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Towards Adaptive Water Quality Indexing: Integrating Fuzzy Logic for Improved Contaminant Detection and Treatment Planning

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Abstract **-** Water quality management is increasingly challenged by the compounded effects of climate change and the rise of contaminants of emerging concerns such as pharmaceutical residues, microplastics, Personal care products and other anthropogenic activities, which traditional treatment systems struggle to address efficiently. As such, monitoring and assessing water resources becomes mandatory not only to trace the levels and effects of such pollutants in water systems but also to estimate the actual cost of treating the water under varying contamination scenarios. Effective evaluation of water quality indicators is essential to determine the suitability of water for various human and ecological needs. Water Quality Indexing is an accepted method used to synthesise complex water quality data into a single representative value. Water quality index (WQI) models are essential to measure pollution levels and guide assessments of the impairment of specific water resources. However, prevalent WQI tools are typically site-specific and cannot be applied to rivers in locations separate from where they were developed, unless in cases where such rivers share similar physical characteristics, pollutant profiles, and water quality parameters. This limits their adaptability across regions with distinct hydrological conditions and land-use practices. Further, a significant limitation is the inability of the current index interpretation to identify and isolate "rogue" pollutants responsible for the negative scoring of the water quality. They also do not provide estimates of the cost associated with treating specific contaminants, aside from generic treatment costs. In response to these limitations, this paper proposes developing an adaptive and interpretable WQI framework based on fuzzy logic theory. The model offers improved accuracy and context and aligns treatment cost estimates with water quality status, enabling more efficient budget planning and resource allocation in water management systems.

Keywords**:** Water Quality Index (WQI); Fuzzy Logic Approach; Emerging Water Pollutants; Water Treatment Cost Estimation; Adaptive Water Resource Management.

1. Introduction

South Africa faces chronic water stress, with future projections estimating less than 1000 cubic meters of water available per person each year [1]. The country's freshwater resources suffer from numerous challenges, including climate variability, agricultural runoff, mining discharges, land use changes, industrial waste, growing human settlements, and the influx of emerging pollutants like pharmaceutical residues, microplastics, and endocrine disruptors [2] and [3]. Water treatment technologies are often not designed to handle these emerging contaminants, leading to bioaccumulation in aquatic ecosystems [4]. Consequently, determining the suitability of water for use must go beyond traditional chemical and microbial assessments.

Water Quality Indexing (WQI) has become a widely used tool for transforming complex water quality datasets into a single, interpretable score [2], [5] and [6]. However, most WQI models are rigid; they assume linear relationships and offer little insight into specific contaminants' source or relative toxicity. As noted by [6], these traditional indices lack spatial adaptability and contextual distinction [7]. Numerous researchers [8], [9], [10] and [11] have used artificial neural network (ANN) to analyse water quality conditions. ANN typically comprises one input layer, one or more hidden layers and an output layer, with neurons in each layer arranged/connected in parallel. This layered ANN architecture supports feedforward and backpropagation processes. Most modern ANN models also support weight updates, regularisation, batching, shuffling, evaluation, and skip layers processes [8], [9] and [10]. Studies by [6] [7], [8] and [9] used the Broyden-Fletcher-Goldfarb-Shanno (BFGS) algorithm to perform backpropagation training and channel weight optimisation. However, the choice of techniques and accuracy in operation depend on the operating system and the quantity and quality of available data [12] and [13].

Fuzzy inference systems that consider different criteria and local conditions for regions has been developed to simplify and predict the quality of water bodies [14]. Fuzzy logic methods use heuristic if–then rules to model relationships between input and output variables, but they lack a systematic procedure for defining model parameters, which are typically based on expert knowledge [15]. To this end, this study proposes the use of an adaptive neuro-fuzzy inference system (ANFIS) for predicting water quality in river systems in South Africa with an integrated costing framework and investigates its utility in a global context.

ANFIS improves upon basic fuzzy systems by incorporating a neural network that learns from data and adjusts membership functions and rules over time. By mimicking human reasoning, fuzzy logic systems employ linguistic variables and memberships, while Artificial Neural Networks enable them to learn from historical data [16] and [17].

Together, the Adaptive Neuro-Fuzzy Inference System (ANFIS) forms a powerful hybrid approach that can handle nonlinearity, uncertainty, and imprecision [17], all key characteristics of water systems, yielding a robust and adaptable WQI. Furthermore, this approach makes it possible to connect water quality scores directly with treatment cost estimates, adding valuable context to policy and management decisions.

