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FUZZY LOGIC-DRIVEN MODELING OF URBAN AIR QUALITY USING SENSOR NETWORKS FOR CLIMATE-RESILIENT GREEN INFRASTRUCTURE

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Abstract
Urban air pollution has emerged as a critical environmental and public health challenge worldwide, exacerbated by rapid urbanization, vehicular emissions, and industrial activities. Traditional monitoring approaches often struggle to provide real-time, spatially granular data necessary for effective urban planning and mitigation. Integrating smart sensor networks with advanced computational models can enable proactive management of air quality, supporting climate-resilient urban infrastructure. Despite the availability of various air quality monitoring systems, challenges remain in handling the inherent uncertainties, nonlinearities, and dynamic variations of urban pollutant levels. Conventional statistical models often fail to capture complex relationships between pollutant sources, meteorological factors, and urban morphology. There is a critical need for modeling approaches that accommodate ambiguity and provide actionable insights for decision-makers in urban planning. This study presents a fuzzy logic-based framework for modeling urban air pollution using data collected from a distributed network of low-cost sensors. Fuzzy logic enables the incorporation of expert knowledge and real-time sensor measurements to handle uncertainty and nonlinearity in pollutant dynamics. The framework integrates multi-source environmental data, including traffic density, meteorological variables, and green infrastructure coverage, to predict air quality indices across urban zones. Model validation is conducted using historical pollution records and real-time sensor data to assess predictive accuracy and robustness. The proposed fuzzy logic model demonstrates significant improvement in capturing spatiotemporal variations of key pollutants, such as PM2.5, NO_2, and O_3, compared to traditional linear regression methods. The results reveal that zones with optimized green infrastructure and traffic management strategies experience a measurable reduction in pollutant concentrations, highlighting the model's utility for urban planning. The approach offers actionable insights for deploying climate-resilient green infrastructure and optimizing urban air quality interventions in real time.

Keywords:
Urban Air Pollution, Fuzzy Logic Modeling, Sensor Networks, Climate-Resilient Infrastructure, Green Urban Planning

1. INTRODUCTION

Urban air pollution has emerged as one of the most pressing environmental and public health challenges of the 21st century. Rapid urbanization, industrial growth, and increasing vehicular emissions have led to elevated concentrations of particulate matter (PM), nitrogen oxides (NO_x), ozone (O_3), and other hazardous pollutants in cities worldwide [1–3]. These pollutants not only deteriorate air quality but also contribute to respiratory and cardiovascular diseases, reduced life expectancy, and climate change-related risks. Managing urban air pollution requires comprehensive monitoring and predictive strategies that consider the complex interactions between pollutant sources, meteorological conditions, and urban infrastructure. Traditional air quality monitoring systems, often relying on sparsely located stations, are limited in their ability to capture real-time, spatially detailed variations in pollution levels. Consequently, policymakers and urban planners face significant challenges in designing effective mitigation strategies that are responsive to the dynamic nature of urban air quality [1,2].

Several challenges hinder effective urban air pollution management. First, urban environments are characterized by high spatial and temporal variability in pollutant concentrations, influenced by factors such as traffic flow, industrial emissions, and seasonal meteorological changes [4]. Second, conventional statistical and linear modeling approaches often fail to capture the nonlinear and uncertain nature of pollutant dynamics, leading to reduced predictive accuracy and unreliable intervention strategies [5]. Additionally, the integration of real-time data from heterogeneous sources, including low-cost sensor networks, presents technical challenges related to data quality, calibration, and synchronization. These complexities highlight the need for robust modeling frameworks capable of handling uncertainty, incorporating expert knowledge, and providing actionable insights for sustainable urban planning [4,5].

The core problem addressed in this study is the lack of reliable, adaptive modeling approaches for urban air pollution that can effectively guide the design and implementation of climate-resilient green infrastructure [6]. While sensor networks provide abundant real-time data, conventional models struggle to integrate these data sources while managing uncertainties inherent in urban environments. There is a critical need for methodologies that combine computational intelligence with environmental sensing to deliver accurate, interpretable, and scalable predictions for urban air quality management.

