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# Multi-Criteria Evaluation Based on MOORA for Improving Water Treatment Operations

**Gayung Prasasti[1], Eko Darmanto[2], Supriyono[3], Stella Putri Tomya[4]**

[1,2,3,4]Department of Information Systems, Faculty of Engineering, Universitas Muria Kudus, Kudus, Indonesia
Email: [1]202153062@std.umk.ac.id, [2]eko.darmanto@umk.ac.id, [3]supriyono.si@umk.ac.id, [4]stellaptomya@gmail.com

**Abstract**

Access to clean and sustainable drinking water continues to be a significant concern, especially in areas with considerable variability in source quality. This study used the Multi-Objective Optimization on the Basis of Ratio Analysis (MOORA) approach to evaluate and rank 22 drinking water sources in Central Java, Indonesia, according to several physicochemical characteristics. The study process starts with the entry of sub-district, village, time, and laboratory result data, subsequently leading to the establishment of assessment criteria and their corresponding weights. Subsequent to the MOORA computations, rankings are produced and compiled into a detailed report. The results indicate that sources X21, X19, and X18 got the best ratings, signifying excellent water quality conditions, whereas X12 rated lowest, underscoring the necessity for focused action. In contrast to conventional evaluation methods, MOORA provides computational efficiency, clear prioritizing, and less subjectivity, facilitating consistent and reproducible multi-criteria evaluations. The results offer practical suggestions for enhancing water treatment processes, prioritizing resource distribution, and directing future incorporation of Internet of Things (IoT) monitoring for real-time assessment and adaptive management. This method integrates technical evaluation with pragmatic policy formulation, enhancing operational efficiency and promoting long-term sustainability in water delivery systems.

**Keywords**: MOORA, water quality assessment, multi-criteria decision-making, water treatment optimization, IoT integration, resource prioritization

## 1. INTRODUCTION

Access to clean, safe, and sustainable drinking water is vital for protecting public health, promoting economic development, and maintaining environmental integrity. In several global locations, including some areas of Indonesia, maintaining the quality of drinking water is a multifaceted and persistent issue influenced by natural variability, human activities, and limitations within water treatment systems. Conventional evaluation techniques, such as unidimensional evaluations or composite metrics like the Water Quality Index (WQI), have

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historically been employed to encapsulate water quality conditions for policymakers and stakeholders. Although these methods provide useful insights, they frequently neglect to account for the intricate trade-offs among several, and perhaps contradictory, quality measures. Improvements in turbidity levels may coincide with increased nitrate concentrations, necessitating decision-makers to reconcile conflicting health, environmental, and operational factors [1].

The Multi-Objective Optimization based on Ratio Analysis (MOORA) technique provides a systematic, quantitative resolution to these deficiencies. MOORA is acknowledged for its computational simplicity, stability, and flexibility, and has been effectively utilized in many decision-making scenarios, such as engineering design, environmental resource allocation, and water quality management. In contrast to traditional Water Quality Index (WQI) methodologies, MOORA facilitates the simultaneous evaluation of many criteria while maintaining clarity in trade-off analysis, hence allowing for more informed, repeatable, and data-driven prioritizing. This capacity is crucial in situations where subjective weighing techniques may add bias or obscure findings, as MOORA guarantees that rankings are systematic and comprehensible to both technical specialists and non-technical stakeholders [2], [3].

The applications of MOORA in water-related fields have showcased its adaptability and significance in tackling various hydrological issues. In India, it has been employed to prioritize groundwater sources by judiciously considering chemical and physical criteria, hence assuring equal access to clean drinking water across areas with diverse geochemical profiles [4]. The approach has facilitated multi-method evaluations of river water quality, shown by the Mahanadi River, where it amalgamated statistical analysis, water quality indexes, and optimization models to generate comprehensive, multi-faceted rankings [5]. Moreover, MOORA has been modified for the selection of wastewater treatment methods, achieving improved performance through statistical enhancements to the MULTIMOORA framework. The Haraz River in Iran has been employed to inform multi-criteria water quality management techniques that consider hydrological circumstances and socio-economic limitations, offering a complete instrument for sustainable resource control [6], [7].

The urgent requirement for a comprehensive, multi-criteria strategy is apparent in Central Java, Indonesia, where water utilities encounter intricate and evolving quality challenges. Seasonal monsoon rains induce notable turbidity increases, whilst widespread rice cultivation and plantation agriculture result in nutrient and pesticide runoff, compromising source water quality. The variability in elevation and topography further affects the chemical and microbiological characteristics of various sources, resulting in challenges in applying consistent treatment methods. Under these circumstances, conventional evaluation methods frequently neglect

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the interaction among physical, chemical, and biological elements, rendering them less efficient for long-term planning and operational decision-making [8].

