Journal of Environmental Informatics 39(2) 152-164 (2022)

Journal of Environmental Informatics

www.iseis.org/jei

Monte Carlo-Based Agricultural Water Management under Uncertainty: A Case Study of Shijin Irrigation District, China

G. Q. Yang[1, 2], M. Li[1], and P. Guo[1 *]

[1] Centre for Agricultural Water Research in China, China Agricultural University, Beijing 100083, China
[2] Institute of Environmental Science, Taiyuan University of Science and Technology, Taiyuan, Shanxi 030024, China

Received 11 May 2016; revised 18 October 2016; accepted 25 Novermber 2018; published online 14 September 2020

ABSTRACT. Considering the multiple uncertainties in agricultural water resources management systems, this paper established an agricultural water optimal allocation model under uncertainty for Shijin irrigation district (ID). Uncertainties of four parameters, including precipitation, available groundwater, purchase prices of crops and crop cultivated area, were fully considered. Agricultural water allocation schemes were obtained based on the distribution characteristics simulation of the four parameters using Monte Carlo simulation technique. In order to thoroughly analyze the results, the relationship between system benefits and water amounts was shown using 3D diagram. The optimized results show that total water use amount of 2016 ([217.460, 218.017] $\times 10^6$ m^3 for surface water irrigation and [51.765, 66.266] $\times 10^6$ m^3 for groundwater irrigation) remains fairly static compared with the average level from 2003 to 2013, and irrigation water allocated to winter wheat is considerably larger than that to maize. The significant drop of the purchase price of maize has an apparent effect on water allocation. For winter wheat, surface water allocation of 2016 increases from 129.445 $\times 10^6$ to 174.905 $\times 10^6$ m^3, and groundwater allocation increases from 24.511 $\times 10^6$ m^3 to 35.379 $\times 10^6$ m^3. For maize, surface water allocation of 2016 decreases from 88.329 $\times 10^6$ to 42.846 $\times 10^6$ m^3, and groundwater allocation decreases from 34.733 $\times 10^6$ to 23.865 $\times 10^6$ m^3. Water allocation amounts for the five subareas of Shijin ID are 54.326 $\times 10^6$, 31.187 $\times 10^6$, 51.899 $\times 10^6$, 39.311 $\times 10^6$, and 33.779 $\times 10^6$ m^3 respectively during the irrigation period of winter wheat, and are 16.693 $\times 10^6$, 8.677 $\times 10^6$, 16.151 $\times 10^6$, 14.004 $\times 10^6$, and 10.752 $\times 10^6$ m^3 during the irrigation period of maize. Moreover, cumulative probability distribution functions of surface water and groundwater allocation amounts for winter wheat and maize were obtained. Further, the linear relations between the difference in purchase price and the difference in water allocation of winter wheat and maize were obtained as well. These results will help decision makers learn detailed water distribution information and thus help make comprehensive irrigation schemes under uncertainty in future.

Keywords: agricultural water allocation, optimization, uncertainty, Monte Carlo simulation.

1. Introduction

Agriculture is the biggest consumer of limited water resources and water scarcity had led to an increasing interest in optimization modeling of agricultural water resources systems (Li et al., 2016). There are many uncertainties in agricultural water management systems, such as the stochastic characters of precipitation, groundwater, irrigation quota, and so on (Mun et al., 2015). Considering the uncertainties in agricultural water resources planning and management is significant from both scientific and societal perspectives (Hassanzadeh et al., 2015). Many recent researches on agricultural water management under uncertainty have been reported. For example, Wang et al. (2016) developed a type-2 fuzzy interval programming method and applied it to the conjunctive use of surface water and groundwater in the Zhangweinan River Basin, China. Niu et al. (2016) developed an interactive two-stage fuzzy stochastic programming method and applied it to Hetao irrigation district, China. Zeng et al. (2016) developed a joint-probabilistic interval multistage programming method for planning water resources management under uncertainty. Liu et al. (2015) developed a fuzzy-boundary interval programming method and applied it to water quality management in the Three Gorges Reservoir Region of Xiangxi River, China. Xu (2012) developed an interval-parameter stochastic chance-constrained programming model for urban water supply system including the municipal, agricultural and industrial sectors. These researches are worth learning by converting complex optimization problems under uncertainty into simple expressions based on interval and fuzzy techniques. However, the expressive information of these methods is limited and these models are not portable in most cases. In addition, accurate measurements of certain parameters such as irrigation and rainfall are critical to effectively manage water resources for crop production (Mun et al., 2015). However, the measured data actually vary in a certain range over time, and deterministic optimization models are inadequate to completely reflect the reality of agricultural water management. Therefore, stochastic mathematical methods based on probability and mathematical statistics theories can be introduced into agricultural water resources allocation optimization models in

* Corresponding author. Tel.: +86 10 62738496; fax: +86 10 62737796.
E-mail address: guop@cau.edu.cn (P. Guo).

SSN: 1726-2135 print/1684-8799 online
 doi:10.3808/jei.202000441

order to provide a more detail description on the uncertainties of agricultural water management.

Monte Carlo (MC) simulation is such a stochastic mathematical method based on the theory of probability and statistics (Metropolis and Ulam, 1949), which was proposed to check the feasibility of potential solutions (Xu and Qin, 2013). MC simulation has great superiority in handling a variety of uncertain factors, because it can be useful to represent the uncertainty in the parameter estimation by random simulations (Gelman, 2015). The process of MC simulation under uncertainty includes distribution determination of uncertain factors and sampling based on probability distributions, evaluation of estimators and statistics test (Hunt and Miles, 2015). MC simulation has been widely used in fields such as inancial engineering and macroeconomics. (Wang and Sloan, 2011; Greal, 2012) and it has been gradually introduced in agriculture water allocation recently. Many hydrological elements that affect agricultural water allocation are stochastic, such as runoff, precipitation, groundwater availability. MC simulation is suitable to solve agricultural water problems with properties of uncertainty. For example, Shen et al. (2015) randomly permutated daily rainfall values by MC simulation in a hydrologic uncertain model. Assumaning et al. (2014) used MC simulation to predict uncertain decay of subsurface contaminant in time and space for risk assessment and site remediation.

In order to better solve the multiple uncertainties in agricultural water management systems, it is necessary to integrate MC simulation with optimization models for agricultural water management. Graveline et al. (2012) proposed a methodology to assess uncertainty in hydro-economic models using MC simulations. The simulations were based on farming models developed for Midi-Pyrenees and Alsace, France. Matsui et al. (2006) studied the impacts of herbicide application on farming schedules by simulating the uncertainties and evaluating the sorption of herbicide decomposition using MC simulation. As an effective assessment tool, MC simulation conduces to fully reflect uncertainties in agricultural water resources management. However, incorporating MC simulation with optimization models in agricultural water management has been reported in limited cases, and this will be one of the focuses of this study.

Agriculture in China is facing chronic water shortages, which is an important social and political issue with many domestic and international implications (Veeck, 2013). As China is undergoing a challenging period, during which, agriculture began to develop rapidly with economic development. Meanwhile, water supply shortage has become a growing concern for the Chinese government and the public (Su, 2013; He et al., 2020; Huang et al., 2020; Guo et al., 2020; Chen et al., 2020). Efficient water allocation is needed to deal with shrinking water resources. Efficient water allocation will be embodied by economic prices and the purchase prices of crops directly reflect the expenditures of agricultural systems. Hence, it is necessary for stakeholders and policy makers to evaluate tradeoffs between profitable crop production (related to the purchase prices of crops) and limited agricultural water resources (Ziolkowska, 2015). However, variability of the purchase prices of crops is a practical difficulty when evaluating water resources (Kim and Kaluarachchi, 2016). In China, from 2008, the government has implement institution of the purchasing and storage of maize, leading to the purchase price of maize increases every year, with 600 RMB/t higher than that of imported maize (RMB is the currency units of China). This results in the massive influxes of imported maize and the substitute for maize and as a direct result, maize stocks face a huge overcapacity problem. In 2016, the supply-demand of agriculture in China is facing reform, and maize market takes a major step. This leads to a significant reduce of the prices of maize and the huge price differential is unprecedented. How to re-allocate agricultural water resources with the consideration of stochastic distribution of the purchase prices of crops under such a new situation is a challenging that deserves attentions by decision makers.

Therefore, the aim of this paper will develop an agricultural water management model by fully considering the stochastic characteristics of both hydrological and economic elements based on MC simulation. The potential of the developed model is shown by applying to a case study in Shijin irrigation district (ID), in northern China. Shijin ID is a main grain-producing area and it is influenced inevitably by the current economic situation of China. The effect of purchase prices of crops on agricultural water allocation based on the developed model will be analyzed in detail, and a series of agricultural water allocation schemes under current economic situation will be obtained, which will provide strategy suggestions for further administration on agricultural water resources of Shijin ID.

