A Hybrid Spherical Fuzzy–Machine Learning Model for Multi-Criteria Decision-Making in Sustainable Water Resource Management

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***Abstract*—The aim of this study is to develop an innovative, multi-dimensional, and uncertain decision-making model that can identify the most appropriate alternative irrigation method for the efficient use of water resources in agriculture. In this context, the proposed model is based on the integrated use of spherical fuzzy sets, machine learning, MEREC, and WASPAS methods. The evaluations obtained from ten experts were converted into spherical fuzzy numbers, and the experts' importance weights were objectively calculated using machine learning. Criteria weights were determined using the MEREC method, and alternatives were ranked using the WASPAS method. This hybrid approach both reduces expert subjectivity and objectively reflects the relationships between criteria. According to the findings, feasibility/technological suitability (0.152) emerged as the most important criterion, followed by environmental impacts (0.144). Among the alternatives, drip irrigation (2.226) was identified as the most suitable option for efficient use of water resources. This result demonstrates that modern, technology-based irrigation systems should be a priority in sustainable agricultural policies. This study's contribution to the literature is its ability to bring objectivity, transparency, and the ability to manage high uncertainty to decision-making processes in agricultural water management. The model offers both methodological innovation and a practical decision-support tool at the application level.**

***Keywords*—Irrigation activities; water use; decision-making model; machine learning; MEREC; WASPAS**

I. Introduction

Identifying the most appropriate alternative irrigation methods for sustainable water management in agriculture is crucial because each region's climate, soil structure, plant species, and economic capacity vary. Therefore, the same method cannot be expected to yield the most efficient results in every situation. Choosing the best irrigation method both conserves limited water resources and increases production efficiency [1]. Furthermore, determining the right method is critical for the efficient use of limited budgets and the rapid implementation of implementation strategies. Decision-making in this process is influenced by many different factors. Water efficiency refers to the extent to which water is delivered to the plant root zone without wasting water and is a key indicator of sustainable agriculture. Cost determines the economic viability of the system's installation, operation, and maintenance. Energy consumption is particularly important due to the pumps and pressure lines used in modern systems, as energy costs directly impact production costs. Applicability and technological compatibility indicate the compatibility of the selected method with existing infrastructure and technical capacity. Plant yield and quality directly reflect the impact of the irrigation method on agricultural output and are the most tangible measures of success for farmers [2]. Environmental impacts include soil salinity, erosion, and changes in groundwater levels that may be caused by excessive or inappropriate water use. Ease of maintenance and operation is a factor that determines the long-term sustainability of a method, as complex systems may not be managed effectively, especially by producers with limited technical knowledge. However, the number of studies in the literature that evaluate these criteria holistically is quite limited. Most studies focus on a single factor or are limited to a specific geographical context. This creates a significant gap in the literature, as there is insufficient comparative data to determine which irrigation method is most effective under which conditions. This gap creates uncertainty in decision-making processes and makes it difficult for practitioners to select the most appropriate system. Furthermore, the varying weights of criteria depending on the situation highlight the need for multi-criteria analyses. Therefore, this gap in the existing literature represents a research problem that needs to be addressed from both theoretical and practical perspectives. New studies on this topic will significantly contribute to identifying strategies to increase water efficiency and support sustainable agricultural production.

This study aims to identify the most effective alternative irrigation methods for the efficient use of water resources in agriculture. The primary motivation for the study is increasing water scarcity, the impacts of climate change, and the need for sustainability in agricultural production. The lack of systematic multi-criteria comparisons of irrigation methods in the existing literature creates a significant research gap. Therefore, this study aims to fill this gap at both the theoretical and practical levels. A holistic decision-making model for selecting alternative irrigation methods was developed. The model is based on a hybrid approach that integrates expert opinions with fuzzy logic. In this context, seven criteria were identified for use in the evaluation following a comprehensive literature review. These criteria are water efficiency, cost, energy consumption, applicability, plant yield and quality, environmental impacts, and ease of maintenance and operation. The alternatives comprise sprinkler irrigation, drip irrigation, surface irrigation, subsurface irrigation, and microsprinkler irrigation. Expert assessments were collected from ten different experts and converted into spherical fuzzy numbers. Expert importance weights were calculated using a machine learning-based method, thus reducing the influence of subjective evaluations. The importance levels of the criteria were determined using the MEREC method, allowing the contribution of each criterion to the model to be objectively measured. The resulting weights were used to rank the performance of the alternatives using the WASPAS method. This integrated approach provides a decision support framework that takes both uncertainties into account and is computationally efficient. The study seeks to answer the following research questions: 1) Which alternative irrigation method is the most effective for the sustainable management of water resources in agriculture? 2) What are the most decisive factors in the decision-making process among the seven criteria determined? 3) How does the diversity of expert opinions affect the ranking of alternatives? 4) To what extent is the spherical fuzzy-based approach effective in reducing uncertainty compared to traditional fuzzy methods? 5) What advantages does the integrated use of the MEREC and WASPAS methods provide in multi-criteria decision-making processes? By addressing these research questions, the study proposes an innovative decision-making model that will increase water efficiency in the agricultural sector and provide a strategic reference framework for policy developers and practitioners.

This study addresses a clear methodological and practical gap in the literature by proposing a hybrid decision-making framework that goes beyond existing fuzzy-based MCDM applications in agricultural water management. Unlike prior studies that typically rely on static expert-driven fuzzy weighting and conventional ranking techniques, the proposed model uniquely combines spherical fuzzy sets with machine learning–assisted data structuring, the objective weighting capability of the MEREC method, and the compensatory–noncompensatory evaluation mechanism of WASPAS within a single integrated framework. This specific configuration is fundamentally novel in that spherical fuzzy sets are employed not merely as a linguistic extension, but as a means to capture hesitation and uncertainty in irrigation-related expert judgments, while machine learning is used to enhance data consistency and reduce subjectivity prior to weighting and ranking. To the best of our knowledge, no existing study in the irrigation method selection literature has systematically integrated these four components to jointly address uncertainty modeling, objective criterion weighting, and robust alternative ranking. Consequently, the proposed approach offers a structurally distinct and methodologically advanced decision-support tool for the efficient use of water resources in agriculture.

The proposed model developed in this study has several advantages over previously presented decision-making models in the literature: 1) First, the model utilizes machine learning techniques to calculate the importance weights of experts. This approach allows for objective weighting based not only on the opinions of experts but also on their demographic characteristics, areas of expertise, experience levels, and academic backgrounds. The vast majority of existing models in the literature treat experts as equal or base weights on subjective assessments. This increases the risk of subjectivity and inconsistency in the decision-making process. However, the machine learning-based approach used in this study systematically evaluates differences among experts, providing more objective, reliable, and data-driven weightings. This increases the accuracy and confidence levels of the model and enhances the scientific validity of decision-making results. 2) The second advantage of the model is the use of spherical fuzzy sets in the decision-making process. These new-generation fuzzy sets have a higher uncertainty representation capacity compared to classical, intuitionistic, and Pythagorean fuzzy sets. By defining membership, non-membership, and degrees of uncertainty independently, the spherical fuzzy structure models the uncertainties and knowledge gaps in expert opinions in a much more realistic and flexible manner. This allows for more effective management of uncertainty in the decision-making environment and increased consistency of results. Furthermore, the spherical fuzzy approach offers advantages over other sets in terms of both ease of calculation and interpretability. This contributes to the model's robustness both theoretically and practically. 3) The MEREC (Method Based on the Removal Effects of Criteria) technique used in the study is another significant advantage of the model. Entropy, CRITIC, or standard statistical methods are frequently used in the literature for criterion weighting; however, these methods generally fail to adequately reflect the mutual influences between criteria. The MEREC method analyzes the change in overall performance when each criterion is removed from the system, revealing the true impact of each criterion. This feature allows the model to better capture inter-criterion sensitivity and ensure more objective, reliable, and data-driven decision-making outcomes. The MEREC method offers higher accuracy and significance than other techniques, particularly in areas such as water management, where multidimensional environmental and technical factors are evaluated simultaneously. Considering all these advantages together, the proposed model offers a holistic approach that is both methodologically innovative and provides high accuracy, flexibility, and consistency in decision-making processes.

The remainder of the study is as follows: Section II includes the research gap in the literature. Section III focuses on the proposed model. The results are denoted in Section IV. Section V makes a comparative discussion. Section VI highlights the main conclusion.

