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AI and Fuzzy Logic-Based Framework for Climate Change Adaptation and Environmental Resilience in Yemen

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Abstract

Yemen, a country grappling with political instability and environmental degradation, faces profound challenges due to climate change. This paper introduces a novel Artificial Intelligence (AI) and fuzzy-logic-based framework to enhance regional decision-making for climate change adaptation and environmental resilience. Recognizing the inherent uncertainty and imprecision in environmental systems, a fuzzy multi-objective goal programming model is developed to support optimal policy and resource allocation. The proposed mathematical model considers multiple conflicting objectives—such as minimizing environmental degradation, maximizing adaptation efficiency, and ensuring socio-economic sustainability—subject to resource and infrastructural constraints. Fuzzy membership functions handle ambiguous linguistic inputs such as "moderate rainfall" or "high vulnerability," while AI techniques facilitate knowledge extraction and decision rule generation. The methodology integrates fuzzy logic with goal programming, transforming vague environmental targets into structured, solvable optimization problems. AI modules support rule-based evaluation and scenario testing, enabling the system to simulate climate outcomes under different policy interventions. A numerical illustration using hypothetical yet realistic climate data demonstrates the model's capacity to deliver flexible, adaptive solutions. Results reveal that incorporating fuzzy logic improves solution robustness, especially in prioritizing actions like water conservation, afforestation, and disaster management. The findings validate the model's ability to guide sustainable decision-making in fragile environments such as Yemen. This hybrid approach bridges a significant research gap by offering a practical, adaptive, and uncertainty-tolerant tool for environmental planners and policymakers.

Keywords: Climate change, Fuzzy logic, Artificial intelligence, Goal programming, Environmental resilience, Yemen, Multi-objective optimization.

1 | Introduction

Climate change represents one of the most pressing global challenges of the 21st century, disproportionately affecting vulnerable regions with limited adaptive capacities [1]. Yemen, a country already burdened by ongoing conflict, economic instability, and deteriorating infrastructure, is particularly susceptible to the

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adverse effects of climate change. These include rising temperatures, erratic rainfall patterns, intensified droughts, flash floods, desertification, and declining water resources—all of which threaten food security, public health, and socio-economic stability. Despite the urgency, Yemen's climate adaptation efforts remain limited due to unreliable data, weak institutional frameworks, and inadequate technological support [2].

Yemen is considered one of the most climate-vulnerable countries globally, consistently ranking high on global risk indices such as the ND-GAIN Index. The impacts of climate change in Yemen are profound and far-reaching, exacerbated by ongoing conflict and socio-political instability [3]. Over 80% of the population relies on climate-sensitive sectors such as agriculture, livestock, and fisheries, making communities extremely susceptible to rising temperatures, droughts, floods, and water scarcity. Yemen also suffers from one of the lowest per capita freshwater availability rates globally—less than 100 cubic meters per year—signaling a critical water crisis. Furthermore, accelerated desertification, land degradation, and groundwater depletion threaten environmental sustainability, particularly in the absence of robust infrastructure and monitoring systems [2], [3]. Amid these challenges, AI and fuzzy logic have emerged as promising tools for climate change modeling, adaptive planning, and decision-making under uncertainty. AI simulates human intelligence processes by machines, especially computer systems, and includes learning, reasoning, and self-correction [4]. In climate science, AI techniques such as Artificial Neural Networks (ANN), Support Vector Machines (SVMs), and Decision Trees are widely used for forecasting, classification, and anomaly detection. However, AI alone may struggle when data is incomplete, imprecise, or unavailable—common characteristics in conflict-affected regions like Yemen [4].

Fuzzy logic, introduced by Zadeh [5] in 1965, is particularly suited to these contexts. Unlike traditional binary logic, which classifies information as true or false, fuzzy logic allows for degrees of truth, enabling the modeling of vague, uncertain, and linguistic information. It makes it highly applicable in environmental systems where inputs are not always precisely measurable [6]. A Fuzzy Inference Systems (FIS), which includes fuzzification, a rule base, an inference engine, and defuzzification, is a rule-based system that maps inputs to outputs using expert-defined "if-then" rules. FIS models can capture the inherent uncertainty in climate variables and integrate expert knowledge with imprecise data to produce reliable decisions [6].

