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RESEARCH ARTICLE

An inexact risk management model for agricultural land-use planning under water shortage

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Abstract Water resources availability has a significant impact on agricultural land-use planning, especially in a water shortage area such as North China. The random nature of available water resources and other uncertainties in an agricultural system present risk for land-use planning and may lead to undesirable decisions or potential economic loss. In this study, an inexact risk management model (IRM) was developed for supporting agricultural land-use planning and risk analysis under water shortage. The IRM model was formulated through incorporating a conditional value-at-risk (CVaR) constraint into an inexact two-stage stochastic programming (ITSP) framework, and could be used to control uncertainties expressed as not only probability distributions but also as discrete intervals. The measure of risk about the second-stage penalty cost was incorporated into the model so that the trade-off between system benefit and extreme expected loss could be analyzed. The developed model was applied to a case study in the Zhangweinan River Basin, a typical agricultural region facing serious water shortage in North China. Solutions of the IRM model showed that the obtained first-stage land-use target values could be used to reflect decision-makers' opinions on the long-term development plan. The confidence level α and maximum acceptable risk loss β could be used to reflect decision-makers' preference towards system benefit and risk control. The results indicated that the IRM model was useful for reflecting the decision-makers' attitudes toward risk aversion and could help seek cost-effective agricultural land-use planning strategies under complex uncertainties.

Keywords agricultural land-use planning, risk management, CVaR, uncertainty, water shortage

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1 Introduction

Agricultural land-use planning is of significant importance for agriculture practices which rely heavily on the distribution and quality of available water resources. In many parts of the world like China, the availability of water resources constrains the development of local agriculture in terms of its significant effects on the planning of agricultural land-use and irrigation (Liu et al., 2007). Therefore, agricultural land-use planning should take water availability into account. Over the past years, efforts were undertaken for agricultural land-use planning issues. For example, El-Shishiny (1988) developed a goal programming model for planning the development of newly reclaimed lands. Shakya and Leuschner (1990) proposed a multi-objective land-use planning model for a Nepalese hills farm. Raju and Kumar (1999) reported a multi-criterion decision-making approach for agricultural irrigation planning. Glen and Tipper (2001) proposed a mathematical programming model for improving the planning in a semi-subsistence farm. Lu et al. (2012) developed a strategic agricultural land-use planning approach in response to water-supplier variation under parameter uncertainty. In an agricultural land-use management system, many system components and their relationships may be uncertain. For example, spatial and temporal variations exist in many system components, such as available amount of water and land-use targets. Furthermore, fluctuations are associated with crop prices that are functions of many stochastic factors. These could be further compounded by not only interactions among the uncertain parameters, but also their economic implications (Li et al., 2006). Such uncertainties would bring risks to planning practices and might lead to undesirable decisions or potential economic loss. Therefore, methods that can deal with uncertainties and risks are desirable for these kinds of planning problems.

In recent decades, a magnitude of inexact optimization techniques were developed to tackle uncertainties in environmental management problems. A majority of these techniques were based on fuzzy, stochastic and interval methods, as well as their combinations (Wagner et al., 1994; Chang et al., 1996; Huang, 1996; Russell and Campbell, 1996; Kira et al., 1997; Qin et al., 2007; Guo et al., 2008; Xu and Qin, 2010; Li et al., 2010, 2012). Among various inexact methods, inexact two-stage stochastic programming (ITSP) models, firstly proposed by Huang and Loucks (2000), have been widely used in many environmental management problems under water resources variation (Maqsood et al., 2005; Huang et al., 2007, 2012, 2013; Li and Huang, 2008, 2009; Suo et al., 2011; Huang et al., 2012). For example, Maqsood et al. (2005) incorporated fuzzy programming into an ITSP model for handling water resource allocation problems. The integrated model was able to reflect the pre-defined water policies in optimization and describe multiple uncertainties presented as stochastic, interval, and fuzzy information. Suo et al. (2011) proposed an inventory-theory-based interval-parameter two-stage stochastic programming (IB-ITSP) model through integrating inventory theory into an interval-parameter two-stage stochastic optimization framework. Li et al. (2012) proposed a two-stage inexact-probabilistic programming (TIPP) method for water quality management in Zhangweinan River Basin, through coupling ITSP with chance-constrained programming. Li et al. (2013) developed an inexact two-stage stochastic credibility constrained programming (ITSCCP) method, through incorporating the credibility constrained programming and ITSP model within an optimization framework. These studies found that the ITSP model was effective in analyzing pre-defined policies and dealing with parameter uncertainties presented in both stochastic and interval formats. However, ITSP is a risk-neutral two-stage stochastic programming model because it is concerned with the optimization of an expectation objective without risk control issues. In this model, the possible loss is computed as the expected value of different probability conditions. Therefore, the severity of extreme risks might be underestimated.

The Conditional Value-at-Risk (CVaR) model presents a new risk measurement method based on probability distributions of random variables. It is modified from the Value-at-Risk (VaR) model which is widely used for portfolio selection (Rockafellar and Uryasev, 2000). It is performed by assessing the likelihood (at a specific confidence level) that a specific loss will exceed the value at risk. Previously, although application of CVaR in land-use management was relatively rare, there were a few studies on water resources and disaster management through the CVaR model (Webby et al., 2007; Yamout et al., 2007; Piantadosi et al., 2008; Shao et al., 2011; Noyan, 2012). For example, Yamout et al. (2007) investigated the applicability of a stochastic programming model with CVaR and other five types of models in dealing with water resources allocation problems in east central Florida. Piantadosi et al. (2008) developed a stochastic dynamic programming model with CVaR for supporting urban storm water management. These studies showed that CVaR-based models can not only analyze the trade-off between system benefit and potential risks that exist under extreme conditions, but also generate linear models to tackle risk rather than nonlinear ones. However, it cannot deal with the multiple forms of system uncertainties. Based on the advantages and disadvantages of the CVaR and ITSP models, Shao et al. (2011) developed a CVaR-based ITSP model for supporting water resources allocation problems and applied it to a hypothetic case study. It was found that the CVaR-based ITSP model showed a number of advantages: 1) help establish an effective linkage between the pre-defined decisions, the associated economic implications and the potential risk; 2) deal with uncertainties expressed as not only probability distributions but also discrete intervals; 3) generate reasonable risk-averse decision alternatives under different risks and multiple uncertainties. However, the application of the CVaR-based ITSP model to real case studies, especially agricultural land-use planning, was rarely reported in the past few decades.

Therefore, this study aims to develop an inexact risk management (IRM) model for a real case of agricultural land-use planning issue under water resources shortage. The model is named as inexact risk management model because it is capable of handling multiple uncertainties — both interval parameters and probabilistic distributions — as well as controlling the risk at extreme probability levels to generate reasonable management schemes. The IRM model would be applied to an agricultural land-use planning case in the Zhangweinan river basin, China, one of the main food and cotton producing regions in North China with serious water shortage. Decision risk caused by the random nature of agricultural water supply, which is of significant importance for agricultural land use management, would be analyzed through this model. Results under different risk levels and risk decision space would be analyzed, which would be helpful for risk management in agricultural land-use planning problems.

