A Low-Impact Development–Based Multi-Objective Optimization Model for Regional Water Resource Management under Impacts of Climate Change

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Under the urgency of rational water resource allocation and effective urban flooding control, a multi-objective interval birandom chance-constrained programming (MIBCCP) model is developed for supporting regional water resource management under multiple uncertainties and climate change in this study. Two objectives were included in this model, which are the minimization of total system costs and the maximization of total pollutant treatment amounts. The major advantage of the proposed MIBCCP model is that it realized the effective combined utilization of conventional and nonconventional water sources under complexities and uncertainties through incorporating compromise programming, birandom chance-constrained programming, and interval linear programming within a general framework. This way effectively overcomes water shortage issue and reduces urban flood frequency under climate change. A water supply management system of the educational park in Tianjin was used as a study case for demonstration. A variety of adaptive water allocation alternatives and construction schemes for LID (low-impact development) projects under RCP4.5 and RCP8.5 (representative concentration pathway 4.5 and 8.5) scenarios were obtained to deal with possible changes arising from increasing rainfall and runoff in the future. It is concluded that the proposed MIBCCP model provided the effective linkage between the utilization of nonconventional water resources and urban flood prevention and offered insights into the trade-off between economic benefits and environmental protection.

Keywords: birandom variable, low-impact development, water resource management, climate change, uncertainty

INTRODUCTION

With the current rapid improvement in socioeconomic development, industrialization, and urbanization, urban water scarcity is becoming an overwhelmingly urgent issue on a global scale, and this is particularly prominent in China (Loomis et al., 2019). For example, the average annual water scarcity in China is up to $4.00 \times 10^8 \, \mathrm{m}^3$, nearly two-thirds of China's cities are suffering from a water shortage, and 443–525 million city people live with high water scarcity. Meanwhile, China's urban water consumption continues to increase at an annual rate of 4–8% over the most recent decade (Wang et al., 2019). The conflict between increased water demand

and limited available water resources has become particularly evident in most cities in China. Currently, urban water resource management patterns mainly focus on the reasonable exploitation and effective utilization of conventional water resources (including surface and underground water). In fact, nonconventional water resources, such as rainwater and reclaimed water, have significant advantages in regard to water resource allocation and management (Ye et al., 2018). For instance, the utilization of rainwater has the effect of reducing the water supply cost by replacing potable water used for flushing toilets and watering of gardens, and reclaimed water distributes for industrial demand with an overall positive environmental impact. The combination of conventional and nonconventional water resources from a quantity and quality viewpoint is thus expected.

In addition to water scarcity, modern urban water resource management is also confronted with the huge challenges presented by increasingly frequent urban flooding, which can cause substantial economic damage and human distress (Kundzewicz et al., 2018). Over the last decades, annual urban flooding damage in China has exceeded 10 billion USD, and the number of flood fatalities is greater than approximately 1,000 (Kundzewicz et al., 2019). Moreover, a series of research on the water resource management under climate change indicated that the climate change could aggravate water scarcity seriously and cause urban flooding frequently through affecting regional rainfall, temperature, evaporation, and hydrological cycle, leading to a huge challenge on water resource management (Shang et al., 2015; Mahmoud and Gan, 2018; Xia et al., 2019; Zhang et al., 2019). In order to deal with such challenges, the Chinese government initiated the "Sponge City" Program in 2013, which incorporates (LID) concepts to improve the urban drainage infrastructure and address urban flooding (Song et al., 2019; Xu et al., 2019). As a sustainable, innovative, and effective stormwater runoff control method, LID projects have advantages in controlling stormwater and urban runoff and storing rainwater as underground water resources compared with non-LID projects. However, the high construction cost associated with these projects may trigger excessive economic burden, which has a negative influence on the development and application of LID technologies. Moreover, many factors, including socioeconomic, meteorological, geographic, and environmental aspects, are involved in the selection and placement processes of LID projects, which bring significant difficulties to the formulation of the LID project optimization models and generation of effective solutions. Therefore, it is important to develop an effective method for optimizing LID project implementation schemes under complexities that improve water use efficiency, explore nonconventional water resources, and control urban flooding with a minimum cost.

For urban water resource management, considering system factors comprehensively, establishing LID projects rationally, combining nonconventional and conventional water resources effectively, dealing with the impact of climate change, and formulating water sources allocations optimization model are suitable methods for resolving urban water scarcity and flood control, and such approaches have been the focus of many studies

in recent years (Mainuddin et al., 1997; Shangguan et al., 2002; Wang et al., 2008; Liu et al., 2011; Sample and Liu, 2014; Bekchanov et al., 2015; Palanisamy and Chui, 2015; Palla and Gnecco, 2015; Eckart et al., 2018; Xu et al., 2018; Ye et al., 2018; Helmia et al., 2019; Huang and Lee, 2019). For instance, Shangguan et al. (2002) developed a recurrence control model for regional optimal allocation of water resource for obtaining maximum efficiency. Liu et al. (2011) presented an optimization approach for the integrated management of water resources, including both nonconventional and conventional water resources. Xu et al. (2018) proposed an optimal water allocation model for industrial sectors based on water footprint accounting to optimize the allocation of nonconventional and conventional water resources in Dalian. Ye et al. (2018) presented a multi-objective optimization model to help optimize the allocation of water resources to different water users in Beijing. Sample and Liu (2014) developed a rainwater analysis and simulation model to optimize rainwater harvesting systems for water supply and runoff capture. Eckart et al. (2018) established a management model to optimize LID implementation strategies with the objective of minimizing peak flow. Huang and Lee (2019) proposed a programming model to solve water shortage of Taiwan under the impact of climate change. Helmi et al. (2019) developed a modeling tool to allocate LID projects in a cost-optimized method. However, above studies mainly sought to establish an optimization model for water resource allocation or LID projects, which considered only single objective for optimization, while in the real practice, there is more than one issue need to be taken into account simultaneously when designing and executing the water resource management strategies, for the sake of achieving a balance among them.

In fact with the increased complexity and our in-depth understanding in the urban water resource system, it is apparent that there is no absolute deterministic water allocation system. Specifically, the water demand exhibits a random nature that is subject to multiple variables, including meteorological factors, socioeconomic conditions, and deviations caused by the subjective judgments and understandings of humans. For example, the ecological water demand would be different with the change of runoff and biodiversity. Similarly, some economic and engineering factors, which are influenced by the resource availability, technical conditions, and policy regulations, fluctuate in the small ranges. For instance, the supply price of transfer water would fluctuate between 8.8 and 9.2 Yuan/m^3 due to the impact of different technical conditions. Such uncertainties lead to significant difficulties in formulating urban water resource allocation models and generating an optimal management pattern. Currently, a large amount of uncertain optimization techniques have been developed by many researchers with the aim of solving urban water resource management problems (Huang, 1988; Liu et al., 2008; Qin and Huang, 2009; Qin et al., 2011; Dai et al., 2018; Xu et al., 2018; Zhang et al., 2019). For example, Dai et al. (2018) presented a Gini coefficient–based stochastic optimization model for supporting water resource allocation on a watershed scale. Xu et al. (2018) developed a stochastic-based water allocation

optimization model on a watershed scale for supporting water supply planning and wetland restoration activities of the Xiaoqing River watershed. Zhang et al. (2019) proposed an interval multi-objective multi-stage stochastic programming model for finding a reasonable water storage scale and optimizing limited irrigation water resource. Based on the above studies, it can be concluded that many researchers have focused on dealing with the randomness inherent in urban water resource management. However, the above studies mainly utilized random variables with a known distribution type to describe the uncertainties involved in the water resource system, and they rarely observed that water demands in the real world may be subject to twofold randomness with incomplete or uncertain information. Specifically, it is first assumed that the water demands ξ are expressed as the random variables with the normal distributions, that is, $\xi \sim N(\mu, \delta^2)$, where μ and δ denote the mean value and standard deviation, respectively. Based on various survey and estimation results from n group of respondents, n groups of random variables could be obtained, that is, (μ_1, δ_1^2), (μ_2, δ_2^2), (μ_n, δ_n^2), such that μ and δ values are more suitable to be random variables (based on the collected data above) rather than fixed values as are traditional random variables (Xu et al., 2014). Hence, the parameters μ and σ should be described as new random variables, which are the so-called birandom variables, a concept first proposed by Peng and Liu (2007). This concept has been successfully applied to the flow shop scheduling problem, vendor selection problem, and hydropower station operation planning problem (Xu and Zhou, 2009; Xu and Ding, 2011; Xu and Tao, 2012).

As mentioned above, following three aspects of urban water resource management still need to be improved. First, current optimization models often pay attention to only one aspect of water resource allocation or LID project exploration. In fact, it is necessary to develop a comprehensive optimization model that incorporates the exploration of LID projects into the urban water management scheme. Second, because water demands directly affect the accuracy and rationality of the results due to the supply–demand constraint, it is important to develop a birandom optimization method to avoid the deviation caused by the birandomness of the water demands. Third, the climate change exerts the influences on the water availability and the occurrence of urban flood, which should be incorporated into the optimization model for integrated water resource management. As such, the main goal of this study was to develop a (MIBCCP) model under climate change for supporting the urban water resource management. The proposed model aims to optimize water resource allocation and address the urban flooding under uncertainties and different climate change scenarios, while minimizing the total system costs and maximizing the treated pollutant amount. The rest of this study is organized as follows: *Materials and Methods* introduce the descriptions of the compromise programming, birandom chance-constrained programming, and interval linear programming and describe formulation and the solution procedure of the MIBCCP model. An overview of the reference education park and the MIBCCP model for this park are proposed in *Case Study*. In

Results Analysis and Discussion, the variations in the obtained solutions and impact of climate change on water resource management are analyzed and discussed. Finally, the conclusions summarizing this study are presented in the last section.

METHODOLOGY

To establish a cost-effective and environmentally friendly water resource management pattern, multiple objectives for the programming model should be taken under consideration, so that the model is capable of tackling the economic and environmental objectives simultaneously. Moreover, the estimation and expression of uncertain factors are critical for generating a rational and reliable management strategy of the urban water system, as many of the system parameters are associated with various types of the uncertainties. Therefore, an inexact multi-objective equilibrium chance-constrained programming model with the birandom and interval variables (i.e., MIBCCP) was developed for addressing these issues.

