Optimizing regional irrigation water use by integrating a two-level optimization model and an agro-hydrological model

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Abstract

Water scarcity has been a crucial issue for sustainable irrigated agriculture in the arid regions. In these regions where conserving water is paramount, optimal allocation and utilization of irrigation water is particularly important. In this study, a process-based regional economic optimization (PBREOP) model was developed for maximizing irrigation water use efficiency and economic benefit of an irrigation system. The PBREOP model is a two-level optimization model with combined use of an agro-hydrological model (SWAP-EPIC). The first level (farm scale) dealt with the optimal distribution of irrigation water and cropping pattern considering various crops and soils in a subsystem, using a non-linear programming technique. The second level (district scale) sought out the optimal strategy for irrigation water allocation among different subsystems using a dynamic programming algorithm. The crop water production functions (CWPFs) were an important component of the first-level objective function. They were derived with the SWAP-EPIC model considering different irrigation alternatives. The model was solved using the decomposition-harmonization method for large systems. The Yingke Irrigation District (YID) in the middle Heihe River basin, Northwest China was used as a case to test the PBREOP model. Nine CWPFs for three major crops and three major soils were firstly derived based on the simulations of different irrigation levels and climate conditions (20 years). Next, the PBREOP model for YID was established with 11 subsystems, and applied to the irrigation water use optimization under five water supply scenarios. Results showed that the total economic benefit in YID could be increased by 15% on average through the optimization of water allocation and cropping pattern with the same water supply amount

as that of the current situation. A variation range of the risk was also obtained with considering the impacts of climate uncertainties. Scenario analysis showed that the total irrigation water could be reduced by 23% on average without benefit reduction when compared to the benefit of the present situation. Model test indicated that the proposed PBREOP model can efficiently optimize irrigation water use and cropping pattern on a regional scale.

Keywords: irrigation strategy, crop water production function, SWAP-EPIC, economic optimization, cropping pattern, climate uncertainty

1. Introduction

Water scarcity has been a major constraint to social-economic development around the world in the last few decades. The problem will be likely exacerbated due to the rapid increase in population, a dryer climate, and expansion of water demands (IPCC 2007). Food demand continues to rise with increasing population. According to the FAO analysis of developing countries (Bruinsma 2003), most of the increases in agricultural production will be in irrigation systems. Worldwide, the irrigated agriculture as the largest water user is subjected to water allocation cuts due to the rapid growth of water demand for non-agricultural sectors (e.g. domestic, industrial, recreational, ecological and environmental use) in both developed and developing countries (Playán and Mateos 2006; Levidow et al. 2014). Moreover, inefficient usage of irrigation water, particularly in many irrigated areas, has caused significant problems of non-uniformity of irrigation water, man-induced salinization and desertification, and water quality degradation (Pereira et al. 2002; Singh and Panda 2013; Levidow et al. 2014). Water saving will be an urgent issue for the irrigated agriculture sector.

It is noted that the economic return from improvement of management practices is often orders of magnitude larger than that from improvement of structures (Playán and Mateos 2006; Levidow et al. 2014). Nevertheless, regional decision makers prefer to look at water structure improvements for water saving, due to reasons of compromise, and because it can stimulate other economic sectors. At present, inappropriate planning and management in irrigation districts is still one of the main reasons for excessive irrigation and water waste, particularly in many developing countries (Levidow et al. 2014; Playán and Mateos 2006; Jiang et al.

2015). In many irrigation districts throughout the world, there is still a great potential to save water through the optimization of irrigation and land management, besides irrigation structure construction and improvement.

Two approaches are commonly used to develop efficient alternatives for improving water use in irrigation districts; these are based on agro-hydrological process simulation models and optimization models. The simulation models can quantitatively describe complex interactions among plant, soil, water, atmosphere and groundwater. After proper calibration and validation, these models can be adopted to do scenario analysis for searching preferable management strategies. In the last two decades, many models (e.g. SWAP, SWAT, DRAINMOD and SimDualKc) have been widely used for improving irrigation schedules and methods as well as drainage system design (Singh et al. 2006a; Pereira et al. 2009; Ma et al. 2011; Sun and Ren 2014). Most studies are focused on the field scale, and some are also extended in recent years to the regional scale through integration of remote sensing (RS) and geographic information system (GIS) techniques (Singh et al. 2006b; Xu et al. 2011; Jiang et al. 2015). However, using the simulation model only would solve the question of “what if” (Singh 2014), which means the management strategy decisions are based on scenario analysis of several pre-specified alternatives. Thus, the obtained solution was generally a better one as compared with other defined scenarios but not the optimal one, particularly for regional problems. In previous studies, some researchers have attempted to involve optimization algorithms to overcome the shortcomings of the simulation models for irrigation management optimization (Singh 2012; Singh and Panda 2013). The simulation models can be internally or externally

linked with the optimization approaches for field scale issues (Shang and Mao 2006; García-Vila and Fereres 2012; Darshana et al. 2012). On a regional scale, the combined use of simulation and optimization models appears more often in groundwater modeling with loosing linkage (Rejani et al. 2009; Safavi et al. 2010). To our knowledge, there are few reported cases of optimizing regional irrigation water use with an agro-hydrological simulation model. This may primarily because that the spatial variations of land and water resources aggravate the non-linearity and complexity of the agro-hydrological process simulation (Ines et al. 2006).

On the other hand, the optimization models have been extensively applied in irrigation planning and management as part of a strategy to find the optimal utilization of limited water and land resources (Singh 2012). Its application involves the optimization of irrigation scheduling, water allocation, water conveyance operation, and cropping pattern, etc. Various optimization techniques, such as traditional methods of linear programming (LP), non-linear programming (NLP) and dynamic programming (DP), and the artificial intelligence search methods such as genetic algorithms (GA) and simulated annealing (SA), have been widely used to find the optimal solution of the target problem through solving the objective functions subjected to some constraints (Singh and Panda 2012; Ul Haq et al. 2008). Furthermore, the optimization methods with uncertainties (e.g. stochastic programming, fuzzy-parameter programming and interval-parameter programming etc.) are also employed in conventional optimization models for considering uncertainty and randomness in optimization parameters (Ganji et al. 2006; Zhang and Li 2014; Li et al. 2013; Li and Guo 2015). In addition, the large

system optimization theory that uses a multilevel hierarchical structure has become an effective method to solve complex regional optimization problems (Paul et al. 2000; Shangguan et al. 2002). This theory has an advantage of breaking down complex problems into multilevel optimization problems which can be solved individually using simple optimization methods.

