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A Simulation-Based Optimization Model for Control of Soil Salinization in the Hetao Irrigation District, Northwest China

Yunquan Zhang and Peiling Yang *

Center for Agricultural Water Research in China, China Agricultural University, Beijing 100083, China
* Correspondence: yang-pl@163.com

Abstract: The average annual water diversion of the Hetao Irrigation District (HID) from the Yellow River is 4.5 billion cubic meters, mainly used for surface irrigation. Because the groundwater depth is shallow, strong evaporation conditions and unmatched irrigation conditions lead to serious soil salinization in the area; thus, the irrigation area's ecological environment is fragile. Based on the current situation of the Yellow River irrigation project in the area, an interval two-stage robust stochastic optimization model is proposed to address the problem. In 2015, the Shuguang Experimental Station in the middle of the HID, Inner Mongolia, discussed the impact of different degrees of water–salt coordinated regulation on water consumption, yield and price of wheat, maize and sunflower under drip irrigation conditions. The obtained results provide the water shortage and water distribution targets of multiple water sources and multiple water levels in five irrigation areas of the HID. Those water distribution targets were used as the main input parameter and entered into the SALTMOD model based on the principle of water and salt balance. The output included data on groundwater mineralization and groundwater depth. It was observed that (1) integrated interval two-stage robust stochastic programming and the SALTMOD Model to couple optimization model under uncertainty can simulate a model together; (2) systemic risk issues were considered; and (3) the proposed method can be applied to the HID in northwest China to solve the soil salinization control problem. This approach is applicable to arid and semiarid regions that face similar problems.

Keywords: environmental simulation; pollution control; water resources management; eco-hydrology

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1. Introduction

China's saline-alkali land is distributed in 17 provinces including northeast China, north China, northwest China and coastal areas, where the total area of saline-alkali land and wasteland affecting cultivated land exceeds 500 million mu. Among them, the agricultural development potential accounts for more than 10% of the total cultivated land in China [1]. The Hetao Plain is located inland and is the most important agricultural and ecologically fragile area in northwestern China [2]. The rainfall in this area is relatively small, with the annual rainfall only 150~200 mm, while the annual evaporation is as high as 2000~3000 mm, 10~20 times the annual rainfall. Even though water from the Yellow River is introduced into this area, this water resource basically does not flow out through surface runoff. Instead, part of it evaporates and the other part is replenished by groundwater, which causes the salt contained in the water to accumulate in the area over a long time, causing salinization of the soil surface [3]. Moreover, with the gradual enhancement of groundwater evaporation in the region, soil salinization in the Hetao Irrigation District (HID) has aggravated, seriously affecting the ecological, agricultural and socio-economic development of the region [4]. Therefore, the joint application of surface water and groundwater with the optimal scheduling strategy of well and channel combinations can be used to control the groundwater level of the area below the critical depth, and reduce soil salinity in the irrigation area; this can be a reference for controlling soil salinization in the area [5].

In the regional agricultural water and soil resource management system, there are complexities such as runoff, rainfall, planning period supply and demand, and fluctuations in economic parameters, in the measures to control the salinization of surface land, water and salt migration, and droughts or floods, which intensify the work uncertainty. This leads to the use of traditional deterministic optimization methods, such as integer programming, multi-objective programming, dynamic programming, linear programming, and nonlinear programming, that cannot solve these problems. This requires uncertainty optimization technology that is widely used, including interval planning, fuzzy programming and stochastic programming methods [6]. These can be used to solve the problem of uncertainty in the prevention and control of surface land salinization by introducing the concepts of interval parameters, fuzzy number sets and probability density distribution. Among these methods, the interval two-stage robust stochastic programming (ITRM) model has a strong advantage in controlling soil salinization through the well-channel combination method. Its first stage decision must be made before the occurrence of uncertain events, and the second stage decision is a modification of the first stage decision, in order to minimize the "penalty" caused by the infeasible decision of the first stage [7].

Li and Huang et al. found an interval parameter multi-stage stochastic linear programming method (IMSLP) for uncertain water resources decision-making, combining probability density function and discrete interval in the optimization framework [8]. Li and Fu et al. created an interval linear multi-objective programming (ILMP) model for the uncertainty caused by climate change and human activities, and realized synergistic management of irrigated agricultural efficiency, yield increase and water saving [9]. Zhang and Tan et al. formed a multi-objective stochastic programming allocation model based on entropy methods combined with crop level prediction to analyze the ecological and economic trade-offs of irrigated agriculture [10]. The above optimization model is very effective in dealing with uncertain factors; if the optimization methods in the above references are applied to the treatment of saline-alkali land, the systemic risk problem is ignored. After application, it produces soil returning salt and agricultural production reduction. The model results are not absolutely feasible. The robust optimization method can effectively avoid risks in the planning process, and judge the relationship between variable random values and recourse costs in the system. For example, Li and Huang et al. built a two-stage fuzzy stochastic robust programming that represented uncertain parameters as probability density and/or fuzzy membership function, enhancing the robustness of the optimization results, and was used for regional air quality management [11]. Chen et al. set up a robust risk analysis method (RRAM) for uncertain water resources decision-making, combining interval parameter programming and robust optimization in a stochastic programming framework [12]. Tan and Zhang established a robust fractional programming (RFP) method that coupled fractional programming with robust optimization to improve agricultural water efficiency under uncertainty conditions [13].

Yao and Yang et al. utilized SALTMOD to investigate the effects of varying drainage and irrigation practices on root zone salinity and water table depth [14]. In Bahceci and Dinc et al.'s paper, the SALTMOD model was tested with data collected from the Karkin pilot area, and the effects of current irrigation–drainage practices on root zone salinity and drain discharge rate were evaluated [15]. Singh evaluated different options to solve the water-logging and soil salinization problem; the computer-based simulation model, SALTMOD, was applied in a waterlogged area of Haryana state in India [16]. There are uncertainties in the input parameters of crops, groundwater, irrigation and drainage reuse, which affect the simulation results of the SALTMOD model. The model cannot accurately describe the water and salt dynamics of a study area; therefore, combining it with a mathematical model can better solve this problem. In Mao and Yang et al.'s paper, two SALTMOD models are used to separately simulate canal- and well-irrigated areas, and an exchange flux is used as an additional mass balance term to calculate the mass balance of the canal- and well-irrigated areas [17]. In Sarangi and Singh et al.'s paper, comparative performance of artificial neural networks (ANNs) and the conceptual SALTMOD model were used to simulate subsurface drainage effluent and root zone soil salinity in the coastal rice fields of Andhra Pradesh, India. The BPNN with the feed forward learning algorithm was a better model than SALTMOD in predicting salinity of drainage effluent from salt-affected subsurface drained rice fields. [18]. In Singh's paper, after successful calibration and validation, the computer-based simulation model, SALTMOD was applied in a waterlogged area of northwest India [19].

Complexity and uncertainty in agricultural irrigation planning based on soil salinization control at the irrigation district scale, uneven distribution of water resources in agriculture, industry, life and ecology, may result in high-risk water distribution for agriculture (such as lack of water during critical periods of crop growth, salt return to soil, etc.). The existing research has less consideration of systemic risk issues and cannot guarantee the absolute feasibility of model optimal solutions [15–19]. The robust optimization method can embody the function risk, effectively evaluate the risk, avoid the risk in the planning process, balance the relationship between the income and the risk in the regional agricultural water and land resource management system, and can effectively increase the feasibility of the model optimal solution and the stability of the system [20].