Preliminary Definitions and Descriptions of Proposed a Multi-Objective Interval Birandom Chance-Constrained Programming Model

In this section, some definitions, conceptions, and descriptions associated with compromise programming, birandom parameters, and interval numbers are described first in order to formulate and solve the proposed MIBCCP model.

Compromise Programming
Currently, many methods are available for solving multi-objective programming problems, among which the compromise programming is the most commonly used. The solution algorithm of compromise programming is based on the concept of a distance scale d_p, a point which has the shortest distance to the ideal solution from the noninferior solution set. The total performance of all objective functions can be written as follows:

$$Min\, d_p = \min\left\{ \sum_{k=1}^{K} \pi_k^p \left(\frac{Z_k^{\max}(X) - Z_k(X)}{Z_k^{\max} - Z_k^{\min}} \right)^p \right\}^{1/p} \quad (1a)$$

$$1 < p < \infty \quad (1b)$$

$$\pi_k^p > 0 \quad (1c)$$

$$\sum_{k=1}^{K} \pi_k^p = 1 \quad (1d)$$

where $Z_k^{\max}(x)$ and $Z_k^{\min}(x)$ are the maximum and minimum values of each individual objective which can be obtained through the transformation of the original multi-objective programming that is single objective. The introduction of $Z_k^{\max}(x)$ and $Z_k^{\min}(x)$ is used to normalize noncommensurable formats and units in model objectives. $Z_k(X)$ = the value of the objective k; k = the total number of objectives; π_k^p = the corresponding weight of each

objective. The distance scale d_p varies with various p, where $p = \infty$ when decision-makers focus on the specific objective; $p = 1$ is corresponded to the decision-makers, considering all the objectives. Considering the complexity of the MIBCCP model, the item p is designed as 1 for the simplicity in this research.

Introduction of Birandom Variable following the Normal Distribution

Birandom variable, a concept first proposed by Peng and Liu (2007), is a useful tool to deal with problems with twofold randomness and has been successfully applied to many fields (Xu and Zhou, 2009; Xu and Ding, 2011; Xu and Tao, 2012). In this study, the random variable following the normal distribution is considered as the example. For any ω, $\xi(\omega)$ is a birandom variable with normal distribution and is expressed as $N(\mu(\omega), \sigma^2(\omega))$, where $\mu(\omega)$ and $\sigma(\omega)$ are random variables, rather than fixed values of general random variable.

Definition 2.1. A n-dimensional birandom vector ξ is a map from the probability space (Ω, A, Pr) to a collection of n-dimensional random vectors such that $Pr\{\xi(\omega) \in B\}$ is a measurable function with respect to ω for any Borel set B of the real space R^n. Especially, ξ is called a birandom variable as $n = 1$.

Example 2.1. A birandom variable ξ is assumed to follow the normal distribution, if for each ω, $\xi(\omega)$ is a random variable with normal distribution, denoted by $N(\mu(\omega), \sigma^2(\omega))$, where $\mu(\omega)$, $\sigma(\omega)$ are the random variables defined on the probability space (Ω, A, Pr).

Lemma 2.1. Let $\xi = (\xi_1, \xi_2, \ldots, \xi_n)$ be a birandom vector and f be a Borel measurable function from R^n to R. Then $f(\xi)$ is a birandom variable.

Let ξ_1 and ξ_2 be two birandom variables defined on the probability spaces (Ω_1, A_1, Pr_1) and (Ω_2, A_2, Pr_2), respectively. Then $\xi = \xi_1 + \xi_2$ is a birandom variable on $(\Omega_1 \times \Omega_2, A_1 \times A_2, Pr_1 \times Pr_2)$ defined by $\xi(\omega_1, \omega_2) = \xi_1(\omega_1) + \xi_2(\omega_2)$, $(\omega_1, \omega_2) \in (\Omega_1 \times \Omega_2)$.

Interval Number

The interval number is composed of the lower bound and upper bound, which is depicted in **Eq. 1**, where the items a^- and a^+ are the lower and upper bounds of $a_{ij}^\pm$, respectively. The lower and upper bounds represent minimum value and maximum value of $a^\pm$, respectively. Two major advantages of the interval number are the low requirement of data information and the interval optimization model is solved without excessive computational burden (Huang et al., 1992).

$$a_{ij}^\pm = \left[a_{ij}^-, \ a_{ij}^+\right] \tag{2a}$$

Let $a^\pm$ and $b^\pm$ be two interval numbers defined as $a^\pm = [a^-, \ a^+]$ and $b^\pm = [b^-, \ b^+]$, respectively. Some calculation equations of two interval numbers are defined as follows:

$$a^\pm + b^\pm = [a^- + b^-, \ a^+ + b^+] \tag{2b}$$

$$a^\pm - b^\pm = [a^- - b^-, \ a^+ - b^+] \tag{2c}$$

$$a^\pm \times b^\pm = [a^- \times b^-, \ a^+ \times b^+] \tag{2d}$$

$$\frac{a^\pm}{b^\pm} = \left[\frac{a^-}{b^+}, \ \frac{a^+}{b^-}\right] \tag{2e}$$

$$ka^\pm = [ka^-, \ ka^+] \tag{2f}$$

$$\frac{1}{a^\pm} = \left[\frac{1}{a^+}, \ \frac{1}{a^-}\right] \tag{2g}$$

$$ka^\pm = [ka^-, \ ka^+] \tag{2h}$$

$$\frac{1}{a^\pm} = \left[\frac{1}{a^+}, \ \frac{1}{a^-}\right] \tag{2i}$$

Multi-Objective Interval Birandom Chance-Constrained Programming

As stated in the *Introduction* section, the uncertainties associated with the urban water resource management system not only exhibit the random characteristics but also fluctuate in the small ranges. Therefore, in this study, an integrated uncertain multi-objective optimization model including the birandom parameters and interval numbers (MIBCCP) is developed for tackling two types of uncertainties.

$$\text{Minimize } f_1^\pm = C_1^\pm X^\pm \tag{3a}$$

$$\text{Minimize } f_2^\pm = C_2^\pm X^\pm \tag{3b}$$

Subject to:

$$\tilde{\tilde{A}}(\omega) X^\pm \leq \tilde{\tilde{B}}(\omega) \tag{3c}$$

$$D^\pm X^\pm \leq E^\pm \tag{3d}$$

$$X^\pm \geq 0 \tag{3e}$$

$$C_1^\pm, \ C_2^\pm, \tilde{\tilde{A}}(\omega), \ D^\pm \neq 0 \tag{3f}$$

where two objective functions $f_1^\pm$ and $f_2^\pm$, decision variable $X^\pm$, and coefficients $C_1^\pm$, $C_2^\pm$, $A^\pm$, $D^\pm$, and $E^\pm$ are expressed as interval forms. The coefficients $A(\omega)$ and $B(\omega)$ are birandom variables following normal distribution, where they are described as $\tilde{\tilde{A}}(\omega) \sim N(\tilde{A}(\omega), \sigma_A^2)$ and $\tilde{\tilde{B}}(\omega) \sim N(\tilde{B}(\omega), \sigma_B^2)$, respectively. The mean values of stochastic variables also are described as normal random variables, that is, $\tilde{A}(\omega) \sim N(\mu_A, \sigma_{A'}^2)$ and $\tilde{B}(\omega) \sim N(\mu_B, \sigma_{B'}^2)$, respectively. The covariance magnitudes (i.e., σ_A^2 and σ_B^2) are assumed as fixed values, since the variations in the deviation value are limited.

The first and critical step of solving model **3** is to combine two objective functions into one objective through designing various weight coefficients (i.e., w_1 and w_2).

$$\text{Minimize } f^\pm = w_1 * \frac{f_1^{\max} - f_1}{f_1^{\max} - f_1^{\min}} + w_2 * \frac{f_2^{\max} - f_2}{f_2^{\max} - f_2^{\min}} \tag{4a}$$

$$w_1 + w_2 = 1 \tag{4b}$$

where w_1 is the corresponding weight of f_1; w_1 is the corresponding weight of f_2; $f_1^{\max}$, $f_2^{\max}$, $f_1^{\min}$, and $f_2^{\min}$ are the maximum and minimum values of each individual objective which can be obtained through the transformation of the original multi-objective programming, that is, single objective. In this study, depending on local conditions, we consulted 30 local managers with various backgrounds, including the environmental protection bureau, economic development

commission, and civil affairs department. According to the above managers' preferences, w_1 and w_2 were regarded as the weight coefficients of economic objective and environmental objective, and nine groups of weight coefficients (i.e., $w_1 = 0.1$ and $w_2 = 0.9$, $w_1 = 0.2$ and $w_2 = 0.8$, $w_1 = 0.3$ and $w_2 = 0.7$, $w_1 = 0.4$ and $w_2 = 0.6$, $w_1 = 0.5$ and $w_2 = 0.5$, $w_1 = 0.6$ and $w_2 = 0.4$, $w_1 = 0.7$ and $w_2 = 0.3$, $w_1 = 0.8$ and $w_2 = 0.2$, and $w_1 = 0.9$ and $w_2 = 0.1$) were designated. Among these, the first three groups were proposed by the managers from economic development commission, who tend to give priority to economic growth; the latter three groups were regulated by the managers from environmental protection bureau, who prefer the improvement in environmental quality. The rest of the groups correspond to the managers from civil affairs department, who focus on the coordinated development of economic growth and environmental protection.