2 Methodology

Consider a management problem wherein the agriculture authority is responsible for planning the land-use for multiple crops and generating irrigation management schemes under water resources shortage. The objective is to maximize the economic benefit of agricultural land-use system in the region over the planning horizon. Based on the local policies of agricultural management, a predefined land-use target should be suggested to each agricultural sector in the region before the available irrigation water resources (generated by reservoir inflow) is known (i.e., a first-stage decision needs to be designed at the beginning of the planning process), so that farmers could arrange their crop production activities according to their targets. Suppose an area of land that is suggested to each crop in each subarea, if the amount is fully irrigated during the growth period, it will result in net benefits to the farmers; however, if no irrigation water is available, either irrigation water must be obtained from alternative and more expensive sources or the land irrigation demand must be curtailed, resulting in penalties on local economy (Huang and Loucks, 2000; Li et al., 2010). Then, when the available irrigation water is known, a second-stage decision has to be made in order to adjust the predefined decision and minimize the penalties due to any infeasibility. This is a typical two-stage stochastic programming (TSP) problem. Uncertainties in many system components and their interrelationships might have significant impacts on decision making, and should be considered in the management problem. Therefore, the problem can be formulated as an inexact two-stage stochastic programming (ITSP) model as follows (Model 1).

System objective: in this ITSP model, the system objective is to maximize the net system benefit, which is generated from target income and recourse cost. Target income is the ideal resulting benefit of the first-stage decision, while recourse cost is the cost of the second-stage decision in case of any infeasibilities (i.e., water shortages), which is an expectation value of different second-stage decisions corresponding to various values of the random event (i.e., irrigation water availability). Thus, the system objective can be formulated as follows:

$$\text{Max } f^{\pm} = \sum_{i=1}^{I}\sum_{j=1}^{J} NB_{ij}^{\pm} LT_{ij}^{\pm} - \sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{k=1}^{K} p_k C_{ij}^{\pm} LD_{ijk}^{\pm}, \tag{1a}$$

where $f^{\pm}$ is the expected net system benefit, CNY; i is the subarea, $i = 1,2,...,I$, and I is the total number of subareas; j is the crop, $j = 1,2,...,J$, , and J is the total number of crops; $NB_{ij}^{\pm}$ is the net production benefit for crop j in subarea i per unit of land if properly irrigated, CNY; $LT_{ij}^{\pm}$ is the land-use target for crop j in subarea i, hectare; k is the available irrigation water scenario (i.e., reservoir inflow scenario), $k = 1,2,...,K$, and K is the total number of scenarios; p_k is the probability of scenario k; $C_{ij}^{\pm}$ is the reduction of net benefit (penalty) for crop j in subarea i when per unit of crop land not irrigated, CNY; $LD_{ijk}^{\pm}$ is the area by which land irrigated target ($LT_{ij}^{\pm}$) is not met under scenario k, hectare.

System constraints: in many land use planning problems, the system constraints might include land availability, irrigation water availability, capital availability, and a number of technical and environmental concerns (Lu et al., 2012). However, the study area in this paper faces serious water shortage, and water availability is the dominant constraint of the management problem. Moreover, this paper aims at studying the risk management caused by water availability. Therefore, only water availability and model-related technical constraints are considered in this model:

$$\sum_{i=1}^{I}\sum_{j=1}^{J} w_j^{\pm}(LT_{ij}^{\pm} - LD_{ijk}^{\pm}) \leqslant W_k^{\pm},\ \forall k, \tag{1b}$$

$$LD_{ijk}^{\pm} \leqslant LT_{ij}^{\pm},\ \forall i,j,k, \tag{1c}$$

$$0 \leqslant LD_{ijk}^{\pm},\ \forall i,j,k, \tag{1d}$$

where $w_j^{\pm}$ is the irrigation quota for crop j, m^3/ha; $W_k^{\pm}$ is the amount of water available for irrigation under scenario k, m^3. Constraint (1b) is irrigation water availability constraint, which ensures that the total irrigation water of agricultural practice in each random scenario would not exceed the available amount of irrigation water. Constraint (1c) is land-use technical constraints to ensure that the land irrigation deficit of a certain subarea in the second-stage decision would be less than the land use target in the first-stage decision. Constraint (1d) is model technical constraint that ensures each decision variable would be non-negative.

Therefore, the problem is formulated as: objective Eq. (1a) subject to constraint (1b) to (1d). Decision variables are $LT_{ij\,opt}^{\pm}$ and $LD_{ijk}^{\pm}$, while the others are input parameters. Uncertainties associated with various system components are presented as either discrete random variables or interval numbers. Parameters with a superscript $\pm$ are interval parameters. For example, the available amount of irrigation water under scenario k is $W_k^{\pm}$, where W_k^- and W_k^+ are the lower and upper bounds of interval number $W_k^{\pm}$, respectively. When W_k^- equals W_k^+, $W_k^{\pm}$ becomes a deterministic number.

Model (1) is a risk-neutral model in the sense that it is concerned with the optimization of an expectation objective. Such a model normally has the tendency to generate optimal solutions that promise a large amount of land-use targeted to the agricultural sector with a high system benefit; meanwhile, the risk of water shortage in such a sector would lead to tremendous losses should an extremely adverse condition occur. Risk aversion could be understood as the behavior of a manager to stay away from risky decision practices, even if these practices have high chances of profits (Carneiro et al., 2010). A common approach to address random risk is to maximize the object function value subjected to a certain level of risk loss. The Conditional Value-at-Risk (CVaR) model, as a modified form of the Value at Risk (VaR) model, could be used to examine the risk loss under specific probabilistic distributions (Andersson et al., 2001). VaR is defined as the maximum loss to be incurred during a certain period or among different scenarios at a given level of cumulative probability distribution, whereas CVaR is defined as the mean loss given that the loss is greater than or equal to the VaR value (Rockafellar and Uryasev, 2002). To reflect and calculate the extreme expected loss in Model (1), the possible risk loss will be estimated and reflected in the model constraints through incorporating CVaR concepts. This leads to the formulation of an inexact risk management model (IRM) based on the ITSP model with CVaR constraints. In detail, an IRM model for agricultural land-use planning can be written as:

$$\text{Max } f^{\pm} = \sum_{i=1}^{I}\sum_{j=1}^{J} NB_{ij}^{\pm} LT_{ij}^{\pm} - \sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{k=1}^{K} p_k C_{ij}^{\pm} LD_{ijk}^{\pm}, \tag{2a}$$

subjected to

$$\text{CVaR}[LT_{ij}^{\pm},\, v(\xi_l)] \leqslant \beta, \tag{2b}$$

$$\sum_{i=1}^{I}\sum_{j=1}^{J} w_j^{\pm}(LT_{ij}^{\pm} - LD_{ijk}^{\pm}) \leqslant W_k^{\pm},\ \forall k, \tag{2c}$$