However, for most irrigation optimization methods, the economic objective functions are based on a set of empiric functions describing mathematical relationships between variables, typically the crop water production functions (CWPFs). For example, the CWPFs of the models proposed by Jensen (1968) or FAO (Doorenbos and Kassam 1979) are usually integrated with water balance equation to form the basis of economic objective functions. These have been successfully used in irrigation optimization both on field and regional scales (Alvarez et al. 2004; Garg and Dadhich 2014). CWPFs are generally expressed as a simple polynomial function that describes the crop production (yield or dry matter) response to water use (evapotranspiration or crop transpiration) or water applied in the field (irrigation or irrigation plus rainfall). CWPFs were traditionally obtained from long-term field experiment, and this is expensive and time-consuming. In addition, the CWPFs are site-specific and also vary in different climatic years, especially when yield is expressed as a function of applied irrigation water (Saseendran et al. 2015). Most uncertainty methods directly consider the uncertainty and randomness of meteorological factors (mainly rainfall) in the objective functions. Nevertheless, the uncertainty of CWPFs itself resulting from the changes of environment was rarely involved. Using the calibrated simulation model to determine the

CWPFs has the advantages of time and effort saving, especially for regional problems (Saseendran et al. 2015). It is also convenient to consider the climate uncertainties for CWPFs. In addition, the dynamic processes (e.g. changes in capillary rise and percolation) can be well described using the process simulation model.

In summary, the method of integrating the optimization and process simulation models is preferred recently, but is still rarely applied for regional land and irrigation water management, mainly due to the complexity of agro-hydrological processes (Singh 2012). It would therefore be attractive to find a practical and convenient way to integrate the simulation model and the optimization model for searching optimal irrigation management strategy on a district scale.

The objective of this study is to develop a process-based regional economic optimization (PBREOP) model by integrating a two-level optimization model and an agro-hydrological model (SWAP-EPIC) (Xu et al., 2013). The two-level optimization model could be solved by using the decomposition-harmonization method of large system (Shangguan et al. 2002). The SWAP-EPIC model was adopted to derive CWPFs with considering climate uncertainties, and these CWPFs were used as the important component of the first-level objective functions of the PBREOP model. The PBREOP model aimed at determining the optimal irrigation water allocation and cropping pattern to achieve overall maximum economic benefit under limited water resources on a regional scale. This model was then tested in a case study in the Yingke Irrigation District (YID) in the middle Heihe River basin, Northwest China, in order to find the optimal use of multiple irrigation water (surface water and groundwater) and optimal cropping pattern under different water supply scenarios.

2. Methodology

2.1 System consideration

When formulating the PBREOP model, the whole irrigation district was regarded as a system that could be irrigated with surface water, groundwater or both together. This irrigation system was made up of multiple subsystems, each of which contained many farmlands composed of different types of soils and crops. A typical example is an irrigation system dominated by a main canal with many subsystems controlled by the sub-canals. Optimization can therefore be conceptualized as two levels, i.e., irrigation management optimization among different subsystems and among farmlands in each subsystem, which was adopted in the PBREOP model. The model formulation and calculation procedure are presented in Fig. 1, and the two-level structure is shown in detail in Fig. 2. The first level dealt with the optimal water and crop area allocation among various combination units of crop and soil (i.e. crop-soil units) in each subsystem, using non-linear programming (NLP). The CWPFs describing the crop yield-irrigation relationship, as the basis for composing the objective function of the first level, were generated using the calibrated SWAP-EPIC model, corresponding to the different crop-soil units. The second level was related to the optimal allocation of irrigation water among different subsystems, and was solved using dynamic programming (DP).

The two levels were solved individually and integrated through the information exchanges of allocated irrigation water amount and net irrigation benefit of each subsystem (Figs. 1 and 2). The PBREOP model within the whole system was solved iteratively between

the two levels until the ending criteria were satisfied. In each iteration, the optimal solution for the first level was restricted to the allocated irrigation water from the second level. The solution for the second level was based on the benefit of each subsystem calculated from the first level (Fig. 2). The detailed description of PBREOP model is provided in the following sections.

2.2 PBREOP model structure

2.2.1 First level: optimization of irrigation water and crop area allocation among crop-soil units in each subsystem

A non-linear programming model was developed in order to maximize the net irrigation benefit in an irrigation subsystem through optimizing the irrigation water distribution and cropping pattern. The detailed mathematical model was as follows:

Objective function:

$$MaxG_i = B_g - C_g + NB_e \quad (1)$$

where B_g is the gross benefit of grain crops; C_g is the cost of grain crops; NB_e is the net benefit of economic crops. They are formulated as follows:

$$B_g = \sum_{k=1}^K \left(Y \left(X_{iks} + X_{ikg} \right) \times A_{ik} \times P_k \right) \quad (1a)$$

$$C_g = \sum_{k=1}^K \left(C_{as} \times A_{ik} \times X_{iks} / \eta_s + C_{ag} \times A_{ik} \times X_{ikg} / \eta_g + C_{pk} \times Y \left(X_{iks} + X_{ikg} \right) \times A_{ik} \right) \quad (1b)$$

$$NB_e = \sum_{m=1}^M \left(V_m \times \left(X_{ims} + X_{img} \right) \times A_{im} \right) \quad (1c)$$

where the definitions of these symbols are presented in Table 1.

Constraints:

Available total surface water:

$$0 < \sum_{k=1}^K (X_{iks} \times A_{ik} / \eta_s) + \sum_{m=1}^M (X_{ims} \times A_{im} / \eta_s) \leq Q_{is} \quad (2)$$

Available total groundwater:

$$0 < \sum_{k=1}^K (X_{ikg} \times A_{ik} / \eta_g) + \sum_{m=1}^M (X_{img} \times A_{im} / \eta_g) \leq Q_{ig} \quad (3)$$

Minimum and maximum irrigation depth:

$$X_{k \min} < X_{iks} + X_{ikg} < X_{k \max}, \quad X_{m \min} < X_{ims} + X_{img} < X_{m \max} \quad (4)$$

Available total crop area:

$$\sum_{k=1}^K A_{ik} + \sum_{m=1}^M A_{im} < A_i, \quad A_{ik} > A_{ik \min}, \quad A_{im} > A_{im \min}, \quad A_{im} \leq A_{im \max} \quad (5)$$

where the minimum available cultivated area was determined according to the minimum required crop production per capita. The maximum area constraint for economic crops was imposed for the balance of cropping pattern. The definitions of these symbols are presented in Table 1. The CWPF (i.e. $Y_{ik}(X)$ in Eq. 1) for each crop-soil unit was expressed as a non-linear function that could be obtained through the simulations of the SWAP-EPIC model.

2.2.2 Crop water production functions

The CWPF was obtained through fitting the relationship of the different levels of total irrigation water amount (TIW) in the field and the corresponding maximum crop yields. For each crop-soil unit, this procedure was carried out using the SWAP-EPIC model (Xu et al. 2013). The SWAP-EPIC model was a modified agro-hydrological model that embedded the crop growth model EPIC (Williams et al. 1989) in the original SWAP model (Kroes and Van Dam 2003). It can simulate soil water flow, heat and solute transport, and crop growth and yield. A detailed description of linkage between SWAP and EPIC has been given by Xu et al.

217 (2013).