Next, the constraint with birandom variables (3c) is converted into its interval equivalent based on the birandom equilibrium chance-constrained algorithm. The selection of the equilibrium chance measure is because it is a real number and is convenient for decision-makers to rank potential solutions (Peng and Liu, 2007). The original stochastic constraint could be reformulated as follows:

$$
\begin{aligned}
&\tilde{\tilde{A}}(\omega)X^{\pm} \leq \tilde{\tilde{B}}(\omega) \Leftrightarrow Ch^{e}\left\{\tilde{\tilde{A}}(\omega)X^{\pm} \leq \tilde{\tilde{B}}(\omega)\right\} \geq 1 - \alpha_r \\
&\Leftrightarrow Pr\left\{\omega \in \Omega \middle| Pr\left\{\tilde{\tilde{A}}(\omega)X^{\pm} \leq \tilde{\tilde{B}}(\omega)\right\} \geq 1 - \alpha_r\right\} \geq 1 - \alpha_r \\
&\Leftrightarrow \mu_A X^{\pm} + \Phi^{-1}(\alpha_r)\sqrt{(X^{\pm})^T \sigma_A X^{\pm} + (\sigma_B)^2} \\
&+ \Phi^{-1}(\alpha_r)\sqrt{(X^{\pm})^T \sigma_{A'} X^{\pm} + (\sigma_{B'})^2} \leq \mu_B, \qquad \forall r
\end{aligned}
\tag{5}
$$

where α_r represent predetermined probability violation levels. The principle of designing α_r value is ensuring its ranges are wide enough. In order to generate a variety of decision alternatives and provide more choosing opportunities to decision-makers, a relatively wide range of designed parameter is necessary. Referring to the studies (Xu et al., 2009; Wang et al., 2018), in this study, the constraint violation level is designed as 0.01, 0.05, and 0.1, respectively.

Then, the interactive two-step algorithm proposed by Huang et al. (1992) is used for transforming the intermediate interval linear programming model into two submodels, which correspond to the upper and lower bounds of objective function values, respectively. The submodel corresponding to the lower bound of objective function is formulated first as (Xu and Zhou, 2009; Xu and Tao, 2012):

$$
\text{Minimize } f^{-} = C^{-} X^{-}
\tag{6a}
$$

Subject to:

$$
\begin{aligned}
&\mu_A X^{-} + \Phi^{-1}(\alpha_r)\sqrt{(X^{-})^T \sigma_A X^{-} + (\sigma_B)^2} \\
&+ \Phi^{-1}(\alpha_r)\sqrt{(X^{-})^T \sigma_{A'} X^{-} + (\sigma_{B'})^2} \leq \mu_B, \qquad \forall r
\end{aligned}
\tag{6b}
$$

$$
D^{+} X^{-} \leq E^{-}
\tag{6c}
$$

$$
X^{\pm} \geq 0
\tag{6d}
$$

Based on obtained solutions from model **6**, the submodel representing the upper bound of the objective function f^{+} is formulated as follows:

$$
\text{Minimize } f^{+} = C^{+} X^{+}
\tag{7a}
$$

Subject to:

$$
\begin{aligned}
&\mu_A X^{+} + \Phi^{-1}(\alpha_r)\sqrt{(X^{+})^T \sigma_A X^{+} + (\sigma_B)^2} \\
&+ \Phi^{-1}(\alpha_r)\sqrt{(X^{+})^T \sigma_{A'} X^{+} + (\sigma_{B'})^2} \leq \mu_B, \qquad \forall r
\end{aligned}
\tag{7b}
$$

$$
D^{-} X^{+} \leq E^{+}
\tag{7c}
$$

$$
X^{+} \geq X^{-}
\tag{7d}
$$

Finally, the solutions of objective values and decision variables under various α_r values are obtained, that is, $f_{1,opt}^{\pm} = [f_{1,opt}^{-}, f_{1,opt}^{+}]$, $f_{2,opt}^{\pm} = [f_{2,opt}^{-}, f_{2,opt}^{+}]$ and $X_{opt}^{\pm} = [X_{opt}^{-}, X_{opt}^{+}]$, respectively. The MIBCCP model developed in this study can not only reflect two distinct objectives including the economic and environmental aspects but also describe uncertain parameters as the birandom variables and interval numbers, leading to the interval solutions under various weight combinations and vio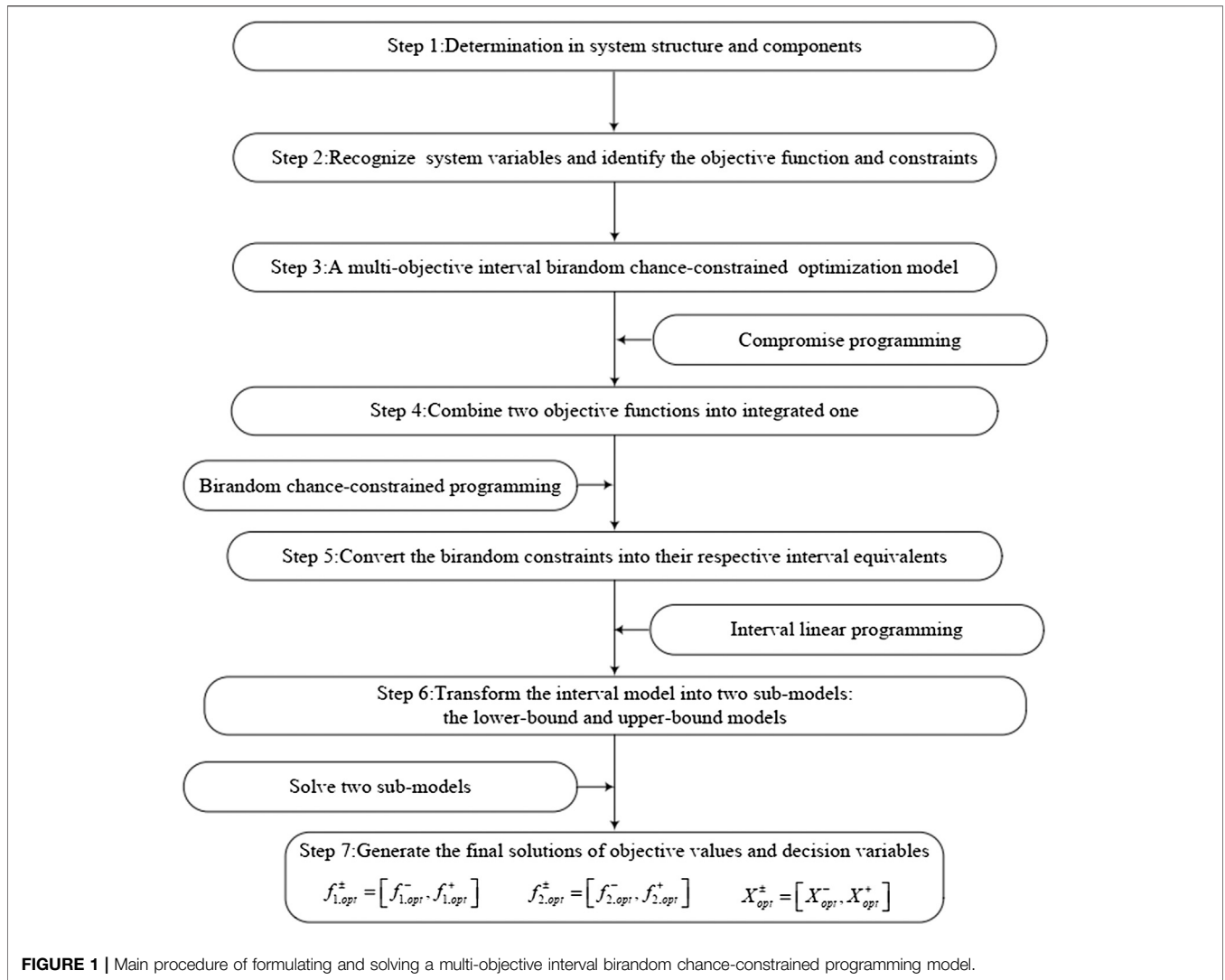lation levels for supporting the decision-making process. **Figure 1** shows the procedures for formulating and solving an MIBCCP model, which are summarized as follows:

Step 1: Investigate the water resource management system and recognize system structure and components, respectively.
Step 2: Identify all types of uncertain variables as the birandom variables and interval numbers and determine the objective function and constraints in the optimization model.
Step 3: Establish an MIBCCP model based on step 1 and step 2.
Step 4: Combine two objectives into a single objective based on the compromise programming method.
Step 5: Convert the birandom constraints into their respective interval equivalents based on equilibrium chance-constrained measure.
Step 6: Transform the interval model into two submodels through an interactive two-step algorithm, which correspond to the lower bound and upper bound models, respectively.
Step 7: Solve two submodels and generate the final solutions of objective values and decision variables under various conditions.

CASE STUDY

Overview of the Study Area

To demonstrate the advancement of the proposed optimization model for optimizing the allocation of water resource and addressing urban flooding with minimal LID project construction cost, an education park water system in Tianjin, China, was taken as an example. As shown in **Figure 2**, the reference park is a national demonstration zone of vocational education reform and innovation in China, located at latitude 38°34′–40°15′N and longitude 116°43′–118°4′E, and it covers an

FIGURE 1 | Main procedure of formulating and solving a multi-objective interval birandom chance-constrained programming model.
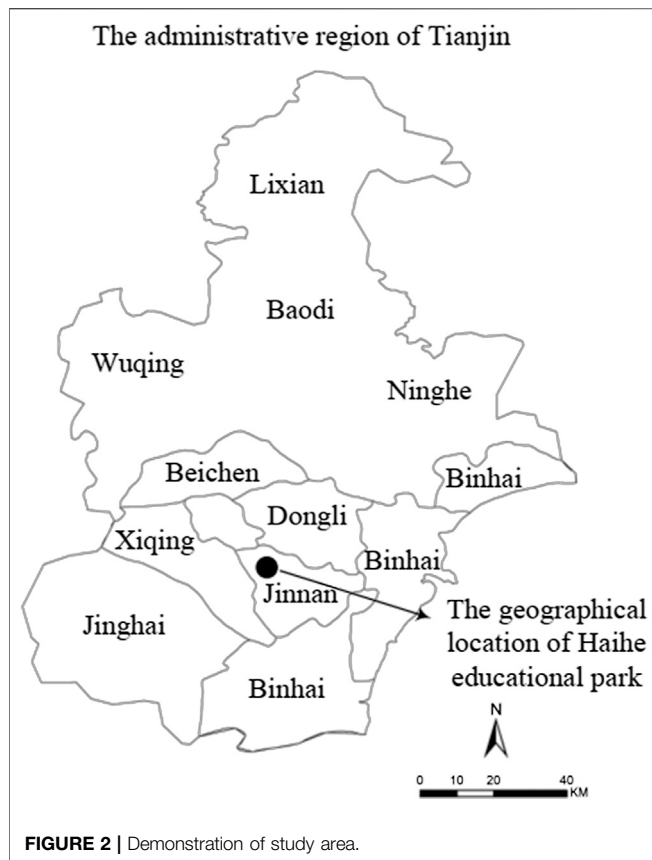
area of 37 km^2 with a total population of 0.2 million. The annual rainfall is about 480 –520 mm, 75% of which is concentrated in the months of June, July, and August. As a demonstration area constructed with "three-zone linkage" (educational zone, residential zone, and industrial zone), the reference park clearly has high requirements in regard to water availability and water supply safety. However, its existing water provision is incapable of meeting the scale expansion needs of the park in the future, which is mainly reflected in the following aspects: i) water scarcity is an urgent problem in this area. The water resource per capita is 160 m^3/a, which is only about 7% of the average level in China; ii) the major water source for this park is the local reservoir, and no alternative sources are available. As such, this single water source will affect the water supply security; iii) the capability of water conservation and retention has declined due to the decrease in puddle and lake areas; moreover, increased concrete areas has also reduced the penetration of rainwater into the soil. The on-site survey result indicated that this park often undergoes flooding, which would be exacerbated under climate change; iv) intrinsic uncertainties are associated with the water resource system of this park, including the volatility in water demands and fluctuations in the prices of water resource. The current water resource management plan neglects the uncertain features and potential risk caused by climate change that can affect the accuracy and rationality of the water allocation strategy. Therefore, it is important that an effective water resource optimization model is formulated to help mitigate and/or solve the above issues.

