Official Journal of the World Water Council
Water Policy

Water Policy Vol 24 No 6, 878 doi: 10.2166/wp.2022.236

A framework for optimal rank identification of resource management systems using probabilistic approaches in analytic hierarchy process

Ravi Gorripati [a,*], Mainak Thakur[a] and Nagesh Kolagani[b]

[a] Indian Institute of Information Technology Sri City, Chittoor, Andhra Pradesh, India
[b] Centurion University of Technology and Management, Odisha, India
*Corresponding author. E-mail: ravi.g@iiits.in

RG, 0000-0003-0564-1360

ABSTRACT

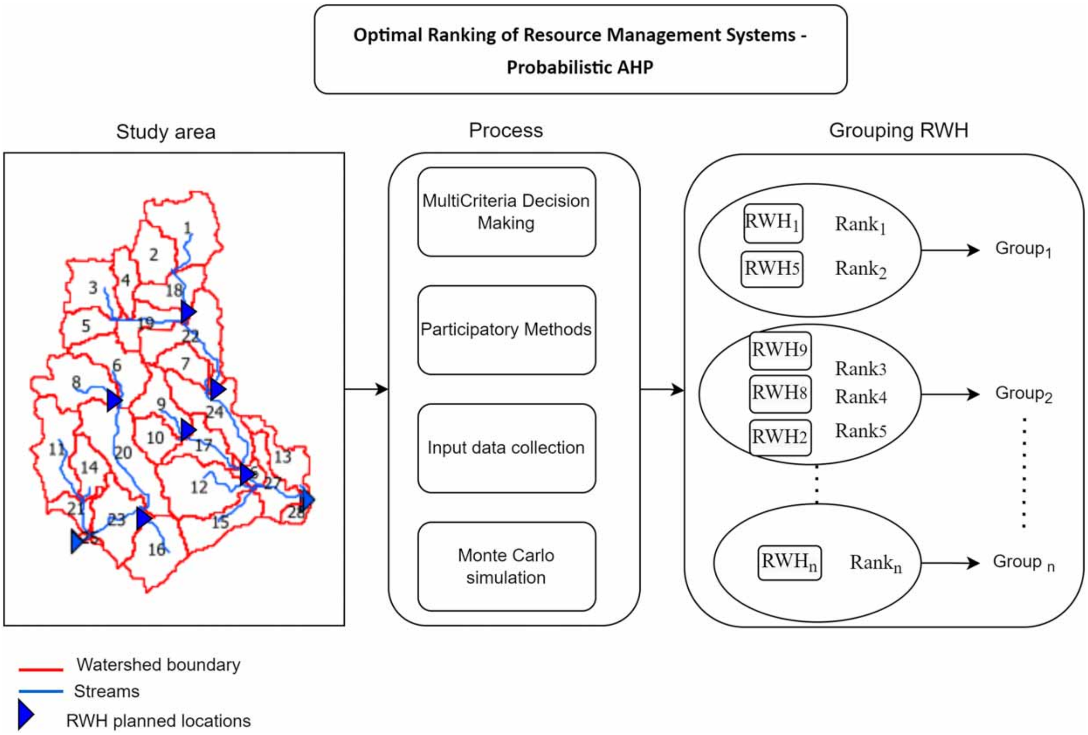
A resource management system is likely to succeed if stakeholders get involved in analyzing and choosing from the alternatives. The present work deals with multi-criteria decision models to evaluate rain water harvesting (RWH) structures. Standard practice is to acquire the weights for criteria from stakeholders using analytic hierarchy process (AHP) to predict the RWH structures' performance and rank them. Challenges in this process are that the data collection is laborious and time-consuming, considers limited stakeholders' opinions, and suffers from lower confidence factors. This work proposes a probabilistic approach to AHP using Monte Carlo simulation (MCS) to model uncertainty. The proposal is to collect multiple assessments instead of a single judgment from knowledgeable stakeholders (KSH) with customized questionnaires and to compute the relative importance of criteria using pairwise comparisons. Stochastically similar assessments within the range of these samples are then generated using different distribution functions to compute the performance of the RWH structures. The computed performance correlated well with common stakeholders' (CSH) opinions in the case study involving 10 existing RWH structures with seven different criteria, for all the distributions. The mean relative error with the proposed method is approximately 21% less than the existing point estimate method.

Key words: Analytic hierarchy process (AHP), Monte Carlo simulation (MCS), Multi-criteria decision modeling (MCDA), Participatory modeling (PM)

HIGHLIGHTS

- Handles uncertainty using multi-criteria decision models and the Monte Carlo simulation method.
- Input data modeling via range selection instead of a single value for the study.
- Proposed a probabilistic AHP for analysis of RWH structures with a ranking approach.
- Improved confidence in decision making toward RWH structures priority ranking.

GRAPHICAL ABSTRACT



ABBREVIATIONS

AHP	Analytic hierarchy process
CI	Consistency index
CR	Consistency ratio
CSH	Common stakeholder
ESH	Expert stakeholder
KSH	Knowledgeable stakeholder
PM	Participatory modeling
RI	Random index
RWH	Rain water harvesting
MADM	Multi-attribute decision making
MCDM	Multi-criteria decision modeling
MCS	Monte Carlo simulation
MODM	Multi-objective decision making
ND	Normal distribution
TD	Triangular distribution
UD	Uniform distribution

INTRODUCTION

According to an economic survey conducted in 2020, agriculture is the backbone of the Indian economy and livelihood for 54.6% of the population (Economic Survey, 2020–21). In general, agriculture can be categorized into two types – rainfed agriculture and irrigated agriculture. Irrigated agriculture is further classified into canal irrigation and groundwater irrigation. As far as the total cultivated land is concerned, 48.79% was irrigated, and the remaining 51.21% covers rainfed agriculture, which relies totally on monsoon and suffers from associated risks (Department of Agriculture, Annual Report, 2018–19). Typically, certain crops like groundnut, millets, and legumes are often found in hilly areas that cannot be irrigated and therefore depend on rain. Due to the ever growing need for food grains in the country coupled with the uncertainty of rain, farming has shifted significantly toward groundwater irrigation. It is important to note that, around 89% of groundwater in India is utilized only for agriculture purposes (Groundwater Year Book India, 2019–20). The crisis of groundwater has become a serious concern both in terms of frequency and magnitude. However, the primary reason for the declining groundwater levels is not just climatic changes but excessive water extraction for agricultural/aquatic farming as well as domestic and industrial use (Halder *et al.*, 2020). It is feared that the occurrence of droughts may accelerate due to overexploitation of groundwater and surface water resources, high evapotranspiration, low precipitation, or a combination (Sharma & Smakhtin, 2006; Pai *et al.*, 2016). Mishra (2020) studied hydrological droughts that occurred in 1876, 1899, 1918, 1965, 2000, and 2015 based on the overall severity score, and among all droughts between 1870 and 2018, the recent one in 2015–2018 was considered the most severe causing depletion of agricultural groundwater. As a result, the overall food production and livelihood of as much as 60% of the Indian population were affected (Mishra, 2020).

Predominantly, low rainfall is cited as the most common cause of drought. The fact that the proliferation of tube wells and the availability of power may also instigate drought is often disregarded. Interestingly, along with other probable causes, overexploitation and inadequate rain water harvesting (RWH) structures may be counted as one of the contributing factors to droughts (Kolagani *et al.*, 2015). RWH structures are defined as small structures used to collect rainwater from stream flows and store it for future usage like agriculture, drinking water for cattle, fisheries, and eventually contribute in improving groundwater levels (Mohanty *et al.*, 2020; Eludoyin *et al.*, 2021). As the need for RWH structures is well established, the concerned administrations seek to initiate projects for constructing proper RWH structures to deal with drought situations. In order to materialize this, the Indian government spends 50,000 crores every year for constructing RWH structures to beat the droughts, but the results are found to be suboptimal. The reasons might be improper planning and coordination between different functioning units and poor implementation at the ground level. These RWH structures being small and spread geographically, their planning and implementation do not receive adequate attention and they fall short in meeting user needs. Consequently, local stakeholder involvement is most desirable to execute and achieve expected results in water conservation projects (Teder & Kaimre, 2018; Daher *et al.*, 2019).

