

Article

Identifying Priority Areas for Planning Urban Green Infrastructure: A Fuzzy Artificial Intelligence-Based Framework

Leonardo Massato Nicacio Nomura ¹, Adriano Bressane ^{1,2,*}, Vitoria Valente Monteiro ²,
Inara Vilas Boas de Oliveira ², Grazielle Ruas ^{1,3}, Rogério Galante Negri ² and Alexandre Marco da Silva ^{1,4}

¹ Graduate Program in Civil and Environmental Engineering, São Paulo State University, Bauru City 17033-360, SP, Brazil; leonardo.nomura@unesp.br (L.M.N.N.); graziele.ruas@unesp.br (G.R.)

² Department of Environmental Engineering, Institute of Science and Technology, São Paulo State University, São José dos Campos 12245-000, SP, Brazil; rogerio.negri@unesp.br (R.G.N.)

³ Department of Civil Engineering, School of Engineering, São Paulo State University, Bauru 17033-360, SP, Brazil

⁴ Department of Environmental Engineering, Institute of Science and Technology of Sorocaba, São Paulo State University, Sorocaba 18087-180, SP, Brazil

* Correspondence: adriano.bressane@unesp.br

Abstract: Urban green infrastructure (UGI) plays a key role in fostering sustainability, resilience, and ecological balance in cities. However, the task of identifying priority areas for UGI implementation remains complex due to the multifactorial nature of urban systems and prevailing uncertainties. This study proposes a fuzzy inference system (FIS)-based framework composed of seven interconnected modules designed to assess diverse criteria, including flood vulnerability, water quality, habitat connectivity, vegetation condition, and social vulnerability. The model was applied in the urban watersheds of São José dos Campos, Brazil, a municipality recognized for its smart city initiatives and urban environmental complexity. Through the integration of multi-criteria spatial data, the framework effectively prioritized urban areas, highlighting critical zones for extreme event mitigation, water quality preservation, habitat conservation, and recreational space provision. The case study demonstrated that São José dos Campos, with an 11.73% urbanized area and 737,310 inhabitants, benefits from targeted UGI typologies, including sustainable drainage systems and green public spaces, aligning infrastructure interventions with specific spatial demands. Notably, the expert validation process involving 18 multidisciplinary specialists confirmed the model's relevance and coherence, with the majority classifying the outcomes as "highly coherent". The system's modular structure, use of triangular membership functions, and incorporation of the gamma operator allow for adaptable prioritization across different planning horizons. By offering a transparent, expert-validated, and data-driven approach, the proposed method advances evidence-based decision-making and equips planners with a practical tool for UGI implementation in dynamic urban contexts.

Keywords: greener and healthier cities; human well-being; urban resilience; sustainability



Academic Editors: Lidia Mierzejewska and Alexandru-Ionuț Petrișor

Received: 11 March 2025

Revised: 8 April 2025

Accepted: 10 April 2025

Published: 16 April 2025

Citation: Nomura, L.M.N.; Bressane, A.; Monteiro, V.V.; de Oliveira, I.V.B.; Ruas, G.; Negri, R.G.; da Silva, A.M. Identifying Priority Areas for Planning Urban Green Infrastructure: A Fuzzy Artificial Intelligence-Based Framework. *Urban Sci.* **2025**, *9*, 126. <https://doi.org/10.3390/urbansci9040126>

Copyright: © 2025 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (<https://creativecommons.org/licenses/by/4.0/>).

1. Introduction

As the global population increasingly migrates to urban centers, cities are undergoing transformative changes. These transformations are further intensified by the escalating impacts of climate change, which demand adaptive urban strategies integrated into spatial planning frameworks. This urban shift demands a multifaceted infrastructure to support essential aspects of city life, such as housing, sanitation, transportation, and healthcare

services. Recent studies highlight the pivotal role of such infrastructure in creating environments conducive to human habitation [1,2]. However, the expansion of so-called gray infrastructure often encroaches upon urban green spaces, posing significant risks to environmental quality and public health [3,4]. This reduction in green spaces underscores the importance of identifying priority areas for urban green infrastructure (UGI) planning, a critical endeavor for city planners and policymakers.

UGI represents man-managed natural systems designed to be seamlessly integrated into the urban fabric, including, but not limited to, parks, afforestation areas, stormwater management systems, and green roofs. These elements play a dual role: they are essential for ecological sustainability and serve as spaces for recreation, thus playing a significant social role [5,6]. UGI typologies can be broadly categorized into four groups: vegetated surfaces (e.g., parks, green roofs, green facades), water management systems (e.g., bioswales, vegetated pavements, stormwater wetlands, water circulation systems integrated into urban public spaces), biodiversity corridors (e.g., urban forests, ecological strips), and social–nature interfaces (e.g., community gardens, green plazas). These elements often overlap with Nature-Based Solutions (NBSs) and are most effective when interwoven with gray infrastructure, such as roads, drainage, and energy systems. Recognizing the hybrid nature of these infrastructures is crucial for spatial planning, as urban resilience depends on the co-functioning of green and gray systems. By enhancing environmental quality and expanding the provision of ecosystem services, UGI is fundamental in preserving biodiversity, conserving natural resources, and improving residents' well-being, all of which contribute to the development of healthier and more sustainable urban environments [7].

Despite the recognized importance of UGI, urban planning faces inherent complexities that demand sophisticated decision-making processes capable of balancing diverse objectives and constraints. A notable gap exists in the development of systematic frameworks for identifying priority areas for UGI, crucial for its strategic planning. Current methodologies often fail to address the multifaceted interplay of factors and uncertainties that characterize urban planning [8]. The lack of a comprehensive, data-driven approach capable of dealing with these uncertainties may lead to suboptimal resource allocation, thereby diminishing the potential positive impacts of urban planning interventions. Addressing this challenge, our research introduces an innovative framework centered on the fuzzy inference system (FIS), a distinguished branch of artificial intelligence noted for its exceptional handling of uncertainties. This framework distinguishes itself from conventional AI technologies and decision-support systems through its unique capacity to process imprecise, ambiguous, or subjective information, which is a common challenge in the realm of urban planning.

The FIS leverages fuzzy logic to closely mirror human reasoning [9], presenting a significant advantage in urban green infrastructure (UGI) planning compared with traditional AI that depends on binary logic. This approach excels in managing the qualitative, nuanced data characteristic of UGI planning, enabling a structured decision-making process that accommodates diverse variables and stakeholder perspectives [10]. This adaptability is essential in UGI planning, aiming to balance ecological sustainability with urban development amidst uncertainties. Unlike other AI technologies requiring large, quantifiable datasets, the FIS integrates expert knowledge directly into the decision-making process [9]. This integration is crucial in UGI planning, necessitating expertise across ecology, urban design, and public policy fields. As such, the FIS-based framework is uniquely suited for addressing the complexities of UGI planning, providing a nuanced, inclusive decision-making approach that aligns with the varied values and priorities of urban communities. This method signifies a notable advancement in developing resilient, sustainable urban environments.

This study contributes novel advancements to the field in several key aspects. First, it proposes an integrated, multi-criteria FIS-based framework capable of accommodating both biosphere and geosphere demands—an approach not yet operationalized in prior UGI studies. Second, unlike conventional data-driven models that require extensive, high-resolution datasets or operate as opaque “black-box” systems, our model combines fuzzy logic with expert-derived rules to enable transparency, interpretability, and adaptability across varying data conditions. Third, the modular architecture of the seven interconnected FISs enables planners to generate flexible prioritization scenarios through the tuning of the gamma operator, supporting short-, medium-, and long-term strategies. These contributions address persistent gaps in scalability, uncertainty management, and typology specificity, thus offering a robust alternative to existing DSS approaches in UGI planning [10].

Our objectives include: (i) highlighting the necessity for a data-driven framework in identifying priority UGI planning areas amidst uncertainties; (ii) introducing an FIS-based model to identify such areas and suggest appropriate UGI typologies based on specific urban demands; (iii) implementing and validating this framework in a real-world urban context to provide practical insights; and (iv) offering a decision-support tool to enhance urban sustainability and resilience through informed UGI planning.

This paper was structured into five main sections: “Related Works”, presents a literature review contextualizing the study; “Theoretical Background”, introduces key fuzzy logic concepts underlying the model [9]; “Fuzzy Inference System Modeling”, details the design of the FIS-based framework; “Application of the Proposed Framework”, demonstrates real-world validation; and “Final Remarks”, discusses the implications and potential of the proposed framework in advancing UGI planning and sustainability. Figure 1 presents a flowchart detailing each step of the proposed framework.