II. Literature Review

Applicability, or technological suitability, is one of the key criteria when determining alternative irrigation methods for the efficient use of water resources in agriculture. Given the challenges of climate change, the use of technologies that can increase productivity and efficiency in agriculture, including precision agriculture, drones, and climate information systems, is crucial. In today's world, the development of systems such as remote sensing with artificial intelligence-based decision-making tools also promotes the efficient use of water resources in agriculture. These technologies include software applications, water management applications, nutrient management, temperature measurement, and soil health analysis tools. These technologies can also contribute to climate change-resilient crop development, irrigation water management, fostering local knowledge, and increasing agricultural yields, ensuring food security. Vedovello et al. [3] provided an overview of hydrogel technologies as adaptable solutions to address challenges such as water scarcity and soil degradation in agriculture. Indeed, hydrogels offer agricultural innovations that address challenges associated with traditional agricultural practices and technologies while also providing some answers for the future of these technologies. Singh and Singh [4] examined the impact of UAV use in Indian agriculture on precision agriculture, crop monitoring, and pesticide application. They assess technological advancements, infrastructure, regulatory frameworks, farmer perceptions, and financial accessibility of UAV technology.

Environmental impacts are another effective criterion in determining alternative irrigation methods for the efficient use of water resources in agriculture. Ultimately, water efficiency in agriculture is a critical element of sustainable water management, particularly in rural areas, and is vital for ensuring environmental sustainability in rural areas where water resources are limited [5]. While traditional surface irrigation has been reported to cause environmental consequences such as water loss, advanced alternatives such as drip and sprinkler systems have been observed to improve irrigation infrastructure and promote climate-smart agricultural practices [6]. Saini et al. [7] investigated the behaviors and perspectives of rural and regional urban water consumers regarding water consumption. They develop a conceptual model of the factors affecting the amount of water consumed, including the barriers that hinder water conservation. Yasmeen et al. [8] examined the synergy of water use efficiency between 2006 and 2020 between the aggregation of water resources at the provincial and regional levels in China and the integration of innovative conservation technologies.

Cost is another important criterion when determining alternative irrigation methods for the efficient use of water resources in agriculture. The initial investment cost of irrigation systems designed for efficient water use can be high. This is because sprinkler and drip irrigation systems, while achieving efficiency by using less water, require operator control, operation, and monitoring [9]. Furthermore, while external factors such as regulations, national water policies, financial incentives, government subsidies, and technology provide solutions for efficient water supply in agriculture, they can also be considered among the factors affecting costs [10]. Chaudhary et al. [11] summarized the fundamental aspects of sprinkler and precision irrigation, their development and prospects, particularly in Asian countries. This approach leverages significant advances in sprinkler systems for precision applications to increase net crop production, conserve irrigation water, maximize irrigation uniformity, and improve fertilizer management with minimal leakage loss. On the other hand, Bhavsar et al. [12] comprehensively examined numerous IoT-enabled smart micro-irrigation systems, including smart sprinkler systems and smart drip irrigation, to reduce water and energy waste. The aim is to find the most appropriate irrigation strategy.

Energy consumption is another important criterion in determining alternative irrigation methods for the efficient use of water resources in agriculture. The agricultural sector consumes large amounts of water and energy through irrigation, collection, pumping, water treatment, land preparation, fertilizer production, agricultural machinery, processing, and storage [13]. In other words, energy is used both directly and indirectly for the efficient use of water resources in agriculture, while the energy provided to modern and sustainable agricultural production systems and processing is one of the main factors in the growth of agricultural production [14]. Yang et al. [15] established a framework for examining water and energy consumption at every stage of the crop growth process, including growth, planting, germination, ripening, and harvesting. Pomoni et al. [16] aimed to reveal the environmental, water, and energy impacts of traditional agriculture and a new soilless cultivation technology, namely hydroponic agriculture.

The results of the literature review indicate that certain criteria are important in determining alternative irrigation methods for the efficient use of water resources in agriculture. These criteria include applicability (technological suitability), environmental impacts, cost, and energy consumption. Since it is not possible to improve all criteria simultaneously, the study aims to identify the most important criterion. This aims to address a gap in the literature on this topic. This study accomplishes this by analyzing a new decision-making model.

III. METHODOLOGY

This section relates to the formulations of spherical fuzzy sets (SFSs), dimensionality reduction, MEREC, and WASPAS. Using these formulations, the methodology of the manuscript is constructed. The methodology includes SFSs to minimize uncertainty, while dimensionality reduction is used to determine the level of experts. Additionally, after calculating the criterion priority value from MEREC, comparative results of WASPAS and RAWEC are obtained in ranking the alternatives. The diagram of the methodology is presented in Fig. 1.

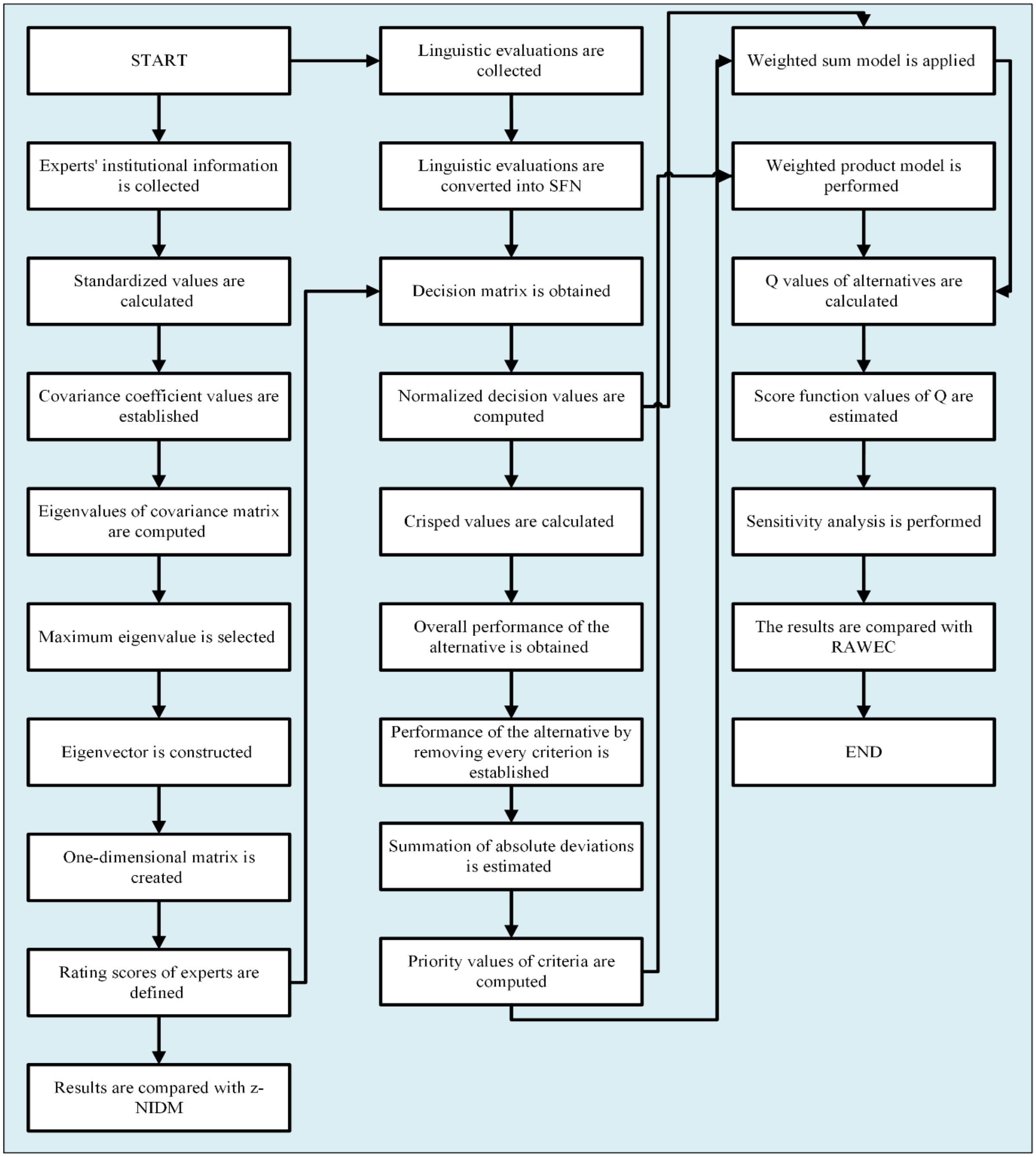

Fig. 1. Diagram of the methodology.

A. Dimensionality Reduction

Creating a decision matrix by calculating the unweighted average of expert evaluations has been criticized. Due to this criticism, different approaches have been developed in the literature. While dimensionality reduction is primarily used to reduce the number of variables in machine learning, it is preferred in MCDM due to its objectivity in calculating the experts' ratings. This approach aims to obtain rating scores for experts using information provided by the experts on the websites of their affiliated institutions. The assumption here is that if an institution's knowledge is high, the institution is of high quality; if the institution is good, the expert working there is also qualified. Under this assumption, the calculation steps can be summarized as follows [17].