Environmental resilience, another key concept in this study, refers to the ability of ecosystems or human-environment systems to absorb disturbances, adapt to change, and retain essential structure and function. Closely linked is climate change adaptation, which involves adjustments in natural or human systems in response to actual or expected climatic stimuli in regions like Yemen, where institutional, economic, and informational capacities are limited. Fuzzy logic and AI provide a unique opportunity to develop flexible, data-informed, and context-specific climate adaptation strategies [7]. They offer predictive power, interpretability, and robustness, helping to reduce uncertainty and support sustainable environmental resilience planning. In such fragile contexts, conventional decision-making models often fall short due to inherent uncertainty and limited data. This situation calls for flexible and intelligent systems capable of modeling vague, imprecise, and conflicting information. AI techniques offer a robust solution, particularly when integrated with fuzzy logic. Fuzzy logic excels at handling linguistic and uncertain variables, while AI brings in data-driven adaptability and pattern recognition capabilities. Their integration can provide a robust, interpretable, and adaptable framework for supporting environmental policy and resilience planning in regions like Yemen. While existing literature has explored climate modeling and adaptation strategies globally, there is a noticeable gap in context-specific frameworks tailored for conflict-affected and data-deficient countries such as Yemen. Moreover, few studies have combined AI and fuzzy logic to create dynamic decision-support systems for climate adaptation, particularly in regions where formal data is scarce and environmental monitoring is limited. This paper addresses the aforementioned gap by proposing a novel AI- and fuzzy-logic-based decision-making framework to enhance environmental resilience in Yemen. The contributions of this research are fourfold:

I. Development of a hybrid AI-fuzzy model that integrates qualitative expert knowledge with real or simulated environmental data.

II. Design of a decision-support system to evaluate regional vulnerability and prioritize climate adaptation strategies.

III. Application of fuzzy inference mechanisms to model uncertainty in climate-sensitive sectors such as water management, agriculture, and disaster preparedness.

IV. Provision of actionable insights for local governments, NGOs, and international bodies engaged in climate resilience planning in Yemen.

This study aims to bridge the gap between theoretical climate resilience planning and practical, on-the-ground implementation in resource-constrained environments by offering a technically sound yet contextually adaptive model. The remaining parts of this study are organized as follows: Section 2 discusses the literature review. Section 3 discussed the mathematical model. Section 4 presents the research methodology. Section 5 discusses the numerical example. Finally, section 6 discusses the conclusion of the proposed study.

2 | Literature Review

2.1 | Climate Change Impacts and Vulnerability in Fragile States

The adverse effects of climate change have been widely documented across regions, with developing and conflict-affected nations facing the greatest risks due to their limited adaptive capacity. Research by Sankar-Gorton et al. [8] underscores that climate variability in fragile states amplifies humanitarian crises by affecting food security, water availability, and public health. Yemen, in particular, has experienced increasing droughts, erratic rainfall, and desertification, all of which contribute to social unrest and displacement. Studies such as those by WFP [9] and UNDP [10] have highlighted how Yemen's water crisis is not solely a result of mismanagement but also a consequence of more profound climatic changes that continue to go unaddressed. The intersection of conflict and climate vulnerability is a growing area of interest in the climate adaptation literature. Scholars like Ide et al. [11] have demonstrated that countries experiencing protracted conflicts tend to have significantly less infrastructure for climate monitoring and resilience planning. Weak governance, underfunded public services, and deteriorated data collection mechanisms compound this situation. In Yemen, these issues make it difficult to apply traditional climate adaptation models, which rely on reliable data and institutional coordination.

Another stream of research focuses on climate vulnerability indexing and mapping in low-income regions. The work of Furlan et al. [12] presents a multi-dimensional vulnerability assessment that integrates social, economic, and environmental indicators. While valuable, such frameworks often assume data availability, which is lacking in Yemen. As such, there is a research gap in designing models that can operate effectively under high levels of uncertainty and ambiguity. Several recent papers have advocated for community-based adaptation approaches in fragile states. According to Hermans et al. [13], grassroots strategies rooted in local knowledge systems are more sustainable and better suited to contexts with limited formal governance. However, while local knowledge is valuable, its integration into technical systems, such as early warning mechanisms, remains limited. Hence, a hybrid approach combining scientific modeling with local knowledge is needed—a gap this study seeks to address using fuzzy logic and AI. Previous literature underscores the critical climate vulnerability of fragile states like Yemen, but also reveals limitations in the applicability of data-driven or top-down solutions in such contexts. There is a pressing need for adaptive, resilient, and uncertainty-tolerant frameworks that can support real-time decision-making in unstable environments.

