Journal of Cleaner Production 345 (2022) 131182

Contents lists available at ScienceDirect

Journal of Cleaner Production

journal homepage: www.elsevier.com/locate/jclepro

Crop-growth-based spatially-distributed optimization model for irrigation water resource management under uncertainties and future climate change

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ARTICLE INFO

Handling Editor: Mingzhou Jin

Keywords:
Robust possibilistic programming
Climate change
Water footprint
NSGA-II
Spatial distributions
Uncertainties

ABSTRACT

The spatially distributed AquaCrop-multiobjective robust possibilistic programming (distributed AquaCrop-MORPP) model that considers spatially-distributed land, soil and management features has been proposed for irrigation scheduling optimization under uncertain conditions. Compared with traditional simulation-optimization models, it improved the robustness of decision making by optimizing irrigation amounts and dates considering physical crop growth process and the spatial heterogeneity of soil, crop and irrigation. Additionally, it enhanced the AquaCrop-optimization model by handling uncertainties presented as fuzzy and stochastic variables. Moreover, it enhanced the applicability of multi-objective programming (MOP) by balancing contradictory relationships between the objectives of the net economic benefit and field water use efficiency, which were simulated and calculated by the spatially-distributed AquaCrop model. Fifty groups of optimal Pareto solutions were obtained by solving the spatially-distributed AquaCrop-MORPP model using a fast and elitist multi-objective genetic algorithm (NSGA-II) method. Subjective decision-making methods (e.g., Technique for order preference by similarity to an ideal solution (TOPSIS) and prospect theory) were used to select specific alternatives from the Pareto solutions to provide recommendations for managers from different viewpoints. The alternatives that maximized field water use efficiency or net economic benefit separately were selected to cope with emergencies. To obtain optimal irrigation scheduling under future climate change, the RCP4.5 future climate scenario was integrated with the spatially-distributed AquaCrop-MORPP model. The model was verified by applying it to the Yingke Irrigation District (YID), Heihe River Basin (HRB), China. The results showed that the maximum field water use efficiency and net economic benefit in 2021 improved by 24% and 1.3% than those in 2012 for the alternative selected by TOPSIS method. The irrigation scheduling with varied irrigation dates improved by 3.7% and 5% than the irrigation scheduling with fixed irrigation dates for field water use efficiency and net economic benefit, separately. The study provides a framework about how to build spatially-distributed crop simulation-optimization model with consideration of tradeoffs amid multiple objectives to optimize irrigation schedules, and how to select alternatives based on managers' risk attitudes, and offer a series of Pareto solutions for managers.

1. Introduction

Water contradictions between increasing water demands and limited supplies of water are increasingly serious issues, particularly in arid and semiarid regions (Zhang et al., 2018). Agricultural water contradictions are highly affected by climate change, which impacts weather conditions (e.g., rainfall, evapotranspiration and runoff), and farmland microclimates (Li et al., 2020; Wang et al., 2019). Thus, it is essential to explore optimal water allocation schemes under climate change scenarios to cope with emergencies. Precise irrigation is an effective tool to alleviate water contradictions because it can allocate water resources based on actual weather, soil and crop conditions, efficiently improving water use efficiency. Therefore, it is critical to optimize irrigation scheduling based on precise irrigation with consideration of future climate change scenarios to alleviate water contradictions and achieve sustainable agricultural development.

Simulation models are helpful tools for depicting irrigation water consumption and crop growth. They can compare the results by

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https://doi.org/10.1016/j.jclepro.2022.131182
Received 8 October 2021; Received in revised form 19 January 2022; Accepted 27 February 2022
Available online 1 March 2022

changing irrigation water inputs and obtain relatively good water allocation schemes while considering the actual agro-hydrological characteristics and spatial heterogeneities of soil types, weather conditions and crop types. Comparisons among different irrigation schemes cannot help managers find global optimal results. Spatially-distributed simulation-optimization models have been proposed to improve this problem (Schoups et al., 2006; Chen et al., 2016; Wang et al., 2020). The usually adopted models include the spatially-distributed AquaCrop-optimization model and spatially-distributed SWAP-optimization model. Compared with the spatially-distributed SWAP-optimization model, the spatially-distributed AquaCrop-optimization model needs less input data and is easily operated, which makes it widely used in irrigation water resource management (Han et al., 2019, 2020; Li et al., 2020). Although some studies have adopted spatially-distributed AquaCrop-optimization models to optimize irrigation amount, these studies neglected the effects of irrigation dates on water use efficiency and yields. Therefore, in this paper, the irrigation amounts and dates are optimized simultaneously by using the spatially distributed AquaCrop-optimization model at a regional scale.

Another common disadvantage of the optimization models in the spatially-distributed AquaCrop-optimization models is that they usually adopt the yield as the only objective but do not consider the field water use efficiency. Field water use efficiency matters for both regional managers and local farmers because water use will influence the cost of crop production and is an important indicator of sustainable development. Meanwhile, yield and field water use efficiency are contradictory, which means that emphasizing one objective will weaken the other (Mosleh et al., 2017; Li et al., 2018). Many published optimization model studies have considered field water use efficiency (Wang et al., 2019; Yue et al., 2020). However, they often used coefficients to calculate water seepage in the field and ignored the influences of the spatial variability of soil, weather conditions and irrigation. Thus, the introduction of a distributed simulation model is a good way to improve the performance of multi-objective optimization models and balance the relationship between the yield and field water use efficiency. Precipitation also affects the water use efficiency. The concept of blue and green water would help to separate and quantify the influence of irrigation water and precipitation (Cao et al., 2014). Therefore, the field water use efficiency calculated by efficient blue and green water should be integrated into the AquaCrop simulation and multi-objective optimization model.

The irrigation water resource system is full of uncertainties because of the complex hydro-meteorological conditions and supply-demand environments of water resources. The uncertainties expressed as fuzzy numbers could be handled by fuzzy mathematical programming (FMP) methods. For dealing with fuzzy numbers in the constraints, the usually adopted FMP approaches mainly include possibility-constrained programming (PCP), credibility-constrained programming (CCP), and robust possibility programming (RPP) (Li et al., 2013; Lu et al., 2016; Inuiguchi and Ramik., 2000). The above three methods can improve the robustness of decisions by considering the various risk attitudes of managers on stochastic events, which are risk appetite, risk neural and risk aversion (Zhang et al., 2016; Pishvaee et al., 2012). Compared with the PCP and CCP methods, the RPP model can not only quantify risk attitudes but also avoid unacceptable risks in economic losses (Peykani et al., 2018). Therefore, the RPP model needs to be incorporated with the spatially-distributed AquaCrop model and multiobjective optimization model for irrigation scheduling optimization under uncertainties.

There are many methods available for the spatially-distributed simulation-optimization modelling, such as the NSGA-II method and the parallel genetic algorithm (PGA). Compared with the PGA method, the NSGA-II method is highly efficient for addressing the MOP problem because it can obtain the Pareto frontier composed of multiple groups of optimal water allocation schemes (Hojjati et al., 2018; Tabari and Soltani, 2013). Nevertheless, too many schemes could be confusing for managers, and thus, multiple-criteria decision-making methods (MCDMs) could be used to help select at least one water allocation scheme according to the preferences of decision makers. The subjective multiple criteria decision-making method (SMCDM) is extensively applied to decision making because it can expose the subjectivities and preferences of managers and is closer to actual applications (Wang et al., 2020). The SMCDM is categorized into deterministic (DSMCDM) and uncertain (USMCDM) decision methods, and TOPSIS and prospect theory are typical representations of the above two methods (Li et al., 2019; Grishina et al., 2017; He et al., 2019). As implied, the DSMDCM method deals with the events that happen determinedly, while the USMCDM handles the events that occur randomly. The above two methods can offer managers various perspectives. Excluding the abovementioned two alternatives, extreme alternatives that tend to one objective excessively and alternatives under future climate-change scenarios can help managers deal with emergencies (Shahvari et al., 2019; Xu et al., 2020).

The objective of this study is to develop a framework for managing irrigation scheduling under uncertainties. The framework includes a spatially-distributed AquaCrop model, multiobjective programming (MOP), robust possibility programming (RPP), NSGA-II, TOPSIS and prospect theory methods. First, spatially-distributed AquaCrop multi-objective programming (distributed AquaCrop-MOP) is established by coupling the spatially-distributed AquaCrop model with the MOP model. It could optimize irrigation amounts and irrigation dates simultaneously and balance the relationship between the yield and field water use efficiency, which were measured by the spatially-distributed AquaCrop model. Second, the spatially-distributed AquaCrop-MORRP model is developed by integrating RPP into the spatially-distributed AquaCrop-MOP model, which can handle uncertainties expressed as fuzzy numbers, and stochastic variables. Third, the NSGA-II method is applied to solve the spatially-distributed AquaCrop-MORRP model to obtain optimal Pareto solutions. Finally, the TOPSIS and prospect theory methods are used to select alternatives from Pareto solutions to provide more alternatives for managers from different views. The proposed model is employed in a study area of Yingke District (YID), Heihe River Basin (HRB), China, to verify its application.

