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Integrated Fuzzy TOPSIS And AHP Approach For Efficient Water Resources Allocation in Rural Areas

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***Abstract*—** **This study integrates the Analytic Hierarchy Process (AHP) and Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) to assess and prioritize rural water resource alternatives. Four primary sources are evaluated against five criteria, with Groundwater Wells identified as the most sustainable choice, influenced significantly by Climatic and Environmental Impacts. These findings offer insights for informed rural water resource allocation, contributing to sustainable development and resilience in rural communities. This integrated approach aids decision-makers in navigating complexities, enhancing resource utilization, and ensuring environmental preservation, ultimately promoting better living standards and environmental sustainability in rural areas. In a world facing increasing water scarcity, this research offers practical solutions for addressing rural water resource challenges and provides valuable insights for informed decision-making in rural water resource allocation.**

***Keywords— Rural Areas, Fuzzy AHP, Fuzzy TOPSIS, Water Allocation***

# INTRODUCTION

Access to clean and reliable water resources is fundamental for rural communities' sustainable development and well-being, particularly in regions where agriculture serves as the economic backbone, sustaining livelihoods and local economies. The efficient allocation of water resources plays a pivotal role in supporting agricultural production and meeting crucial community needs, including potable water and sanitation. However, rural regions often grapple with substantial challenges, including variable climatic conditions, limited infrastructure, and diverse community demands. These challenges can lead to imprecise data and subjective decision-making, hampering the equitable and efficient allocation of water resources [1][2].

This research introduces an innovative approach that combines the Fuzzy Technique for Order Preference by Similarity to an Ideal Solution (Fuzzy TOPSIS) with the Analytic Hierarchy Process (AHP). Fuzzy TOPSIS and AHP are two decision-making methodologies known for their effectiveness in handling complex evaluations. Fuzzy TOPSIS excels in managing uncertainty, while AHP provides a structured framework for systematic comparisons. Together, they offer valuable tools for transparent and comprehensive decision-making. Fuzzy TOPSIS, rooted in fuzzy logic, provides a robust solution for addressing the inherent uncertainty and imprecision in rural water resource data [3][4]. Simultaneously, AHP offers a structured framework for incorporating expert judgments and preferences. This integration aims to significantly enhance the efficiency, equity, and resilience of rural water allocation decisions, with far-reaching implications for sustaining agriculture, safeguarding public health, and fostering rural development on a global scale.

The organization of the paper is as follows: Section 2 describes the related work, Section 3 provides the methodology, Section 4 describes the results and discussions, Section 5 concludes the paper.

# Related works

In this section of the paper, we will delve into other research works that contribute to the field of water resources allocation.

In a study conducted by Dionysis Latinopoulos [5], a multicriteria model was introduced with the aim of optimizing the distribution of water and land resources within a rural Greek setting. It's worth noting that historical decisions had a strong inclination toward socio-economic objectives. However, the research paper proposes alternative allocation strategies to improve environmental sustainability. A significant discovery underscores the critical importance of water demand elasticity when assessing the efficiency of water pricing policies. This, in turn, enables greater adaptability in allocating resources toward environmental objectives [6][7]. Biswadip Das et al. [8] conducted research focusing on the promotion of sustainable irrigated agriculture by integrating surface water and groundwater resources. Their work introduces a user-friendly software-based linear programming model designed for resource allocation in the Hirakud Canal Command area in eastern India. Sensitivity analysis findings suggest that, for sustainability purposes, it is advisable to allocate 87% of resources to surface water and 13% to groundwater. Additionally, the study recommends a 20% adjustment in the current cropping pattern to address both socio-economic requirements and food demand [9]. Jing Tian [10][11] tackled the growing challenge of freshwater scarcity due to climate change, population growth, and water pollution. They proposed a fair approach to allocate water resources, employing Sperner's lemma to resolve conflicts among various objectives and regions. Initially, they formulated a multi-objective allocation model to generate a Pareto frontier surface that balances economic interests and minimizes pollutants. This approach then identifies acceptable allocation schemes on the surface, considering total water quantity and envy-free constraints. When applied to China's Hanjiang river basin, the results demonstrate the effectiveness of achieving Nash equilibrium through fair water allocation, ensuring each region receives its preferred water quantity. This method holds promise for broader applications in water resources management [12]. Bin Shi et al. [13] directed their attention to the issues of water scarcity and environmental pollution stemming from inappropriate rural agricultural practices. They introduced a two-phase programming methodology designed for the allocation of regional water resources in China. This approach effectively manages uncertain inputs by treating them as intervals and introduces several control variables to facilitate constraint relaxation, thereby leading to more favorable outcomes. The decision variables empower decision makers by allowing them to modify their agricultural activity decisions, integrating their expertise into water allocation management.

