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Integrated multi-objective chance-constrained fuzzy interval linear programming model with principal component analysis for optimizing agricultural water resource management under uncertainties

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ABSTRACT

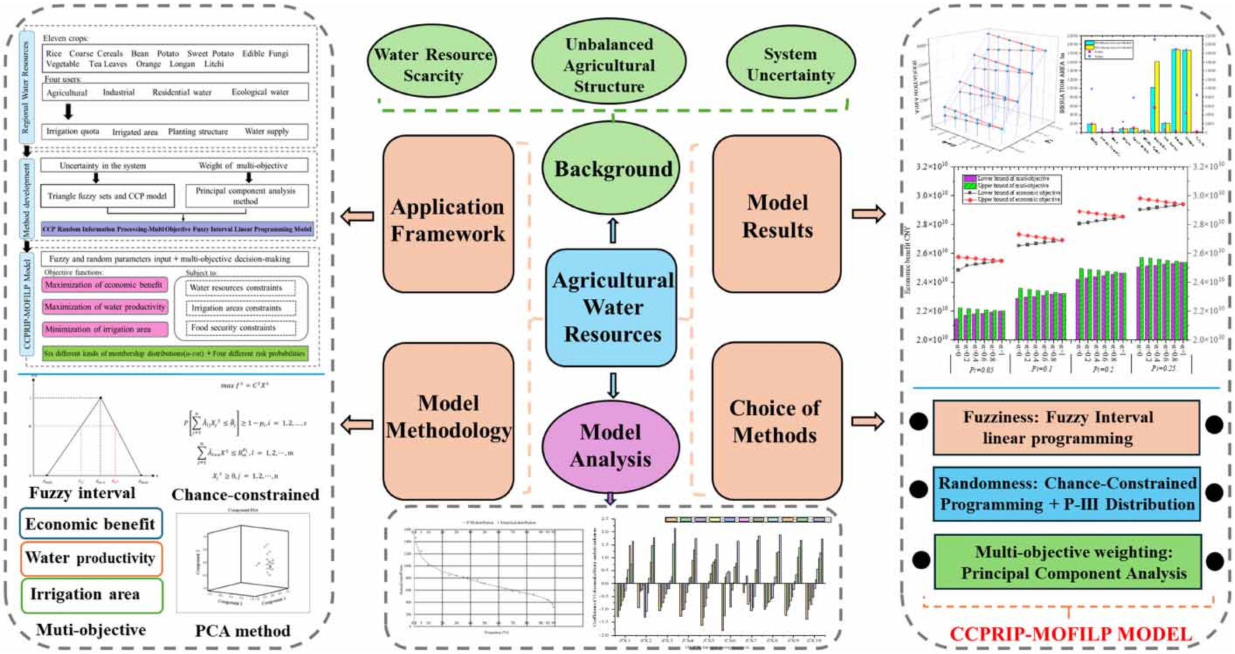
This study addresses the pivotal challenge of water resource allocation in urban environments by introducing a novel approach – a multi-objective chance-constrained fuzzy interval linear programming model integrated with principal component analysis (PCA). This innovative model aims to alleviate subjectivity in urban water management processes, particularly in adjusting water demands across various sectors. The proposed model incorporates correlation analysis to identify dimensionality-reducing factors of multitarget components, determining the proportion of each target component relative to the total components. Fuzzy sets are applied to irrigation water resource allocation quantity, segmented into six levels of fuzzy membership to analyze the stochasticity of water supply. Results demonstrate the model's efficacy, revealing that variations in risk probabilities impact water supply, necessitating positive water management strategies to enhance agricultural efficiency and negative strategies to mitigate the risk of inadequate water supply. Key findings emphasize the significance of agricultural water availability and the structure of irrigation water use in optimal resource allocation. Importantly, the study showcases the enhanced precision achieved through the proposed multi-objective chance-constrained fuzzy interval linear programming with PCA, thereby refining the optimization outcomes for water management under multifaceted objectives.

Key words: chance constraint, multi-objective, principal component analysis, water resources

HIGHLIGHTS

- Development of a multi-objective chance-constrained fuzzy interval model.
- Integration principal component analysis to improve the optimal solutions.
- Application of a multidimensional analysis to effectively assess risk probabilities.
- Optimization of agricultural water resources under varying constraints.
- Offering strategic recommendations for agricultural cropping structures.

GRAPHICAL ABSTRACT



1. INTRODUCTION

In contemporary societies, water resources serve as the linchpin of regional development, forming a pivotal human-ecology-industry-centered water supply and demand network (Jin *et al.* 2019; Zhang *et al.* 2022a, 2022b, 2022c). Given the escalating challenges of water scarcity and population growth, the allocation of water resources is essential to social development, as it often dictates the quality of regional development. Therefore, the optimal allocation of water resources has become one of the focus on research in natural resource science (Naghdi *et al.* 2021; Jiang *et al.* 2022; Wu *et al.* 2022; Cheng *et al.* 2023).

As urban centers expand, intensified competition among water-consuming sectors, stringent environmental policies and regulations, and a rise in extreme weather occurrences engender increasingly intricate uncertainties. These factors accentuate the shortcomings and antiquation of prior water management systems (Ju *et al.* 2023). To confront these uncertainties inherent in water management systems, this study has devised a programming model aimed at the optimal allocation of urban water resources. This model integrates multi-objective fuzzy interval linear programming, chance-constrained programming (CCP), and principal component analysis (PCA), with agricultural water resources programming serving as its cornerstone (Sivagurunathan *et al.* 2022).

Fuzzy set theory facilitates the transformation of information into a range-based format within a given fuzzy space, as demonstrated through triangular fuzzy sets (Zadeh 1965; Nagarajan *et al.* 2019). By establishing a fuzzy membership function, the information can be converted into rational intervals distributed across fuzzy levels. This process yields the interval fuzzy representation of a variable at a designated fuzzy set level. In addition, employing a two-stage arithmetic approach helps delineate the distribution space of the optimization objective (Zeraatkar & Afsari 2021; Chang *et al.* 2022). To address the uncertainty inherent in programming models and the challenge of objective weighting within multi-objective models, Zhang *et al.* (2022a, 2022b, 2022c) proposed an approach called full fuzzy-dependent linear fractional programming. This approach integrates fuzzy correlated-chance programming, fuzzy plausibility-constrained programming, and linear fractional programming into a unified framework specifically designed for irrigation programming. This effectively addresses the fuzzy uncertainty associated with ratio objectives. Yang *et al.* (2020) solved fuzzy multi-objective linear fractional programming problems using an approach based on the superiority and inferiority measurement method. Chen *et al.* (2022) introduced a type-2 fuzzy bi-level programming method coupled with a fuzzy ranking algorithm to address fuzzy information on subordinate functions in programming agricultural water resource systems. Pandiya *et al.* (2024)

constructed a nonparametric transcendental fuzzy preference programming model to derive optimal weights from a fuzzy two-by-two comparison matrix. Wan *et al.* (2020) presented interval-valued Atanassov intuitionistic fuzzy preference relations (IV-AIFPRs) to objectively establish the weights of decision makers (DMs) by assessing the consistency level of individual IV-AIFPRs. This approach integrates individual IV-AIFPRs into collective weights.

Most previous studies have employed optimization models founded on fuzzy linear programming to address fuzzy parameters, relying on consistency level assessments or settings of fuzzy preference models for decision-making regarding events (Wan *et al.* 2020; Pandiya *et al.* 2024). While these studies possess their strengths in addressing uncertainty or decision preference issues, they notably underestimate the complexities confronted by water management systems (Zhang *et al.* 2023a, 2023b). In practice, water resource systems frequently contend with both fuzziness and randomness issues that are inherently intertwined (Deng *et al.* 2022). For instance, while water sector demand exhibits fuzziness, surface water resource supply is characterized by random distribution, necessitating the establishment of a comparative relationship between water demand and supply within water resources management systems (Zhou *et al.* 2023). Furthermore, the allocation of weights in multi-objective programming has long grappled with the challenge of subjective decision-making. This constraint curtails the accuracy of multi-objective linear programming results and undermines the establishment of a rational water usage framework in reality (Wang *et al.* 2022).

In order to achieve a more comprehensive optimization, a CCP random information processing-multi-objective fuzzy interval linear programming model (CCPRIP-MOFILP) is employed, which integrates the PCA and CCP methods. This approach aims to capture the uncertainty inherent in water resource systems through a combination of fuzzy and stochastic programming. This method offers the following advantages:

(i) The model establishes six α-cut levels for crop irrigation quotas within the fuzzy agricultural water resource system. The fuzzy space of each level is incorporated into the multi-objective framework of the model for optimization, which enables the exploration of scenarios and inclusion of precise fuzzy interval parameters.
(ii) By considering four different risk levels that violate the constraints of the probability distribution, the model effectively addresses the randomness of maximum supply of surface water. This simulation mirrors real-world scenarios in Xiamen City, China, which enables the integration of MOFILP with stochastic programming methods. This integration helps mitigate the impact of uncertainty in water resource optimization and allocation systems.
(iii) The programming model utilizes PCA to analyze the correlations and significance between multi-objective component factors. It derives the component weights essential for the multi-objective programming model. Compared with the previous analytic hierarchy process (AHP) method, the PCA method offers a more detailed explanation of the components and a multilevel comparison structure. Consequently, it enables multi-objective programming models with multiple uncertainties to yield objective results that help DMs establish the criteria for regional water allocation (Ren *et al.* 2019; Zhang *et al.* 2023a, 2023b).

