agronomy

MDPI

Article

A Fuzzy Credibility-Constrained Fuzzy Multi-Objective Programming Model for Optimizing Irrigation Strategies to Balance Citrus Yield and Quality Under Uncertainty

Fan Zhang [1,2], Xinyu Zhang [2], Zihan Wu [2], Shanshan Guo [1,*] and Sufen Wang [1]

[1] State Key Laboratory of Efficient Utilization of Agricultural Water Resources, China Agricultural University, Beijing 100083, China; zhang_fan@bjfu.edu.cn (F.Z.); wangsuf@cau.edu.cn (S.W.)
[2] Jixian National Forest Ecosystem Observation and Research Station, National Ecosystem Research Network of China (CNERN), School of Soil and Water Conservation, Beijing Forestry University, Beijing 100083, China; zhang_xinyu_9@bjfu.edu.cn (X.Z.); wuzihan54652388@bjfu.edu.cn (Z.W.)
* Correspondence: hbpxgss@cau.edu.cn

Abstract

Optimizing irrigation strategies to simultaneously enhance crop yield and fruit quality under water scarcity is a critical challenge for sustainable agriculture. This study addresses this challenge by developing a novel fuzzy credibility-constrained fuzzy multi-objective programming (FCC-FMOP) model for irrigation planning under uncertainty. The model incorporates stochastic hydrologic factors, decision-maker preferences, and complex interrelationships among fruit quality attributes and market dynamics. Applied to a citrus-producing region in Southwest China prone to seasonal drought, the approach demonstrates its capability to reconcile multiple objectives under fuzzy constraints. The key findings include the following: (1) The IVIF-TOPSIS analysis quantitatively revealed that yield was the paramount objective for decision-makers in the study region, followed by single fruit weight, highlighting the economic drivers that must be balanced with qualitative metrics. (2) The FCC-FMOP model effectively balances yield and quality objectives while adapting to real-world fuzzy constraints, proving to be both robust and practical. (3) Compared with conventional practices, the proposed irrigation strategy—calibrated under varying credibility levels (β = 0.55, 0.75, and 0.95)—significantly improves yield, fruit weight, hue angle, water content, and soluble sugar content. Performance evaluation using synthetic degree (SD), the sustainability index (SI), and approximation degree (AD) confirmed the model's superiority over single-objective models and conventional practices. The FCC-FMOP model provides a scalable and decision-maker-oriented tool for sustainable irrigation management in water-limited environments.

Keywords: irrigation scheduling; water scarcity; fuzzy multi-objective programming; citrus yield-quality tradeoff

check for updates

Academic Editor: Koffi Djaman

Received: 24 October 2025
Revised: 23 November 2025
Accepted: 25 November 2025
Published: 27 November 2025

Citation: Zhang, F.; Zhang, X.; Wu, Z.; Guo, S.; Wang, S. A Fuzzy Credibility-Constrained Fuzzy Multi-Objective Programming Model for Optimizing Irrigation Strategies to Balance Citrus Yield and Quality Under Uncertainty. *Agronomy* **2025**, *15*, 2739. https://doi.org/10.3390/agronomy15122739

Copyright: © 2025 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (https://creativecommons.org/licenses/by/4.0/).

1. Introduction

There has been a significant increase in the demand for the quantity and quality of fruits around the world [1]. However, the escalating resource scarcity caused by the same reasons are compelling us to maximize quantity and quality in a sustainable manner. Especially under a water-deficit scenario, it necessitates minimizing water consumption without compromising quality and yield. Citrus is one of the most widely cultivated and diverse fruit types globally. As a leading fruit in China's irrigated areas, it faces constraints

from limited water resources. Climate change and anthropogenic activities are two critical factors affecting citrus yield and quality. Frequent heatwaves and seasonal droughts have introduced significant uncertainty in citrus production [2,3]. In China, most citrus orchards rely on rain-fed or natural runoff irrigation methods [4]. The timing and volume of water supplies often fail to meet the physiological water requirements of citrus due to the features of rainfall and runoff. Therefore, there is an urgent need to develop appropriate irrigation strategies that balance fruit yield and quality, enhancing nutritional content and fruit set while efficiently conserving irrigation water [5,6].

Citrus is an economically vital fruit crop, and its quality attributes directly influence market value. Consequently, the demand for high-quality citrus is escalating. Global warming has escalated the frequency of extreme rainfall and evaporation events [7], making water scarcity a key constraint in agricultural production. In the major citrus-producing areas of southern China, rainfall is relatively abundant but unevenly distributed across time and space. Seasonal droughts and structural water shortages in the region lead to unstable citrus yields and compromised fruit quality. Crop quality encompasses appearance, nutritional value, storability, transportability, flavor profile, and suitability for processing. The determination of optimal deficit irrigation parameters and the execution of precision irrigation techniques are instrumental in improving fruit quality [4,8]. Deficit irrigation (DI) has demonstrated its efficacy in balancing vegetative and reproductive growth in fruits, curbing excessive development, and achieving water conservation while enhancing citrus quality [9]. DI effectively reduces the titratable acidity (TA) of citrus and elevates the maturity index (MI) [10]. Studies on the impact of DI on citrus have largely focused on applying appropriate water stress during non-critical periods of water demand [11]. Kuşçu et al. [12] suggest that excessive water stress, even outside sensitive periods, can impact fruit quality. This indicates that the effect of DI on citrus fruit quality is related to the level of water stress under deficit irrigation. Water stress during budbreak to bloom enhances citrus flowering [9], yet it may impair pollination, leading to excessive fruit drop [8]. When water stress is applied during the fruit expansion and early maturation stages, osmotic adjustments increase sugar concentration and acidity in citrus, thereby enhancing the acceptability of citrus flavor [13]. Additionally, severe water stress during the fruit expansion phase may affect fruit size [14]. The availability of water resources directly dictates citrus yield and quality. However, current research has not yet addressed how to simultaneously consider multiple quality indicators of crops and the impact of crop quality on market prices [15,16]. Meanwhile, there are few reports constructing quantitative models that account for the relationships among different quality indicators, as well as the responses of yield and quality to water quantity.

Irrigation water resource optimization is inherently complex, involving the randomness of rainfall and runoff and decision-makers' predictive inclinations regarding water availability and their preferences in the decision-making process. The unpredictability of rainfall and runoff introduces variability in water supply, affecting the reliability of irrigation systems and posing significant challenges to irrigation water management [17]. Decision-makers exhibit diverse attitudes towards water resource forecasting (optimistic, neutral, pessimistic), which influence their strategic planning and resource allocation [18]. Furthermore, prioritizing yield or quality in decision-making process can lead to different irrigation management strategies, each with a unique impact on water use efficiency and agricultural sustainability [19]. Incorporating these factors into irrigation water allocation decisions requires a sophisticated approach that can accommodate the multifaceted nature of the issue. Developing random fuzzy multi-objective optimization models that account for the stochastic nature of hydrological variables and decision-makers' subjective biases is crucial for devising effective water management strategies [20]. Additionally, understand-

ing how to balance the competing objectives of maximizing crop yield and quality while ensuring water resource sustainability is a key area that requires further research [21].

To bridge these research gaps, this study aims to develop an integrated modeling framework that can (1) quantitatively reconcile the trade-offs between citrus yield and multiple quality indicators (single fruit weight, hue angle, fruit water content, and soluble sugar); (2) explicitly incorporate decision-makers' subjective preferences and their attitudes towards hydrological uncertainty; (3) generate robust irrigation strategies under varying credibility levels. To this end, we propose a fuzzy credibility-constrained fuzzy multi-objective programming (FCC-FMOP) model, which integrates a modified Rao model for water–yield–quality relationships, the interval-valued intuitionistic fuzzy TOPSIS (IVIF-TOPSIS) method for weighting objectives, and fuzzy credibility constraints for handling uncertainty. Finally, the proposed framework is applied to a seasonal drought area in Southwest China to help achieve efficient and sustainable citrus production.

2. Methodology

In order to address the complex challenge of fruit yield and quality amidst multifaceted uncertainties from nature, the market, and decision-makers, and tailor optimal irrigation strategies for specific growth stages of fruits, three key issues should be investigated:

(1) Water volume significantly impacts not only crop yield but also quality, which necessitates the integration of water–yield and water–quality response relationships into the optimization of limited irrigation resources.

(2) Farmers' income is jointly influenced by yield and market prices determined by fruit quality and the supply–demand of markets. However, the intricate influence of yield and various quality metrics on income is ambiguous. The interrelationship of water, yield, and quality metrics makes it even more complicated. The allocation of irrigation water resources in districts should simultaneously account for the yield and the diverse quality indicators.

(3) Irrigation water resource optimization is a complex system. The stochastic characteristics of rainfall and runoff, decision-makers' forecasting tendencies towards available water (optimistic, moderate, pessimistic), and decision-making preferences (yield priority, quality priority) all influence decision-making schemes. Incorporating these factors into the allocation schemes of water resources in irrigation districts merits further research.