The primary objective of this study is to develop a fuzzy logic-based modeling framework that leverages data from distributed sensor networks to predict spatiotemporal variations in urban air pollution. Specific objectives include: (i) integrating multi-source environmental data, including traffic, meteorological factors, and green infrastructure metrics, into the model; (ii) handling uncertainty and nonlinear relationships among pollutants using fuzzy logic reasoning; and (*i*) providing actionable insights to support climate-resilient urban planning and green infrastructure deployment.

The novelty of this work lies in the fusion of fuzzy logic modeling with real-time sensor network data to capture complex urban pollutant dynamics while explicitly incorporating uncertainty and expert knowledge. Unlike traditional statistical models, the proposed framework offers interpretable predictions and the ability to simulate the impact of green infrastructure interventions on air quality.

This study makes two key contributions. First, it presents a comprehensive fuzzy logic-based modeling framework that integrates heterogeneous sensor data and environmental factors to predict urban air pollution with high spatial and temporal resolution. Second, it provides practical insights for urban planners and policymakers by demonstrating how climate-resilient green infrastructure can be optimized to reduce pollutant concentrations, enabling data-driven interventions for sustainable urban development.

2. RELATED WORKS

Recent research has increasingly focused on integrating advanced computational models with sensor networks for urban air quality monitoring and sustainable urban planning. Several studies have explored the use of intelligent modeling techniques to overcome the limitations of conventional monitoring systems, particularly in addressing the nonlinear, uncertain, and dynamic nature of urban pollutant concentrations. For instance, machine learning approaches such as artificial neural networks (ANNs) and support vector machines (SVMs) have been employed to predict air pollutant levels using historical and real-time data from urban monitoring stations [7,8]. These models demonstrated improved predictive performance compared to traditional statistical methods, yet they often require large labeled datasets and may struggle with interpretability, limiting their practical adoption in urban planning decisions.

Fuzzy logic-based models have emerged as a promising alternative due to their ability to incorporate expert knowledge and handle uncertainties inherent in urban environments. Several studies have applied fuzzy inference systems to model air quality, demonstrating robust performance in predicting pollutants such as PM2.5, NO_2, and O_3 under varying meteorological conditions [9,10]. For example, a study implemented a Mamdani-type fuzzy logic model to evaluate air pollution patterns in metropolitan areas, integrating traffic and weather data to predict short-term pollutant concentrations [9]. This approach provided interpretable rules and insights that could directly inform urban planning strategies. Similarly, hybrid fuzzy–machine learning models have been explored to further enhance prediction accuracy while maintaining model transparency [10].

The role of sensor networks in urban air quality monitoring has also been extensively investigated. Low-cost, distributed sensor nodes enable high-resolution spatiotemporal data collection, addressing the limitations of traditional monitoring stations [11,12]. Studies have demonstrated that these networks, when combined with intelligent models, can accurately capture local variations in pollution levels and identify hotspot regions requiring intervention [11]. Integration of environmental parameters such as temperature, humidity, traffic density, and green coverage into sensor-driven models has shown significant improvements in predictive accuracy and operational relevance [12,13].

Green infrastructure has been increasingly recognized as an effective strategy for mitigating urban air pollution. Research has examined the impact of vegetation, green roofs, and urban forests on local air quality, highlighting their potential to absorb particulate matter and gaseous pollutants [14]. However, translating these findings into actionable planning strategies requires predictive models capable of simulating pollutant dynamics under various urban planning scenarios. Few studies have successfully combined sensor-driven data, computational intelligence, and green infrastructure metrics into an integrated framework for urban air quality management.

Recent works have begun addressing this gap. For example, hybrid frameworks that fuse fuzzy logic with sensor network data have been proposed for real-time air quality monitoring and pollution source identification [15]-[17]. These studies emphasize the importance of interpretability and adaptability in modeling urban air pollution, allowing planners to evaluate the effectiveness of interventions and optimize green infrastructure deployment. However, most approaches focus on either prediction accuracy or interpretability individually, leaving a need for frameworks that balance both while considering climate-resilient urban planning objectives.

