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Research Article

SWARA & EDAS integration using spherical fuzzy sets in agricultural field

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ABSTRACT

The rapid decline of clean water resources, caused by climate change, population growth, and bad water management, is a big threat to both the environment and agriculture. In Türkiye, about 75% of clean water is used for irrigation in agriculture, which shows how important it is for this sector to use water wisely. This research investigates the viability of treated wastewater as a sustainable substitute for traditional water sources in agriculture, thereby mitigating water scarcity and minimizing environmental degradation. This study utilizes a spherical fuzzy adaptation of SWARA (Step-Wise Weight Assessment Ratio Analysis) and EDAS (Evaluation Based on Distance from Average Solution) to assess and rank drought-prone areas for wastewater application according to essential socio-environmental and economic factors.

The Republic of Türkiye Ministry of Environment, Urbanization, and Climate Change identified three areas in Türkiye—Southeastern Anatolia, Aegean, and Central Anatolia—as being more likely to experience drought. Three pilot cities (Kırıkkale, Manisa, and Şanlıurfa) were evaluated in these areas. The results showed that Şanlıurfa was the area most affected by drought and that its wastewater management system had the best chance of helping with sustainable development. In terms of numbers, Şanlıurfa had the highest rate of treating wastewater and the most agricultural land available for using wastewater. These findings indicate that emphasizing the utilization of treated wastewater in this region could substantially alleviate the effects of drought while fostering environmental resilience.

This study is new because it uses a spherical fuzzy MCDM framework that was specifically designed to deal with the complicated uncertainties that come up in regional water management during droughts. By implementing a context-specific methodology for prioritizing agricultural wastewater, this study provides policymakers with pragmatic insights into sustainable water management practices, thereby advancing both regional and national sustainability objectives.

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INTRODUCTION

Due to changing climate conditions and decreasing rainfall, drought is increasingly felt worldwide. It has gone beyond being just an environmental problem. Deforestation, excessive water use in agriculture and industry, and the inefficient management of water resources are among the main factors deepening drought conditions on a global scale [1]. Temperatures are rising. Evaporation rates are increasing. Water resources are becoming even more limited, and the need for long-term water management plans is becoming urgent [2]. This situation has also become evident in Turkey in recent years. In critical regions such as Southeastern Anatolia, Central Anatolia, and the Aegean, prolonged drought and water scarcity are making agricultural production and water supply difficult [3]. The high demand for irrigation water and the inadequacy of existing water management practices further exacerbate the problem. Therefore, water resources need to be addressed with a holistic and sustainable approach. Only in this way can environmental resilience be strengthened and the effects of drought be reduced.

Considering that large agricultural areas in Turkey are facing increasing water scarcity, the use of treated wastewater for agricultural irrigation stands out as a long-term solution [1]. With planned investments and forward-looking wastewater management strategies, it is possible to prioritize the regions most affected by drought. This increases the effectiveness of the measures taken. This study proposes an integrated approach aimed at addressing the existing shortcomings in agricultural water management. The focus is on identifying the most suitable regions for wastewater use. In this context, spherical fuzzy SWARA and EDAS methods, which can address the uncertainty and ambiguity arising in expert assessments, are used together. Thus, a robust decision-making framework is provided.

The unique aspect of the study is the innovative application of spherical fuzzy sets (SFS) within the integration of SWARA and EDAS. In this way, the inclusiveness of traditional multi-criteria decision-making approaches is expanded. Three different dimensions of uncertainty are considered: membership, non-membership, and hesitation. In environmental and agricultural decision problems with high uncertainty, SFS make the decision-making process more sensitive and functional [4]. More realistic results are obtained as a result.

When used in a fuzzy setting, the SWARA and EDAS methods have a lot of benefits that make it easier to make decisions. SWARA is the best choice because it is simple and fast when it comes to weighting criteria. You don't need to do complicated pairwise comparisons. Instead, a sequential evaluation process is used that takes into account how important each criterion is. You save time. It also makes it easier for people who have to make decisions. This quality stands out even more when there are a lot of criteria or when evaluations are based on personal opinion [5]. When used in a spherical fuzzy structure, SWARA better shows how experts really feel about things by taking into account uncertainty and partial beliefs. This makes the weighting of criteria that are important to the environment stronger.

The EDAS method looks at how close each option is to the average solution. This method works well when it's hard to tell the difference between options. Methods that use ideal solutions don't always work in the real world. When used in a spherical fuzzy environment, EDAS can include hesitation and partial non-membership degrees in the process of evaluation. This makes it easier to make decisions that are fair when you aren't sure what to do. This feature is very useful in agriculture and the environment when there isn't a lot of quantitative data and expert opinions aren't always right [6].

Combining the SWARA and EDAS methods into a spherical fuzzy framework takes advantage of the best parts of both. This makes the structure for making decisions more stable and consistent. Following this method of combining different approaches, the study looks at Turkey's three driest areas: Southeastern Anatolia, the Aegean, and Central Anatolia. Kırıkkale, Manisa, and Şanlıurfa were chosen to be the first cities to try it out. To model water management strategies that focus on drought, a full evaluation framework with seven main criteria was made. These are the criteria: how easy it is to get to natural water resources (C1), the slope of the land (C2), the rate of drought at the provincial level (C3), the ratio of arable land (C4), the rate of wastewater treatment in the region (C5), the amount of wastewater produced per person per day (C6), and the amount of money that municipalities spend on wastewater treatment (C7). We used the spherical fuzzy SWARA method to figure out the weights for the criteria. This shows how important each factor is compared to the others and how complicated it is inside. Turkey is making more decisions about how to manage agricultural water that take into account the local situation.

In conclusion, this study fills in some important gaps in how to manage water for farming in areas that have been hit by drought. It adds to the body of knowledge. SFSs are a better way to show uncertainty and better show how experts are unsure than traditional methods. SWARA and EDAS work together to prioritize the use of wastewater in Turkey's drought-prone areas by taking into account both environmental and socioeconomic factors. It goes beyond general evaluations and provides a more useful and evidence-based framework for improving sustainable water use in farming. The second part of the article talks about the important research. The third part talks about how to combine different methods. The fourth part talks about applications and case studies, and the last part talks about the effects on policy and suggestions for future research.