2.1. Rao Model for Simulating Water–Yield and Water–Quality Relationships

The water–yield relationship is usually estimated by the Rao model [22], and the model can be expressed as follows [23]:

$$\frac{Y_a}{Y_{ck}} = \prod_{i=1}^{I}\left[1 - \gamma_i\left(1 - \frac{ET_{ai}}{ET_{cki}}\right)\right] \quad (1)$$

where Y_a is the crop yield under water deficit treatments; Y_{ck} is potential maximum crop yield, which is assumed as the yield under the control treatment; ET_{ai} and ET_{cki} are the crop water consumption of water deficit treatments and the control treatment at stage i, respectively; and γ_i is Rao's water deficit sensitivity index of crop yield. Q_{ck} is defined as the fruit quality parameter under the control treatment. For the water–yield production function, the crop yield under the control treatment (Y_{ck}) is acceptable to replace the potential crop yield because the difference between the two is small. However, it is unreasonable to represent the fruit potential quality by Q_{ck}, since the fruit quality of citrus tends to increase first and then decrease with the aggravation of water deficit, especially for the chemical quality of fruit. Therefore, we modify $(1 - ET_{ai}/ET_{cki})$ in the Rao model to

$(1 - ET_{ai}/ET_{cki} - B_i)^2$, where B_i is the compensation value of relative water deficit in each stage when the fruit quality parameters are maximized. The quadratic relationship between the relative water consumption and the relative fruit quality parameters describes the response trend of fruit quality with the aggravation of water deficit. In addition, since the actual fruit quality may be greater than that of control treatment but the maximum value on the right side of Equation (1) is 1, we add the empirical coefficient A_0. The modified Rao model can be expressed as

$$Q_a = Q_{ck} \cdot A_0 \cdot \prod_{i=1}^{I} \left[1 - C_i \left(1 - \frac{ET_{ai}}{ET_{cki}} - B_i \right)^2 \right] \quad (2)$$

where Q_a and Q_{ck} are the fruit quality of water deficit treatments and the control treatment, respectively. In this study, the fruit quality metrics of citrus are the single fruit weight (SFW), hue angle (HA), fruit water content (FWC), and soluble sugar (SS); C_i is Q-Rao's water deficit sensitivity index of fruit quality parameter; and the other parameters are as previously defined.

2.2. Interval-Valued Intuitionistic Fuzzy TOPSIS (IVIF-TOPSIS)

The concept of intuitionistic fuzzy sets was proposed by Atanassov et al. [24], which includes three aspects of information: membership, non-membership, and hesitancy. It is more flexible and practical than traditional fuzzy sets in dealing with fuzziness and uncertainty. An intuitionistic fuzzy set in $X = \{x_1, \ldots, x_n\}$ can be defined as

$$\widetilde{A} = \{x, \mu_A(x), v_A(x) | x \in X\} \quad (3)$$

where $\mu_A(x)$ and $v_A(x)$ are the membership and non-membership functions of an element x $\in$ X, respectively, with the condition $0 \leq \mu_A(x) + v_A(x) \leq 1$. The hesitancy degree of decision-makers is measured by $\pi_A(x) = 1 - \mu_A(x) + v_A(x)$. However, sometimes it is difficult to express the specific values of membership, non-membership, and hesitation in the [0,1] interval. To solve this problem, Atanassov and Gargov [24] proposed interval intuitionistic fuzziness. The membership and non-membership degrees in interval-valued intuitionistic fuzzy sets (IVIFSs) are represented by subsets in the interval [0,1]. An interval-valued triangle intuitionistic fuzzy set (IVIFS) in X is defined as

$$\widetilde{A}^{\pm} = \{x, \mu_A^{\pm}(x), v_A^{\pm}(x) | x \in X\} \quad (4)$$

where $\mu_A^{\pm}(x)$ and $v_A^{\pm}(x)$ are interval numbers within [0,1]. For each x, the $\mu_A^{\pm}(x)$ and $v_A^{\pm}(x)$ can be described as intervals such as [a,b] and [c,d], and thus Equation (4) is simplified as $\widetilde{A}^{\pm} = \{[a, b], [c, d]\}$, where $b + d \leq 1$. Taking the most commonly used triangular fuzzy number as an example, the typical intuitionistic fuzzy set and interval-valued intuitionistic fuzzy set is shown in Figure 1.

The Technique for Order Preference by Similarity to an Ideal Solution (TOPSIS) is a widely used method in multiple criteria decision-making. When applying IVIF in TOPSIS, the importance weights of different criteria can be calculated through the following steps.

(1) Create a decision-maker group which consists of M decision-makers (DMs);
(2) Collect the importance judgment of each decision-maker towards different criteria (C), which are formulated by their knowledge and expertise;
(3) Formulate the judgment matrix according to the correspondence of linguistic variables and interval-valued intuitionistic fuzzy numbers (Table 1). The judgment matrix can be expressed as follows:

$$\begin{array}{c} \\ DM_1 \\ DM_2 \\ \vdots \\ DM_m \end{array} \begin{array}{c} \begin{array}{cccc} C_1 & C_2 & \cdots & C_n \end{array} \\ \begin{pmatrix} \widetilde{\alpha}_{11}^{\pm} & \widetilde{\alpha}_{21}^{\pm} & \cdots & \widetilde{\alpha}_{n1}^{\pm} \\ \widetilde{\alpha}_{12}^{\pm} & \widetilde{\alpha}_{22}^{\pm} & \cdots & \widetilde{\alpha}_{n2}^{\pm} \\ \vdots & \vdots & \ddots & \vdots \\ \widetilde{\alpha}_{1m}^{\pm} & \widetilde{\alpha}_{2m}^{\pm} & \cdots & \widetilde{\alpha}_{nm}^{\pm} \end{pmatrix} \end{array} \tag{5}$$

where $\widetilde{\alpha}_{nm}^{\pm}$ is fuzzy number of C_n and DM_m.

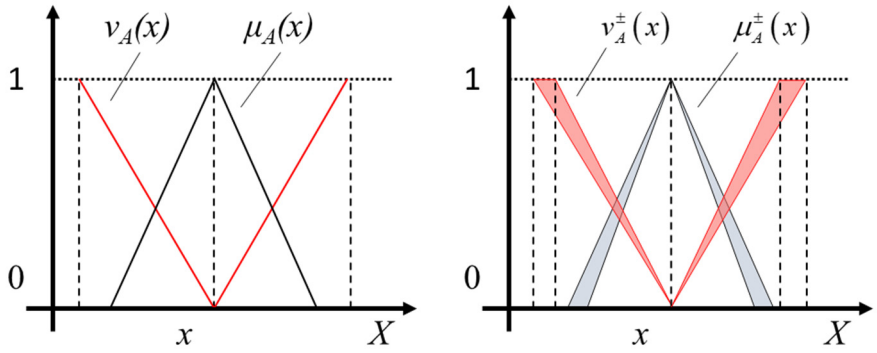


Figure 1. Typical triangle intuitionistic fuzzy set (**a**) and interval-valued triangle intuitionistic fuzzy set (**b**).

Table 1. Correspondence of linguistic variables and interval-valued intuitionistic fuzzy numbers [25].

Linguistic Variables	Interval-Valued Intuitionistic Fuzzy Numbers
Very important (VI)	([0.80, 0.90], [0.05, 0.10])
Important (I)	([0.65, 0.75], [0.10, 0.20])
Medium (M)	([0.45, 0.55], [0.35, 0.45])
Unimportant (U)	([0.25, 0.35], [0.55, 0.65])
Very unimportant (VU)	([0.00, 0.10], [0.80, 0.90])

(4) Calculate average interval fuzzy number $(\widetilde{r}_1^{\pm}, \widetilde{r}_2^{\pm}, \ldots, \widetilde{r}_m^{\pm})$ of Mth decision-makers through the following equation [21]:

$$\widetilde{r}_n^{\pm} = \sum_{m=1}^{M} \frac{1}{M} \widetilde{r}_{nm}^{\pm} = \left(\begin{array}{c} \left[1 - \prod_{m=1}^{M} (1 - a_{nm})^{1/\mathrm{M}}, 1 - \prod_{m=1}^{M} (1 - b_{nm})^{1/\mathrm{M}} \right], \\ \left[\prod_{m=1}^{M} (c_{nm})^{1/\mathrm{M}}, \prod_{m=1}^{M} (d_{nm})^{1/\mathrm{M}} \right] \end{array} \right) \tag{6}$$

where $\widetilde{\alpha}_{nm}^{\pm} = ([a_{nm}, b_{nm}], [c_{nm}, d_{nm}])$.

(5) Calculate interval-valued intuitionistic fuzzy positive ( ) and negative ( ) ideal rating.

For positive criteria

$$\widetilde{r}_n^{best} = \left(\begin{array}{c} [\max(a_{n1}, a_{n2}, \cdots, a_{nm}), \max(b_{n1}, b_{n2}, \cdots, b_{nm})], \\ [\min(c_{n1}, c_{n2}, \cdots, c_{nm}), \min(d_{n1}, d_{n2}, \cdots, d_{nm})] \end{array} \right) \tag{7}$$

$$\widetilde{r}_n^{worst} = \left(\begin{array}{c} [\min(a_{n1}, a_{n2}, \cdots, a_{nm}), \min(b_{n1}, b_{n2}, \cdots, b_{nm})], \\ [\max(c_{n1}, c_{n2}, \cdots, c_{nm}), \max(d_{n1}, d_{n2}, \cdots, d_{nm})] \end{array} \right) \tag{8}$$

For negative criteria

$$\widetilde{r}_n^{best} = \begin{pmatrix} [\min(a_{n1}, a_{n2}, \cdots, a_{nm}), \min(b_{n1}, b_{n2}, \cdots, b_{nm})], \\ [\max(c_{n1}, c_{n2}, \cdots, c_{nm}), \max(d_{n1}, d_{n2}, \cdots, d_{nm})] \end{pmatrix} \quad (9)$$

$$\widetilde{r}_n^{worst} = \begin{pmatrix} [\max(a_{n1}, a_{n2}, \cdots, a_{nm}), \max(b_{n1}, b_{n2}, \cdots, b_{nm})], \\ [\min(c_{n1}, c_{n2}, \cdots, c_{nm}), \min(d_{n1}, d_{n2}, \cdots, d_{nm})] \end{pmatrix} \quad (10)$$

(6) Calculate the distance between the aggregated fuzzy weight of each criterion and the best (d_n^+) or worst (d_n^-) values using Euclidean distance as follows [26]:

$$d_n^+ = \sqrt{\frac{1}{4} \cdot \left[\left(a_n^+ - a_n'\right)^2 + \left(b_n^+ - b_n'\right)^2 + \left(c_n^+ - c_n'\right)^2 + \left(d_n^+ - d_n'\right)^2 \right]} \quad (11)$$

$$d_n^- = \sqrt{\frac{1}{4} \cdot \left[\left(a_n^- - a_n'\right)^2 + \left(b_n^- - b_n'\right)^2 + \left(c_n^- - c_n'\right)^2 + \left(d_n^- - d_n'\right)^2 \right]} \quad (12)$$

where $\widetilde{r}_n^{best} = ([a_n^+, b_n^+], [c_n^+, d_n^+])$, $\widetilde{r}_n^{worst} = ([a_n^-, b_n^-], [c_n^-, d_n^-])$, $\widetilde{r}_n^{\pm} = ([a_n', b_n'], [c_n', d_n'])$.

