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A hybrid fuzzy-stochastic programming method for water trading within an agricultural system

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ABSTRACT

In this study, a hybrid fuzzy-stochastic programming method is developed for planning water trading under uncertainties of randomness and fuzziness. The method can deal with recourse water allocation problems generated by randomness in water availability and, at the same time, tackle uncertainties expressed as fuzzy sets in the trading system. The developed method is applied to a water trading program within an agricultural system in the Zhangweinan River Basin, China. Results can reflect the decisions for water allocation and crop irrigation under various flow levels; this allows corrective actions to be taken based on the predefined policies for cropping patterns and can thus help minimize the penalty due to water deficit. The results indicate that trading can release excess water while still keeping the same agricultural revenue obtained in a non-trading scheme. This implies that trading scheme is effective for obtaining high economic benefit, particularly for one water-resources scarcity region. Results also indicate that the effectiveness of the trading program is explicitly affected by uncertainties expressed as randomness and fuzziness, which challenges the users to make decisions of their water demands due to uncertain water availability. Sensitivity analysis is also conducted to analyze the impacts of trading costs, demonstrating that the trading efforts could become ineffective when the trading costs are too high.

1. Introduction

Over the past decades, controversial and conflict-laden water resources allocation issue has challenged decision makers due to rising demand pressure for freshwater associated with a variety of factors such as population growth, economic development, food security, environmental concern, and climate change. Shrinking water availability and deteriorating water quality have exacerbated such competitions, leading to complexities in generating desired decisions for usable freshwater allocation. Practically, around 70% of global freshwater diverted to agriculture and, at the same time, irrigation water demand is still increasing because the farmland being irrigated continues to be expanded (Cai et al., 2003). Water shortage is subject to increasing pressure particularly for many semi-arid and arid regions that are mainly characterized by low rainfall and high evaporation. When the demand for water has reached the limits of what the natural system can provide with, water shortage may become a major obstacle to social and economic development for the region. Awareness of growing water scarcity has led to increasing interest in modeling of water resources systems, both in terms of supply and demand, with the aim of developing and implementing appropriate water resources infrastructure and management strategies (Davies and Simonovic, 2011).

Market-based approach to water allocation problem has been advocated, which has been expected to provide gains in economic efficiency since water can be reallocated from lower- to higher-value when water becomes increasingly scarce (Turral et al., 2005). Water trading, which is market-based strategy and can provide cost-effective and flexible-reallocation compliance in watershed, has been recognized as one of the most promising policy alternatives for addressing water shortage problems. Trading helps equalize the marginal prices faced by various water users, thereby providing information about the value of water in alternative uses and creating compatible incentives (Chong and Sunding, 2006; Wang, 2011). The concept of water trading has received an increasing amount of attention amidst a growing world population, with its increased need for food security and associated impacts on increasingly scarce water resources (Dabrowski et al., 2009). Especially in semi-arid and arid regions, valuable water can be released through trading to improve deteriorated water quality and endangered ecosystems (Rosegrant et al., 1995; Landry, 1998).

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Nomenclature

i	agricultural irrigation subarea, and $i = 1,2,\ldots,15$
j	the main crops in the river basin, $j = 1$ for wheat, $j = 2$ for maize, and $j = 3$ for cotton
h	water level of inflow, $h = 1,2,\ldots,7$ with $h = 1$ representing low level, $h = 7$ representing very-high level
$\widetilde{B}_{ij}$	benefit parameter for crop j in subarea i per unit of water allocated (US$/ha), which is expressed as fuzzy sets with known trapezoidal membership functions
$\widetilde{C}_{ij}$	reduction of net benefit (economic loss) per unit of water not delivered to crop j in subarea i (US$/ha), which is expressed as fuzzy sets with known trapezoidal membership functions, and $\widetilde{C}_{ij} \geqslant \widetilde{B}_{ij}$
Y_{ijh}	probabilistic deficit of cropland that cannot be irrigated by the surface water under level h (ha), which is the recourse decision variable
f	net system benefit over the planning horizon ($)
p_h	related probability of inflow level, with $p_h > 0$ and $\sum p_h = 1$
$\widetilde{\theta}_j$	irrigation coefficient for crop j in subarea i (10^3 m^3/ha), which is used for identifying the relationship between water and cropland
$\widetilde{\gamma}$	fuzzy tolerance measure for water availability
R_h	available flow from the reservoir under level h (m^3)
X_{ij}	irrigation target of crop j in subarea i (ha), which is the first-stage decision variable
$X_{ij}^{\max}$	maximum irrigation area of crop j in subarea i (ha)
$X_{ij}^{\min}$	minimum irrigation area of crop j in subarea i (ha)
W_{ij}	water permit to crop j in subarea i (m^3)

Previously, numerous water trading programs have been established and/or under development throughout the world (Becker et al., 1996; Tisdell, 2001; Brookshire et al., 2004; Dabrowski et al., 2009; Smajgl et al., 2009; Zaman et al., 2009; Kirnbauer and Baetz, 2012). However, such trading programs in practice have not always been implemented successfully on account of the heterogeneity of the river basins to which they are applied, due to the variety of hydrological and climatic regimes within each basin as well as the inherent difficulties in assessing economic impacts and tradable permits.

In water trading programs, uncertainties that exist in many system parameters and their interrelationships could intensify the conflict-laden issue of water allocation among multiple competing interests (e.g., municipal, industrial, agricultural and ecological). Although a number of research efforts have disclosed that water trading effectiveness is explicitly influenced by various uncertainties existing in water resources systems, the problem induced by randomness in water availability has not been well treated (Jenkins and Lund, 2000; Etchells et al., 2004; Gohar and Ward, 2010; Deviney et al., 2012; Xu et al., 2012; Graveline et al., 2012). For example, available water resources are influenced by stochastic events such as temperature and precipitation, which are not measured with certainty but in fact represented as a probability distribution around the actual streamflow. A random water supply can make trading efficient in a dry season, while it may become unnecessary during a wet season (Luo et al., 2007). The targeted water use (associated with various municipal, industrial and agricultural activities) often needs be optimally allocated in order to get a maximized system benefit. However, such efforts can be complicated since the water-use targets are often determined before the amount of available water is known. If the target is regulated high, it will bring high net-system benefit when water demand is satisfied; however, it can result in penalties if the demand cannot be met; conversely, reducing target means a low risk of penalties when water is in shortage but it will also not maximize the utility of water resources. Such a recourse problem could become further complicated by not only interactions among uncertain system components but also economic implications of water trading. Moreover, in water resources allocation problems, uncertainties may exist as multiple levels: vagueness and/or impreciseness in the outcomes of a random sample, and randomness and/or fuzziness in the lower and upper bounds of an interval (Li and Huang, 2009). These complexities have placed water trading programs beyond the conventional systems analysis methods.

The aim of this study is to develop a hybrid fuzzy-stochastic programming method for planning water trading, where uncertainties can be directly communicated into the optimization process through representing the uncertain parameters as fuzzy sets, random variables, and their combinations. The paper will be organized as follows: Section 2 is devoted to advancing the hybrid fuzzy-stochastic programming method, such that how stochastic programming to be coupled with fuzzy programming are described; Section 3 provides a case study for examining the potential for irrigation water trading as a measure to improve the utility of water resources in the Zhangweinan River Basin; Section 4 presents result analysis and discussion, where both trading efficiency on allocated water and cropped area and trading-cost consequence on the system effectiveness are analyzed; some conclusions are drawn in Section 5.

2. Methodology

When uncertainties are expressed as probability distributions while decisions need to be made periodically over time, the study problem can be formulated as a two-stage stochastic programming (TSP) with recourse model. In TSP, decision variables are divided into two subsets: those that must be determined before the realizations of random variables are disclosed and those (recourse variables) that will be determined after the realized values of the random variables are available (Birge and Louveaux, 1988; Huang and Loucks, 2000; Li et al., 2010a). Therefore, the TSP methods require decision makers to assign a cost to recourse activities that are taken to ensure feasibility of the second-stage problem. This means that, in TSP, infeasibilities in the second stage are allowed at a certain penalty (i.e. the second-stage decision is used to minimize penalty that may appear due to any infeasibility). A TSP model can be formulated as follows:

$$\text{Max} \quad f = cx - E[Q(x,\omega)] \tag{1a}$$

$$\text{s.t.} \quad Ax \leqslant b \tag{1b}$$

$$x \geqslant 0 \tag{1c}$$

where x is the first-stage anticipated decisions made before the random variables are observed, and $Q(x, \xi)$ is the optimal value, for any given Ω, of the following nonlinear program:

$$\min \quad q(y,\omega) \tag{2a}$$

$$\text{s.t.} \quad W(\omega)y = h(\omega) - T(\omega)x \tag{2b}$$

$$y \geqslant 0 \tag{2c}$$

where y is the second-stage decision variables (i.e. recourse variables) that depend on the realization of the first-stage random vector; $q(y, \omega)$ denotes the second-stage cost function; $\{T(\omega), W(\omega), h(\omega)|\omega \in \Omega\}$ are model parameters with reasonable dimensions, and are functions of the random vector (ω). For given values of the first-stage variables (x), the second-stage problem can be decomposed into independent linear sub-problems, with one sub-problem for each realization of the uncertain parameters. Then, model (1) can be reformulated as:

$$\text{Max} \quad f = cs - E[\min_{y \geqslant 0} q(y, \omega)|T(\omega)x + W(\omega)y = h(\omega)] \tag{3a}$$

$$\text{s.t.} \quad Ax \leqslant b \tag{3b}$$

$$x \geqslant 0 \tag{3c}$$

The above TSP problem is generally nonlinear, and the set of feasible constraints is convex only under some particular distributions. However, the problem can be equivalently formulated as a linear programming model by assuming discrete distributions for the uncertain parameters (Birge and Louveaux, 1988; Huang and Loucks, 2000). Let random vector ω possess a discrete and finite distribution, with support $\Omega = \{\omega_1, \omega_2, \ldots, \omega_s\}$. Denote p_h as the probability of realization of scenario ω_h, with $p_h > 0$ and $\sum_{h=1}^{s} p_h = 1$. The expected value of the second-stage optimization problem can be expressed as:

$$E[Q(x, \omega)] = \sum_{h=1}^{s} p_h Q(x, \omega_h) \tag{4}$$

Then, based on the assumption of discrete distributions for the uncertain parameters, model (1) can be equivalently converted into the following linear program:

$$\text{Max} \quad f = cx - \sum_{h=1}^{s} p_h q(y_h, \omega_h) \tag{5a}$$

$$\text{s.t.} \quad Ax \leqslant b \tag{5b}$$

$$T(\omega_h)x + W(\omega_h)y_{\omega_h} = h(\omega_h), \omega_h \in \Omega \tag{5c}$$

$$x \geqslant 0 \tag{5d}$$

$$y_h \geqslant 0 \tag{5e}$$

The TSP model can provide a linkage between the pre-regulated policies (i.e. policies that are first formulated before values of random variables are known) and the associated economic implications (i.e. recourse actions which are made after the random variables are disclosed). In comparison, chance-constrained programming (CCP) can effectively reflect reliability of satisfying (or risk of violating) system constraints under uncertainty (Guo et al., 2010). In CCP, it is required that the constraints be satisfied under given probabilities. Based on the CCP concept, a TSP model with chance constraints can be formulated as follows:

$$\text{Max} \quad f = \sum_{j=1}^{n_1} c_j x_j - \sum_{j=1}^{n_2} \sum_{h=1}^{s} p_h d_j y_{jh} \tag{6a}$$

$$\text{s.t.} \quad \sum_{j=1}^{n_1} a_{rj} x_j \leqslant b_r, \quad r = 1, 2, \ldots, m_1 \tag{6b}$$

$$\Pr\left\{ \sum_{j=1}^{n_1} a_{ij} x_j + \sum_{j=1}^{n_2} a_{ij} y_{jh} \leqslant w_{ih} \right\} \geqslant \gamma_i, \quad i = 1, 2, \ldots, m_2; \quad h = 1, 2, \ldots, s \tag{6c}$$

$$x_j \geqslant 0, \quad j = 1, 2, \ldots, n_1 \tag{6d}$$

$$y_{jh} \geqslant 0, \quad j = 1, 2, \ldots, n_2; \quad h = 1, 2, \ldots, s \tag{6e}$$

where γ_i ($\gamma_i \in [0,1]$) is a probability level that constraint i should be satisfied with at least. Model (6) can tackle decision problems whose coefficients (input data) are not certainly known but can be represented as chances or probabilities, where probabilistic information for a limited number of uncertain parameters can be incorporated within the optimization framework. The main advantage of the stochastic programming methods is that they do not simply reduce the complexity of the programming problems; instead, they allow decision makers to have a complete view of the effects of uncertainties and the relationships between uncertain inputs and resulting solutions (Huang, 1998). However, in real-world practical problems, it is often difficult to build a probability distribution due to the lack of data or the high cost for acquiring the data. Various uncertainties may be related to the errors in acquired data, the variations in spatial and temporal units, and the incompleteness or impreciseness of observed information (Freeze et al., 1990; Mendoza et al., 1993). This can lead to dual uncertainties of randomness and fuzziness due to the fact that decision makers express different subjective judgments upon a same problem (Li et al., 2010b).

Fuzzy programming is effective in tackling ambiguous and vague information in decision-making problems, which are classified into three categories in view of the forms of uncertainties: (i) fuzzy flexible programming (FFP), (ii) fuzzy possibilistic programming (FPP), and (iii) robust programming (RP) (Zadeh, 1975; Dubois and Prade, 1988; Inuiguchi and Tanino, 2000; Li et al., 2009). In detail, FFP can deal with decision problems under fuzzy goal and constraints; however, it has difficulties in tackling ambiguous coefficients of the objective function and constraints. RP improves upon FFP by allowing fuzzy parameters in the constraints to be represented by possibility distributions; however, the main limitations of this method remain in its difficulties in tackling uncertainties in a non-fuzzy decision space. In FPP, fuzzy parameters that are regarded as possibility distributions are introduced into the modeling frameworks. FPP can handle ambiguous coefficients in the left- and right-hand sides of the constraints and in the objective function. Therefore, one potential approach for accounting for such complex uncertainties is to introduce FPP into model (6), leading to a hybrid fuzzy stochastic programming model as follows:

$$\text{Max} \quad f = \sum_{j=1}^{n_1} \tilde{c}_j x_j - \sum_{j=1}^{n_2} \sum_{h=1}^{s} p_h \tilde{d}_j y_{jh} \tag{7a}$$

$$\text{s.t.} \quad \sum_{j=1}^{n_1} \tilde{a}_{rj} x_j \leqslant \tilde{b}_r, \quad r = 1, 2, \ldots, m_1 \tag{7b}$$

$$\sum_{j=1}^{n_1} \tilde{a}_{ij} x_j + \sum_{j=1}^{n_2} \tilde{a}'_{ij} y_{jh} \leqslant \tilde{w}_{ih}, \quad i = 1, 2, \ldots, m_2; \quad h = 1, 2, \ldots, s \tag{7c}$$

$$x_j \geqslant 0, \quad j = 1, 2, \ldots, n_1 \tag{7d}$$

$$y_{jh} \geqslant 0, \quad j = 1, 2, \ldots, n_2; \quad h = 1, 2, \ldots, s \tag{7e}$$

where x_j ($j = 1,2,\ldots,n_1$) are first-stage decision variables; y_{jh} ($j = 1,2,\ldots,n_2$ and $h = 1,2,\ldots,s$) are second-stage decision variables; $\tilde{c}_j$ ($j = 1,2,\ldots,n_1$) and $\tilde{d}_j$ ($j = 1,2,\ldots,n_2$) are fuzzy coefficients in the objective function; $\tilde{a}_{ij}$ ($i = 1,2,\ldots,m_2$ and $j = 1,2,\ldots,n_1$) and $\tilde{a}'_{ij}$ ($i = 1,2,\ldots,m_2$ and $j = 1,2,\ldots,n_2$) are fuzzy coefficients in constraints; $\tilde{w}_{ih}$ ($i = 1,2,\ldots,m_2$ and $h = 1,2,\ldots,s$) are independent random variables with known probability distributions.

To solve model (7), an "equivalent" deterministic version can be defined. This can be realized by using fuzzy tolerance measure and CCP approach, which consist of fixing a probability $\tilde{q}_i$ ($\tilde{q}_i \in [0,1]$) for uncertain constraint i and imposing the condition that the constraint should be satisfied with at least a probability level of $\tilde{\gamma}_i = 1 - \tilde{q}_i$ ($i = 1,2,\ldots,m_2$ and $0 \leqslant \tilde{\gamma}_i \leqslant 1$). Then, the above fuzzy-stochastic constraint can be converted as:

$$\Pr\left\{ \sum_{j=1}^{n_1} \tilde{a}_{ij} x_j + \sum_{j=1}^{n_2} \tilde{a}'_{ij} y_{jh} \leqslant \tilde{w}_{ih} \right\} \geqslant \tilde{\gamma}_i, \quad i = 1, 2, \ldots, m_2; \quad h = 1, 2, \ldots, s \tag{8}$$