218 The model parameters for SWAP-EPIC, related to soil hydraulic properties and crop
219 growth, had to be firstly calibrated and validated with the experimental data. Model
220 simulations were then performed with different levels of TIW during crop growth period. TIW
221 was initially set to 0 mm (i.e. only with rainfall), and then incrementally increased up to the
222 specified maximum value. The irrigation method, crop calendar and irrigation frequency for
223 each crop were defined by referring to local agricultural advisers. The specific irrigation
224 scheduling for each TIW was determined based on the crop growth stages and their sensitivity
225 indices in order to achieve possible maximum yield. This meant that the simulation avoided
226 water stress in very sensitive stages. Note that CWPFs are also affected by the different
227 climate conditions in different years. Therefore, many years of simulations need to be
228 conducted to determine the functions that consider climatic effects and uncertainties on crop
229 yields. Other factors such as crop varieties, soil conditions and fertilization as well as
230 irrigation method were assumed to be unchanged for each simulation year.

231 Based on the simulated yield values of many years, the 20th, 50th and 80th percentile
232 values were selected for each TIW, which respectively represented higher, average and lower
233 levels of crop yields due to different climatic effects. The climate condition was considered
234 favorable with higher level and unfavorable with lower level of crop yields, under the
235 condition of same irrigation amount. Using the three levels of crop yields, three non-linear
236 curves of CWPFs could be fitted for each crop-soil unit, representing the favorable, average
237 and unfavorable climate conditions, respectively. Thus, the effects of climate uncertainties

could be included in the optimization.

2.2.3 Second level: optimization of irrigation water allocation among subsystems

Taking every subsystem as a stage, the irrigation water allocation for each subsystem was seen as the sequential allocation for each stage. Hence, for the second level of PBREOP model, a dynamic programming model was formulated for optimizing the irrigation water among subsystems in order to maximize the total benefit of the whole irrigation system. The subsystem benefit (G_i in Eq. 1) obtained by the first level was expressed as the function of allocated water amount ($G(Q_i)$) and used in this level. In the current version, the groundwater was supposed to be just pumped as supplements for surface water in each subsystem, and thus its amount was only taken as general variable for simplification. The mathematical model was described as follows:

1. Stage variables: each subsystem as a stage variable, with $i=1, 2, \dots, N$. This is the same as the number of subsystem in Table 1.

2. State variables: total available surface water at intake of each subsystem, defined as S_i .

3. Decision variables: allocated water amount for each subsystem, defined as Q_i (i.e. $Q_{is}+Q_{ig}$).

4. Objective function: the objective function was to maximize the total benefit of the whole irrigation system. It was expressed as the summed benefit of all subsystems minus the management costs, i.e.

$$MaxP = \sum_{i=1}^N (G(Q_i) - M_s \times Q_{is} - M_g \times Q_{ig}) \quad (6)$$

5. System equation: surface water allocation equation at each subsystem intake, i.e.

$$S_{i+1} = S_i - Q_{is} \quad (7)$$

6. Constrains:

Total available surface water amount of the whole system:

$$\sum_{i=1}^N Q_{is} / u_s \leq Q_s \quad (8)$$

Total available groundwater amount of the whole system:

$$\sum_{i=1}^N Q_{ig} / u_g \leq Q_g \quad (9)$$

Allowable maximum and minimum total allocated water for each subsystem:

$$\sum_{k=1}^K (X_{k \min} \times A_{ik}) + \sum_{m=1}^M (X_{m \min} \times A_{im}) \leq (Q_{ig} \times \eta_g + Q_{is} \times \eta_s) \leq \sum_{k=1}^K (X_{k \max} \times A_{ik}) + \sum_{m=1}^M (X_{m \max} \times A_{im}) \quad (10)$$

7. Initial condition: the total available surface water of the whole system, i.e. $S_1 = Q_s$

$$8. \text{ Recurrence formulation: } f(S_i) = \max \{ g(S_i, Q_i) + f(S_{i+1}) \} \quad (11)$$

where $f(S_i)$ is the maximum benefit when the whole system is at the state of S_i , and $g(S_i, Q_i)$ is

the benefit of the stage i with the decision Q_i at the state of S_i , i.e. Eq. (6). The other symbol

definitions are given in Table 1.

2.3 Model solution

The PBREOP model was solved using the decomposition-harmonization method for large systems (Shangguan et al. 2002). The execution started from the first level, which was initially given a set of available water for subsystems (Q_{is} and Q_{ig}) (Fig. 2). Taking the allocated irrigation water for subsystems as the coordinated variables, the coupling constraint should be satisfied for water allocation using Eqs. (2-3) and Eqs. (8-9). The steps for solving were as follows:

(1) the optimal results were solved individually for each subsystem under the given

water amount (Q_{is} and Q_{ig}) in the first level. The optimal allocation of irrigation water and crop area were obtained for crop-soil units in each subsystem, as well as the correspondingly maximal net irrigation benefit $G_i(Q_i)$.

(2) the benefit $G_i(Q_i)$ was then input into the second level. With the dynamic programming method, the second level was optimized based on the imported $G_i(Q_i)$ to get an optimized benefit of the whole system, i.e. $P(Q_s+Q_g)$. Meantime, the optimized irrigation water allocation for each subsystem (Q_{is} and Q_{ig}) was obtained and then transferred back to the first level as new coordinated variables.

(3) with the feedback of updated Q_{is} and Q_{ig} , the first level was optimized once again and provided the new irrigation benefit $G_i(Q_i)$ of subsystems for driving the second level again.

This calculation was repeatedly iterated until the following criterion was satisfied:

$$\frac{|P(Q_s + Q_g)^{l+1} - P(Q_s + Q_g)^l|}{P(Q_s + Q_g)^l} \leq \omega \quad (12)$$

where l is number of iteration; ω is the maximum threshold of the difference between iterations, and is set to 0.005.

3 Case study

3.1 Description of the study area

The YID (38°50'-38°58' N, 100°17'-100°34' E), located in middle oasis of the Heihe River basin, Northwest China (Fig. 3), was selected as a case to test the developed PBREOP model. The Heihe River basin is the second largest inland river basin of China and is facing severe water scarcity and water conflict. Excessive river water diversion for the agricultural sector has caused serious ecological challenges to the downstream areas, e.g., degradation of

lacustrine ecosystems, demise of large tracts of vegetation, and land desertification due to less water allocation (Feng et al. 2004). Therefore, the river water allocated to the middle oasis is planned to be reduced from 900 to 600 million m³. This promotes the implementation of water saving practices (WSPs) since 2000 (Jiang et al. 2015).

The YID is the third largest irrigation district in the middle oasis, covering an area of 19200 ha. Its topography varies between 1456-1600 m from southwest to northeast. The climate is typically a cold, arid continental climate with an annual average precipitation of around 125 mm (90% of rainfall distributed between March and September), and an average annual reference evapotranspiration (ET_o) of around 1200 mm.