2. METHODOLOGY

2.1. Fuzzy interval linear programming

The interval fuzzy linear programming can be expressed as follows:

$$\max f^{\pm} = C^{\pm} X^{\pm} \tag{1a}$$

subject to:

$$\sum_{j=1}^{n} \tilde{A}_{lj} X_j^{\pm} \leq \tilde{B}_j, \; l = 1, 2, \cdots, m \tag{1b}$$

$$X_j^{\pm} \geq 0, \; j = 1, 2, \cdots, n \tag{1c}$$

where $C^{\pm} \in \{\aleph^{\pm}\}^{1^*n}$ and $\aleph^{\pm}$ denote the interval parameters; $X^{\pm} \in \{x^{\pm}\}^{n^*1}$ and $x^{\pm}$ denote the interval variables; and $\tilde{A}_{lj} \in \{\beth^{\pm}\}^{m^*n}$, $\tilde{B}_j \in \{\beth^{\pm}\}^{m^*1}$, and $\beth^{\pm}$ denote the fuzzy parameters defined as follows:

$$\tilde{A}_{lj} = [\mathrm{L}_{\tilde{\mathrm{A}}}(\alpha),\ \mathrm{U}_{\tilde{\mathrm{A}}}(\alpha)] \tag{2a}$$

$$\tilde{B}_j = [\mathrm{L}_{\tilde{\mathrm{B}}}(\alpha),\ \mathrm{U}_{\tilde{\mathrm{B}}}(\alpha)] \tag{2b}$$

where $\mathrm{L}_{\tilde{\mathrm{N}}}(\alpha) \cong \min\{\mathrm{x} \in \mathrm{R} | \mu_{\tilde{\mathrm{N}}}(\mathrm{x}) \geq \alpha\}$ and $\mathrm{U}_{\tilde{\mathrm{N}}}(\alpha) \cong \max\{\mathrm{x} \in \mathrm{R} | \mu_{\tilde{\mathrm{N}}}(\mathrm{x}) \geq \alpha\}$; $\tilde{\mathrm{N}}$ is a fuzzy set defined on R with the membership function $\mu_{\tilde{\mathrm{N}}}(*)$ and $\tilde{\mathrm{N}} \cong \{\mathrm{x} \in \mathrm{R} | \mu_{\tilde{\mathrm{N}}}(\mathrm{x}) \geq \alpha\}$, where $\alpha \in [0,\ 1]$. The modeling approach employed fuzzy sets and intervals to address uncertainties, creating interval fuzzies based on the degree of membership (Kaushik & Kumar 2022). However, uncertainty manifests not only through the fuzzification of natural attributes but also extends to the resolution of stochastic attribute problems (Kheirollahi *et al.* 2022). In this context, the study incorporated classical stochastic probability distributions into the right-hand side parameters of the constraints, substituting the fuzzy right-hand side parameters (Boukezzoula *et al.* 2022). This methodology extends beyond fuzzifying natural attributes; it aims to address uncertainty by integrating stochastic attribute solutions into the modeling framework.

$$\max f^{\pm} = C^{\pm} X^{\pm} \tag{3a}$$

subject to:

$$\sum_{j=1}^{n} \tilde{A}_{lj} X^{\pm} \leq B_m^{P_i}, \quad l = 1,\ 2,\ \cdots,\ m \tag{3b}$$

$$X_j^{\pm} \geq 0, \quad j = 1,\ 2,\ \cdots,\ n \tag{3c}$$

The membership function is a fundamental concept in portraying fuzzy sets, its construction is pivotal for the practical application of fuzzy sets (Deng & Deng 2021). In this study, the triangular membership function was utilized to map the fuzzy subset of the domain onto the domain within the range [0, 1]. Under complete fuzziness, this function defines the upper bound, lower bound, and most credible value of the fuzzy parameter (Figure 1). Assuming the existence of fuzzy set A with $\mu_A(x)$ as its triangular membership function, its lowest possible value $A_{\min}$, highest possible value $A_{\max}$, and most plausible value $A_{\alpha=1}$ can be derived from its function X_A. When considering fuzzy set A under the α-cut of the membership function, the interval limit value of fuzzy parameter$\tilde{A}$ is represented by $[A_\alpha^-, A_\alpha^+] = [(1-\alpha)A_{\min} + \alpha A_{\alpha=1},\ (1-\alpha)A_{\max} + \alpha A_{\alpha=1}]$. The membership function is expressed as follows:

$$\alpha = \mu(x) = \begin{cases} 0 & x \leq A_{\min} \text{ or } x \geq A_{\max} \\ \dfrac{A_\alpha^- - A_{\min}}{A_{\alpha=1} - A_{\min}} & A_{\min} < x < A_{\alpha=1} \\ \dfrac{A_{\max} - A_\alpha^+}{A_{\max} - A_{\alpha=1}} & A_{\alpha=1} < x < A_{\max} \\ 1 & x = A_{\alpha=1} \end{cases} \tag{4}$$

2.2. Chance-constrained programming approach

The CCP approach is often used to determine whether conditional parameters – bound by objective facts and adhering to the traits of probability distributions within the confines of natural conditions – possess stochastic properties (Xie & Ahmed 2020 2020). These properties introduce uncertainty into the programming model when seeking the global optimal solution of the planning model. To address the stochastic uncertainty embedded in model parameters, this study utilized a CCP model. The

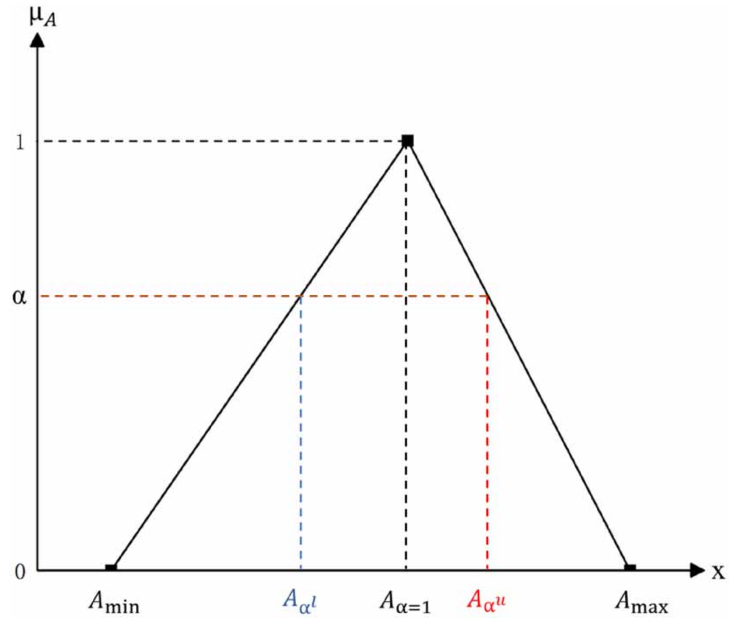


Figure 1 | α-cut for triangular fuzzy membership function.

CCP model can be written as follows:

$$\text{Min } f(x) \tag{5a}$$

$$P[c_i(x) \leq d_i(x)] \geq 1 - p_i, \quad i = 1, 2, \ldots, s \tag{5b}$$

$$x \geq 0 \tag{5c}$$

where $c_i(x) \in C(x)$, $d_i(x) \in D(x)$, and $x \in X$; $C(x)$, $D(x)$ represent the set of mappings within the probability space X. P_i denotes the probability level associated with the random event, and m represents the number of constrained events.

When the left and right parameters in the constraint equations exhibit uncertainty, the constraints become more complex and exhibit nonlinear behavior. However, in the CCP model, not all parameters within C*(x)* and D*(x)* are random elements. In cases where the parameters on the left side are deterministic, while those on the right side are ambiguous, the constraint equations can be transformed into linear programming equations. Thus, the feasible constraint set can be expressed as follows (Ren *et al.* 2019):

$$C_i \leq D_i(x)^{(P_i)}, \quad i = 1, 2, \ldots, s \tag{6}$$

The equation $d_i(x)^{(P_i)} = F_i^{-1}(P_i)$ represents the inverse of the cumulative distribution function denoted as d_i[*i.e.*, $F_i(b_i)$], and $i(P_i)$ is the probability of violating the constraints. In the CCP model, this equation addresses the stochasticity problem of parameters on the right-hand side of the constraints by assigning a probability value $P_i(P_i \in [0, 1])$ to the occurrence of the uncertainty event. Each constraint should adhere to the probability value of $1 - P_i$. The general form of the research model was derived by combining the provisions of the CCP model and FILP approach to the uncertainty.

$$\max f^{\pm} = C^{\pm} X^{\pm} \tag{7a}$$

subject to:

$$P\left[\sum_{j=1}^{n} \tilde{A}_{lj} X_j^{\pm} \le \tilde{B}_j\right] \ge 1 - p_i, \quad i = 1, 2, \ldots, s \tag{7b}$$

$$\sum_{j=1}^{n} \tilde{A}_{l\times n} X^{\pm} \le B_m^{p_i}, \quad l = 1, 2, \cdots, m \tag{7c}$$

$$X_j^{\pm} \ge 0, \quad j = 1, 2, \cdots, n \tag{7d}$$

2.3. PCA process

In this study, the MOFILP model was employed to consider agricultural irrigation water consumption and irrigated area within the realm of multi-objective optimization. However, it should be noted that DMs may attribute the different levels of importance and judgment to various objectives (Yeo *et al.* 2020). Regardless of whether the DMs prioritize economic benefits or emphasize the efficiency of water resource utilization, their perspectives introduce subjective influences into the overall programming model. To mitigate this subjective interference, the PCA method was incorporated in this study. This method leverages multidimensional reduction analysis to transform the optimal allocation ratios of agricultural irrigation water and land-use areas into factor weights associated with the principal components. This approach aims to reduce the impact of subjective judgments in the modeling process. The simplified steps of the PCA method are as follows:

Step 1: Standardize the raw data to eliminate the effect of the dimension (generated from SPSS software).
Step 2: Establish the matrix of correlation coefficients between variables R.
Step 3: Calculate the eigenvalues and eigenvectors of the correlation coefficient matrix R.
Step 4: Extract the principal components and calculate the composite score.

To find additional principal components, the second, third, and possibly fourth principal components must be derived. Each subsequent principal component should encapsulate information that was not captured by the preceding component. In statistical terms, this means ensuring that the covariance between these principal components is zero. Geometrically, this means ensuring that the directions of these principal components are orthogonal (Ibebuchi & Richman 2023).

In PCA, the correlation analysis for component indicators is realized by the algorithm defined in the method itself, while in the similar AHP algorithm, it needs to set up judgment matrices for each target first, and use manual inter-comparison between the targets to set up judgment matrices according to the relative importance (Gao & Gao 2022). The study chose the former for the target weighting analysis, which is helpful to avoid the human subjective will to interfere with the decision-making results.

