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Coupling ecological water requirement to optimize water resources under changing climatic conditions

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Abstract:

Meeting ecological water requirements (EWR) is important for guaranteeing watershed system stability in many arid and semi-arid lands. Rainfall–runoff relationships under the effects of climate change may induce many adverse changes for EWR. Inherent uncertainties in water resources management and potential variations in EWR should both be considered to obtain desired water allocation strategies under changing climatic conditions. In this research, an integrated approach was proposed through incorporation of copula functions and a Markov Chain Monte Carlo (MCMC) simulation into a general chance-constrained programming (CCP) modeling framework. The proposed method was found effective for water resource management with respect to the following: (a) tackling correlated features in watershed rainfall and inflow under climate change based on copula–MCMC simulations, (b) obtaining runoff distributions using the copula sampling method under multiple climate change scenarios, (c) analyzing fluctuations of EWR based on varied monthly flows with consideration of diverse runoff distributions, and (d) obtaining desired water allocation strategies through the developed CCP model with consideration of EWR and water shortage risks. Application of the developed method to water resources management in the city of Dalian (China) indicated that the EWR in the watersheds of Dalian would suffer large variations under changing climatic conditions. Moreover, in comparison with the supply in 2025, the increase of water supply from transferring water from the Dahuofang Reservoir (Hun River) would be 6942–33,772, 6942–25,472, and 2849–14,259 Mt with risk tolerance levels of 20%, 50%, and 80%, respectively.

Keywords: water resources management; ecological water requirement; copula functions; Markov Chain Monte Carlo (MCMC) simulation; chance constrained programming (CCP) model.

1 Introduction

Water resources management is regarded as a complicated, adaptive, and integrated decision-making unit for maintaining ecological, economic, and social functions of water systems (Mayer et al., 2014; RazaviToosi and Samani, 2016). Satisfaction of ecological water requirement (EWR) is thus an important way to maintain watershed structure and the corresponding ecosystems in many arid and semi-arid lands (Ling et al., 2016). However, EWR could be influenced by adverse spatiotemporal variations in water availabilities under combined changes of climate change conditions (Bracken et al., 2018; Giuliani and Castelletti, 2016; Prasad et al., 2015). Many countries are facing increasing challenges in balancing water resources utilization with ecological protections (Benda et al., 2016; Gao et al., 2014). Thus, decision-making approaches to long-term water resources management highlight the importance of nonstationary and uncertain perspectives of EWR and water allocation strategies.

Ecological flow assessment has been applied widely to describe the amount of water flow required to sustain watershed ecosystems and human livelihoods (Acreman, 2016). Zeng et al. (2017) focused on tradeoffs between ecological and irrigative water usages. Zhang et al. (2016a) analyzed multiyear trends of the annual and seasonal changes in ecological flow. Pastor et al. (2014) proved that two methods were effective in analyzing ecological flow (i.e., the variable monthly flow (VMF) and Tessmann methods) for many large-scale watershed ecosystems. O'Brien et al. (2018) introduced a scenario-based ecological flow assessment method with consideration of the socioecological consequences of varied flows. Many studies have demonstrated the effects of climate change on ecological flow and water resources supplies (Zhang et al., 2017). For example, Veettil and Mishra (2016) incorporated EWR within a framework of water security assessment under climate change impacts. Incorporating Bayesian theory into the framework for EWR analysis, O'Brien et al. (2018) proposed a robust regional-scale approach in order to achieve the desired strategies for ecological protection. It is necessary to tackle the nonstationary frequency of water availability for EWR, especially when influenced by correlated features in rainfall and inflow of a watershed, in conjunction with the subjective decisions of stakeholders in water resources management (Bracken et al., 2018; Chen et al., 2019; Haghighi et al., 2018; Nasr-Azadani et al., 2017; Xue et al., 2016). Previously, statistical methods, such as Monte Carlo simulation, Latin hypercube sampling, and Copula functions, were incorporated to support nonstationary analysis in water resources management (Pal and Talukdar, 2020). For example, Trindade et al. (2019) analyzed variations in long-term water infrastructure investments based on Monte Carlo sampling. Traditional methods of EWR analysis should also be improved to reflect variations in both water supply and demand, especially under the climate-change background (Gibbs et al., 2018).

A water management system (WMS) is generally proposed to provide sustainable strategies regarding adapting to water availability, resolving human vulnerability, and fulfilling ecosystem and human needs with balanced water supply and demand (Cook and Bakker, 2012; Xue et al., 2016). Inherent uncertainties of a WMS and potential interactions with EWR could influence the effectiveness of water allocation strategies (Brookfield and Gnau, 2016; Wang and Huang, 2014). Specifically, given changing environmental, economic, and social conditions, it is difficult to predict definitively the characteristics of future water demand and supply (Brookfield and Gnau, 2016). Concurrently, integration of future technological innovation could partly offset any increase in water demand (Psomas et al., 2017). It is likely that the additional time and cost requirements of adaptive alternatives would be met to mitigate the uncertain conditions (Brookfield and Gnau, 2016). Although previous research has considered the inherent uncertainties in a WMS, uncertainties of EWR under the background of climate change have rarely been considered in terms of water resources allocation or reservoir operation (He et al., 2018).

