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An Interval Quadratic Fuzzy Dependent-Chance Programming Model for Optimal Irrigation Water Allocation under Uncertainty

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Abstract: In this study, an interval quadratic fuzzy dependent-chance programming (IQFDCP) model is proposed for irrigation water management under uncertainty. This model can deal with the interval and fuzzy uncertainties encountered in optimal irrigation water resources allocation problems. It takes optimal credibility level of system revenue as the objective function for addressing the conflict between maximum system revenue and the credibility level of the system revenue. By providing three scenarios of precipitation, the optimal solutions are obtained. The developed model is applied to a case study for irrigation water allocation in Minqin Oasis, Wuwei city, northwest China. This study can help determine how much irrigation water should be allocated to different crops under the maximum credibility level of the system revenue. The optimal solutions can provide a certain credibility level of system revenue corresponding to different scenarios and mitigate the system-failure risk level of water shortages in arid areas. Moreover, because the IQFDCP can objectively reflect the interrelationship among crop irrigation water amount, system revenue, and system-failure risk level, the results are able to provide advices to decision makers for efficiently managing water resources in different scenarios.

Keywords: uncertainty; irrigation water resources allocation; interval quadratic programming; fuzzy dependent-chance programming; credibility level

1. Introduction

Water resources are the basis for food security, and water resource scarcity will lead to the variation of grain production, which is considered as the source of food crisis [1]. Meanwhile, water scarcity is a structural condition in arid regions of the world, which can be further exacerbated by drought events [2]. It has a significant effect on the rapid development of the economy and agricultural production. The increase in the use of domestic water and industrial water has led to the reduction of water in agriculture irrigation [3]. Moreover, there is growing recognition of the need to reduce agricultural groundwater use in response to the rapid aquifer depletion [4]. Many regions reliant on irrigated agriculture have proposed policies to manage groundwater use [5]. In semi-arid and arid areas that rely heavily on irrigated agriculture, the role of agricultural water is even more critical [6]. In addition, the strategic interaction between water allocation and stakeholder preferences is also a continuing problem [7]. Therefore, reasonable allocation of limited irrigation water resources is becoming increasingly critical [8], and efficient water allocation schemes should be used to guarantee water use security and improve the water use efficiency [9]. Generally, maximizing the system revenue considering the cost of consuming excessive irrigation water is a common objective for agricultural water management. However, under these circumstances, the risk level of water shortages has not

been fully considered, thereby affecting the results of optimal irrigation water resource allocation. In view of the present situation, how to effectively allocate the limited irrigation water resources to balance the maximum economic benefits and minimize the risk is an urgent problem to be solved.

In order to solve the above problems, Frizzone et al. developed a separable linear programming model for optimizing agricultural water-resources allocation in an irrigation district [10]. Burgschweiger et al. used a nonlinear programming model for planning in water supply systems where it was highly desirable [11]. Keramatzadeh et al. formulated linear programming and multi objective linear programming models for determining solutions that can maximize the net return to farmers [12]. Ahmad and Tang developed a multi-objective linear programming for optimal water allocation based on satisfaction and economics [13]. The above studies indicated that optimizing the irrigation water allocation has substantial potential to increase the net returns from agriculture and reduce irrigation water.

However, many uncertainties caused by various factors in agricultural water management systems should be taken into account [14], and these parameters should not be simply described as deterministic. These uncertainties generate enormous challenges for practical water resources allocation and water quality management [15]. Therefore, introducing uncertain parameters into optimization models can effectively solve such problems. The interval parameter programming (IPP), which is used to deal with the uncertainties expressed as interval in the model, can provide a stable and flexible solution for decision makers without knowing the specific distribution information of parameters [7]. Ishibuchi and Tanaka investigated mathematical programming problems whose objective function has interval coefficients, to maximize the economic benefits of objective function [16]. Guo et al. developed an interval-parameter two-stage stochastic semi-infinite programming (ITSSP) method for water resources management under uncertainty [17]. Many parameters in real life have fuzzy attributes, such as income or credibility level. In 1965, Zadeh put forward the “fuzzy theory”, which was mainly used to study some fuzzy problems [18]. Li et al. developed an interval-fuzzy multistage programming (IFMP) method for water resources management [19]. Maqsood et al. presented an interval-parameter fuzzy two-stage stochastic programming (IFTSP) method for planning water-resources-management systems under uncertainty [20].

Generally, the above optimization models of water resources allocation only considered the economic benefits of irrigation systems, ignoring their credibility level. Fuzzy dependent-chance programming (FDCP) method was considered as a useful tool for dealing with the risk of the objective function [21]. The main principle of FDCP method is that the objective function must be maintained at a given credibility level [22]. FDCP has been improved on the concept of feasible set and different from the other fuzzy mathematical programming methods that need to conform to some pre-determined credibility levels. For example, Liang and Gao used a fuzzy goal dependent-chance programming model for formulating the fuzzy capital budgeting problem [23]. Peng and Zhou developed a fuzzy multi-objective dependent-chance programming model in the field of urban water supply [24]. However, all above uncertainty models belong to the class of linear models which has limitations when the marginal utility nonlinearly affects the revenue and/or the cost coefficients [25,26]. Interval quadratic programming (IQP) is capable of dealing with nonlinearity in the objective function as well as handling uncertainties [27]. Li et al. used an inexact two-stage quadratic programming to show that schemes for allocating irrigation water among different crops monthly under various flow levels are effective for achieving high economic benefits [28]. Therefore, IQP integrated with FDCP method is considered as an effective way to estimate the optimal irrigation water allocation under uncertainty and is especially applicable in agricultural water management to obtain the maximum system revenue and credibility level simultaneously.

In general, the above problems can be addressed by an interval quadratic fuzzy dependent-chance programming (IFDCQP) approach. The basic concept of this model is the use of credibility level theory for balancing the maximum economic benefits and minimum risk level [29]. The developed model is applied to a case study for allocating limited irrigation water in Minqin Oasis, northwest China.

The maximum credibility level of system revenue can be obtained. Moreover, the results under different scenarios can reflect the interrelationships among crop irrigation water scheme, system revenue, and system-failure risk level.