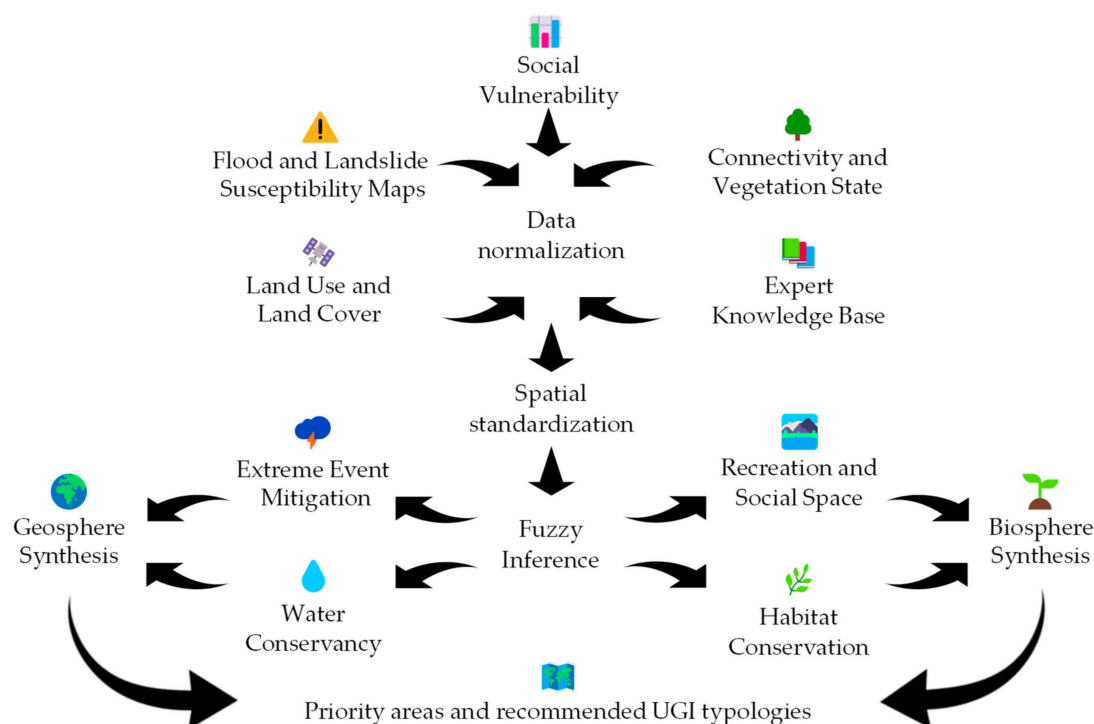


Figure 1. Flowchart of the proposed research framework.

2. Related Works

To search for the most reliable, relevant, and up-to-date related works, the Science Direct, Scopus, and Web of Science databases were used, in which the following query was applied: title-abs-key (“green infrastructure” or “green space” or “green building”) and

(“sustainable city” or “healthy city”) and (“artificial intelligence” or “fuzzy system”) and (limit-to (pubstage, “final”)) and (limit-to (doctype, “ar”)) and limit-to (subjarea, “eng.” or “env.”)) and (limit-to (pub year, “from 2014 to 2023”)) and (limit-to (language, “English”)). Thus, 181 articles were found and preliminarily screened. After excluding those outside the scope, eight works related to DSS to face challenges associated with the management of UGI were selected and are discussed below.

Several research studies have emerged in the domain of UGI planning. Table 1 highlights the diversity of methodologies applied in UGI planning and their respective limitations. While each approach offers unique advantages, they also present challenges that need to be considered when implementing UGI projects, such as bias from expert input, potential oversimplification, data requirements, interpretability issues, and the complexity of integrating diverse data sources and expert knowledge.

Table 1. Methodologies applied in UGI planning and respective limitations.

Study	Methodology	Limitations in UGI Planning
Bressane et al. [11]	Neuro-Fuzzy Adaptive Inference System	Reliance on expert input for criteria weighting may introduce bias.
Carvalho Maria et al. [12]	Decision tree algorithm	May overlook subtle patterns due to simplicity; potential oversimplification.
Lin et al. [13]	Machine learning techniques	Requires extensive data for training; can be difficult to interpret (“black box”).
Bressane et al. [14]	Fuzzy-based decision support systems	Subjective set and rule base construction could lead to variability in outcomes.
Zarei and Nik-Bakht [15]	Fuzzy-based DSS and Conceptual Framework	Similar to [14], with added complexity in integrating inputs.
Barbosa et al. [16]	Computer-aided tool	May not fully account for dynamic changes or urban development over time.
Massaro et al. [17]	Decision Support System Optimizing	High dependency on accurate, real-time data.
Langemeyer et al. [18]	Bayesian Belief Networks	Need for deep domain expertise and computational resources.

Bressane et al. [11] and Carvalho Maria et al. [12] concentrated on optimizing urban afforestation management. Bressane et al. [11] employed a combination of an Analytical Hierarchy Process and a Neuro-Fuzzy Adaptive Inference System to assess tree falling risks, while Carvalho Maria et al. [12] utilized the decision tree algorithm to achieve the same objective, utilizing artificial intelligence tools to detect tree issues and enhance management practices.

Lin et al. [13] applied machine learning techniques to analyze the relationship between UGI spatial patterns and heat island intensity, revealing that green space characteristics significantly impact heat island intensity and providing valuable insights for land use and land cover (LULC) planning.

Numerous other research studies with diverse focuses and methodologies have also emerged. Bressane et al. [14] introduced a fuzzy-based DSS for participatory UGI management, merging technical expertise with community insights, promising enhanced participatory linear park management.

Similarly, Zarei and Nik-Bakht [15] proposed the same approach to integrate citizen engagement into urban projects, facilitating knowledge extraction from the literature for new initiatives by researchers and practitioners. Barbosa et al. [16] proposed an innovative approach for selecting cost-effective areas for UGI restoration, employing a computer-aided

tool to identify management zones within green and blue infrastructure that align with various conservation objectives, aiming for an optimal spatial UGI design that balances biodiversity protection and the delivery of ecosystem services.

Massaro et al. [17] presented a DSS optimizing UGI design using climatic data, environmental sensing, and occupancy patterns, incorporating computer vision techniques. Langemeyer et al. [18] harnessed Bayesian Belief Networks to assess demand for ecosystem services (ESs) from green roofs, offering insights for local policy, particularly regarding the effectiveness of UGI in delivering ESs.

In addition to the approaches discussed above, recent advances in multi-criteria decision-making (MCDM) further support prioritization efforts in complex systems. For instance, methods based on the Analytic Hierarchy Process (AHP) have been employed to evaluate suitability for sustainable construction and land use planning [19,20]. Furthermore, hybrid fuzzy models—such as the hesitant fuzzy VIKOR—have demonstrated improved ranking capabilities in medical and spatial domains [21]. These studies underscore the flexibility of MCDM tools and inform the positioning of our FIS-based approach as a robust alternative that balances interpretability, adaptability, and data-driven rigor.

While the literature review reveals extensive research on UGI management and data-driven decision-making, existing approaches often struggle to handle the intricate interactions of various factors and uncertainties inherent in UGI planning, particularly when using a Geographic Information System (GIS). GIS analyses frequently involve indirect spatial data acquisition and rely on multisource data [22], which can vary in scale, reference system, and equipment precision [23]. Data can be either analog or digital, and the representation can be raster- or vector-based [24]. Hence, the search for suitable alternatives to address the integrated treatment of data subject to such variations holds the potential for significant advancements in multi-criteria analysis applied to the identification of priority areas for UGI planning.

In this context, we propose the development and evaluation of a framework based on the FIS, a methodology that has been widely and promisingly applied across various fields, including participatory planning [25], impact assessment [26], and environmental management [10]. This alternative approach, grounded in the FIS, has the potential to overcome the challenges posed by diverse data sources, making it a promising tool for dealing with uncertainties and addressing the multifaceted nature of UGI planning.

To guarantee technical alignment with our proposed framework, we emphasize that insights from UGI-related decision support systems directly informed the construction of our FIS-based approach. Specifically, limitations such as reliance on expert bias [11], oversimplification [12], data-intensive requirements [13], and interpretability issues [17] shaped the definition of input criteria and fuzzy rule structures used in our system. For example, the integration of expert knowledge in our fuzzy rule base responds to challenges faced by machine learning models that operate as “black boxes”, while our modular FIS architecture overcomes integration issues highlighted in prior GIS-dependent studies [22,24]. Thus, the empirical findings and constraints of prior UGI methodologies served as a foundation for the FIS framework proposed herein, underscoring a direct methodological progression rather than a thematic digression.

3. Theoretical Background

An FIS can be structured through the specification of input and output variables, membership functions, fuzzy rules, and an inference mechanism, as delineated in prior studies [10,27]. In the current research, the input variables are conceptualized as indicators for the demand in mitigating extreme events, maintaining water quality, habitat preser-

vation, and facilitating leisure and recreation activities. Conversely, the output variables delineate the prioritization categories for UGI implementation.

Unlike classical logic models, where membership functions are binary, indicating a state of either true (1) or false (0), fuzzy logic employs a continuous scale from 0 to 1 to express membership (φ) within a fuzzy set. This gradation allows for the depiction of membership degrees through various function shapes, such as linear (triangular or trapezoidal), sigmoid, or quadratic, thereby facilitating the representation of linguistic terms within a fuzzy set context [10]. In this investigation, these linguistic values (ai), corresponding to the demand levels (lower, medium, higher) and implementation priority (very small, small, moderate, large, very large), are articulated.

Compared with traditional AI approaches—such as neural networks or decision trees—the FIS presents distinct advantages for urban planning applications. While conventional models typically require large, structured datasets and often function as ‘black boxes’ with limited transparency, the FIS accommodates small, imprecise, or subjective datasets through rule-based modeling. This makes it particularly suitable for planning contexts marked by uncertainty, heterogeneous data, and multidimensional decision criteria. Moreover, the FIS enables expert-driven customization and interpretability, which are essential for policy-sensitive domains such as green infrastructure planning.

The continuum of membership values enhances the depiction of truth, introducing a flexible and authentic approach to managing uncertainties inherent in real-world phenomena [10]. As an element’s value nears the soft boundaries between overlapping concepts, the uncertainty level escalates. This study employs triangular-shaped membership functions to represent such uncertainties effectively (Figure 2).