The following methods have been proposed previously for analysis of WMS uncertainties: 1) uncertainties of water availability, especially under climate-change effects, were considered based on multiple series of representative scenarios (e.g., Representative Concentration Pathway (RCP) 4.5 and RCP 8.5) (Xie et al., 2017). For example, previous climate research provided multiple scenarios of the relative effects of uncertain climate change on water availability (Gaivoronski et al., 2012; Whateley and Brown, 2016). Moreover, scenarios of future conditions have been applied widely in uncertainty analysis of socioeconomic and climate change indicators (Huskova et al., 2016; Safavi et al., 2015); 2) Sampling methods (e.g., Monte Carlo, Latin hypercube, and copula sampling) were used to address the randomness of available water resources (Liu et al., 2017). Zhang et al. (2017) proposed historical and future operating methods for deriving adaptive operating rules considering both historical information and future projections of a WMS. The varied availability of surface water could be obtained by Monte Carlo sampling in a numerical model (Liu et al., 2017); and 3) Correlated uncertainties could also be determined using statistical methods (e.g., relevance analysis and copula functions) (Wang et al., 2017). As flexible statistical approaches, Bayesian and copula methods can capture the joint distributions of correlated parameters at different time scales (Ren et al., 2020; Xu and Valocchi, 2015; Yang et al., 2018). O'Brien et al. (2018) proposed a hybrid approach based on ecological flow and Bayesian theory to support decision-making strategies for adaptation practices. Copula theory has been applied broadly in multivariate frequency analysis to evaluate the characteristics of nonstationarity (Bracken et al., 2018). Nguyen-Huy et al. (2017) analyzed the joint influence of the El Niño–Southern Oscillation and the Interdecadal Pacific Oscillation Tripole Index on seasonal precipitation based on vine copulas. Based on copula theory, Miao et al. (2016) presented comprehensive analysis of the joint probabilistic characteristics of precipitation and temperature on the Loess Plateau of China. Many other joint distributions of drought characteristics in watersheds have been constructed using copula functions (Zhang et al., 2015).

Previous, single- or multi- objective optimizing models were applied in water resource management, considering multiple water resources requirements in socio-economic activities (Tarebari et al., 2018). Almazan-Gomez et al. (2018) introduced a water management model to simulate scarcity scenarios and to measure the associated default rates of ecological flow. Hydrological simulations were also integrated into optimizing management models to obtain desired water allocation plans in consideration of watershed characteristics (Lobanova et al., 2017). In order to tackle the issues of stochastic processes in stream flow of WMS, uncertainty analysis methods can also be incorporated within a general framework of optimizing techniques (Wang and Huang, 2014; Xu et al., 2015; Zhang et al., 2020). For example, Lv et al. (2018) proposed an interval chance-constrained programming (CCP) model based on a Monte Carlo simulation for regional ecosystem planning under uncertainty. Tan et al. (2016) proposed a robust interval fuzzy programming approach for identifying sustainable agricultural and industrial production strategies at the watershed scale in a highly uncertain environment. Yu et al. (2018) proposed a copula-based stochastic programming method for allocating regional resources that considered random and uncertain parameters in objective function and constraint conditions. Lei et al. (2018) proposed a stochastic optimization model for hydropower generation reservoirs, in which a transition probability matrix was calculated based on copula functions. Furthermore, owing to random variations of parameters, a WMS is challenged by failure of occurrence in water allocation to multiple users (e.g., water shortage risk). Thus, a risk-based balance inexact optimization model is required to reflect the risky conditions in water resources management (Xie et al., 2016). Borgomeo et al. (2018) expanded risk-based decision analysis to explore possible ways of enhancing robustness in engineered water resources systems under different risk attitudes of stakeholders. Chen et al. (2020) proposed an optimizing model to explore strategies of dual risk aversion in water resources and carbon reduction.

Although many previous studies have considered EWR, research on water resources allocation focusing on EWR and the water shortage risk in a WMS under the background of climate change is lacking. Therefore, the objective of this study was to propose a hybrid approach for improvement of typical methods of water resources management in terms of EWR and water shortage risk under the effects of climate change. Considering environmental and socioeconomic water shortage risk, the developed method evaluates fluctuations in precipitation under multiple climate change scenarios, analyzes correlated features of runoff and precipitation, and incorporates variations in EWR into water allocation management. In detail, precipitation fluctuations were analyzed based on daily climate data from three general circulation models (i.e., BCC-CSM1.1, BCC-CSM1.1(m), and BNU-ESM) under the RCP 4.5 and RCP 8.5 scenarios. Correlations between runoff and precipitation were analyzed using a hybrid copula–Markov Chain Monte Carlo (MCMC) simulation method. Fluctuations of EWR were analyzed based on copula sampling and VMF methods. Desired water allocation strategies were obtained using a CCP model with consideration of environmental and socioeconomic water shortage risk under the climate change scenarios. Considering the complexities in EWR in water resources allocation, the developed approach was demonstrated through application to the city of Dalian, China.

2 Optimizing water resources considering ecological water requirements under climate change

In long-term water resources management, decision makers should pay attention to nonstationary and uncertain characteristics of ecological flow and water allocation strategies. The nonstationary features of ecological flow arise from fluctuations in watershed runoff. Previously, watershed runoff, which is correlated with rainfall, has generally been analyzed using rainfall–runoff models (Watson et al., 2019). Traditionally, climate change effects are described into multiple downscaled climate-change scenarios related to future rainfall and temperature. Therefore, watershed runoff analysis must be improved through incorporation of the relationship between runoff and rainfall under various climate change scenarios. Also, methods of EWR analysis should incorporate runoff variations with consideration of the relationship between rainfall and runoff under the effects of climate change. Moreover, the risk attitude of stakeholders to water allocation strategies influences the effectiveness of water allocation strategies. The risk tolerance level (RTL) of stakeholders to water shortages should be considered to obtain desired water allocation strategies.