2. Methodology

2.1. The spatially-distributed AquaCrop model

The AquaCrop model can reflect the responses of yield to irrigation scheduling under deficient irrigation (Zhang et al., 2013). The irrigation dates and irrigation amounts are optimized simultaneously because they both affect the crop yield. Because irrigation scheduling is different for crops with various soil types and weather conditions, the spatially-distributed AquaCrop model is developed by dividing the study area into several homogeneous decision-making units. The formulation of the spatially-distributed AquaCrop model can be found in Wang et al. (2021).

2.2. Optimization model under uncertainties

(1) Water footprint based on the spatially-distributed AquaCrop model

The water footprint of crop yield production at the irrigation district scale is described as follows:

$$GPWF = BWF + GWF = 10 \times (IR + ER)/Y \tag{1}$$

where $GPWF$ is the yield production water footprint (m^3/kg); BWF and GWF are the blue water footprint and green water footprint (m^3/kg), respectively; IR and ER are the irrigation amount and rainfall (mm), respectively; and Y is the yield (kg/ha).

The effective water footprint rate for yield is introduced in this paper because not all irrigation amounts are used for evapotranspiration caused by soil water exchanges, and the expression is shown as follows.

$$R_{ET} = (BWF_{ET} + GWF)/GPWF = ET/(IR + ER) \quad (2)$$

where R_{ET} is effective water footprint rate. BWF_{ET} is the effective blue water footprint (m^3/kg). ET is the actual evapotranspiration over the whole growth period (mm), affected by soil water stress and the crop coefficient, and simulated by the spatially-distributed AquaCrop model.

$$ET_{day} = E_{day} + T_{rday} = K_r \times K_e \times ET_{0,day} + K_S \times K_{C_{Tr}} \times ET_{0,day} \quad (3)$$

where E_{day} and Tr_{day} represent daily soil evaporation and crop transpiration (mm/day), respectively, and Kr, Ke, Ks and Kc_{Tr} denote the evaporation reduction coefficient, the evaporation coefficient, the soil water stress coefficient, and the crop transpiration coefficient, respectively. These four parameters all change from zero to one, and a higher value corresponds to a smaller water stress. $ET_{0,day}$ signifies the daily crop potential evapotranspiration (mm/day).

$$ET = \sum_{t=1}^{T} ET_{day,t} \quad (4)$$

where $ET_{day,t}$ implies the actual daily crop evapotranspiration (mm/day). T indicates the length of the growth period and is 110 days, 155 days and 155 days for wheat, seed corn and field corn, respectively.

(2) Multiple-objective robust possibilistic programming (MORPP)

The MORPP model is used to trade off the objectives of net economic benefit and field water use efficiency and deals with the uncertainties presented as fuzzy numbers and stochastic variables, shown as follows:

Objective 1 - maximizing the field water use efficiency

$$\max f_1 = \sum_{i=1}^{I} (BWF_{ET,i} + GWF_i)/GPWF_i \quad (6)$$

where f_1 is the field water use efficiency defined as the sum of effective blue water and green water divided by the sum of blue water and green water. i is the subscript of decision-making units (DMUs), derived from overlying the soil layer and crop layer based on the GIS platform, and the division results are shown in Table 1. I is the numbers of DMUs. $BWF_{ET,i}$ is the effective blue water footprint of the ith DMU (m^3/kg), GWF_i is the green water footprint of the ith DMU (m^3/kg), and $GPWF_i$ is the sum of the blue water footprint and green water footprint of the ith DMU (m^3/kg).

Objective 2 -maximizing the net economic benefit

$$Max f_2 = \sum_{i=1}^{I} (P_{c,i}(\omega) Y_i(WA_{it}, ID_{it}) A_i - B_i^{\sim} WA_i A_i) \quad (7)$$

where f_2 denotes the net economic benefit defined as the gross economic benefit from the yield minus the water cost (10^4 Yuan). $Y_i(WA_{it}, ID_{it})$ implies the yield per area (kg/ha), expressed as a function of irrigation amount (WA_{it}) and irrigation date (ID_{it}), obtained from running the spatially-distributed AquaCrop model under known WA_{it} and ID_{it}. WA_{it} and ID_{it} represent irrigation amounts (mm) and irrigation dates (day) of DMUs during growth period t and are the decision variables of the optimization model. $P_{c,i}(w)$ and $B_i^{\sim}$ signify crop prices expressed as stochastic variables and water costs characterized by fuzzy numbers (Yuan/m^3), respectively. w indicates the probability of the distribution function of crop price. A_i is the planting area of the crop at the ith DMU (ha).

2.2.1. Constraints

(1) Water availability constraints

$$Nec\left(\sum_{i=1}^{I}\left(\sum_{t=1}^{T} WA_{i,t}\right)A_i \Big/ 1000 \le \eta Q^{\sim}\right) \ge \delta_s \quad (8)$$

where η is the canal water-use coefficient, $Q^{\sim}$ denotes available water resources (fuzzy numbers, 10^4 m^3), and δ_s indicates the necessary level (with a higher value indicating a larger confidence level).

(2) Irrigation amount constraints

$$WA_{it,min} \le WA_{it} \le WA_{it,\max} \quad \forall i, t \quad (9)$$

where $WA_{it,min}$ and $WA_{it,\max}$ represent the minimum and maximum water allocation at growth period t for the crop at ith DMU (mm), respectively.

(3) Irrigation date constraints

$$ID_{it,\min} \le ID_{it} \le ID_{it,\max} \quad \forall i, t \quad (10)$$

where $ID_{it,min}$ and $ID_{it,\max}$ signify the initial and final irrigation dates of growth period t for the crop at the ith DMU (day), respectively.

(4) Crop evapotranspiration constraints

$$ET_{ai} \le ET_{mi} \quad \forall i \quad (11)$$

where ET_{ai} and ET_{mi} denote the actual crop evapotranspiration and maximum crop evapotranspiration (mm) of the ith DMU, respectively. ET_{ai} is simulated by the spatially-distributed AquaCrop model.

(5) Nonnegative constraints

$$WA_{it} \ge 0 \quad T_{it} \ge 0 \quad \forall i, t \quad (12)$$

(6) The mapping relationship between the number of decision variables and the number of DMUs

$$NDMU_i = \sum_{t=1}^{T} 2NWA_{it} \quad \forall i \quad (13)$$

where $NDMU$ and NWA mean the numbers of decision variables and numbers of DMUs, respectively. There are ten DMUs and seventy-four decision variables.

Table 1
Initial and final irrigation dates (T_{min} and T_{max}) and minimum and maximum water allocations (WA_{min} and WA_{max}) of seed corn, field corn and wheat at various growth periods.

Growth period	Jointing stage	Heading stage	Grouting stage	Mature stage	Jointing stage	Heading stage	Grouting stage
Crops	Seed corn/field corn				wheat		
T_{min} (day)	27	58	83	110	22	49	79
T_{max} (day)	57	82	109	142	48	78	97
WA_{min} (mm)	83	83	75	75	83	83	75
WA_{max} (mm)	165	165	150	150	165	165	150

2.3. The spatially-distributed AquaCrop-MORPP model and solving methods

The framework of the spatially-distributed AquaCrop-MORPP model is shown in Fig. 1. The initial individuals composed of decision variables generated randomly based on the NSGA-II method are input into the coupled spatially-distributed AquaCrop-MORPP model. In the coupled model, the operations are as follows: the spatially-distributed AquaCrop model is called to simulate the yields and ETA under given individuals, which are inputted into the MORRP model to calculate the objective values of each individual. After the above process, the calculated objectives of all individuals are sent back to the NSGA-II platform to conduct evolutions of individuals where individuals with higher ranks will have higher probabilities of evolving to the next generation. The new individuals are input into the spatially-distributed AquaCrop-MORPP model to repeat the above processes until the Pareto frontier is attained. The steps of formulating the framework of the spatially-distributed AquaCrop-MORPP model are shown as follows:

(1) Build the spatially-distributed AquaCrop model based on section 2.1.
(2) Develop the multiple-objective robust possiblistic (MORPP) model according to section 2.2.
(3) Establish the spatially-distributed AquaCrop-MORPP model on the basis of section 2.3.
(4) Solve the spatially-distributed AquaCrop-MORPP model and obtain the Pareto frontier by adopting the NSGA-II method, as shown in section 2.3.
(5) Obtain alternatives by using the TOPSIS and prospect theory methods from the Pareto frontier, displayed in section 2.4.

The NSGA-II is used to solve the spatially-distributed AquaCrop-MORPP model, which can obtain multiple groups of Pareto solutions, and the detailed process is as follows:

(1) Determine decision variables (74 decision variables (irrigation amounts and irrigation dates) for 10 DMUs).
(2) Randomly generate the parent population according to the decision variables, change interval and number of selected chromosomes.
(3) Calculate the objective values of chromosomes with the help of the spatially-distributed AquaCrop-MORPP model.

