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INTELIGÊNCIA ARTIFICIAL FUZZY NA TOMADA DE DECISÕES AMBIENTAIS: A HABILIDADE DE LIDAR COM A INCERTEZA REALMENTE IMPORTA?

São José dos Campos

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Trabalho de graduação apresentado como requisito parcial para a obtenção do título de Bacharel em Engenharia Ambiental pela Universidade Estadual Paulista "Júlio de Mesquita Filho".

Orientador: Prof. Dr. Adriano Bressane

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FUZZY ARTIFICIAL INTELLIGENCE IN ENVIRONMENTAL DECISION-MAKING: DOES THE ABILITY TO DEAL WITH UNCERTAINTY REALLY MATTER?

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São José dos Campos, 21 de novembro de 2023.

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RESUMO

Declaração do Problema. As ciências ambientais enfrentam desafios complexos marcados por incertezas. Métodos tradicionais de modelagem podem ter dificuldade em capturar efetivamente as nuances dessas incertezas. Como uma abordagem promissora, o estudo discute a lógica fuzzy (LF) como uma alternativa ainda pouco explorada. *Questão de Pesquisa*. Embora o potencial da LF em lidar com a incerteza seja amplamente reconhecido, essa capacidade realmente é capaz de aprimorar a tomada de decisões ambientais? *Objetivo*. Este estudo visa aprofundar a compreensão do papel e da importância da inteligência artificial fuzzy no enfrentamento da incerteza nas ciências ambientais. O objetivo é contribuir não apenas para a compreensão teórica, mas também para aplicações práticas nesse campo. *Método*. Ao longo da pesquisa realizou-se uma revisão de 24 estudos, comparando o desempenho de modelos fuzzy com outros métodos de inteligência artificial em diversas aplicações ambientais. As vantagens da LF no manejo da incerteza, suas bases teóricas e suas aplicações práticas foram discutidas. *Conclusões*. Os modelos baseados em LF consistentemente superaram outros métodos na ampla maioria dos estudos revisados, especialmente em cenários caracterizados por complexidade e incerteza. No entanto, o estudo não advoga pela substituição de outros métodos por modelos fuzzy. Em vez disso, recomenda uma comparação caso a caso, em que a LF seja considerada. *Implicações Práticas*. O estudo oferece insights para profissionais e formuladores de políticas. A natureza transparente e interpretável dos modelos fuzzy, aliada à sua capacidade de lidar com incertezas, os posiciona como uma alternativa promissora na tomada de decisões ambientais. Formuladores de políticas podem aproveitar a confiabilidade dos modelos fuzzy para apoiar políticas sustentáveis apoiadas por inteligência artificial.

Palavras-chave: Lógica fuzzy, Ciência ambientais, Análise comparativa.

ABSTRACT

Statement of Problem. The environmental sciences face complex challenges marked by uncertainties. Traditional modeling methods may struggle to capture the nuances of these uncertainties effectively. As a promising direction, the study discusses the fuzzy logic (FL) as an alternative that is still less explored. *Research question*. While the potential of FL in addressing uncertainty is widely acknowledged, is this ability really capable of enhancing environmental decision-making? *Purpose.* This study aims to delve into the understanding of the role and significance of fuzzy artificial intelligence in addressing uncertainty within environmental sciences. The goal is to contribute not only to theoretical understanding but also practical applications in environmental sciences. *Method*. The research employs a comprehensive review of 24 studies, comparing the performance of fuzzy models against other artificial intelligence methods in various environmental applications. The study analyzes the strengths of FL in handling uncertainty, its theoretical foundations, and its practical applications. *Conclusions.* Out of the studies reviewed, fuzzy-based models consistently outperformed other methods in the vast majority, particularly in scenarios characterized by complexity and uncertainty. However, the study does not advocate for the replacement of other methods by fuzzy models. Instead, it recommends a case-by-case comparison for optimal selection. *Practical Implications*. The study provides actionable insights for practitioners and policymakers. The transparent and interpretable nature of FL models, coupled with their ability to handle nuanced uncertainties, positions them as a promising alternative in environmental decision-making. Policymakers can leverage the reliability of FL models in AI-aided sustainable policies.

Keywords: Fuzzy logic, Environmental sciences, Comparative analysis.

SUMÁRIO

1. INTRODUÇÃO

No domínio das ciências ambientais, as aplicações de inteligência artificial (IA) têm demonstrado um potencial significativo para lidar com desafios complexos. Entre os vários paradigmas da IA, os sistemas de inferência fuzzy (SIF) surgem como uma abordagem promissora, permitindo o tratamento de incertezas (MAKHAZHANOVA et al., 2020). Este estudo explora a questão-chave: a capacidade do SIF de lidar com incerteza realmente importa no contexto das ciências ambientais?

A engenharia ambiental enfrenta problemas complexos, caracterizados por interações multifacetadas e incertezas inerentes (GEARY et al., 2021). Condições ambientais exibem variações espaciais significativas, manifestando microambientes diversos mesmo em uma área geográfica relativamente pequena. Flutuações temporais, impulsionadas por mudanças sazonais, ciclos naturais ou eventos extremos, amplificam ainda mais a complexidade. Compreender e prever a dinâmica temporal de parâmetros ambientais apresenta desafios consideráveis.

Além disso, sistemas ambientais são intrinsecamente complexos, apresentando interações não lineares entre inúmeros componentes (ALTIERI, 2022). Essa complexidade representa uma barreira para modelagem precisa e previsão de comportamentos futuros. A interação de fatores ecológicos, geológicos e climáticos adiciona camadas de complexidade aos sistemas ambientais. A coleta de dados ambientais também envolve instrumentos e metodologias sujeitos a limitações técnicas (CHENG et al., 2022), introduzindo incertezas nos conjuntos de dados.

A modelagem matemática, fenomenológica e estatística de processos ambientais frequentemente exige simplificações e aproximações devido à complexidade dos sistemas (WEIGAND et al., 2023), introduzindo incertezas nos modelos, especialmente ao tentar capturar as complexidades dos fenômenos naturais. Assim, métodos tradicionais podem ter dificuldade em capturar as nuances dessas incertezas de maneira eficaz. Os SIF, com a capacidade de lidar com a incerteza, apresentam uma alternativa promissora para aprimorar os processos de tomada de decisão em contextos ambientais.

O corpo existente de conhecimento na interseção de IA baseada em SIF e tomada de decisão ambiental revela uma lacuna de pesquisa, na medida em que a extensão em que essa capacidade é crucial para melhorar o desempenho dos modelos permanece pouco explorada. Enquanto estudos reconhecem o potencial dos SIF, falta uma compreensão abrangente sobre a relevância específica do tratamento da incerteza por modelos fuzzy. Essa lacuna é especialmente significativa, pois sistemas ambientais inerentemente envolvem incertezas, e a compreensão do impacto da lógica fuzzy (LF) torna-se imperativa para maiores avanços nesse campo de pesquisa.

Historicamente, a teoria de conjuntos fuzzy na tomada de decisões encontrou suas raízes no domínio de sistemas baseados em conhecimento, onde obteve amplo reconhecimento por sua eficácia no tratamento da incerteza (KAHRAMAN; GÜNDOGDU, 2021). Inicialmente, suas aplicações estavam concentradas em sistemas projetados por especialistas humanos, oferecendo um framework intuitivo e flexível para codificação do pensamento humano. Essa adoção inicial estabeleceu a LF como uma solução preferencial para capturar e formalizar conhecimento incerto, tornando-a promissora para sistemas de suporte à decisão (SSD) onde incertezas são inerentes.