$$LD_{ijk}^{\pm} \leqslant LT_{ij}^{\pm},\ \forall i,j,k, \tag{2d}$$

$$0 \leqslant LD_{ijk}^{\pm},\ \forall i,j,k, \tag{2e}$$

where Eq. (2b) means that the acceptable loss should not exceed a threshold; β is the maximum acceptable loss (i.e., threshold) set by decision-makers. According to Rockafellar and Uryasev (2002), the following equation can be used to compute the value of CVaR(x):

$$\begin{aligned}\text{CVaR}(x) &= E\{|\xi \in R|\psi(x,\xi) \geqslant \alpha\} \\ &= (1-\alpha)^{-1}\int_{L(x,\omega)>\xi_\alpha(x)} L(x,\omega)p(\omega)\mathrm{d}\omega,\end{aligned} \tag{3a}$$

where x is the vector of decision variables; $p(\omega)$ is the probability that the loss is not greater than ξ which represents a threshold; ω is a random parameter with a probability distribution $p(\omega)$; ξ is the maximum loss; α is the predefined confidence level; $\xi_\alpha(x)$ means the maximum loss associated with the cumulative probability α and the decision variables; $L(x,\omega)$ is the loss function; $\psi(x,\xi)$ is the cumulative distribution function of $L(x,\omega)$. In order to solve the optimization model involved with CVaR, discrete scenarios of CVaR should be used (Rockafellar and Uryasev, 2002).

$$\text{CVaR}(x) = \xi_\alpha + \frac{1}{1-\alpha}\sum_{s=1}^{S} p_s \eta_s,\ \forall s \tag{4a}$$

subjected to

$$L_s(x_n,\omega) - \xi_\alpha - \eta_s \leqslant 0,\ \forall s \tag{4b}$$

$$\eta_s \geqslant 0,\ \forall s \tag{4c}$$

where p_s is the probability of scenario s; s is the index of scenarios where $s = 1, 2, \ldots, S$, and S is the total number of scenarios; ξ_α and η_s are positive auxiliary variables.

Thus, Model (2) can be converted to:

$$\text{Max } f^{\pm} = \sum_{i=1}^{I}\sum_{j=1}^{J} NB_{ij}^{\pm} LT_{ij}^{\pm} - \sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{k=1}^{K} p_k C_{ij}^{\pm} LD_{ijk}^{\pm} \tag{5a}$$

subjected to

$$\xi_\alpha + \frac{1}{1-\alpha}\sum_{k=1}^{K} p_k \eta_k \leqslant \beta,\ \forall k \tag{5b}$$

$$L_k(LD_{jk},\, \omega) - \xi_\alpha - \eta_k \leqslant 0,\ \forall k \tag{5c}$$

$$\eta_k \geqslant 0,\ \forall k \tag{5d}$$

$$\sum_{i=1}^{I}\sum_{j=1}^{J} w_j^{\pm}(LT_{ij}^{\pm} - LD_{ijk}^{\pm}) \leqslant W_k^{\pm},\ \forall k \tag{5e}$$

$$LD_{ijk}^{\pm} \leqslant LT_{ij}^{\pm},\ \forall i,j,k \tag{5f}$$

$$LD_{ijk}^{\pm} \geqslant 0,\ \forall i,j,k \tag{5g}$$

where $L_k(LD_{jk},\omega)$ is the loss function at scenario k; α is the confidence level, indicating that the cumulative probability of loss being lower than ξ_α is α; ξ_α is an auxiliary variable, which is the maximum loss at the cumulative probability α; β is the maximum acceptable loss set; η_k is a positive auxiliary variable.

Model (6) can be transformed into two deterministic submodels, which correspond to the lower and upper bounds of the desired objective function value. This transformation process is based on an interactive algorithm, which is different from best/worst case analysis (Huang et al., 1994). The resulting solutions provide intervals for the objective function and decision variables, and can be interpreted for generating decision alternatives (Li et al., 2006). Since the objective is to maximize the net system benefit, the submodel corresponding to the upper-bound objective function value (i.e.,f^{+}) is first desired. Thus, we have (assume $NB_{ij}^{\pm} > 0$, $C_{ij}^{\pm} > 0$, and $W_k^{\pm} > 0$):

$$\text{Max} f^{+} = \sum_{i=1}^{I}\sum_{j=1}^{J} NB_{ij}^{\pm}(LT_{ij}^{-} + \Delta LT_{ij} z_{ij})$$

$$-\sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{k=1}^{K}p_k C_{ij}^{-} LD_{ijk}^{-} \quad (6a)$$

subjected to

$$\xi_\alpha + \frac{1}{1-\alpha}\sum_{k=1}^{K}p_k\eta_k \leqslant \beta, \forall k \quad (6b)$$

$$L_k(LD_{jk}^{-},\omega) - \xi_\alpha - \eta_k \leqslant 0, \forall k \quad (6c)$$

$$\eta_k \geqslant 0, \forall k \quad (6d)$$

$$\sum_{i=1}^{I}\sum_{j=1}^{J} w_j^{-}(LT_{ij}^{-} + \Delta LT_{ij}z_{ij} - LD_{ijk}^{-}) \leqslant W_k^{+}, \forall k \quad (6e)$$

$$LD_{ijk}^{-} \leqslant LT_{ij}^{-} + \Delta LT_{ij}z_{ij}, \forall i,j,k \quad (6f)$$

$$LD_{ijk}^{-} \geqslant 0, \forall i,j,k \quad (6g)$$

$$z_{ij} \geqslant 0, \forall i,j \quad (6h)$$

where z_{ij} and LD_{ijk}^{-} are decision variables; $\Delta LT_{ij} = LT_{ij}^{+} - LT_{ij}^{-}$. Let z_{opt}, $LD_{ijk\,opt}^{-}$ and f_{opt}^{+} be the solutions of submodel (6). The optimized first-stage variable are $LT_{ij\,opt}^{\pm} = LT_{ij}^{-} + \Delta LT_{ij}z_{ij}$, which correspond to the optimized upper-bound objective-function value. Then, the submodel corresponding to f^{-} can be formulated as follows:

$$\text{Max } f^{-} = \sum_{i=1}^{I}\sum_{j=1}^{J} NB_{ij}^{-}(LT_{ij\,opt}^{\pm}) - \sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{k=1}^{K}p_k C_{ij}^{+} LD_{ijk}^{+} \quad (7a)$$

subjected to

$$\sum_{i=1}^{I}\sum_{j=1}^{J} w_j^{+}(LT_{ij\,opt}^{\pm} - LD_{ijk}^{+}) \leqslant W_k^{-}, \forall k \quad (7b)$$

$$LD_{ijk}^{+} \leqslant LT_{ij\,opt}^{\pm}, \forall i,j,k \quad (7c)$$

$$LD_{ijk}^{-} \leqslant LD_{ijk}^{+}, \forall i,j,k \quad (7d)$$

where LD_{ijk}^{+} are decision variables. Suppose $LD_{ijk\,opt}^{+}$ and f_{opt}^{-} are solutions from the submodel. Thus, solutions for model (6) under the optimized first-stage decision ($LT_{ij\,opt}^{\pm}$) can be obtained as follows:

$$f_{opt}^{\pm} = [f_{opt}^{-}, f_{opt}^{+}] \quad (8a)$$

$$LT_{ij\,opt}^{\pm} = LT_{ij}^{-} + \Delta LT_{ij}z_{ij}, \forall i,j \quad (8b)$$

$$LD_{ijk\,opt}^{\pm} = [LD_{ijk\,opt}^{-}, LD_{ijk\,opt}^{+}], \forall i,j,k \quad (8c)$$