Therefore, the purpose of this study was to develop a method of coupling interval two-stage robust stochastic programming (ITRSP) with the SALTMOD model to jointly dispatch surface water and groundwater resources to deal with land salinization. The ITRSP model can address multiple concerns of two-level decision-makers and the robustness of runoff and obtained optimization schemes. Furthermore, by coupling with the SALTMOD model, the ecological and environmental impacts of irrigation and drainage measures, the objective and subjective factors of decision-making, and the environmental impacts of groundwater depth changes in the irrigation area are fully considered. Thus, the developed model can optimally allocate limited irrigation water, wells, and canals in a sustainable way. As shown in Figure 1, the developed method was then applied to a practical case for the HID of Inner Mongolia, northwest China. The results obtained from the model can help local decision-makers formulate a low-cost optimal allocation strategy under limited water supply that controls the groundwater burial depth below the critical depth, and further contribute to green agricultural development.

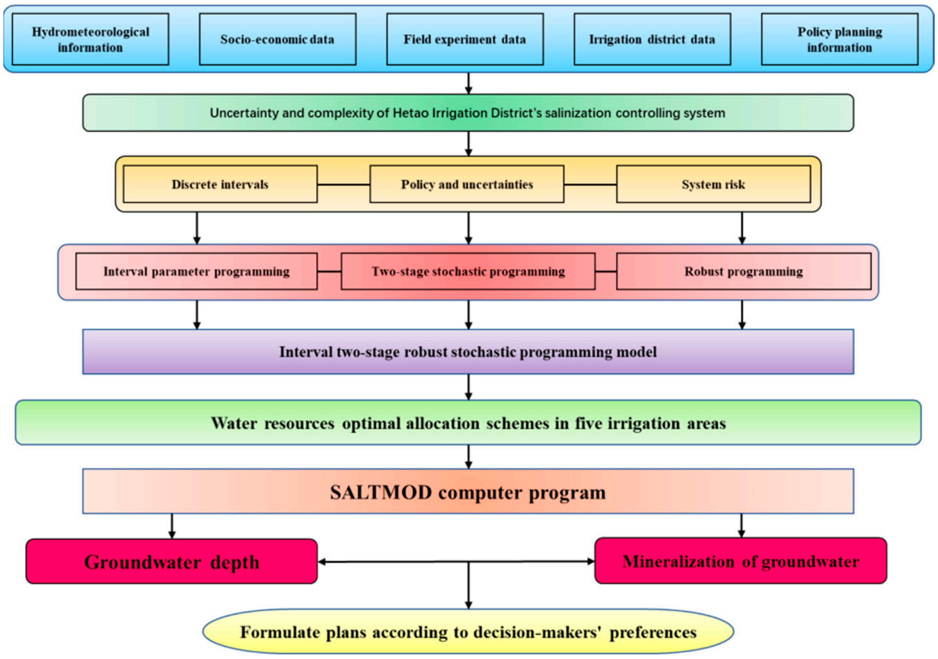


Figure 1. Framework of ITRSP and SALTMOD Coupled Model.

2. Modeling Formulation

2.1. Establishment of the Interval Two-Stage Robust Stochastic Programming Model

This study takes the water requirement of crops in the HID as the decision-making variable, introduces water cost and a water shortage penalty coefficient, and determines the optimal allocation of water resources in the HID in two stages [21–24].

To indicate the uncertainty, an interval parameter is introduced to represent the uncertainty parameter. "+" indicates the upper limit of the parameter, "−" indicates the lower limit of the parameter, then the interval two-stage robust stochastic programming (ITRM) model is established [25].

$$\min f^{\pm} = \sum_{i=1}^{m}\sum_{j=1}^{n} C_{ij}{}^{\pm} W_{ij}{}^{\pm} + \sum_{i=1}^{m}\sum_{j=1}^{n} D_{ij}{}^{\pm} \sum_{k=1}^{3} P_k S_{ijk}{}^{\pm} + \alpha \sum_{i=1}^{m}\sum_{j=1}^{n}\sum_{k=1}^{3} P_k \left(D_{ij}{}^{\pm} S_{ijk}{}^{\pm} - P_k \sum_{k=1}^{3} D_{ij}{}^{\pm} S_{ijk}{}^{\pm} + 2\theta_{ijk}{}^{\pm} \right) \tag{1}$$

subject to:

(1) Water demand constraint

$$W_{ijmax}{}^{\pm} \geq \sum_{i=1}^{m}\sum_{j=1}^{n} W_{ij}{}^{\pm} \geq W_{ijmin}{}^{\pm} \ (\forall i, j) \tag{2}$$

where

W_{ijmax}: the maximum water requirement for crop j normal growth
W_{ijmin}: the minimum water requirement for crop j normal growth

(2) Recourse variable constraint

$$\begin{cases} D_{ij}{}^{\pm} S_{ijk}{}^{\pm} - P_k \sum_{k=1}^{3} D_{ij}{}^{\pm} S_{ijk}{}^{\pm} + \theta_{ijk}{}^{\pm} \geq 0 \ \ (\forall i, j, k) \\ \theta_{ijk}{}^{\pm} \geq 0 \end{cases} \tag{3}$$

(3) Water source maximum water supply constraint

$$W_{imax} \geq \sum_{j=1}^{n} W_{ij}{}^{\pm} \ \ (\forall i, j) \tag{4}$$

where W_{imax}: water source i maximum water supply, m^3

(4) Surface available water constraint and groundwater available constraint

$$Q_{ij}{}^{\pm} + q_{ik}{}^{\pm} - Q_{si}{}^{\pm} - \sum_{j=1}^{n} \left(W_{ij}{}^{\pm} - S_{ijk}{}^{\pm} \right) = Q_{im}{}^{\pm} \geq Q_{imin} \ (i = 1,\ 2,\ \ldots,\ \mathrm{n}) \tag{5}$$

$$Q_{ij}{}^{\pm} + q_{ik}{}^{\pm} - Q_{si}{}^{\pm} - \sum_{j=1}^{n} \left(W_{ij}{}^{\pm} - S_{ijk}{}^{\pm} \right) = Q_{im}{}^{\pm} \geq Q_{imin} (i = n+1,\ n+2,\ \ldots,\ m) \tag{6}$$

(5) Groundwater depth constraint

$$\begin{cases} H_t \leq \overline{H} - Z_\alpha \\ H_t \geq \overline{H} - X_\alpha \end{cases} \forall t \tag{7}$$

where $\overline{H}$: average ground elevation

Z_α: critical depth of groundwater in each period
X_α: maximum allowable depth of groundwater at each time quantum

(6) Salt content constraint

$$S_{imax} \geq \sum_{j=1}^{n} S_{ij}^{\pm} \; (\forall i, j) \tag{8}$$

where S_{imax} : water source i maximum salt content

(7) Non-negative constraint

$$W_{ij}^{\pm} \geq S_{ijk}^{\pm} \geq 0 \;\; (\forall i, j) \tag{9}$$

2.2. Solution of the Interval Two-Stage Robust Stochastic Programming Model

According to the characteristics of the interval two-stage robust stochastic programming model, the parameters are represented by intervals, and there are uncertainties in the $W_{ij}^{\pm}$. Huang and Loucks [26] found it difficult to judge what value is required to minimize the system cost; therefore, they introduced the decision variable z_{ij}, $z_{ij} \in [0,1]$, and transformed $W_{ij}^{\pm} = W_{ij}^{-} + \Delta W_{ij} z_{ij}$. Among them $\Delta W_{ij} = W_{ij}^{+} - W_{ij}^{-}$, and it is a certain value.