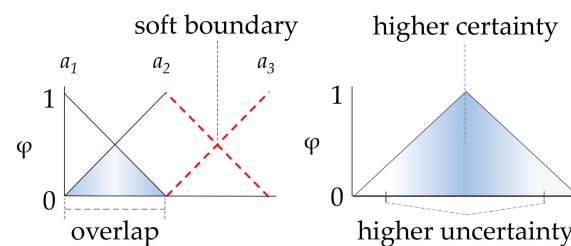


Figure 2. Uncertainty modeled by a triangular-shaped membership function.

Fuzzy rules articulate the correlation between input and output variables, outlining the transformation of inputs into outputs [10]. The inference engine operationalizes these rules through fuzzy logic operations like OR (Max), AND (Min), and GAMMA (γ), producing the output variables. In our model, the GAMMA operator is utilized, defined by:

$$\varphi = (\Sigma_f)^\gamma \times (\Pi_f)^{1-\gamma}$$

where φ is the membership, Σ_f and Π_f represent the fuzzy algebraic sum and product, respectively, and γ is the GAMMA operator, defined between zero and 1.

The GAMMA operator was selected for fuzzy inference due to its ability to interpolate between the restrictive behavior of the fuzzy product ($\gamma = 0$) and the permissive behavior of the fuzzy sum ($\gamma = 1$), offering enhanced control over the system’s decision sensitivity [28,29].

This flexibility is particularly valuable in UGI planning, where different planning horizons demand distinct levels of prioritization stringency. In this framework, the value of γ was adjusted to reflect temporal planning perspectives:

- $\gamma = 1$ (short-term horizon): prioritizes only areas with the most critical and convergent demands, promoting immediate and targeted action.

- $\gamma = 0.5$ (medium-term horizon): balances selectivity with inclusiveness, supporting mid-range planning that addresses both urgent and emerging needs.
- $\gamma = 0$ (long-term horizon): adopts a more inclusive strategy, identifying a broader set of areas with moderate or latent demands that require proactive planning.

This structured use of γ enables the framework to support adaptive planning strategies by controlling the level of restrictiveness in the inference process. These values were defined in alignment with the planning logic and sensitivity levels desired for each horizon, and follow the fuzzy logic literature that recognizes the operator's role in modulating inference behavior based on context [30,31].

This foundational overview underscores the modeling process's steps: defining linguistic terms, establishing membership function shapes, and crafting fuzzy rules, all underpinned by expert knowledge (Figure 3).

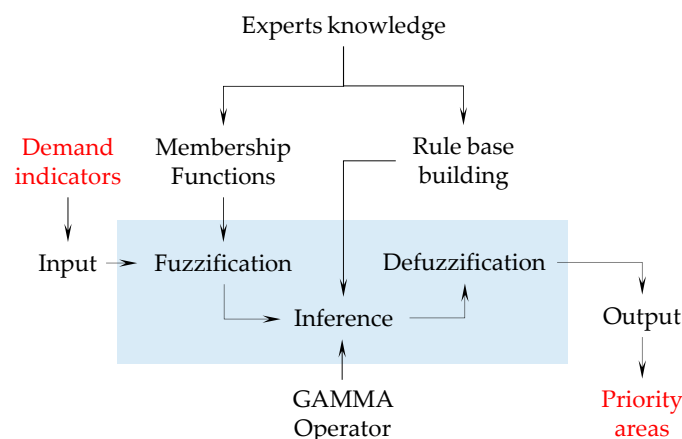


Figure 3. Fuzzy logic-based modeling process. The blue background highlights the main modules of the FIS, while the red text identifies the system's input and output variables.

4. Fuzzy Inference System Modeling

The proposed framework encompasses seven distinct FISs, designed to advance UGI planning through a comprehensive, data-driven approach. Each FIS is tailored to assess specific criteria, thereby facilitating enhanced decision-making processes for UGI prioritization (Figure 4).

The input data for the FIS framework were obtained from multiple public and institutional sources. Land use and land cover (LULC) data were derived from remote sensing classification of Sentinel-2 imagery (10 m resolution) using supervised classification techniques validated against field points. Flood and landslide susceptibility maps were obtained from the Brazilian Geological Survey (CPRM) based on topographic and lithological models [32]. Social vulnerability indicators were derived from census tract data provided by the Brazilian Institute of Geography and Statistics [33], including variables related to housing quality, income, and infrastructure. Riparian buffer conditions and vegetation states were assessed using high-resolution aerial imagery and vegetation indices (e.g., NDVI), processed via QGIS. All spatial layers were resampled to a common grid resolution (30 m), normalized to a 0–1 scale, and clipped to the study area using a standardized urban watershed boundary. Reclassification routines were applied based on thresholds from the literature to assign fuzzy linguistic values (low, medium, high). These preprocessing steps ensured data consistency and spatial comparability across all FIS modules.

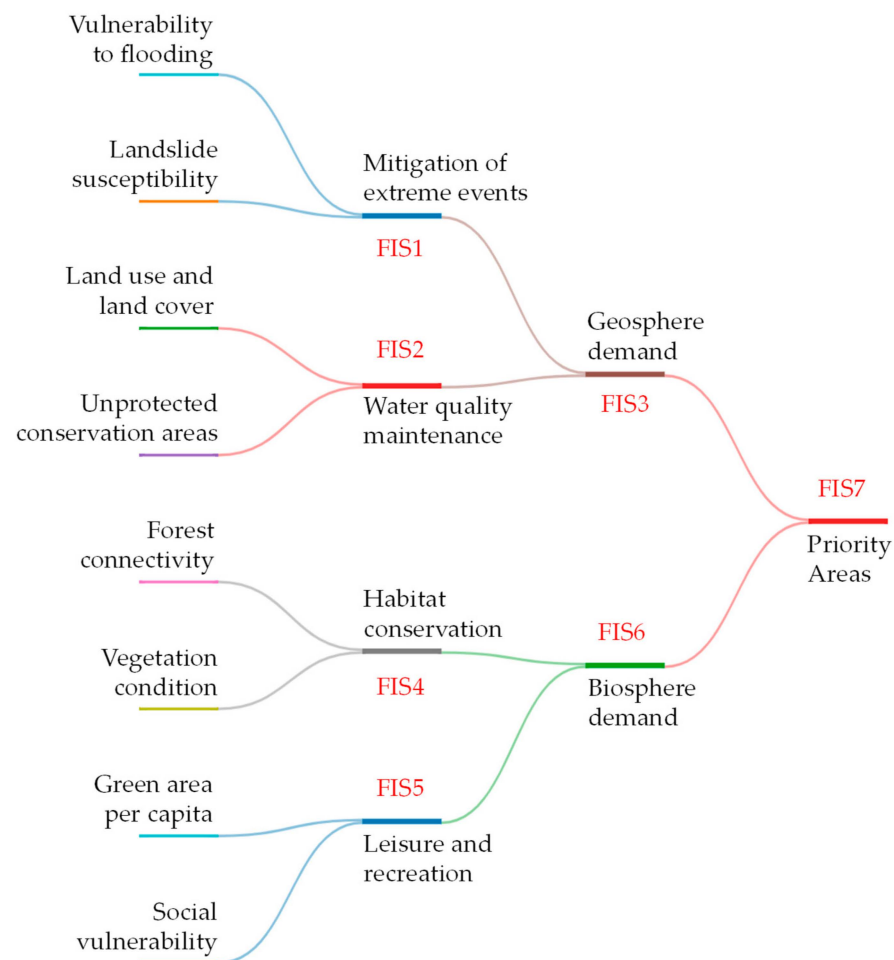


Figure 4. FIS-based framework proposed to identify priority areas for UGI planning.

The variables used in the FIS were selected based on their relevance to the multidimensional demands of UGI planning. These criteria—such as flood vulnerability, water quality, vegetation condition, and social vulnerability—were chosen through a review of the scientific literature and urban planning guidelines, prioritizing indicators commonly used to assess geosphere and biosphere pressures [34,35]. Each input variable was normalized to a continuous scale from 0 to 1, following a standard fuzzy logic preprocessing approach that ensures compatibility with membership functions and rule-based reasoning [29]. The normalization procedure assigned 0 to the least critical condition (lowest demand) and 1 to the most critical (highest demand), with intermediate values of 0.25, 0.5, and 0.75 used to represent graduated levels of intensity. The specific criteria for mapping raw data to this standardized scale were adapted from existing methods in environmental modeling. For example:

- Flood and landslide vulnerability: derived from multi-criteria risk indices incorporating slope, soil, and hydrological data [32];
- Water quality demand: inferred from land use categories and vegetation cover in riparian areas [34,36];
- Habitat connectivity and vegetation condition: classified based on ecological fragmentation and forest succession stage [10,37];
- Social vulnerability: scored using spatial census indicators for infrastructure, income, and human capital [35].

The initial system (FIS1) is dedicated to identifying areas that require urgent interventions to mitigate extreme events, taking into account factors such as vulnerability to

flooding and landslide susceptibility. FIS2 focuses on evaluating regions demanding water quality maintenance, utilizing LULC data and the proximity to unprotected conservation areas as primary criteria. Subsequently, FIS3 synthesizes the outputs from FIS1 and FIS2 to prioritize areas based on geosphere-related needs, while FIS4 integrates criteria associated with forest connectivity and vegetation condition to address habitat maintenance requirements. FIS5 assesses potential locations for leisure and recreation, considering the green area per capita and social vulnerability indicators. The outputs of these systems are further analyzed by FIS6 to derive priorities based on biosphere demands. Ultimately, FIS7 integrates the findings to identify priority areas for UGI implementation, considering both biosphere and geosphere demands.