Stakeholders are often required to analyze multiple alternatives of RWH structures to select an optimal fit based on practical constraints like construction cost and time (Hadihardaja & Grigg, 2011). A simple and elegant multi-criteria decision model such as linear weighted summation would help to make such decisions. The use of optimized models to address challenging real-life situations has been the focus of interest in many diverse intelligent decision support systems. For instance, a few prominent decision-making approaches are multi-attribute decision making (MADM), multi-objective decision making (MODM), and multi-criteria decision modeling (MCDM). The MADM approach determines how to find the best alternative by handling data and utilizing a set of parameters (Chen & Hwang, 1992). MODM helps to bring transparency in solving complex issues that involve multiple criteria and multiple stakeholders sensitive to the consequences. Furthermore, it selects the best from multiple objects with simultaneous and optimized evaluation (Zavadskas *et al.*, 2019).

Mateo (2012) proposed an integrated model combining the MODM with the MADM model. This improved MADM is found to be superior to MODM in terms of the problem-solving approach for selecting alternative mechanisms (Akbaş & Bilgen, 2017). On the other hand, MCDM is a reliable and beneficial model for decision making that converts stakeholder's opinions into statistics (San Cristóbal, 2011). Also, these methods mainly focus on quantitative analysis. Depending on the stakeholder's requirements, an evaluation of the right decision is carried out overcoming the challenges such as uncertain expert judgment and bias. While using MCDM for water resource management, the comprehensive problem structuring, the detailed proposal of alternatives, and stakeholder's trade-offs should be established for effective decision making (Stewart & Scott, 1995).

Analytical or quantitative models illustrated above rank the alternatives and assist the stakeholders to choose the most suitable ones. It is also observed that researchers mostly tend to use analytic hierarchy process (AHP) as part of MCDM (Mahammad & Islam, 2021). The AHP is a well-structured technique for analyzing and organizing complex decisions based on mathematics and human psychology (Saaty, 1980, 1990). The approach lies in quantifying the weights of decision criteria taking into account individual experts and common stakeholder's experiences. Furthermore, this helps to estimate the relative importance of criteria through pairwise comparisons using specially designed questionnaires. AHP approach has been employed in the existing literature for various domains, for example, optimal site identification for RWH structure (Wu *et al.*, 2018), and partially collapsed building failure analysis in the construction domain (Alaneme *et al.*, 2020). Similarly, Do & Kim (2012) developed an evaluation model to select optimal concrete repair patching material.

Notably, stakeholder participation has yielded better results with fewer conflicts and helped develop a framework using AHP toward facilitating rank alternatives (Kolagani *et al.*, 2015). Researchers employed AHP to analyze drinking water sustainability in India (Poonia & Punia, 2018). Furthermore, AHP was implemented for optimum irrigation maintenance budget allocation for rural water supply in Bangladesh (Sikder & Salehin, 2015). In conventional AHP, the input data collection process is used to evaluate the relative importance of criteria. For this reason, stakeholders were approached to provide a value by comparing one criterion with other criteria. Later, weights were computed for criteria, exercising the AHP method (Elewa *et al.*, 2021). When multiple structures have the same weight, the confidence in the decision is reduced. However, stakeholders participate in the process of calibrating the system based on the actual performance of the RWH structures.

While participatory methods are democratic and result in the effective use of resources, they also add cognitive load to the stakeholders. The subjectivity in the stakeholders' judgment or personal bias is an inevitable issue in this process. Even before the common stakeholders can participate in any simulation or decision making, they need to be appropriately trained, educated, and stimulated to think, which may be difficult and time-consuming. In fact, AHP is a powerful tool and inherently suitable when there are heterogeneous stakeholders. It enables the analysis of complex decisions with long-term effects, using multiple evaluation criteria. However, the uncertainties in the input data, especially from varied stakeholders, may severely impact the confidence on the results. It is therefore proposed to address this aspect using additionally generated data with the help of different probabilistic distribution functions. The current paper is an effort to make decision-making more robust and dependable under varied conditions of inputs.

The proposed approach is to channel expert stakeholders' inputs in a probabilistic model based on Monte Carlo simulation (MCS) and to generate a large number of probabilistically equivalent inputs. MCS-aided AHP (MCS-AHP) technique has been used in the literature to minimize sensitivity and uncertainty and applied in several areas such as flood susceptibility mapping (Dahri & Abida, 2017), identifying the most appropriate locations for turbine positioning (Díaz *et al.*, 2022), tunnel collapse risk evaluation (Kim *et al.*, 2022), soil erosion hazard, landslide susceptibility mapping, environmental risk assessment (Orosun *et al.*, 2022), and policies regarding pollution.

However, the application of this MCS-AHP technique in evaluating the RWH system is the first of its kind. Primarily to increase the confidence of stakeholders to participate in decision making and improve the planning and execution of resource management such as RWH structures, we have used various distribution functions and compared the results. Furthermore, this work has been validated with a case study village – E. Palaguttapalle, located in the southern part of India in the Chittoor district of the state of Andhra Pradesh. This particular village has several RWH structures. To be specific, it contains about 200 inhabitants, and they primarily rely on agriculture for their livelihood. Furthermore, groundwater contributes approximately 90% of the net irrigated area, and surface water contributes 10% of the same. As a continuation of the AHP and related work that is already underway in the village, and since the village provides a good demonstrative example of water management projects in the region, it was selected to conduct the study here.

The paper is organized as follows. Section 'Methodology' describes the process to compute the criteria weights and rank the alternatives. Section 'Case Study' discusses the implementation of the proposed probabilistic AHP method in a case study village. Section 'Results' illustrates the outcomes, and Section 'Discussion' discusses the advantages and challenges regarding the proposed method. Finally, Section 'Conclusion' concludes the work with possible research directions.

METHODOLOGY

The performances of RWH systems have already been evaluated through participatory frameworks with the help of AHP and single point estimate (Kolagani *et al.*, 2015). To the best of authors' knowledge, especially in this domain, the proposed probabilistic MCS-AHP approach (probabilistic AHP) to capture multiple stakeholders' perceptions is unique. The probabilistic AHP approach is useful in capturing stakeholders' perceptions, thereby minimizing the uncertainties and sensitivities involved in this sophisticated process. In fact, multiple probability distributions have been explored to derive stakeholders' responses, and the results have been compared.

The framework of the participatory model is illustrated in Figure 1. The initial work involves stakeholder classification, where *Stakeholders* are categorized based on their experience in RWH structures construction, knowledge in water conservation, and educational qualifications. The interaction with the stakeholders has been conducted using the key informant interview approach. It helps to model the *Criteria Identification* through literature review and brainstorming with domain experts and local stakeholders (KSH and CSH) based on the RWH information. The next task focuses on *Input Data Collection*, where knowledgeable stakeholder (KSH) provides inputs on criteria using pairwise comparison with the help of a questionnaire. Subsequently, the proposed probabilistic AHP model is implemented using *Monte Carlo Simulation* with various probability distribution functions generated using the collected data from KSH. Then, criteria weights were calculated in order to compute the RWH structure performance. Additionally, *Model Validation* has been done by comparing evaluated performance with an observed performance by common stakeholder (CSH), and finally rank the alternatives.

Stakeholder classification

Stakeholders are defined as individuals who are impacted by the system. In other words, they benefit or face losses due to the system (Kolagani *et al.*, 2015). For instance, farmers, farm laborers, residents, decision makers, and funding agencies could be considered as stakeholders in the RWH structures. Here, the notion of stakeholders is augmented by considering three different types, such as CSH, KSH, and expert stakeholders (ESH). The people impacted by RWH structures are classified as CSH. Specific persons with practical knowledge to plan and implement RWH structures are categorized under KSH. The ESH refers to those involved in planning and implementing at least 10 RWH structures.