(7) Generate the closeness coefficient (CC) of each criterion as follows:

$$CC_n = \frac{d_n^-}{d_n^+ + d_n^-} \quad (13)$$

(8) Obtain the weight (w_n) of each criterion as follows:

$$w_n = \frac{CC_n}{\sum_{n=1}^{N} CC_n} \quad (14)$$

2.3. Fuzzy Credibility-Constrained Fuzzy Multi-Objective Programming Model

The fuzzy credibility-constrained fuzzy multi-objective programming (FCC-FMOP) model is integrated using fuzzy credibility-constrained programming (FCCP) and fuzzy multi-objective programming (FMOP). The FCC-FMOP approach leverages the strengths of two techniques to simultaneously handle multiple conflicting objectives, fuzzy goals, and fuzzy constraints in real-world problems. The FCC-FMOP model can be expressed as follows [27]:

$$\min \widetilde{F}_u = e \cdot x \lesssim \widetilde{F}_u^0, \ \ u = 1, \ldots, p \quad (15)$$

$$\max \widetilde{F}_l = h \cdot x \gtrsim \widetilde{F}_l^0, \ \ l = p+1, \ldots, N \quad (16)$$

s.t.

$$Cr[g(x) \leq \widetilde{o}] \geq \beta \quad (17)$$

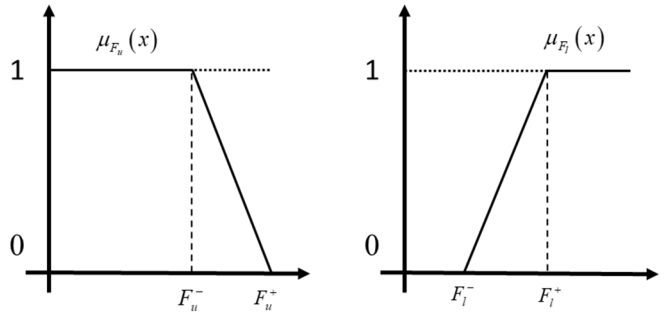
$$Cr[k(x) \geq \widetilde{q}] \geq \beta \quad (18)$$

$$z(x) \leq t \quad (19)$$

$$x \geq 0 \quad (20)$$

where x is the decision variable; ~ denotes the fuzzy environment; the signs $\lesssim$ and $\gtrsim$ represent essentially smaller than or equal to and greater than or equal to; e and h are coefficients of objective function; $\widetilde{F}_u$ and $\widetilde{F}_l$ are uth negative (the smaller the better) and lth positive (the larger the better) objectives, and the membership function of them is shown in Figure 2; $\widetilde{F}_u^0$ and $\widetilde{F}_l^0$ are the aspiration levels that the decision-maker wants to obtain [28]; Cr is the credibility measure of the fuzzy event; $g(x)$, $k(x)$, and $z(x)$ are functions with x as

the independent variable; t is the deterministic constraint; $\widetilde{o}$ and $\widetilde{q}$ are fuzzy numbers in the constraints; and β is the credibility level of the fuzzy event.



(a) Membership function of negative objectives (b) Membership function of positive objectives

Figure 2. The membership functions of negative ( ) (**a**) and positive ( ) (**b**) objectives.

To solve the FCC-FMOP model, the fuzzy relationship in objectives and fuzzy numbers in constraints should be handled first, and then the multi-objective model is transformed into a single-objective model to generate optimization results. The specific solving steps can be found as follows:

(1) Formulate the FCC-FMOP model.

(2) Transform the fuzzy credibility constraints as general linear constraints [29]. When the fuzzy numbers are triangular fuzzy numbers such as $\widetilde{o} = (\underline{o}, o, \overline{o})$, $\widetilde{q} = \left(\underline{q}, q, \overline{q}\right)$, and $\beta > 0.5$, the fuzzy credibility constraints $Cr[g(x) \leq \widetilde{o}] \geq \beta$ and $Cr[k(x) \geq \widetilde{q}] \geq \beta$ can be converted as $g(x) \leq o + (1 - 2 \cdot \beta) \cdot (o - \underline{o})$ and $q + (2 \cdot \beta - 1) \cdot (\overline{q} - q) \leq k(x)$, respectively. After determining the value of β, the FCC-FMOP model can be transformed into a typical FMOP model.

(3) Collect the judgment about the importance of different objectives, and calculate the importance weight w_n of each objective through IVIF-TOPSIS.

(4) Establish the membership function of objectives as follows [30]:

For negative objectives

$$\mu_{F_u}(x) = \begin{cases} 1 & , F_u(x) \leq F_u^- \\ \frac{F_u^+ - F_u(x)}{F_u^+ - F_u^-} & , F_u^- \leq F_u(x) \leq F_u^+ \\ 0 & , F_u^+ \leq F_u(x) \end{cases} \tag{21}$$

For positive objectives

$$\mu_{F_l}(x) = \begin{cases} 1 & , F_l^+ \leq F_l(x) \\ \frac{F_l(x) - F_l^-}{F_l^+ - F_l^-} & , F_l^- \leq F_l(x) \leq F_l^+ \\ 0 & , F_l(x) \leq F_l^- \end{cases} \tag{22}$$

(5) Transform the FMOP model as the following single-objective model with the goal of maximizing satisfaction λ_n based on w_n and the membership function of objectives [31]:

$$\max \sum_{n=1}^{N} w_n \cdot (\lambda_u + \lambda_l), \quad n = u + l \tag{23}$$

s.t.

$$\lambda_u \le \frac{F_u^+ - F_u(x)}{F_u^+ - F_u^-} \tag{24}$$

$$\lambda_l \le \frac{F_l(x) - F_l^-}{F_l^+ - F_l^-} \tag{25}$$

$$g(x) \le o + (1 - 2 \cdot \beta) \cdot (o - \underline{o}) \tag{26}$$

$$q + (2 \cdot \beta - 1) \cdot (\overline{q} - q) \le k(x) \tag{27}$$

$$z(x) \le t \tag{28}$$

$$x \ge 0 \tag{29}$$

(6) Code the above optimization model in software (such as MATLAB, GAMS, and LINGO) to generate the optimization results.
(7) Change the credibility level β and solve the model under each credibility level.
(8) Obtain the solution set of the FCC-FMOP model under different decision-making preferences of decision-makers.

2.4. Model Performance Evaluation Method

To examine the performance of the proposed model in dealing with multiple objectives, three indexes, including synthetic degree (SD), sustainability index (SI), and approximation degree of ideal objective value (AD), are involved for evaluating the comprehensive performance of the optimization model [27].

Synthetic degree (SD):

$$SD = \frac{1}{2} \cdot \sin(\frac{360^\circ}{N}) \cdot \sum_{n=1}^{N} (w_n \varphi_n \cdot w_{n+1} \varphi_{n+1}) \tag{30}$$

$$\varphi = \frac{f_n - f_n^{\min}}{f_n^{\max} - f_n^{\min}} \tag{31}$$

$$\varphi = 1 - \frac{f_n - f_n^{\min}}{f_n^{\max} - f_n^{\min}} \tag{32}$$

Sustainability index (SI):

$$SI = \left(\prod_{n=1}^{N} w_n \varphi_n \right)^{\frac{1}{N}} \tag{33}$$

where N is the number of the objective; w_n is the weighted value of objective n; φ_n is the normalized value of objective n ($w_{n+1}\varphi_{n+1} = w_1\varphi_1$); fn is the obtained value of objective n; fnmin and fnmax are the minimum and maximum values of objective n; Equations (31) and (32) are, respectively, for the objectives of 'the larger the better' and 'the smaller the better'.

The approximation degree of ideal objective value (AD) is calculated as follows:

$$AD = \frac{D^-}{D^- + D^+} \tag{34}$$

$$D^+ = \sqrt{\sum_{n=1}^{N} (w_n \sigma_n - w_n \sigma_n^+)^2} \tag{35}$$

$$D^- = \sqrt{\sum_{n=1}^{N} (w_n \sigma_n - w_n \sigma_n^-)^2} \tag{36}$$

$$\sigma_n = \frac{f_{nm}}{\sqrt{\sum_{m=1}^{M} (f_{nm})^2}} \tag{37}$$

where D^+ and D^- are distances from obtained objective value to positive and negative ideal objective; ${\sigma_n}^+$ and ${\sigma_n}^-$ are positive and negative ideal objective values of objective n; σ_n is the standardized value of objective n; M is the number of models participating in the evaluation; and f_{nm} is the value of the nth target and the mth model.