Impact of Climate Change on the Study Area

Over the last decades, climate change has significantly aggravated water scarcity and intensified frequency of extreme weather events (such as urban flooding and droughts) in China (Niu et al., 2008; Yu et al., 2008; Guo et al., 2019). Hence, it is necessary to detect future changes in rainfall over a region by using the simulation techniques in order to identify the influence exerted by climate change and generate an optimal water resource management strategy. PRECIS is a regional climate model system developed at the Met Office Hadley Centre, United Kingdom (Rao et al., 2014). It is advantageous in simulating

FIGURE 2 | Demonstration of study area.

TABLE 1 | Average annual rainfall under various periods and scenarios.

Item	Emission scenario	Period			
		2025 (mm)	2050 (mm)	2075 (mm)	2100 (mm)
Average annual Rainfall	RCP4.5	512.58	593.57	695.24	823.24
	RCP8.5	766.76	880.56	1,029.55	1,214.87

the change trend of climatic variables due to its easy-to-use operation, high computational precision, and wide suitability. In this study, the average annual rainfall in the reference park was predicted under four periods (2025, 2050, 2075, and 2100) and two emission scenarios (RCP4.5 and RCP8.5) by the PRECIS model, which are shown in **Table 1**. From **Table 1**, it can be seen that the average annual rainfall shows an upward trend among four periods under the impact of climate change in the future.

Description of the Water Resource System
Figure 3 presents the water network in the studied region. Based on the natural conditions, geographical position, and surface runoff of the reference park, the water resource management system for this park is conceptualized as 12 nodes, including four water sources, six water users, and LID, and non-LID projects. The major water sources are transfer water, tap water,

reclaimed water, and rain water, which are used for living, industry, tertiary industry, construction, ecology, and other water users. Considering a water-saving plan, green ecological requirements, and traditional water source allocation principles of the city of Tianjin, this study made some adjustment as follows: i) "planning of recycled water utilization of Tianjin" highlights that the utilization of reclaimed water should be considered for livelihood water with the maximal value of 30 L/d per capita. Hence, the water sources for livelihood water would be transfer water, tap water, and reclaimed water. ii) According to "technical specifications for construction and community rainwater utilization engineering," rainwater can be used for green space irrigation and road watering. Therefore, the demand for ecology water could be met by reclaimed water and rainwater, which are harvested via the LID and non-LID projects in this study. iii) Other water users should include the water source loss caused by water transfer, including transfer water loss and tap water loss.

Formulation of the Multi-Objective Interval Birandom Chance-Constrained Programming Model Under Climate Change
As mentioned in the above sections, the generation and execution of a rational water resource management strategy under climate change, including the determination of the system components, design of the system operation pattern, and generation of water allocation alternatives, are directly related to the coordinated development of local socioeconomy and environmental factors.

Therefore, the MIBCCP model for tackling the water supply problem of the park was formulated, as shown in **Figure 4**. This model was used to identify and determine the optimal water allocation strategy under climate change, which could enhance the economic efficiency, reduce environmental water pollution, and avoid the negative effects caused by various uncertainties associated with the water resource management system. The formulation and solution procedures of the MIBCCP model in this study are summarized as follows:

Step 1: Investigate the water resource management system and recognize system structure and confirm the impact of climate change.
Step 2: Identify all types of uncertain variables as the birandom variables and interval numbers and determine the objective function and constraints in the MIBCCP model based on step 1.
Step 3: Establish the MIBCCP model depended on step 2.
Step 4: Solve the MIBCCP model and generate the solutions of objective values and decision variables under different conditions.
Step 5: Analyze and discuss the results obtained in step 4 and support managers to make a trade-off between the economic benefits and environmental benefits, identify the relation between the system cost and the joint constraint violation risk, and deal with the impact of climate change.
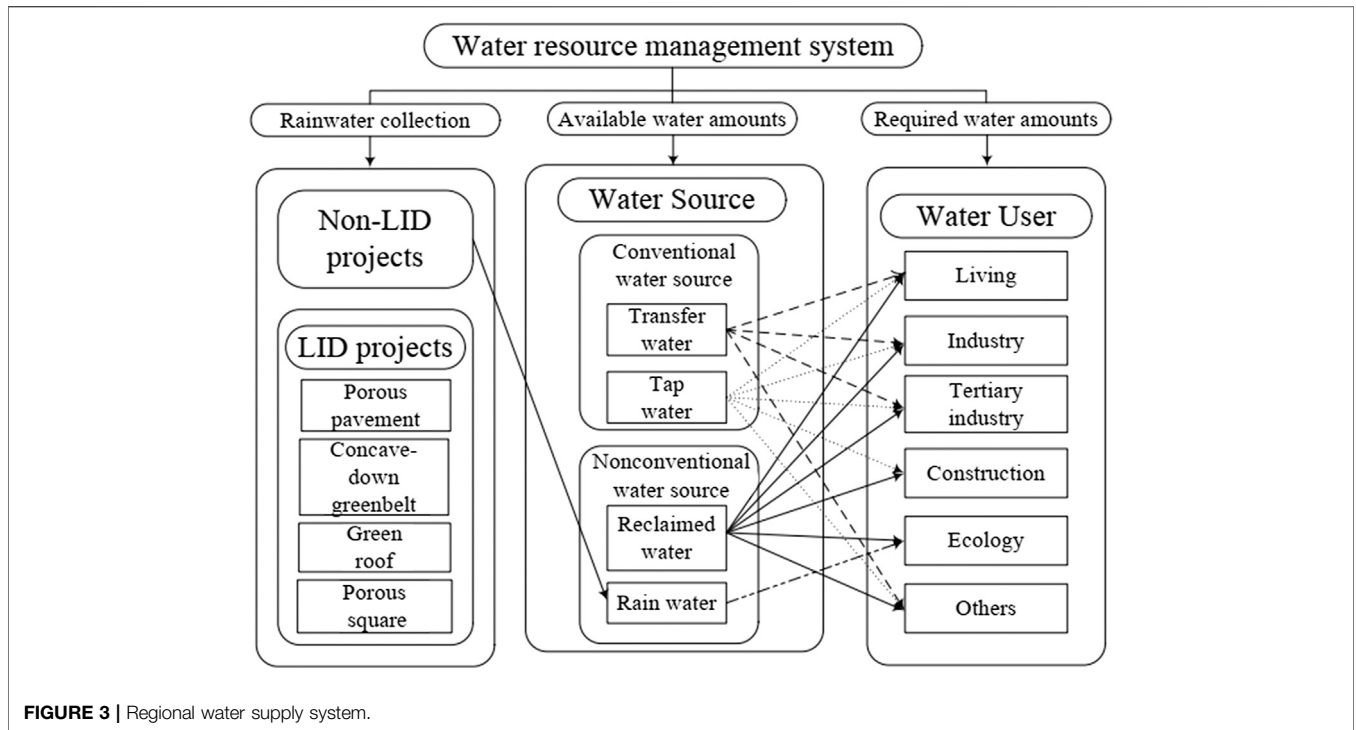
FIGURE 3 | Regional water supply system.

Objective Functions

i. Economic objective

$$\text{minimize } f_C^{\pm} = \sum_{n=1}^{N} \sum_{m=1}^{M} CA_{n,m}^{\pm} gA_{n,m} + \sum_{i=1}^{I} \sum_{j=1}^{J} CX_{i,j}^{\pm} gX_{i,j}^{\pm} \quad (8a)$$

where $f_C^{\pm}$ = construction costs and water resource allocation costs (RMB); $CA_{n,m}^{\pm}$ = construction price of project n in area m (RMB/m^2). n ($g = 1, 2, \ldots, N$) = index of the project type; $n = 1$ represents non-LID projects; $n = 2$ represents LID projects; m ($m = 1, 2, \ldots, M$) = index of the area type; $m = 1$ represents pavement; $m = 2$ represents greenbelt; $m = 3$ represents roofs; $m = 4$ represents square; $A_{n,m}$ = decision variables representing the area of project n at area m (m^2); $CX_{i,j}^{\pm}$ = water transferred cost from water source i to water user j (RMB/m^3); $X_{i,j}^{\pm}$ = decision variables representing water amounts transferred from water source i to water user j (m^3), i ($i = 1, 2, \ldots, I$) = index of water resource type; $i = 1$ represents transfer water; $i = 2$ represents tap water; $i = 3$ represents reclaimed water; $i = 4$ represents rainwater; j ($j = 1, 2, \ldots, J$) = index of water user type; $j = 1$ represents livelihood; $j = 2$ represents industry; $j = 3$ represents tertiary industry; $j = 4$ represents construction; $j = 5$ represents ecology; $j = 6$ represents other water user, as shown in **Figure 2**, when $i = 1$, $j = 1, 2, 3$, and 6; when $i = 2$, $j = 1, 2, 3, 4$, and 6; when $i = 3$, $j = 1, 2, 3, 4, 5$, and 6; when $i = 4$, $j = 5$. The economic target (**8a**) was designed to realize the minimization of the construction costs related to LID and non-LID projects and water resource allocation costs.

i. Environmental objective

$$\text{maximize } f_E^{\pm} = \sum_{n=1}^{N} \sum_{m=1}^{M} LgK_m^{\pm} gA_{2,m} \quad (8b)$$

where $f_E^{\pm}$ = total treatment amount of total suspended solids (TSS) (ton); L = the amount per unit area of TSS in the study area (t/m^3); $K_m^{\pm}$ = TSS treatment efficiency of LID projects at area m. The environmental objective (**8b**) endeavors to maximize the total treatment amount of TSS.