Por outro lado, a verdadeira amplitude do potencial de um SIF orientado por dados ainda carece de maiores estudos, especialmente na sua comparação com métodos mais amplamente explorados (KALIBATIENĖ; MILIAUSKAITĖ, 2021). Ao contrário da aceitação generalizada de sistemas especialistas fuzzy, sua integração com aprendizado de máquina (AM), para reconhecimento de padrões em tarefas de agrupamento, regressão e classificação, é muito menos conhecida e aplicada entre os pesquisadores no campo ambiental. Isso é especialmente evidente quando comparado à aplicação extensiva de redes neurais, por exemplo. Ao contrário das redes neurais que operam como caixas-pretas, o fuzzy fornece modelos transparentes e interpretáveis (AYALA et al., 2020). Essa interpretabilidade é crucial em SSDs, especialmente em campos como a engenharia ambiental, onde as partes interessadas buscam uma compreensão clara do raciocínio por trás de recomendações ou decisões.

O principal objetivo deste estudo foi discutir a importância da capacidade da inteligência artificial fuzzy em tratar a incerteza no âmbito da tomada de decisões ambientais. Para tanto, buscou-se verificar a eficácia dos modelos fuzzy em comparação com outras metodologias amplamente aplicadas à estudos ambientais. Em outras palavras, o estudo não busca apenas preencher uma lacuna de pesquisa, mas também fornecer insights para que pesquisadores e formuladores de políticas no campo ambiental possam explorar o potencial dos modelos fuzzy para tomada de decisões ambientais baseadas em dados.

2. ARTIGO SUBMETIDO

2.1 Fuzzy artificial intelligence in environmental decision-making: does the ability to deal with uncertainty really matter?

Abstract

Statement of Problem. The environmental sciences face complex challenges marked by uncertainties. Traditional modeling methods may struggle to capture the nuances of these uncertainties effectively. As a promising direction, the study discusses the fuzzy logic (FL) as an alternative that is still less explored. *Research question*. While the potential of FL in addressing uncertainty is widely acknowledged, is this ability really capable of enhancing environmental decision-making? *Purpose.* This study aims to delve into the understanding of the role and significance of fuzzy artificial intelligence in addressing uncertainty within environmental sciences. The goal is to contribute not only to theoretical understanding but also practical applications in environmental sciences. *Method*. The research employs a comprehensive review of 24 studies, comparing the performance of fuzzy models against other artificial intelligence methods in various environmental applications. The study analyzes the strengths of FL in handling uncertainty, its theoretical foundations, and its practical applications. *Conclusions.* Out of the studies reviewed, fuzzy-based models consistently outperformed other methods in the vast majority, particularly in scenarios characterized by complexity and uncertainty. However, the study does not advocate for the replacement of other methods by fuzzy models. Instead, it recommends a case-by-case comparison for optimal selection. *Practical Implications*. The study provides actionable insights for practitioners and policymakers. The transparent and interpretable nature of FL models, coupled with their ability to handle nuanced uncertainties, positions them as a promising alternative in environmental decision-making. Policymakers can leverage the reliability of FL models in predicting environmental impacts, water quality indices, and drought patterns for more informed and sustainable policies.

Keywords: Fuzzy logic, Environmental sciences, Comparative analysis.

Introduction

In the realm of environmental sciences, applications of artificial intelligence (AI) have demonstrated significant potential for addressing complex challenges. Among the various AI paradigms, fuzzy inference systems (FIS) have emerged as a promising approach, enabling a nuanced representation and treatment of uncertainty (Makhazhanova et al., 2020). This study delves into the key question: does the ability of FIS to handle uncertainty truly matter for environmental monitoring and assessment?

Environmental practitioners and researchers face several issues characterized by multifaceted interactions and inherent uncertainties, which stem from a convergence of factors (Geary et al., 2021). For instance, environmental conditions exhibit significant spatial variations, manifesting as diverse microenvironments even within a relatively small geographic area. Temporal fluctuations, driven by seasonal changes, natural cycles, or extreme events, further amplify the complexity. Understanding and predicting the temporal dynamics of environmental parameters pose considerable challenges.

In addition, environmental systems are inherently complex, featuring non-linear interactions among myriad components (Altieri, 2022). This complexity represents a barrier to precise modeling and prediction of future behaviors. The interplay of ecological, geological, and climatic factors adds layers of intricacy to the systems being studied. Moreover, the process of collecting environmental data involves instruments and methodologies that are not immune to technical limitations (Cheng et al., 2022). Instrumental errors, sensor failures, and other technical issues introduce uncertainties into the dataset, necessitating rigorous quality assurance and control measures.

Mathematical, phenomenological, and statistical modeling of environmental processes often demands simplifications and approximations due to the complexity of the systems (Weigand et al., 2023). These simplifications introduce uncertainties into the models, particularly when attempting to capture the intricacies of natural phenomena. Thus, traditional methods may struggle to capture the nuances of these uncertainties effectively. With the ability to deal with uncertainty, FIS may present a promising alternative for enhancing environmental monitoring and assessment processes, a hypothesis that we seek to verify in the present study.

The existing body of knowledge in the intersection of FIS-based AI and environmental monitoring and assessment reveals a research gap, hence the extent to which this capability is crucial for improving models' performance remains a subject under-explored. While studies acknowledge the potential of FIS, there is a lack of comprehensive understanding into the specific relevance of uncertainty treatment by fuzzy models. This gap is particularly significant as environmental systems inherently entail uncertainties, and understanding the impact of FIS becomes imperative to further advancing the field.

Historically, fuzzy set theory found its roots in the domain of knowledge-based systems, where it gained widespread recognition for its adeptness in handling uncertainty (Kahraman and Gündogdu, 2021). Initially, its applications were concentrated in expert systems designed by users, offering an intuitive and flexible framework for encoding approximate reasoning. This early adoption established FIS as a go-to solution for capturing and formalizing vague or imprecise knowledge, making it well-suited for environmental monitoring and assessment where uncertainties are inherent.

On the other hand, the true breadth of data-driven FIS' potential has yet to be fully explored, especially in comparison to more extensively explored methods

(Kalibatienė and Miliauskaitė, 2021). In contrast to the widespread acceptance of fuzzy expert systems, its integration with machine learning (ML) approaches for clustering, regression, and classification tasks is relatively less-known among researchers and practitioners in the environmental field. This is particularly evident when compared to the extensive application of artificial neural networks (ANN), for instance.

The crux of the matter lies in the unique strengths of FIS. Unlike ANN that operate as black boxes, fuzzy provides transparent and interpretable models (Ayala et al., 2020). This interpretability is crucial in decision support systems (DSS), especially in fields like environmental science, where stakeholders require a clear understanding of the reasoning behind recommendations or decisions. If FIS can be proven to significantly enhance DSS in handling uncertainty—especially in comparison to the more prevalent methods—it could signify a paradigm shift.