3. Case Study

3.1. Study Area

Pujiang County (Figure 3), located in Chengdu, Sichuan Province, China (30.32 °N, 103.43 °E), is renowned for its citrus cultivation. The region has a subtropical humid monsoon climate, fertile soils, and diverse topography. The annual average rainfall is 1113.82 mm, the daily average relative humidity is 81.49%, and the daily average temperature is 16.59 °C. The citrus industry in Pujiang County is influenced by variable rainfall and fluctuating market prices, affecting both yield and quality. Climate change, frequent high temperatures, and seasonal droughts exacerbate water scarcity, posing a significant constraint to citrus production in the county.

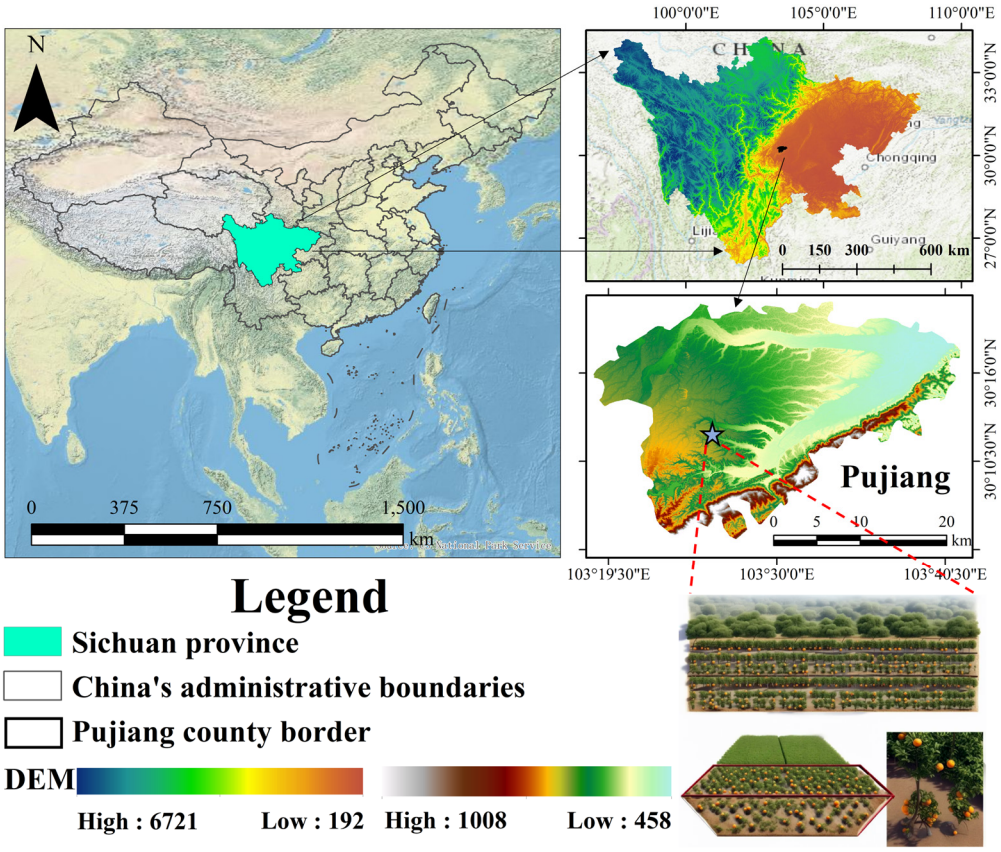


Figure 3. Geolocation of the study area.

To address these challenges effectively, we introduce the FCC-FMOP model. This model integrates decision-makers' subjective tendencies with stochastic elements, balancing the competing objectives of maximizing citrus yield, optimizing quality, and ensuring water resource sustainability. It formulates appropriate strategies for the optimization of irrigation water allocation, supporting the sustainable production of citrus in Pujiang County.

3.2. Model Formulation

For optimizing the irrigation schedule of citrus planting, the fuzziness from decision-maker's judgment and conflicting objectives can be addressed by formulating the FCC-FMOP model. The model assumes that irrigation water can be supplied as scheduled. This represents an ideal scenario for identifying the biophysical potential of optimized irrigation. In practice, water delivery may be constrained by infrastructure capacity, water rights, or policy regulations. The results should thus be interpreted as a target strategy, and the model can be adapted to incorporate specific local water delivery constraints in future applications. The parameters used in the FCC-FMOP model can be found in Table 2 and the specific objectives and constraints are shown as follows.

Table 2. Parameters used in the FCC-FMOP model.

Indices	Definition
i	Index of growth stage (i = 1, 2, 3, 4)
t	Index of irrigation period (t = 1, 2, . . ., 36)
max	Abbreviation for maximum
min	Abbreviation for minimum
Decision variables	
IW_t	Water consumption of fruit trees during period t
IRR_t	Irrigation water amount during period t
Parameters	
A_0^{SFW}, A_0^{HA}, A_0^{FWC}, A_0^{SS}	Empirical coefficient of single fruit weight, hue angle, fruit water content, and soluble sugar, respectively
AW_t	Available water for irrigation citrus (mm)
R_t	Surplus available water (mm)
B_i^{SFW}, B_i^{HA}, B_i^{FWC}, B_i^{SS}	Relative water deficit value of single fruit weight, hue angle, fruit water content, and soluble sugar during growth stage i, respectively
C_i^{SFW}, C_i^{HA}, C_i^{FWC}, C_i^{SS}	Rao's water deficit sensitivity index of single fruit weight, hue angle, fruit water content, and soluble sugar during growth stage i, respectively
$\widetilde{DI}$	Maximum irrigation quota under deficit irrigation, which is a fuzzy number (mm)
EP_i and EP_t	Effective precipitation during growth stage i and irrigation period t (mm)
ET_{cki}	Evapotranspiration of control treatment during growth stage i (mm)
F1, . . ., F5	Objective function of yield (kg), single fruit weight (g), hue angle, fruit water content (%), and soluble sugar (mg/mL), respectively
$\widetilde{WD}_t$	Minimum water demand during irrigation period t (mm)
Y_{ck}, SFW_{ck}, HA_{ck}, FWC_{ck}, and SS_{ck}	Yield (kg), single fruit weight (g), hue angle, fruit water content (%), and soluble sugar (mg/mL) under control treatment, respectively.
β	Credibility level of fuzzy event
γ_i	Rao's water deficit sensitivity index
η	Irrigation water use efficiency

3.2.1. Objectives

Generally, the goal of farmers is to gain more economic benefit through increasing yield and quality. Therefore, the objectives include maximizing yield, single fruit weight, hue angle, fruit water content, and soluble sugar.

(1) Maximizing yield is calculated as follows:

$$Max\ F_1 = Y_{ck} \cdot \prod_{i=1}^{I} \left[1 - \gamma_i \left(1 - \frac{IW_i}{ET_{cki}} \right) \right] \geq \widetilde{Y}_0 \tag{38}$$

(2) Maximizing single fruit weight is calculated as follows:

$$Max\ F_2 = SFW_{ck} \cdot A_0^{SFW} \cdot \prod_{i=1}^{I} \left[1 - C_i^{SFW} \left(1 - \frac{IW_i}{ET_{cki}} - B_i^{SFW} \right)^2 \right] \geq \widetilde{SFW_0} \tag{39}$$

(3) Maximizing hue angle is calculated as follows:

$$Max\ F_3 = HA_{ck} \cdot A_0^{HA} \cdot \prod_{i=1}^{I} \left[1 - C_i^{HA} \left(1 - \frac{IW_i}{ET_{cki}} - B_i^{HA} \right)^2 \right] \geq \widetilde{HA_0} \tag{40}$$

(4) Maximizing fruit water content is calculated as follows:

$$Max\ F_4 = FWC_{ck} \cdot A_0^{FWC} \cdot \prod_{i=1}^{I} \left[1 - C_i^{FWC} \left(1 - \frac{IW_i}{ET_{cki}} - B_i^{FWC} \right)^2 \right] \geq \widetilde{FWC_0} \tag{41}$$

(5) Maximizing soluble sugar is calculated as follows:

$$Max\ F_5 = SS_{ck} \cdot A_0^{SS} \cdot \prod_{i=1}^{I} \left[1 - C_i^{SS} \left(1 - \frac{IW_i}{ET_{cki}} - B_i^{SS} \right)^2 \right] \geq \widetilde{SS_0} \tag{42}$$

3.2.2. Constraints

(1) The correspondence of the irrigation period and growth stage is calculated as follows:

$$EP_i = \begin{cases} EP_1 = \sum_{t=1}^{t=3} EP_t \\ EP_2 = \sum_{t=4}^{t=9} EP_t \\ EP_3 = \sum_{t=10}^{t=24} EP_t \\ EP_4 = \sum_{t=25}^{t=36} EP_t \end{cases} \tag{43}$$

$$IW_i = \begin{cases} IW_1 = \sum_{t=1}^{t=3} IW_t \\ IW_2 = \sum_{t=4}^{t=9} IW_t \\ IW_3 = \sum_{t=10}^{t=24} IW_t \\ IW_4 = \sum_{t=25}^{t=36} IW_t \end{cases} \tag{44}$$

(2) The actual evapotranspiration constraint is calculated as follows:

$$IW_t = \begin{cases} ET_{\max}\ ,\ \ 0 \leq EP_t - ET_{\max} \\ IRR_t + EP_t,\ \ 0 > EP_t - ET_{\max} \end{cases} \tag{45}$$

(3) The available water constraint is calculated as follows:

$$R_0 = 0 \tag{46}$$

$$R_{(t-1)} = R_0 + AW_{(t-1)} - IRR_{(t-1)} \quad (t = 2) \tag{47}$$

$$R_{(t-1)} = R_{(t-2)} + AW_{(t-1)} - IRR_{(t-1)} \quad (t > 2) \tag{48}$$

$$IRR_t \leq AW_{(t)} + R_0 \quad (t = 1) \tag{49}$$

$$IRR_t \leq AW_{(t)} + R_{(t-1)} \quad (t > 1) \tag{50}$$

(4) The deficit irrigation constraint is calculated as follows:

$$Cr\left(\sum_{t=1}^{T} IRR_t \leq \widetilde{DI}\right) \geq \beta \tag{51}$$

(5) The water demand constraint is calculated as follows:

$$Cr\left(\widetilde{WD}_t \leq IRR_t + EP_t\right) \geq \beta, \quad \forall t \tag{52}$$

(6) The non-negative constraint is calculated as follows:

$$IRR_t \geq 0, \quad \forall t \tag{53}$$

3.3. Data Collection

The relevant data, derived from local statistical yearbooks and experimental studies by Chen et al., encompass soil moisture content and evapotranspiration in citrus cultivation [32]. The time intervals were set at 10 days, resulting in 36 data periods over the span of one year. The parameters required for the Rao model, as determined by Chen et al.'s research, are presented in Table 3. The fuzzy numbers of water shortage irrigation and citrus quality are presented in Table 4.