The major crops are corn (forage corn and grain corn), spring wheat and vegetables, which are mainly irrigated with canal water from Heihe River and supplemented by groundwater. Flood (basin or border) irrigation methods are commonly used by local farmers. More than 90% of total water supply is required for irrigation per year. This will need to be gradually cut in the future. The YID has an extensive canal network consisting of one main canal and eleven sub-canals. Since 2000, WSPs have been gradually implemented in the YID, which primarily focus on irrigation structure construction. The main canal, about 97% of secondary canals and 60% of tertiary canals have been lined, and the water projects have been rebuilt. Nevertheless, Jiang et al. (2015) showed that the poor irrigation management led to uniform distribution of canal water and lower irrigation efficiency. Typically, farmers diverted excessive irrigation water in upper canal areas, resulting in the deficit of irrigation water in the lower canal areas. Thus, the groundwater was often exploited as supplemental irrigation

source for vegetables in lower canal areas. Overall, it is essential to explore optimal irrigation and cropping strategies for the YID in order to improve the present water use situations and ensure the economic benefit responding to the reduction of river water allocation.

3.2 Model setup considering alternative water supply scenarios

Four major crops (forage corn, grain corn, spring wheat and vegetables) were selected according to the crop survey in 2012 and 2013 (Fig. 3). The soils can be simplified into three major types according to the soil survey (Table 2). All types of vegetables were considered as an economic crop, and its net benefit per unit of applied water was used in the optimization. Hence, a total of nine crop-soil combination units were considered in the case study. The SWAP-EPIC model as calibrated by Jiang et al. (2015) was run for each unit, and nine CWPFs were generated for describing the crop yield-irrigation water relationships. The water deficit sensitivity index of crop (Ghahraman and Sepaskhah 1997) and the optimized irrigation schedules of each crop from Guo et al. (2014) and Fu et al. (2014) were referred in the simulations. The TIW for all crops was initially set to 0 mm, and then increased from 200 to 900 mm and 680 mm, with 100 mm and 80 mm increments for corn and wheat, respectively. Eleven canal command areas were defined according to the distribution of canals in the YID (Fig. 3). Daily weather data for 20 years (1994-2013), including maximal and minimal temperature, rainfall, solar radiation, wind speed and relative humidity, were collected from Zhangye meteorological station (100°25' E, 38°51' N, 1425 m) in the study area. The daily averages of reference evapotranspiration (ET_0) and monthly averages of rainfall during 1994-2013 are shown in Fig. 4. The crop prices and the cost of crop production

were determined by market surveys and local farmers. The water price was collected from Yingke Irrigation Management Office. The detailed basic data used in the model are provided in Table 3.

Five levels of water supply (total amount of groundwater and canal water) were defined according to the government planning (Table 4). The river water was gradually reduced until it approached the minimum planned amount, i.e. 27% reduction compared to present water diversion. Meanwhile, groundwater extraction was decreased by 19% for sustainable use and kept unchanged in all scenarios (Ji et al. 2005).

The sensitivity analysis of the model was firstly performed to test the effects of the main parameters and constraints. Optimization was then conducted for each water supply level using these basic data and parameters for the YID. Optimal irrigation allocation among different canals and crop-soil units could be obtained, and the corresponding cropping pattern was also optimized. In order to consider the uncertainties of CWPFs in different climate conditions, the optimization was conducted for each level of water supply using the three types of CWPF curves (average, favorable and unfavorable) as described in section 2.2.2. All other factors including the irrigation method, total crop area, crop variety, canal water conveyance efficiency, etc., were assumed to be unchanged.

When using one type of CWPFs, the optimal strategy may have an economic risk caused by possible yield reduction due to annual climate variation. In order to assess the economic risk, a new variable was introduced and defined as follows (García-Vila and Fereres 2012):

$$R = \text{Max}\{|P - P_f|, |P - P_u|\} \quad (13)$$

where P_f and P_u are the total benefit for favorable and unfavorable year, respectively.

3.3 Results

3.3.1 Crop water production functions

A series of discrete yield-irrigation points for each of nine crop-soil units was obtained through the 20 years of simulations using the SWAP-EPIC model (Fig. 5). For all crop-soil units, the crop yield increased linearly with the increase of irrigation amount at lower TIW levels ($TIW < 500\text{mm}$), and became stable at higher TIW levels ($TIW > 500\text{mm}$). This was because the crop water demand could be satisfied and over-irrigation may occur at high levels of TIW. Thus, this non-linear relationship was expressed using quadratic functions similar to some previous studies (Tong and Guo 2013; Darshana et al. 2012). The three types of CWPF curves representing different climatic years were then obtained for each crop-soil unit (Fig. 5). The coefficients of CWPFs are presented in Table 5, together with the maximal yield and corresponding irrigation depth based on the CWPFs. It can be seen that the CWPFs for the same crop are different with different soil types. Generally, the yield for all crops was larger in soil type 1. Under rain-fed condition ($TIW=0$), the crop yield in soil type 1 was 20% and 30% higher than that in soil types 2 and 3, respectively. This may be related to the layered soil structure for soil type 1, i.e., the loamy soil underlain by very coarse sandy soil, which leads to better water retention in the root zone when less irrigation water is applied (Clothier et al. 1977). The difference in crop yield between different soil types becomes very small at high TIW levels (less than 5%). Even with the same irrigation amount and soil type, crop yields were still diverse due to climatic differences such as precipitation, temperature and wind

speed.

3.3.2 Optimized results

With CWPFs as described above the optimized irrigation water allocation and cropping pattern were obtained at different water supply levels for the YID using the PBREOP model. The optimized total benefit (P) and economic risk (R) are presented in Table 6 and Fig. 6. Results showed that the P could be effectively increased through the optimization of irrigation water allocation and cropping pattern.

Under the present irrigation water supply (i.e. level 0), the optimized total benefit of the YID reached 298 million Yuan on average, an increase of 15% compared to the present (260 million Yuan). The benefit fluctuated between 308 and 285 million Yuan due to climate uncertainty, with an economic risk (R) of 13.4 million Yuan (Table 6). The optimized irrigation water allocation among sub-canals was more even distribution than that at present. The amount ranged from 593 to 662 mm when using the average curve of CWPFs (Fig. 7a) while that of the present was from 414 to 898 mm. The boxes in Fig.7 show the variations of allocated irrigation water due to climate uncertainty (using different CWPFs). The optimized average irrigation depth (i.e. TIW) for each crop and the corresponding crop area are provided in Table 6 at present water supply level. Results showed that the area and irrigation water allocation was given priority to vegetables and then to grain corn (Table 6). This was also consistent with our sensitivity analysis showing that vegetables and grain corn with higher benefit returns had priority in irrigation water and crop area allocation, especially at high water supply level. The area and irrigation water of vegetables both increased up to an upper

limit, this being 40% of the total crop area and 700 mm, respectively. The area of grain corn decreased by 10% with an average TIW ranging from 571 to 592 mm for different climatic years. While the area of forage corn and wheat was reduced to the minimum, with the average TIW for these crops was 556-571 mm and 331-379 mm, respectively. In addition, there were obvious spatial differences in TIW allocation in the whole YID (Fig. 8). This was mainly due to differences in cropping structure and soil type among different canal command areas.