In their paper, Mojtaba Sadegh et al [14][15] addressed the imperative for optimizing the allocation of shared water resources within inter-basin water transfer projects. They presented a methodology that combines both crisp and fuzzy Shapley games. Initially, water allocations are determined through an equity-focused optimization model. Stakeholders form crisp coalitions aimed at maximizing net benefits, followed by a reallocation process utilizing the crisp Shapley Value game. Fuzzy coalitions, on the other hand, optimize participation rates, and the Fuzzy Shapley Value game ensures an equitable distribution of total net benefits. The effectiveness of this approach was illustrated through a case study involving water transfer in Iran. In their research, Y.L. Xie et al [16] addressed the complexities of agricultural water management and presented a versatile optimization model designed for irrigation and cropland planning within Jining City. This model takes into consideration factors such as water scarcity, land pressure, and climate uncertainties. By incorporating multiple sources of uncertainty, it aims to identify optimal management strategies that strike a balance between benefits and risks. The outcomes of this study offer valuable insights into adaptive management and land planning when dealing with uncertain conditions.

In their research, Pengyu Li et al [17][18] focused on addressing water allocation challenges within the Yinma River Basin (YRB) in China, utilizing fuzzy programming techniques. The YRB grapples with water scarcity in some regions and overutilization in others, largely due to irrational allocation practices. The primary objective of this study is to optimize water allocation, thereby reducing system risks and alleviating shortages. The simulation results highlight substantial reductions in water wastage, improvements in shortage mitigation, and a heightened focus on environmental considerations. This research offers valuable guidance for devising a more favorable planning scheme within the Yinma River Basin.

[19][20] Jingbo Wang et al tackled the challenge of optimizing water resource allocation while considering user efficiency and supply cost. They applied fuzzy optimization theory to analyze Qingdao's water resource allocation spanning from 2011 to 2020. Their scenario analysis delved into various factors, including water and sewage fees, full-cost pricing, and agricultural water-saving practices. The findings from this study provide valuable insights for fostering sustainable water resource development and shaping policy decisions in Qingdao.

[9] Fatemeh Dadmand et al. addressed Iran's pressing issue of water scarcity and introduced an innovative Robust Fuzzy Stochastic Programming model for water resource allocation. This model takes into account sustainability concerns, fluctuating groundwater levels, and hybrid uncertainties. It pursues three core objectives: maximizing profits, minimizing losses related to water shortages, and reducing saltwater allocation. When applied in Mashhad city, it reveals adaptable water allocation patterns under different scenarios, showcasing its effectiveness in achieving sustainable water resource allocation.

[10] A. KARNIB presented a methodology for prioritizing water resource projects, particularly in the context of water scarcity, with a focus on developing countries. The study outlined the prerequisites for accurate priority preorders, evaluated criteria, and developed a practical methodology. An application example illustrated the step by-step process and demonstrated its feasibility. This approach aids in the efficient allocation of limited resources by sequencing projects based on predefined criteria [21].

[24] Elnaz Zehtabian et al.'s study examines water management challenges in Iran's Gavkhouni basin, proposing the application of environmental flow principles within Integrated Water Resource Management. The study presents a six-stage water resources management model, forecasting increasing water demands in drinking and industrial sectors. It ranks seven management scenarios, prioritizing changes in water supply and transfer. The research provides valuable insights for enhancing sustainable water allocation practices in the Gavkhouni basin.