Constraints

i. Constraint for water resource availability

$$X_{1,1}^{\pm} + X_{1,2}^{\pm} + X_{1,3}^{\pm} + X_{1,6}^{\pm} \leq Q \pm \quad (8c)$$

$$X_{2,1}^{\pm} + X_{2,2}^{\pm} + X_{2,3}^{\pm} + X_{2,4}^{\pm} + X_{2,6}^{\pm} \leq Q \pm \quad (8d)$$

$$X_{3,1}^{\pm} + X_{3,2}^{\pm} + X_{3,3}^{\pm} + X_{3,4}^{\pm} + X_{3,5}^{\pm} + X_{3,6}^{\pm} \leq Q \pm \quad (8e)$$

$$X_{4,5} \leq Q_{YK} \quad (8f)$$

where $Q_W^{\pm}$ = transfer water availability (m^3); $Q_Z^{\pm}$ = tap water availability (m^3); $Q_{ZS}^{\pm}$ = reclaimed water availability (m^3); Q_{YK} = rainwater availability (m^3). The constraints (**8c**) to (**8f**) regulate the water amounts, including the transfer, tap, reclaimed, and, rainwater, so they do not exceed their maximum availability.

ii. Constraint for the water supply–demand balance

$$X_{1,1}^{\pm} + X_{1,2}^{\pm} + X_{1,3}^{\pm} \geq \tilde{\tilde{Q}}_S \quad (8g)$$

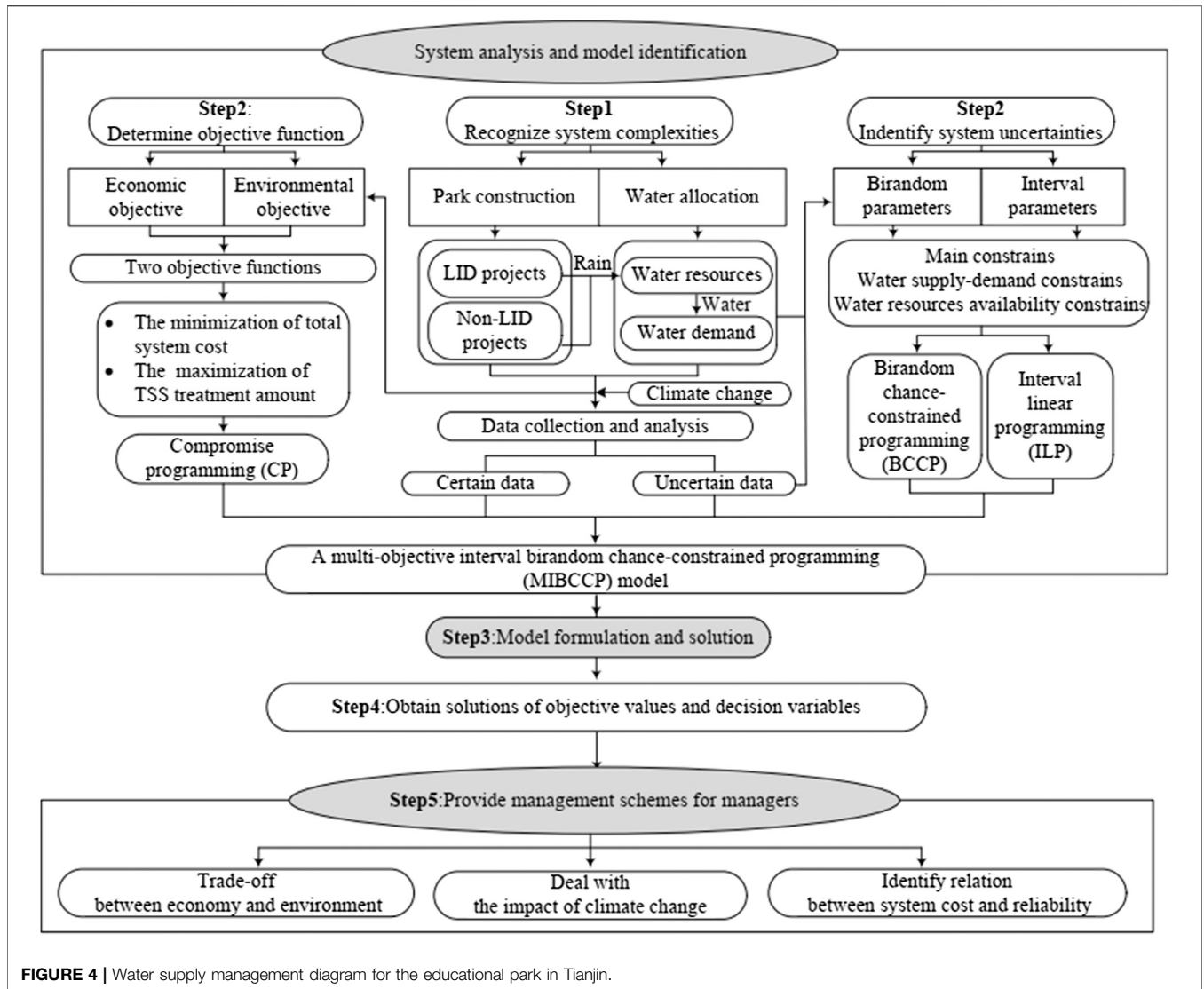$$X_{1,2}^{\pm} + X_{2,2}^{\pm} + X_{3,2}^{\pm} \geq \tilde{\tilde{Q}}_g \quad (8h)$$

FIGURE 4 | Water supply management diagram for the educational park in Tianjin.

$$X_{1,3}^{\pm} + X_{2,3}^{\pm} + X_{3,3}^{\pm} \geq \tilde{\tilde{Q}}_{ds} \qquad (8i)$$

$$X_{2,4}^{\pm} + X_{3,4}^{\pm} \geq \tilde{\tilde{Q}}_{j} \qquad (8j)$$

$$X_{3,5}^{\pm} + X_{4,5}^{\pm} \geq \tilde{\tilde{Q}}_{e} \qquad (8k)$$

$$X_{1,6}^{\pm} + X_{2,6}^{\pm} + X_{3,6}^{\pm} \geq \tilde{\tilde{Q}}_{q} \qquad (8l)$$

where $\tilde{\tilde{Q}}_S$ = total demand of livelihood water (m^3); $\tilde{\tilde{Q}}_g$ = total demand of industrial water (m^3); $\tilde{\tilde{Q}}_{ds}$ = total water demand of tertiary industry (m^3); $\tilde{\tilde{Q}}_j$ = total demand of construction water (m^3); $\tilde{\tilde{Q}}_e$ = total demand of ecological water (m^3); $\tilde{\tilde{Q}}_q$ = total water demand of other users (m^3). The constraints (**8g**) to (**8l**) serve to regulate the allocated water amounts from each water resource to be higher than or equal to the required water amounts.

iii.   Constraint of conventional water resource utilization

$$\left(X_{1,1}^{\pm} + X_{1,2}^{\pm} + X_{1,3}^{\pm} + X_{2,1}^{\pm} + X_{2,2}^{\pm} + X_{2,3}^{\pm} + X_{2,4}^{\pm}\right) \leq R_T^{\pm} gGDP \quad (8m)$$

$$X_{1,2}^{\pm} + X_{2,2}^{\pm} \leq R_I^{\pm} gMAV_I \qquad (8n)$$

$$X_{1,3}^{\pm} + X_{2,3}^{\pm} \leq R_{DS}^{\pm} gMAV_{DS} \qquad (8o)$$

where GDP = gross domestic product of the reference park (10^4 RMB); $R_I^{\pm}$ = maximum conventional water resource availability of the gross domestic product ($m^3/10^4$ RMB); MAV_I = added product of industry (10^4 RMB); $R_I^{\pm}$ = maximum available conventional water amounts of the added industrial product ($m^3/10^4$ RMB); MAV_{DS} = added product of tertiary industry (10^4 RMB); $R_{DS}^{\pm}$ = maximum conventional water resource availability of the added tertiary industrial product ($m^3/10^4$ RMB). The constraints (**8m**) to (**8o**) restrict the allocated water amounts of transfer water and tap water not to exceed their utilization limitations of the GDP, added industrial products, and added tertiary industrial products, respectively.

iv.   Constraint of reclaimed water reuse rate

$$\frac{\left(X_{3,1}^{\pm} + X_{3,2}^{\pm} + X_{3,3}^{\pm} + X_{3,4}^{\pm} + X_{3,5}^{\pm} + X_{3,6}^{\pm}\right)}{\eta g \left(Q_s + Q_g + Q_{ds} + Q_j\right)} \geq \mu^{\pm} \qquad (8p)$$

where $\mu^{\pm}$ = reuse rate of reclaimed water; η = sewage discharge coefficient. The constraint (**8p**) regulates the sewage water amounts to be reclaimed following a designated ratio.

v.   Constraint of the LID projects

$$A_{1,1} + A_{1,2} = A_P \tag{8q}$$

$$A_{2,1} + A_{2,2} = A_G \tag{8r}$$

$$A_{3,1} + A_{3,2} = A_R \tag{8s}$$

$$A_{4,1} + A_{4,2} = A_S \tag{8t}$$

$$\sum_{n=1}^{N} \sum_{m=1}^{M} F_{n,m} g A_{n,m} g Q_{yh} = Q_{ys} \tag{8u}$$

$$Q_{YK} = Q_{ys} \tag{8v}$$

where A_p = available area of the pavement in the lark, m^2; A_G = available area of the greenbelt in the lark, m^2; A_p = available area of the roof in the lark, m^2; A_p = available area of the square in the lark, m^2; Q_{ys} = rainfall runoff of the lark, m^3; $F_{n,m}$ = runoff coefficient of projects n at the construction area m; Q_{yh} = average rainfall of the lark during one year, m^3; Q_{yx} = storage volume of rainfall, m. The constraints (**8q**) to (**8t**) are used to control the construction area of the LID projects in the pavement, greenbelt, roof, and square areas. The constraints (**8u**) to (**8v**) regulate the rainfall runoff and the rainwater availability, respectively.

