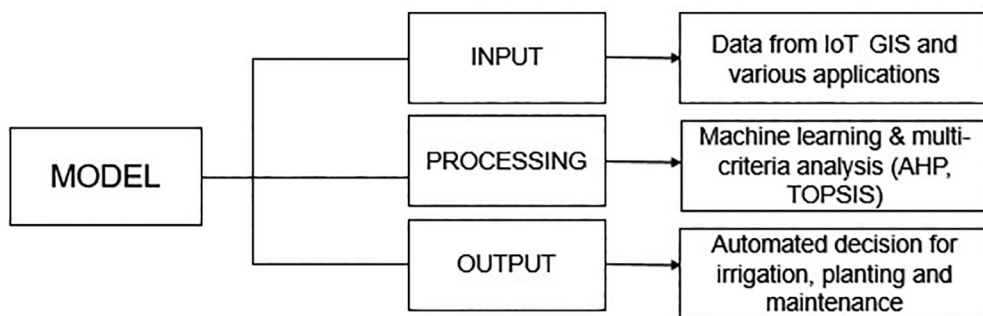


Fig. 1. Conceptual model for sustainable management of urban green infrastructure using smart technologies.

Table 2. The layers of the model.

Layer	Main functions	Data	Benefit
Sensor	Data collection	Climate indicators	Real-time monitoring
Analytical	Processing	KPIs	Performance assessment
Management	Decisions	Analysis	Sustainable management

information, enabling accurate assessment and effective decision-making.

The AI component was not restricted to a single algorithm, since the proposed framework is conceptual. However, the literature synthesis identified three functional groups of algorithms as most relevant: (i) predictive models for environmental forecasting, (ii) classification algorithms for vegetation-stress detection, and (iii) multi-criteria decision-support methods for intervention prioritisation.

Results

The study evaluates the integrated contribution of IoT, GIS, and AI through KPI-based assessment and multi-criteria analysis.

Case study application: Tsar Simeon Garden, Plovdiv

To demonstrate the practical applicability of the proposed conceptual model, a case study was conducted using environmental and spatial data from a representative urban green space in Plovdiv.

Figure 2 shows a map illustrating the spatial dimension of the proposed model and the integration of GIS and remote-sensing technologies. It is an NDVI and visualizes the distribution of vegetation within Tsar Simeon Garden and its surrounding urban environment. The dark areas are low or near-zero NVDI values, corresponding to the central water body

and fountain rather than missing data.

Site description

Tsar Simeon Garden in Plovdiv was selected to illustrate the applicability of the conceptual model. The area is 7 ha, and it is an important part of the city’s green infrastructure. This was justified by the fact that Plovdiv has a very high urban heat island effect with temperatures often rising to over 35 °C during summer, causing severe stress to the vegetation (Ivanov et al. 2025). The woody vegetation is represented mainly by mature individuals of *Platanus orientalis* L., *Tilia cordata* L., and *Aesculus hippocastanum* L., which provide key regulating ecosystem services. Their ecological role makes the site suitable for testing the integration of spatial analysis and multi-criteria evaluation within the proposed model.

High visitor pressure, mature tree stands, and vulnerability to heat stress highlight the need for data-driven management approaches. These factors make the Tsar Simeon Garden an appropriate case for applying the conceptual model.

Case study illustration using secondary environmental data

In order to show the potential application of the proposed conceptual model, secondary environmental data were used for Plovdiv region for a representative summer season. The selected time period was one week between 10–16 July 2025.