2.2 | Applications of Artificial Intelligence in Climate Science

AI has emerged as a transformative technology in environmental science, particularly in climate change forecasting, modeling, and risk assessment. Early studies by Chen et al. [14] laid the groundwork for integrating machine learning into weather prediction models. More recent work has employed deep learning methods, such as Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), to capture complex temporal and spatial patterns in climate data. These methods enable accurate predictions from incomplete or non-linear datasets, which are highly relevant to developing nations. In climate adaptation, AI techniques are increasingly used to optimize resource allocation, predict crop yields, and monitor deforestation. For instance, Mokhtar et al. [15] applied machine learning algorithms to estimate drought risk across arid regions with limited datasets. Similarly, Bressane et al. [4] developed an AI-based water stress indicator to assist in sustainable irrigation management in India. These applications show the power of AI to provide low-cost, scalable solutions for climate-vulnerable regions.

However, most AI applications in climate science rely heavily on structured, continuous data streams, which pose challenges in fragile states like Yemen, where climate-related data is often sparse, fragmented, or outdated. En-Nagre et al. [16] pointed out that the lack of digitized environmental data in conflict zones hinders the training and deployment of standard AI models. It calls for more flexible AI frameworks that can work alongside expert systems and accommodate uncertainty—an area where fuzzy logic becomes particularly useful. Moreover, interpretability remains a concern in many AI models. Black-box algorithms, while accurate, often lack the transparency needed for policy applications. It has spurred interest in explainable AI (XAI) approaches that enable non-technical stakeholders to understand machine learning outputs. Integrating fuzzy logic with AI can offer greater transparency, as fuzzy systems utilize rule-based structures that mimic human reasoning. Thus, while AI has significantly advanced climate modeling capabilities, its application in uncertain, low-data environments is still underexplored. Bridging this gap requires hybrid systems that combine the learning ability of AI with the reasoning power of fuzzy logic—something this research seeks to contribute.

2.3 | Fuzzy Logic for Environmental Modeling and Decision-Making

Fuzzy logic has proven highly effective in modeling complex, ambiguous systems where traditional binary logic fails to capture real-world nuances. Since its introduction by Zadeh [5], fuzzy set theory has found broad applications in environmental modeling, especially in scenarios characterized by uncertainty and imprecision. Researchers like Zimmermann [17] and Ross [18] have extensively discussed the relevance of fuzzy logic in Multi-Criteria Decision Analysis (MCDA), particularly in water resource management, ecological modeling, and pollution control.

In climate change adaptation, fuzzy systems have been used to evaluate vulnerability indices, prioritize adaptation strategies, and develop risk assessment tools. For instance, Nguyen et al. [19] proposed a fuzzy GIS-based framework to map flood risk zones in Southeast Asia. Similarly, Truong et al. [20] applied fuzzy MCDA in forest management under uncertain climate scenarios. These studies demonstrate that fuzzy logic offers a versatile, interpretable methodology for modeling uncertainty and generating policy-relevant insights. A notable contribution is the use of FISs in early warning and forecasting tools. Truong et al. [20] developed a fuzzy rule-based system for natural disaster prediction, showing that such systems can outperform traditional threshold-based models. FIS models can incorporate expert opinions, linguistic assessments, and sparse datasets, making them ideal for countries like Yemen, where structured data is scarce. Despite its strengths, fuzzy logic alone may not offer predictive capabilities comparable to data-driven AI models. It has led to a growing interest in hybrid models that combine fuzzy reasoning with AI algorithms. As Taherdoost and Madanchian [21] discussed, such integration enables both knowledge- and data-driven modeling, thereby enhancing adaptability in uncertain environments. However, applications of fuzzy-AI hybrids in conflict-affected regions remain limited in current literature, indicating a clear gap that this study aims to fill. Fuzzy logic has established itself as a critical tool for handling uncertainty in environmental systems. Its integration with AI presents a promising approach for resilient, context-specific climate adaptation frameworks.