vi.   Other constraints

$$X_{1,6}^{\pm} = \theta_{Ts} g \left(X_{1,1}^{\pm} + X_{1,2}^{\pm} + X_{1,3}^{\pm} \right) \tag{8w}$$

$$X_{2,6}^{\pm} = \theta_{Ta} g \left(X_{2,1}^{\pm} + X_{2,2}^{\pm} + X_{2,3}^{\pm} + X_{2,4}^{\pm} \right) \tag{8x}$$

$$A_{n,m} \geq 0 \tag{8y}$$

$$X \pm \geq 0 \tag{8z}$$

where θ_{Ts} = transmission loss coefficient of transfer water; θ_{Ta} = transmission loss coefficient of tap water. The constraints (**8w**) to (**8x**) regulate the transmission losses of the transfer water and tap water, respectively. The constraints (**8y**) to (**8z**) require the decision variables to be greater or equal to zero. Based on compromise programming and stochastic equilibrium chance-constrained programming methods described in *Materials and Methods*, two objectives (including economic and environmental objectives) were first combined into a single objective; then, the birandom constraints (including water supply–demand balance constraints) were converted into their interval equivalents; next, the interval form objective function and constraints were transferred to their respective two deterministic forms. Finally, the interval solutions under various constraints violation levels (i.e., 0.01, 0.05, and 0.1) were obtained, that is,

$f_{C \; opt}^{\pm} = [f_{C \; opt}^-, f_{C \; opt}^+], f_{E \; opt}^{\pm} = [f_{E \; opt}^-, f_{E \; opt}^+], A_{n,m \; opt}^{\pm} = [A_{n,m \; opt}^-, A_{n,m \; opt}^+]$, and $X_{i,j \; opt}^{\pm} = [X_{i,j \; opt}^-, X_{i,j \; opt}^+]$, respectively

Data Information

The model parameters can be divided into two types in this study, which included engineering parameters and water resource system parameters.

Engineering Parameters

Engineering parameters composed of construction costs, runoff coefficients, TSS treatment efficiencies, and available areas of LID and non-LID projects, which are shown in **Table 2**. The available areas are subjected to the park-scale limitation and remain unchanged, where they are expressed as deterministic values that came from Tianjin Statistics Bureau. The construction cost and TSS treatment efficiency have significant variations caused by policy regulations and technical condition, where they exhibited the uncertain characteristics with known upper and lower bounds. Accordingly, it is essential to define them as the interval numbers.

Water Resource System Parameters

According to on-site survey results, historical data record (from 2010 to 2018), Tianjin Statistics Bureau, and Tianjin Statistics yearbook, water resource system parameters include water provision cost, available water amount, and users' requirements, and their detailed data information is displayed in **Table 3**. Among them, users' requirements are affected by population, production scale, and local meteorological condition. Therefore, they are designed as the birandom variables with normal probability distribution. The water supply cost and available water amount own the small variation range and thus are assumed to be the interval number.

RESULTS ANALYSIS AND DISCUSSION

Results Analysis

Table 4 displays the optimal solutions of the MIBCCP model under different constraint violation levels (i.e., α) and different weight combinations. Based on the description of the interval linear programming in the *Methodology* section, the solutions for the two objective function values and some decision

TABLE 2 | Parameters associated with the low-impact development and non–low-impact development projects.

Item	Type of project	
	LID projects	Non-LID projects
Runoff coefficient	0.3	0.9
Available pavement area (m^2)	9,000	9,000
Available greenbelt area (m^2)	3,200	3,200
Available roof area (m^2)	14,000	14,000
Available square area (m^2)	5,600	5,600
TSS treatment efficiencies of the pavement	[0.85, 0.92]	0
TSS treatment efficiencies of the greenbelt	[0.85, 0.92]	0
TSS treatment efficiencies of the roof	[0.85, 0.92]	0
TSS treatment efficiencies of the square	[0.50, 0.70]	0
Construction costs in the pavement (RMB/m^2)	[168.12, 222.96]	[132.64, 188.32]
Construction costs in the greenbelt (RMB/m^2)	[190.43, 294.53]	[147.95, 196.54]
Construction costs in the roof (RMB/m^2)	[225.87, 336.29]	[194.32, 298.40]
Construction costs in the square (RMB/m^2)	[443.55, 588.81]	[398.16, 544.10]

TSS, total suspended solids; LID, low-impact development; non-LID, non–low-impact development.

TABLE 3 | Parameters related to the water resource system.

Parameters	Value
Interval parameters	
Supply price of transfer water	[8.8, 9.2] RMB/m³
Supply price of tap water	[7.2, 7.8] RMB/m³
Supply price of reclaimed water	[4.3, 4.7] RMB/m³
Supply price of rain water	[2.2, 2.8] RMB/m³
Available amount of transfer water	[11,000, 14,000] 10³ m³
Available amount of tap water	[30,000, 35,000] 10³ m³
Available amount of reclaimed water	[15,000, 18,000] 10³ m³
Birandom parameters	
Parameters	Probability distribution
Total water demand of livelihood	$N \sim (\mu, 23.38)$ $\mu \sim$ (1,829, 16.26)
Total water demand of industry	$N \sim (\mu, 19.09)$ $\mu \sim$ (1,168, 13.39)
Total water demand of tertiary industry	$N \sim (\mu, 8.61)$ $\mu \sim$ (175, 6.41)
Total water demand of construction	$N \sim (\mu, 7.41)$ $\mu \sim$ (117, 5.61)
Total water demand of ecology	$N \sim (\mu, 19.01)$ $\mu \sim$ (1,158, 13.34)
Total water demand of other users	$N \sim (\mu, 23.38)$ $\mu \sim$ (578, 10.01)

variables could be presented as interval numbers. For instance, when $\alpha = 0.1$, $w_1 = 0.1$, and $w_2 = 0.9$, the TSS treatment amounts would range from 31.6×10^3 to 34.2×10^3 tons. The system costs would change from 35.75 to 43.77 million RMB. The transfer water amount allocated to livelihood would fluctuate from 6.07 to 8.47 million m³. The solutions of the two objectives correspond to the upper bound of the environmental benefit and the lower bound of the system costs, which are obtained under the most optimistic conditions (e.g., high TSS treatment efficiency as well as low construction and water allocation prices) when the interval decision variables (e.g., water resource allocation amounts) are at their lower bounds; although the solutions corresponding to the lower bound of the environmental benefit and the higher bound of the system costs are associated with the most conservative conditions when the water resource allocation amounts reach their higher bound levels. In fact, the flexibility and adjustability of the interval decision variables are beneficial for the decision-maker when inserting more implicit knowledge (e.g., socioeconomic conditions) into the optimize model so that they can formulate a more satisfactory and applicable decision scheme. Moreover, some interval decision variables indicate that there is no difference between their upper bound value and lower bound value. For example, when $\alpha = 0.1$, $w_1 = 0.1$, and $w_2 = 0.9$, the solutions of 8.00 million m³ and 1.44 million m³ are the tap water amounts allocated to industry and tertiary industry users. This is because these decision variables are insensitive to the variations in interval parameters.

Considering that the obtained solutions are affected by the interactive influence of the above two factors (weight coefficient combination and violation level), for the sake of reflecting the impact exerted by each factor, the variation trend of the solutions was analyzed under the context of changes to one factor as the other factor remains unchanged. First, when the three violation levels were maintained as stable ($\alpha = 0.1$), the selection of the construction schemes exhibited an obvious difference under various weight combinations. The high w_1 value would help to raise the economic benefits; otherwise, as w_2 climbs, the environmental

benefits would increase. For instance, the non-LID projects are favored when the system costs are more of a concern, where $w_1 = 0.9$ and $w_2 = 0.1$. Under α value of 0.1, the difference in values between the non-LID project construction area and LID project construction area for pavement, greenbelt, roof, and square areas were 9.0×10^3, 3.2×10^3, 14.0×10^3, and 5.6×10^3 m², respectively. Conversely, with the change in weight combinations from $w_1 = 0.9$ and $w_2 = 0.1$ to $w_1 = 0.1$ and $w_2 = 0.9$, the difference in values would be 3.8×10^3, 3.2×10^3, -14.0×10^3, and 5.6×10^3 m², respectively. This variation is because LID projects can bring increased environmental benefits. Moreover, selection of the water allocation strategy is also dependent on the weight coefficients. For example, it is established that the water demand of the tertiary industry is satisfied by tap water and reclaimed water with the values of 144 and 38.01 million m³, where $w_1 = 0.1$ and $w_2 = 0.9$. However, when the system focuses on the economic benefit ($w_1 = 0.9$ and $w_2 = 0.1$), reclaimed water with its low allocation price would be the preferred source, and thus, the water demand of the tertiary industry would be provided in total by reclaimed water. A similar situation was also reflected in the different climate change scenario and time period. For example, under the RPC 4.5 scenario, when $w_1 = 0.1$ and $w_2 = 0.9$, tap water would be used to meet the water demand of the construction industry in 2025, with the values of 123.5 million m³. When $w_1 = 0.9$ and $w_2 = 0.1$, the water demand of the tertiary industry would be provided in total by reclaimed water due to its high economic characteristic. The function of weight coefficients was to provide different water resource management schemes for managers. If the environmental quality is relatively poor and needs to be improved, managers should focus on the environmental benefits and choose the scheme under the high w_2. Conversely, they could prefer to increase the economic benefits and select the scheme under the high w_1.