Constraint (8) is generally nonlinear, and the set of feasible constraints is convex only for some particular distributions and certain levels of $\tilde{q}_i$. Based on the CCP technique, the fuzzy-stochastic constraint (i.e. formula 8) can be transformed to the following deterministic fuzzy equivalent (Iskander, 2005):

$$\sum_{j=1}^{n_1}\tilde{a}_{ij}x_j+\sum_{j=1}^{n_2}\tilde{a}'_{ij}y_{jh}\leqslant \tilde{w}_{ih}^{\tilde{q}_i},\quad i=1,2,\ldots,\quad m_2;\quad h=1,2,\ldots,s \tag{9}$$

where $\tilde{w}_{ih}^{\tilde{q}_i}=F_i^{-1}(\tilde{q}_i)$, given the cumulative distribution function of $\tilde{w}_{ih}$ [i.e. $F_i(\tilde{w}_{ih})$] and the probability of violating constraint i ($\tilde{q}_i$). Then, model (7) can be rewritten as follows:

$$\text{Max}\ \ f=\sum_{j=1}^{n_1}\tilde{c}_jx_j-\sum_{j=1}^{n_2}\sum_{h=1}^{s}p_h\tilde{d}_jy_{jh} \tag{10a}$$

$$\text{s.t.}\ \sum_{j=1}^{n_1}\tilde{a}_{rj}x_j\leqslant\tilde{b}_r,\ \ r=1,2,\ldots,m_1 \tag{10b}$$

$$\sum_{j=1}^{n_1}\tilde{a}_{ij}x_j+\sum_{j=1}^{n_2}\tilde{a}'_{ij}y_{jh}\leqslant\tilde{w}_{ih}^{\tilde{q}_i},\ \ i=1,2,\ldots,m_2;\ \ h=1,2,\ldots,s \tag{10c}$$

$$x_j\geqslant 0,\ \ j=1,2,\ldots,n_1 \tag{10d}$$

$$y_{jh}\geqslant 0,\ \ j=1,2,\ldots,n_2\ \ h=1,2,\ldots,s \tag{10e}$$

A two-step solution method is proposed to solve the above model. Its solutions can be presented as combinations of probabilistic and possibilistic information, and thus offer flexibility in result interpretation and decision-alternative generation. The possibility distributions of fuzzy parameters can be characterized as fuzzy sets. For example, fuzzy parameter $\tilde{b}_r=(\underline{b}_r,b_{r1},b_{r2},\bar{b}_r)$ can be presented as a triangular fuzzy set when $b_{r1}=b_{r2}$, or a trapezoidal fuzzy set when $b_{r1}<b_{r2}$. Parameter $\tilde{a}_{ij}$ under each α-cut level can be included within a closed interval: $[(1-\alpha)\underline{b}_r\ +\alpha(b_{r1}),(1-\alpha)(b_{r2})+\alpha(\bar{b}_r)]$. An α-cut can be defined as a set of elements that belong to a fuzzy set at least to a membership grade of α; this grade is also called the degree of confidence or the degree of plausibility (Zimmermann, 1996). It ranges from 0 to 1, and can be pre-regulated. The most credible value is assigned a membership grade of 1; any number that falls short of the lowest possible value or exceeds the highest possible value will get a membership grade of 0. Then, model (10) can be directly transformed into two deterministic submodels that correspond to the lower and upper bounds of the objective-function value.

Lower submodel

$$f^l=\sum_{j=1}^{n_1}[(1-\alpha)\underline{c}_j+\alpha c_{j1}]x_j-\sum_{j=1}^{n_2}\sum_{h=1}^{s}p_h[(1-\alpha)\bar{d}_j+\alpha d_{j2}]y_{jh} \tag{11a}$$

$$\text{s.t}\ \sum_{j=1}^{n_1}[(1-\alpha)\bar{a}_{rj}+\alpha a_{rj2}]x_j\leqslant[(1-\alpha)\underline{b}_r+ab_{r1}],\ \ r=1,2,\ldots,m_1 \tag{11b}$$

$$\sum_{j=1}^{n_1}[(1-\alpha)\bar{a}_{ij}+\alpha a_{ij2}]x_j+\sum_{j=1}^{n_2}[(1-\alpha)\underline{a}'_{ij}+\alpha a'_{ij1}]y_{jh}\leqslant w_{ij}^{[(1-\alpha)q_i+\alpha q_{i1}]},\ \ i=1,2,\ldots,m_2;\ \ h=1,2,\ldots,s \tag{11c}$$

$$x_j\geqslant 0, j=1,2,\ldots,n_1 \tag{11d}$$

$$y_{jh}\geqslant 0, j=1,2,\ldots,n_2;\ \ h=1,2,\ldots,s \tag{11e}$$

Upper submodel

$$f^u=\sum_{j=1}^{n_1}[(1-\alpha)\bar{c}_j+\alpha c_{j2}]x_j-\sum_{j=1}^{n_2}\sum_{h=1}^{s}p_h[(1-\alpha)\underline{d}_j+\alpha d_{j1}]y_{jh} \tag{12a}$$

$$\text{s.t.}\ \sum_{j=1}^{n_1}[(1-\alpha)\underline{a}_{rj}+\alpha a_{rj1}]x_j\leqslant(1-\alpha)\bar{b}_r+\alpha b_{r2},\ \ r=1,2,\ldots,m_1 \tag{12b}$$

$$\sum_{j=1}^{n_1}[(1-\alpha)\underline{a}_{ij}+\alpha a_{ij1}]x_j+\sum_{j=1}^{n_2}[(1-\alpha)\bar{a}'_{ij}+\alpha a'_{ij2}]y_{jh},\leqslant w_{ih}^{[(1-\alpha)\bar{q}_i+\alpha q_{i2}]},\ \ r=1,2,\ldots,m_2;\ \ h=1,2,\ldots s \tag{12c}$$

$$x_j\geqslant 0, j=1,2,\ldots,n_1 \tag{12d}$$

$$y_{jh}\geqslant 0,\ \ j=1,2,\ldots,n_2;\ \ h=1,2,\ldots,s \tag{12e}$$

Then, solving submodels (11) and (12) under various α-cut levels (i.e. $\alpha\in[0,1]$), a set of solutions associated with probabilistic and possibilistic information for the objective and decision variables can be obtained as follows:

$$x_{jopt}=\left[x_{jopt}^l,x_{jopt}^u\right],\forall j \tag{13a}$$

$$y_{jhopt}=\left[y_{jhopt}^l,y_{jhopt}^u\right],\forall j,h \tag{13b}$$

$$f_{opt}=\left[f_{opt}^l,f_{opt}^u\right] \tag{13b}$$

3. Case study

The Zhangweinan River Basin is a tributary of the Haihe River, China. The basin covers parts of Shanxi, Henan, Hebei, Shandong Provinces as well as Tianjing Municipality, with an area of approximately 37,700 km^2. The river basin is located in the semi-arid and semi-humid monsoon climate zone, with an average year temperature of around 14 °C and annual precipitation of 608.4 mm. Precipitation varies largely among different seasons, of which more than 50% occur in July and August. The rain falls in spring, autumn and winter seasons occupy 8–16%, 13–23% and 2% of the total precipitation per year, respectively. The basin is one of the main food and cotton producing areas in the north China. Economic development and population growth in the study area continue to increase the demands for water, while satisfying these demands places increasing stress on local decision makers to support the needs for food, urban, industrial, and environmental water uses. Although the achievements of irrigation in ensuring food security and improving rural welfare have been remarkable, a number of problems (e.g., large water use, low irrigation efficiency, and environmental concerns) for irrigated agriculture have been raised. The Yuecheng Reservoir lies in Ci County of Hebei Province and Anyang County of Henan Province. It is the largest reservoir in the Zhanghe River that is one of the two main tributaries of the Zhangweinan River Basin. The reservoir has a controlled area of 18,100 km^2 and a capacity of 1.3 billion m^3. The reservoir provides storage for water supply for two cities of Anyang and Handan and irrigation for two large agricultural areas of Minyou and Zhangnan (i.e. which are further divided into 15 subareas, as shown in Fig. 1). The main land cover is cropland with cultivated crops, including wheat, maize, cotton, rice, bean, oilseed and vegetable. Wheat, maize and cotton are three main crop products. Besides crop framing, livestock husbandry, and agricultural residents also need water supplied by the reservoir. The main livestock are ox, sheep, pig and domestic fowl (chicken, duck, goose and turkey).

Since this area is one of the driest regions in China, it faces serious water scarcity. The water availability per capita is about 212 m^3 (occupying only 7.42% of the average level in China), which is far below the average level of 1000 m^3 per capita (i.e. an internationally accepted definition for water scarcity) (DRIZRA, 2008). Besides, the temporal distribution of precipitation is uneven. Most of the precipitation in one year is in the flood season in summer (e.g., rainfall during June to September accounts for about 70% of total annual precipitation), while the demand from the agricultural activities cannot often be satisfied in the dry seasons. Similar to most semi-arid and arid regions of the world, agriculture is highly dependent on the diversion of water resources for irrigation. Besides, a number of impacts such as growing population, food security challenge, emerging industrial sector, rapid economy development, lead to rising water demands from both urban and rural sectors, and thus increasing pressure on water supplies and irrigations. The inflow of Yuecheng reservoir is largely decreased due to the reduced precipitation and increased reservoirs and

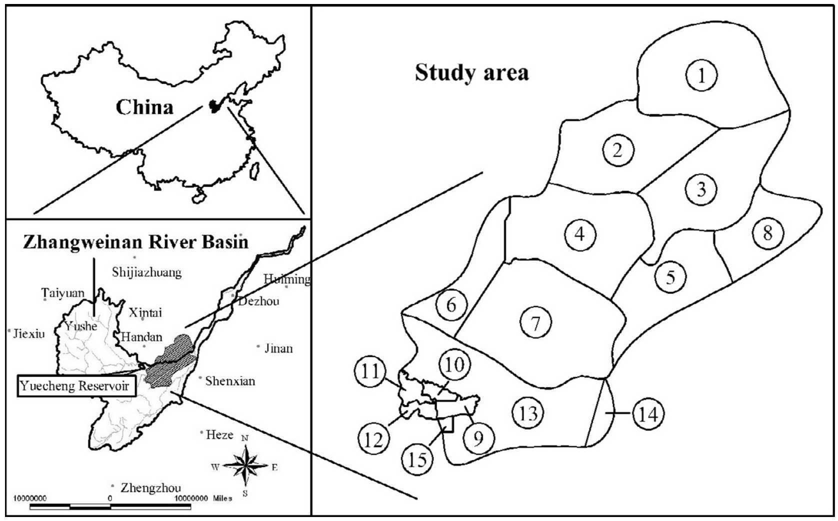

Fig. 1. The study system.