3 Case study

3.1 Description of the study system

The developed model is applied to the Zhangweinan River Basin, a typical agricultural region facing serious water shortage in North China. The basin is approximately 37,700 km^2, ranging in longitude from 112°E to 118°E, and in latitude from 35°N to 39°N. It stretches through Shanxi, Henan, Hebei, Shandong provinces and Tianjin municipality (EBCZR, 2003). The topography of the basin consists of mountainous areas in the west and plain areas in the east. The basin is located in the semi-arid, semi-humid monsoon climate of temperate zone, with an average annual temperature of 14°C and an average annual precipitation of 608.4 mm. Precipitation varies greatly among different seasons. For example, precipitation in summer, especially in July and August, accounts for more than half of annual precipitation, while that in winter accounts for only 2% of annual precipitation (EBCZR, 2003). Soils in the basin are mainly heavy clay loams, loams, or sand soil, which are suitable for crop cultivation (EBCZR, 2003). Many crops are planted in the basin, such as wheat, maize, cotton, oil plants, and vegetables. Among them, wheat, maize, and cotton are the main crops and consume the majority of irrigation water[1)].The average water amount per capita in the Zhangweinan River Basin is 212 m^3, which is only 7.42% of the average level in China. Conflicts exist among these competing crops in different districts due to limited irrigation water availability. Moreover, serious water scarcity is associated with large temporal variations of precipitation and drought often occurs in this agricultural area[1)]. Therefore, sound planning of agricultural land-use with respect to various water availabilities is the main concern of local government.

In this study, the agricultural are irrigated by Yuecheng Reservoir is chosen as the study area. Yuecheng Reservoir is the largest reservoir in the Zhangweinan River Basin, which is responsible for irrigation of 146.67 × 10^3 ha crop land. The average inflow of the reservoir is 0.76 × 10^9 m^3 from 1962 to 2007, with a maximum inflow of 4.82 × 10^9 m^3 and a minimum inflow of 0.03 × 10^9 m^3[2)]. According to the administrative division, the districts are divided into 15 subareas (presented in Fig. 1).

In this case, the authority is responsible for planning

1) HRCC (Hai River Conservancy Committee) (2003). Investigation and Evaluation of Water Resources in Zhangweinan River.
2) DRIZRA (Design and Research Institute of Zhangweinan River Administration) (2008). Management Policy and Operation Regulation Report of Yuecheng Reservoir.

three crops' land-use in 15 subareas and generating land irrigation scheme under water shortage and water resources variation. Since local agricultural development heavily relies on the availability of water supply, the adaptive strategies to water resources variation are of high importance to local government. When the amount of available water is insufficient, water shortage would occur, leading to a loss of benefit. However, the extent of the damage may change from economic loss to system impairment when the degree of water shortage increases. When water insufficiency reaches an extreme high level, the impairment may lead to collapse of regional socio-economic system. Furthermore, the existence of multiple uncertainties associated with the land-use system will aggravate the risk of system impairment and failure. Therefore, it is also desired that the risk control be considered in agricultural land-use planning. The problem under consideration turns into how to effectively plan various agricultural land-use in order to achieve a maximum benefit under uncertainties, subjected to the constraint of a certain level of risk aversion. To solve such a problem, the proposed IRM model in Section 2 will be used. In the modelling formulation process, some simplification of the study system is made:

1) Only surface irrigation water as well as agricultural land areas supposed to be irrigated by surface water from the Yuecheng Reservoir are considered. The groundwater irrigation subsystem in the study area is not included because surface water supply is the key random factor and would contribute the main decision risk, while the ground water supply is comparatively very stable. This paper focuses on risk analysis of the land use management system, thus we only focus on surface water.

2) Three main kinds of agricultural land-use type: wheat, maize and cotton, are considered. According to the management policy and regulations[1)], surface irrigation water is mainly used to irrigate the above three types of agricultural land. Other agricultural land use types like vegetable, oil plant, and fruit, merely consume any surface water from Yuecheng Reservoir and thus are neglected.

3) Only water shortage and variation are considered as the impact factors of the agricultural land use planning. Other factors, such as non-point source pollution control and fluctuations of economic conditions, have only minor influence on the planning decision process according to EBCZR (2003).

3.2 Data acquisition

To facilitate modeling formulation, a large number of modeling parameters are required, such as unit land-use benefit/cost, unit irrigation quota, and available irrigation water resources. These data vary with different crops and planning zones. It is difficult to provide them as deterministic values since they frequently fluctuate with the variation of many other factors. Therefore, they are considered as intervals with lower and upper bounds arising from a wide range of field investigation, historical data (2004–2009), and literature references. Table 1 presents the land-use target ($LT_{ij}^{\pm}$) for each crop in each

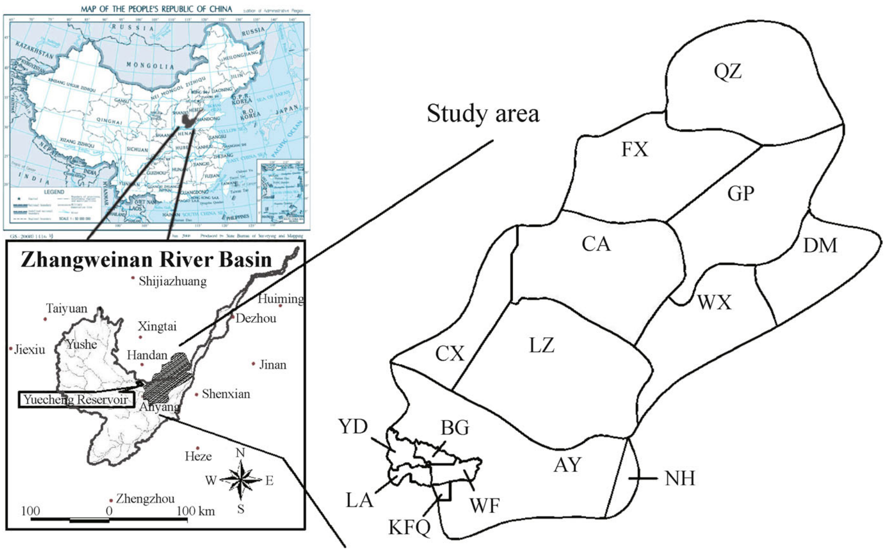

Fig. 1 The study area. (QZ, Quzhou county; FX, Feixiang county; GP, Guangping county; CA, Cheng'an county; WX, Wei county; CX, Ci Xian county; LZ, Linzhang county; DM, Daming county; WF, Wenfeng district; BG, Beiguan district; YD, Yindu district; LA, Long'an district; AY, Anyang county; NH, Neihuang county; KFQ, Kaifaqu.)