Moreover, the variable situations of the obtained solutions under the different fixed weight coefficient combinations are discussed in order to examine the influences caused by violation level design on the generated decision schemes. First, when two weight coefficients are maintained as stable ($w_1 = 0.9$ and $w_2 = 0.1$), as the increase in the probabilistic level, the total water amounts supplied to four water users were decreased. For example, at the three α levels of 0.01, 0.05, and 0.1, the water amounts transferred to meet the demands of livelihood were 18,496.3, 18,435.9, and $18,403.6 \times 10^3$ m³, respectively; similarly, the water amounts allocated to industry and the rainwater amount collected by LID and non-LID projects increased from 9,333.0 and $11,866.8 \times 10^3$ m³ to 9,775.8 and $11,782.9 \times 10^3$ m³, respectively. Meanwhile, the results own the same trends under climate change. For example, under the RPC 8.5 scenario, when α increases from 0.01 to 0.1, the water demand of the construction industry provided by reclaimed water was reduced in 2,100, being from $1,288.4 \times 10^3$ to $1,235.2 \times 10^3$ m³; the tap water allocated to industry would decrease to $3,920.8 \times 10^3$ from $4,160.6 \times 10^3$ m³. The main reason for this result is that the decrease in α value meant the constraints with the birandom variables would be strict, such that the water demand amounts would increase. On the contrary, the increase in the violation level of α means that the satisfied extent of the constraint has become weak, leading to a decrease in the water demand.

TABLE 4 | Part of solutions of multi-objective interval birandom chance-constrained programming model under various α values and weight combinations.

Item			Water allocation amount (10^3 m^3)														
			Transfer water allocation				Tap water allocation					Reclaimed water allocation					
A	w_1	w_1	User[a]	User[b]	User[c]	User[f]	User[a]	User[b]	User[c]	User[d]	User[f]	User[a]	User[b]	User[c]	User[d]	User[e]	User[f]
0.1	0.1	0.9	[607.31, 846.56]	0	0	[48.58, 67.72]	7,751.7	8,000	1,440	1,235.2	1,474.2	4,578.8	3,782.9	380.1	0	2,349.7	3,908.5
	0.9	0.1	[607.31, 846.56]	0	0	[48.58, 67.72]	12,330.5	3,920.8	0	0	1,300.1	0	7,862.1	1,820.1	1,235.2	0	4,082.6
0.05	0.1	0.9	[608.38, 848.05]	0	0	[48.67, 67.84]	7,722.5	8,000	1,440	1,253.7	1,473.3	4,629.6	3,812.1	399.9	0	2,224.8	3,933.6
	0.9	0.1	[608.38, 848.05]	0	0	[48.67, 67.84]	12,352.1	4,004.1	0	0	1,308.5	0	7,808	1,839.9	1,253.7	0	4,098.4
0.01	0.1	0.9	[610.38, 850.83]	0	0	[48.83, 68.07]	7,667.8	8,000	1,440	1,288.4	1,471.7	4,724.7	3,866.8	437.2	0	1,990.6	3,980.7
		0.1	[610.38, 850.83]	0	0	[48.83, 68.07]	12,392.5	4,160.6	0	0	1,324.2	0	7,706.2	1,877.2	1,288.4	0	4,128.1

Item			Construction area (10^3 m^2)								Values of objectives		System costs(10^6 RMB)		Rainwater amount (10^3 m^3)
			Pavement		Greenbelt		Roof		Square		Economic objective (10^6 RMB)	Environment objective (10^4 ton)	Water allocation cost	Construction cost	
A	w_1	w_2	Non-LID	LID	Non-LID	LID	Non-LID	LID	Non-LID	LID					
0.1	0.1	0.9	6.41	2.59	3.20	0	0	14.00	5.60	0	[35.74, 43.77]	[31.6,34.2]	[7.15, 10.17]	[28.60, 33.60]	9,333.0
	0.9	0.1	9.00	0	3.20	0	14.00	0	5.60	0	[34.05, 41.97]	0	[6.62, 9.55]	[27.43, 32.42]	11,682.7
0.05	0.1	0.9	6.92	2.08	3.20	0	0	14.00	5.60	0	[35.77, 43.80]	[30.7,33.2]	[7.13, 10.15]	[28.64, 33.64]	9,487.0
	0.9	0.1	9.00	0	3.20	0	14.00	0	5.60	0	[34.14, 42.07]	0	[6.62, 9.55]	[27.53, 32.53]	11,711.8
0.01	0.1	0.9	7.89	1.11	3.20	0	0	14.00	5.60	0	[35.81, 43.86]	[28.8,31.2]	[7.13, 10.08]	[28.71, 33.74]	9,775.8
	0.9	0.1	9.00	0	3.20	0	14.00	0	5.60	0	[34.33, 42.29]	0	[6.62, 9.55]	[27.71, 32.74]	11,766.4

LID, low-impact development; non-LID, non–low-impact development projects.

The changes in the combinations of weight coefficients and violation levels exerted an influence on the decision variables, but they also influenced the objective value. The economic and environmental objectives under various weight combinations and violation levels were estimated and are shown in **Figure 5A**. From **Figure 5A**, it was apparent that regardless of the α levels, the values of two objectives both keep the same trend with the change in weight combinations, considering the obtained solutions are affected by the interactive influence of the above two factors (w and α); thus, in order to reflect the impact exerted by w, the variation trend of the solutions was analyzed under a stable constraint violation, which was selected as 0.1. Specifically, when w_1 increased from 0.1 to 0.8 and w_2 simultaneously decreased from 0.9 to 0.2 under $\alpha = 0.1$, the economic objective and environmental objective remained unchanged with the values of 35.75, 43.77 million RMB and 31.6, 34.2 ×10^3 tons. When w_1 and w_2 changed to 0.9 and 0.1, the two objectives decreased especially fast to 34.05, 41.97 million RMB and 0 tons. This indicated that the values of two objectives were insensitive to the weight shift before w_1 reaches 0.8. Only when $w_1 = 0.9$ and $w_2 = 0.1$ could the solution of environmental objective would decrease, which means the decision-makers considering environmental benefits are not the key factor for determining the optimal water resource allocation strategy. Meanwhile, the solution of economic objective corresponding to the total cost of the system would decrease, which represents the decision-makers focus on the economic benefit and aim to reduce the system costs.
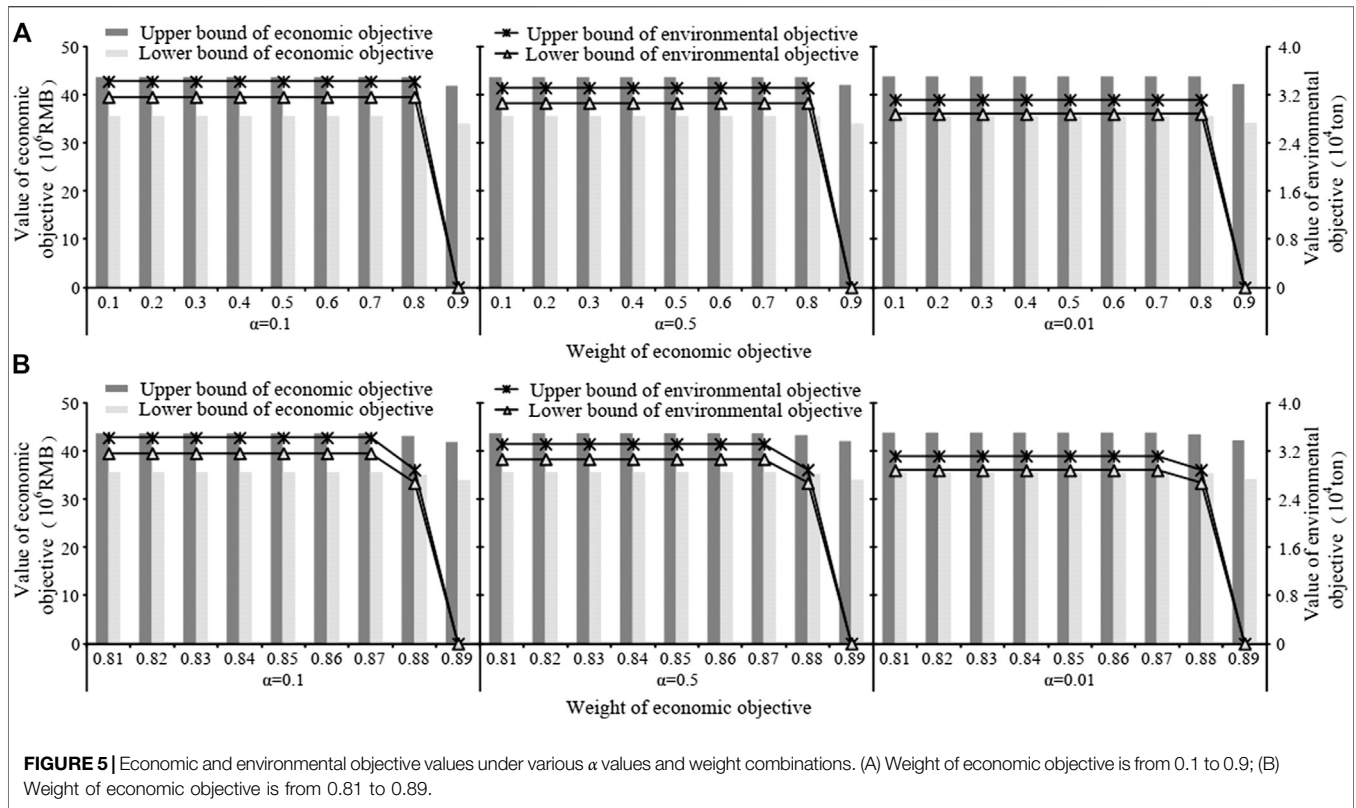
In order to further reflect the sensitive range of objective functions, two objectives values under different weight coefficients (changing between from $w_1 = 0.8$, $w_2 = 0.2$ and, $w_1 = 0.9$, $w_2 = 0.1$) were estimated and displayed in **Figure 5B**. As demonstrated in **Figure 5B**, it was apparent that the values of two objectives decreased fast only when w_1 shifted from 0.87 to 0.89 and w_2 ranged from 0.11 to 0.13, respectively. For example, under an α value of 0.1, TSS treatment amounts are 31.6, 34.2 ×10^3 tons, 26.7, 28.9 ×10^3 tons, and 0 ton under the three weight coefficient combinations (i.e., $w_1 = 0.87$ and $w_2 = 0.13$, $w_1 = 0.88$ and $w_2 = 0.12$, and $w_1 = 0.89$ and $w_2 = 0.11$). The total system costs also showed the similarly downward trend with the values of 35.75, 43.77, 35.27, 43.29, and 34.05, 41.97 million RMB. Hence, if the managers wanted other results for system costs and treatment amount of TSS, they could adjust the parameters of the optimization model by choosing different w_1 and w_2 values between the above range.