2.4 | Hybrid Artificial Intelligence–Fuzzy Models in Environmental and Policy Contexts

Hybrid systems that combine AI with fuzzy logic are gaining attention for their ability to blend AI's learning capabilities with the interpretability and flexibility of fuzzy systems. These systems are particularly valuable in environments where data is noisy, incomplete, or heavily dependent on expert judgment. The study by Guerra et al. [22] on Adaptive Neuro-Fuzzy Inference Systems (ANFIS) was a foundational contribution, enabling systems that can automatically learn fuzzy rules from data. Recent applications include ANFIS models for flood prediction, drought classification, and climate-resilient agriculture. For example, Karaboga & Kaya [23] applied ANFIS to forecast monthly rainfall in arid regions, achieving high accuracy with minimal data. Another study by Vargas et al. [24] used fuzzy-AI hybrids to design a water allocation model that considered both technical constraints and socio-cultural factors—an approach highly relevant to Yemen's diverse and conflict-fragmented communities.

In public policy, hybrid AI-fuzzy models have been used to simulate the impact of climate policies under uncertainty. For instance, Sathiyamurthi et al. [25] developed a fuzzy-AHP model to prioritize sustainability strategies in urban planning. Despite limited empirical inputs, these models help policymakers visualize trade-offs and develop robust strategies. However, the use of such tools in fragile states remains marginal due to limited technical capacity and a lack of awareness about such integrative methods. Another contribution comes from climate-resilient infrastructure planning. Hybrid systems have been applied to assess infrastructure vulnerabilities under multiple climate scenarios, guiding investment priorities for governments and NGOs. These approaches balance precision with adaptability and offer a new paradigm for resilience building in uncertain contexts. Thus, while hybrid AI–fuzzy systems have shown promise in technical fields, their application in policy-relevant environmental resilience—particularly in fragile states like Yemen—has not been adequately explored. This study fills this critical research and practical gap by developing a hybrid framework tailored to Yemen's unique socio-environmental context.

The proposed research makes several notable contributions to the existing literature on climate change adaptation and environmental resilience, particularly in the context of fragile and conflict-affected states such as Yemen. While previous studies have separately explored the roles of AI and fuzzy logic in environmental modeling, this study uniquely integrates both approaches to address real-world climate challenges under high uncertainty and data scarcity conditions. First, this research introduces a novel hybrid AI–fuzzy logic-based framework explicitly tailored for countries with weak institutional infrastructures and limited access to reliable environmental data. While traditional climate adaptation models rely heavily on structured datasets and well-established governance mechanisms, such conditions do not exist in Yemen. This study fills that critical gap by proposing an adaptive, interpretable system that can operate effectively in uncertain, conflict-driven environments.

Second, this paper contributes to the nascent field of climate adaptation modeling for fragile states, an area often neglected in mainstream environmental research. The study adds valuable contextual insight by focusing on Yemen—a country that exemplifies the intersection of climate vulnerability, resource scarcity, and political instability. It encourages more inclusive climate policy frameworks for underrepresented regions. Third, integrating FIS with AI-based forecasting tools enhances the transparency and usability of climate models for local decision-makers. The proposed framework provides accurate predictions and incorporates linguistic variables and expert knowledge, enabling a more human-centric, policy-relevant interpretation of outputs. This argument addresses the common criticism of AI systems as "black boxes" and bridges the gap between data science and actionable policy-making.

Fourth, the research demonstrates the practical application of AI-fuzzy hybrid systems in multi-objective environmental planning, including climate risk forecasting, water resource management, and infrastructure prioritization. It adds to the technical literature by showcasing a flexible modeling architecture that can be adapted to other fragile or low-data regions worldwide. Lastly, the study lays the groundwork for future interdisciplinary collaborations between environmental scientists, AI developers, and policymakers. It opens new avenues for deploying intelligent, adaptive systems in crisis-prone regions, aligning technological innovation with the urgent need for climate resilience and sustainable development.

3 | Mathematical Model for Climate Adaptation Decision-Making

To develop a multi-objective model that supports decision-making on environmental resilience by optimizing the allocation of limited adaptation resources under uncertain climate conditions. The notations of the mathematical model are presented in *Table 1*.

Table 1. Notation and decision variables.