2. Methodology

2.1. Interval Quadratic Programming (IQP)

Quadratic programming (QP) is an effective tool to solve practical problems, which can better reflect the nonlinear problem of an objective function. Interval quadratic programming (IQP) is an extension of traditional quadratic programming by incorporating interval parameter programming (IPP) into a QP optimization framework. The general function of nonlinearity and uncertainty with interval variable/parameter are expressed as follows [27]:

$$\text{Max } f^\pm = \sum_{j=1}^n \left[c_j^\pm x_j^\pm + d_j^\pm (x_j^\pm)^2 \right] \tag{1a}$$

subject to

$$\sum_{j=1}^n a_j^\pm x_j^\pm \leq b_j^\pm, j = 1, 2, \dots, m \tag{1b}$$

$$x_j^\pm \geq 0, j = 1, 2, \dots, m \tag{1c}$$

where f^\pm is the objective function, $a_j^\pm, b_j^\pm, c_j^\pm, d_j^\pm$ represent the interval numbers of the model respectively, x_j^\pm is the decision variable. “±” is the upper and lower bounds on the interval parameters.

It is necessary to consider whether the coefficients of IQP (i.e., b_j^\pm and c_j^\pm) have the same sign, which is related to the solution result. For solving the IQP model, we need to discuss it in two aspects.

When the c_j^\pm and d_j^\pm have the same sign, i.e., when $c_j^\pm \geq 0, d_j^\pm$ should also be ≥ 0 , and vice versa. Let the former k_1 pairs be positive, i.e., $c_j^\pm \geq 0$ and $d_j^\pm \geq 0$ ($j = 1, 2, \dots, k_1$) and the latter k_2 pairs be negative, i.e., $c_j^\pm < 0$ and $d_j^\pm < 0$ ($j = k_1 + 1, k_1 + 2, \dots, n$), $k_1 + k_2 = n$. Under these conditions, the objective function f^\pm can be converted into [27]:

$$f^+ = \sum_{j=1}^{k_1} \left[c_j^+ x_j^+ + d_j^+ (x_j^+)^2 \right] + \sum_{j=k_1+1}^n \left[c_j^+ x_j^- + d_j^+ (x_j^-)^2 \right] \tag{1d}$$

$$f^- = \sum_{j=1}^{k_1} \left[c_j^- x_j^- + d_j^- (x_j^-)^2 \right] + \sum_{j=k_1+1}^n \left[c_j^- x_j^+ + d_j^- (x_j^+)^2 \right] \tag{1e}$$

When the c_j^\pm and d_j^\pm have the different sign, under this situation, it becomes difficult to determine whether x_j^+ or x_j^- corresponds to the highest f^+ . A mid-value quadratic programming submodel should first be formulated through letting all left- and/or right-hand side coefficients be equal to their mid-values [27,30]. For example, consider an IQP problem as follows.

$$\text{max } f^\pm = \sum_{j=1}^n c_j^\pm x_j^\pm + d_j^\pm (x_j^\pm)^2 \tag{1f}$$

subject to

$$\sum_{j=1}^n a_j^\pm x_j^\pm \leq b_j^\pm, j = 1, 2, \dots, m \tag{1g}$$

$$x_j^\pm \geq 0, j = 1, 2, \dots, m \tag{1h}$$

The mid-values quadratic programming submodel is

$$\max f_{mv} = \sum_{j=1}^n (c_j)_{mv} (x_j)_{mv} + (d_j)_{mv} (x_j)_{mv}^2 \tag{1i}$$

subject to

$$\sum_{j=1}^n (a_j)_{mv} (x_j)_{mv} \leq (b_j)_{mv}, j = 1, 2, \dots, m \tag{1j}$$

$$(x_j)_{mv} \geq 0, j = 1, 2, \dots, m \tag{1k}$$

where $(c_j)_{mv}, (d_j)_{mv}, (a_j)_{mv}, (b_j)_{mv}$ are mid-values of $c_j^\pm, d_j^\pm, a_j^\pm, b_j^\pm$ (e.g., $(c_j)_{mv} = \frac{(c_j^+ + c_j^-)}{2}$), and $x_{mvopt} = \{(x_j)_{mvopt} | \forall j\}$ can be obtained by Equation (1i) to Equation (1k), we have

$$f_j^+(x_{jopt}^+) \geq f_j^+(x_{jopt}^-), \text{ when } f' \{(x_j)_{mvopt}\}^+ > 0 \tag{1l}$$

$$f_j^+(x_{jopt}^+) \leq f_j^+(x_{jopt}^-), \text{ when } f' \{(x_j)_{mvopt}\}^+ < 0 \tag{1m}$$

The upper and lower bound models are shown as

$$\left. \begin{aligned} f^+ &= c_j^+ x_j^+ + d_j^+ (x_j^+)^2 \\ f^- &= c_j^- x_j^- + d_j^- (x_j^-)^2 \end{aligned} \right\}, \text{ when } f' \{(x_j)_{mvopt}\}^+ > 0 \tag{1n}$$

$$\left. \begin{aligned} f^+ &= c_j^+ x_j^- + d_j^+ (x_j^-)^2 \\ f^- &= c_j^- x_j^+ + d_j^- (x_j^+)^2 \end{aligned} \right\}, \text{ when } f' \{(x_j)_{mvopt}\}^+ < 0 \tag{1o}$$

2.2. Fuzzy Dependent-Chance Programming Theory (FDCP)

For two fuzzy events $(\tilde{a}$ and $\tilde{b})$ satisfying fuzzy membership function $\mu_{(x)}$, there are three different forms: (1) Possibility measure (Pos): The possibility of a fuzzy event (i.e., $Pos(\tilde{a} \leq \tilde{b})$) is defined as $Pos\{\tilde{a} \leq \tilde{b}\} = \sup\{\min(\mu_a(x), \mu_b(y)) | x, y \in R, x \leq y\}$; (2) Necessity measure (Nec): Likewise, the necessary of $Nec(\tilde{a} \leq \tilde{b})$ denotes the impossibility of the opposite event, and it's defined as $Nec\{\tilde{a} \leq \tilde{b}\} = \inf\{\max(\mu_a(x), 1 - \mu_b(y)) | x, y \in R, x \leq y\}$; (3) Credibility measure (Cr): The credibility is shown as $Cr\{\tilde{a} \leq \tilde{b}\} = \frac{1}{2} (Pos\{\tilde{a} \leq \tilde{b}\} + Nec\{\tilde{a} \leq \tilde{b}\})$ for improving their limitations by combining possibility and necessary measures [31].

