Fuzzy-based criteria for groundwater quality classification of selected rural areas in North-West Province, South Africa

Oluwakayode Samuel Oyedokun[1], and Olanrewaju Bola Wojuola[1]
[1]Department of Physics, North-West University, Mahikeng, South Africa
E-mail: olu.oyedokun@nwu.ac.za

Abstract: Groundwater is a major source of freshwater in rural and peri-urban communities in the developing world. In this study, a fuzzy logic method based on the concept of fuzzy set theory was investigated for assessing the physicochemical properties of groundwater for drinking purposes. The application of fuzzy-based criteria was demonstrated using limits prescribed by the South African National Standards (SANS) for water quality. Both deterministic and fuzzy logic methods were applied to forty-two groundwater samples collected from rural communities in the North-West Province of South Africa. Ten key parameters including total hardness (TH), calcium (Ca^{2+}), magnesium (Mg^{2+}), electrical conductivity (EC), pH, iron (Fe^{2+}), chloride (Cl^-), sulphate (SO_4^{2-}), fluoride (F^-), and nitrate (NO_3^-) were selected for their significant influence on groundwater quality. Water quality classes were expressed using four linguistic terms often used by experts: “excellent,” “good,” “fair,” and “unacceptable.” The fuzzy logic classification yielded 31% of samples as “unacceptable”, 0% as “fair”, 50% as “good”, and 19% as “excellent”, with associated degrees of certainty ranging from 25% to 80%. The findings clearly indicate that the existing classification criteria fail to provide the necessary degree of overlapping definitions required for effective fuzzy logic model implementation.

Keywords: Water quality, Membership function, Fuzzy rule, Degree of certainty, Classification

1. Introduction

Groundwater quality for drinking purposes is as important as its availability. Even after using standard sampling techniques and analysis for monitoring water quality, the final decision based on this data is an essential step, as uncertainties are inherent at every stage. The prescribed limits for various quality indicators in drinking water are proposed by both local and international organizations, like the South African National Standards (SANS) and the World Health Organization [1, 2]. These regulatory limits contain uncertainties, as these are extrapolated values from localized studies [3, 4]. Information on the condition and regional trends in water quality is necessary to evaluate suitable guidelines, quality assessment, and adoption of prescribed limits by relevant regulatory bodies. The literature presents various methods for evaluating drinking water quality and classification [1, 4]. Nonetheless, most studies adopt a deterministic framework, in which water quality parameters are assessed solely by comparing their measured values with some standards established by regulatory authorities. Such an approach fails to account for the inherent uncertainties present at different stages of the evaluation process, potentially limiting the reliability and robustness of the resulting decisions [4, 5]. Among the various approaches developed over the past few decades, the Water Quality Index (WQI) has emerged as one of the most widely applied methods for assessing water quality. However, this approach has notable limitations, as certain parameters within the index equations can disproportionately influence the overall decision, often without sufficient scientific justification. Consequently, there is a need for more advanced classification methods capable of accommodating these uncertainties when evaluating drinking water quality.

Water quality experts typically classify water as “desirable”, “acceptable”, and “unacceptable” based on guideline values established by various regulatory bodies [3]. However, in borderline cases, making a clear decision becomes challenging due to the multiple sources of uncertainty inherent in the process. Such uncertainties may arise at different stages, including sampling and analysis, selection of quality criteria, and imprecision in the final decision output values. Therefore, the monitored data and regulatory limits should not be treated as crisp sets but rather as fuzzy sets that can better account for inherent variability and imprecision. Few studies have proposed that fuzzy set-based approaches be utilized to manage the uncertainties associated with drinking water quality assessment [3, 6, 7]. Considering the critical importance of uncertainty handling in evaluating drinking water quality, and the proven flexibility of fuzzy set theory in supporting decisions under imprecise conditions, this study applies a fuzzy classification approach to assess groundwater quality for drinking purposes in rural communities of the North-West Province, South Africa.