MOORA's capacity to amalgamate several, disparate characteristics into a cohesive ranking framework renders it particularly pertinent for this region. By establishing an objective hierarchy of source performance, utilities may discern both the highest-quality sources to prioritize for direct distribution and the most problematic sources for targeted interventions. This guarantees that resources, be they financial, technological, or operational, are allocated effectively, with a clear comprehension of the trade-offs inherent in each action. The method's transparency enhances confidence and responsibility among utilities, regulators, and the communities they serve [9].

This study employed MOORA to assess and rank 22 unique water sources in Central Java, each defined by 22 separate quality indicators encompassing physical, chemical, and microbiological factors. The aim was to create a comprehensive and clear rating system that emphasizes both the highest-performing sources and those needing urgent intervention. The research highlights the relative strengths and limitations of each source, offering practical insights for treatment enhancement, infrastructure investment, and policy formulation [10].

This technique has substantial potential for incorporation into future water management systems, in addition to its immediate practical advantages. In conjunction with real-time monitoring technologies, such as Internet of Things (IoT) sensor networks, MOORA-based evaluations might provide ongoing assessment, early warning systems for contamination incidents, and adaptive treatment methods attuned to fluctuating circumstances. The integration of predictive analytics and metaheuristic optimization methods might augment the model's effectiveness, facilitating long-term strategy planning based on thorough, data-driven assessments [11].

This study's methodology seeks to connect technical evaluation with implementable management methods, therefore bridging the divide between water quality monitoring and efficient operational decision-making. This facilitates a transition towards more transparent, evidence-based, and sustainable water governance in Central Java, with potential relevance to other places with analogous quality and resource allocation issues. This comprehensive, multi-faceted approach signifies a significant advancement in tackling the ongoing and dynamic issues of ensuring safe and dependable drinking water across varied environmental and socio-economic settings [12]-[16].

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## 2. METHODS

The MOORA approach was utilized to assess 22 drinking water samples from diverse service locations under the jurisdiction of a regional water utility in an area with elevation differences ranging from 2 to 624 meters above sea level. Each option denoted a distinct geographic water source or delivery location and was evaluated based on four criteria: Total Dissolved Solids (TDS), temperature, pH, and turbidity. These characteristics were chosen since they are fundamental physicochemical indicators in both WHO and Indonesian national drinking water standards [17], [19], and they directly affect adherence to health rules and operational treatment criteria.

pH and temperature were designated as benefit criteria due to their influence on treatment efficacy, chemical stability, and consumer acceptability [17]. Total Dissolved Solids (TDS) and turbidity were considered cost factors since they indicate the concentration of dissolved solids and suspended particles, hence elevating treatment expenses and operating hazards [19]. The incorporation of temperature is operationally critical in this context, as it affects disinfection efficacy, chlorine residual stability, and consumer acceptance, particularly in tropical climates where seasonal fluctuations and elevation variations can alter water temperature. This parameter selection guarantees that the assessment comprehensively addresses both public health and operational performance factors in a balanced manner, conforming to industry best practices and regulatory standards.

Figure 1 show a flow diagram explaining the research stages of evaluating drinking water quality in Central Java using the MOORA method. The process begins with collecting regional administrative data (sub-districts and villages) as well as technical data (laboratory test results and observation periods) which become system input. The next stage involves determining the assessment criteria (TDS, pH, temperature and turbidity) along with their weighting according to WHO standards and national regulations. The MOORA method is then implemented through three main stages: formation of a decision matrix, data normalization, and calculation of optimization values by considering benefit (pH and temperature) and cost (TDS and turbidity) criteria. The results of the analysis are in the form of water source rankings which are then integrated into the Decision Support System (DSS) to produce operational recommendations. This diagram clearly visualizes the research flow from data collection to decision making, emphasizing a systematic and data-driven approach in evaluating the 22 water sources in the study area. The final results of the study show water sources X21, X19, and X18 as the best, while X12 requires special intervention, providing a scientific basis for more effective water source management.

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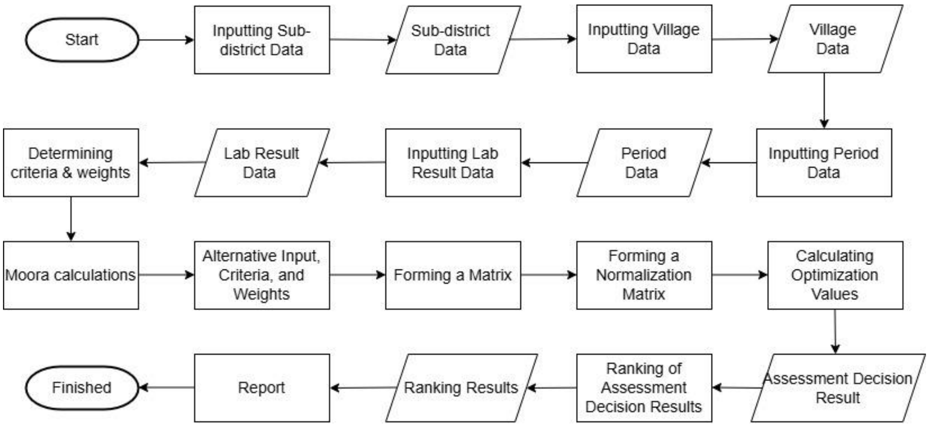

**Figure 1.** Research Diagram

Laboratory analysis adhered to established protocols: pH was assessed with a calibrated digital pH meter, turbidity with a nephelometer, total dissolved solids (TDS) with a conductivity meter, and temperature with a mercury thermometer. The results were organized into an Excel spreadsheet and formatted as the decision matrix input for MOORA analysis.

