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Review

Fuzzy Machine Learning Applications in Environmental Engineering: Does the Ability to Deal with Uncertainty Really Matter?

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Abstract: *Statement of Problem*: Environmental engineering confronts complex challenges characterized by significant uncertainties. Traditional modeling methods often fail to effectively address these uncertainties. As a promising direction, this study explores fuzzy machine learning (ML) as an underutilized alternative. *Research Question*: Although the potential of fuzzy logic is widely acknowledged, can its capabilities truly enhance environmental engineering applications? *Purpose*: This research aims to deepen the understanding of the role and significance of fuzzy logic in managing uncertainty within environmental engineering applications. The objective is to contribute to both theoretical insights and practical implementations in this domain. *Method*: This research performs a systematic review carried out in alignment with PRISMA guidelines, encompassing 27 earlier studies that compare fuzzy ML with other methods across a variety of applications within the field of environmental engineering. *Results*: The findings demonstrate how fuzzy-based models consistently outperform traditional methods in scenarios marked by uncertainty. The originality of this research lies in its systematic comparison and the identification of fuzzy logic's transparent, interpretable nature as particularly suited for environmental engineering challenges. This approach provides a new perspective on integrating fuzzy logic into environmental engineering, emphasizing its capability to offer more adaptable and resilient solutions. *Conclusions*: The analysis reveals that fuzzy-based models significantly excel in managing uncertainty compared to other methods. However, the study advocates for a case-by-case evaluation rather than a blanket replacement of traditional methods with fuzzy models. This approach encourages optimal selection based on specific project needs. *Practical Implications*: Our findings offer actionable insights for researchers and engineers, highlighting the transparent and interpretable nature of fuzzy models, along with their superior ability to handle uncertainties. Such attributes position fuzzy logic as a promising alternative in environmental engineering applications. Moreover, policymakers can leverage the reliability of fuzzy logic in developing ML-aided sustainable policies, thereby enhancing decision-making processes in environmental management.

Keywords: environmental engineering; machine learning; fuzzy systems

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Citation: Bressane, A.; Garcia, A.J.d.S.; Castro, M.V.d.; Xerfan, S.D.; Ruas, G.; Negri, R.G. Fuzzy Machine Learning Applications in Environmental Engineering: Does the Ability to Deal with Uncertainty Really Matter? *Sustainability* **2024**, *16*, 4525. https://doi.org/10.3390/su16114525

Received: 22 April 2024
Revised: 15 May 2024
Accepted: 20 May 2024
Published: 27 May 2024

1. Introduction

In the field of environmental engineering, the application of machine learning (ML) has shown significant promise in tackling complex challenges. Among various ML paradigms, fuzzy inference systems (FISs) are particularly notable. FISs are computational frameworks based on fuzzy set theory, introduced by [1], which allow for reasoning about data that are uncertain or imprecise. FISs utilize a set of fuzzy rules and membership functions to model complex systems, offering a transparent and interpretable approach to handle uncertainty effectively [2]. This study explores a critical question: is the capability of FISs to address uncertainty indeed pivotal for environmental engineering applications?

Environmental engineers and researchers encounter numerous challenges marked by complex interactions and inherent uncertainties. These challenges arise from a combination of factors, including environmental conditions that vary significantly across small geographic areas and temporal changes driven by seasons, natural cycles, or extreme events [3]. Such variability complicates the understanding and prediction of environmental parameters over time.

Moreover, environmental systems are characterized by non-linear interactions among numerous components, adding a layer of complexity to the modeling and prediction of future behaviors [4]. The collection of environmental data is not without its technical challenges, including instrumental errors and sensor failures, which introduce further uncertainties into the data, emphasizing the need for stringent quality control measures [5].

The modeling of environmental processes often necessitates simplifications that introduce additional uncertainties, especially in capturing the nuances of natural phenomena [6]. Consequently, traditional methods may falter in effectively accounting for these uncertainties. FISs, with their inherent ability to manage uncertainty through fuzzy logic, offer a promising alternative for enhancing environmental engineering applications—a hypothesis this study aims to validate.

Despite acknowledging the potential of FISs, the literature reveals a gap in understanding their specific relevance in treating uncertainty within environmental systems—a critical aspect given the inherent uncertainties of such systems. This gap underscores the necessity to delve into the impact of FISs on advancing the field [1,7].

Historically, fuzzy set theory has been pivotal in knowledge-based systems for its proficiency in managing uncertainty [1,8]. Initially favored in expert systems for its intuitive and flexible approach to encoding approximate reasoning, FISs have been recognized as a valuable tool for environmental applications, where dealing with uncertainties is crucial. However, the full potential of data-driven FISs, especially compared to more extensively explored methods like artificial neural networks (ANN), remains underexplored in environmental engineering [9].

The unique strengths of FISs lie in their transparency and interpretability, unlike the "black box" nature of ANNs. This clarity is essential in decision support systems (DSSs), particularly in environmental engineering, where stakeholders demand a clear rationale behind recommendations [10]. Should FISs prove to significantly improve DSSs in managing uncertainty over prevalent methods, it could herald a paradigm shift in the field.

This study aims to shed light on the role and significance of fuzzy ML in addressing uncertainty in environmental engineering. Through a thorough literature review, we seek to validate the effectiveness of fuzzy models against other methods, aiming to enrich both theoretical understanding and practical applications of FISs. Ultimately, this research strives to bridge the identified research gap and furnish actionable insights for researchers, practitioners, and policymakers, potentially inaugurating a new chapter where FISs's unique capabilities are pivotal in navigating environmental uncertainties.

Following this introduction, the study proceeds to explore the foundational principles of fuzzy theory within the "Theoretical Background" Section, and subsequently, the "Comparative Analysis" Section reviews related works. The concluding Section, "Final Remarks", synthesizes these discussions to offer actionable insights for both practitioners and policymakers.

2. Theoretical Background

In recent decades, fuzzy inference systems (FISs) have seen substantial advancements, highlighted by extensive research underscoring their effectiveness as tools for intelligent decision-making processes [11]. At their core, FISs are predicated on the principle of capturing and managing uncertainty within datasets, facilitating a nuanced depiction of complex real-world phenomena.

A cornerstone of FISs is the introduction of linguistic variables, a concept that fundamentally changes our interaction with and perception of uncertain information [12]. In environmental engineering, this allows for a more accurate representation of environmental parameters that are inherently imprecise, such as pollutant levels or climate data. Unlike traditional binary logic, which is predicated on absolute truth values (true or false), FISs recognize the existence of "shades of gray" in real-world scenarios. Linguistic variables allow for the formalized expression and manipulation of these nuances. These variables are defined by values that are words or sentences in natural language, employing linguistic rather than crisp numerical values to represent a continuum within the variable's domain [13].

