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A Non-Deterministic Integrated Optimization Model with Risk Measure for Identifying Water Resources Management Strategy

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ABSTRACT. Water resources system planning often exhibits high modeling error and uncertainty. Uncertainty in system parameters as well as their interrelationships can strengthen the conflict-laden issue of water allocation among competing interests. In this study, a non-deterministic integrated optimization model with risk measure is developed for planning water resources management. It can (i) deal with complex uncertainties described as probability distributions, fuzzy sets, and their combinations, (ii) provide an effective linkage between the predefined policies and the associated economic implications, and (iii) reflect policymakers' preferences to the tradeoff between system benefit and economic loss. The developed model is then applied to planning water resources allocation of the Heshui River Basin (China), where 960 scenarios are analyzed under various uncertainty and risk measures. Results disclose that (i) not only uncertainties of fuzziness and randomness but also risk attitudes of decision makers have significant impacts on water-allocation scheme and system benefit; (ii) the selection of a suitable alternative among solutions under different α, μ and λ values is complicated; (iii) water shortage would occur when water availability is less than the promised target; (iv) agriculture would encounter most serious scarcity compared to municipal and industry; (v) the conflict between economic development and agricultural sustainability would be a challenged issue that would enforce the local authority to adjust water-allocation policy. The findings can provide superior fundamental understanding of the study basin to improve water-allocation decisions under complex uncertain condition.

Keywords: conditional value-at-risk, integrated optimization, non-deterministic, scenario analysis, water resources

1. Introduction

1.1. Importance and Motivation

With population growth, economic development and climate change, challenges on securing sufficient and clean water supply are amplifying. Climate change is closely related to variations in precipitation, temperature, evapotranspiration rate, and snow/glacier melting; these variations are amplified in hydrological cycle, and consequently alter water resources availability and allocation. Agriculture is the largest user of the world's freshwater resources, consuming yearly 70% of all abstracted water and resulting locally in severe water scarcity (Mouratiadou et al., 2016). Water also plays an important role in almost every stage of energy development (including extraction, production and processing of fossil fuels, electricity generation, and treatment of wastes from energy-related activities). By 2030, water demand is expected to increase by 40%, energy by 50% and food by 50% in respect to 2010 levels; approximately 75% of the world's population will face water scarcity in future (Martinez-Hernandez et al., 2017). It is challenging to effectively plan and make optimal utilization of limited water resources to meet current and future demands for socioeconomic sustainable development, which calls for novel approaches that involve the diversification of water-supply options and the effective management of water resources (Bichai et al., 2018).

The fundamental goal of water resources planning is to match water demand by the socioeconomic activities with the supply of water through administrative control and management (Li et al., 2011; Dong et al., 2013). Optimization is recognized as a powerful tool for investigating economic benefit of policy decision and for planning water resources system in an effective and efficient way. Nevertheless, achieving a preferred water resources allocation strategy is difficult since social and institutional systems as well as the economics of water use are interconnected, and continuously varying, while many conflicting factors have to be balanced due to complexities of the real-world problems. A noteworthy complexity is the inherent uncertainty and the intrinsic risk involved with such water management practices. Uncertainty can be existed in observation data,

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data processing, parameter estimation and model structure, due to the inherent unpredictability of system and simplification in model formulation. Climate change is likely to be predictable over the next century due to consistently increasing greenhouse gas emissions, which can bring more complexities and uncertainties for water resources predication and allocation (Su et al., 2021). Understanding how water resources system would be affected by various uncertainties is important for developing desired management strategies (Li et al., 2008; Ewertowska et al., 2017; Moeini and Soltani-nezhad, 2020; Yu et al., 2020).

1.2. Literature Review

Many studies about non-deterministic models showed that uncertainties in water resources system have effects on the outputs of simulation, optimization and decision making. Dunn et al. (2012) analyzed the impact of uncertainty in climate change on the relationships among water resources, land use and diffuse pollution. Borgomeo et al. (2014) tested the robustness of water resources management under uncertainty using stochastic weather generator to construct probability distribution of the frequency of future water shortage. Nazemi and Wheater (2014) investigated effects of uncertainty in the natural inflow regime that altered different parts of water resources system using stochastic analysis technique. Dutta et al. (2016) planed agricultural water management and determined the optimum cropping pattern under fuzzy environment. Forio et al. (2017) analyzed the effect of the major environmental variables predicting ecological water quality through the application of fuzzy models. Hussien et al. (2018) presented a risk-based approach for the water, energy and food nexus considering the uncertainties associated with supply-demand balance and seasonal variability. Ortiz-Partida et al. (2019) proposed a two-stage stochastic optimization model to maximize economic benefits from reservoir deliveries through integrating stochastic inflows into a water allocation system with multiple demands and various constraints. Ma et al. (2020) advanced an interval stochastic bi-level programming method for balancing the water-energy nexus tradeoff between two-level decision makers under uncertainties expressed as probability distributions and interval values.

In general, fuzzy programming methods are effective in dealing with decision problems under fuzzy goal and constraints and handling ambiguous coefficients in the objective function and constraints (Huang et al., 2002; Li et al., 2010). Two-stage and multistage stochastic programming methods consider the expectation as the preference criterion while comparing the random variables to find the best decisions; consequently, it is a risk neutral approach. They focus on employing the expected values of the random variables; optimal solutions leading to a maximum system benefit (or a minimum system cost) can be achieved due to the maximization of economic benefit (or the minimization of cost) in the objective function. The possible loss is computed as the expected value of different probability conditions, such that the severity of extreme risks may be somewhat underestimated. This may somewhat overlook the extreme effects as the minimization of the expected value can hardly guarantee minima under all probability levels. Decision-makers and stakeholders cannot agree on the full set of risks and consequences and the probability of their occurrences (Li et al., 2010; Gaivoronski et al., 2012; Borgomeo et al., 2018).

Conditional value-at-risk (CVaR) is a risk measure based on probability distributions of measure into fuzzy and stochastic optimization framework, which is capable of handling possibilistic and probabilistic uncertainties as well as considering the potential economic loss (Piantadosi et al., 2008; Wang et al., 2017; Ji et al., 2020). Previously, a number of studies were reported on the application of CVaR risk measure to water resources management problems. Khor et al. (2014) introduced CVaR measure into a mixed-integer quadratic programming model to address risk management for an integrated water network synthesis problem. Hu et al. (2016) proposed a multi-objective optimization model with conditional value-at-risk constraints to consider water allocation equality in the agricultural, domestic, and industrial sectors. Soltani et al. (2016) formulated a conditional value at risk-based model for planning agricultural water management problem in association with uncertainties of probability and interval formats. Fu et al. (2018) proposed an interval CVaR two-stage stochastic programming model for reflecting the uncertainty of water system and the coordination between water allocation and risk preference under different representative concentration pathways scenarios. Naserizade et al. (2018) proposed a stochastic model based on CVaR and multiobjective optimization for optimal placement of sensors in water distribution system with the minimization of risk. Khorshidi et al. (2019) used CVaR concept for reservoir operation management of Dorudzan basin (Iran), and results showed that the model can determine the operation policy that keeps the associated risks in the acceptable range.

In general, in water resources management problems under non-deterministic condition, high risk is positively correlated with high return as well as high loss. A risk-averse approach that considers the effects of the variability of random outcomes (e.g., random cost) would provide more robust solutions compared to a risk-neutral approach (Noyan, 2012; Li et al., 2017). Water resources management problems are not only affected by each individual type of uncertainty, but also complicated by the complex interactions of different uncertain components. Spatial and temporal variabilities in water availability are driven by complex natural factors (e.g., hydrologic cycle, water demand, and geographical feature of river system) as well as by various human factors (e.g., population growth, socio-economic development, water resource exploitation, and river management policy) (Li et al., 2011; Steinfeld et al., 2020). The error and uncertainty can be transferred from one modeling domain to another. The effects of inaccuracies in estimating the streamflow can further extend to water allocation, system assessment, as well as management strategy, resulting in the corresponding risk of economic efficiency loss (Nazemi and Wheater, 2014; Fu et al., 2021; Zhai et al., 2021; Zhang et al., 2021). Therefore, one potential approach for better accounting for the uncertainties and the risks is to incorporate CVaR measure within the non-deterministic optimization methods.

1.3. Objective

The objective of this study aims to develop (i) a non-deterministic integrated optimization model with risk measure for tackling uncertainties of fuzziness and randomness and examining decision makers' attitudes toward risk aversion; (ii) apply the developed model to planning water resources allocation of the Heshui River Basin (in China), where results under multiple scenarios corresponding to uncertainty and risk levels will be obtained. Results will be analyzed to reveal how incorporating a risk measure affects the optimal solutions and demonstrate the computational effectiveness of the proposed model. The rest of this paper is organized as follows. Section 2 describes the development of modeling formulation. Section 3 focuses on the case study (i.e. the approach for planning water resources allocation of Heshui River basin). Results for system benefit, CVaR cost, and water-allocation pattern under multiple scenarios are presented and analyzed in section 4. Finally, section 5 discusses the key findings and presents main conclusions.

2. Methodology

Consider a problem wherein a water resources manager is responsible for allocating water to multiple users over a multiperiod horizon with the objective of maximizing the total net benefit. Given a quantity of water that is promised to a user, if this water is delivered, it will result in net benefits to the local economy; however, if the promised water is not delivered, either the water must be obtained from alternative and more expensive sources or the demand must be curtailed, resulting in penalties to the local economy. The available water and the reservoir-storage capacity are random variables, and the relevant water-allocation plan would be of dynamic feature. Multi-stage stochastic programming (MSP) is effective for reflecting uncertainties expressed as random variables through a multi-layer scenario tree, which permitted revised decisions in each stage based on the sequentially realized uncertain events (Birge and Louveaux, 1997; Li et al., 2006). Chance-constrained programming (CCP) can effectively reflect the reliability of satisfying (or risk of violating) system constraints under uncertainty (Huang, 1998; Tan et al., 2011). Thus, based on MSP and CCP techniques, the study problem can be formulated as:

$$\text{Max} \quad f = \sum_{i=1}^{I}\sum_{t=1}^{T} NB_{it} \cdot WT_{it} - \sum_{i=1}^{I}\sum_{t=1}^{T}\sum_{k=1}^{K_t} p_{tk} \cdot EP_{it} \cdot WS_{itk} \tag{1a}$$

subject to:

$$ST_{(t+1)k} = ST_{tk} + \widehat{WQ_{tk}} - [A_a e_t (\frac{ST_t + ST_{t+1}}{2}) + A_0 e_t] - RF_{tk}, \ \forall t;\ k = 1, 2, \cdots, K_t \tag{1b}$$

$$\Pr\{ST_{tk} \le RSC\} \ge \varphi, \ \forall t;\ k = 1, 2, \cdots, K_t \tag{1c}$$

$$\sum_{i=1}^{I} (WT_{it} - WS_{itk}) \le RF_{tk}, \ \forall t;\ k = 1, 2, \cdots, K_t \tag{1d}$$

$$ST_{tk} \ge RSV, \ \forall t;\ k = 1, 2, \cdots, K_t \tag{1e}$$

$$\sum_{k=1}^{k_T} p_{Tk} \cdot ST_{Tk} \ge ST_T, \ \ k = 1, 2, \cdots, K_T \tag{1f}$$

$$WD_{it\max} \ge WT_{it} \ge WD_{it\min} \ge 0, \quad \forall i, t;\ k = 1, 2, \cdots, K_t \tag{1g}$$

$$WT_{it} - WS_{itk} \ge MIW_{it}, \quad \forall i, t;\ k = 1, 2, \cdots, K_t \tag{1h}$$

$$WS_{itk} \ge 0, \quad \forall i, t;\ k = 1, 2, \cdots, K_t \tag{1i}$$

The detailed nomenclatures for the variables and the parameters are provided in the Appendix. In detail, constraint (1b) presents the mass balance for water resources in each period (i.e., the change in storage equals inflows minus releases and evaporation losses), where the evaporation loss is assumed to be a linear function of the average storage of reservoir; constraint (1c) specifies that the storage amount must not exceed reservoir capacity under all scenarios, where the storage capacities are fixed with a probability level that represents the admissible risk of violating the uncertain capacity constraints; constraint (1d) means that the water allocated to users and surplus water diverted (when flow level is high) will not exceed the amount of water released from the reservoir; constraint (1e) requires that the reservoir's storage cannot lower a reserve level under all scenarios; constraint (1f) stipulates that the expected final storage in the reservoir should not be below a specified target level; constraint (1g) indicates that water-allocation target should satisfy the users' minimum necessities but not exceed their maximum requirements; constraint (1h) denotes that allocated water should meet the minimum requirement for each user; constraint (1i) stipulates that the water shortage is non-negative.