Criteria identification

Stakeholder participation is considered crucial for implementing an efficient and successful resource management system (Teder & Kaimre, 2018; Daher *et al.*, 2019). But, stakeholders' participation should be systematic

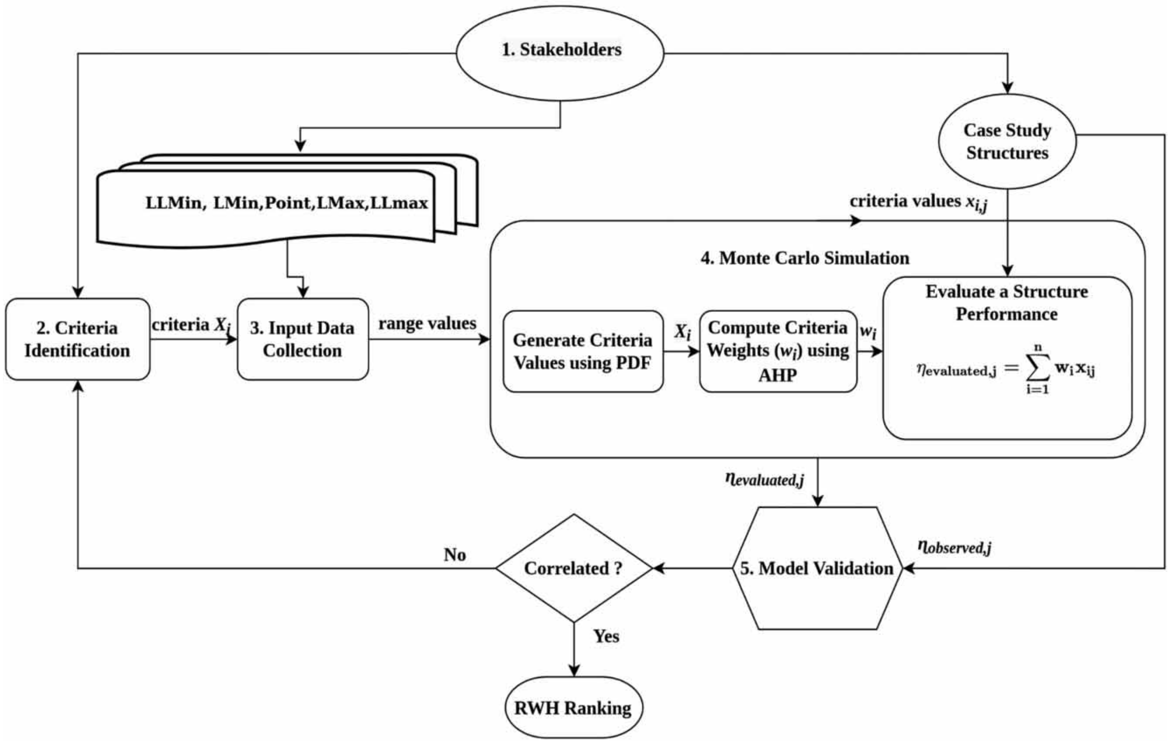


Fig. 1 | Framework of participatory model calibration.

and should lead to more insights into the criteria identification process. Key participation along with a quantitative model can successfully measure the structure's performance factors. These factors express the value or utility of a solution and are denoted as criteria (X_i). For example, a set of criteria can reflect the performance of a planned or constructed RWH along with the social impact. Criteria identification can either be gathered from relevant literature or technical experts. In either of these cases, the criteria discussion with the local stakeholders is necessary as the RWH structures rely on multiple factors such as social, cultural, climatic, and economic factors that vary from village to village. The stakeholders may either prioritize a set of existing criteria or mark a few as irrelevant, and even add new criteria. Hence, identifying relevant criteria is imperative before starting the modeling or simulation process.

The criteria identification procedure has been adopted by Kolagani *et al.* (2015) after performing the technical validation processes. In this connection, personal interviews with expert stakeholders have been conducted. For the RWH structures, the set of criteria is given as follows:

- *Potential water inflow* (c_1) depends on catchment area, rainfall, and runoff percentage.
- *Site suitability* (c_2) is defined by the slope of the land and soil permeability.
- *The extent of utilization* (c_3) depends on different purposes such as irrigating farms, drinking water for people and animals, fishing, and preventing soil erosion.
- *Stakeholders' initiative* (c_4) can be estimated based on involvement at the time of planning and implementation of RWH.
- *Social equity* (c_5) is evaluated by stakeholders' involvement based on social and economic status.

- *Spatial equity* (c_6) decides based on the water tradeoff between downstream and upstream stakeholders.
- *Ease of maintenance* (c_7) based on stakeholders' effort to preserve the RWH.

Input data collection

Stakeholders' inputs are collected in a systematic manner adhering to the AHP procedure. Let us assume that there are n criteria for making a decision. In general, an $n \times n$ comparison matrix C is obtained, comparing each criterion with every other criterion. The comparison matrix elements are denoted as $c_{i,j}$. Therefore, the diagonal elements are 1 ($c_{i,i} = 1$). Furthermore, the lower matrix elements are the reciprocal of the upper matrix ($c_{j,i} = 1/c_{i,j}$) for all i,j matrix indices. Hence, any pairwise comparison matrix is reciprocal symmetric, and the variable $c_{j,i}$ is dependent on $c_{i,j}$. Since it is assumed that $\{c_{i,j} | i > j\}$ are independent, then the stakeholder addresses only $n(n-1)/2$ comparisons. The entries $c_{i,j}$ with condition $i < j$ measure the importance of criterion i compared to criterion j. The criterion importance is measured on a scale of {1/9:1:9} as mentioned in Table 1. For instance, $c_{i,j} = 1$ indicates equal significance for both criteria, and $c_{i,j} = 9$ represents criterion j is of higher importance than criterion i. Whereas $c_{i,j} = 1/9$ indicates criterion i is more important than criterion j (Saaty, 2001).

$$C = \begin{bmatrix} 1 & c_{12} & \cdots & c_{1n} \\ 1/c_{12} & 1 & \cdots & c_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ 1/c_{1n} & 1/c_{2n} & \cdots & 1 \end{bmatrix} \tag{1}$$

An adaptive range selection mechanism was employed to make the existing method more accurate and reliable. A questionnaire with $n(n-1)/2$ questions of n criteria was prepared, and a detailed explanation of each question was provided to the KSH. They were asked to provide five assessments in multiple iterations using pairwise criteria comparison instead of a single assessment as in conventional AHP. In the first iteration, KSHs assessed one value (point) for each question by comparing criteria. In the second iteration, the KSHs assessed two values for each question referred to as *likely minimum (LMin)* and *likely maximum (Lmax)* values. Finally, in the third iteration, the same set of KSHs provided two more values: *least likely minimum (LLMin)* and *least likely maximum (LLmax)*, which are taken as the extremities of possible values. Meeting various stakeholders in multiple iterations helped avoid bias and gain qualitative inputs.

Table 1 | Pairwise comparison scale.

Scale	Description
1	Equally important
2	Equally to moderate important
3	Moderately important
4	Moderate to strongly important
5	Strongly important
6	Strongly to very strongly important
7	Very strongly important
8	Very strongly to extremely important
9	Extremely important
$\frac{1}{2}, \frac{1}{3}, \cdots \frac{1}{9}$	Reciprocals

Monte Carlo simulation with AHP

In order to overcome the challenge of a limited set of decisions from available stakeholders, a MCS-based probabilistic approach is proposed to generate random values to imitate the stakeholders' decisions (Baumgärtner *et al.*, 2013). In this process, an equal probability of $1/k$ is assigned to inputs from the available k stakeholders in order to be fair (Rosenbloom, 1997; Lafleur, 2011). Notably, a random selection procedure is applied for $c_{i,j}$ from the available k stakeholders and computed weights using AHP (Saaty, 2003). The simulation process begins after the hierarchy of alternatives is defined, using a decision tree with three levels. At the first level is the general goal of the decision. The criteria form the second level, and the alternatives are at the third level.

The steps of the simulation are listed below.

Step 1: Generate $c_{i,j}$ values: In input data collection, KSH has made a criteria comparison and provided *least likely minimum(LLMin)* and *least likely maximum(LLMax) values*. Now, using MCS, we generated an arbitrarily large number of $c_{i,j}$ using Normal, Triangular, and Uniform distribution approaches within the range of *least likely minimum* and *least likely maximum values* provided by KSH. The parameters of these distributions are taken from the sample characteristics. The mean and standard deviation (SD) are taken from the mean and SD of the KSHs' input values. This process helps to analyze and infer a better distribution mechanism for ranking.