Results indicated that the optimized total benefit P in the YID showed a decrease trend when the total irrigation water supply was reduced from level 0 to level 5 (Fig. 6). The P for average climatic year (i.e. P_a) was reduced from 2% to 16% for level 1-5 as compared to level 0. However, P_a was still higher than the present benefit up to level 4. The variation in total benefit represented the economic risks due to climate variation (Fig. 6). The average irrigation amount in the YID was reduced from 624 to 502 mm for level 0-5, and the differences of allocated irrigation water among sub-canal became larger (Fig. 7). Moreover, the boxes in Fig. 7 showed the greater influences of climate variations at the lower water supply conditions. For allocation among crops, the irrigation water still seems to be firstly allocated to vegetables from water supply level 0 to 5, while this became less than its maximum value of 700 mm at lower water supply levels. The irrigation for the other three crops was also gradually reduced to the minimum from level 0 to 5 (Table 6), and the spatial differences become smaller at lower levels as more corn and wheat units were irrigated with their minimum value (Fig. 8).

Note that the area of grain corn increased as the vegetable area decreased (Table 6). This

is consistent with grain corn becoming the more beneficial crop as water supply drops as shown in the sensitivity analysis. Overall, the optimization was largely influenced by the upper bound of irrigation depth constraints for vegetables. These had the strongest influence on the total benefit because of their linear relationship to irrigation water, according to the sensitivity analysis. This meant that this upper constraint would be satisfied first in the optimization processes, particularly at high water supply levels.

Results suggested that the water supply could be cut down to level 4 after optimization of irrigation and land management in YID. This would result in a saving of 23% irrigation water (Table 4) with very little reduction in benefit (Fig. 6). The associated R equaled 11.3 million Yuan because of climate uncertainties (Table 6). The detailed allocation of irrigation water and crop area for each canal is shown in Fig. 7e and Fig. 9c respectively. The optimal amount of irrigation water was reduced to 524 mm in average over the whole area, and ranged from 430 to 556 mm for sub-canals (Fig. 7e). The irrigation water allocated to corn and wheat was close to the minimum (Table 6). The optimal planting area for grain corn and vegetables reached 39-45% and 31-37% of the total crop area respectively under different climate years; a decrease of 2-8% and an increase of 15-22% compared to the present (Table 6). Conversely, the area of forage corn was reduced to about 18% from the present 29%. Regard to the practical situation, this suggested optimization results could be realized primarily through improving the water and land management. More attention needs to be paid to ensuring the timely and uniform allocation of canal water to match the field crop demands, and improving field irrigation efficiency (e.g. adopting modernized border irrigation and surface leveling

techniques) for adapting the reduced field irrigation amount.

4. Discussion

The case study showed that the developed PBREOP model was an effective and practical tool for the regional optimization of irrigation water allocation and cropping pattern. The model presented two major advantages that made it distinctive. First, the introduction of SWAP-EPIC model made it easy to obtain CWPFs for different crop-soil units and climate conditions when calculating regional optimization. This approach can well incorporate the important factors of spatial soil variations in the PBREOP model, besides the differences of crop species. In addition, the introduction of three type CWPFs can also include impacts of climate uncertainty into the objective functions, and thereby the economic risks could be provided in optimization. Therefore, the PBREOP model could be more reasonable with considering above-mentioned environmental effects, as compared with the previous regional optimization models (Shangguan et al. 2002; Sethi et al. 2006; Garg and Dadhich 2014; Homayounfar et al. 2014). Second, it should be noted that the two-level model structure efficiently reduced the complexity of regional optimization problems, in which each level was relatively independent and could be solved individually. Meanwhile, the connection between subsystems and the whole system was incorporated into the solving process with a coordination algorithm. In such a way, as compared to the previous studies (Kuo et al. 2000; Paul et al. 2000; García-Vila and Fereres 2012; Zhang et al. 2014), the PBREOP model could not only have a feasible computation, but also well consider the benefit coordination between different levels and the various environmental effects in the whole irrigation system.

The sensitivity analysis in the case study also showed that the model was sensitive to the constraints of crop area and maximum/minimum irrigation depth. Obtaining optimal results requires accurately determining values for these constraints. The relationships between the benefit of economic crops and irrigation were expressed as a linear function in the optimization model due to the difficulties for obtaining the CWPfFs of various economic crops. This meant that the optimization for economic crops was not affected by the soil types and climate condition, and hence the irrigation water tends to be allocated to economic crops preferentially when water is plentiful. This would have negative impacts on the optimization, and more attention therefore needs to be paid to improving the description of economic crops in further investigations.

5. Conclusion

A process-based regional economic optimization model (PBREOP) was formulated for maximizing the net economic benefit through optimizing the allocation of irrigation water and crop area in irrigation systems. It was based on a two-level optimization model combined with an agro-hydrological model (SWAP-EPIC), and solved using the decomposition-harmonization method for large systems.

The first level dealt with the optimal distribution of irrigation water and crop area in each subsystem, and the second level determined the optimal strategy for irrigation water allocation among the subsystems. The SWAP-EPIC model was adopted to generate the crop water production functions (CWPfFs) for different soil-crop units while taking climate conditions into consideration, which were the basis to comprise the first-level objective

function and also readily realized. The two levels were connected through exchange of irrigation water allocation and net benefit of each subsystem. This provides a practical and efficient means of calculating regional optimization.

The PBREOP model was tested and applied to a case study of the Yingke Irrigation District (YID) in the middle Heihe River basin, an arid inland region of Northwest China. Optimized results showed that an increase of 15% of the total benefit could be obtained for YID with an economic risk of 11.3 million Yuan under the present water supply level, when taking into account climate uncertainty. Scenario analysis for five water supply levels indicated that 23% of irrigation water could be reduced on average without reducing present benefit. The case study showed that the PBREOP model was an effective tool for regional optimization of irrigation water allocation and cropping pattern. The model could better consider the effects of soil and climate conditions when forming CWPFs for optimizations.

In summary, this study presented a reference method for maximizing the net agricultural economic return by optimizing regional water and land resources use, and this can be applied in most of irrigation districts of the world. The applicability of the model to larger scales and the uncertainties of other factors (e.g. price volatility) require further investigation.

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512 **References**

513 Alvarez, J., Valero, J., Martin-Benito, J., Mata, E.L., 2004. MOPECO: An economic
514 optimization model for irrigation water management. *Irrig. Sci.* 23(2), 61-75.

515 Bruinsma, J., 2003. World agriculture: Towards 2015/2030. An FAO perspective. In
516 Bruinsma J (Ed.), (432). London, UK: Earthscan Publications Ltd.

517 Clothier, B.E., Scotter, D.R., Kerr, J.P., 1977. Water-retention in soil underlain by a
518 coarse-textured layer-theory and a field application. *Soil Sci.* 123(6), 392-399.

519 Doorenbos, J., Kassam, A.H., 1979. Yield response to water. FAO Irrigation and Drainage
520 Paper No. 33. Rome, Italy.

521 Darshana, Pandey, A., Ostrowski, M., Pandey, R.P., 2012. Simulation and optimization for
522 irrigation and crop planning. *Irrig. Drain.* 61(2), 178-188.

523 Feng, Q., Liu, W., Su, Y.H., Zhang, Y.W., Si, J.H., 2004. Distribution and evolution of water
524 chemistry in Heihe River basin. *Environ. Geol.* 45(7), 947-956.