The primary aim of this study is to elucidate the role and significance of fuzzy artificial intelligence in dealing with uncertainty within the realm of environmental sciences. As we delve further into the literature review, our goal is to verify the effectiveness of fuzzy models in comparison to other methodologies. By doing so, we aspire to contribute not only to the theoretical understanding of FIS but also to its practical applications. In other words, the study seeks not only to fill the identified research gap but also to provide actionable insights for researchers, practitioners and policymakers in the field. This may unlock a new era where the unique strengths of FIS become a cornerstone in addressing the uncertainties inherent in environmental monitoring and assessment.

In the next section, 'Advancing understanding of FIS', the main concepts and principles of fuzzy theory are addressed, aiming to contribute for the better understanding of its theoretical background, particularly in addressing uncertainty, and providing transparent and interpretable models. 'Comparative analysis in practical applications' section showcases a review of the most reliable, relevant, and up-to-date related works. As final remarks, 'Actionable insights for practitioners and policymakers' section forward-looking approach aims to bridge the identified gap between theoretical understanding and practical applications.

Advancing understanding of fuzzy logic

In recent decades, FIS has undergone significant advancements, with extensive research showcasing its potency as a tool for intelligent decision-making (Wu and Zeshui, 2021). Fundamentally, FIS operates on the principle of capturing and managing uncertainty in data, allowing for a more nuanced representation of complex real-world phenomena.

At the heart of FIS, the introduction of linguistic variables is a pivotal concept that transforms the way we perceive and interact with uncertain information (Tavana and Hajipour, 2020). Unlike classic logic, which relies on binary distinctions—something is either true or false—FIS acknowledges the shades of gray inherent in real-world situations. Linguistic variables provide a formalized mechanism for expressing and manipulating these shades of meaning. A linguistic variable is a parameter whose values are words or sentences in a natural language. Instead of using crisp numerical values, FIS employs linguistic values that encompass a range of values within the variable's domain (Figure 1).

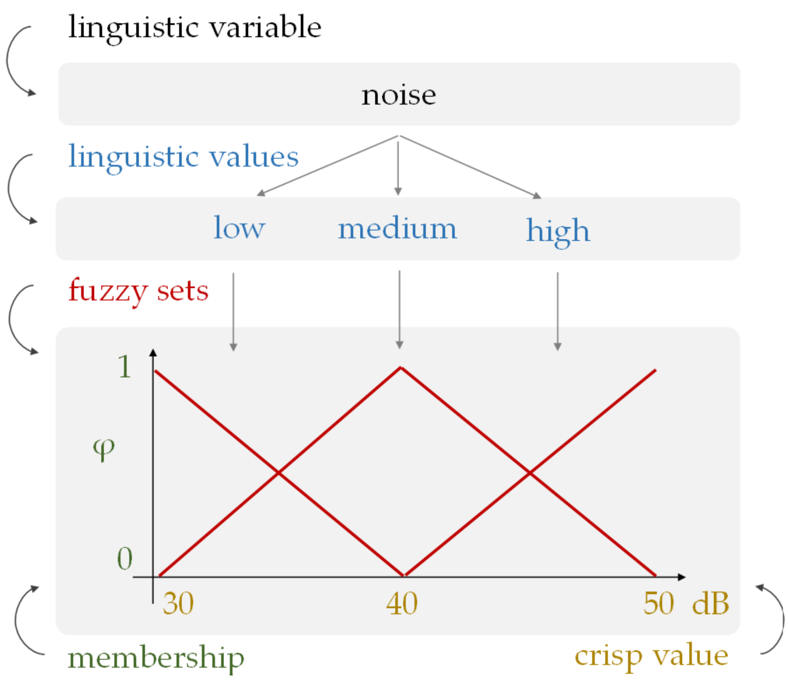

Figure 1. Fundamental concepts of fuzzy set theory.

Let's take an example in the context of environmental monitoring and assessment, considering as a linguistic variable the "noise pollution." In classical logic, you might categorize it as a binary valence or even multiple intervals, but always based on hard thresholds. However, the real-world experience of soundscape is more nuanced. Using FIS, this variable could include linguistic values to better capture the subjective nature of acoustic perception. For instance, in this fuzzy approach, the comfort level in a building, "noise pollution" might have values like: "low": [20, 40] dB; "medium": [30, 50] dB; and "high": [40, 60] dB. Each term is associated with a membership function (MF) that assigns degrees of membership (φ) to the concept modeled by a fuzzy set. Considering a specific noise level, for instance 48 dB, due to the soft boundaries and overlapping intervals, this value can exhibit membership in more than one linguistic value. In this case, the noise level of 48 dB might has 0.4 membership in "medium" and 0.6 in "high" fuzzy sets. This overlapping region signifies a zone of uncertainty, where a crisp value can pertain to more than one linguistic value, reflecting the inherent ambiguity or imprecision often present in real-world scenarios (Asmus et al., 2021). This characteristic of FIS allows for a more nuanced representation of uncertainty, making it a valuable tool for handling complex and uncertain information in environmental sciences (Figure 2).

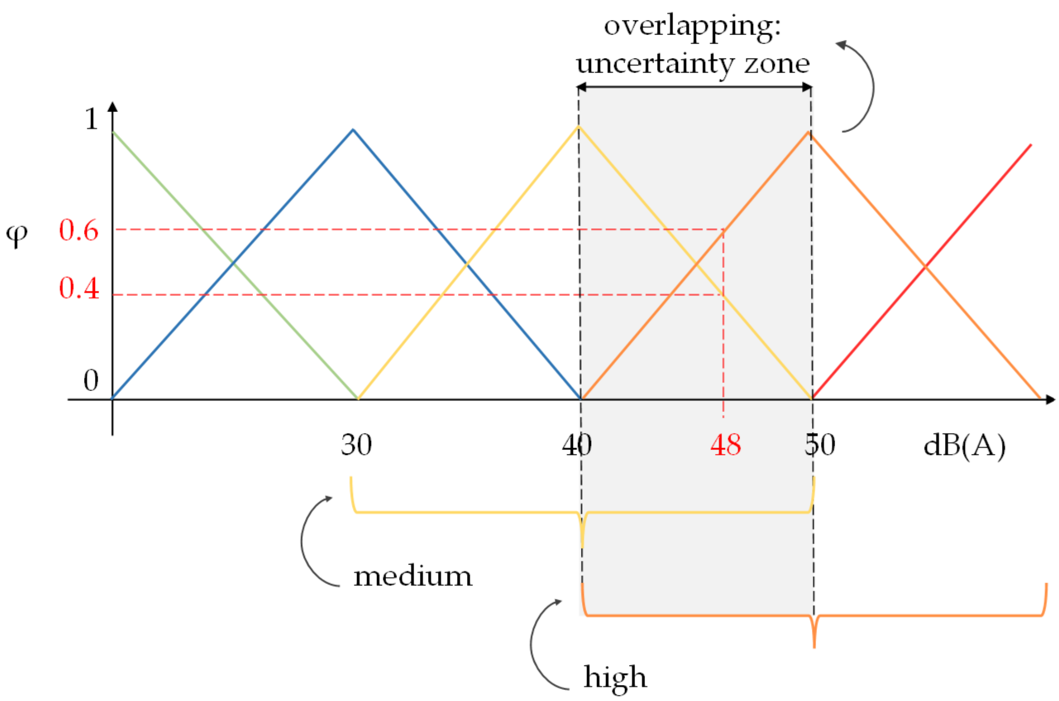

Figure 2. Fuzzy overlapping region between linguistic values.