It is important to note that the resulting priority areas are not assumed to be spatially homogeneous across all UGI typologies. Instead, the framework identifies dominant demands (e.g., flood mitigation, water quality, recreation) and recommends typologies based on these primary needs. As such, each area may be associated with different UGI categories depending on the prevailing environmental and social indicators. In some locations, overlapping demands may lead to multifunctional infrastructure recommendations. This approach reflects the heterogeneity of urban environments and the necessity of place-based planning strategies.

In the quantification of demands related to flood vulnerability and landslide susceptibility, this study incorporates indices developed by [32], which consider a range of environmental factors including slope, soil type, riverbed characteristics, terrain morphology, amplitude, and the density of structural lineaments. This comprehensive approach facilitates a nuanced assessment, where the severity of conditions is stratified on a scale from 0 (least critical) to 1 (most critical), with intermediary conditions assigned values of 0.25, 0.5, and 0.75, respectively.

For evaluating the necessity of water quality maintenance, LULC data were scrutinized to determine the prevalence of impervious surfaces, following the methodology proposed by [34]. The categorization of demand was based on the degree of urbanization, with built-up areas denoted as high demand (scored as 1), and a descending order of priority given to exposed soil (0.8), herbaceous or shrub cover (0.6), tree cover (0.4), and wetland areas (0.2), culminating with water bodies (0) as the lowest demand.

The study also explores the impact of vegetation cover absence on sediment transport into water channels, which may result in siltation affecting water flow and quality, as described by [36]. The retention capabilities of riparian forests for pollutants are compromised in the absence of adequate vegetation cover, necessitating the assessment of unprotected conservation areas. Different ground cover states within riparian buffer zones are evaluated, ranging from no vegetation (1), indicating the highest demand for intervention, to advanced secondary growth or forested savanna (0), signifying the lowest. Intermediate states such as pioneer vegetation (0.75), early secondary growth (0.5), and mid-secondary growth (0.25) are scored accordingly, reflecting varying levels of water quality maintenance demand.

Forest connectivity is determined by prioritizing strategic areas for the maintenance of biodiversity and the promotion of ecosystem services [38]. According to [37] there are eight categories representing degrees of forest connectivity urgency, ranging from minimum to maximum. In the present study, these categories are scored as lower (0) and higher (1) demand, with intermediate categories scored as 0.15, 0.3, 0.45, 0.60, 0.75, and 0.9, respectively. Likewise, the vegetation condition considers the stage of forest regeneration, where absent vegetation is considered the most critical situation, or, in other words, there is a higher demand for UGI (scored as 1), followed by pioneer vegetation (0.75), early secondary growth (0.5), wooded savanna or mid-secondary growth (0.25), and forested savanna or advanced secondary growth (0), as proposed by [39].

The per capita green area is calculated as the percentage obtained by dividing the vegetated area by the total population. A ratio of 15 m² per inhabitant is considered as a reference according to the literature [40]; therefore, areas with this ratio equal to or greater than this are scored as lower demand (0). In turn, social vulnerability encompasses infrastructure and the urban environment, human capital, income and employment, and housing dimensions [35]. The most critical condition corresponds to 100% of people living in vulnerable conditions, i.e., higher demand (scored as 1), followed by 60 to 90% (0.9), 30 to 60% (0.75), 10 to 30% (0.5), 0 to 10% (0.25), and 0% scored as 0.

As described above, for each demand indicator variable, the reference values from the literature were standardized, using a scale ranging from 0 to 1. Then, in the variable fuzzification stage, each FIS assigns three linguistic values to input variables, classifying areas as having lower, medium, or greater demand. These demand categories are modeled using triangle-shaped membership functions (Table 2).

Table 2. Fuzzy triangle-shaped membership function.

	Demand	Parameters (a, b, c) *
Demand indicator variable	lower	(0, 0, 0.5)
	medium	(0, 0.5, 1)
	greater	(0.5, 1, 1)

* Parameters 'a' and 'c' locate the base, and 'b' locates the peak of the triangle-shaped membership function.

Triangular membership functions was selected for this study due to their computational efficiency, simplicity, and proven effectiveness in applications where data are limited or where interpretability is essential [29,31]. These functions are particularly suitable when expert knowledge is the primary source for defining fuzzy sets, as they require only three parameters and allow for straightforward rule construction and tuning [30]. Moreover, in environmental and spatial decision-making contexts such as UGI planning—where data uncertainty is common—triangular functions offer a practical balance between expressiveness and transparency [10,41]. Regarding parameter determination, the values for (a, b, c) were defined based on the standardized scales of input indicators and refined through iterative expert consultation, consistent with participatory FIS design methodologies [14]. Specifically, endpoints 'a' and 'c' delineate the lower and upper bounds of each linguistic category (e.g., “low”, “medium”, “high”), while 'b' represents the peak (maximum membership value). The adopted configuration—(0, 0, 0.5) for “low”, (0, 0.5, 1) for “medium”, and (0.5, 1, 1) for “high”—reflects an even distribution across the normalized range [0–1], allowing symmetric overlap between categories and ensuring continuity in the fuzzification process. This structure also aligns with prior FIS applications in environmental modeling, enhancing comparability and replicability [10].

In turn, the fuzzy rule base was developed using a knowledge-driven approach, relying on expert elicitation and established domain literature to define the logical relationships between input and output variables. Specifically, for each FIS module, fuzzy rules were formulated based on how combinations of demand indicators—such as flood vulnerability and vegetation cover—correlate with the need for UGI interventions. This approach is consistent with methodologies adopted in participatory environmental modeling, where rules are defined to reflect qualitative expert knowledge in the absence of large training datasets [31]. Each rule in the base follows the standard IF–THEN format, such as: IF flood vulnerability is high AND vegetation condition is poor, THEN the priority is very high. The linguistic values used (e.g., low, medium, high) correspond to the triangular membership functions defined in Table 2. Rule combinations were selected to reflect realistic environmental interactions and spatial patterns, ensuring that they are both in-

interpretable and applicable to real-world urban conditions. For example, in FIS1 (extreme event mitigation), areas with both high slope and poor drainage were prioritized more heavily than those meeting only one of these criteria. The rule base structure was reviewed in iterative sessions with domain specialists in urban planning, hydrology, and ecology, ensuring consistency, plausibility, and alignment with planning practices. Additionally, a parsimonious design principle was followed to avoid unnecessary rule proliferation, using three linguistic categories for inputs to limit the total number of rules while preserving decision quality [29].

The construction of fuzzy rule sets, while grounded in domain knowledge and literature, is inherently subject to expert judgment and may introduce cognitive or institutional biases. These biases can affect the weighting of certain criteria, the interpretation of linguistic thresholds, or the prioritization logic embedded in the rules. To mitigate these effects, this study employed a multi-pronged strategy: (i) triangulation of rules with scientific literature and regulatory standards; (ii) validation of preliminary rules through a workshop involving municipal planners, ecologists, and engineers; and (iii) consistency checks against empirical data distributions for each input variable. This approach enhances the objectivity and contextual relevance of the fuzzy inference process.

The output variables can take on five linguistic values, categorizing areas as having very small, small, moderate, large, or very large priority (Figure 5). When this output enters a subsequent FIS, a new fuzzification occurs using three linguistic values. This is done to prevent a significant increase in the number of rules resulting from the combination of these values, thereby avoiding unnecessary computational processing costs. The rule base that guides the inference engine is shown in Table 3.

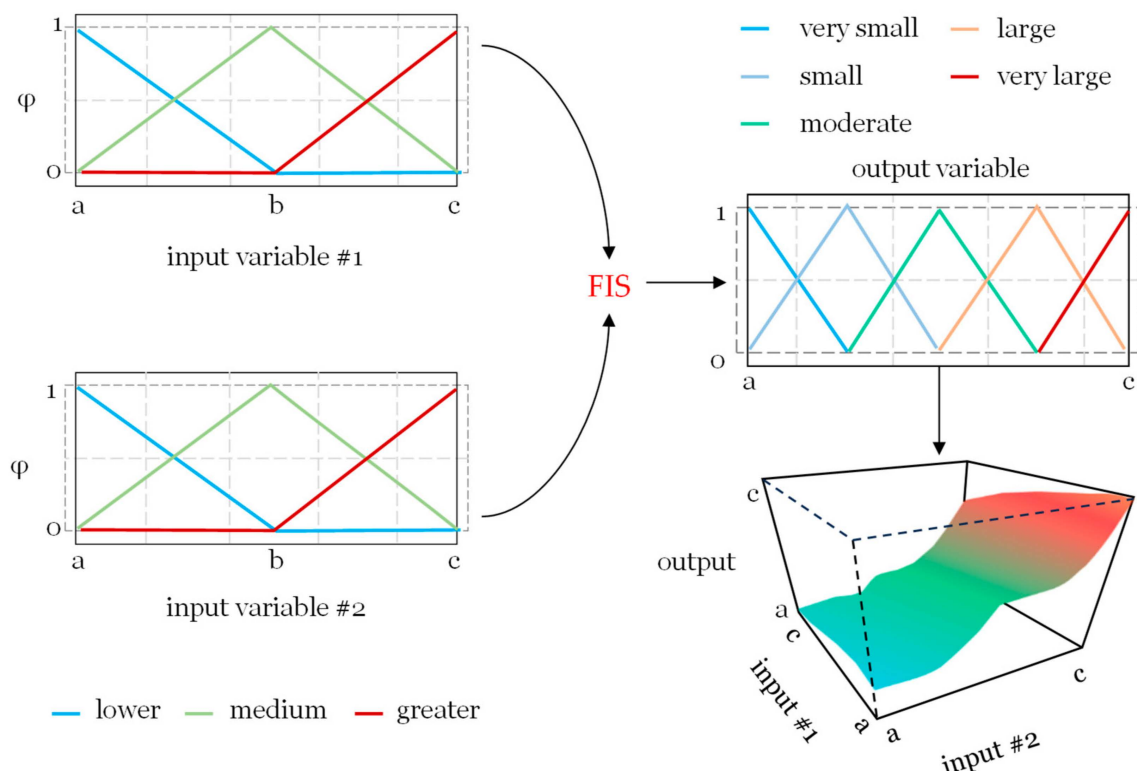


Figure 5. Fuzzification of input and output variables into linguistic values.