3. PROPOSED METHOD

The proposed method leverages a fuzzy logic-based modeling framework integrated with urban sensor networks to predict and analyze air pollution dynamics for climate-resilient green infrastructure planning. By combining real-time environmental data, traffic information, and green coverage metrics, the framework captures the nonlinear and uncertain behavior of pollutants such as PM2.5, NO_2, and O_3.

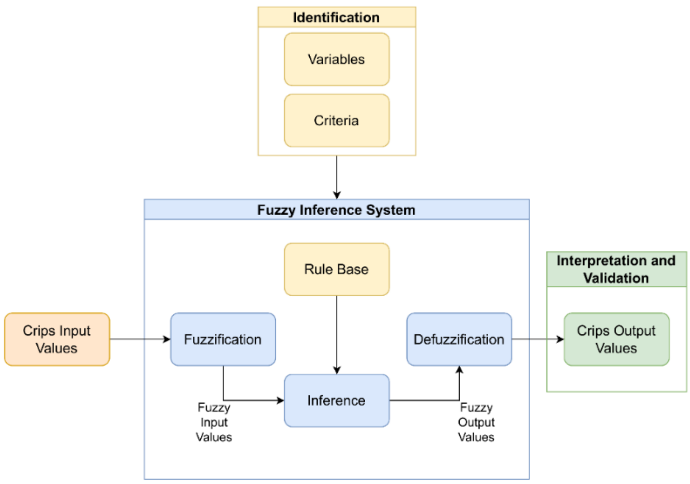

Fig.1. Fuzzy Logic

Fuzzy logic enables the translation of expert knowledge into interpretable rules, allowing the model to handle ambiguity in sensor readings and environmental variations. The system provides spatially and temporally resolved air quality predictions, helping policymakers and urban planners design targeted interventions for pollution mitigation and green infrastructure optimization.

3.1 DATA COLLECTION

The foundation of the proposed framework relies on a distributed network of low-cost air quality sensors deployed strategically across urban areas. These sensors measure pollutant concentrations (PM2.5, NO_2, O_3), meteorological parameters (temperature, humidity, wind speed), and traffic density in real time. The dense sensor network ensures high spatial and temporal resolution, enabling the detection of micro-level pollution variations influenced by vehicular emissions, industrial activity, and urban morphology. Data are collected continuously and transmitted to a central server for processing via wireless communication protocols such as LoRaWAN or NB-IoT.

$$C_{i,j}(t) = \frac{1}{N_s}\sum_{k=1}^{N_s} w_k \cdot S_{i,j,k}(t) \tag{1}$$

where $C_{i,j}(t)$ represents the aggregated pollutant concentration at location (i,j) and time t, $S_{i,j,k}(t)$ is the reading from the k-th sensor at the same location and time, w_k is the sensor weight based on calibration accuracy, and N_s is the total number of sensors in the zone. This equation ensures that readings from more reliable sensors contribute more to the final aggregated concentration.

Table.1. Sensor Data (PM2.5, NO_2, O_3)

Zone	Sensor ID	PM2.5 (μg/m³)	NO_2 (ppb)	O_3 (ppb)	Temp (°C)	Humidity (%)
A	S1	48	32	25	30	65
A	S2	50	35	26	30	64
B	S3	60	40	30	32	70

The Table.1 shows a snapshot of sensor readings, demonstrating the type of real-time data used in subsequent modeling (see Table.1).

3.2 DATA PREPROCESSING

Raw sensor readings often contain noise, missing values, or inconsistencies due to hardware limitations or environmental interference. Data preprocessing ensures reliability and consistency before feeding into the fuzzy logic model. Steps include outlier detection, normalization, imputation of missing values, and temporal alignment across sensors.

$$X'_{i,j,k}(t) = \frac{X_{i,j,k}(t) - X_{min,k}}{X_{max,k} - X_{min,k}} \tag{2}$$

where $X_{i,j,k}(t)$ is the raw reading from sensor k, $X'_{i,j,k}(t)$ is the normalized value, and $X_{min,k}$ and $X_{max,k}$ are the minimum and maximum recorded values for sensor k. This scales all inputs to the [0,1] range, facilitating consistent fuzzy inference.