Model (1a ~ 1i) can reflect uncertainties with known probability distributions; it is still unqualified when dual uncertainties of randomness and fuzziness are both existed. For example, the amount of available water may have statements expressed as "probably 350 × 10^6 to 380 × 10^6 m^3" or "possibly 350 × 10^6 to 380 × 10^6 m^3". This leads to dual uncertainties (randomness and fuzziness) due to the fact that decision makers express different subjective judgments upon a same problem. In addition, vague information may exist in economic data and technical data of objective function and constraints. Fuzzy programming (FP) based on fuzzy set theory, which serves as a useful mathematical tool to facilitate the description of complex and ill-defined systems, is effective for quantifying the vague information without the sample size requirement (Zadeh, 1975; Inuiguchi and Tanino, 2000; Li et al., 2010). The general notation of a fuzzy set can be presented as follows (Zimmermann, 1995):

$$\tilde{A}(x) = \{x, \mu_{\tilde{A}}(x) \mid x \in X \text{ and } \mu_{\tilde{A}}(x) \in [0,1]\} \tag{2}$$

where $X = \{x\}$ is a universe set of elements; $A(x)$ is a fuzzy set of X; $\mu_{\tilde{A}}(x)$ is the membership function or grade of membership. The $\mu_{\tilde{A}}(x)$ value ranges from 0 to 1, where 1 represents full membership and 0 denotes non-membership. The membership function of any fuzzy set $\tilde{A}$ may conveniently be expressed

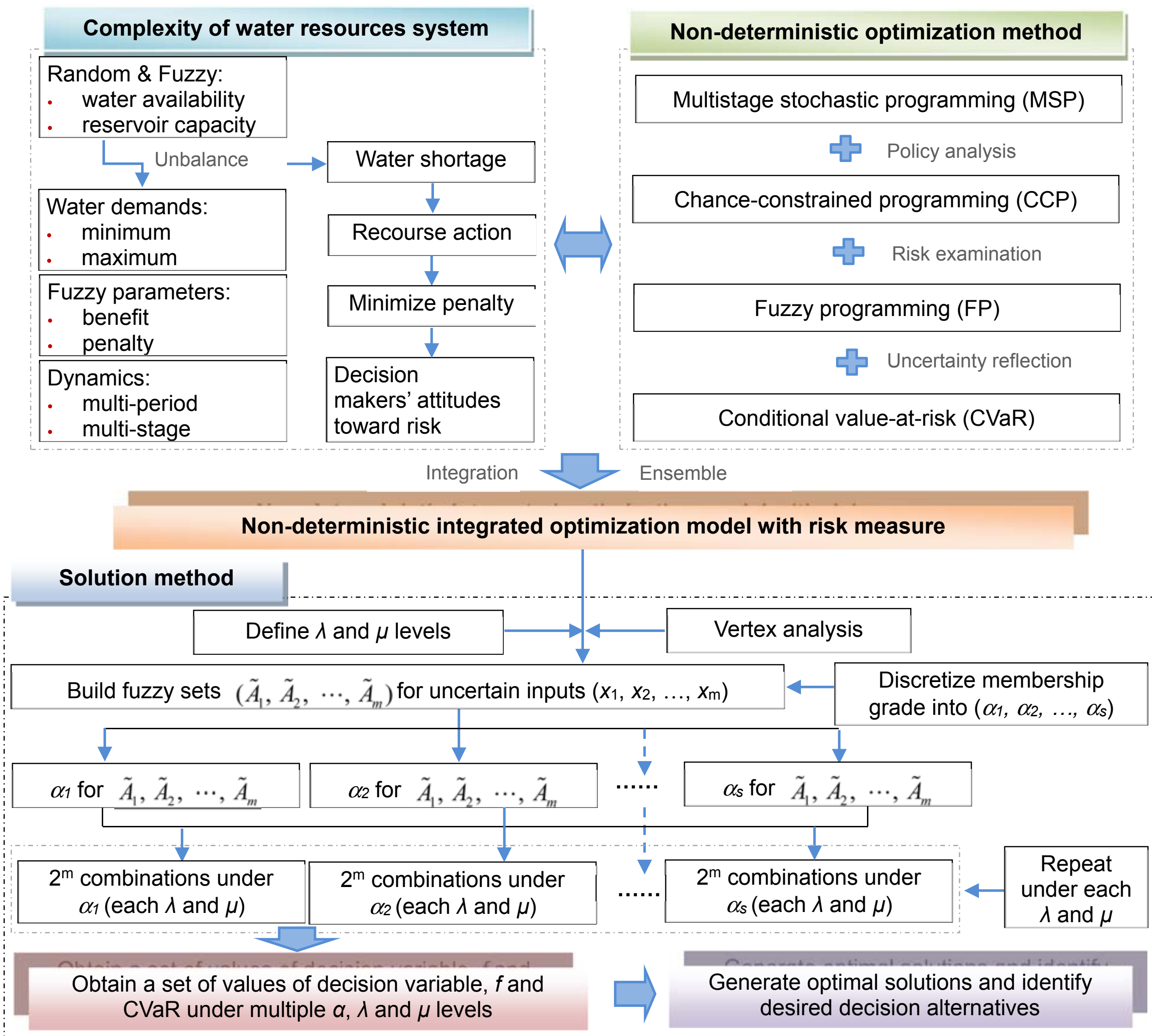

Figure 1. Outline of the developed model.

for all $x \in X$ in canonical form (Dubois and Prade, 1986):

$$\mu_{\tilde{A}}(x) = \begin{cases} f_{\tilde{A}}(x) & \text{when } x \in [a,b), \\ 1 & \text{when } x \in [b,c], \\ g_{\tilde{A}}(x) & \text{when } x \in (c,d], \\ 0 & \text{otherwise.} \end{cases} \tag{3}$$

where $a, b, c, d \in X$ and $a \le b \le c \le d$, $f_{\tilde{A}}$ is a real-valued function that is increasing and right-continuous, and $g_{\tilde{A}}$ is a real-valued function that is decreasing and left-continuous. An α-cut is defined as the set of elements that belong to fuzzy set A at least to the degree of α that is also called the degree of confidence or the degree of plausibility. The α-cut can be described as follows (Zimmermann, 1995):

$$\tilde{A}_\alpha = \{x \,|\, \mu_{\tilde{A}}(x) \ge \alpha,\ x \in X\} \tag{4}$$

where $\tilde{A}_\alpha$ is the α-cut level of A, and it consists of all components of X whose membership grade is greater than or equal to α. The support of fuzzy set A is defined by the classical set as follows:

$$\text{supp}(\tilde{A}) = \{x \,|\, \mu_{\tilde{A}}(x) > 0\} \tag{5}$$

The convexity condition ensures that the support is in an interval. To handle decision-making problems in association with randomness and fuzziness, FP can be introduced into the framework of model (1a ~ 1i). Thus, we have:

$$\text{Max } \tilde{f} = \sum_{i=1}^{I}\sum_{t=1}^{T} \widetilde{NB}_{it} \cdot WT_{it} - \sum_{i=1}^{I}\sum_{t=1}^{T}\sum_{k=1}^{K_t} p_{tk} \cdot \widetilde{EP}_{it} \cdot WS_{itk} \tag{6a}$$

subject to:

$$ST_{(t+1)k} = ST_{tk} + \widetilde{\widetilde{WQ_{tk}}} - [A_a e_t (\frac{ST_t + ST_{t+1}}{2}) + A_0 e_t] - RF_{tk},\ \forall t;\ k = 1,\ 2,\ \cdots,\ K_t \tag{6b}$$

$$\Pr\{ST_{tk} \le RSC\} \ge \tilde{\varphi},\ \forall t;\ k = 1,\ 2,\ \cdots,\ K_t \tag{6c}$$

$$\sum_{i=1}^{I}(WT_{it} - WS_{itk}) \le RF_{tk},\ \forall t;\ k = 1,\ 2,\ \cdots,\ K_t \tag{6d}$$

$$ST_{tk} \ge RSV,\ \forall t;\ k = 1,\ 2,\ \cdots,\ K_t \tag{6e}$$

$$\sum_{k=1}^{k_T} p_{Tk} \cdot ST_{Tk} \ge ST_T,\ \ k = 1,\ 2,\ \cdots,\ K_T \tag{6f}$$

$$WD_{it\max} \ge WT_{it} \ge WD_{it\min} \ge 0,\quad \forall i, t;\ k = 1,\ 2,\ \cdots,\ K_t \tag{6g}$$

$$WT_{it} - WS_{itk} \ge MIW_{it},\ \forall i, t;\ k = 1,\ 2,\ \cdots,\ K_t \tag{6h}$$

$$WS_{itk} \ge 0\ \forall i, t;\ k = 1,\ 2,\ \cdots,\ K_t \tag{6i}$$

where $\widetilde{NB_{it}}$ and $\widetilde{EP_{it}}$ are fuzzy coefficients in the objective function, $\tilde{\varphi}$ is fuzzy tolerance measure ($0 \le \tilde{\varphi} \le 1$), and $\widetilde{\widetilde{WQ_{tk}}}$ is fuzzy-random variable. To solve the above model, vertex analysis, based on the α-cut concept and interval analysis, can be used for computing functions of fuzzy variables. Using the concept of α-cut, each fuzzy variable can be converted into a group of intervals with various α levels. The detailed definitions related to vertex analysis can be found in a number of literatures (Dong and Shah, 1987; Chen et al., 1998; Li et al., 2010).