2.4. CCP random information processing-multi-objective fuzzy interval linear programming model

In this study, the programming model prioritizes addressing two key uncertainty problems, i.e., the stochasticity and fuzziness inherent in the model parameters, to simultaneously optimize agricultural irrigation water resources and crop land area. Moreover, to ensure objective prioritization and achieve optimum results, a multi-objective linear programming model was developed. This model integrates various methodologies, including the CCP model, triangular fuzzy set, and PCA method. Termed as the CCPRIP-MOFILP model in Equation (15), it integrates these techniques to enhance the optimization process and provide a holistic framework for decision-making in agricultural resource allocation and land-use planning.

$$\max f_1^{\pm}(x) = \tilde{A}X^{\pm} + B \tag{8a}$$

$$\max f_2^{\pm}(x) = CX^{\pm} + \tilde{D} \tag{8b}$$

$$\max f_3^{\pm}(x) = EX^{\pm} + F \tag{8c}$$

subject to:

$$P\left[\sum_{j=1}^{n} \tilde{A}_{lj} X_j^{\pm} \le \tilde{B}_j\right] \ge 1 - p_i, \quad i = 1, 2, \ldots, s \tag{8d}$$

$$X^{\pm} \ge 0 \tag{8e}$$

In practice, the general comparative equation was derived by transforming the constraints into an equivalent form. In addition, the interval fuzzy set/number, obtained by converting the triangular fuzzy set using α-cut intervalization, was utilized for the fuzzy parameters. This process yielded feasible computational equations for the CCPRIP-MOFILP model. These equations incorporated the fuzzy parameters represented as interval fuzzy numbers/sets, which resulted in a computational framework that accommodates uncertainties and optimizes the objectives within the multi-objective linear programming model as follows:

$$\max f_1^{\pm}(x) = A^{\pm}X^{\pm} + B \tag{9a}$$

$$\max f_2^{\pm}(x) = CX^{\pm} + D^{\pm} \tag{9b}$$

$$\max f_3^{\pm}(x) = EX^{\pm} + F \tag{9c}$$

subject to:

$$\sum_{j=1}^{n} \tilde{g}_{l\times n}X^{\pm} \le h_m^{P_i}, \quad l = 1, 2, \cdots, m \tag{9d}$$

$$X_j^{\pm} \ge 0, \quad j = 1, 2, \cdots, n \tag{9e}$$

After addressing the challenges related to fuzzy parameters and the stochastic nature of the probability distributions within the model, the PCA method was used to analyze the factor structures within the principal components. The factor analysis results yielded factor weights associated with the objectives. These factor weights provide insights into the significance and contributions of each objective within the multi-objective framework to aid in determining their relative importance in the optimization process.

In this study, PCA, triangular fuzzy sets, and CCP were used to address the uncertainties arising from water resource planning. These methods were collectively integrated into the newly established framework, CCPRIP-MOFILP. This framework was designed to handle two main sources of uncertainty: stochastic events related to surface water supply and the uncertainty represented by fuzzy sets in determining water-use quotas for irrigated agricultural areas. The combination of these methodologies enhances the robustness of the model in managing and optimizing water resource allocation under various uncertain conditions. The comprehensive methodology for the resolution is as follows:

Step 1: Establish the CCPRIP-MOFILP model.
Step 2: Transition the CCPRIP-MOFILP model from an MOFILP model to a multiple subobjective model, ensuring adherence to constraints established for all subobjective functions.
Step 3: Convert the random variables into crisp numbers that conform to a probability distribution using the CCP model.
Step 4: Translate the triangular fuzzy parameters into rational interval numbers and model the upper and lower bounds of the fuzzy sets via the interval linear programming method.
Step 5: Resolve the solution set of each subobjective model, encompassing the decision variables and a single-objective function.
Step 6: Utilize the PCA method to derive principal component factor weights for each objective.
Step 7: Iterate through steps (3)–(6) using an identical probability distribution to address the solution set of fuzzy parameters, employing different α-cut grading.
Step 8: Repeat steps (3)–(7) to obtain the global optimal solution of the model across varying probabilities.

3. APPLICATION

3.1. Problem statement

Xiamen City is located in the southeastern area of Fujian Province (24 °23′–24 °54 N, 117 °53′–118 °26 E), along the southeastern coastline of China. It is densely populated and has undergone significant economic development. However, this region lacks major rivers, as evidenced by the short river mileage, narrow riverbeds, and shallow rivers within its territory (Zhang *et al.* 2022a, 2022b, 2022c; Sun *et al.* 2023). Xiamen has subtropical maritime monsoon climate characterized by an average annual temperature of 20.7 °C and average annual rainfall of 1,513.3 mm. In particular, the city is frequently struck by typhoons from July to September (Jiang *et al.* 2023).

As of 2022, Xiamen was designated as a Special Economic Zone by the State Council of China, aside from being a major city, port, and tourist destination. Xiamen has six districts (Figure 2) covering a total area of 1,700.61 km^2. It boasts a resident population of 5.380 million and has achieved an urbanization rate of 90.19%. Considered as one of the fastest-growing urban centers in China, Xiamen thrives on its robustly developed manufacturing and service sectors. Its accelerated growth is underpinned by liberal economic policies and a highly favorable business environment. However, Xiamen continues to grapple with the lack of freshwater resources owing to high evapotranspiration and limited precipitation. In 2022, the city's water resources per capita was 229 m^3, which is significantly lower than the national average for that year (Shangshang *et al.* 2024) . Furthermore, Xiamen's primary agricultural zones lie beyond the main island, characterized by relatively outdated production techniques and the inequitable distribution of water for irrigation. These areas exhibit an irrational development pattern and inefficient use of agricultural water resources, which contribute to the low efficiency of water resource utilization in the agricultural sector (Ren *et al.* 2021) .

To formulate a water allocation strategy for Xiamen, a comprehensive understanding of the city's unique characteristics, such as its separate islands and sizable inland area, is required. This study addresses the challenge of meeting the water demands of a developed economy of a port city, while ensuring sufficient provisions to meet basic agricultural needs and sustain the resident population. Such divergent objectives are inherently complex and make multi-objective programming a suitable approach to analyze the water-related challenges of a city grappling with water scarcity and high demand (Zeng *et al.* 2023). In the multi-objective programming model, Xiamen City's agricultural water utilization structure must be optimized. This means delving into the specifics, such as the opinions regarding the acreage allocated to various crops, and analyzing their economic viability and water-use efficiency in accordance with agricultural irrigation quantities and crop-planting patterns. The model accounts for various uncertainties stemming from natural factors and market dynamics, including the surface water supply following random probability distributions and fuzzy agricultural irrigation water quotas (Fu *et al.* 2012; Kumar & Sen 2020; Chen *et al.* 2022). In addition, an objective data

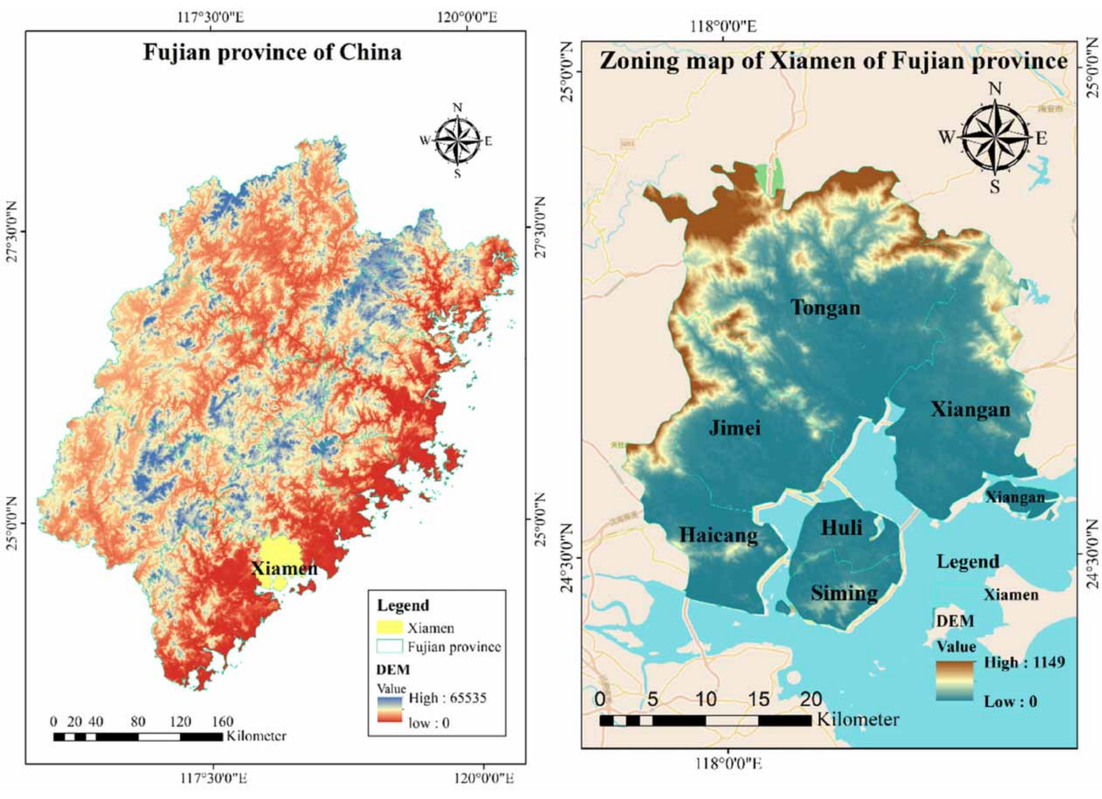


Figure 2 | Zoning map of Xiamen City in Fujian Province.

organization approach was adopted to address the subjective inclinations of DMs. The PCA method was used to conduct factor analysis on the objectives and derive the objective principal component scores. This method aims to scientifically evaluate the weights of multiple objectives to ensure rational and objective policy outcomes. In response to these challenges and technical pathways, this study developed the CCPRIP-MOFILP model to conduct an in-depth analysis of agricultural water allocation in Xiamen City to optimize the crop irrigation water-use structure. The crops considered include rice, coarse cereals, beans, potatoes, sweet potatoes, edible fungi, vegetables, tea leaves, oranges, longans, and litchis (Xing *et al.* 2021).

3.2. Model formulation

A combination of multi-objective programming, fuzzy sets, PCA, and CCP was employed to explore the optimal allocation of agricultural water resources in Xiamen City. The resulting framework was encapsulated in the CCPRIP-MOFILP model, a linear programming model designed to achieve the following objectives:

(a) Maximize economic benefits: Given Xiamen City's stature as an economic powerhouse with a robust industrial landscape, promoting its economic growth is paramount.
(b) Maximize agricultural water productivity: Enhancing water productivity expands the scope of agricultural water allocation while ensuring the optimal results for each objective.
(c) Minimize irrigated area: Minimizing irrigated areas is crucial to acknowledge the significance of agricultural development in Xiamen City's overall livelihood program. This aligns with the city's development plans while ensuring food security for its populace.

Figure 3 shows the research framework of this model. It illustrates the interplay and integration of various methodologies to address the challenges of optimizing agricultural water resource allocation in the city.