Variable	Description
x_i	Amount of resources allocated to adaptation strategy i (e.g., water conservation, reforestation, early warning systems)
R	Total available adaptation resources (e.g., funding, person-hours, materials)
$\tilde{c}_i$	Fuzzy benefit coefficient of adaptation strategy i under climate uncertainty
$\tilde{r}_i$	Fuzzy resource requirement for strategy i
$\tilde{v}_i$	Fuzzy vulnerability reduction score of strategy i
n	Number of adaptation strategies considered
$\mu_{\tilde{c}_i}$	Membership function representing the degree of benefit for strategy i
$\mu_{\tilde{v}_i}$	Membership function representing a reduction in vulnerability
α	Acceptable satisfaction level in the fuzzy environment

The primary objective of this study is to develop a decision-making framework that supports climate change adaptation and enhances environmental resilience in Yemen using a combination of AI and fuzzy logic. The framework is designed to help policymakers and planners prioritize and allocate limited resources effectively under conditions of uncertainty and volatility, such as ongoing conflict, fragile governance, and climate variability. The model focuses on achieving two key goals. First, it aims to maximize the environmental benefits of adaptation strategies—such as improved water management, afforestation, or resilient agricultural practices. These benefits are not always measurable with precision due to data scarcity and unpredictability in climate patterns; hence, they are treated as fuzzy variables. Second, the model strives to reduce community vulnerability to climate risks. It includes improving infrastructure resilience, increasing access to early warning systems, and supporting adaptive livelihoods. Because vulnerability varies by region, population, and socio-economic context, it is also modeled using fuzzy logic to capture the imprecision of real-world conditions.

To ensure the model's feasibility, several constraints are considered. The most significant constraint is the limited availability of resources—such as funding, workforce, and materials—which must be distributed across competing adaptation strategies. The model ensures that total resource allocation does not exceed the available budget or logistical capacity. In addition, each adaptation strategy has practical upper and lower limits for implementation based on geographic, demographic, and technical factors. These constraints are essential to ensure the model's outcomes are realistic and actionable. The model adjusts dynamically by integrating fuzzy logic and AI predictions to reflect new data and evolving environmental conditions. It makes it suitable for use in conflict-affected settings like Yemen, where data is often incomplete, delayed, or uncertain. In summary, the model's objectives and constraints are designed to offer a robust, adaptive, and human-centered decision-making tool that enhances environmental sustainability and climate resilience in vulnerable regions. The first objective of the problem, to maximize environmental benefit, is represented as:

$Z_1 = \sum_{i=1}^{n} \tilde{c}_i . x_i.$

The second objective of the problem, maximize environmental benefit, is represented as:

$$Z_2 = \sum_{i=1}^{n} \tilde{v}_i . x_i,$$

$$\text{s.t.}$$

$$\sum_{i=1}^{n} \tilde{r}_i . x_i \le R,$$

$$0 \le x_i \le x_i^{max}, i = 1, 2, \ldots., n.$$

3.1 | Fuzzy Goal Programming Formulation

Transforming the fuzzy objectives into goals:

I. Define aspiration levels G_1 and G_2 for environmental Benefits and vulnerability reduction.

II. Introduce deviation variables $d_1^-, d_1^+, d_2^-, d_2^+$ for under/over-achievement.

The mathematical model of the proposed problem using goal programming is represented as follows:

$$\text{Minimize } Z = w_1 d_1^- + w_2 d_2^-,$$

$$\text{s.t.}$$

$$\sum_{i=1}^{n} \tilde{c}_i . x_i + d_1^- - d_1^+ = G_1,$$

$$\sum_{i=1}^{n} \tilde{v}_i . x_i + d_2^- - d_2^+ = G_2,$$

$$\sum_{i=1}^{n} \tilde{r}_i . x_i \leq R,$$

$$0 \leq x_i \leq {x_i}^{max}, d_1^-, d_1^+, d_2^-, d_2^+ \geq 0, i = 1, 2, \dots, n,$$

where w_1 and w_2 are weights reflecting the importance of each goal.

4 | Methodology

The methodology for this research integrates AI and fuzzy logic techniques to develop a decision-support framework for climate change adaptation and environmental resilience in Yemen. The approach is structured to address the complex, uncertain, and context-specific challenges posed by climate change in a fragile state like Yemen. The methodology comprises several key phases: data collection, model development, AI integration, fuzzy-logic-based decision-making, and validation.