The event is not necessarily valid when the possibility of a fuzzy event is 1. Similarly, when the necessity of the event is 0, the event may be established. However, the credibility level of the fuzzy event is 1, it is bound to be established. Besides, if the credibility level is 0, it will not be established. Therefore, the decision confusion caused by traditional fuzzy membership calculation can be solved [32].

In uncertainty decision systems, decision makers often select schemes with maximal chance to meet the event. Because the payoff function is presented as fuzzy, decision makers hope to maximize the chance function of these events. In order to solve these problems, a fuzzy dependent-chance programming was proposed [29], based on maximizing the credibility level of uncertainty events under uncertain environments. In a fuzzy environment, the standard fuzzy dependent-chance programming is shown as follows:

$$\text{Max } f = Cr\{f_k(x, \varepsilon) \geq 0, k = 1, 2, \dots, q\} \tag{2a}$$

subject to

$$g_j(x, \varepsilon) \leq 0, j = 1, 2, \dots, p \tag{2b}$$

where f is the objective function; Cr is the credibility level; x is the n -dimensional decision variable; ε is the fuzzy variable; $\{f_k(x, \varepsilon) \geq 0, k = 1, 2, \dots, q\}$ is the fuzzy event and $g_j(x, \varepsilon) \leq 0, j = 1, 2, \dots, p$ is the uncertain environment.

Let ε be a triangular fuzzy variable (r_1, r_2, r_3) , Cr is a membership function, then the credibility level of $x \geq \varepsilon$ can be expressed as:

$$Cr\{x \geq \varepsilon\} = \begin{cases} 0 & \text{if } x \leq r_1 \\ \frac{x-r_1}{2(r_2-r_1)} & \text{if } r_1 \leq x \leq r_2 \\ \frac{x+r_3-2r_2}{2(r_3-r_2)} & \text{if } r_2 \leq x \leq r_3 \\ 1 & \text{if } x \geq r_3 \end{cases} \tag{2c}$$

In general, a meaningful credibility level should be greater than 0.5 [33]. Therefore, based on the definition of the above credibility level, the objective function can be transformed into the case where the objective function is greater than 0.5:

$$Max f = Cr\left\{\frac{x+r_3-2r_2}{2(r_3-r_2)} \geq \varepsilon\right\} \rightarrow Cr\{x \geq (2r_3-2r_2)\varepsilon + 2r_2 - r_3\} \tag{2d}$$

Therefore, it can be seen that the fuzzy dependent-chance programming model is transformed into a linear programming model.

2.3. Interval Quadratic Fuzzy Dependent-Chance Programming (IQFDCP) Model

In a fuzzy environment, the standard IQFDCP model form is

$$Max f^\pm = Cr\left(\left(\sum_{j=1}^n [c_j^\pm x_j^\pm + d_j^\pm (x_j^\pm)^2]\right) > \tilde{F}\right) \tag{3a}$$

subject to

$$\sum_{j=1}^n a_j^\pm x_j^\pm \leq b_j^\pm, j = 1, 2, \dots, m \tag{3b}$$

$$x_j^\pm \geq 0, j = 1, 2, \dots, m \tag{3c}$$

where f^\pm is the objective function that indicates the maximum credibility level of the system revenue; Cr is the credibility level; a_j^\pm, c_j^\pm , and d_j^\pm are parameters of the model; x_j^\pm is the decision variable; and \tilde{F} is the fuzzy number.

The framework of the developed model is shown in Figure 1. The detailed solution process can be summarized as follows:

- (1) Determine the input parameters of the model and its fuzzy membership functions.
- (2) Analyze the credibility level of the model. According to the triangular fuzzy membership functions, the developed model can be transformed into its equivalent model.
- (3) If the c_j^\pm, d_j^\pm in interval quadratic function have the same sign, we can formulate the upper and lower bound submodels corresponding to f^+ and f^- .
- (4) If the c_j^\pm, d_j^\pm in interval quadratic function have different signs, we should formulate and solve mid-values model first, have $f^+(x_j^+)$ and $f^-(x_j^-)$ or $f^+(x_j^-)$ and $f^-(x_j^+)$ whether $f' \left\{ (x_j)_{mvopt} \right\}^+$ is more than 0.
- (5) Solve the above submodels and obtain the optimal objective function and the decision variables.

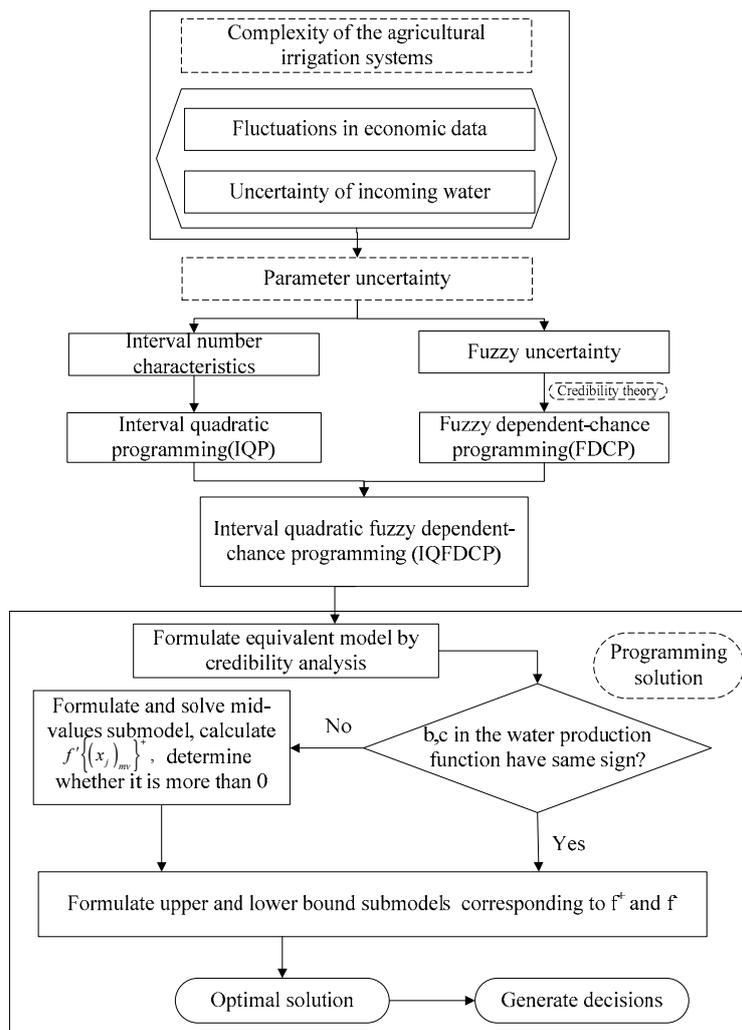


Figure 1. The framework of the interval quadratic fuzzy dependent-chance programming (IQFDCP) model.