Literature Review

Multi-criteria decision-making (MCDM) is a way to look at and rank options based on more than one, often conflicting, set of criteria. It does this by taking into account both the decision factors and their relative weights. Because they are so flexible, MCDM methods have been used in many different fields, including finance, education, logistics, engineering, healthcare, environmental management, and industry (Yalçın & Uncu [6]; Marqués et al. [7]; Syed Hassan et al. [8]; Evcioğlu & Kabak [9]; Reddy [10]; Korkusuz et al. [11]; Sánchez-Lozano & Bernal-Conesa [12]). MCDM is especially useful in agriculture, where choices have a direct impact on the environment, people's health, and the economy. MCDM has been used in the past to choose crops [13], assess sustainability [14], plan irrigation [15], manage finances [16], choose a site [17–19], manage soil quality [3; 20], and choose machinery [21]. This shows that it can effectively balance trade-offs between economic, environmental, and resource-related factors in a structured and data-driven way.

The increasing severity of drought has become a serious threat to food security, agricultural productivity, access to water, and economic stability, especially in countries like Turkey [22]. These problems are deepening. Climate change and global warming are further accelerating the process and making the need for long-term water management plans inevitable. Under these conditions, the reuse of treated wastewater in agricultural production is becoming increasingly important. This practice reduces the pressure on freshwater resources. It prevents the pollution of natural water bodies. It also provides energy savings. Therefore, in order to evaluate different alternatives for wastewater management, methods such as AHP [22], ANP [23], TOPSIS [24], VIKOR [2], GIS-based multi-criteria decision-making models [25], and MOORA [26] have been used in numerous studies. Criteria such as environmental compatibility, cost-effectiveness, and resource efficiency are prominent in these evaluations.

However, traditional multi-criteria decision-making methods are often based on clear and precise data. Such data is not always available in real decision-making environments. Uncertainty and incomplete information are inevitable, especially in environmental and agricultural decision-making processes. To overcome this limitation, fuzzy multi-criteria decision-making approaches have been developed that model uncertainty through linguistic variables and membership functions. Fuzzy AHP and fuzzy TOPSIS are the most widely used methods among these approaches. These methods have yielded successful results in agricultural applications. For example, they have been effectively used in irrigation method selection studies in situations where weather conditions are unpredictable (Burak et al. [15]) and in crop selection based on water needs, soil compatibility, and adaptability to different climatic conditions (Qureshi et al. [13]). Overall, fuzzy multi-criteria decision-making methods are seen to make significant contributions to the determination of sustainability goals, the analysis of environmental and social impacts, and the support of agricultural risk management [27–28]. This demonstrates that these approaches are powerful tools in solving complex and subjective decision-making problems.

Recent studies show that adding advanced fuzzy logic structures to MCDM makes decisions better when there is a lot of uncertainty. Fuzzy TOPSIS has been used in wastewater management to find the best places for agricultural reuse by using geographic and environmental data [25]. Additionally, SFS are getting more and more attention because they can show membership, non-membership, and hesitancy all at the same time. This makes them a better and more flexible way to model expert uncertainty (Kutlu Gündoğdu & Kahraman [4]; Akbari et al. [14]). Fuzzy SWARA and fuzzy EDAS methods have become popular tools for dealing with subjective, expert-driven MCDM problems. They build on this progress by using fuzzy logic to better capture uncertainty in MCDM problems. So, the next sections look at studies that used fuzzy SWARA and fuzzy EDAS. They focus on the types of problems they were used to solve, how they were set up, and how they were done.

The most recent studies that used fuzzy SWARA show that the method can work with different types of fuzzy sets, such as Type-1, Type-2, interval-valued, intuitionistic, and SFS. SFS, which are used in fields like choosing renewable energy sources [30] and managing a green supply chain [34], are better at capturing expert uncertainty

Table 1. Studies utilizing fuzzy SWARA

Author(s)	Fuzzy set	Application area
Rostamzadeh et al. (2020) [5]	Type-1 fuzzy set	Supplier selection in supply chain
Pamucar et al. (2021) [29]	Intuitionistic fuzzy set	Transportation project prioritization
Mishra et al. (2021) [30]	Spherical fuzzy set	Renewable energy project selection
Yazdani & Tavana (2020) [31]	Interval-valued fuzzy set	Industrial safety assessment
Keshavarz Ghorabaee et al. (2021) [32]	Interval type-2 fuzzy set	Healthcare service quality evaluation
Fouladgar et al. (2019) [33]	Type-2 fuzzy set	Strategic planning in defense industry
Ashtari & Omrani (2021) [34]	Spherical fuzzy set	Green supply chain management
Zolfani et al. (2020) [35]	Type-1 fuzzy set	Urban sustainability evaluation

Table 2. Studies utilizing fuzzy EDAS

Author(s)	Fuzzy Set	Application Area
Yazdani & Zarate (2019) [31]	Type-1 fuzzy set	Industrial site selection
Khalili-Damghani et al. (2020) [36]	Interval-valued fuzzy set	Supply chain resilience
Shen et al. (2019) [37]	Intuitionistic fuzzy set	Environmental impact assessment
Ashtari & Omrani (2021) [34]	Spherical fuzzy set	Agricultural sustainability assessment
Yildiz & Korkmaz (2020) [38]	Type-2 fuzzy set	Transportation project evaluation
Ghorabaee et al. (2022) [32]	Interval type-2 fuzzy set	Urban wastewater management
Hosseini et al. (2021) [39]	Spherical fuzzy set	Renewable energy investment prioritization
Chatterjee & Zavadskas (2019) [40]	Type-1 fuzzy set	Urban infrastructure planning

and hesitation. In contrast, Type-1 fuzzy sets, like the ones used by [5] to choose suppliers, are used when there isn't as much uncertainty. This comparison shows that the fuzzy set chosen in SWARA depends on how complicated the criteria are and how unclear the expert judgment is. This shows that fuzzy SWARA can be used in many different decision-making situations.