The websites of k institutions, where k experts work, are examined. The f numerical information about the institutions is collected. This information includes the number of business partners the institutions have collaborated with and the years they have been in operation. Based on these variables, an institution is considered high-quality if it has been operating for a long time. Similarly, the more business partners it has, the better the institution. In other words, the matrix (B) in Eq. (1) is created using the data from the relevant variables indicating the institution's qualification.

$$B = \begin{bmatrix} b_{11} & \cdots & b_{1f} \\ \vdots & \ddots & \vdots \\ b_{k1} & \cdots & b_{kf} \end{bmatrix} \quad (1)$$

When the value range and unit sizes of the variables differ from each other, standardized values (r) are calculated with the help of Eq. (2) to Eq. (4) using arithmetic mean $(\bar{b})$ and centred values (c).

$$\bar{b}_j = \frac{\sum_{i=1}^{k} b_{ij}}{k} \quad (2)$$

$$c_{ij} = b_{ij} - \bar{b}_j \quad (3)$$

$$r_{ij} = \frac{c_{ij}}{\sqrt{\sum_{i=1}^{k} c_{ij}^2}} \quad (4)$$

Afterwards, covariance coefficient values (cov) between standardized variables are established via Eq. (5). Thus, the covariance matrix (A) formed in Eq. (6) is obtained.

$$cov_{jt} = \frac{1}{k}\left(\sum_{i=1}^{k}(r_{ij} - \bar{r}_j)(r_{it} - \bar{r}_t)\right) \quad (5)$$

$$A = \begin{bmatrix} cov_{11} & \cdots & cov_{1f} \\ \vdots & \ddots & \vdots \\ cov_{f1} & \cdots & cov_{ff} \end{bmatrix} \quad (6)$$

where, $\bar{r}$ is the average value of the standardized variable and is estimated using Eq. (2). Next, f eigenvalues of the covariance matrix (ξ) are computed by Eq. (7). Then, the maximum eigenvalue (ξ^*) is selected with Eq. (8) for saving the maximum variance.

$$\det(A - \xi_i \mathrm{I}) = 0 \quad (7)$$

$$\xi^* = \max \xi_i \quad (8)$$

where, I is the identity matrix with dimensions fxf. Later, the eigenvector (Y) is constructed with the help of Eq. (9):

$$(A - \xi^* \mathrm{I})Y = 0 \quad (9)$$

Finally, a one-dimensional matrix (H) is created via Eq. (10), then the rating scores of experts (rs) are defined as Eq. (11):

$$H = BY \quad (10)$$

$$rs_i = \frac{h_i}{\sum_{i=1}^{k} h_i} \quad (11)$$

where, h is the items of one-dimensional matrix. The multiplication operation in Eq. (10) is matrix multiplication.

B. SFSs

Fuzzy sets define different degrees to measure uncertainty. From the set family formed by the degrees of membership (α), non-membership (β), and hesitancy (γ), SFSs are defined by the sum of the squares of these degrees. In other words, an SFS $(\tilde{F})$ of the universe of discourse $(\mathcal{S})$ is described as in Eq. (12) [18].

$$\tilde{F} = \left\{x, \left(\alpha_{\tilde{F}}(x), \beta_{\tilde{F}}(x), \gamma_{\tilde{F}}(x)\right) \middle| x \in \mathcal{S}\right\} \quad (12)$$

where, these degrees are between zero and one. These degrees are the satisfied conditions in Eq. (13):

$$0 \le \alpha_{\tilde{F}}^2(x) + \beta_{\tilde{F}}^2(x) + \gamma_{\tilde{F}}^2(x) \le 1;\ \forall x \in \mathcal{S} \quad (13)$$

The refusal degree is computed with Eq. (14):

$$\varsigma_{\tilde{F}}(x) = \sqrt{1 - \alpha_{\tilde{F}}^2(x) - \beta_{\tilde{F}}^2(x) - \gamma_{\tilde{F}}^2(x)} \quad (14)$$

Consider that $\tilde{F}$ and $\tilde{G}$ are two SFNs. Then, basic operators are identified with Eq. (15) to Eq. (18):

$$\tilde{F} + \tilde{G} = \left\{ \begin{array}{c} \sqrt{\alpha_{\tilde{F}}^2 + \alpha_{\tilde{G}}^2 - \alpha_{\tilde{F}}^2\alpha_{\tilde{G}}^2}, \beta_{\tilde{F}}\beta_{\tilde{G}}, \\ \sqrt{(1 - \alpha_{\tilde{G}}^2)\gamma_{\tilde{F}}^2 + (1 - \alpha_{\tilde{F}}^2)\gamma_{\tilde{G}}^2 - \gamma_{\tilde{F}}^2\gamma_{\tilde{G}}^2} \end{array} \right\} \quad (15)$$

$$\tilde{F} \times \tilde{G} = \left\{ \begin{array}{c} \alpha_{\tilde{F}}\alpha_{\tilde{G}}, \sqrt{\beta_{\tilde{F}}^2 + \beta_{\tilde{G}}^2 - \beta_{\tilde{F}}^2\beta_{\tilde{G}}^2}, \\ \sqrt{(1 - \beta_{\tilde{G}}^2)\gamma_{\tilde{F}}^2 + (1 - \beta_{\tilde{F}}^2)\gamma_{\tilde{G}}^2 - \gamma_{\tilde{F}}^2\gamma_{\tilde{G}}^2} \end{array} \right\} \quad (16)$$

$$\lambda\tilde{F} = \left\{ \begin{array}{c} \sqrt{1 - (1 - \alpha_{\tilde{F}}^2)^{\lambda}}, \beta_{\tilde{F}}^{\lambda}, \\ \sqrt{(1 - \alpha_{\tilde{F}}^2)^{\lambda} - (1 - \alpha_{\tilde{F}}^2 - \gamma_{\tilde{F}}^2)^{\lambda}} \end{array} \right\} \quad (17)$$

$$\tilde{F}^{\lambda} = \left\{ \begin{array}{c} \alpha_{\tilde{F}}^{\lambda}, \sqrt{1 - (1 - \beta_{\tilde{F}}^2)^{\lambda}}, \\ \sqrt{(1 - \beta_{\tilde{F}}^2)^{\lambda} - (1 - \beta_{\tilde{F}}^2 - \gamma_{\tilde{F}}^2)^{\lambda}} \end{array} \right\} \quad (18)$$

Assume that $\tilde{F}_i$ be the sequence of SFNs and $\sum_{i=1}^{n} w_i = 1$. Then, weighted arithmetic mean $(\tilde{\mathcal{A}})$ is calculated using Eq. (19):

$$\tilde{\mathcal{A}}_{\tilde{F}_i} = \left\{ \begin{array}{c} \sqrt{1 - \prod_{i=1}^{n}\left(1 - \alpha_{\tilde{F}_i}^2\right)^{w_i}}, \\ \prod_{i=1}^{n} \beta_{\tilde{F}_i}^{w_i}, \\ \sqrt{\prod_{i=1}^{n}\left(1 - \alpha_{\tilde{F}_i}^2\right)^{w_i} - \prod_{i=1}^{n}\left(1 - \alpha_{\tilde{F}_i}^2 - \gamma_{\tilde{F}_i}^2\right)^{w_i}} \end{array} \right\} \quad (19)$$

Similarly, weighted geometric mean $(\tilde{\mathcal{G}})$ is computed with Eq. (20):

$$\tilde{\mathcal{G}}_{\tilde{F}_i} = \left\{ \begin{array}{c} \prod_{i=1}^{n} \alpha_{\tilde{F}_i}^{w_i}, \\ \sqrt{1 - \prod_{i=1}^{n}\left(1 - \beta_{\tilde{F}_i}^2\right)^{w_i}}, \\ \sqrt{\prod_{i=1}^{n}\left(1 - \beta_{\tilde{F}_i}^2\right)^{w_i} - \prod_{i=1}^{n}\left(1 - \beta_{\tilde{F}_i}^2 - \gamma_{\tilde{F}_i}^2\right)^{w_i}} \end{array} \right\} \quad (20)$$

Score (SF) and accuracy (AF) functions are identified by Eq. (21) and Eq. (22), respectively.

$$SF(\tilde{F}) = \left(2\alpha_{\tilde{F}} - \frac{\gamma_{\tilde{F}}}{2}\right)^2 - \left(\beta_{\tilde{F}} - \frac{\gamma_{\tilde{F}}}{2}\right)^2 \quad (21)$$

$$AF(\tilde{F}) = \alpha_{\tilde{F}}^2 + \beta_{\tilde{F}}^2 + \gamma_{\tilde{F}}^2 \quad (22)$$

C. SF-MEREC-Based SF-WASPAS

MEREC-based WASPAS is a hybrid approach that ranks alternatives by combining two models after determining objective criteria priorities. This hybrid approach aims to minimize uncertainty by integrating SFSs. This manuscript analysis process is described below [19].

