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Group Decision-Making of Agricultural Stakeholders towards Sustainable Groundwater Resources Management: A Case Study in North Khorasan

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Abstract

Groundwater is a vital resource for agriculture in arid regions which its over-extraction has led to significant challenges of declining water levels and increased scarcity. This study addresses the urgent need for sustainable groundwater management by employing an inclusive group decision-making approach involving diverse stakeholders, with a focus on farmers. Overlooking the participation of farmers in the decision-making approach led to ineffective policies. Utilizing Multi-Criteria Decision-Making (MCDM) methods, specifically the fuzzy Shannon entropy and Fuzzy TOPSIS techniques, the research prioritizes strategies for reducing groundwater consumption in the Safi-Abad region of North Khorasan, Iran. Qualitative data from stakeholder interviews provided insights into the challenges and opportunities related to groundwater use, revealing two primary strategies: (i) transitioning to low water-demand crops; and (ii) adopting modern irrigation systems. These approaches not only promise significant reductions in water usage but also support sustainable agricultural practices. The findings highlighted the importance of stakeholder collaboration in implementing effective water management policies, ensuring responsible resource use, and securing long-term viability. This study served as a model for future research, advocating for mixed methods integrating qualitative and quantitative analyses to inform policy recommendations and improve water resource management.

Keywords: Agricultural water management, Decision-making, Farmers role, Stakeholder participation, Water conservation strategies

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Introduction

Groundwater is a critical resource for agricultural production, particularly in arid and semi-arid regions where surface water is limited (Noori *et al*., 2021; Priyan, 2021). However, excessive and imbalanced groundwater extraction has led to declining groundwater levels, the drying up of wells, and exacerbated water scarcity, particularly in the agricultural sector (Noori *et al*., 2021).

Iran, located in an arid and semi-arid region, faces significant challenges in water resource management. Over the past decades, the per capita renewable water availability has drastically declined due to population growth, climate change, and inefficient agricultural practices (Madani, 2014; Ashraf *et al*., 2017). Recent studies indicate that Iran's renewable water resources have decreased from approximately 4,500 cubic meters per capita in the 1970s to less than 1,600 cubic meters per capita in recent years, pushing the country into a state of water stress (Emerald Expert Briefings, 2023). This alarming trend has resulted in severe water scarcity, particularly in agricultural regions where groundwater over-extraction has become a critical issue (Noori *et al*., 2021; Haghshenas Haghighi *et al*., 2024). A notable example of this crisis in Iran is the Safi-Abad plain in North Khorasan province, a dry region characterized by an arid climate, limited surface water resources, and heavy reliance on groundwater for agriculture. The salinization of the groundwater in this region is predominantly intensified by over-extraction, making forms of saline and brackish issues and the drying up of wells. Given that agriculture is the primary occupation in Safi-Abad and groundwater is the main water source, it is imperative to develop strategies to reduce groundwater extraction and ensure sustainable water management. Addressing these challenges requires a holistic approach to decision-making that considers the economic, environmental, and social impacts of water resource management (Meran *et al*., 2021; Moltz *et al*., 2020).

In real-world agricultural water resource decision-making, multiple stakeholders-including farmers, local authorities, water managers, and policymakers-play crucial roles. Each stakeholder brings unique knowledge, skills, and experiences that must be integrated into the decision-making process (Permono & Kurniati, 2024; Lee *et al*., 2022; Ahmadi *et al*., 2020). Given the complexity of factors influencing water consumption in agriculture, a single decision-maker cannot adequately address all aspects of the issue (Lee *et al*., 2022; Nouri *et al*., 2023). Therefore, group decision-making involving diverse stakeholders is essential to achieve precise and reliable outcomes (Khanzadi *et al*., 2009; Cai *et al*., 2004).

Recognizing the importance of stakeholder participation, this study examines group decision-making processes among agricultural stakeholders in the Safi-Abad region of North Khorasan province, Iran. By integrating the perspectives of farmers, policymakers, and water managers, this research aims to identify effective strategies for sustainable groundwater management and contribute to the broader discourse on water resource conservation in arid regions.

The scarcity and inappropriate use of water resources, particularly within the agricultural sector, have prompted research to increasingly focus on policies and strategies aimed at reducing water consumption. Multi-Criteria Decision-Making (MCDM) methods have gained considerable importance in recent years and are widely applied across various real-world contexts (Kacprzak, 2019). In agriculture, where multiple influential factors - such as farmer income, production costs, and water consumption levels - influence the selection of effective strategies for reducing water usage, a multi-criteria group decision-making approach is essential for identifying optimal solutions. This section provides a review of the literature on the application of MCDM in groundwater management (Table 1).