This research proposed a comprehensive framework for water resources management under changing climatic conditions based on integration of copula–MCMC simulations, ecological flow analysis, and a CCP model under two climate change scenarios (Figure 1). Four steps are adopted in the proposed approach: (i) tackling correlated features in watershed rainfall and inflow based on copula–MCMC simulations, (ii) obtaining runoff distributions using the copula sampling method under the climate change scenarios, (iii) analyzing variations of EWR based on the VMF method with consideration of the runoff distributions, and (iv) obtaining desired water allocation strategies based on the CCP model taking into account environmental and water shortage risk.

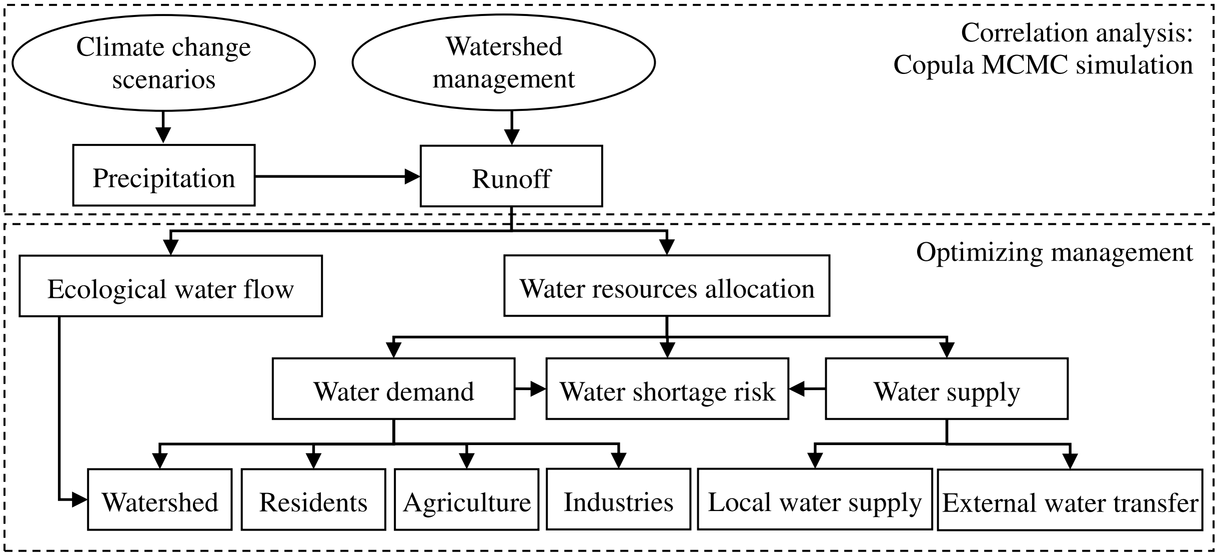

Fig.1 Framework for water resources management under climate change conditions

2.1 Inflow analysis

As precipitation and runoff are two correlated random variables, copula functions are introduced to indicate the fluctuations of runoff and rainfall influenced by climate change effects (Guo et al., 2017). According to Sklar's theorem (Sklar, 1959; Zhang et al., 2016b), copula functions can be used to describe the joint distributions of correlated random variables. The joint probability density function (PDF) of the two random variables [i.e., $f_{X,Y}(x,y)$] can be expressed as Equation 1 (Vergni et al., 2015):

$$f_{X,Y}(x,y) = c\left(F_X\left(x\right), F_Y\left(y\right)\right) f_X\left(x\right) f_Y\left(y\right) \tag{1}$$

where X and Y are two correlated random variables (i.e., precipitation and runoff), $F_X(x)$ and $F_Y(y)$ are their marginal cumulative distribution functions (CDFs), respectively, $c(\bullet)$ is the fitted copula function, and $f_X(x)$ and $f_Y(y)$ represent the probability density functions (PDFs) of X and Y, respectively. Multiple copula functions have been applied widely in watershed inflow analysis (e.g., Archimedean copulas, and Gumbel-Hougaard copula) (Kong et al., 2015). For example, one-parameter Archimedean copulas have been used widely in hydrologic frequency analysis (Kong et al., 2015). To select the best-fitted copula functions, two indicators (i.e., root mean square error (RMSE) and Nash–Sutcliffe efficiency (NSE)) were used to examine the performance of the copula functions (Equations 2 and 3) (Sadegh et al., 2017).

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}\left[\tilde{f}_i - f_i(\theta)\right]^2}{n}} \tag{2}$$

$$NSE = 1 - \frac{\sum_{i=1}^{n}\left[\tilde{f}_i - f_i(\theta)\right]^2}{\sum_{i=1}^{n}\left[\tilde{f}_i - \bar{\tilde{f}}_i\right]^2} \tag{3}$$

where the indicators of $RMSE \in [0, +\infty)$ and $NSE \in (-\infty, 1]$ indicate the extents of variations in observed and predicted values, $\tilde{f}$ represents the joint probability in observed variables of precipitation and runoff, and f is their joint probability predicted by copula functions.

2.2 Ecological water requirement under uncertain conditions

The VMF method can be used to analyze EWR (Pastor et al., 2014; Steffen et al., 2015). As shown in Equation 4, the minimum EWR would be 30% of mean monthly flow (MMF) during high-flow seasons, 45% of MMF during intermediate-flow seasons, and 60% of MMF during low-flow seasons; in extremely dry conditions (i.e., MMF < 1 m^3

s^{-1}), there is no EWR allocation.

$$EW = \begin{cases} 30\%m, \ if \ \ m \geq 80\%a \\ 45\%m, \ if \ \ 80\%a > m \geq 40\%a \\ 60\%m, \ if \ \ m < 40\%a \end{cases} \tag{4}$$

where *EW* is the minimum amount of ecological water requirement, *m* indicates MMF, and *a* is mean annual flow.