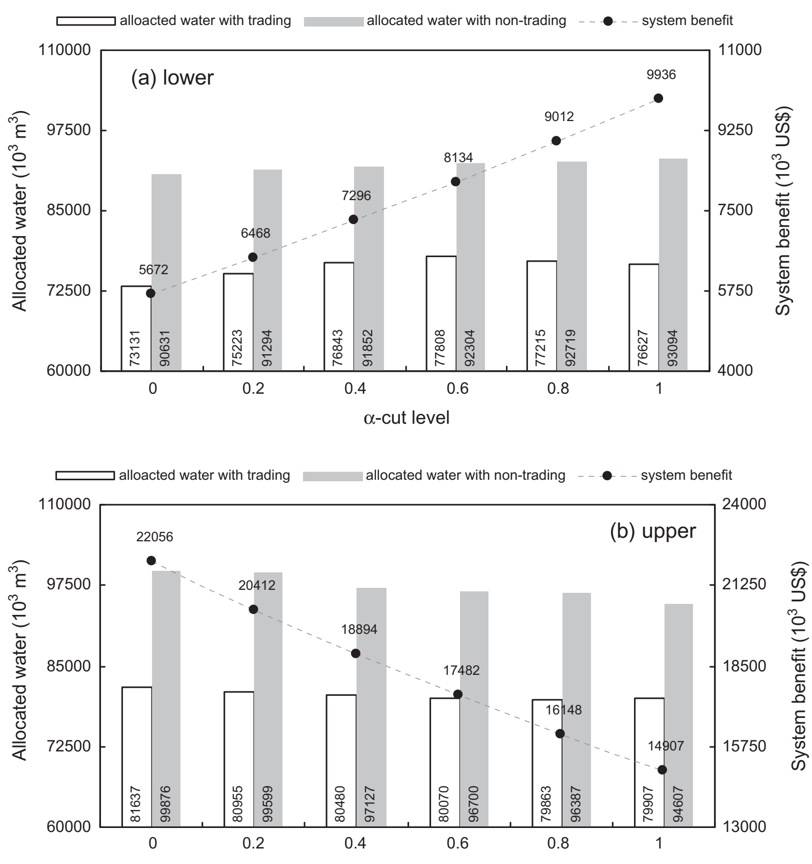

Fig. 2. Solutions for allocated water with trading and non-trading schemes.

diversion channels in the upper reaches of Zhanghe River. These factors point to the continued challenges of guarding against the regional water demands exceeding its supplies, such that water shortage turns into more and more serious for regional agricultural sector. Moreover, spatial and temporal variations exist in system components such as available inflows, cropland targets, and economic benefits/costs. These complexities could become further compounded by not only interactions among many uncertain system components but also their economic implications. Based on the hybrid fuzzy-stochastic approach advanced in Section 2, the agricultural water allocation problem in a non-trading scheme can be formulated as follows:

Table 1
Net benefit (unit: US$$10^3$/ha).

Subarea	Wheat	Maize	Cotton
1	(0.335, 0.369, 0.405, 0.445)	(0.423, 0.465, 0.512, 0.563)	(0.294, 0.323, 0.356, 0.391)
2	(0.366, 0.403, 0.443, 0.487)	(0.529, 0.582, 0.640, 0.704)	(0.391, 0.429, 0.473, 0.520)
3	(0.360, 0.396, 0.435, 0.479)	(0.515, 0.566, 0.624, 0.686)	(0.294, 0.323, 0.356, 0.391)
4	(0.391, 0.429, 0.473, 0.520)	(0.538, 0.592, 0.651, 0.717)	(0.309, 0.340, 0.374, 0.411)
5	(0.345, 0.379, 0.417, 0.459)	(0.420, 0.462, 0.508, 0.559)	(0.283, 0.311, 0.342, 0.377)
6	(0.338, 0.372, 0.409, 0.450)	(0.428, 0.470, 0.517, 0.569)	(0.289, 0.318, 0.350, 0.385)
7	(0.392, 0.431, 0.474, 0.522)	(0.543, 0.597, 0.657, 0.723)	(0.305, 0.335, 0.368, 0.405)
8	(0.357, 0.393, 0.432, 0.475)	(0.461, 0.508, 0.558, 0.614)	(0.215, 0.237, 0.261, 0.287)
9	(0.360, 0.396, 0.435, 0.479)	(0.420, 0.462, 0.508, 0.559)	(0.147, 0.162, 0.179, 0.196)
10	(0.375, 0.413, 0.454, 0.499)	(0.477, 0.524, 0.577, 0.635)	(0.304, 0.335, 0.368, 0.405)
11	(0.360, 0.396, 0.435, 0.479)	(0.510, 0.551, 0.605, 0.665)	(0.361, 0.397, 0.437, 0.481)
12	(0.204, 0.225, 0.247, 0.272)	(0.351, 0.386, 0.424, 0.467)	(0.181, 0.199, 0.219, 0.242)
13	(0.372, 0.409, 0.450, 0.495)	(0.448, 0.492, 0.542, 0.596)	(0.169, 0.186, 0.205, 0.225)
14	(0.351, 0.386, 0.424, 0.467)	(0.469, 0.516, 0.567, 0.624)	(0.294, 0.323, 0.355, 0.391)
15	(0.392, 0.431, 0.474, 0.522)	(0.461, 0.508, 0.558, 0.614)	–

Table 2
Economic penalty (unit: US$$10^3$/ha).

Subarea	Wheat	Maize	Cotton
1	(0.503, 0.553, 0.609, 0.669)	(0.561, 0.617, 0.679, 0.747)	(0.589, 0.648, 0.713, 0.784)
2	(0.538, 0.592, 0.651, 0.717)	(0.691, 0.760, 0.836, 0.919)	(0.740, 0.814, 0.895, 0.985)
3	(0.531, 0.584, 0.642, 0.706)	(0.671, 0.738, 0.812, 0.893)	(0.571, 0.628, 0.691, 0.759)
4	(0.575, 0.633, 0.696, 0.766)	(0.703, 0.773, 0.851, 0.936)	(0.589, 0.648, 0.713, 0.784)
5	(0.514, 0.565, 0.622, 0.684)	(0.561, 0.618, 0.679, 0.747)	(0.552, 0.607, 0.668, 0.735)
6	(0.506, 0.557, 0.612, 0.673)	(0.569, 0.626, 0.689, 0.758)	(0.581, 0.639, 0.704, 0.774)
7	(0.571, 0.628, 0.691, 0.759)	(0.708, 0.778, 0.856, 0.942)	(0.589, 0.648, 0.713, 0.784)
8	(0.528, 0.580, 0.638, 0.702)	(0.606, 0.667, 0.733, 0.807)	(0.457, 0.502, 0.553, 0.608)
9	(0.538, 0.592, 0.651, 0.717)	(0.557, 0.612, 0.674, 0.741)	(0.363, 0.399, 0.439, 0.483)
10	(0.560, 0.616, 0.677, 0.745)	(0.638, 0.702, 0.772, 0.850)	(0.628, 0.690, 0.759, 0.835)
11	(0.538, 0.592, 0.651, 0.716)	(0.663, 0.729, 0.802, 0.882)	(0.740, 0.814, 0.895, 0.985)
12	(0.358, 0.394, 0.434, 0.477)	(0.492, 0.541, 0.595, 0.655)	(0.438, 0.482, 0.530, 0.583)
13	(0.554, 0.609, 0.670, 0.737)	(0.594, 0.653, 0.718, 0.790)	(0.420, 0.462, 0.508, 0.559)
14	(0.524, 0.577, 0.635, 0.698)	(0.618, 0.680, 0.748, 0.823)	(0.627, 0.690, 0.759, 0.835)
15	(0.581, 0.639, 0.704, 0.774)	(0.614, 0.675, 0.743, 0.817)	–

$$\text{Max } f=\sum_{i=1}^{I}\sum_{j=1}^{J}\widetilde{B}_{ij}X_{ij}-\sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{h=1}^{H}p_h\widetilde{C}_{ij}Y_{ijh} \tag{14a}$$

$$\text{s.t. } \tilde{\theta}_j X_{ij}\leqslant W_{ij},\ \forall i,j \tag{14b}$$

$$\tilde{\theta}_j(X_{ij}-Y_{ijh})=W_{ij}\widetilde{R}_j/\sum_{i=1}^{I}\sum_{j=1}^{J}W_{ij},\ \text{ if }\sum_{i=1}^{I}\sum_{j=1}^{J}W_{ij}\geqslant\widetilde{R}_j,\ \forall i,j,h \tag{14c}$$

$$\Pr\left\{\sum_{i=1}^{I}\sum_{j=1}^{J}\tilde{\theta}_j(X_{ij}-Y_{ijh})\leqslant\widetilde{R}_j\right\}\geqslant\tilde{\gamma},\ \text{ if }\sum_{i=1}^{I}\sum_{j=1}^{J}W_{ij}<\widetilde{R}_j,\ \forall h \tag{14d}$$

$$X_{ij}^{\min}\leqslant X_{ij}\leqslant X_{ij}^{\max},\ \forall i,j \tag{14e}$$

$$X_{ij}-Y_{ijh}\geqslant 0,\ \forall i,j,h \tag{14f}$$

$$0\leqslant Y_{ijh},\ \forall i,j,h \tag{14g}$$

The detailed nomenclatures for the variables and parameters are provided in Appendix. Model (14) under consideration is how to generate desired decision alternatives for agricultural activities and water uses based on the given objectives/restrictions, in order to maximize total system benefit.