Table 1- Related literature on the application of MCDM in groundwater management

Authors	The study region	Methodology	Purpose of the study
Pocco *et al.* (2023)	Arid Zone Basin of the Atacama Desert (In South America), Caplina basin.	Analytical Hierarchy Process (AHP) - based GIS approach	Determining potential sources of groundwater using a Multi-Criteria Decision-Making technique with remote sensors
Tork *et al.* (2021)	Nekouabad area located in the central plateau of Iran	AHP and COPRAS	Determining the effectiveness and rank the scenarios for the modernization of surface water distribution system in reducing water withdrawal from the aquifers
Radmehr *et al.* (2022)	Iran	Combining hierarchical analysis and the fuzzy Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS).	Proposes a new framework of strategic planning with multi-criteria decision-making to develop sustainable water management alternatives for large scale water resources systems
Hamidifar *et al.* (2023)	Iran	Analytical hierarchy process (AHP), Fuzzy-AHP, and technique for order preference by similarity to ideal solution (TOPSIS)	Examining the effective criteria for water supply projects in rural areas
Xuân Thảo & Nhung (2019)	Vietnam	Fuzzy MCDM models	Selection of the best water reuse application of the existing options
Ali & Khan (2020)	Pakistan	Fuzzy VIKOR method	Evaluating the impact of climate change on the agriculture sector
Alamanos *et al.* (2018)	Greek, lake Karla watershed	Multi attribute utility theory (MAUT), analytic hierarchy process (AHP), elimination and choice expressing reality (ELECTRE), and technique for order of preference by similarity to ideal solution (TOPSIS)	Evaluating water resource management (WRM) strategies and selecting the most appropriate among them
Garai & Garg (2022)	Purulia district, West Bengal, India	Multi-criteria decision making method for water resource management problems based on possibility measures under generalized single valued non-linear bipolar neutrosophic environment	Defining the available water resources in the agriculture field
Hadelan *et al.* (2020)	Croatia	Analytical hierarchy process (AHP),	Comparing and ranking three possible locations for the construction of an irrigation system in different parts of Croatia
Noori *et al.* (2021)	Gamasiab Basin in Kermanshah province, Iran	Fuzzy ELECTRE III	The main goal of the modified method is to better manage uncertainties in the evaluation process by considering both quantitative and qualitative criteria through group decision-making
Sheikhipoor *et al.* (2018)	Shahrekord aquifer, Iran	Simple additive weighting (SAW) and MTAHP, a hybrid of modified TOPSIS and analytic hierarchy process models.	Prioritizing groundwater management scenarios from an aquifer.
Pourmand *et al.* (2020)	Varamin region, Iran	Interval type-2 fuzzy sets combined with the TOPSIS model	optimizing the allocation of water and reclaimed wastewater across domestic, agricultural, and industrial sectors, and to restore groundwater quantity and quality
Yilmaz *et al.* (2010)	Gediz River Basin in Turkey	Simple additive weighting (SAW), compromise programming (CP) and technique for order preference by similarity to ideal solution (TOPSIS)	developing a water resource management model that facilitates indicator-based decisions, with respect to environmental, social and economic dimensions in a multiple criteria perspective

In most reviewed studies, the role of farmers as primary stakeholders in agricultural water consumption decisions has been overlooked, leading to potential resistance during the implementation of top-down policies. This gap highlights the need for research that actively involves diverse stakeholders, particularly farmers, in decision-making processes aimed at reducing water consumption. Multi-Criteria Decision-Making (MCDM) methods, especially when integrated with fuzzy models, have proven effective in optimizing water allocation, reducing costs, and promoting sustainable water management practices. To bridge these gaps, this study utilizes F-Shannon's entropy and F-TOPSIS methods to support stakeholder-inclusive, region-specific decision-making for sustainable groundwater management in a drought-affected agricultural region of Iran. The paper is structured as follows: first, the case study and methodology are introduced; second, the results of applying F-Shannon's entropy and F-TOPSIS are presented; and finally, the findings and their implications are discussed.

Materials and Methods

The Study Region

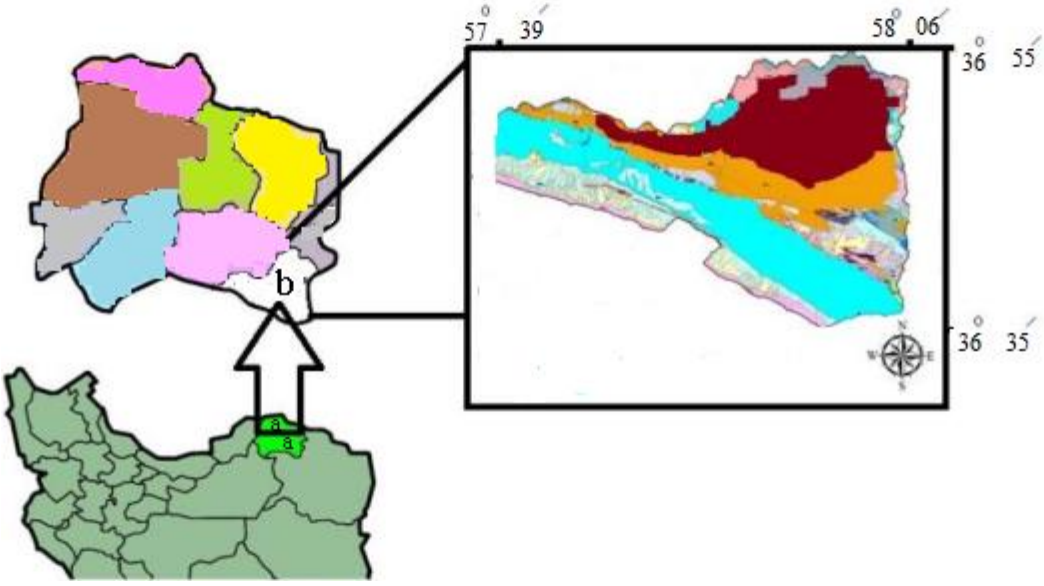

Figure 1- The geographical location of the study area in North Khorasan province, Iran
North Khorasan province, Iran
Safi-Abad rural district in North Khorasan province

The Safi-Abad plain, located in North Khorasan province, Iran, is a critical arid region characterized by limited precipitation, lack of permanent rivers, and scarce high-quality surface water resources. (Fig. 1). Groundwater accounts for approximately 79% of the total water consumption, with 90% used by the agricultural sector (Esfarayen Water Landscape, 2021). Given that farmers are the primary consumers of groundwater, their active participation in decision-making is essential for developing effective and acceptable water conservation strategies. This study employs the F-Shannon's entropy–F-TOPSIS hybrid approach to engage farmers as key stakeholders, ensuring sustainable groundwater use and enhancing the implementation of conservation measures in the region.