For the decision model in which n criteria are considered to rank m alternatives, evaluations from k experts are collected with a linguistic scale. These linguistic evaluations are converted into SFNs, and their weighted averages are calculated by Eq. (23):

$$\tilde{d}_{ij} = \left\{\alpha_{\tilde{d}_{ij}}, \beta_{\tilde{d}_{ij}}, \gamma_{\tilde{d}_{ij}}\right\} = \tilde{\mathcal{A}}_{\tilde{E}^{t}_{ij}} \quad (23)$$

where, $\tilde{E}^{t}{}_{ij}$ refers to SFN of the linguistic evaluation of j^{th} criterion of i^{th} alternative for t^{th} expert. $\tilde{\mathcal{A}}$ is the weighted arithmetic mean defined in Equation (19) using the rating scores of experts as weights. Next, normalized decision values $(\tilde{\mathfrak{y}})$ are computed with Eq. (24) and Eq. (25):

$$\tilde{\mathfrak{y}}_{ij} = \left\{\alpha_{\tilde{d}_{ij}}, \beta_{\tilde{d}_{ij}}, \gamma_{\tilde{d}_{ij}}\right\}; for\ benefical\ criterion \quad (24)$$

$$\tilde{\mathfrak{y}}_{ij} = \left\{\gamma_{\tilde{d}_{ij}}, \beta_{\tilde{d}_{ij}}, \alpha_{\tilde{d}_{ij}}\right\}; for\ cost\ criterion \quad (25)$$

Afterwards, crisped values $(\mathfrak{h})$ are calculated by Eq. (26):

$$\mathfrak{h}_{ij} = \frac{1}{2}\left(\begin{array}{c} 1 + \left(\alpha_{\tilde{\mathfrak{y}}_{ij}}\right)^2 \\ -\left(\beta_{\tilde{\mathfrak{y}}_{ij}}\right)^2 - \left(\gamma_{\tilde{\mathfrak{y}}_{ij}}\right)^2 - \ln\left(1 + \left(\varsigma_{\tilde{\mathfrak{y}}_{ij}}\right)^2\right) \end{array}\right) \quad (26)$$

The overall performance of the alternative (G) is obtained with the help of Eq. (27):

$$G_i = \ln\left(1 + \left(\frac{1}{n}\sum_j \left|\mathfrak{h}_{ij}\right|\right)\right) \quad (27)$$

The performance of the alternative by removing every criterion (G') is established using Eq. (28):

$$G'_{ij} = \ln\left(1 + \left(\frac{1}{n}\sum_{f\ f\neq j} \left|\mathfrak{h}_{if}\right|\right)\right) \quad (28)$$

Next, the summation of absolute deviations (K) is estimated by Eq. (29):

$$K_j = \sum_i \left|G'_{ij} - G_i\right| \quad (29)$$

The last step of MEREC is about the computation of priority values (pv) of criteria with Eq. (30):

$$pv_j = \frac{K_j}{\sum_{j=1}^{n} K_j} \quad (30)$$

Afterwards, the weighted sum model $\left(\tilde{Q}^{(1)}\right)$ is applied using Eq. (31).

$$\tilde{Q}_i^{(1)} = \sum_{j=1}^{n} pv_j \tilde{\mathfrak{y}}_{ij} \quad (31)$$

Similarly, the weighted product model $\left(\tilde{Q}^{(2)}\right)$ is performed via Eq. (32):

$$\tilde{Q}_i^{(2)} = \prod_{j=1}^{n} \left(\tilde{\mathfrak{y}}_{ij}\right)^{pv_j} \quad (32)$$

Next, the $\tilde{Q}$ values of alternatives are calculated by Eq. (33) [20].

$$\tilde{Q}_i = \varphi \tilde{Q}_i^{(1)} + (1 - \varphi)\tilde{Q}_i^{(2)} \quad (33)$$

Finally, score function values of $\tilde{Q}$ are estimated with the help of Eq. (34) for ranking of alternatives.

$$Q_i = SF\left(\tilde{Q}_i\right) \quad (34)$$

IV. Analysis

This section relates to the results of the methodology in Fig. 1.

A. *Obtaining the Rating Scores of Experts*

Experts with at least ten years of work experience are selected. Data from the website is analyzed using the experts' institutional information. The institutions' business partners, period of activity, and number of countries they operate in are obtained. This information is used to create the matrix in Eq. (1). The matrix is shown in Table I.

TABLE I. INFORMATION ABOUT THE INSTITUTIONAL BUSINESS PARTNERS

	Business Partners	**Activity Period**	**Operation Country**
Expert.1	16	16	6
Expert.2	21	16	5
Expert.3	23	21	5
Expert.4	32	26	4
Expert.5	33	33	6
Expert.6	24	22	4
Expert.7	25	18	3
Expert.8	35	35	6
Expert.9	29	15	4
Expert.10	34	24	6

According to the variables in Table I, the average business partner is 27.2 with a standard deviation of 6.03. Similarly, the minimum activity period is 15. The range of operation country is between 3 and 6. The descriptive statistics are shared in Table II.

TABLE II. DESCRIPTIVE STATISTICS

	Business Partners	**Activity Period**	**Operation Country**
Average	27.2	22.6	4.9
Deviation	6.030	6.666	1.044
Max	35	35	6
Min	16	15	3

Standardized values are calculated with the help of Eq. (2) to Eq. (4) using arithmetic mean and centered values in Table II. The standardized values are given in Table III.

TABLE III. STANDARDIZED VALUES

	Business Partners	Activity Period	Operation Country
Expert.1	-.587	-.313	.333
Expert.2	-.325	-.313	.030
Expert.3	-.220	-.076	.030
Expert.4	.252	.161	-.273
Expert.5	.304	.493	.333
Expert.6	-.168	-.028	-.273
Expert.7	-.115	-.218	-.575
Expert.8	.409	.588	.333
Expert.9	.094	-.361	-.273
Expert.10	.357	.066	.333

Covariance coefficient values between standardized variables in Table III are established via Eq. (5). Thus, the covariance matrix formed in Eq. (6) is summarized in Table IV.

TABLE IV. COVARIANCE MATRIX

	Business Partners	Activity Period	Operation Country
Business Partners	.100	.075	.016
Activity Period	.075	.100	.045
Operation Country	.016	.045	.100

Next, the 3 eigenvalues of the covariance matrix are computed by Eq. (7). These eigenvalues are illustrated in Table V with explained variances. Then, the maximum eigenvalue is selected with Eq. (8) for saving the maximum variance. The maximum eigenvalue is .19569.

TABLE V. EIGENVALUES WITH EXPLAINED VARIANCES

	Value	Explained Variance
Eigenvalue.1	.19569	65.23%
Eigenvalue.2	.018526	6.18%
Eigenvalue.3	.085784	28.59%

The first eigenvalue contains 65.23% of the variance, which is considered a relatively high rate. Later, eigenvector is constructed with the help of Eq. (9). The results are displayed in Table VI.

TABLE VI. ITEMS OF EIGENVECTOR

	Vector
1	.603644
2	.675852
3	.422891

A one-dimensional matrix is created via Eq. (10). This matrix is exhibited in Table VII.

TABLE VII. ONE-DIMENSIONAL MATRIX

	First-dimension
Expert.1	23.009
Expert.2	25.605
Expert.3	3.191
Expert.4	38.580
Expert.5	44.761
Expert.6	31.048
Expert.7	28.525
Expert.8	47.320
Expert.9	29.335
Expert.10	39.282

Finally, the items in Table VII are normalized. Thus, the rating scores of experts are defined as Eq. (11). The rating scores of experts are presented in Fig. 2.

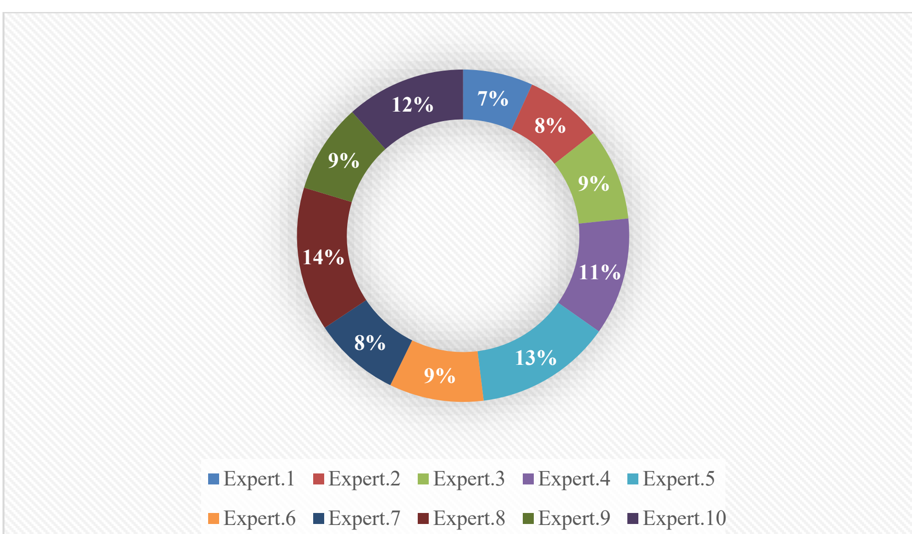

Fig. 2. Rating scores of experts.