To make water allocation more benefit-effective, a water trading program is established that allows users to reallocate licensed water without violating the overall water availability (i.e. volume of available water resources). Water rights regimes based on queuing principles lead to an inefficient allocation of water resources and may also result in other inefficiencies, such as overuse of land and inadequate adoption of capital-intensive conservation

Table 3
Irrigation demand and water permit.

Subarea	Minimum irrigation (ha)			Maximum irrigation (ha)			Water permit (10^3 m^3)		
	Wheat	Maize	Cotton	Wheat	Maize	Cotton	Wheat	Maize	Cotton
1	1038	1062	520	2470	2524	1251	5190	3540	1566
2	1542	1201	630	3615	2970	1462	7710	4000	1890
3	857	630	331	2120	1620	760	4280	2100	990
4	1638	1030	1094	3948	2457	2718	8190	3432	3276
5	1530	1368	101	3604	3362	203	7650	4560	261
6	687	685	67	1630	1687	136	3435	2290	171
7	2916	2640	405	6940	6400	867	14580	8800	1080
8	1242	595	41	2936	1447	83	6210	1980	101
9	1188	1206	82	2732	2916	193	5940	4020	216
10	252	249	5	607	605	12	1260	840	18
11	387	378	4	910	907	9	1935	1260	11
12	1170	954	157	2794	2268	343	5850	3180	405
13	4795	5500	280	11700	13050	655	24000	18334	810
14	813	263	63	1931	652	174	4062	874	162
15	153	144	–	364	360	–	765	480	–

Table 4
Available water to agricultural irrigation.

α-cut level Probability ($\tilde{q}$)	α = 0 [0.05, 0.40]	α = 0.2 [0.07, 0.37]	α = 0.4 [0.09, 0.34]	α = 0.6 [0.11, 0.31]	α = 0.8 [0.13, 0.28]	α = 1 [0.15, 0.25]
Water availability (10^6 m^3)						
Very low (p = 0.165)	[7.32, 9.41]	[7.57, 9.29]	[7.78, 9.17]	[7.94, 9.04]	[8.09, 8.92]	[8.23, 8.77]
Low (p = 0.095)	[29.91, 35.49]	[30.57, 35.17]	[31.13, 34.85]	[31.57, 34.49]	[31.97, 34.16]	[32.33, 33.78]
Low-medium (p = 0.140)	[70.53, 79.18]	[71.55, 78.68]	[72.42, 78.18]	[73.10, 77.63]	[73.72, 77.13]	[74.28, 76.51]
Medium (p = 0.250)	[112.88, 116.93]	[113.36, 116.70]	[113.77, 116.47]	[114.09, 116.21]	[114.38, 115.97]	[114.64. 115.68]
Medium–high (p = 0.200)	[138.17, 146.26]	[139.13, 145.80]	[139.94, 145.33]	[140.58, 144.81]	[141.16, 144.37]	[141.68, 143.77]
High (p = 0.100)	[188.94, 198.84]	[190.11, 198.27]	[191.10, 197.70]	[191.88, 197.07]	[192.59, 196.50]	[193.23, 195.79]
Very-high (p = 0.050)	[255.28, 265.75]	[256.52, 265.15]	[257.57, 264.55]	[258.40, 263.87]	[259.15, 263.27]	[259.82, 262.52]

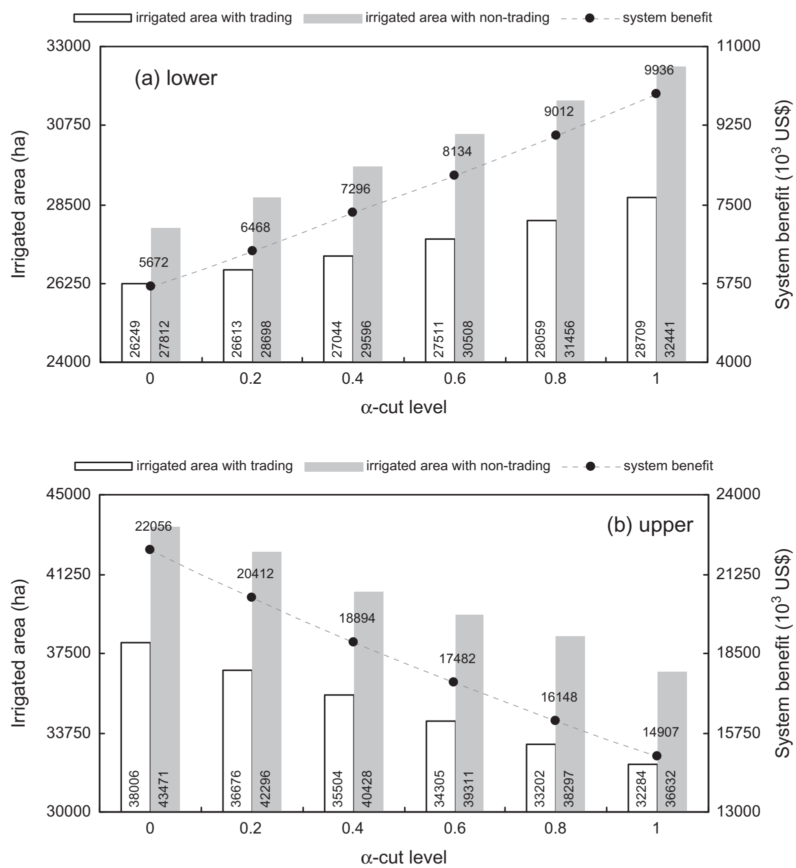

Fig. 3. Solutions for irrigated area with trading and non-trading schemes.

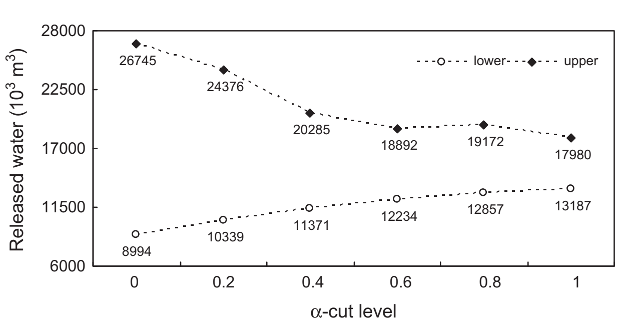

Fig. 4. Released water through trading scheme.

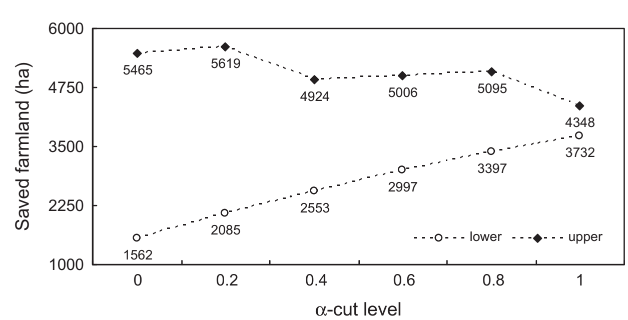

Fig. 5. Saved farmland through trading scheme.

technologies. Water trading based on transferable water rights has been advanced as a solution to these problems. It is widely recognized that irrigation water trading has considerable potential to increase the economic productivity of water by encouraging its movement from low to high valued uses where there is sufficient physical and institutional flexibility in the system to permit crop diversification (Gohar and Ward, 2010). When water is tradable, each cropland is no longer limited by its own water permit, but theoretically by the total water permit (i.e. water right) and the aggregate supply of total irrigable water of the entire system. Water can thus be transferred to its most valuable users with trading scheme. Although a number of studies have examined measures to increase effective water supplies or reduce water demands, no research to date has examined economically efficient and culturally acceptable water institutions for improving the economic performance of regional agricultural water use. To examine the potential for irrigation water trading as a measure to improve the economic efficiency of agricultural water use of the watershed, the study problem can be reformulated as follows:

$$\text{Min} \quad Z = \sum_{i=1}^{I}\sum_{j=1}^{J}\left(X_{ij} - \sum_{h=1}^{H} p_h Y_{ijh}\right) \tag{15a}$$

$$\text{s.t.} \quad \sum_{i=1}^{I}\sum_{j=1}^{J}\widetilde{B}_{ij}X_{ij} - \sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{h=1}^{H} p_h \widetilde{C}_{ij} Y_{ijh} \geqslant f_{\text{opt}} \tag{15b}$$

$$\sum_{i=1}^{I}\sum_{j=1}^{J}\tilde{\theta}_j X_{ij} \leqslant \sum_{i=1}^{I}\sum_{j=1}^{J} W_{ij} \tag{15c}$$

$$\Pr\left\{\sum_{i=1}^{I}\sum_{j=1}^{J}\tilde{\theta}_j (X_{ij} - Y_{ijh}) \leqslant \widetilde{R}_j\right\} \geqslant \tilde{\gamma}, \ \forall h \tag{15d}$$

$$X_{ij}^{\min} \leqslant X_{ij} \leqslant X_{ij}^{\max}, \ \forall i,j \tag{15e}$$

$$X_{ij} - Y_{ijh} \geqslant 0, \ \forall i,j,h \tag{15f}$$

$$0 \leqslant Y_{ijh}, \ \forall i,j,h \tag{15g}$$

where f_{opt} is the objective-function value obtained from model (14), which is the optimized value of net system benefit. The objective of model (15) is to minimize the total amount of water allocated under trading, where assume that all croplands in all subareas will participate in the trading activities and the trading system is an ideal market (Coase, 1960). Constraint (15b) ensures that the net system benefit with trading should be no less than that with non-trading scheme (i.e. maintaining the same economic value in the non-trading scheme). Water trading gives farmers greater flexibility in making decisions about their priorities for water use.