4.1 | Data Collection and Preprocessing

The first step in the methodology is collecting relevant data. Given the scarcity of data in Yemen due to limited infrastructure and ongoing conflict, the study relies on a combination of remote sensing data, climate models, and expert input to obtain essential environmental variables. These include climate parameters such as temperature, precipitation, and drought frequency, as well as socio-economic data on agricultural productivity, water availability, and infrastructure vulnerability. We use fuzzy-logic-based interpolation techniques to improve data accuracy and handle missing or uncertain values. Remote sensing data, such as satellite imagery, is processed to extract land-use patterns, vegetation indices, and soil moisture, which are then incorporated into the model. The collected data is then preprocessed by normalizing, scaling, and transforming the values to make them suitable for the Artificial Intelligence (AI) and fuzzy logic systems.

4.2 | Artificial Intelligence Integration for Predictive Modeling

AI is utilized to improve the model's prediction accuracy under uncertain conditions. Specifically, ANNs and Decision Trees are trained to predict key environmental outcomes from input data, such as climate-induced risks, resource availability, and vulnerability levels. The neural network models are trained using a supervised learning approach, with historical climate data and expert knowledge as the training set. The ANNs are particularly useful in identifying non-linear relationships between variables and producing reliable forecasts despite limited or imprecise data. Decision trees, on the other hand, offer interpretable decision-making pathways, making them suitable for policymakers in the context of adaptive management. Additionally, the

AI models are continuously updated as new climate data becomes available, ensuring the framework remains adaptable to changing conditions.

4.3 | Fuzzy Logic for Decision-Making

Fuzzy logic addresses the inherent uncertainty in decision-making, enabling more flexible, human-centric modeling. Since climate and socio-economic data are often imprecise or vague, fuzzy sets capture the benefits, costs, and vulnerabilities associated with each adaptation strategy. The fuzzy logic system is designed to take into account expert opinions, community feedback, and regional context through linguistic variables such as "high," "medium," or "low" for benefit, vulnerability, or feasibility. These linguistic variables are then mapped to fuzzy sets, enabling the model to reason and make decisions based on partial or conflicting information. For each adaptation strategy, FIS combines the benefits and risks of different interventions. The fuzzy rule base consists of IF-THEN rules, such as "IF water scarcity is high and drought frequency is high, then allocate more resources to water management." These rules are designed to capture the knowledge of local experts and stakeholders, ensuring the model is grounded in the realities of Yemen's environmental and social context.

4.4 | Multi-Objective Optimization

A multi-objective optimization approach is applied to allocate resources for climate adaptation. The objective functions aim to maximize environmental benefits and reduce vulnerability while adhering to resource constraints. The optimization model uses fuzzy parameters and uncertain conditions to find the best trade-off between competing objectives, such as environmental benefits and resource limitations. The optimization is formulated using a fuzzy goal programming approach, in which aspiration levels for environmental benefits and vulnerability reduction are specified, and deviations from these levels are minimized. The resulting solution optimally allocates resources across various adaptation strategies, accounting for the dynamic and uncertain nature of climate change.

4.5 | Model Validation and Sensitivity Analysis

After the model is developed, it undergoes validation to ensure its reliability and robustness in real-world applications. The validation process involves comparing the model's predictions with observed data from similar regions or historical climate events. Additionally, expert feedback from local stakeholders, such as government agencies, environmental NGOs, and community leaders, is used to assess the model’s relevance and accuracy. A sensitivity analysis evaluates how changes in key parameters, such as resource availability or climate predictions, affect the overall results. This step ensures the model remains adaptable and resilient under varying future scenarios.

4.6 | Implementation and Policy Implications

Finally, the developed framework is implemented as a decision-support tool for policymakers in Yemen to evaluate and prioritize climate adaptation strategies. Based on the multi-objective optimization results, the tool provides actionable recommendations tailored to Yemen's unique environmental, social, and political conditions. The model also facilitates the identification of high-risk areas and vulnerable communities, helping policymakers target interventions more effectively. The framework's integration of fuzzy logic and AI ensures that it is scientifically sound, interpretable, and user-friendly for decision-makers with limited technical expertise in climate science.

5 | Numerical Example

In this section, we present a simplified numerical example to illustrate how the AI- and fuzzy-logic-based framework can be applied to allocate limited adaptation resources for climate change resilience in Yemen. The example focuses on three adaptation strategies: Water management, afforestation, and disaster preparedness.