2. Study System

2.1. Study Area

Shijin ID, located in Hebei Province, China, is a large ID with the irrigation area of 1.627×10^3 ha. The source of surface water for irrigation comes from Gangnan Reservoir and Huangbizhuang Reservoir in the upper reaches. Many pumping wells are discretely distributed in Shijin ID. Groundwater from wells is used as a supplemental source of water to irrigate crops during water shortage periods or irrigates areas that far away from surface water source regions. The main crops in Shijin ID include winter wheat and maize. Besides, cotton and soybean are planted in a small amount. The growing period for winter wheat is from October to June in next year and the growing period for maize focuses from June to September. Most of the land are used for crop rotation of winter wheat and maize (Yang et al., 2015). The study area contains five main irrigation regions which connects with the reservoir and they are mainly distributed in the southern part of Shijin ID. The canal distributions of the study area are shown as Figure 1. From Figure 1(a), it can be seen that the canal distribution presents tree structure, including main canal, trunk canal, sub-main canal, branch canal, lateral canal and sub-lateral canal. The flow direction of the main canal is from west to east and the flow direction of trunk canals is from north to south. The five studied subareas were divided based on the control area of each trunk canal as shown in Figure 1(b).

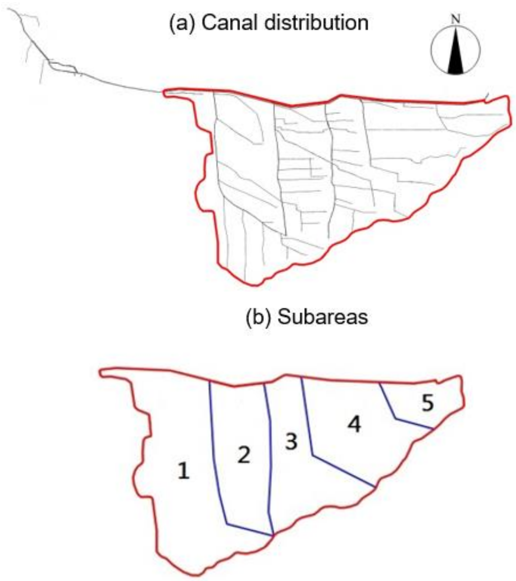


Figure 1. Study area: (a) Canal distribution, (b) Subareas.

2.2. Modeling Formulation

2.2.1. System Objective

In agricultural systems, many system objectives are economic-related, such as maximizing system economic benefits (Kim and Kaluarachchi, 2016). Hence, the system objecttive in this study is to maximize the revenue of local farmers. The expression is provided as follows:

$$\max\ f^{*} = \sum_{i=1}^{iCrop}\sum_{j=1}^{iSubarea} C_{C,i}^{*} A_{ij}^{*} Y_{m,i} \prod_{k=1}^{iStage_i}\left(\frac{ET_{c,ijk}^{*}}{ET_{cm,ik}}\right)^{\lambda_{ik}} - \sum_{i=1}^{iCrop}\sum_{j=1}^{iSubarea}\sum_{k=1}^{iStage_i} C_{Ws,j} Ws_{ijk}^{*} - \sum_{i=1}^{iCrop}\sum_{j=1}^{iSubarea}\sum_{k=1}^{iStage_i} C_{Wg} Wg_{ijk}^{*} \tag{1}$$

where i is the index for crops (i = 1, 2, …, $iCrop$); j is the index for subareas (j = 1, 2, …, $iSubarea$); k is the index for growth stage of crop i (k = 1, …, $iStage_i$); f^{*} is the benefit of local farmer (RMB); $C_{C,i}^{*}$ is the purchase price of crop i (RMB/kg); A_{ij}^{*} is the planting area of crop i in subarea j (ha); $Y_{m,i}$ is the maximum yield of crop i under given management conditions (kg/ha); $ET_{c,ijk}^{*}$ is the actual evapotranspiration of crop i in subarea j during growth stage k (mm); $ET_{cm,ik}$ is the maximum evapotranspiration of crop i during growth stage k (mm); λ_{ik} is the sensitivity to water stress of crop i during growth stage k; $C_{Ws,j}$ is the surface water price for local farmers in district j (RMB/m^3); W_{ijk}^{*} is the surface water availability for crop i in district j during growth stage k (m^3); C_{Wg} is the groundwater cost for local farmers (RMB/m^3); Wg_{ijk}^{*} is the groundwater availability for crop i in district j during growth stage k (m^3). Among above parameters, f^{*}, $C_{C,i}^{*}$, A_{ij}^{*}, W_{ijk}^{*}, and Wg_{ijk}^{*} are uncertain parameters.

In the objective function, the yields of different crops are calculated by Jensen model, from which, relative yield through relative evapotranspiration can be obtained (Igbadun et al., 2007). The decision variables are surface water availability W_{ijk}^{*} and groundwater availability Wg_{ijk}^{*}. Meanwhile, the actual evapotranspiration $ET_{c,ijk}^{*}$ can be calculated by the decision variables using water balance equation. Therefore, it is obvious that the system has an objective with nonlinear characteristic. Then the revenue of local farmers can be obtained based on the purchase prices of crops.

There are many factors affecting crop growth, such as solar radiation, temperature, plant moisture stress and nutrition (Muchow et al., 1990; Amir and Sinclair, 1991). However, many of these influence factors have been reflected in the Jensen model, so these is no need to consider so many factors in optimization modeling of agricultural water resources systems for this study. Considering excessive factors will generate a complex optimization model with complicated calculation procedures.

2.2.2. System Constraints

The constraints of the developed model contain evapotranspiration constraints, water availability constraints and nonnegative constraints.

(1) Evapotranspiration constraints

These constraints restrict the reasonable ranges of $ET_{c,ijk}^{*}$. Crop evapotranspiration must be larger than the minimum evapotranspiration and smaller than the maximum evapotranspiration. The constraints can be expressed as follows:

$$ET_{c,ijk}^{*} \geq ET_{c\min,ik} \qquad \forall i,j,k \tag{1}$$

$$ET_{c,ijk}^{*} \leq ET_{\mathrm{cm},ik} \qquad \forall i,j,k \tag{2}$$

$$ET_{c,ijk}^{*} = 0.1\frac{Ws_{ijk}^{*} + Wg_{ijk}^{*}}{A_{ij}^{*}} + P_{ijk}^{*} \qquad \forall i,j,k \tag{3}$$

where P_{ijk}^{*} is the precipitation for crop i in district j during the growth stage k (mm).

(2) Surface water availability constraint

This constraint restricts the maximum surface water availability and it can be expressed as follows:

$$\sum_{i=1}^{iCrop}\sum_{j=1}^{iSubarea}\sum_{k=1}^{iStage_i} W_{s_{s,j}}^{*} \leq Wsa \tag{4}$$

where $\eta_{s,j}$ is the utilization coefficient of surface water for irrigation in district j; Wsa is the amount of surface water availability for irrigation (m^3).

(3) Groundwater availability constraint

This constraint restricts the maximum groundwater availability in each district and it can be expressed as follows:

$$\sum_{i=1}^{iCrop}\sum_{k=1}^{iStage_i} \frac{W_{g_{ijk}}^{*}}{\eta_{g,j}} \leq Wga_j \qquad \forall j \tag{5}$$

where $\eta_{g,j}$ is the utilization coefficient of groundwater for irri-

Table 1. Parameters in Jensen Model for All Growth Stages

Crop	Parameters	Growth Stages					
Winter Wheat	Name	Seedling	Overwintering	Reviving	Booting	Heading	Ripening
	λ	0.1721	0.0411	0.0591	0.1694	0.3108	0.1895
	ET_{cm} (mm)	66.00	80.40	115.96	134.00	67.00	127.82
	Y_m (kg/ha)	7569					
Maize	Name	Seedling	Booting	Tasseling	Ripening		
	λ	0.0557	0.1106	0.3197	0.2113		
	ET_{cm} (mm)	28.50	62.80	133.00	201.00		
	Y_m (kg/ha)	6900					

Table 2. Parameters of Gamma Distribution of Precipitation in Crops' Growth Stages

Crop	Parameters	Growth Stages					
Winter wheat	Name	Seedling	Overwintering	Reviving	Booting	Heading	Ripening
	phat	1.536	1.525	0.814	1.517	3.443	3.214
	pci	2.213	0.441	1.497	1.300	0.757	2.063
	χ^2	0.02660	0.323	0.009	0.144	0.416	1.537
Maize	Name	Seedling	Booting	Tasseling	Ripening		
	phat	2.235	8.303	5.863	11.211		
	pci	2.383	1.551	1.154	0.995		
	χ^2	0.1521	0.886	0.619	0.329		

Note: *phat* is the shape parameter; *pci* is the scale parameter; χ^2 is the Chi-square statistics.

gation in district j; Wga_j is the amount of groundwater availability for irrigation in district j (m^3).

(4) Nonnegative constraints

These constraints require that the decision variables must be nonnegative.

$$Ws_{ijk}^{*} \geq 0 \quad \forall i,j,k \tag{6}$$

$$Wg_{ijk}^{*} \geq 0 \quad \forall i,j,k \tag{7}$$

2.3. Data Sources

Winter wheat and maize were chosen as the study crops in this study because they occupy the most planting areas of the studied irrigation regions. Let *iCrop* = 2, with i = 1 representing winter wheat and i = 2 representing maize; *iSubarea* = 5 represents the five subareas according to trunk canal distributions; $iStage_1$ = 6 represents six growth stages of winter wheat, including seedling, overwintering, reviving, booting, heading and ripening; $iStage_2$ = 4, represents four growth stages of maize, including seedling, booting, tasseling and ripening. The growth parameters of the Jensen model of the two crops come from Farmland Irrigation Research Institute, Chinese Academy of Agricultural Sciences (Yang et al., 2015) and the related values of the parameters are shown in Table 1.