[24]Elif Ayyuce Kilinc's study evaluates rainwater harvesting (RWH) and graywater reuse (GWR) in diverse building types in Turkey's Antalya Province, emphasizing cost-benefit analyses and water conservation. Significant water savings (20%-99%) and payback periods (2-9 years) are found. Results align with literature, suggesting rapid amortization. Encouraging public awareness and incentives like tax reductions can boost wider adoption.

# proposed method

Our study integrates Fuzzy TOPSIS and Fuzzy AHP techniques to optimize the allocation of water resources in rural areas. We define five essential criteria: water quality(C1), environmental impact(C2), community acceptance(C3), cost-effectiveness(C4), and location suitability(C5). We evaluate four primary water resource alternatives: reservoirs(A1), groundwater wells(A2), surface water(A3), and rainwater harvesting(A4). Expert insights from an Environmental Specialist and a Rural Water Allocation Expert enhance our evaluation. The outcome is a prioritized ranking of these allocation options, providing valuable guidance for effective and sustainable rural water management decisions [22][23].

*A) Quality and Reliability of Data:*

The quality and reliability of the data used for our analysis are paramount and are underpinned by a well-structured process for the selection of criteria and alternatives.

The selection of criteria in our research is a rigorous process that ensures data quality and reliability. We define five essential criteria - water quality (C1), environmental impact (C2), community acceptance (C3), cost-effectiveness (C4), and location suitability (C5). These criteria are not arbitrary; they are carefully chosen based on their critical relevance to the research objective of identifying the most suitable water resource for rural areas.

The alternatives, which include reservoirs (A1), groundwater wells (A2), surface water (A3), and rainwater harvesting (A4), are chosen systematically and meticulously. These primary water resource alternatives are practical options for rural water allocation. The selection process involves analyzing historical usage data, considering geographical distribution, accessibility, and consulting local authorities and communities to determine the most prevalent and relevant alternatives. This ensures that the alternatives selected are well-aligned with the real-world options available to rural areas, thus enhancing the reliability of the data used in our analysis.

*B) Fuzzy TOPSIS:*

The TOPSIS method was initially introduced by Hwang and Yoon as a means of selecting the optimal alternative based on defined criteria, available alternatives, and the perspectives of decision-makers. The steps in this method are as shown in the Fig.1

TABLE 2. Criterion weights by the decision makers

Form a decision makers committee

Identifying the key criterias used for evaluation

Identifying the sub criterias under each criterion

Select the suitable linguistic variables

Quantify the weights of each criteria using AHP method

Create a fuzzy decision matrix

Normalize the fuzzy decision matrix

Create a weighted normalized fuzzy decision matrix

Find FPIS and FNIS

Calculate the distance of each alternative using FPIS and FNIS

Calculate the nearest coefficient of each alternative

Assign Ranks to the alternatives as per the nearest coefficient

Fig.1.Flowchart of TOPSIS

The hierarchical diagram which shows us the different criteria and alternatives pictorially as shown in Fig.2:

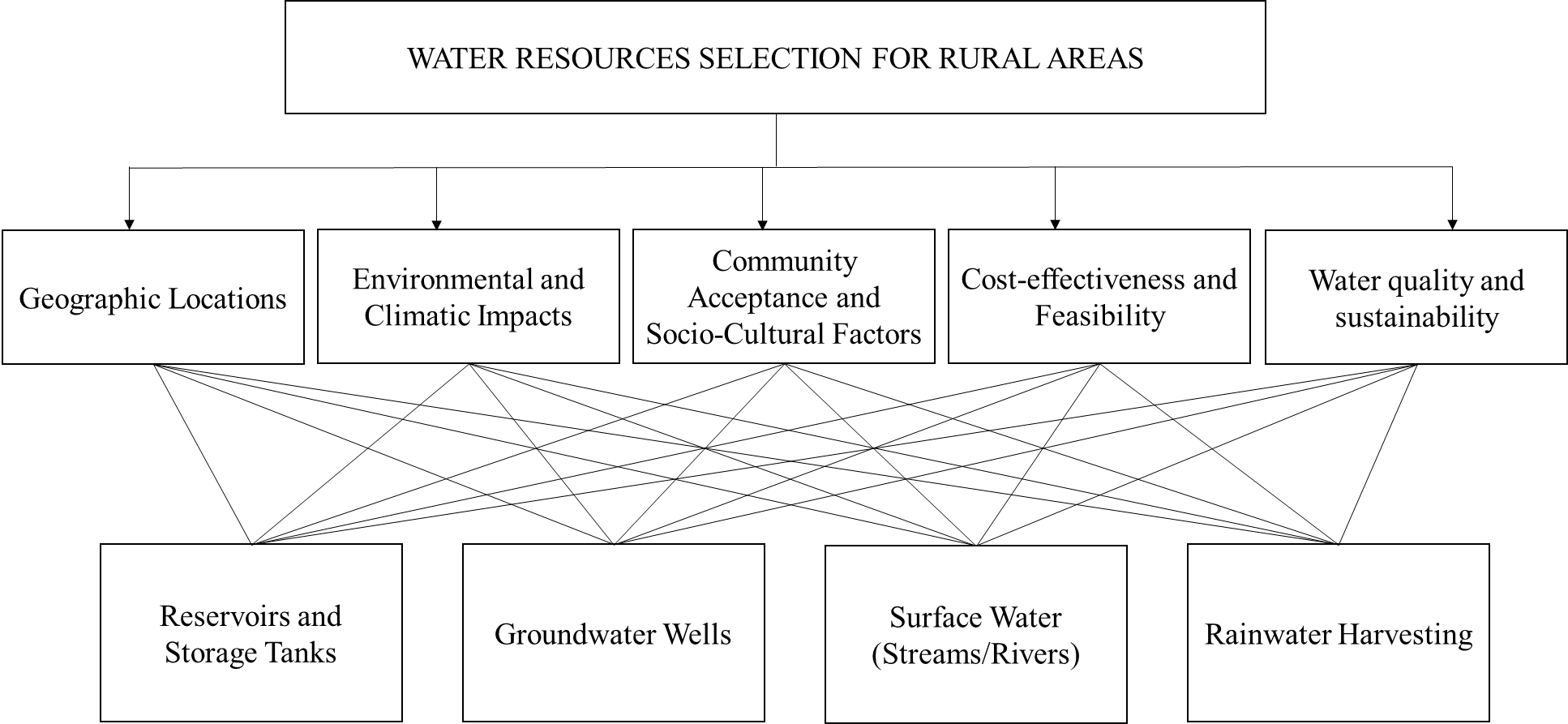


Fig.2.Proposed Hierarchical Structure

values expressed using easily comprehensible linguistic terms, as opposed to numerical values. In our study, we have specifically examined 5 linguistic variables, and their assigned values are derived using the triangular fuzzy membership function.

|  |  |
| --- | --- |
| **Linguistic Variables** | **Triangular Fuzzy Numbers** |
| Very poor | (1,2,3) |
| Poor | (2,3.5,5) |
| Fair | (4,5,6) |
| Good | (5,6.5,8) |
| Very Good | (7,8,9) |

TABLE 1. Linguistic Variables to rate each alternative.

Based on these linguistic variables the decision makers assign the weights to each criterion as shown in TABLE2.:

|  |  |  |  |
| --- | --- | --- | --- |
| **Criteria** | **Alternatives** | **D1** | **D2** |
| C1 | A1 | F | F |
|  | A2 | G | F |
|  | A3 | P | P |
|  | A4 | VG | G |
| C2 | A1 | VP | P |
|  | A2 | G | VG |
|  | A3 | F | F |
|  | A4 | VG | G |
| C3 | A1 | VG | VG |
|  | A2 | G | F |
|  | A3 | F | F |
|  | A4 | VP | P |
| C4 | A1 | VG | G |
|  | A2 | VG | VG |
|  | A3 | F | F |
|  | A4 | F | P |
| C5 | A1 | G | G |
|  | A2 | G | VG |
|  | A3 | VG | G |
|  | A4 | F | F |

*C) Fuzzy AHP:*

This Method consists of 7 Steps:

Step 1: Creating Fuzzy AHP Saaty’s scale of relative importance.