Table 3. Rule basis of a fuzzy inference system.

Input #1	Input #2	Output
lower	lower medium greater	very small small moderate
medium	lower medium greater	small moderate large
greater	lower medium greater	moderate large very large

After classifying urban areas based on their priority using the FIS7 output, specific green infrastructure typologies are recommended by the proposed framework according to the preceding FIS outputs (Table 4). For instance, if the high-priority level is due to the need for mitigating extreme events, a suggested green infrastructure typology could be the implementation of sustainable drainage systems (SDSs). SDSs are designed to effectively manage stormwater runoff, reducing the risk of flooding and erosion in urban areas.

Table 4. Recommendations for mainstreaming green infrastructure.

Demand/FIS	Typology 1	Typology 2	Typology 3	Typology 4	Typology 5
FIS1: Mitigation of extreme events	Sustainable drainage systems: including retention basins and permeable pavements to manage stormwater runoff and reduce flooding	Natural retaining walls: using vegetation and engineering techniques to create natural barriers against landslides and erosion	Wildlife refuges: native vegetation areas that provide safe habitats for wildlife, aiding in biodiversity preservation	Coastal vegetation belts: planting coastal vegetation like mangroves and dunes to protect against coastal erosion and storms	Urban infiltration parks: green spaces designed to absorb rainwater and recharge groundwater, mitigating urban flooding
FIS2: Water quality maintenance	Constructed wetlands: artificial wetland systems that naturally filter and purify water, improving its quality	Bioretention swales: channels planted with vegetation to capture and treat stormwater runoff before it enters water bodies	Floating treatment wetlands: floating islands with aquatic plants that help remove pollutants from water bodies	Riparian buffer zones: planting native vegetation along water bodies to reduce runoff and filter contaminants	Stormwater ponds: engineered ponds designed to detain and treat stormwater, enhancing water quality before release
FIS4: Habitat conservation	Green roofs: rooftop gardens with native plants to provide habitat for birds and insects	Pollinator gardens: planted with native flowers to support pollinators like bees and butterflies	Wildlife corridors: linear green spaces that connect natural habitats, facilitating wildlife movement	Artificial nesting structures: installing birdhouses and bat boxes to support urban wildlife	Aquatic habitats: creating ponds or small water bodies for amphibians and aquatic species in urban areas
FIS5: Leisure and recreation	Community parks: multi-use parks with playgrounds, sports facilities, and picnic areas for diverse recreational activities	Botanical gardens: showcasing a variety of plant species and providing a serene environment for relaxation	Green trails: pedestrian and cycling paths with lush greenery for a pleasant outdoor experience	Outdoor fitness zones: equipped with exercise stations and open spaces for fitness enthusiasts	Plaza gardens: small urban plazas transformed into green spaces for leisure and social gatherings

This includes structures like stormwater ponds, permeable pavements, green roofs, and rain gardens, which help control rainfall and minimize damage from extreme weather events. Such green infrastructure significantly contributes to urban resilience in the face of adverse climate events [42].

To provide greater clarity and usability for urban planning, the green infrastructure typologies recommended by the framework are grouped into four functional categories: (i) hydrological systems (e.g., sustainable drainage systems, wetlands, stormwater ponds); (ii) ecological connectivity and habitat support (e.g., wildlife corridors, green roofs, aquatic

habitats); (iii) recreational and social green spaces (e.g., parks, green trails, botanical gardens); and (iv) environmental quality interventions (e.g., riparian buffers, bioretention swales, permeable pavements). This classification reflects their intended roles in urban systems and facilitates integration with spatial planning instruments, enabling decision-makers to align infrastructure investments with specific urban needs.

Conversely, if the demand is for leisure and recreational spaces, a recommended green infrastructure typology could be the establishment of urban parks and recreational zones. These areas are designed to offer spaces for relaxation, physical activity, and community gatherings, featuring amenities such as playgrounds, sports facilities, walking trails and picnic areas. Mainstreaming such UGI can enhance the quality of life for urbanites, promote physical and mental well-being, and foster a sense of community engagement. As cities continue to grow and face various challenges, prioritizing and expanding UGI contribute significantly to the overall health and happiness of urban residents, while also serving essential ecological functions, such as maintaining the hydrological cycle and providing ecological corridors for the gene flow of fauna and flora.

To ensure the robustness and applicability of the proposed FIS framework for UGI planning, an expert validation process was conducted. This process aimed to assess the relevance of the selected indicators, the coherence of the model's inference process, and the applicability of the results to real-world urban planning scenarios. The validation was performed through a structured consultation with a panel of 18 experts selected based on their experience and expertise in environmental sciences, urban sustainability, and infrastructure planning. The expert panel included: (i) academics and researchers from universities and research institutes specializing in environmental studies and sustainability; (ii) public and private sector professionals, including environmental engineers, urban planners, and government officials from state environmental agencies; and (iii) multidisciplinary experts, such as project supervisors and environmental managers from private companies and public administration bodies.

The consultation was conducted via an online survey using the Google Forms platform. The survey covered three key dimensions:

- Relevance of the indicators—experts were asked to evaluate the coherence and suitability of the indicators used in the model to identify priority areas for UGI implementation;
- Suggestions for inclusion or modification of indicators—experts were given the opportunity to propose additional indicators or suggest modifications to existing ones;
- Evaluation of model coherence and applicability—experts assessed the overall structure, inference process, and the validity of the results obtained from the case study application.

5. Application of the Proposed Framework

To validate the proposed FIS-based framework, we conducted a case study in the city of São José dos Campos, located in the eastern region of the state of São Paulo, Brazil. The urban watersheds of this municipality were selected due to their representativeness of rapid urbanization, environmental variability, and high relevance in regional sustainability planning. Additionally, the city holds ISO 37120, 37122, and 37123 certifications as a smart city, ensuring the availability of high-quality spatial and socio-environmental data, which is essential for implementing and evaluating data-driven planning models. Its urban fabric encompasses ecologically sensitive zones, dense urban cores, and socially vulnerable areas—conditions that are suitable for testing the framework's capacity to reconcile conflicting geosphere and biosphere demands. Although the indicators used are context-specific, the modularity and adaptability of the framework support its transferability to other urban contexts, provided that locally relevant data are available. This area offers a

diverse set of conditions that are ideal for testing the framework's ability to integrate and prioritize conflicting geosphere and biosphere demands. Figure 6 illustrates the geographic boundaries and spatial configuration of the selected urban watersheds that served as the spatial domain for FIS application.

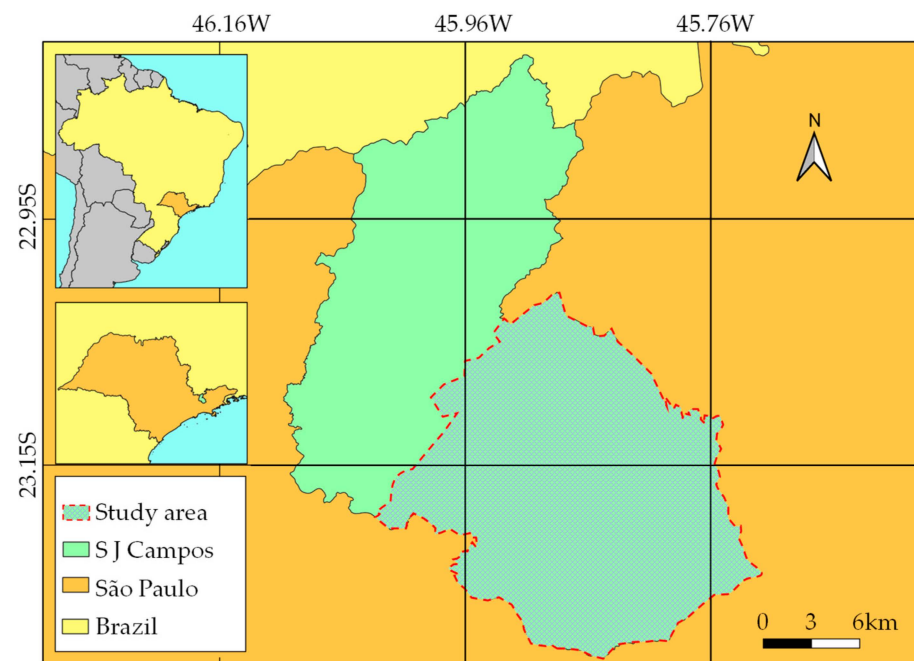


Figure 6. The study area—urban watersheds of São José dos Campos, Brazil.