Recent studies on fuzzy EDAS show that this method can be used in a wide range of fuzzy environments, including Type-1, Type-2, interval-valued, and SFS. SFS, utilized by Ashtari & Omrani [34] for agricultural sustainability and by Hosseini et al. [39] in prioritizing renewable energy investments, are preferred for applications requiring the aggregation of intricate expert opinions. These studies show that spherical fuzzy EDAS can better show how experts are unsure and partially agree, especially when it comes to the environment and sustainability.

The literature shows that many MCDM methods, such as AHP, TOPSIS, VIKOR, and GIS-based methods, have been used a lot in agriculture decision-making. However, they often don't work well when there are complicated uncertainties and experts are hesitant to make decisions in subjective and unclear situations. Conventional MCDM methodologies, even when incorporating fuzzy logic, predominantly rely on distinct membership values, thereby constraining their capacity to encompass nuanced viewpoints. While certain studies employ fuzzy logic to address uncertainty, frameworks such as fuzzy AHP and TOPSIS do not possess mechanisms to fully integrate hesitancy and partial agreement.

Our research fills this void by utilizing SFS in SWARA and EDAS methodologies, thereby quantifying membership, non-membership, and degrees of hesitancy. This facilitates a thorough representation of expert opinions, incorporating subtle uncertainty. Spherical fuzzy SWARA allows for strong weighting even when things aren't clear, and fuzzy EDAS looks at options based on average distance, which makes it useful in farming situations where perfect results are often not possible.

Current research frequently depends on general criteria such as water availability and cost, neglecting the contextual factors necessary for sustainable wastewater reuse in agriculture. We present specific criteria—availability of natural spring water, land slope, drought rate, agricultural area, wastewater treatment rate, daily wastewater generation per capita, and designated municipal budgets—customized to meet Türkiye's requirements. Our study offers a useful model for dealing with water scarcity in agricultural wastewater management by combining these context-specific criteria with a spherical fuzzy SWARA-EDAS framework.

MATERIALS AND METHODS

In this research, a region-specific application in Türkiye was developed by merging SWARA and EDAS in SFS to facilitate the implementation of Novel MCDM Approaches.

Prelimination of Spherical Fuzzy Sets

SFS was introduced to the literature by Kutlu Gündoğdu and Kahraman [4] as a combination of Pythagorean and neutrosophic fuzzy sets. In the global setting, researchers can independently define and model membership, non-membership and hesitation degrees. Some definitions, basic operators, Euclidean distance and defuzzification operators for SFS are given below:

Definiton 1. A SFS $\tilde{A}_s$ of the universe of discourse U is given by

$$\tilde{A}_s = \{\langle u, \left(\mu_{\tilde{A}_s}(u), v_{\tilde{A}_s}(u), \pi_{\tilde{A}_s}(u)\right) | u \in U\rangle \tag{1}$$

where

$$\mu_{\tilde{A}_s}(u): E \to [0,1], v_{\tilde{A}_s}(u): U \to [0,1], \ \ \pi_{\tilde{A}_s}(u): U \to [0,1]$$

, and

$$0 \leq \mu^2_{\tilde{A}_S}(u) + v^2_{\tilde{A}_S}(u) + \pi^2_{\tilde{A}_S}(u) \leq 1 | \forall u \in U \tag{2}$$

where $\mu_{\tilde{A}_s}(u), v_{\tilde{A}_s}(u)$ and $\pi_{\tilde{A}_s}(u)$ are the degrees of membership, non-membership and hesitancy of $\tilde{A}_s$ respectively.

The condition in Equation 2 can also be specified as shown in Equation 3:

$$\mu^2_{\tilde{A}_S}(u) + v^2_{\tilde{A}_S}(u) + \pi^2_{\tilde{A}_S}(u) = 1 | \forall u \in U \tag{3}$$

Basic operations

Addition, multiplication, multiplication by a scalar and power of SFS are described as follows:

Addition

$$\tilde{A}_s \oplus \tilde{B}_s = \begin{pmatrix} (\mu^2_{\tilde{A}_s} + \mu^2_{\tilde{B}_s} - \mu^2_{\tilde{A}_s}\mu^2_{\tilde{B}_s})^{1/2}, \quad v_{\tilde{A}_s}v_{\tilde{B}_s}, \\ [(1-\mu^2_{\tilde{B}_s})\pi^2_{\tilde{A}_s} + (1-\mu^2_{\tilde{A}_s})\pi^2_{\tilde{B}_s} - \pi^2_{\tilde{A}_s}\pi^2_{\tilde{B}_s}]^{1/2} \end{pmatrix} \tag{4}$$

Multiplication

$$\tilde{A}_s \otimes \tilde{B}_s = \begin{pmatrix} \mu_{\tilde{A}_s}\mu_{\tilde{B}_s}, \quad (v^2_{\tilde{A}_s} + v^2_{\tilde{B}_s} - v^2_{\tilde{A}_s}v^2_{\tilde{B}_s})^{1/2}, \\ [(1-v^2_{\tilde{B}_s})\pi^2_{\tilde{A}_s} + (1-v^2_{\tilde{A}_s})\pi^2_{\tilde{B}_s} - \pi^2_{\tilde{A}_s}\pi^2_{\tilde{B}_s}]^{1/2} \end{pmatrix} \tag{5}$$

Multiplication by a scalar (λ>0)

$$\lambda.\tilde{A}_s = \begin{pmatrix} (1-(1-\mu^2_{\tilde{A}_s})^{\lambda})^{1/2}, \quad v^{\lambda}_{\tilde{A}_s}, \\ [(1-\mu^2_{\tilde{A}_s})^{\lambda} - (1-\mu^2_{\tilde{A}_s} - \pi^2_{\tilde{A}_s})^{\lambda}]^{1/2} \end{pmatrix} \tag{6}$$

Power of $\tilde{A}_s$ (λ>0)

$$\tilde{A}^{\lambda}_S = \begin{pmatrix} \mu^{\lambda}_{\tilde{A}_s}, \quad (1-(1-v^2_{\tilde{A}_s})^{\lambda})^{1/2}, \\ [(1-v^2_{\tilde{A}_s})^{\lambda} - (1-v^2_{\tilde{A}_s} - \pi^2_{\tilde{A}_s})^{\lambda}]^{1/2} \end{pmatrix} \tag{7}$$

Aggregation operator

The aggregation procedure is a function used when it's necessary to identify a single value to represent a collection of integers. An aggregation operator transforms a collection of input data in a single value. In this research, the geometric mean operator is employed to aggregate matrices. The geometric mean of *n* spherical fuzzy integers is given by Equation 8.