F-Shannon's Entropy –F- TOPSIS Hybrid Approach

The decision-making process involves identifying options and establishing criteria for selecting optimal strategies. Multi-Criteria Decision-Making (MCDM) techniques are used to rank these options, especially when multiple decision-makers (DMs) are involved to account for diverse priorities and subjective judgments (Kacprzak, 2020; Sadi-Nezhad & Damghani, 2010).

Fuzzy set theory, introduced by Zadeh (1965), provides a framework for handling ambiguity in evaluations. (Chen, 2000; Hatami-Marbini & Kangi, 2017). Fuzzy Group Decision-Making (FGDM) methods are effective in water resource management, particularly when decision-makers face constraints such as limited time or incomplete data (Kaya & Kahraman, 2010).

The Technique for Order Preference by Similarity to Ideal Solution (TOPSIS), introduced by Hwang & Yoon (1981), evaluates alternatives based on their distances from the Positive Ideal Solution (PIS) and the Negative Ideal Solution (NIS). Traditional TOPSIS relies on precise data, which is often unrealistic. To address this, fuzzy adaptations of TOPSIS have been developed, enabling decision-makers to handle ambiguity effectively (Chen, 2000; Hatami-Marbini & Kangi, 2017).

In MCDM, assigning weights to criteria is critical for aligning decisions with objectives. The fuzzy Shannon entropy method is particularly useful for determining weights when criteria are represented as fuzzy numbers, capturing uncertainty effectively (Mohammadi *et al*., 2020). In this study, we combined the fuzzy Shannon entropy method with Fuzzy TOPSIS to support group decision-making among agricultural stakeholders, aiming to reduce groundwater consumption.

The extended Fuzzy TOPSIS for GDM

In this study, we employed an extended TOPSIS method based on fuzzy numbers to address group decision-making challenges. Unlike traditional approaches that aggregate individual decision matrices into a collective matrix using arithmetic or geometric means, our method utilizes all individual decision data without aggregation. This allows for a more nuanced ranking of alternatives and the identification of the optimal choice (Kacprzak, 2017). A key step in this method involves transforming the decision matrices provided by decision-makers (DMs) into matrices of alternatives. Each alternative's matrix is formed from assessments across all criteria as evaluated by all DMs (Kacprzak, 2020). The positive ideal solution (PIS) and negative ideal solution (NIS) are defined as matrices of maximum and minimum assessments, respectively. The distances of alternatives from the PIS and NIS are calculated as distances between matrices, and the coefficient of relative closeness to the PIS is used to rank alternatives and select the best option (Kacprzak, 2020).

In this section, the applied approach is presented. Consider an MCDM problem for group decision-making. Let $(m \geq 2)$ $\{A_1, A_2, \dots, A_m\}$ be a discrete set of m feasible alternatives, $\{C_1, C_2, \dots, C_n\}$ $(n \geq 2)$ be a finite set of criteria. $w = (w_1, w_2, \dots, w_n)$ be the vector of criteria weights, such that $0 \leq w_j \leq 1$

Let $\{DM_1, DM_2, \dots, DM_k\}$ $(k \geq 2)$ be a group of decision-makers.

Each DM presents a decision matrix in the following form:

$$X^K = \begin{array}{c} \\ A_1 \\ A_2 \\ \vdots \\ A_m \end{array} \begin{array}{c} \begin{array}{cccc} C_1 & C_2 & \cdots & C_n \end{array} \\ \begin{bmatrix} x_{11}^k & x_{12}^k & \cdots & x_{1n}^k \\ x_{21}^k & x_{22}^k & \cdots & x_{2n}^k \\ \vdots & \vdots & \vdots & \vdots \\ x_{m1}^k & x_{m2}^k & \cdots & x_{mn}^k \end{bmatrix} \end{array} \quad (1)$$

where $x_{ij}^k = (a_{x_{ij}^k}, b_{x_{ij}^k}, c_{x_{ij}^k}, d_{x_{ij}^k})$ is a positive trapezoidal fuzzy number representing the rating of alternative $A_i\ (i = 1, 2, .., m)$ with respect to criterion $C_j = (j = 1, 2, .., n)$ provided by decision-maker $DM_k\ (k = 1, 2, .., K)$

A very popular way of constructing the fuzzy decision matrix X^K is to use linguistic variables to evaluate the ratings of alternatives concerning various criteria (Kacprzak, 2017; Hatami-Marbini & Kangi, 2017). Decision-makers (DMs) rate alternatives using linguistic expressions, which are then represented as trapezoidal fuzzy numbers to capture fuzzy judgments. Fig. 2 and Table 2 shows the fuzzy numbers represent the linguistic variables. These variables are used to characterize the performance rating of each alternative for each attribute (Hatami-Marbini & Kangi, 2017).

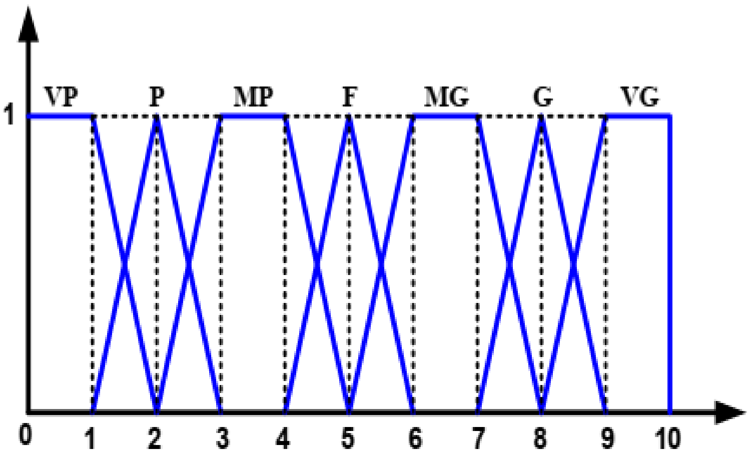

Figure 2- Performance rating of Alternatives

Table 2- The linguistic variables for the ratings of the alternatives and their representation by FNs