The municipality comprises 737,310 inhabitants (in 2023) and covers a total area of 1099.409 km², with 11.73% designated as urbanized zones. It boasts 94.7% of urban households along public roads adorned with trees, while 66.4% enjoy adequate sanitary infrastructure. When compared with other cities in Brazil, it ranks 961st for road afforestation and 125th out of 5570 for proper sanitary infrastructure [33].

Taking into account factors such as technological advancements, urban economy, quality of life, sustainability, and response capability to face natural disasters, São José dos Campos has been certified as the first smart city in Brazil [43], complying with the conformity indicators established by the International Organization for Standardization—ISO. It fully adheres to ISO 37120, focusing on quality of life and sustainability, ISO 37122, which pertains to technology, and ISO 37123, which deals with the city's economy and its capacity for prevention and action in the face of natural disasters [44–46].

The proposed fuzzy model can be considered a strategic tool for UGI planning, particularly due to its ability to handle uncertainty and generate diverse scenarios by varying the values of the gamma operator. This flexibility allows adjusting the prioritization approach according to different time horizons, optimizing the allocation of resources and efforts. Figure 7 presents the identification of priority areas through the integrated assessment of all indicator parameters derived from preceding analyses considering a short-term horizon ($\gamma = 1$), in which the focus can be on prioritizing a smaller quantity of areas with more urgent demands, addressing immediate needs. In the medium term ($\gamma = 0.5$), the model would provide the capacity to establish an intermediate scenario. This allows for a more balanced approach, addressing areas with significant demands but with a more extended implementation perspective. In the long term ($\gamma = 0$), the model could be adjusted to prioritize a larger quantity of areas, encompassing existing but less urgent demands.

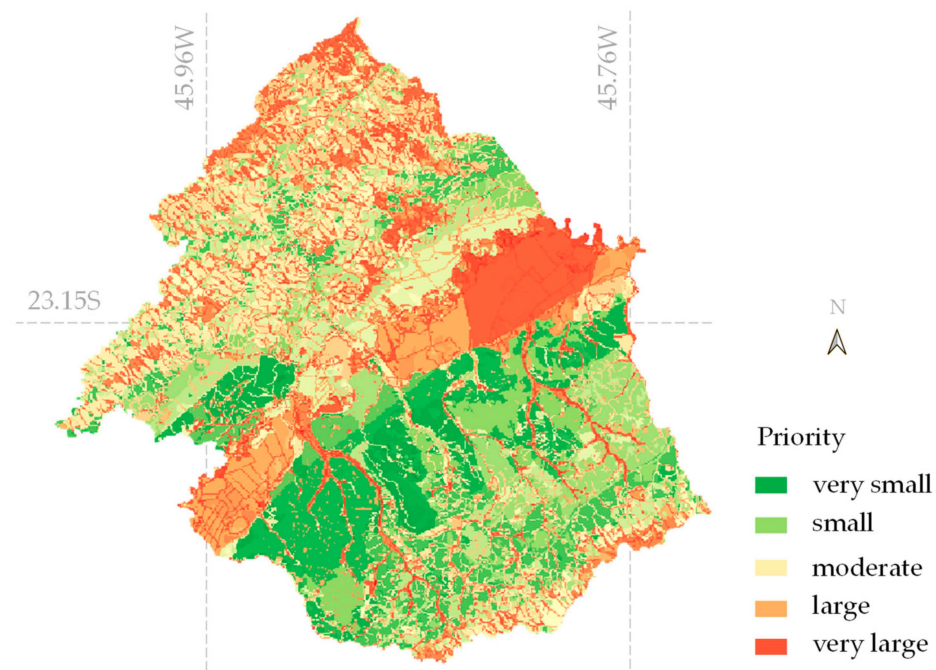


Figure 7. Urban areas prioritized for implementing UGI in a short-term horizon.

The selection of γ values is grounded in the operational mechanics of the GAMMA operator in fuzzy inference. When $\gamma = 1$, the output is driven by the fuzzy algebraic sum, producing a more permissive aggregation—suitable for identifying critical areas in short-term planning. When $\gamma = 0$, the output is based on the algebraic product, leading to more stringent prioritization and wider coverage, ideal for long-term, inclusive interventions. The intermediate value $\gamma = 0.5$ balances these extremes. This parameterization enables planners to tailor spatial priorities to different implementation timeframes by adjusting the sensitivity of the decision rules. The temporal flexibility enables efficient resource management, considering the gradual evolution of urban conditions. In addition, it also allows for a comprehensive and sustainable vision, considering the gradual transformation of the urban environment over time. Thus, the model not only provides a dynamic approach to current demands but also becomes an adaptable tool for strategic urban planning across different time horizons.

From the results, it is evident that the proposed tool effectively classified the study areas concerning demands related to extreme event mitigation, water quality maintenance, habitat conservation, and spaces for leisure and recreation. This comprehensive classification provides an evidence-based understanding of urban green infrastructure (UGI) demands, enabling targeted and effective planning.

For example, in areas where habitat conservation emerged as the primary demand for prioritization, the recommended green infrastructure typologies, such as green roofs, pollinator gardens, wildlife corridors, artificial nesting structures, and aquatic habitats, as listed in Table 4, align with the ecological needs of the area. This promotes biodiversity and enhances the overall health of the urban ecosystem. Conversely, in areas where leisure and recreation were identified as the main demand, the FIS recommends typologies like community parks, botanical gardens, green trails, outdoor fitness zones, and plaza gardens. These interventions not only contribute to the physical and mental well-being of urban residents but also foster a sense of community engagement. The suggested UGI typologies align with the recreational needs of the area, promoting a healthier and more socially vibrant urban environment.

6. Expert Validation

The majority of experts rated the proposed indicators as “relevant” or “highly relevant” for identifying priority areas for UGI implementation (Figure 8). While some experts expressed minor concerns about specific indicators—such as the indirect role of vulnerability levels in decision-making—there was a strong consensus on maintaining all proposed indicators without exclusions.

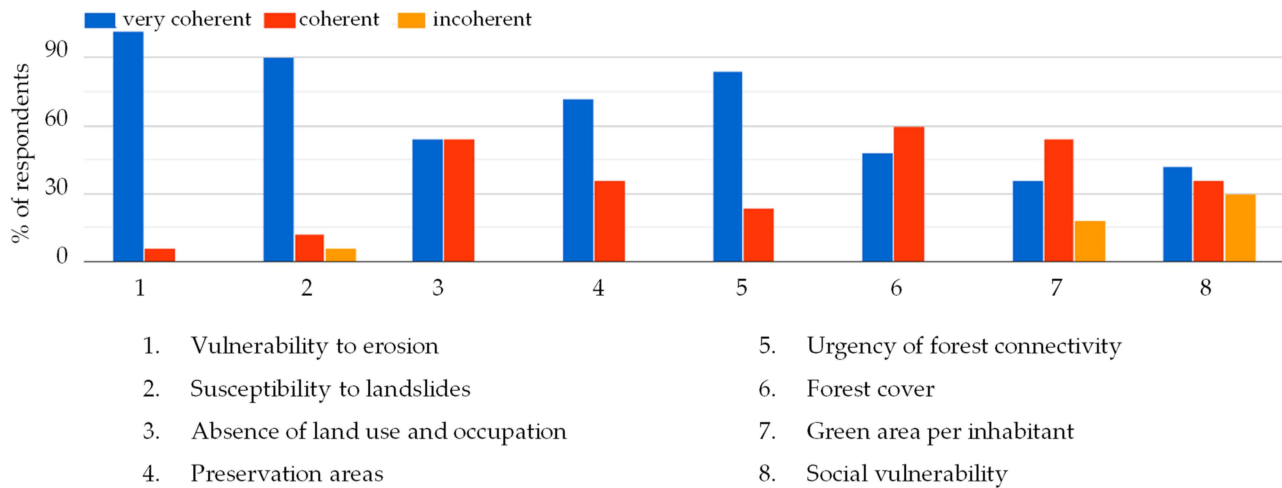


Figure 8. Experts’ perceptions of the relevance of the proposed indicators.

Interestingly, when asked whether additional indicators should be included, most experts indicated that the current set of indicators was comprehensive and sufficient. However, a specific suggestion was made to consider an indicator related to resource prioritization under budget constraints, highlighting the importance of financial feasibility in urban sustainability planning.

The coherence of the model’s results was also positively evaluated (Figure 9). Most experts classified the model’s outcomes as “highly coherent”, with some responses indicating that results were simply “coherent” but never inconsistent or unreliable. The structured inference process and the ability of the model to classify urban areas into four priority categories—extreme event mitigation, water quality maintenance, habitat conservation, and leisure and recreation enhancement—were particularly well-received.