The formulated application equations in this case study are as follows:

3.3. Objective functions

Maximize the economic benefits:

$$\max E_P^{\pm} = \max \sum_{i=1}^{11} (POC_i \cdot YOC_i \cdot IAOC_i - COC_i \cdot IAOC_i) \tag{10a}$$

Maximize agricultural water productivity:

$$\max P_W^{\pm} = \max \left[\frac{\sum_{i=1}^{11} (YOC_i \cdot IAOC_i)}{\left(\widetilde{IQOC}_i \cdot \dfrac{IAOC_i}{\text{IWUE}} \right)} \right] \tag{10b}$$

Minimize the irrigated area:

$$\max I_A^{\pm} = \max \left(\text{TIAS} - \sum_{i=1}^{11} IAOC_i \right) \tag{10c}$$

3.4. Constraint conditions

Water supply constraints:

$$\sum_{i=1}^{11} \left(\widetilde{IQOC}_i \cdot \frac{IAOC_i}{COC_i} \right) + \text{WDSI} + \text{WDTI} + \text{DWC} + \text{EWC} \leq \text{GE} + \text{MSOF}W^{P_i} \tag{10d}$$

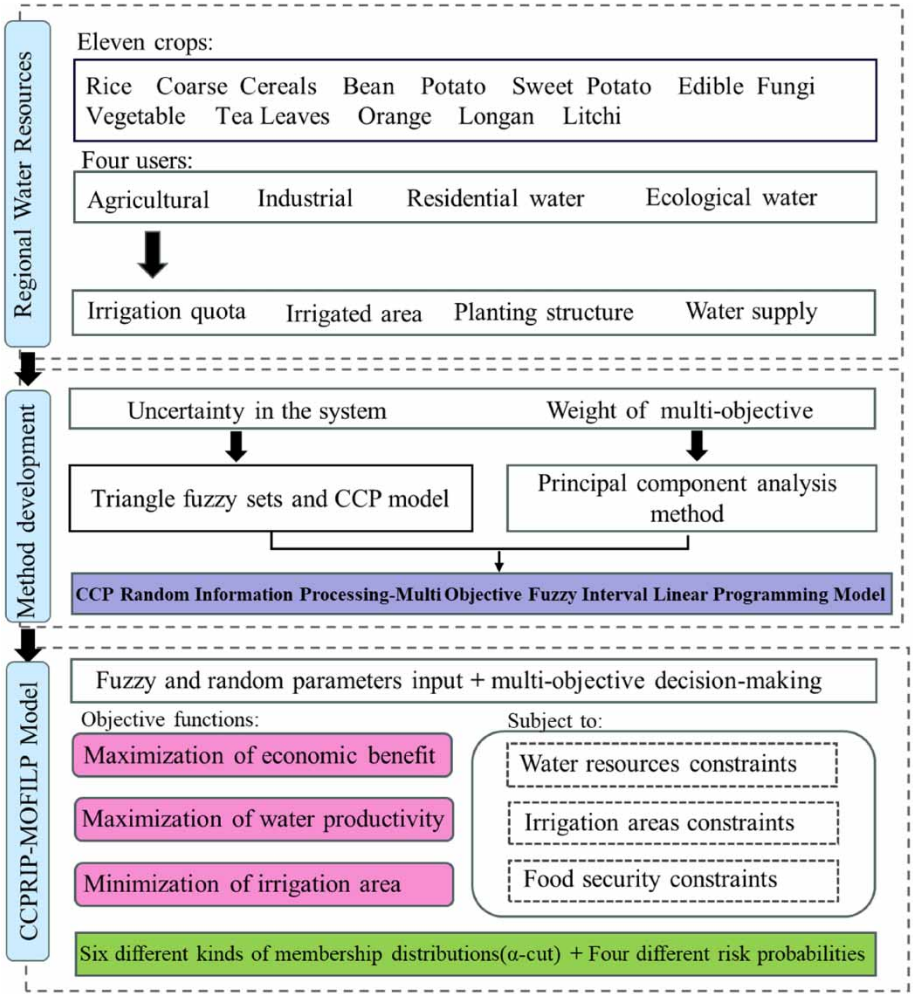


Figure 3 | Research framework and the CCPRIP-MOFILP model.

Groundwater constraints:

$$GE \leq MEOG \tag{10e}$$

Irrigation area constraint:

$$IAOC_{i\,\mathrm{min}} \leq IAOC_i \leq IAOC_{i\,\mathrm{max}} \tag{10f}$$

$$\sum_{i=1}^{11} IAOC_i \leq \mathrm{TIAS} \tag{10g}$$

Food security constraints:

$$PCFR \cdot PISA \leq \sum_{i=1}^{4} IAOC_i \cdot YOC_i \tag{10h}$$

3.5. Parameter explanation

i is the crop index (1 = rice, 2 = coarse cereals, 3 = beans, 4 = potatoes, 5 = sweet potatoes, 6 = edible fungi, 7 = vegetables, 8 = tea leaves, 9 = oranges, 10 = longans, 11 = litchi)
POC_i: Price of crop i (yuan/t)
YOC_i: Yield of crop i (t/ha)
$IAOC_i$: Irrigation area of crop i (10^3 ha)
$IAOC_{i\,\min}$: Minimized irrigation area of crop i (10^3 ha)
$IAOC_{i\,\max}$: Maximum irrigation area of crop i (10^3 ha)
COC_i: Cost of crop i (yuan/ha)
$\widetilde{IQOC_i}$: Irrigation quota of crop i (m^3/ha) (fuzzy parameters)
IWUE: Irrigation water-use efficiency of study area
TIAS: Total irrigation area of the study area (10^3 ha)
WDSI: Water demand of the secondary industry (10^3 m^3)
WDTI: Water demand of the tertiary industry (10^3 m^3)
DWC: Domestic water consumption (10^3 m^3)
EWC: Ecological water consumption (10^3 m^3)
GE: Groundwater exploration (10^3 m^3)
MEOG: Maximum exploration of groundwater (10^3 m^3)
MSOFW: Maximum supply of surface water (10^3 m^3) (random parameter)
PCFR: Per capita food requirement (t/p)
PISA: Population in the study area (10^3 p)

In the proposed model, the parameter $\widetilde{IQOC_i}$ adheres to the traits of fuzzy variables, and was analyzed and resolved using the fuzzy interval programming methodology. Within the confines of the total water resource constraint in Xiamen City, the peak supply of surface water follows a stochastic probability distribution. To determine the maximum surface water supply under the distinct probability of violating constraints, this study generated P-III hydrological curves derived from runoff data from 2002 to 2022. The available surface water resources corresponding to the four distinct risk probabilities are 7.53×10^8 m^3, 8.28×10^8 m^3, 9.13×10^8 m^3, and 9.79×10^8 m^3.

The principal parameter integrals of the formulated model are listed in Tables 1 and 2. The datasets in these tables were obtained via field surveys, supplemented by information from the yearbook of the Xiamen Special Economic Zone (Statistical Yearbook 2002–2023).

In the research model, three primary objectives are delineated: maximizing economic benefits, maximizing agricultural water productivity, and minimizing irrigated area. These objectives are constrained by factors such as water availability,

Table 1 | The basic crop parameters

Crops (*i*)	YOC (kg/ha)	Irrigation quota (m^3/ha)	$IAOC_{min}$ (ha)	$IAOC_{max}$ (ha)	POC (¥/kg)	COC (¥/ha)
Rice	7,590	5,385	1,882	9,798	2.84	16,500
Coarse cereals	6,650	4,070	181	655	3.86	8,000
Bean	2,750	4,574	112	794	5.62	11,500
Potato	1,621	4,650	837	2,415	5.66	37,500
Sweet potato	6,675	5,420	917	7,843	6.24	30,000
Edible fungi	30,500	2,620	112	406	16.28	75,000
Vegetable	105,880	4,950	5,587	21,002	1.16	15,000
Tea leaves	4,050	4,295	547	2,058	54.02	30,000
Orange	45,675	5,250	228	18,831	4.22	22,500
Longan	75,623	4,846	4,383	18,716	18.12	81,000
Litchi	6,848	4,592	108	8,469	10.32	13,500

Table 2 | The basic model parameters

TA (10^4ha)	TPR (10^4P)	FDP (kg/P)	SW (10^4ha)	EW (10^4ha)	DW (10^4ha)	TW (10^4ha)	IC
6.98	528	300	14,469	6743	25,912	11,343	0.59

cultivation area, and food security. These constraints confine each objective within defined boundaries, precipitating potential conflicts among objectives within these limits. Resolving such conflicts constitutes the crux of the CCPRIP-MOFILP model. Following the tenets of multi-objective linear programming, the optimal solution for each of the three objectives is attained through the simplex method. This step is executed subsequent to utilizing computational code developed with LINGO11 software (Voulgaropoulou *et al.* 2022). Upon securing optimal solutions for the three objectives, the Weighting Method concept in multi-objective optimization is applied to introduce weighting coefficients, thus determining the priority of each objective function (Cui *et al.* 2024). To ascertain these weighting coefficients, the study employs the PCA method. Herein, the proportion of total component variance explained by each objective serves as the weighting coefficient for multi-objective optimization. The Pareto optimal solution of the CCPRIP-MOFILP model, signifying the optimal solution for the entire research scheme, is derived as the sum of the product of each obtained weighting coefficient and the corresponding objective function value.

The rules governing the extraction of principal components in the PCA process were deduced from a dimensionality reduction factor analysis of the raw data, predicated on the proportion of variance explained by each component relative to the total variance explained (Obiri *et al.* 2021). The study incorporated social development data from Xiamen spanning the period 2012–2022 as the analyzed indicators, which were utilized to generate correlation analysis outcomes and derive the total variance interpretation of the analyzed cases. These indicators encompassed various metrics such as GDP per capita, end-of-year employment figures, total retail sales of consumer goods, fixed asset investment, local financial revenue, total exports, total value of primary industry, total value of secondary industry, total value of tertiary industry, and per capita disposable income of urban and rural residents. Given the inconsistency in dimensionality among the aforementioned social development data, the initial step in PCA involved standardizing the data to mitigate dimensionality effects (Huang *et al.* 2023). Furthermore, to ascertain the validity of employing the PCA method for the research case, the KMO (Kaiser–Meyer–Olkin) and Bartlett's test were conducted. As per methodological criteria, the KMO value necessitates exceeding or equaling 0.6, while the Sig value must be less than or equal to 0.05 to satisfy the PCA method's validity test. As illustrated by the test outcomes in Table 4, the study met these criteria. From a practical standpoint, the weight coefficients assigned to the three objectives correspond to the variance interpretations of the three principal components extracted. These coefficients have undergone rigorous testing and computation, proving to be highly indicative of the total variance interpretation. Consequently, the weights attributed to the objectives approximate representations of the direction and exigencies of the study area's social development.

Table 3 presents the correlation coefficient matrix obtained after conducting a correlation analysis of the indicator factors using the PCA method. Most variables in the original dataset had correlation coefficients exceeding 0.3, indicating a substantial degree of correlation between them. This study assessed the suitability of the dataset using the KMO measure of sampling adequacy and Bartlett's test of sphericity. A KMO value of 0.623 and significance level below 0.05 were obtained, as shown in Table 4. These findings confirmed the strong correlation within the dataset, which supports the application of the PCA method to obtain accurate results in this study.