Fuzzy sets, by design, extend traditional binary logic to accommodate partial membership, reflecting the reality that elements may belong to a set to varying degrees, a reflection of the inherent uncertainties present within data [14]. This is particularly relevant in environmental engineering where parameters such as soil quality or water purity are not absolute but vary continuously. Addressing uncertainty is a fundamental aspect of the fuzzy inference system (FIS) framework, distinguishing it from classical AI models that operate on binary outcomes. FISs excel in environments characterized by partial truths or varying degrees of certainty, presenting a more nuanced approach to decision-making [15]. The integration of membership functions (MFs) is pivotal in this context, offering a quantitative method to express uncertainty, thereby facilitating a more authentic representation of parameters within models. For example, in environmental applications, MFs can be used to describe varying pollution levels or gradations in water quality, enabling more precise monitoring and decision-making.

The process of selecting an appropriate MF shape is crucial, as it should align with the characteristics of the variables under consideration and the specific uncertainties they embody [16]. For instance, in modeling pollutant dispersion, different MF shapes can better capture the gradual transition of pollutant concentration levels. Each MF shape brings its unique advantages, making it more or less suited to different scenarios; thus, MF shapes provide a comprehensive toolkit for diverse FIS applications (Table 1).

Transparency and interpretability remain hallmark strengths of FISs. In contrast to the opaque nature of models such as neural networks, FISs offer explicit insights into their reasoning processes, making them invaluable for stakeholders, including policymakers and practitioners, who seek to understand the underlying logic of decisions [17]. This transparency is critical in environmental engineering, where decisions about resource management or pollution control require clear justification.

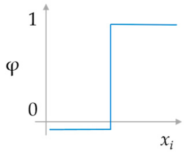
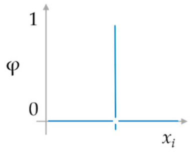
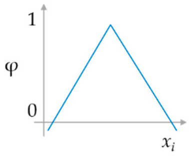
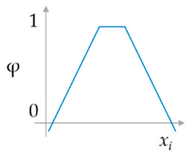
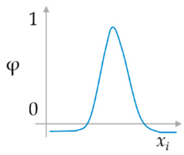
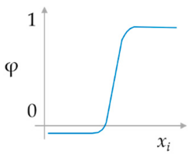
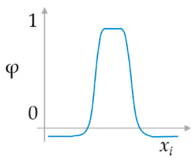
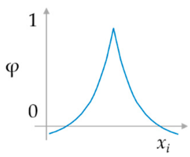
In decision support systems (DSSs), the fuzzy inference mechanism mirrors human reasoning by encapsulating the nuanced process through which experts arrive at decisions. This emulation is grounded in a structured rule-based approach that intricately maps input variables to outputs, offering a sophisticated model for decision-making [18]. For example, in environmental impact assessments, FISs can integrate diverse data inputs to provide comprehensive and justifiable conclusions. The core components of a fuzzy inference system (FIS) that facilitate this include (Figure 1) the following:

- Fuzzy implication: This element is essential for establishing the logical framework within which the FIS operates. Unlike the binary "if. . .then" logic found in classical systems, fuzzy implication introduces a spectrum of certainty levels. This feature allows for the representation of conclusions with varying degrees of confidence, closely mirroring the conditional reasoning present in human thought processes.
- Fuzzy aggregation: Central to synthesizing a coherent output from multiple inputs, fuzzy aggregation transcends the binary limitations of "AND" and "OR" operators found in classical logic. In the fuzzy domain, these operators are interpreted with greater flexibility, enabling the integration of multiple rule-based outcomes into a

singular, comprehensive conclusion. This aggregation process is pivotal in assimilating diverse pieces of information, reflecting the multifaceted nature of expert decision-making. This aggregation process is pivotal in assimilating diverse pieces of information, such as temperature and humidity levels, for holistic environmental assessments.

– Fuzzy composition: This component facilitates the integration of various input contributions towards formulating a final decision. Distinct from classical composition, which rigidly delineates set memberships, fuzzy composition embraces the potential overlap between fuzzy sets. This overlap signifies the inherent ambiguity and complexity of real-world scenarios, allowing for a more inclusive and representative approach to decision synthesis.

Table 1. The commonly utilized shapes of MFs.

MF	Shape	Property
Crisp		Represents a binary decision-making framework where membership is either 0 (non-member) or 1 (member), without allowing for any gradation between these two states.
Singleton		Confers full membership to a precise value within the fuzzy set, indicating an absolute certainty of either inclusion or exclusion.
Triangular		Best applied in situations where the progression from non-membership to full membership is relatively steep, allowing for a clear delineation of boundaries.
Trapezoidal		Provides a more gradual transition than triangular functions, making it well-suited for contexts requiring a softer delineation between membership grades.
Gaussian		Ideal for modeling scenarios where membership decreases symmetrically from a central peak, offering a smooth transition across membership levels.
Sigmoidal		Appropriate for instances where the shift from non-membership to full membership is smooth, yet not necessarily symmetrical, across the spectrum.
Generalized Bell		Offers the flexibility to adjust the curve's shape to closely match the characteristics of the system being modeled, allowing for tailored representations of uncertainty.
Laplacian		Useful in modeling phenomena that display a symmetric pattern and a swift transition between different states of membership.

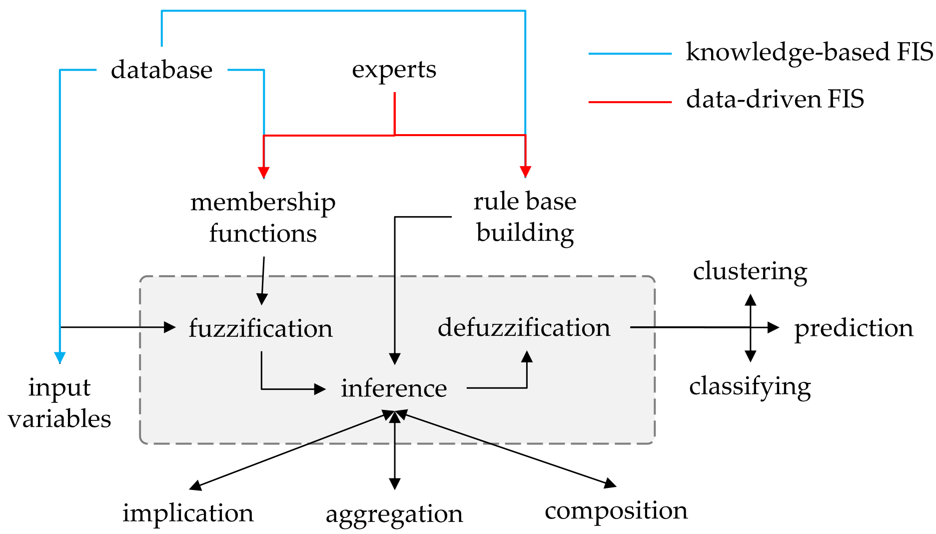


Figure 1. Key components of FIS inference mechanism.