2.3 Water resources management based on chance-constraint programming

The CCP method is effective in reflecting the reliability of water shortage risk under uncertainty. The CCP method does not require that all constraints be totally satisfied; instead, they can be satisfied in a proportion of cases within given probabilities. A general stochastic linear programming problem can be formulated as shown in equation 5 (Wu et al., 2015):

$$\max \ CX \tag{5a}$$

s.t.

$$A(t)X \leq B(t) \tag{5b}$$

$$x_j \geq 0, \ x_j \in X, \ j = 1, \ 2, \ \cdots, \ n \tag{5c}$$

where *X* is a vector of decision variables, and *A*(*t*), *B*(*t*), and *C*(*t*) are sets with random elements defined on probability space *T*, where $t \in T$. To solve model (5), an 'equivalent' deterministic version can be defined. This can be realized using a CCP approach, which consists of fixing a certain level of probability $p_i \in [0,\ 1]$ for each constraint *i* and imposing the condition that the constraint be satisfied with at least a probability of $1 - p_i$. The set of feasible solutions is thus restricted by the following constraints:

$$\Pr\{t \mid a_i(t)X \le b_i(t)\} \ge 1 - p_i,\ a_i(t) \in A(t),\ b_i(t) \in B(t),\ i = 1,\ 2,\ \cdots,\ m \tag{6}$$

When a_i are deterministic and b_i are random, constraint (5b) can be converted into Equation 7:

$$a_i(t)x \le b_i(t)^{(p_i)},\ \forall i \tag{7}$$

Model 5 is transformed into the following CCP model (Equation 8):

$$\max\ C\ X \tag{8a}$$

s.t.

$$a_i(t)x \le b_i(t)^{(p_i)},\ a_i\ (t) \in A_i\ (t),\ b_i\ (t) \in B_i\ (t),\ i = 1,\ 2,\ \cdots,\ m \tag{8b}$$

$$x_j \ge 0,\ x_j \in X\ ,\ j = 1,\ 2,\ \cdots,\ n \tag{8c}$$

Consider a practical problem of water allocation to multiple water users during a dry season. The manager could present the problem by minimizing allocation costs and fulfilling water demand under random changes of watershed flow. Uncertain information regarding water supply and ecological runoff would occur under the background of climate change. Thus, the CCP model could be adopted as follows (Equation 9).

$$\min f = \sum_{i=1}^{m}\sum_{j=1}^{n}\sum_{k=1}^{q} c_{ijk} x_{ijk} \tag{9a}$$

s.t.

Constraint 1: EWR per month (i.e., ew_{ia}).

$$\sum_{a=1}^{12} ew_{ia} \geq EW_i \geq 0, \ \forall i \tag{9b}$$

Constraint 2: Water allocation to users, e.g., industries, agriculture, and residents.

$$\sum_{i=1}^{m} x_{ijk} \geq T_{jk}, \ \forall j, \text{ k} \tag{9c}$$

Constraint 3: Balance of water demand and supply

$$\sum_{i=1}^{m}\sum_{j=1}^{n}\sum_{k=1}^{q} x_{ijk} \leq \left[\sum_{i=1}^{m} m_i + \sum_{i'=1}^{m'} l_{i'} - \sum_{a=1}^{12} ew_{ia}\right]^{(P)}, \ \forall i \tag{9d}$$

Constraint 4: Nonnegative variables.

$$c_{ijk},\ m_i,\ l_{i'}, x_{ijk}, ew_{ia}, T_{ijk} \geq 0, \forall i, j, k \tag{9e}$$

where f is cost of water allocation management, c_{ijk} is per unit cost of water supplied by the i^{th} river for the k^{th} water user of the j^{th} district, x_{ijk} is the amount of water allocation by the i^{th} river for the k^{th} water user of the i^{th} district, ew_{ia} is the EWR in the a^{th} month for the i^{th} water source, EW_i is the EWR of the i^{th} river, T_{ijk} is the water demand of the k^{th} water user in the j^{th} district supplied by the i^{th} river, m_i is the supply capacity of the i^{th} local water source, and $l_{i'}$ is the water supply capacity of the i'^{th} transferred water source.

3 Case study

Dalian, is an important coastal city in the south of Liaoning Province in China. The city comprises eight districts, i.e., the Municipal zone and Jinzhou, Wafangdian, Pulandian, Zhuanghe, Changhai, Changxingdao, and Huayuankou districts. Following recent socioeconomic development, conflicts between water demand and water supply in Dalian have become increasingly evident. The supply of water to most of the city depends on local water sources such as the Biliu, Dasha, Yingna, Fuzhou, and Zhuang rivers, and the transferred water source of the Hun River in the city of Fushun. The Hun River will support a certain amount of Dalian's water resource from 2025. The WMS in Dalian comprises rivers, reservoirs, links, and water purifying plants. From the base year of 2010, two planning horizons were considered in this study: 2025 and 2030. The objective of the

CCP model was to minimize the energy consumption of the WMS.

4 Results and discussions

4.1 Correlations between runoff and precipitation under climate change

Statistical data related to precipitation and runoff in Dalian were obtained from hydrology yearbooks. Association parameters of precipitation and runoff were estimated based on the copula–MCMC simulation in the framework of the Multivariate Copula Analysis Toolbox (Sadegh et al., 2017). Suitability of the association parameters in the copula functions was analyzed based on the methods of RMSE and NSE. The results of the association parameters of precipitation and runoff are presented in Table 1. As indicated by the indicators of RMSE and NSE, the best-fitted association parameters could be described by the Frank copula function.