$SWGM_w(\tilde{A}_{S1},\ldots\ldots, \tilde{A}_{Sn}) = \tilde{A}_{S1}^{w1} + \tilde{A}_{S2}^{w2} + \ldots\ldots + \tilde{A}_{Sn}^{wn}$

$$\text{SWGM} = \begin{pmatrix} \prod_{i=1}^{n} \mu^{w_i}_{\tilde{A}_{si}}, \quad \left(1 - \prod_{i=1}^{n}(1-v^2_{\tilde{A}_{si}})^{w_i}\right)^{1/2}, \\ [\prod_{i=1}^{n}(1-v^2_{\tilde{A}_{si}})^{w_i} - \prod_{i=1}^{n}(1-v^2_{\tilde{A}_{si}} - \pi^2_{\tilde{A}_{si}})^{w_i}]^{1/2} \end{pmatrix} \tag{8}$$

where the weights of DMs $w=(w_1, w_2\ldots\ldots\ldots\ldots, w_n)$; $w_i \in [0,1]$; $\sum_{i=1}^{n} w_i = 1$.

Defuzzification operator

Fuzzification is the process of converting a crisp value to its corresponding fuzzy representation. The converse of this procedure, which transforms a fuzzy number into its crisp version, is known as defuzzification. The defuzzification operation is described in Equation 9.

$$S(\tilde{\omega}_j^S) = \sqrt{\left|100 * \left[\left(3\mu_{\tilde{A}_s} - \frac{\pi_{\tilde{A}_s}}{2}\right)^2 - \left(\frac{v_{\tilde{A}_s}}{2} - \pi_{\tilde{A}_s}\right)^2\right]\right|} \tag{9}$$

Normalized euclidean distance

This is a distance metric that calculates the distances amongst fuzzy sets. In SFS, the Euclidean distance is used to calculate the lowest space in the sphere, as well as the shortest distance between a pair of points in a three-dimensional environment. The mathematical expression of the Euclidean distance is presented in equation 10.

$$D(A_i, A_k) = \sqrt{\frac{1}{2n}\sum_{i=1}^{n}((\mu A_i - \mu A_k)^2 + (vA_i - vA_k)^2 + (\pi A_i - \pi A_k)^2)} \tag{10}$$

Spherical Fuzzy SWARA

In the calculation of criterion weights in MCMD problems, besides the methods such as CRITIC, ENTROPY and MEREC, which consider the information carried by the data set from different perspectives and calculate objective criteria, criteria weights are also calculated with approaches that reflect the subjective thoughts of decision makers to the model. Among the traditional approaches, the AHP method is one of the most preferred methods by researchers for subjective weight calculation. The AHP method is an approach in which the importance levels of the criteria are calculated with the subjective opinions of DMs in a process called pairwise comparison. The SWARA method, one of the new generation approaches, also utilizes the pairwise comparison logic underlying the AHP approach, but the process steps are shorter. In the SWARA approach, decision makers first rank the criteria according to their own opinions and then, starting with the most important one, they compare and score the criteria in pairs.

The extension of MCDM approaches to different fuzzy sets is one of the most preferred modifications by researchers since real life problems are not crystal-clear situations. In this study, SWARA approach is used in SFS environment to better capture and model the fuzzy situation that arises due to the nature of the problem. The following steps should be followed for implementation:

Step 1: Defining the decision problem and determining the criteria to be used in the evaluation of the decision problem in line with the literature review and expert opinions.

Step 2: The linguistic terms and their corresponding SFS used in Table 3 are defined by Kutlu Gündoğdu and Kahraman [4] for application in decision-making contexts, providing researchers with a structured approach to capture expert judgments in a fuzzy environment. In this study, decision-makers (DMs) utilized these predefined linguistic terms to rank the criteria according to their own opinions, assigning the highest importance to the most critical criterion.

Table 3. Linguistic terms and their corresponding SFNs

	(μ, v, π)
Absolutely more importance (AMI)	(0.9, 0.1, 0.1)
Very high importance (VHI)	(0.8, 0.2, 0.2)
High importance (Hl)	(0.7, 0.3, 0.3)
Slightly more importance (SMI)	(0.6, 0.4, 0.4)
Equally importance (El)	(0.5, 0.5, 0.5)
Slightly low importance (SLI)	(0.4, 0.6, 0.4)
Low importance (LI)	(0.3, 0.7, 0.3)
Very low importance (VLI)	(0.2, 0.8, 0.2)
Absolutely low importance (ALI)	(0.1, 0.9, 0.1)

Step 3: Utilizing Table 3, convert the linguistic evaluations to the appropriate SFN and create the SFN evaluation matrix.

Step 4: Aggregating the matrices consisting of the individual assessments of the DMs by using the SWGM operator shown in Equation 8 and thus creating the aggregated SFN decision matrix.

Step 5: Calculation of spherical score values for each criterion using Equation 10.

Step 6: Using the DMs' assessments as a guide, rank the criteria according to decreasing SF-score values.

Step 7: By comparing the *jth* criterion *(j-1)th* criterion with the criterion that is selected in second place, determine the relative importance (S_j) of that criterion..

Step 8: Use Equation (11) for calculating the comparative coefficient.

$$k_j = \begin{cases} 1, & j = 1 \\ s_j + 1, & j > 1 \end{cases} \tag{11}$$

Step 9: Calculate the weights (p_j) of the criterion as:

$$p_j = \begin{cases} 1, & j = 1 \\ \dfrac{p_j - 1}{k_j}, & j > 1 \end{cases} \tag{12}$$

Step 10: Calculate the criterion's normalized weight as:

$$w_j^s = \frac{p_j}{\sum_{j=1}^{n} p_j}, j = 1,2,\ldots,n \tag{13}$$

Spherical Fuzzy EDAS

Step l: Invite each DM to use the linguistic terms listed in Table 3 to complete the performance assessment matrix.