Table 3. Coefficients of Rao model [2].

Items	Parameters	Growth Stage of Citrus				Empirical Coefficient A_0
		Stage I	Stage II	Stage III	Stage IV	
Single fruit weight	C_i	−0.461	0.603	0.683	0.395	1.019
	B_i	0.000	0.038	0.000	0.072	
Hue angle	C_i	0.218	0.439	0.352	0.335	0.985
	B_i	0.173	0.000	0.066	0.158	
Fruit water content	C_i	0.012	0.238	0.186	0.018	1.005
	B_i	0.000	0.154	0.003	0.000	
Soluble sugar	C_i	−0.227	0.643	0.508	1.651	1.099
	B_i	0.263	0.124	0.000	0.233	
Yield	γ_i	0.101	0.157	0.376	0.115	-

Table 4. Fuzzy numbers of water shortage irrigation and citrus quality.

Items	Fuzzy Numbers
I (mm)	(142.5, 172.5, 202.5)
Yield (kg)	(33,500, 34,000, 34,500)
Single fruit weight (g)	(170, 180, 190)
Hue angle	(64, 64.5, 65)
Fruit water content (%)	(74.5, 75, 75.5)
Soluble sugar (mg/mL)	(110, 120, 130)

In addition, a panel of four experts, comprising two senior agronomists specialized in citrus production and two agricultural water resource managers, was convened to

determine the relative importance of the optimization objectives. The selection criteria for experts were a minimum of 10 years of relevant field experience. The experts' judgements were collected independently using the linguistic variables defined in Table 1.

The required hydrological and crop data, including soil moisture content, evapotranspiration, and effective precipitation, were obtained from local statistical yearbooks and the experimental study of Chen et al. [32]. The parameters for the modified Rao model were directly adopted from Chen et al. [4], as listed in Table 3.

4. Results Analysis and Discussion

4.1. The Importance Weights of Yield and Quality Indicators

The score results in Table 5 show that all four experts assigned the highest VI importance level to yield, indicating a strong preference for yield over other quality metrics. Single fruit weight and fruit water content each received VI level preferences from two experts, suggesting that these attributes, in addition to yield, are also significant for decision-making. Utilizing the IVIF-TOPSIS approach, the importance weights for yield and quality were determined. The resulting weight ranking of yield and quality indicators presented in Table 5 indicate that yield ranks as the highest priority, followed by single fruit weight, fruit weight content, and soluble sugar. Hue angle is considered the least important among the five criteria. The weight ranking accords closely with the score results of the experts, showing the efficiency of the IVIF-TOPSIS approach in quantifying decision-makers' preferences.

Table 5. Decision propensity ranking obtained by IVIF-TOPSIS.

Criteria	DM1	DM2	DM3	DM4	Aggregated Fuzzy Weight	d^+	d^-	CC_j	W_j	Rank
Yield	VI	VI	VI	VI	([0.80, 0.90], [0.05, 0.10])	0.02	0.66	0.98	0.215	1
Single fruit weight	I	VI	I	VI	([0.74, 0.84], [0.08, 0.15])	0.03	0.61	0.95	0.209	2
Hue angle	M	I	M	I	([0.66, 0.77], [0.16, 0.25])	0.12	0.48	0.80	0.177	5
Fruit water content	VI	I	M	VI	([0.70, 0.82], [0.15, 0.23])	0.05	0.57	0.92	0.203	3
Soluble sugar	VI	I	I	M	([0.77, 0.87], [0.06, 0.13])	0.06	0.55	0.89	0.197	4

4.2. Optimal Irrigation Strategies Balancing Yield and Quality

Utilizing the subjective decision-making criteria established above, we integrate the water–yield–quality nexus. Based on this, the FCC-FMOP model is employed to derive the optimal irrigation strategies that balance both yield and quality. The model provides allocation plans for water distribution at various growth stages under different credibility levels.

Figure 4 depicts the weighted satisfaction (objective membership of fuzzy goal programming × weight coefficient) and optimization objectives across different credibility levels. The results show that the optimized strategies derived from the FCC-FMOP model significantly outperform the baseline of the status quo. At a credibility level of $\beta = 0.55$, it yields a 0.59% increase in yield, a 45.68% increase in single fruit weight, a 2.95% improvement in hue angle, a 4.20% increase in fruit water content, and an 8.21% decrease in soluble sugar. When the credibility level is raised to $\beta = 0.75$, the respective improvements are 8.73%, 41.36%, 2.62%, 4.20%, and 11.79%, respectively. At the highest credibility level of $\beta = 0.95$, the enhancements of soluble sugars increase, but the enhancements of other qualities decrease, with increases of 7.91% in yield, 37.90% in single fruit weight, 2.46% in hue angle, 4.20% in fruit water content, and 15.37% in soluble sugar. This study demonstrates that the FCC-FMOP model, at varying credibility levels, significantly improves key fruit quality parameters. The model's application at $\beta = 0.55$, $\beta = 0.75$, and $\beta = 0.95$ consistently yields positive outcomes, with the highest improvements observed at the lowest credibility level ($\beta = 0.55$), where yield and single fruit weight show the most significant increases of 9.59% and 45.68%, respectively. These results underscore the

model's potential for optimizing fruit production and quality under different risk levels. The model substantially improves the current production and quality of citrus cultivation, aligning with the subjective preferences of decision-makers and stakeholders.

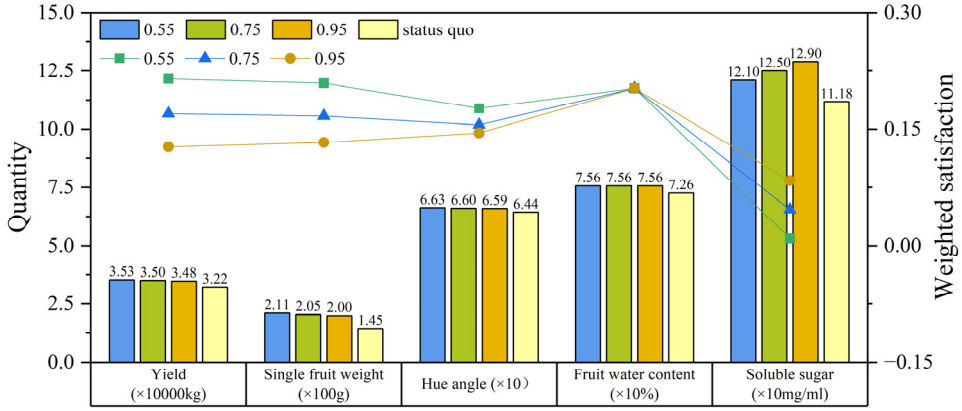


Figure 4. Weighted satisfaction and optimization objective results under varying levels of credibility.

The trade-offs among objectives became evident as the credibility level (β) increased. The optimized yield, single fruit weight, and hue angle showed a decreasing trend from $\beta = 0.55$ to $\beta = 0.95$, whereas soluble sugar content improved. This inverse relationship can be explained by the model's response to a more conservative water allocation strategy under higher β levels. A higher β signifies a greater aversion to risk, leading the model to reserve water for more critical periods, thereby inducing mild water stress during certain growth stages. This stress is known to concentrate solutes like sugars in the fruit [10,13], but at the cost of reducing overall biomass accumulation and fruit size [14]. As credibility increased, a decline was observed in weighted satisfaction with yield, single fruit weight, and fruit water content, while weighted satisfaction with soluble sugar content improved. Notably, weighted satisfaction with fruit water content remained stable. With the increasing drought stress and citrus comprehensive quality (at a credibility level of $\beta = 0.95$), the goal is to balance yield, single fruit weight, hue angle, and soluble sugar, while ensuring fruit water content. The results in Figure 4 show the advantage of the optimization model, and the confliction among the five objectives and the analysis of different scenarios can help decision-makers recognize the change in different objectives and make reasonable and sustainable decisions for citrus production.

The optimal irrigation strategies across different credibility levels are shown in Figure 5. This study zeroes in on the pivotal growth stages within the citrus maturation process: the developmental stage, the blooming stage, the nascent fruiting stage, and the zenith fruiting stage. During the developmental and blooming stages, up to the first half of the nascent fruiting stage, irrigation under all three credibility scenarios is set to zero. This implies that rainfall can meet the water demand of these stages and no extra irrigation is required for nearly 180 days. At all credibility levels, water allocation is predominantly concentrated within the period from $t = 20$ to $t = 26$. When $\beta = 0.55$, irrigation water exhibits a relatively high allocation between $t = 20$ and $t = 24$, followed by a decline at $t = 25$, and subsequently rises again. At $\beta = 0.75$, compared with lower credibility levels, the allocation to irrigation water increases at $t = 25$ but decreases at $t = 26$. At $\beta = 0.95$, in contrast to $\beta = 0.75$, a marked reduction in irrigation water allocation is observed during $t = 20$ to $t = 22$. The results show that with the increase in credibility levels, as the irrigation water demand improves and the water availability decreases, the highest irrigation water allocation occurs at a credibility level of 0.55, exceeding by 6.62% and 15.41% in total irrigation consumption compared with the 0.75 and 0.95 scenarios.