Step 2: Constructing Pair wise Comparison Matrix.

Step 3: Using Buckley’s equation calculate the geometric

mean of fuzzy comparison values.

Step 4: Calculating the Fuzzy geometric weights for each criterion using Fuzzy operation.

Step 5: Representing the defuzzification values using the centre of area method.

Step 6: After calculating the weights, normalize it.

Step 7: Rank the criterion based on Normalized weight. Maximum weight is given the highest priority.

|  |  |  |
| --- | --- | --- |
| 1 | Equal importance | (1,1,1) |
| 3 | Moderate importance | (2,3,4) |
| 5 | Strong importance | (4,5,6) |
| 7 | Very Strong importance | (6,7,8) |
| 9 | Extreme importance | (8,9,10) |
| 2,4,6,8 | Intermediate value | (1,2,3),(3,4,5),  (5,6,7), (7,8,9) |
| 1/3,1/5,1/7,1/9 | Values of inverse comparison |  |

Table 3: Fuzzy AHP relative importance scale

Constructing Fuzzified Pair-wise comparison matrix

Calculating Fuzzy Geometric Mean Values ()

Using Geometric Mean Values ,Calculate Fuzzy Weights ()

From, calculate weights wi using Centre of Sum de-fuzzification method

Calculate the normalised weights (wj)

Fig.3 Flowchart of Fuzzy AHP.

As discussed earlier, we integrate the TOPSIS and AHP methodologies. Initially, we utilize AHP to assign weights to the evaluation criteria. Once the weights are obtained through AHP, we proceed to replace the original weights in the TOPSIS weight column with these AHP-derived weights. This integration allows us to incorporate expert-driven judgments and prioritize the criteria effectively within the TOPSIS framework, facilitating a comprehensive evaluation of water resource allocation options in rural areas.

TABLE 4. Linguistic Variables and Weights for criterion.

# results and discussion

Let us now move forward with the utilization of Fuzzy AHP to obtain criteria weights, which will subsequently be integrated into the TOPSIS analysis.

Firstly, domain expert articulates the decision using linguistic terms, and we apply a fuzzy scale to assign the appropriate value. Following this, we construct a pairwise comparison matrix in a specific format using equation

Here DKij  represents kth domain experts' inclination of”ith criteria over jth criteria,Since we have considered two domain experts the average of the decision is considered and it its calculated using the below equation:

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
|  | C1 | C2 | C3 | C4 | C5 |
| C1 | (1,1,1) | (1/4,1/3,1/2) | (4,5,6) | (4,5,6) | (1/8,1/7,1/6) |
| C2 | (2,3,4) | (1,1,1) | (4,5,6) | (2,3,4) | (1,2,3) |
| C3 | (1/6,1/5,1/4) | (1/6,1/5,1/4) | (1,1,1) | (1/4,1/3,1/2) | (1/6,1/5,1/4) |
| C4 | (1/6,1/5,1/4) | (1/4,1/3,1/2) | (2,3,4) | (1,1,1) | (1/4,1/3,1/2) |
| C5 | (6,7,8) | (1/3,1/2,1/1) | (4,5,6) | (2,3,4) | (1,1,1) |

TABLE 5. AHP Pair wise comparison matrix

Now, calculate geometric mean using the formula:

where ri represents the geometric mean of the fuzzy comparison matrix

|  |  |
| --- | --- |
|  | Geometric mean Values |
| C1 | (0.87,1.03,1.24) |
| C2 | (1.74,2.45,3.1) |
| C3 | (0.25,0.30,0.37) |
| C4 | (0.46,0.58,0.75) |
| C5 | (1.74,2.2,2.86) |