When W_{ij} approaches its lower bound (when z_{ij} = 0), the water distribution costs for crops are minimum, but when the water allocation is less than the crop water requirement, the penalty cost of the crop will increase. Similarly, if the crop water requirement is met and W_{ij} is close to its upper limit (when z_{ij} = 1), the cost of crop penalties is reduced, but in order to meet the water demand of crops, the cost of water distribution will increase.

By introducing z_{ij}, the pre-target water distribution $W_{ij}^{\pm}$ and the decision variable optimal value z_{ijopt} can be obtained by using $W_{ij}^{\pm} = W_{ij}^{-} + \Delta W_{ij} z_{ijopt}$. When the value is a known condition, W_{ij} can be determined by this equation when the cost of the irrigation system is at a minimum. Using Matlab software to obtain $f_{opt}^{\pm}$ and $S_{ijopt}^{\pm}$, the final optimal allocation of water resources in the HID can be determined. According to the above solution and the interactive algorithm proposed by Xu and Diwekar [27], the ITRSP model was divided into two sub-models, since the goal of the model is to minimize the cost; therefore, the model corresponding to f^{-} was first solved:

$$\min f^{-} = \sum_{i=1}^{m}\sum_{j=1}^{n} C_{ij}^{-}\left(W_{ij}^{-} + \Delta W_{ij} z_{ij}\right) + \sum_{i=1}^{m}\sum_{j=1}^{n} D_{ij}^{-} \sum_{k=1}^{3} P_k S_{ijk}^{-} + \alpha \sum_{i=1}^{m}\sum_{j=1}^{n}\sum_{k=1}^{3} P_k \left(D_{ij}^{-} S_{ijk}^{-} - P_k \sum_{k=1}^{3} D_{ij}^{-} S_{ijk}^{-} + 2\theta_{ijk}^{-} \right) \tag{10}$$

subject to:

$$\left\{ \begin{array}{c} W_{ijmax}^{-} \geq \sum\limits_{i=1}^{m}\sum\limits_{j=1}^{n} W_{ij}^{-} + \Delta W_{ij} z_{ij} \geq W_{ijmin}^{+} \; (\forall i, j) \\ Q_{ij}^{+} + q_{ik}^{+} - Q_{si}^{-} - \sum\limits_{j=1}^{n} \left(W_{ij}^{-} + \Delta W z_{ij} - S_{ijk}^{-} \right) = Q_{im}^{-} \geq Q_{imin} (i = 1, 2, \ldots, n) \\ Q_{ij}^{+} + q_{ik}^{+} - Q_{si}^{-} - \sum\limits_{j=1}^{n} \left(W_{ij}^{-} + \Delta W z_{ij} - S_{ijk}^{-} \right) = Q_{im}^{-} \geq Q_{imin} (i = n+1, n+2, \ldots, m) \\ \left\{ \begin{array}{l} H_t \leq \overline{H} - Z_{\alpha} \\ H_t \geq \overline{H} - X_{\alpha} \end{array} \right. \forall t \\ W_{imax} \geq \sum\limits_{j=1}^{n} W_{ij}^{+} \; (\forall i, j) \\ S_{imax} \geq \sum\limits_{j=1}^{n} S_{ij}^{+} \; (\forall i, j) \\ D_{ij}^{-} S_{ijk}^{-} - P_k \sum\limits_{k=1}^{3} D_{ij}^{-} S_{ijk}^{-} + \theta_{ijk}^{-} \geq 0, \forall i, j, k \\ \theta_{ijk}^{-} \geq 0, \forall i, j, k \\ W_{ij}^{-} + \Delta W_{ij} z_{ij} \geq S_{ijk}^{-} \geq 0 \;\; (\forall i, j) \end{array} \right. \tag{11}$$

Among them, z_{ij} and S_{ijk}^{-} are decision variables, and S_{ijopt}^{-}, z_{ijopt}, f_{opt}^{-} are model solutions. Similarly, the objective function upper bound sub-model is obtained as:

$$\min f^{+} = \sum_{i=1}^{m}\sum_{j=1}^{n} C_{ij}{}^{+}(W_{ij}{}^{-} + \Delta W_{ij}z_{ij}) + \sum_{i=1}^{m}\sum_{j=1}^{n} D_{ij}{}^{+}\sum_{k=1}^{3} P_k S_{ijk}{}^{+} + \alpha \sum_{i=1}^{m}\sum_{j=1}^{n}\sum_{k=1}^{3} P_k\left(D_{ij}{}^{+}S_{ijk}{}^{+} - P_k\sum_{k=1}^{3} D_{ij}{}^{+}S_{ijk}{}^{+} + 2\theta_{ijk}{}^{+}\right) \quad (12)$$

subject to:

$$\begin{cases} W_{ijmax}{}^{+} \geq \sum\limits_{i=1}^{m}\sum\limits_{j=1}^{n} W_{ij}{}^{-} + \Delta W_{ij}z_{ij} \geq W_{ijmin}{}^{-}\ (\forall i, j) \\ Q_{ij}{}^{-} + q_{ik}{}^{-} - Q_{si}{}^{+} - \sum\limits_{j=1}^{n}\left(W_{ij}{}^{-} + \Delta W z_{ij} - S_{ijk}{}^{+}\right) = Q_{im}{}^{+} \geq Q_{imin}(i = 1, 2, \ldots, n) \\ Q_{ij}{}^{-} + q_{ik}{}^{-} - Q_{si}{}^{+} - \sum\limits_{j=1}^{n}\left(W_{ij}{}^{-} + \Delta W z_{ij} - S_{ijk}{}^{+}\right) = Q_{im}{}^{+} \geq Q_{imin}(i = n+1, n+2, \ldots, m) \\ \begin{cases} H_t \leq \overline{H} - Z_\alpha \\ H_t \geq \overline{H} - X_\alpha \end{cases} \forall t \\ W_{imax} \geq \sum\limits_{j=1}^{n} W_{ij}{}^{-}\ (\forall i, j) \\ S_{imax} \geq \sum\limits_{j=1}^{n} S_{ij}{}^{-}\ (\forall i, j) \\ D_{ij}{}^{+}S_{ijk}{}^{+} - P_k\sum\limits_{k=1}^{3} D_{ij}{}^{+}S_{ijk}{}^{+} + \theta_{ijk}{}^{+} \geq 0, \forall i, j, k \\ \theta_{ijk}{}^{+} \geq 0, \forall i, j, k \\ W_{ij}{}^{-} + \Delta W_{ij}z_{ij} \geq S_{ijk}{}^{+} \geq 0\ \ (\forall i, j) \\ S_{ijk}{}^{+} \geq S_{ijk}{}^{-}\ \ \forall i, j, k \end{cases} \quad (13)$$

After solving and calculating $S_{ijopt}{}^{+}$ and $f_{opt}{}^{+}$, and combining the two sub-models, the solution of the interval two-stage robust stochastic programming model was as follows:

$$f_{opt}{}^{\pm} = \left[\, f_{opt}{}^{-},\ f_{opt}{}^{+}\right]$$

$$S_{ijopt}{}^{\pm} = \left[\, S_{ijopt}{}^{-}, S_{ijopt}{}^{+}\right]\ (\forall i, j)$$

$$z_{ij} = z_{ijopt}\ \ (\forall i, j)$$

The water optimal distribution target is:

$$O_{ij}{}^{\pm} = W_{ijopt}{}^{\pm} - S_{ijopt}{}^{\pm}\ (\forall i, j)$$

where O_{ij}: the water optimal distribution target for water source i to crop j.