According to Table 5, the PCA algorithm employed in this study revealed the loadings of the three principal components, indicating the respective weights assigned to the three optimization objectives: 0.863, 0.074, and 0.038, respectively. Collectively, these principal components (1, 2, and 3) explain approximately 97.54% of the total variance. Figure 4 shows the eigenvalue distribution across all components. The principal components 1, 2, and 3 were the most ranked, occupying predominant positions within the distribution. The plot of the components in Figure 4 shows the close proximity of all components in the spatial context, indicating that principal components 1, 2, and 3 distinctly represent the entire array of components. In other words, the representativeness of these principal components is high, while the correlations between them are strong. This suggests that these principal components effectively encapsulated the overall objectives. Thus, the three objective functions incorporated in this study accurately reflected the outcomes of the optimal water resource allocation.

Table 3 | Correlation matrix

Correlation	x1	x2	x3	⋯	x9	x10
x1	1	0.8	0.86	⋯	0.97	0.97
x2	0.8	1	0.85	⋯	0.85	0.84
x3	0.86	0.85	1	⋯	0.95	0.94
x4	0.96	0.8	0.95	⋯	0.99	0.98
x5	0.95	0.7	0.88	⋯	0.95	0.96
x6	0.73	0.71	0.76	⋯	0.75	0.76
x7	0.6	0.87	0.79	⋯	0.71	0.69
x8	0.96	0.9	0.94	⋯	0.98	0.97
x9	0.97	0.85	0.95	⋯	1	0.99
x10	0.97	0.84	0.94	⋯	0.99	1

Table 4 | KMO and Bartlett's test

KMO and Bartlett's test		
Kaiser–Meyer–Olkin Measure of Sampling Adequacy		0.62
Bartlett's Test of Sphericity	Approx. Chi-square	202.54
	df	45.00
	Sig.	0.00

Table 5 | Total variance explained

	Initial eigenvalues		Extraction sums of squared loadings	
Component	% of variance	Cumulative %	% of variance	Cumulative %
1	86.33	86.33	86.33	86.33
2	7.4	93.72	7.4	93.72
3	3.81	97.54	3.81	97.54
4	1.46	99		
5	0.67	99.67		
6	0.21	99.88		
7	0.1	99.97		
8	0.02	99.99		
9	0.01	100		
10	0	100		

4. RESULTS AND DISCUSSION

4.1. Results analysis

In this study, the model was configured with six α-cut levels (0, 0.2, 0.4, 0.6, 0.8, and 1) and four probabilities (0.05, 0.1, 0.2, and 0.25) for analysis. The primary objective was to translate multiple fuzzy conditions into a manageable mathematical model using linear operations. This approach allows the visualization and analysis of the impact of various degrees of fuzziness on the desired outcomes.

Figure 5 shows the dataset illustrating the maximum allocation of surface water derived from the optimal water resource allocation model under various risk probabilities; this elucidates the outcomes of irrigation water resource allocation at

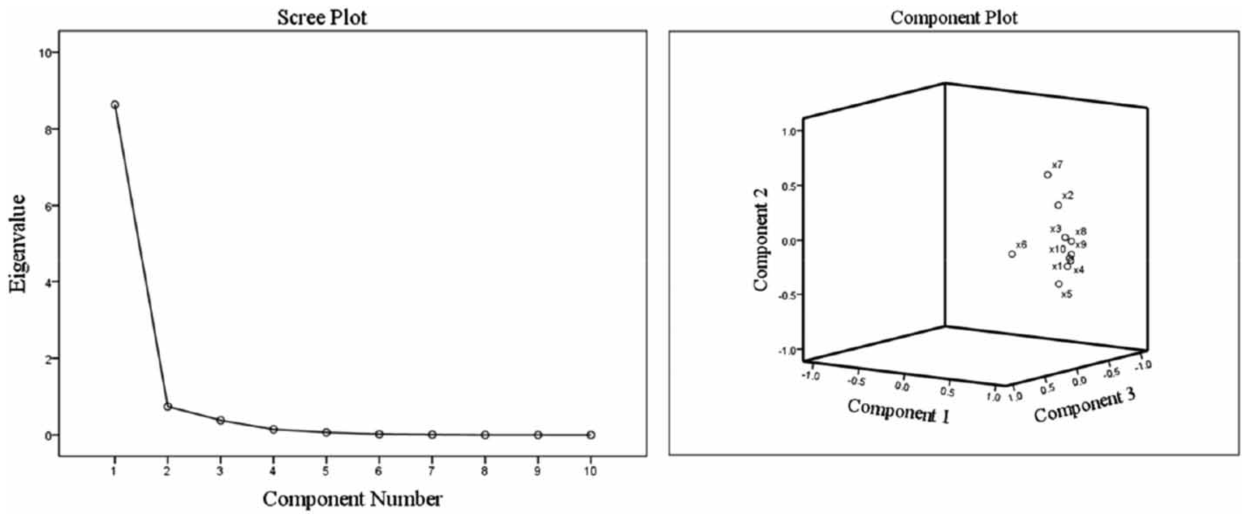


Figure 4 | Scree and component plots.

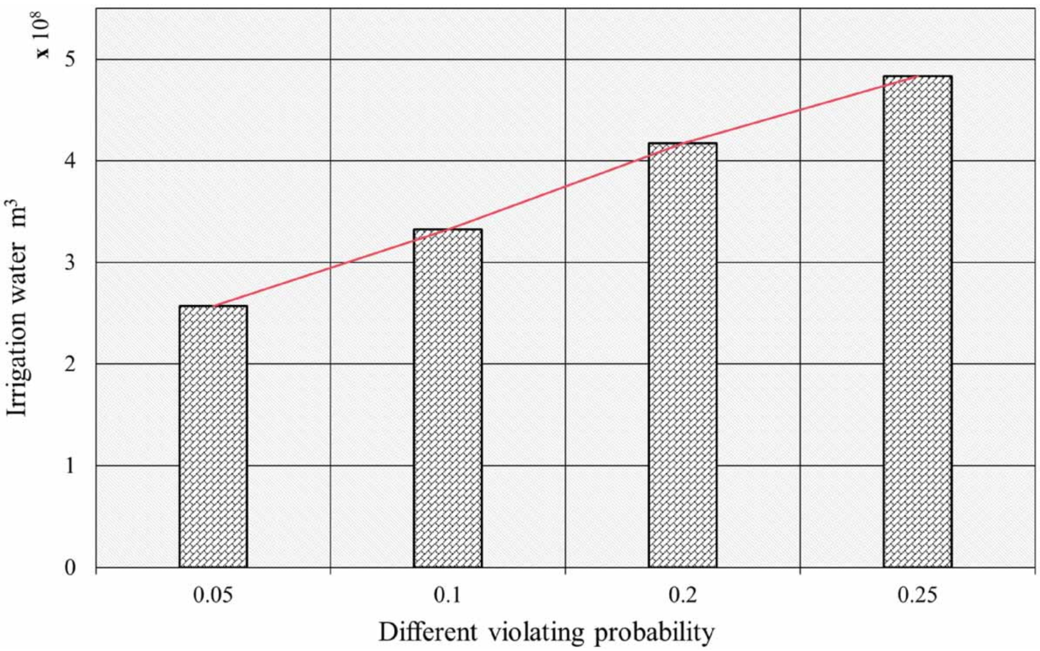


Figure 5 | Irrigation water resources under different probabilities of violation risk.

distinct probability levels. A notable trend was the increase in irrigation water allocation as the risk probability increased. For instance, at the risk probability $P_i = 0.05$, the amount of irrigation water allocated was 2.57×10^8 m^3; at the risk probability $P_i = 0.25$, the amount of irrigation water allocated surged to 4.83×10^8 m^3. This trend was attributed to the gradual relaxation or tightening of constraints that defined the optimum quantity as the probability distribution exceeded the constraint violation limit. Figure 6 shows that at each α-cut level, no changes were observed in the irrigation water utilization outcomes. This suggests that the maximum supply of surface water was fully exhausted under the prevailing risk probability, underscoring the stark reality of water scarcity in the agricultural sector of Xiamen City.

Figure 6 shows the outcomes derived from the model's optimal allocation of the irrigated area across six α-cut levels and four risk probability levels. When $P_i = 0.05$ and $\alpha = 0$, the lower and upper limits of the irrigated area are 2.91×10^4 and

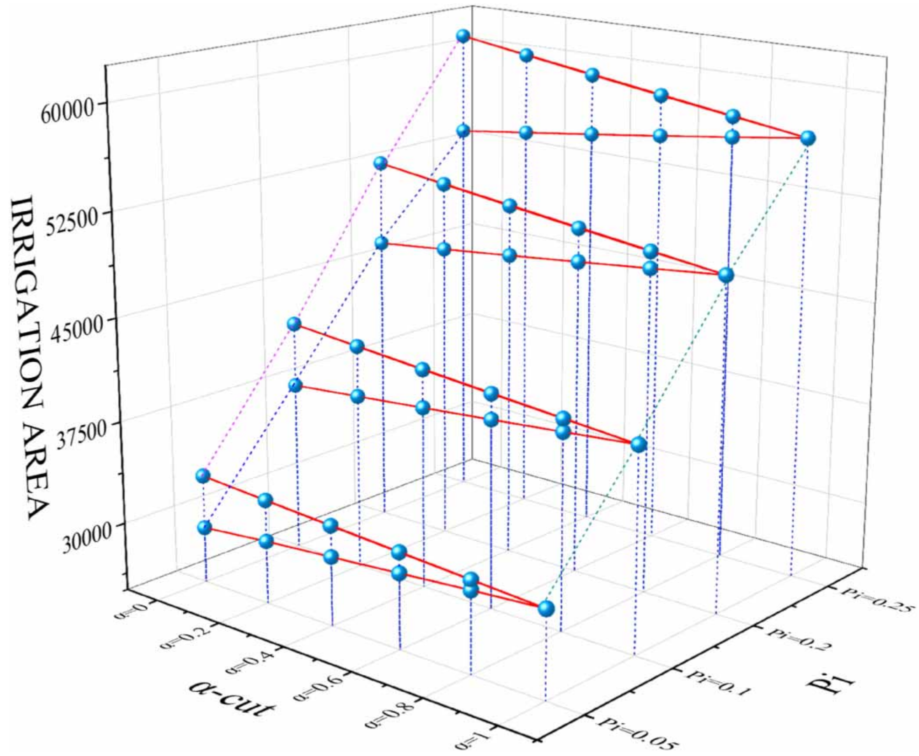


Figure 6 | Irrigation area based on multiple uncertainties under various probabilities of violation risk and α-cuts.