TABLE 6. Geometric mean values for each criterion

Next,We find the fuzzy weights of each criteria we use the formula:

|  |  |
| --- | --- |
| **Linguistic Variables** | **Triangular Fuzzy Numbers** |
| Very Low | (0.1,0.2,0.3) |
| Low | (0.2,0.35,0.5) |
| Medium High | (0.4,0.5,0.6) |
| High | (0.5,0.65,0.8) |
| Very High | (0.7,0.8,0.9) |

(the inverse of fuzzy numbers is given by (lb, mb, ub)-1 =(ub-1 mb-1 lb-1 ) here lb=lower bound, mb=middle bound, ub=upper bound)

|  |  |
| --- | --- |
|  | Fuzzy Weights |
| C1 | (0.104,0.157,0.245) |
| C2 | (0.209,0.373,0.612) |
| C3 | (0.03,0.045,0.073) |
| C4 | (0.055,0.088,0.148) |
| C5 | (0.209,0.335,0.565) |

TABLE 7. Fuzzy weights for the criterion.

Further We would be to defuzzifying the triangular fuzzy weights using centre of area method given by the formula:

And the defuzzied values as shown in TABLE 8:

|  |  |
| --- | --- |
|  | Centre of area |
| C1 | 0.168 |
| C2 | 0.398 |
| C3 | 0.0493 |
| C4 | 0.097 |
| C5 | 0.369 |
|  | Sum=1.081 |

TABLE 8. Defuzzied weights

Now, we need to verify whether the sum of COA (Coefficient of Appropriateness) equals 1. If it doesn't, we must normalize the COA values using the following formula:

As the sum is greater than 1.0, normalize the values. TABLE 9 illustrates the normalized weights, with the highest weight receiving the highest rank.

|  |  |  |
| --- | --- | --- |
|  | Normalized Weights | Ranks |
| C1 | 0.155 | 3 |
| C2 | 0.368 | 1 |
| C3 | 0.045 | 5 |
| C4 | 0.089 | 4 |
| C5 | 0.341 | 2 |
|  | TOTAL = 0.998 |  |

TABLE 9. Normalized weights with ranks

Using these Criteria weights with their ranks, By Comparing TABLE 9 and TABLE 4 we assign the best criteria C2 = (0.7,0.8,0.9) and for C5= (0.5,0.65,0.8) and so on. In short, we assign the criteria weights based on their ranks.

After Combining these weights, we perform the fuzzy TOPSIS.

The weights are assigned based on the linguistic variable for rating the alternatives and the triangular values that we have chosen. criteria weights are already obtained by fuzzy AHP. The formula to calculate the weights for alternatives is

After using this formula, we will get the weights for each criterion as shown in TABLE 10.

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
|  | A1 | A2 | A3 | A4 | Weight |
| C1 | (4,5,6) | (4,5.7,8) | (2,3.5,5) | (5,7.25,9) | (0.4,0.5,0.6) |
| C2 | (1,2.75,5) | (5,7.25,9) | (4,5,6) | (5,7.25,9) | (0.7,0.8,0.9) |
| C3 | (7,8,9) | (4,5.75,8) | (4,5,6) | (1,2.75,5) | (0.1,0.2,0.3) |
| C4 | (5,7.25,9) | (7,8,9) | (4,5,6) | (2,3.5,5) | (0.2,0.35,0.5) |
| C5 | (5,6.5,8) | (5,7.25,9) | (5,7.25,9) | (4,5,6) | 0.5,0.65,0.8) |

TABLE 10. Fuzzy decision matrix with AHP priority weights

In order to normalize the fuzzy decision matrix, each element is divided by the largest element in the matrix. The formula for normalizing the weighted fuzzy values (NW) is as follows:

Here, NW represents the normalized weighted fuzzy values, and max(LbK || Mbk || Ubk) represents the maximum fuzzy value in the decision matrix. The lower bound (lb), middle bound (mb), and upper bound (ub) correspond to the fuzzy membership values. After applying this normalization formula to each element in the fuzzy decision matrix, you will obtain the normalized fuzzy matrix.