2.3. Introduction of the SALTMOD Model

The SALTMOD model was developed by Professor Oosterbaan and Senna of the Netherlands International Institute for Land Reclamation and Improvement (ILRI) based on the principle of water–salt balance, in the irrigation district of arid and semi-arid areas. The obtained irrigation and drainage measures showed that water and salinity change regularly in the aeration zone and phreatic water in different seasons of the year [28]. The model is mainly used to simulate and predict displacement and drainage salinity, groundwater depth, mineralization of soil water, groundwater and drainage, etc. Idris and Nazmi et al. [29] found it can also simulate farmers' responses to soil salinity, waterlogging, water scarcity, etc., and is suitable for different agricultural types, such as irrigated or non-irrigated agriculture, paddy fields or dry crops. The model has been successfully applied to the plains of Mashtul in Egypt and the coastal plains of Leziria Grande in Portugal.

The SALTMOD model is based on the principle of water and salt balance. The main input parameters include meteorology, soil, crops, irrigation and drainage, groundwater, etc.; the main output data includes groundwater depth, groundwater mineralization, soil salinity, and displacement. Based on local climatic conditions, crop growth, etc., the SALTMOD model can be divided into one to four simulation seasons, and the water–salt balance in the vertical direction of the soil is divided into four layers: aquifer, transition layer, root layer and surface layer; for each layer both water balance and salt balance are entered as seasonal data and all factors are assumed to be evenly distributed throughout the study area.

The water–salt model has some shortcomings. For example, it is not flexible in inputting irrigation water or salinity data. Only one salinity value can be set, and the salinity of irrigation water for each season cannot be distinguished. Therefore, in the simulation study alternate irrigation of brackish and fresh water is limited [30].

In this research, based on the current situation of the Yellow River irrigation project in the HID of Inner Mongolia, the interval two-stage robust stochastic programming model is proposed to address the surface land salinization problem. The obtained results provide water shortage and water distribution targets of multiple water sources and multiple water levels in five irrigation areas. Those water distribution targets are used as main input parameters, and are substituted into the SALTMOD model based on the principle of water balance and salt balance, the output includes data on groundwater mineralization and groundwater depth.

3. Application

3.1. Regional Overview

The HID of Inner Mongolia is located in the western part of the Inner Mongolia Autonomous Region. It is one of the three largest irrigation districts in China and the largest one song artesian irrigation district in Asia. As shown in Figure 2, it is located between 105°12′ to 109°53′ east longitude and 40°13′ to 42°28′ north latitude. The total land area of the irrigation area is 11 million mu, and the existing irrigation area is 574,000 hm^2. From south to north, it can be divided into five irrigation areas, namely Yigan, Jiefangzha, Yongji, Yichang and Urad irrigation areas. The HID is located on a plateau, far from the ocean. It is affected by the Mongolian high pressure, with a large amount of wind and sand and less rainfall, forming a more typical continental monsoon climate. It is also an important commodity grain and oil production base in China. The main food crops are wheat, maize and sunflower, as well as cash crops such as processed tomato, watermelon and pepper. The irrigation area is located in an arid and semi-arid zone. Tainfall is sparse and the evaporation intensity is large. Without irrigation from the Yellow River, there would be no agricultural development [31].

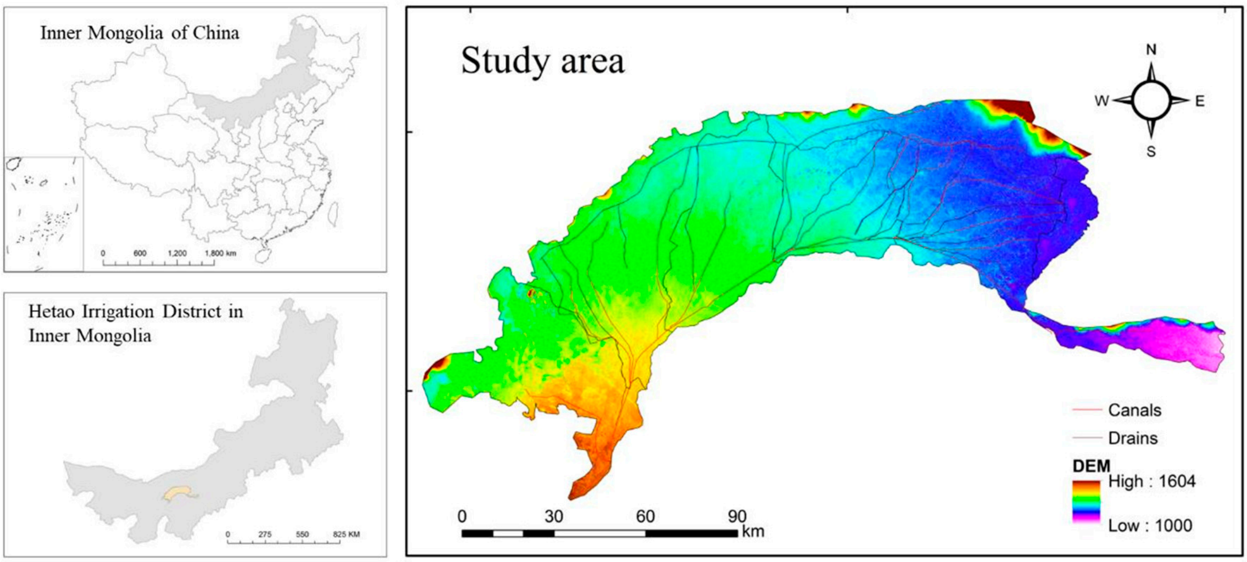


Figure 2. The geographical position of the study area.

The northeastern part of the Hetao Plain, where the HID is located, is the Yinshan Mountains. Rocks in the mountain area are strongly weathered and the salt is decomposed.

The low-lying areas of the plain have poor drainage, the water level is elevated, and the shallow groundwater has a high salt content. Water and salt rise to the surface through the soil capillary water, the water evaporates, and the salt remains on the surface. In addition, the formation of saline-alkali is supplemented by drought and waterlogging disasters. Long-term salinity has resulted in barren land and long-term stagnant food production. The lives of the masses are miserable. They eat red sorghum and wild vegetables, drink bitter and salty water, and live in earthen houses and cottages, strongly affected by the ecological, agricultural, and socio-economic development of the region [32].

3.2. Data Collection and Analysis

Three crops, wheat, corn and oil sunflower, were selected as research objects. Based on data from the 1985 to 2015 *Inner Mongolia Statistical Yearbook*, *Bayannaoer Statistical Yearbook*, and *Bayannaoer Water Resources Bulletin*, as well as data obtained from field surveys, water levels were divided into three categories: low, medium, and high [33]. According to the historical statistics of runoff and rainfall in the HID, it was concluded that the probability of occurrence of medium flow is greater than that of high flow and low flow, and the probability of occurrence of high flow and low flow is basically the same, consistent with the normal distribution law. Therefore, this study assumed that the probability of occurrence for three incoming water levels in the forecast year are 0.2, 0.6, and 0.2, respectively [34]. According to statistical data, Table 1 lists the upper and lower limits of the amount of surface and groundwater available for each administrative area under different incoming water levels in the forecast year.

Table 1. Allowable water of each district under different water levels.