Many parameters in the developed model are uncertain, such as, precipitation, groundwater amount, purchase prices of crops, planting area. The key of MC simulation is to analyze the uncertain parameters accurately, and then describe the value ranges and distribution characteristics of these uncertain parameters. This study will reflect the characteristics of different kinds of uncertain parameters by MC simulation.

Precipitation is a typical stochastic parameter and the amounts of single rain often present lognormal distribution (Biondini, 1976; Limpert et al., 2001). In most regions of China, precipitation in summer is basically matched with normal distribution, while in winter, precipitation obey non-normal distribution in most cases on annual and seasonal scale. Most areas in China, including northwest, northern and northeast parts, belong to continental climates, and the distribution of the precipitation in these areas deviates normal distribution seriously (Li et al., 1998; Fang et al., 2009; Zhang et al., 2009; Bai et al., 2014). For monthly precipitation, the gamma distribution is the more suitable probability model (Mooley, 1973; Husak et al., 2007). Shijin ID belongs to continental climates. According to the monthly precipitation data from 2002 to 2013, the distribution of precipitation disobeyed normal distribution; however, Gamma distribution can describe it well (Tang et al., 2014; Fan et al., 2015). This paper simulated the precipitation in each growth stage of crops using Gamma distribution based on MC simulation. Through fitting the precipitation dataset spanning from 2002 to 2013 by Matlab, the corresponding parameters of Gamma distribution of precipitation are obtained and shown in Table 2. The maximum Chi-square statistic of the fitting parameters is 1.537 which is less than the refusal area $x_{1,0.05}^{2}$ = 3.84. Therefore, using Gamma distribution to describe precipitation is feasible.

Groundwater availability is uncertain as well. Groundwater availability was regarded to obey interval distribution because past statistical information of groundwater availability is so limited to fit probability distribution with specific forms such as normal distribution. Groundwater availabilities of each subarea are listed as Table 3.

In order to make comparisons among different years, monthly purchase prices of winter wheat and maize are chosen, among which, the purchase prices of the harvest month of the two crops were selected. That is, the purchase price of winter wheat was based on the price of June and the purchase price of maize was based on the price of October. The purchase prices of the two crops were expressed as interval forms, with C_w representing the purchase price of winter wheat and C_m representing the purchase price of maize (see Table 4). Particularly, the purchase prices of the two crops in 2016 refer to the corresponding prices in April.

Table 3. Groundwater Availability of Each Subarea ($\times 10^6$ m^3)

Subarea	Groundwater Availability
Subarea 1	[19.29, 21.45]
Subarea 2	[14.61, 23.40]
Subarea 3	[5.97, 7.70]
Subarea 4	[6.86, 7.14]
Subarea 5	[12.06, 21.41]

Table 4. Purchase Prices of Winter Wheat and Maize (RMB/kg)

Year	Purchase Price of Winter Wheat C_w	Purchase Price of Maize C_m
2003	[1.04, 1.07]	[1.30, 1.34]
2004	[1.54, 1.60]	[1.30, 1.35]
2005	[1.48, 1.51]	[1.40, 1.42]
2006	[1.40, 1.45]	[1.58, 1.60]
2007	[1.66, 1.70]	[1.79, 1.81]
2008	[1.68, 1.70]	[1.55, 1.58]
2009	[2.04, 2.10]	[1.60, 1.63]
2010	[2.08, 2.14]	[2.05, 2.08]
2011	[2.10, 2.12]	[2.20, 2.21]
2012	[1.90, 2.10]	[1.90, 1.93]
2013	[2.50, 2.52]	[2.28, 2.29]
2016	[2.40, 2.46]	[1.50, 1.67]

According to statistic data, the planting areas of winter wheat and maize approximately obey normal distributions, and the relevant parameters of fitted normal distributions can be seen in Table 5. Although there is a significant change in the purchase prices of maize in 2016, the planting area of maize was considered to remain relatively unchanged over the past years because (1) farmers are accustomed to adopt previous planting patterns since they are insensible of how much area is proper with few references; (2) famers rarely plant other crops and there are abundant rainfall during the growth period of maize, thus farmers can still obtain benefits through planting maize even without irrigation.

In total, the distribution characteristics of the uncertain parameters of the developed model are shown in Table 6. There are in total three types of distributions for the four uncertain parameters. It is difficult with heavy workload if using tradetional method to solve the developed model, thus MC simulation was adopted to address these uncertain parameters.

3. Result Analysis

According to the solution process of MC simulation, firstly, discretize the four kinds of uncertain parameters into a number of parameters based on their distribution characteristics; secondly, optimize the obtained parameters of the four kinds of uncertain parameters and a large number of optimal solutions were obtained; thirdly, comprehensively analyze and discuss theses optimal solutions. The research process is shown in Figure 2.

3.1. Analysis of System Benefit and Irrigation Amounts

3.1.1. Optimal Results from 2003 to 2013

Through solving the developed model of uncertain parameters based on historical data, the relationship between system benefit and irrigation amount (both surface water and groundwater) was obtained from 2003 to 2013 (see Figure 3). From Figure 3(a), it can be seen that during the growth period of winter wheat under the economic situation in previous years, the average surface water irrigation amount is 129.445 $\times 10^6$ m^3, ranging from 84.775 $\times 10^6$ to 166.000 $\times 10^6$ m^3; the average groundwater irrigation amount is 24.511 $\times 10^6$ m^3, ranging from 4.198 $\times 10^6$ to 47.410 $\times 10^6$ m^3; the average system benefit is 911.084 $\times 10^6$ RMB, ranging from 583.183 $\times 10^6$ to 1295.569 $\times 10^6$ RMB. As Figure 3(a) shows, data points present hierarchical structure on the axis of system benefit. The reason is that the economic parameters of the model are expressed as piecewise intervals (see Table 4). The discontinuity of the purchase prices of crops leads to the randomly generated data by using MC simulation. As the table shows, the purchase prices of crops have discrete distribution forms. Especially the purchase prices of 2003 and 2013 have large difference than other years. The purchase prices of crops in 2003 was the lowest, with only [1.04, 1.07] RMB/kg for winter wheat, leading to the optimized data concentrate on the bottom of Figure 3(a), i.e., concentrate on the location with system benefit of 600.786 $\times 10^6$ RMB. For 2013, the purchase prices of crops was the highest ([2.50, 2.52] RMB/kg for winter wheat); therefore, the optimized data concentrate on the top of Figure 3(a), i.e., concentrate on the location with system benefit of 1255.797 $\times 10^6$ RMB.

From Figure 3(b), during the growth period of maize under the economic situation in previous years, the average surface water irrigation amount is 88.329 $\times 10^6$ m^3, ranging from 51.927 $\times 10^6$ to 132.761 $\times 10^6$ m^3; the average groundwater irrigation amount is 34.733 $\times 10^6$ m^3, ranging from 12.168 $\times 10^6$ to 51.024 $\times 10^6$ m^3. Irrigation amount for maize is less than winter wheat from 2003 to 2013. It is because that maize can produce more food from less water attributing to its higher crop water productivity under the same irrigation conditions (Zwart and Bastiaanssen, 2004). The growth period of maize is mainly in summer and autumn with abundant precipitation, while the period of winter wheat is mainly in droughty winter and spring. The water consumption of winter wheat during its growth period greatly exceeds the precipitation. Thus, supplemental irrigation is very important to winter wheat production (Liu et al., 2002). As there is abundant precipitation during the growth period of maize, it needs only a small amount of irrigation for maize to obtain larger economic outputs. In addition, the purchase prices of both winter wheat and maize remain the same basically, therefore, the purchase price is not the major reason

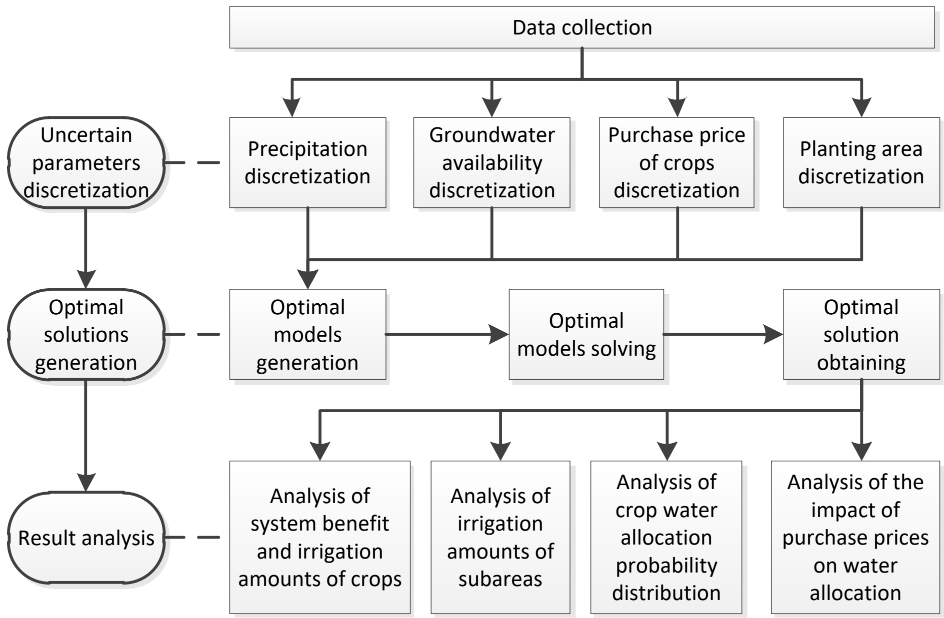


Figure 2. Flow chart of the study.

that affects the irrigation water allocation amount.