Table 1 Parameter estimation of precipitation and runoff in Dalian City

Unit: 10^{-3} MWh/t

Copula Functions	RMSE	NSE	Mean values of association parameters (θ)	Confdence intervals (95%) of θ
Gaussian	0.289	0.989	0.3367	[0.2861, 0.3897]
t	0.290	0.989	0.3354	[0.2726, 0.3925]
Clayton	0.322	0.987	0.4641	[0.3595, 0.5957]
Frank	0.277	0.990	2.0506	[1.6813, 2.4423]
Gumbel	0.288	0.989	1.2837	[1.2261, 1.3629]

Referred to both Schneider et al. (2017) and Liu and Zuo (2012), daily precipitation data under the background of climate change were driven by three general circulation models, i.e., BCC-CSM1.1, BCC-CSM1.1(m), and BNU-ESM (hereafter, BC1, BC2, and BNU, respectively). Moreover, it was assumed that the above data would follow RCP 4.5 and RCP 8.5, achieving radiative forcing of 4.5 and 8.5 W m^{-2} , respectively, at the end of the century (Riahi et al., 2011; Thomson et al., 2011). Thus, two planning years (i.e., 2025 and 2030) and six scenarios of climate change were considered in this study. The daily precipitation data under the climate change scenarios were derived from downscaled climate change scenarios related to the meteorological stations in Dalian obtained from NWAI-WG data (http://stdown.agrivy.com). Monthly precipitation characteristics of the watersheds of Dalian under the climate change scenarios are shown in Table S1. The variations in precipitation of the watersheds of Dalian can be described as follows. In relation to the Biliu and Yingna rivers, the maximum amount of precipitation in 2025 and 2030 was estimated under the climate change scenarios of RCP 8.5-BC2 and RCP 8.5-BC1, respectively, while the minimum amount of precipitation in 2025 and 2030 was estimated under RCP 4.5-BNU and RCP 8.5-BC2, respectively. In relation to the Zhuang River, the maximum amount of precipitation in 2025 and 2030 was estimated under the climate change scenarios of RCP 8.5-BC1 and RCP 4.5-BC2, respectively, while the minimum amount of precipitation in 2025 and 2030 was estimated under RCP 8.5-BNU and RCP 8.5-BC1, respectively. In relation to the Dasha and Fuzhou rivers, the maximum amount of precipitation in 2025 and 2030 was estimated under the climate change scenarios of RCP 8.5-BC2 and RCP 8.5-BC1, respectively, while the minimum amount of precipitation in 2025 and 2030 was estimated under RCP 4.5-BNU and RCP 8.5-BC2, respectively.

4.2 Variations in runoff and precipitation under climate change

Incorporating the association parameters between precipitation and runoff, data analysis was conducted based on the copula sampling method. From the correlated sampling data related to precipitation amount and runoff velocity in the watersheds of Dalian, variations in runoff velocity under climate change scenarios were obtained (Figure 2). Fluctuation in runoff velocity influenced the amount of EWR greatly. To quantify the variations in runoff velocity under the background of climate change, the indicator of the coefficient of variation (CV) was introduced, estimated as the ratio of the standard deviation to the mean value (Table S2). Of all Dalian's watersheds, the Fuzhou River would have the largest variation in runoff velocity under the RCP 4.5-BC1 and RCP 8.5-BNU scenarios, while the Yingna River would have relatively small variations in runoff velocity under the RCP 4.5-BNU and RCP 8.5-BC1 scenarios. In terms of climate change scenario, runoff velocity in the Dalian watersheds would have small variations under RCP 8.5-BC2 in 2025 and under RCP 4.5-BNU in 2030. Meanwhile, runoff velocity in Dalian's watersheds would exhibite large variation under RCP 4.5-BNU in 2025 and under RCP 8.5-BC2 in 2030. Results indicated that runoff velocity in Dalian's watersheds would have small variation in winter (i.e., November–February).