Administrative Region	Inflow Level	Available Water (10^8 m^3)		Probability
		Surface Water	Groundwater	
LinHe	Low	[10.4, 10.6]	[3.5, 3.7]	0.2
	Middle	[10.5, 11.2]	[3.6, 4.2]	0.6
	High	[10.7, 12.8]	[4.0, 4.8]	0.2
DengKou	Low	[5.7, 5.9]	[4.5, 4.8]	0.2
	Middle	[8.2, 8.6]	[5.2, 5.9]	0.6
	High	[12.0, 12.7]	[8.3, 9.8]	0.2
HangJinHou banner	Low	[9.2, 9.6]	[3.3, 3.6]	0.2
	Middle	[10.0, 10.8]	[4.1, 4.8]	0.6
	High	[11.3, 12.2]	[7.7, 8.2]	0.2
Wuyuan	Low	[9.9, 10.8]	[3.0, 3.5]	0.2
	Middle	[10.5, 10.9]	[4.2, 4.6]	0.6
	High	[11.3, 12.8]	[5.2, 5.8]	0.2
Urad Front banner	Low	[5.9, 8.2]	[2.7, 3.2]	0.2
	Middle	[9.8, 13.2]	[4.4, 5.8]	0.6
	High	[12.2, 16.5]	[6.6, 7.2]	0.2

Data on the area of the three crops planted in the typical year of 2015 were selected as known conditions. It was also assumed that the planting structure of the three crops in the forecast year would not change to determine the optimal water supply target [35]. Table 2 shows the planting area of three crops in different administrative regions and the water demand data under sufficient irrigation conditions for different crops under advanced decision. Both were determined based on the survey data provided by the HID Administration and the measured data collected at the Shuguang Experimental Station in the middle reaches of the HID, Inner Mongolia in 2015.

Table 2. Water demand prediction analysis of each administrative region.

Administrative Region	Crop Acreage/10^3 hm^2				Water Demand of Crop/mm			
	Wheat	Maize	Sunflower	Total	Wheat	Maize	Sunflower	Total
LinHe	19.93	3.24	3.69	26.86	[300, 310]	[635, 650]	[320, 335]	[1255, 1295]
DengKou	85.77	9.28	10.16	105.21	[252, 268.5]	[580, 595.5]	[232.5, 250]	[1064.5, 1114]
HangJinHou banner	52.40	14.35	13.19	79.94	[286.5, 302.5]	[590.5, 600.5]	[300, 308.5]	[1177, 1211.5]
Wuyuan	60.51	15.85	33.62	109.98	[296.5, 305.5]	[630, 645]	[303, 315.5]	[1229.5, 1266]
Urad Front banner	34.29	6.98	10.52	51.79	[295, 302.5]	[628, 635]	[305, 325.5]	[1228, 1263]

In the planning and utilization of agricultural water resources, if the estimated water availability meets the crop water demand, there will only be the cost of Yellow River water diversion; if the crop water demand is not met, the water shortage penalty will result [36]. Table 3 shows the maximum and minimum original water volume of each administrative area of the HID, and the corresponding diversion costs and water shortage penalty coefficients, in combination with relevant references.

Table 3. Cost of water delivery and water shortage penalty coefficient under different water conditions.

Region	Headwaters	Max. Original Water/10^8 m^3	Min. Original Water/10^8 m^3	Net Benefit	Penalty Coefficient
LinHe	Surface water	13.27	10.44	[2.6, 3.2]	[3.2, 4.2]
	Groundwater	4.65	3.55	[2.8, 3.5]	[3.5, 4.8]
DengKou	Surface water	13.42	5.70	[3.5, 5.0]	[4.5, 6.2]
	Groundwater	5.20	4.46	[3.9, 4.8]	[4.8, 6.5]
HangJinHou banner	Surface water	12.60	10.18	[6.3, 7.9]	[7.2, 8.5]
	Groundwater	4.37	3.62	[7.8, 8.5]	[8.3, 9.6]
Wuyuan	Surface water	13.25	10.00	[3.2, 4.2]	[3.8, 7.2]
	Groundwater	5.52	3.01	[4.8, 5.5]	[5.8, 7.0]
Urad Front banner	Surface water	17.24	5.90	[7.9, 9.2]	[8.6, 9.6]
	Groundwater	2.94	2.70	[8.6, 9.8]	[9.5, 10.8]

4. Results Analysis

4.1. Optimized Water Distribution Plan

Using Matlab 7 software and Lingo 11 programming, the ITRSP model for multi-water source allocation in the HID of Inner Mongolia was robustly solved. The water shortage under different robust coefficients in the forecast year was obtained according to the calculation results of the sub-model, followed by the optimal allocation water volume at different flow levels [37]. The results are shown in Table 4.

Table 4 shows that for the Linhe District, the optimal decision variable $z_{ijopt0.2}$ was 0.2, and the corresponding optimal water supply for surface water and groundwater were 4.12×10^8 m^3 and 2.26×10^8 m^3, respectively. The optimal allocation of water was close to the lower limit of the predicted water demand, and the water shortage was 0, indicating that for this region, the benefit of increased crop yield is less than the cost of water caused by increased water consumption. Therefore, in selecting the risk of crop yield increase or decrease, the model can be selected to meet the basic water requirements of the crop; the optimal allocation of surface water and groundwater was equal to the optimal water supply target and was less than the minimum original water volume of Linhe District, 1.044×10^9 and 3.55×10^8 m^3, respectively, indicating that no external water was used [38].

Table 4. Results of optimal allocation of water resources at different water levels of each administrative region.

Administrative Region	Headwaters	Inflow Level	Pk	Optimal Water Supply Target/10^8 m^3	Water Shortage/m^3	Optimal Allocation of Water/m^3	Decision Variable
LinHe	Surface water	Low	0.2	4.12	0	4.12	0.2
		Middle	0.6	4.12	0	4.12	0.2
		High	0.2	4.12	0	4.12	0.2
	Groundwater	Low	0.2	2.26	0	2.26	0.2
		Middle	0.6	2.26	0	2.26	0.2
		High	0.2	2.26	0	2.26	0.2
DengKou	Surface water	Low	0.2	12.64	[2.23, 4.31]	[8.15, 10.02]	0.15
		Middle	0.6	12.64	[1.68, 3.35]	[8.28, 10.68]	0.15
		High	0.2	12.64	0	12.64	0.15
	Groundwater	Low	0.2	7.15	0	7.15	0.15
		Middle	0.6	7.15	0	7.15	0.15
		High	0.2	7.15	0	7.15	0.15
HangJinHou banner	Surface water	Low	0.2	15.34	[4.45, 6.72]	[8.62, 10.15]	0.35
		Middle	0.6	15.34	[3.18, 5.92]	[8.87, 10.37]	0.35
		High	0.2	15.34	[2.62, 5.59]	[9.18, 11.12]	0.35
	Groundwater	Low	0.2	5.58	[1.12, 2.15]	[3.05, 3.56]	0.35
		Middle	0.6	5.58	[1.03, 2.12]	[3.11, 3.69]	0.35
		High	0.2	5.58	[0, 0.87]	[4.42, 5.14]	0.35
Wuyuan	Surfacewater	Low	0.2	10.02	[5.68, 7.76]	[4.44, 5.36]	0.48
		Middle	0.6	10.02	[3.34, 6.15]	[5.86, 6.82]	0.48
		High	0.2	10.02	0	10.02	0.48
	Groundwater	Low	0.2	5.18	[2.12, 3.35]	[2.28, 3.47]	0.48
		Middle	0.6	5.18	[2.01, 3.28]	[2.46, 3.52]	0.48
		High	0.2	5.18	0	5.18	0.48
Urad Front banner	Surface water	Low	0.2	20.50	[8.62, 12.14]	[10.08, 12.25]	0.52
		Middle	0.6	20.50	[7.28, 10.62]	[11.14, 12.98]	0.52
		High	0.2	20.50	0	8.65	0.52
	Groundwater	Low	0.2	8.65	0	8.65	0.52
		Middle	0.6	8.65	0	8.65	0.52
		High	0.2	8.65	0	8.65	0.52