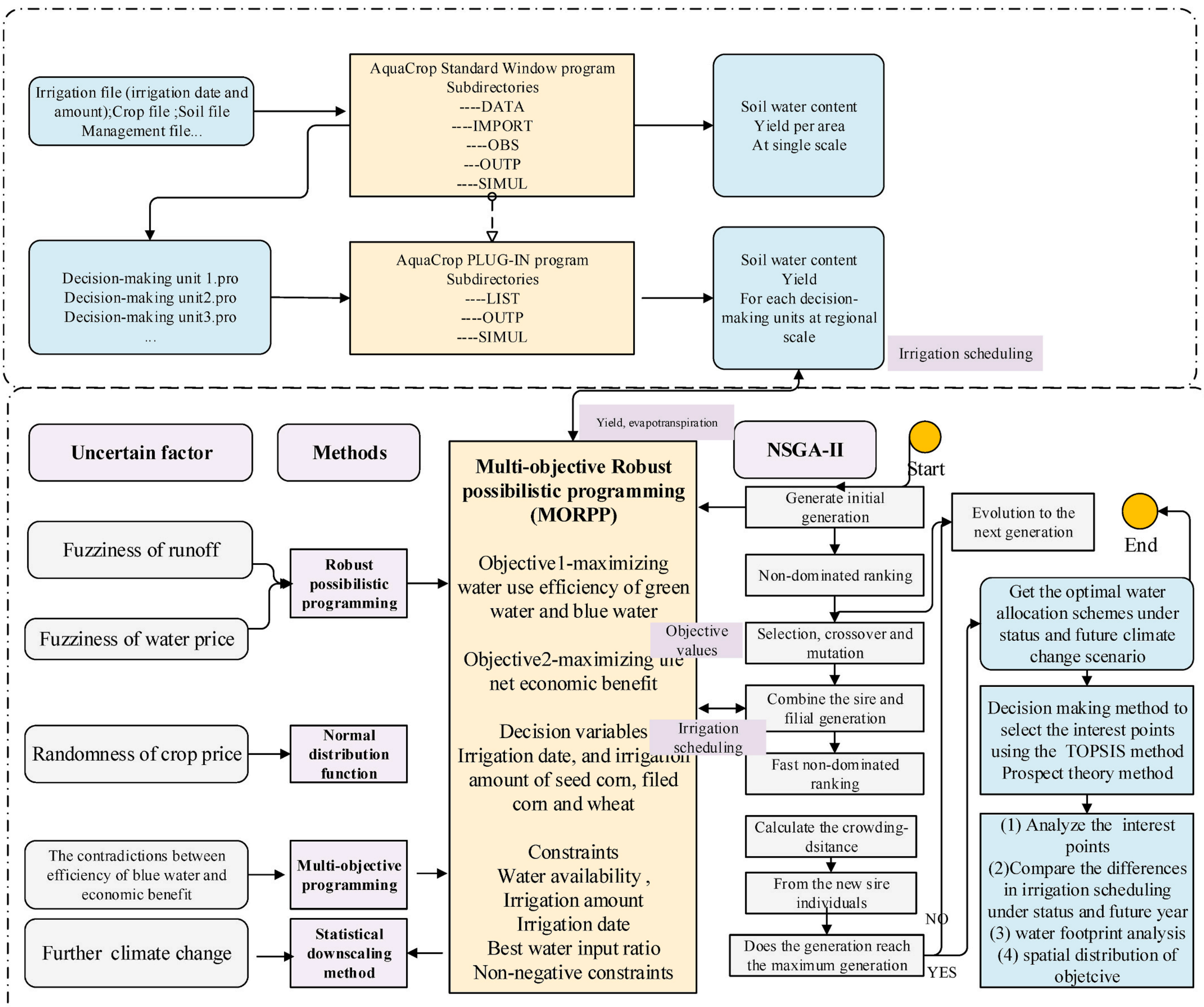


Fig. 1. Framework of the spatially-distributed AquaCrop-MORPP model.

(4) Assign the rank (level) of the first parent population on the basis of the nondominant solution.
(5) Generate child population with applied selection, crossover and the mutation operator.
(6) Combine parent chromosomes and child chromosomes to form a new population and sort the new population by the fast nondominant solution.
(7) Create the parent population for the next iteration based on the selected chromosome and fast nondominant solution.
(8) Judge that is the convergence criterion satisfied. If yes, optimal irrigation amounts, irrigation dates, and objective functions are attained; if not, turn to step (5).
(9) End.

2.4. Multicriterion decision-making methods (DCDM)

The TOPSIS and prospect theory methods are applied to select alternatives from multiple groups of optimal Pareto solutions from different views of decision making.

(1) TOPSIS method

The alternative with the smallest relative distance value will be selected in the TOPSIS method, and the detailed steps are shown as follows:

Step 1 : operate normalization vectors

$$f_{ij}=\frac{f_{ij}-\min(f_{ij})}{\max(f_{ij})-\min(f_{ij})} \tag{14}$$

Step 2 : get the normalized decision matrix

$$R=(r_{ij})_{m\times n}=(f_{ij}W_j)_{m\times n} \tag{15}$$

where i and j represent the subscripts of alternatives and objectives, respectively. m and n are the numbers of alternatives and objectives, respectively. f_{ij} means the normalized value of the jth objective of the ith alternative. W_j is the weight of the jth objective, which is determined by the analytic hierarchy process (AHP) method (Zhang et al., 2018). The weights of the field water use efficiency and net economic benefit are 0.4 and 0.6, respectively. r is the weighted normalized value of the jth objective of the ith alternative. R is the normalized decision matrix.

Step3 : determine ideal points

The ideal points include the positive and negative ideal points (s_j^+ ands_j^-), where the positive ideal points denote the best values of multiple objectives, and the negative ideal points represent the worst values of multiple objectives. The principles of determining ideal points are shown as follows:

$$s_j^+=\max_{1\le i\le m}\{r_{ij}\}(j=1,\dots n)$$

$$s_j^-=\min_{1\le i\le m}\{r_{ij}\}(j=1,\dots n) \tag{16}$$

Step 4 : Calculate the distances ($ED_{i+(i-)}$) of the ith alternative to the ideal points based on the two-dimensional Euclidean distance.

$$ED_{i+(i-)}=\sqrt{\sum_{j=1}^{n}\left(r_{ij}-s_j^{+(-)}\right)^2}\quad i=1,\dots m \tag{17}$$

Step 5 : Calculate the relative distance (C_i) of the ith alternative

$$C_i=\frac{ED_{i+}}{ED_{i-}+ED_{i+}}\quad i=1,2,\dots m \tag{18}$$

Step 6 : Rank the alternatives and choose the alternative with the smallest C value.

(2) Prospect theory method

The prospect value is composed of a positive prospect value of gains and a negative prospect value of losses. The prospect value is calculated by multiplying the prospect utility value by the decision weight. The prospect utility values of gains and losses are transformed from gains and losses based on the utility functions. The utility functions measure the degrees to which gains or losses satisfy ideal expected values. The decision weights are converted from occurrence probabilities of alternatives according to the weight functions of gains and losses, which can quantify the risk attitudes of managers on risk events. The utility functions and weight functions of gains and losses are shown in Fig. 2.

Step 1–2 : normalize vectors and select ideal points

These two steps are the same as step 1 and step 3 in the TOPSIS method.

Step 3 : compute the prospect utility value

$$\Delta f_{ij}=\begin{cases}d(f_{ij},f_0) & f_{ij}\ge f_0\\ -d(f_{ij},f_0), & f_{ij}<f_0\end{cases}$$

$$v(f_{ij})^{+(-)}=\begin{cases}\Delta f_{ij}^{\alpha} & \Delta f_{ij}\ge 0\\ -\theta(-\Delta f_{ij})^{\beta}, & \Delta f_{ij}\le 0\end{cases} \tag{19}$$

where f_0 implies the ideal points, including the positive and negative ideal points, respectively, and f_{ij} donates the jth objective value of the ith alternative. $d(f_{ij},f_0)$ represents the absolute distance between the jth objective of the ith alternative and ideal point, while Δf_{ij} is the relative distance. If Δf_{ij} is larger than zero, it indicates gains; otherwise, it indicates losses. $v(f_{ij})^{+(-)}$ signifies the negative and positive prospect utility values of the jth objective of the ith alternative, transformed from gains and losses based on Eq. (19). α (β) expresses the relationship between gains (losses) and corresponding prospect utility values, α, $\beta<1$ represents the decreasing sensitivity degree, θ is the curve abruptness, and $\theta>1$ indicates loss aversion.

Step 4 : calculate prospect values of alternatives

$$V_i=\sum_{j=1}^{n}\Pi^{+}(p_j)v(f_{ij})^{+}+\sum_{j=1}^{n}\Pi^{-}(p_j)v(f_{ij})^{-}$$

$$\Pi^{-(+)}(p_j)=\frac{p^{\gamma(\varepsilon)}}{1-p)(1-p)(1-p)^{\gamma(\varepsilon)})^{1/\gamma(\varepsilon)}} \tag{20}$$

where p_j represents the occurrence probability of the jth objective of the ith alternative, $\Pi^{-}(p_j)$ and $\Pi^{+}(p_j)$ denote the decision weights of the jth objective for losses and gains, respectively, and γ and ε describe the relationship between occurrence probability and decision weight from perspectives of losses and gains, respectively.