Apart from the weight coefficient combinations, the values of two objectives were also influenced by the levels of α. As shown in **Figure 5A**, various α values resulted in different solutions. The value of economic objective decreased with the increase in α value. In contrast, the value of environmental objective increased with the growth level of α. For example, when $w_1 = 0.1$ and α increased from 0.01 to 0.1, the total treatment of TSS exhibited an upward trend from 28.8, 31.2 ×10^3 tons to 31.6, 34.2 ×10^3 tons. Inversely, the costs of the system decreased to 35.75, 43.77 million RMB from 35.71, 43.85 million RMB. This is because the α level represents the constraint violation risk of water supply–demand balance. The

low α level corresponded to a low violation risk with a high water demand, leading to a high water allocation amount, which caused an increase in the system cost. Conversely, a high α value was associated with a high violation risk, which was accompanied by a low water supply amount. The variation in the α level provides a variety of water resource management schemes to the managers, which reflected the trade-off between the system economy and risk. Generally, the water demand can be divided into two categories: rigid demand and flexible demand. For example, the industrial water demand must be satisfied in its entirety subjected to its production characteristic. Conversely, the living water demand has a high elasticity and is able to reduce the water requirement through a series of water-saving measures under the water shortage scenario. The elastic characteristics of water demand allow the managers to design the water provision schemes according to local situation. Specifically, for the area where the economic development is relatively backward and simultaneously suffers from water shortage, it is suitable to select the scheme under the high α level which is capable of increasing the economic benefits and decreasing the water provision amounts, although it also may result in the high system failure risk. Conversely, the managers could choose the strategy under the low α level so that the water supply security would be enhanced by raising water supply amounts and system costs. Tianjin, as one of the most prosperous cities in China, always faces severe water shortage and thus has the superiority on economic development and the inferiority on water resource availability at the same time. Therefore, it is suggested that a compromise alternative (i.e., $\alpha = 0.95$) be adopted as the decision basis for the generation of final water resource management scheme in this study, which is helpful in realizing the balance between system economy and failure risk.
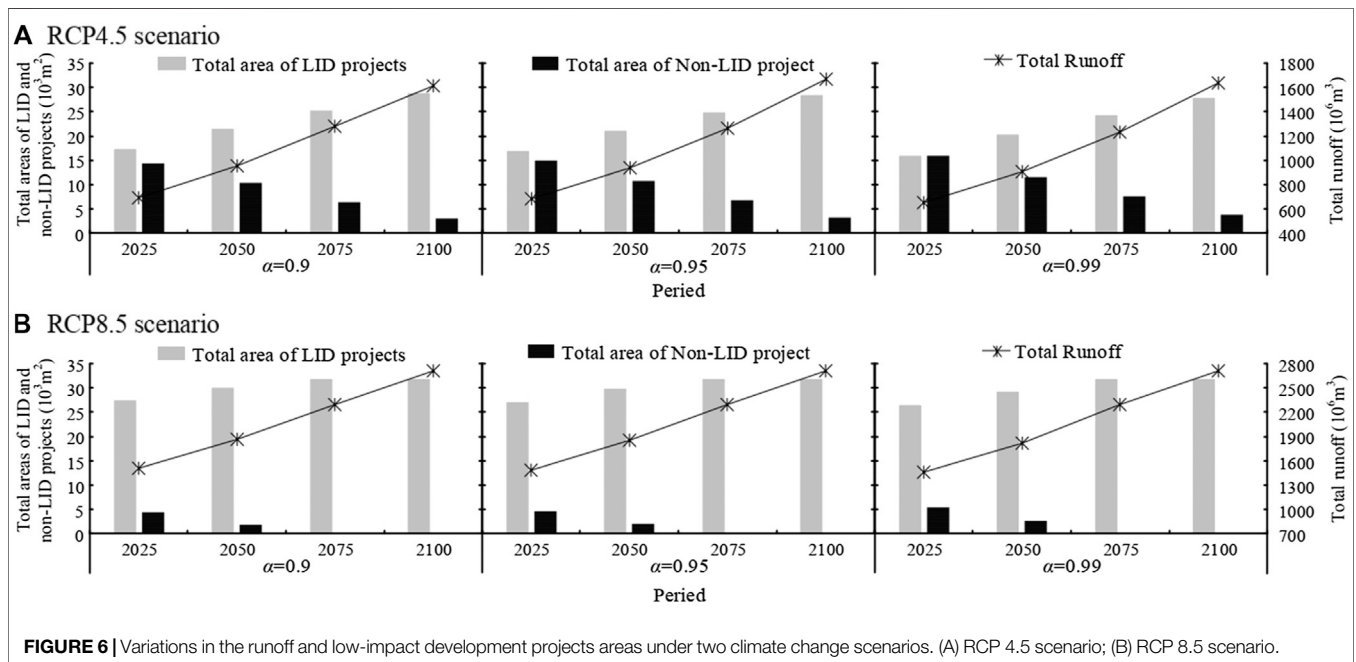
Discussion

In order to evaluate the influence caused by climate change on the water resource management, the generated runoff of the studied region and LID project implementation scheme were estimated under the two climate change scenarios (RCP4.5 and RCP8.5) with four periods (2025, 2050, 2075, and 2100), which were displayed in **Figure 6**. As shown in **Figure 6**, under fixed α level, the runoff of the park and area of LID projects would increase from 2025 to 2100 under both two scenarios. For example, with an α value of 0.1, when the period changes from 2025 to 2100, the runoffs in the RCP4.5 and RCP8.5 scenarios would increase from 696.7 to 1,510.0 million m^3 to 1,610.26 and 2,704.3 million m^3; meanwhile, the areas of LID projects would be upward from 17.35 and 27.4 thousand m^2 to 28.8 and 31.8 thousand m^2, respectively. That is because the climate change could lead to the growths in regional rainwater and runoff, which might trigger the rainfall flood. The similar results were also reported by other studies (Zahmatkesh et al., 2014; Yoon et al., 2015; Guo et al. (2019a)). For instance, Zahmatkesh et al. (2014) found that climate change led to the increase in the urban stormwater runoff volume of the Bronx River watershed, New York City. Yoon et al. (2015) proposed a methodology for the evaluation

FIGURE 5 | Economic and environmental objective values under various *α* values and weight combinations. (A) Weight of economic objective is from 0.1 to 0.9; (B) Weight of economic objective is from 0.81 to 0.89.

of the overflow probability of urban streams under climate change in the Uicheon Basin of Korea and obtained results showed that 100-year peak flow in the future would increase by 58.1% compared with historical conditions. Moreover, to deal with the increase in the flooding risk caused by climate change, the LID project

is recommended as climate mitigation measures in this research, which was capable of alleviating the adverse impact of increased stormwater based on the collection and retention facilities of the rainwater. The obtained results are consistent with the related studies, such as Guo et al. (2019b),

FIGURE 6 | Variations in the runoff and low-impact development projects areas under two climate change scenarios. (A) RCP 4.5 scenario; (B) RCP 8.5 scenario.

Morvarid et al. (2019), and Hou et al. (2019). Specifically, it is concluded that the LID projects are beneficial to reduce the flooding risk and cope with the stormwater management issue arising from heavy rainfall under climate change. On the other hand, the above studies formulated the urban water management model with the aid of hydrological software (i.e., SWMM), which has excellent performance in describing the hydraulic connections and relationships among various water sources and users. In this study, an MIBCCP model based on compromise programming, birandom chance-constrained programming and interval linear programming is proposed for identifying the uncertainties associated with the urban water resource management system and generating a variety of water allocation patterns reflecting the trade-off between system economy and reliability; however, it also has difficulties in obtaining more accurate solutions due to oversimplified hydrologic and hydraulic equations. Therefore, it is necessary to enhance the accuracy and applicability of the proposed model through incorporating the output of some hydrological models into the optimization process.

Moreover, the MIBCCP model still needs to be improved, especially in the following three aspects. First, the objective function in this study is assumed as a linear form; in fact, system cost could exhibit the economy-of-scale feature, and the relationship between water supply cost and distance may be nonlinear, rather than the linear one. This will lead to a nonlinear objective function. Because the focus of this research is to apply birandom variables and interval numbers for supporting water resource management issue, it is thus desired to examine the possibility of the integrated model of MIBCCP and nonlinear programming in the future. Second, the compromise programming is used to combine two objectives into an integrated one. In fact, many types of multi-objective methods are available, such as the genetic algorithm and the interactive approximation algorithm. How to select an appropriate solution method through the comparison analysis is very critical. Third, two traditional objectives are considered in the MIBCCP model. In fact, other objectives, including the ecological stability and social acceptance, also obtained more attentions and thus deserved further research.

CONCLUSION

Under the urgency of rational water resource allocation and effective urban flooding control, a (MIBCCP) model under climate change is developed in this study. The MIBCCP model incorporates compromise programming, birandom chance-constrained programming, and interval linear

programming within a general framework, where each technique offers a unique contribution toward the enhancement of the model capability in tackling the complexities and uncertainties. A water supply management system of educational park in Tianjin was used to demonstrate the applicability of the proposed method. A variety of water allocation patterns are obtained through adjusting predetermined constraint violation levels and weight combinations, which indicated that MIBCCP was useful in helping local managers gain in-depth insights into the water management system under climate change, realize the utilization of nonconventional water source and application in LID projects, and analyze the trade-offs between system economy and reliability, as well as establish the cost-effective environmentally friendly water provision strategies. Meanwhile, optimal construction schemes for LID projects under two scenarios were identified by the MIBCCP model to deal with the rainfall flood control issue under climate change. The successful application in the park is expectable for providing a good demonstration to the water management problem in other regions of China. In the future, high-precision hydrological simulation models and other multi-objective programming methods should be incorporated into the proposed model for tackling more complex issues.

DATA AVAILABILITY STATEMENT

All datasets generated for this study are included in the article.

AUTHOR CONTRIBUTIONS

YX, ZB, and GH conceived and designed the research. WL, HY, and ZB collected the data. YX, ZB, GH, and HY formulated the optimization model. ZB, YX, and GH performed the data analyses and manuscript preparation. ZB, YX, WL, and HY wrote the paper. GH, WL, and YX gave the comments and helped in revising the paper.

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