Linguistic variable	Fuzzy number
Very poor (VP)	(0, 0, 1, 2)
Poor (P)	(1, 2, 2, 3)
Medium poor (MP)	(2, 3, 4, 5)
Fair (F)	(4, 5, 5, 6)
Medium good (MG)	(5, 6, 7, 8)
Good (G)	(7, 8, 8, 9)
Very good (VG)	(8, 9, 10, 10)

Next, in order to ensure comparability of criteria, the fuzzy decision matrix X^K is normalized. The normalized fuzzy decision matrix

$$Y^K = \begin{array}{c} \\ A_1 \\ A_2 \\ \mathrm{M} \\ A_m \end{array} \begin{array}{c} \begin{array}{cccc} C_1 & C_2 & \mathrm{L} & C_n \end{array} \\ \begin{bmatrix} y_{11}^k & y_{12}^k & \mathrm{L} & y_{1n}^k \\ y_{21}^k & y_{22}^k & \mathrm{L} & y_{2n}^k \\ \mathrm{M} & \mathrm{M} & \mathrm{M} & \mathrm{M} \\ y_{m1}^k & y_{m2}^k & \mathrm{L} & y_{mn}^k \end{bmatrix} \end{array} \quad (2)$$

is calculated using the following formulas:

$$y_{ij}^k = \begin{cases} \left(\dfrac{a_{x_{ij}^k}}{max_i d_{x_{ij}^k}}, \dfrac{b_{x_{ij}^k}}{max_i d_{x_{ij}^k}}, \dfrac{c_{x_{ij}^k}}{max_i d_{x_{ij}^k}}, \dfrac{d_{x_{ij}^k}}{max_i d_{x_{ij}^k}}\right) \\ \left(\dfrac{min_i a_{x_{ij}^k}}{d_{x_{ij}^k}}, \dfrac{min_i a_{x_{ij}^k}}{c_{x_{ij}^k}}, \dfrac{min_i a_{x_{ij}^k}}{b_{x_{ij}^k}}, \dfrac{min_i a_{x_{ij}^k}}{a_{x_{ij}^k}}\right) \end{cases} \quad (3)$$

Using the vector of criteria weights $w = (w_1, w_2, \ldots, w_n)$, the weighted normalized fuzzy decision matrix is calculated for each DM.

$$V^K = \begin{array}{c} \\ A_1 \\ A_2 \\ \mathrm{M} \\ A_m \end{array} \begin{array}{c} \begin{array}{cccc} C_1 & C_2 & \mathrm{L} & C_n \end{array} \\ \begin{bmatrix} V_{11}^k & V_{12}^k & \mathrm{L} & V_{1n}^k \\ V_{21}^k & V_{22}^k & \mathrm{L} & V_{2n}^k \\ \mathrm{M} & \mathrm{M} & \mathrm{M} & \mathrm{M} \\ V_{m1}^k & V_{m2}^k & \mathrm{L} & V_{mn}^k \end{bmatrix} \end{array} \quad (4)$$

Where

$$v_{ij}^k = w_j y_{ij}^k = (w_j a_{y_{ij}^k}, w_j b_{y_{ij}^k}, w_j c_{y_{ij}^k}, w_j d_{y_{ij}^k}) \quad (5)$$

The matrices V^k form the basis for the construction of weighted normalized fuzzy decision matrices for each alternative A_i.

$$W^{i}=\begin{array}{c} \\ DM_1 \\ DM_2 \\ \vdots \\ DM_k \end{array}\begin{array}{c} \begin{array}{cccc} C_1 & C_2 & \cdots & C_n \end{array} \\ \begin{bmatrix} v_{i1}^{1} & v_{i2}^{1} & \cdots & v_{in}^{1} \\ v_{i1}^{2} & v_{i1}^{2} & \cdots & v_{in}^{2} \\ \vdots & \vdots & \vdots & \vdots \\ v_{i1}^{k} & v_{i2}^{k} & \cdots & v_{in}^{k} \end{bmatrix} \end{array} \qquad (6)$$

Matrices W^i constitute the basis for the ranking of the alternatives and the selection of the best one using the fuzzy TOPSIS method.

The positive ideal solution A^+ is determined as follows:

$$A^{+}=\begin{array}{c} \\ DM_1 \\ DM_2 \\ \vdots \\ DM_k \end{array}\begin{array}{c} \begin{array}{cccc} C_1 & C_2 & \cdots & C_n \end{array} \\ \begin{bmatrix} v_{1}^{1+} & v_{2}^{1+} & \cdots & v_{k}^{1+} \\ v_{1}^{2+} & v_{2}^{2+} & \cdots & v_{n}^{2+} \\ \vdots & \vdots & \vdots & \vdots \\ v_{1}^{k+} & v_{2}^{k+} & \cdots & v_{n}^{k+} \end{bmatrix} \end{array} \qquad (7)$$

Where $v_j^{k+}=\max_i v_{ij}^k$ and the negative ideal solution A^- is determined as follows:

$$A^{-}=\begin{array}{c} \\ DM_1 \\ DM_2 \\ \vdots \\ DM_k \end{array}\begin{array}{c} \begin{array}{cccc} C_1 & C_2 & \cdots & C_n \end{array} \\ \begin{bmatrix} v_{1}^{1-} & v_{2}^{1-} & \cdots & v_{k}^{1-} \\ v_{1}^{2-} & v_{2}^{2-} & \cdots & v_{n}^{2-} \\ \vdots & \vdots & \vdots & \vdots \\ v_{1}^{k-} & v_{2}^{k-} & \cdots & v_{n}^{k-} \end{bmatrix} \end{array} \qquad (8)$$

Where $v_j^{k-}=\min_i v_{ij}^k$

Next, the distances of each alternative A_i represented by matrix W^i from PIS are calculated as follows:

$$d_i^+ = \sum_{k=1}^{K}\sum_{j=1}^{n} d\left(v_{ij}^k, v_j^{k+}\right) \qquad (9)$$

And from NIS

$$d_i^- = \sum_{k=1}^{K}\sum_{j=1}^{n} d\left(v_{ij}^k, v_j^{k-}\right) \qquad (10)$$

Using these distances, the relative closeness coefficient RC_i to PIS for each alternative A_i is calculated as follows:

$$RC_i = \frac{d_i^-}{d_i^+ + d_i^-} \qquad (11)$$

According to the descending values of RC_i all alternatives A_i are rank ordered and the best one is selected.