Step 5 : reckon weight and rank the alternatives

Because the probabilities of alternatives are unknown, they are optimized together to obtain the united probabilities, and the processes are shown as follows:

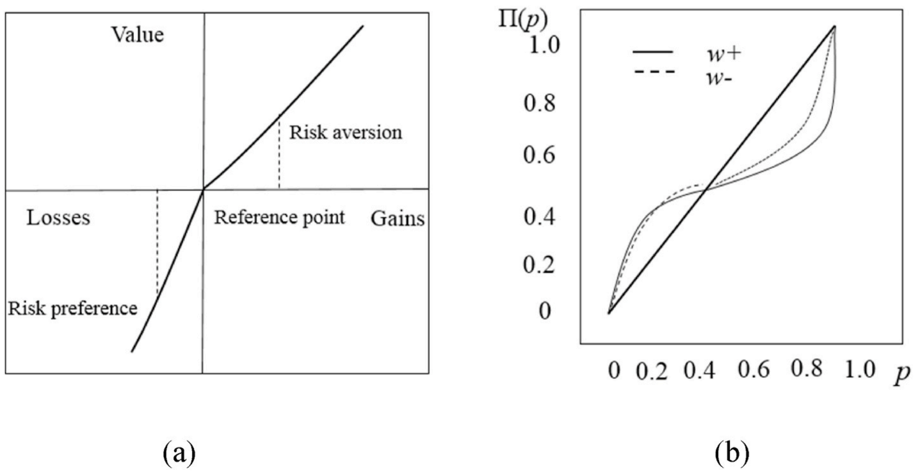


Fig. 2. a and b are the utility functions and weight functions of gains and losses.
Notes: p is the occurrence probability of events, w^- is the decision weight of losses, and w^+ is the decision weight of gains, transformed from p based on the weight function. $\Pi(p)$ is the decision weight.

$$\max V = (V_1(a_1), V_2(a_2), \ldots V_m(a_m)) = \sum_{i=1}^{m}\sum_{j=1}^{n}\Pi^+(p_j)v(\Delta f_{ij})^+ + \sum_{i=1}^{m}\sum_{j=1}^{n}\Pi^-(p_j)v(\Delta f_{ij})^-$$

$$\text{s.t.} \quad \sum_{j=1}^{n} p_j = 1, p_j \geq 0 \tag{21}$$

The optimal $p^* = (p_1^*, p_2^*, \ldots, p_n^*)$ can be obtained by solving the above model, which is transformed into corresponding decision weights. The optimal prospect values of alternatives are as follows:

$$V_i = \sum_{j=1}^{n}\Pi^+(p_j^*)v(\Delta f_{ij})^+ + \sum_{j=1}^{n}\Pi^-(p_j^*)v(\Delta f_{ij})^- \tag{22}$$

where V represents the prospect value of all alternatives and V_i denotes the prospect value of the ith alternative.

3. Case study

3.1. Study area

The Yingke Irrigation District (YID) is located in the middle oasis of the Heihe River Basin (HRB) and the main food production base of China, as shown in Fig. 3. The crops are mainly wheat, seed corn, and field corn. The reference evapotranspiration (*ET0*) is approximately 1200 mm, while the precipitation is approximately 125 mm, which belongs to semiarid and arid districts (Zhang et al., 2018). Crop production is mainly derived from irrigation because natural rainfall cannot satisfy the water demands of crops. The irrigation resources are composed of surface water from the HRB and groundwater as supplementary water resources. There were four soil types in the study areas, and the compositions of the soil types are shown in Table 2.

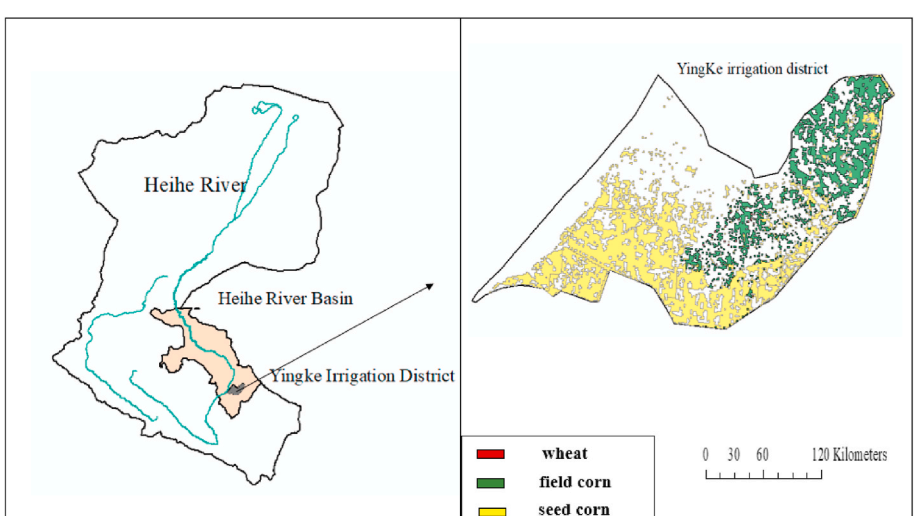


Fig. 3. The geographical location of the study area.

Table 2
Classifications and compositions of four types of soils at different soil depths of the YID (type 1, type 2, type 3 and type 4 are denoted as T1, T2, T3, and T4, respectively).

Types	0–80 cm (%)				80–140 cm (%)			
	Clay	Silt	Sand	classification	Clay	Silt	Sand	classification
T1	15.22 ± 2	55 ± 1	29.78 ± 1	Silt loam	17.17 ± 3	53.56 ± 3	29.27 ± 3	Silt loam
T2	11.99 ± 3	51.52 ± 2	36.49 ± 3	Silt loam	6.57 ± 1	32.67 ± 3	60.76 ± 3	Sandy loam
T3	14.33 ± 3	54.31 ± 1	31.37 ± 2	Silt loam	16.66 ± 2	44.41 ± 2	38.93 ± 2	loam
T4	14.43 ± 2	43.46 ± 3	42.11 ± 2	loam	16.09 ± 3	43.51 ± 3	40.40 ± 3	loam

3.2. Problem statement

Previous studies used distributed AquaCrop-optimization models to optimize irrigation amounts, but the influences of irrigation dates on the yield were neglected, and irrigation amounts and irrigation dates were unable to be optimized simultaneously. Except for the above problem, a contradictory relationship between the field water use efficiency and economic benefit was not considered, where emphasizing one may result in another being unacceptable. Furthermore, the ignorance of spatial variability is not in accordance with actual conditions because the changes in soil types, weather types and crop types will influence the water demand, field water use efficiency and crop yield. Therefore, it is essential to optimize irrigation amounts and irrigation dates concurrently, as well as trade off contradictory relationships between field water use efficiency and economic benefit with consideration of spatial heterogeneities of soils, weather, and crops. Agricultural water contradictions alter with climate change, and the corresponding optimal irrigation scheduling will be different under various climate change scenarios; thus, it is necessary to optimize irrigation scheduling under climate change in the future to cope with emergencies.

3.3. Data collection

The water price and available water resources are both expressed as fuzzy numbers that are composed of the minimum possible, possible and maximum possible values, which are determined by the respective minimum, mean and maximum values of the historical water price and historical water resource supply. The fuzzy numbers of water prices and available water resources are expressed as [0.30, 0.32, 0.34] Yuan/m^3 and [1.07, 1.09, 1.11] $\times 10^8$ m^3, respectively. The initial and final dates at each growth period are set based on the irrigation periods gained from the Annual Report of Water Conservancy (2012). The crop price is characterized by a stochastic normal distribution, which is fitted on the basis of daily crop-price time series from January 01, 2017 to May 03, 2020 acquired from the website (https://cif.mofcom.gov.cn/cif/html/dataCenter/). The average crop prices of wheat, field corn and seed corn are 2.43, 1.82 and 2.50, respectively. The standard deviations of crop prices are 0.04, 0.03 and 0.03 independently. The hydrometeorological data in 2021 under the RCP4.5 scenario from Wang et al. (2019) are input data of the spatially-distributed AquaCrop-MORPP model to optimize optimal irrigation scheduling for the future year. The land-use type in 2021 is assumed to be the same as that in 2012. The initial and final irrigation dates at different growth periods of three crops, four soil types and ten decision-making units are shown in Tables 1–3.

Table 3
Ten divided decision-making units (DMU_S) of the YID by overlying soil types and crop types.

Decision-making units (DMU)	Soil types	Crop types	Weather condition
DMU1	T1	Field corn	Zhangye station
DMU2	T3	Field corn	Zhangye station
DMU3	T4	Field corn	Zhangye station
DMU4	T1	Seed corn	Zhangye station
DMU5	T2	Seed corn	Zhangye station
DMU6	T3	Seed corn	Zhangye station
DMU7	T4	Seed corn	Zhangye station
DMU8	T1	Wheat	Zhangye station
DMU9	T3	Wheat	Zhangye station
DMU10	T4	Wheat	Zhangye station

4. Results analysis

This subsection is composed of an analysis of the optimal irrigation scheduling, the spatial distributions of field water use efficiency and net economic benefit, and optimal Pareto solutions in 2012 and 2021.