Step 2: compute criteria weights

Step 2a: Perform consistency check of generated random values of step 1 using Equation (2). If the consistency ratio CR > 0.1, i.e., the difference is more significant than 10%, then discard the sample set and generate another set of $c_{i,j}$ values. The next step would be to construct a comparison matrix C, as described in the Input Data Collection section above.

$$\mathrm{CR} = \frac{\mathrm{CI}}{\mathrm{RI}} \tag{2}$$

$$\mathrm{CI} = \frac{(E_{\max} - n)}{[(n-1) \times \mathrm{RI}]} \tag{3}$$

where CI represents the consistency index, n denotes the number of criteria, $E_{\max}$ represents the largest eigenvalue in the matrix, and RI is the random index obtained from Table 2.

Step 2b: Compute the relative weights w_i by using the unique Eigenvector method of Equation (3).

$$CW = E_{\max} W \tag{4}$$

$$\begin{bmatrix} 1 & c_{12} & \cdots & c_{1n} \\ 1/c_{12} & 1 & \cdots & c_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ 1/c_{1n} & 1/c_{2n} & \cdots & 1 \end{bmatrix} \begin{bmatrix} w_1 \\ w_2 \\ \vdots \\ w_n \end{bmatrix} = E_{\max} \begin{bmatrix} w_1 \\ w_2 \\ \vdots \\ w_n \end{bmatrix}$$

where C represents the comparison matrix, W represents the eigenvalues, and $E_{\max}W$ represents the eigenvector corresponding to the largest eigenvalue.

Table 2 | Random index (RI) values based on matrix size (n) (Saaty, 1980).

n	1	2	3	4	5	6	7	8	9	10
RI	0.0	0.0	0.58	0.90	1.12	1.24	1.32	1.41	1.45	1.51

Step 3: evaluate structure performance

Step 3a: Compute the performance of alternatives and rank them.

$$\eta_{\text{evaluated},j} = \sum_{i=1}^{n} w_i x_{i,j} \tag{5}$$

The performance of alternatives is computed using Equation (5), where $\eta_{\text{evaluated},\,j}$ measures the performance of the jth structure, n denotes the number of criteria, w_i denotes the relative weight of ith criterion, x_{ij} denotes the jth structure's ith criterion value collected from ESH. The $x_{i,j}$ is expressed on a scale of 0–100%, where the mean of the criteria values is considered as the performance of that structure. With these performance values of all structures, the alternatives are rank-ordered.

Step 3b: Aggregate the alternative structure's ranks in the form of a *rank versus structures* for a better understanding, as shown in Tables 5 and 6. The *rank versus structures* could help in identifying the probabilistically better ones among all the existing structures. The process is further explained in the Results and Discussion section.

Model validation

The model is evaluated on 10 existing RWH structures available in the case study village. RWH structures include check dams, rockfill dams, and small ponds. The authors collected relevant and required data that are used to develop and test the model. The details are given in the Case Study section.

As part of the validation, a total of 44 stakeholders are met in person. In these 44 stakeholders, 19 KSHs are identified and are requested for five assessments by doing a pairwise criteria comparison. Using these assessments, we computed criteria weights w_i. In addition, five ESHs are identified among all KSH from whom individual criterion values $x_{i,j}$ are collected for all structures. In the next step, the structure's performance is computed and represented as evaluated performance $\eta_{\text{evaluated}}$. Finally, an interaction is conducted among the 20 CSHs to rate the selected structure's overall performance based on their experience and satisfaction. Since this rating is based on their satisfaction, it is called observed performance η_{observed} and is measured on a scale of 0–100%. The ratings of the jth structure provided by the CSHs are averaged to find $\eta_{\text{observed},j}$ in specific for jth structure.

Finally, to measure the correlation between observed performance η_{observed} and evaluated performance $\eta_{\text{evaluated}}$, we used the Spearman rank correlation coefficient metric. It compares generated ranks between $\eta_{\text{evaluated}}$ and η_{observed}. If the correlation is statistically significant, then the model is said to be valid and has correctly incorporated stakeholders' inputs.

The following hypothesis is tested to know the correlation between η_{observed} and $\eta_{\text{evaluated}}$ and also tested to know if it is statistically significant or not. Two hypotheses were considered as given below:

$$\left.\begin{array}{l}\text{Null hypothesis } (H_0)\text{: Probabilistic AHP does not improve} \\ \quad \text{confidence on generated ranking.} \\ \text{Alternative hypothesis } (H_1)\text{: Probabilistic AHP improves} \\ \quad \text{confidence on generated raking.}\end{array}\right\} \tag{A}$$

The probability p-value is used for hypothesis testing. Acceptance or rejection decisions regarding the hypotheses are made based on the obtained p-value. The relative error (e_r %) percentage is computed using Equation (6) and is observed to restrict the minimal difference between evaluated and observed; details are given in Table 9.

$$e_r\% = \left(\frac{|\eta_{\text{evaluated}} - \eta_{\text{observed}}|}{\eta_{\text{observed}}}\right) \times 100 \tag{6}$$

Case study

To validate the proposed methodology, a village – E. Paalaguttapalle is chosen in southern India (location depicted in Figure 2) that has been using several RWH structures over the last 20 years and a significant number of KSHs. Specifically, the village area is about 500 hectares, half of it was utilized as agricultural land, and the remaining half area is inhabited by rivers, lakes, roads, forests, and common lands. In total agricultural land, 50 hectares are irrigated, and the remaining 200 hectares use rainfed cultivation. Typically, agriculture was primarily dependent on open wells until the late 1980s. RWH structures recharged these wells. Subsequently, agriculture practices switched to bore wells, started cultivating commercial crops by irrigating with huge amounts of water and adopted PVC pipe technology for water transportation to nearby fields. Table 3 demonstrates the farmer's classification; based on that observation, half of the families are marginal farmers, one-fourth are small farmers, and medium and semi-medium farmers share the other quarter.

Model implementation

The flowchart of the present work based on the probabilistic AHP approach is depicted in Figure 3. The method increases the stakeholder's confidence by enhancing the quality of their decisions and is also further calibrated based on the considered village case study. The model presented in this work prompts the stakeholders to discuss different alternatives and reach a consensus. In this work, criteria have been identified from stakeholders' inputs in a participatory approach, and the identified criteria mainly depend on local social conditions. To eliminate biases, it is critical to choose CSH, KSH, and ESH from diverse social and economic categories and to use a stratified sampling procedure. Furthermore, 20 KSHs were selected from each category of farmers, as shown in

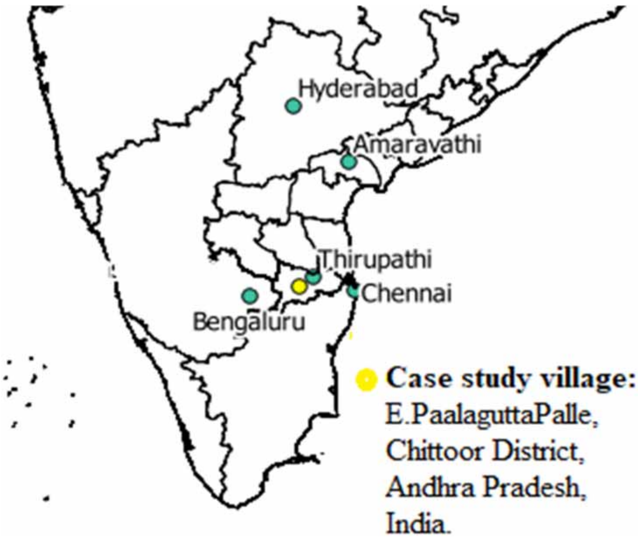


Fig. 2 | Illustration of case study village.

Table 3 | Farmers classification based on landholding (Agriculture Census Division, 2018).