As discussed above, fuzzy sets extend traditional binary set theory to handle partial membership, acknowledging that elements can belong to a set to varying degrees due to the soft boundaries (Bhardwaj and Sharma, 2021). This flexibility aligns with the inherent uncertainties present in data, where the boundaries between categories are often blurred.

Addressing uncertainty is a key aspect of the FIS theoretical framework. Unlike classical AI models that deal in absolutes, FIS thrives in the domain of partial truths or degrees of certainty (Goswami and Purkayastha, 2020). The introduction of MF allows for the representation of uncertainty in a quantitative manner, enabling a more realistic modeling of model parameters. Thus the fuzzy functions help model the uncertainty inherent in many real-world systems. Choosing the appropriate MF shape for modeling a variable (x_i) depends on the nature of the variables being modeled and the desired representation of uncertainty (Jain and Sharma, 2020). Each shape has its strengths and is better suited to different cases, providing a versatile toolkit for FIS applications (Figure 3). Some common shapes of MF include:

- crisp (type-0 fuzzy): a clear-cut, yes-or-no determination of membership; it does not allow for intermediate values between 0 (not member) and 1 (member);

- singleton: assigns a full membership to a specific value; it represents absolute certainty that an element either belongs or does not belong to a fuzzy set.

- triangular: suitable for situations where the transition from non-membership to full membership is relatively abrupt;

- trapezoidal: offers a more gradual rise and fall compared to triangular functions, suitable for situations with a smoother transition;

- gaussian: useful for modeling situations where the degree of membership decreases symmetrically from the peak;

- sigmoidal (S-shaped): suitable for situations where the transition from non-membership to full membership is smooth but not necessarily symmetric;

- generalized bell: offers flexibility in shaping the curve to match specific system characteristics; and

- laplacian: suitable for situations where one aims to model phenomena that exhibit characteristics of symmetry and rapid transition between states.

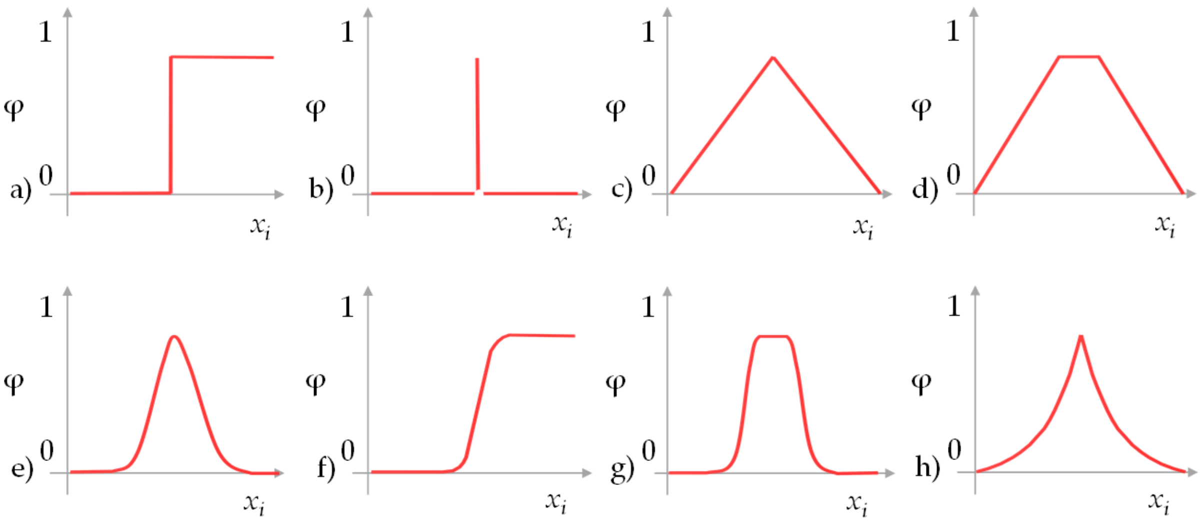

Figure 3. Common fuzzy membership functions: a) crisp; b) singleton, c) triangular; d) trapezoidal; e) gaussian; f) sigmoidal; g) generalized bell; and h) laplacian.

MFs play a central role in quantifying the degree of membership or belonging of an element to a fuzzy set. These functions define how much an element possesses the characteristics represented by a fuzzy set. The introduction of MFs is fundamental because it enables a nuanced representation of uncertainty, a key aspect in addressing the complexities of decision-making (Figure 4).

As the field advanced, different types of FIS emerged, each catering to varying levels of uncertainty (Mohammadzadeh et al., 2019). Understanding their distinctions provides insights into choosing the most suitable type for specific applications. Let us delve into the fundamental distinctions among these types:

- type-0: classical logic with crisp membership functions, limited capability to handle uncertainties, typically applied in straightforward and well-defined systems;

- type-1: an extension with more expressive power, and improved ability to handle uncertainties, commonly used in various fields due to enhanced flexibility;

- type-2: MF themselves have degrees of uncertainty, suitable for complex systems with high levels of uncertainties;

- type-3: advanced capability to address evolving uncertainties, required by highly dynamic and adaptive systems where uncertainties change over time.

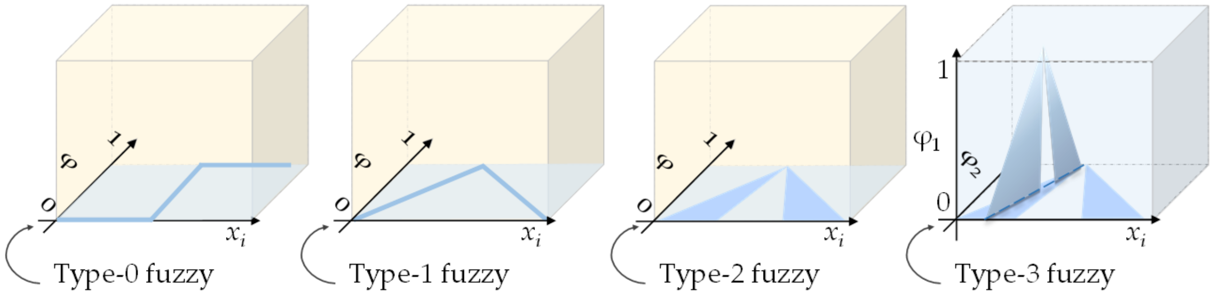

Figure 4. Comparison of types of fuzzy sets.

Transparency and interpretability are inherent strengths of FIS. Unlike complex black-box models such as neural networks (Buhrmester et al., 2021), FIS provides clear insights into the inference process. Stakeholders, including policymakers and practitioners, benefit significantly from this interpretability, gaining a deeper understanding of the rationale behind the system's outputs.

In DSS, the mechanism of fuzzy inference emulates the human reasoning process by capturing the essence of how experts make decisions. It commonly relies on a set of rules that relate input to output variables, following a structured format (Adilova, 2020). Overall, a FIS address (Figure 5):

- fuzzy implication: defines how conditions in the rule base imply conclusions; while classical implication uses connectors like "if... then," fuzzy implication deals with degrees of certainty;

- fuzzy aggregation: combines conclusions derived from various rules to produce a single output; in classical logic, operators like "AND" and "OR" are equivalent, but in fuzzy inference system, these operators have more flexible interpretations; and

- fuzzy composition: relates the contribution of different input variables to the final conclusion; in contrast to classical composition, fuzzy composition allows the overlap of fuzzy sets.