Model (6a ~ 6i) can reflect coefficients (in both objective and constraints) in association with fuzzy and random features; nevertheless, solutions of model (6a ~ 6i) can bring about tremendous losses when an extremely adverse condition occurs. CVaR is useful for examining the risk loss under specific probabilistic distributions (Andersson et al., 2001). CVaR is defined as the mean loss, given that the loss is greater than or equal to value-at-risk (VaR), which can be used in the conjunction with VaR and is applicable to the estimation of risks with non-symmetric return-loss distributions (Rockafellar and Uryasev, 2002; Soleimani and Govindan, 2014). Let $f(x, y)$ be a loss function depending upon the decision vector x and a random vector y with a probability density function $p(y)$. The probability of $f(x, y)$ not exceeding a threshold value η can be defined as:

$$\psi(x,\ \eta) = \int_{f(x,\ y)\le\eta} p(y)dy \tag{7}$$

Given a confidence level $\mu \in (0, 1)$, the VaR associated with the decision variable (x) can be expressed as:

$$VaR_\mu(x) = \min\{\eta \in R : \psi(x,\ \eta) \ge \mu\} \tag{8}$$

The corresponding CVaR is the conditional expectation of the loss of the portfolio (expected value) exceeding or equal to the VaR (Rockafellar and Uryasev, 2002):

$$CVaR_\mu(x) = (1-\mu)^{-1}\int_{f(x,\ y)\ge VaR_\mu(x)} f(x,\ y)p(y)dy \tag{9}$$

The CVaR is a coherent risk measure and takes into account the extremely large losses that may occur. Then, Equation (9) has the following equivalent form:

$$CVaR_\mu(x) = \min_{\eta\in R} F_\mu(x,\ \eta) \tag{10a}$$

$$F_\mu(x,\ \eta) = \eta + (1-\mu)^{-1}E[(f(x,\ y)-\eta]^+ \tag{10b}$$

where $E(\cdot)$ denotes the expectation value with respect to $p(y)$ and $[t]^+ = \max\{t,\ 0\}$. Assuming random vector $y = \{y_1, y_2, \ldots, y_K\}$, then $F_\mu(x,\ \eta)$ can be calculated approximately as follows:

$$F_\mu(x,\ \eta) = \eta + (1-\mu)^{-1}\sum_{k=1}^{K} p_k[f(x,\ y_k)-\eta]^+ \tag{11}$$

where p_k is the probability of scenario y_k. Risk measures incorporated in optimization problems can allow consideration of preferences on random outcomes. Thus, introducing the CVaR concept into model (6a ~ 6i), a non-deterministic integrated optimization model with risk measure, which is capable of handling risk and uncertainty emerging from parameters variability, can be formulated as:

$$\text{Max } \tilde{f} = \sum_{i=1}^{I}\sum_{t=1}^{T}\widetilde{NB_{it}} \cdot WT_{it} - \sum_{i=1}^{I}\sum_{t=1}^{T}\sum_{k=1}^{K_t} p_{tk} \cdot \widetilde{EP_{it}} \cdot WS_{itk} - \lambda[\eta + (1-\mu)^{-1}\sum_{k=1}^{K_t} p_{tk}v_{tk}] \tag{12a}$$

subject to:

$$ST_{(t+1)k} = ST_{tk} + \widetilde{\widetilde{WQ_{tk}}} - [A_a e_t (\frac{ST_t + ST_{t+1}}{2}) + A_0 e_t] - RF_{tk},\ \forall t;\ k = 1,\ 2,\ \cdots,\ K_t \tag{12b}$$

$$\Pr\{ST_{tk} \le RSC\} \ge \tilde{\varphi},\ \forall t;\ k = 1,\ 2,\ \cdots,\ K_t \tag{12c}$$

$$\sum_{i=1}^{I}(WT_{it} - WS_{itk}) \le RF_{tk},\ \forall t;\ k = 1,\ 2,\ \cdots,\ K_t \tag{12d}$$

$$ST_{tk} \ge RSV,\ \forall t;\ k = 1,\ 2,\ \cdots,\ K_t \tag{12e}$$

$$\sum_{k=1}^{k_T} p_{Tk} \cdot ST_{Tk} \ge ST_T,\ \ k = 1,\ 2,\ \cdots,\ K_T \tag{12f}$$

$$WD_{it\max} \ge WT_{it} \ge WD_{it\min} \ge 0,\quad \forall i, t;\ k = 1,\ 2,\ \cdots,\ K_t \tag{12g}$$

$$WT_{it} - WS_{itk} \ge MIW_{it},\quad \forall i, t;\ k = 1,\ 2,\ \cdots,\ K_t \tag{12h}$$

$$v_{tk} \geq \sum_{i=1}^{I}\sum_{j=1}^{J} \widetilde{EP_{it}} \cdot WS_{itk} - \eta, \quad k = 1,\ 2,\ \cdots,\ K_t \tag{12i}$$

$$WS_{itk} \geq 0, \quad \forall i, t;\ k = 1,\ 2,\ \cdots,\ K_t \tag{12j}$$

$$\eta \geq 0 \tag{12k}$$

where μ is a confidence level; λ is a goal programming weight, through changing λ value, decision makers can acquire the compromise between the expected system benefit and the system failure risk; η is the system's maximum loss under μ level; v_{tk} is the positive auxiliary variable; $\lambda[\eta + (1 - \mu)^{-1}\sum_{k=1}^{K_t} p_{tk}v_{tk}]$ denotes the risk function of CVaR under μ level. The possibility distributions of fuzzy parameters can be characterized as fuzzy sets. Solutions can be obtained by repeating the process via changing α, λ and μ levels. Then, the final solutions for the objective-function value and decision variables under a set of α, λ and μ levels can be obtained. Figure 1 provides an outline of the integrated model that incorporates non-deterministic optimization techniques (MSP, CCP and FP) and risk measure (CVaR) within a general framework. The detailed computational processes can be summarized as follows:

- Step 1: Formulate a non-deterministic integrated optimization model with risk measure [i.e., model (12a) ~ (12k)].
- Step 2: Discretize the range of membership grade [0, 1] into a finite number of α-cut levels (i.e., $\alpha_1, \alpha_2, ..., \alpha_s$). For each membership grade α_j, find the corresponding intervals for fuzzy sets.
- Step 3: According to Iskander (2005), transform stochastic-fuzzy constraint (i.e., Formula (12c)) to one deterministic fuzzy equivalent ($ST_{tk} \leq RSC^{\tilde{\xi}}$, $\forall t$; $k = 1,\ 2,\ \cdots,\ K_t$, where $\tilde{\xi} = 1 - \tilde{\varphi}$). Assume that fuzzy tolerance measure is presented as trapezoidal fuzzy numbers $\tilde{\varphi} = (\underline{\varphi},\ \varphi_1,\ \varphi_2,\ \overline{\varphi})$, then, $\tilde{\xi} = (\underline{\xi},\ \xi_1,\ \xi_2,\ \overline{\xi}) = (1 - \overline{\varphi},\ 1 - \varphi_2,\ 1 - \overline{\varphi}_1,\ 1 - \underline{\varphi})$.
- Step 4: Identify acceptable risk levels (i.e., μ and λ values).
- Step 5: Under each μ and λ, take one end point from each of the intervals (under an α-cut level), there are 2^m combinations for m fuzzy sets.
- Step 6: Solve 2^m $\tilde{f}$ sub-models, a set of objective-function values ($f_1, f_2, \cdots, f_{2m}$) can be obtained, and then identify the minimum and the maximum $\tilde{f}$.
- Step 7: Repeat Step 6 at every α-cut level.
- Step 8: Repeat the computational processes (Step 4 to Step 7) at every λ and μ, and a set of values of f and CVaR can be obtained.
- Step 9: Generate final solutions (e.g., optimal target, water shortage, and actual water allocation) and identify desired decision alternatives.

3. Description of Case Study

The developed approach is applied to a representative case of water resources management for the Heshui River Basin (at the upper reaches of the Ganjiang River, Jiangxi province), which is under growing pressure with population growth and economic development increasing competition among multiple interesting users. The County of Yongxin had a total population of 529,252 in 2019. The Heshui River is the center of this county. All large and small streams belong to the Heshui River system and most of the streams from the south or from the north flow into the Heshui River. The county utilizes the Heshui River to provide resources for its water supply, agricultural irrigation, fishery farming, industrial production, and navigation. In 2019, the county achieved a gross local product of 10.9 billion yuan, with an annual growth rate of 7.4%. Agriculture is traditionally the primary sector in the study area; rice, wheat, grain, rapeseeds and vegetables are the principal crops and main agricultural income sources. In 2019, the total output value of agriculture, forestry, livestock and fishery reached 3.2 billion yuan, with an annual growth rate of 3.3%. The county's industry is mainly comprised of mining, manufacturing, construction, transportation and other industries. Recently, many tourism sites and relics within the region have been attracting more and more tourists, leading to promoted transportation, food and service industries. In 2019, the added value of its tertiary industry increased by 8.3%, higher than those of other industries. Rapid economic growth and fast urbanization process have exerted ever-increasing pressure on the local water resource allocation, lead to obvious gap between water supply and water demand.

Table 1. Net Benefit and Penalty

	Period 1	Period 2	Period 3
Net benefit when water demand is satisfied ($/m³):			
Municipal	(1.42, 1.52, 1.65, 1.80)	(1.55, 1.68, 1.75, 1.95)	(1.68, 1.81, 2.00, 2.17)
Industry	(1.07, 1.18, 1.31, 1.43)	(1.16, 1.27, 1.35, 1.50)	(1.28, 1.39, 1.51, 1.65)
Agriculture	(0.54, 0.59, 0.66, 0.72)	(0.59, 0.65, 0.71, 0.78)	(0.65, 0.71, 0.79, 0.87)
Penalty when water is not delivered ($/m³):			
Municipal	(2.54, 2.79, 3.03, 3.37)	(2.79, 3.07, 3.31, 3.67)	(3.04, 3.35, 3.60, 4.00)
Industry	(1.92, 2.11, 2.31, 2.54)	(2.11, 2.32, 2.50, 2.74)	(2.30, 2.53, 2.75, 3.01)
Agriculture	(0.95, 1.05,1.38, 1.29)	(1.04, 1.14, 1.26, 1.41)	(1.14, 1.25, 1.37, 1.53)

With water management issues becoming progressively more focused on sustainability, the impacts of system components on water supply and water demand have become even more pertinent. Table 1 presents the data of benefit and penalty, which are presented in terms of fuzzy sets with known trapezoidal membership functions. They are mainly from governmental reports and public survey. The economic penalty is associated with the acquisition of water from higher-priced alternatives and/or the negative consequences generated from the curbing of regional development plans when the promised water is not delivered. Table 2 shows the available water from the river basin and the associated probabilities of occurrence in the planning periods. Shortages in water supply would occur if insufficient water is available, such that the regulated targets cannot be satisfied (i.e., shortage = regulated target – available water).