The first step, Parameter Selection, involved identifying the four criteria described above based on regulatory standards and operational priorities. The second phase, Weight Assignment, allocated weights of 0.30 for pH, 0.15 for temperature, 0.30 for TDS, and 0.25 for turbidity. The baseline weighting was obtained from literature [19] and later modified to align with operational significance in the research region. Alternative weighting methodologies, including expert opinion, entropy weighting, and Bayesian algorithms, are acknowledged [17], although were not implemented in this study to ensure consistency with previous research and to enable comparison with analogous water quality evaluations. The third phase, Data Pre-processing, entailed consolidating the raw measurements into a master spreadsheet and ensuring completeness and uniformity. Each option, designated A1 to A22, corresponds to a unique sample site within the network. For each option, total dissolved solids (TDS) in mg/L, temperature in °C, pH, and turbidity in NTU were documented. The data were organized into a rectangular decision matrix XX, with rows denoting the possibilities and columns indicating the criterion. The matrix was standardized by vector normalization to accommodate varying units and scales. The fourth phase, MOORA Computation, categorized pH and temperature as advantageous criteria, but TDS and turbidity were designated as detrimental criteria. The normalized values were multiplied by their corresponding weights, and the overall performance score for each alternative was derived by subtracting the total of the weighted cost criteria from the total of the

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weighted benefit criteria. Finally, the DSS Integration step incorporated the MOORA results into the decision support system, enabling automated ranking display, report generation, and operational decision-making.

### 2.1. Study Area and Data Collection

This research was carried out at a regional water utility tasked with delivering and overseeing drinking water quality throughout several service areas in Central Java. The utility predominantly depends on surface water sources like the Sani River, which undergo seasonal variations and confront several pollution challenges, including turbidity changes during the monsoon and agricultural runoff from adjacent farmlands. Monthly water quality measurement occurred from July 2024 to January 2025 at 22 service sites, encompassing distribution taps and village ends. Four principal factors were examined: pH (dimensionless), turbidity (Nephelometric Turbidity Units, NTU), total dissolved solids (TDS, mg/L), and temperature (°C). These indicators were chosen for their essential significance in regulatory compliance, operational decision-making, and their influence on consumer perception of water quality [17], [19].

### 2.2 MOORA Computation

The MOORA method was implemented to rank the sampled water sources based on their overall suitability for drinking water distribution. The analysis proceeded through the following steps:
A decision matrix $X_{ij} = [x_{ij}]$ was constructed where $x_{ij}$ represents the value of criterion $j$ (e.g., TDS) for alternative $i$ (e.g., sampling site $A_1$, $A_2$, ..., $A_{22}$). The matrix thus comprised 22 rows (water sources) and 4 columns (quality parameters).

$$X=\begin{bmatrix} x_{1,1} & \cdots & x_{1,n} \\ \vdots & \ddots & \vdots \\ x_{n,1} & \cdots & x_{n,n} \end{bmatrix} \tag{1}$$

Criteria were classified as either benefit or cost based on their desirability in drinking water:
Benefit: Higher values indicate better quality. In this study, pH (within an optimal range) and temperature (in the palatability range of 20–26 °C) were treated as benefit criteria.
Cost: Lower values are preferred. Turbidity and TDS were classified as cost criteria due to their negative impact on aesthetic and health-related water quality.
To eliminate unit inconsistencies and make criteria comparable, vector normalization was applied:

$$n_{ij}=\frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}^2}} \tag{2}$$

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Where $n_{ij}$ is the normalized value, and $m$ is the number of alternatives [7]. Weights of 0.3, 0.15, 0.3, and 0.25 were applied to TDS, Temperature, pH, and Turbidity respectively. Although other studies have used entropy weighting or expert judgment [17], this study prioritized a baseline implementation of MOORA without subjective influence. The MOORA composite index for each alternative $i$ was calculated as:

$$R_i = \sum_{j\in B} n_{ij} - \sum_{j\in C} n_{ij} \tag{3}$$

With weights considered, the equation above becomes:

$$R_i = \sum_{j\in B} w_j n_{ij} - \sum_{j\in C} w_j n_{ij} \tag{4}$$

Where $B$ and $C$ represent the sets of benefit and cost criteria, respectively [12]. A higher $R_i$ score implies better overall water quality suitability. Alternatives were ranked in descending order of their $R_i$. The top-ranked sources were interpreted as most suitable for continued or expanded use, while the lowest-ranked sources were flagged for remediation or reduced reliance.