3.30×10^4 ha, $P_i = 0.05$, $\alpha = 0.2$, the result of irrigated area is lower limit 2.96×10^4 ha and upper limit 3.26×10^4 ha. When $P_i = 0.05$, $\alpha = 0.4$, the result of irrigated area is lower limit 3.00×10^4 ha and upper limit 3.23×10^4 ha. It suggests that under identical risk probability constraints, the irrigated area exhibited a phenomenon in which the upper limit decreased while the lower limit increased as the α-cut level increased. This trend can be ascribed to the triangular fuzzy parameter irrigation water quota, which delineates the fluctuation in the irrigated area of a crop under different degrees of fuzziness. This parameter stems from constraints on the expansion of irrigated areas imposed by fluctuations in the irrigation quota, all within the context of limited water resources. Post α-cut processing, the triangular membership function underwent a certain degree of fuzziness modification that was dependent on the varying levels of constraint cutting, thereby confining the scope of the fuzzy space to different degrees. In addition, a quadrant contraction in the model's traits occurred. As the α-cut level approached 1, indicating the moment when the fuzzy parameter ceased to represent a fuzzy space, the model generated the most accurate value for the objective function. For instance, when $P_i = 0.05$ and $\alpha = 1$, the interval transformed into a deterministic value of 3.13×10^4 ha, and when $P_i = 0.2$ and $\alpha = 1$, the interval transformed into a deterministic value of 4.93×10^4 ha.

Figure 6 also shows that as P_i increased, both the upper and lower limits of the irrigated area increased across various α-cut levels. For instance, when $P_i = 0.1$ and $\alpha = 0$, the upper and lower limits of the irrigated area reached 4.22×10^4 ha and 3.75×10^4, and when $P_i = 0.2$ and $\alpha = 0$, the upper and lower limits of the irrigated area reached 5.26×10^4 and 4.65×10^4 ha. Besides, when $P_i = 0.25$ and $\alpha = 0$, the upper and lower limits reached 6.10×10^4 and 5.36×10^4 ha, respectively, which shows the significant increase in the irrigated agricultural area, highlighting the pivotal role of surface water supply in determining the irrigated area. P_i is also used in research as the risk probability of violating constraints and plays an important role in water use decision problems. For example, economic growth is a primary objective for most DMs, this means that the decision-making process may result in an imbalance in the allocation of water resources. Policymaking on urban water allocation will benefit by factoring in considerations based on risk probability, thereby enhancing the rationale and efficacy of policy programs.

A case study with a risk probability of $P_i = 0.25$ and $\alpha = 0.2$ was chosen to demonstrate the allocation and optimization process for irrigation water and crop-planting structures for 11 distinct crops, as shown in Figure 7. Different crops possess

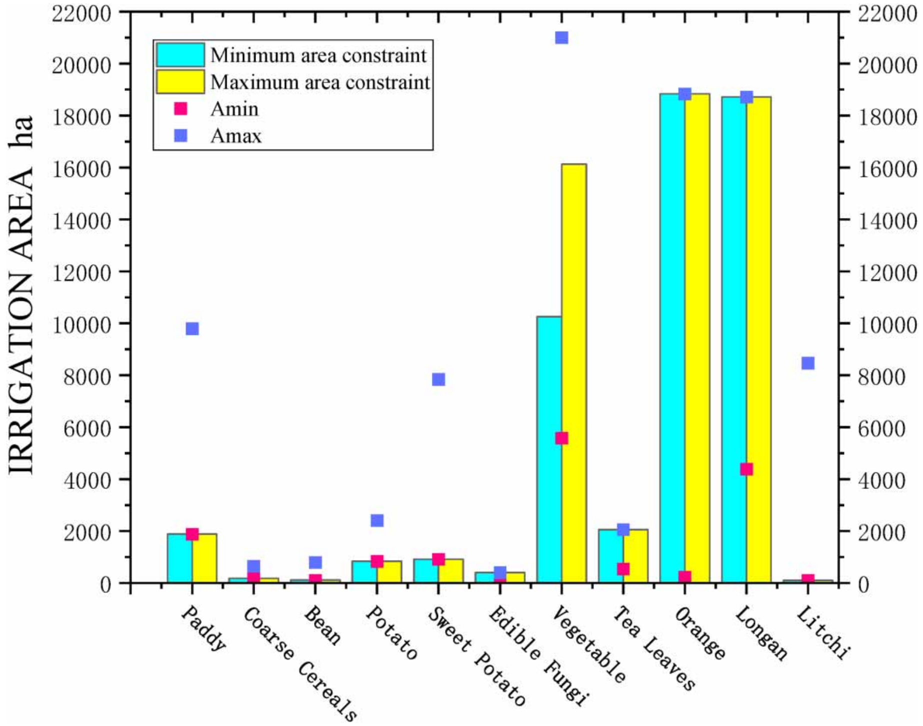


Figure 7 | Optimized space with maximized and minimized irrigated area restrictions for 11 crops ($P_i = 0.25$, $\alpha = 0.2$).

unique characteristics that influence their optimum allocation. For instance, crops such as rice, coarse cereals, and beans, the maximum restricted acreage is 9,798, 655, 794 ha and the minimum restricted acreage is 1,822, 181, 112 ha while the actual maximum acreage after programming is 1,822, 181, 112 ha and the actual minimum acreage is 1,822, 181, 112 ha. They are essential to maintaining food security despite their relative inexpensiveness and average yield. In contrast, high-value crops such as vegetables, oranges, and longans command higher prices and provide higher yields, the maximum restricted acreage is 21,002, 18,831, 18,716 ha and the minimum restricted acreage is 5,587, 228, 4,383 ha, whereas the actual maximum acreage after programming is 5,587, 10,848, 18,716 ha and the actual minimum acreage is 5,587, 7,131, 18,716 ha, respectively. In the model's attempt to optimize the planting structure and allocate agricultural water resources, adherence to the planting limit to maintain food security is prioritized. The emphasis shifts to crops with higher economic value and potential yield when attempting to optimize profit margins. This strategic allocation approach maintains the balance between essential food production and maximizing economic returns within the given constraints.

Figure 8 shows the development trajectory of the single economic benefit objective along with the economic benefit trend under a multi-objective optimization configuration, considering a multilevel analysis with six α-cut levels and four risk probabilities. The data reflect that the economic benefit after multi-objective programming is 86.3% of the share of the single-objective economic benefit at each level of risk probabilities, which is consistent with the results of the weighting coefficients for multi-objective programming. This result was attributed to the constraints imposed by various uncertainties. The expected economic benefit was reduced to balance the effects of multiple factors in multi-objective optimization, thereby rendering comprehensive optimization outcomes. The observed trend in the expected economic benefits parallels the previous analysis of agricultural irrigation water usage. For every 0.05–0.1 increase in the probability of risk P_i, the maximum surface water supply will be enhanced by at least 7.24–10.2%. As the maximized agricultural irrigation water use steadily increased across various risk probabilities P_i, it contributed to the increase in the irrigated area, fostering economic growth. For single-objective economic benefit, P_i from 0.05 to 0.25, the agricultural economic scale (with $\alpha = 1$) is increased from 2.55×10^{10} to 2.94×10^{10} yuan, while for multi-objective optimization the agricultural economic benefit (with $\alpha = 1$) is increased from 2.20×10^{10} to 2.54×10^{10} yuan. On the other hand, both single and multi-objective economic benefits exhibited a trend of fuzzy interval parameter aggregation and convergence as the α-cut levels increased under the same risk probability P_i. This agreement with previous findings underscores the direct influence of both agricultural irrigation water

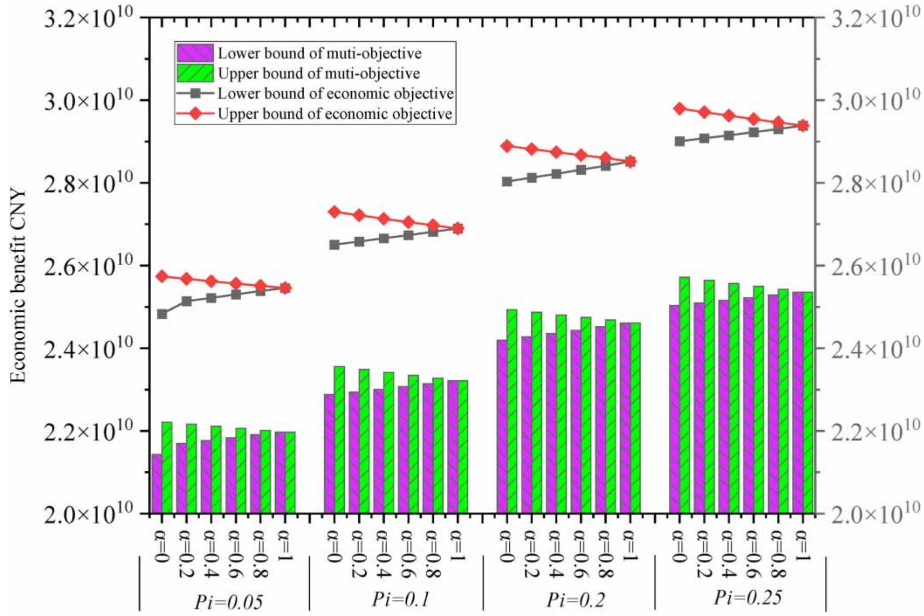


Figure 8 | Upper and lower bounds of the interval of the economic efficiency objective in the case of multi-objective joint optimization and single-objective optimization.

quotas and crop-planting structures on the developmental potential of each objective and the outcomes of optimal water resource allocation. The cumulative evidence emphasizes the interplay between agricultural irrigation practices, crop-planting strategies, and the city's economic benefits. Therefore, to optimize the economic benefits and water resource allocation in Xiamen City, the application of decision analysis methods must be combined with the resolution of multiple uncertainties. This integrated approach aids in determining an adaptive allocation strategy that aligns with the city's development needs in the current scenario.

Figure 9 shows the production efficiency of agricultural water resources in Xiamen City and presents an analysis of the efficiency curve trend. When $P_i = 0.05$, $\alpha = 0$, the upper and lower limits of agricultural water productivity are 43.0 t/m^3 and 37.5 t/m^3, respectively, whereas when P_i is kept constant and $\alpha = 0.2$, 0.4, 0.6, the upper and lower limits of agricultural water productivity are 42.4, 41.8, 41.3 and 38.0, 38.5, 39.1 t/m^3, respectively. Notably, the upper limit of agricultural water resource production efficiency increased while the lower limit decreased as the α-cut level increased from 0 to 1. This trend agrees with previous analyses of irrigated agricultural water resources and economic efficiency. However, a different result was obtained with regard to the impact of increased risk probability on the agricultural water resource production efficiency. Unlike the influence of α-cut levels, the efficiency did not exhibit significant changes owing to the increase in risk probabilities. This result was attributed to the manner in which the components of the objective function, particularly those associated with stochastic parameters, were streamlined within the linear system. The processed objective function remained primarily influenced by fuzzy uncertainty and was not affected by randomly distributed events. For instance, when $P_i = 0.05$ and $\alpha = 0.2$, the upper and lower bounds of the objective function for agricultural water productivity were 38.0 and 42.4 t/m^3, respectively. This result holds true in scenarios when $P_i = 0.1$, $\alpha = 0.2$; $P_i = 0.2$, $\alpha = 0.2$; and $P_i = 0.25$, $\alpha = 0.2$. This observation emphasizes that while the α-cut levels affected the agricultural water resource efficiency, changes in risk probability have minimal influence on efficiency owing to the controlled nature of the objective function within the model's structure.