1) DRIZRA (Design and Research Institute of Zhangweinan River Administration) (2008). Management Policy and Operation Regulation Report of Yuecheng Reservoir.

subarea. As some of the crop land in the study area is irrigated by groundwater, only land-use that is supposed to be supplied by Yuecheng Reservoir is considered in this study. The land-use targets in Table 1 are presented in hectares. For each type of crop land, a corresponding irrigation quota exists, which is the water demand per unit of land in the crop's growth period. In this basin, the irrigation quota for wheat is [3.12, 3.46] $\times 10^3$ m^3/ha, while that for maize and cotton are [2.08, 2.31] $\times 10^3$ m^3/ha and [2.08, 2.31] $\times 10^3$ m^3/ha, respectively.

Table 2 presents the net irrigation benefit ($NB_{ij}^{\pm}$) and penalty ($C_{ij}^{\pm}$) of each kind of land-use in each subarea. The two parameters can be calculated by the equations below:

$$NB_{ij}^{\pm} = Y_{ij}^{\pm} \times b_{ij}^{\pm}, \tag{9a}$$

$$C_{ij}^{\pm} = NB_{ij}^{\pm} + AC_{ij}^{\pm}, \tag{9b}$$

where $Y_{ij}^{\pm}$ is the yield for crop j in subarea i when per unit land is fully irrigated, (tonne/hectare); $b_{ij}^{\pm}$ is the net benefit of per unit yield for crop j in subarea i, which is the subtraction value of sales price and production cost, (10^3 CNY/tonne); $AC_{ij}^{\pm}$ is the additional cost in case of water shortage. If no surface irrigation water is delivered, either irrigation water must be obtained from more expensive water sources (e.g., groundwater) or the land irrigation demand must be curtailed, resulting in penalties on local economy. $AC_{ij}^{\pm}$ are estimated values according to groundwater irrigation cost and economic loss by crop yield reduction, $AC_{ij}^{\pm} > 0$. In this paper, only data of $NB_{ij}^{\pm}$ and $C_{ij}^{\pm}$ are presented while that of $Y_{ij}^{\pm}$, $b_{ij}^{\pm}$, and $AC_{ij}^{\pm}$ are omitted.

As the inflow of the Yuecheng Reservoir is stochastic and varies significantly in different years, it is divided into seven discrete intervals with probabilities to approximate the stochastic inflow value. Thus, seven reservoir inflows are generated, which are named by very-low, low, low-medium, medium, medium-high, high, and very-high, respectively. Division of inflows derives from the natural inflow distribution (P-III distribution) of the reservoir, which is presented in Fig. 2. For each inflow, an interval number representing the available amount of water for irrigation could be generated. Table 3 presents the available water for irrigation ($W_k^{\pm}$) and the corresponding probabilities (p_k) under different reservoir inflows.

4 Results analysis

4.1 Land-use planning and management schemes under different risk levels

The optimization model is coded and solved by LINGO 11.0, which is a commercial optimization platform. Since IRM is based on ITSP, the solutions show characteristics of an ITSP model. Firstly, the objective function values and most of the decision variables are interval numbers, indicating the promulgation effect of interval inputs. For example, when α = 0.90 and β = 250 $\times$ 10^6 CNY, the objective function value would be [53.22, 149.96] $\times$ 10^6 CNY. The solution corresponding to the upper bound of the system benefit (i.e., $f^{\pm}$) is obtained under the most optimistic condition (e.g., high net benefit income) when the land irrigation deficits (i.e., $LD_{ijk}^{\pm}$) are at their lower bounds; meanwhile, the objective function value corre-

Table 1 Agricultural land-use targets

Subarea	Agricultural land-use targets, $LT_{ij}^{\pm}$ /(ha·yr^{-1})		
	Wheat	Maize	Cotton
QZ	[1730, 1830]	[1770, 1870]	[870, 1000]
FX	[2570, 2680]	[2000, 2200]	[1050, 1150]
GP	[1430, 1570]	[1050, 1200]	[550, 650]
CA	[2730, 2925]	[1716, 1820]	[1820, 2080]
WX	[2550, 2670]	[2280, 2490]	[144, 174]
CX	[1145, 1207.5]	[1145, 1250]	[95, 117.5]
LZ	[4860, 5140]	[4400, 4740]	[600, 734]
DM	[2070, 2175]	[990, 1072.5]	[55.5, 64.5]
WF	[1980, 2025]	[2010, 2160]	[120, 150]
BG	[420, 450]	[420, 450]	[6, 12]
YD	[645, 675]	[630, 675]	[4.5, 7.5]
LA	[1950, 2070]	[1590, 1680]	[225, 255]
AY	[8000, 8667.5]	[9167.5, 10000]	[450, 492.5]
NH	[1354.7, 1430.6]	[437, 483]	[89.7, 128.8]
KGQ	[255, 270]	[240, 270]	0

Table 2 Net land-use benefits and penalties

	Subarea	Wheat	Maize	Cotton
Net benefit when the crop land is irrigated, $NB_{ij}^{\pm}$ /(10^3CNY·ha^{-1})	QZ	[2.18, 2.67]	[2.75, 3.25]	[1.91, 3.43]
	FX	[2.38, 2.90]	[3.44, 4.09]	[2.54, 4.41]
	GP	[2.34, 2.85]	[3.35, 3.96]	[1.91, 3.31]
	CA	[2.54, 3.14]	[3.50, 4.17]	[2.01, 3.43]
	WX	[2.24, 2.74]	[2.73, 3.25]	[1.84, 3.19]
	CX	[2.20, 2.69]	[2.78, 3.30]	[1.88, 3.38]
	LZ	[2.55, 3.11]	[3.53, 4.20]	[1.98, 3.43]
	DM	[2.32, 2.83]	[3.00, 3.54]	[1.40, 2.57]
	WF	[2.34, 2.90]	[2.73, 3.22]	[0.96, 1.96]
	BG	[2.44, 3.04]	[3.10, 3.75]	[1.98, 3.68]
	YD	[2.34, 2.90]	[3.25, 3.91]	[2.35, 4.41]
	LA	[1.33, 1.73]	[2.28, 2.80]	[1.18, 2.45]
	AY	[2.42, 3.00]	[2.91, 3.46]	[1.10, 2.33]
	NH	[2.28, 2.81]	[3.05, 3.62]	[1.91, 3.68]
	KGQ	[2.55, 3.18]	[3.00, 3.59]	–
Penalty when crop land is not irrigated, $C_{ij}^{\pm}$ /(10^3CNY·ha^{-1})	QZ	[3.27, 3.42]	[3.65, 3.75]	[3.83, 3.93]
	FX	[3.50, 3.65]	[4.49, 4.59]	[4.81, 4.91]
	GP	[3.45, 3.60]	[4.36, 4.46]	[3.71, 3.81]
	CA	[3.74, 3.89]	[4.57, 4.67]	[3.83, 3.93]
	WX	[3.34, 3.49]	[3.65, 3.75]	[3.59, 3.69]
	CX	[3.29, 3.44]	[3.70, 3.80]	[3.78, 3.88]
	LZ	[3.71, 3.86]	[4.60, 4.70]	[3.83, 3.93]
	DM	[3.43, 3.58]	[3.94, 4.04]	[2.97, 3.07]
	WF	[3.50, 3.65]	[3.62, 3.72]	[2.36, 2.46]
	BG	[3.64, 3.79]	[4.15, 4.25]	[4.08, 4.18]
	YD	[3.50, 3.65]	[4.31, 4.41]	[4.81, 4.91]
	LA	[2.33, 2.48]	[3.20, 3.30]	[2.85, 2.95]
	AY	[3.60, 3.75]	[3.86, 3.96]	[2.73, 2.83]
	NH	[3.41, 3.56]	[4.02, 4.12]	[4.08, 4.18]
	KGQ	[3.78, 3.93]	[3.99, 4.09]	[4.08, 4.18]