Fuzzy Shannon's Entropy Method

In multi-criteria decision-making (MCDM), decision-makers must assign weights to criteria to reflect their relative importance. While these weights may lack direct economic significance, they are essential for modeling decision-making preferences and structures (Izadikhah & Salehi, 2014; Opricovic & Tzeng, 2004).

The evaluation of criteria often leads to diverse opinions highlighting the need for a systematic approach to weight assignment. Weighting methods can be categorized into two types: subjective and Objective methods. Objective methods are particularly useful when reliable subjective weights are difficult to obtain. In this study, we employ the Shannon entropy method, extended for imprecise data by Hosseinzadeh Lotfi and Fallahnejad (2010), to calculate criteria weights. This approach is effective for handling interval and fuzzy data, ensuring a robust and objective weighting system (Jafarnejad *et al*., 2012).

The steps of fuzzy Shannon's entropy are explained as follows:

Step 1: Transforming Fuzzy Data into Interval Data Using α-Level Sets

The α-level set of a fuzzy variable $\tilde{x}_{ij}$ is defined as the set of elements that belong to the fuzzy variable $\tilde{x}_{ij}$ with a membership of at least α i.e,

$$\left(\tilde{x}_{ij}\right)_{\alpha} = \left\{\tilde{x}_{ij} \in R \mid \mu_{\tilde{x}_{ij}}(\tilde{x}_{ij}) \geq \alpha\right\} \qquad (12)$$

The α-level set can also be expressed in the following interval form:

$$[x_{ij}{}^{l}\ , x_{ij}{}^{U}] = \left[\left(\tilde{x}_{ij}\right)_{\alpha}^{L}, \left(\tilde{x}_{ij}\right)_{\alpha}^{U}\right] = \qquad (13)$$

$$\left[min_{\tilde{x}_{ij}}\left\{x_{ij}\in R\mid \mu_{x_{ij}}(x_{ij})\geq\alpha\right\},\ max_{\tilde{x}_{ij}}\left\{x_{ij}\in R\mid \mu_{x_{ij}}(x_{ij})\geq\alpha\right\}\right]$$

Where 0 < α ≤ 1. By setting different levels of confidence, namely 1-α, fuzzy data are transformed into different α-level sets $\{(\tilde{x}_{ij})_\alpha \mid 0<\alpha\leq 1\}$, which are all intervals (Jafarnejad *et al.*, 2012).

Step 2: The Normalized Decision Matrix

Suppose $A_1, A_2, \ldots, A_m$ are m possible alternatives among which decision-makers have to choose, $C_1, C_2, \ldots, C_n$ are criteria with which alternative performance is measured. X_{ij} is the rating of alternative A_i with respect to criterion C_j, which is not known exactly; we only know that $X_{ij} \in [X_{ij}^L, X_{ij}^U]$. An MCDM problem with interval data can be expressed in matrix format as follows (Izadikhah & Salehi, 2014):

	C_1	C_2	....	C_n
A_1	$[X_{11}^L, X_{11}^U]$	$[X_{12}^L, X_{12}^U]$		$[X_{1n}^L, X_{1n}^U]$
A_2	$[X_{21}^L, X_{21}^U]$	$[X_{32}^L, X_{22}^U]$		$[X_{2n}^L, X_{2n}^U]$
.				
.				
A_m	$[X_{m1}^L, X_{m1}^U]$	$[X_{m2}^L, X_{m2}^U]$		$[X_{mn}^L, X_{mn}^U]$

(14)

Now we calculate the normalized decision matrix as follows. The normalized values $\bar{n}_{ij}{}^L$ and $\bar{n}_{ij}{}^U$ are calculated as:

$$\bar{n}_{ij}{}^L = \frac{x_{ij}{}^L}{\sum_{j=1}^m[x_{ij}{}^L + x_{ij}{}^U]} \quad j = 1,\ldots,m\ ,\ i = 1,\ldots,n \tag{15}$$

$$\bar{n}_{ij}{}^U = \frac{x_{ij}{}^U}{\sum_{j=1}^m[x_{ij}{}^L + x_{ij}{}^U]} \quad j = 1,\ldots,m\ ,\ i = 1,\ldots,n \tag{16}$$

This normalization is the norm L1 version of the normalization method proposed by Jahanshahloo *et al.* (2006). The interval $[\bar{n}_{ij}{}^L, \bar{n}_{ij}{}^U]$ is the normalized of interval $[X_{ij}{}^L, X_{ij}{}^U]$. The normalization method mentioned above preserves the property that the ranges of normalized interval numbers belong to [0, 1].