## 3. RESULTS AND DISCUSSION

### 3.1. MOORA-based Calculation Results of the Real Data

The MOORA approach was utilized to assess 22 drinking water samples obtained from service points within the distribution network of a regional water utility situated in a topographically varied region of Central Java, Indonesia, with altitudes spanning from 2 to 624 meters above sea level. Each alternative was linked to a distinct geographic water source or delivery node and evaluated based on four critical parameters—Total Dissolved Solids (TDS), temperature, pH, and turbidity—chosen for their adherence to WHO and national drinking water standards, as well as their direct operational significance to treatment processes. In alignment with public health and water quality management standards, pH and temperature were categorized as benefit criteria, while TDS and turbidity were identified as cost criteria, so ensuring the assessment encompassed both regulatory adherence and operational performance requirements.

**Table 1.** Criteria

| Criteria | Parameter | Weight | Type |
|---|---|---|---|
| C1 | TDS | 0.3 | Cost |
| C2 | Temperature | 0.15 | Benefit |
| C3 | pH | 0.3 | Benefit |
| C4 | Turbidity | 0.25 | Cost |

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**Table 2.** Conversion Table of Water Quality Values

| Parameter | Range | Converted Value |
|---|---|---|
| TDS (mg/L) | < 100 | 5 |
| | 100 - 200 | 4 |
| | 201 - 300 | 3 |
| | 301 - 400 | 2 |
| | > 400 | 1 |
| Temperature (°C) | 28 - 30 | 5 |
| | 25 - 27 | 4 |
| | 22 - 24 | 3 |
| | 19 - 21 | 2 |
| | < 19 or > 30 | 1 |
| pH | 7.0 - 7.5 | 5 |
| | 6.5 - 6.9 or 7.5 - 8.0 | 4 |
| | 6.0 - 6.4 or 8.1 - 8.5 | 3 |
| | 5.5 - 5.9 or > 8.5 | 2 |
| | < 5.5 | 1 |
| Turbidity (NTU) | < 1.0 | 5 |
| | 1.0 - 2.0 | 4 |
| | 2.1 - 3.0 | 3 |
| | 3.1 - 5 | 2 |
| | > 5 | 1 |

**Table 3.** Site Actual Data

| Water Source | TDS | Temp. | Ph | Kekeruhan |
|---|---|---|---|---|
| X1 | 280 | 22 | 7,2 | 0 |
| X2 | 163 | 22 | 7 | 0 |
| X3 | 116 | 23 | 7 | 0,21 |
| X4 | 214 | 23 | 7 | 0 |
| X5 | 165 | 22 | 7,1 | 0 |
| X6 | 115 | 22 | 7 | 0 |
| X7 | 219 | 22 | 7,3 | 0,35 |
| X8 | 145 | 23 | 7,3 | 0,03 |
| X9 | 185 | 23 | 7,7 | 5,17 |
| X10 | 155 | 23 | 7,4 | 0,18 |
| X11 | 139 | 23 | 7,7 | 1,56 |
| X12 | 159 | 24 | 7,8 | 0,24 |
| X13 | 134 | 23 | 7,6 | 2,75 |
| X14 | 143 | 23 | 7,7 | 6,75 |
| X15 | 178 | 23 | 7,6 | 1,38 |
| X16 | 158 | 23 | 7,4 | 4,49 |
| X17 | 142 | 23 | 7,3 | 0,01 |
| X18 | 184 | 23 | 7,5 | 6,84 |
| X19 | 474 | 29 | 7,8 | 0,44 |
| X20 | 195 | 29 | 7,4 | 0,18 |
| X21 | 241 | 29 | 7,5 | 2,2 |

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| Water Source | TDS | Temp. | Ph | Kekeruhan |
|---|---|---|---|---|
| X22 | 164 | 29 | 7,4 | 0,01 |

**Table 4.** Converted Values for the Decision Matrix

| Alternative | TDS | Temp. | pH | Turbidity |
|---|---|---|---|---|
| A1 | 3 | 3 | 5 | 5 |
| A2 | 4 | 3 | 5 | 5 |
| A3 | 4 | 3 | 5 | 5 |
| A4 | 3 | 3 | 5 | 5 |
| A5 | 4 | 3 | 5 | 5 |
| A6 | 4 | 3 | 5 | 5 |
| A7 | 3 | 3 | 5 | 5 |
| A8 | 4 | 3 | 5 | 5 |
| A9 | 4 | 3 | 4 | 1 |
| A10 | 4 | 3 | 5 | 5 |
| A11 | 4 | 3 | 4 | 4 |
| A12 | 4 | 3 | 4 | 5 |
| A13 | 4 | 3 | 4 | 3 |
| A14 | 4 | 3 | 4 | 1 |
| A15 | 4 | 3 | 4 | 4 |
| A16 | 4 | 3 | 5 | 2 |
| A17 | 4 | 3 | 5 | 5 |
| A18 | 4 | 3 | 5 | 1 |
| A19 | 1 | 5 | 4 | 5 |
| A20 | 4 | 5 | 5 | 5 |
| A21 | 3 | 5 | 5 | 3 |
| A22 | 4 | 5 | 5 | 5 |