Diverse FIS types have emerged, catering to varying degrees of uncertainty. The transition from type-0 (classical logic) through type-3 systems (capable of evolving with uncertainties) underscores the evolution and adaptability of FISs in complex scenarios [19].

While FISs boast significant advantages in dealing with uncertainty and enhancing decision-making transparency, they are not without their challenges, particularly when dealing with sparse or noisy data. The efficacy of FISs heavily relies on the judicious selection of linguistic variables and MFs, a task that can be daunting given the complexity of optimizing fuzzy sets for specific scenarios. Nonetheless, this flexibility and precision in managing uncertainty make FISs a critical tool for advancing environmental engineering practices.

This overview of FISs underscores its pivotal role in managing uncertainty and providing clear, interpretable models, thereby facilitating informed decisions. By embracing uncertainty in decision-making models, FISs pave the way for the development of more resilient and adaptive systems in environmental engineering.

3. Comparative Analysis

In conducting a comparative analysis for practical applications, our research undertook a systematic review of the existing literature, adhering to the PRISMA protocol for systematic reviews [20]. The use of the PRISMA protocol allowed us to enhance the reliability and reproducibility of the review findings in the context of environmental engineering research. By providing a structured approach to literature selection, data extraction, and analysis, PRISMA ensures that the review process is transparent and comprehensive. This protocol helps in minimizing bias, allowing for a more accurate and objective synthesis of the existing evidence. Consequently, the use of PRISMA strengthens the validity of our conclusions and supports the development of evidence-based recommendations for environmental management practices.

To identify relevant works, we utilized databases such as Web of Science and Science Direct, employing a comprehensive search strategy with the query: title-abs-key ("environmental engineering") AND ("artificial intelligence" OR "machine learning" OR "fuzzy") AND ("comparison" OR "comparative analysis" OR "benchmarking") AND (limit-to (pubstage, "final")) AND (limit-to (doctype, "ar")) AND limit-to (subjarea, "eng" OR "env") AND (limit-to (pubyear, "from 2014 to 2023")) AND (limit-to (language, "English")). During the identification phase, after removing duplicates, we screened titles and abstracts for relevance based on pre-defined inclusion criteria; that is, studies were required to directly relate to the comparative analysis of fuzzy machine learning and other ML methods in environmental engineering applications. Articles meeting these criteria were subjected to a full-text review to assess their suitability. The selection criteria emphasized the diversity of environmental engineering applications, ensuring a broad representation of fuzzy ML applications across various domains such as water quality, air pollution, climate modeling, and soil analysis. After eliminating duplicates across databases, our initial search resulted in 216 articles. A two-stage screening process refined this to 27 peer-reviewed articles, which formed the foundation of our theoretical framework (Figure 2). Then, the studies synthesis involved a comparative analysis of performance among fuzzy and other ML methods.

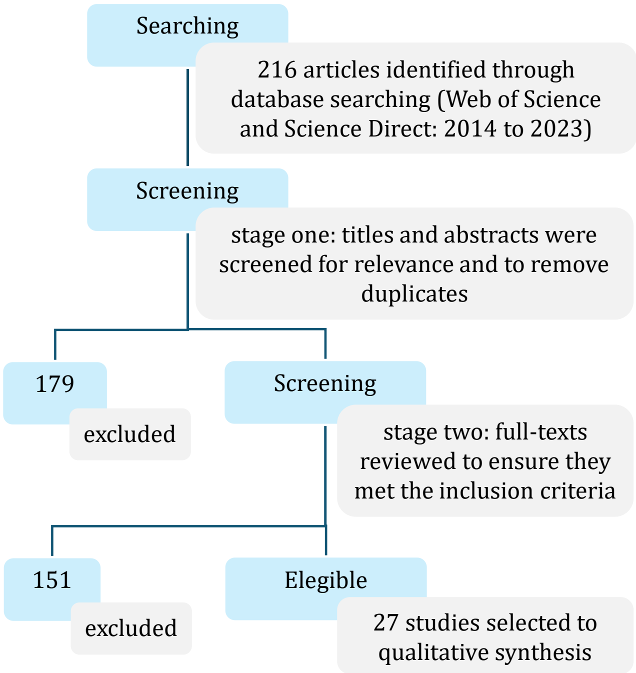


Figure 2. Systematic literature review process.

Primarily focusing on studies incorporating fuzzy ML among the evaluated alternatives, we noted that ANN-based methods constituted the predominant majority. Collectively, the reviewed studies compared 35 ML methods, with a distribution as follows: fuzzy logic (FIS-based), decision trees (TREE-based), neural networks (ANN-based), hybrid methods (H-based), and miscellaneous methods (MM-based) (Figure 3 and Table 2).

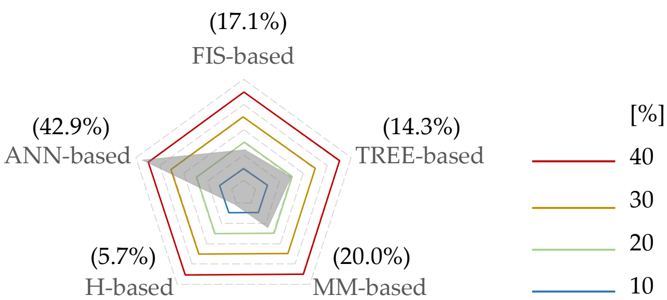


Figure 3. ML methods across the reviewed studies.

Table 2. ML methods across reviewed studies.