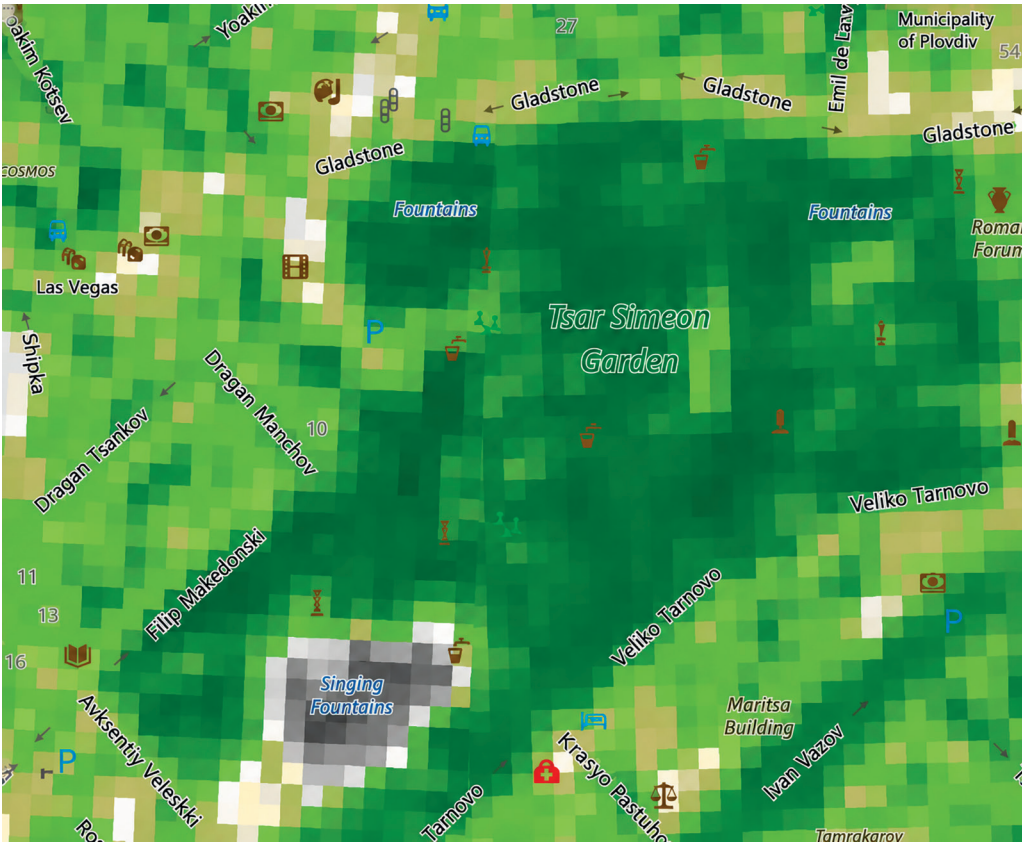


Fig. 2. NDVI-based spatial distribution of vegetation in Tsar Simeon Garden, Plovdiv, derived from Sentinel-2 imagery (Copernicus Programme).

Data sources

Data sources used for empirical validation are presented in Table 3. The datasets represent publicly available environmental information at the city level and were

used as proxy inputs to approximate the environmental conditions of the selected urban green space.

These datasets were processed in Excel to derive the environmental KPIs.

Table 3. Data sources used for empirical validation.

Data type	Variables	Source / Institution	Location
Meteorological data	Air temperature, Relative humidity	https://www.wunderground.com/	Plovdiv
Air quality data	PM _{2.5} , PM ₁₀	https://www.aqi.in/	Plovdiv
Vegetation indices (NDVI)	Sentinel-2 Level-2A reflectance bands	https://apps.sentinel-hub.com/eo-browser	Plovdiv

Environmental data used for KPI derivation

Table 4 presents meteorological data and air quality data.

Table 5 presents NDVI values. NDVI

was used as a supporting vegetation-related proxy indicator to assist in the derivation and interpretation of vegetation-related KPIs, rather than as a standalone KPI within the evaluation framework.

Table 4. Meteorological data and air quality data.

Date	Mean Temp, °C	Max Temp, °C	PM _{2.5} , µg·m ⁻³	PM ₁₀ , µg·m ⁻³	Humidity, %
10.07.2025	23.1	29.2	10	22	33
11.07.2025	24.1	29.6	8	18	35
12.07.2025	25.8	32.9	8	18	32
13.07.2025	26.4	34.9	9	18	23
14.07.2025	27.2	36.8	10	21	21
15.07.2025	27.6	34.9	8	20	25
16.07.2025	28.4	35.3	7	19	29

Table 5. NDVI values (Sentinel-2).