Comprehensively considering the irrigation water amount of the two crops, the surface irrigation water amount concentrates in a particular range ([217.440, 218.136] $\times 10^6$ m^3) with the average level of 217.774 $\times 10^6$ m^3. Groundwater irrigation amount ranges from 51.765 $\times 10^6$ to 66.266 $\times 10^6$ m^3. The ball distribution of both surface water and groundwater for the two crops concentrates in a small range as seen in Figure 3(c). This favorable allocation result is because that the allocation results of the two crops are considered simultaneously.

3.1.2. Optimal Results in 2016

The No. 1 Central Document coming from the Central Committee of the Communist Party of China declared the specific deployment and requirement of maize, that is, actively and steadily promote the purchase and storage reform of maize according to the principles of market-set price, and separation of price and subsidy. The aim of the reform is to make the maize market in China integrate with international market in next few decades. In 2016, the purchase price of maize has fallen substantially as seen in Table 4. The purchase prices of winter wheat and maize respectively are [2.40, 2.46] RMB/kg and [1.50, 1.67] RMB/kg in April in 2016, with the price differential is 0.9 RMB/kg. While the purchase prices of winter wheat and maize remained about the same during 2003 to 2013, with the biggest price differential is 0.4 RMB/kg in 2009. The influence of the significant decrease of maize on economic benefit and irrigation water allocation under the new policy is pretty conspicuous. Based on the purchase price of crops in April in 2016, the relationship of the optimized system benefits and irrigation water amount (both surface water and groundwater) is shown in Figure 4.

From Figure 4(a), during the growth period of winter wheat under the new economic situation, the average surface water irrigation amount is 174.905 $\times 10^6$ m^3, ranging from 153.108 $\times 10^6$ to 192.992 $\times 10^6$ m^3; the average groundwater irrigation amount is 35.379 $\times 10^6$ m^3, ranging from 22.326 $\times 10^6$ to 52.933 $\times 10^6$ m^3; the average system benefit is 1066.755 $\times 10^6$ RMB, ranging from 1012.847 $\times 10^6$ to 1123.634 $\times 10^6$ RMB. For maize as seen from Figure 4(b), the average surface water irrigation amount is 42.846 $\times 10^6$ m^3, ranging from 24.637 $\times 10^6$ to 64.658 $\times 10^6$ m^3; the average groundwater irrigation amount is 23.865 $\times 10^6$ m^3, ranging from 8.427 $\times 10^6$ to 39.755 $\times 10^6$ m^3. Irrigation amount of maize is far less than that of winter wheat, attributing to the purchase prices of crops in 2016. The economic outputs of maize is lower than that of winter wheat under the same water quantity, leading to the water allocation give priority to winter wheat. The ball distribution of the total water allocation of winter wheat and maize concentrates on a small range as seen in Figure 4(c). Total average surface water allocation amount remains at 217.751 $\times 10^6$ m^3, with the lower bound of 217.460 $\times 10^6$ m^3 and the upper bound of 218.017 $\times 10^6$ m^3. Total groundwater allocation amount ranges from 51.765 $\times 10^6$ to 66.266 $\times 10^6$ m^3.

3.1.3. Optimal Results Comparison

Compared the optimal results of 2016 with the results of 2013, the system economic benefit in 2016 deceases slightly, dropping from 1255.797 $\times 10^6$ to 1066.754 $\times 10^6$ RMB. The main reason is the purchase price of maize decreases significantly, with the decrease amplitude achieves around 30% through the comparison of the purchase price in 2013 and 2016, and the purchase price of winter wheat remains probably the same. Therefore, the economic benefit in 2016 is lower than that of 2013. In terms of the water allocation amount, more water will be allocated to winter wheat, and the amount increases from 153.956 $\times 10^6$ m^3 during 2003 ~ 2013 period to 210.284 $\times 10^6$ m^3 in 2016

Table 5. Planting Areas of the Two Crops of Each Subarea (ha)

Subarea	Planting Area of Winter Wheat	Planting Area of Maize
Subarea 1	N(13752.42, 239.46^2)	N(13914.13, 91.60^2)
Subarea 2	N(8236.83, 232.43^2)	N(8225.17, 223.91^2)
Subarea 3	N(12887.85, 545.34^2)	N(12887.85, 545.34^2)
Subarea 4	N(9417.83, 19.00^2)	N(9760.17, 124.33^2)
Subarea 5	N(8449.10, 832.30^2)	N(8449.10, 832.30^2)

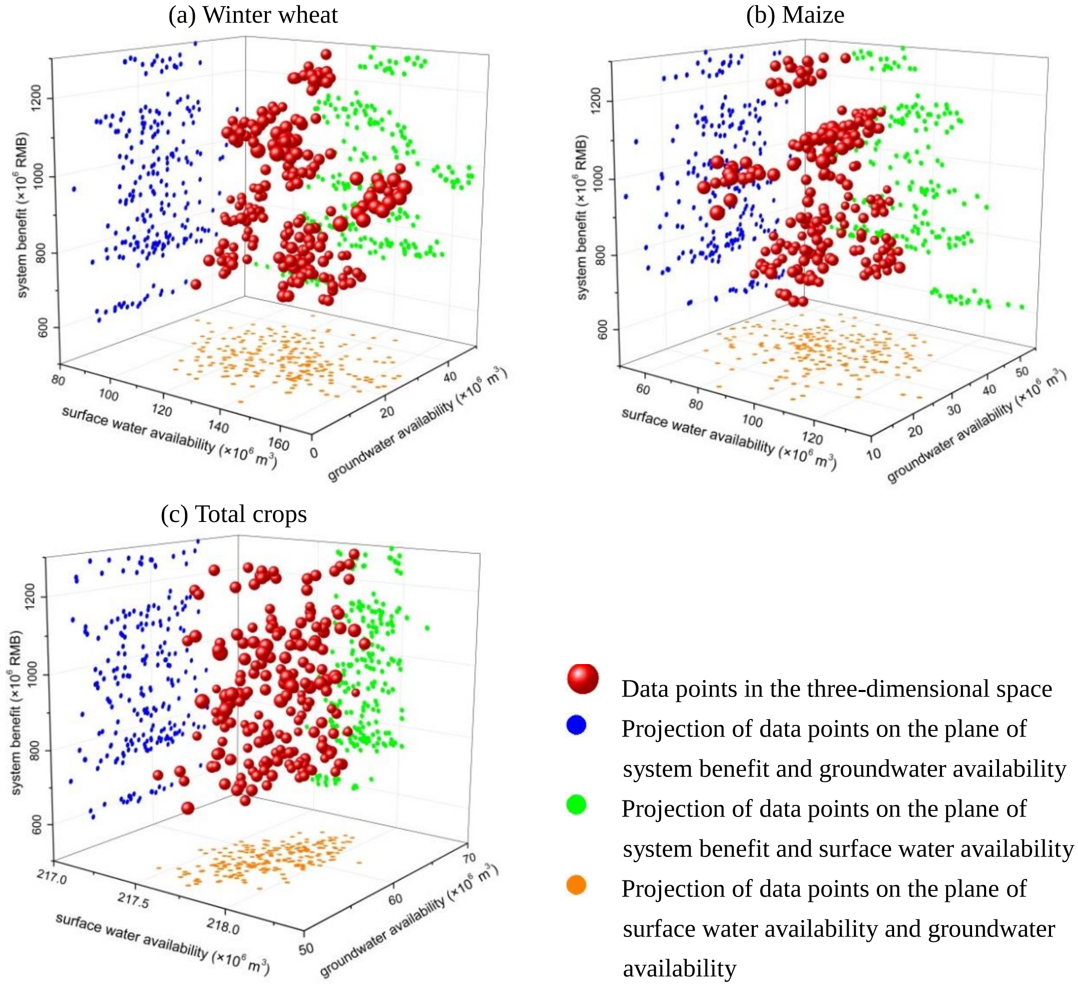


Figure 3. Three dimensional scatter plot of the relationship between system benefit and irrigation amount (both surface water and groundwater) from 2003 to 2013.

in general. This phenomenon shares the same reason as that of the decreased economic benefit.

Figure 5 shows the results comparison between 2016 and the average level from 2003 to 2013. Total water allocation amount remain approximately the same. Total surface water allocation amount in 2016 achieves the upper bound of surface water availability basically compared with the results of previous years, and the same trend applies to groundwater allocation amount. However, winter wheat is allocated more surface water than before, increasing from 129.445 $\times 10^6$ to 174.905 $\times 10^6$ m^3 as the average level, and groundwater allocation increases from 24.511 $\times 10^6$ to 35.379 $\times 10^6$ m^3. However, the average surface water allocation amount for maize decreases from 88.329 $\times 10^6$ m^3 in previous years to 42.846 $\times 10^6$ m^3 in 2016, and the average groundwater allocation amount decreases from 34.733 $\times 10^6$ m^3 in previous years to 23.865 $\times 10^6$ m^3 in 2016. This phenomenon shows that the substantial fall of the price of maize significantly affects the allocation schemes.