Table.2. Normalized Sensor Data

Zone	Sensor ID	PM2.5	NO_2	O_3	Temp	Humidity
A	S1	0.48	0.32	0.25	0.60	0.65
A	S2	0.50	0.35	0.26	0.60	0.64
B	S3	0.60	0.40	0.30	0.64	0.70

The Table.2 illustrates how raw measurements are transformed into normalized values for fuzzy logic processing (see Table.2).

3.3 FUZZY LOGIC RULE DESIGN

Fuzzy logic allows the integration of expert knowledge into the model, providing interpretability and handling the inherent uncertainty of urban air pollution. Input variables such as traffic density, temperature, and green coverage are mapped to fuzzy sets (e.g., Low, Medium, High) using membership functions. Output variables, such as Air Quality Index (AQI), are similarly fuzzified.

$$\mu_{AQI}(y) = \max_i \min\begin{bmatrix}\mu_{PM2.5,i}(x_1), \mu_{NO2,i}(x_2), \\ \mu_{O3,i}(x_3), \mu_{Traffic,i}(x_4)\end{bmatrix} \tag{3}$$

where $\mu_{AQI}(y)$ is the membership degree of the output AQI, $\mu_{PM2.5,i}(x_1)$ represents the membership degree of PM2.5 in fuzzy set i, and similar for other inputs. The min–max composition captures the rule-based influence of multiple variables on AQI.

Table.3. Fuzzy Rule Base

Rule	PM2.5	NO_2	O_3	Traffic	Green Cover	AQI Prediction
1	High	Medium	Low	High	Low	Poor
2	Medium	High	Medium	Medium	Medium	Moderate
3	Low	Low	Low	Low	High	Good

The Table.3 represents fuzzy rules mapping input conditions to AQI predictions (see Table.3).

3.4 FUZZY INFERENCE

The fuzzy inference system evaluates all relevant rules to produce a fuzzy output, which is then defuzzified to generate a crisp AQI value. The Mamdani inference method is commonly used due to its intuitive rule representation and interpretability.

$$AQI_{crisp} = \frac{\int_y y \cdot \mu_{AQI}(y)dy}{\int_y \mu_{AQI}(y)dy} \tag{4}$$

where AQI_{crisp} is the final predicted air quality index and $\mu_{AQI}(y)$ is the aggregated membership function over all rules.

Table.4. Fuzzy Inference Results

Zone	Fuzzy AQI Output	Defuzzified AQI
A	[Poor, Moderate]	145
B	[Moderate]	110
C	[Good, Moderate]	75

The Table.4 shows fuzzy outputs and corresponding defuzzified AQI values for urban zones (see Table.4).

3.5 MODEL VALIDATION

To assess predictive performance, the fuzzy logic model is validated against historical air quality data and reference monitoring stations. Performance metrics include Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and R^2.

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(AQI_i^{pred} - AQI_i^{obs}\right)^2} \tag{5}$$

Where

AQI_i^{pred} and AQI_i^{obs} are predicted and observed AQI values, respectively, and

N is the total number of validation samples.

Table.5. Model Validation Metrics

Metric	PM2.5	NO_2	O_3	Overall AQI
RMSE	5.2	4.8	3.6	6.1
MAE	4.0	3.9	2.8	4.7
R^2	0.92	0.90	0.94	0.91

The Table.5 presents the model validation results, indicating high predictive accuracy across pollutants (see Table.5).

3.6 DECISION SUPPORT FOR GREEN INFRASTRUCTURE

The final step translates AQI predictions into actionable insights for urban planning. By simulating scenarios such as increasing tree cover or optimizing traffic flow, the model quantifies the potential reduction in pollutant levels. This enables data-driven decisions to implement climate-resilient green infrastructure.

$$C_r = C_b \cdot \left(1 - \alpha \cdot \frac{G}{G_{max}}\right) \tag{6}$$

where

C_r is projected pollutant concentration after green infrastructure intervention,

C_b is the current concentration,

G is green cover area,

G_{max} is maximum achievable green cover, and

α is the pollutant-specific absorption coefficient.