Metric	Value
NDVI min	0.00
NDVI max	0.90
NDVI mean	0.43

KPI calculation based on secondary and proxy data

The KPI values used in the model are based on a combination of secondary environmental data, remote sensing information, and literature-based proxy estimates. NDVI served as a proxy indicator of vegetation conditions and contributed to the derivation and interpretation of vegetation-related KPIs, such as the GCI and Biodiversity Index. In contrast, the final evaluation framework is based on the selected KPIs, which serve as the primary criteria in the multi-criteria analysis. UCI, GCI, and Biodiversity Index were estimated using literature-established ranges and proxy-based assumptions. Air-Quality Improvement was calculated as a PM₁₀-based relative score using the observed mean PM₁₀ concentration and a bench-

mark threshold value. CO₂ sequestration was incorporated as a literature-based ecological estimate for mature urban vegetation.

Table 6 presents the resulting KPI values and their normalised scores.

Using a mean PM₁₀ value of 19.4 µg·m⁻³ and a benchmark of 40 µg·m⁻³, the resulting normalised score was approximately 0.52.

IoT-related measurements support thermal and air-quality indicators, GIS and remote sensing contribute to vegetation-related indicators, and AI-enabled multi-criteria analysis supports the aggregation and interpretation of the resulting performance profile. The results show relatively higher performance for CO₂ sequestration and biodiversity, moderate performance for air quality improvement and urban cooling, and comparatively lower performance for green coverage.

Table 7 presents the AHP-derived weights assigned to the five selected environmental KPIs used in the multi-criteria evaluation framework. The highest relative importance was assigned to UCI and Air-Quality Improvement, reflecting the

Table 6. Environmental KPIs derived from secondary and proxy data.

Indicator	Value	Normalised (0–1)	Type	Description
Urban Cooling Index, °C	1.0	0.50	Estimated	Vegetation-induced cooling effect
Green Coverage Index, m ² per capita	4.3	0.43	Derived	Proxy for green space availability
Biodiversity Index	0.60	0.60	Proxy	Ecological stability indicator
CO ₂ Sequestration, t·ha ⁻¹ ·year ⁻¹	7.2	0.72	Literature-based	Carbon capture potential
Air-Quality Improvement	0.52	0.52	Calculated	PM-based improvement potential

importance of heat stress and particulate pollution in the studied urban context.

Table 7. AHP-derived weights of the selected environmental KPIs.

Indicator	Weight
Urban Cooling Index	0.25
Air-Quality Improvement	0.20
Green Coverage Index	0.20
Biodiversity Index	0.20
CO ₂ Sequestration	0.15

The AHP-derived weights indicate that thermal regulation and air-quality-related performance are the most influential dimensions in the evaluation framework, followed by vegetation provision, biodiversity, and carbon sequestration. These weights were subsequently used in the TOPSIS analysis to assess the aggregated environmental performance of the case study. The weighting scheme is based on Saaty's (1980) methodology and represents an expert-based prioritisation of the selected KPIs.

Multi-criteria evaluation using AHP–TOPSIS framework

The multi-criteria evaluation of environmental performance was conducted using a combined AHP–TOPSIS approach.

Five key environmental indicators were used as evaluation criteria: UCI, GCI, Biodiversity Index, CO₂ Sequestration, and Air-Quality Improvement.

These KPIs were derived from secondary environmental data (temperature, relative humidity, PM_{2.5}, PM₁₀, and NDVI) and complemented by literature-based proxy estimates. The input variables were processed and transformed into normalised KPI values, enabling their integration into a unified multi-criteria decision-making framework.

The relative importance of the KPIs was determined using AHP, based on expert judgment. The pairwise comparison matrix was constructed based on expert judgment from a panel of specialists, and consistency ratios (CR < 0.1) were also used to ensure the reliability. The results represent the relative importance of thermal regulation, air quality, vegetation provision, biodiversity, and carbon sequestration in an urban environmental setting.