1.1 Fuzzy set theory

Fuzzy set theory is particularly well-suited for decision-making in complex systems where the problem context is often unclear or imprecise. It is commonly employed to handle uncertain or vague information in a non-probabilistic manner, enabling the integration of multiple parameters into modelling and evaluation processes. The concept of fuzzy sets, which describes imprecision and vagueness, was first introduced by Zadeh [8] and has since been widely applied in decision-making and evaluation across various fields under uncertain conditions [9, 10]. Fuzzy set theory can be regarded as a generalization of classical set theory. In classical set theory, the membership function of a set takes the value 1 for elements within the set and 0 for elements outside it. By contrast, a fuzzy set is defined by a membership function that maps elements from the domain of interest, such as concentration measurements, onto a continuous interval between 0 and 1. The shape of the membership function curve reflects the degree to which a specific value belongs to a given set, thereby providing a weighting that captures partial membership. Mathematically, the membership function of a fuzzy set A, defined over a domain X, is expressed as:

$$\mu_A : X \rightarrow [0, 1] \tag{1}$$

The set A is defined in terms of its membership function by

$$\mu_A : \begin{Bmatrix} 1 & x \textit{ is full member of } A \\ \epsilon(0,1) & x \textit{ is partial member of } A \\ 0 & x \textit{ is not member of } A \end{Bmatrix} \tag{2}$$

For a set to be considered a fuzzy set, its membership function μ_A must satisfy specific conditions to ensure that classical set operations such as complement, union, and intersection are consistently extended to fuzzy sets.

$$Excellent : \mu_{pH} = \begin{Bmatrix} 0, & if\ x \leq 6.3 \\ \frac{x - 6.3}{6.5 - 6.3}, & if\ x\ \epsilon\ [6.3, 6.5) \\ 1.0, & if\ x\ \epsilon\ (6.5, 7.5) \\ \frac{7.8 - x}{7.8 - 7.5}, & if\ x\ \epsilon\ (7.5, 7.8] \\ 0, & if\ x \geq 7.8 \end{Bmatrix} \tag{3}$$

$$Good : \mu_{pH} = \begin{Bmatrix} 0, & if\ x \leq 5.9 \\ \frac{x - 5.9}{6.0 - 5.9}, & if\ x\ \epsilon\ [5.9, 6.0) \\ 1.0, & if\ x\ \epsilon\ (6.0, 6.4) \\ \frac{6.5 - x}{6.5 - 6.4}, & if\ x\ \epsilon\ (6.5, 6.4) \\ 0, & if\ x = 6.5 \\ \frac{x - 7.5}{7.7 - 7.5}, & if\ x\ \epsilon(7.5, 7.7) \\ 1.0, & if\ x = (7.7, 8.3) \\ \frac{8.5 - x}{8.5 - 8.3}, & if\ x\ \epsilon\ (8.3, 8.5] \\ 0, & if\ x \geq 8.5 \end{Bmatrix} \tag{4}$$

$$Fair : \mu_{pH} = \begin{Bmatrix} 0, & if\ x \leq 5.5 \\ \frac{x - 5.5}{5.6 - 5.5}, & if\ x\ \epsilon\ [5.5, 5.6) \\ 1.0, & if\ x\ \epsilon\ (5.6, 5.9) \\ \frac{6.0 - x}{6.0 - 5.9}, & if\ x\ \epsilon\ (5.9, 6.0) \\ 0, & if\ x\ \epsilon\ (6.0, 8.0) \\ \frac{x - 8.3}{8.5 - 8.3}, & if\ x\ \epsilon\ (8.3, 8.5) \\ 1.0, & if\ x\ \epsilon\ (8.5, 9.5) \\ \frac{9.7 - x}{9.7 - 9.5}, & if\ x\ \epsilon\ (9.5, 9.7] \\ 0, & if\ x \geq 9.7 \end{Bmatrix} \tag{5}$$

$$Unacceptable : \mu_{pH} = \begin{Bmatrix} 1.0, & if\ x < 5.5 \\ 0, & if\ x > 5.5 \\ 1.0, & if\ x > 9.7 \end{Bmatrix} \tag{6}$$

The membership function can be normalized by dividing it by its maximum value so that it attains a value of one at least once within the domain X. The use of fuzzy numbers, along with the aggregation of fuzzy sets, has been proposed as an effective technique for managing uncertainties in decision-making related to environmental quality criteria [11, 12]. The complete analytical procedure for the fuzzy logic evaluation model includes regulatory criteria and classification, selection of water quality parameters, fuzzification of water quality parameters, fuzzy relationship matrix, rule-based creation, defuzzification, and performance evaluation [3].