2. Methodology

2.1. Data Acquisition and Preparation

This study draws on two main sources of water quality data. The first is historical data collected by the South African Department of Water and Sanitation between 2006 and 2018. The second includes recent field data gathered during campaigns conducted from 2022 to 2023, which were used to validate and update the dataset. These field campaigns followed a stratified sampling design to account for seasonal variation, with samples collected from 16 monitoring sites along the uMsundusi River in KwaZulu-Natal, Durban. Physicochemical and biological parameters, including nitrate (NO_3), total dissolved solids (TDS), pH, electrical conductivity (EC), and turbidity, were analysed using methods outlined in the Standard Methods for the Examination of Water and Wastewater [18]. Table 1 summarises the minimum and maximum values of the parameters used in this study.

Table 1: Descriptive Statistics of Water Quality Parameters.

Water Quality Parameter	Min (2006-2018)	Max (2006-2018)	SD	Min (2022-2023)	Max (2022-2023)	SD
pH	7.0	8.56	0.40	7.1	8.4	0.55
ORP (mV)	92.5	257.3	41.0	87.4	248.5	50.4
EC (µS/cm)	64	1394	369.7	77	1136.7	262.6
TDS (ppm)	37	754	199.4	39	568.3	131.3
DO (%)	2.20	57	12.7	87.2	102.4	3.9
NO_3 (mg/L)	0.06	19.22	6.9	1.43	3.87	0.71
Turbidity (FNU)	8.46	149.67	33.34	–	<1	–

2.2. Parameter Selection and Weights

Seven key water quality parameters were selected for inclusion in the WQI model based on sensitivity analysis and correlation matrix filtering. These parameters were chosen for their relevance to both conventional and emerging pollutants, as well as their availability in field and historical datasets.

While some frameworks like the British Columbia Water Quality Index (BCWQI) use non-normalised weights to reflect contaminant severity [19], this study adopted a more adaptable approach. Initial weights were assigned to each parameter based on their environmental significance and impact on water usability, then normalised to ensure the final WQI remained on a consistent 0–100 scale. The selected parameters and their respective weights are shown in Table 2.

Table 2: Water Quality Parameters and Weights.

Parameter	Unit	Original Weight	Normalised Weight
DO	% Sat	0.17	0.207
pH	pH	0.16	0.195
EC	µS/cm	0.11	0.134
Temp	°C	0.10	0.122
TDS	ppm	0.10	0.122
NO_3	mg/L	0.10	0.122
Turbidity	FNU	0.08	0.098

This weighting configuration ensures that parameters with greater environmental or health significance, such as dissolved oxygen and pH, carry slightly more influence in the final index. At the same time, it maintains balance with parameters like nitrate and electrical conductivity that serve as indicators of potential wastewater intrusion. The final WQI is designed to be responsive to both regulatory thresholds and real-time monitoring needs. The final WQI score is constrained to a 0–100 scale through sub-index transformation, ensuring consistent interpretation across samples.

2.3. Tables and Figures

The Water Quality Index (WQI) is a composite score. Each sub-index *qi* is calculated as shown in Eqn (1):

$$q_i = 100 \times \left(1 - \frac{V_i}{S_i}\right) \tag{1}$$

qi is the sub-index for the *i-th* parameter, *Vi* is the measured value of the *i-th* parameter, and *Si* is the WHO/South African standard for parameter *i* (e.g., S_{NO3} = 50 mg/L), ensuring comparability across regions

The weight Wi is inversely proportional to Si as shown in Eqn (2)

$$W_i = \frac{1}{S_i} \tag{2}$$

Finally, the composite WQI is computed by Eqn (3)

$$WQI = \sum_{i=1}^{n} (q_i \, , W_i) \tag{3}$$

2.4. Adaptive Neuro-Fuzzy Model (ANFIS)

The Adaptive Neuro-Fuzzy Inference System (ANFIS) used in this study is built on a five-layer feed-forward architecture, designed to combine the strengths of fuzzy logic and neural networks. This hybrid model was developed and fine-tuned using a mix of historical and field-collected water quality data.

To evaluate its performance, the ANFIS was benchmarked against two conventional models: a standard three-layer backpropagation neural network with 15 hidden nodes and a support vector regression model with a radial basis kernel. Compared to these, ANFIS demonstrated an 18% reduction in prediction error with a root mean square error of 4.2 and required 23% fewer training epochs, confirming its efficiency and accuracy. This advantage stems from its hybrid learning approach:

- Layer 1 uses Gaussian membership functions (μ = 0.2 to 0.8) to convert input values into fuzzy categories.
- Layer 2 calculates the firing strength of each fuzzy rule by multiplying the input memberships, effectively measuring how well each rule applies to the input data
- Layer 3 normalises these firing strengths to ensure balanced influence across all rules.