3.2. Analysis of Irrigation Amounts of Subareas

This study uses scatter plots to study the surface water and groundwater allocation conditions of each subarea under the new economic policy (see Figure 6). As surface water and

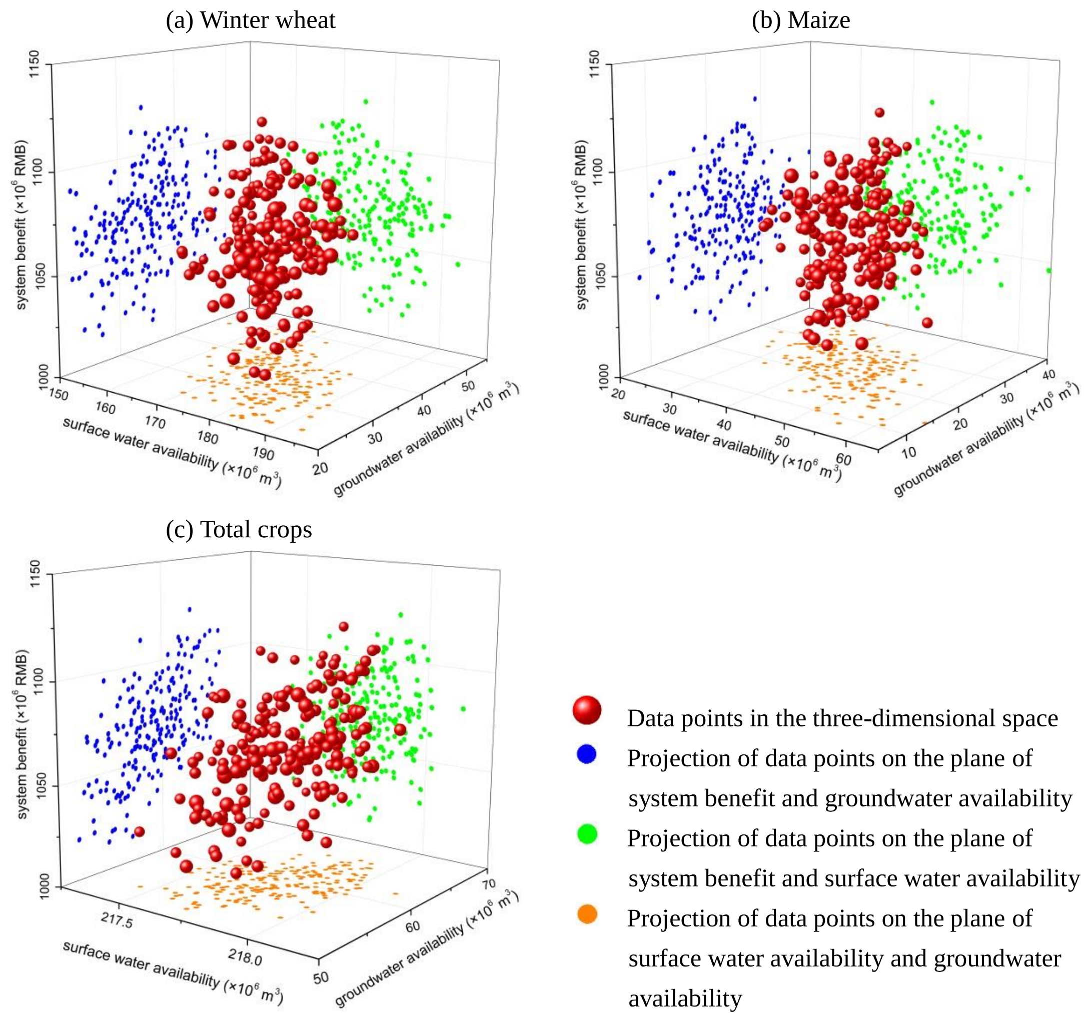
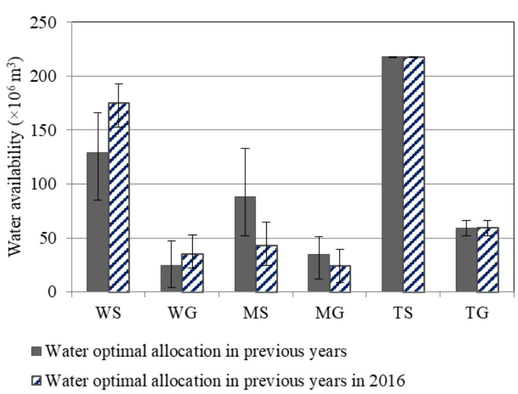


Figure 4. Three dimensional scatter plot of the relationship between system benefit and irrigation amount (both surface water and groundwater) in 2016.



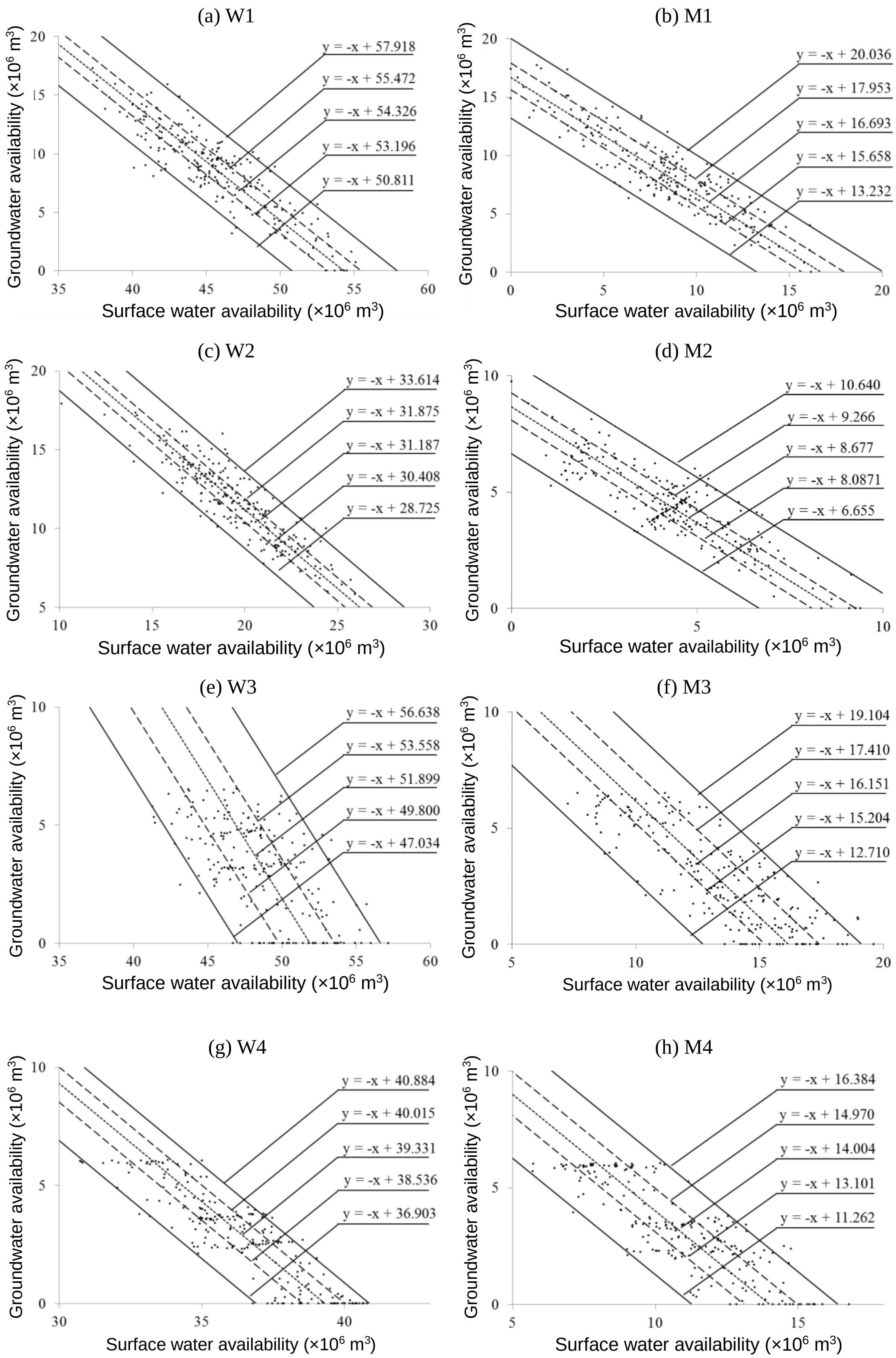
Note: WS means the surface water allocation of winter wheat; WG means groundwater allocation of winter wheat; MS means surface water allocation of maize; MG means groundwater allocation of maize; TS means total surface water allocation; TG means total groundwater allocation; The upper and lower endpoints of error bars mean the maximum and the minimum water allocation amounts.