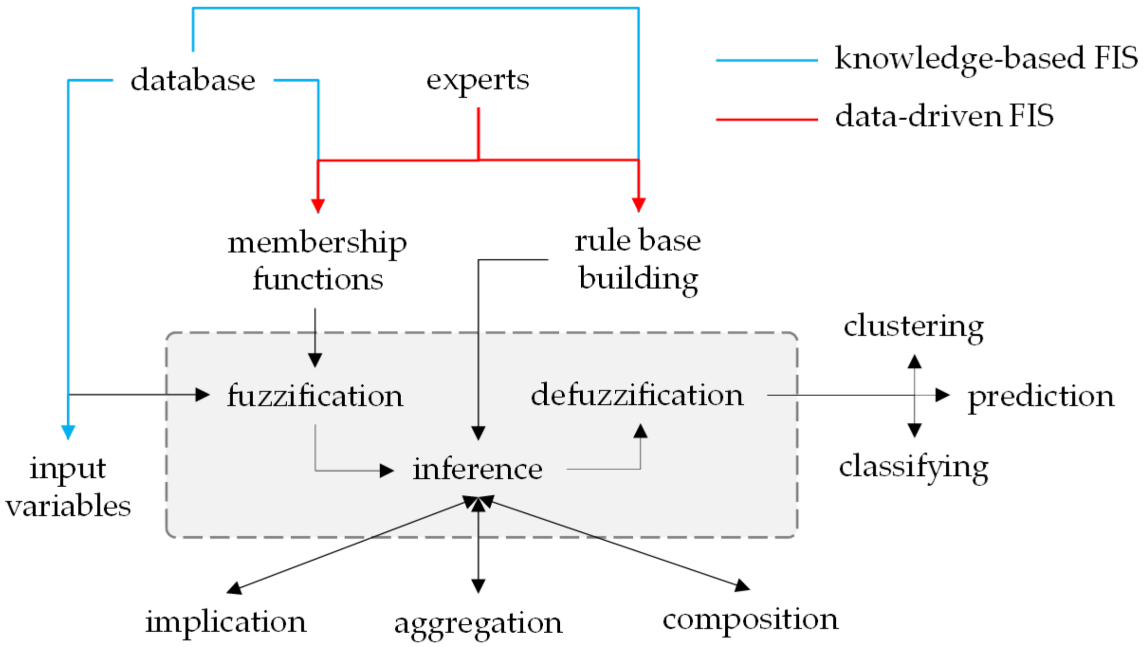

Figure 5. Main components and mechanisms of a FIS.

While FIS exhibit notable strengths in handling uncertainty and providing transparent decision-making processes, they are not without limitations when compared to other ML methods (Özer et al., 2020). One significant drawback is their sensitivity to the quality and quantity of input data. FIS may struggle when faced with sparse or noisy datasets, impacting the accuracy and reliability of their predictions. Furthermore, the performance of FIS is highly dependent on the appropriate selection of linguistic variables and membership functions, posing a challenge in situations where determining the optimal fuzzy sets is non-trivial.

This section sought to provide an overview of FIS and its main features relevant for dealing with uncertainty. Its ability to deal with nuances of uncertain information, coupled with transparent models, opens avenues for more informed choices. Considering uncertainty in decision models can lead to more resilient and adaptive systems for environmental monitoring and assessment.

Comparative analysis in practical applications

To search for related works, the Science Direct database were used, the world's leading source for scientific and medical research, in which the following query was applied: title-abs-key (“environmental science” or “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”)). Thus, 216 articles were found and preliminarily screened. After excluding those outside the scope, 28 works that compared fuzzy AI with other methodologies in environmental applications have been selected and discussed below.

While the investigation primarily centered on studies incorporating fuzzy-based methodologies among the evaluated alternatives, it is noteworthy that ANN-based methods constituted the predominant majority. Collectively, the reviewed studies encompassed the comparison of 35 AI methods (Figure 6), with only rooted in fuzzy logic (FIS-based), 5 in decision trees (TREE-based), 15 grounded in neural networks (ANN-based), 2 relying on hybrid methods (H-based), and the remaining 7 constituting miscellaneous methods (MM-based).

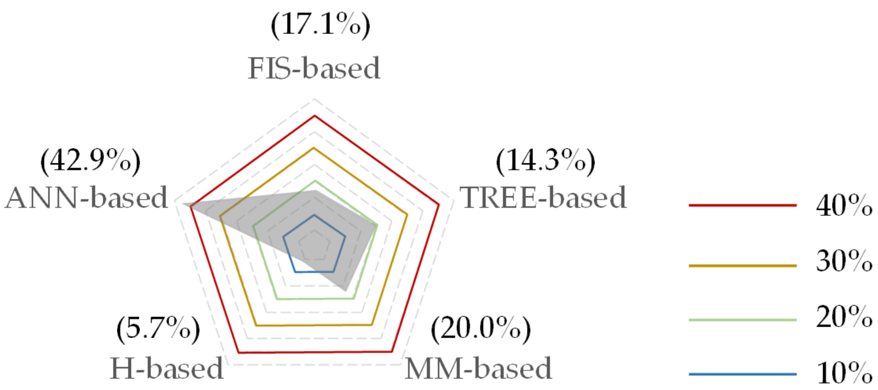

Figure 6. Artificial intelligence methods across the reviewed studies.

Recognizing the inherent uncertainties in climatic conditions, Goyal et al. (2014) aimed to address the challenges associated with 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 (ANFIS). The comparative analysis shed light on the performance of these models, revealing that both 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 techniques when dealing with the uncertainties inherent in subtropical climates.

The relevance of addressing the complexity in COD concentration predictions motivated Ay and Kisi (2014) to explore advanced methods to enhance the modeling of chemical oxygen demand (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. (2014) 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 (TiO2) 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. (2014) used ANN and neuro-fuzzy (NF)models to predict NOx concentration in the air considering other parameters. The study revealed that the NF model proved to be more compatible to measure 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. (2014) applied AI 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 AI models and present reliable results.

Piotrowski et al. (2015) 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. (2015), ANNs, 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 techniques 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 (Estalaki et al., 2016). 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. (2016) developed an RBF model, interfaced with the proposed hybrid fuzzy clustering-ranking 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.

Groundwater quality assessment has its issues due to the inherent uncertainties in measures and analysis, but AI techniques have proven useful regarding these issues. Therefore, Vadiati et al. (2016) developed a Mamdani fuzzy inference system approach to assess groundwater quality. Besides, to present generalized hybrid fuzzy indices, well-known groundwater quality indexes were selected. The results showed that hybrid indices revealed more accurate assessments compared to standard indices and others.

Nadiri et al. (2017) 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. (2017) 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. (2018) 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 artificial intelligence methodologies, ANN and ANFIS was carried out by Nabavi-Pelesaraei et al. (2018), 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 nuanced 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. 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 (2018) 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. (2018) 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. (2018). 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. (2019) 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. (2019), 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 streamflows for upstream and downstream locations, respectively. The capacity to handle uncertainty, a characteristic inherent in fuzzy logic-based models, certainly played a crucial role in ANFIS-PSO superior performance in this modeling daily.