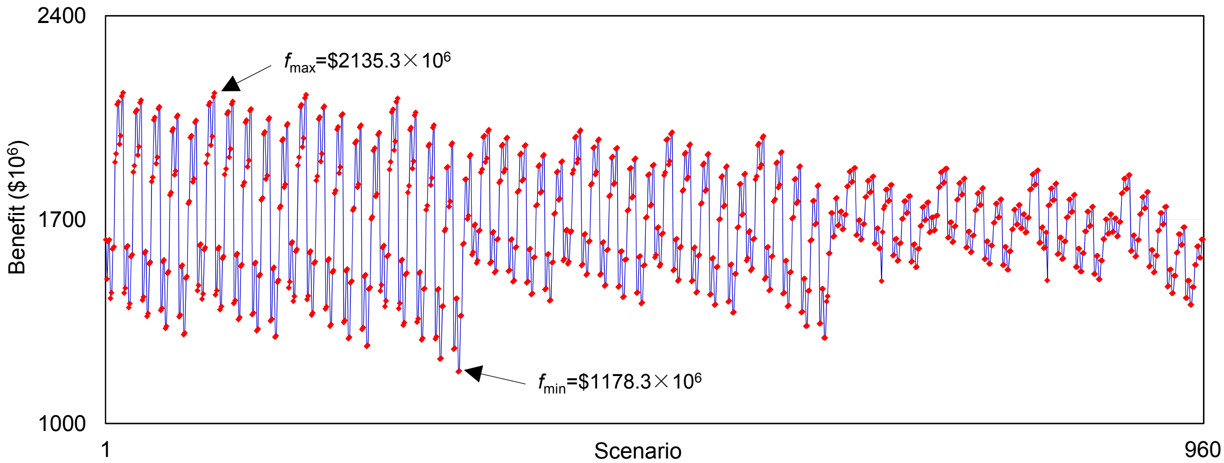

Figure 2. System benefits under 960 scenarios.

Table 2. Available Water (10^6 m^3) and Related Probability

	p value	Available water
Period 1 ($t = 1$)		
Low (L)	0.122	(322.3, 335.2, 345.6, 360.1)
Low-medium (Lm)	0.283	(364.0, 378.6, 390.8, 407.0)
Medium (M)	0.404	(443.1, 462.8, 480.9, 506.1)
High (H)	0.191	(638.2, 663.7, 684.2, 712.7)
Period 2 ($t = 2$)		
Low (L)	0.183	(336.9, 345.0, 354.6, 365.2)
Medium (M)	0.585	(441.8, 462.1, 478.3, 501.2)
High (H)	0.232	(641.7, 665.4, 688.3, 717.0)
Period 3 ($t = 3$)		
Low (L)	0.155	(310.9, 323.7, 338.5, 352.6)
Medium (M)	0.631	(417.7, 434.2, 452.8, 471.7)
High (H)	0.214	(636.1, 658.4, 675.7, 702.8)

4. Result and Discussion

In this study, three α-cut levels (0, 0.5 and 1), four values for μ (from 0.6 to 0.99) and five values for λ (from 0.1 to 1) were investigated. For each α-cut level, sixteen conditions were examined based on different combinations of fuzzy intervals. Figure 2 presents the solutions for system benefit under 960 scenarios. Results reveal that different combinative considerations on uncertain inputs lead to changed system benefits. Different combinations of α, λ and μ levels would notably influence the optimal objective-function value. For example, when $\alpha = 0$, $\mu = 0.6$ and $\lambda = 0.1$, system benefit would reach its maximum value (f_{max} = \$2135.3 × 10^6); when $\alpha = 0$, $\mu = 0.99$ and $\lambda = 1$, the minimum system benefit would be achieved (f_{min} = \$1178.3 × 10^6). If the concept of uncertainty degree (UD) is used for evaluating levels of uncertain parameters, we can define $UD(f) = (f_{max} - f_{min}) \times 100\% / (f_{max} + f_{min})$. Then, the UD of system benefit is 28.9%. Results can thus help decision makers acquire the compromise between system benefit and system-failure risk as well as generate a range of decision alternatives in response to uncertainty.

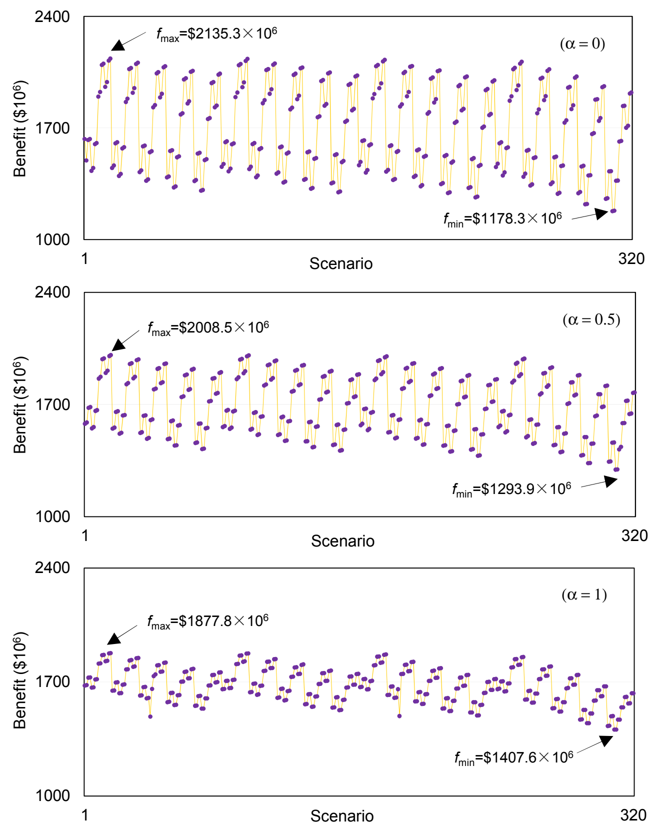

Figure 3. Variation of system benefit with α level.

Figures 3 to 5 show the variation of system benefit with α, μ and λ levels, respectively. In this study, each α-cut level denotes a sub-set of elements that belong to a fuzzy set at least to a membership degree of α (also named degree of plausibility). The results indicate that α-cut level has significant effect on the objective-function value (i.e., the expected system benefit). When $\alpha = 0$, the minimum and maximum system benefits would respectively be 1178.3 and 2135.3 million US\$; they would form lower and upper bounds for system benefit (i.e., $f_{\alpha=0}$ = \$[1178.3, 2135.3] × 10^6). When α = 1, the system benefit would be in the range of $[1407.6, 1877.8] × 10^6. Under a lower degree of plausibility (i.e., a lower α level), the interval is wider; conversely, a higher degree of plausibility would lead to a narrower intervall. When α = 0, the highest upper-bound system benefit may be achieved under advantageous conditions; however, the system

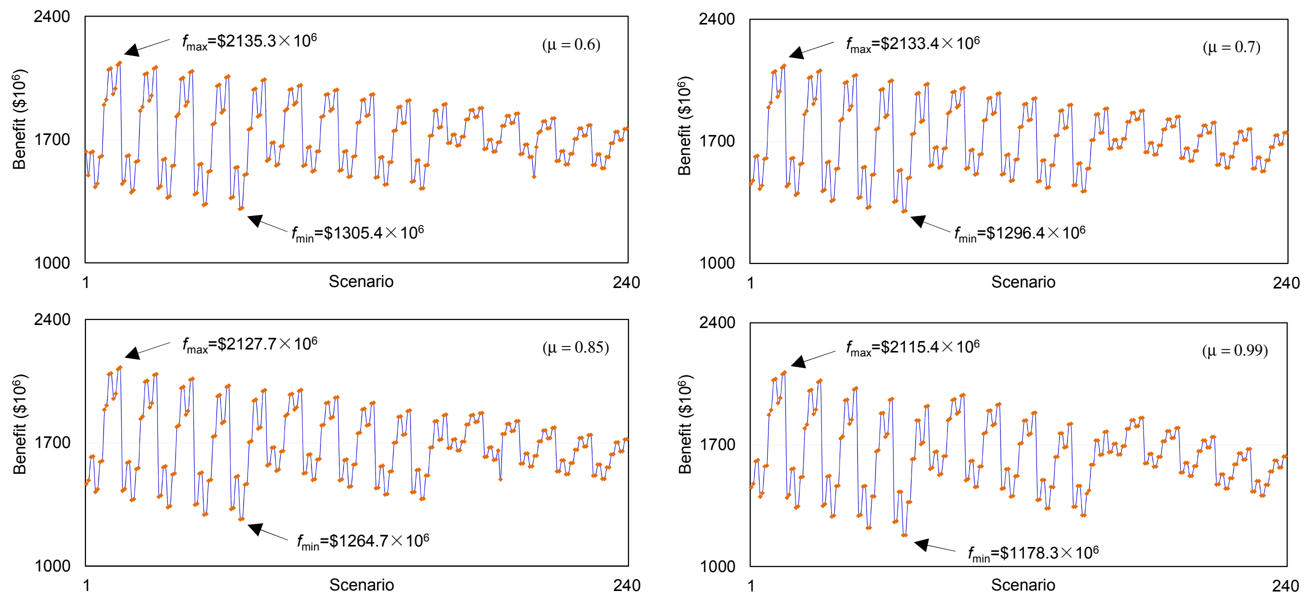

Figure 4. Relationship between system benefit and μ level.

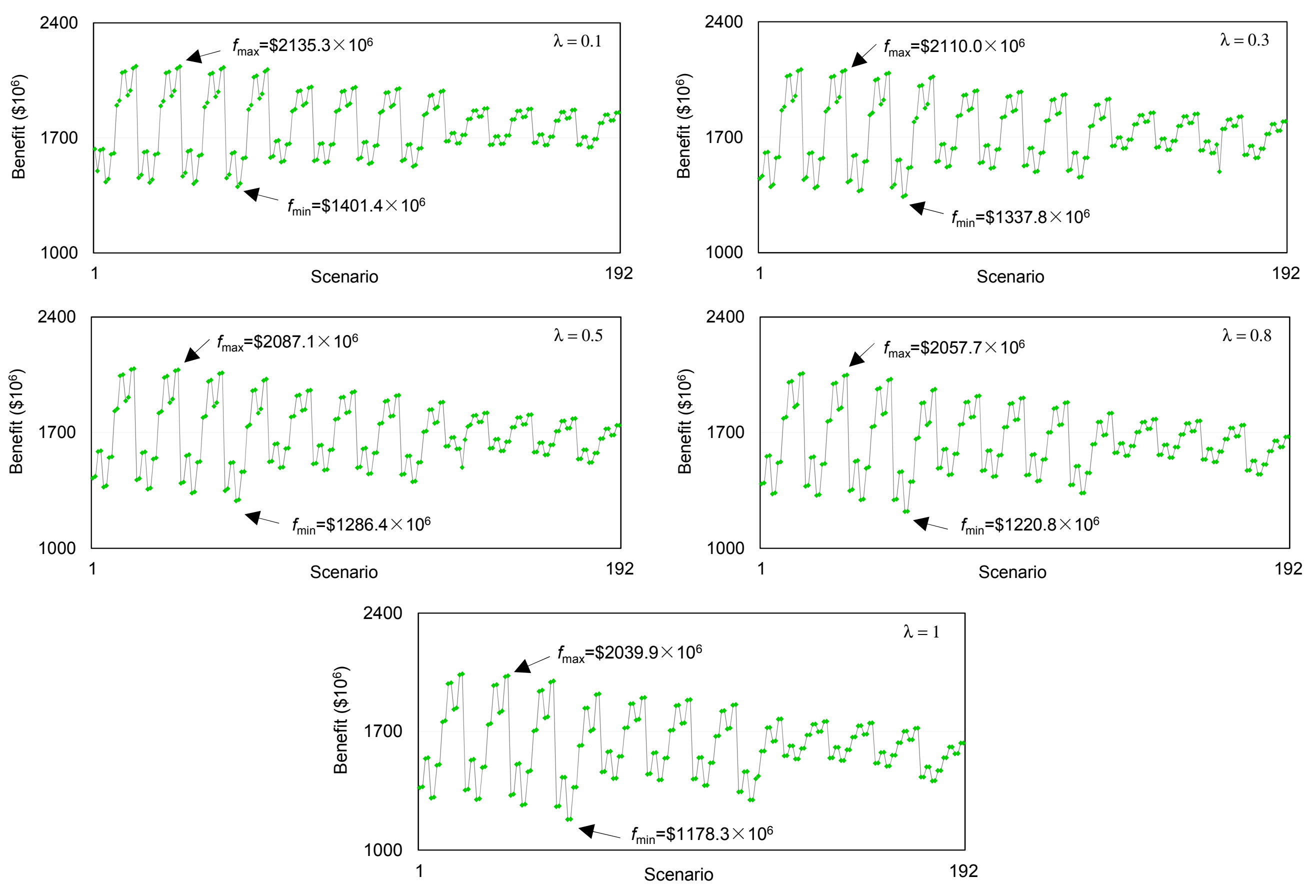

Figure 5. Relationship between system benefit and λ level.