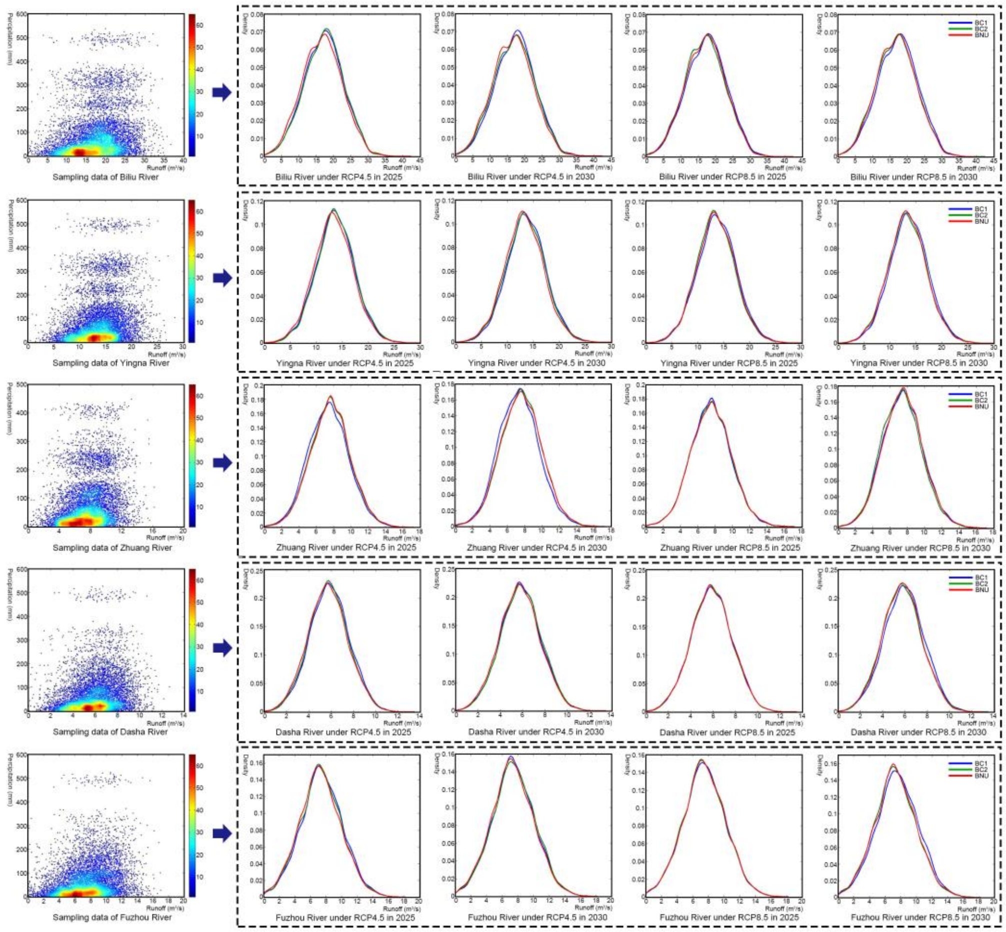

Fig.2 Distributions of runoff velocity in Dalian's watersheds under multiple climate change scenarios based on the copula sampling method.

Similar to runoff velocity, runoff in Dalian's watersheds varied according to the climate change scenario (Table S3). For example, the Fuzhou River would have the largest variations in runoff, while the Yingna River would have relatively small variation in runoff under changing climatic conditions. The runoff of Dalian's watersheds would be supported mainly by the Biliu and Yingna rivers, accounting for nearly 60% of total watershed runoff. In terms of climate change scenario, runoff in the watersheds of Dalian would have small variations under RCP 8.5-BC1 in 2025 and under both RCP 4.5-BC2 and RCP 8.5-BC2 in 2030. Conversely, runoff in the watersheds of Dalian would have large variations under RCP 8.5-BC2 in 2025 and under RCP 8.5-BC1 in 2030.

4.3 Ecological water requirement

The amount of EWR was influenced greatly by variation in runoff velocity under the various climate change scenarios. Fluctuations of EWR are illustrated in Figure 3. It can be seen that the Biliu and Yingna rivers would require more ecological water in comparison with the other rivers in Dalian. As indicated by the CVs in ecological water requirement (Table S4), the Fuzhou River would have the largest variation in EWR, while the Yingna River would have relatively small variation in EWR. In terms of climate change scenario, the EWR under RCP 8.5-BC1 and RCP 4.5-BNU would be larger than that under the other scenarios in 2025 and 2030. Meanwhile, the EWR in the watersheds of Dalian would have large variations under RCP 8.5-BC2 in 2025 and under RCP 8.5-BC1 in 2030.

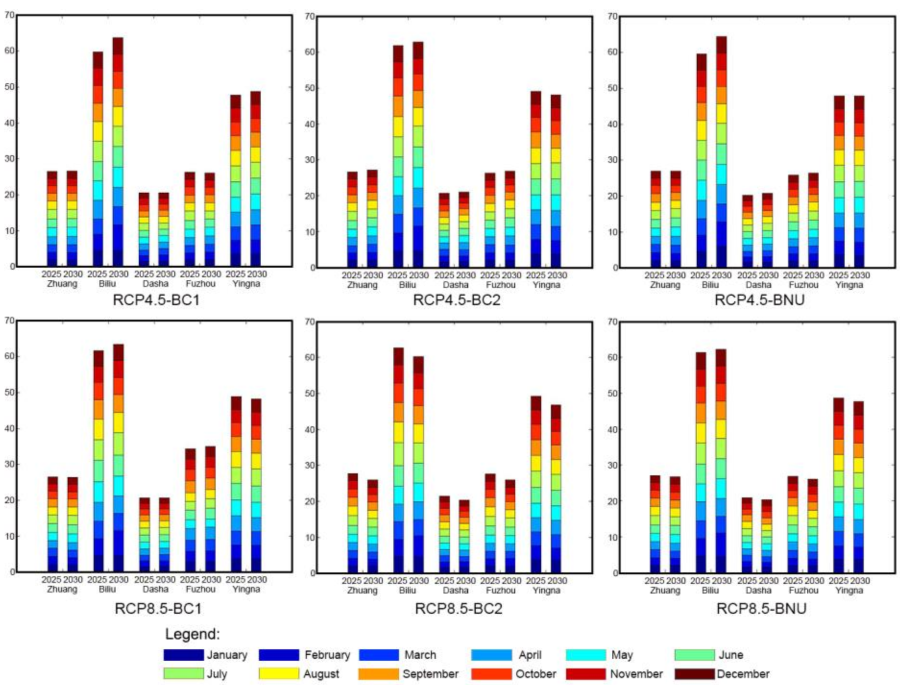

Fig. 3 Monthly ecological water requirement in Dalian (mean values) in 2025 and 2030. Unit: m^3/s.