4.1. Optimal irrigation scheduling

(a) Pareto frontier and evaluation results

Fig. 4 shows the Pareto frontier composed of 50 groups of non-dominated solutions (optimal Pareto solutions) as well as the positive and negative ideal points. The positive ideal point is the point with both maximum field water use efficiency and net economic benefit. The negative ideal point is the point with both minimum field water use efficiency and net economic benefit. Fig. 4 shows that the field water use efficiency contradicts the net economic benefit. The reason would be the different influences of increasing water allocation on water use efficiency and net economic benefit. More water allocation will increase actual crop evapotranspiration (ETA) and generate higher yields and further larger net economic benefits under deficient irrigation. However, not all irrigation amount is used for ETA. Excessive irrigation will lead to water losses, such as deep infiltration. Under this circumstance, the incremental ETA is smaller than the increase degree of water allocation, resulting in field water use efficiency decreasing with water allocation. The 31st and 33rd alternatives are selected as extreme alternatives with the maximum net economic benefit and maximum field water use efficiency, respectively. All the optimal alternatives are screened by TOPSIS and the prospect theory method, and the relatively optimum alternatives are chosen based on the evaluated indicator values.

Fig. 5 shows the indicator values of 50 groups of alternatives based on TOPSIS and the prospect theory method. The 4th and 43rd

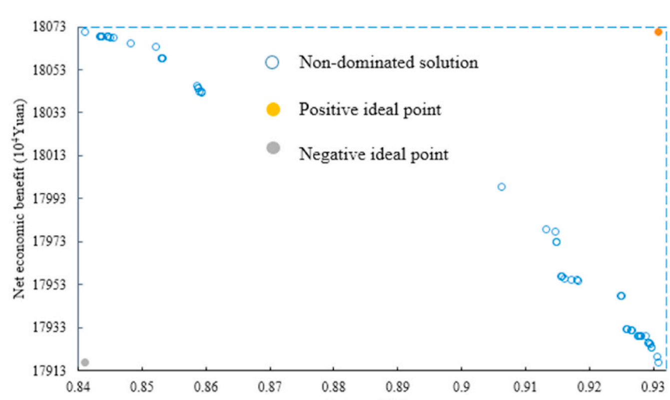


Fig. 4. Pareto frontier composed of 50 groups of nondominated solutions (optimal Pareto solutions), positive and negative ideal points.

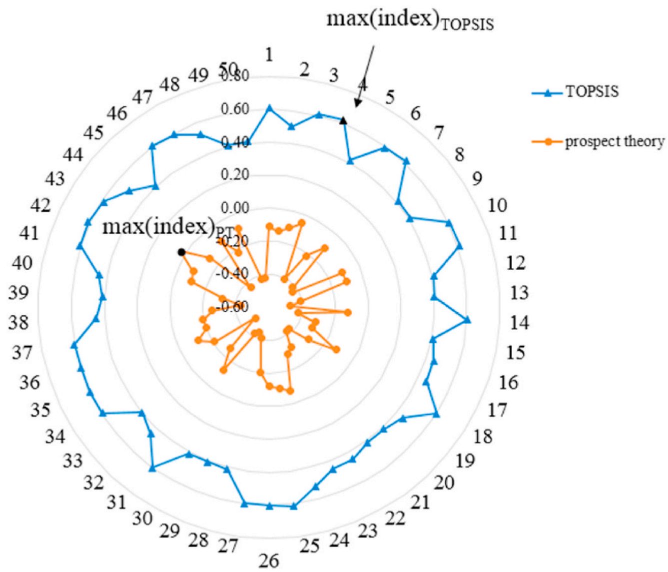


Fig. 5. Indicator values calculated by TOPSIS and prospect theory methods for 50 alternatives, where the 4th and 43rd alternatives possess the maximum values of the two methods.

alternatives in 2012 have the largest indicator values according to TOPSIS and the prospect theory method, respectively, and are selected as the optimum schemes of the two methods.

(b) Optimal irrigation scheduling of interest points

Fig. 6 (a) and (b) show the optimal irrigation schedules of the 4th, 43rd, 31st, and 33rd alternatives. Fig. 6 (a) shows that the irrigation amounts of most DMUs under the 31st alternative are higher than those under the other three alternatives. The reason is that the net economic benefit is positively correlated with water allocation under deficient irrigation. The irrigation amount at most DMUs under the 33rd alternative is lower than the DMUs under the other three alternatives. This is because the field water use efficiency presents a negative relationship with water allocation. Water allocations of the 4th and 43rd alternatives are between 33rd alternative and 31st alternative, indicating that these two alternatives can obtain compromised optimal irrigation scheduling.

Fig. 6 (a) reveals that the water allocation of crops on the first irrigation date is lower than that on other irrigation dates, while the water allocation at other irrigation periods is the same, which is caused by different water demands at various growth periods. Meanwhile, one crop with different soil types has various water allocation, which shows the influence of soil characteristics on water allocation patterns. Thus, it is necessary to integrate spatial variability into the optimization modeling of irrigation scheduling. Under the same irrigation scheduling, crops under T2 obtained the largest yields, followed by those under T3, T4, and T1. The reason is that soil type 2 has the least difference between the wilting point and the field capacity and then has the smallest water stress. With regard to water allocation patterns, seed corn with T4 under the 4th and 43rd alternatives was taken as an example. The total water allocation was 545 mm and 424 mm, the yield was 10.63×10^3 kg/ha and 10.52×10^3 kg/ha, and the field water use efficiency was 0.8 and 0.99 for the 4th and 43rd alternatives, respectively. The results reveal that the variation degree of water allocation is higher than the changed ranges of the yield. This can be explained by reasons that excessive water allocation will exceed the field capacity and further generate deep infiltration that is ineffective for increasing crop yield.

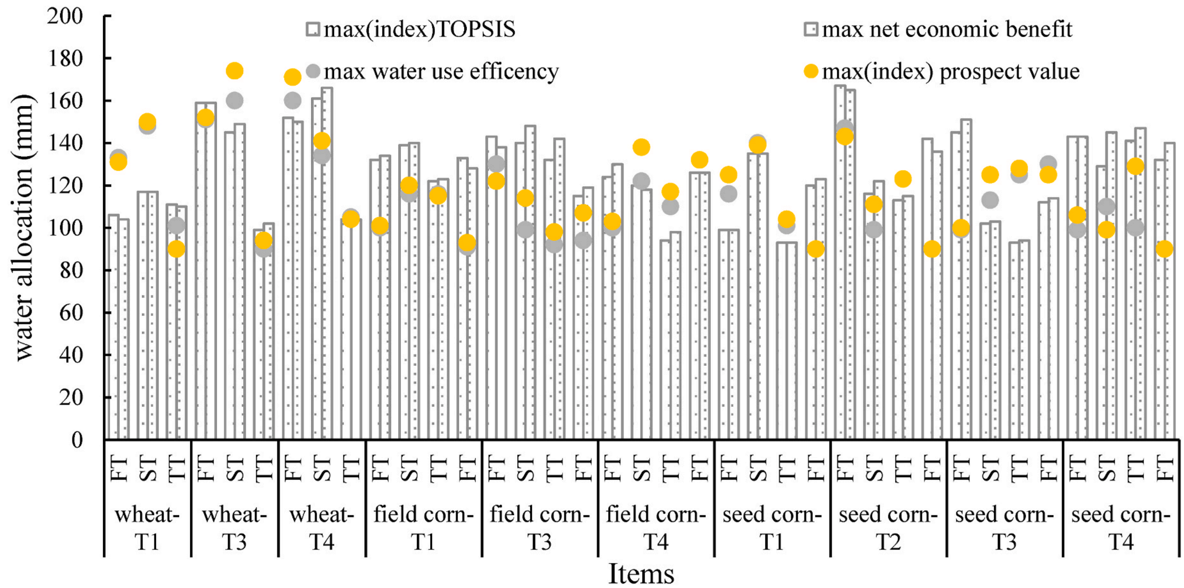
The differences in irrigation dates of the four alternatives are relatively small. The reasons are that the irrigation date is affected by the soil water content (SWC) and water allocation pattern. For one soil type, the SWC and associated water stresses (e.g., water stress influencing canopy development) at different growth periods are affected by irrigation amounts at various irrigation periods. In general, a higher irrigation amount at the first irrigation will lead to a delayed second irrigation date, belonging to a dynamic balanced process. For different soil types, the water stress will be smallest for the soil type with the lowest water difference between the field capacity and wilting point under the same irrigation amount. This means that the irrigation date of the crop with the soil type with lower water stress will be delayed compared with other soil types, but it is also influenced by the water allocation amount at each irrigation date, presenting a dynamic balanced process.

Table 4 shows the results of the total yield, water allocation, net economic benefit, and field water use efficiency of the 4th, 43rd, 31st, and 33rd alternatives. This indicates that the 31st alternative can achieve the maximum net economic benefit but the smallest field water use efficiency, while the 33rd alternative presents the opposite tendency. The net economic benefit and field water use efficiency under the 4th and 43rd alternatives stand between the 31st and 33rd alternatives. This result reveals that yield and net economic benefit are positively correlated with water allocation, while field water use efficiency is negatively correlated with water allocation. This implies that water stress is hard to avoid and exists in some periods throughout the growth period because of limited irrigation times. More water allocation will shorten the times of water shortages and alleviate the degree of water shortages, which is beneficial to crop growth and yield. In summary, managers could select corresponding optimal irrigation scheduling on the basis of the above four alternatives. Compared with prospect theory, optimal irrigation scheduling selected by the TOPSIS method is more likely to achieve a higher net economic benefit. This is because subjective weights play an important role in final decisions, and objectives with higher weights will have more probability to be chosen. The irrigation scheduling chosen by the prospect theory method tends to reach higher field water use efficiency. This is because the negative prospect value of the net economic benefit is larger than that of the field water use efficiency due to its higher decision weight, and the changing degree of the positive prospect value is larger than that of the negative prospect value. Therefore, if managers want to achieve optimal irrigation scheduling with slight preferences on the net economic benefit, they could select the 4th alternative. Otherwise, they could choose the 43rd alternative.