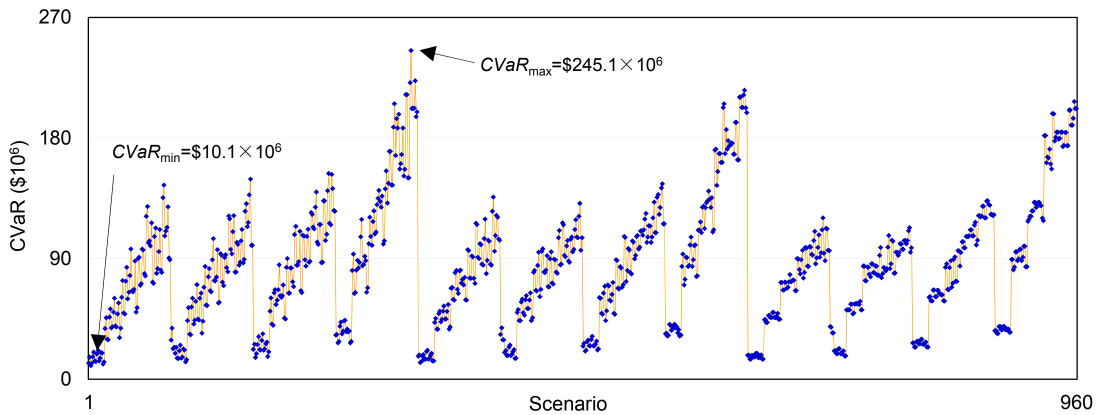

Figure 6. CVaR costs under 960 scenarios.

may encounter the lowest lower-bound benefit under demanding conditions. When $\alpha = 1$, the system would achieve the lowest upper-bound benefit under advantageous conditions; the highest lower-bound benefit would exist under demanding conditions. Therefore, there is tradeoff between the water-allocation benefit and the system-failure risk. More in-depth analysis of the projected applicable system conditions is needed to identify the desired decision alternative.

The results show that, as μ value rises, system benefit would slightly decrease (Figure 4). For instance, system benefits would be $[1305.4, 2135.3] × 10^6 ($\mu = 0.6$) and $[1178.3, 2115.4] × 10^6 ($\mu = 0.99$). Besides, a higher λ value (corresponding to an increased risk-control level) could result in a lower system benefit (Figure 5). When λ value is changed from 0.1 to 1, system benefits would reduce from $[1401.4, 2135.3] × 10^6 to $[1178.4, 2039.9] × 10^6. Generally, both higher μ and λ levels would lead to a reduced system benefit; nevertheless, a higher μ value (a higher confidence level) is associated with a lower system-failure risk and a higher λ value (based on a risk-aversive attitude) corresponds to an increased risk-control level. Decision makers could assign different α, μ and λ values to adjust risk-control levels based on their preferences. Among the three factors (i.e., α, μ and λ), α level has the most observable effect on system benefit, implying that fuzzy information (e.g., benefit and cost data, stream flow, and storage capacity) would significantly impact the objective-function value and the associated decision alternative. Results can provide more useful information for decision makers regarding tradeoffs among system benefit, certainty and reliability.

Figure 6 presents the solutions for CVaR cost under all scenarios. Results show different combinations of α, μ and λ levels would influence the CVaR cost. When $\alpha = 0$, $\mu = 0.6$ and $\lambda = 0.1$, the system would possess the lowest CVaR cost (i.e. $CVaR_{min}$ = $10.1 × 10^6). When $\alpha = 0$, $\mu = 0.99$ and $\lambda = 1$, the highest CVaR cost would be obtained ($CVaR_{max}$ = $245.1 × 10^6). The CVaR cost would range from $10.1 × 10^6 to 245.1× 10^6 and the matching UD is 92.1%. Figure 7 shows the variation of CVaR cost with α and μ levels. When $\mu = 0.6$, CVaR costs would be $[10.1, 144.7] × 10^6 ($\alpha = 0$) and [14.9, 120.2] × 10^6 ($\alpha = 1$), indicating that the interval of CVaR cost becomes narrow with α level. Besides, results show that the CVaR cost would increase as μ value is raised. For example, when $\alpha = 0.5$, the CVaR costs would be $[12.5, 135.8] × 10^6 ($\mu = 0.6$) and [32.1, 215.4] × 10^6 ($\mu = 0.99$). Figure 8 provides the change of CVaR cost with λ level. For example, the CVaR cost would be $[10.1, 43.9] × 10^6 when $\lambda = 0.1$; while the lower- and upper-bound CVaR costs would increase to $[78.7, 245.1] × 10^6 (under $\lambda = 1$). Generally, both higher μ and λ levels would lead to an increased CVaR cost but a lower system-failure risk.

An optimized set of water-target values (i.e., the first-stage decision variables) could be identified under varying system conditions. This optimized set could help approach to the highest possible system benefit under uncertainty. Figure 9 presents water-allocation targets under several typical scenarios, which correspond to minimum and maximum system benefits under α levels of 0, 0.5 and 1, respectively. Results indicate that α, μ and λ levels can affect the water-allocation target. The α level is associated with water availability and reservoir storage capacity, which thus could directly lead to varied water-allocation targets (with the highest influence). For example, when $\alpha = 0$, water-allocation targets for agriculture would range from 143.4 × 10^6 m^3 ($\mu = 0.99$, $\lambda = 1$) to 158.6 × 10^6 m^3 ($\mu = 0.6$, $\lambda = 0.1$) in period 1; when $\alpha = 1$, water-allocation target for agriculture would be a deterministic value in period 1 (i.e. 143.4 × 10^6 m^3). The results point out that a lower α-cut level would result in a wider interval for water-allocation target. The total allocation targets for municipal, industry and agriculture would be [1266.4, 1486.3] × 10^6 m^3 ($\alpha = 0$), [1273.5, 1452.8] × 10^6 m^3 ($\alpha = 0.5$), and [1292.6, 1435.7] × 10^6 m^3 ($\alpha = 1$).

The optimized allocation target for agriculture would reach its minimum value under demanding conditions since this user is associated with the lowest benefit. Variation in the values of allocation targets reflects different policies for managing the water resources under uncertainty. If water allocation targets are regulated too low, the corresponding policy may result in less water shortage and thus lower penalty but, at the same time, more waste of resources would be generated when streamflow level is high. Conversely, if water-allocation targets are too high, a higher risk of penalty would be generated when the promised water cannot be satisfied under demanding conditions (e.g., when the water flow level is low). Therefore, different policies in regulating the water-allocation targets are associated with dif-

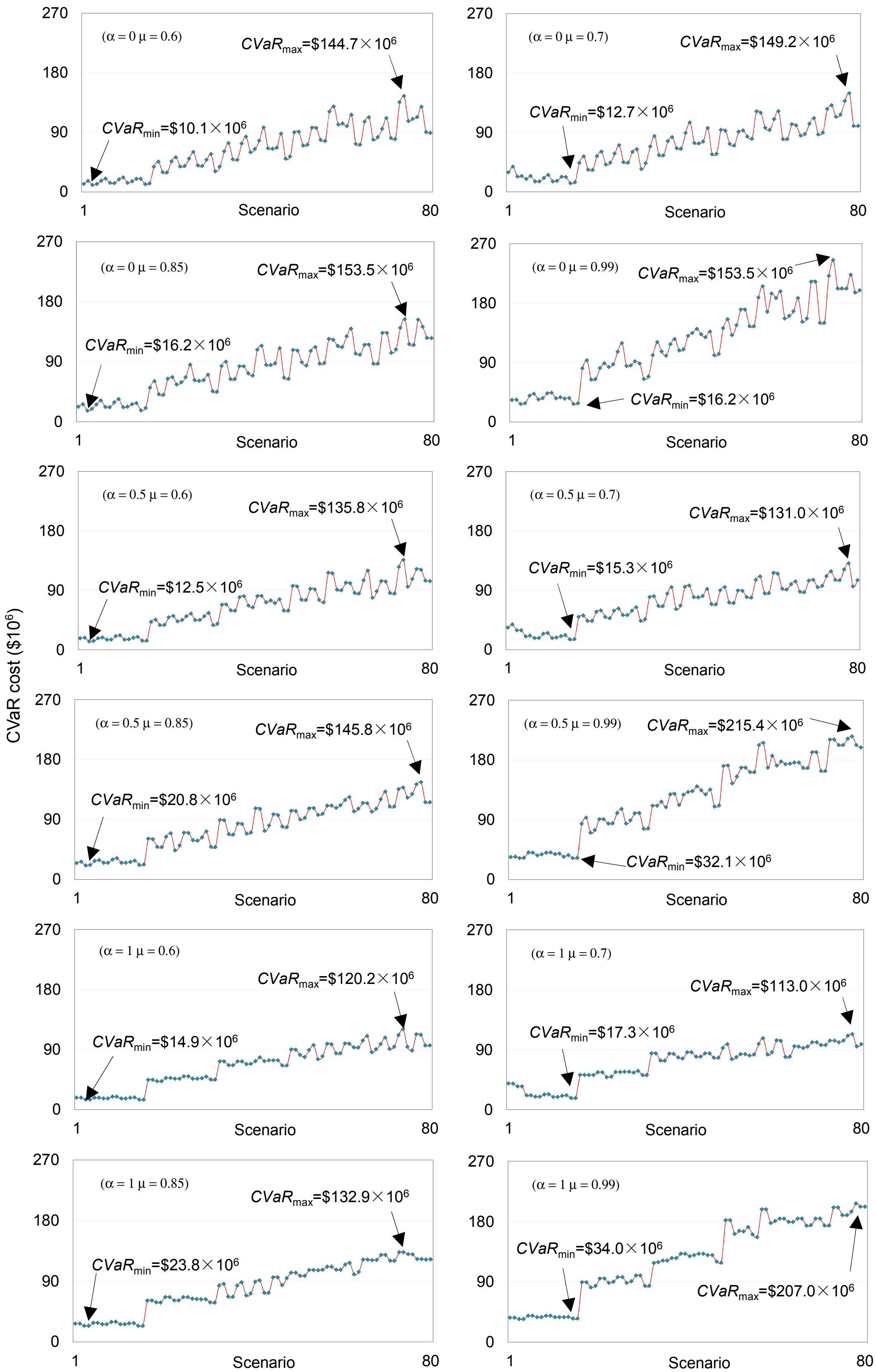

Figure 7. CVaR costs under different α and μ levels.