S.No.	Classes	Landholding (hectares)
1	Marginal farmers	Below 1.0
2	Small farmers	1.0–2.0
3	Semi-medium farmers	2.0–4.0
4	Medium farmers	4.0–10.0
5	Large farmers	10.0 and above

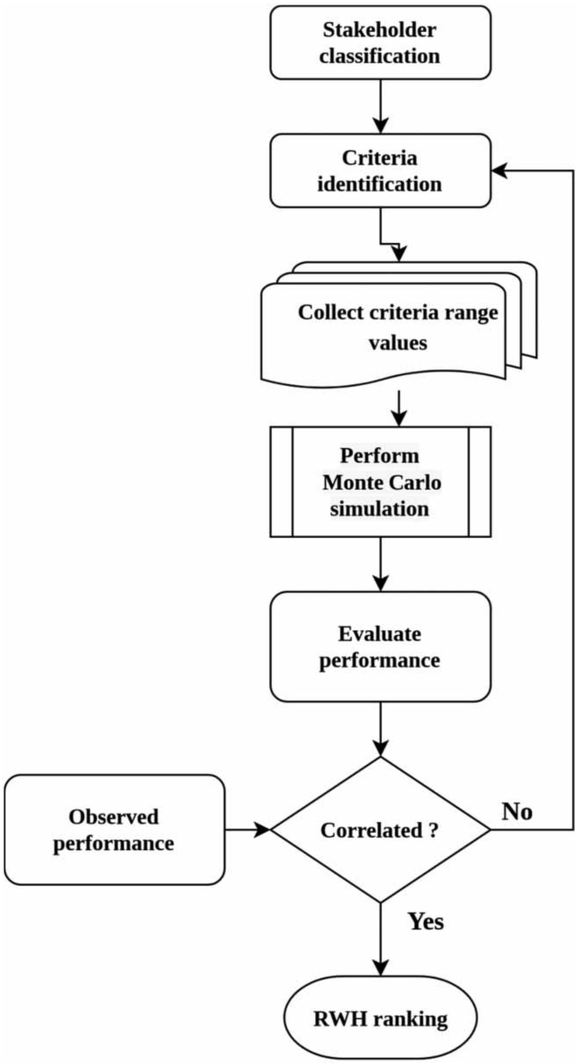


Fig. 3 | Flowchart of the proposed work.

Table 3. Typically, interactions took place with every individual KSH. Furthermore, from all the available KSH, only five ESH were selected based on their experience in RWH structures implementation, and subsequently, the criteria values x_i's were collected.

The proposed MCS approach is implemented with asymmetric triangular distribution (TD), normal distribution (ND), and uniform distribution (UD) to overcome the limitations of the point estimate approach. The results are analyzed and compared with the point estimate method with respect to the RWH ranking.

RESULTS

In the probabilistic AHP, the MCS with various probability distribution functions is employed for augmenting various stakeholders' inputs. Notably, out of the available 20 stakeholders' input data, 17 stakeholders satisfied the consistency check, whereas the remaining three stakeholders failed. Typically, an asymmetric TD (or ND or UD) is applied over 10,000 iterations considering 17 stakeholders' inputs. The difference between the point estimate result of criterion weight and the MCS approach outcome is shown in Figure 4, which considers only one stakeholder's input for one criterion. The histogram of weights for one criterion with one such stakeholder for each iteration is illustrated in Figure 4. In this case, the median weight calculated point estimate using the point method is 0.24. However, the histogram is more likely to vary with many possibilities instead of a single point estimate.

Furthermore, the MCS approach is repeated over 10,000 iterations by sampling across multiple stakeholders in the form of asymmetric TD, ND, and UD. The parameters of the distributions are considered as per the values observed from 17 stakeholders' inputs. The yields of one criterion weights distribution using TD, ND, and UD by considering all stakeholders' inputs are presented in Figure 5. The TD reported that the first criterion weights mean 0.28, and the standard deviation is 0.06. For the same criterion, the ND simulation showed a mean of 0.30, and the standard deviation was 0.07. Considering UD, the mean is 0.30, and the standard deviation is 0.04.

We computed each RWH structure's performance using Equation (5) of MCS over 10,000 iterations for better ranking. Figure 6 illustrates the histogram of performance for one RWH structure using synthetically generated

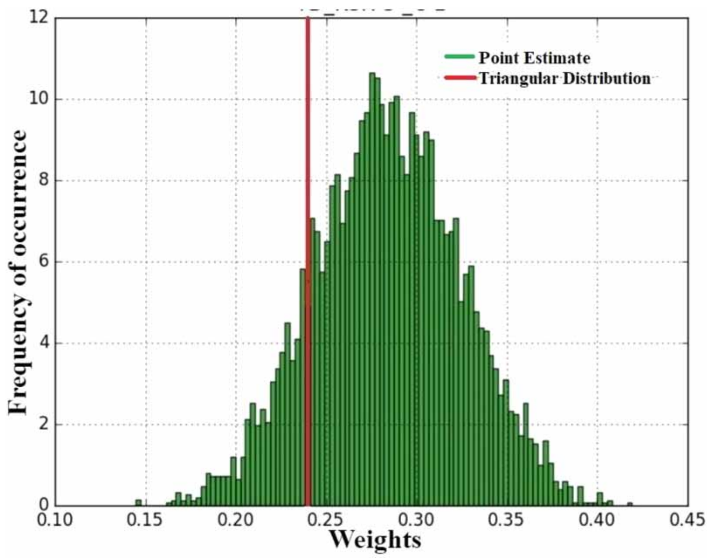


Fig. 4 | One stakeholder inputs weight distribution using MCS with TD.

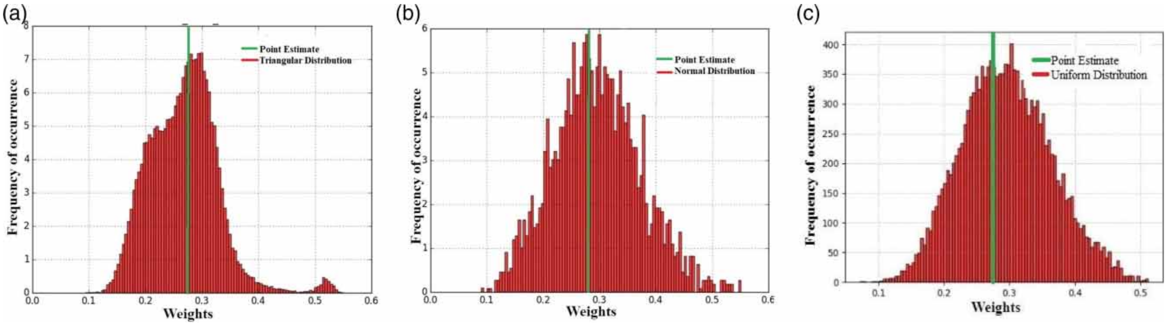


Fig. 5 | Weight distribution of one criterion using MCS with TD, ND, and UD. (a) Triangular distribution. (b) Normal distribution. (c) Uniform distribution.

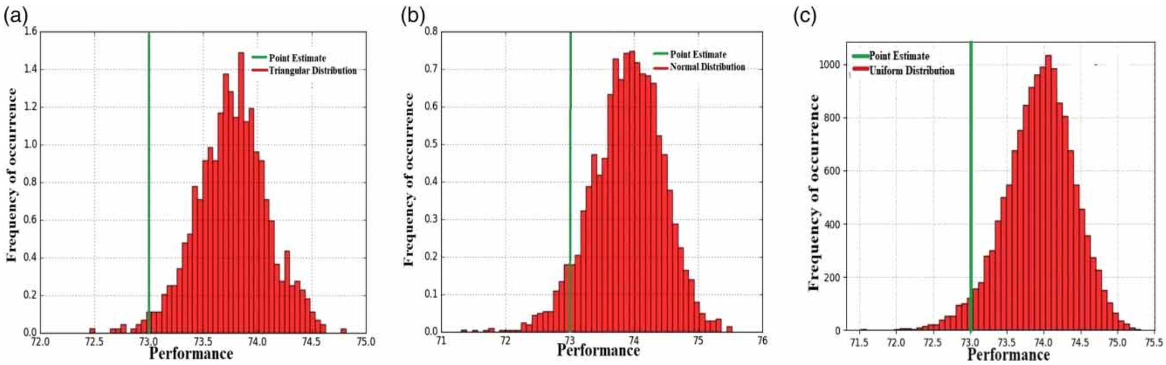


Fig. 6 | Performance distribution of one RWH using MCS with TD, ND, and UD. (a) Triangular distribution. (b) Normal distribution. (c) Uniform distribution.

data using TD, ND, and UD distributions. The mean values of all three cases are found to be 74 and are compared with the point estimate median value of 73 of the same RWH.