As can be seen from rating scores in Fig. 2, the most important evaluation is Expert.8 with .140. This expert's institution has the maximum business partners, operation county and activity period. Moreover, as a second method to compare the results, the z-NIDM method is applied. The comparative results are visualized in Fig. 3.

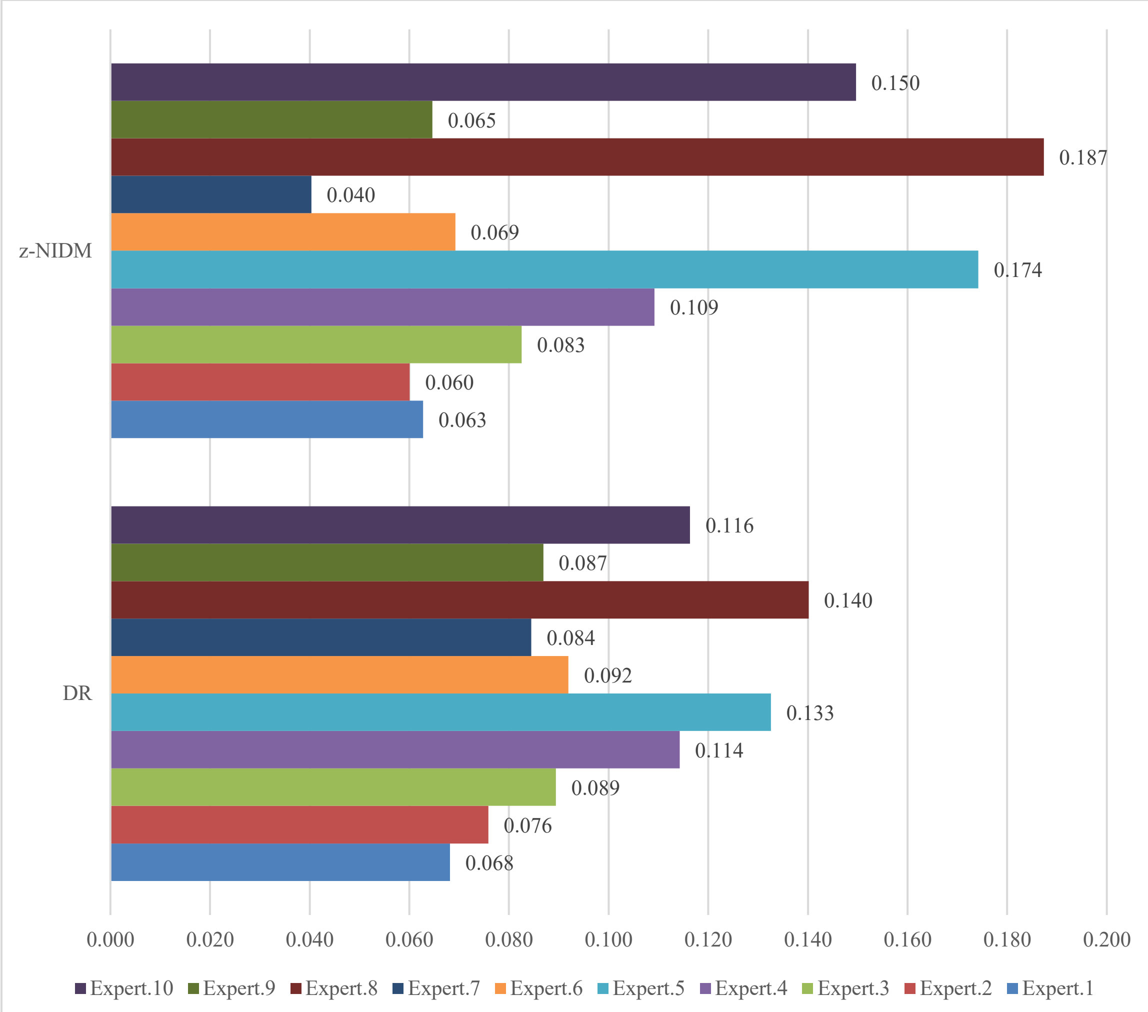

Fig. 3. Comparative results for experts.

Pearson and Spearman correlation coefficients between two approaches are obtained for results. Pearson coefficient is .939 and Spearman coefficient is .944. These coefficients are very high. In other words, the results are consistent and reliable.

B. *Weighting of Criteria and Ranking of Alternatives*

Alternative irrigation methods for efficient use of water resources in agriculture are sprinkler irrigation (SPR), drip irrigation (DRP), surface irrigation (channel or flood) (SRF), subsurface irrigation (SBS), and micro sprinkler irrigation (MCR). The criteria effective in the selection of these alternatives are presented with their short codes in Table VIII.

Linguistic evaluations from 10 experts are collected with a linguistic scale shared in Fig. 4.

TABLE VIII. CRITERIA LIST WITH SHORT CODES

Definition	Short Code
Water Efficiency (Savings)	WEF
Cost	CST
Energy Consumption	ECN
Applicability/Technological Compatibility	APT
Plant Yield and Quality	PTQ
Environmental Impacts	EVI
Ease of Maintenance and Operation	EMO

Using the initials of the linguistic scale in Fig. 4, the experts' evaluations are summarized in Table IX. For example, VHI is of very high importance.

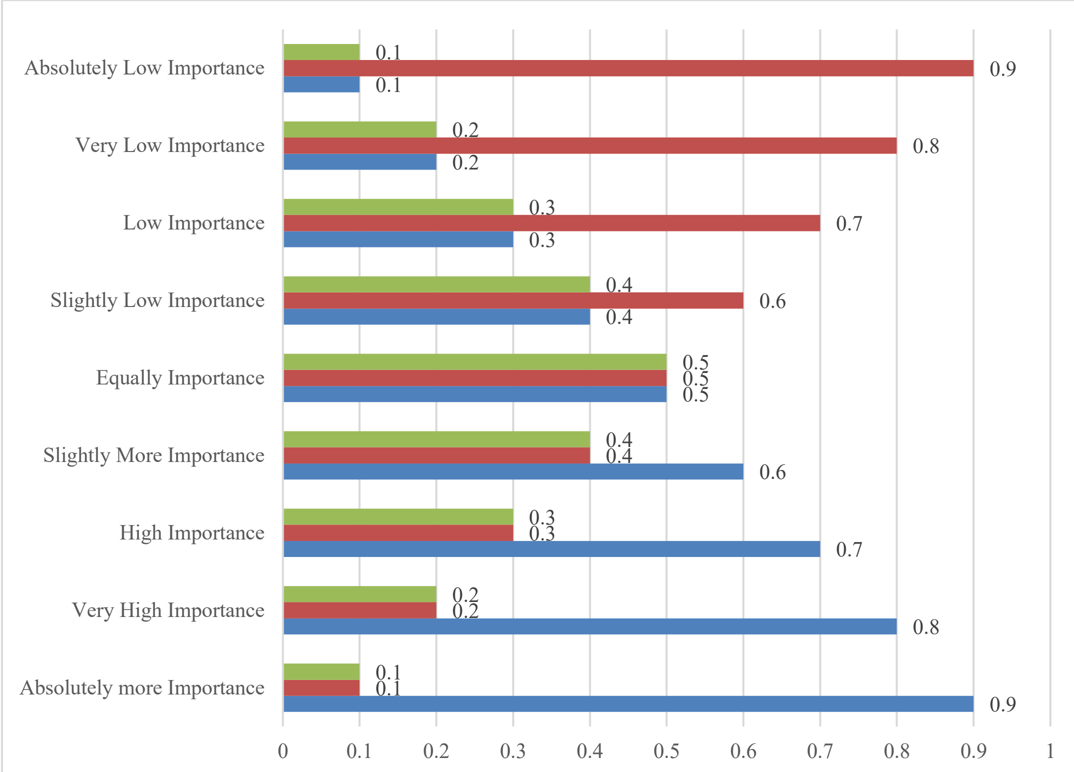

Fig. 4. Linguistic scales.