- Layer 4 applies linear functions to each rule's output, using coefficients that are optimised during training to fit the data.
- Layer 5 then converts the fuzzy outputs into a final Water Quality Index score using centroid-based defuzzification.

Throughout the 12-iteration training process, the system automatically adjusted rule weights to improve accuracy. The dataset was split into 70% for training and 30% for testing. Training was carried out using a hybrid algorithm that combines gradient descent, backpropagation, and the least squares method to minimise error and accelerate learning. This approach ensured the model achieved fast convergence while maintaining a strong ability to generalise across unseen data.

2.5 Integration of Treatment Costing Framework

The ANFIS WQI model was extended to include a treatment costing framework, enabling the estimation of the economic implications of different water quality management scenarios. The costing model quantifies the expenses associated with pollution mitigation measures, such as chemical dosages of Aluminium Sulphate, Polymer coagulants, Lime, Sodium hydroxide, and operational costs. The specific adjustments are linked with WQI scores that are based on selected water quality parameters. The treatment cost *C* is computed using Eqn (4)

$$C = \sum_{j=1}^{m} (D_j , P_j) \quad (4)$$

Where: *Dj* is the dosage of treatment chemical *j*, typically expressed in mg/L based on water quality conditions, and *Pj* is the unit cost of chemical *j*, usually in monetary units per kg of the chemicals.

By linking WQI scores directly to estimate treatment costs, the model carries out a scenario-based analysis and weighs each chemical against the score. The chemical dosages are critical in the costing framework, and the model weighs them considering WQI score and key water quality parameters such as turbidity, NO_3 and DO. Thus, this integrated ANFIS-Costing model supports evidence-based decision making in the management of water treatment.

3. Results

3.1 Model Validation

The ANFIS model demonstrated strong predictive capability across both training and testing phases. The residuals were homogenous, and the regression coefficients approached unity, reflecting a strong fit. Quantitative evaluation yielded an R^2 value of 0.93 for the training set (n=247) and 0.89 for the testing set (n=106), indicating high explanatory power. RMSE of 4.2 on the 0 - 100 WQI scale suggests the model's predictions were within ±5% of actual measured values for approximately 89% of the samples. Notably, the model-maintained accuracy even at extreme ends of the index spectrum of WQI<30 and WQI>80, where traditional linear models often underperform due to nonlinear interactions between parameters. The results confirm that the trained ANFIS was able to effectively predict the Water Quality Index with high accuracy. Refer to Table 3 below:

Table 3: Model Performance Benchmarking.

Metric	ANFIS (Proposed)	ANN (3-layer)	SVM (RBF Kernel)
Training R^2	0.93	0.87	0.85
Testing R^2	0.89	0.82	0.79
RMSE (WQI 0-100)	4.2	5.1	5.8
Training Time (min)	18	12	9
Parameter Interactions Captured	92%	73%	68%

3.2 Treatment Costing Framework

The integration of the costing framework demonstrated its utility in optimising resource allocation. For example, a WQI score below 40 (poor quality) required significantly higher treatment costs compared to scores above 60 (good quality). This feature empowers decision-makers to prioritise interventions based on both water quality and financial constraints.

4. Discussion

The results underscore the ability of Adaptive Neuro-Fuzzy techniques to outperform traditional methods in water quality indexing. Importantly, this approach not only produces an accurate index but also highlights which components most affect water quality. Furthermore, by tying this index to treatment cost estimates, water authorities can prioritise resources more efficiently and respond faster to changing conditions.

This adaptability makes the framework valuable in developing regions where water conditions fluctuate and resources for extensive treatment are limited. Importantly, the procedure can be calibrated to reflect local conditions and policy priorities, adding a powerful tool for water authorities to manage their resources effectively. Compared to traditional methods, this approach allows for non-linearity in water components and combines human-like fuzzy rules with powerful neural network training. Enables direct linkage of water quality to treatment cost estimates, a key consideration for policymakers.

5. Conclusion

This study successfully demonstrated the ability of a Fuzzy Logic-Enhanced Water Quality Index framework to integrate multivariate water data into a single, actionable indicator. The Adaptive Neuro-Fuzzy approach, trained and tested against historical and field data, provided robust, accurate and adaptable results. Importantly, this framework assesses water quality and guides treatment decisions by estimating associated treatment costs, which is a crucial consideration for policymakers and water utility managers. Future research should extend this framework to incorporate additional parameters and water bodies, and integrate climate variability and land use controls to reflect changing conditions in a more comprehensive manner.

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