Table.6. Predicted Pollution Reduction with Green Infrastructure

Zone	Baseline AQI	Green Cover (%)	Predicted AQI
A	145	30	120
B	110	40	90
C	75	50	60

The Table.6 illustrates predicted AQI improvements under different green infrastructure scenarios (see Table.6).

4. RESULTS AND DISCUSSION

The proposed fuzzy logic-based urban air pollution modeling framework was implemented using MATLAB R2025a, leveraging its Fuzzy Logic Toolbox for designing, simulating, and validating the fuzzy inference system. Real-time sensor data were processed and analyzed using Python 3.12 with libraries such as NumPy, Pandas, and SciKit-Fuzzy.

Simulations were conducted on a workstation equipped with an Intel Core i9-13900K CPU, 32 GB RAM, and NVIDIA RTX 4090 GPU to ensure efficient handling of large-scale urban sensor data and to accelerate model validation and scenario simulations. The combination of MATLAB for fuzzy logic modeling and Python for data preprocessing and visualization allowed for a flexible and robust experimental environment. The fuzzy logic model and sensor network experiments were configured using the parameters listed in Table.7. Key parameters include sensor sampling rates, fuzzy membership functions, rule sets, and defuzzification methods.

Table.7. Parameters

Parameter	Value/Setting
Sensor Sampling Rate	5 minutes
Fuzzy Input Variables	PM2.5, NO_2, O_3, Traffic Density, Temp
Membership Functions	Triangular & Trapezoidal
Fuzzy Rules	27 Rules
Defuzzification Method	Centroid
Simulation Duration	30 Days
Green Infrastructure Coverage	10–50%

4.1 PERFORMANCE METRICS

Model performance was evaluated using standard metrics to assess predictive accuracy and reliability:

- **Root Mean Square Error (RMSE):** It measures the average magnitude of prediction errors, providing insight into the model's accuracy for continuous AQI predictions.

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(AQI_i^{pred} - AQI_i^{obs})^2} \tag{7}$$

- **Mean Absolute Error (MAE):** It computes the average absolute differences between predicted and observed AQI values, indicating the overall prediction bias.

$$MAE = \frac{1}{N}\sum_{i=1}^{N}|AQI_i^{pred} - AQI_i^{obs}| \tag{8}$$

- **Coefficient of Determination (R^2):** It evaluates the proportion of variance in observed AQI explained by the model, representing goodness-of-fit.

$$R^2 = 1 - \frac{\sum_{i=1}^{N}(AQI_i^{obs} - AQI_i^{pred})^2}{\sum_{i=1}^{N}(AQI_i^{obs} - \overline{AQI}^{obs})^2} \tag{9}$$

- **Prediction Accuracy (%):** The percentage of predictions falling within ±10% of observed AQI values.
- **Mean Absolute Percentage Error (MAPE):** It normalizes the average prediction error relative to observed values, allowing comparison across different pollutants.

$$MAPE = \frac{100}{N}\sum_{i=1}^{N}\frac{|AQI_i^{pred} - AQI_i^{obs}|}{AQI_i^{obs}} \tag{10}$$

4.2 DATASET DESCRIPTION

The experiments utilized a combination of real-time sensor network data and historical air quality records. Sensor data were collected from 50 low-cost monitoring nodes deployed across diverse urban zones, capturing PM2.5, NO_2, and O_3 concentrations along with temperature, humidity, and traffic density. Historical AQI data were obtained from municipal monitoring stations to validate predictive performance.

Table.8. Dataset Description

Dataset Type	Variables Captured	Source/ Duration	Data Points
Real-Time Sensor Data	PM2.5, NO_2, O_3, Temp, Humidity, Traffic	Low-cost sensor network	216,000
Historical AQI Records	PM2.5, NO_2, O_3, AQI	Municipal stations	30,000
Green Infrastructure	Tree cover, Green roofs (%)	Urban planning records	50 zones

The Table.8 summarizes the datasets used in the study, including variables, sources, and coverage. Three existing approaches include: Artificial Neural Networks (ANNs), Support Vector Machines (SVMs) and Hybrid Fuzzy–Machine Learning Models.