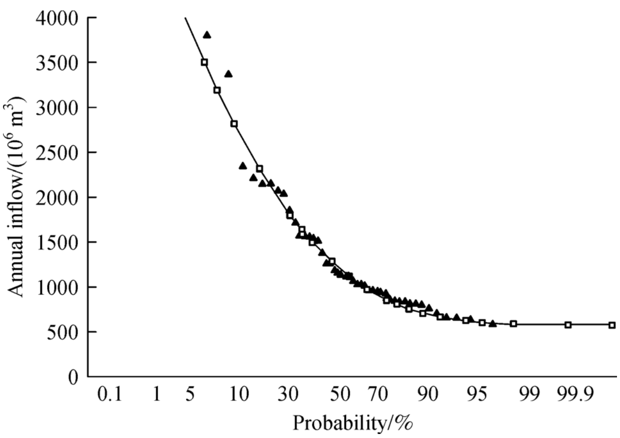

Fig. 2 Annual inflow distribution of Yuecheng Reservoir (from 1956 to 2000).

Table 3 Available water resources for irrigation under different reservoir inflows

Reservoir inflow level	Probability	Available water resources for irrigation, $W_k^{\pm}$ /(10^6 m^3· yr^{-1})
Very-Low	0.17	0
Low	0.09	[19.58, 53.39]
Low-Medium	0.14	[53.39, 108.05]
Medium	0.25	[108.05, 127.25]
Medium-High	0.20	[127.25, 168.16]
High	0.10	[168.16, 222.76]
Very-High	0.05	[233.06, 302.71]

sponds to the most pessimistic condition when the land irrigation deficits reach their upper-bound levels. In practical applications, the decision-makers could adjust the decision variables within their solution intervals by incorporating the stakeholder's implicit knowledge and preference.

Secondly, the obtained solutions from the IRM model show the tendency to achieve high benefit under a specific CVaR constraint. Generally, irrigation water would firstly be guaranteed to the maize sector, followed by the cotton and then the wheat sectors. For example, when $\alpha = 0.90$ and $\beta = 240 \times 10^6$ CNY, the solutions of $LD_{422}^{\pm}$, $LD_{432}^{\pm}$, $LD_{412}^{\pm}$ would be 0, [0, 1820] ha and 2,730 ha. This indicates that, under low scenario in CA, there would be no unirrigated land for maize; but [0, 1820] ha and 2,730 ha unirrigated land would occur for cotton and wheat, respectively. The results of $LD_{524}^{\pm}$, $LD_{534}^{\pm}$, $LD_{514}^{\pm}$ would be 0, 0, 2,550 ha. This indicates that, under medium scenario in WX, there will be no unirrigated land for maize and cotton, while a shortage level of 2,550 ha land would occur for wheat. The solutions of $LD_{725}^{\pm}$, $LD_{735}^{\pm}$, $LD_{715}^{\pm}$ (all zeroes) denote that, under a medium-high scenario in LZ, there would be no unirrigated land for all crops. This is because maize would bring the highest benefit when the crop is fully irrigated and would be subjected to the highest penalty if the promised land-use is not irrigated; cotton and wheat, however, would have lower benefits and penalties.

Solutions of the IRM model also possess characteristics of a CVaR model where the trade-off between system benefit and risk control could be analyzed. This could be reflected by assigning different α values (confidence levels) to the model, given a fixed β value. Take solutions under $\beta = 240 \times 10^6$ CNY while $\alpha = 0.82$, 0.83, 0.84 as an example (as presented in Supplementary material), a number of decision variables such as land-use targets ($LT_{ij}^{\pm}$),and land irrigation deficit ($LD_{ijk}^{\pm}$) would vary with the change of α. For example, the land-use target of cotton in QZ ($LT_{131\ opt}^{\pm}$) would decrease from1,000 ha to 910 ha and 870 ha when α value increases from 0.82 to 0.83 and 0.84. When available irrigation water is at the low level, the land irrigation deficit of maize in CX ($LD_{622}^{\pm}$) would be (1,250, [994, 1145] and [0, 1145]) ha under $\alpha = 0.82$, 0.83, 0.84, respectively; while when available irrigation water is at the medium level, the land irrigation deficit of wheat in LZ ($LD_{714}^{\pm}$)would be ([0, 2698], [0, 1466] and [0, 325]) ha when α value is 0.82, 0.83 and 0.84, respectively. This shows that with the increase of confidence level (i.e., α value), land-use targets would decrease, leading to reduced amount of land irrigation deficits under the same irrigation water availability condition; and thus the extreme risk could be lowered and the system reliability be enhanced. On the contrary, when α value is lower, the solutions would result in a higher possibility of system loss under extreme conditions. Different values of the decision variables would also lead to different objective function values ($f^{\pm}$) of the model, which would be [52.47, 150.15] $\times 10^6$ CNY, [53.64, 149.13] $\times 10^6$ CNY and [53.92, 147.07] $\times 10^6$ CNY under $\alpha = 0.82$, 0.83, and 0.84, respectively. This indicates that, higher confidence level (i.e., α value) would correspond to a lower possible maximum system benefit (i. e., lower upper bound value of system benefit) and a more stable system outcome (i.e., narrower interval range of system benefit); conversely, if the planner aims towards a greater return, a higher risk may have to be confronted. Generally, the effect of risk measure on the modeling outputs could be adjusted by changing α value. In real-world applications, the decision-makers may need to choose between a conservative solution with a lower benefit and a more risky solution with a higher benefit. Thus, a trade-off analysis would have to be made.