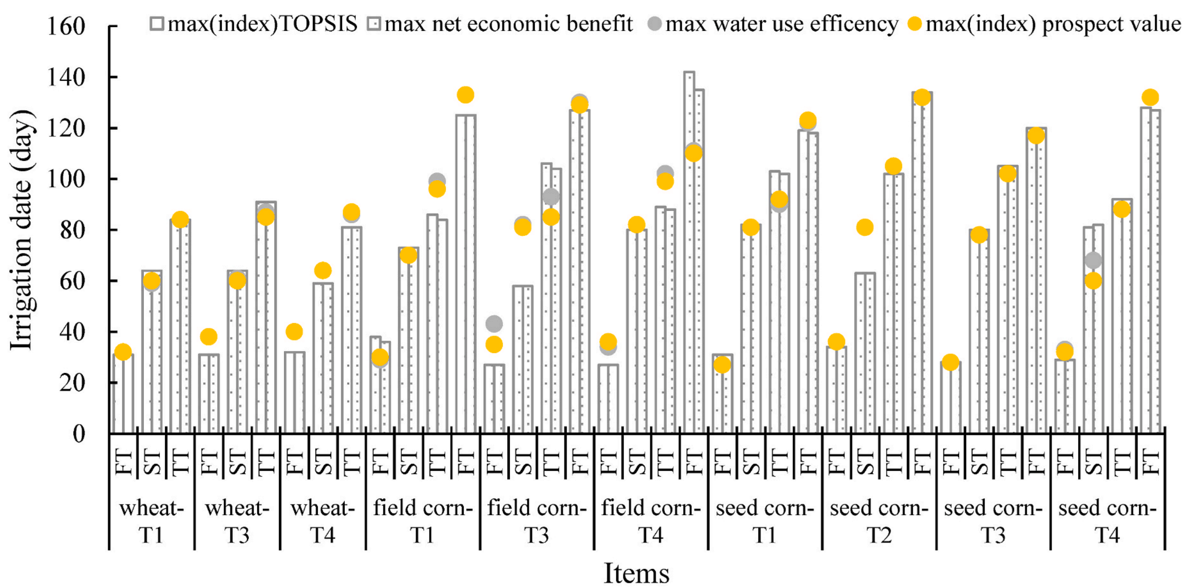
4.2. Spatial distribution of the field water use efficiency and net economic benefit

Fig. 7 (a) and (b) show the spatial distributions of the field water use efficiency and net economic benefit. The field water use efficiency and net economic benefit of ten DMUs are calculated separately and spread on a spatial scale. Fig. 7 (a) indicates that wheat has a relatively small planting area, and the field water use efficiency is 0.998, 0.995, and 0.994 for T1, T3, and T4, respectively. Field corn is mainly planted in the northwest under T1, T3, and T4. The field water use efficiencies are 0.96, 0.91, and 0.86. The seed corn has the largest planting area, planted in four soil types, and distributed in the west and southwest districts, and the field water use efficiency represents 0.86, 0.83, 0.807 and 0.81 for the four soil types, respectively. This indicates that wheat possesses the largest field water use efficiency, ranked by field corn and seed corn. This is because wheat has the smallest water allocation and field corn retains the largest yield per area compared with other crops.

Fig. 7 (b) reveals that seed corn has the largest net economic benefit, followed by field corn and seed corn, which are comprehensive results of planting area, yield per area and crop price. Taking T3 as an example, the planting areas of wheat, field corn and seed corn are 260 ha, 700 ha, and 2573 ha, respectively. The yield per area of these three crops was 7.6×10^3 kg/ha, 11.49×10^3 kg/ha, and 10.63×10^3 kg/ha, respectively, and the crop prices were 2.43 Yuan/m^3, 1.82 Yuan/m^3 and 2.5 Yuan/m^3, respectively. The net economic benefit presented above



(a)



(b)

Fig. 6. (a), and (b). Optimal irrigation amounts and irrigation dates of ten DMUs at different growth periods for 4th, 43rd, 31st, 33rd alternativesNote FT, ST, TT and FT represent the first irrigation event, the second irrigation event, the third irrigation event, and the fourth irrigation event at the jointing stage, heading stage, grouting and mature stages, respectively.

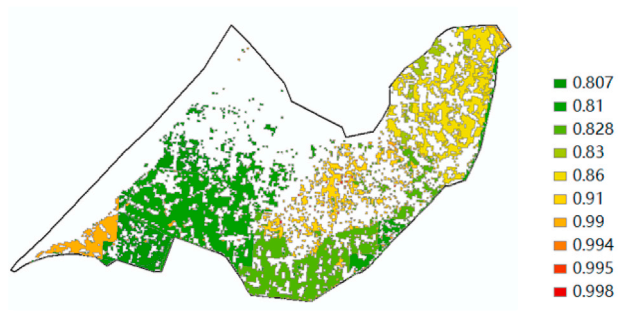
Table 4
YID yield, water allocation (WA), net economic benefit (NB) and field water use efficiency (FWUE) for the 4th, 43rd, 31st and 33rd alternatives.

Items	Yield (10^4 kg)	WA (10^4 m^3)	NB (10^4 Yuan)	FWUE
4th alternative	1018.5	4670.4	18063.79	0.85
43rd alternative	1013.3	4307.7	17998.66	0.91
31st alternative	1020.2	4795.2	18070.81	0.84
33rd alternative	1007.7	4151.2	17916.53	0.93

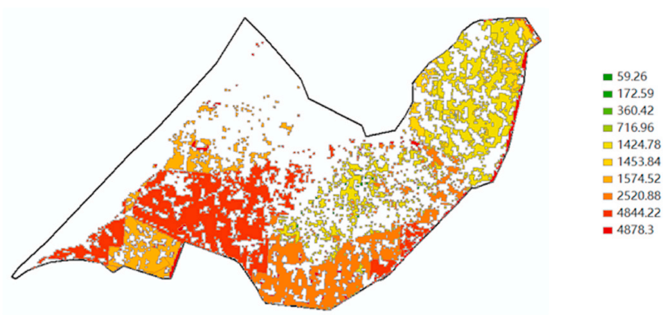
considers the comprehensive effects of planting areas, yield per area and crop prices, which can help managers grasp the spatial distribution rules of crops with different attributes and further reach higher field water use efficiency and net economic benefit.

4.3. Irrigation scheduling in the current year and future year

Fig. 8 shows the daily potential evapotranspiration (PET) and rainfall during the whole growth period of the three crops in 2012 and 2021. The PET in 2021 (812 mm) is smaller than that in 2012 (913 mm), while the



(a)



(b)

Fig. 7. (a), and (b). Spatial distributions of the field water use efficiency and net economic benefit for ten DMUs.

rainfall in 2021 (135 mm) is higher than that in 2012 (116 mm). The Pareto frontier (optimal irrigation scheduling) in 2021 is optimized and compared with the Pareto frontier in 2012 because actual crop evapotranspiration and water allocation are affected by PET and rainfall, and the result is shown in Fig. 9.

Fig. 9 illustrates that the maximum and minimum net economic benefits in 2021 are both larger than those in 2012, and field water use efficiency presents the same tendency as the net economic benefit. This means that the same net economic benefit in 2021 requires less water allocation compared with 2012 because rainfall in 2021 is higher and steady than that in 2012. The 43rd and 33rd alternatives represent the extreme conditions with maximum field water use efficiency and maximum net economic benefit. The 33rd and 24th alternatives in 2021 chosen by the TOPSIS and prospect theory methods, respectively, are compared with the 43rd and 4th alternatives in 2012, as shown in Table 5.

The 4th and 24th alternatives selected by the TOPSIS method as one group and 43rd and 33rd alternatives as one group are compared separately, according to the different alternative selection methods. Compared with the 4th alternative, the 33rd alternative has higher yields, net economic benefits and field water use efficiency. Compared with the 43rd alternative, the 24th alternative has a higher yield and lower field water use efficiency. The above phenomena are generated because rainfall distributions during the whole growth period in 2021 are increasingly even higher than those in 2012, resulting in smaller water stresses and higher yields. Consequently, the different alternatives have various emphases. If managers want to achieve higher net economic benefits in the future year, they can choose the 33rd alternative. Otherwise, they can select the 24th alternative.

5. Discussion

This section is composed of (1) a comparison of the differences in irrigation scheduling with varied irrigation dates and fixed irrigation dates and (2) a comparison with interval quadratic programming (IQP).

