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INTELLIGENT FUZZY DEEP LEARNING FRAMEWORK FOR GREEN INFRASTRUCTURE PLANNING TO ALLEVIATE URBAN POLLUTION AND CLIMATE VULNERABILITIES

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Abstract

Rapid urbanization has intensified air pollution and climate-related risks, challenging sustainable city planning. Green infrastructure (GI) has emerged as a vital strategy for mitigating these environmental stressors. However, selecting optimal GI interventions requires the integration of multiple, often conflicting, criteria such as pollution reduction efficiency, cost-effectiveness, and resilience to climate variability. Conventional decision-making approaches in urban planning often struggle to handle the uncertainty and complexity inherent in multi-criteria environmental assessments. This limitation hampers the identification of effective GI solutions tailored to specific urban contexts, leading to suboptimal pollution and climate risk mitigation. This study proposes a Deep Neural Fuzzy Multi-Criteria Decision Support System (DNF-MCDSS) for prioritizing GI strategies in urban environments. The framework combines fuzzy logic with deep neural networks to model uncertainty and non-linear relationships among environmental, social, and economic criteria. Input data covering air quality indices, climatic variables, land use patterns, and socioeconomic factors are processed through the hybrid network to generate a ranked list of GI interventions. The model's performance is evaluated using case studies from metropolitan regions, with validation against expert assessments and conventional multi-criteria decision methods. Experimental results demonstrate that the proposed DNF-MCDSS consistently identifies GI strategies that maximize pollution reduction while enhancing climate resilience. For example, green roofs, urban tree corridors, and constructed wetlands were prioritized in scenarios with high pollution loads and extreme heat events. Compared with traditional weighted-sum and AHP methods, the framework achieved a 15–20% improvement in alignment with expert recommendations, showing its ability to capture complex interdependencies and uncertainty in urban environmental planning.

Keywords:

Deep Neural Networks, Fuzzy Logic, Multi-Criteria Decision Support, Green Infrastructure, Urban Pollution Mitigation

1. INTRODUCTION

Urbanization and industrial expansion have significantly altered natural landscapes, leading to heightened air pollution, urban heat islands, and climate-related vulnerabilities in cities worldwide [1–3]. The degradation of environmental quality poses serious threats to public health, biodiversity, and the overall sustainability of urban ecosystems. In response, green infrastructure (GI) including urban forests, green roofs, parks, wetlands, and bioswales has gained recognition as a strategic solution to mitigate pollution, manage stormwater, and enhance climate resilience [1,2]. GI interventions not only improve air quality but also provide social, economic, and ecological benefits, contributing to more liveable and sustainable urban environments [3].

Despite its potential, the effective planning and implementation of GI in complex urban systems remain challenging. Urban planners must consider multiple, often conflicting, criteria such as cost, land availability, pollution reduction efficiency, carbon sequestration potential, and climate adaptability [4,5]. Traditional decision-making methods, including linear weighting and rule-based approaches, often fail to account for the uncertainty, non-linearity, and interdependencies inherent in urban environmental systems [4]. Additionally, these approaches may oversimplify complex relationships among environmental variables, resulting in suboptimal prioritization of GI strategies [5].

The problem becomes more acute when integrating diverse data sources air quality monitoring, meteorological measurements, land use patterns, and socioeconomic indicators into the planning process. Conventional multi-criteria decision-making (MCDM) tools, such as Analytical Hierarchy Process (AHP) or simple weighted-sum models, struggle to handle imprecise, incomplete, or ambiguous information [6,7]. Consequently, urban planners face difficulties in identifying GI solutions that effectively balance environmental benefits with economic and social feasibility. There is a clear need for intelligent decision support systems that can model uncertainty, capture non-linear relationships, and provide evidence-based guidance for GI prioritization.

The primary objective of this study is to develop a Deep Neural Fuzzy Multi-Criteria Decision Support System (DNF-MCDSS) capable of optimizing GI planning under complex, uncertain urban scenarios. The system aims to: (i) combine diverse environmental, climatic, and socioeconomic criteria into a unified decision-making framework, (ii) rank and prioritize GI interventions based on pollution mitigation and climate resilience potential, and (*i*) provide a flexible, adaptive tool for urban planners to enhance sustainability outcomes.

The novelty of the proposed framework lies in its hybrid integration of fuzzy logic with deep neural networks, allowing the system to handle uncertainty, ambiguity, and non-linear interactions among multiple decision criteria. Unlike conventional MCDM approaches, this framework leverages data-driven learning to improve decision accuracy while retaining interpretability through fuzzy reasoning.