The tradeoff between system benefit and risk aversion could also be analyzed by assigning different β values (maximum acceptable risk loss) in the model constraints when α is fixed. Figures 3 and 4 present examples of the optimized land-use targets and related irrigation management schemes generated by the IRM model under different β values ($\beta_1 = 260 \times 10^6$ CNY, $\beta_2 = 250 \times 10^6$ CNY, $\beta_3 = 240 \times 10^6$ CNY). For example, the optimized land-use target for maize in WF (T_{92opt}) would decrease from 2,160 ha to 2,104 ha and 2,010 ha when α is fixed at 0.90 and β changes from β_1 to β_3. When the available quantity of irrigation water is at the low-medium level, the amount of unirrigated wheat in AY would be ([7611, 8000], [6919, 8000] and [5207, 8000]) ha under β_1, β_2, and β_3, respectively. The corresponding expected system benefits

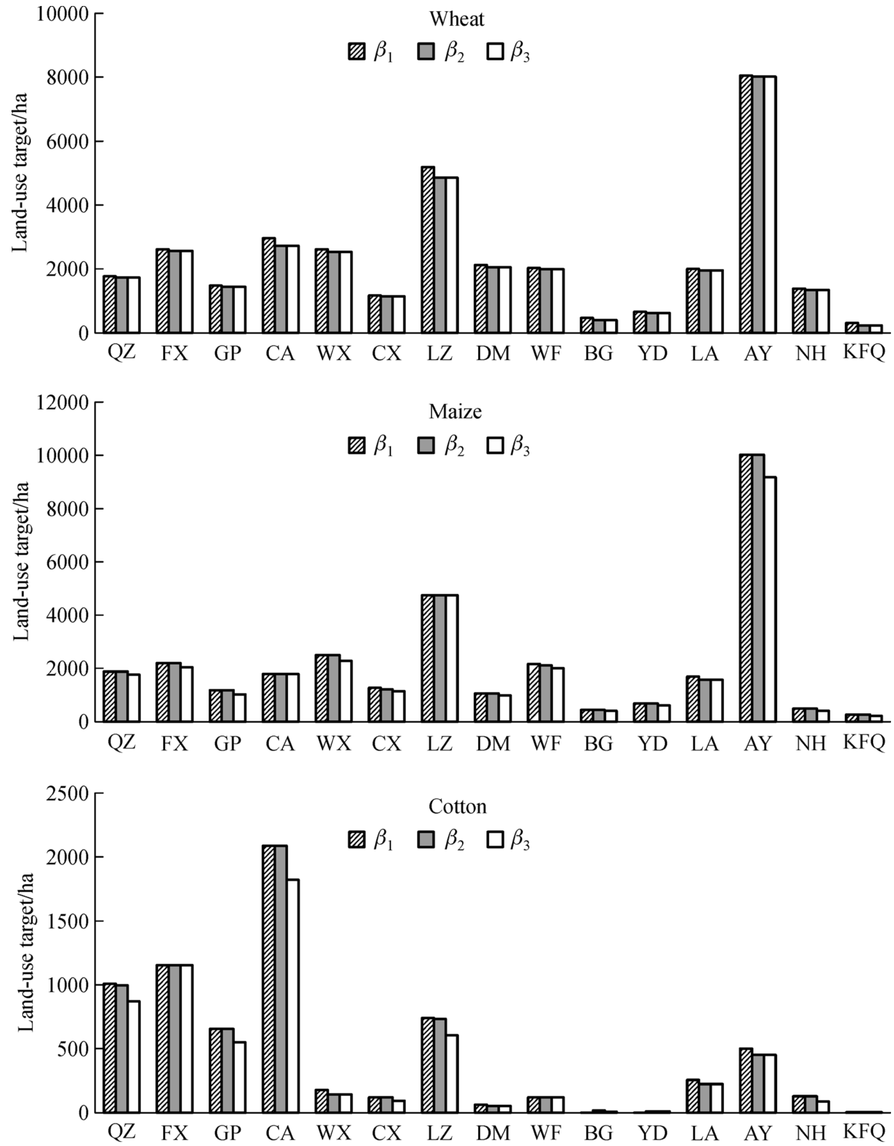

Fig. 3 Optimized land-use targets of three crops under different β levels when α is 0.90. ($\beta_1 = 260 \times 10^6$ CNY, $\beta_2 = 250 \times 10^6$ CNY, $\beta_3 = 240 \times 10^6$ CNY).

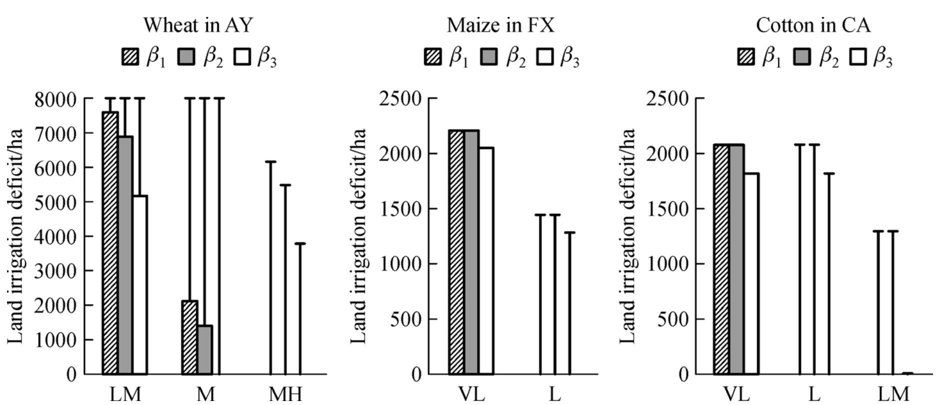

Fig. 4 Land irrigation deficits of wheat in AY, maize in FX and cotton in CA under different β levels when α is 0.90. ($\beta_1 = 260 \times 10^6$ CNY, $\beta_2 = 250 \times 10^6$ CNY, $\beta_3 = 240 \times 10^6$ CNY).

under different β values would be [52.47, 150.15] $\times 10^6$ CNY, [53.22, 149.96] $\times 10^6$ CNY and [53.92, 147.07] $\times 10^6$ CNY, respectively. Generally, as β decreases, the land-use targets will decrease, leading to a decreased amount of land irrigation deficits and a lower expected system benefits with a narrower interval range of the objective function value. The reason is that when the acceptable risk loss decreases, the risk constraint would become stringent; consequently, the planning scheme with a lower system benefit is more attractive to decision-makers. On the contrary, a higher β value would result in alternatives with a higher system benefit.

4.2 Risk decision-making analysis

Risk sensitivity analysis is of significant importance for risk decision-making. In the IRM model, risk parameters are α and β, where α is confidence level of the system while β is the acceptable risk loss of the decision-maker. After a number of test runs, it was found that, if β value is too small, the optimal solutions would not be obtained as the risk constraint is too stringent; meanwhile, when β value is very large, the risk constraint becomes insignificant as the decision-makers are willing to accept a high economic loss. Figure 5 shows the sensitivity analysis results for the effects of α and β on system benefit. As described in Section 2, the CVaR constraints are directly incorporated into the submodel corresponding to f^+, thus only the effects on the upper bound of system benefit are analyzed. It appears that different combinations of α and β levels would influence the optimal objective value. A lower acceptable risk loss (β) and a higher confidence level (α) could give rise to a lower system benefit; conversely, a higher acceptable risk loss and a lower confidence level would create a higher system benefit. Thus, land-use managers could assign different α and β values to adjust risk-control levels based on their preferences.