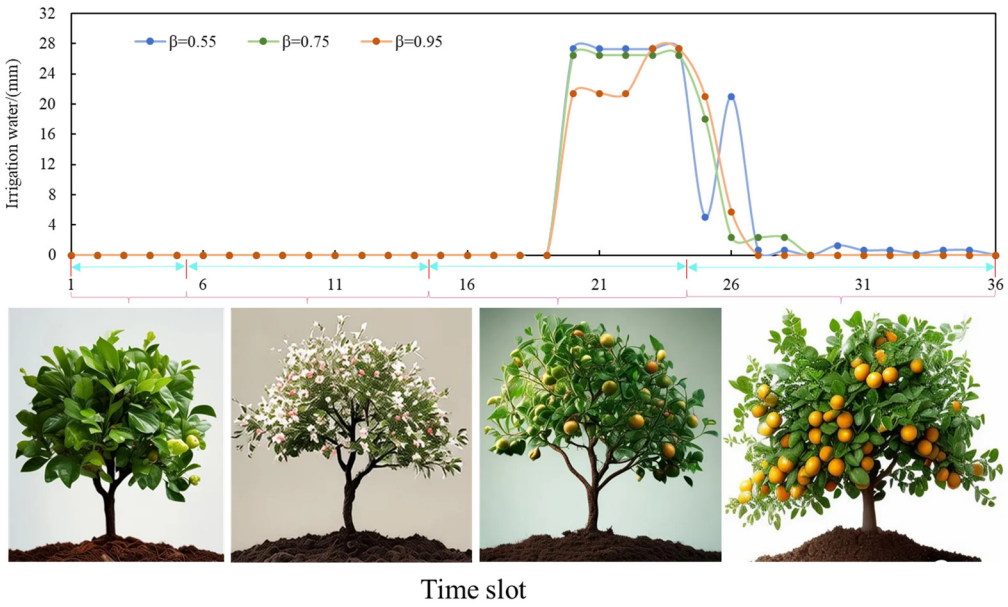


Figure 5. Optimized water distribution results under varying levels of credibility.

This indicates the significant influence of the evaluation of water situations from decision-makers on irrigation regulation. Overall, the trends of irrigation water use across the three credibility levels are similar. High irrigation water is maintained during the latter half of the nascent fruiting stage, with a certain level of irrigation water retained at the zenith fruiting stage to ensure complete fruit development in citrus.

4.3. Performance Evaluation of the FCC-FMOP Model

Compared with the simplistic assignment of subjective parameter coefficients when constructing a two-dimensional linear model, the FCC-FMOP model, which integrates decision tendency evaluation, fully accounts for the multiple preferences of decision-makers regarding citrus yield and quality. Utilizing single-objective models, we obtained optimal irrigation strategies for citrus yield and quality metrics across three levels of credibility and varying objective preferences. The results are detailed in Figure 6.

Since low credibility levels denote an optimistic evaluation of the whole situation, the comparison of the water allocation strategies in three scenarios could help decision-makers recognize the source of the possible high risk when choosing a low credibility scenario. Regarding irrigation strategies, the results show that before the zenith fruiting stage, the irrigation allocation across three credibility levels from single-objective models and FCC-FMOP is similar, which is consistent with the fact that the zenith fruiting stage is key to the fruit yield and quality. However, with the increase in credibility level from 0.55 to 0.95, the water allocation at the zenith fruiting stage has decreased for both single-objective models and FCC-FMOP, highlighting the necessity for increased flexibility in water resource supply at the zenith fruiting stage. Compared with single-objective models, the FCC-FMOP tends to decrease the water supply fluctuations to reduce water use and alleviate water deficit risk.

Meanwhile, a comparison of different models can help reveal the competition relationship among objectives and their preference for water deficit. At all credibility levels, the water allocation for maximizing yield and maximizing single fruit weight is highly coincident, showing the least competition between these two objectives. At credibility levels of $\beta = 0.55$ and $\beta = 0.75$, compared with the maximizing yield, maximizing hue angle and maximizing soluble sugar reduce the water allocation of $i = 24$ and later for all credibility levels, denoting that a water deficit in the zenith fruiting stage helps increase hue angle

and soluble sugar. At credibility levels of $\beta = 0.95$, the water allocation of maximizing hue angle is consistent to maximizing yield, while maximizing soluble sugar reduces irrigation water at the nascent fruiting stage and increases irrigation water at the zenith fruiting stage. There is a significant difference in water allocation for maximizing fruit water content at different credibility levels, showing that the water distribution has little influence on the fruit water content.

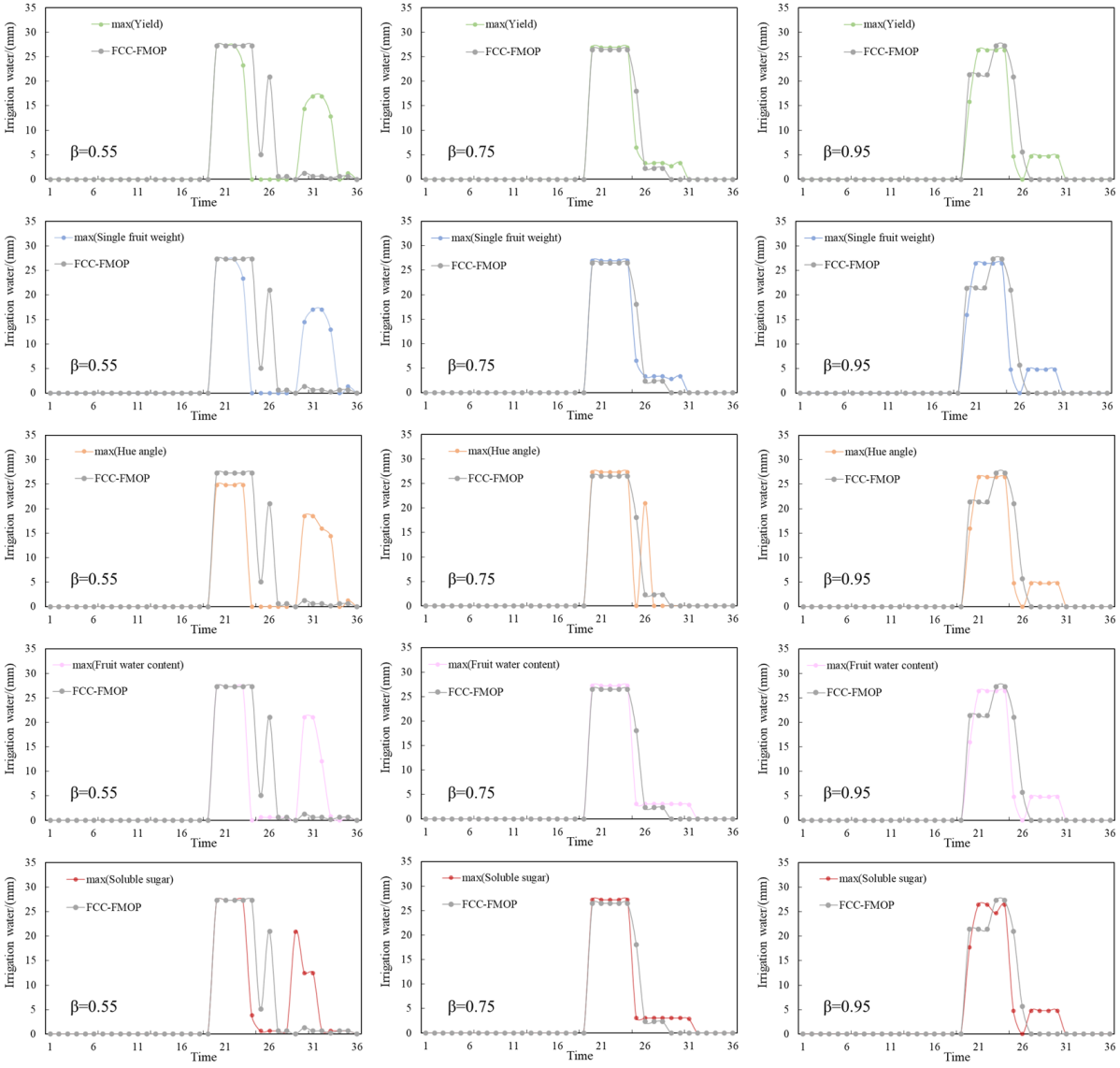


Figure 6. Water allocation under different confidence levels for different decision propensities.

Compared with single-objective models, the FCC-FMOP model makes trade-offs among different objectives by regulating the water deficit degree and irrigation time, especially at the zenith fruiting stage. For $\beta = 0.55$ and 0.75, the FCC-FMOP model decreases the water consumption after $i = 27$. For $\beta = 0.95$, compared with single-objective models, the FCC-FMOP model increases irrigation water before $t = 26$ and reduces irrigation water after $t = 26$. The results in Figure 6 show the responses of irrigation strategies to multiple objectives but cannot show the associated yield and quality indicators.