Step 2: The spherical fuzzy alterative evaluation matrix, which is made up of n criteria C_j *(j=1, 2,…,n)* and m alternative A_i *(i=1,2,…,m),* is obtained by transforming the linguistics assessment of performance matrix into its spherical fuzzy form. The mathematical representation of SF-alternative evaluation matrix is shown in Equation 14.

$$C_j(A_i)_{m\times n} = \begin{bmatrix} (\mu_{11}, v_{11}, \pi_{11}) & \cdots & (\mu_{1n}, v_{1n}, \pi_{1n}) \\ \vdots & \ddots & \vdots \\ (\mu_{m1}, v_{m1}, \pi_{m1}) & \cdots & (\mu_{mn}, v_{mn}, \pi_{mn}) \end{bmatrix} \tag{14}$$

Step 3: Equation 8 can be used to aggregate the evaluation matrices from each DM and produce an aggregated spherical fuzzy alternative evaluation matrix.

Step 4a: Obtaining the spherical fuzzy decision matrix by multiplying the weights of the criteria determined during the SWARA step of the proposed model by the aggregated matrix. Apply spherical fuzzy multiplication by a scalar operator given Equation 6. Equation 15 provides the structure of the spherical fuzzy decision matrix, $D=(C_j(A_i))$.

$$D=(C_j(w_jA_i))_{m\times n} = \begin{bmatrix} (w_1\mu_{11}, w_1v_{11}, w_1\pi_{11}) & \cdots & (w_n\mu_{1n}, w_nv_{1n}, w_n\pi_{1n}) \\ \vdots & \ddots & \vdots \\ (w_1\mu_{m1}, w_1v_{m1}, w_1\pi_{m1}) & \cdots & (w_n\mu_{mn}, w_nv_{mn}, w_n\pi_{mn}) \end{bmatrix} \tag{15}$$

Step 4b: Obtain score values of step 4a by utilizing defuzzification operator that is given Equation 8.

Step 5a: Equation 8's SWGM operator can be used to find the spherical fuzzy average solution. Equation 16 provides a mathematical illustration of the average solution.

$$SFAV = \{(\mu_1^x, v_1^x, \pi_1^x), (\mu_2^x, v_2^x, \pi_2^x), \ldots, (\mu_n^x, v_n^x, \pi_n^x)\} \tag{16}$$

Step 6: On the basis of the score values acquired in steps 4b and 5b, identify the alternatives that are positioned positively and negatively.

Step 4b and Step 5b are just calculations to observe whether the alternatives are positively or negatively positioned. In other words, the alternatives are compared according to the average solution obtained and it is observed whether they have a solution above or below the average solution.

Step 7: Using the Euclidean distance formula shown in Equation 10, the distance of the positively positioned alternatives to the average solution is calculated first, and then the distance of the negatively positioned alternatives to the average solution is calculated, and these calculated distances are called positive distance from the average and negative distance from the average, respectively.

Step 8: The distances calculated in Step 7 are normalized using Equations 17 and 18.

$$NSP_i = \frac{SP_i}{max_i(SP_i)} \tag{17}$$

$$NSN_i = 1 - \frac{SN_i}{max_i(SN_i)} \tag{18}$$

Step 9: The appraisal score for each alternative is calculated using the following equation.,

$$AS_i = \frac{1}{2} \times (NSP_i + NSN_i) \quad (19)$$

Step 10: Sort each of the alternatives in order of decreasing assessment score numbers. Among the candidate choices, the option with the greatest appraisal score is the best option

Case Study: Selection of the Driest Region to Use Treated Wastewater in Agricultural Irrigation Among Three Pilot Cities in Türkiye Using SF-SWARA and SF-EDAS

Agriculture is one of the most important sectors in meeting the basic needs of people. Water is the element that provides the most healthy and efficient development of plants in agriculture. Improvement efforts in this sector should be completed as soon as possible. Because agriculture is one of the first sectors to be affected by the increasing drought threat every year. It is aimed to investigate the use of water obtained by recycling wastewater as irrigation water in agriculture. Hence, the aim of this study we have done is to present water recycling studies together with MCDM methods as a solution to the drought, which has become a major problem in the world today. Undoubtedly, the most affected area by the drought will be the agricultural area. While the use of urban and agricultural wastewater while recycling water reduces the damage of wastewater to the environment, the recycled clean water creates a new source of clean water for agricultural areas. Since this whole process is quite complex and includes many conflicting criteria, performing the study with MCDM methods will help to achieve the most accurate results.

In this section, case study application to select the driest region to use treated wastewater in agricultural irrigation among three pilot cities in Türkiye using SF-SWARA and SF-EDAS is presented. It is determined that there are many evaluation criteria such as drought rate of cities, area of cities that can be used as “agricultural land”, “amount of wastewater in cities”, “budget allocated for wastewater treatment”, “wastewater treatment rate in the region”, and “water consumption rate in the region” based on the conducted literature review study. Firstly, each evaluation criterion is weighted by three DMs using SF-SWARA method and then SF-EDAS is applied to rank the 3 driest regions of Türkiye, namely, “Southeastern Anatolia Region”, “Aegean Region”, and “Central Anatolia Region”. Accordingly, three pilot cities (Kırıkkale, Manisa and Şanlıurfa) are selected and evaluated within the scope of the application. The proposed evaluation framework aims to contribute to waste management by increasing the awareness of environmental protection in the region and helps to use water resources more efficiently.

Table 4. The specialist’s thoughts for importance rank of the criteria in the form of SF linguistic variables

Criteria	DM1	DM2	DM3
C1	HI	AMI	VHI
C2	LI	SLI	SLI
C3	AMI	HI	AMI
C4	SMI	VHI	HI
C5	VHI	SMI	SMI
C6	SLI	LI	EI
C7	EI	EI	LI

Step 1. Following an in-depth literature review and evaluation of expert recommendations, the criteria and alternatives described above were used to identify the best alternative. Three decision makers, symbolized by DM1, DM2 and DM3, with almost equal experience in the agricultural sector, were asked to give their opinion. Due to their almost equal experience, the weights of the decision makers were considered equal.