Another fact from Fig. 5 is that α and β have different sensitivity levels. When the α value is fixed, different objective values can be obtained at different β levels. However, with an increase of the β value, the variation degree of the objective value would decrease gradually. This indicates that the risk constraint in effect is weakening. When β increases to approximately 260 $\times 10^6$ CNY, the objective value under different α levels would be nearly constant, indicating that the risk constraint is of insignificant effect. Moreover, different α values would correspond to different feasible β value ranges. Thus, α and β values in the CVaR constraint should be properly chosen in order to avoid invalidation of risk control.

By analyzing the relationship between α and β values, the risk decision space of this agricultural land-use planning system could be generated, as illustrated in Fig. 6. The black line denotes the minimum feasible β values ($\beta_{\min}$) under different α values, while the gray line denotes the maximum sensitive β values ($\beta_{\max}$) under various α values. When β value is lower than $\beta_{\min}$, the system would be infeasible; when β value is higher than $\beta_{\max}$, the optimized planning schemes under different β values would be the same. The two lines divide the decision space into 3 parts: infeasible area, sensitive area, and stable area. Infeasible area means risk decisions (i.e., combination of α and β values) in the area are invalid, because the system would not generate proper management schemes under this condition. Sensitive area means that the optimized management scheme would change with different risk levels in this area, while stable area means the optimized management schemes under different risk decisions in this area would be the same. In the risk decision space, decisions in sensitive area demand the manager's particular attention for a small change of risk level might result in significant difference on management schemes. Generally, the infeasible area is very large, indicating that the system would bear a certain risk in many cases because of sever water scarcity and large water resource variation. This is because water scarcity in this area is so severe that management can hardly be done under a low system risk loss with a high confidence level. Sensitive area is very narrow compared to the large stable

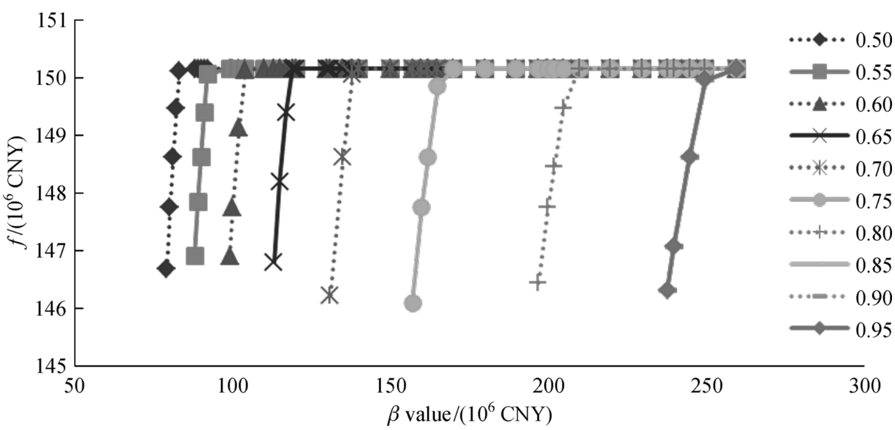

Fig. 5 Distribution of the upper bounds of the system benefits under different α and β values.

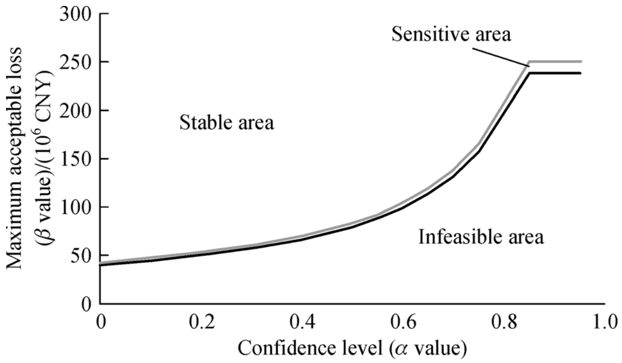

Fig. 6 The risk decision space of the agricultural land-use planning system. (The black line denotes the minimum feasible β value under different α value, while the gray line denotes the maximum sensitive β value under various α values. A higher α value would result in lower extreme risk and higher system reliability, while a higher β value would result in higher system benefit with a higher extreme risk and lower system reliability.)

area, which means the optimized management schemes under system risk are comparatively stable. The risk decision space generated by the IRM model would be very useful for land-use managers to gain insights and make decisions.

Although reasonable solutions could be generated by the developed IRM model, it also shows a few limitations and needs improvement in further studies. As for the presented case study, only surface water was considered and many system constraints were neglected for simplicity. Since groundwater plays a significant part in agricultural irrigation in this basin and many other agricultural areas, and some other constraints might come into effect under certain conditions, integration of groundwater and more system constraints into the model framework deserves future research efforts. As for the mathematic model, the IRM model may encounter difficulties when the model's right side parameters are highly uncertain (i.e., parameters with wide intervals). Such a limitation could be solved through incorporation of other effective tools such as fuzzy flexible programming or chance-constrained programming. In addition, the obtained solutions from the IRM model are represented as a number of alternatives under different risk control levels. Selection of a suitable alternative among the obtained interval solutions under different α and β values is of significant complexity and might affect the applicability of this model. A potential solution might be the use of multiple attribute decision-making (MADM) methods.

5 Conclusions

An inexact risk management (IRM) model was developed in this study to support agricultural land-use planning and risk analysis under water shortage. A risk measure, as described by CVaR, was incorporated within the IRM model to represent the expected losses under extreme water resource conditions. A real case in the Zhangweinan River Basin, China, was studied to demonstrate the applicability of the proposed model. Planning schemes and their economic implications under different risk levels were analyzed and risk decision space was generated. Solutions analysis of the IRM model show that: 1) with the increase of confidence level (i.e., α value), land-use targets would decrease, leading to reduced amount of land irrigation deficits under water shortage and a lower possible maximum system benefit, and thus the extreme risk could be lowered and the system reliability be enhanced; 2) as the maximum acceptable risk loss (i.e., β value) increases, the land-use targets will increase, leading to increased land irrigation deficits under water shortage and higher expected system benefits; 3) the risk decision space can be generated by the relationship between feasible α and β, which could be divided into infeasible area, sensitive area, and stable area; 4) in the study agricultural system, infeasible area of the risk decision space is very large, indicating that the system might be infeasible unless proper risk management actions are taken, while sensitive area is very narrow compared to the large stable area, which means the management schemes under system risk are comparatively stable. Generally, the results indicated that the IRM model was useful for reflecting the decision-maker's attitude toward risk management in agricultural land use planning and could help seek cost-effective strategies under complex uncertainties.

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