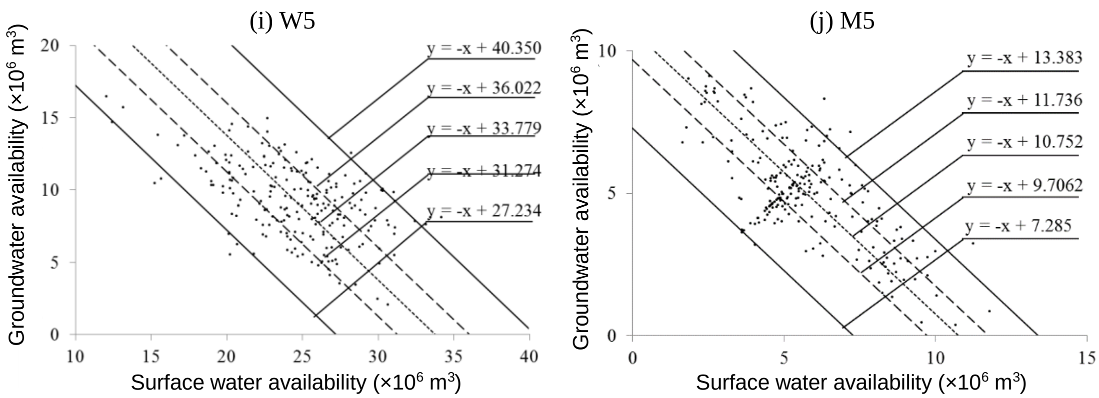
Figure 5. Comparison of optimization results.

Table 6. Distributions of the Four Uncertain Parameters

Parameters	Distributions
Precipitation	Gamma Distribution
Groundwater Availability	Interval Distribution
Purchase Price of Crops	Interval Distribution
Planting Area	Normal Distribution

groundwater are of equal importance, the form of $y = -x + c$ was adopted to fit the trend line, where x and y represent surface water availability and groundwater availability respectively, and c represents the summation of surface water availability and groundwater availability. It can be seen from Figure 6 that the average water allocation amounts for winter wheat from subarea 1 to subarea 5 are 54.326×10^6, 31.187×10^6, 51.899×10^6, 39.311×10^6 and 33.779×10^6 m^3; for maize are 16.693×10^6, 8.677×10^6, 16.151×10^6, 14.004×10^6 and 10.752×10^6 m^3. In all subareas, the optimal allocation amount for winter wheat is larger than that for maize and the proportion is about 3:1. Figure 6 also provides the intervals of 95% and 50% confidence


(a) W1
y = -x + 57.918
y = -x + 55.472
y = -x + 54.326
y = -x + 53.196
y = -x + 50.811
(b) M1
y = -x + 20.036
y = -x + 17.953
y = -x + 16.693
y = -x + 15.658
y = -x + 13.232
(c) W2
y = -x + 33.614
y = -x + 31.875
y = -x + 31.187
y = -x + 30.408
y = -x + 28.725
(d) M2
y = -x + 10.640
y = -x + 9.266
y = -x + 8.677
y = -x + 8.0871
y = -x + 6.655
(e) W3
y = -x + 56.638
y = -x + 53.558
y = -x + 51.899
y = -x + 49.800
y = -x + 47.034
(f) M3
y = -x + 19.104
y = -x + 17.410
y = -x + 16.151
y = -x + 15.204
y = -x + 12.710
(g) W4
y = -x + 40.884
y = -x + 40.015
y = -x + 39.331
y = -x + 38.536
y = -x + 36.903
(h) M4
y = -x + 16.384
y = -x + 14.970
y = -x + 14.004
y = -x + 13.101
y = -x + 11.262
Groundwater availability (×10^6 m^3)
Surface water availability (×10^6 m^3)



Note: The dotted line represents the median of the optimal range; The imaginary line represents the allocation bounds of 50% confidence level; The solid line represents the allocation bounds of 95% confidence level; The first letter of the figure name means the kind of crops, with W representing winter wheat and M representing maize, and the second letter means the number of subarea, for example, W1 means the water allocation results of winter wheat in subarea 1.

Figure 6. Irrigation water allocation amount of each subarea in 2016.

levels of irrigation water allocation amounts. For example, optimal irrigation water amount of winter wheat has a 50% possibility occurs among the range of [53.196, 55.472] $\times 10^6$, [30.408, 31.875] $\times 10^6$, [49.800, 53.558] $\times 10^6$, [38.536, 40.015] $\times 10^6$, and [31.274, 36.022] $\times 10^6$ m^3 of the five subareas, respectively. Optimal irrigation water amount of maize has a 50% possibility occurs among the range of [15.658, 17.953] $\times 10^6$, [8.087, 9.266] $\times 10^6$, [15.204, 17.410] $\times 10^6$, [13.101, 14.970] $\times 10^6$, and [9.706, 11.736] $\times 10^6$ m^3 of the five subareas, respectively. The water allocation width of winter wheat is about 2.746 $\times 10^6$ m^3, while the width of maize is about 1.916 $\times 10^6$ m^3, slightly smaller than that of winter wheat. Figure 6 gives the water allocation targets of winter wheat and maize in 2016. When using the developed model, decision makers can adjust actual water allocations for surface water and groundwater based on water availability and precipitation conditions.

3.3. Analysis of Crop Water Allocation Probability Distribution

In order to study crops' water allocation conditions in 2016, the cumulative probability distributions of winter wheat and maize were plotted as shown in Figure 7. Optimal water allocation condition under a certain probability can be obtained from the cumulative probability distributions. For example, the probability of surface water to winter wheat that less than 174.688 $\times 10^6$ m^3 is 50%, and the probability of groundwater to winter wheat that less than 35.466 $\times 10^6$ m^3 is 50%. Likewise, the probability of surface water to maize that less than 42.979 $\times 10^6$ m^3 is 50%, and the probability of groundwater to maize that less than 24.198 $\times 10^6$ m^3 is 50%.

3.4 The Impact of Purchase Prices of Crops on Water Allocation

Purchase prices of crops directly affect the economic benefits and thus affect the irrigation water allocation. In order to analyze the influence relations between purchase prices and water allocation of winter wheat and maize, the relationship between the difference of purchase price of winter wheat and maize and the difference of water allocation amount of winter wheat and maize was studied based on the optimal results of both 2016 and 2003 ~ 2013 period (see Figure 8). It can be seen from Figure 8 that there keeps a linear relationship between the difference of purchase price and the difference of water allocation amount of winter wheat and maize. The fitting formula is $\Delta S = 130.733\Delta C + 29.975$, and correlation coefficient R^2 is above 0.935. The fitting effect is good and the fitting formula can be used to describe the relation between the difference of purchase price and the difference of water allocation amount. When $\Delta C = 0$, i.e., the purchase prices of winter wheat and maize are the same, then $\Delta S = 22.190$, indicating that the water optimal allocation for maize is 22.190 $\times 10^6$ m^3 greater than that for winter wheat. From Figure 8, it can also be seen that data points are discrete when $\Delta C = 0.23$, with a large difference to the trend line. In other words, when $\Delta C = 0.23$, ΔS has a larger freedom degree, indicating that water resources can be adjusted between winter wheat and maize in a larger range. That is, when the purchase prices of winter wheat is 0.23 RMB/kg higher than that of maize, the benefits obtained from winter wheat and maize are approximately equal, and water resources are adjustable between the two crops.

4. Discussions

This paper developed an agricultural water allocation model under uncertainty by coupling with MC simulation for the five subareas in Shijin ID. For the study area, Yang (2016) developed a fuzzy interval multiobjective programming approach and a decision support system for irrigation scheduling. However, in our study, the method based MC simulation is adopted to deal with the multiple uncertainties. The study analyzed optimal water allocation under the current economic situation which has not been considered in previous studies.

The determination of the purchase prices of crops is important as they affect the allocation schemes directly. Generally,