The first column under associated weights of Table 4 contains the derived weights of criteria using point estimate values obtained with the method explained in Kolagani *et al.* (2015). The following three columns represent derived mean weights of criteria using TD, ND, and UD with MCS. The statistical procedure of generating additional data points, instead of the stakeholder opinions, has also inferred the same conclusions. Tables 5–7 provide individual rank frequencies of RWH structures based on the simulated value by TD, ND, and UD, respectively. The ranks obtained for the 10 RWH structures in Tables 5–7 using this probabilistic AHP method are found to be different in a few cases from those obtained by the state-of-the-art point estimate method. However, the main advantage of the method is that probabilistic AHP enhances confidence in the ranking and decision-making process. In our experimental approach, the 10 case study RWH structures are ranked using simulations by different distributions. Some of them consistently have the same rank, as shown in Table 5, structure 5 is given Rank 1, in all the 10,000 iterations; Rank 2 is given to structure 1, 66 times, and to structure 6, 9934 times. Each column in the matrix totals to 10,000 representing stakeholders' opinions.

The observed performance of the 10 RWH structures collected from 20 CSH along with the evaluated performance using Equation (5) in the simulation is provided in Table 8. The values correlate well for all three distributions. Furthermore, the *p*-value is less than 0.05 threshold signifying there is strong evidence against

Table 4 | Derived weights using various distributions in probabilistic AHP.

		Associated weights			
S.No	Criteria	Point estimate	Triangular distribution	Normal distribution	Uniform distribution
1	Potential water inflow	0.25	0.28	0.30	0.30
2	Site suitability	0.18	0.21	0.22	0.22
3	Ease of maintainability	0.10	0.13	0.13	0.14
4	Social equity	0.10	0.12	0.12	0.12
5	Extent of utilization	0.11	0.09	0.08	0.08
6	Spatial equity	0.12	0.11	0.10	0.11
7	Stakeholder initiative	0.14	0.06	0.05	0.05
		1	1	1	1

Table 5 | Using probabilistic interpretation (triangular distribution) of ranking of alternatives.

Rank	RWH 1	RWH 2	RWH 3	RWH 4	RWH 5	RWH 6	RWH 7	RWH 8	RWH 9	RWH 10
1	0	0	0	0	10,000	0	0	0	0	0
2	66	0	0	0	0	9,934	0	0	0	0
3	6,978	0	0	0	0	66	2,956	0	0	0
4	2,954	0	102	0	0	0	6,940	2	0	2
5	2	0	2,712	0	0	0	102	6,593	0	591
6	0	0	6,507	1	0	0	2	2,095	0	1,395
7	0	0	679	577	0	0	0	1,308	0	7,436
8	0	0	0	9,422	0	0	0	2	0	576
9	0	3	0	0	0	0	0	0	9,997	0
10	0	9,997	0	0	0	0	0	0	3	0

Table 6 | Using probabilistic interpretation (normal distribution) of ranking of alternatives.

Rank	RWH 1	RWH 2	RWH 3	RWH 4	RWH 5	RWH6	RWH 7	RWH 8	RWH 9	RWH 10
1	0	0	0	0	10,000	0	0	0	0	0
2	90	0	0	0	0	9,909	0	0	0	1
3	5,349	0	10	0	0	77	4,550	0	0	14
4	4,444	0	111	0	0	11	5,217	112	0	105
5	117	0	1,362	0	0	3	170	5,916	0	2,432
6	0	0	6,166	8	0	0	62	1,280	1	2,483
7	0	0	2,350	264	0	0	1	2,674	2	4,709
8	0	0	1	9,726	0	0	0	18	7	248
9	0	14	0	2	0	0	0	0	9,976	8
10	0	9,986	0	0	0	0	0	0	14	0

Table 7 | Using probabilistic interpretation (uniform distribution) of ranking of alternatives.

Rank	RWH 1	RWH 2	RWH 3	RWH 4	RWH 5	RWH 6	RWH 7	RWH 8	RWH 9	RWH 10
1	0	0	0	0	10,000	0	0	0	0	0
2	99	0	0	0	0	9,900	0	0	0	1
3	5,456	0	2	0	0	97	4,440	0	0	5
4	4,410	0	80	0	0	2	5,378	35	0	95
5	35	0	1,394	0	0	1	123	5,686	0	2,761
6	0	0	5,905	3	0	0	59	1,234	0	2,799
7	0	0	2,619	79	0	0	0	3,042	0	4,260
8	0	0	0	9,918	0	0	0	3	1	78
9	0	4	0	0	0	0	0	0	9,995	1
10	0	9,996	0	0	0	0	0	0	4	0

Table 8 | Structure-wise observed and evaluated performance.

		Evaluated performance			
RWH index	**Observed performance**	**Point estimate**	**Triangular distribution**	**Normal distribution**	**Uniform distribution**
1	75	73	74	74	74
2	61	59	60	61	61
3	70	71	71	71	71
4	61	69	69	69	69
5	87	78	80	80	80
6	75	74	76	77	77
7	67	72	74	74	74
8	71	71	72	72	72
9	65	63	65	66	65
10	67	69	71	71	71
	r_s	**0.90**	**0.90**	**0.90**	**0.90**
	p-value	**0.0003**	**0.0003**	**0.0003**	**0.0003**

the null hypothesis (A). It is also found that in the cases of TD, ND, and UD simulations, obtained correlation values are high.

The relative error was computed using Equation (6) for each distribution and also compared with the point estimate method, as shown in Table 9. Note that the relative error due to the proposed method (last 3 columns of Table 9) is lower than the same calculated by the point estimate method. The mean relative error is reduced by around 21% [$=\{(4.8-3.8)/4.8\} \times 100\%$] by the proposed method. This phenomenon is visually illustrated for individual RWH in Figure 7. After investigating the results of these three distributions, it can be inferred that TD and UD are more suitable for decision making with probabilistic AHP as it is closer to the observed performance.

Table 9 | Structure-wise relative error percentage (e_r %) on various probabilistic distribution.

RWH index	Point estimate	Triangular distribution	Normal distribution	Uniform distribution
1	3	1	1	1
2	3	2	0	0
3	1	1	1	1
4	13	12	12	12
5	10	8	8	8
6	2	1	2	2
7	9	9	9	9
8	0	1	1	1
9	3	0	2	0
10	4	3	3	3
Total	**48**	**38**	**39**	**37**

Finally, the structures were divided into four groups based on their rank frequency to prioritize in decision making. In Tables 5–7, the RWH structures have been ranked from 1 to 10 by MCS using different distributions. If we extract the maximum value in each column in these tables, we get the corresponding rank of that particular RWH. These ranks have been transferred to columns in Table 10. Grouping alternatives that are of similar importance instead of precise ranking may provide an opportunity for the policymakers to select single or multiple RWH structures from the same group or different groups. Therefore, RWH structures 5 and 6 are ranked 1 and 2 with high performance in different simulations (Table 8). Hence, they are grouped under 'Gr1'. Similarly, RWH 1 and 7 form another group 'Gr2' for exhibiting similar evaluated performance. RWH 8, RWH 3, and RWH 10 are contained in the 'Gr3' group, and RWH 4, RWH 9, and RWH 2 form the 'Gr4' group. The individual ranks in each distribution are similar, except in the case of point estimate where the rank for RWH 10 is different, because of which it falls into different groups with respect to point estimate and the other distributions.

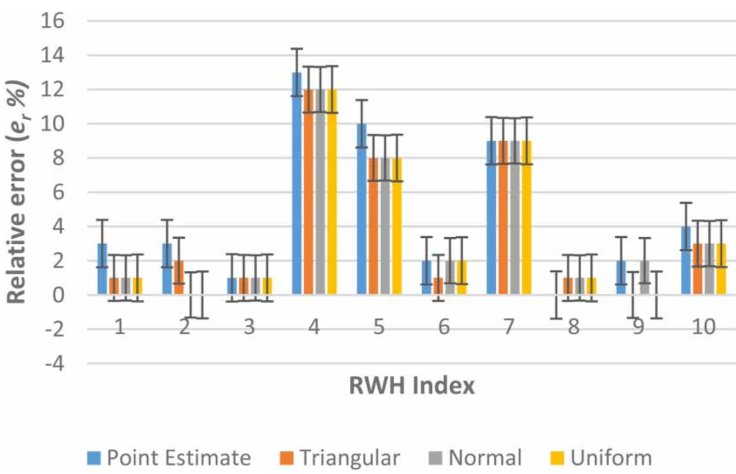


Fig. 7 | Illustration of relative error (%) for each structure.