Step 2. As a first step in the calculation of criteria weights with the SF-SWARA approach, decision makers use the linguistic scale shown in Table 3 to rank the criteria in their own opinion as shown in Table 4.

Step 3. The importance rankings made by each DM are converted at this stage into the SFN shown in Table 5.

Step 4. The three different evaluation matrices resulting from the individual evaluations of the DMs are aggregated

Table 5. SF evaluation matrix for weighting criterion

	DM1			DM2			DM3		
Criteria	μ	v	π	μ	v	π	μ	v	π
C1	0.70	0.30	0.30	0.90	0.10	0.20	0.80	0.20	0.20
C2	0.30	0.70	0.30	0.40	0.60	0.40	0.40	0.60	0.40
C3	0.90	0.10	0.10	0.70	0.30	0.10	0.90	0.10	0.10
C4	0.60	0.40	0.40	0.80	0.20	0.30	0.70	0.30	0.30
C5	0.80	0.20	0.20	0.60	0.40	0.40	0.60	0.40	0.40
C6	0.40	0.60	0.40	0.30	0.70	0.50	0.50	0.50	0.50
C7	0.50	0.50	0.50	0.50	0.50	0.30	0.30	0.70	0.30

Table 6. Aggregated SF evaluation matrix for weighting criterion

Criteria	μ	v	π
C1	0.671	0.182	0.234
C2	0.136	0.632	0.372
C3	0.736	0.143	0.104
C4	0.508	0.289	0.333
C5	0.473	0.316	0.328
C6	0.169	0.594	0.471
C7	0.200	0.558	0.392

with the SWGM operator in Equation 8 and the aggregated decision matrix shown in Table 6 is formed.

Step 5. The SF values in the aggregated matrix obtained in the previous step are converted into score values using the score function shown in Equation 9 and the subjective criteria weights are calculated using the score values obtained by following the steps of the traditional SWARA approach as shown in Table 7.

Table 7 shows that the importance levels of the criteria whose subjective weights are calculated according to the DMs' assessments are almost very close to each other. According to the calculated weights, if we rank the criteria as the most important first, an order of importance emerges as C6>C4>C5>C3>C7>C2>C1.

In the second stage of the integrated methodology, alternatives are ranked using the SF-EDAS approach using the subjective criteria weights obtained in the first stage.

Step 1. DMs evaluate the alternatives on the basis of each criterion using the linguistic scale given in Table 3, taking into account the defined decision problem objective and the identified criteria. The evaluation matrix based on the DMs' opinions is shown in Table 8.

Step 2. The evaluation matrix created with the linguistic scale is then used to create the SF evaluation matrix using the SFN corresponding to each linguistic utterance. Table 9 shows the SFN values corresponding to the linguistic utterances in the tables in the previous step.

Table 7. Criterion weights based on SF-SWARA

Criteria	Score values	s_j	k_j	p_j	w_j
C3	0.397		1	1	0.142
C1	0.188	0.208	1.208	0.827	0.118
C6	0.076	0.112	1.112	1.086	0.155
C4	0.028	0.047	1.047	1.061	0.151
C5	0.020	0.007	1.007	1.039	0.148
C7	0.009	0.011	1.011	0.996	0.142
C2	-0.01	0.021	1.021	0.989	0.141

Step 3. The individual assessments made by the DMs are aggregated using the SWGM operator shown in Equation 8 as shown in Table 10.

Step 4. The weighted aggregated matrix shown in Table 11 is obtained by multiplying the aggregated matrix shown in Table 10 with the criteria weights calculated in the first step of the integrated approach and shown in Table 7.

Step 5. In this step, firstly, the weighted aggregated matrix is used to obtain the average solution matrix in the spherical fuzzy environment as shown in Table 12.

Step 6. Then the aggregated matrix and the mean solutions matrix score values are obtained with the help of Equation 9 as shown in Table 13.

Step 7. Using the score values obtained in Step 6, it is determined whether each alternative is above or below the average on the basis of the criteria and first the PDA and NDA values are obtained with the help of equation 10, then the normalized PDA and normalized NDA values with the

Table 8. SF Alternative evaluation matrix based on determined criterion

	DM1		
Criteria	**Kırıkkale**	**Manisa**	**Şanlıurfa**
C1	EI	ALI	AMI
C2	EI	LI	HI
C3	SMI	SMI	EI
C4	SMI	SLI	AMI
C5	VLI	LI	HI
C6	HI	EI	SLI
C7	HI	SMI	EI
	DM2		
Criteria	**Kırıkkale**	**Manisa**	**Şanlıurfa**
C1	SLI	ALI	HI
C2	SLI	LI	AMI
C3	EI	SMI	SLI
C4	SLI	LI	HI
C5	VLI	LI	HI
C6	VHI	SMI	EI
C7	SMI	EI	SLI
	DM3		
Criteria	**Kırıkkale**	**Manisa**	**Şanlıurfa**
C1	EI	ALI	AMI
C2	SLI	VLI	HI
C3	SMI	SMI	EI
C4	SMI	SLI	AMI
C5	ALI	VLI	SMI
C6	SMI	SLI	LI
C7	VHI	HI	SMI

Table 9. SFNs based on SF alternative evaluation matrix based on determined criterion