2. Data Analysis

A total of 42 groundwater samples were collected during the study conducted by Masindi and Foteinis [1] from different locations in the rural areas of North-West Province, following standard sampling protocols. These groundwater sources are primarily used for drinking purposes. The samples were analysed for 13 physicochemical water quality parameters in accordance with standard analytical procedures. Initial water quality decisions were made using a deterministic approach based on guideline values prescribed by South African National Standards (SANS) and the classification values proposed by Masindi and Foteinis [1]. In this approach, each parameter was evaluated independently, resulting in separate classifications. The same classification values were used in the fuzzy logic model to evaluate groundwater quality for drinking purposes. The most significant determinants of drinking water quality from the 13 analysed parameters, including pH, electrical conductivity (EC), total hardness (TH), chloride (Cl^-), calcium (Ca^{2+}), iron (Fe^{2+}), magnesium (Mg^{2+}), sulphate (SO_4^{2-}), fluoride (F^-), and nitrate (NO_3^-), were considered [3]. In the fuzzy logic approach, these 10 parameters were grouped into four categories described as drinking water limit (group A), aesthetic limit (group B), fluoride, and nitrate in line with rural groundwater quality conditions, and to reduce computational complexity. Specifically, pH, Fe^{2+}, Cl^-, and SO_4^{2-} were classified as the first group, EC, TH, Ca^{2+}, and Mg^{2+} formed the second group, F^- and NO_3^- were treated as separate parameters due to their critical significance in drinking water quality criteria. Fuzzy membership functions were developed for all 10 selected parameters using the trapezoidal membership function, representing possible concentration of a water quality parameter onto degrees of membership ranging from 0 to 1 (Eqns. 1-2). The transformation of water quality parameters into linguistic terms such as "excellent", "good", "fair", and "unacceptable" is illustrated with the pH parameter defined by Eqns. (3) – (6). The input parameters in each group, and the combination of the groups with fluoride and nitrate were incorporated into the Mamdani fuzzy logic model for groundwater quality classification.

In a fuzzy rule-based system, expert knowledge on the classification of an object, in this case, water quality parameters, is expressed in the form of IF–THEN rules. Each rule consists of a set of antecedent propositions that include attribute names, such as pH, EC, TH, Ca^{2+}, Mg^{2+}, Cl^-, SO_4^{2-}, F^-, and NO_3^-, along with their corresponding attribute values or linguistic descriptors such as "excellent", "good", "fair", or "unacceptable". These linguistic descriptions are inherently imprecise, reflecting both the limited understanding of the individual and the combined health impacts of these parameters on rural communities. This linguistic fuzzy logic model was employed, where both the antecedent and consequent components are expressed as fuzzy propositions. A computational framework for fuzzy logic in MATLAB version 2021b was utilized to estimate the relationship between the consequent and the antecedent parts of the rules. This approach enables the drinking water quality to be described in a fuzzy manner, with an associated degree of certainty.

In this study, a total of 80 fuzzy rules formulated based on domain knowledge of drinking water quality were applied using the Mamdani inference approach with the max–min operator to evaluate groundwater quality [12]. Representative rules developed based on the domain knowledge were designed for the groups and their combination with fluoride, and nitrate. A sample rule from the 24 rules created for the physicochemical parameters in group A is presented below.

Rule 1: If pH is "excellent"; iron is "fair"; chloride is "good"; sulphate is "good"; Then: groundwater sample quality is "good" for drinking purposes.

For the second group, a representative rule from the 16 rules formulated for drinking water quality classification is presented below.

Rule 1: If TH is "excellent"; calcium is "fair"; magnesium is "good"; EC is "good"; Then: groundwater sample quality is "good" for drinking purposes.

The outputs from groups A and B were subsequently combined with the other two parameters to derive the final water quality classification. In total, 40 fuzzy rules were applied within the fuzzy logic system, integrating the results of the first and second groups with fluoride, and nitrate. A representative rule encompassing the two groups, and the two parameters is presented below.