Due to the use of secondary and proxy-based data, the TOPSIS evaluation was performed at an aggregated level, focusing on overall environmental performance rather than comparison among multiple discrete alternatives.

The results indicate a moderate level

of environmental performance, with relatively strong carbon sequestration and biodiversity potential, moderate air quality and cooling performance, and comparatively low green coverage. The combined AHP–TOPSIS approach demonstrates the applicability of the proposed framework as a decision-support tool for smart urban green infrastructure management.

From a technological perspective, the results also provide a quantitative indication of the framework’s effectiveness. The derived KPI scores and the aggregated TOPSIS value show that the combined use of IoT-type environmental inputs, GIS/remote sensing data, and AI-supported decision analysis can generate measurable environmental performance outputs, even under data-constrained urban conditions.

Scenario-based simulation of management interventions

Three intervention scenarios were defined to represent possible smart management

strategies:

1. Vegetation cover improvement scenario;
2. Smart irrigation and localised cooling response scenario;
3. Smart green infrastructure management scenario.

In all scenarios, the KPI values were computed using the computational model described in the Methods section, using scenario-specific intervention inputs derived from the model framework rather than arbitrary assumptions. The KPI values were then evaluated to determine the potential effects of various intervention strategies on overall system performance. Vegetation-related KPIs (GCI, Biodiversity, CO₂ sequestration) were simulated using proportional relationships linked to NDVI increase under each scenario.

The resulting KPI values are presented in Table 8.

The simulated KPI values were evaluated using the same AHP–TOPSIS framework applied in the baseline analysis. The AHP-derived weights were preserved

Table 8. Model-generated KPI values under alternative management scenarios.

KPI	Baseline	Scenario 1	Scenario 2	Scenario 3
Urban Cooling Index	0.59	0.66	0.72	0.87
Air Quality Improvement	0.54	0.55	0.56	0.57
CO ₂ Sequestration	0.72	0.78	0.72	0.80
Green Coverage Index	0.43	0.55	0.46	0.58
Biodiversity Index	0.60	0.68	0.62	0.72

to ensure methodological consistency across scenarios.

The overall environmental performance scores were calculated using the model-generated KPI values presented in Table 8 and the AHP-derived weights shown in Table 7. Table 9 presents the weighted environmental performance scores.

Table 9. Weighted environmental performance scores based on model-generated KPI values.

Scenario	Score
Baseline	0.57
Scenario 1	0.64
Scenario 2	0.62
Scenario 3	0.71

The results demonstrate that all scenarios have a positive impact on the overall environmental performance compared to the baseline. In the vegetation enhancement scenario, ecological performance improves notably, particularly in terms of green coverage and biodiversity. In the smart irrigation scenario, improvements are primarily associated with thermal regulation and air quality.

The highest performance is obtained in the third scenario, which integrates multiple smart management strategies. This confirms that combined interventions can generate synergistic effects across environmental indicators.

The increase in weighted environmental performance from 0.57 (baseline) to 0.71 (integrated scenario) demonstrates the ability of the proposed framework to quantitatively differentiate the environmental benefits of alternative management strategies.

Discussion

Results of the case study show the application of the proposed conceptual framework in examining urban green infrastructure based on spatial and environmental data. In particular, the use of NDVI for the evaluation reveals spatial variations in the vegetation density that support the examination of other indicators like the GCI and UCI. Places characterised by low vegetation density have lower cooling efficiency and poor ecosystem function, confirming the significance of spatial data in decision-making.

These results are in line with previous studies showing the role of urban vegetation in improving microclimate conditions, air quality and biodiversity (Barwise and Kumar 2020, Viecco et al. 2021, Rezvani

et al. 2023). In this study, the contribution is not in redefining these effects, but in organising them within a KPI-based framework supported by GIS and remote sensing data.

Similar approaches can already be observed in different cities. For example, Barcelona uses GIS together with real-time environmental data to support the maintenance of urban green areas (Chen et al. 2023). In Singapore, IoT sensors automate irrigation and help reduce water use (Safira n.d.). Copenhagen uses green roofs as part of its climate adaptation strategy and monitors their stormwater retention performance (Københavns Kommune 2023).