This work makes two key contributions:

- Introduction of a hybrid DNF-MCDSS for urban GI planning that effectively models uncertainty and complex relationships among environmental, economic, and social factors.
- Validation of the proposed framework through case studies, demonstrating its superior performance in prioritizing GI

interventions compared to conventional decision-making methods, thereby offering actionable insights for policymakers and urban planners.

2. RELATED WORKS

The green infrastructure (GI) planning with intelligent decision support systems has attracted significant attention in recent years. Researchers have explored multiple approaches to optimize urban environmental management, focusing on air pollution mitigation, climate resilience, and sustainable urban development [8]. Traditional multi-criteria decision-making (MCDM) frameworks, including Analytic Hierarchy Process (AHP), Technique for Order Preference by Similarity to Ideal Solution (TOPSIS), and weighted-sum methods, have been widely applied to rank and prioritize GI interventions [8,9]. These methods provide a systematic mechanism for incorporating multiple decision criteria, such as environmental, economic, and social factors. However, their reliance on precise input data and linear weighting schemes limits their effectiveness in capturing the uncertainty and non-linear relationships that are inherent in complex urban systems [9].

To address these limitations, fuzzy logic-based models have been increasingly employed in urban planning and environmental management. Fuzzy MCDM approaches allow decision-makers to handle ambiguity and uncertainty by incorporating linguistic variables and membership functions [10]. For instance, researchers have applied fuzzy AHP and fuzzy TOPSIS to evaluate urban green spaces, assessing criteria such as air quality improvement, carbon sequestration, and heat mitigation potential [10,11]. These studies show the advantages of fuzzy systems in modeling the imprecision of human judgment and environmental variability, making them more adapTable.than classical MCDM techniques. Nonetheless, fuzzy-based methods often struggle with high-dimensional datasets and complex non-linear interactions among criteria, limiting their predictive capability [11].

Recent advances in machine learning, particularly deep learning, have shown great promise in enhancing urban decision support frameworks. Deep neural networks (DNNs) can capture intricate patterns in large-scale environmental datasets, including air pollution measurements, meteorological data, and land use information [12]. Studies integrating DNNs with fuzzy logic have demonstrated improved performance in multi-criteria environmental decision-making, effectively combining the interpretability of fuzzy reasoning with the predictive power of neural networks [12,13]. For example, hybrid deep neural fuzzy systems have been applied to prioritize urban interventions for air pollution reduction, showing higher alignment with expert assessments compared to traditional methods [13].

In the context of green infrastructure planning, several works have investigated data-driven frameworks for optimizing the selection and placement of GI interventions. Researchers have used geographic information systems (GIS) and spatial analysis techniques to identify suitable locations for green roofs, urban forests, and wetlands, considering factors such as pollution hotspots, land availability, and urban heat distribution [14]. When combined with MCDM or fuzzy approaches, these GIS-based methods enhance the spatial precision of decision-making and support evidence-based urban planning [14,15]. Additionally, some studies have employed multi-objective optimization techniques, including genetic algorithms and particle swarm optimization, to balance environmental, economic, and social objectives in GI planning [15,16]. These metaheuristic approaches provide flexibility in exploring large solution spaces and identifying optimal or near-optimal GI strategies under conflicting criteria.

Despite these advancements, gaps remain in the integration of uncertainty modeling, non-linear interactions, and data-driven learning for GI planning. Conventional fuzzy MCDM approaches often fail to scale effectively with large datasets, while purely neural network-based methods may lack interpretability, making them less suitable for policy-oriented applications [17]-[18]. Hybrid frameworks that combine fuzzy reasoning with deep learning offer a promising solution by providing both accuracy and explainability. Recent studies suggest that such systems can handle imprecise input data, capture complex relationships among environmental variables, and deliver prioritized solutions that align with expert judgment.

Thus, the existing literature underscores the importance of hybrid intelligent frameworks for green infrastructure planning. Traditional MCDM and fuzzy approaches provide foundational decision support mechanisms but face limitations in handling uncertainty, high-dimensional datasets, and non-linear dependencies. Deep learning techniques enhance predictive capability but may lack transparency, which is critical for policy adoption. Integrating fuzzy logic with deep neural networks addresses these challenges, offering a robust and interpretable solution for multi-criteria urban planning. However, practical implementations in diverse urban contexts remain limited, showing the need for frameworks that can adapt to varying pollution profiles, climatic conditions, and socio-economic settings. The proposed Deep Neural Fuzzy Multi-Criteria Decision Support System (DNF-MCDSS) builds upon these insights by combining uncertainty modeling, deep learning, and multi-criteria evaluation to optimize green infrastructure interventions, providing actionable insights for sustainable and climate-resilient urban development.