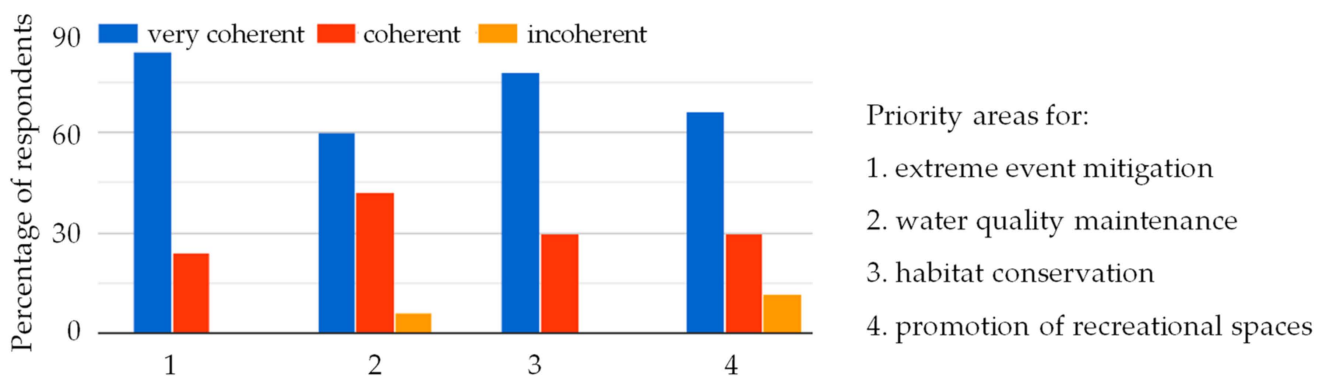


Figure 9. Experts’ perceptions of the coherence of the results from the application of the proposed model in the study area.

When asked about potential improvements, most experts did not identify any critical weaknesses in the model. However, one recommendation was to incorporate an open-ended question in future validation forms, allowing respondents to provide qualitative insights beyond the structured survey format.

The expert validation process confirmed the scientific rigor and practical applicability of the proposed framework. The overwhelmingly positive feedback on indicator selection, model coherence, and inference accuracy suggests that the FIS-based approach is a viable tool for guiding urban green infrastructure planning. Moreover, the interaction with specialists provided valuable insights for future refinements, particularly regarding the integration of economic constraints into the decision-making process.

This validation reinforces the study's contributions to urban sustainability, demonstrating that data-driven methodologies can effectively support policy and planning decisions. Future research can build upon this foundation by expanding the expert panel, integrating financial optimization models, and applying the framework across diverse urban contexts to enhance its adaptability and scalability.

7. Limitations and Future Research Directions

While the proposed FIS-based framework has demonstrated both technical feasibility and conceptual robustness, several limitations should be considered and acknowledged to inform future research and support broader applicability.

First, the study did not include a comparative evaluation with alternative decision-support methodologies, such as Multi-Criteria Decision Analysis, machine learning approaches, or GIS-only models. This omission reflects the study's primary aim of developing and validating a novel, expert-driven FIS architecture tailored to specific urban planning challenges. Nevertheless, benchmarking the framework against established methodologies is essential to strengthen its empirical foundation and should be prioritized in future research.

Second, the framework currently operates using static, secondary spatial data and expert-defined rule bases. While these choices ensure transparency and interpretability, they may not adequately reflect dynamic urban conditions. Incorporating real-time environmental monitoring and crowdsourced data sources would enhance the model's adaptability and responsiveness to temporal changes.

Third, although we employed expert validation to assess the coherence of the model and the relevance of its indicators, the framework does not yet integrate broader stakeholder engagement processes. The absence of participatory mechanisms, such as public input or multi-level institutional review, may limit its applicability within inclusive planning contexts.

Fourth, the framework was applied to a single case study—São José dos Campos, Brazil. While this city presents a relevant context of urban environmental complexity, the generalizability of the model to other urban systems with different socio-ecological and governance characteristics remains untested.

To advance the framework's utility and scope, future research should focus on benchmarking its performance against other UGI planning methods; applying it to diverse geographic and institutional settings; incorporating participatory and real-time data inputs; developing hybrid models that integrate fuzzy logic with optimization or predictive tools; and exploring its integration into municipal GIS platforms or digital twin systems to enable real-time planning support.

8. Conclusions

This study presents a fuzzy inference system (FIS)-based framework to identify priority areas for urban green infrastructure (UGI), addressing the complex demands of urban resilience and sustainability. Through seven interconnected modules, the model systematically integrates environmental and social indicators to classify urban areas and recommend tailored UGI typologies, such as sustainable drainage systems, riparian buffers,

and community parks. Its application in São José dos Campos, Brazil, a smart city with diverse urban environmental conditions, demonstrates the framework's effectiveness in supporting targeted planning across multiple time horizons.

By enabling the adjustment of prioritization sensitivity via the gamma operator and adopting transparent, expert-informed rule bases, the framework accommodates uncertainties and promotes informed decision-making. Importantly, it offers a clear pathway for policymakers by aligning with municipal planning instruments—such as master plans and ecological zoning—while ensuring integration with commonly used GIS platforms. Furthermore, the framework provides a practical decision-support pathway for policymakers by aligning its modular structure with existing urban planning instruments such as municipal master plans, ecological zoning, and resilience strategies. By utilizing accessible GIS platforms and transparent rule-based logic, the framework facilitates institutional adoption, allowing planners to integrate UGI prioritization seamlessly into regulatory processes and policy development.

Although the model relies on secondary data and expert judgment, its modular structure and validation by multidisciplinary experts confirm its practical applicability. Future research should extend the framework to diverse urban contexts, integrate real-time data inputs, and explore participatory planning mechanisms to further its scalability and responsiveness. In doing so, this approach will strengthen the role of artificial intelligence in sustainable urban governance, contributing to climate adaptation and the long-term resilience of cities.

Author Contributions: Conceptualization, A.B.; formal analysis, L.M.N.N., V.V.M., I.V.B.d.O., G.R. and A.M.d.S.; funding acquisition, A.B.; investigation, A.B., L.M.N.N. and A.M.d.S.; methodology, V.V.M., I.V.B.d.O., G.R. and R.G.N.; project administration, A.B.; software, L.M.N.N., V.V.M., I.V.B.d.O. and R.G.N.; validation, A.B., V.V.M., I.V.B.d.O., G.R., R.G.N. and A.M.d.S.; writing—original draft, A.B., L.M.N.N., V.V.M., I.V.B.d.O., G.R., R.G.N. and A.M.d.S. All authors have read and agreed to the published version of the manuscript.

Funding: We gratefully acknowledge the Brazilian Federal Agency for Support and Evaluation of Graduate Education (CAPES) for its support through the CAPES-Print program (grant number 88887.936587/2024-00), the National Council for Scientific and Technological Development (CNPq) (grant number 401721/2023-0), and the São Paulo Research Foundation (FAPESP) (grant number 2023/03387-5).

Data Availability Statement: The raw data supporting the conclusions of this article will be made available by the authors on request.

Conflicts of 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.

References

1. Wang, S.; Bai, X.; Zhang, X. Urbanization can benefit agricultural production with large-scale farming in China. *Nat. Food* **2021**, *2*, 183–191. [[CrossRef](#)] [[PubMed](#)]
2. Huang, S.; Xiao, X.; Tian, T.; Che, Y. Seasonal influences on preferences for urban blue–green spaces: Integrating land surface temperature into the assessment of cultural ecosystem service value. *Sustain. Cities Soc.* **2024**, *102*, 105237. [[CrossRef](#)]
3. Nieuwenhuijsen, N.J. Green Infrastructure and Health. *Annu. Rev. Public Health* **2021**, *42*, 317–328. [[CrossRef](#)] [[PubMed](#)]
4. Akomolafe, O.O.; Olorunsogo, T.; Anyanwu, E.C.; Osasona, F.; Ogugua, J.O.; Daraojimba, O.H. Air Quality and Public Health: A Review of Urban Pollution Sources and Mitigation Measures. *Eng. Sci. Technol. J.* **2024**, *5*, 259–271. [[CrossRef](#)]
5. Hansen, R.; Olafsson, A.S.; Van Der Jagt, A.P.; Rall, E.; Pauleit, S. Planning multifunctional green infrastructure for compact cities: What is the state of practice? *Ecol. Indic.* **2019**, *96*, 99–110. [[CrossRef](#)]
6. Enssle, F.; Kabisch, N. Urban green spaces for the social interaction, health and well-being of older people—An integrated view of urban ecosystem services and socio-environmental justice. *Environ. Sci. Policy* **2020**, *109*, 36–44. [[CrossRef](#)]