The case study aligns with these approaches by showing how spatial layers and performance indicators can be combined to support more informed decision-making.

In Bulgaria, the conditions for the implementation of an integrated approach using digitalisation are still rather poorly developed. Solutions that are currently implemented (such as green roofs or local monitoring systems) in isolated cases. They are not linked to a single platform or coordinated political framework. This highlights the need for a more integrated approach that supports climate adaptation and long-term resilience.

Interpretation of the model

The effects discussed in this section are interpreted through the proposed conceptual model for smart management of urban green infrastructure. The expected environmental, social, and economic impacts are linked to the KPI system, which allows these outcomes to be tracked and evaluated in a structured way. These impacts represent projected results of apply-

ing the model, not independent empirical findings.

The model is designed to support sustainable management by combining smart technologies with KPIbased assessment. Its benefits are expected across environmental, social, and economic dimensions, but its performance needs to be evaluated regularly, especially as technologies and urban conditions change (Georgieva et al. 2025a,b).

Limitations of the study

The study is primarily conceptual and does not include full empirical validation with long-term real-world data. The framework is illustrated through a case study, but has not yet been tested in real-world operational settings. This leaves room for future practical testing and development.

The case study provides an initial illustration of how the framework can be used to structure and interpret spatial and environmental data in an urban context. However, this does not constitute full validation of its effectiveness, and its practical applicability needs to be confirmed through further empirical research.

Several limitations have been identified. Firstly, there may be a lack of IoT sensor coverage. Secondly, data obtained from remote sensing technique may be limited by cloud cover, in addition to the frequency of image capture. Lastly, there is a certain level of subjectivity involved in expert-based evaluation, even after the consistency check. These factors highlight the need for adaptive calibration of the model parameters.

The study also does not provide a quantitative evaluation of the standalone performance of IoT, GIS and AI technologies, as the focus is placed on their integrated use within a unified decision-sup-

port framework.

Challenges and practical limitations in applying the model

Although the proposed conceptual model offers clear environmental, economic and social benefits, several practical challenges may affect its implementation in real-world conditions. Firstly, financial investment is required in the implementation of smart technologies. Secondly, compliance with regulations and technical standards must be ensured in the management of green infrastructure, which may involve different regulatory frameworks, such as green roofs. Thirdly, qualified green infrastructure specialists are required to ensure the effective use of green infrastructure and innovative technologies. This highlights the need for coordinated efforts between local authorities, educational institutions and the private sector.

In the Bulgarian context, several additional constraints may affect the practical implementation of the model. These include uneven levels of municipal digitalisation across cities, limited longterm environmental datasets, and institutional or financial barriers that can slow down the deployment of IoT and GIS infrastructures. Such contextspecific factors should be taken into account when applying the model in real urban environments.

Conclusions

This study presents a conceptual model for managing urban green infrastructure using smart technologies. The aggregated citylevel test demonstrated that IoT measurements, GIS indicators, and remote-sensing vegetation data can be inte-

grated into a coherent KPI set and evaluated through an AHP–TOPSIS framework, producing clear and data-driven insights.

Scenario-based simulation further showed that the model effectively differentiates between management options, with integrated strategies – combining vegetation enhancement, irrigation optimisation, and air quality measures – achieving the highest performance. The integrated scenario resulted in an increase in the weighted environmental performance score from 0.57 to 0.71.

The framework may prove useful in data-scarce urban environments, but its practical applicability needs to be confirmed through further empirical testing.

Several limitations remain. The pilot study covers a relatively small area, expert judgment influences the multicriteria evaluation, and data availability and sensor coverage vary across urban areas. These factors may affect the broader applicability of the model and require further investigation.

Despite these constraints, the model provides a flexible and scalable framework that can support municipalities in adopting more evidence-based and technology-supported planning. Future work should include larger pilot studies, long-term monitoring, and an assessment of practical implementation challenges.

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