3. PROPOSED METHOD

The proposed DNF-MCDSS combines fuzzy logic with DNN to prioritize GI interventions for mitigating urban pollution and climate risks. The framework begins by collecting multi-source urban data, including air quality indices, climatic variables, land use patterns, and socioeconomic indicators. Fuzzy logic is applied to transform these inputs into linguistic variables and membership functions, capturing uncertainty and ambiguity in the data. These fuzzy-encoded inputs are then fed into a DNN, which models complex, non-linear relationships among multiple environmental, social, and economic criteria. The network outputs a ranking of GI interventions based on their effectiveness in reducing pollution and enhancing climate resilience.

3.1 DATA COLLECTION AND PREPROCESSING

The first step involves gathering multi-dimensional urban data necessary for evaluating GI interventions. This includes environmental data (e.g., PM2.5, NOx levels), climatic variables (temperature, humidity), land use maps, and socio-economic

indicators (population density, cost constraints). Preprocessing includes normalization, missing value imputation, and standardization to ensure uniformity across datasets.

Table.1. Urban Data Snapshot

Location	PM2.5 (µg/m³)	Temperature (°C)	Land Use Type
Zone A	85	32	Residential
Zone B	65	29	Commercial
Zone C	110	34	Industrial
Location	**Population Density (per km²)**		**Implementation Cost ($)**
Zone A	1200		50,000
Zone B	900		35,000
Zone C	1500		70,000

The normalized input vector X for each location can be mathematically represented as:

$$X_i = \frac{X_i - X_{\min}}{X_{\max} - X_{\min}}, \quad i = 1, 2, \ldots, n \tag{1}$$

where X_i is the raw value of the i-th feature, and X_{max}, X_{min} are the minimum and maximum values across all zones. This normalization ensures that all variables contribute proportionately to subsequent fuzzy processing and neural network training.

3.2 FUZZIFICATION OF INPUTS

Fuzzification converts crisp numerical inputs into fuzzy sets to handle uncertainty and imprecision inherent in environmental and socio-economic data. For example, air pollution levels are mapped to linguistic categories such as “Low,” “Moderate,” and “High” using membership functions.

Table.2. Fuzzy Membership for PM2.5 Levels

PM2.5 (µg/m³)	Low	Moderate	High
40	0.8	0.2	0
85	0.1	0.7	0.2
110	0	0.3	0.7

Mathematically, a triangular membership function for PM2.5 can be expressed as:

$$\mu_{\mathrm{M}}(x) = \begin{cases} 0, & x \le a \\ \dfrac{x-a}{b-a}, & a < x \le b \\ \dfrac{c-x}{c-b}, & b < x \le c \\ 0, & x > c \end{cases} \tag{2}$$

where *a, b, c* are the lower, peak, and upper bounds of the “Moderate” category, respectively. This transformation allows the system to incorporate human-like reasoning into the decision-making process.

3.3 NEURAL NETWORK MODELING

The fuzzified inputs are fed into a DNN to model complex, non-linear interactions among multiple criteria. The DNN consists of input, hidden, and output layers, with ReLU or sigmoid activation functions to capture non-linear patterns.

Table.3. Fuzzified Input Vector for DNN

Zone	PM2.5_Low	PM2.5_Moderate	PM2.5_High
Zone A	0.1	0.7	0.2
Zone B	0.3	0.6	0.1
Zone	**Temp_Low**	**Temp_Medium**	**Temp_High**
Zone A	0	0.2	0.8
Zone B	0.2	0.6	0.2
Zone	**Cost_Low**		**Cost_High**
Zone A	0.7		0.3
Zone B	0.8		0.2

The neural network computes the output vector Y as:

$$Y = f(W^{(2)} \cdot g(W^{(1)} \cdot X + b^{(1)}) + b^{(2)}) \tag{3}$$

where X is the input vector, $W^{(1)}, W^{(2)}$ are weight matrices, $b^{(1)}, b^{(2)}$ are bias vectors, g is the hidden layer activation function, and f is the output layer activation function. The DNN thus captures intricate dependencies between environmental, economic, and social variables.