7. Kamjou, E.; Scott, M.; Lennon, M. A Bottom-Up Perspective on Green Infrastructure in Informal Settlements: Understanding nature's benefits through lived experiences. *Urban For. Urban Green.* **2024**, *94*, 128231. [CrossRef]
8. Marçal, J.; Shen, J.; Antizar-Ladislao, B.; Butler, D.; Hofman, J. Assessing inequalities in urban water security through geospatial analysis. *PLoS Water* **2024**, *3*, e0000213. [CrossRef]
9. Bressane, A.; Garcia, A.J.D.S.; Castro, M.V.D.; Xerfan, S.D.; Ruas, G.; Negri, R.G. Fuzzy machine learning applications in environmental engineering: Does the ability to deal with uncertainty really matter? *Sustainability* **2024**, *16*, 4525. [CrossRef]
10. Guarini, M.R.; Sica, F.; Segura, A. Artificial Intelligence (AI) Integration in Urban Decision-Making Processes: Convergence and Divergence with the Multi-Criteria Analysis (MCA). *Information* **2024**, *15*, 678. [CrossRef]
11. Bressane, A.; Bagatini, J.A.; Biagolini, C.H.; Roveda, J.A.F.; Roveda, S.R.M.M.; Fengler, F.H.; Longo, R.M. Neuro-fuzzy modeling: A promising alternative for risk analysis in urban afforestation management. *Braz. For. Sci.* **2018**, *42*, e420106. [CrossRef]
12. Carvalho Maria, T.R.B.; Biondi, D.; Behling, A.; dos Reis, A.R.N.; Zamproni, K.; Ho, T.L. Application of artificial intelligence for tree risk assessment optimization in Itanhaém–São Paulo, Brazil. *Urban For. Urban Green.* **2023**, *81*, e127844. [CrossRef]
13. Lin, J.; Qiu, S.; Tan, X.; Zhuang, Y. Measuring the relationship between morphological spatial pattern of green space and urban heat island using machine learning methods. *Build. Environ.* **2023**, *228*, e109910. [CrossRef]
14. Bressane, A.; Biagolini, C.H.; Mochizuki, P.S.; Roveda, J.A.F.; Lourenço, R.W. Fuzzy-based methodological proposal for participatory diagnosis in the linear parks management. *Ecol. Indic.* **2017**, *80*, 153–162. [CrossRef]
15. Zarei, F.; Nik-Bakht, M. Citizen engagement body of knowledge—A fuzzy decision maker for index-term selection in built environment projects. *Cities* **2021**, *112*, 103137. [CrossRef]
16. Barbosa, A.; Martín, B.; Hermoso, V.; Arévalo-Torres, J.; Barbière, J.; Martínez-López, J.; Domisch, S.; Langhans, S.D.; Balbi, S.; Villa, F.; et al. Cost-effective restoration and conservation planning in Green and Blue Infrastructure designs. A case study on the Intercontinental Biosphere Reserve of the Mediterranean: Andalusia (Spain)–Morocco. *Sci. Total Environ.* **2019**, *652*, 1463–1473. [CrossRef] [PubMed]
17. Massaro, A.; Birardi, G.; Manca, F.; Marin, C.; Birardi, V.; Giannone, D.; Galiano, A.M. Innovative DSS for intelligent monitoring and urban square design approaches: A case of study. *Sustain. Cities Soc.* **2021**, *65*, e102653. [CrossRef]
18. Langemeyer, J.; Wedgwood, D.; McPhearson, T.; Baró, F.; Madsen, A.L.; Barton, D.N. Creating urban green infrastructure where it is needed: A spatial ecosystem service-based decision analysis of green roofs in Barcelona. *Sci. Total Environ.* **2020**, *707*, e135487. [CrossRef]
19. Gyani, J.; Ahmed, A.; Haq, M.A. MCDM and various prioritization methods in AHP for CSS: A comprehensive review. *IEEE Access* **2022**, *10*, 33492–33511. [CrossRef]
20. Mangan, P.; Pandi, D.; Haq, M.A.; Sinha, A.; Nagarajan, R.; Dasani, T.; Keshta, I.; Alshehri, M. Analytic hierarchy process based land suitability for organic farming in the arid region. *Sustainability* **2022**, *14*, 4542. [CrossRef]
21. Sekar, K.R.; AnulHaq, M.; Kumar, A.; Shalini, R.; Poojalaxmi, S. An improved ranking methodology for malignant carcinoma in multicriterian decision making using hesitant VIKOR fuzzy. *Theor. Comput. Sci.* **2022**, *929*, 81–94. [CrossRef]
22. Liu, X.; Niu, N.; Liu, X.; Jin, H.; Ou, J.; Jiao, L.; Liu, Y. Characterizing mixed-use buildings based on multi-source big data. *Int. J. Geogr. Inf. Sci.* **2018**, *32*, 738–756.
23. Nikiforova, A.A.; Fleis, M.E.; Kazantsev, N.N. Multi-scale soil-landscape maps as the basis of geographic information systems for soil melioration. *IOP Conf. Ser. Earth Environ. Sci.* **2019**, *368*, 12038. [CrossRef]
24. Zhou, G.; Pan, Q.; Yue, T.; Wang, Q.; Sha, H.; Huang, S.; Liu, X. Vector and Raster Data Storage based on Morton Code. *Int. Arch. Photogramm. Remote Sens. Spat. Inf. Sci.* **2018**, *42*, 2523–2526. [CrossRef]
25. Mehryar, S.; Sliuzas, R.; Sharifi, A.; Reckien, D.; van Maarseveen, M. A structured participatory method to support policy option analysis in a social-ecological system. *J. Environ. Manag.* **2017**, *197*, 360–372. [CrossRef] [PubMed]
26. Mohandes, S.R.; Kaddoura, K.; Singh, A.K.; Elsayed, M.Y.; Banihashemi, S.; Antwi-Afari, M.F.; Olawumi, T.O.; Zayed, T. Application of a hybrid fuzzy-based algorithm to investigate the environmental impact of sewer overflow. *Smart Sustain. Built Environ.* **2024**. [CrossRef]
27. Bačić, S.; Tomić, H.; Rogulj, K.; Andlar, G. Fuzzy decision-making valuation model for urban green infrastructure implementation. *Energies* **2024**, *17*, 5162. [CrossRef]
28. Pedrycz, W.; Gomide, F. *Fuzzy Systems Engineering: Toward Human-Centric Computing*; John Wiley & Sons: Hoboken, NJ, USA, 2007.
29. Ross, T.J. *Fuzzy Logic with Engineering Applications*; John Wiley & Sons: Hoboken, NJ, USA, 2005.
30. Zimmermann, H.J. *Fuzzy Set Theory—And Its Applications*; Springer Science & Business Media: Berlin/Heidelberg, Germany, 2011.
31. Mendel, J.M. *Uncertain Rule-Based Fuzzy Systems: Introduction and New Directions*, 2nd ed.; Springer: Berlin/Heidelberg, Germany, 2017.
32. Bitar, O.Y. *Susceptibility Charts to Gravitational Mass Movements and Floods: Explanatory Technical Note*; IPT/CPRM: São Paulo, Brazil, 2014.
33. Brazilian Institute of Geography and Statistics. Municipalities in Brazil—Overview. 2023. Available online: <https://cidades.ibge.gov.br/brasil/sp/sao-jose-dos-campos/panorama> (accessed on 10 January 2025).
34. Hwang, S.A.; Hwang, S.J.; Park, S.R.; Lee, S.W. Examining the relationships between watershed urban land use and stream water quality using linear and generalized additive models. *Water* **2016**, *8*, 155. [CrossRef]

35. Spielman, S.E.; Tuccillo, J.; Folch, D.C.; Schweikert, A.; Davies, R.; Wood, N.; Tate, E. Evaluating social vulnerability indicators: Criteria and their application to the Social Vulnerability Index. *Nat. Hazards* **2020**, *100*, 417–436. [\[CrossRef\]](#)
36. Cordeiro, G.G.; Vasconcelos, V.; Salemi, L.F.; Nardoto, G.B. Factors affecting the effectiveness of riparian buffers in retaining sediment: An isotopic approach. *Environ. Monit. Assess.* **2020**, *192*, 735. [\[CrossRef\]](#)
37. Joly, C.A. BIOTA/FAPESP: The Biodiversity Virtual Institute—Translating Research on Biodiversity and Ecosystem Services into Policies in a Megadiverse Country. In *Applied Ecology and Human Dimensions in Biological Conservation*; Springer: Berlin/Heidelberg, Germany, 2014; pp. 211–224.
38. Ribeiro, M.P.; de Mello, K.; Valente, R.A. How can forest fragments support protected areas connectivity in an urban landscape in Brazil? *Urban For. Urban Green.* **2022**, *74*, 127683. [\[CrossRef\]](#)
39. Mota MT, D.; Galvao AL, D.S.; Bressane, A.; Negri, R.G.; Roveda JA, F.; Roveda SR, M. A fuzzy-based methodological proposal for analysing green areas in urban neighborhoods. *Anais da Academia Brasileira de Ciências* **2022**, *94* (Suppl. S4), e20210015. [\[CrossRef\]](#) [\[PubMed\]](#)
40. Bressane, A.; Mochizuki, P.S.; Roveda, J.A.F.; Roveda, S.R.M.M.; de Medeiros, G.A.; Ribeiro, A.Í.; Martins, A.C.G. Management support system of urban green areas. *RevSbau* **2015**, *10*, 30–42. [\[CrossRef\]](#)
41. Bortolan, G.; Degani, R. A review of some methods for ranking fuzzy subsets. *Fuzzy Sets Syst.* **1985**, *15*, 1–19. [\[CrossRef\]](#)
42. Junqueira, J.R.; Serrao-Neumann, S.; White, I. Managing urban climate change risks: Prospects for using green infrastructure to increase urban resilience to floods. In *The Impacts of Climate Change*; Elsevier: Amsterdam, The Netherlands, 2021; pp. 379–396.
43. Mello Torres, J.G.; de Andrade, N.; Neto, P.L.D.O.C. Analysis of the European and Brazilian Rankings of Smart Cities: A case study of São José dos Campos and Toulouse. *Int. J. Adv. Eng. Res. Sci.* **2019**, *6*, 91–115. [\[CrossRef\]](#)
44. *ISO 37.120*; Indicators for Urban Services and Quality of Life. International Organization for Standardization: Geneva, Switzerland, 2014.
45. *ISO 37.123*; Indicators for Resilient Cities. International Organization for Standardization: Geneva, Switzerland, 2019.
46. *ISO 37.122*; Indicators for Smart Cities. International Organization for Standardization: Geneva, Switzerland, 2019.

Disclaimer/Publisher’s Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.