TABLE IX. LINGUISTIC EVALUATIONS

Expert.1	WEF	CST	ECN	APT	PTQ	EVI	EMO
SPR	VLI	ALI	ALI	VLI	VLI	SLI	ALI
DRP	AI	VHI	HI	AI	AI	AI	SMI
SRF	SLI	SLI	SMI	EI	SMI	SLI	SLI
SBS	SMI	SMI	SMI	SMI	EI	EI	EI
MCR	LI	LI	SLI	LI	VLI	LI	VLI
Expert.2	WEF	CST	ECN	APT	PTQ	EVI	EMO
SPR	LI	VLI	ALI	LI	ALI	SLI	LI
DRP	VHI	AI	VHI	AI	AI	VHI	VHI
SRF	EI	HI	SMI	HI	EI	HI	HI
SBS	EI	SMI	EI	EI	EI	EI	EI
MCR	SLI	VLI	VLI	VLI	SLI	LI	SLI
Expert.3	WEF	CST	ECN	APT	PTQ	EVI	EMO
SPR	VLI	VLI	VLI	VLI	SLI	SLI	ALI
DRP	AI	AI	AI	AI	HI	VHI	AI
SRF	SMI	EI	SMI	SMI	SLI	HI	HI
SBS	SMI	EI	EI	SMI	SMI	EI	SMI
MCR	LI	LI	VLI	LI	VLI	SLI	VLI
Expert.4	WEF	CST	ECN	APT	PTQ	EVI	EMO
SPR	LI	LI	ALI	ALI	VLI	SLI	VLI

DRP	SMI	HI	AI	HI	AI	VHI	AI
SRF	HI	EI	HI	HI	EI	SMI	SMI
SBS	SMI	EI	SMI	EI	SMI	EI	SMI
MCR	SLI	SLI	SLI	LI	SLI	VLI	SLI
Expert.5	WEF	CST	ECN	APT	PTQ	EVI	EMO
SPR	ALI	SLI	VLI	SLI	SLI	ALI	VLI
DRP	AI	AI	SMI	SMI	SMI	SMI	VHI
SRF	EI	SMI	SLI	SMI	SMI	HI	SMI
SBS	SMI	EI	EI	SMI	SMI	EI	EI
MCR	VLI	LI	LI	VLI	VLI	SLI	VLI
Expert.6	WEF	CST	ECN	APT	PTQ	EVI	EMO
SPR	LI	SLI	ALI	ALI	ALI	ALI	SLI
DRP	SMI	HI	HI	AI	HI	VHI	HI
SRF	SMI	HI	EI	SLI	SMI	EI	SLI
SBS	SMI	SMI	SMI	SMI	SMI	EI	EI
MCR	SLI	VLI	VLI	SLI	VLI	VLI	VLI
Expert.7	WEF	CST	ECN	APT	PTQ	EVI	EMO
SPR	ALI	ALI	VLI	VLI	LI	SLI	ALI
DRP	SMI	HI	HI	HI	VHI	AI	VHI
SRF	EI	SLI	SMI	HI	HI	SMI	EI
SBS	EI	EI	SMI	SMI	SMI	EI	SMI
MCR	SLI	LI	LI	SLI	SLI	VLI	VLI
Expert.8	WEF	CST	ECN	APT	PTQ	EVI	EMO
SPR	ALI	ALI	SLI	LI	ALI	ALI	ALI
DRP	HI	SMI	AI	SMI	VHI	SMI	SMI
SRF	SMI	SMI	EI	HI	SMI	EI	EI
SBS	SMI	EI	SMI	SMI	EI	EI	EI
MCR	VLI	LI	LI	SLI	SLI	SLI	VLI
Expert.9	WEF	CST	ECN	APT	PTQ	EVI	EMO
SPR	VLI	SLI	ALI	VLI	ALI	SLI	ALI
DRP	SMI	SMI	VHI	SMI	VHI	SMI	AI
SRF	SMI	SMI	HI	EI	HI	SMI	HI
SBS	EI	SMI	SMI	EI	EI	SMI	SMI
MCR	VLI	SLI	VLI	SLI	LI	SLI	VLI
Expert.10	WEF	CST	ECN	APT	PTQ	EVI	EMO
SPR	SLI	ALI	VLI	SLI	LI	ALI	SLI
DRP	HI	VHI	HI	VHI	HI	VHI	AI
SRF	SMI	SLI	SLI	HI	SMI	SMI	HI
SBS	SMI	SMI	SMI	SMI	SMI	SMI	EI
MCR	LI	LI	SLI	SLI	VLI	LI	LI

These linguistic evaluations in Table IX are converted into SFNs according to Fig. 4. Then, weighted averages are calculated by Eq. (23) using rating scores of experts in Fig. 2 as weights. Thus, the decision matrix that accepts the weighted average values as elements is obtained. This matrix is displayed in Table X.

TABLE X. DECISION MATRIX

	WEF	CST	ECN	APT	PTQ	EVI	EMO
SPR	(.271,.777,.222)	(.316,.756,.248)	(.23,.809,.203)	(.301,.741,.261)	(.273,.765,.253)	(.342,.729,.285)	(.254,.788,.232)
DRP	(.781,.236,.243)	(.8,.214,.217)	(.815,.2,.201)	(.794,.222,.23)	(.808,.207,.205)	(.784,.231,.232)	(.833,.181,.192)
SRF	(.601,.425,.399)	(.585,.445,.385)	(.593,.44,.383)	(.652,.369,.347)	(.616,.412,.381)	(.627,.398,.374)	(.626,.404,.365)
SBS	(.598,.423,.409)	(.573,.453,.437)	(.597,.427,.411)	(.595,.426,.412)	(.587,.435,.422)	(.55,.478,.46)	(.567,.46,.443)
MCR	(.337,.694,.301)	(.35,.694,.286)	(.33,.7,.293)	(.378,.664,.322)	(.341,.702,.291)	(.366,.679,.309)	(.291,.746,.246)

Normalized decision values are computed with Eq. (24) and Eq. (25). All criteria are beneficial. For this reason, Eq. (24) is used. In other words, normalized decision values and the decision matrix's elements are the same. Next, crisped values are calculated by Equation (26). The crisped values are shown in Table XI.

The overall performance of the alternative is obtained with the help of Eq. (27). The overall performance values are visualized in Fig. 5.

TABLE XI. CRISPED VALUES

	WEF	CST	ECN	APT	PTQ	EVI	EMO
SPR	.089	.115	.066	.109	.090	.133	.079
DRP	.626	.655	.678	.645	.667	.631	.706
SRF	.380	.363	.372	.446	.399	.413	.412
SBS	.376	.344	.374	.373	.362	.317	.337
MCR	.134	.143	.130	.163	.136	.154	.103

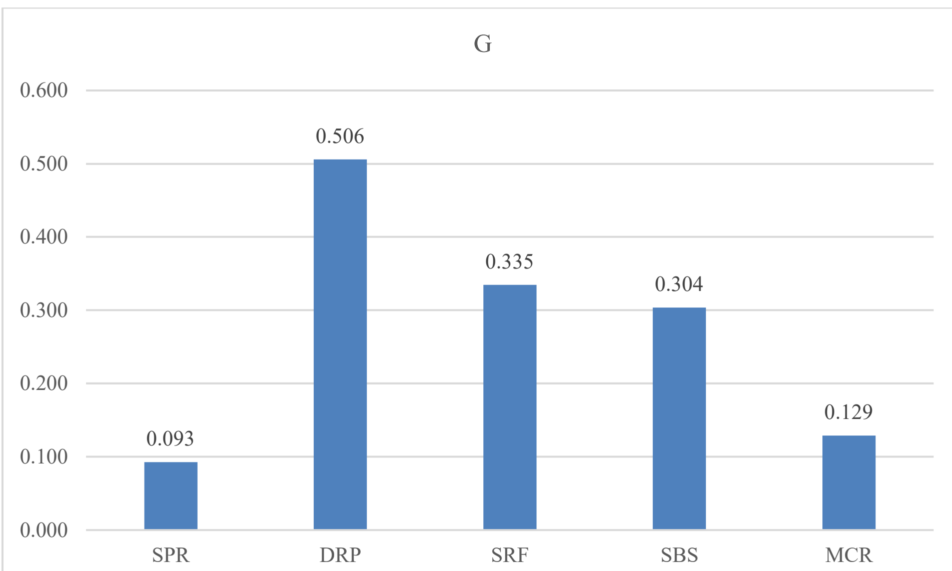

Fig. 5. Overall performance values.

The performance of the alternative by removing every criterion is established using Eq. (28). The results are illustrated in Table XII.

Next, the summation of absolute deviations is estimated by Eq. (29). The summation values are presented in Fig. 6.

The last step of MEREC is about the computation of priority values of criteria with Eq. (30). The results are shown in Fig. 7.