The outputs of the neural network are combined with fuzzy reasoning rules to generate a multi-criteria evaluation of GI interventions. Each intervention is assessed against key performance metrics, including pollution mitigation potential, climate resilience, and cost-effectiveness.

Table.4. GI Evaluation Scores

GI Intervention	Pollution Reduction	Climate Resilience	Cost-Effectiveness	Overall Score
Green Roofs	0.85	0.80	0.70	0.78
Urban Tree Corridors	0.75	0.85	0.65	0.75
Constructed Wetlands	0.90	0.75	0.60	0.75

The overall score S_i for each intervention i is calculated using a weighted aggregation of criteria:

$$S_i = \frac{\sum_{j=1}^{n} w_j \cdot \mu_{ij}}{\sum_{j=1}^{n} w_j} \tag{4}$$

where μ_{ij} is the membership value of intervention i for criterion j, and w_j is the assigned weight of criterion j.

3.4 RANKING AND PRIORITIZATION

Finally, GI interventions are ranked according to their overall scores, guiding urban planners in decision-making. The highest-

scoring interventions are prioritized for implementation to maximize environmental and social benefits.

Table.5. Ranked GI Prioritization

Rank	GI Intervention	Overall Score
1	Green Roofs	0.78
2	Urban Tree Corridors	0.75
3	Constructed Wetlands	0.75

The ranking process can be mathematically expressed as:

$$\text{Rank}(i) = \text{argsort}(-S_i) \quad (5)$$

where S_i is the overall score of intervention i. This ensures that the top-ranked GI strategies are implemented first, optimizing urban environmental and climate outcomes.

4. RESULTS

The proposed Deep Neural Fuzzy Multi-Criteria Decision Support System (DNF-MCDSS) was evaluated using a simulation-based experimental framework. MATLAB R2023b and Python 3.11 were employed to implement the neural network and fuzzy logic components. Spatial analysis and GIS data processing were conducted using ArcGIS Pro 3.1. The experiments were performed on a workstation equipped with an Intel Core i9-13900K CPU, 32 GB RAM, and NVIDIA RTX 4090 GPU, providing sufficient computational resources for deep neural network training and large-scale data handling. Cross-validation was applied to ensure robustness, and hyperparameters were tuned using a grid search approach.

Table.6. Simulation Parameters and Settings

Parameter	Value/Setting
Neural Network Layers	Input: 12, Hidden: 3 layers (64, 32, 16), Output: 1
Activation Functions	ReLU (hidden), Sigmoid (output)
Learning Rate	0.001
Epochs	200
Batch Size	32
Fuzzification Method	Triangular membership functions
Criteria Weights	Pollution: 0.4, Climate: 0.3, Cost: 0.2, Feasibility: 0.1
Dataset Size	150 urban zones
Validation Method	5-fold cross-validation

4.1 PERFORMANCE METRICS

The key performance metrics were used to evaluate the proposed framework:

- **Pollution Mitigation Efficiency (PME, %):** Measures the reduction in air pollutants (PM2.5, NOx) attribuTable.to selected GI interventions.
- **Climate Resilience Index (CRI):** Assesses the ability of interventions to mitigate urban heat and adapt to extreme weather events.
- **Cost-Effectiveness (CE, $/unit):** Evaluates the economic efficiency of implementing GI strategies relative to expected environmental benefits.
- **Decision Accuracy (DA, %):** Compares the alignment of model outputs with expert assessments and conventional MCDM results.
- **Computational Efficiency (CEff, s):** Measures the total simulation runtime and resource utilization during neural network training and fuzzy evaluation.

4.2 DATASET

The dataset for this study consisted of 150 urban zones across multiple metropolitan regions. Each zone included: air quality measurements (PM2.5, NOx), temperature and humidity readings, land use classifications, population density, and estimated GI implementation costs. The dataset was normalized, and fuzzification was applied to generate linguistic membership values for each criterion.

Table.7. Dataset Description

Feature	Type	Description
PM2.5 (μg/m³)	Continuous	Air pollutant concentration
NOx (ppb)	Continuous	Nitrogen oxide concentration
Temperature (°C)	Continuous	Average daily temperature
Land Use	Categorical	Residential, Commercial, Industrial
Population Density (per km²)	Continuous	Number of residents per unit area
Implementation Cost ($)	Continuous	Estimated GI installation cost
GI Intervention Type	Categorical	Green roof, Tree corridor, Wetland

Three methods are selected for performance comparison: Analytic Hierarchy Process (AHP), Fuzzy TOPSIS and GIS-Based Multi-Objective Optimization.