5. DISCUSSION

Given the strong connection between the surface water resource supply and annual runoff, these have a significant impact on the overarching objectives of maximizing economic benefits and augmenting agricultural water-use efficiency. Hence, when formulating an optimal water resource allocation model, it is important to consider the uncertainties affecting the surface water supply. Compared with the Integrated Multi-Objective Stochastic Fuzzy Programming model (IMOSFP), the CCPRIP-MOFILP model strategically integrated CCP to systematically address the inherently stochastic nature of the surface

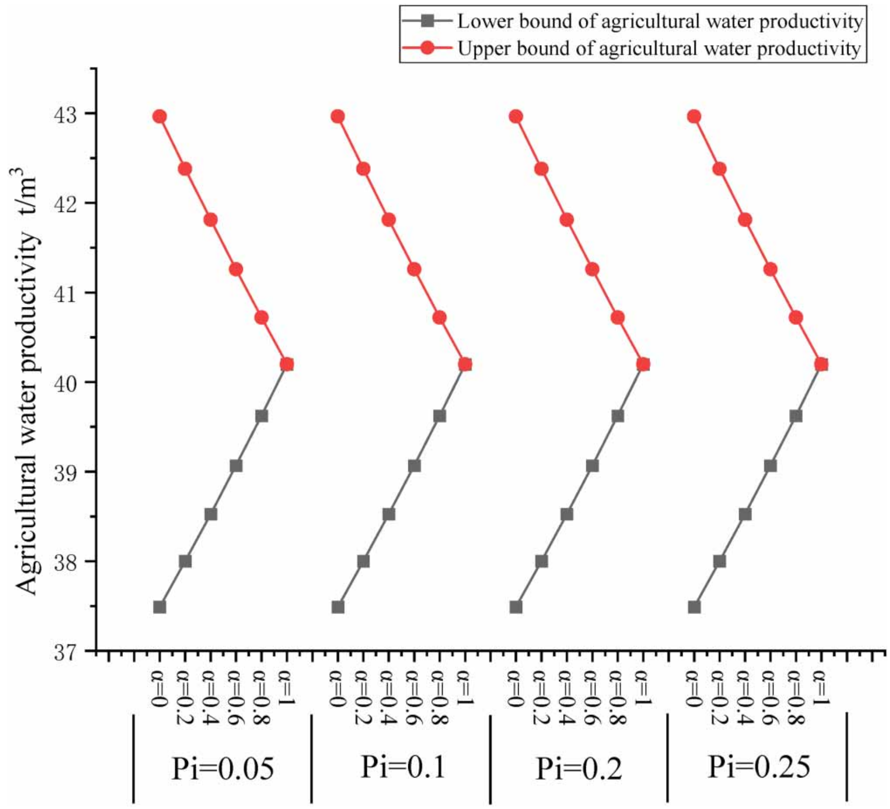


Figure 9 | Upper and lower bounds for maximized and minimized agricultural water productivity under multiple uncertainties.

water supply. This combination includes the methodological analysis of the annual runoff and the probabilistic distribution characteristics listed in Tables 6 and 7. This analysis is shown by the P-III hydrological curves in Figure 10, which illustrate the treatment and representation of uncertainties surrounding the water resource supply. This comprehensive approach ensures a more resilient and nuanced treatment of the uncertainty embedded within the optimal allocation model.

When the risk probability $P_i = 0$, the water availability outcome becomes certain, enabling the use of the IMOSFP model for water allocation analysis. Specifically, at $P_i = 0$, the focus is on maximizing the surface water supply, leading to the extraction of fuzzy interval memberships using the α-cut. During this period, the derived objective function, such as the upper and lower bounds of maximized economic benefits, remains unaffected by the P_i. In contrast, the CCPRIP-MOFILP model covers a broader range of P_i values (0.05, 0.1, 0.2, and 0.25), influencing the upper and lower bounds of the objective function. This divergence indicates that the decision space within the IMOSFP model was significantly constrained and lacked a flexible constraint deflation space. Such constraints are not conducive to aiding DMs in formulating and implementing water resource policies. In contrast, the CCPRIP-MOFILP model utilizes CCP to process randomized information to facilitate a more expansive space for optimizing and allocating water resources. This approach increases the flexibility in decision-making for water resource policymaking and implementation.

Within the realm of multi-objective result impact analysis, the CCPRIP-MOFILP model has integrated the PCA method. This approach introduces the dimensionality reduction factor analysis of water resources into the model results analysis. This premise involves optimizing the allocation of the principal components of the model by weighting the target ideas while minimizing the loss of pertinent information. This process involves the conversion of multiple indicators into a condensed set of composite indicators, commonly referred to as the principal components.

The derived composite indicators (i.e., principal components) were meticulously crafted as linear combinations of the original variables in the CCPRIP-MOFILP model. Each principal component was designed to exhibit no correlation with other principal components, thereby ensuring superior ordering performance compared with the original variables. Following the PCA of the various downscaling factors and indicators, the factor weight coefficients were analyzed using the

Table 6 | The empirical frequencies and statistical parameters

Year	Yearly precipitation *x* (mm)	Serial number	Size-ranking of annual rainfall x	Modal ratio coefficient Ki	$P = m/(n+1)$(%)
2002	875.8	1	1,469.3	1.99	4.55
2003	532.6	2	1,245.2	1.68	9.09
2004	720	3	1,011.9	1.37	13.64
2005	1,011.9	4	875.8	1.18	18.18
2006	1,245.2	5	849.9	1.15	22.73
2007	798.4	6	845.1	1.14	27.27
2008	849.9	7	819.2	1.11	31.82
2009	434.7	8	810.5	1.10	36.36
2010	819.2	9	798.4	1.08	40.91
2011	583.9	10	773	1.05	45.45
2012	773	11	720	0.97	50.00
2013	845.1	12	716.1	0.97	54.55
2014	619.5	13	643.6	0.87	59.09
2015	810.5	14	619.5	0.84	63.64
2016	1,469.3	15	583.9	0.79	68.18
2017	537.7	16	554.4	0.75	72.73
2018	554.4	17	537.7	0.73	77.27
2019	643.6	18	532.6	0.72	81.82
2020	320.9	19	434.7	0.59	86.36
2021	365.2	20	365.2	0.49	90.91
2022	716.1	21	320.9	0.43	95.45

Table 7 | Adapter calculation

			Third wiring $Cs = 3Cv$	
Frequency *P* (%)	Horizontal distance to $p = 50\%$	*x*	Kp	xp
1	−2.33	0	1.89	1,397.42
5	−1.64	0.68	1.56	1,153.43
10	−1.28	1.04	1.4	1,035.13
20	−0.84	1.48	1.23	909.43
50	0.00	2.33	0.96	709.80
75	0.67	3.00	0.78	576.71
90	1.28	3.61	0.66	487.99
95	1.64	3.97	0.6	443.63
99	2.33	4.65	0.5	369.69

Statistical Package for the Social Sciences (SPSS) software. The results are shown in Figure 11. In the figure, lines 1, 2, and 3 correspond to the indicators following dimensionality reduction factor analysis, combined into composite indicators according to the definition outlined in the PCA. These were represented as principal components 1, 2, and 3, and signify the weights attributed to the objective function of the model in this study. In the preceding case study, the interpretation of the variance of these principal components within the model was presented. Moreover, based on the

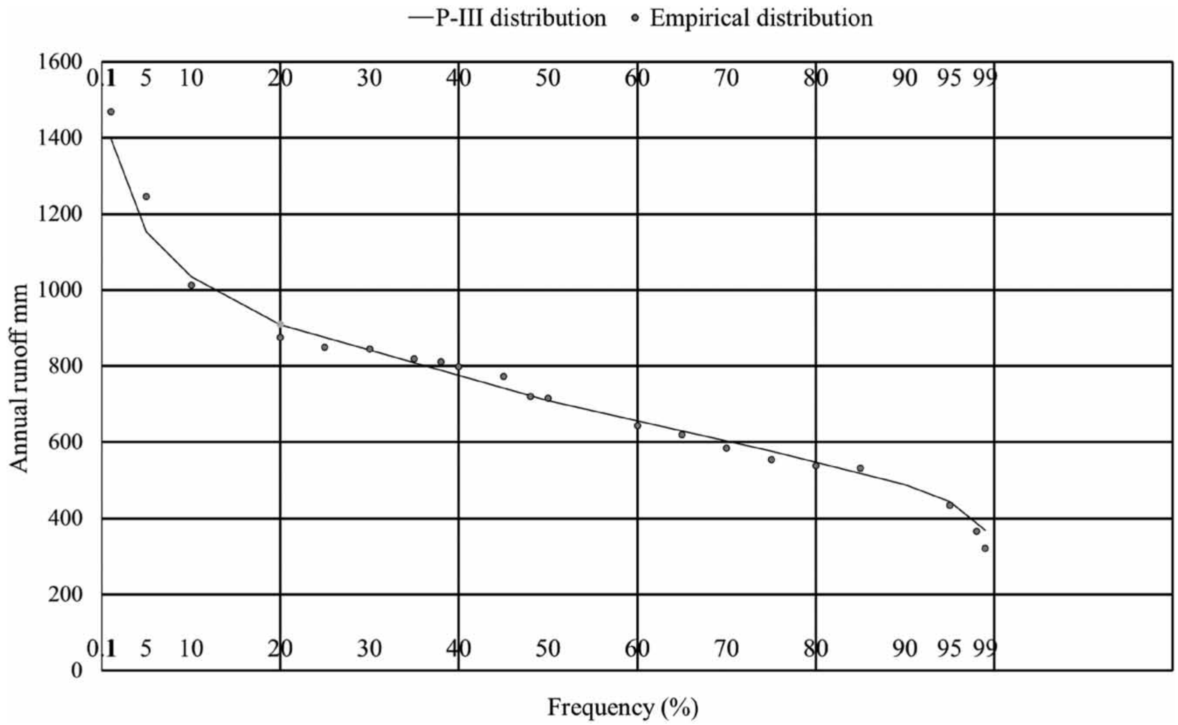


Figure 10 | P-III hydrological curves.