3. Case Study

3.1. Study Area

The study area, located in Minqin Oasis, Wuwei city, Gansu province, northwest China, is shown in Figure 2. Minqin Oasis covers an area of 2745 km² and lies between 102°45′–103°55′ E and 38°20′–39°10′ N in the contiguous zone and between the Badain Jaran desert and Tengger desert [34]. The annual average precipitation is 113 mm, while the annual evapotranspiration reaches 2644 mm [35]. Minqin Oasis is mainly focused on agricultural production, and agricultural water is the largest water use section of Minqin Oasis, accounting for 70–80% of the total water consumption. The surface water resource is delivered only from the Shiyang River, which originates from the Qilian mountains [36]. There are three irrigation districts in study area: Changning irrigation district (CN), Huanhe irrigation district (HH), and Hongyashan irrigation district (HYS). CN and HH are fully irrigated by groundwater, and HYS is irrigated by both groundwater and surface water. The study crops consist of grain crops (e.g., spring wheat, maize) and economic crops (e.g., cotton). The main irrigation method is furrow irrigation.

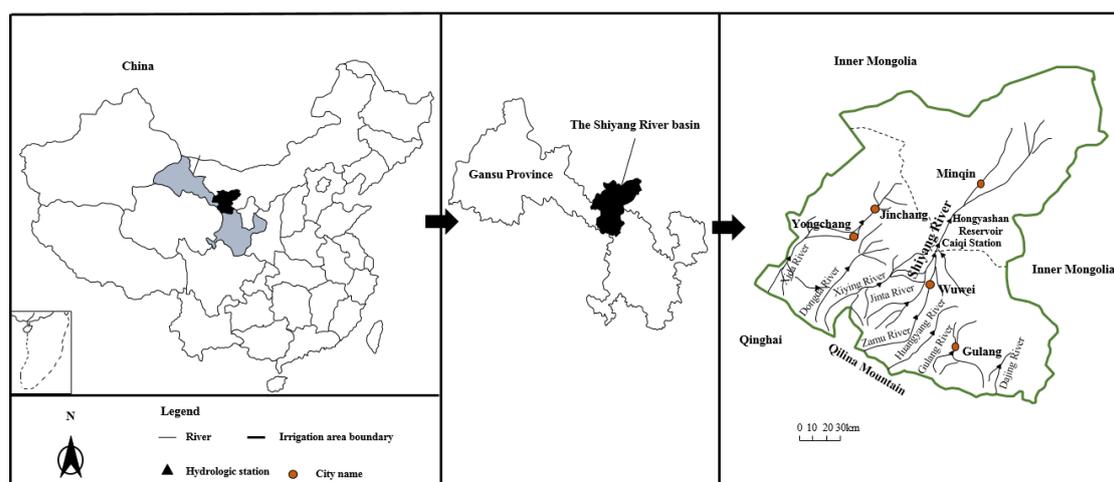


Figure 2. Sketch map of the Minqin Oasis in northwest China

3.2. Problem Statement

Minqin Oasis is the most important agricultural county of Wuwei City, and over 90% of the arable land requires irrigation [36]. As water consumption increased in the middle reaches of the Shiyang River, the surface water discharged into the Minqin Oasis gradually decreased, shrinking from $5.14 \times 10^8 \text{ m}^3$ in 1956 to only $1.79 \times 10^8 \text{ m}^3$ in 2006 [32]. Moreover, the amount of extracted groundwater accounts for over 85% of annual water consumption of the oasis [34]. Owing to excessive extraction, the groundwater table has continuously declined. The desertification and salinization of the region are serious and have become the growing concerns. Therefore, irrigation water resources are increasingly limited, and the disparity between supply and demand of agricultural water resources is expanding. Therefore, it is necessary to optimize irrigation basin water resources so as to alleviate the contradiction between supply and demand.

3.3. Data Collection and Processing

Surface water inflow and groundwater withdrawal in the three irrigation districts in Minqin Oasis from 2006 to 2016 are shown in Figures 3–6. The groundwater availability in three irrigation districts shows a downward trend due to the government issues in limiting the amount of groundwater extraction to protect the local ecological environment. The surface water inflow of HYS onward has gradually stabilized from 2014. Therefore, it is reasonable to select the groundwater and the surface water in 2016 as the current situation. The historical records of precipitation data are collected from the Minqin Oasis meteorological station [37] from 1986 to 2016. The category of different precipitation levels was based on the frequency analysis method. Let p express the frequency for dividing different precipitation levels, then the corresponding categories are shown as follows: $p < 25\%$ corresponds to wet year level, $25\% \leq p \leq 75\%$ corresponds to normal year level, and $p > 75\%$ corresponds to dry year level [28]. The actual precipitation and the water requirement corresponding to the whole growth period of three crops are shown in Table 1. Some basic information on typical crops can be obtained according to the 2016 Statistical Yearbook of Minqin Oasis and Minqin Oasis Sub-irrigation Area (See Table 2) [38].

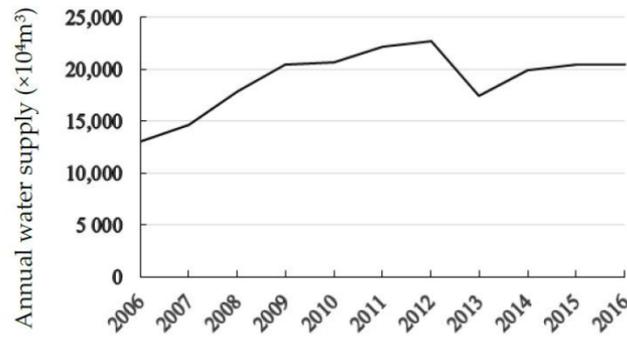


Figure 3. Surface water inflow of the Hongyashan irrigation district (HYS) from 2006 to 2016.