Table 4 shows that for Dengkou County, the optimal decision variable $z_{ijopt0.15}$ = 0.15, then the corresponding optimal water supply for surface water and groundwater is 1.264×10^9 and 7.15×10^8 m^3, respectively. With $z_{ijopt0.52}$ = 0.52 in Urad Front Banner, the corresponding optimal amounts of surface water and groundwater are 2.05×10^9 and 8.65×10^8 m^3, respectively. For Dengkou County and Urad Front Banner, the water shortage for both groundwater and surface water was 0 at the high water level. As can be seen in Table 3, the cost of surface water is lower than of groundwater. In order to ensure maximum benefits, in the process of water resources allocation, the surface water allocation is prioritized. Dengkou County had a small amount of water shortage at low and medium water levels. The surface water shortages reached 2.23×10^8~4.31×10^8 and 1.68×10^8~3.35×10^8 m^3, respectively, which indicates that the crop water demand in this area is relatively low compared to the soil salinization in this area. At the low incoming water level in Dengkou County, the optimal allocation of surface water and groundwater was 8.15×10^8~1.002×10^9 and 7.15×10^8 m^3, respectively, both larger than the minimum original water volume of 5.7×10^8 and 4.46×10^8 m^3, respectively, indicating that some external water was used. However, because the amount of groundwater resources was less than the amount of surface water resources, and the cost of mining is high, the optimal allocation of water should mainly come from surface water [39].

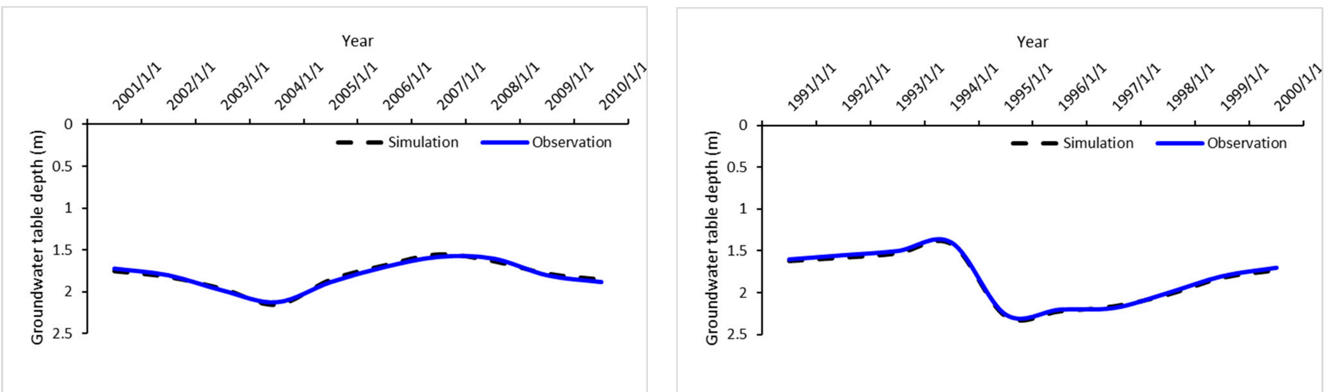
As seen in Table 4, for HangJinHou banner, the optimal decision variable $z_{ijopt0.35}$ = 0.35, and the corresponding optimal water supply for surface water and groundwater was 1.534×10^9 and 5.58×10^8 m^3, respectively. The water shortage in HangJinHou banner was relatively large at low incoming water levels. The surface and groundwater shortages reached 4.45 × 10^8~6.72 × 10^8 and 1.12 × 10^8~2.15 × 10^8 m^3, respectively. This shows that the region needs a larger amount of crop water, which is related to the larger crop cultivation area in the region. At a low incoming water level, the optimal allocation of surface water and groundwater in HangJinHou banner was 8.62 × 10^8~1.015 × 10^9 and 3.05 × 10^8~3.56 × 10^8 m^3, respectively, both less than the minimum original water volume of 1.018 × 10^9 and 3.62 × 10^8 m^3, respectively, indicating that water resources were scarce at low water supply levels; considering the higher cost of water, the amount of water allocated to crops should be relatively reduced [40].

As seen in Table 4, for Wuyuan County, the optimal decision variable $z_{ijopt0.48} = 0.48$, and the corresponding optimal water supply for surface water and groundwater was 1.002 × 10^9 and 5.18 × 10^8 m^3, respectively. In Wuyuan County, the surface water and groundwater shortage were only at the high water supply level, which means that at the high water supply level, water resources basically meet the water demand.

Based on the calculation results, the overall water supply structure of the HID was further calculated. At the low incoming water level of the forecast year, the ratio of surface water use was 63.2%, and the proportion of groundwater was 36.8%. At the middle incoming water level of the forecast year, the ratio of surface water use was 65.8%, and the proportion of groundwater was 34.2%. At the high incoming water level of the forecast year, the ratio of surface water use was 67.9%, and the proportion of groundwater was 32.1%. This suggests that the optimized proportion of surface water consumption increased, which has certain practical significance for mitigating groundwater over-exploitation, controlling groundwater below a critical depth, and preventing soil salinization in the HID.

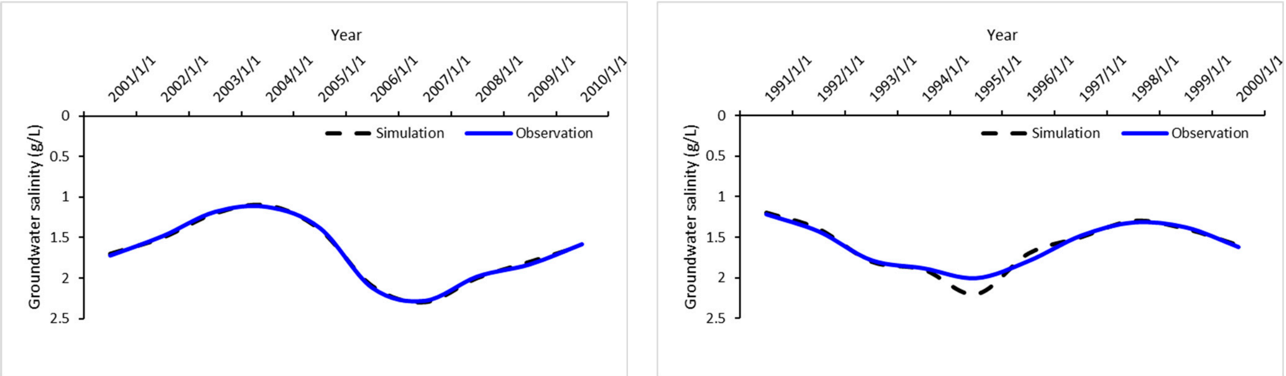
4.2. Salt Control Analysis

The SALTMOD model was calibrated and validated using 1990–2010 field data for groundwater table depth and groundwater salinity (Figures 3 and 4). For groundwater table depth, the Nash–Sutcliffe efficiency (NSE) values were 0.68 (in calibration) and 0.65 (in validation), and the coefficient of correlation (R^2) 0.71 (in calibration) and 0.74 (in validation). For groundwater salinity, the NSE values were 0.66 (in calibration) and 0.58 (in validation), and the R^2 0.72 (in calibration) and 0.65 (in validation); thus, the SALTMOD modeling simulated the water and salt transport law in the HID very well. Multi-source, multi-region and different water-supply targets obtained from the two-stage robust stochastic optimization model as main parameters were input into the SALTMOD model based on the principle of water and salt balance. The output includes data such as groundwater mineralization and groundwater burial depth [41].