Step 3: Calculation of the Concentration Index for Each Criterion with Interval Data

This is accomplished by solving the following two non-linear models:

$$E_j^L = min(-\frac{1}{\ln(m)})\sum_{i=1}^m x_{ij}{}^U \ln(x_{ij}{}^U) \tag{17}$$

Subject to

$$\bar{n}_{ij}{}^L \leq x_{ij} \leq \bar{n}_{ij}{}^U$$

$$E_j^U = max(-\frac{1}{\ln(m)})\sum_{i=1}^m x_{ij}{}^L \ln(x_{ij}{}^L) \tag{18}$$

Subject to

$$\bar{n}_{ij}{}^L \leq x_{ij} \leq \bar{n}_{ij}{}^U$$

After some simple calculation, we have:

$$E_j^L = (-\frac{1}{\ln(m)})\sum_{i=1}^m n_{ij}{}^U \ln(n_{ij}{}^U) \tag{19}$$

$$E_j^U = (-\frac{1}{\ln(m)})\sum_{i=1}^m n_{ij}{}^L \ln(n_{ij}{}^L) \tag{20}$$

Therefore, we have $E_j^L \leq E_j^U$

Step 4: The Amount of Dispersal for Each

Criterion

$$d_j^L = 1 - E_j^U \quad (21)$$

$$d_j^U = 1 - E_j^L \quad (22)$$

Therefore, we have $d_j^L \leq d_j^U$

Step 5: Calculation of the Weights of Criteria

$$W_j{}^L = \frac{d_j^L}{\sum_{j=1}^{n}[d_j^L + d_j^U]} \quad (23)$$

$$W_j{}^U = \frac{d_j^U}{\sum_{j=1}^{n}[d_j^L + d_j^U]} \quad (24)$$

Therefore, we $w_j{}^L \leq w_j{}^U$ and the interval weight of criterion Cj is $[w_j{}^L, w_j{}^U]$.

Selection of Participants

In Multi-Criteria Decision Making (MCDM), there are no rigid rules for determining the selection of experts. However, in previous studies, experts are generally chosen based on two key criteria: i. Subject-specific knowledge and industry experience, and ii. The author's professional and personal connections, often utilizing convenience sampling.

In this study, in-person interviews were conducted with various stakeholder groups from relevant organizations, including: Managers of the North Khorasan Agriculture Organization, Staff from the North Khorasan Regional Water Company, and Managers from the North Khorasan Department of Environment and Exemplary farmers. The questionnaire, consisting primarily of open-ended items, was designed to explore their views and experiences regarding reducing groundwater consumption in agriculture. A total of 57 interviews were conducted (see Table 3).

Table 3- Frequency of Stakeholder Participation

Participants Class	Number of Participants
Managers and staff members of the Regional Water Company	2
Agriculture Organization Managers	3
Managers of Natural Resources and Environment Organization	2
Farmers	50
Total	57

Results

According to previous studies review, upstream documents, expert opinions, and insights from university professors, as well as the environmental conditions of the region, the most significant strategies and criteria were identified (see Table 4).

Table 4- Strategies and criterions

Criteria	C_1	" Increasing income from cultivation"	Alternatives (Strategies)	$A_{1,}$	Reducing a portion of the cultivated area in exchange for receiving cash subsidies.
	C_2	"Reducing production costs"			
	C_3	"Preventing the depletion of groundwater reserves"		$A_{2,}$	Reducing groundwater extraction in exchange for cash subsidies.
	C_4	" Job creation in the agricultural sector"			
	C_5	"Increasing retention in rural areas"		$A_{3,}$	Increasing Water Prices in Exchange for Higher Crop Prices
	C_6	" Increasing crop yields "			
	C_7	" Preventing Drought Occurrence"		$A_{4,}$	Adopting Modern Irrigation Systems in Place of Traditional ones.
	C_8	"Groundwater quality (preventing water salinity)"			
	C_9	"Preventing land subsidence"		$A_{5,}$	Prioritizing the cultivation of autumn crops to utilize rainfall in fall, winter, and spring.
	C_{10}	" Enhancing soil quality"			
	C_{11}	"Reducing energy consumption in water extraction"		$A_{6,}$	Reducing the cultivated area of high water-demanding crops and replacing them with low water-demanding crops.
	C_{12}	"Preserving The Natural Ecosystem (Flora and Fauna)"			

Table 5- The weight of criteria calculated using method fuzzy Shannon entropy method

No.			$[E_j^L, E_j^U]$	$[D_j^L, D_j^U]$	$[W_j^L, W_j^U]$	W_j
1	C_1	" Increasing income from cultivation"	[0.434357, 0.866069]	[0.133931,0.565643]	[0.016167, 0.06828]	0.042224
2	C_2	"Reducing production costs"	[0.528068, 0.812953]	[0.187047, 0.471932]	[0.022579,0.056968]	0.039774
3	C_3	" Preventing the depletion of groundwater reserves "	[0.508902, 0.813787]	[0.186213, 0.491098]	[0.022478, 0.059282]	0.04088
4	C_4	" Job creation in the agricultural sector"	[0.43132, 0.870612]	[0.129388, 0.56868]	[0.015619, 0.068647]	0.042133
5	C_5	"Increasing retention in rural areas"	[0.479694, 0.840219]	[0.159781, 0.520306]	[0.019288, 0.062808]	0.041048
6	C_6	" Increasing crop yields "	[0.418325, 0.873132]	[0.126868, 0.581675]	[0.015315, 0.070216]	0.042765
7	C_7	" Preventing Drought Occurrence"	[0.402583, 0.866895]	[0.133105, 0.597417]	[0.016068 ,0.072116]	0.044092
8	C_8	"Groundwater quality (preventing water salinity)"	[0.502786, 0.820005]	[0.179995, 0.497214]	[0.021728, 0.06002]	0.040874
9	C_9	"Preventing land subsidence"	[0.486124, 0.830636]	[0.169364, 0.513876]	[0.020444, 0.062031]	0.041238
10	C_{10}	" Enhancing soil quality"	[0.450453, 0.847213]	[0.1527877, 0.54954]	[0.018443, 0.066337]	0.04239
11	C_{11}	" Reducing energy consumption in water extraction "	[0.50606, 0.823436]	[0.176564, 0.49394]	[0.021313, 0.059625]	0.040469
12	C_{12}	"Preserving The Natural Ecosystem (Flora and Fauna)"	[0.431427, 0.870811]	[0.129189, 0.568573]	[0.015595, 0.068634]	0.042114

Table 6- The results of TOPSIS fuzzy method regarding the prioritization of strategies to reduce the consumption of underground water.