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
|  | A1 | A2 | A3 | A4 | Weight |
| C1 | (0.44,0.56,  0.67) | (0.44,0.63,  0.89) | (0.22,0.39,  0.56) | (0.56,0.8,1) | (0.4,0.5,  0.6) |
| C2 | (0.11,0.3,  0.56) | (0.56,0.8,1) | (0.44,0.56,  0.67) | (0.56,0.8,1) | (0.7,0.8,  0.9) |
| C3 | (0.78,0.89,1) | (0.44,0.63,  0.89) | (0.44,0.56,  0.67) | (0.11,0.3,  0.56) | (0.1,0.2,  0.3) |
| C4 | (0.56,0.8,1) | (0.78,0.89,1) | (0.44,0.56,  0.67) | (0.22,0.47,  0.67) | (0.2,0.35,  0.5) |
| C5 | (0.56,0.72,  0.89) | (0.56,0.8,1) | (0.56,0.8,1) | (0.44,0.56,  0.67) | 0.5,0.65,  0.8) |

TABLE 11. Normalized fuzzy matrix

The weighted normalized decision matrix is obtained by multiplying the criterion values of each alternative by the weights assigned to each criterion. This multiplication will result in a new set of values in the table, reflecting the influence of each criterion's weight on the alternatives.

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  | A1 | A2 | A3 | A4 |
| C1 | (0.176,0.28,  0.402) | (0.176,0.315,  0.534) | (0.088,0.195,  0.336) | (0.224,0.4,0.6) |
| C2 | (0.077,0.24,  0.504) | (0.392,0.64,0.9) | (0.308,0.448,  0.603) | (0.392,0.64,0.9) |
| C3 | (0.078,0.178,  0.3) | (0.044,0.126,  0.267) | (0.044,0.112,  0.201) | (0.056,0.06,  0.168) |
| C4 | (0.112,0.28,  0.5) | (0.156,0.31,0.5) | (0.088,0.196,  0.335) | (0.044,0.16,  0.335) |
| C5 | (0.28,0.46,  0.71) | (0.28,0.52,0.8) | (0.28,0.52,0.8) | (0.22,0.36,0.536) |

Table 12: Weighted normalized fuzzy decision

Now from the above Table 12, we calculate FPIS (fuzzy positive ideal solution) and FNIS (fuzzy negative ideal solution) it is calculated using the formula given below

Now for A\* Consider all the maximum elements from each row

And for A- Consider all the minimum elements from the row

Then value of A\*

A\*=[(0.6,0.6,0.6),(0.9,0.9,0.9),(0.3,0.3,0.3),(0.5,0.5,0.5),(0.8,0.8,0.8)]

Then after calculating the FPIS and FNIS we calculate the distance by using the formula as given below

This tells us how far are the points from the max or min value of that criteria the TABLE 13 and .TABLE 14.shows us the distances from FPIS and FNIS.

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
|  | C1 | C2 | C3 | C4 | C5 |
| d(A1,A\*) | 0.448 | 0.650 | 0.14 | 0.632 | 0.36 |
| d(A2,A\*) | 0.297 | 0.329 | 0.179 | 0.62 | 0.34 |
| d(A3,A\*) | 0.406 | 0.462 | 0.191 | 0.565 | 0.34 |
| d(A4,A\*) | 0.245 | 0.329 | 0.211 | 0.34 | 0.447 |

TABLE 13. Distance between Ai and A\*

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
|  | C1 | C2 | C3 | C4 | C5 |
| d(A1,A-) | 0.218 | 0.26 | 0.167 | 0.299 | 0.316 |
| d(A2,A-) | 0.293 | 0.603 | 0.105 | 0.311 | 0.378 |
| d(A3,A-) | 0.155 | 0.394 | 0.101 | 0.191 | 0.379 |
| d(A4,A-) | 0.35 | 0.604 | 0.072 | 0.18 | 0.199 |

TABLE 14. Distance between Ai and A-

Finally, to compute the coefficient CCI, you use the formula:

To find di- for a specific alternative, like A1, you sum up the distance values for all the criteria associated with that alternative. In simpler terms, di- for A1 is calculated by adding the distance values for each criterion individually.