Models (14) and (15) can be solved using the two-step solution method as described in Section 2. Table 1 presents the related net benefits when the targeted croplands are irrigated by the surface water from the reservoir, which are presented in terms of fuzzy sets with known trapezoidal membership functions. Net benefit is calculated based on equation $\widetilde{B}_{ij} = Y_{ij} \cdot \Delta I_{ij} \cdot \widetilde{NB}_{ij}$, where Y_{ij} means the yield per unit of cropland (tonne/ha), ΔI_{ij} denotes increased yield due to the cropland irrigated (%), and $\widetilde{NB}_{ij}$ means the net benefit of per unit of crop (US$/tonne). The parameter inputs are mainly calculated based on representative data from a number of governmental reports and literatures (HRCC, 2003; GEF, 2007; Li et al., 2010a). For instance, the yield per unit of wheat is

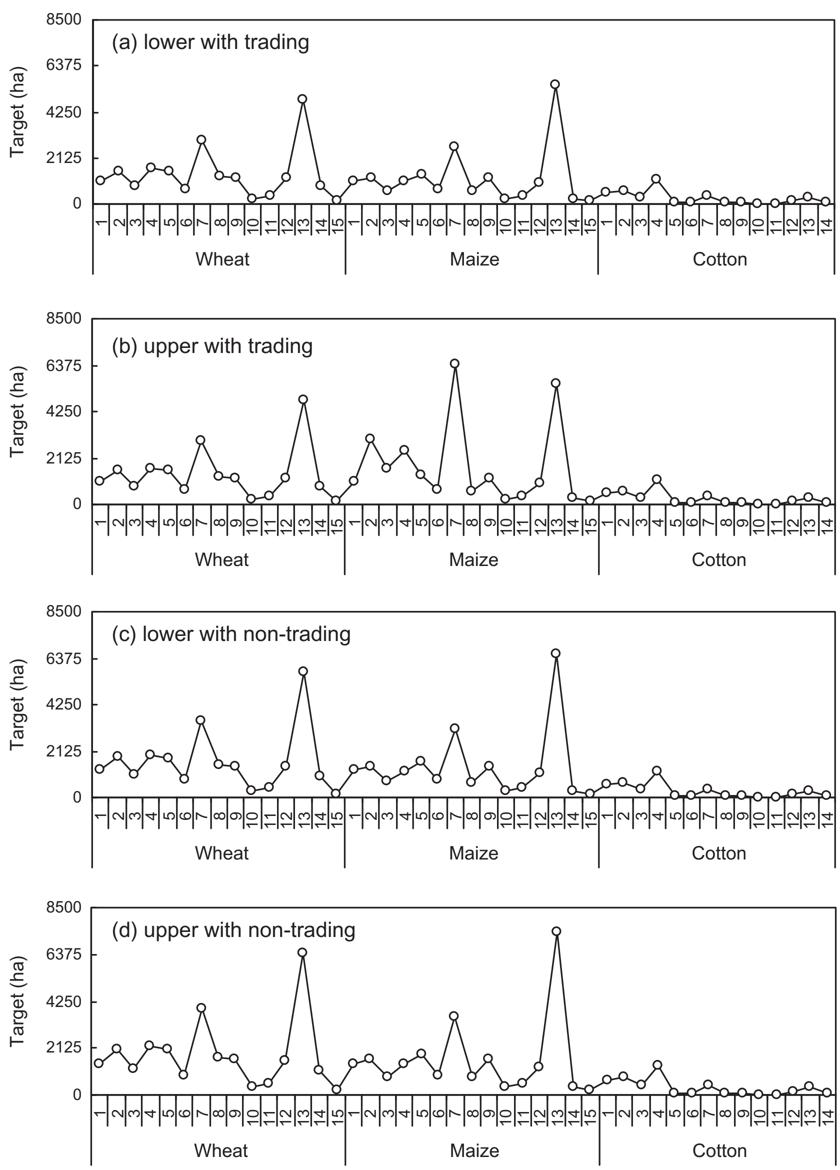

Fig. 6. Irrigation targets with trading and non-trading schemes ($\alpha = 1$).

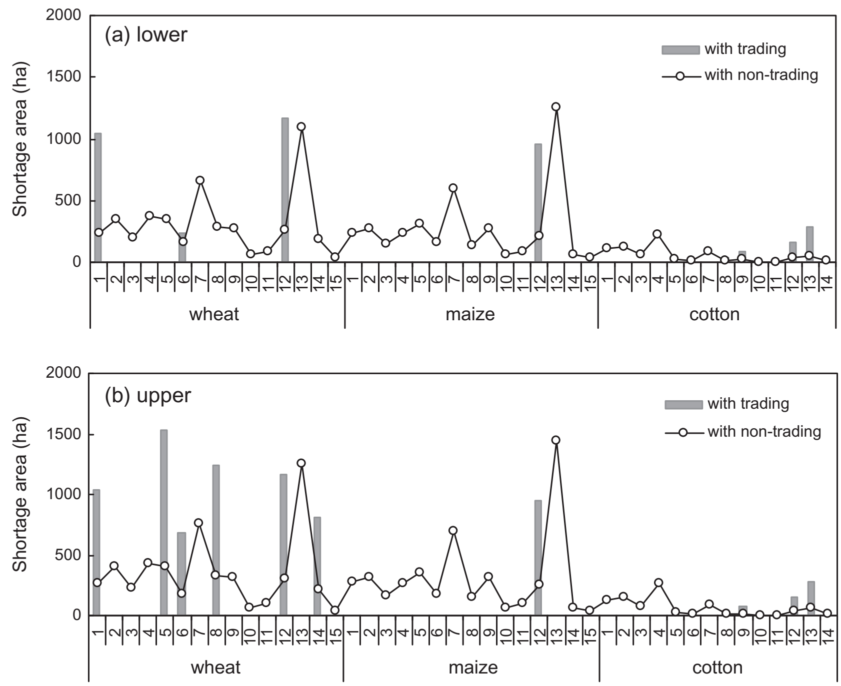

Fig. 7. Irrigation shortages with trading and non-trading under medium flow ($\alpha = 1$).

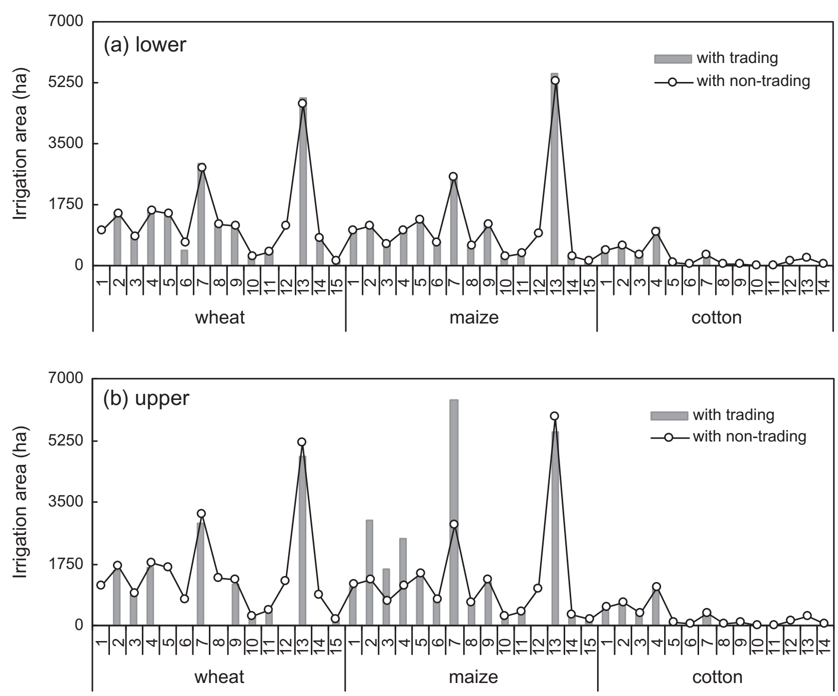

Fig. 8. Actual irrigation areas with trading and non-trading under medium flow ($\alpha = 1$).

approximately 5.6 tonne/ha in subarea 1, the increased yield (ΔI_{ij}) for wheat is about 0.6, and the net benefit from wheat is (0.10, 0.11, 0.12, 0.13) US$/tonne and expressed as fuzzy sets. Correspondingly, the net benefit ($\widetilde{B}_{ij}$) for wheat in subarea 1 can be calculated as (0.335, 0.369, 0.405, 0.445) US$/ha, as listed in Table 1. When the targeted croplands are irrigated, a net benefit to the local economy will be generated for each area of crop irrigated. Table 2 provides the economic penalty when the promised water cannot be delivered to the farmers. The economic penalty is the reduction of net benefit (economic loss) and larger than the net benefit, due to the negative consequences generated from the curbing of targeted cropland plan. Table 3 shows the minimum and maximum irrigation requirement as well as water permit for each cropland. Table 4 provides the available irrigation water associated with probabilistic and possibilistic information.