5.1. Comparison of irrigation scheduling with fixed irrigation dates

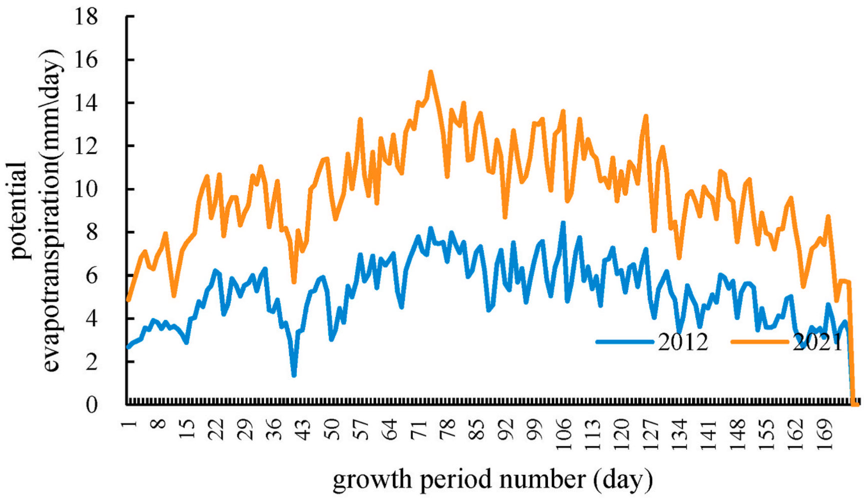
The irrigation scheduling with fixed irrigation dates is compared with the optimal irrigation scheduling under 4th and 43rd alternatives in 2012 because the irrigation date affects the yield and field water use efficiency, where water allocation on fixed irrigation dates is set to be the same for the 4th and 43rd alternatives to make sure that the only difference of the optimization model is the irrigation date. In addition, the results are shown in Table 6.

5.2. Comparison with interval quadratic programming (IQP)

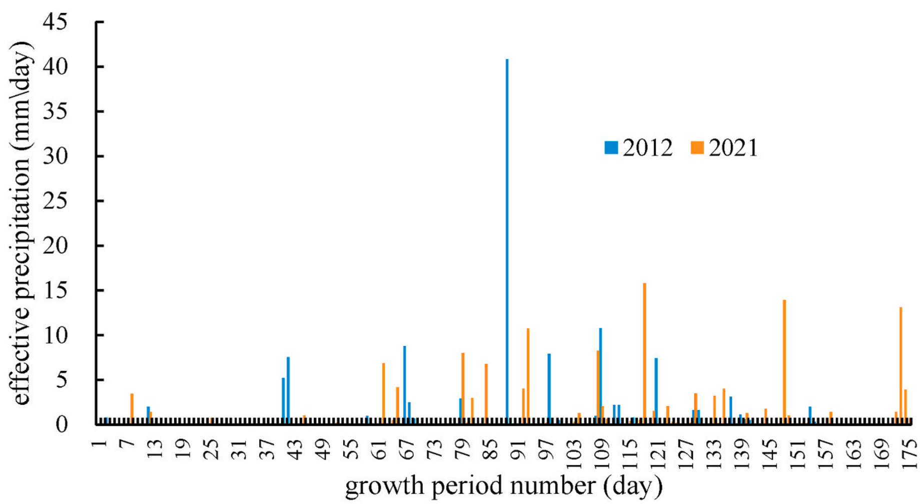
Li et al. developed the IQP model to optimize irrigation water resources among wheat, field corn and seed corn (Li et al., 2017). They fitted interval quadratic water production functions to express the relationship between water allocation and crop growth. The water allocation is presented as interval numbers to express uncertainties in decisions. The irrigation water amounts were [75.64, 89.15] cm, [70.82, 75.33] cm and [53.37, 55.31] cm for field corn, seed corn and wheat, respectively. Taking the 4th alternative as an example, the water allocation amounts are 52.6 cm, 53.0 cm and 46.4 cm for field corn at DMU1, DMU2 and DMU3, respectively. The water allocation amounts were 44.7 cm, 53.8 cm, 45.2 cm and 54.5 cm for seed corn at DMU4, DMU5, DMU6 and DMU7, respectively. The water allocation amounts were 33.4 cm, 40.3 cm and 41.7 cm for wheat at DMU8, DMU9 and DMU10, respectively. The results reveal that the water allocation amount obtained from the spatially-distributed AquaCrop-MORPP model is smaller than that of the IQP model because the IQP model only considers the objective of maximum yield, resulting in water allocation around the water threshold corresponding to maximum yield. Namely, compared with the IQP model, the spatially-distributed AquaCrop-MORPP model can optimize the irrigation amount and irrigation date concurrently and achieve water savings and is more advantageous. The yield per area obtained from the IQP model represents 11.47 ton/ha, 9.94 ton/ha and 6.98 ton/ha for field corn, seed corn and wheat, respectively. The yield per area was 11.24 ton/ha, 11.50 ton/ha, and 11.78 ton/ha for the field corn at the three DMUs, respectively. The yield per area was 10.47 ton/ha, 10.76 ton/ha, 10.28 ton/ha and 10.63 ton/ha for the seed corn at the four DMUs. The yield per area was 7.21 ton/ha, 7.35 ton/ha and 7.6 ton/ha for wheat at the three DMUs. The yield per area of the field corn obtained from the spatially-distributed AquaCrop-MORPP model covers the yield attained from the IQP model, and the yield of the seed corn and wheat is larger than that of the IQP model. This is because optimizing the irrigation amount and irrigation date can both improve the crop yield. It also indicates that the spatially-distributed AquaCrop-MORRP model could improve yield compared with the IQP model, which is more applicable to conduct irrigation water resource management. The advantages, disadvantages and contributions of the distributed AquaCrop-MORPP model and IQP model are shown in Table 7.

6. Conclusion

In this study, a distributional optimal decision-making framework was built to optimize irrigation scheduling (irrigation date and irrigation amount) under uncertainties. It established a spatially-distributed AquaCrop-MORRP model and developed TOPSIS and prospect theory methods to select alternatives to provide managers with relatively optimum alternatives from different views. The developed approach was employed in the Yingke Irrigation District (YID), Heihe River Basin (HRB), to verify its application. The results showed that the maximum field water use efficiency and net economic benefit in 2021 were higher than those in 2012. The irrigation scheduling with varied irrigation dates was more advanced than the irrigation scheduling with fixed



(a)



(b)

Fig. 8. (a) and (b). Daily evapotranspiration and rainfall during the whole crop growth period in 2012 and 2021.

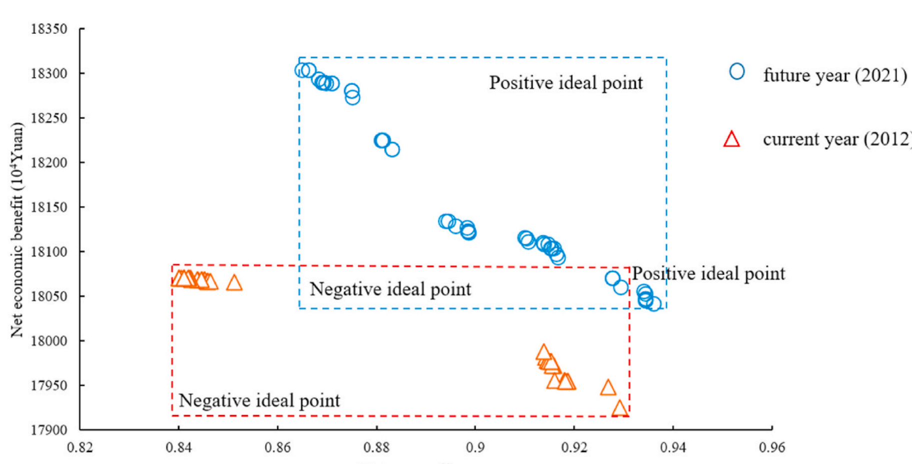


Fig. 9. Pareto frontier composed of 50 groups of optimal Pareto solutions and respective positive and negative ideal points for 2012 and 2021.

Table 5
The yield, water allocation (WA), net economic benefit (NB), and field water use efficiency (FWUE) of the YID for the 4th, 24th, 43rd and 33rd alternatives.

Items	Yield (10^4 kg)	WA (10^4 m^3)	NB (10^4 Yuan)	FWUE
4th alternative	1018.5	4670.4	18063.79	0.85
24th alternative	1021.6	4425.6	18280	0.88
43rd alternative	1013.3	4307.7	17998.66	0.91
33rd alternative	1022.9	4465.1	18303	0.87

Table 6
The yield, water allocation (WA), net economic benefit (NB), and field water use efficiency (FWUE) of the YID for the 4th and 43rd alternatives and alternatives with fixed irrigation dates.

Items	Yield (10^4 kg)	WA (10^4 m^3)	NB (10^4 Yuan)	FWUE
4th alternative	1018.5	4670.4	18063.79	0.85
Fixed irrigation dates	960.79	4670.4	17191	0.82
43rd alternative	1013.3	4307.7	17998.66	0.91
Fixed irrigation dates	960.32	4307.7	17182	0.87

The irrigation scheduling with varied irrigation dates is more advanced than that with fixed irrigation dates for both the 4th and 43rd alternatives. The results show that compared with irrigation scheduling with fixed irrigation dates, optimizing irrigation dates will increase yields by 6% and 5%, net economic benefits by 5% and 4%, and field water use efficiencies by 4% and 4% for the 4th and 43rd alternatives, respectively. Therefore, irrigation scheduling with varied irrigation dates has higher robustness and advantages than irrigation scheduling with fixed irrigation dates.