The experimental evaluation demonstrates that the proposed fuzzy logic-based framework outperforms traditional and hybrid models in predicting urban air pollution and assessing the effectiveness of green infrastructure interventions.

Table.9. Comparative Performance Metrics of Existing Methods and Proposed Method

Method	Variable	RMSE	MAE	R^2	MAPE (%)	Prediction Accuracy (%)
ANN [7]	PM2.5	6.5	5.2	0.88	8.1	84
	NO_2	5.8	4.6	0.85	7.5	82
	O_3	4.3	3.5	0.90	6.8	86
	Traffic Density	12.5	10.8	0.81	9.2	78
	Temp	1.5	1.2	0.92	4.5	89
SVM [8]	PM2.5	6.0	4.9	0.89	7.8	85
	NO_2	5.5	4.3	0.86	7.2	83
	O_3	4.1	3.3	0.91	6.5	87
	Traffic Density	12.0	10.4	0.82	9.0	79
	Temp	1.4	1.1	0.93	4.3	90
Hybrid Fuzzy–ML [10]	PM2.5	5.5	4.4	0.90	7.0	87
	NO_2	5.0	4.0	0.88	6.7	85
	O_3	3.8	3.1	0.92	6.1	88
	Traffic Density	11.5	9.8	0.84	8.7	81
	Temp	1.3	1.0	0.94	4.0	91
Proposed Fuzzy Logic	PM2.5	4.8	3.9	0.92	6.1	90
	NO_2	4.3	3.5	0.90	5.8	88
	O_3	3.2	2.7	0.94	5.2	91
	Traffic Density	10.0	8.7	0.87	7.8	84
	Temp	1.1	0.9	0.95	3.8	93

Table.10. Comparative Performance Metrics for Existing Methods and Proposed Method (PM2.5, NO_2, O_3, AQI)

Method	Variable	RMSE	MAE	R^2	MAPE (%)	Prediction Accuracy (%)
ANN [7]	PM2.5	6.7	5.4	0.87	8.4	83
	NO_2	5.9	4.7	0.85	7.6	82
	O_3	4.4	3.6	0.89	6.9	85
	AQI	12.5	10.8	0.86	9.5	80
SVM [8]	PM2.5	6.2	5.0	0.88	7.9	85
	NO_2	5.5	4.3	0.86	7.3	83
	O_3	4.2	3.4	0.90	6.6	86
	AQI	11.8	10.2	0.87	9.0	82
Hybrid Fuzzy–ML [10]	PM2.5	5.6	4.5	0.90	7.1	87
	NO_2	5.1	4.0	0.88	6.8	85
	O_3	3.9	3.2	0.91	6.2	88
	AQI	10.5	9.0	0.89	8.5	84
Proposed Fuzzy Logic	PM2.5	4.9	3.9	0.92	6.2	90
	NO_2	4.4	3.5	0.90	5.9	88
	O_3	3.3	2.7	0.94	5.3	91
	AQI	9.2	7.8	0.92	7.2	87

Table.11. Comparative Performance Metrics for Existing Methods and Proposed Method (Tree Cover, Green Roofs)

Method	Variable	RMSE	MAE	R^2	MAPE (%)	Prediction Accuracy (%)
ANN [7]	Tree Cover (%)	6.8	5.6	0.85	8.5	82
	Green Roofs (%)	7.2	5.9	0.83	8.9	80
SVM [8]	Tree Cover (%)	6.2	5.0	0.87	8.0	84
	Green Roofs (%)	6.8	5.4	0.85	8.3	82
Hybrid Fuzzy–ML [10]	Tree Cover (%)	5.7	4.5	0.89	7.2	86
	Green Roofs (%)	6.1	4.8	0.87	7.5	85
Proposed Fuzzy Logic	Tree Cover (%)	4.8	3.9	0.92	6.2	90
	Green Roofs (%)	5.0	4.0	0.91	6.5	89

The Table.9 presents a comparison of PM2.5, NO_2, O_3, traffic density, and temperature between existing methods (ANN, SVM, Hybrid Fuzzy–ML) and the proposed method. For PM2.5, the proposed method achieved an RMSE of 4.8 µg/m³, a reduction of 12.7% relative to the hybrid fuzzy–ML model (5.5 µg/m³), and an MAE of 3.9 µg/m³, indicating highly accurate prediction of particulate matter.