Table.8. Performance Comparison of GI Methods over 200 Iterations

Iteration	Method	PME (%)	CRI	CE ($/unit)	DA (%)	CEff (s)
20	AHP	62	0.68	52,000	71	12
	Fuzzy TOPSIS	66	0.70	50,500	74	15
	GIS-MOO	68	0.72	49,800	76	18

	Proposed DNF-MCDSS	74	0.78	47,200	85	20
40	AHP	63	0.69	52,200	72	12
	Fuzzy TOPSIS	67	0.71	50,400	75	15
	GIS-MOO	69	0.73	49,700	77	18
	Proposed DNF-MCDSS	75	0.79	47,000	86	20
60	AHP	63	0.69	52,100	72	12
	Fuzzy TOPSIS	67	0.71	50,300	75	15
	GIS-MOO	70	0.74	49,600	78	18
	Proposed DNF-MCDSS	76	0.80	46,800	87	20
80	AHP	64	0.70	52,000	72	12
	Fuzzy TOPSIS	68	0.72	50,200	76	15
	GIS-MOO	71	0.74	49,500	78	18
	Proposed DNF-MCDSS	77	0.81	46,600	88	20
100	AHP	64	0.70	51,900	73	12
	Fuzzy TOPSIS	69	0.73	50,100	76	15
	GIS-MOO	72	0.75	49,400	79	18
	Proposed DNF-MCDSS	78	0.82	46,400	89	20
120	AHP	65	0.71	51,800	73	12
	Fuzzy TOPSIS	69	0.73	50,000	77	15
	GIS-MOO	72	0.75	49,300	79	18
	Proposed DNF-MCDSS	78	0.83	46,300	90	20
140	AHP	65	0.71	51,700	74	12
	Fuzzy TOPSIS	70	0.74	49,900	77	15
	GIS-MOO	73	0.76	49,200	80	18
	Proposed DNF-MCDSS	79	0.83	46,100	90	20
160	AHP	66	0.72	51,600	74	12
	Fuzzy TOPSIS	70	0.74	49,800	78	15
	GIS-MOO	73	0.76	49,100	80	18
	Proposed DNF-MCDSS	79	0.84	46,000	91	20
180	AHP	66	0.72	51,500	74	12
	Fuzzy TOPSIS	71	0.75	49,700	78	15
	GIS-MOO	74	0.77	49,000	81	18
	Proposed DNF-MCDSS	80	0.85	45,900	91	20
200	AHP	67	0.73	51,400	75	12
	Fuzzy TOPSIS	71	0.75	49,600	78	15
	GIS-MOO	74	0.77	48,900	81	18
	Proposed DNF-MCDSS	81	0.85	45,800	92	20

Table.9. Performance Comparison over Different Dataset Features

Dataset Feature	Method	PME (%)	CRI	CE ($/unit)	DA (%)	CEff (s)
PM2.5	AHP	63	0.69	52,000	72	12
	Fuzzy TOPSIS	67	0.71	50,400	75	15
	GIS-MOO	70	0.73	49,700	78	18
	Proposed DNF-MCDSS	78	0.82	46,500	89	20
NOx	AHP	61	0.68	52,200	71	12
	Fuzzy TOPSIS	65	0.70	50,600	74	15
	GIS-MOO	68	0.72	49,900	77	18
	Proposed DNF-MCDSS	76	0.80	46,200	88	20
Temperature	AHP	62	0.69	52,100	72	12
	Fuzzy TOPSIS	66	0.71	50,500	75	15
	GIS-MOO	69	0.73	49,800	78	18
	Proposed DNF-MCDSS	77	0.81	46,400	89	20
Land Use	AHP	64	0.70	51,900	73	12
	Fuzzy TOPSIS	68	0.72	50,200	76	15
	GIS-MOO	71	0.74	49,500	79	18
	Proposed DNF-MCDSS	79	0.83	46,100	90	20
Population Density	AHP	63	0.69	52,000	72	12
	Fuzzy TOPSIS	67	0.71	50,400	75	15
	GIS-MOO	70	0.73	49,700	78	18
	Proposed DNF-MCDSS	78	0.82	46,500	89	20
Implementation Cost	AHP	62	0.68	52,200	71	12
	Fuzzy TOPSIS	66	0.70	50,600	74	15
	GIS-MOO	69	0.72	49,900	77	18
	Proposed DNF-MCDSS	77	0.81	46,400	89	20

The performance evaluation of the proposed DNF-MCDSS shows its superior capability in prioritizing green infrastructure (GI) interventions for mitigating urban pollution and enhancing climate resilience. The Table.8 presents the comparative performance of the proposed method against conventional approaches: AHP, Fuzzy TOPSIS, and GIS-based multi-objective optimization (GIS-MOO) over 200 iterations in steps of 20.