Rule 1: If group A is "fair"; group B is "good"; fluoride is "fair"; nitrate is "good"; Then: groundwater sample quality is "fair" for drinking purposes.

3. Results

In the deterministic approach, the physicochemical quality of drinking water was assessed by directly comparing the measured concentrations of the 10 selected parameters with the prescribed threshold values. Deterministic assessment of drinking water quality, based on measured values compared to prescribed limits set by organizations such as WHO or SANS, typically yields results expressed in linguistic terms such as "excellent", "good", "fair", or "unacceptable" as shown in Table 2. Similarly, in the Water Quality Index (WQI) approach, the overall water quality may still be classified as "excellent" even if some critical parameters have been assigned little or no weight, potentially masking important risk factors [5].

Physicochemical parameters	SANS limits	Excellent	Good	Fair	Unacceptable
pH	5.5 - 9.7	7	6 or 8	5 or 9	<5 or >10
EC (mS/m)	170	85	127.5	170	>170
Total Hardness (mg/l)	300	150	225	300	>300
Magnesium, Mg^{2+} (mg/l)	100	50	75	100	>100
Calcium, Ca^{2+} (mg/l)	300	150	225	300	>300
Iron, Fe^{2+} (µg/L)	2000	1000	1500	2000	>2000
Chloride, Cl^-, (mg/l)	300	150	225	300	>300
Fluoride, F^- (mg/l)	1.5	0.75	1.125	1.5	>1.5
Sulphate, SO_4^{2-} (mg/l)	500	250	375	500	>500
Nitrate, NO_3^- (mg/l)	11	5.5	8.25	11	>11

Table 1. The limits prescribed by South African National Standards and their proposed classification by Masindi and Foteinis [1]

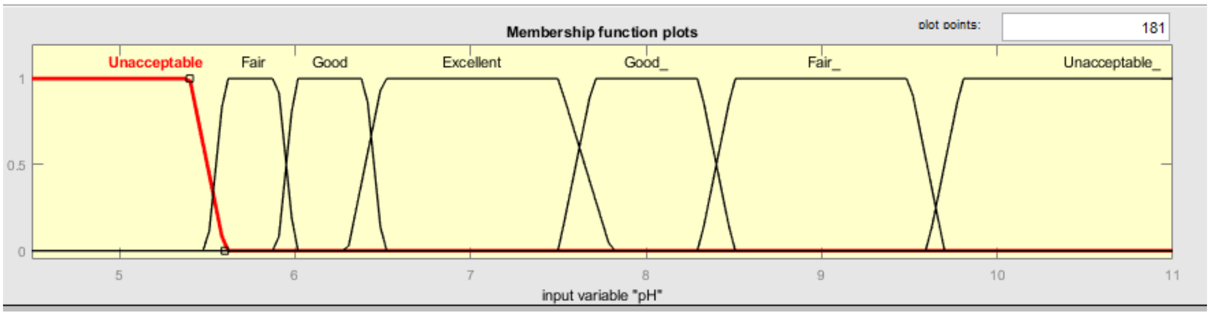

Fig. 1. Trapezoidal membership function of pH parameter with four quality categories