Table 10 | Group ranking in various probabilistic distributions vs. point estimate.

Rank	RWH Index				Group
	Point Estimate	Triangular Distribution	Normal Distribution	Uniform Distribution	
1	RWH 5	RWH 5	RWH 5	RWH 5	Gr1
2	RWH 6	RWH 6	RWH 6	RWH 6	
3	RWH 1	RWH 1	RWH 1	RWH 1	Gr2
4	RWH 7	RWH 7	RWH 7	RWH 7	
5	RWH 3	RWH 8	RWH 8	RWH 8	Gr3
6	RWH 8	RWH 3	RWH 3	RWH 3	
7	RWH 4	RWH 10	RWH 10	RWH 10	
8	RWH 10	RWH 4	RWH 4	RWH 4	Gr4
9	RWH 9	RWH 9	RWH 9	RWH 9	
10	RWH 2	RWH 2	RWH 2	RWH 2	

DISCUSSION

It is imperative for resource management systems, such as groundwater management, drinking water supply, and sanitation to meet stakeholder requirements. Participatory methods in planning and decision making have a higher likelihood of success in such systems like RWH. Since stakeholders often need to review multiple alternatives of RWH, a simple and elegant multi-criteria decision model like AHP is helpful. The prior work of point estimate uses the AHP to compute criteria weights by collecting only one value from stakeholders by comparing criteria (Kolagani *et al.*, 2015). These weights are used to compute the performance of RWH structures and rank them. The frequency with which one RWH structure is ranked better than another decides its final score.

The present paper proposes a more reliable probabilistic AHP approach in the area of multi-criteria decision making. Typically, while working on a problem of ranking RWH structures in a particular village using participatory AHP, criteria comparison values are collected from stakeholders. If this is just a single point estimate, there exist few challenges. In socio-economic domains like this, the stakeholders are knowledgeable but not comfortable with subjective assessments and quantification. Therefore, a five point estimate is more reasonable than a single point one, since the stakeholders are supposed to estimate between a least likely minimum and a least likely maximum. However, repeated interactions for collecting multiple values add cognitive overload and bring up resistance in stakeholders. Maintaining the data collection as objective as possible in such uncertain situations is quite tricky and needs to be handled carefully. Focus group meetings have the advantage of reaching consensus and reducing the number of interactions. When stakeholders are engaged in this manner, the decision making is more transparent, and is consensus based, making it also easier for policy makers to act on it. From the stakeholder perspective, the data they have given is less prone to subjective bias since they have arrived at it in small groups.

The current work recommends generating values using various probability distribution functions between the bounds of the collected five values and computing criteria weights. This proposed probabilistic AHP method is good support to decision making when there is no clear winner in the final scores of the alternatives. The probabilistic interpretation of the final scores with statistical significance enhances the confidence in decision making.

We experimented with the mechanism on 10 existing RWH structures and seven different criteria. Different distributions were explored to generate possible values within the range provided by the stakeholders. The CSH ranked the alternative structures from their experience of that RWH structure's performance. This is the model validation stage, where the computed ranks by the model and observed performance of structures are compared. Eventually, the ranking of alternatives can be interpreted with statistical significance for policy makers to make decisions. As shown in this case study, it is better to obtain input values as distributions rather than single point estimates, it ultimately helps reduce the error between observed and evaluated performance. Also, it is sufficient to use either uniform distribution or asymmetric triangular distribution for this particular case study as normal distribution offers no additional improvements.

Furthermore, in implementing alternatives as in the case of RWH structures, instead of ranking the alternatives as individual entities, group ranking gives some degree of freedom to policy makers. When the RWH has to be constructed, the policy makers may have additional new constraints like financial, time, or locational constraints, such as road access for transport and soil type. With the grouping of alternatives, the policy makers can choose any of the structures within a group, without violating the stakeholder preferences. The group rankings for the method mostly agree with that of the point estimates for this case study, except structures 3 and 8, 4 and 10 whose position gets reversed while using probabilistic AHP with the MCS approach.

As far as the challenges for implementing the proposed method are concerned, though the tools are open source, the policy makers may need some training in their use. There is also cognitive overload on the stakeholders while collecting the data, hence facilitation skills are required for group consensus. Classifying stakeholders and taking estimates from only ESH or KSH, and engaging CSH only for final model validation is also seen to reduce the cognitive load on the stakeholders.

CONCLUSION

In this work, a probabilistic extension to AHP is proposed for making refined decisions taking uncertainties into account. A methodology is designed that uses MCS and is applied to a case study by collecting data and performing the appropriate simulation. It has been found that the results are consistent with the data collected from the stakeholders. Again, when the final scores of the alternatives are interpreted using the proposed probabilistic AHP, there is a significant improvement in confidence levels compared with the point estimate approach.

The success of environmental projects is highly dependent on the degree of engagement of stakeholders at every stage due to complex socio-economic issues. Stakeholders also offer local knowledge and perspectives that may not be necessarily available to experts or decision makers. Similarly, the latest global trends and scientific insights brought by external experts can enrich the local stakeholders' views. The use of participatory methods is fraught with its own difficulties. For multi-criteria decision making, obtaining quantitative data from stakeholders requires time and effort, and is often uncertain due to the difficulty in quantifying values associated with each criterion.

Since the inputs are obtained by the participatory method, the criteria importance would typically change if the region is changed. Thus, the choice of localized inputs is essential for a satisfactory solution. Even though the experiments were carried out for a specific village, the proposed hybrid method (probabilistic AHP) is generic and can be quickly adopted for further planning and improving resource management systems in different places. A future extension to our work is two-fold. Firstly, it is to perform a similar experimental setup for different villages and consolidate the learning for adaptive ranking. The second approach is to consider various multi-criteria decision-making frameworks and model them using participatory methods. One interesting exploration would be to verify whether the same methodology can be applied to a village of a completely different locality or does it require any modification to the method.

ACKNOWLEDGEMENTS

We thank all farmers residing in the case study village for providing valuable inputs, and we are grateful to Prof. Uma Garimella for constantly encouraging us to do research and improving paper quality by proofreading.

DATA AVAILABILITY STATEMENT

All relevant data are included in the paper or its Supplementary Information.

CONFLICT OF INTEREST STATEMENT

The authors declare no conflict of interest.

REFERENCES

Agriculture Census Division (2018). *Categorization of farmers. Ministry of Agriculture & Farmers Welfare*. Government of India, New Delhi, India. Available at: https://pib.gov.in/Pressreleaseshare.aspx?PRID=1562687 (Accessed 6 February 2022).

Akbaş, H. & Bilgen, B. (2017). An integrated fuzzy QFD and TOPSIS methodology for choosing the ideal gas fuel at WWTPs. *Energy 125*, 484–497. doi:10.1016/j.energy.2017.02.153.

Alaneme, G. U., Ezeokpube, G. C. & Mbadike, E. M. (2020). Failure analysis of a partially collapsed building using analytical hierarchical process. *Journal of Failure Analysis and Prevention 21*(1), 160–171. doi:10.1007/s11668-020-01040-3.

Annual Report (2018–19). *Department of Agriculture, Cooperation and Farmers Welfare, Ministry of Agriculture and Farmers Welfare*. Government of India, New Delhi, India. Available at: https://agricoop.nic.in/sites/default/files/AR_2018-19_Final_for_Print.pdf (accessed 2 February 2021).

Baumgärtner, A., Binder, K., Hansen, J. P., Kalos, M. H., Kehr, K., Landau, D. P., Levesque, D., Müller-Krumbhaar, H., Rebbi, C., Saito, Y. & Schmidt, K. (2013). *Applications of the Monte Carlo Method in Statistical Physics*, Vol. 36. Springer Science & Business Media.

Chen, S. J. & Hwang, C. L. (1992). Fuzzy multiple attribute decision making methods. In *Fuzzy Multiple Attribute Decision Making*. Springer, Berlin, Heidelberg, pp. 289–486. doi:10.1007/978-3-642-46768-4_5.