Kaabi et al. (2019) 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 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 coefficient of determination (R^2) for 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. (2020) 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 the 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 climatic context.

Ly et al. (2021) aimed to explore various machine learning techniques 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. (2022). 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 algorithms (GA), could further enhance the accuracy of the models.

Kılıç and Topuz (2023) aimed to estimate the concentration of potentially toxic elements (PTE) 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 emphasize the efficacy of FLRA in providing accurate estimations 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. (2023a) 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 (Poly-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. (2023) 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 performance 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. (2023b) 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. (2023) aimed to develop a smart DSS for the monitoring, prediction, and control of water consumption in power plants (PPs) utilizing AI 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 AI 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 AI methods in comparative analyses within environmental applications (ANFIS, C5, CCNN, DL-ANN, DT, ELM, ELM-NN, FA-ANFIS, FFNN, FLRA, FSC, GEP, GRNN, K-MLP, KNN, LFL, LM-ANN, LR, LS-SVR, M5, MARS, MFL, MLP, MLR, PNN, POLY-NN, RBF, RF, RT, SCFL, SFL, SGB, SICM, SVM, WNN). Fuzzy-based models demonstrated equal performance or outperformed other methods in 22 out of the 28 reviewed studies (78.6%), followed by SVM (10.7%), ANNs (7.1%), and MMs (3.6%) (Figure 7). 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.

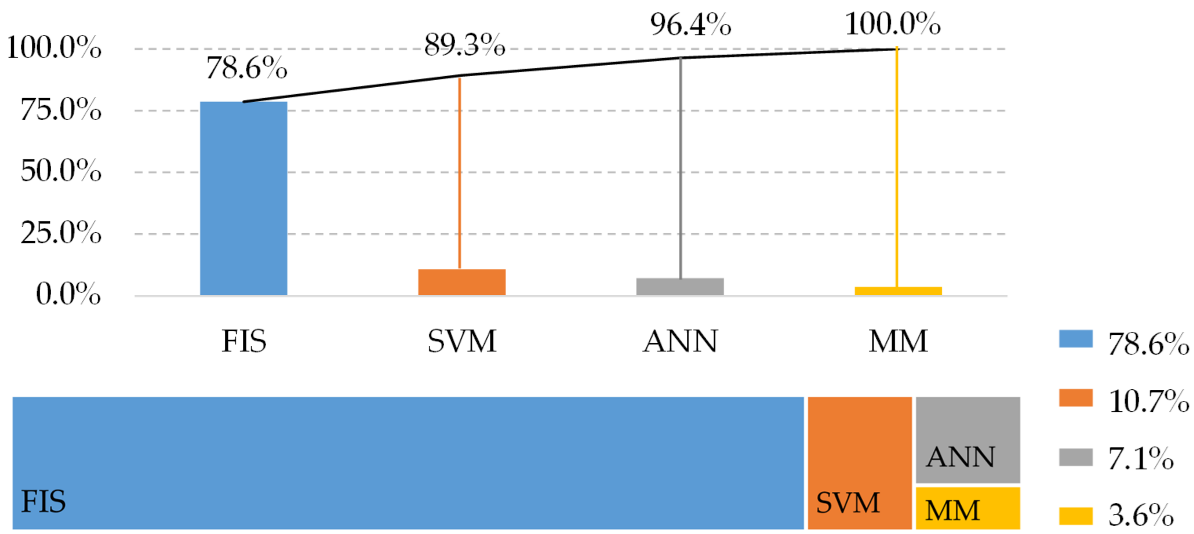

Figure 7. AI methods performance across the reviewed studies.

On the other hand, while FIS 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 AI alternatives. As highlighted by Gibert et al. (2018), the versatility of fuzzy models in handling uncertain information makes them well-suited for environmental data science. Therefore, while FIS 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.

Actionable insights for practitioners and policymakers

The theoretical underpinnings of FIS offer a robust framework for addressing uncertainty in complex systems, as demonstrated by its successful application in various environmental modeling scenarios. From water quality dynamics to tree species identification and drought prediction, FIS has consistently exhibited its ability to handle nuanced, imprecise, and dynamic information. The incorporation of linguistic variables, membership functions, and fuzzy inference mechanisms provides a means to represent and process uncertainty, making FIS a valuable tool for environmental monitoring and assessment in diverse fields.

Practically, FIS presents actionable insights for practitioners and policymakers in several ways. Firstly, the transparency and interpretability of FIS stands out as a distinct advantage. Unlike black-box models such as neural networks, FIS provides clear insights into the decision-making process. This transparency is crucial for stakeholders, including policymakers, to gain a deeper understanding of the rationale behind the system's outputs. Moreover, the adaptability of FIS to different scenarios and its ability to handle uncertainty make it suitable for real-world applications where data is often imprecise or incomplete. The hybrid fuzzy models, as demonstrated in predicting compressive strength in geopolymers and groundwater quality assessment, showcase the flexibility of FIS in combining the strengths of different models for improved accuracy.

For policymakers, the reliability of FIS in predicting environmental impacts, water quality indices, and drought patterns can inform more informed decision-making. The ability of FIS to capture and quantify uncertainty provides a valuable tool for risk assessment and management. The application of FIS in sustainable groundwater resource management, considering economic, environmental, and political aspects, underscores its potential in guiding policies toward socio-optimal and sustainable outcomes.

In conclusion, the hypothesis regarding the effectiveness of FIS is substantiated by the majority of the reviewed studies. The synergy between theoretical foundations and practical applications positions FIS as a powerful ally for practitioners and policymakers grappling with the complexities of environmental monitoring and assessment. The nuanced representation of uncertainty, transparency, and consistent performance across diverse scenarios make FIS a valuable asset in bridging the gap between theoretical understanding and actionable insights in real-world applications. As the environmental challenges become more intricate, FIS emerges as a reliable compass for navigating uncertainty and making decisions that resonate with the intricacies of the natural world.

References

Adnan, R. M., Liang, Z., Trajkovic, S., Zounemat-Kermani, M., Li, B., & Kisi, O. (2019). Daily streamflow prediction using optimally pruned extreme learning machine. Journal of Hydrology, 577, 123981.

Aghbashlo, M., Hosseinpour, S., Tabatabaei, M., Dadak, A., Younesi, H., & Najafpour, G. (2016). Multi-objective exergetic optimization of continuous photo-biohydrogen production process using a novel hybrid fuzzy clustering-ranking approach coupled with RBF neural network. International Journal of Hydrogen Energy, 41(41), 18418-18430.

Alizadeh, M. R., Nikoo, M. R., & Rakhshandehroo, G. R. (2017). Hydro-environmental management of groundwater resources: a fuzzy-based multi-objective compromise approach. Journal of Hydrology, 551, 540-554.

Altieri, A. (2022). Glassy features and complex dynamics in ecological systems. arXiv preprint arXiv:2208.14956.

Asadi, S., Hassan, M., Nadiri, A., & Dylla, H. (2014). Artificial intelligence modeling to evaluate field performance of photocatalytic asphalt pavement for ambient air purification. Environmental Science and Pollution Research, 21, 8847-8857.