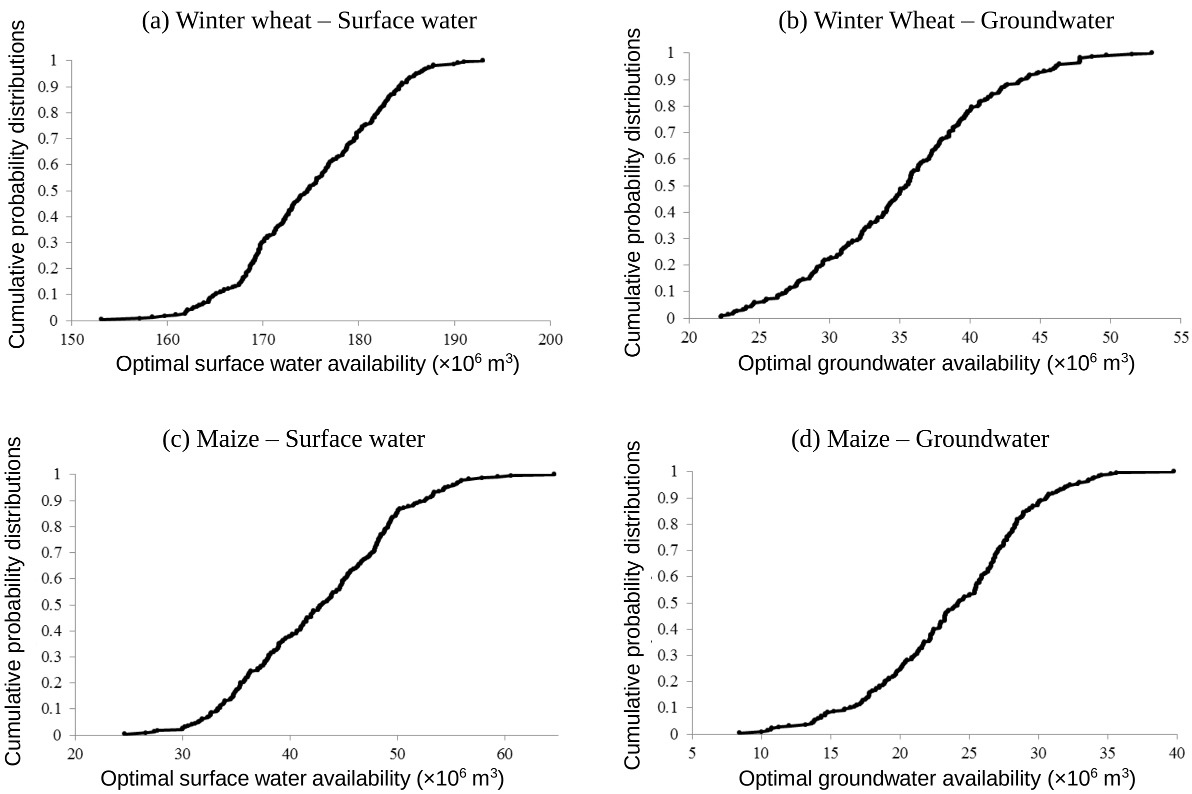
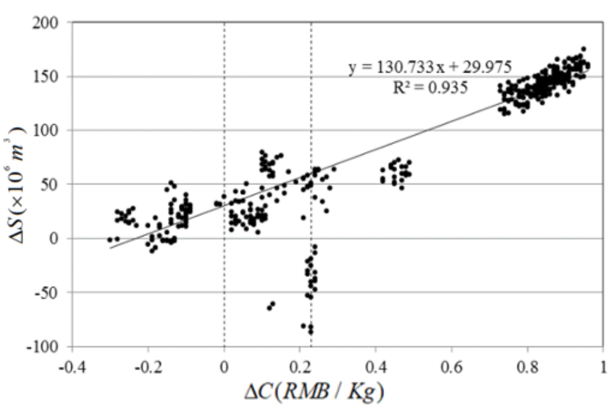


Figure 7. Cumulative distribution curve of crop water allocation amount in 2016.



Note: ΔC ($\Delta C = C_w - C_m$) means the difference of purchase price of winter wheat and maize; ΔS ($\Delta S = S_w - S_m$) means the difference of the optimal water allocation (the summation of surface water amount and groundwater amount) of winter wheat and maize; the solid line is the fitted trend line and the two dash lines are auxiliary lines.

Figure 8. Influence relation between purchase prices and water allocation of crops.

three aspects deserve consideration when determining the purchase prices of crops. Firstly, the purchase prices of crops should select the prices in the harvest period from the angle of system benefit, that is, for winter wheat, the purchase of June should be chosen and for maize, the price of October should be chosen. Secondly, from the angle of crop planting, the planting area value is determined in the early stage of crop planting, and the purchase price in this stage will directly affect the planting area and thus affect the system benefit during the whole growth period of crops. Thirdly, during the irrigation periods, water allocation may be affected by the purchase prices of crops. From this point, the purchase price of crops during the irrigation period should be chosen. From sowing to harvest, there is a long period during which the economic situation may change. Generally, the purchase price of a certain growth period may be chosen as the input of optimization model. This paper selected the purchase prices of crops in April in 2016 as one of the inputs of the developed model. In fact, this purchase price does not belong to the three aspects when determining the purchase prices of crops mentioned above. However, the purchase prices of crops in April of 2016 are the newest price data which can represent the newest economic situation. The purchase price in which stage should be chosen deserves further study.

In previous years, the purchase prices of winter wheat and maize remain the same basically, while there is a significant decrease of the purchase price of maize in 2016, with the decrease amplitude achieves 0.90 RMB/kg (see Figure 5). From Figure 8, the scatters occur in the right side under the purchase price of maize in 2016, experiencing a big gap compared with the results in previous years. The optimal results in 2016 were optimized in the new economic situation, without any references from previous years because the changes of the purchase price of maize is rare. Therefore, facing the allocation schemes under previous economic situation and under the new economic situation, which scheme farmers should choose has a great uncertainty and need verification using future data.

Through the detailed analysis on the optimal results of the developed model, MC simulation is considered as an effective tool in dealing with different kinds of stochastic parameters. MC simulation enables the results to be expressed as probability distributions intuitively which overcomes the limitation of traditional optimization method. In the field of agricultural water management, coupling the MC simulation into optimization model has large potentialities.

5. Conclusions

This paper studied the irrigation water allocation schemes for winter wheat and maize and for the five subareas in Shijin ID based on the developed water allocation optimization model considering the uncertainties of precipitation, water availability, purchase prices of crops, planting area using MC simulation. Results show that water allocation amount to winter wheat in 2016 should more than previous years for higher economic benefits. On the contrary, water allocation of maize would be less owning to its purchase price fell sharply in 2016.

The total optimal water allocation amount remains fairly static compared with average level from 2003 to 2013, while winter wheat is given priority in water allocation. For winter wheat, surface water allocation of 2016 increases from 129.445 $\times 10^6$ to 174.905 $\times 10^6$ m^3, while groundwater allocation increases from 24.511 $\times 10^6$ to 35.379 $\times 10^6$ m^3. During the irrigation period of winter wheat, water allocation amount for the five subareas of Shijin ID are 54.326 $\times 10^6$, 31.187 $\times 10^6$, 51.899 $\times 10^6$, 39.311 $\times 10^6$, and 33.779 $\times 10^6$ m^3, respectively. During the irrigation period of maize, water allocation amount for the five subareas of Shijin ID are 16.693 $\times 10^6$, 8.677 $\times 10^6$, 16.151 $\times 10^6$, 14.004 $\times 10^6$, and 10.752 $\times 10^6$ m^3. Relationship between benefits and water amounts was shown using 3D diagram. Cumulative probability distributions of both surface water and groundwater for winter wheat and maize were obtained in 2016. In addition, there keeps a linear relationship between the difference of purchase price and the difference of water allocation amount of winter wheat and maize. However, when the purchase price of winter wheat is 0.23 RMB/kg higher than maize, the benefits obtained from winter wheat and maize are approximately equal and water resources are adjustable between the two crops, indicating that water resources can be adjusted between winter wheat and maize more freely.

The application of the proposed method into a real case study of Shijin ID demonstrated that it is feasible to deal with the multiple uncertainties using MC simulation in agricultural water management systems. MC simulation is an effective method in handling the value ranges and distribution characteristics of uncertain parameters. MC simulation enables the results to be expressed as probability distributions intuitively, and the integration of MC simulation with optimization models in agricultural water management can solve the complex practical problem under multiple uncertainties. It will become a favorable tool in tacking the complexity in agricultural water management.

Acknowledgments. This research was supported by the Government Public Research Funds for Projects of Ministry of Agriculture (201203077), the National Natural Science Foundation of China (51321001, 51709195, 41807130).

References

Amir, J. and Sinclair, T.R. (1991). A model of the temperature and solar-radiation effects on spring wheat growth and yield. *Field Crops Res.*, 28(1-2), 47-58. https://doi.org/10.1016/0378-4290(91)90073-5

Assumaning, G.A. and Chang, S.Y. (2014). State and parameter estimation in three-dimensional subsurface contaminant transport modeling using kalman filter coupled with Monte Carlo sampling. *J. Environ. Inf.*, 24(2), 80-89. https://doi.org/10.3808/jei.201400280

Bai, B., Lu, D.R., Chen, X.J., Han, H.T., and Wang, Y.H. (2014). Normal distribution characteristics of precipitation in Lanzhou region. *J. Arid Meteorol.*, 32(1), 123-127.

Biondini, R. (1976). Cloud motion and rainfall statistics. *J. Appl. Meteorol.*, 15(3), 205-224. https://doi.org/10.1175/1520-0450(1976015 <0205:CMARS>2.0.CO;2

Creal, D. (2012). A survey of sequential Monte Carlo methods for economics and finance. *Econom. Rev.*, 31(3), 245-296. https://doi.org/10.1080/07474938.2011.607333

Chen, X.J., Huang, G., Li Y.P., An, C.J., Feng, R.F., Wu, Y.H., and Shen, J. (2020). Functional PVDF ultrafiltration membrane for Tetrabromobisphenol-A (TBBPA) removal with high water recovery. *Water Res.*, 181. https://doi.org/10.1016/j.watres.2020.115952

Fan, L., Yan, Z., Chen, D., and Fu, C. (2015). Comparison between two statistical downscaling methods for summer daily rainfall in Chongqing, China. *Int. J. Climatol.*, 35(13), 3781-3797. https://doi.org/10.1002/joc.4246

Fang, J.G., Mao, M.C., and Cheng, X.X. (2009). The Analysis of statistics distribution characteristics on precipitation in Shaanxi. *J. Northwest Univ.*, 39(1), 131-136. https://doi.org/10.16152/j.cnki.xdxbzr.2009.01.014

Gelman, A. (2007). Data Analysis Using Regression and Multilevel/Hierarchical Models, Cambridge University Press. https://doi.org/10.1017/CBO9780511790942