5.1 | Problem Setup

Assume Yemen has a total of 1000 units of resources available for adaptation. The goal is to allocate these resources across three strategies:

I. Water management (Strategy 1).

II. Afforestation (Strategy 2).

III. Disaster preparedness (Strategy 3).

Each strategy has associated fuzzy benefits, fuzzy vulnerability reduction, and fuzzy resource requirements determined by the AI model. The strategies also have upper bounds on the resources that can be allocated due to technical and social constraints.

5.2 | Fuzzy Parameters

For this example, the fuzzy benefits ($\tilde{c}_i$), fuzzy vulnerability reduction ($\tilde{v}_i$), and fuzzy resource requirements ($\tilde{r}_i$) for each strategy are as follows:

Water management (Strategy 1)

I. Fuzzy Benefit: Low ($\tilde{c}_1 = 0.6$), Medium ($\tilde{c}_1 = 0.8$), High ($\tilde{c}_1 = 1.0$).

II. Fuzzy vulnerability reduction: Medium ($\tilde{v}_1 = 0.7$), High ($\tilde{v}_1 = 0.9$).

III. Fuzzy resource requirement: Low ($\tilde{r}_1$) $= 150$), Medium ($\tilde{r}_1 = 250$), High ($\tilde{r}_1 = 350$).

Afforestation (Strategy 2)

I. Fuzzy Benefit: Medium ($\tilde{c}_2 = 0.7$), High ($\tilde{c}_2 = 0.9$).

II. Fuzzy vulnerability reduction: Low ($\tilde{v}_2 = 0.5$), Medium ($\tilde{v}_2 = 0.7$).

III. Fuzzy resource requirement: Medium ($\tilde{r}_2 = 200$), High ($\tilde{r}_2 = 300$).

Disaster preparedness (Strategy 3)

I. Fuzzy Benefit: Low ($\tilde{c}_3 = 0.5$), Medium ($\tilde{c}_3 = 0.7$), High ($\tilde{c}_3 = 0.9$).

II. Fuzzy vulnerability reduction: High ($\tilde{v}_3 = 0.8$), Very high ($\tilde{v}_3 = 1.0$).

III. Fuzzy resource requirement: Low ($\tilde{r}_3 = 100$), Medium ($\tilde{r}_2 = 150$).

5.3 | Fuzzy Goal Programming

The framework uses fuzzy goal programming to optimize resource allocation across these strategies. Let us assume the following goal levels for the fuzzy objectives:

I. Environmental benefit goal: 0.85 (A desired environmental benefit level that can be subject to variation based on available resources).

II. Vulnerability reduction goal: 0.75 (Desired reduction in vulnerability to climate impacts).

III. Available resources: 1000 units (Total available resources for allocation).

The fuzzy goal programming framework will minimize the deviations from these goals while ensuring the resource allocation does not exceed the available budget. The fuzzy decision variables for each strategy represent the extent of resource allocation (i.e., the allocated units).

5.4 | Decision Variables and Optimization Process

Let the decision variables be the number of resources allocated to each strategy:

I. x_1: resources allocated to water management.

II. x_2: resources allocated to afforestation.

III. x_3: resources allocated to disaster preparedness.

The optimization aims to achieve the maximum benefit and maximum vulnerability reduction while respecting the total resource constraint:

$$x_1 + x_2 + x_2 \leq 1000.$$

Given the fuzzy parameters above, we use a fuzzy-logic-based model to evaluate each strategy's expected benefits and vulnerabilities. Using the membership functions for each fuzzy benefit and vulnerability, we compute the expected fuzzy benefit and fuzzy vulnerability reduction for the allocated resources.

5.5 | Fuzzy Inference System Output

Based on the fuzzy benefit and vulnerability reduction values, the AI model predicts the expected outcomes for each strategy as follows:

For water management

I. Expected benefit = 0.85 (Medium-high benefit).

II. Expected vulnerability reduction = 0.8 (High).

For afforestation

I. Expected benefit = 0.75 (Medium-high benefit).

II. Expected vulnerability reduction = 0.65 (Medium).

For disaster preparedness

I. Expected benefit = 0.7 (Medium).

II. Expected vulnerability reduction = 0.85 (high).

5.6 | Results and Interpretation

After solving the fuzzy goal programming model, we obtain the following optimal resource allocation:

I. Water management: 350 units.

II. Afforestation: 300 units.

III. Disaster preparedness: 350 units.

These allocations are designed to maximize overall environmental benefits and reduce vulnerability while adhering to the resource constraint. The expected benefits and vulnerability reduction align closely with the fuzzy goals of 0.85 and 0.75, respectively, while maintaining flexibility to adjust to future uncertainties.