Asmus, T., Sanz, J. A., Dimuro, G. P., Bedregal, B., Fernández, J., & Bustince, H. (2021). N-Dimensional admissibly ordered interval-valued overlap functions and its influence in interval-valued fuzzy-rule-based classification systems. IEEE Transactions on Fuzzy Systems, 30(4), 1060-1072.

Ay, M., & Kisi, O. (2014). Modelling of chemical oxygen demand by using ANNs, ANFIS and k-means clustering techniques. Journal of Hydrology, 511, 279-289.

Ayala, H. V. H., Habineza, D., Rakotondrabe, M., & dos Santos Coelho, L. (2020). Nonlinear black-box system identification through coevolutionary algorithms and radial basis function artificial neural networks. Applied Soft Computing, 87, 105990.

Bagheri, M., Bazvand, A., & Ehteshami, M. (2017). Application of artificial intelligence for the management of landfill leachate penetration into groundwater, and assessment of its environmental impacts. Journal of Cleaner Production, 149, 784-796.

Bhardwaj, N., & Sharma, P. (2021). An advanced uncertainty measure using fuzzy soft sets: Application to decision-making problems. Big Data Mining and Analytics, 4(2), 94-103.

Bressane, A., Fengler, F. H., Roveda, S. R. M. M., Roveda, J. A. F., & Martins, A. C. G. (2018). Arboreal identification supported by fuzzy modeling for trunk texture recognition. Trends in Computational and Applied Mathematics, 19, 111-125.

Bressane, A., Gomes, I. G., da Rosa, G. C. S., Brandelik, C. C. M., Silva, M. B., Siminski, A., & Negri, R. G. (2023b). Computer-aided classification of successional stage in subtropical Atlantic Forest: A proposal based on fuzzy artificial intelligence. Environmental Monitoring and Assessment, 195(1), 184.

Bressane, A., Goulart, A. P. G., Melo, C. P., Gomes, I. G., Loureiro, A. I. S., Negri, R. G., ... & Thomé, R. F. (2023a). A Non-Hybrid Data-Driven Fuzzy Inference System for Coagulant Dosage in Drinking Water Treatment Plant: Machine-Learning for Accurate Real-Time Prediction. Water, 15(6), 1126.

Cheng, J. C., Chen, W., Chen, K., & Wang, Q. (2020). Data-driven predictive maintenance planning framework for MEP components based on BIM and IoT using machine learning algorithms. Automation in Construction, 112, 103087.

Choubin, B., Darabi, H., Rahmati, O., Sajedi-Hosseini, F., & Kløve, B. (2018). River suspended sediment modelling using the CART model: A comparative study of machine learning techniques. Science of the Total Environment, 615, 272-281.

Choubin, B., Malekian, A., Samadi, S., Khalighi-Sigaroodi, S., & Sajedi-Hosseini, F. (2017). An ensemble forecast of semi-arid rainfall using large-scale climate predictors. Meteorological Applications, 24(3), 376-386.

Dou, X., & Yang, Y. (2018). Evapotranspiration estimation using four different machine learning approaches in different terrestrial ecosystems. Computers and Electronics in Agriculture, 148, 95-106.

Estalaki, S. M., Kerachian, R., & Nikoo, M. R. (2016). Developing water quality management policies for the Chitgar urban lake: application of fuzzy social choice and evidential reasoning methods. Environmental Earth Sciences, 75, 1-16.

Geary, W. L., Bode, M., Doherty, T. S., Fulton, E. A., Nimmo, D. G., Tulloch, A. I., ... & Ritchie, E. G. (2020). A guide to ecosystem models and their environmental applications. Nature Ecology & Evolution, 4(11), 1459-1471.

Gibert, K., Horsburgh, J. S., Athanasiadis, I. N., & Holmes, G. (2018). Environmental data science. Environmental Modelling & Software, 106, 4-12.

Goswami, M., & Purkayastha, B. S. (2020). A Fuzzy Based Approach for Empirical Analysis of Unstructured Data. Journal of Computational and Theoretical Nanoscience, 17(9-10), 4375-4379.

Goyal, M. K., Bharti, B., Quilty, J., Adamowski, J., & Pandey, A. (2014). Modeling of daily pan evaporation in sub tropical climates using ANN, LS-SVR, Fuzzy inference system, and ANFIS. Expert systems with applications, 41(11), 5267-5276.

He, Z., Wen, X., Liu, H., & Du, J. (2014). A comparative study of artificial neural network, adaptive neuro fuzzy inference system and support vector machine for forecasting river flow in the semiarid mountain region. Journal of Hydrology, 509, 379-386.

Jain, A., & Sharma, A. (2020). Membership function formulation methods for fuzzy inference system systems: A comprehensive review. Journal of Critical Reviews, 7(19), 8717-8733.

Kaab, A., Sharifi, M., Mobli, H., Nabavi-Pelesaraei, A., & Chau, K. W. (2019). Combined life cycle assessment and artificial intelligence for prediction of output energy and environmental impacts of sugarcane production. Science of the Total Environment, 664, 1005-1019.

Kahraman, C., & Gündogdu, F. K. (2021). Decision making with spherical fuzzy sets. Studies in fuzziness and soft computing, 392, 3-25.

Kalibatienė, D., & Miliauskaitė, J. (2021). A hybrid systematic review approach on complexity issues in data-driven fuzzy inference systems development. Informatica, 32(1), 85-118.

Kılıç, K., & Topuz, D. (2023). The evaluation of potentially toxic elements using artificial neural networks and fuzzy linear regression analysis methods in cappadocian volcanic ash soils of Turkey. Heliyon, 9(9).

Ly, Q. V., Nguyen, X. C., Lê, N. C., Truong, T. D., Hoang, T. H. T., Park, T. J., ... & Hur, J. (2021). Application of Machine Learning for eutrophication analysis and algal bloom prediction in an urban river: A 10-year study of the Han River, South Korea. Science of The Total Environment, 797, 149040.

Makhazhanova, U. T., Murzin, F. A., Mukhanova, A. A., & Abramov, E. P. (2020). Fuzzy inference system of Zadeh and decision-making in the field of loan. Journal of theoretical and applied Information Technology, 98(06), 1076-1086.

Manzar, M. S., Benaafi, M., Costache, R., Alagha, O., Mu'azu, N. D., Zubair, M., ... & Abba, S. I. (2022). New generation neurocomputing learning coupled with a hybrid neuro-fuzzy model for quantifying water quality index variable: A case study from Saudi Arabia. Ecological Informatics, 70, 101696.

Nabavi-Pelesaraei, A., Rafiee, S., Mohtasebi, S. S., Hosseinzadeh-Bandbafha, H., & Chau, K. W. (2018). Integration of artificial intelligence methods and life cycle assessment to predict energy output and environmental impacts of paddy production. Science of the total environment, 631, 1279-1294.

Nadiri, A. A., Gharekhani, M., Khatibi, R., & Moghaddam, A. A. (2017). Assessment of groundwater vulnerability using supervised committee to combine fuzzy inference system models. Environmental Science and Pollution Research, 24, 8562-8577.

Nadiri, A. A., Shokri, S., Tsai, F. T. C., & Moghaddam, A. A. (2018). Prediction of effluent quality parameters of a wastewater treatment plant using a supervised committee fuzzy inference system model. Journal of cleaner production, 180, 539-549.