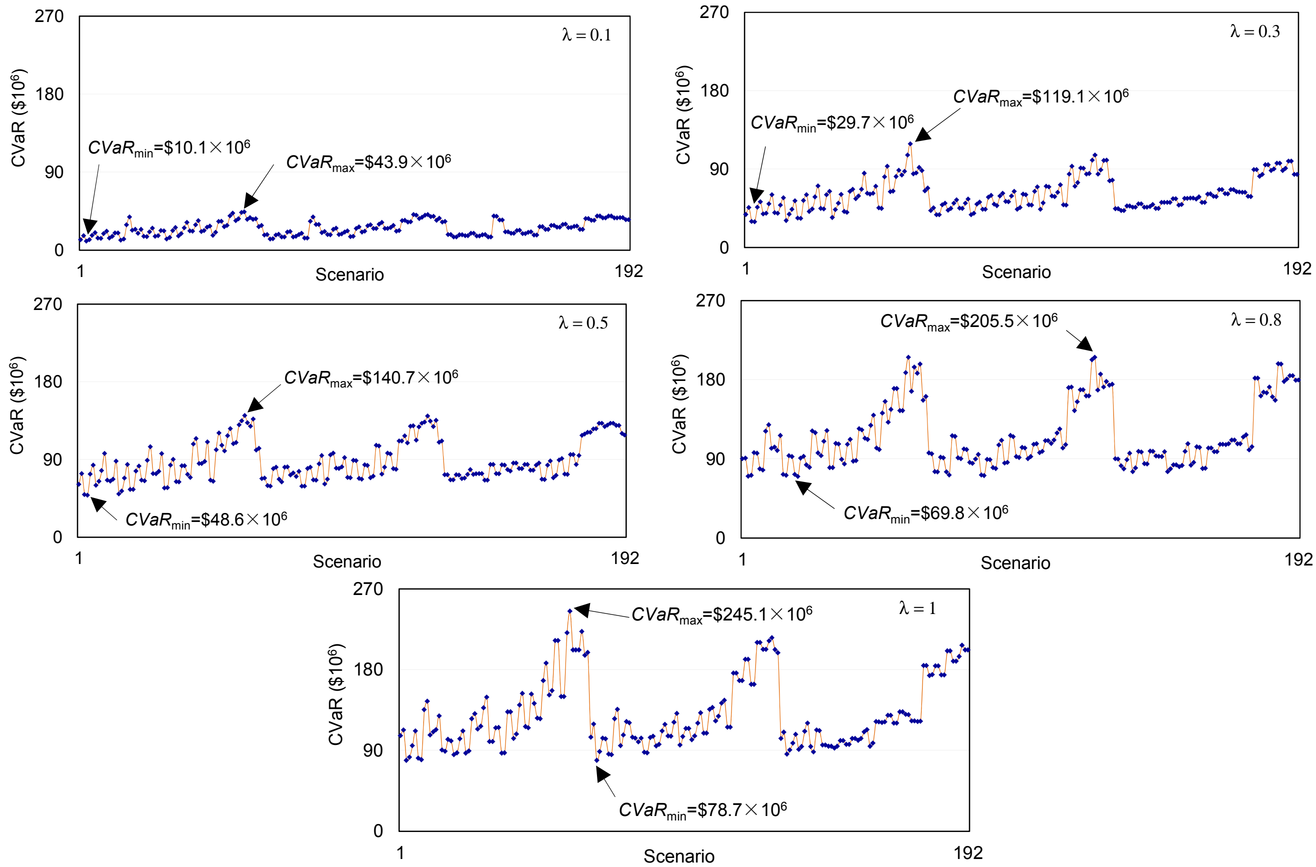

Figure 8. CVaR costs under different λ levels.

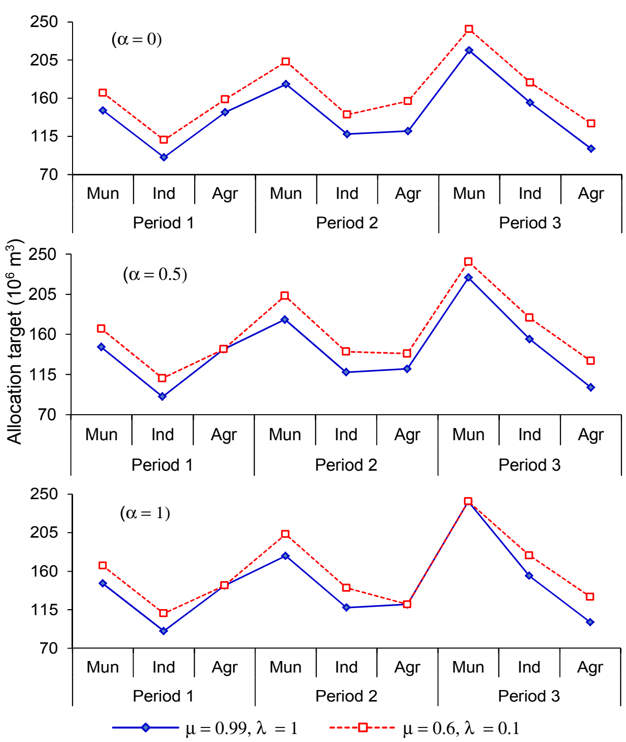

Figure 9. Optimal targets under several typical scenarios.

ferent benefits and penalties.

Figure 10 shows the optimal amounts of water allocated (respectively corresponding to lower and upper system benefits) to municipal, industry and agriculture over the planning horizon under several typical scenarios. Symbols "LLL" and "HHH" denote low and high stream flows in all of the three periods, respectively. For example, when flow levels are all low in the three periods (i.e., LLL), the amount of water allocation corresponding to the minimum system benefit would be 977.4 × 10^6 m^3 ($\alpha = 0$, $\mu = 0.99$, $\lambda = 1$); the related water shortage would be in the range of 289.0 × 10^6 m^3 and 508.9 × 10^6 m^3. The amount of water allocation under the maximum system benefit would be 1085.2 × 10^6 m^3 ($\alpha = 0$, $\mu = 0.6$, $\lambda = 0.1$) and the water shortage would be [181.2, 401.1] × 10^6 m^3. Among all users, municipal is the largest water consumer, accounting from [44.0, 45.8]% of the total water allocation. Water allocation schemes would be different from each other as α, μ and λ levels are changed; this reveals that both uncertainties (randomness and fuzziness) and risk attitudes impact water allocation schemes. Among all users, the shortage for municipal is the lowest under all flow levels. The municipal use should be of the highest priority since it brings the highest benefit when its water demand is satisfied; meanwhile, it is subject to the highest penalty if the promised water is not delivered. Agriculture would encounter serious water shortage, particularly when streamflow levels are low over the planning horizon. When the targeted water cannot be sup-

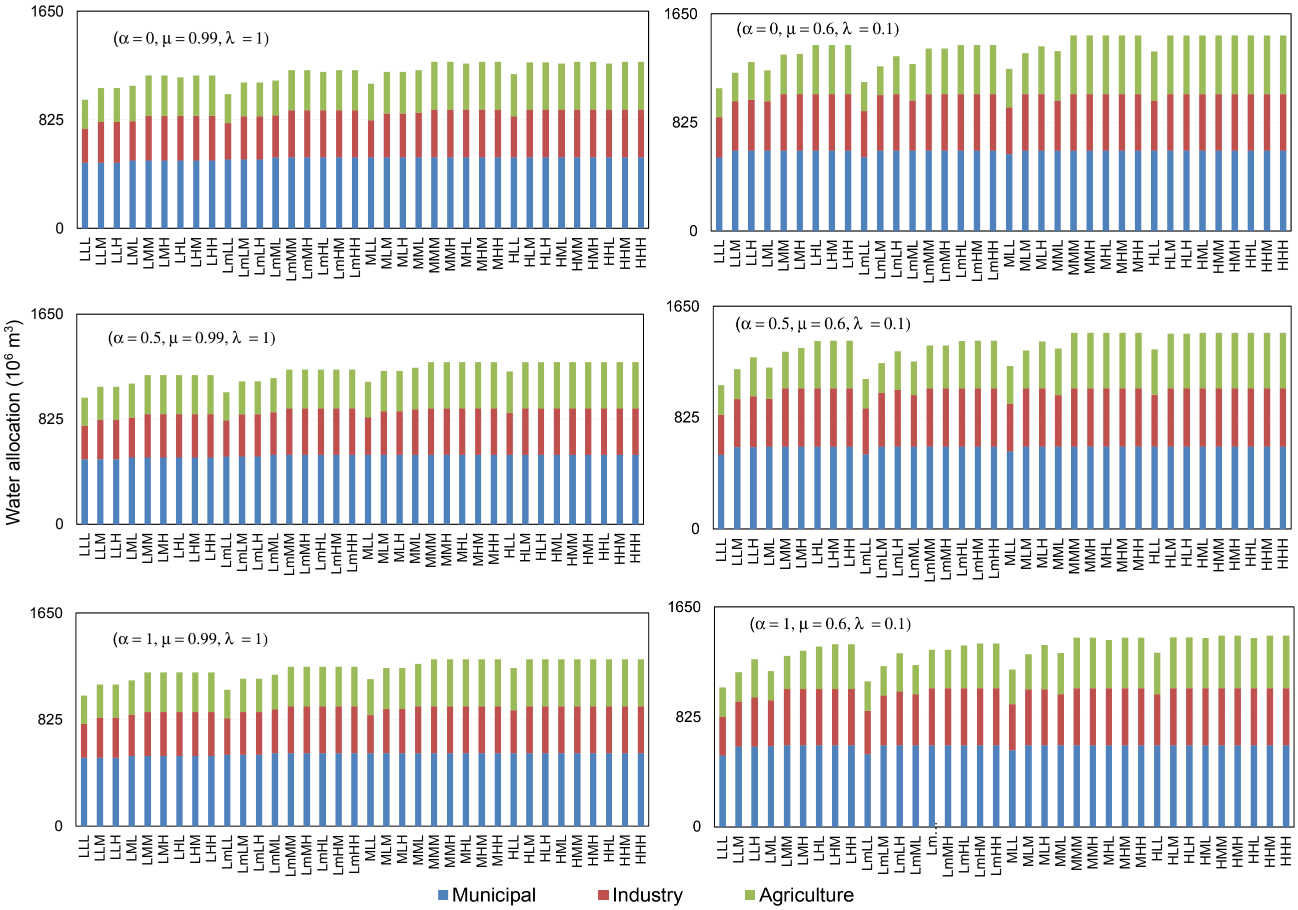

Figure 10. Water allocation to each user under several typical scenarios.

plied, the local farmers often obtain water through overexploiting groundwater; the largely uncontrolled groundwater use can produce far-reaching environmental and social problems (e.g., water table depletion, groundwater quality degradation, destruction of associated water ecosystem, proliferation of free-riding behaviors). In future, restrictions for municipal water allocation may be introduced when streamflow is very low, which may be used to demonstrate the implied value of water by the losses that occur in the agricultural sector (the marginal value of crops foregone).