(**a**) (**b**)

Figure 3. Simulated versus observed groundwater table depths during (**a**) calibration from January 2001 to January 2010, and (**b**) verification from January 1991 to January 2000.



(**a**) (**b**)

Figure 4. Simulated versus observed groundwater table values during (**a**) calibration from January 2001 to January 2010, and (**b**) verification from January 1991 to January 2000.

From 2010 to 2014, the combination of wells with canals was not implemented, and from 2015 to 2019, surface water and groundwater joint scheduling was implemented in the HID.

The HID has low precipitation and high evaporation, the movement of groundwater belongs to the type of vertical infiltration and evaporation, and the salt content of irrigation water is about 0.5 g/L; this leads to serious secondary soil salinization in the HID. As shown in Figures 5 and 6, with the implementation of combined measures of wells with canals in the HID in 2015, for many years the groundwater table depth increased by approximately 0.3 m on average, and the groundwater salinity decreased by approximately 0.2 g/L on average. These two phenomena have a synergistic effect. However, the promotion of the combined measures of wells with canals should increase the area and extend the time to prevent the occurrence of salt return in the Wu Yuan irrigation area.

Figure 5. *Cont.*

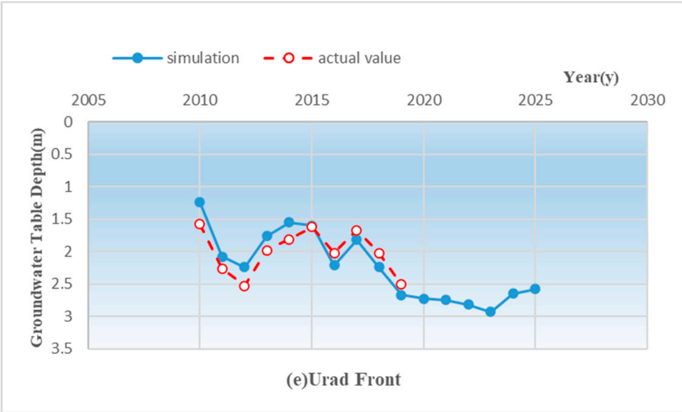


Figure 5. Comparison of simulated and measured values of groundwater depth.

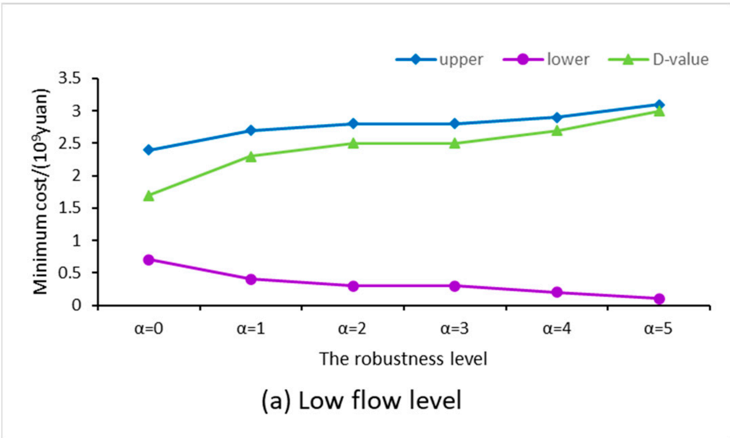
Figure 6. Comparison of simulated and measured values for water mineralization.

The measured groundwater depths in the different administrative areas of the HID were compared with the groundwater depth data output by the SALTMOD model. It was concluded that after combining wells and canals, over many years of pumping, the groundwater levels in the different administrative areas of the HID decreased by approximately 0.3 m [42].

The measured values of groundwater salinity in different administrative areas of the HID were also compared with those of groundwater salinity output by the SALTMOD model. It was concluded that after combining the wells and canals, the soil salt content in the different administrative areas of the HID will decrease slightly. The wheat, corn and oil sunflower roots have larger growth space, wider distribution, and enhanced stress resistance, which promote the high quality and yield of the three crops.

4.3. Risk Analysis under Different Incoming Water Conditions

The model was solved to obtain the minimum comprehensive cost of surface water and groundwater in the five irrigation areas in the case of joint dispatch $f_{opt} = 1.38 \times 10^9$ ~3.24×10^9 yuan. Due to the different water distribution forms and the uncertainty of the system, the final cost was given as an interval value to accommodate different water distribution decisions [43]. In order to illustrate the effect of the robustness coefficient on the objective function value, the change of the objective function value of the water cost with the robustness coefficient at the three levels of low-medium-high water supply was calculated. The calculation results are shown in Figure 7.



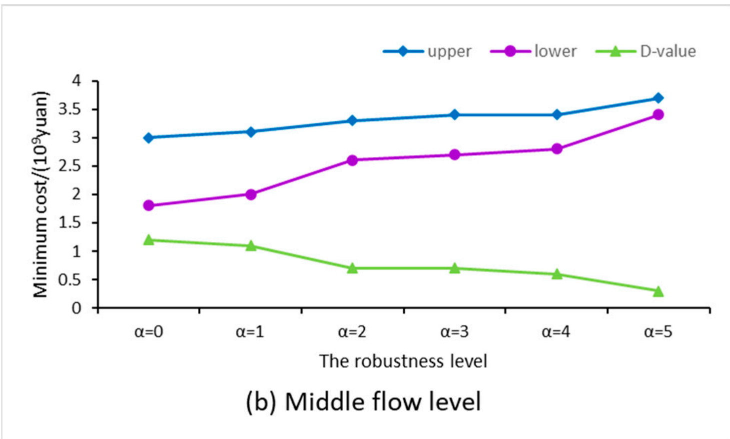


Figure 7. *Cont.*

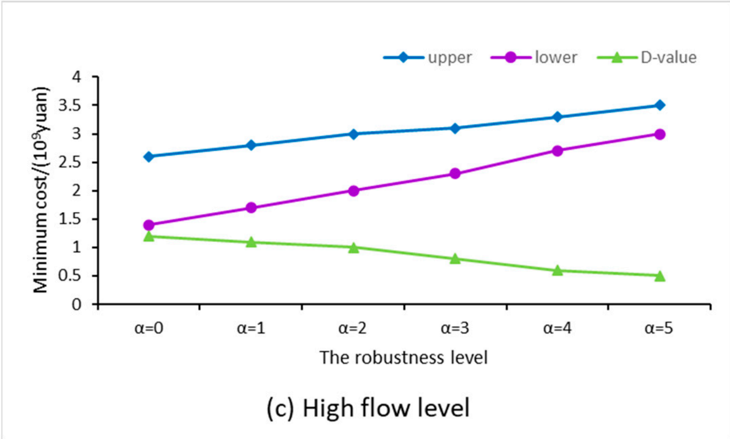


Figure 7. Minimum cost of water optimal allocation of different water levels under different α.

Under three types of incoming water probability, the robust coefficient α changes from 0 to 5 [44]. From Figure 7, it can be seen that the minimum cost of optimal allocation of water resources varies with α: (1) at the low water supply level: when α = 0, the model is an ordinary interval two-stage stochastic programming model, which means that decision-makers think more about the economics of the system and ignore the system risks. The minimum cost is 1.7×10^9~2.4×10^9 yuan; as α increases, the objective function gradually increases. When α = 5, the minimum cost is between 3×10^9~3.1×10^9 yuan. (2) At the middle water supply level: the objective function value gradually increases with the increase of α, and the minimum cost increases from 1.8×10^9~3×10^9 yuan to 3.4×10^9~3.7×10^9 yuan. (3) At the high water supply level: the objective function value also gradually increases with the increase of α, and the minimum cost increases from 1.4×10^9~2.6×10^9 to 3×10^9~3.5×10^9 yuan.