The validated water quality data were aggregated into a master spreadsheet, guaranteeing completeness, correctness, and consistency prior to analysis. Each alternative, labeled A1 to A22, represented a unique sample site under the jurisdiction of the regional water company. For each of the 22 possibilities, four characteristics were documented: Total Dissolved Solids (TDS, mg/L), water temperature (°C), pH, and turbidity (NTU). These indicators were chosen for their conformity with both WHO and Indonesian national drinking water standards, as well as their practical significance in water treatment decision-making [17], [19]. This unprocessed information was the basis for the decision matrix employed in the MOORA calculation.

Subsequent to data verification, the measurements were structured into a rectangular decision matrix X, with each row denoting an option (A1–A22) and each column representing one of the four criteria. The initial column had TDS values, the subsequent column encompassed temperature data, the third column included pH measurements, and the fourth column represented turbidity levels. Organizing the material in this standardized manner guaranteed compliance with

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the MOORA algorithm, facilitating systematic normalization, weighing, and ranking of alternatives. The choice matrix may therefore be articulated as:

$$X=\begin{bmatrix} 3\ 3\ 5\ 5 \\ 4\ 3\ 5\ 5 \\ 4\ 3\ 5\ 5 \\ 3\ 3\ 5\ 5 \\ 4\ 3\ 5\ 5 \\ 4\ 3\ 5\ 5 \\ 3\ 3\ 5\ 5 \\ 4\ 3\ 5\ 5 \\ 4\ 3\ 4\ 1 \\ 4\ 3\ 5\ 5 \\ 4\ 3\ 4\ 4 \\ 4\ 3\ 4\ 5 \\ 4\ 3\ 4\ 3 \\ 4\ 3\ 4\ 1 \\ 4\ 3\ 4\ 4 \\ 4\ 3\ 5\ 2 \\ 4\ 3\ 5\ 5 \\ 4\ 3\ 5\ 1 \\ 1\ 5\ 4\ 5 \\ 4\ 5\ 5\ 5 \\ 3\ 5\ 5\ 3 \\ 4\ 5\ 5\ 5 \end{bmatrix}$$

Each criterion was normalized using vector normalization. The normalized values were weighted at 0.3, 0.15, 0.3, and 0.25 respectively, and the final score $R_i$ for each alternative was computed using the MOORA formula. The $R_i$ score is obtained by subtracting the sum of weighted cost criteria from the sum of weighted benefit criteria for each alternative. The higher the $R_i$, the better the overall water quality. The normalisation coefficients are calculated as follows:

$$C_1=\sqrt{3^2+4^2+4^2+\ldots+4^2+3^2+4^2}=17.5784$$

$$C_2=\sqrt{3^2+3^2+3^2+\ldots+5^2+5^2+5^2}=16.1864$$

$$C_3=\sqrt{5^2+5^2+5^2+\ldots+5^2+5^2+5^2}=22.0681$$

$$C_4=\sqrt{5^2+5^2+5^2+\ldots+5^2+3^2+5^2}=20.1742$$

Thus, the decision matrix becomes

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$$n=\left[\frac{3}{C_1}\ \frac{3}{C_2}\ \frac{5}{C_3}\ \frac{5}{C_4}\ \frac{4}{C_1}\ \frac{3}{C_2}\ \frac{5}{C_3}\ \frac{5}{C_4}\ \vdots\vdots\vdots\vdots\ \frac{3}{C_1}\ \frac{5}{C_2}\ \frac{5}{C_3}\ \frac{3}{C_4}\ \frac{4}{C_1}\ \frac{5}{C_2}\ \frac{5}{C_3}\ \frac{5}{C_4}\right]$$

Or,

$$n=\begin{bmatrix} 0.1707 & 0.1853 & 0.2266 & 0.2478 \\ 0.2276 & 0.1853 & 0.2266 & 0.2478 \\ 0.2276 & 0.1853 & 0.2266 & 0.2478 \\ 0.1707 & 0.1853 & 0.2266 & 0.2478 \\ 0.2276 & 0.1853 & 0.2266 & 0.2478 \\ 0.2276 & 0.1853 & 0.2266 & 0.2478 \\ 0.1707 & 0.1853 & 0.2266 & 0.2478 \\ 0.2276 & 0.1853 & 0.2266 & 0.2478 \\ 0.2276 & 0.1853 & 0.1813 & 0.0496 \\ 0.2276 & 0.1853 & 0.2266 & 0.2478 \\ 0.2276 & 0.1853 & 0.1813 & 0.1983 \\ 0.2276 & 0.1853 & 0.1813 & 0.2478 \\ 0.2276 & 0.1853 & 0.1813 & 0.1487 \\ 0.2276 & 0.1853 & 0.1813 & 0.0496 \\ 0.2276 & 0.1853 & 0.1813 & 0.1983 \\ 0.2276 & 0.1853 & 0.2266 & 0.0991 \\ 0.2276 & 0.1853 & 0.2266 & 0.2478 \\ 0.2276 & 0.1853 & 0.2266 & 0.0496 \\ 0.0569 & 0.3089 & 0.1813 & 0.2478 \\ 0.2276 & 0.3089 & 0.2266 & 0.2478 \\ 0.1707 & 0.3089 & 0.2266 & 0.1487 \\ 0.2276 & 0.3089 & 0.2266 & 0.2478 \end{bmatrix}$$