Figure 11 compares water allocation patterns under different α-cut levels (corresponding to lower and upper system benefits). Under the worst-case scenario, when flow levels are all low over the planning horizon, the total of allocated water would be [977.4, 1085.2] × 10^6, [994.3, 1065.6] × 10^6 and [1011.2, 1046.0] × 10^6 m^3 under α levels of 0, 0.5 and 1; nevertheless, the total water demands range from 1266.4 × 10^6 m^3 to 1515.2 × 10^6 m^3, indicating a severe shortage in water supply under each α-cut level. Although the probability of the worst-case scenario is low, the penalties due to the occurrence of such an extreme event are high. Therefore, an optimal policy that is formulated based on the analyses of not only the system benefits but also the related risks and the associated penalties would be acquired.

5. Concluding Remarks

In this study, a non-deterministic integrated optimization model with risk measure has been developed for planning water resources system under uncertainty. The developed model can tackle uncertainties presented as probability distributions, fuzzy sets, and their combinations. Risk-aversion measures are incorporated into the optimization framework to reflect the preference of decision makers, such that the tradeoff between system benefit and extreme expected loss are investigated. Vertex analysis approach is proposed for solving the model, such that solutions under different α, μ and λ levels can be generated by solving a series of deterministic models.

The conventional two-stage and multistage stochastic programming models consider the expectation as the preference criterion while comparing the random variables to find the best decisions, based on an assumption that decision makers are risk neutral. In comparison, the developed model is capable of handling probabilistic and possiblistic uncertainties which are often related to resource availability as well as taking into the account the average loss exceeding the value-at-risk. Results (from the integrated optimization model) can reflect the decision makers' attitudes towards risk aversion and generate all potential options for decision making in association with different

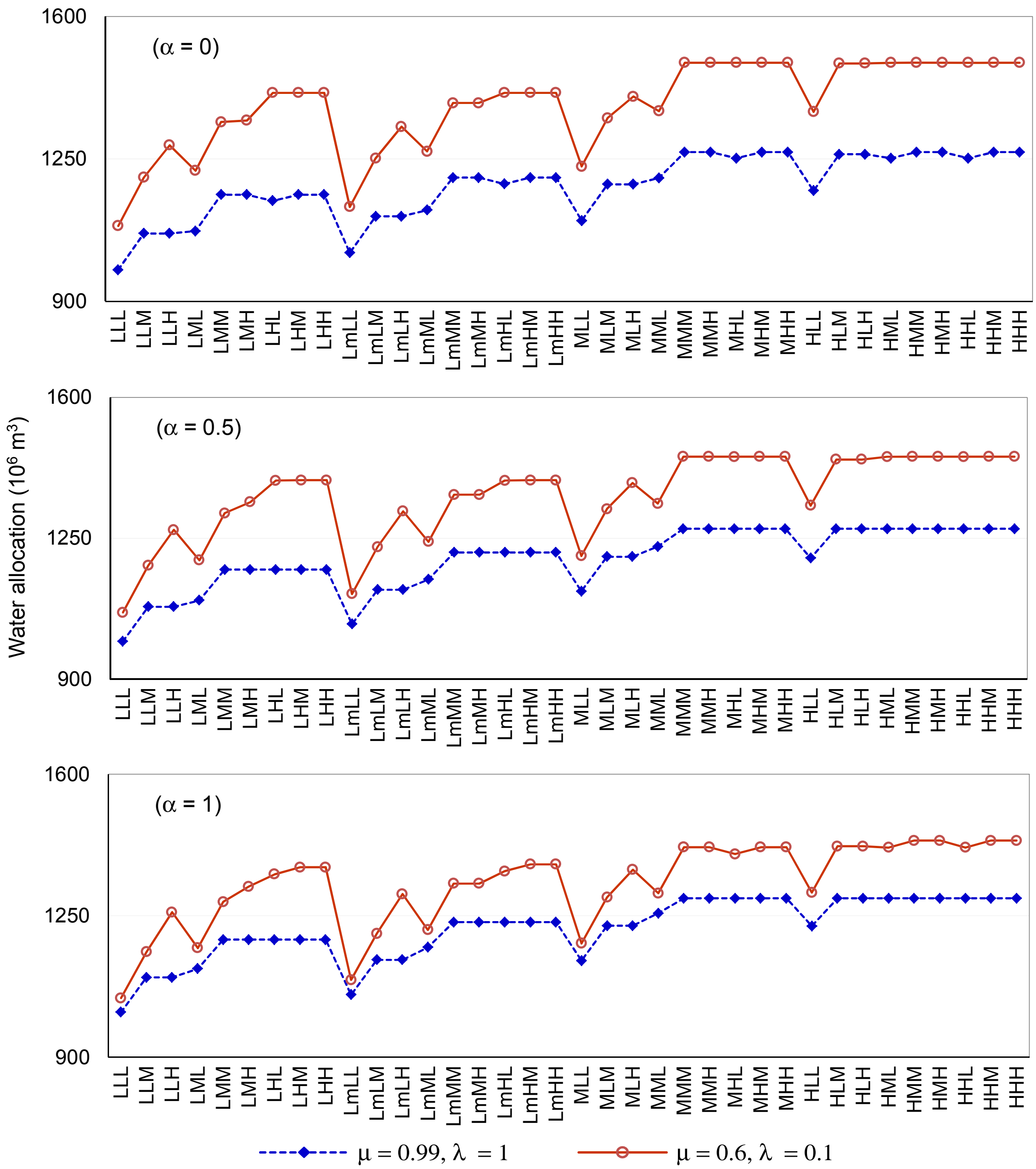

Figure 11. Water allocation patterns under several typical scenarios.

system-reliability levels.

The developed model has been applied to a case study of planning water resources management in the Heshui River Basin. In the modeling formulation, penalties are exercised with recourse against any infeasibility, which permits analyzing policies that are associated with different levels of economic consequences when the promised water-allocation targets are violated. CVaR measure is used in the objective function for addressing the expected loss under extreme conditions (i.e., risk aversion). A number of uncertainty and risk measures (i.e., α, μ and λ) are designed, such that 960 scenarios have been examined. Results indicate that deficits would occur when the available water amounts are less than the promised targets. The water-allocation schemes would be different from each other as α, μ and λ levels are changed; this reveals that random and fuzzy uncertainties as well as decision makers' attitudes towards risk aversion can impact water-allocation schemes. Among all users, municipal is the largest water consumer (occupying [44.0, 45.8]% of the total water allocation). Agriculture would encounter serious water shortage particularly when streamflow levels are low over the planning horizon.

Results disclose that different policies in regulating the water-allocation targets are associated with different levels of system benefit, economic penalty, and system-failure risk. Both higher μ and λ levels lead to a reduced system benefit and an increased CVaR cost, such that decision makers could assign different μ and λ values to adjust risk-control levels based on their preferences. However, the selection of a suitable alternative among the obtained solutions under different α, μ and λ values is challenged. To make the final decision, not only the attitudes of decision makers toward risks, but also their abilities of comprehensive consideration and integrated assessment to different schemes have to be considered.

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References

Andersson, F., Mausse, H., Rosen, D., and Uryasev, S. (2001). Credit risk optimization with conditional value-at-risk criterion. *Math. Program.*, 89(2), 273-291. https://doi.org/10.1007/PL00011399

Bichai, F., Grindle, A.K., and Murthy, S.L. (2018). Addressing barriers in the water-recycling innovation system to reach water security in arid countries. *J. Clean. Prod*., 171, S97-S109. https://doi.org/10.1016/j.jclepro.2016.07.062

Birge, J.R., and Louveaux, F.V. (1997). *Introduction to Stochastic Programming*. Springer, New York, NY.

Borgomeo, E., Hall, J.W., Fung, F., Watts, G., Colquhoun, K., and Lambert, C. (2014). Risk-based water resources planning: incurporating probabilistic nonstationary climate uncertainties. *Water Resour. Res*., 50, 6850-6873. https://doi.org/10.1002/2014WR015558

Borgomeo, E., Mortazavi-Naeini, M., Hall, J.W., and Guillod, B.P. (2018). Risk, robustness and water resources management under uncertainty. *Earth's Future,* 6(3), 468-487. https://doi.org/10.1002/2017EF000730

Chen, H.K., Hsu, W.K., and Chiang, W.L. (1998). A comparison of vertex method with JHE method. *Fuzzy Sets Syst*., 95, 201-214. https://doi.org/10.1016/S0165-0114(96)00307-7

Dong, C., Schoups, G., and van de Giesen, N. (2013). Scenario development for water resource planning and management: A review. *Technol. Forecast. Soc. Change*, 80, 749-761. https://doi.org/10.1016/j.techfore.2012.09.015

Dong, W., and Shah, H.C. (1987). Vertex method for computing functions of fuzzy variables. *Fuzzy Sets Syst*., 24, 65-78. https://doi.org/10.1016/0165-0114(87)90114-X

Dubois, D., and Prade, H. (1986). Fuzzy sets and statistical data. *Eur. J. Oper. Res*., 25, 345-356. https://doi.org/10.1016/0377-2217(86)90266-3

Dunn, S.M., Brown, I., Sample, J., and Post, H. (2012). Relationships between climate, water resources, land use and diffuse pollution and the significance of uncertainty in climate change. *J. Hydrol*., 434-435, 19-35. https://doi.org/10.1016/j.jhydrol.2012.02.039

Dutta, S., Sahoo, B.C., Mishra, R., and Acharya, S. (2016). Fuzzy stochastic genetic algorithm for obtaining optimum crops pattern and water balance in a farm. *Water Resour. Manag*., 30(12), 40978 https://doi.org/10.1007/s11269-016-1406-7

Ewertowska, A., Pozo, C., Gavaldà, J., Jiménez, L., and Guillén-Gosálbez, G. (2017). Combined use of life cycle assessment, data envelopment analysis and Monte Carlo simulation for quantifying environmental efficiencies under uncertainty. *J. Clean. Prod*. 166, 771-783. https://doi.org/10.1016/j.jclepro.2017.07.215

Forio, M.A.E., Mouton, A., Lock, K., Boets, P., Tien, N.T.H., Ambarita, M.N.D., Musonge, P.L.S., Dominguez-Granda, L., and Goethals, (2017). Fuzzy modelling to identify key drivers of ecological water quality to support decision and policy making. *Environ. Sci. Policy*, 68, 58-68. https://doi.org/10.1016/j.envsci.2016.12.004