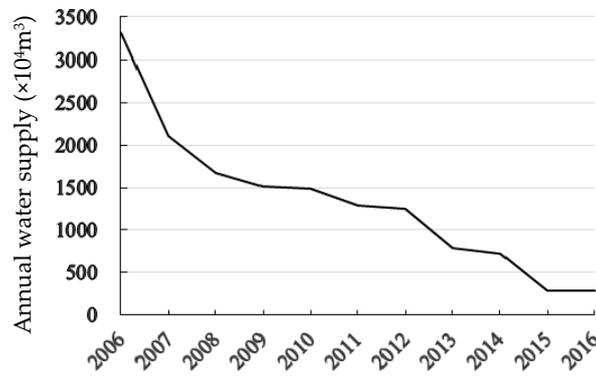


Figure 4. Groundwater availability of the Changning irrigation district (CN) from 2006 to 2016.

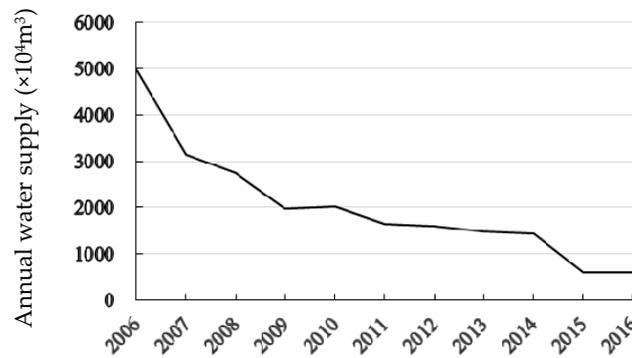


Figure 5. Groundwater availability of the Huanhe irrigation district (HH) from 2006 to 2016.

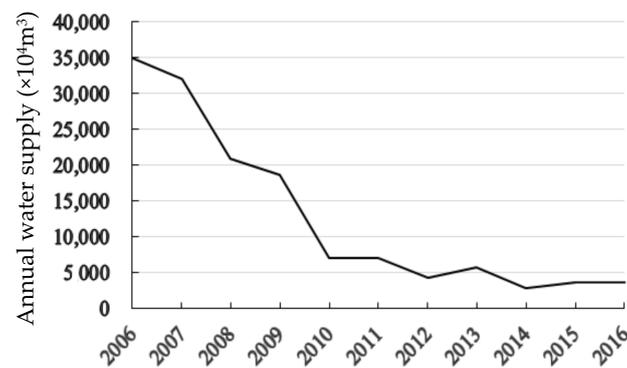


Figure 6. Groundwater availability of HYS from 2006 to 2016.

Table 1. The whole growth stage water demand of different crops and precipitation statistics of Minqin Oasis under typical years.

Typical Year	Crop	Precipitation (P)/mm	Water Demand (ET_{max})/mm
Wet year (2002)	Spring wheat	(98.6, 120.6)	658.0
	Maize	(124.1, 151.7)	561.0
	Cotton	(135.8, 166.0)	375.3
Normal year (1998)	Spring wheat	(77.0, 94.2)	677.4
	Maize	(79.8, 97.6)	590.6
	Cotton	(90.5, 110.6)	396.8
Dry year (2013)	Spring wheat	(34.1, 41.7)	695.9
	Maize	(68.9, 84.3)	589.8
	Cotton	(76.0, 92.8)	398.5

Table 2. Basic data of three irrigation districts and crops.

Irrigation Area	Crop	Acreage/ha	Price/Yuan	Surface Water/ $\times 10^4 \text{ m}^3$	Ground Water/ $\times 10^4 \text{ m}^3$
CN	Spring wheat	153.4	(2.4, 2.7)	0	(260, 289)
	Maize	530.3	(2.5, 2.8)		
	Cotton	0	(7.0, 8.0)		
HH	Spring wheat	439.7	(2.4, 2.7)	0	(530, 589)
	Maize	1214.7	(2.5, 2.8)		
	Cotton	0	(7.0, 8.0)		
HYS	Spring wheat	3764.9	(2.4, 2.7)	(20180, 22422)	(3231, 3590)
	Maize	6868.2	(2.5, 2.8)		
	Cotton	709.1	(7.0, 8.0)		

Note: CN: Changning irrigation district; HH: Huanhe irrigation district; HYS: Hongyashan irrigation district.

In this model, the system revenue is vague and imprecise due to managers' subjective judgments, which can be better reflected by fuzzy membership functions. Thus, fuzzy theory is introduced to describe this parameter. The triangular fuzzy number (r_1, r_2, r_3) of the system revenue can be obtained by using the planting area data of the past 5 years (2012–2017) and the corresponding economic parameters. In this case, r_1, r_2, r_3 in the triangular fuzzy number of evaluation values were "poor", "general" and "good". Therefore, the acreage and economic parameters are selected from 2012–2017 as the lowest, average, the highest value calculation, and $r_1 = 2.89 \times 10^9$ Yuan, $r_2 = 3.21 \times 10^9$ Yuan, $r_3 = 4.32 \times 10^9$ Yuan.

3.4. Application of IQFDPC Model

Based on the above uncertainty theory, this study developed the IQFDPC model to solve practical problems of optimal irrigation water resources allocation under uncertainty. The objective function is to maximize the credibility level of system revenue subject to a series of constraints.