Table 7
advantages, disadvatages and contributions of the distributed AquaCrop-MORPP model and IQP model.

models	advantages	Disadvantages	Contributions
Distributed AquaCrop-MORPP model	Get Pareto solutions considering crop growth process and multiple objectives and uncertainties	Calculation efficiency is relatively low	Develop a technique combing simulation model and optimization model, and deal with multiple uncertainties in the model
IQP model	Get optimal solutions in interval numbers, and improve robustness of decisions	The optimal solutions are lack of spatially-distribution precision	Identify uncertainties in the agricultural water resources systems

irrigation dates. Optimal irrigation scheduling could save water and improve the yield compared with interval quadratic programming (IQP). It was proven to be a reliable and effective tool for dealing with irrigation scheduling optimization in semiarid and arid districts.

It has the following advantages: (1) the optimized irrigation amount and date could be optimized simultaneously. (2) It could balance the contradictory relationship between field water use efficiency and net economic benefit measured by the spatially-distributed AquaCrop model. (3) It can handle uncertainties characterized by fuzzy numbers and stochastic variables. (4) It could select alternatives considering the risk attitudes and subjectivities of managers and obtain the optimal Pareto frontier under the current and future RCP4.5 scenarios.

The developed model showed performances of the distributed AquaCrop- MORRP model in optimizing irrigation schedules in the arid and semi-arid districts. However, a disadvantage of the model is that the running time is so high, reaching about a week, which is because there are many time of interactions between distributed AquaCrop model and the optimization model concerning multiple calling external programming. Formulating a replace model with the same functions with the distributed AquaCrop model but higher running efficiency to couple with optimization model to optimize irrigation schedules which will be explored in the future studies.

CRediT authorship contribution statement

Youzhi Wang: Conceptualization, Methodology, Software, Writing – original draft. **Shan Shan Guo:** Data curation, Reviewing and editing. **Ping Guo:** Visualization, Supervision.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements

This study was financially supported by National Natural Science Foundation of China (No. 41871199)

References

Cao, X.C., Wu, P.T., Wang, Y.B., Zhao, X.N., 2014. Agriculture water utilization assessment based on water footprint of grain production evaluation in irrigated farmland of China. J. Nat. Resour. 29 (11), 1826–1835.
Chen, S., Shao, D.G., Li, X.D., Lei, C.X., 2016. Simulation-optimization modeling of conjunctive operation of reservoirs and ponds for irrigation of multiple crops using an improved artificial bee colony algorithm. Water Resour. Manag. 30 (9), 2887–2905.
Grishina, N., Lucas, C.A., Date, P., 2017. Prospect theory-based portfolio optimization: an empirical study and analysis using intelligent algorithms. Quant. Finance 17 (3), 353–367.
Han, C.Y., Zhang, B.Z., Chen, H., Wei, Z., Liu, Y., 2019. Spatially distributed crop model based on remote sensing. Agric. Water Manag. 218 (1), 165–173.
Han, C.Y., Zhang, B.Z., Chen, H., Liu, Y., Wei, Z., 2020. Novel approach of upscaling the FAO AquaCrop model into regional scale by using distributed crop parameters derived from remote sensing data. Agric. Water Manag. 240 (1), 106288.
He, H., Chen, A., Yin, M., Ma, Z., You, J., Xie, X., Wang, Z., An, Q., 2019. Optimal allocation model of water resources based on the prospect theory. Water 11 (6), 1289.
Hojjati, A., Monadi, M., Faridhosseini, A., Mohammadi, M., 2018. Application and comparison of NSGA-II and MOPSO in multi-objective optimization of water resources systems. J. Hydrol. Hydromechanics 66 (3), 323–329.
Inuiguchi, M., Ramík, J., 2000. Possibilistic linear programming: a brief review of fuzzy mathematical programming and a comparison with stochastic programming in portfolio selection problem. Fuzzy Set Syst. 111 (1), 3–28.
Li, Z., Huang, G., Zhang, Y.M., Li, Y.P., 2013. Inexact two-stage stochastic credibility constrained programming for water quality management. Resour. Conserv. Recycl. 122–132.
Li, M., Jiang, Y., Guo, P., Li, J., 2017. robust. Trans. Chin. Soc. Agric. Mach. 5, 199–207.
Li, M., Fu, Q., Singh, V.P., Liu, D., 2018. An interval multi-objective programming model for irrigation water allocation under uncertainty. Agric. Water Manag.
Li, M., Li, J., Singh, V.P., Fu, Q., Liu, D., Yang, G., 2019. Efficient allocation of agricultural land and water resources for soil environment protection using a mixed optimization-simulation approach under uncertainty. Geoderma 353, 55–69.
Li, J., Jiao, X.Y., Jiang, H.Z., Song, J., Chen, L., 2020. Optimization of irrigation scheduling for maize in an arid oasis based on simulation–optimization model. Agronomy 10 (7), 10070935.
Li, M., Fu, Q., Singh, V.P., Liu, D., Liu, T.X., Zhou, Y., 2020. Managing agricultural water and land resources with tradeoff between economic, environmental, and social considerations: a multi-objective non-linear optimization model under uncertainty. Agric. Syst. 178, 102685.
Lu, H.W., Du, P., Chen, Y.Z., He, L., 2016. A credibility-based chance-constrained optimization model for integrated agricultural and water resources management: a case study in South Central China. J. Hydrol. 537, 408–418.
Mosleh, Z., Salehi, M.H., Amini, F.A., Jafari, A., Mehnatkesh, A., Esfandiarpoor, B.I., 2017. Sustainable allocation of agricultural lands and water resources using suitability analysis and mathematical multi-objective programming. Geoderma 303, 52–59.
Pishvaee, M.S., Razmi, J., Torabi, S.A., 2012. Robust possibilistic programming for socially responsible supply chain network design: a new approach. Fuzzy Set Syst. 206, 1–20.
Schoups, G., Addams, C.L., Minjares, J.L., Gorelick, S.M., 2006. Sustainable conjunctive water management in irrigated agriculture: model formulation and application to the Yaqui Valley, Mexico. Water Resour. Res. 42 (10).
Shahvari, N., Khalilian, S., Mosavi, S.H., Mortazavi, S.A., 2019. Assessing climate change impacts on water resources and crop yield: a case study of Varamin plain basin, Iran. Environ. Monotor Assess. 191-134.

Tabari, M.M.R., Soltani, J., 2013. Multi-objective optimal model for conjunctive use management using SGAs and NSGA-II models. Water Resour. Manag. 27 (1), 37–53.
Wang, Y.Z., Liu, L., Guo, P., Zhang, C.L., Zhang, F., Guo, S.S., 2019. An inexact irrigation water allocation optimization model under climate change. Stoch. Environ. Res. Risk Assess. 33 (1), 271–285.
Wang, M., Yu, H., Jing, R., Liu, H., Chen, P., Li, C., 2020. Combined multi-objective optimization and robustness analysis framework for building integrated energy system under uncertainty. Energy Convers. Manag. J. 208, 112589.
Wang, Y.Z., Guo, S.S., Yue, Q., Mao, X.M., Guo, P., 2021. Distributed simulation-optimization model with consideration of uncertainty for agricultural water resources management. under reviewe Water Resour. Res.
Xu, H., Ma, C., Xu, K., Lian, J., Long, Y., 2020. Staged optimization of urban drainage systems considering climate change and hydrological model uncertainty. J. Hydrol. 587, 124959.
Yue, Q., Wang, Y., Liu, L., Niu, J., Guo, P., Li, P., 2020. Type-2 fuzzy mixed-integer bi-level programming approach for multi-source multi-user water allocation under future climate change. J. Hydrol. 591, 125332.
Zhang, W.H., Liu, W.Z., Xue, Q.W., Chen, J., Han, X.Y., 2013. Evaluation of the AquaCrop model for simulating yield response of winter wheat to water on the southern Loess Plateau of China,. Water Sci. Technol.
Zhang, K., Li, Y.P., Huang, G.H., Jin, S.W., 2016. Planning regional ecosystem sustainability under multiple uncertainties—an interval stochastic credibility-constrained programming approach. Ecol. Indicat. J. 70, 134–150.
Zhang, C.L., Li, M., Guo, P., 2018. An interval multistage joint-probabilistic chance-constrained programming model with left-hand-side randomness for crop area planning under uncertainty. J. Cleaner Prod. J. 167, 1276–1289.
Zhang, C.L., Zhang, F., Guo, S.S., 2018. Inexact nonlinear improved fuzzy chance-constrained programming model for irrigation water management under uncertainty. J. Hydrol. 556, 397–408.
Zhang, F., Guo, S.S., Ren, C.F., Guo, P., 2018. Integrated IMO-TSP and AHP method for regional water allocation under uncertainty. J. Water Resour. Plann. Manag. 122 (6).