Weights are applied to this calculation by mutiplying the corresponding columns with $0.3, 0.15, 0.3$, and $0.25$. That is,

$$n(w)=\left[\frac{3}{C_1}(0.3)\ \frac{3}{C_2}(0.15)\ \frac{5}{C_3}(0.3)\ \frac{5}{C_4}(0.25)\ \frac{4}{C_1}(0.3)\ \frac{3}{C_2}(0.15)\ \frac{5}{C_3}(0.3)\ \frac{5}{C_4}(0.25)\ \vdots\vdots\vdots\vdots\ \frac{3}{C_1}(0.3)\ \frac{5}{C_2}(0.15)\ \frac{5}{C_3}(0.3)\ \frac{3}{C_4}(0.25)\ \frac{4}{C_1}(0.3)\ \frac{5}{C_2}(0.15)\ \frac{5}{C_3}(0.3)\ \frac{5}{C_4}(0.25)\right]$$

Or,

$$n(w)=\begin{bmatrix}0.0512 & 0.0278 & 0.0680 & 0.0620\\0.0683 & 0.0278 & 0.0680 & 0.0620\\0.0683 & 0.0278 & 0.0680 & 0.0620\\0.0512 & 0.0278 & 0.0680 & 0.0620\\0.0683 & 0.0278 & 0.0680 & 0.0620\\0.0683 & 0.0278 & 0.0680 & 0.0620\\0.0512 & 0.0278 & 0.0680 & 0.0620\\0.0683 & 0.0278 & 0.0680 & 0.0620\\0.0683 & 0.0278 & 0.0544 & 0.0124\\0.0683 & 0.0278 & 0.0680 & 0.0620\\0.0683 & 0.0278 & 0.0544 & 0.1983\\0.0683 & 0.0278 & 0.0544 & 0.0620\\0.0683 & 0.0278 & 0.0544 & 0.0372\\0.0683 & 0.0278 & 0.0544 & 0.0124\\0.0683 & 0.0278 & 0.0544 & 0.1983\\0.0683 & 0.0278 & 0.0680 & 0.0248\\0.0683 & 0.0278 & 0.0680 & 0.0620\\0.0683 & 0.0278 & 0.0680 & 0.0124\\0.0171 & 0.0463 & 0.0544 & 0.0620\\0.0683 & 0.0463 & 0.0680 & 0.0620\\0.0512 & 0.0463 & 0.0680 & 0.0372\\0.0683 & 0.0463 & 0.0680 & 0.0620\end{bmatrix}$$

Using these values, the $R_i$ scores are calculated using equation (4). Thus,

**Table 5.** The $R_i$ score for each alternative

| Site | Max (C2 + C3) | Min (C1 + C4) | $R_i$ score | Rank |
|---|---|---|---|---|
| A1 | 0,0958 | 0,1132 | -0,0174 | 9 |
| A2 | 0,0958 | 0,1302 | -0,0345 | 13 |
| A3 | 0,0958 | 0,1302 | -0,0345 | 14 |
| A4 | 0,0958 | 0,1132 | -0,0174 | 10 |
| A5 | 0,0958 | 0,1302 | -0,0345 | 15 |
| A6 | 0,0958 | 0,1302 | -0,0345 | 16 |
| A7 | 0,0958 | 0,1132 | -0,0174 | 11 |
| A8 | 0,0958 | 0,1302 | -0,0345 | 17 |
| A9 | 0,0822 | 0,0807 | 0,0015 | 5 |
| A10 | 0,0958 | 0,1302 | -0,0345 | 18 |
| A11 | 0,0822 | 0,1178 | -0,0357 | 20 |
| A12 | 0,0822 | 0,1302 | -0,0480 | 22 |
| A13 | 0,0822 | 0,1054 | -0,0233 | 12 |
| A14 | 0,0822 | 0,0807 | 0,0015 | 6 |
| A15 | 0,0822 | 0,1178 | -0,0357 | 21 |