Studies	Environmental Parameters	ML Methods
Goyal et al. [21]	Daily Evaporation	ANN, LS-SVR, FIS, ANFIS
Ay and Kisi [22]	COD Concentration	MLR, MLP, RBF, GRNN, ANFIS, k-MLP
He et al. [23]	River Flow	ANN, ANFIS, SVM
Asadi et al. [24]	NOx Concentration	ANN, NF
Tayfur et al. [25]	Hydraulic Conductivity	SFL, MFL, LM-ANN, NF
Piotrowski et al. [26]	Water Temperature	MLP, ANFIS, WNN, KNN
Olyaie et al. [27]	Suspended Sediment Load	ANNs, ANFIS, WNN, SRC
Estalaki et al. [28]	Water Quality	ER, FSC, SWMM, MUSIC
Aghbashlo et al. [29]	Photo-Biohydrogen Production	RBF, FCR
Nadiri et al. [30]	Strength of Geopolymers	SFL, MFL, LFL
Bagheri et al. [31]	Landfill Leachate Penetration	FIS, ANN
Bressane et al. [32]	Arboreal Recognition	FIS, C5, CCNN, KNN, PNN, MLP, RF, DT, SGB, SVM
Nabavi-Pelesaraei et al. [33]	Energy Output	ANN, ANFIS
Dou and Yang [34]	Daily Evapotranspiration	ELM, ANFIS, ANN, SVM
Choubin et al. [35]	Suspended Sediment Load	CART, ANFIS, MLP, SVM
Nadiri et al. [36]	Effluent Water Parameters	FIS, SCFL
Raei et al. [37]	Urban Stormwater	MLP, NSGA-II, Fuzzy α-cut, DSS
Adnan et al. [38]	Daily Streamflow	ANFIS-PSO, MARS, M5, OP-ELM
Kaab et al. [39]	Environmental Impacts	ANN, ANFIS
Roy et al. [40]	Reference Evapotranspiration	FA-ANFIS, Ensembles
Ly et al. [41]	Water Quality Modeling	LR, DL-ANN, ANFIS
Manzar et al. [42]	Water Quality Index	GRNN, Elm-NN, FFNN, SVM, LR, NF
Kılıç and Topuz [43]	PTE in Volcanic Ash Soils	ANN, FLRA
Bressane et al. [44]	Coagulant Dose in Water Treatment	FIS, ANFIS, CCNN, GEP, P-NN, PNN, RF, RBN, SGB, SVM
Oyounalsoud et al. [45]	Drought Indices	FIS, ANFIS
Bressane et al. [46]	Successional Stages Classification	FIS, ANN, Ensembles, SVM
Nakhaei et al. [47]	Water Consumption	RF, ANFIS, RT

Recognizing the inherent uncertainties in climatic conditions, Goyal et al. [21] aimed to address the challenges associated with the accurate modeling of daily evaporation predictions in subtropical climates. The methods under comparison included ANN, least squares support vector regression (LS-SVR), FIS, and adaptive neuro-fuzzy inference systems (ANFISs). The comparative analysis shed light on the performance of these models, revealing that both the FIS and LS-SVR surpassed the traditional empirical methods, Hargreaves and Samani (HSG), and Stephens–Stewart (SS). In this context, the FIS and LS-SVR methods demonstrated superior predictive capabilities, emphasizing the importance of considering advanced modeling methods when dealing with the uncertainties inherent in subtropical climates.

The relevance of addressing the complexity in chemical oxygen demand (COD) concentration predictions motivated Ay and Kisi [22] to explore advanced methods to enhance the modeling of COD. In comparing various methods, including multi-linear regression (MLR), MLP, radial basis function network (RBF), generalized regression neural network (GRNN), and two distinct ANFIS techniques (subtractive clustering and grid partition), the study found that the k-means clustering combined with MLP, referred to as the k-MLP method, outperformed the alternatives. The k-means clustering step likely helped in grouping similar patterns within the data, enabling the subsequent MLP to focus on learning the specific characteristics of each cluster. This adaptability to the data's structure might have been more efficient in representing the intricate relationships in COD concentration compared to the fuzzy-based ANFIS techniques.

The study conducted by He et al. [23] aimed to compare the performance of three forecasting models—ANN, ANFIS, and support vector machine (SVM)—in predicting river flow within the semiarid mountain region of northwestern China. The investigation revealed that the SVM model notably outperformed both the ANN and ANFIS counterparts in the task of river flow forecasting, particularly when applied to validation datasets. This highlights the superior performance of the SVM model in addressing specific geographical conditions related to river flow predictions in the semiarid mountain region, emphasizing its effectiveness as a robust and accurate method in such environmental scenarios. The SVM model's ability to find optimal decision boundaries in high-dimensional spaces allows it to capture the underlying structure of the river flow data more effectively. In the specific geographical conditions of the semiarid mountain region, there might be non-linear relationships and complex interactions influencing river flow.

The application of titanium dioxide (TiO_2) as a photocatalyst in asphalt pavement has gained attention because of its air purifying properties. However, monitoring the parameters to predict the conditions and the air pollutant concentrations is difficult due to the nonlinear nature of these parameters. Asadi et al. [24] used ANN and neuro-fuzzy (NF) models to predict NO_x concentrations in the air, considering other parameters. The study revealed that the NF model proved to be more compatible for measuring NOx concentrations.

Hydraulic conductivity is an important parameter for modeling and managing groundwater. However, estimating hydraulic conductivity is usually expensive and time-consuming. Therefore, Tayfur et al. [25] applied ML-based models of Sugeno fuzzy fuzzy logic (SFL), Mamdani FL (MFL), MLP neural network associated with Levenberg–Marquardt (LM-ANN), and neuro-fuzzy (NF) to estimate hydraulic conductivity. The results showed that SFL and NF provided acceptable performance, while ANN and MFL had poor performance. A supervised intelligent committee machine (SICM) was also used to combine the results of the previous ML models and present reliable results.

Piotrowski et al. [26] compared various data-driven models for the prediction of water temperature in rivers, encompassing MLP, ANFIS, wavelet neural networks (WNN), and the k-nearest neighbor approach (KNN). Among the models compared, the fuzzy-based alternative, specifically ANFIS, demonstrated superior performance by consistently achieving lower error rates in the vast majority of comparisons. This underscores the efficacy of the ANFIS in enhancing the accuracy of water temperature predictions and highlights its relevance for addressing uncertainties associated with such environmental predictions. The findings suggest that the utilization of fuzzy-based models can contribute to more reliable and precise water temperature forecasts in river systems.