Daher, B., Hannibal, B., Portney, K. E. & Mohtar, R. H. (2019). Toward creating an environment of cooperation between water, energy, and food stakeholders in San Antonio. *Science of The Total Environment 651*, 2913–2926. doi:10.1016/j.scitotenv.2018.09.395.

Dahri, N. & Abida, H. (2017). Monte Carlo simulation-aided analytical hierarchy process (AHP) for flood susceptibility mapping in Gabes Basin (southeastern Tunisia). *Environmental Earth Sciences 76*(7). doi:10.1007/s12665-017-6619-4.

Díaz, H., Teixeira, A. P. & Soares, C. G. (2022). Application of Monte Carlo and fuzzy analytic hierarchy processes for ranking floating wind farm locations. *Ocean Engineering 245*, 110453. https://doi.org/10.1016/j.oceaneng.2021.110453.

Do, J.-Y. & Kim, D.-K. (2012). AHP-based evaluation model for optimal selection process of patching materials for concrete repair: focused on quantitative requirements. *International Journal of Concrete Structures and Materials 6*(2), 87–100. doi:10.1007/s40069-012-0009-9.

Economic Survey (2020–21). *Economic Division, Department of Economic Affairs, Ministry of Finance*. Government of India, New Delhi, India. Available at: https://www.indiabudget.gov.in/economicsurvey/doc/echapter_vol2.pdf (accessed 2 February 2021).

Elewa, H., Zelenakova, M. & Nosair, A. (2021). Integration of the analytical hierarchy process and GIS spatial distribution model to determine the possibility of runoff water harvesting in dry regions: Wadi Watir in Sinai as a case study. *Water 13*(6), 804. doi:10.3390/w13060804.

Eludoyin, A., Eludoyin, O., Martins, T., Oyinloye, M. & Eslamian, S. (2021). Water security using rainwater harvesting. *Handbook of Water Harvesting and Conservation*, 57–67. doi:10.1002/9781119478911.ch4.

Groundwater Year Book India (2019–20). *Central Groundwater Board, Ministry of Jal Shakti, Department of Water Resources, River Development and Ganga Rejuvenation*. Government of India, Faridabad, India. Available at: http://cgwb.gov.in/Ground-Water/GW%20YEAR%20BOOK%202019-20%20ALL%20INDIA%20FINAL%20752021%20(1).pdf (accessed 2 February 2021).

Hadihardaja, I. K. & Grigg, N. S. (2011). Decision support system for irrigation maintenance in Indonesia: a multi-objective optimization study. *Water Policy 13*(1), 18–27. doi:10.2166/wp.2010.051.

Halder, S., Roy, M. B. & Roy, P. K. (2020). Analysis of groundwater level trend and groundwater drought using Standard Groundwater Level Index: a case study of an eastern river basin of West Bengal, India. *SN Applied Sciences 2*(3). doi:10.1007/s42452-020-2302-6.

Kazimieras Zavadskas, E., Antucheviciene, J. & Kar, S. (2019). Multi-objective and multi-attribute optimization for sustainable development decision aiding. *Sustainability 11*(11), 3069. doi:10.3390/su11113069.

Kim, J., Kim, C., Kim, G., Kim, I., Abbas, Q. & Lee, J. (2022). Probabilistic tunnel collapse risk evaluation model using analytical hierarchy process (AHP) and Delphi survey technique. *Tunnelling and Underground Space Technology 120*, 104262. https://doi.org/10.1016/j.tust.2021.104262.

Kolagani, N., Ramu, P. & Varghese, K. (2015). Participatory model calibration for improving resource management systems: case study of rainwater harvesting in an Indian village. *JAWRA Journal of the American Water Resources Association 51*(6), 1708–1721. doi:10.1111/1752-1688.12351.

Lafleur, J. M. (2011). Probabilistic AHP and TOPSIS for multi-attribute decision-making under uncertainty. In *2011 Aerospace Conference*. doi:10.1109/aero.2011.5747655.

Mahammad, S. & Islam, A. (2021). Assessing the groundwater potentiality of the Gumani River Basin, India, using geoinformatics and analytical hierarchy process. In: *Groundwater and Society*, pp. 161–187. doi:10.1007/978-3-030-64136-8_8.

Mateo, J. R. S. C. (2012). The renewable energy industry and the need for a multi-criteria analysis. *Green Energy and Technology*, 1–5. doi:10.1007/978-1-4471-2346-0_1.

Mishra, V. (2020). Long-term (1870–2018) drought reconstruction in context of surface water security in India. *Journal of Hydrology 580*, 124228. doi:10.1016/j.jhydrol.2019.124228.

Mohanty, S., Bardhan, T. & Dey, A. (2020). Rain water harvesting: a viable way to combat water crisis. *Food and Scientific Reports 1*(7). Available at: https://foodandscientificreports.com/details/rain-water-harvesting-a-viable-way-to-combat-water-crisis.html (Accessed 5 June 2022).

Orosun, M. M., Usikalu, M. R., Oyewumi, K. J., Onumejor, C. A., Ajibola, T. B., Valipour, M. & Tibbett, M. (2022). Environmental risks assessment of kaolin mines and their brick products using Monte Carlo simulations. *Earth Systems and Environment 6*, 157–174. https://doi.org/10.1007/s41748-021-00266-x.

Pai, D. S., Guhathakurta, P., Kulkarni, A. & Rajeevan, M. N. (2016). Variability of meteorological droughts over India. In: *Observed Climate Variability and Change over the Indian Region*, pp. 73–87. doi:10.1007/978-981-10-2531-0_5.

Poonia, A. & Punia, M. (2018). A question on sustainability of drinking water supply: a district level analysis of India using analytic hierarchy process. *Water Policy 20*(4), 712–724. doi:10.2166/wp.2018.104.

Rosenbloom, E. S. (1997). A probabilistic interpretation of the final rankings in AHP. *European Journal of Operational Research 96*(2), 371–378. doi:10.1016/s0377-2217(96)00049-5.

Saaty, T. L. (1980). *The Analytic Hierarchy Process: Planning, Priority Setting, Resource Allocation*. McGraw-Hill, New York, USA.

Saaty, T. L. (1990). How to make a decision: the analytic hierarchy process. *European Journal of Operational Research 48*(1), 9–26. doi:10.1016/0377-2217(90)90057-i.

Saaty, T. L. (2001). Deriving the AHP 1-9 scale from first principles. In: *Proceedings 6th ISAHP*, Berna, Suiza. doi:10.13033/isahp.y2001.030.

Saaty, T. L. (2003). Decision-making with the AHP: why is the principal eigenvector necessary. *European Journal of Operational Research 145*(1), 85–91. doi:10.1016/s0377-2217(02)00227-8.

San Cristóbal, J. R. (2011). Multi-criteria decision-making in the selection of a renewable energy project in Spain: the Vikor method. *Renewable energy 36*(2), 498–502. doi:10.1016/j.renene.2010.07.031.

Sharma, B. R. & Smakhtin, V. U. (2006). *Potential of Water Harvesting as a Strategic Tool for Drought Mitigation*. International Water Management Institute (IWMI), New Delhi.

Sikder, A. H. M. K. & Salehin, M. (2015). Multi-criteria decision making methods for rural water supply: a case study from Bangladesh. *Water Policy 17*(6), 1209–1223. doi:10.2166/wp.2015.111.

Stewart, T. J. & Scott, L. (1995). A scenario-based framework for multicriteria decision analysis in water resources planning. *Water Resour. Res. 31*(11), 2835–2843. doi:10.1029/95WR01901.

Teder, M. & Kaimre, P. (2018). The participation of stakeholders in the policy processes and their satisfaction with results: a case of Estonian forestry policy. *Forest Policy and Economics 89*, 54–62. doi:10.1016/j.forpol.2017.05.007.

Wu, R.-S., Molina, G. L. L. & Hussain, F. (2018). Optimal sites identification for rainwater harvesting in northeastern Guatemala by analytical hierarchy process. *Water Resources Management 32*(12), 4139–4153. doi:10.1007/s11269-018-2050-1.

First received 18 October 2021; accepted in revised form 18 May 2022. Available online 4 June 2022