Nakhaei, M., Ahmadi, A., Gheibi, M., Chahkandi, B., Hajiaghaei-Keshteli, M., & Behzadian, K. (2023). A Smart Sustainable Decision Support System for Water Management oF Power Plants in Water Stress Regions. Expert Systems with Applications, 120752.

Olyaie, E., Banejad, H., Chau, K. W., & Melesse, A. M. (2015). A comparison of various artificial intelligence approaches performance for estimating suspended sediment load of river systems: a case study in United States. Environmental monitoring and assessment, 187, 1-22.

Oyounalsoud, M. S., Abdallah, M., Yilmaz, A. G., Siddique, M., & Atabay, S. (2023). A new meteorological drought index based on fuzzy inference system: Development and comparative assessment with conventional drought indices. Journal of Hydrology, 619, 129306.

Özer, T. A. L. O., YAVUZ, E., & ÇOŞKUN, H. (2020). On the statistical limits of strongly measurable fuzzy valued functions. Konuralp Journal of Mathematics, 8(1), 62-69.

Piotrowski, A. P., Napiorkowski, M. J., Napiorkowski, J. J., & Osuch, M. (2015). Comparing various artificial neural network types for water temperature prediction in rivers. Journal of Hydrology, 529, 302-315.

Raei, E., Alizadeh, M. R., Nikoo, M. R., & Adamowski, J. (2019). Multi-objective decision-making for green infrastructure planning (LID-BMPs) in urban storm water management under uncertainty. Journal of Hydrology, 579, 124091.

Roy, D. K., Barzegar, R., Quilty, J., & Adamowski, J. (2020). Using ensembles of adaptive neuro-fuzzy inference system and optimization algorithms to predict reference evapotranspiration in subtropical climatic zones. Journal of Hydrology, 591, 125509.

Tavana, M., & Hajipour, V. (2020). A practical review and taxonomy of fuzzy expert systems: methods and applications. Benchmarking: An International Journal, 27(1), 81-136.

Tayfur, G., Nadiri, A. A., & Moghaddam, A. A. (2014). Supervised intelligent committee machine method for hydraulic conductivity estimation. Water resources management, 28, 1173-1184.

Vadiati, M., Asghari-Moghaddam, A., Nakhaei, M., Adamowski, J., & Akbarzadeh, A. H. (2016). A fuzzy-logic based decision-making approach for identification of groundwater quality based on groundwater quality indices. Journal of Environmental Management, 184, 255-270.

Weigand, T. M., Farthing, M. W., & Miller, C. T. (2023). Groundwater Models. In Oxford Research Encyclopedia of Environmental Science.

Wu, H., & Zeshui, X. U. (2021). Fuzzy inference system in decision support: Methods, applications and future trends. International Journal of Computers Communications & Control, 16(1).

Yue, W., Cai, Y., Rong, Q., Li, C., & Ren, L. (2014). A hybrid life-cycle and fuzzy-set-pair analyses approach for comprehensively evaluating impacts of industrial wastewater under uncertainty. Journal of Cleaner Production, 80, 57-68.

3. CONSIDERAÇÕES GERAIS

Os fundamentos teóricos da lógica fuzzy oferecem uma estrutura robusta para lidar com a incerteza em sistemas complexos, evidenciada por sua aplicação bem-sucedida em diversos cenários de modelagem ambiental. Da dinâmica da qualidade da água à identificação de espécies de árvores e previsão de secas, a FL consistentemente demonstra sua capacidade de lidar com informações matizadas, imprecisas e dinâmicas. A incorporação de variáveis linguísticas, funções de pertinência e mecanismos de inferência fuzzy oferece um meio de representar e processar a incerteza, tornando a FL uma ferramenta valiosa para a tomada de decisões em diversos campos.

Na prática, os modelos FL apresentam insights acionáveis para profissionais e formuladores de políticas de várias maneiras. Em primeiro lugar, a transparência e interpretabilidade dos modelos FL destacam-se como uma vantagem distinta. Ao contrário de modelos de caixa-preta como redes neurais, a FL fornece insights claros sobre o processo de tomada de decisões. Essa transparência é crucial para que partes interessadas, incluindo formuladores de políticas, compreendam melhor a lógica por trás das saídas do sistema. Além disso, a adaptabilidade da FL a diferentes cenários e sua capacidade de lidar com a incerteza a tornam adequada para aplicações do mundo real, onde os dados muitas vezes são imprecisos ou incompletos. Os modelos híbridos fuzzy, como demonstrado na previsão da resistência à compressão em geopolímeros e avaliação da qualidade da água subterrânea, mostram a flexibilidade da FL ao combinar as vantagens de diferentes modelos para uma precisão aprimorada.

Para os formuladores de políticas, a confiabilidade dos modelos FL na previsão de impactos ambientais, índices de qualidade da água e padrões de seca pode informar uma tomada de decisão mais fundamentada. A capacidade da FL de capturar e quantificar a incerteza oferece uma ferramenta valiosa para avaliação e gestão de riscos. A aplicação da FL na gestão sustentável de recursos hídricos subterrâneos, considerando aspectos econômicos, ambientais e políticos, destaca seu potencial em orientar políticas para resultados socioeconômicos e sustentáveis.

Em conclusão, a sinergia entre os fundamentos teóricos e as aplicações práticas posiciona a FL como uma aliada poderosa para profissionais e formuladores de políticas que lidam com as complexidades da tomada de decisões ambientais. A representação matizada da incerteza, a transparência e o desempenho consistente em diversos cenários fazem da FL um ativo valioso para preencher a lacuna entre a compreensão teórica e insights acionáveis em aplicações do mundo real. À medida que os desafios ambientais se tornam mais intrincados, a FL surge como uma bússola confiável para navegar na incerteza e tomar decisões que ressoam com as complexidades do mundo natural.

4. REFERÊNCIAS

ALTIERI, A. Glassy features and complex dynamics in ecological systems. arXiv preprint arXiv:2208.14956, 2022.

AYALA, H. V. H. et al. Nonlinear black-box system identification through coevolutionary algorithms and radial basis function artificial neural networks. Applied Soft Computing, v. 87, p. 105990, 2020.

CHENG, J. C. P. et al. Data-driven predictive maintenance planning framework for MEP components based on BIM and IoT using machine learning algorithms. Automation in Construction, v. 112, p. 103087, 2020.

GEARY, W. L. et al. A guide to ecosystem models and their environmental applications. Nature Ecology & Evolution, v. 4, n. 11, p. 1459-1471, 2020.

KAHRAMAN, C.; GÜNDOGDU, F. K. Decision making with spherical fuzzy sets. Studies in fuzziness and soft computing, v. 392, p. 3-25, 2021.

KALIBATIENĖ, D.; MILIAUSKAITĖ, J. A hybrid systematic review approach on complexity issues in data-driven fuzzy inference systems development. Informatica, v. 32, p. 85-118, 2021.

MAKHAZHANOVA, Ulzhan T. et al. Fuzzy logic of Zadeh and decision-making in the field of loan. Journal of theoretical and applied Information Technology, v. 98, p. 1076-1086, 2020.

WEIGAND, Timothy M.; FARTHING, Matthew W.; MILLER, Casey T. Groundwater Models. In: Oxford Research Encyclopedia of Environmental Science. 2023.