In the study by Olyaie et al. [27], ANN, ANFIS, WNN, and the conventional sediment rating curve (SRC) were compared to assess their efficacy in estimating suspended sediment load in two gauging stations within the United States. The WNN demonstrated the highest level of accuracy, emerging as the most precise method for predicting in the specified context. The findings emphasize the significance of considering different modeling methods and affirm the efficacy of WNN in enhancing the accuracy of suspended sediment load predictions. The wavelet transform employed in WNN allows for a multi-resolution analysis of the data, enabling the model to adapt to both high and low-frequency components in the time series. The specific characteristics of suspended sediment load data, including temporal variations and non-linear relationships, may have been better accommodated by the WNN's architecture. Thus, the adaptability of WNN to capture detailed temporal changes and variations in sediment load could have contributed to its superior accuracy compared to ANFIS.

The uncertainties in management of lake water justified the application of evidential reasoning (ER) and fuzzy social choice (FSC) techniques to assess policies governing water supply and water quality management in the context of Chitgar Lake [28]. The utilization of the stormwater management model (SWMM) and the model for urban stormwater improvement conceptualization (MUSIC) for simulating the lake watershed added depth to the analysis. The key finding suggests that the FSC method, distinguished by its direct incorporation of stakeholders' utility functions, demonstrates greater promise in the evaluative framework for water supply and water quality management in Chitgar Lake. This comparison underscores the efficacy of FSC in addressing uncertainties and integrating stakeholder preferences, providing valuable insights for decision-makers in water resource management.

Aghbashlo et al. [29] developed a RBF model interfaced with the proposed hybrid fuzzy clustering-ranking (FCR) algorithm to simultaneously maximize the rational and process-energetic efficiencies and minimize the normalized exergy destruction. In order to evaluate the capability of the proposed approach, the conventional fuzzy optimization algorithm was also applied. The proposed algorithm predicted optimum values that were more suitable compared with the conventional fuzzy method. The algorithm developed in this study may be promising for other approaches regarding cost-effective and environmentally friendly operational parameters.

Nadiri et al. [30] aimed to predict the compressive strength (CS) of geopolymers prepared from alumina-silica using a hybrid fuzzy model. The study compared three models: SFL, MFL, and Larsen FL (LFL). The primary objective of the research was to assess the performance of these models and identify the most effective one. The comparison revealed that the SFL model outperformed both the MFL and LFL models in predicting CS. Despite each model exhibiting advantages, the superior performance of SFL emphasized its efficacy in this specific application. To harness the strengths of each model, the authors introduced a hybrid approach—supervised committee fuzzy logic (SCFL). This integration resulted in a significant improvement compared to the individual models, showcasing the potential for enhanced predictive accuracy by combining complementary features from different fuzzy models.

Bagheri et al. [31] undertook a comparative assessment of FIS and ANN modeling approaches to simulate landfill leachate penetration into groundwater. The primary objective was to evaluate the performance of these models and discern their effectiveness in capturing the complex dynamics of leachate migration. Both modeling approaches demonstrated success in training and testing, showcasing several instances of perfect matches between observed and simulated values. Remarkably, the coefficient of determination for the FIS-trained model surpassed that of the neural networks, reaching a highly precise value of 0.99998. This result highlights the exceptional accuracy and reliability of the FIS model in capturing the intricate processes associated with landfill leachate penetration into groundwater.

Bressane et al. [32] introduced a fuzzy model for the identification of tree species, aiming to enhance accuracy in arboreal trunk texture recognition. The study compared the performance of the fuzzy-based system with several established classification algorithms, including the boosted rule-based model (C5), cascade-correlation neural network (CCNN), KNN, probabilistic neural network (PNN), MLP, random forest (RF), decision tree (DT), stochastic gradient boosting (SGB), and SVM. The findings revealed that the SVM and fuzzy model exhibited superior performance compared to widely used classification algorithms. This suggests that the fuzzy-based approach is a competitive and reliable method for arboreal trunk texture recognition, emphasizing its potential as an effective tool in tree species identification.

A comparative analysis of two ML methods, ANN and ANFIS, was carried out by Nabavi-Pelesaraei et al. [33], aiming to forecast energy output and evaluate environmental impacts in paddy cultivation within Guilan province, Iran. The study emphasized the significance of ANFIS, showcasing its rapid and accurate data prediction capabilities. Despite the prompt performance of ANFIS, the overall accuracy of the ANN approach surpassed it. This underscores the trade-offs between speed and comprehensive accuracy in the context of energy output and environmental impact forecasting. ANN models, with their ability to learn and adapt to complex patterns, might have effectively captured the diverse and intricate relationships within the dataset, allowing for more accurate predictions. However, reducing the complexity of the dataset can also potentially improve the accuracy of deep learning models. As noted by Bolón-Canedo and Remeseiro [48] and supported by Kabir and Garg [49], simplifying the dataset through dimensionality reduction techniques can lead to faster convergence and improved model performance. This approach aligns with the principle of Kolmogorov complexity, which denotes the length of the shortest computer program that produces a given output, suggesting that a less complex dataset can enhance model accuracy and efficiency. The trade-off observed between the speed of ANFIS and the overall accuracy of ANN emphasizes the importance of considering the specific requirements of the application.

Dou and Yang [34] conducted a comparative assessment to explore the feasibility and efficacy of the extreme learning machine (ELM) and ANFIS for estimating daily evapotranspiration across diverse ecosystems. The study involved a comparison of these models with conventional ANN and SVM models. The conclusion asserts that the advanced ELM and ANFIS models exhibited comparable performance, surpassing other methods assessed. Consequently, both models are recommended as pivotal complements to traditional approaches due to their inherent robustness and flexibility.

Choubin et al. [35] conducted a comparative analysis to assess the accuracy of the classification and regression tree (CART) model against four other commonly used models in modeling time series of suspended sediment load (SSL) in rivers. The models under comparison included ANFIS, MLP, and SVM. The study aimed to determine the most effective model for predicting SSL over time. The results revealed that the CART model demonstrated superior performance in predicting SSL, with SVM ranking as the second-best model. The superior performance of the CART model can be attributed to the nature of the data and the specific characteristics of the CART algorithm. CART, being a tree-based model, may have been better suited to capture non-linear relationships and complex patterns in the SSL time series.

An analysis to assess the performance of various models in predicting the quality of effluent water parameters in a wastewater treatment plant was conducted by Nadiri et al. [36]. The study specifically compares individual FIS models, including Takagi–Sugeno, Mamdani, and Larsen, with the SCFL model. The results indicate that the SCFL model outperforms the individual FIS models in predicting effluent water parameters. This highlights the superiority of the combined approach, emphasizing its potential for enhanced predictive accuracy in the context of wastewater treatment plant processes.