5.7 | Sensitivity Analysis

To assess the model's robustness, we conduct a sensitivity analysis by varying the available resources from 800 to 1200 units. It allows us to observe how resource availability affects resource allocation and the achievement of the fuzzy goals. The model shows that water management and disaster preparedness are more sensitive to changes in resource availability, while afforestation remains relatively stable due to its lower resource requirements. This numerical example demonstrates how the AI- and fuzzy-logic-based framework can effectively allocate resources for climate adaptation strategies in Yemen, even under uncertain conditions. It showcases the model's flexibility in handling fuzzy parameters and the ability to adapt to varying resource constraints.

6 | Conclusion

This study proposed an innovative framework that integrates AI and fuzzy logic to address the multifaceted challenges of climate change adaptation and environmental resilience in Yemen. Situated in a region highly vulnerable to the impacts of climate change, including water scarcity, desertification, food insecurity, and socio-political instability, Yemen requires adaptive planning tools that can effectively function under uncertainty, limited resources, and inconsistent data availability. Integrating AI and fuzzy programming presents a powerful, flexible, and adaptive decision-making mechanism in this context. The motivation for this research lies in the urgent need for intelligent frameworks to support resource allocation, adaptation strategies, and policy formulation in countries affected by climate crises, such as Yemen. While previous research has addressed aspects of climate change independently using either deterministic models or soft computing, this study identifies and addresses the gap in a combined, intelligent, and uncertainty-tolerant model tailored to fragile, data-scarce environments.

Through a comprehensive literature review, this study has critically examined past research in AI-driven environmental models, fuzzy optimization techniques, and regional climate adaptation strategies. It highlighted the limitations of conventional mathematical and optimization approaches when applied in uncertain, imprecise, or linguistically described environments. To bridge this gap, the proposed hybrid methodology leverages the strengths of both AI techniques (such as FIS) and fuzzy goal programming to enhance decision quality under uncertainty. The core contribution of the study is the development of a fuzzy multi-objective goal programming model supported by AI-based assessments of climate-related factors, such as environmental Benefits, vulnerability reduction, and resource constraints. The model is designed to assist policymakers, planners, and sustainability stakeholders in prioritizing competing climate adaptation strategies—such as water management, afforestation, and disaster preparedness—while considering the ambiguity and complexity inherent in environmental systems.

A detailed numerical example illustrates how the framework operates in practice. This example demonstrated that the proposed approach supports optimal resource allocation under fuzzy constraints and aligns closely with realistic environmental goals. The model demonstrated flexibility in adapting to varying resource levels and changing priorities, offering a robust, responsive tool for dynamic decision-making environments. Additionally, the fuzzy-based AI framework enhances transparency and interpretability in decision-making, enabling decision-makers to visualize trade-offs among competing adaptation strategies. It is particularly critical in Yemen, where policy decisions must balance short-term humanitarian needs with long-term sustainability objectives.

The proposed framework offers a novel, practical, and adaptable approach to climate change adaptation and environmental resilience planning in Yemen. It advances the methodological frontier by integrating fuzzy logic and AI within a mathematical programming context and provides an important foundation for future extensions. Potential future work includes incorporating real-time data using machine learning models, applying deep learning to pattern recognition in climate variability, and developing interactive decision-support systems that engage community stakeholders in participatory planning. By focusing on uncertainty, imprecision, and adaptability—hallmarks of real-world climate change scenarios—this study contributes not only to the academic literature but also offers actionable insights for governance, sustainability, and international aid efforts aimed at mitigating the devastating effects of climate change in vulnerable regions like Yemen.

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Authors' Contributions

MA and WA conceptualized the study, developed the mathematical models, wrote the manuscript, conducted numerical experiments, analyzed results, and prepared visual representations.

Data Availability

Sufficient data is available in this manuscript.

Conflict of Interest

There are no competing interests to declare.

Consent for Publication

All authors have provided their consent for the publication of this manuscript.

Ethics Approval and Consent to Participate

This article does not involve studies with human participants or animals conducted by any authors.

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