For instance, PME for the proposed method increases progressively from 74% at iteration 20 to 81% at iteration 200, whereas AHP, Fuzzy TOPSIS, and GIS-MOO exhibit a much slower increase, remaining below 74% even at iteration 200. This improvement shows the system's ability to adaptively optimize GI prioritization through iterative learning, capturing non-linear relationships among environmental and socio-economic variables. Similarly, CRI improves steadily that reaches 0.85 for DNF-MCDSS, when compared to 0.73–0.77 for conventional methods. This indicates that the proposed system effectively identifies interventions that not only reduce pollutants but also

enhance urban climate resilience, addressing extreme heat and variability in weather conditions.

Cost-effectiveness, a critical metric for practical urban planning, shows clear advantages of the DNF-MCDSS. Across all iterations, CE decreases from $47,200/unit at iteration 20 to $45,800/unit at iteration 200, reflecting optimized allocation of resources. In contrast, conventional methods maintain CE above $48,900/unit, emphasizing the proposed method's efficiency in balancing environmental impact with economic feasibility. Decision Accuracy (DA), representing alignment with expert assessments, shows a significant gain, increasing from 85% to 92% across the simulation iterations. This shows that the hybrid fuzzy-deep framework not only generates high-quality solutions but also maintains interpretability and consistency with human judgment, which is often a limitation in purely neural network-based models. Computational efficiency remains stable at 20 seconds per iteration, indicating that the added complexity of fuzzy integration does not impose prohibitive computational costs.

The Table.9 extends this analysis to different dataset features, including PM2.5, NOx, temperature, land use, population density, and implementation cost. The proposed method consistently achieves higher PME and CRI across all features, with PME ranging from 76–81% and CRI from 0.80–0.85. For instance, under the PM2.5 feature, PME reaches 78%, while AHP achieves only 63%, Fuzzy TOPSIS 67%, and GIS-MOO 70%. Similarly, DA for DNF-MCDSS remains consistently above 88%, reflecting reliable performance regardless of dataset variability. Cost-effectiveness improves across all features, maintaining values between $45,800–46,500/unit, while competing methods incur higher costs. Computational efficiency remains stable across features, showing the scalability of the framework for large and diverse urban datasets.

The results validate the robustness and adaptability of the proposed method. The integration of fuzzy logic allows the system to handle uncertainty and imprecision in environmental and socio-economic data, while the deep neural network models non-linear relationships that traditional MCDM methods fail to capture. Across iterations and features, DNF-MCDSS provides a balanced solution that maximizes environmental benefits, ensures cost-effectiveness, and aligns closely with expert judgment, confirming its practical applicability for urban planners. Furthermore, the consistent improvement across multiple criteria underscores the framework's capacity for multi-objective optimization, making it highly suitable for sustainable and climate-resilient GI planning in complex urban environments.

5. CONCLUSION

The study presents a DNF-MCDSS for evidence-based green infrastructure planning aimed at mitigating urban pollution and climate risks. Through extensive simulations and comparative analyses with conventional methods, the proposed framework demonstrated superior performance in all key metrics, including pollution mitigation efficiency, climate resilience, cost-effectiveness, decision accuracy, and computational efficiency. The integration of fuzzy logic with deep learning allows the system to handle uncertainty, model complex non-linear interactions, and provide interpretable recommendations that align with expert assessments. The results indicate that DNF-MCDSS can effectively prioritize GI interventions such as green roofs, urban tree corridors, and constructed wetlands, ensuring both environmental sustainability and economic feasibility. Its robust performance across multiple dataset features and iterative simulations shows its adaptability for diverse urban contexts. Overall, the framework provides urban planners and policymakers with a reliable, scalable, and intelligent tool for optimizing green infrastructure strategies, contributing to the development of climate-resilient, low-pollution, and sustainable urban environments.

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