Raei et al. [37] introduced a methodology aimed at aiding decision-making in green infrastructure planning for urban stormwater management, particularly under conditions of uncertainty. The study compared the performance of several methods, including MLP, NSGA-II multi-objective optimization, fuzzy α-cut technique, and a DSS model based on social choice theory. The findings underscore the superior effectiveness of the fuzzy-based alternative, emphasizing its capability in handling uncertainty within the context of urban stormwater management planning.

In the study conducted by Adnan et al. [38], the primary objective was to perform a comparative analysis to assess the efficacy of soft computing models in predicting daily streamflow. The methods compared include the ANFIS with particle swarm optimization (ANFIS-PSO), multivariate adaptive regression splines (MARS), and model tree (M5). The findings elucidate that, overall, the OP-ELM (online sequential extreme learning machine) and ANFIS-PSO models exhibit superior performance in modeling daily stream flows for upstream and downstream locations, respectively, reducing the prediction error of other ML methods by 12%. The capacity to handle uncertainty, a characteristic inherent in fuzzy logic-based models, certainly played a crucial role in ANFIS-PSO's superior performance in this daily modeling.

Kaab et al. [39] compared the performance of ANN and ANFIS models for predicting the environmental impacts and output energy of sugarcane production in planted and ratoon farms. The results show that in planted farms, ANN outperforms ANFIS in all aspects, while in ratoon farms, ANFIS attain higher accuracy than ANN. The computed coefficients of determination (R^2) for the prediction of environmental impacts obtained by ANN models are higher than those obtained by ANFIS models in planted sugarcane production, indicating that ANN models outperform ANFIS in this aspect. However, in ratoon sugarcane production, the coefficients of determination (R^2) for the prediction of environmental impacts obtained by ANFIS are higher than those for ANN. Therefore, both ANN and ANFIS have the ability to predict with high accuracy, but the choice between the models depends on the specific farm type.

The performance of various prediction models, encompassing standalone and ensemble models, was evaluated by Roy et al. [40] for forecasting reference evapotranspiration in subtropical climatic zones. The study identified the fuzzy-based firefly algorithm (FA-ANFIS) as the most accurate standalone model. While ensemble models demonstrated improved performance compared to individual models, their effectiveness was comparable to that of FA-ANFIS. The potential superiority of FA-ANFIS can be attributed to the firefly algorithm's (FA) ability to optimize the parameters of the model more efficiently, resulting in a more accurate modeling of reference evapotranspiration. The use of fuzzy logic may have also played a crucial role in managing the uncertainty inherent in climatic data, thereby contributing to the model's robustness in a subtropical context.

Ly et al. [41] aimed to explore various ML methods for water quality modeling in an urban river, focusing on eutrophication analysis and algal bloom prediction. The study compared machine learning algorithms, including linear regression (LR), deep learning artificial neural network (DL-ANN), and ANFIS, with the goal of developing a user-friendly web application. The results revealed that ANFIS outperformed other algorithms, providing accurate estimations for both classification and regression tasks. The uncertainty associated with water quality predictions, especially in the context of eutrophication and algal bloom events, underscores the relevance of employing robust and adaptive models like ANFIS.

A comparative analysis of six computational models to quantify the water quality index (WQI), including generalized regression neural network (GRNN), Elman neural network (Elm-NN), feed forward neural network (FFNN), SVM, LR, and NF was performed by Manzar et al. [42]. The results indicated that the NF model outperformed the other models, demonstrating the highest level of accuracy in WQI quantification. The study highlights the importance of considering uncertainties in water quality assessments and suggests that introducing additional models, such as WNN, gradient boosting, genetic programming, and genetic algorithm (GA), could further enhance the accuracy of the models.

Kılıç and Topuz [43] aimed to estimate the concentration of potentially toxic elements (PTEs) in Cappadocian volcanic ash soils, employing ANN and fuzzy linear regression analysis (FLRA). The study revealed that the FLRA method exhibited the lowest error and high R^2 values in comparison to the ANN method. Additionally, the predictive power of the FLRA method was found to be superior to that of the ANN method. The findings show the efficacy of FLRA in providing accurate and robust predictions for PTE concentrations in volcanic ash soils, showcasing its potential for environmental applications.

The dosage of coagulant in water treatment involves uncertainties due to the dynamic and complex nature of quality parameters, including fluctuating raw water, variations in pollutant concentrations, and changes in the water source characteristics. To deal with this, Bressane et al. [46] conducted an assessment of various machine learning methods for the real-time accurate prediction of coagulant dosage in drinking water treatment. The comparative analysis encompassed FIS, ANFIS, CCNN, gene expression programming (GEP), polynomial neural network (P-NN), probabilistic neural network (PNN), random forest (RF), radial basis network (RBN), SGB, and SVM. The study revealed that the FIS method yielded the smallest error, surpassing the other machine learning methods in performance. This underscores the effectiveness of the FIS in providing accurate predictions for coagulant dosage in real-time drinking water treatment scenarios.

Oyounalsoud et al. [45] developed models based on FIS and ANFIS, which were compared to nine conventional drought indices and correlated with multiple indicators. The study found that the average of the best-performing FIS outperformed all conventional indices. Additionally, when the average output of the best-performing FIS was used for training, the best ANFIS had a correlation of 0.809 with upper soil moisture. The best ANFIS also had a correlation of 0.941 with the rainfall anomaly drought index (RAI), which was the best-performing conventional drought index. The validation results showed that the developed models had similar performances to the RAI in most cases and yielded better predictions in subtropical and tropical regions.

The classification of successional stages in the subtropical Atlantic Forest involves uncertainties due to the complex and dynamic nature of ecological systems. Succession is a gradual and dynamic process in which plant communities undergo various changes over time. Bressane et al. [44] aimed to assess and compare the performance of various ML methods for the computer-aided classification of successional stages in the subtropical Atlantic Forest. The study compared the performance of different ML methods, including FIS, ANN, classifier committees, and SVM. The results indicated that the FIS method outperformed the other ML methods, achieving the highest performance. The classification by FIS exhibited almost perfect agreement with the classifications conducted by human experts. The FIS method's success in achieving results comparable to human classifications underscores its capability to handle uncertainties inherent in the subtropical Atlantic Forest's successional stages. The FIS model's ability to emulate human-like classifications suggests its robustness in dealing with the complexity and uncertainty associated with ecological classifications.