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| Site | Max (C2 + C3) | Min (C1 + C4) | $R_i$ score | Rank |
|---|---|---|---|---|
| A16 | 0,0958 | 0,0930 | 0,0027 | 4 |
| A17 | 0,0958 | 0,1302 | -0,0345 | 19 |
| A18 | 0,0958 | 0,0807 | 0,0151 | 3 |
| A19 | 0,1007 | 0,0790 | 0,0217 | 2 |
| A20 | 0,1143 | 0,1302 | -0,0159 | 7 |
| A21 | 0,1143 | 0,0884 | 0,0259 | 1 |
| A22 | 0,1143 | 0,1302 | -0,0159 | 8 |

Table 5 displays the MOORA calculation outcomes for drinking water quality in December 2024. The top alternative was A21 ("Water Source X21"), with a final score of +0.0259. The result was influenced by favorable water quality parameters: a pH of 7.5, a temperature of 29 °C, total dissolved solids (TDS) of 241 mg/L, and turbidity of 2.2 NTU. Despite turbidity surpassing the optimal threshold of <1 NTU, the advantageous balance of the other parameters mitigated this deviation, leading to the highest overall ranking. A19 ("Water Source X19") followed closely in second place with a score of +0.0217, characterized by an optimal pH of 7.8 and low turbidity of 0.44 NTU. However, it exhibited a relatively high total dissolved solids (TDS) level of 474 mg/L, necessitating continued monitoring [17]. A18 ("Water Source X18") was ranked third (+0.0151), exhibiting a stable pH of 7.5 and moderate total dissolved solids (TDS) of 184 mg/L, while its turbidity was relatively high at 6.84 NTU. A12 ("Water Source X12") achieved the lowest score in the rankings, recorded at −0.0480. Although turbidity (0.24 NTU) and TDS (159 mg/L) are within acceptable limits, the relatively low temperature (24 °C) and less favorable pH (7.8) negatively impacted performance. A15 and A11 also received low rankings as a result of high turbidity, highlighting its considerable effect on the overall score.

A significant pattern emerged among various alternatives (A1–A8, A10), which exhibited the same maximum benefit values (0.0958) yet differed in final rankings owing to discrepancies in cost-related criteria. This demonstrates MOORA's ability to incorporate both benefit and cost elements into a comprehensive assessment [19]. A1 and A4 attained identical benefit scores; however, A1 was ranked higher because of its lower cost score. A9 and A14, both achieving the same final scores (+0.0015), exhibited differences in their parameter profiles—A9 demonstrated superior performance in TDS (185 mg/L), whereas A14 recorded a lower turbidity value (5.17 NTU compared to 6.75 NTU). These examples demonstrate MOORA's capacity to uncover nuanced trade-offs that single-parameter assessments or composite indices alone would not capture [17], [19].

From an operational standpoint, prioritizing high-ranking sources such as A21, A19, and A18 for direct supply or minimal treatment can lead to reductions in operational costs and resource utilization. Conversely, lower-ranking sources such

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as A12 and A15 warrant further interventions, including enhanced filtration or optimized chemical dosing. The ranking results inform adaptive monitoring strategies, indicating that consistently high-performing sources (e.g., A19) may necessitate less frequent testing, whereas lower-performing sites (e.g., A11, A12) require more frequent monitoring to mitigate potential risks [17].

These rankings are integrated into the Decision Support System (DSS) developed in this study. The DSS dashboard facilitates the storage and visualization of rankings, allowing stakeholders to access performance summaries and detailed parameter analyses in real time. This integration enables swift, evidence-informed decision-making, consistent with established practices for MCDM-based water quality management [19]. The system integrates field measurements, MOORA-based ranking, and intuitive visual tools to facilitate a proactive, data-driven, and sustainable strategy for regional water resource management.

### 3.2. Discussion

The MOORA Calculation module within the Decision Support System (DSS) automates the multi-criteria decision-making process through vector normalization, classification of parameters into benefit and cost categories, and the generation of composite scores based on weighted criteria [17], [19]. The ranked results are updated in real time and presented on the system dashboard, allowing operators to promptly identify priority water sources for treatment or monitoring. This real-time feedback loop improves operational responsiveness and facilitates transparent decision-making consistent with contemporary MCDM-based water management practices. The Report Generation and Management module enables users to export ranking results in various formats for documentation, regulatory compliance, and internal performance review. This module facilitates the easy retrieval of historical data for trend analysis, auditing, or strategic planning purposes. The modular architecture of the DSS enhances its extensibility, facilitating future integration of features such as geospatial mapping of water sources, mobile-based field data collection, and connections with automated water treatment systems [19].

The system was developed utilizing open-source technologies to guarantee cost-effectiveness, accessibility, and long-term maintainability, which are essential for implementation in regional and rural utilities. The frontend interface was developed using PHP and HTML, with JavaScript enhancements to enhance interactivity and usability, especially for non-technical users. The backend logic layer, implemented in PHP, incorporates MOORA computation scripts within controller files to minimize processing latency and facilitate dynamic result updates.