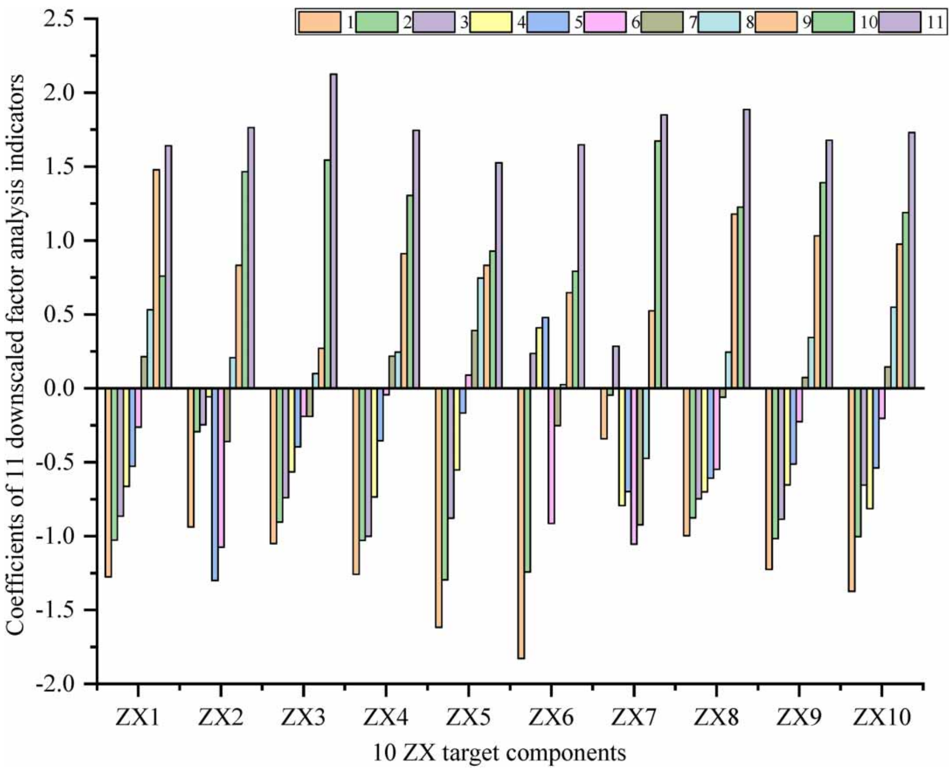


Figure 11 | Distribution of factor weight coefficients of multiple downscaling factors with multiple indicators.

results of data analysis using the SPSS software, the standardized factor coefficients of the 11 indicators were delineated sequentially in the radar charts. These results show the distribution of the 11 indicators collated into a single radar chart, facilitating the comparative analysis of their disparities. The radar chart is an intuitive tool that shows the correlation analysis results of each indicator that corresponds with its standardized factor coefficient. This presentation method provides a clearer depiction of the relationships and variations between the indicators in this study. Subsequently, the system analyzes these outcomes to establish prioritized composite indicators, which serve as the basis for configuring the reference weight outcomes in MOFILP. In particular, the IMOSFP model, which leveraged the AHP method, could achieve analogous analytical outcomes. However, the accuracy of these results is susceptible to disturbances due to the structural nuances of the AHP method. The AHP method involves hierarchical layers, including target, criterion, and indicator layers. During the construction phase of the criterion layer, a judgment matrix and consistency testing are required. Constructing this judgment matrix requires subjective opinions to compare the importance of indicators, thereby influencing the sorting outcomes. This subjective involvement introduces uncertainty into the decision-making process to yield relatively subjective analytical results. In contrast, the CCPRIP-MOFILP model, which integrates the PCA method, employed a dimensionality reduction factor analysis approach to circumvent the subjective ranking of the indicators. This strategy mitigated the amplification of uncertainty in the decision-making process, thereby ensuring a more objective and robust analytical framework.

The establishment of the CCPRIP-MOFILP model and subsequent analysis conducted in this study have culminated in a novel approach to address water utilization challenges in the midst of multiple uncertainties while advancing the development of the component factor validation system. This study delved into the realm of uncertainty, demonstrating the utilization of the FILP method to construct a fuzzy parameter processing system centered on triangular fuzzy sets. Within the framework of triangular membership functions, it is possible to determine the upper and lower bounds of fuzzy parameters while identifying the most reliable values. This indicates a quantitative relationship that can confine uncertainty values within a finite region. The stable range of the fuzzy set $\mu_{\tilde{N}}$, mapped onto the domain space X, was determined through the α-cut under various degree-of-membership conditions. Analogous procedures can be applied to other fuzzy membership functions, such as trapezoidal membership functions featuring intricate membership relations. These functions can also leverage the α-cut method to deal with hierarchical memberships within the optimization model and derive fuzzy quantitative relationships. This approach facilitates the more comprehensive handling of higher-order fuzzy problems.

This study proposed a random information processing mechanism, demonstrating the key role of the CCP model in addressing uncertainties characterized by random attributes. This mechanism aims to establish random probability distributions within the water supply space, which is contingent upon the varying risk probabilities of constraint violations. To derive the value of the surface water supply random variable, this study adapted a local stormwater runoff system. It calculated the annual runoff index, conforming to the gamma distribution, and constructed the P-III hydrologic curve. Its advantage is providing DMs with a scientific basis for formulating economic and environmental policies, and water resource planning objectives. This approach enables simultaneous risk management and the pursuit of profitability, in accordance with the requirements of the economy, market dynamics, ecological balance, and the population. The random information processing method provides a novel approach to resolve the uncertainty within quantitative relationships. Moreover, it provides a versatile application space in the optimization model, augmenting its flexibility and utility in real-world decision-making scenarios.

The MOFILP model can be used to obtain the optimal solution for managing agricultural water resources under multi-objective joint optimization conditions. By incorporating the PCA method, decision-making insights were further augmented through the correlation and significance analysis of the dimensionality reduction component factors. This method fortified the weight relationship within the multi-objective optimization model. Within the framework encompassing fuzzy sets, random distributions, and a multi-objective optimization system, the programming model navigated multiple uncertainties, providing an optimization framework characterized by unity in terms of approach but multifaceted in terms of execution. The modeling approach provides decision support solutions that cater to the various perspectives of DMs. By leveraging these alternative solutions, DMs can comprehensively evaluate various viewpoints, harnessing the feedback provided by the CCPRIP-MOFILP model in a timely manner. This, in turn, facilitates the optimization of agricultural water resource irrigation systems and crop-planting structures in Xiamen City. The iterative nature of this approach allows informed and adaptable decision-making in the management of agricultural water resources, aligning policies with evolving needs and considerations.

6. CONCLUSION

In the programming problem, linear programming is applicable to the scenario where the highest power of the variable in the objective function and constraint condition is only 1, which means the model can be solved by simplex method, and has the advantages of high efficiency and convenient expansion of the model, which is in line with the actual application scenarios of resource planning and production planning. However, in nonlinear programming, the highest power of the variable in the objective function and constraint conditions is greater than 1, which is accompanied by other basic elementary functions. This complex variable form is beyond the actual production norms, and the operation is quite difficult, which is not conducive to the construction of resource planning models, but it can be used in financial market analysis and engineering modeling in complex scenarios.

In this study, a MOFILP model integrated with PCA was proposed to optimize water resource allocation and agricultural operations in Xiamen City. The CCPRIP-MOFILP model systematically considered the benefits and losses of different decisions by examining the correlations between constituent factors and analyzing the uncertainty in agricultural water resource programming using fuzzy sets and stochastic probability distributions. The model established risk relationships and hierarchical structures based on the stochastic nature of the water resource supply and the complexity of fuzzy irrigation systems. This approach effectively solved water resource optimization problems and improved the stability and control of water resource utilization systems. The CCPRIP-MOFILP model was applied to the agricultural water resource allocation system in Xiamen City to maximize economic benefits, optimize agricultural water productivity, and minimize agricultural irrigation areas, while complying with constraints such as the water supply and demand equilibrium, limitations on agricultural irrigation areas, and ensuring food security. The study established six α-cut levels and four risk probabilities. Through hierarchical operations, global optimization results were obtained for single objectives. Following PCA, optimized allocation results were obtained for multiple objectives. This comprehensive approach allowed robust decision-making and efficient resource allocation in the complex domain of agricultural water resource management.

The results of this study can be summarized as follows. (i) With the increased risk probability P_i of violating the random probability distribution, augmenting the supply of agricultural water resources is essential to promote the agricultural development of Xiamen City. This helps DMs formulate either radical or conservative agricultural water resource supply strategies in accordance with the natural resource and economic development trends of the year. (ii) Within the trend of multi-objective synergistic optimization, the key components of optimization are the economic benefits, agricultural water resource productivity, and irrigated area. Prioritizing the supply of agricultural water resources and optimizing crop irrigation structures have emerged as the factors in water resource allocation. DMs are compelled to adopt conservative strategies for agricultural development if the risk of water scarcity increases or if the crop cultivation structure deteriorates. (iii) Fuzzy set and CCP methods effectively synergized with linear programming models, enhancing the optimization of water resource allocation systems. Concurrently, the employment of PCA methods aided in the rationalization and objective formulation of agricultural water resource optimization policies tailored to the needs of Xiamen City.

While this study endeavors to analyze various uncertainties and compare weight allocations, there are certain limitations inherent in the methodology employed for constructing the model. Firstly, while the research outlines methods for incorporating fuzziness, randomness, and objective weight allocations into a multi-objective linear programming model to establish a risk-based decision-making framework for water resource utilization in the study area, it somewhat neglects the examination of fuzziness and randomness in other industrial sectors within the model. Secondly, the study lacks a clear research strategy for addressing the potential impacts of climate change. Thirdly, although the study employs a variety of methods in conjunction with optimization efforts, it does not harness more advanced linear programming techniques to establish an interoperability pipeline between methods. Moving forward, enhancements to the existing linear programming method could involve the utilization of interval type-2 fuzzy set methodology, incorporating an examination of the secondary membership space of fuzzy sets. This would allow for the exploration of uncertainty in water usage sectors such as industry and commerce, thereby refining the sophistication of the programming model. Additionally, leveraging climate change prediction tools could prove instrumental in bolstering water resource management and agricultural cultivation analysis. The study could consider integrating remote sensing technology to develop a Geographic Information System (GIS) tailored to the study area. Such a system would facilitate access to uncertainty information within the model and enable the use of the GIS platform to model agricultural cropping patterns under various seasonal and climate change scenarios.

CREDIT AUTHORSHIP CONTRIBUTION STATEMENT

Ruoyu Yin: Conceptualization, Methodology, Software, Data curation, Formal analysis, Writing original draft preparation. Lei Jin: Supervision, Project administration, Funding acquisition, Resources, review & editing. Haiyan Fu: Supervision, Funding acquisition. Yurui Fan: Method instruction, review. Xi Zhang: Data collection, Investigation. Li Wang: Review, Rewriting & editing.

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DATA AVAILABILITY STATEMENT

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

CONFLICT OF INTEREST

The authors declare there is no conflict.

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