Decision using deterministic method				Decision using FL
Excellent	Good	Fair	Unacceptable	
1.TH; Ca^{2+}; Mg^{2+}; EC; pH; Fe^{2+}; Cl^-; SO_4^{2-}; F^-			NO_3^-	Unacceptable (38)
2. Ca^{2+}; Mg^{2+}; EC; Fe^{2+}; Cl^-; SO_4^{2-}; F^-	TH; pH		NO_3^-	Unacceptable (38)
3. Ca^{2+}; Mg^{2+}; EC; pH; Fe^{2+}; Cl^-; SO_4^{2-};	NO_3^-	TH	F^-	Unacceptable (38)
4. Ca^{2+}; Mg^{2+}; EC; pH; Fe^{2+}; Cl^-; SO_4^{2-}; F^-	TH		NO_3^-	Unacceptable (38)
5. TH; Ca^{2+}; Mg^{2+}; EC; pH; Fe^{2+}; Cl^-; SO_4^{2-}; F^-			NO_3^-	Unacceptable (38)
6. Ca^{2+}; Mg^{2+}; EC; pH; Fe^{2+}; Cl^-; SO_4^{2-}; F^-;	TH		NO_3^-	Unacceptable (38)
7. Ca^{2+}; Mg^{2+}; pH, Fe^{2+}; F^-	SO_4^{2-}	TH	EC; Cl^-; NO_3^-	Good (67)
8. Ca^{2+}; Fe^{2+}; F^-	pH	Cl^-	TH; Mg^{2+}; EC; SO_4^{2-}; NO_3^-	Good (67)
9. Ca^{2+}; Mg^{2+}; EC; pH; Fe^{2+}; Cl^-; SO_4^{2-}; F^-; NO_3^-	TH			Excellent (72)
10. Ca^{2+}; Mg^{2+}; EC; Fe^{2+}; Cl^-; SO_4^{2-}; F^-	pH		TH; NO_3^-	Good (67)
11. Ca^{2+}; Mg^{2+}; EC; Fe^{2+}; Cl^-; SO_4^{2-}; F^-; NO_3^-	TH, pH			Excellent (72)
12. Ca^{2+}; Mg^{2+}; EC; pH; Fe^{2+}; Cl^-; SO_4^{2-}; F^-	TH		NO_3^-	Unacceptable (38)
13. Ca^{2+}; Fe^{2+}; Cl^-; SO_4^{2-}; F^-	EC; pH	Mg^{2+}	TH; NO_3^-	Good (67)
14. Ca^{2+}; Mg^{2+}; EC; Fe^{2+}; Cl^-; SO_4^{2-}; F^-; NO_3^-		TH; pH		Good (25)
15. TH; Ca^{2+}; Mg^{2+}; EC; pH; Fe^{2+}; Cl^-; SO_4^{2-}; F^-; NO_3^-				Excellent (80)
16. Ca^{2+}; Mg^{2+}; EC; Fe^{2+}; Cl^-; SO_4^{2-}; F^-	TH; pH	NO_3^-		Good (51)
17. TH; Ca^{2+}; Mg^{2+}; EC; Fe^{2+}; Cl^-; SO_4^{2-}, F^-	pH	NO_3^-		Good (51)
18. Ca^{2+}; Mg^{2+}; pH; Fe^{2+}; SO_4^{2-}; F^-; NO_3^-	EC; Cl^-	TH		Excellent (72)
19. Ca^{2+}; Mg^{2+}; EC; pH; Fe^{2+}; Cl^-; SO_4^{2-}; F^-			TH; NO_3^-	Good (67)
20. Ca^{2+}; Mg^{2+}; pH; Fe^{2+}; Cl^-; SO_4^{2-}	EC		TH; F^-; NO_3^-	Good (67)
21. Ca^{2+}; pH; Fe^{2+}; SO_4^{2-}	Mg^{2+}	F^-	TH; EC; Cl^-; NO_3^-	Good (67)