In this study, a crop water production function for the whole growth period of the crops ($Y = a + bET + cET^2$) is used to decide how much water needs to be allocated to different crops. a, b and c are the empirical coefficients in the quadratic crop water production functions. The interval quadratic regression analysis method is adopted based on quadratic programming to analyze crop yield and water consumption in the whole growth period [39]. Accordingly, the model is formulated as follows:

$$\max f^\pm = Cr \left(\left(\sum_{i=1}^I \sum_{j=1}^J A_{ij} B_{ij}^\pm (a + b \bullet (SW_{ij}^\pm + GW_{ij}^\pm + P_{ij}^\pm) + c(SW_{ij}^\pm + GW_{ij}^\pm + P_{ij}^\pm)^2) \right) > \tilde{F} \right) \quad (4a)$$

subject to

Surface water supply constraint

$$\sum_{j=1}^J A_{ij}(10SW_{ij}^{\pm} / \eta_1) \leq Q_i^{\pm}, \forall i \tag{4b}$$

Groundwater supply constraint

$$\sum_{j=1}^J A_{ij}(10GW_{ij}^{\pm} / \eta_2) \leq G_i^{\pm}, \forall i \tag{4c}$$

Water requirement for normal growth of crops

$$ET_{\min ij} \leq SW_{ij}^{\pm} + P_{ij}^{\pm} + GW_{ij}^{\pm} \leq ET_{\max ij}, \forall i, j \tag{4d}$$

Grain security constraint

$$\sum_{i=1}^I \sum_{j=1}^J A_{ij} \left(a + b \bullet (SW_{ij}^{\pm} + GW_{ij}^{\pm} + P_{ij}^{\pm}) + c (SW_{ij}^{\pm} + GW_{ij}^{\pm} + P_{ij}^{\pm})^2 \right) \geq \bar{Y} \times S \tag{4e}$$

Non-negative constraint

$$SW_{ij}^{\pm} \geq 0, GW_{ij}^{\pm} \geq 0, \forall i, j \tag{4f}$$

The meaning of the parameters and variables in the model above is shown in Table 3.

Table 3. Explanation of parameters.

Parameters and Variables	Meaning and Description
Cr	The credibility level of the event
\pm	The upper and lower limits of the parameters
\tilde{F}	System revenue ($\times 10^9$ Yuan)
i	Different irrigation areas
j	Different crop types
A_{ij}	Acreage (hm^2)
B_{ij}	Purchase price (Yuan/kg)
a, b, c	The parameters of the crop water production function
SW_{ij}	The total amount of surface water in the whole growth period (mm), the decision variables
GW_{ij}	The total amount of groundwater in the whole growth period (mm), the decision variables
η_1	The availability factor of surface water
η_2	The availability factor of groundwater
P_{ij}	The precipitation during the whole growth period (mm)
$ET_{\max ji}$	Maximum water demand (mm)
$ET_{\min ji}$	Minimum water demand (mm)
Q_i	The amount of available surface water (m^3)
G_i	The amount of available groundwater (m^3)
\bar{Y}	The minimum grain demand of per capita (kg)
S	The total population of research area

The basic framework of this model is an interval quadratic programming model under uncertainty. Moreover, it combines with the characteristics of parameters, namely the parameters A_{ij} , B^{\pm}_{ij} , b are positive, a , c are negative. Thus, a mid-values quadratic programming submodel needs to be formulated as

$$Maxf_{mv} = Cr \left(\left(\sum_{i=1}^I \sum_{j=1}^J A_{ij} (B_{ij})_{mv} \left(a + b \bullet ((SW_{ij})_{mv} + (GW_{ij})_{mv} + (P_{ij})_{mv}) + c \left((SW_{ij})_{mv} + (GW_{ij})_{mv} + (P_{ij})_{mv} \right)^2 \right) \right) > \tilde{F} \right) \tag{5a}$$

subject to

$$\sum_{j=1}^J A_{ij}(10(SW_{ij})_{mv} / \eta_1) \leq (Q_i)_{mv}, \forall i \tag{5b}$$

$$\sum_{j=1}^J A_{ij}(10(GW_{ij})_{mv} / \eta_2) \leq (G_i)_{mv}, \forall i \tag{5c}$$

$$ET_{\min ij} \leq (SW_{ij})_{mv} + (GW_{ij})_{mv} + (P_{ij})_{mv} \leq ET_{\max ij}, \forall i, j \tag{5d}$$

$$\sum_{i=1}^I \sum_{j=1}^J A_{ij} \left(a + b \bullet \left((SW_{ij})_{mv} + (GW_{ij})_{mv} + (P_{ij})_{mv} \right) + c \left((SW_{ij})_{mv} + (GW_{ij})_{mv} + (P_{ij})_{mv} \right)^2 \right) \geq \bar{Y} \times S \tag{5e}$$

$$(SW_{ij})_{mv} \geq 0, (GW_{ij})_{mv} \geq 0, \forall i, j \tag{5f}$$

The optimal solutions for $(SW_{ij})_{mvopt}$, $(GW_{ij})_{mvopt}$ can be obtained by solving model (4), and the bound distribution for SW_{ij}^+ , GW_{ij}^+ can be identified according to Equations (1n) and (1o). Then, model (4) can be transformed into two deterministic submodels, the submodel corresponding to f^+ can be expressed as

$$Max f^+ = Cr \left(\left(\sum_{i=1}^I \sum_{j=1}^J A_{ij} B_{ij}^+ \left(a + b \bullet (SW_{ij}^+ + GW_{ij}^+ + P_{ij}^+) + c (SW_{ij}^+ + GW_{ij}^+ + P_{ij}^+)^2 \right) \right) > \tilde{F} \right) \tag{6a}$$

subject to

$$\sum_{j=1}^J A_{ij}(10SW_{ij}^+ / \eta_1) \leq Q_i^+, \forall i \tag{6b}$$

$$\sum_{j=1}^J A_{ij}(10GW_{ij}^+ / \eta_2) \leq G_i^+, \forall i \tag{6c}$$

$$ET_{\min ij} \leq SW_{ij}^+ + P_{ij}^+ + GW_{ij}^+ \leq ET_{\max ij}, \forall i, j \tag{6d}$$

$$\sum_{i=1}^I \sum_{j=1}^J A_{ij} \left(a + b \bullet (SW_{ij}^+ + GW_{ij}^+ + P_{ij}^+) + c (SW_{ij}^+ + GW_{ij}^+ + P_{ij}^+)^2 \right) \geq \bar{Y} \times S \tag{6e}$$

$$SW_{ij}^+ \geq 0, GW_{ij}^+ \geq 0, \forall i, j \tag{6f}$$

where SW_{ij}^+ , GW_{ij}^+ are the decision variables, the solution can provide the maximum credibility level of system revenue, and the submodel corresponding to f^- can be expressed as

$$Max f^- = Cr \left(\left(\sum_{i=1}^I \sum_{j=1}^J A_{ij} B_{ij}^- \left(a + b \bullet (SW_{ij}^- + GW_{ij}^- + P_{ij}^-) + c (SW_{ij}^- + GW_{ij}^- + P_{ij}^-)^2 \right) \right) > \tilde{F} \right) \tag{7a}$$