The study conducted by Nakhaei et al. [47] aimed to develop a smart DSS for the monitoring, prediction, and control of water consumption in power plants (PPs) utilizing ML and multi-criteria decision making (MCDM) methods. The primary objectives were to enhance efficiency and resource management in PP operations. In the comparative analysis, the random forest (RF), ANFIS, and random tree (RT) methods were evaluated. Among the evaluated methods, the ANFIS demonstrated superior performance, achieving a correlation coefficient exceeding 0.99. The study's success in developing a smart DSS underscores the potential of ML methods, particularly ANFIS, in addressing the uncertainties associated with water consumption management in PP.

The works reviewed in this present study encompassed a total of several ML methods in comparative analyses within environmental engineering applications. Fuzzy-based models demonstrated equal performance or outperformed other methods in 21 out of the 27 reviewed studies (77.8%), followed by SVM (10.7%), ANN (7.1%), and MM (4.4%) (Figure 4). Therefore, the hypothesis that FIS presents a promising alternative for enhancing environmental monitoring and assessment processes by dealing with uncertainty is confirmed based on the findings of the present study.

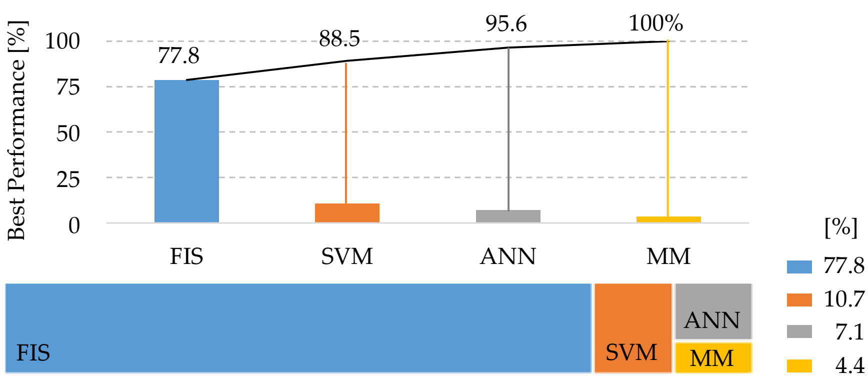


Figure 4. ML method performances across the reviewed studies.

On the other hand, while FISs have consistently showcased their superiority in environmental applications, it is crucial to emphasize that this study does not advocate for the replacement of other methods with fuzzy models. Instead, it underscores the importance of conducting a case-by-case comparison when selecting ML alternatives. As highlighted by Gibert et al. [50], the versatility of fuzzy models in handling uncertain information makes them well-suited for environmental engineering. The advancements in fuzzy systems, particularly in handling uncertainty, have significantly influenced the theoretical foundations and practical implementations of environmental engineering models. Improved uncertainty management has enhanced the accuracy and reliability of predictions, allowing for more nuanced and adaptive environmental models. These advancements facilitate better decision-making and policy development by providing clearer insights into the variability and complexity of environmental data.

In sum, by comparing the performance of FISs to other ML models across the environmental applications addressed in the present study, several trends emerge. Studies, such as those by Goyal et al. [21] and Piotrowski et al. [26], have shown that FIS consistently demonstrates superior predictive capabilities, particularly in handling the uncertainties inherent in complex environmental data. For instance, FIS and least squares support vector regression (LS-SVR) outperformed traditional empirical methods in modeling daily evaporation predictions in subtropical climates. Similarly, ANFIS was found to excel in predicting water temperatures in rivers. The adaptability of FIS to different environmental parameters and conditions is further evidenced by Bagheri et al. [31], where FIS achieved exceptionally high accuracy in modeling landfill leachate penetration into groundwater, surpassing neural networks. While some studies, such as He et al. [23], found SVM to be superior in specific scenarios like river flow forecasting in semiarid regions, the general trend indicates that FISs often match or exceed the performance of other models, such as ANN and SVM, by offering robust and interpretable solutions. This adaptability and resilience make FISs a valuable tool for environmental management, supporting more reliable decision-making and policy formulation in dynamic and uncertain environments. Therefore, while FISs should not be seen as a universal, one-size-fits-all solution, fuzzy-based models deserve consideration when choosing the best method for supporting environmental decision-making, as they can offer superior performance in specific contexts, as verified in our review.

4. Challenges and Future Directions

4.1. Computational Challenges

Implementing fuzzy-based models in real-world environmental systems presents several computational challenges that can affect their adoption in both industry and academia. Fuzzy-based models, especially those involving large sets of rules and membership functions, can be computationally intensive. The complexity increases exponentially with the number of input variables and the granularity of the fuzzy sets, leading to significant processing time and resource requirements. This high computational demand can be a barrier to real-time applications and scalability [8,51].

Environmental data are often noisy, incomplete, and heterogeneous, requiring extensive preprocessing to ensure the reliability of fuzzy-based models. Handling missing data and outliers and ensuring data consistency can be computationally demanding and may require sophisticated data imputation and cleaning techniques [52].

Designing and optimizing membership functions and fuzzy rules to accurately reflect real-world scenarios is a critical challenge. This process often involves trial and error, expert knowledge, and extensive computational resources to fine-tune the parameters for optimal performance. Automated methods like genetic algorithms or machine learning-based optimization can help but add to the computational burden [53].

Fuzzy-based models are often integrated with other machine learning models or physical simulation systems to enhance their performance. Ensuring seamless integration and interoperability between different models and systems can be complex and computationally intensive, particularly in large-scale or real-time applications [51].

Environmental systems also require real-time monitoring and decision-making, which necessitates fast and efficient computation. Fuzzy-based models must be able to process large volumes of data in real-time, which can be challenging due to their inherent complexity [46]. Scaling these models to handle increasing data volumes and computational demands without compromising performance is a significant hurdle [15].

4.2. Research Directions

The systematic review confirmed the significant potential of fuzzy ML models in handling uncertainty and enhancing decision-making in environmental engineering. In this context, future research must focus on integrating hybrid models, advancing uncertainty quantification methods, and developing real-time, application-specific, and scalable solutions to fully realize the capabilities of fuzzy ML in this field [51].

Future research should focus on developing and refining hybrid models that combine the strengths of FISs with other machine learning (ML) techniques, such as ANN, SVM, and DT. These hybrid approaches can leverage the interpretability of FISs and the predictive power of other ML models to handle complex environmental datasets more effectively. For instance, integrating FISs with deep learning models could enhance the capability of handling high-dimensional and non-linear data typical in environmental applications [15].

Enhancing methods for quantifying and managing uncertainty within FIS frameworks is crucial. Future studies should explore advanced techniques for uncertainty quantification (UQ) that can be integrated into FISs, providing more robust predictions and better confidence intervals for decision-makers. This includes the development of new membership functions and fuzzy rules that can better capture the variability and uncertainties in environmental data [8].