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MySQL served as the relational database management system for storing all pertinent datasets, encompassing raw water quality measurements, processed decision matrices, and ranking outputs. This database design facilitates efficient query execution and secure data management, incorporating indexing on frequently accessed fields to enhance performance. Development and testing were conducted locally with XAMPP, facilitating offline functionality in low-bandwidth settings and enabling straightforward deployment to additional utility networks. Visual Studio Code functioned as the main integrated development environment (IDE), offering version control integration, debugging tools, and code linting to ensure programming quality.

The DSS design facilitates efficient data flow from acquisition to decision-making, minimizes the risk of human error in manual calculations, and enhances the traceability of analytical results. The application of MOORA in this modular and open-source framework facilitates objective, data-driven assessment of water sources, while maintaining adaptability to various operational contexts in Indonesia [17], [19]. The capacity to function effectively on local infrastructure with minimal server reliance renders it a scalable option for regional utilities encountering comparable multi-criteria water management issues.

The MOORA-based Decision Support System (DSS) created for the regional water utility shows significant potential for improving water quality management; nonetheless, various limitations indicate areas for enhancement. The current evaluation framework includes four physicochemical parameters: pH, turbidity, total dissolved solids (TDS), and temperature. These parameters were chosen for their adherence to WHO and national drinking water standards [17], [19]. Although these parameters are crucial for baseline assessment, they do not capture the complete range of water quality risks. Key indicators, including microbial contamination (e.g., E. coli), heavy metals (e.g., lead, arsenic), and nutrient levels (e.g., nitrates, phosphates), are not addressed by the current system. The inclusion of these additional variables would enhance the assessment of water safety and improve the capacity to mitigate public health risks. The current deployment on a local XAMPP server provides accessibility in low-bandwidth environments and cost-effectiveness for small-scale utilities; however, it presents limitations regarding scalability, multi-user access, and remote collaboration. Adopting a cloud-based architecture may facilitate role-based access control, support concurrent operations across multiple locations, and enhance mobile compatibility, thereby enabling real-time data entry from the field and improving team coordination [17].

A further limitation is the system's inability to interoperate with external data sources. The DSS currently operates as an independent platform, lacking integration with national water quality databases, hydrological monitoring systems,

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or meteorological data services. Implementing these integrations may enhance contextual analysis and support early warning systems for seasonal variations in water quality or contamination incidents. Additionally, integrating the DSS with machine learning algorithms may facilitate predictive modeling, anomaly detection, and forecasting of water quality trends by utilizing historical patterns and environmental variables [19].

The user interface was designed for simplicity and non-technical usability; however, systematic user testing with utility staff is necessary to ensure long-term adoption and satisfaction. Improvements including interactive dashboards, localized language options, simplified navigation structures, and embedded user guidance may enhance accessibility for laboratory technicians and field operators.

In conclusion, the existing MOORA-DSS offers a systematic, clear, and replicable method for assessing water quality across multiple criteria. Future developments should concentrate on four key areas: (1) broadening the range of parameters to encompass microbiological and chemical risks, (2) transitioning to a scalable cloud-based infrastructure, (3) facilitating interoperability with external environmental data systems, and (4) enhancing user experience through continuous design improvements and feedback mechanisms. Implementing these advancements would enhance the system's analytical depth, operational flexibility, and overall value for water utilities in Indonesia and similar contexts globally [17], [19].

## 4. CONCLUSION

This study has successfully created and put into use a MOORA-based Decision Support System (DSS) to check the quality of drinking water for a regional water utility in Central Java, Indonesia, which has a lot of elevation changes (2–624 m above sea level). The algorithm rated the 22 water sources based on four physicochemical factors: pH, turbidity, total dissolved solids (TDS), and temperature. The results showed obvious differences in performance amongst the sources. High-ranking sites like X21, X19, and X18 had the best parameter balances and needed just a little modification. On the other hand, low-ranking sources like X12 had traits that needed more thorough intervention. These results confirm that MOORA can manage trade-offs with more than one criterion and give operational decision-makers a clear, unbiased framework to work with. The system's operational utility goes beyond only rating; it also allows for risk-based monitoring schedules, better allocation of treatment resources, and easier standardized reporting for regulatory compliance. The DSS makes drinking water services more trustworthy by combining analytical rigor with a user-friendly digital interface. This increases transparency, improves evidence-based governance, and can make people trust drinking water services more. The modular architecture also makes it possible for other utilities in Indonesia to use it and for it to be used in

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other areas that have comparable multi-criteria evaluation problems. This study also helps to connect environmental engineering and information systems by showing how a strong MCDM technique may be turned into a tool for making decisions in real time. To fix the existing constraint on the scope, future enhancements should incorporate more criteria, such heavy metals, microbiological pollution, and nutritional levels. They should also make the system work better with national and regional environmental databases. Combining predictive analytics with mobile data collecting techniques might make things even more responsive and efficient. The MOORA-DSS is a technically solid, reproducible, and effective way to improve water quality management in places where resources are limited, even with its existing limitations.

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