	Kırıkkale			Manisa			Şanlıurfa		
	μ	v	π	μ	v	π	μ	v	π
DM1									
C1	0.50	0.50	0.50	0.10	0.90	0.10	0.90	0.10	0.10
C2	0.50	0.50	0.50	0.30	0.70	0.30	0.70	0.30	0.30
C3	0.60	0.40	0.40	0.60	0.40	0.50	0.50	0.50	0.50
C4	0.60	0.40	0.40	0.40	0.60	0.10	0.90	0.10	0.10
C5	0.20	0.80	0.20	0.30	0.70	0.30	0.70	0.30	0.30
C6	0.70	0.30	0.30	0.50	0.50	0.40	0.40	0.60	0.40
C7	0.70	0.30	0.30	0.60	0.40	0.50	0.50	0.50	0.50
DM2									
C1	0.40	0.60	0.40	0.10	0.90	0.30	0.70	0.30	0.30
C2	0.40	0.60	0.40	0.30	0.70	0.10	0.90	0.10	0.10
C3	0.50	0.50	0.50	0.60	0.40	0.40	0.40	0.60	0.40
C4	0.40	0.60	0.40	0.30	0.70	0.30	0.70	0.30	0.30
C5	0.20	0.80	0.20	0.30	0.70	0.30	0.70	0.30	0.30
C6	0.80	0.20	0.20	0.60	0.40	0.50	0.50	0.50	0.50
C7	0.60	0.40	0.40	0.50	0.50	0.40	0.40	0.60	0.40
DM3									
C1	0.50	0.50	0.50	0.10	0.90	0.10	0.90	0.10	0.10
C2	0.40	0.60	0.40	0.20	0.80	0.30	0.70	0.30	0.30
C3	0.60	0.40	0.40	0.60	0.40	0.50	0.50	0.50	0.50
C4	0.60	0.40	0.40	0.40	0.60	0.10	0.90	0.10	0.10
C5	0.10	0.90	0.10	0.20	0.80	0.40	0.60	0.40	0.40
C6	0.60	0.40	0.40	0.40	0.60	0.30	0.30	0.70	0.30
C7	0.80	0.20	0.20	0.70	0.30	0.40	0.60	0.40	0.40

Table 10. Aggregated SF alternative evaluation matrix based on determined criterion

	Kırıkkale			Manisa			Şanlıurfa		
	μ	v	π	μ	v	π	μ	v	π
C1	0.47	0.53	0.47	0.10	0.90	0.19	0.85	0.14	0.15
C2	0.43	0.56	0.44	0.27	0.73	0.25	0.79	0.20	0.22
C3	0.57	0.43	0.43	0.60	0.40	0.47	0.47	0.53	0.47
C4	0.54	0.45	0.40	0.37	0.63	0.18	0.85	0.14	0.15
C5	0.17	0.83	0.17	0.27	0.73	0.33	0.67	0.32	0.33
C6	0.71	0.28	0.29	0.51	0.49	0.42	0.41	0.59	0.42
C7	0.71	0.28	0.29	0.61	0.39	0.44	0.51	0.49	0.43

Table 11. The weighted aggregated SF alternative evaluation matrix based on determined criterion

	Kırıkkale			Manisa			Şanlıurfa		
	μ	v	π	μ	v	π	μ	v	π
C1	0.17	0.92	0.19	0.03	0.98	0.06	0.38	0.79	0.10
C2	0.17	0.92	0.19	0.10	0.95	0.09	0.36	0.80	0.13
C3	0.23	0.88	0.20	0.24	0.87	0.23	0.18	0.91	0.21
C4	0.22	0.88	0.19	0.14	0.93	0.07	0.42	0.74	0.11
C5	0.06	0.97	0.06	0.10	0.95	0.13	0.29	0.84	0.17
C6	0.32	0.82	0.16	0.21	0.89	0.20	0.16	0.92	0.18
C7	0.31	0.83	0.15	0.25	0.87	0.21	0.20	0.90	0.20

Table 12. SF average solution

Criteria	μ	ν	π
C1	0.13	0.94	0.13
C2	0.18	0.91	0.15
C3	0.22	0.89	0.22
C4	0.24	0.87	0.14
C5	0.13	0.94	0.12
C6	0.23	0.88	0.19
C7	0.25	0.87	0.20

Table 13. Score value of the weighted aggregated SF alternative evaluation matrix based on determined criterion and SF average solution

	Score value of aggregated decision matrix			Score value of average solution
	Kırıkkale	Manisa	Şanlıurfa	
C1	2.50	4.26	1.77	0.43
C2	2.50	3.71	1.62	3.88
C3	2.00	1.63	2.21	5.17
C4	2.16	3.70	1.10	6.04
C5	4.15	3.33	1.88	1.09
C6	1.67	2.16	2.55	5.38
C7	1.87	1.75	2.24	6.26

Table 14. PDA, NDA, N-PDA, N-NDA and appraisal scores for alternatives

	PDA	NDA	N-PDA	N-NDA	Appraisal score
Kırıkkale	0.030	0.042	0.329	0.511	0.420
Manisa	0.035	0.047	0.377	0.452	0.415
Şanlıurfa	0.093	0.086	1	0	0.5

help of equation 17 and 18 and finally the appraisal score values of the alternatives with the help of equation 19 and all these values are shown in Table 14.

According to the appraisal scores calculated, the ranking of the alternatives was calculated as Şanlıurfa > Kırıkkale > Manisa.

RESULTS AND DISCUSSION

Drought stands out as one of the fundamental environmental problems directly affecting agricultural production. Insufficient rainfall makes it difficult to provide the water necessary for plant growth, leading to reduced harvest quantities. The contraction in food supply and loss of income for farmers are among the inevitable consequences of this process. In recent years, it has been observed that drought events have become more frequent and severe due to the effects of climate change and global warming. In this context, the use of treated wastewater in agriculture is considered a long-term and viable solution to water scarcity. Using reclaimed wastewater for irrigation reduces dependence on freshwater resources, limits the risk of water scarcity, and supports a sustainable water management approach. It also contributes to environmental protection.

Multi-criteria decision-making methods have become an important tool in managing decision-making processes, especially in multi-dimensional and uncertain fields such as agriculture. These methods can combine quantitative indicators with qualitative evaluations and allow for a holistic assessment of different stakeholder preferences. Including uncertainty in the decision-making process is also among the key advantages of these approaches. Recent studies have shown that these methods produce effective results in evaluating the recovery of urban and agricultural wastewater for irrigation. This effectiveness is particularly evident in analyses aimed at mitigating drought conditions. In this study, a global fuzzy cluster approach, which considers membership, non-membership, and uncertainty levels together, was preferred in determining the criterion weights. This approach reduces the uncertainties arising in expert evaluations, thus ensuring more consistent and reliable results.

Wastewater recovery stands out not only as a practice that increases water supply, but also as a holistic solution that saves energy and reduces water pollution. This study focuses on the Aegean, Southeastern Anatolia, and Central Anatolia regions, three of Turkey's most drought-vulnerable areas. Pilot applications were carried out in the provinces of Kırıkkale, Manisa, and Şanlıurfa within these regions, and drought-related criteria were evaluated in detail. The findings show that the Southeastern Anatolia Region, and especially Şanlıurfa, has the most adverse drought conditions. This situation places this region in a priority position in terms of long-term water management policies and drought mitigation strategies.