525 Fu, Y., Li, M., Guo, P., 2014. Optimal allocation of water resources model for different
526 growth stages of crops under uncertainty. *J. Irrig. Drain. Eng.* 140(6).

527 Ghahraman, B., Sepaskhah, A.R., 1997. Use of a water deficit sensitivity index for partial
528 irrigation scheduling of wheat and barley. *Irrig. Sci.* 18(1), 11-16.

529 Ganji, A., Ponnambalam, K., Khalili, D., Karamouz, M., 2006. A new stochastic optimization
530 model for deficit irrigation. *Irrig. Sci.* 25(1), 63-73.

531 García-Vila, M., Fereres, E., 2012. Combining the simulation crop model AquaCrop with an

532 economic model for the optimization of irrigation management at farm level. Eur. J.
533 Agron. 36(1), 21-31.

534 Garg, N.K., Dadhich, S.M., 2014. Integrated non-linear model for optimal cropping pattern
535 and irrigation scheduling under deficit irrigation. Agric. Water Manage. 140, 1-13.

536 Guo, P., Wang, X., Zhu, H., Li, M., 2014. Inexact fuzzy chance-constrained nonlinear
537 programming approach for crop water allocation under precipitation variation and
538 sustainable development. J. Water Resour. Plann. Manage. 140(9), 5014003.

539 Homayounfar, M., Lai, S.H., Zomorodian, M., Sepaskhah, A.R., Ganji, A., 2014. Optimal
540 Crop Water Allocation in Case of Drought Occurrence, Imposing Deficit Irrigation with
541 Proportional Cutback Constraint. Water Resour. Manage. 28(10), 3207-3225.

542 Ines, A., Honda, K., Das Gupta, A., Droogers, P., Clemente, R.S., 2006. Combining remote
543 sensing-simulation modeling and genetic algorithm optimization to explore water
544 management options in irrigated agriculture. Agric. Water Manage. 83(3), 221-232.

545 IPCC, 2007. *Climate Change 2007: Impacts, adaptation and vulnerability: Contribution of*
546 *Working Group II to the fourth assessment report of the Intergovernmental Panel on*
547 *Climate Change* (Vol. 4). Cambridge, UK: Cambridge University Press.

548 Jensen, M.E., 1968. Water consumption by agricultural plants (Chapter 1). In Kozlowski TT
549 (Ed.), *Water Deficits in Plant Growth* (1-22). New York: Academic Press.

550 Ji, X.B., Kang, E.S., Zhao, W.Z., Cheng, R.S., Xiao, S.C., Jin, B.W., 2005. Analysis on
551 supply and demand of water resources and evaluation of the security of water resources
552 in irrigation region of the middle reaches of Heihe River , Northwest China. Scientia

553 Agricultura Sinica (05), 974-982 (in Chinese with English abstract)

554 Jiang, Y., Xu, X., Huang, Q., Huo, Z., Huang, G., 2015. Assessment of irrigation performance
555 and water productivity in irrigated areas of the middle Heihe River basin using a
556 distributed agro-hydrological model. Agric. Water Manage. 147, 67-81.

557 Kroes, J.G., van Dam, J.C., 2003. Reference Manual SWAP; Version 3.0. 3 (Alterra-Report
558 773: pp. 211). Wageningen: Alterra, Green World Research.

559 Kuo, S.F., Merkley, G.P., Liu, C.W., 2000. Decision support for irrigation project planning
560 using a genetic algorithm. Agric. Water Manage. 45(3), 243-266.

561 Kuo, S.F., Liu, C.W., 2003. Simulation and optimization model for irrigation planning and
562 management. Hydrol. Process. 17(15), 3141-3159.

563 Levidow, L., Zaccaria, D., Maia, R., Vivas, E., Todorovic, M., Scardigno, A., 2014.
564 Improving water-efficient irrigation: Prospects and difficulties of innovative practices.
565 Agric. Water Manage. 146, 84-94.

566 Li, M., Guo, P., 2015. A coupled random fuzzy two-stage programming model for crop area
567 optimization-a case study of the middle Heihe River basin, China. Agric. Water Manage.
568 155, 53-66.

569 Li, M., Guo, P., Fang, S.Q., Zhang, L.D., 2013. An inexact fuzzy parameter two-stage
570 stochastic programming model for irrigation water allocation under uncertainty. Stoch.
571 Environ. Res. Risk. Assess. 27(6), 1441-1452.

572 Ma, Y., Feng, S.Y., Huo, Z.L., Song, X.F., 2011. Application of the SWAP model to simulate
573 the field water cycle under deficit irrigation in Beijing, China. Math. Comput. Modell.

574 54(3-4), 1044-1052.

575 Paul, S., Panda, S.N., Kumar, D.N., 2000. Optimal irrigation allocation: A multilevel
576 approach. *J. Irrig. Drain. Eng.* 126(3), 149-156.

577 Pereira, L.S., Oweis, T., Zairi, A., 2002. Irrigation management under water scarcity. *Agric.*
578 *Water Manage.* 57(3), 175-206.

579 Pereira, L.S., Paredes, P., Cholpankulov, E.D., Inchenkova, O.P., Teodoro, P.R., Horst, M.G.,
580 2009. Irrigation scheduling strategies for cotton to cope with water scarcity in the
581 Fergana Valley, Central Asia. *Agric. Water Manage.* 96(5), 723-735.

582 Playán, E., Mateos, L., 2006. Modernization and optimization of irrigation systems to
583 increase water productivity. *Agric. Water Manage.* 80(1-3), 100-116.

584 Rejani, R., Jha, M.K., Panda, S.N., 2009. Simulation-optimization modeling for sustainable
585 groundwater management in a coastal basin of orissa, India. *Water Resour. Manage.*
586 23(2), 235-263.

587 Sethi, L.N., Panda, S.N., Nayak, M.K., 2006. Optimal crop planning and water resources
588 allocation in a coastal groundwater basin, Orissa, India. *Agric. Water Manage.* 83(3),
589 209-220.

590 Safavi, H.R., Darzi, F., Marino, M.A., 2010. Simulation-optimization modeling of
591 conjunctive use of surface water and groundwater. *Water Resour. Manage.* 24(10),
592 1965-1988.

593 Saseendran, S.A., Ahuja, L.R., Ma, L., Trout, T.J., McMaster, G.S., Nielsen, D.C., Ham, J.M.,
594 Andales, A.A., Halvorson, A.D., Chávez, J.L., Fang, Q.X., 2015. Developing and

595 normalizing average corn crop water production functions across years and locations
596 using a system model. *Agric. Water Manage.* 157, 65-77.

597 Shang, S.H., Mao, X.M., 2006. Application of a simulation based optimization model for
598 winter wheat irrigation scheduling in North China. *Agric. Water Manage.* 85(3),
599 314-322.

600 Shangguan, Z.P., Shao, M.A., Horton, R., Lei, T.W., Qin, L., Ma, J.Q., 2002. A model for
601 regional optimal allocation of irrigation water resources under deficit irrigation and its
602 applications. *Agric. Water Manage.* 52(2), 139-154.