4.4 Water resources optimization under changing climatic conditions

(1) Water resources management model

A water resources optimization model was applied to water allocation for multiple water users (i.e., agricultural sector, industrial sectors, service sector, residents, and other users) in the eight districts of Dalian (Table S5). Dalian's water demands and supplies are listed in Table S6. In consideration of the water allocation project from the Hun River to Dalian, considerable energy would be supplied to the water resources management system in Dalian (Table S7). Thus, energy consumption was chosen as the objective of the water resources optimization model. The model could be presented to find desired water allocation strategies by minimizing allocation energy consumption, guaranteeing ecological runoff, and fulfilling water demands under the background of climate change. Therefore, model (9) was changed into model (10):

$$\min f = \sum_{i=1}^{5}\sum_{j=1}^{8}\sum_{k=1}^{5} c_{ijk} x_{ijk} \tag{10a}$$

s.t.

$$\sum_{a=1}^{12} ew_{ia} \geq EW_i \geq 0,\ \forall i \tag{10b}$$

$$\sum_{k=1}^{5} x_{ijk} \geq T_{ijk}, \forall j,\ i \tag{10c}$$

$$\sum_{i=1}^{5}\sum_{j=1}^{8}\sum_{k=1}^{5} x_{ijk} \leq \left[\sum_{i=1}^{5} m_i + l_{i'} - \sum_{a=1}^{12} ew_{ia}\right]^{(P)},\ \forall i \tag{10d}$$

$$c_{ijk},\ m_i,\ l_{i'}, x_{ijk}, ew_{ia}, T_{ijk} \geq 0, \forall i, j, k \tag{10e}$$

(2) Water allocation strategies under multiple climate change scenarios

Water allocation strategies in Dalian are described in Figures S1-S2 and Tables S8–S19. Considering the influence of the risk attitude of stakeholders to water allocation strategies, the RTLs of stakeholders to water shortages (i.e., 20%, 50%, and 80%) were incorporated in the water resources management model. The water resources demands of Changhai, Changxingdao, and Huayuankou districts would be supported by the Yingna and Fuzhou rivers in 2025 and 2030. Water suppliers in the other districts would vary dramatically in 2025 under the effects of climate change, especially under RCP 4.5-BC1. Agriculture, residents, and other users in Pulandian would benefit most from the Hun River water transfer project. In terms of local water sources, the socioeconomic activities of the Municipal zone and Jinzhou, Changhai, Changxingdao, and Huayuankou districts would be supported mainly by the Biliu and Yingna rivers in 2025 and 2030. Except for the services sector, water users in Pulandian and Zhuanghe would be supported mainly by the Hun River. Meanwhile, the Hun River would play a more important role in Dalian's water supply in 2030 in comparison with its contribution in 2025. Under the influence of the effects of climate change, the ratios of local water sources to transferred water sources in 2025 would vary extensively in relation to the agricultural sector in Wafangdian, Pulandian, and Zhuanghe districts, as well as the industrial sector and other users in Zhuanghe. Conversely, the ratios in 2030 would not vary so dramatically.

(3) Water supply of the watersheds in consideration of ecological flows

Water supply would vary with RTL and the effect of climate change. Fluctuations of water demand from transferred and local sources are presented in Table S20. Comparison of the water supply under different climate change scenarios revealed the following. (a)

The Yingna River would support more water resources under RCP 8.5-BC1 in 2025 and RCP 4.5-BC1 in 2030 with RTL of 80%, and support less water resources under RCP 8.5-BC1 in 2025 with RTL of 20%. (b) The Biliu River would support more water resources under RCP 8.5-BC1 in 2025 and 2030 with RTL of 20%, and support less water resources under RCP 4.5-BC2 in 2025 with RTL of 80% and under RCP 8.5-BC2 in 2030 with RTL of 80%. (c) The Dasha and Zhuang rivers would support more water resources under RCP 8.5-BC1 and RCP 4.5-BNU in 2025 with RTL of 20%. Conversely, the amount of water supported by the Dasha and Zhuang rivers in 2030 would decrease dramatically. (d) The Hun River would support more water resources under RCP 4.5-BC1 in 2025 and RCP 4.5-BNU in 2030 with RTL of 80%, and support less water resources under RCP 4.5-BNU in 2025 with RTL of 20% and under RCP 8.5-BNU in 2030 with RTL of 50%.

In consideration of the supply capacity of reservoirs in 2020, the water supplies of reservoirs in 2025 and 2030 under the multiple climate change scenarios and RTLs of the stakeholders are illustrated in Figure 4. As supported by the transferred water project from the Dahuofang Reservoir on the Hun River, water supplies of most local reservoirs would be fulfilled in 2025 and 2030, except for the Songshu and Liuda reservoirs. Therefore, the current supply capacity of the Songshu and Liuda reservoirs should be increased by 0.99–2.21 and 0.67–2.18 times, respectively, by 2025.

(2) Energy consumption

Under the desired allocation strategies of water resources, the amount of energy consumption in the Dalian WMS is presented in Table 2. Energy consumption would increase in conjunction with the supply from the transferred water source. In detail, compared with the supply in 2025, the increase of the water supply of the Hun River would be 6942–33,772, 6942–25,472, and 2849–14,259 Mt with RTLs of 20%, 50%, and 80%, respectively. Concurrently, the amount of energy consumption would increase by 0.16–2.17, 0.16–1.03, and 0.06–0.34 times with RTLs of 20%, 50%, and 80%, respectively.