subject to

$$\sum_{j=1}^J A_{ij}(10SW_{ij}^- / \eta_1) \leq Q_i^-, \forall i \tag{7b}$$

$$\sum_{j=1}^J A_{ij}(10GW_{ij}^- / \eta_2) \leq G_i^-, \forall i \tag{7c}$$

$$ET_{\min ij} \leq SW_{ij}^- + P_{ij}^- + GW_{ij}^- \leq ET_{\max ij}, \forall i, j \tag{7d}$$

$$\sum_{i=1}^I \sum_{j=1}^J A_{ij} \left(a + b \bullet (SW_{ij}^- + GW_{ij}^- + P_{ij}^-) + c (SW_{ij}^- + GW_{ij}^- + P_{ij}^-)^2 \right) \geq \bar{Y} \times S \tag{7e}$$

$$SW_{ij}^- \geq 0, GW_{ij}^- \geq 0, \forall i, j \tag{7f}$$

The optimal solution of the model under different scenarios can be obtained as

$$f^\pm = [f^-, f^+] \tag{8a}$$

$$SW_{ij}^\pm = [SW_{ij}^-, SW_{ij}^+] \tag{8b}$$

$$GW_{ij}^\pm = [GW_{ij}^-, GW_{ij}^+] \tag{8c}$$

4. Result Analysis

This model incorporates interval and fuzzy programming into an optimization irrigation water allocation model and introduces the credibility theory combined with the triangular fuzzy membership function to obtain the maximum credibility level under the maximum system revenues. The result is presented in the form of interval values, which can give decision makers a decision space with the upper and lower bounds. Moreover, considering the different precipitation scenarios, decision makers can choose the better irrigation amount of crops corresponding to the interval values of risk level and system revenue. In summary, uncertainty theory is introduced into the optimization irrigation water management framework, which can enhance the practicability and feasibility of the model. Therefore, decision makers have access to a certain level of decision space and relevant decision information.

Table 4 shows the results of optimal allocation of irrigation water resources based on different precipitation scenarios in three irrigation districts. The HYS district is irrigated by both surface water and groundwater, and the price of surface water is less than that of the groundwater. Therefore, when surface water is sufficient to meet the irrigation water demand, the amount of allocated groundwater for the three crops is much less than that of surface water in HYS district. In addition, CN and HH districts are irrigated by only groundwater. The groundwater supply is limited in order to reduce groundwater extraction, leading to decreased irrigation water for crops. By comparing the irrigation water of three crops under different scenarios, it is obvious that there is water competition among the three crops with limited irrigation water resources.

Table 4. Optimal irrigation water allocation in different scenarios (mm).

Irrigation District	Typical Year	Irrigation Sources	Irrigation Water Allocation for Different Crops		
			Spring Wheat	Maize	Cotton
CN	Wet year	Surface water	0	0	0
		Groundwater	(267.2, 279.4)	(293.3, 289.8)	0
	Normal year	Surface water	0	0	0
		Groundwater	(275.9, 286.5)	(290.7, 287.7)	0
	Dry year	Surface water	0	0	0
		Groundwater	(320.2, 322.8)	(278.0, 277.2)	0
HH	Wet year	Surface water	0	0	0
		Groundwater	(250.3, 262.2)	(239.1, 234.8)	0
	Normal year	Surface water	0	0	0
		Groundwater	(258.8, 259.2)	(236.1, 232.3)	0
	Dry year	Surface water	0	0	0
		Groundwater	(302.2, 304.7)	(220.3, 219.4)	0
HYS	Wet year	Surface water	(459.9, 481.9)	(278.4, 306.4)	(186.4, 212.8)
		Groundwater	0	(130.9, 130.5)	(22.9, 26.7)
	Normal year	Surface water	(486.3, 503.4)	(364.4, 380.0)	(242.1, 282.4)
		Groundwater	0	(128.7, 130.8)	(44.2, 24.0)
	Dry year	Surface water	(538.8, 546.4)	(374.1, 388.3)	(287.3, 315.7)
		Groundwater	0	(131.4, 132.6)	(18.4, 6.9)

Figure 7 shows the system revenue value (i.e., R) under the wet, normal and dry year level, namely, (3.53, 3.58), (3.58, 3.62), (3.54, 3.57) ($\times 10^9$ Yuan). The normal year level of system revenue is the highest, followed by wet year level, dry year level. R in different scenarios is higher than the general value r_2 in the triangular fuzzy number, but less than r_3 . It can be concluded that the system

revenue in different scenarios is higher than the “normal” level, but it is difficult to achieve the “good” level. The range of the interval decreased gradually, that is, 0.05, 0.04, and 0.03. The fluctuation of system revenue is small, and the risk space of irrigation water will decrease accordingly.

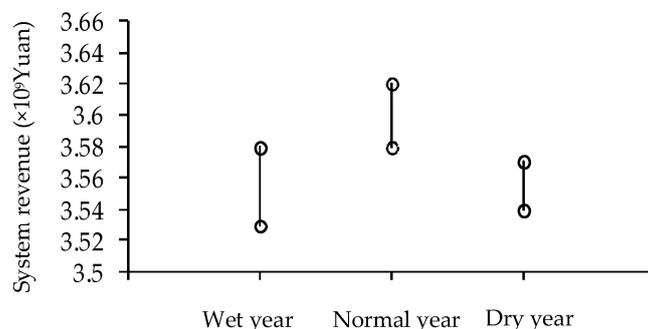


Figure 7. The system revenue in different scenarios in Minqin Oasis.

The comparison of the optimal irrigation water and actual irrigation water (take the normal year in 2016 as an example) is shown in Table 5. It can be seen that the optimal irrigation water is less than the actual irrigation water. Taking CN and HH districts as examples, reducing groundwater usage to optimum irrigation levels can control groundwater exploitation effectively because the amount of irrigation water is decreased greatly, but the risk level of the revenue system increased. There are two reasons to explain why farmers might be using more water than the optimal irrigation water amount. On the one hand, the characteristics of the IQDCP model is that it belongs to interval quadratic programming framework. When the system revenue gradually approaches the maximum values, the increase of crops irrigation water amount has little effect on the system revenue. However, in the actual irrigation system, the farmers are willing to gain this small benefit at the cost of such an increased crop irrigation water amount. On the other hand, the agricultural irrigation facilities in the Minqin Oasis are backward. Under the current conditions, the level of agricultural water management is relatively low, and the irrigation methods are not efficient, resulting in a lower water use efficiency and a larger waste of water resources. Ultimately, the water used by farmers is higher than the optimized amount of irrigation water.