22. Ca^{2+}; Mg^{2+}; EC; pH; Fe^{2+}; Cl^-; SO_4^{2-}	TH	NO_3^-	F^-	Good (67)
23. Ca^{2+}; pH; Fe^{2+}; SO_4^{2-}	Mg^{2+}; F^-	Cl^-	TH; EC; NO_3^-	Good (67)
24. Ca^{2+}; Mg^{2+}; pH; Fe^{2+}; Cl^-; SO_4^{2-}	F^-	EC	TH; NO_3^-	Good (67)
25. Ca^{2+}; Mg^{2+}; Fe^{2+}; Cl^-; SO_4^{2-}; NO_3^-	EC; pH		F^-; TH	Good (67)
26. Ca^{2+}; Mg^{2+}; pH; Fe^{2+}; SO_4^{2-}	F^-		TH; EC; Cl^-; NO_3^-	Good (67)
27. Ca^{2+}; Mg^{2+}; pH; Fe^{2+}; Cl^-; SO_4^{2-}	EC	F^-	TH; NO_3^-	Good (67)
28. Ca^{2+}; Mg^{2+}; EC; pH; Fe^{2+}; Cl^-; SO_4^{2-}	TH		F^-; NO_3^-	Unacceptable (38)
29. TH; Ca^{2+}; Mg^{2+}; EC; Fe^{2+}; Cl^-; SO_4^{2-}; NO_3^-	pH		F^-	Unacceptable (38)
30.TH; Ca^{2+}; Mg^{2+}; EC; pH; Fe^{2+}; Cl^-; SO_4^{2-}		F^-	NO_3^-	Good (67)
31. Ca^{2+}; Mg^{2+}; EC; pH; Fe^{2+}; Cl^-; SO_4^{2-}; NO_3^-	TH		F^-	Unacceptable (38)
32. TH; Ca^{2+}; Mg^{2+}; EC; pH; Fe^{2+}; Cl^-; SO_4^{2-}	F^-; NO_3^-			Good (67)
33. TH; Ca^{2+}; Mg^{2+}; EC; Fe^{2+}; Cl^-; SO_4^{2-}; NO_3^-	pH		F^-	Unacceptable (38)
34. TH; Ca^{2+}; Mg^{2+}; EC; pH; Fe^{2+}; Cl^-; SO_4^{2-}; NO_3^-			F^-	Unacceptable (38)
35. Ca^{2+}; Fe^{2+}; Cl^-; SO_4^{2-}; F^-	Mg^{2+}; EC; pH		TH; NO_3^-	Good (67)
36. pH; Fe^{2+}; SO_4^{2-}	Ca^{2+}	Mg^{2+}; F^-	TH; EC; Cl^-; NO_3^-	Unacceptable (38)
37. TH; Ca^{2+}; Mg^{2+}; EC; Fe^{2+}; Cl^-; SO_4^{2-}; F^-	pH		NO_3^-	Good (67)
38. TH; Ca^{2+}; Mg^{2+}; EC; pH; Fe^{2+}; Cl^-; SO_4^{2-}, F^-; NO_3^-				Excellent (72)
39. TH; Ca^{2+}; Mg^{2+}; EC; Fe^{2+}; Cl^-; SO_4^{2-}; F^-; NO_3^-	pH			Excellent (72)
40. TH; Ca^{2+}; Mg^{2+}; EC; pH; Fe^{2+}; Cl^-; SO_4^{2-}; F^-	NO_3^-			Good (67)
41. TH; Ca^{2+}; Mg^{2+}; EC; Fe^{2+}; Cl^-; SO_4^{2-}; F^-; NO_3^-	pH			Excellent (72)
42. TH; Ca^{2+}; Mg^{2+}; EC; pH; Fe^{2+}; Cl^-; SO_4^{2-}; F^-; NO_3^-				Excellent (72)

Table 2. Comparison of groundwater quality classification by deterministic and fuzzy logic approach

Fluoride was considered one of the most critical parameters, because its concentration exceeds 1.5 mg/l recommended by SANS in drinking water which can lead to severe health impacts, including skeletal and dental fluorosis [3]. Accordingly, an exclusive fuzzy rule was defined such that any sample with a fluoride concentration above 1.5 mg/l would be classified as “unacceptable.” However, the degree of certainty for this classification was further refined based on the consideration of other parameters. In the Mamdani max–min inference system, the minimum membership value from each rule is first determined using the fuzzy “min” operator, subsequently, the maximum value from this set of minimums is selected, representing the degree of belongingness of the water sample to a specific quality category [3]. In this study, the mean of maxima defuzzification method was employed. Based on this approach, the results of all 42 groundwater samples were evaluated and are presented in Table 2. The fuzzy logic method proved particularly valuable for samples with parameter values falling within the safety margin. In such cases, uncertainty plays a critical role in decision-making, as the likelihood of decision errors increases when values are near threshold limits.

A comparison between the decisions derived from the fuzzy logic model and those obtained through deterministic evaluation is presented in Table 2. The results indicate that the water quality of sample 15 is classified as “excellent” with the highest certainty level of 80%, followed by 7 other samples with a certainty level of 72%. For example, in the case of borehole sample 15 evaluated using the deterministic approach, all parameters (TH, Ca^{2+}, Mg^{2+}, EC, pH, Fe^{2+}, Cl^-, SO_4^{2-}, F^-, NO_3^-) were classified as excellent, for borehole sample 18, seven parameters (Ca^{2+}; Mg^{2+}; pH; Fe^{2+}; SO_4^{2-}; F^-; NO_3^-) were classified as excellent, two parameters (EC and Cl^-) were placed in the good category, while total hardness fell into the fair category. Such a fragmented decision regarding drinking water quality often provides an ambiguous picture, even for scientists and engineers, and becomes even more challenging when this information must be communicated to the general population.