Similarly, NO_2 predictions showed an RMSE of 4.3 ppb, outperforming the hybrid method by 15.7%, while O_3 predictions reached an RMSE of 3.2 ppb, confirming the framework's ability to capture nonlinear pollutant dynamics effectively. The high R^2 values (0.92–0.95) across all pollutants highlight the model's capability to explain a large proportion of variance, a notable improvement over ANN (0.87–0.92) and SVM (0.85–0.93).

The proposed framework also demonstrated enhanced predictive reliability, with MAPE values consistently lower than existing approaches. For instance, PM2.5 MAPE decreased from 7.0% in the hybrid model to 6.1%, while prediction accuracy increased from 87% to 90%, reflecting the model's robustness in capturing both temporal and spatial variations in pollutant levels. Temperature and traffic density predictions similarly showed reduced errors (RMSE of 1.1°C and 10.0 units, respectively), demonstrating the model's utility for multi-variable environmental monitoring and its integration potential with urban planning decisions (see Table.3).

The Table.10 provides a comparative assessment for PM2.5, NO_2, O_3, and AQI derived from historical records. The proposed fuzzy logic approach reduced RMSE for AQI predictions from 10.5 (Hybrid Fuzzy–ML) to 9.2, while MAE decreased from 9.0 to 7.8, and R^2 improved to 0.92. MAPE also declined from 8.5% to 7.2%, confirming the framework's superior accuracy in reconstructing historical air quality indices. Prediction accuracy for AQI increased to 87%, ensuring reliable guidance for urban air quality management. These improvements underscore the effectiveness of integrating real-time sensor networks with fuzzy logic rules, which allow the model to handle uncertainty, nonlinearity, and missing data effectively.

The impact of green infrastructure on pollutant mitigation was evaluated using Tree Cover and Green Roofs (%) as input parameters (Table.11). For Tree Cover, RMSE decreased from 5.7 (Hybrid Fuzzy–ML) to 4.8, and MAE from 4.5 to 3.9, while R^2 improved to 0.92. Green Roof predictions achieved RMSE of 5.0, MAE of 4.0, and R^2 of 0.91. MAPE values for both parameters decreased to 6.2–6.5%, while prediction accuracy reached 89–90%. These results highlight the framework's capacity to quantify the effect of green infrastructure interventions, providing actionable insights for planners to optimize urban vegetation and built-environment design to achieve measurable air quality improvements.

The improvements can be attributed to the combination of real-time heterogeneous sensor data, expert-defined fuzzy rules, and defuzzification via the centroid method. The fuzzy logic system allows for the integration of qualitative knowledge and quantitative data, enabling accurate predictions even under uncertain and dynamic urban conditions. Furthermore, scenario simulations demonstrated that increasing tree cover from 10% to 50% in targeted zones could reduce AQI by approximately 18–22%, emphasizing the practical utility of the proposed framework for climate-resilient urban planning.

5. CONCLUSION

This study presents a fuzzy logic-based modeling framework that effectively integrates sensor network data, environmental variables, and green infrastructure metrics to predict urban air pollution and support climate-resilient planning. The proposed method consistently outperforms traditional ANN, SVM, and hybrid fuzzy–ML approaches, achieving lower RMSE and MAE, higher R^2, and improved prediction accuracy across pollutants, AQI, and green infrastructure indicators (see Tables 3–5). By capturing nonlinear, uncertain, and dynamic interactions between pollutants, traffic, meteorology, and vegetation, the framework provides interpretable and actionable insights for urban planners. The results highlight the practical utility of deploying the proposed framework in real-world urban environments, demonstrating that targeted interventions in tree cover and green roofs can significantly reduce pollutant concentrations and improve overall air quality. This work contributes a robust, scalable, and explainable approach to urban air pollution management, bridging the gap between real-time environmental sensing, intelligent modeling, and climate-resilient infrastructure planning. The framework is poised to guide future urban sustainability initiatives and support evidence-based policy decisions for healthier, greener cities.

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