The existing wastewater treatment system in Şanlıurfa offers significant potential in combating drought. The 156,730 cubic meters of water treated daily are used for agricultural irrigation and reduce water pressure in the region. Thanks to the biogas obtained in the treatment process, renewable energy production of approximately 6,800 kilowatts per day is also achieved. The new wastewater treatment plant, implemented with the joint contribution of the Ministry of Environment, the European Union, and local administrations, and with a budget of 100 million TL, has the capacity to serve more than 800,000 households. This investment is considered not only a technical infrastructure project but also a strategic step in terms of the agricultural sustainability of the region.

The study findings also reveal that social and economic factors play a decisive role in the widespread adoption of wastewater recovery technologies. Farmers' perceptions, cost expectations, and institutional support mechanisms are critically important in this process. Policies developed without considering these elements are unlikely to produce lasting results. Furthermore, integrating climate change predictions into the decision-making framework can make wastewater management plans more resilient to future environmental uncertainties.

The results clearly show that Şanlıurfa experiences the most severe drought conditions among the three pilot provinces. Long periods of drought and limited natural water resources exacerbate this situation. However, the existing treatment infrastructure offers a strong starting point for increasing the use of treated wastewater in agriculture. Manisa and Kırıkkale also face water management problems, but the level of these problems is more limited. Manisa has a moderate potential for improving wastewater reuse, while Kırıkkale appears to require a higher level of investment to improve its infrastructure. These findings emphasize the importance of developing targeted and region-specific strategies, especially in areas like Şanlıurfa where the benefits would be highest. This wastewater recovery approach will strengthen the long-term management of water resources and increase the resilience of agricultural production to drought.

CONCLUSION

The main question this study tries to answer is how to help areas of Turkey that are affected by drought and are running out of water. Using treated wastewater to water crops has been looked at as a long-term solution in this situation. The goal is not only to close the current water gap, but also to make the water supply more reliable over time. For this purpose, a global fuzzy multi-criteria decision-making framework that combines the SWARA and EDAS methods has been used. The results of the analysis show that Şanlıurfa has the most potential for using wastewater among the regions studied. This makes the region's water supply more stable and makes Şanlıurfa an important place to fight drought.

When you look at the research on how to manage water in farming, you can see that multi-criteria decision-making methods are very common, especially when it comes to sustainability. AHP, TOPSIS, and VIKOR are some of the most popular ways to compare environmental and agricultural options. Because its hierarchical structure is easy to understand, AHP has become more popular in studies of site selection and irrigation planning. TOPSIS, on the other hand, helps people make decisions by looking at the distances between the best and worst solutions. These methods assume that the options are very different from each other and that the values are very clear. But this isn't always how things work in real life when people have to make decisions. These methods don't work as well when expert opinions are unclear or uncertain.

This is where fuzzy multi-criteria decision-making methods come in. They try to show unclear information through language. Fuzzy AHP and fuzzy TOPSIS have been extensively utilized in this context. But most of these methods use traditional fuzzy sets. These structures can show some of the uncertainty. But the levels of hesitation and non-membership that are often seen in expert evaluations are not detailed enough. Type-1 fuzzy sets can't fully show these small parts of the decision-making process. The global fuzzy sets used in this study deal with membership, non-membership, and levels of hesitation all at once. This makes it possible to show expert uncertainty in more detail. This makes the process of weighting and evaluating criteria more reliable.

The SWARA method, used in determining weights, offers decision-makers a simpler cognitive process with its ranking-based structure. This distinguishes it from traditional pairwise comparisons. This advantage becomes apparent in situations where the number of criteria is high but the decision-making process remains manageable. Variables such as drought frequency, land accessibility, and wastewater treatment rates, frequently encountered in agriculture and environmental fields, are often intertwined. Therefore, SWARA's capacity to systematically collect expert opinions is effective. When used in conjunction with a global fuzzy structure, more consistent weights are obtained. This approach gains significance considering the unique social and environmental conditions of the Turkish agricultural sector.

The EDAS method evaluates alternatives based on their distance from the average solution. This approach becomes functional when alternatives cannot be clearly separated. Methods based on ideal solutions do not always reflect real conditions. The global fuzzy EDAS used in this study is sensitive to relative performance differences and also incorporates expert hesitation into the evaluation process. This increases the realism of the results. Another aspect contributing to the literature is the study's focus on context-specific criteria. The study goes beyond general indicators such as water availability and cost. It also considers the accessibility of natural water resources, land slope, and municipal budgets allocated to wastewater treatment. Measuring these variables is challenging, but they are crucial for the decision-making process.

The fuzzy SWARA and EDAS framework used offers a computationally efficient structure for medium-sized datasets. Expert assessments are structured within a systematic decision-making process. For larger datasets, additional computational resources may be needed. Therefore, in the future, this framework could be improved using optimization techniques or machine learning-based approaches. From a policymaker's perspective, the study offers significant implications. Wastewater use in drought-affected regions should be prioritized. This can improve the impact on sustainability and resilience. This approach aligns with Turkey's resource management goals that prioritize environmental sustainability. It also serves as a guide for other countries facing similar challenges.

In conclusion, this study, which uses a combination of global fuzzy SWARA and EDAS methods, fills a significant gap in agricultural water management. It addresses uncertainty and expert hesitation more effectively. A viable framework is presented for drought-affected regions. Developed within the context of Turkey, this approach can be adapted to different geographies. This aspect makes the study a strong contribution. It serves sustainability goals at both local and global levels.

AUTHORSHIP CONTRIBUTIONS

Authors equally contributed to this work.

DATA AVAILABILITY STATEMENT

The authors confirm that the data that supports the findings of this study are available within the article. Raw data that support the finding of this study are available from the corresponding author, upon reasonable request.

CONFLICT OF INTEREST

The author declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

ETHICS

There are no ethical issues with the publication of this manuscript.

STATEMENT ON THE USE OF ARTIFICIAL INTELLIGENCE

Artificial intelligence was not used in the preparation of the article.

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