No.			d_i^-	d_i^+	RC_i	Rank
1	$A_{1,}$	Reducing a portion of the cultivated area in exchange for receiving cash subsidies.	10.66619	8.367691	0.560379	4
2	$A_{2,}$	Reducing groundwater extraction in exchange for cash subsidies.	11.12382	7.87999	0.585347	3
3	$A_{3,}$	Increasing Water Prices in Exchange for Higher Crop Prices	3.65702	15.28742	0.193039	6
4	$A_{4,}$	Adopting Modern Irrigation Systems in Place of Traditional ones.	13.40303	5.577716	0.706138	2
5	$A_{5,}$	Prioritizing the cultivation of autumn crops to utilize rainfall in fall, winter, and spring.	7.158848	11.84819	0.376642	5
6	$A_{6,}$	Reducing the cultivated area of high water-demanding crops and replacing them with low water-demanding crops.	14.29616	4.700346	0.752568	1

The strategies for reducing groundwater consumption were prioritized using the Multi-Criteria Decision-Making (MCDM) model. This approach was chosen due to its ability to handle complex decision-making processes involving multiple criteria and stakeholder preferences. First, the relative importance of the criteria was determined using the fuzzy Shannon entropy method**.** This method was particularly useful for addressing uncertainties in stakeholder inputs and ensuring a robust weighting process. By incorporating fuzzy logic, the model effectively captures the vagueness and subjectivity inherent in stakeholder judgments, leading to more reliable results. The results, summarized in Table 5 revealed that the criterion "Preventing Drought Occurrence" (C_7) had the highest weight, indicating its critical importance in the decision-making process. This finding underscores the stakeholders' concern about the long-term impacts of drought on agricultural sustainability.

Next, the strategies were evaluated and prioritized using the Fuzzy TOPSIS method. This method was selected for its ability to handle imprecise data and provide a clear ranking of alternatives based on their proximity to ideal solutions. The results, presented in Table 6, identified the following ranking of strategies:

1. Reducing the cultivated area of high water-demanding crops and replacing them with low water-demanding crops (Strategy 6).
2. Adopting modern irrigation systems in place of traditional ones (Strategy 4).
3. Reducing groundwater extraction in exchange for cash subsidies (Strategy 2).
4. Reducing a portion of the cultivated area in exchange for receiving cash subsidies (Strategy 5).
5. Prioritizing the cultivation of autumn crops to utilize rainfall in fall, winter, and spring (Strategy 3).
6. Increasing water prices in exchange for higher crop prices (Strategy 1).

This prioritization, based on factors such as water savings, economic impacts, and social acceptability, provides a clear roadmap for stakeholders to implement effective measures for sustainable groundwater management. The high ranking of crop replacement and modern irrigation systems reflects their potential to address both water scarcity and agricultural productivity challenges. These strategies are particularly relevant in regions where groundwater depletion has reached critical levels, threatening both food security and environmental stability.

Conclusion and Discussion

This study highlights the urgent need for innovative strategies to address groundwater depletion in agriculture. The over-extraction of groundwater, driven by population growth and climate change, poses a significant threat to food security and environmental sustainability. Without immediate action, the continued depletion of groundwater resources could lead to irreversible ecological damage and severe socio-economic consequences. The magnitude of the challenge is compounded by increasing frequency of droughts and the rising demand for water due to expanding urban populations and agricultural needs. By combining stakeholder insights with MCDM techniques, the research identified two key strategies: transitioning to low water-demand crops and adopting modern irrigation systems.

The top-ranked strategy, transitioning from high water-demanding crops to low water-demanding alternatives, aligns with global evidence supporting this approach. For instance, Boser *et al*. (2024) found that switching to lower water-intensity crops in California agriculture could reduce water consumption by up to 93%. Similarly, Davis *et al*. (2017) demonstrated that replacing existing crops with more suitable alternatives in specific areas of the U.S. could improve water resource efficiency. While the overall water use reduction from these crop replacements was modest (about 5%), significant local water savings were achieved, particularly in drought-prone regions like California. These findings highlight the potential of this strategy to significantly reduce water use, especially in regions facing severe water scarcity. Moreover, recent studies show that adopting such crop strategies could potentially reduce farmers' vulnerability to water price fluctuations and ensure more stable agricultural productivity in the long term.

In addition to reducing water consumption, the adoption of low water-demand crops can contribute to rural development by diversifying income sources for farmers. In many regions, reliance on a single high water-demand crop has led to economic vulnerability due to price fluctuations and water scarcity. By introducing alternative crops, farmers can spread their risks and tap into emerging markets for niche products, such as organic or drought-resistant varieties. This diversification can strengthen local economies and improve livelihoods in rural communities.

The second-ranked strategy, adopting modern irrigation systems, has also proven effective in reducing water waste**.** Modern irrigation technologies, such as drip and sprinkler systems, enable precise water application, minimizing losses due to evaporation and runoff. These systems are particularly beneficial in arid and semi-arid regions, where water resources are limited and must be used efficiently**.** Studies such as Çebi *et al*. (2023) reported water savings of 66–73% when drip irrigation replaced traditional flood irrigation in rice farming. Similarly, Tsakmakis *et al*. (2017) and Leghari *et al*. (2024) demonstrated that modern irrigation systems not only conserve water but also improve crop yields. These results underscore the importance of investing in advanced irrigation technologies to optimize water use in agriculture. In addition to the water efficiency gains, studies have shown that modern irrigation practices can also lead to better uniformity in crop yields, further improving farm productivity.