4. Result and discussion

Figs. 2 and 3 present the values of allocated water, irrigated cropland, and system benefit with trading and non-trading

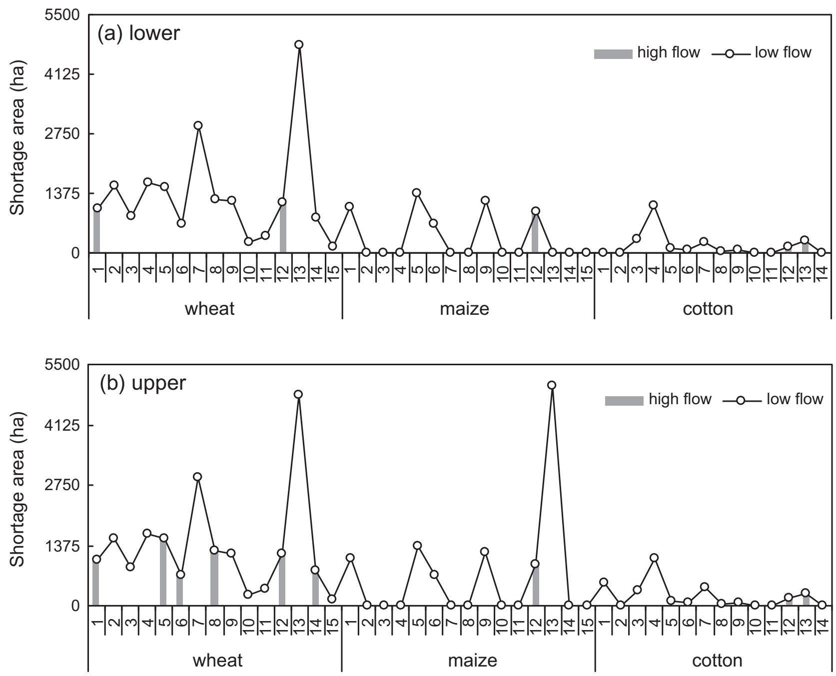

Fig. 9. Irrigation shortages under low and high flows ($\alpha = 1$ and trading).

schemes. Six α-cut levels (0, 0.2, 0.4, 0.6, 0.8 and 1) were examined; for each α-cut level, lower and upper submodels (i.e. two extreme situations) were solved. Results indicate that water-allocation and crop-irrigation schemes would both be shifted when water is tradable. For the study agricultural system in a non-trading scheme, water is conventionally allocated to each farmland in proportion to its water permit; in comparison, with the trading scheme, each crop in each subarea is no longer constrained by its own water permits but theoretically by the total water availability. Through trading, croplands with higher profitability and higher irrigation efficiency can buy credits to those with lower economic benefit and lower irrigation efficiency, leading to the water permit pre-regulated for each crop being reallocated. When $\alpha = 0$ (i.e. the lowest possibility degree), with non-trading scheme, the system would consume [90631, 99876] $\times 10^3$ m^3 of water to achieve [5672, 22056] $\times 10^3$ US$ of benefit; in comparison, with trading scheme, the system would consume [73131, 81637] $\times 10^3$ m^3 of water to acquire the same benefit; the irrigation croplands would be [27812, 43471] ha with non-trading and [26249, 38006] ha with trading; correspondingly, the released water and saved farmland would be [8994, 26745] $\times 10^3$ m^3 and [1562, 5465] ha through trading (as shown in Figs. 4 and 5). In comparison, when $\alpha = 1$ (i.e. the highest possibility degree), the system would consume [93094, 94607] $\times 10^3$ m^3 of water with non-trading and [76627, 79907] $\times 10^3$ m^3 of water with trading to obtain [9936, 14907] $\times 10^3$ US$ of benefit; the released water and saved farmland through trading would be [13187, 17980] $\times 10^3$ m^3 and [3732, 4348] ha, respectively.

For the study system in a non-trading scheme, water is conventionally allocated to each farmland in proportion to its water permit. When water is tradable, each farmland is no longer limited by its own water right, but theoretically by the total water permit and the aggregate supply of total irrigable water of the entire system. Thus, water can be transferred to its most valuable users in a trading scheme, particularly when available water is scarce in the dry season. In addition, different α-cut levels are associated with varied system conditions (i.e. water availabilities, irrigation efficiencies, and benefit/penalty parameters), and thus would lead to shifted results for water allocation, irrigation area, released water, saved farmland, as well as system benefit.

Fig. 6 presents irrigation targets of (i.e. cropped area irrigated by reservoir's surface water) wheat, maize and cotton in the fifteen subareas with trading and non-trading schemes (when $\alpha = 1$), where symbols "1" and "15" denote "subarea 1" and "subarea 15", respectively. The results indicate that the optimized irrigation targets would be different from non-trading to trading. For example, the irrigation targets for wheat in subarea 1 would be [1238, 1393] ha with non-trading and 1038 ha with trading. The total irrigation targets of all subareas would be [49419, 55668] ha with non-trading and [41893, 49839] ha with trading. Variation in the values of cropland targets reflects different policies for managing water resources and planning agricultural activities under uncertainty. A higher target level would lead to a higher benefit but, at the same time, a higher risk of water shortage (corresponding to a higher penalty level) when available flow is low; however, a lower target level would result in a higher water surplus (and thus a higher wastage for farmland and a lower system benefit) when flow is high.

Deficits would occur if the available water resources from the reservoir couldnot meet the irrigation demands. Fig. 7 presents the irrigation shortages (i.e. unirrigated area) when inflow level is medium. Under the medium flow, the total shortages would reduce from [9472, 10876] ha with non-trading to [3963, 7994] ha with trading. Fig. 8 shows the results for actual irrigation cropland with non-trading and trading schemes ($\alpha = 1$). The actual irrigated cropland is the difference between the cropped area (irrigation targets) and the unirrigated area (i.e. due to water shortage) under a given streamflow condition with an associated probability and possibility level. Under the medium flow level, the irrigated croplands would be [39947, 44792] ha with non-trading and [37930, 41845] ha with trading.

The modeling results can reflect the decisions for water allocation and crop irrigation under various flow levels. This allows corrective actions to be taken based on the predefined policies for cropping patterns, and can thus help minimize the penalty due to water deficit. Fig. 9 compares the results for actual irrigation croplands under low and high flow levels (with trading and $\alpha = 1$). When the available flow is low, the water volume deficiency is high (i.e. more cropland cannot be irrigated); in comparison, the irrigation shortage may be relatively low under high flow level. When the total irrigable water is adequate in a wet season (e.g., high flow), each farmland's irrigation requirement can easily be satisfied, such that trading becomes unnecessary. However, it could be effective in a dry season (e.g., low flow). This implies that the effectiveness of a trading system is also influenced by the randomness in the total supply of irrigable water.

The above results from models (14) and (15) show the effectiveness of water trading under an ideal market (i.e. without consideration of trading cost). In practice, transaction costs, which include the costs of creating, monitoring, and enforcing water rights, need to be considered before establishing a trading system (Bate, 2002). In this study, to quantify the effectiveness of the trading program, the effects of trading cost were measured. Figs. 10 and 11 show the relationship between released water and trading cost (i.e. lower and upper) under various α-cut levels. For example, for the lower bound ($\alpha = 1$), the volume of released water would decrease from 13187×10^3 m^3 to 18×10^3 m^3 when the trading cost increase from 0 to 2981×10^3 US$; for the upper bound ($\alpha = 1$), the volume of released water would decrease from 17980×10^3 m^3 to 216×10^3 m^3 when the trading cost increase from 0 to 4174×10^3 US$. The mean water volume (i.e. low and upper) that can be released through trading would decrease with increased trading cost, which implies that the effectiveness of a trading program has a monotone decreasing relationship to the trading cost. The results also indicate that the trading program would fail when the trading cost is too high. For example, under $\alpha = 1$, the lower-bound released water through trading would be -378×10^3 m^3 when the lower trading cost approaches 3080×10^3 US$; the upper-bound released water through trading would be -455×10^3 m^3 when the upper trading cost approaches 4323×10^3 US$. Under such a situation, it would be ineffective to establish a trading program.