With the change of optimal allocation of water resources [45], the system cost shows a certain change law: (1) the increase of the robust coefficient causes the system cost to increase. When $\alpha \geq 2$, the cost is almost unchanged, indicating that the system has stabilized. (2) With the increase of the robust coefficient, the difference between the upper and lower limits of the cost becomes smaller, the stability of the system increases, and the economy and stability are well balanced.

5. Discussion

The interval two-stage stochastic optimization model is very effective in dealing with uncertain factors, but it ignores the risk issues in a saline-alkali land management system. After application, it can cause problems, such as soil salt return, agricultural production reduction and water shortage, in key periods of crop growth; thus, model results are not absolutely feasible. The robust optimization method can effectively avoid risks during the planning process and weigh the relationship between variable random values and recourse costs in the system. It is introduced into the interval two-stage stochastic programming model and coupled with the SALTMOD model. The results obtained can make the economy and stability of the saline-alkali land treatment system better balanced [46].

5.1. Precision Analysis of Water Distribution Model with the Actual Situation

Taking the agricultural water situation of HangJinHou banner in 2017 as an example, the model accuracy analysis was performed [47]. According to the statistics 2017 was calculated as the middle level of water supply. From the agricultural water in HangJinHou banner, the actual surface water and groundwater use was compared with the calculation results in the model. The results are shown in Table 5. The relative errors of the optimal allocation of surface water and groundwater were within 10%, the RMSE was approximately 30% and the d-index was smaller than 0.5. Overall, the model optimization results were consistent with the actual situation.

Table 5. Actual value and error analysis of water.

Administrative Region	Surface Water				
	Calculated Value/10^8 m^3	**Actual Value/10^8 m^3**	**Relative Error/%**	**RMSE**	**d-Index**
HangJinHou banner	[8.87, 10.37]	11.48	9.40	0.32	0.42
Administrative Region	**Groundwater**				
	Calculated Value/10^8 m^3	**Actual Value/10^8 m^3**	**Relative Error/%**	**RMSE**	**d-Index**
HangJinHou banner	[3.11, 3.69]	3.90	4.60	0.35	0.49

Through analysis, it is known that the planting structure data of the typical year 2015 was used as the known conditions when the model was optimized and solved, and the planting structure was adjusted accordingly in 2017, resulting in certain errors in the model [48]. However, the planting structure in the model can be adjusted through related parameters to reduce the error; surface water has a slightly larger error because the runoff cycle is more complicated than groundwater.

5.2. Precision Analysis of the Salt Control Model

The 2014–2016 output of the HID's Urat irrigation area through the SALTMOD model was used to compare the groundwater depth and mineralization of the groundwater with the measured values [49,50]. Among them, the combination of wells and canals was not implemented before 2015. After 2015, surface water and groundwater joint dispatching was implemented in the Urat irrigation area.

The comparison of the annual groundwater depth and actual measured values of the Urat irrigation area from 2014 to 2016 is shown in Table 6. The changing process of groundwater depth is shown in Figure 5e. Only the relative error of the simulation in 2014 was slightly greater than 15%, the rest were within 10%, and the RMSE for three years was smaller than 0.2. The simulation accuracy was high [51,52]. The comparison of the measured and simulated groundwater mineralization in the Urat irrigation area from 2014 to 2016 is shown in Table 7 and Figure 6e. The average relative error of mineralization of groundwater in the Urat irrigation area was between 12% and15%, and the RMSE for three years was within 0.1. The simulated values better reflect the dynamic changes of root salinity for main crops in the HID, and more accurately simulated the process of salt reduction due to the combination of wells and canals from 2015 to 2019 [53,54].

Table 6. Comparison of measured and simulated groundwater levels in the Urat irrigation area from 2014 to 2016.

	Measured Value (m)	Simulated Value (m)	Relative Error	RMSE	d-Index
2014	1.81	1.55	16.90%	0.18	0.13
2015	1.62	1.60	1.10%	0.01	0.997
2016	2.02	2.21	6.34%	0.13	0.01
The annual average	1.82	1.79	2.26%	0.02	0.002

Table 7. Comparison of measured and simulated groundwater mineralization in the Urat irrigation area from 2014 to 2016.

	Measured Value (g/L)	Simulated Value (g/L)	Mean Relative Error	RMSE	d-Index
2014	2.67	2.79	13.52%	0.08	0.002
2015	2.84	2.83	5.18%	0.01	0.988
2016	2.88	2.74	14.78%	0.10	0.002
The annual average	2.80	2.79	5.06%	0.007	0.002

6. Conclusions

In this study, an interval two-stage robust stochastic programming (ITRSP) and SALTMOD coupling model was established to coordinate agricultural irrigation and environmental protection under a variety of uncertainties, and to address risk issues in saline-alkali land management systems. The developed ITRSP-SALTMOD model can reflect the interaction of agricultural irrigation and salt control issues into a framework to support policy makers in developing comprehensive plans at the irrigation district scale. It can support agricultural irrigation and drainage under different robust coefficients, and then formulate related current policies to control the groundwater burial depth of irrigation districts below a critical depth while reducing groundwater mineralization. At the same time, it can also be used to reduce the cost of saline-alkali land management systems and realize considerable social and economic system benefits. In addition, it can provide solutions for protecting the agro-ecological environment of the HID and achieve green development in the region. The ITRSP-SALTMOD coupling model is a good example that can be applied and extended to salinized areas mainly distributed in Xinjiang, Gansu, Qinghai, Inner Mongolia, Ningxia and other areas in northwest China, as well as the eastern coastal areas.

With the aid of the model, several discoveries were found, as follows: (a) combining uncertainty and risk can avoid the shortcomings of the traditional interval two-stage stochastic programming method, and introduce robust optimization to seek the minimum water cost of optimal water resources allocation to prevent and control soil salinity, avoiding the situation of concentrating risk losses in a certain irrigation area. (b) Through an interval two-stage robust stochastic optimization model, from 2015, the implementation of combined surface water and groundwater use of optimal dispatching schemes had a positive significance for regulating groundwater depth and changing soil water and salt dynamics. (c) The SALTMOD model can better simulate the dynamic changes of the groundwater burial depth and soil root layer salinity in the irrigation districts of different administrative areas in the HID, providing a basis for decision-makers to reasonably control salt in the future. Correspondingly, specific suggestions for decision-makers can be summarized as follows: based on the existing "Three North" shelter forest system construction project in the HID, the crop planting structure should be adjusted, and the resistance to drought, smoke and salt-alkali crops, such as Sophora japonica, increased, improving salt control efficiency, while promoting local economic growth; governmental support and financial subsidies should be advocated, and the optimal dispatching scheme for expanding the combined use of surface water and groundwater promoted and applied in arid and semi-arid areas. Furthermore, consciousness and robust methods for identification of risk adoption should be considered in decision-making, such as the conditional value at risk (CVaR) method, which could fortify the reliability of interval two-stage (ITS) strategies. Since there are interactive relationships between water supply, irrigation, precipitation, water consumption and water demand in the irrigation district, multi-stage programming should be considered; due to the particularity of the complex system of water resources, it is necessary to introduce intuitionistic fuzzy sets to obtain the water resources allocation scheme based on group decision-making. These are worthy of further research in the future.

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