Modern irrigation systems also offer opportunities for integrating renewable energy sources, further enhancing their sustainability. Solar-powered irrigation pumps, for example, can provide a clean and cost-effective alternative to conventional diesel-powered systems. This combination of water-saving technologies and renewable energy can reduce greenhouse gas emissions and promote climate-resilient agriculture. Moreover, the adoption of smart irrigation systems equipped with sensors and IoT technology allows for real-time monitoring and control, ensuring optimal water use based on crop needs and weather conditions. Such precision in water delivery helps farmers respond more effectively to fluctuating climate conditions, such as prolonged dry spells or unseasonal rainfall.

These strategies not only reduce water consumption but also enhance agricultural productivity and economic outcomes. To support their implementation, policymakers should provide financial incentives, technical training, and market access for low water-demand crops. For example, subsidies for seeds and equipment, as well as guaranteed purchase agreements for low water-demand crops, can encourage farmers to adopt these practices. Additionally, investments in modern irrigation infrastructure are essential to ensure sustainable water management in the region. Governments and agricultural organizations should collaborate to promote the widespread adoption of these technologies through subsidies, awareness campaigns, and capacity-building programs. Public-private partnerships can play a crucial role in scaling up these initiatives and ensuring their long-term success.

To facilitate the transition to sustainable agricultural practices, it is vital to address the knowledge gap among farmers regarding new technologies and crop management techniques. Training programs, extension services, and demonstration projects can help farmers understand the benefits and operational aspects of modern irrigation systems and low water-demand crops. Collaborations with agricultural research institutes and universities could also accelerate the development and dissemination of region-specific crop management strategies. Furthermore, fostering farmer-to-farmer learning networks can accelerate the diffusion of best practices and innovations within the agricultural community.

Future research should focus on evaluating the long-term impacts of these strategies and exploring additional innovative practices to further enhance water sustainability in agriculture. For instance, integrating renewable energy sources into irrigation systems or developing drought-resistant crop varieties could offer additional benefits. Rainwater harvesting, on the other hand, can supplement groundwater supplies during dry periods, providing a buffer against water scarcity.

Another promising area for future research is the development of integrated water resource management (IWRM) frameworks that consider the interconnections between groundwater, surface water, and atmospheric water. Such frameworks can help optimize water allocation across different sectors, including agriculture, industry, and domestic use.

By embracing these enhancements, the agricultural sector can contribute significantly to sustainable water resource management, ensuring food security in an increasingly resource-constrained world. The findings of this study provide a foundation for policymakers, researchers, and practitioners to develop and implement effective solutions for groundwater conservation, ultimately contributing to the resilience and sustainability of agricultural systems globally. Ultimately, the success of these strategies depends on the collective efforts of all stakeholders, including governments, farmers, researchers, and private sector actors. Collaborative governance models that prioritize participatory decision-making and equitable benefit-sharing can foster trust and cooperation among stakeholders, paving the way for transformative change in water management practices.

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مقاله پژوهشی

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تصمیم‌گیری گروهی ذینفعان بخش کشاورزی برای مدیریت پایدار منابع آب زیرزمینی: مطالعه موردی خراسان شمالی

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چکیده

منابع آب زیرزمینی به‌عنوان یک منبع حیاتی برای کشاورزی در مناطق خشک محسوب می شوند که برداشت بی‌رویه از آن‌ها منجر به چالش‌های جدی مانند کاهش سطح آب و افزایش کم‌آبی شده است. این مطالعه با تمرکز بر نیاز فوری به مدیریت پایدار منابع آب زیرزمینی، از رویکرد تصمیم‌گیری گروهی مشارکتی با حضور ذینفعان متنوع، به‌ویژه کشاورزان، استفاده می‌کند. نادیده گرفتن مشارکت کشاورزان در فرآیند تصمیم‌گیری منجر به سیاست‌های ناکارآمد شده است. این پژوهش با به‌کارگیری روش‌های تصمیم‌گیری چندمعیاره (MCDM)، به‌ویژه تکنیک‌های آنتروپی شانون فازی و TOPSIS فازی، راهبردهای کاهش مصرف آب زیرزمینی در منطقه صفی‌آباد شمال خراسان، ایران را اولویت‌بندی می‌کند. داده‌های کیفی حاصل از مصاحبه با ذینفعان، بینش‌هایی در مورد چالش‌ها و فرصت‌های مرتبط با استفاده از آب زیرزمینی ارائه می‌دهد و دو راهبرد اصلی را شناسایی می‌کند: (۱) انتقال به کشت محصولات کم‌آب‌بر و (۲) پذیرش سیستم‌های آبیاری مدرن. این راهبردها نه تنها کاهش قابل توجهی در مصرف آب را نوید می‌دهند، بلکه از شیوه‌های کشاورزی پایدار نیز حمایت می‌کنند. یافته‌ها بر اهمیت همکاری ذینفعان در اجرای سیاست‌های مؤثر مدیریت آب تأکید می‌کنند تا استفاده مسئولانه از منابع تضمین شده و پایداری بلندمدت حاصل شود. این مطالعه به‌عنوان الگویی برای پژوهش‌های آینده عمل می‌کند و از روش‌های ترکیبی که تحلیل‌های کیفی و کمی را ادغام می‌کنند، برای ارائه توصیه‌های سیاستی و بهبود مدیریت منابع آب حمایت می‌کند.

واژه‌های کلیدی: تصمیم‌گیری، راهبردهای حفاظت از آب، مدیریت آب کشاورزی، مشارکت ذینفعان، نقش کشاورزان

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