Figure 7a–c depicts comparative heatmaps of the distribution of satisfaction levels across various optimization indicators and decision-making tendencies under different levels of fuzzy credibility, generated from the FCC-FMOP model and its single-objective counterparts. Over all credibility levels, Figure 7 highlights the FCC-FMOP model's

consistently high levels of satisfaction across a range of indicators, which underscores its capability to harmonize yield and quality objectives. At all credibility levels, there is a high degree of similarity between maximizing yield, maximizing single fruit weight, maximizing single fruit weight, and FCC-FMOP. At a credibility level of β = 0.55, the objective of maximizing fruit water content exhibits an isolated peak of satisfaction, whereas the objective of maximizing soluble sugar results show concurrently high satisfaction levels for hue angle, fruit water content, and soluble sugar. Meanwhile, maximizing fruit water content and maximizing soluble sugar show a similar and isolated peak of satisfaction at β = 0.75. For the credibility of 0.95, the objective of maximizing yield, maximizing single fruit weight maximizing hue angle, and maximizing fruit water content are consistent. Meanwhile, these four objectives and maximizing soluble sugar are conflicted. The FCC-FMOP model presents a shift from improving yield satisfaction to improving soluble sugar satisfaction in contrast to other credibility levels. The comprehensive satisfaction of the FCC-FMOP model across all indicators and decision-making tendencies, as opposed to the single-objective models, underscores its superiority and adaptability. This positions the FCC-FMOP model as a cutting-edge instrument for sophisticated irrigation management in citrus cultivation, delivering a balanced and efficacious approach to enhance both yield and quality.

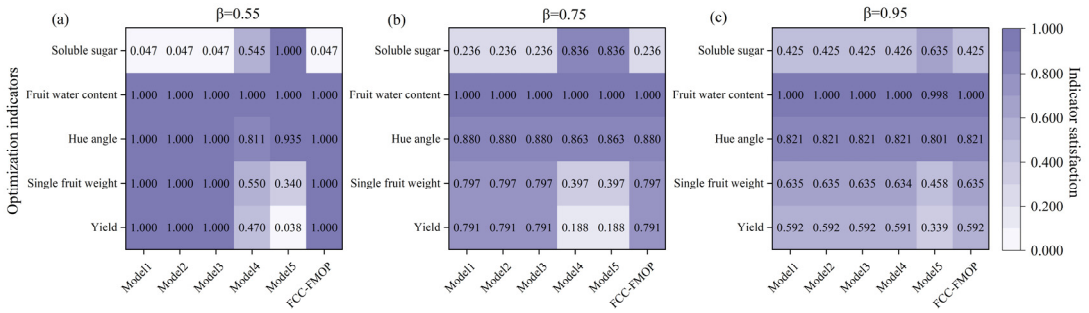


Figure 7. Distribution of objective satisfaction for the FCC-FMOP model and single-objective models when β = 0.55 (**a**), 0.75 (**b**), and 0.95 (**c**). Model 1: maximizing yield; model 2: maximizing single fruit weight; model 3: maximizing hue angle; model 4: maximizing fruit water content; model 5: maximizing soluble sugar.

Figure 8 presents the performance comparison between single-objective models and the FCC-FMOP model across various decision-making scenarios. The model's efficacy is evaluated through the SD, SI, and AD. The results reveal that the FCC-FMOP model is highly effective in maximizing citrus yield and quality through optimized irrigation strategies, compared with the status quo (SD = 0, SI = 0, AD = 0). In particular, compared with single-objective models, the FCC-FMOP model shows obvious advantages in soluble sugar at a credibility level of β = 0.95, indicating that FCC-FMOP can deal well with the conflicting contradictions among configuration objectives of different dimensions.

The FCC-FMOP model, meticulously crafted in its design and planning phase, takes into account the subjective preferences of decision-makers while simultaneously addressing both yield and quality metrics. It provides customized irrigation water optimization strategies for citrus cultivation in Southwest China. By harnessing the IVIF-TOPSIS method and incorporating fuzzy constraints, the model adeptly navigates the complex interplay between practical applications and the integration of subjective and objective factors. To eliminate bias, the selection of the decision-making expert team in this study was executed randomly, ensuring a balanced approach to address coupled constraints. The model's multi-objective optimization results, when juxtaposed with actual yields, underscore its robustness and superiority. The Rao model's quantitative elucidation of the intricate dy-

namics between water volume, yield, and quality enables the precise alignment of diverse market demands and consumer preferences. This enhancement bolsters the model's adaptability to real-world decision-making scenarios, thereby facilitating the implementation of irrigation water allocation strategies for citrus cultivation and the formulation of optimal water use plans for analogous crop production endeavors.

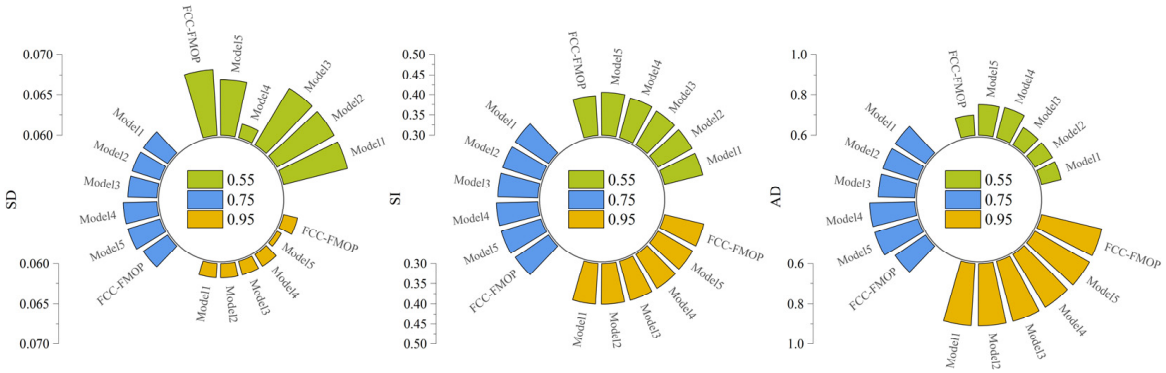


Figure 8. Performance comparison between single-objective models and FCC-FMOP model considering SD, SI, and AD.

4.4. Limitations and Future Research

While this study introduces a novel modeling framework and utilizes parameters derived from local experimental studies [4,32], it is important to note that the optimized irrigation schedules generated by the FCC-FMOP model have not yet been validated through full-scale field trials in commercial citrus orchards. The current comparison with single-objective models demonstrates the theoretical superiority of our approach, but empirical validation is a critical next step. Future research will focus on implementing the proposed irrigation strategies in the field to compare their performance against conventional practices, measuring actual yield, fruit quality parameters, and water use efficiency.

Furthermore, the current model optimizes for biophysical objectives (yield and quality) without explicitly incorporating economic factors such as water costs, energy for irrigation, labor, and market price fluctuations for different quality grades. Although the decision-makers' preferences (e.g., prioritizing yield) indirectly reflect economic drivers, a comprehensive cost–benefit analysis would strengthen the model's practical utility. Future iterations of this model will integrate a pricing model and economic constraints to evaluate the financial profitability and feasibility of the proposed irrigation strategies.

A key consideration in orchard management is the physiological limit of the tree to support and nourish fruits without compromising quality or tree health. While the FCC-FMOP model does not include an explicit fruit load constraint, it inherently addresses this issue through the integration of multiple quality objectives. For instance, the objectives of maximizing single fruit weight and soluble sugar content are in direct competition with unlimited yield increase under excessive irrigation. The model's trade-off mechanism prevents the recommendation of strategies that would lead to an overburdened canopy with small, low-quality fruits. The fact that the model does not simply allocate all water to maximize yield, but instead finds a balanced solution, demonstrates its ability to mimic agronomic wisdom. Nevertheless, explicitly incorporating a tree vigor or fruit load capacity constraint based on canopy size and light interception would be a valuable enhancement for future model development.

The model employs a static set of parameters, meaning it does not dynamically account for inter-annual variability in climate, pest, and disease pressure or tree age. The use of fuzzy credibility constraints helps handle hydrological uncertainty and decision-maker

risk aversion. However, to fully capture the dynamic interplay between environmental stresses and plant physiology, a next-generation model could incorporate real-time weather forecasts, soil sensors, and mechanistic crop growth modules. In addition, the analysis was conducted using a 10-day time step, which is consistent with standard irrigation management practices and the availability of regional hydrological data. While this resolution is sufficient for strategic planning, it might overlook short-term critical periods for fruit quality development. Future work with access to higher-resolution (e.g., daily) data could refine the model to capture these finer temporal dynamics.

5. Conclusions

This research utilizes the Rao model to elucidate the intricate connections between water volume and both yield and quality. By employing the IVIF-TOPSIS approach, it evaluates the subjective preferences of decision-makers and incorporates fuzzy credibility constraints to develop the FCC-FMOP model, which holistically addresses the yield and quality aspects of citrus cultivation. Tailored to specific needs, this model offers optimized irrigation strategies and has been implemented in the principal citrus-growing regions of Southwest China, revealing the following significant insights: (1) The selection of the decision-making expert panel underscores yield as the paramount indicator for citrus production in Pujiang County, with single fruit weight a close second, and color tone as a lower priority. (2) The innovative FCC-FMOP model adeptly balances yield and quality metrics, accommodates real-world scenarios with fuzzy constraints, and has proven to be both robust and user-friendly. (3) The FCC-FMOP model significantly enhances key agricultural metrics—yield, fruit weight, hue angle, water content, and soluble sugar—across credibility levels (β = 0.55, 0.75, 0.95). Improvements are consistently observed, with soluble sugar showing a notable increase at higher β levels. This study provides a transparent and adaptable decision support tool. By explicitly quantifying trade-offs and incorporating uncertainty, the FCC-FMOP model enables the formulation of robust, stakeholder-informed irrigation strategies, ultimately enhancing the sustainability and economic resilience of citrus cultivation in water-scarce regions.