Graveline, N., Loubier, S., Gleyses, G., and Rinaudo, J.D. (2012). Impact of farming on water resources: Assessing uncertainty with Monte Carlo simulations in a global change context. *Agric. Syst.*, 108, 29-41. https://doi.org/10.1016/j.agsy.2012.01.002

Guo, J.H., Huang, G.H., Wang, X.Q., Wu, Y.H., Li, Y.P., Zheng, R.B., and Song, L.M. (2020). Evaluating the added values of regional climate modeling over China at different resolutions. *Sci. Total Environ.*, 718. https://doi.org/10.1016/j.scitotenv.2020.137350

Hassanzadeh, E., Elshorbagy, A., Wheater, H., Gober, P., and Nazemi, A. (2015). Integrating supply uncertainties from stochastic modeling into integrated water resource management: case study of the Saskatchewan River basin. *J. Water Resour. Plann. Manage.*, 142(2). https://doi.org/10.1061/(ASCE)WR.1943-5452.0000581

He, C., Huang, G.H., Liu, L.R., Li, Y.P., Zhang, X.Y., and Xu, X.L. (2020). Multi-dimensional diagnosis model for the sustainable development of regions facing water scarcity problem: A case study for Guangdong, China. *Sci. Total Environ.*, 734. https://doi.org/10.1016/j.scitotenv.2020.139394

Huang, J., Huang, G.H., An, C.J., Xin, X.Y., Chen, X.J., Zhao, Y.Y., Feng, R.F., and Xiong W.H. (2020). Exploring the use of ceramic disk filter coated with Ag/ZnO nanocomposites as an innovative approach for removing Escherichia coli from household drinking water. *Chemosphere*. 245. https://doi.org/10.1016/j.chemosphere.2019.125545

Hunt, P. and Miles, J.N. (2015). An introduction to Monte Carlo simulations in criminal psychology: applications in evaluating biased estimators for recidivism. *J. Crim. Psychol.*, 5(2), 149-156. https://

doi.org/10.1108/JCP-02-2015-0008

Husak, G.J., Michaelsen, J., and Funk, C. (2007). Use of the gamma distribution to represent monthly rainfall in Africa for drought monitoring applications. *Int. J. Climatol.*, 27(7), 935-944. https://doi.org/10.1002/joc.1441

Igbadun, H.E., Tarimo, A.K.P.R., Salim, B.A., and Mahoo, H.F. (2007). Evaluation of selected crop water production functions for an irrigated maize crop. *Agric. Water Manage.*, 94(1-3), 1-10. https://doi.org/10.1016/j.agwat.2007.07.006

Kim, D. and Kaluarachchi, J.J. (2016). A risk-based hydro-economic analysis for land and water management in water deficit and salinity affected farming regions. *Agric. Water Manage.*, 166, 111-122. https://doi.org/10.1016/j.agwat.2015.12.019

Li, L., Zhu, Y.J., and Zhao, B.L. (1998). Rain rate distributions for China from hourly rain gauge data. *Radio Sci.*, 33(3), 553-564. https://doi.org/10.1029/97RS03184

Li, M., Guo, P. and Singh, V.P. (2016). An efficient irrigation water allocation model under uncertainty. *Agric. Syst.*, 144, 46-57. https://doi.org/10.1016/j.agsy.2016.02.003

Limpert, E., Stahel, W.A., and Abbt, M. (2001). Log-normal distributions across the sciences: keys and clues. *BioScience.*, 51(5), 341-352. https://doi.org/10.1641/0006-3568(2001)051[0341:LNDATS]2.0.CO;2

Liu, C., Zhang, X., and Zhang, Y. (2002). Determination of daily evaporation and evapotranspiration of winter wheat and maize by large-scale weighing lysimeter and micro-lysimeter. *Agric. For. Meteorol.*, 111(2), 109-120. https://doi.org/10.1016/S0168-1923(02)00015-1

Liu, J., Li, Y.P., Huang, G.H., and Nie, S. (2015). Development of a fuzzy-boundary interval programming method for water quality management under uncertainty. *Water Resour. Manage.*, 29(4), 1169-1191. https://doi.org/10.1007/s11269-014-0867-9

Matsui, Y., Narita, K., Inoue, T., and Matsushita, T. (2006). Investigating rice-farming pesticide concentrations in river water using a basin-scale runoff model with uncertain inputs. *Trans. ASABE.*, 49 (6), 1723-1735. https://doi.org/10.13031/2013.22295

Metropolis, N. and Ulam, S. (1949). The Monte Carlo method. *J. Am. Stat. Assoc.*, 44(247), 335-341. https://doi.org/10.1080/01621459.1949.10483310

Mooley, D.A. (1973). Gamma distribution probability model for Asian summer monsoon monthly rainfall. *Mon. Weather Rev.*, 101(2), 160-176. https://doi.org/10.1175/1520-0493(1973)101<0160:GDPMFA>2.3.CO;2

Muchow, R.C., Sinclair, T.R., and Bennett, J.M. (1990). Temperature and Solar Radiation Effects on Potential Maize Yield across Locations. *Agron. J.*, 82(2), 338-343. https://doi.org/10.2134/agronj1990.00021962008200020033x

Mun, S., Sassenrath, G.F., Schmidt, A.M., Lee, N., Wadsworth, M.C., Rice, B., Corbitt, J.Q., Schneider, J.M., Tagert, M.L., Pote, J., and Prabhu, R. (2015). Uncertainty analysis of an irrigation scheduling model for water management in crop production. *Agric. Water Manage.*, 155, 100-112. https://doi.org/10.1016/j.agwat.2015.03.009

Niu, G., Li, Y.P., Huang, G.H., Liu, J., and Fan, Y.R. (2016). Crop planning and water resource allocation for sustainable development of an irrigation region in China under multiple uncertainties. *Agric. Water Manage.*, 166, 53-69. https://doi.org/10.1016/j.agwat.2015.12.011

Shen, Z.Y., Chen, L., and Liao, Q. (2015). Effect of rainfall measurement errors on nonpoint-source pollution model uncertainty. *J. Environ. Inf.*, 26(1), 14-26. https://doi.org/10.3808/jei.201400280

Su, L.Y. (2013). Comparative study of water resource management and policies for ecosystems in China and Denmark. *J. Environ. Inf.*, 21(1), 72-83. https://doi.org/10.3808/jei.201300234

Tang, Q., Xiao, H., Guo, C., and Feng, L. (2014). Characteristics of the raindrop size distributions and their retrieved polarimetric ra- dar parameters in northern and southern China. *Atmos. Res.*, 135, 59-75. https://doi.org/10.1016/j.atmosres.2013.08.003

Veeck, G. (2013). China's food security: past success and future challenges. *Eurasian Geogr. Econ.*, 54(1), 42-56. https://doi.org/10.1080/15387216.2013.789669

Wang, C.X., Li, Y.P., Huang, G.H., and Zhang, J.L. (2016). A type-2 fuzzy interval programming approach for conjunctive use of surface water and groundwater under uncertainty. *Information Sciences*. 340, 209-227. https://doi.org/10.1016/j.ins.2016.01.026

Wang, X. and Sloan, I.H. (2011). Quasi-Monte Carlo methods in financial engineering: an equivalence principle and dimension reduction. *Oper. Res.*, 59(1), 80-95. https://doi.org/10.1287/opre.1100.0853

Xu, T.Y. and Qin, X.S. (2013). Solving water quality management problem through combined genetic algorithm and fuzzy simulation. *J. Environ. Inf.*, 22(1), 39-48. https://doi.org/10.3808/jei.201300244

Xu, Y. (2012). Inexact management modeling for urban water supply systems. *J. Environ. Inf.*, 20(1), 34-43. https://doi.org/10.3808/jei.201200218

Yang, G., Guo, P., Huo, L., and Ren, C. (2015). Optimization of the irrigation water resources for Shijin irrigation district in north China. *Agric. Water Manage.*, 158, 82-98. https://doi.org/10.1016/j.agwat.2015.04.006

Yang, G., Liu, L., Guo, P., and Li., M. (2016). A flexible decision support system for irrigation scheduling in an irrigation district in China. *Agric. Water Manage.*, https://doi.org/10.1016/j.agwat.2016.07.019

Zeng, X.T., Li, Y.P., Huang, G.H., and Liu, J. (2016). Modeling water trading under uncertainty for supporting water resources Management in an Arid Region. *J. Water Resour. Plann. Manage.*, 142(040150582). https://doi.org/10.1061/(ASCE)WR.1943-5452.0000593

Zhang, Q., Xu, C.Y., Zhang, Z., Chen, Y.D., and Liu, C.L. (2009). Spatial and temporal variability of precipitation over china, 1951-2005. *Theor. Appl. Climatol.*, 95(1), 53-68. https://doi.org/10.1007/s00704-007-0375-4

Ziolkowska, J.R. (2015). Shadow price of water for irrigation – A case of the High Plains. *Agric. Water Manage.*, 153, 20-31. https://doi.org/10.1016/j.agwat.2015.01.024

Zwart, S.J. and Bastiaanssen, W.G.M. (2004). Review of measured crop water productivity values for irrigated wheat, rice, cotton and maize. *Agric. Water Manage.*, 69(2), 115-133, (in Chinese). https://doi.org/10.1016/j.agwat.2004.04.007