As environmental data collection becomes increasingly automated through IoT sensors and remote sensing technologies, future research should focus on the real-time data processing capabilities of fuzzy ML models. This involves developing adaptive FIS models that can dynamically update and recalibrate in response to new data, ensuring timely and accurate environmental monitoring and assessment [52].

Research should also focus on customizing fuzzy ML models to specific environmental engineering applications, such as water quality monitoring, climate change impact assessment, and sustainable resource management. Tailoring the fuzzy rules and membership functions to the specific characteristics of these applications can enhance model accuracy and reliability [8].

Encouraging interdisciplinary collaboration between environmental engineers, data scientists, and domain experts can lead to more innovative and effective fuzzy ML solutions. Future studies should foster such collaborations to develop models that are not only technically sound but also practically relevant and easily interpretable by stakeholders [15].

Addressing the computational challenges associated with large-scale fuzzy ML models is another critical area for future research. Developing scalable algorithms and leveraging high-performance computing resources can make fuzzy ML models more applicable to extensive environmental datasets, thereby improving their utility in large-scale environmental management projects [51].

Establishing standardized benchmarks and evaluation metrics for comparing the performance of fuzzy ML models with other ML techniques in environmental engineering is essential. Future research should focus on creating comprehensive benchmarking frameworks that can provide consistent and objective assessments of different modeling approaches [53].

By addressing these research directions, the field of environmental engineering can significantly benefit from the enhanced robustness and accuracy of fuzzy ML models, ultimately leading to more informed and effective decision-making in managing environmental challenges.

5. Final Remarks

As addressed in the theoretical background and evidenced by its successful implementation across various environmental modeling scenarios, fuzzy ML offers a robust framework for managing uncertainty in complex systems. From analyzing water quality dynamics to identifying tree species and predicting droughts, fuzzy ML has proven its capability in handling imprecise and dynamic information. The integration of linguistic variables, membership functions, and FISs enables the representation and processing of uncertainty, positioning fuzzy ML as a promising tool for a range of fields in environmental engineering.

Firstly, the transparency and interpretability of FISs are highlighted as key advantages. Unlike "black-box" models such as neural networks, FISs offers clear insights into their decision-making process, essential for stakeholders, including policymakers, to understand the system's rationale fully. For example, when using FISs to predict groundwater quality, stakeholders can see how different inputs such as rainfall, industrial discharge, and soil properties influence the final predictions, thus providing a clear understanding of the model's logic. In terms of practical applications, fuzzy models integrate seamlessly into DSS for environmental management. This integration facilitates stakeholder engagement by offering transparent, interpretable, and robust decision-making tools. By allowing stakeholders to understand the influence of various environmental parameters on outcomes, FISs enhance trust and collaboration in policy formulation. Additionally, the adaptability of FISs to diverse scenarios ensures that policies remain relevant and effective in dynamic environmental conditions. This integration not only supports evidence-based policy-making but also helps in aligning decisions with sustainability goals, thereby fostering more effective and inclusive environmental management practices.

Furthermore, FIS's adaptability to various scenarios and its proficiency in managing uncertain data make it suitable for real-world applications, where data may be imprecise or incomplete. Hybrid fuzzy models, exemplified by their use in predicting compressive strength in geopolymers and assessing groundwater quality, demonstrate the FIS's flexibility in merging the strengths of disparate models to enhance accuracy. In the case of groundwater quality assessment, FISs can handle the inherent uncertainty of fluctuating data, leading to more reliable and interpretable results that can inform better water management policies.

For instance, in predicting compressive strength in geopolymers, FISs can seamlessly integrate various data sources and handle the inherent uncertainty in the measurements, resulting in more accurate predictions. Similarly, in groundwater quality assessment, FISs can adapt to the fluctuating nature of environmental data, providing reliable and interpretable results that can be crucial for environmental management and policy-making.

The ability to UQ with FISs provides additional insights that are invaluable in environmental engineering. By explicitly representing uncertainty, FISs allows decision-makers to assess the confidence level of predictions and to identify the most critical factors contributing to uncertainty. For example, in drought prediction, FISs can help identify which climatic variables are most uncertain and how they impact the overall prediction. This insight enables targeted data collection and more focused efforts to reduce uncertainty, thereby improving the robustness of environmental models.

For policymakers, the reliability of FISs in forecasting environmental impacts, water quality indices, and drought patterns facilitates more informed decision-making. By using FISs, policymakers can gain a more nuanced understanding of environmental phenomena, allowing for the development of more effective and sustainable policies. The ability to interpret and justify decisions based on FIS models can also enhance public trust and support for environmental initiatives.

In conclusion, the hypothesis concerning FIS's effectiveness is supported by the majority of reviewed studies. The reason FISs often outperform other algorithms is their ability to handle and quantify uncertainty, which is intrinsic to environmental systems. While traditional models might struggle with the variability and complexity of environmental data, FISs provide a robust alternative that can model these uncertainties effectively. The confluence of theoretical foundations and practical implementations establishes FISs as an invaluable ally for practitioners and policymakers confronting the complexities of environmental monitoring and assessment. The model's ability to represent uncertainty, coupled with its transparency and consistent performance across various scenarios, renders FISs a crucial tool in narrowing the gap between theoretical insights and actionable intelligence in real-world settings. The adaptability and resilience of fuzzy-based models have significant implications for policy-making in environmental management. These models can effectively accommodate changing conditions and emerging data, making them ideal for developing and implementing sustainable policies. By providing robust and interpretable results, FISs support policymakers in crafting strategies that are both scientifically sound and responsive to the dynamic nature of environmental systems. This adaptability ensures that policies remain relevant and effective over time, even as new environmental challenges arise. As environmental challenges grow more complex, FISs stand out as a dependable guide for navigating uncertainty and making informed decisions that align with the complexities of the natural environment.

Author Contributions: Conceptualization, A.B., S.D.X. and M.V.d.C.; Data curation, A.B. and S.D.X.; Formal analysis, A.J.d.S.G. and G.R.; Investigation, A.J.d.S.G., R.G.N., G.R. and M.V.d.C.; Methodology, A.B.; Project administration, A.B.; Software, A.J.d.S.G.; Validation, R.G.N. and M.V.d.C.; Writing—original draft, A.B., S.D.X., A.J.d.S.G., G.R., R.G.N. and M.V.d.C. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Data Availability Statement: Not applicable.

Conflicts of Interest: The authors declare no conflict of interest.

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