The drawback in the implementation of the proposed classification values by Masindi and Foteinis [1] into fuzzy logic model illustrated in Fig. 1. In all the categories, which include “excellent”, “good”, “fair”, and “unacceptable”, there exists a strong overlap between “excellent” and “good” categories, whereas a little overlap exists between the “fair” and “unacceptable” categories. In the same vein, the remaining 9 parameters (EC, TH, Mg^{2+}, Ca^{2+}, Fe^{2+}, Cl^-, F^-, SO_4^{2-}, and NO_3^-) in Table 1 shows no clear distinction between these two categories; hence, the fuzzy logic model places the two categories exclusively within the “unacceptable” range.

4. Conclusion

In this paper, groundwater quality in rural areas of South Africa was comprehensively examined using the deterministic and fuzzy logic approach, which helped in overcoming certain limitations associated with conventional approach used for groundwater quality indexing. The Fuzzy logic classification with certainty level to each linguistic term, makes the classification more informative and reliable. Decisions expressed as linguistic categories accompanied by certainty levels are far more convincing and easier to communicate, particularly to the general populace. Given the multiple sources of uncertainty involved at various stages of water quality decision-making, the fuzzy logic method provides a more robust and realistic representation of water quality. This study highlights the reliability and robustness of fuzzy logic models in handling risk assessment problems involving uncertainties, imprecision, overlapping boundaries and the need for appropriate classification criteria for fuzzy model implementation.

References

[1] V. Masindi and S. Foteinis, "Groundwater contamination in sub-Saharan Africa: Implications for groundwater protection in developing countries," *Cleaner Engineering and Technology,* vol. 2, p. 100038, 2021.

[2] WHO, *Guidelines for drinking-water quality: incorporating the first and second addenda*. World Health Organization, 2022.

[3] S. Dahiya, B. Singh, S. Gaur, V. Garg, and H. Kushwaha, "Analysis of groundwater quality using fuzzy synthetic evaluation," *Journal of Hazardous Materials,* vol. 147, no. 3, pp. 938-946, 2007.

[4] A. Enitan-Folami, N. Mutileni, J. Odiyo, F. Swalaha, and J. Edokpayi, "Hydrochemical, bacteriological assessment, and classification of groundwater quality in Thulamela Municipality, South Africa: potential health risk," *Human and ecological risk assessment: an international journal,* vol. 26, no. 8, pp. 2044-2058, 2020.

[5] M. Magagula, E. Atangana, and P. Oberholster, "Assessment of the impact of coal mining on water resources in Middelburg, Mpumalanga Province, South Africa: Using different water quality indices," *Hydrology,* vol. 11, no. 8, p. 113, 2024.

[6] M. Vadiati, A. Asghari-Moghaddam, M. Nakhaei, J. Adamowski, and A. Akbarzadeh, "A fuzzy-logic based decision-making approach for identification of groundwater quality based on groundwater quality indices," *Journal of Environmental Management,* vol. 184, pp. 255-270, 2016.

[7] T. Abbasi and S. A. Abbasi, *Water quality indices*. Elsevier, 2012.

[8] L. A. Zadeh, "Toward a theory of fuzzy information granulation and its centrality in human reasoning and fuzzy logic," *Fuzzy sets and systems,* vol. 90, no. 2, pp. 111-127, 1997.

[9] W. Z. Chmielowski, *Fuzzy Control in environmental engineering*. Springer, 2016.

[10] B. E. Fisher, "Fuzzy approaches to environmental decisions: application to air quality," *Environmental Science & Policy,* vol. 9, no. 1, pp. 22-31, 2006.

[11] G. Klir and B. Yuan, *Fuzzy sets and fuzzy logic*. Prentice hall New Jersey, 1995.

[12] E. H. Mamdani, "Advances in the linguistic synthesis of fuzzy controllers," *International Journal of Man-Machine Studies,* vol. 8, no. 6, pp. 669-678, 1976.