Table 5. Comparison of the results from optimal and actual irrigation water allocation.

Irrigation District	Crop	Irrigation Water Amount		Water Saving Amount	Optimized System Revenue (×10 ⁸ Yuan)	Actual System Revenue (×10 ⁸ Yuan)
		Optimization	Actual			
CN	Spring wheat	(275.9, 286.5)	410	(134.1, 123.5)	(3.58, 3.62)	3.2
	Maize	(290.7, 287.7)	405	(114.3, 117.3)		
	Cotton	0	0	0		
HH	Spring wheat	(258.8, 259.2)	410	(151.2, 150.8)	(3.58, 3.62)	3.2
	Maize	(236.1, 232.3)	405	(168.9, 172.7)		
	Cotton	0	0	0		
HYS	Spring wheat	(486.3, 503.4)	536	(49.7, 32.6)		
	Maize	(493.1, 510.8)	563	(69.9, 52.2)		
	Cotton	(286.3, 306.4)	323	(36.7, 16.6)		

In addition, compared with the optimal system revenue and actual system revenue, it can be concluded that the optimal system revenue increased by about 4000×10^4 Yuan. Table 5 shows that the interval quadratic fuzzy dependent-chance programming model for optimal irrigation water allocation has achieved obvious water-saving effect and improved the economic benefit. Based on the fuzzy dependent-chance programming, it is possible to obtain the maximum system revenue and its credibility level. When considering the credibility level, there is a certain risk level for obtaining the theoretical maximum system revenue.

Figure 8 shows the credibility level (λ) of system revenue. The λ values in different scenarios are (0.64, 0.66), (0.67, 0.68) and (0.65, 0.66), respectively. In theory, credibility level represents the satisfaction degree level of constraints and $(1 - \lambda)$ indicates the risk level of the event. Therefore, a decision-maker can choose different irrigation schemes according to the risk level of the system revenue. It can be seen that, under different scenarios, the credibility levels of system revenue are greater than 0.5, ranging from 0.6 to 0.7. On the whole, the degree of credibility level is still low, which means that the system has a greater risk to revenue. The reasons for this situation are

- (1) Compared with the actual situation, the interval of the system revenue of the triangular fuzzy number is too big, especially for obtaining r_3 . The planting area and the price take a more optimistic value. It is difficult to achieve in the actual situation, causing the lower level of credibility of system revenue.
- (2) For three irrigation districts in Minqin Oasis, the CN and HH districts are irrigated by only groundwater. In order to decrease groundwater extraction, irrigation water is reduced, resulting in lower crop yield under the low amount of groundwater availability compared to HYS. Thus, low system revenue is obtained in Minqin Oasis and the credibility level is decreased.
- (3) There is no cotton in CN and HH. The main crops are spring wheat and maize. However, cotton is a major source of income for system, resulting in low system revenue, causing the low credibility level.

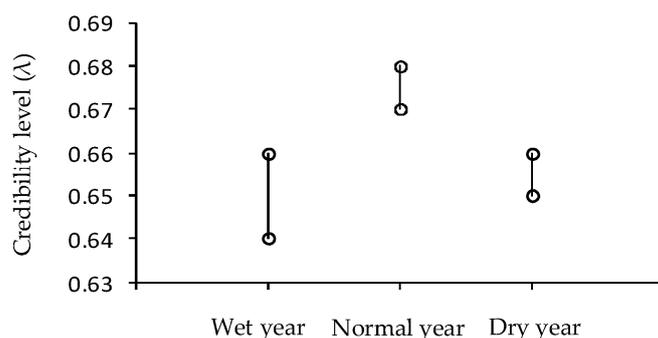


Figure 8. Credibility level of system revenue in different scenarios in Minqin Oasis.

According to Figures 6 and 7, the interval range of system revenue M decreases from 0.05 to 0.03 in different scenarios. The interval range of the credibility level is reduced from 0.02 to 0.01, indicating that system revenue risk space will be correspondingly reduced in different scenarios, and system revenue is relatively decreased with reduced irrigation water.

Decision-makers can determine the optimal irrigation water to different crops according to different scenarios. Moreover, from the mechanism of the optimization model, it can be seen that the system revenue and its credibility level are positively related to the optimization of irrigation water. In other words, when water inflow conforms to the interval value of the model, the greater the amount of irrigation water, the higher the revenue of system, and the higher its credibility level.

5. Conclusions

In this study, an interval quadratic fuzzy dependent-chance programming (IQFDCP) model has been developed for optimal allocation of irrigation water resources. This model combined with credibility level theory to improve the previous irrigation water resources optimization models which only consider the maximum system revenue ignoring the credibility level. At the same time, IQFDCP can address the uncertainties in the agricultural irrigation system. The IQFDCP model can be solved by interval quadratic solution via transferring it into the upper and lower submodels. This study applies the model to Minqin Oasis. The crop water production functions were used to

express the relationship between crop yield and the amount of irrigation water, and their empirical coefficients were simulated by a large number of experimental data. Moreover, the uncertain methods and constraints can reflect the actual situation in the area. The results show that the feasibility of IQFDCP model for optimal allocation of irrigation water and generation of the desired irrigation water allocation plans with the maximum credibility level. Therefore, the optimization results can provide decision makers or farmers with the optimal irrigation water schemes. Compared with the previous studies, it has the following advantages: (a) A potential approach is to integrate IQP and FDCP to handle multiple uncertainties and nonlinearities in irrigation systems; (b) it has the ability to address the confliction of maximum system revenue and credibility level for water management; (c) the proposed method is applied to a real case and provides irrigation water allocation schemes with maximum credibility level under different scenarios.

Although the IQFDCP model can solve uncertainties existing in irrigation management problems, and obtain desired irrigation water with maximum credibility level, more physical processes including transformational processes among atmosphere water, surface water, soil water and groundwater need to be considered in reality. Additionally, irrigation water management policies also have impacts on optimal allocation of irrigation water resources. Taking all these concerns into account is a significant topic that needs to be further studied in the future.

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