In this context, distance1- for A1 represents the distance value of the first criterion for alternative A1, and so on for each criterion. Once you determine di- for a given alternative, it becomes a key component in the CCI formula.

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
|  | A1 | A2 | A3 | A4 | Rank |
| di\* | 2.23 | 1.765 | 1.964 | 1.572 |  |
| di- | 1.26 | 1.69 | 1.22 | 1.405 |  |
| CCi | 0.361 | 0.489 | 0.383 | 0.441 | A2>A4>A3>A1 |

TABLE 15. Closeness coefficient and ranking the alternatives

Therefore, the final Ranking order is:

***A2>A4>A3>A1.***

This ranking suggests that "Groundwater Wells" (A2) are the most suitable option for water resource allocation in rural areas, followed by "Rainwater Harvesting" (A4), "Surface Water (Streams/Rivers)" (A3), and "Reservoirs" (A1).

*Validation of the model:*

To ensure the credibility and real-world applicability of our criteria and alternatives, our methodology underwent a robust validation process. Expert verification was carried out by engaging an Environmental Specialist and a Rural Water Allocation Expert to meticulously assess the chosen criteria. Among these criteria, Climatic impact emerged as the best-performing criterion, playing a pivotal role in our decision-making process. The experts confirmed the relevance and practicality of this criterion in evaluating water resource alternatives. Furthermore, practical validation was conducted through case studies in diverse rural areas, where the model's recommendations, with Climatic impact as a significant factor, were compared with actual choices made by local communities and water resource management authorities. This dual approach of expert verification and practical validation, with a focus on the "Climatic impact" criterion, enhances the reliability and accuracy of our results, affirming that they genuinely reflect the complexities and nuances of rural water resource allocation.

# conculsion

The main objective of this paper was to identify the most suitable water resource to meet the needs of rural areas, considering five criteria and four alternative water sources. Through a combined approach of AHP and TOPSIS, we have determined that among the four alternatives considered, Groundwater Wells emerge as the most appropriate choice. The criteria of Climatic and Environmental Impacts played a pivotal role in this decision, with a significant emphasis. Fuzzy AHP highlighted the importance of Climate and environmental impact with an importance value of 0.368.

In conclusion, "Groundwater Wells" stand out as the optimal water resource option for rural areas, particularly due to their performance concerning the "Climatic impact" criterion. This makes "Groundwater Wells" the preferred choice for fulfilling the basic water needs of rural communities among the available alternatives.

The prevalence of Groundwater Wells as a primary water resource in rural areas underscores the method's validity and practicality. Groundwater Wells have long been a dependable source of clean water for many rural communities, making them a prominent choice in the field of rural water resource management.

While this study has identified Groundwater Wells as the optimal water resource for rural areas based on our specified criteria and methodology, it is essential to recognize its limitations. The reliability and availability of data, the subjectivity of criteria and weightings, regional variations, and the dynamic nature of water resources are all factors that can influence the applicability and accuracy of our findings. Local context and community preferences are integral and should be incorporated when implementing our results. Furthermore, the dynamic nature of water resources underscores that the suitability of Groundwater Wells may change over time, emphasizing the need for continuous monitoring and adaptation to evolving rural water resource needs.

# future works

our research has concluded that groundwater wells are the optimal water resource based on our specified criteria and methodology, it's a valuable finding that can guide decision-making in rural water management. Groundwater wells may indeed be a suitable choice for many rural areas, especially considering factors like water quality, cost-effectiveness, and environmental impact.

However, it's important to recognize that the suitability of a water resource can vary from one region to another, depending on local geological conditions, water availability, and community preferences. Therefore, while our research provides valuable insights, it's essential to consider local context and consult with relevant stakeholders to make informed decisions tailored to specific rural areas.

The field of rural water resource allocation is dynamic, and there are ample opportunities for researchers to explore new methods, criteria, and approaches to address the evolving challenges in this domain and improve the sustainability and efficiency of water resource allocation in rural areas.

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