TABLE XII. G' VALUES

	WEF	CST	ECN	APT	PTQ	EVI	EMO
SPR	.081	.078	.084	.079	.081	.075	.083
DRP	.450	.448	.446	.449	.447	.450	.443
SRF	.295	.297	.296	.288	.293	.292	.292
SBS	.263	.267	.263	.264	.265	.270	.267
MCR	.112	.111	.112	.108	.112	.109	.116

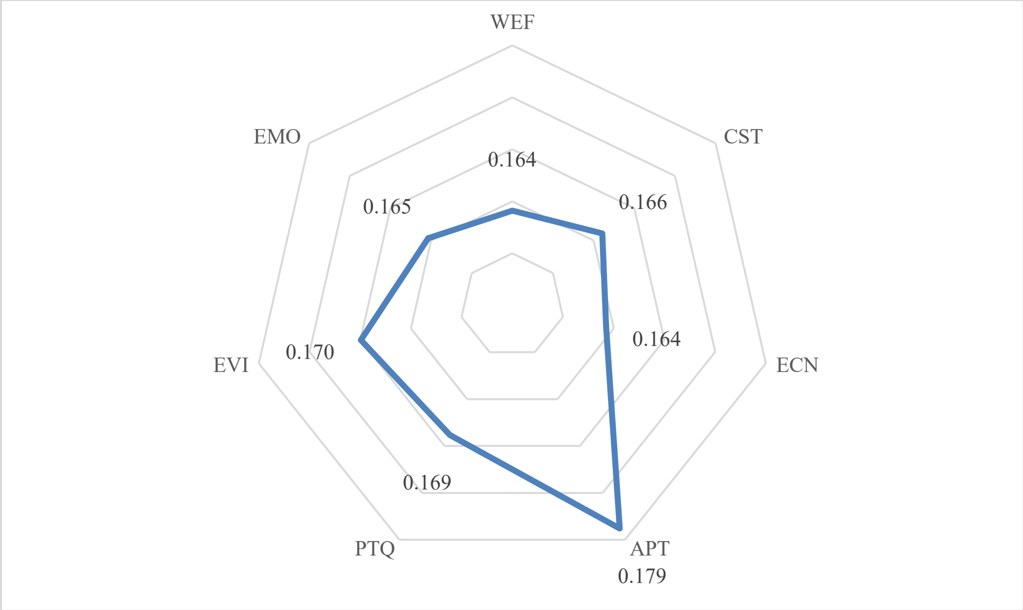

Fig. 6. Summation of absolute deviations.

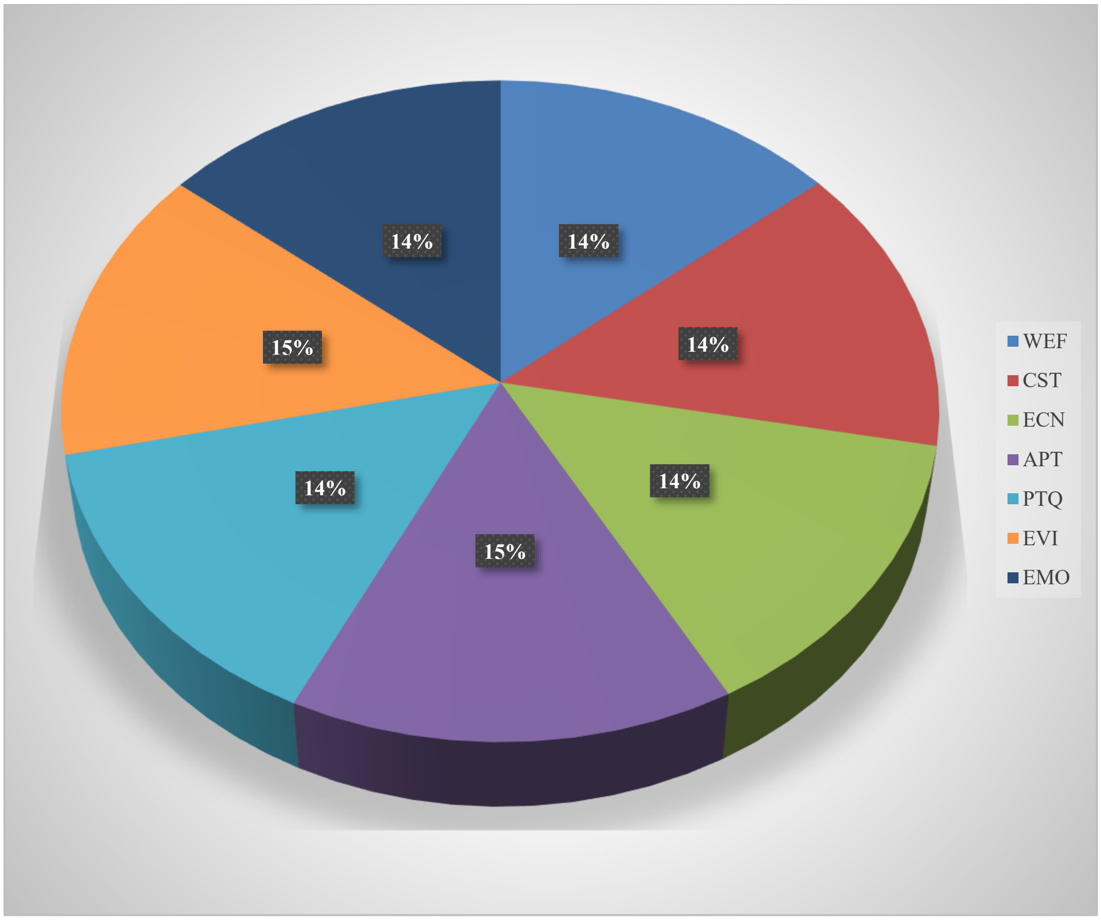

Fig. 7. Priority values of criteria.

When Fig. 7 is examined, the most important criterion effective in the selection of these alternative irrigation methods for efficient use of water resources in agriculture is applicability/technological compatibility with .152. The second important criterion is environmental impacts with .144. Afterwards, weighted sum model is applied using Eq. (31). The weighted sum model result is described in Table XIII.

TABLE XIII. Weighted Sum Model

	$\tilde{Q}^{(1)}$
SPR	(.287,.766,.246)
DRP	(.803,.212,.217)
SRF	(.616,.412,.376)
SBS	(.582,.443,.428)
MCR	(.344,.696,.294)

Similarly, weighted product model is performed via Eq. (32). The weighted product model result is illustrated in Table XIV.

TABLE XIV. Weighted Product Model

	$\tilde{Q}^{(2)}$
SPR	(.282,.768,.244)
DRP	(.802,.214,.218)
SRF	(.614,.413,.377)
SBS	(.581,.444,.429)
MCR	(.341,.698,.293)

Next, the $\tilde{Q}$ values of alternatives are calculated by Eq. (33). The results are summarized in Table XV with φ of .5.

TABLE XV. $\tilde{Q}$ Values ($\varphi = .5$)

	$\varphi\tilde{Q}^{(1)}$	$(1-\varphi)\tilde{Q}^{(2)}$	$\tilde{Q}$
SPR	(.205,.875,.179)	(.202,.876,.177)	(.285,.767,.245)
DRP	(.635,.461,.202)	(.634,.462,.203)	(.802,.213,.218)
SRF	(.46,.642,.309)	(.459,.643,.31)	(.615,.413,.377)
SBS	(.432,.665,.349)	(.431,.666,.35)	(.581,.443,.428)
MCR	(.247,.834,.218)	(.245,.835,.216)	(.342,.697,.294)

Finally, score function values of $\tilde{Q}$ are estimated with the help of Eq. (34) for the ranking of alternatives. The ranking values of alternative irrigation methods for efficient use of water resources are visualized in Fig. 8.

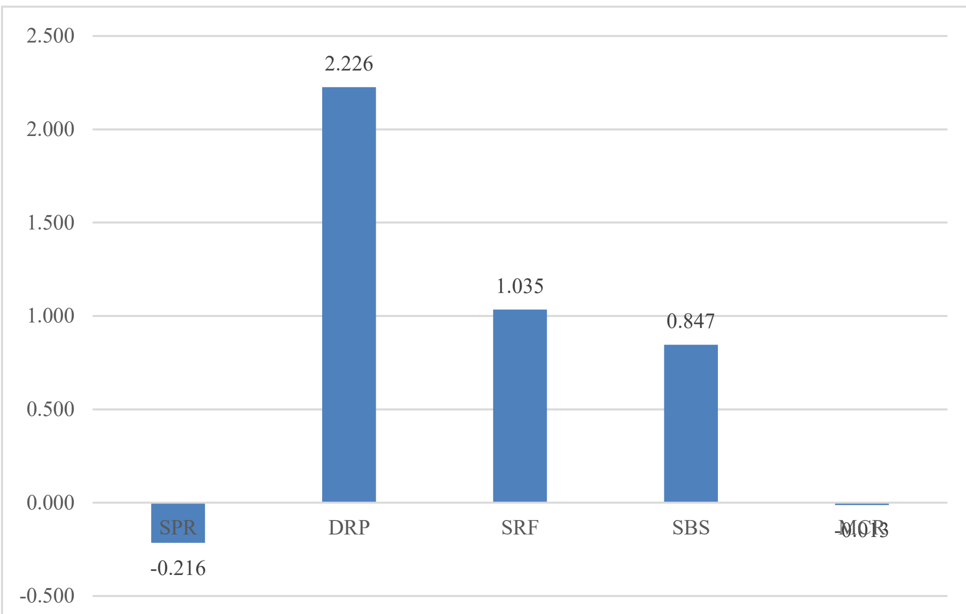

Fig. 8. Defuzzified Q values.