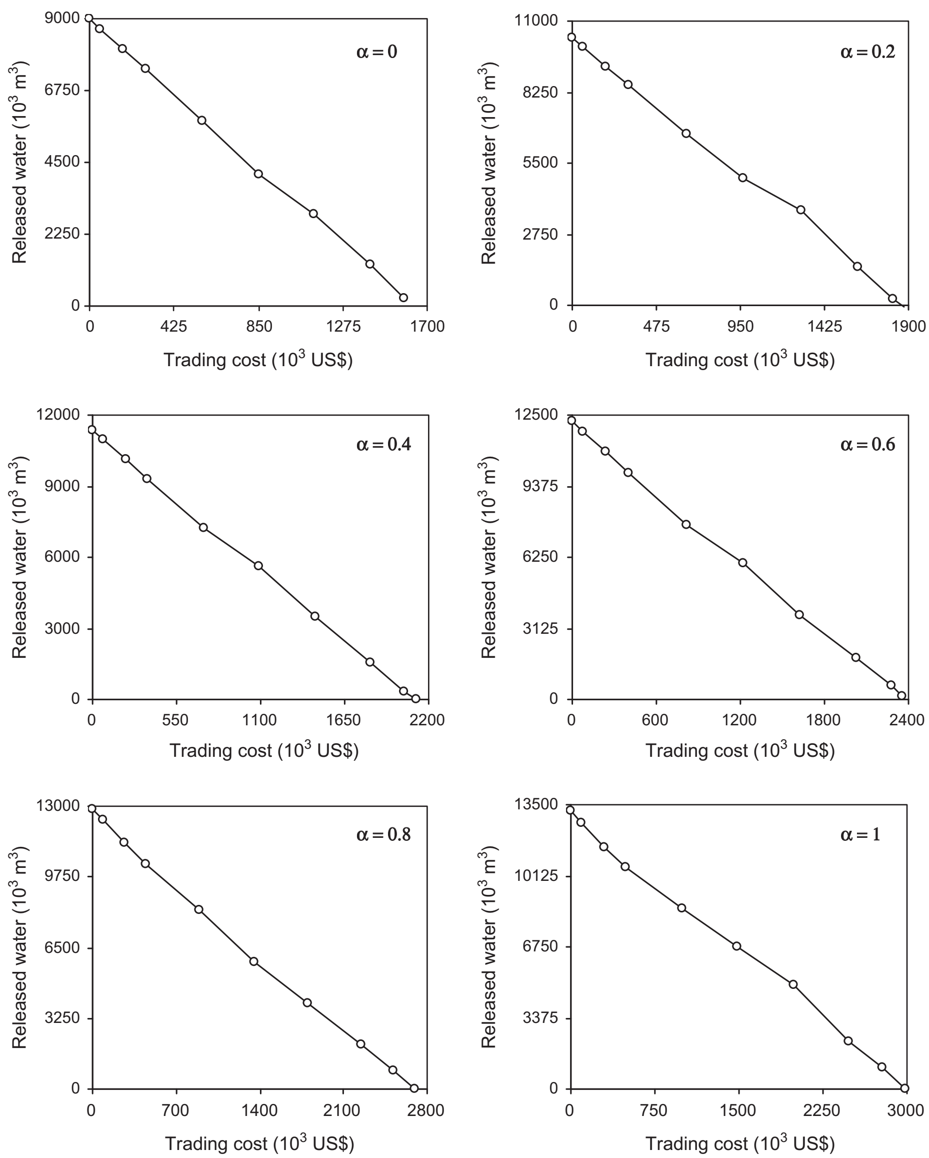

Fig. 10. Relationship between released water and trading cost (lower bound).

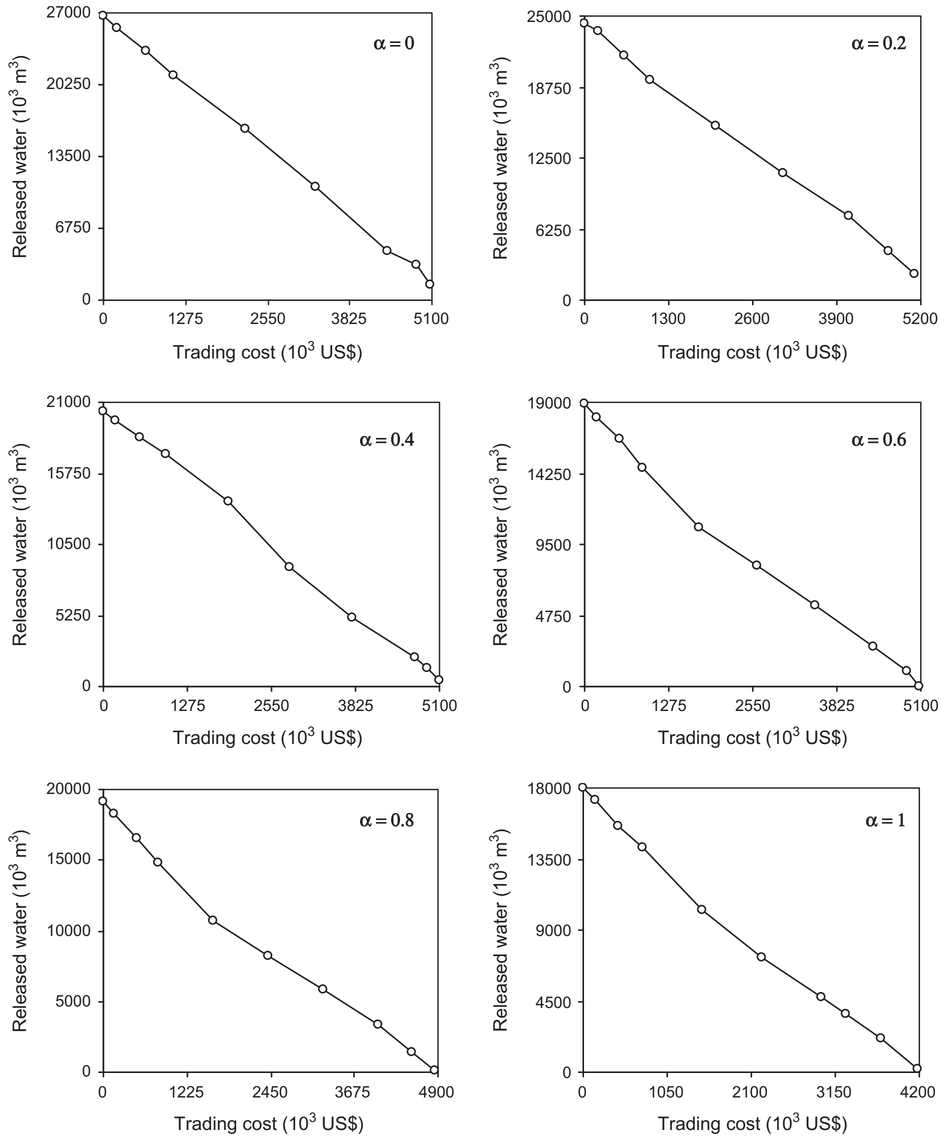

Fig. 11. Relationship between released water and trading cost (upper bound).

5. Conclusions

In this study, a hybrid fuzzy-stochastic programming method has been developed for planning water trading under uncertainty. The developed method has two major advantages in comparison to other optimization techniques for water trading. Firstly, it can incorporate pre-regulated water-allocation policies directly into its modeling formulation, such that an effective linkage between resources-allocation regulations and economic implications (i.e. penalties) caused by improper policies due to uncertainty existence can be provided. Secondly, multiple uncertainties (existed as fuzzy sets, random variables, and their combinations) could be directly communicated into the optimization process, leading to enhanced system robustness for uncertainty reflection. The developed method has been tested with a hypothetical water trading program within multi-crop and multi-farmland system in the Zhangweinan River Basin in China. The results indicate that trading can release excess water while still keeping the same agricultural revenue obtained in a non-trading scheme. This implies that water can be more cost-effective with the trading scheme. Results also show that the effectiveness of the trading program is explicitly affected by uncertainties expressed as randomness and fuzziness, which challenges the users to make decisions of their water demands due to uncertain total water availability. The sensitivity analysis shows that the effectiveness of a trading program is very sensitive to trading cost, and trading could fail when the cost is too high.

The case study shows that the effectiveness of a water trading program is influenced by various factors in the trading system, such as benefit and penalty coefficients, water permits, minimum and maximum water requirements, and total supply of irrigable water. Except for the total irrigable water as a random variable, most other parameters related to elements such as soil type, crop, climate, and cropping technology that vary along time are often not available to be expressed with probability distributions. Water trading problems could be viewed from various perspectives depending on the subjectivity of decision makers and technical professionals. The values of system parameters (e.g., trading ratio) are usually subjectively estimated by decision makers and stakeholders, and thus may merely be obtained as imprecise information (i.e. fuzzy sets); moreover, the estimated values acquired from different sources may differ from each other due to the subjectivity. Such deviations in subjective estimations may lead to both fuzziness and randomness within water trading programs.

Using the fuzzy programming, such variations can be effectively quantified in an optimization framework. This is also reflected in most optimized solutions in the case study. It should be noted that water entitlement is linked to each farmland in China and water is not permitted to be traded without the associated transfer of land. This linkage between farmland and water use would be seen as a source of substantial institutional obstruction to the redistribution of water to alternative uses. However, modeling these values and trade options in China catchments can provide a starting point for potential policy changes to water resources management activities in many semi-arid and arid climate regions.

Acknowledgments

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