603 Singh, A., 2012. An overview of the optimization modelling applications. *J. Hydrol.* 466,
604 167-182.

605 Singh, A., 2014. Simulation-optimization modeling for conjunctive water use management.
606 *Agric. Water Manage.* 141, 23-29.

607 Singh, A., Panda, S.N., 2012. Development and application of an optimization model for the
608 maximization of net agricultural return. *Agric. Water Manage.* 115, 267-275.

609 Singh, A., Panda, S.N., 2013. Optimization and simulation modelling for managing the
610 problems of water resources. *Water Resour. Manage.* 27(9), 3421-3431.

611 Singh, R., Helmers, M.J., Qi, Z., 2006a. Calibration and validation of DRAINMOD to design
612 subsurface drainage systems for Iowa's tile landscapes. *Agric. Water Manage.* 85(3),
613 221-232.

614 Singh, R., Jhorar, R.K., van Dam, J.C., Feddes, R.A., 2006b. Distributed ecohydrological
615 modelling to evaluate irrigation system performance in Sirsa district, India II: Impact of

616 viable water management scenarios. *J. Hydrol.* 329(3-4), 714-723.

617 Sun, C., Ren, L., 2014. Assessing crop yield and crop water productivity and optimizing
618 irrigation scheduling of winter wheat and summer maize in the Haihe plain using SWAT
619 model. *Hydrol. Processes* 28(4), 2478-2498.

620 Tong, F.F., Guo, P., 2013. Simulation and optimization for crop water allocation based on
621 crop water production functions and climate factor under uncertainty. *Appl. Math. Model.*
622 37(14-15), 7708-7716.

623 Haq, Z.U., Anwar, A.A., Clarke, D., 2008. Evaluation of a genetic algorithm for the irrigation
624 scheduling problem. *J. Irrig. Drain. Eng.* 134(6), 737-744.

625 Williams, J.R., Jones, C.A., Kiniry, J.R., Spanel, D.A., 1989. The EPIC crop growth-model.
626 *Trans. ASAE* 32(2), 497-511.

627 Xu, X., Huang, G.H., Qu, Z.Y., Pereira, L.S., 2011. Using MODFLOW and GIS to assess
628 changes in groundwater dynamics in response to water saving measures in irrigation
629 districts of the upper yellow river basin. *Water Resour. Manage.* 25(8), 2035-2059.

630 Xu, X., Huang, G.H., Sun, C., Pereira, L.S., Ramos, T.B., Huang, Q.Z., Hao, Y.Y., 2013.
631 Assessing the effects of water table depth on water use, soil salinity and wheat yield:
632 Searching for a target depth for irrigated areas in the upper Yellow River basin. *Agric.*
633 *Water Manage.* 125, 46-60.

634 Zhang, L., Li, C.Y., 2014. An inexact two-stage water resources allocation model for
635 sustainable development and management under uncertainty. *Water Resour. Manage.*
636 28(10), 3161-3178.

637 Zhang, Z., Ma, H., Li, Q., Wang, X., Feng, G., 2014. Agricultural planting structure
638 optimization and agricultural water resources optimal allocation of Yellow River
639 Irrigation Area in Shandong Province. Desalin. Water Treat. 52(13-15), 2750-2756.

640 Table 1 Definitions of symbols in the process-based regional economic optimization
641 (PBREOP) model

Symbol	Definition
i	Subsystem number ($1 \dots N$)
k	Type of grain crop ($1 \dots K$)
m	Type of economic crop ($1 \dots M$)
$G(Q_i)$	Total net benefit of each subsystem (Yuan), as the function of allocated water (surface water and groundwater)
P	Total economic benefit of the whole irrigation system (Yuan)
A_{ik}	Area of crop k in subsystem i (ha)
A_{im}	Area of economic crop m in subsystem i (ha)
A_{ikmin}, A_{ikmax}	Minimum and maximum area of crop k in subsystem i (ha)
A_{immin}, A_{immax}	Minimum and maximum area of economic crop m in subsystem i (ha)
A_i	Total crop area of subsystem i (ha)
$X_{iks} + X_{ikg}$	Total amount of irrigation water in the field for crop k in subsystem i (mm) (the subscripts s and g denote the surface water and groundwater, respectively)
$X_{ims} + X_{img}$	Total amount of irrigation water in the field for economic crop m in subsystem i (mm)
X_{kmin}, X_{kmax}	Minimum and maximum irrigation amount for crop k (mm)
X_{mmin}, X_{mmax}	Minimum and maximum irrigation amount for crop m (mm)
$Y_{ik}(X)$	Yield of crop k in subsystem i , as a function of irrigation amount (kg ha^{-1})
P_k	Price of crop k (Yuan kg^{-1})
C_{pk}	Cost of crop k production (Yuan kg^{-1})
C_{as}	Price of surface water (Yuan m^{-3})
C_{ag}	Price of groundwater (Yuan m^{-3})
V_m	Average economic benefit per unit of gross irrigation water applied (Yuan m^{-3})

η	Water conveyance efficiency relative to water transport from subsystem to field (the subscripts s and g denote the surface water and groundwater, respectively)
u	Water conveyance efficiency relative to water transport from system to subsystem (the subscripts s and g denote the surface water and groundwater, respectively)
S_i	Available surface water at canal intake of subsystem i
Q_{is}	Total available surface water in subsystem i (m^3)
Q_{ig}	Total available groundwater in subsystem i (m^3)
Q_i	Total allocated water ($Q_{is} + Q_{ig}$) for subsystem i (m^3)
Q_s	Total available surface water for the whole system (m^3)
Q_g	Total available groundwater for the whole system (m^3)
M_s	Cost of management for surface water (Yuan m^{-3})
M_g	Cost of management for groundwater (Yuan m^{-3})

642 Table 2 Soil physical properties of three major soil types in the case study area

Soil type	Depth (cm)	clay <0.002 (mm)	Silt 0.002-0.05 (mm)	Sand 0.05-2 (mm)	Soil texture
1	0-140	14.45±2.0	52.48±3.0	33.07±3.0	Silt loam
2	0-140	17.00±2.0	40.79±3.0	42.21±3.0	Loam
3	0-60	15.16±2.0	51.29±3.0	33.55±3.0	Silt loam
	60-140	15.84±2.0	42.16±3.0	42.00±3.0	Loam

643 Table 3 Basic data used in the optimization model for the case study

Item	Unit	Surface water	Groundwater
Water price	Yuan m ⁻³	0.168	0.88
Water conveyance efficiency relative to water transport from sub-canal to field (η)	-	0.75	0.75
Water conveyance efficiency relative to water transport from main canal to sub-canal (u_s)	-	0.9	-
Cost of management	Yuan m ⁻³	0.05	0.08

Item	Unit	Grain corn	Forage corn	Wheat	Vegetables
Price of crop (P_k)	Yuan kg ⁻¹	3.00	2.31	2.28	-
Cost of crop production (C_{pk}) excluding farmers' labor	Yuan kg ⁻¹	0.50	0.45	0.45	-
Average economic benefit per unit of gross irrigation water applied V_m (excluding farmers' labor)	Yuan m ⁻³	-	-	-	4.16
Maximum net irrigation depth allowed (X_{ikmax} , X_{immax})	mm	900	900	600	700
Minimum net irrigation depth (X_{ikmin} , X_{imin})	mm	450	450	250	500
Minimum total crop area (policy defined)	ha	3200	2437	620	1040
Total available crop area	ha	13424			

644 Table 4. Total available irrigation water amount Q (groundwater and canal water) of
 645 the whole district under different water supply levels. The Q_s and Q_g is the total
 646 available canal water and groundwater amount, respectively. The decrease in
 647 percentage of each water supply level was calculated in comparison to the present.