Fu, Q., Li, L.Q., Li, M., Li, T.X., Liu, D., Hou, R.J., and Zhou, Z.Q. (2018). An interval parameter conditional value-at-risk two-stage stochastic programming model for sustainable regional water allocation under different representative concentration pathways scenarios. *J. Hydrol*., 564, 115-124. https://doi.org/10.1016/j.jhydrol.2018.07.008

Fu, Y.P., Huang, G.H., Liu, L.R. and Zhai, M.Y. (2021). A factorial CGE model for analyzing the impacts of stepped carbon tax on Chinese economy and carbon emission. *Sci. Total Environ.*, 759, 143512. https://doi.org/10.1016/j.scitotenv.2020.143512

Huang, Y.F., Baetz, B.W., Huang, G.H. and Liu, L. (2002). Violation analysis for solid waste management systems: an interval fuzzy programming approach*. J. Environ. Manag.*, 65(4), 431-446. https://doi.org/10.1006/jema.2002.0566

Gaivoronski, A., Sechi, G.M., and Zuddas, P. (2012). Cost/risk balanced management of scarce resources using stochastic programming. *Eur. J. Oper. Res.*, 216, 214-224. https://doi.org/10.1016/j.ejor.2011.06.040

Hu, Z.N., Wei, C.T., Yao, L.M., Li, L., and Li, C.Z. (2016). A multi-objective optimization model with conditional value-at-risk constraints for water allocation equality. *J. Hydrol.*, 542, 330-342. https://doi. org/10.1016/j.jhydrol.2016.09.012

Huang, G.H. (1998). A hybrid inexact-stochastic water management model. *Eur. J. Oper. Res.*, 107, 137-158. https://doi.org/10.1016/S0377-2217(97)00144-6

Hussien, W.A., Memon, F.A., and Savic, D.A. (2018). A risk-based assessment of the household water-energy-food nexus under the impact of seasonal variability. *J. Clean. Prod*., 171, 1275-1289. https://doi.org/10.1016/j.jclepro.2017.10.094

Inuiguchi, M., and Tanino, T. (2000). Portfolio selection under independent possibilistic information. *Fuzzy Sets Syst*., 115, 83-92. https://doi.org/10.1016/S0165-0114(99)00026-3

Iskander, M.G. (2005). A suggested approach for possibility and necessity dominance indices in stochastic fuzzy linear programming. *Appl. Math. Lett.*, 18, 395-399. https://doi.org/10.1016/j.aml.2004.04.010

Ji, L., Huang, G.H., Niu, D.X., Cai, Y.P., and Yin, J.G. (2020). A stochastic optimization model for carbon-emission reduction investment and sustainable energy planning under cost-risk control. *J. Environ. Inform*., 36 (2), 107-118. https://doi:10.3808/jei.202000428

Khor, C.S., Chachuat, B., and Shah, N. (2014). Fixed-flow rate total water network synthesis under uncertainty with risk management. *J. Clean. Prod*., 77, 79-93. https://doi.org/10.1016/j.jclepro.2014.01.023

Khosrojerdi, T., Moosavirad, S.H., Ariafar, S., and GhaeiniHessaroeyeh, M. (2019). Optimal allocation of water resources using a two-stage stochastic programming method with interval and fuzzy parameters. *Nat. Resour. Res.*, 28 (3), 1107-1124. https://doi.org/10.1007/s11053-018-9440-1

Khorshidi, M.S., Nikoo, M.R., Sadegh, M., and Nematollahi, B. (2019). A multi-objective risk-based game theoretic approach to reservoir operation policy in potential future drought condition. *Water Resour. Manag*., 33, 1999-2014. https://doi.org/10.1007/s11269-019-02223-w

Li, Y.F., Li, Y.P., Huang, G.H. and Chen, X. (2010). Energy and environmental systems planning under uncertainty—an inexact fuzzy-stochastic programming approach. *Appl. Energy*, 87(10), 3189-3211. https://doi.org/10.1016/j.apenergy.2010.02.030

Li, Y.P., Huang, G.H., and Nie, S.L. (2006). An interval-parameter multistage stochastic programming model for water resources management under uncertainty. *Adv. Water Resour*., 29, 776-789. https://doi.org/10.1016/j.advwatres.2005.07.008

Li, Y.P., Huang, G.H., Yang, Z.F. and Nie, S.L. (2008). IFMP:

Interval-fuzzy multistage programming for water resources management under uncertainty. *Resour. Conserv. Recy.*, 52(5), 800-812. https://doi.org/10.1016/j.resconrec.2007.11.007

Li, Y.P., Huang, G.H., Guo, P., Yang, Z.F., and Nie, S.L. (2010). A dual-interval vertex analysis method and its application to environmental decision making under uncertainty. *Eur. J. Oper. Res.*, 200, 536-550. https://doi.org/10.1016/j.ejor.2009.01.013

Li, Y.P., Huang, G.H., Nie, S.L., and Chen, X. (2011). A robust modeling approach for regional water management under multiple uncertainties. *Agric. Water Manag.*, 98, 1577-1588. https://doi.org/10.1016/j.agwat.2011.05.008

Li, Y.P., Nie, S., Huang, Charley Z., McBean, E.A., Fan, Y.R., and Huang, G.H. (2017). An integrated risk analysis method for planning water resource systems to support sustainable development of an arid region. *J. Environ. Inform.*, 29(1), 1-15. https://doi.org/10.3808/jei.201700359

Ma, Y., Li, Y.P., Huang, G.H., and Liu, Y.R. (2020). Water-energy nexus under uncertainty: Development of a hierarchical decision-making model. *J. Hydrol.*, 591, 125297. https://doi.org/10.1016/j.jhydrol.2020.125297

Martinez-Hernandez, E., Leach, M., and Yang, A.D. (2017). Understanding water-energy-food and ecosystem interactions using the nexus simulation tool NexSym. *Appl. Energy*, 206, 1009-1021. https://doi.org/10.1016/j.apenergy.2017.09.022

Moeini, R., and Soltani-nezhad, M. (2020). Extension of the constrained gravitational search algorithm for solving multireservoir operation optimization problem. *J. Environ. Inform.*, 36 (2), 70-81. https://doi:10.3808/jei.202000434

Mouratiadou, I., Biewald, A., Pehl, M., Bonsch, M., Baumstark, L., Klein, D., Popp, A., Luderer, G., and Kriegler, E. (2016). The impact of climate change mitigation on water demand for energy and food: An integrated analysis based on the Shared Socio-economic Pathways. *Environ. Sci. Policy*, 64, 48-58. https://doi.org/10.1016/j.envsci.2016.06.007

Naserizade, S.S., Nikoo, M.R., and Montaseri, H. (2018). A risk- based multi-objective model for optimal placement of sensors in water distribution system. *J. Hydrol.*, 557, 147-159. https://doi.org/10.1016/j.jhydrol.2017.12.028

Nazemi, A., and Wheater H.S. (2014). How can the uncertainty in the natural inflow regime propagate into the assessment of water resource systems? *Adv. Water Resour.*, 63, 131-142. https://doi.org/10.1016/j.advwatres.2013.11.009

Noyan, N. (2012). Risk-averse two-stage stochastic programming with an application to disaster management. *Comput. Oper. Res.*, 39, 541-559. https://doi.org/10.1016/j.cor.2011.03.017

Ortiz-Partida, J.P., Kahil, T., Ermolieva, T., Ermoliev, Y., Lane, B., Sandoval-Solis, S., and Wada, Y. (2019). A two-stage stochastic optimization for robust operation of multipurpose reservoirs. *Water Resour. Manag.*, 33, 3815-3830. https://doi.org/10.1007/s11269-019-02337-1

Piantadosi, J., Metcalfe, A.V., and Howlett, P.G. (2008). Stochastic dynamic programming (SDP) with a conditional value-at-risk (CVaR) criterion for management of storm-water. *J. Hydrol.*, 348, 320-329. https://doi.org/10.1016/j.jhydrol.2007.10.007

Rockafellar, R.T., and Uryasev, S. (2002). Conditional value-at-risk for general loss distributions. *J. Bank Fin.*, 26(7), 1443-1471. https: // doi.org/10.1016/S0378-4266(02)00271-6

Soleimani, H., and Govindan, K. (2014). Reverse logistics network design and planning utilizing conditional value at risk. *Eur. J. Oper. Res.*, 237, 487-497. https://doi.org/10.1016/j.ejor.2014.02.030

Soltani, M., Kerachian, R., Nikoo, M. R., and Noory, H. (2016). A conditional value at risk-based model for planning agricultural water and return flow allocation in river systems. *Water Resour. Manag.*, 30, 427-443. https://doi.org/10.1007/s11269-015-1170-0

Steinfeld, C.M.M., Sharma, A., Mehrotra, R., and Kingsford, R.T. (2020). The human dimension of water availability: Influence of management rules on water supply for irrigated agriculture and the environment. *J. Hydrol.*, 588, 125009. https://doi.org/10.1016/j.jhydrol.2020.125009

Su, Y.Y., Li, Y.P., Huang, G.H., Jia, Q.M., and Li, Y.F. (2021). An integrated multi-GCMs Bayesian-neural-network hydrological analysis method for quantifying climate change impact on runoff of the Amu Darya River basin. *Int. J. Climatol.*, 41, 3411-3424. https://doi.org/10.1002/joc.7026

Tan, Q., Huang, G.H. and Cai, Y.P. (2011). Radial interval chance-constrained programming for agricultural non-point source water pollution control under uncertainty. *Agric. Water Manag.*, 98(10), 1595-1606. https://doi.org/10.1016/j.agwat.2011.05.013

Wang, Y.Y., Huang, G.H., and Wang, S. (2017). CVaR-based factorial stochastic optimization of water resources systems with correlated uncertainties. *Stoch. Environ. Res. Risk Assess.*, 31 (6), 1543-1553. https://doi.org/10.1007/s00477-016-1276-9

Yu, B.Y., Wu, P., Sui, J., Ni, J., and Whitcombe, T. (2020). Variation of runoff and sediment transport in the Huai River - A case study. *J. Environ. Inform.*, 35 (2), 138-147. https://doi.org/10.3808/jei.202000429

Zadeh, L.A. (1975). The concept of a linguistic variables and its application to approximate reasoning-1. *Inf. Sci.*, 8, 199-249. https://doi.org/10.1016/0020-0255(75)90036-5

Zhang, Y.F., Li, Y.P., Huang, G.H., and Ma, Y. (2021). A copula-based stochastic fractional programming method for optimizing water-food-energy nexus system under uncertainty in the Aral Sea basin. *J. Clean. Prod.*, 292, 126037. https://doi.org/10.1016/j.jclepro.2021.126037

Zhai, M.Y., Huang, G.H., Liu, L.R., Zheng, B.Y. and Guan, Y.R. (2020). Inter-regional carbon flows embodied in electricity transmission: network simulation for energy-carbon nexus. *Renew. Sustain. Energy Rev.*, 118, 109511. https://doi.org/10.1016/j.rser.2019.109511

Zimmermann, H.J. (1995). *Fuzzy Set Theory and its Applications, third ed*. Kluwer Academic Publishers. https://doi.org/10.1007/978-94-015-8702-0