Author Contributions: Conceptualization, F.Z.; methodology, F.Z.; software, Z.W.; validation, X.Z., S.G. and S.W.; formal analysis, F.Z.; investigation, X.Z.; resources, F.Z.; data curation, X.Z.; writing—original draft preparation, F.Z.; writing—review and editing, S.G., Z.W. and S.W.; visualization, F.Z.; supervision, S.W.; project administration, S.G.; funding acquisition, F.Z. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by the Open Research Fund of State Key Laboratory of Efficient Utilization of Agricultural Water Resources (grant number: SKLAWR-2024-13), Fundamental Research Funds for the Central Universities (grant number: QNTD202508), and the Young Elite Scientist Sponsorship Program by CAST (grant number: YESS20240294).

Data Availability Statement: The original contributions presented in this study are included in the article. Further inquiries can be directed to the corresponding author.

Conflicts of Interest: The authors declare no conflicts of interest.

References

1. Ramírez-Pérez, L.J.; Morales-Díaz, A.B.; Benavides-Mendoza, A.; De-Alba-Romenus, K.; González-Morales, S.; Juárez-Maldonado, A. Dynamic modeling of cucumber crop growth and uptake of N, P and K under greenhouse conditions. *Sci. Hortic.* **2018**, *234*, 250–260. [CrossRef]
2. Zhou, B.; Xu, Y.; Wu, J.; Dong, S.; Shi, Y. Changes in temperature and precipitation extreme indices over China: Analysis of a high-resolution grid dataset. *Int. J. Climatol.* **2016**, *36*, 1051–1066. [CrossRef]

3. Velez, J.E.; Intrigliolo, D.S.; Castel, J.R. Scheduling deficit irrigation of citrus trees with maximum daily trunk shrinkage. *Agric. Water Manag.* **2007**, *90*, 197–204. [CrossRef]
4. Chen, F.; Cui, N.; Jiang, S.; Wang, Z.; Li, H.; Lv, M.; Wang, Y.; Gong, D.; Zhao, L. Multi-objective deficit drip irrigation optimization of citrus yield, fruit quality and water use efficiency using NSGA-II in seasonal arid area of Southwest China. *Agric. Water Manag.* **2023**, *287*, 108440. [CrossRef]
5. Shirgure, P. Research review on Irrigation scheduling and water requirement in citrus. *Sci. J. Rev.* **2013**, *2*, 113–121.
6. Abbas, F.; Fares, A. Best Management Practices in Citrus Production. *Tree For. Sci. Biotechnol.* **2009**, *3*, 1–11.
7. Liu, X.; Zhu, X.; Pan, Y.; Bai, J.; Li, S. Performance of different drought indices for agriculture drought in the North China Plain. *J. Arid. Land.* **2018**, *10*, 507–516. [CrossRef]
8. Khedkar, D.D. Minimal volume irrigation scheduling for citrus cultivation in warud tehsil, maharashtra, india. *Agric. Agric. Sci. Procedia* **2015**, *4*, 365–371. [CrossRef]
9. Zhong, Y.; Fei, L.; Li, Y.; Zeng, J.; Dai, Z. Response of fruit yield, fruit quality, and water use efficiency to water deficits for apple trees under surge-root irrigation in the Loess Plateau of China. *Agric. Water Manag.* **2019**, *222*, 221–230. [CrossRef]
10. Silveira, L.K.; Pavão, G.C.; Dos Santos Dias, C.T.; Quaggio, J.A.; Pires, R.C.D.M. Deficit irrigation effect on fruit yield, quality and water use efficiency: A long-term study on Pêra-IAC sweet orange. *Agric. Water Manag.* **2020**, *231*, 106019. [CrossRef]
11. Panigrahi, P.; Srivastava, A.K. Effective management of irrigation water in citrus orchards under a water scarce hot sub-humid region. *Sci. Hortic.* **2016**, *210*, 6–13. [CrossRef]
12. Kuscu, H.; Turhan, A.; Demir, A.O. The response of processing tomato to deficit irrigation at various phenological stages in a sub-humid environment. *Agric. Water Manag.* **2014**, *133*, 92–103. [CrossRef]
13. Obenland, D.; Campisi-Pinto, S.; Arpaia, M.L. Determinants of sensory acceptability in grapefruit. *Sci. Hortic.* **2018**, *231*, 151–157. [CrossRef]
14. Pérez-Pastor, A.; Ruiz-Sánchez, M.C.; Domingo, R. Effects of timing and intensity of deficit irrigation on vegetative and fruit growth of apricot trees. *Agric. Water Manag.* **2014**, *134*, 110–118. [CrossRef]
15. Romero, C.C.; Dukes, M.D.; Baigorria, G.A.; Cohen, R. Comparing theoretical irrigation requirement and actual irrigation for citrus in Florida. *Agric. Water Manag.* **2009**, *96*, 473–483. [CrossRef]
16. Levy, Y. *Citrus Irrigation*; Institute Agronomique & Veterinaire Hasssan II: Rabat, Morocco, 1998.
17. Zhang, F.; Guo, S.; Liu, X.; Wang, Y.; Engel, B.A.; Guo, P. Towards sustainable water management in an arid agricultural region: A multi-level multi-objective stochastic approach. *Agric. Syst.* **2020**, *182*, 102848. [CrossRef]
18. Guo, S.; Zhang, F.; Engel, B.A.; Wang, Y.; Guo, P.; Li, Y. A distributed robust optimization model based on water-food-energy nexus for irrigated agricultural sustainable development. *J. Hydrol.* **2022**, *606*, 127394. [CrossRef]
19. Zhang, F.; Cui, N.; Guo, S.; Yue, Q.; Jiang, S.; Zhu, B.; Yu, X. Irrigation strategy optimization in irrigation districts with seasonal agricultural drought in southwest China: A copula-based stochastic multiobjective approach. *Agric. Water Manag.* **2023**, *282*, 108293. [CrossRef]
20. Herman, J.D.; Quinn, J.D.; Steinschneider, S.; Giuliani, M.; Fletcher, S. Climate Adaptation as a Control Problem: Review and Perspectives on Dynamic Water Resources Planning Under Uncertainty. *Water Resour. Res.* **2020**, *56*, e24389. [CrossRef]
21. Clark, M.P.; Vogel, R.M.; Lamontagne, J.R.; Mizukami, N.; Knoben, W.J.M.; Tang, G.; Gharari, S.; Freer, J.E.; Whitfield, P.H.; Shook, K.R.; et al. The Abuse of Popular Performance Metrics in Hydrologic Modeling. *Water Resour. Res.* **2021**, *57*, e2020WR029001. [CrossRef]
22. Shi, R.; Wang, J.; Tong, L.; Du, T.; Shukla, M.K.; Jiang, X.; Li, D.; Qin, Y.; He, L.; Bai, X.; et al. Optimizing planting density and irrigation depth of hybrid maize seed production under limited water availability. *Agric. Water Manag.* **2022**, *271*, 107759. [CrossRef]
23. Rao, N.H.; Sarma, P.B.S.; Chander, S. A simple dated water-production function for use in irrigated agriculture. *Agric. Water Manag.* **1988**, *13*, 25–32. [CrossRef]
24. Atanassov, K.; Gargov, G. Interval valued intuitionistic fuzzy sets. *Fuzzy Set. Syst.* **1989**, *31*, 343–349. [CrossRef]
25. Izadikhah, M. Group Decision Making Process for Supplier Selection with TOPSIS Method under Interval-Valued Intuitionistic Fuzzy Numbers. *Adv. Fuzzy Syst.* **2012**, *2012*, 407942. [CrossRef]
26. Xiao, Z.; Wei, G. in Application interval-valued intuitionistic fuzzy set to select supplier. In Proceedings of the 2008 Fifth International Conference on Fuzzy Systems and Knowledge Discovery, Jinan, China, 18–20 October 2008; pp. 351–355.
27. Zhang, X.; Guo, P.; Zhang, F.; Liu, X.; Yue, Q.; Wang, Y. Optimal irrigation water allocation in Hetao Irrigation District considering decision makers' preference under uncertainties. *Agric. Water Manag.* **2021**, *246*, 106670. [CrossRef]
28. Amid, A.; Ghodsypour, S.H.; O'Brien, C. A weighted max–min model for fuzzy multi-objective supplier selection in a supply chain. *Int. J. Prod. Econ.* **2011**, *131*, 139–145. [CrossRef]
29. Zhang, F.; Cai, Y.; Tan, Q.; Wang, X. Spatial water footprint optimization of crop planting: A fuzzy multiobjective optimal approach based on MOD16 evapotranspiration products. *Agric. Water Manag.* **2021**, *256*, 107096. [CrossRef]

30. Zimmermann, H.J. Fuzzy programming and linear programming with several objective functions. *Fuzzy Sets Syst.* **1978**, *1*, 45–55. [CrossRef]
31. Afzali, A.; Rafsanjani, M.K.; Saeid, A.B. A Fuzzy Multi-objective Linear Programming Model Based on Interval-valued Intuitionistic Fuzzy Sets for Supplier Selection. *Int. J. Fuzzy Syst.* **2016**, *18*, 864–874. [CrossRef]
32. Chen, F.; Cui, N.; Jiang, S.; Li, H.; Wang, Y.; Gong, D.; Hu, X.; Zhao, L.; Liu, C.; Qiu, R. Effects of water deficit at different growth stages under drip irrigation on fruit quality of citrus in the humid areas of South China. *Agric. Water Manag.* **2022**, *262*, 107407. [CrossRef]

Disclaimer/Publisher's Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.