Water supply level	Q_s (10^6m^3)	Q_g (10^6m^3)	Q (10^6m^3)	Gross I_g (mm)	Decrease Q_s	Decrease Q_g	Decrease Q
0	82.12	41.09	123.21	857		Present	
1	74.70	33.31	108.01	749	10%	19%	12%
2	69.58	33.31	102.89	715	15%	19%	16%
3	65.58	33.31	98.89	688	20%	19%	20%
4	61.61	33.31	94.92	661	25%	19%	23%
5	57.50	33.31	90.81	634	27%	19%	26%

648 *Note:* Water supply levels refer to scenarios for water saving and conservation where
 649 the level 0 corresponds to the present situation.

650 Table 5. Coefficients of the crop water production functions ($y = ax^2 + bx + c$) for each
651 crop-soil unit.

Type		Coefficient			Calculated value	
		a	b	C	Max yield (kg ha ⁻¹)	Corresponding irrigation (cm)
Grain corn soil type 1	average	-1.1784	160.1	5069	10503.8	68
	favorable	-1.1962	163.6	5509	11099.6	68
	unfavorable	-1.1042	156.2	4522	10046.5	71
Grain corn soil type 2	average	-1.2537	183.0	3271	9949.2	73
	favorable	-1.2692	186.1	3672	10496.8	73
	unfavorable	-1.1672	174.8	2850	9395.9	75
Grain corn soil type 3	average	-1.2556	195.7	2472	10097.0	78
	favorable	-1.3144	202.2	2865	10640.6	77
	unfavorable	-1.2340	194.6	1918	9586.0	79
Forage corn soil type 1	average	-1.3696	198.4	4897	12081.6	72
	favorable	-1.4270	201.8	5386	12517.1	71
	unfavorable	-1.2133	178.5	4354	10922.1	74
Forage corn soil type 2	average	-1.1479	191.9	3062	11085.8	84
	favorable	-1.3431	213.3	3371	11836.0	79
	unfavorable	-1.1867	191.0	2612	10299.8	80
Forage corn soil type 3	average	-1.1364	209.2	1885	11508.7	92
	favorable	-1.2940	222.9	2330	11931.0	86
	unfavorable	-1.1449	201.2	1497	10338.4	88
Wheat soil type 1	average	-1.3587	159.4	2458	7135.4	59
	favorable	-1.5070	163.5	3093	7528.6	54
	unfavorable	-1.4322	161.9	2157	6729.9	57
Wheat soil type 2	average	-1.4587	162.4	2756	7273.1	56
	favorable	-1.6062	169.5	3223	7694.4	53
	unfavorable	-1.3783	152.9	2444	6683.1	55
Wheat	average	-1.6333	188.0	2192	7603.8	58

soil type 3	favorable	-1.4991	181.2	1772	7249.2	60
	unfavorable	-1.4275	173.3	1445	6706.2	61

652 *Note:* the unit of yield was “kg ha⁻¹” and the unit of applied irrigation water was “cm”

653 Table 6 Optimized maximum total benefit, the average net irrigation depth and planting area proportion for each crop in the Yingke Irrigation

654 District

Water supply level	Total benefit (10 ⁸ Yuan)	Economic risk (10 ⁸ Yuan)	Range of net irrigation (mm)				Range of planting area proportion (%)			
			Grain corn	Forage corn	Wheat	Vegetables (double crop per season)	Grain corn	Forage corn	Wheat	Vegetable
Present	2.60						47.7	29.1	7.7	15.5
0	[3.08, 2.98, 2.85]	0.134	[592 571]	[571 556]	[379 331]	700	37.9	17.5	4.6	40.0
1	[2.91, 2.87, 2.77]	0.098	[526 496]	[508 485]	[293 291]	700	[38.8 37.9]	[18.0 17.6]	[4.8 4.7]	[40.0 38.7]
2	[2.85, 2.79, 2.69]	0.107	[494 472]	[482 464]	[271 270]	[700 689]	[39.8 37.9]	[18.2 17.9]	[4.8 4.7]	[39.7 37.6]
3	[2.80, 2.72, 2.61]	0.107	[469 460]	[464 453]	[260 253]	[700 690]	[42.4 38.0]	[18.3 18.1]	[4.8 4.8]	[38.9 34.6]
4	[2.72, 2.63, 2.52]	0.113	[459 452]	[452 450]	[253 250]	[700 683]	[45.5 39.2]	[18.6 18.4]	[4.9 4.9]	[37.3 31.2]
5	[2.65, 2.53, 2.41]	0.123	[461 450]	[450 450]	[250 250]	[700 683]	[51.5 41.2]	[19.3 18.5]	[5.1 4.9]	[34.4 25.1]

655 **Figure captions**

656 Fig.1 Flow chart for the process-based regional economic optimization (PBREOP)

657 model (CWPFs represents the crop water production functions; $\Delta P \leq \omega$ is the
658 termination criterion for model iteration, i.e. the Eq. 12)

659 Fig. 2 Structure of the two-level optimization based on the decomposition and
660 harmonization method (Q is total water supply; MaxP is maximum total benefit;
661 other symbols as in Table 1)

662 Fig.3 Location of the case study area and distribution of canals and crop fields

663 Fig. 4 Distribution of daily average ET_0 and monthly average rainfall in the Yingke
664 Irrigation District over 20 years (1994-2013)

665 Fig. 5 Crop water production functions for different crops-soil units in the Yingke
666 Irrigation District (The fitness coefficients were presented in Table 5).

667 Fig. 6 Total irrigation water amount and optimized maximum total benefit at different
668 water supply levels in the Yingke Irrigation District

669 Fig. 7 Optimal allocation of irrigation water amount for eleven canals at different
670 water supply levels in Yingke Irrigation District (the Z1, ..., FZ, ..., FG are the
671 different canal command areas)

672 Fig. 8 Optimal total irrigation depth (TIW) for each crop at different water supply
673 levels in the Yingke Irrigation District

674 Fig. 9 Cropping pattern in each canal command area at present water supply (a), water
675 supply level 0 and 4 (b and c) (the Z1, ..., FZ, ..., FG are the different canal
676 command areas)

687 Fig. 6

688

690

691 *Note:* the red dash line is the mean irrigation depth over the whole irrigation district.

692 Fig. 8

693

694 *Note:* the box refer to the spatial differences of irrigation depth among different canal
 695 command areas. The yellow points were the average total irrigation amount (TIW) for
 696 each crop in the whole irrigation district.