As can be seen, defuzzified Q values in Fig. 8, the most suitable alternative irrigation method for efficient use of water resources is drip irrigation with 2.226.

C. *Sensitivity Analysis*

Calculations are performed with different φ values and the results are compared. This tests the sensitivity of the results. The ranking values based on φ values are summarized in Table XVI.

TABLE XVI. Results by φ

	0	.1	.2	.3	.4	.5	.6	.7	.8	.9	1
SPR	-.221	-.220	-.219	-.218	-.217	-.216	-.214	-.213	-.212	-.211	-.210
DRP	2.222	2.223	2.224	2.225	2.225	2.226	2.227	2.228	2.229	2.229	2.230
SRF	1.032	1.032	1.033	1.033	1.034	1.035	1.035	1.036	1.037	1.037	1.038
SBS	.845	.845	.845	.846	.846	.847	.847	.847	.848	.848	.849
MCR	-.016	-.016	-.015	-.014	-.014	-.013	-.012	-.012	-.011	-.010	-.010

As can be understood from ranking scores of alternatives in Table XVI, the ranks of alternatives are the same. In other words, the results are reliable and consistent.

D. Comparative Analysis

To validate the results, a second method is used to compare them. The RAWEC method is preferred for this purpose. The crisp values in Table XI are used. The comparative results are presented in Fig. 9.

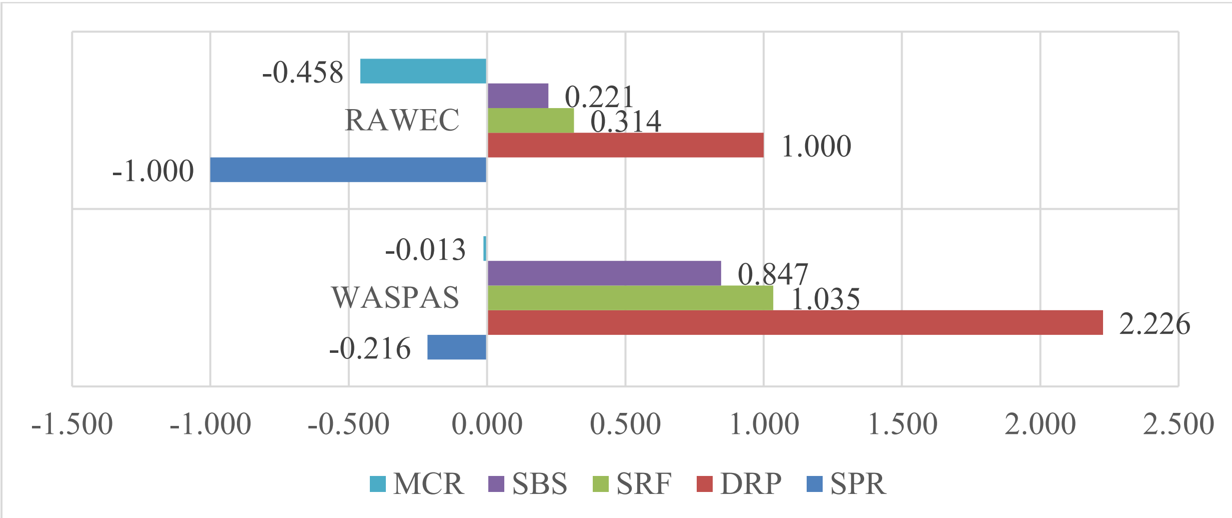

Fig. 9. Comparative analysis for ranking.

Pearson and Spearman correlation coefficients are calculated to determine the consistency between the results of the two methods. These coefficients are 0.972 and 1, respectively. High correlations indicate that the results are valid.

V. Discussion

Applicability, or technological suitability, is one of the key criteria when determining alternative irrigation methods for the efficient use of water resources in agriculture. This is because implementing innovative strategies and leveraging the power of technology can increase the efficient use of water resources in agriculture. This can be achieved through the combined use of artificial intelligence, automated water supply systems, and IoT-based precision irrigation systems in industrial wastewater treatment [21]. In other words, promoting modern and improved water use through irrigation practices and other smart approaches is crucial for sustainable water use [22]. In this context, Et-Taibi et al. [23] argued that IoT-based smart agriculture could be a promising solution. In their study, they introduce a cloud-based smart irrigation system to connect numerous small-scale smart farms and centralize the data they obtain. The system optimizes irrigation water use through comprehensive big data collection, storage, and analysis. Xing and Wang [24] summarized recent advances in molecular breeding, precision agriculture, and innovative water management techniques aimed at improving crop drought resilience, soil health, and overall agricultural productivity. This is because the increasing challenges of climate change and water scarcity make it imperative to increase agricultural productivity and sustainability, especially in arid regions.

Environmental impacts have been identified as another important criterion in determining alternative irrigation methods for the efficient use of water resources in agriculture. Indeed, while the use of water resources has a certain impact on the ecological conditions of a region, it is possible to address three dimensions of environmental impact: wastewater discharge, non-point pollution, and carbon emissions [25]. In addition, the effective application of computerization in the efficient use of water resources in agriculture ensures the improvement of environmental impacts and contributes to the environmentally conscious use of water resources [26]. Kalfas et al. [27] extensively evaluate the link between land use planning, water resources, and global climate change in their study. They state that proper land use planning can guide the establishment of waste management systems that minimize methane emissions and that land use planning affects agricultural practices. On the other hand, Keson et al. [28] aimed to evaluate the performance of land, water and climate relationship in his study using geographic information systems-based tools for optimized planning and management of sustainable production practices.

Drip irrigation [29] is one of the most important alternatives for determining alternative irrigation methods for the efficient use of water resources in agriculture. Drip irrigation is one of the most effective ways to integrate water and fertilizer for productivity in agriculture. Proper application of drip irrigation can reduce nutrient loss and emissions while maintaining nutrient balance in the soil (Yang et al., 2024). In drip irrigation, water, nutrients, and other essential growth substances are precisely delivered directly to the plant's root zone through a hole. This quickly restores plant moisture and nutrient levels, minimizes water stress, and improves overall quality, growth, and productivity [30]. In this context, Sanchis-Ibor et al. [31] focused on the process of switching to drip irrigation in Acequia Real del Júcar (Valencia, Spain). Their aim is to analyze how the estimation and distribution of expected water savings vary across different water planning tools and how they are perceived by the various actors involved in this process.

VI. Conclusion

The aim of this study is to develop a holistic and methodologically advanced decision-making model that enables the identification of the most appropriate alternative irrigation methods for the efficient use of water resources in agriculture. To this end, a novel hybrid framework integrating spherical fuzzy sets, machine learning, MEREC, and WASPAS methods is proposed. Evaluations obtained from ten domain experts were transformed into spherical fuzzy numbers to capture hesitation and uncertainty; expert importance weights were objectively derived using machine learning; criterion weights were determined through the MEREC method; and alternative irrigation methods were ranked using WASPAS.

Beyond its technical outcomes, the primary research contribution of this study lies in advancing the state of the art in AI-assisted multi-criteria decision-making for agricultural water management. Unlike existing studies that predominantly rely on static expert-based fuzzy weighting and conventional ranking schemes, the proposed framework introduces a structured human–AI collaborative mechanism that simultaneously addresses uncertainty modeling, objective expert differentiation, and compensatory–noncompensatory alternative evaluation within a unified architecture. In this sense, the study moves beyond incremental tool-level efficiency improvements and offers a conceptually distinct decision-support paradigm that enhances methodological robustness and interpretability in complex resource management problems. The empirical findings indicate that feasibility and technological suitability constitute the most influential criterion, followed by environmental impacts, while drip irrigation emerges as the most suitable alternative for efficient water use. These results not only corroborate prior empirical insights but also demonstrate how advanced hybrid AI–fuzzy frameworks can yield more nuanced and reliable decision outcomes under uncertainty.

Nevertheless, the study has certain theoretical and technical limitations. The relatively small number of experts, the focus on a specific regional or sectoral context, and the consideration of only seven criteria constrain the generalizability of the findings. From a technical perspective, the machine learning–based expert weighting process is sensitive to dataset size and diversity, which may lead to variability across different samples. In addition, while spherical fuzzy modeling provides a robust representation of uncertainty, it entails relatively high computational complexity. Future research is therefore encouraged to incorporate larger and more diverse expert panels, extend the model to different geographic and agricultural contexts, integrate additional criteria such as socioeconomic and climatic variables, and combine the proposed framework with other AI-driven decision-support systems. Such extensions would further strengthen the generalizability of the model and consolidate its contribution to both methodological research and practical decision-making in sustainable agricultural water management.

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