Table 2 Energy consumption in water resources allocation of Dalian under changing climatic conditions

Unit: MWh

RTLs / Climate change scenarios	2025			2030		
	20%	50%	80%	20%	50%	80%
RCP4.5-BC1	7882	7887	9278	9150	9154	9866
RCP8.5-BC1	2957	4627	7918	9150	9154	10030
RCP4.5-BC2	3056	4656	8174	9150	9154	9943
RCP8.5-BC2	2889	4513	7698	9150	9154	10311
RCP4.5-BNU	2885	4591	8144	9150	9154	10209
RCP8.5-BNU	2920	4540	7868	9150	9154	9866

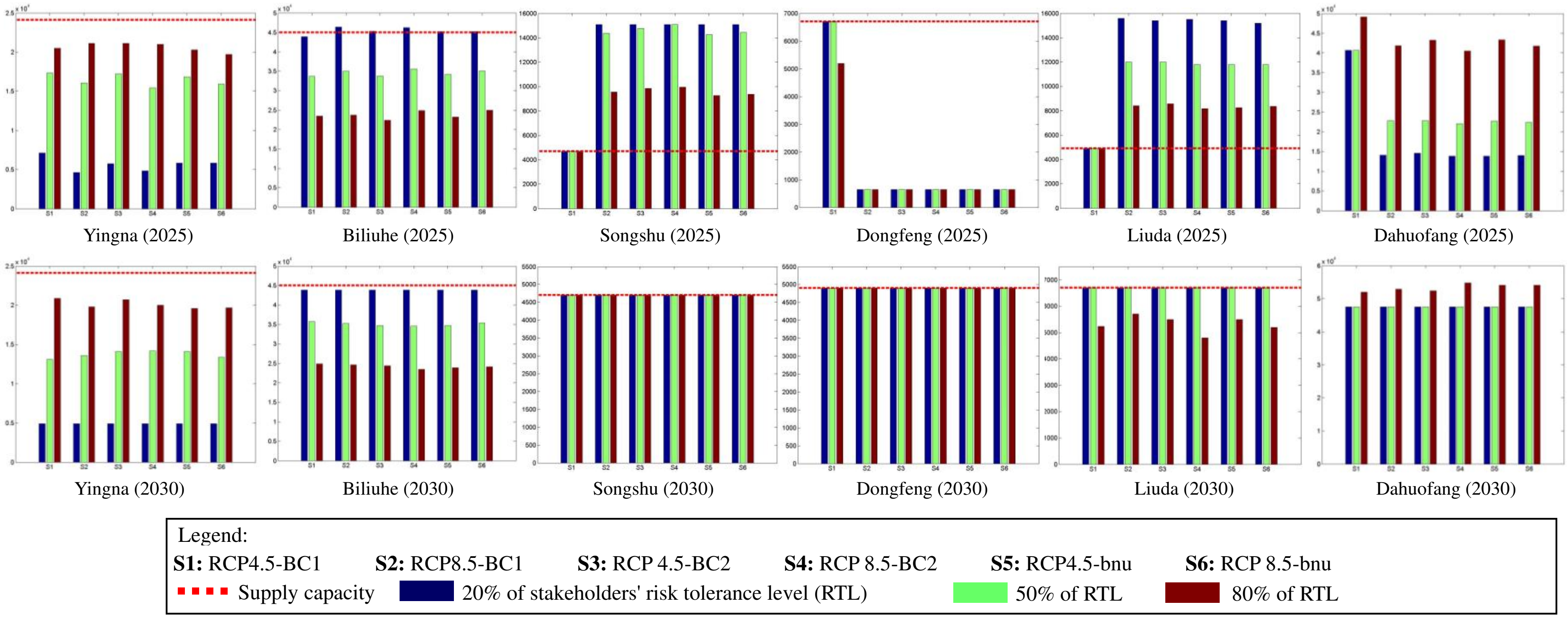

Fig. 4 The allocation of water resources under multiple climate change scenarios in consideration of reservoir supply capacity.

5 Conclusions

Countries throughout the world face increasing challenges in terms of balancing water supply and environmental protection. Although many previous studies have addressed EWR, research on water resources allocation focusing on fluctuations in EWR and water shortage risk in a WMS under the background of climate change is lacking. Thus, the objective of this study was to improve the methods typically used for a WMS with consideration of EWR under uncertain and risky conditions. A hybrid approach was proposed to evaluate fluctuations in precipitation under multiple climate change scenarios, analyze correlated features of runoff and precipitation, and incorporate variations in EWR under precipitation fluctuations into water allocation management. In detail, precipitation fluctuations were analyzed based on daily climate data from three general circulation models under the RCP 4.5 and RCP 8.5 scenarios. Correlations between runoff and precipitation were analyzed using a copula–MCMC simulation method. Fluctuations of EWR were analyzed based on copula sampling and VMF methods. Desired water allocation strategies were obtained based on a CCP model. The RTLs of stakeholders to water shortages (i.e., 20%, 50%, and 80%) were incorporated in the water resources management model. Based on the application of the developed method to water resources management in the city of Dalian (China), the following conclusions were derived. (a) The water resource demands of Changhai, Changxingdao, and Huayuankou districts would be supported by the Yingna and Fuzhou rivers in 2025 and 2030. The water suppliers in the other districts of Dalian would vary dramatically depending on the effects of climate change and the RTLs of stakeholders, especially under RCP 4.5-BC1 in 2025. (b) The EWR in the watersheds of Dalian would suffer large variations, especially under

RCP 8.5-BC2 in 2025 and under RCP 8.5-BC1 in 2030. (c) In comparison with the supply in 2025, the increase of water supply from the Hun River would be 6942–33,772, 6942–25,472, and 2849–14,259 Mt with RTLs of 20%, 50%, and 80%, respectively. (d) The amount of energy consumption would increase by 0.16–2.17, 0.16–1.03, and 0.06–0.34 times with RTLs of 20%, 50%, and 80%, respectively, in conjunction with the increase of water resources in the transferred project. (e) To fulfill the desired strategies in terms of water allocation, the current supply capacity of the Songshu and Liuda reservoirs should be increased by 0.99–2.21 and 0.67–2.18 times, respectively, in the future. To obtain efficient strategies regarding water allocation in Dalian, it is crucial to consider the influence of EWR and water shortage risk in water resources optimization.

Declarations

Ethical Approval All authors kept the 'Ethical Responsibilities of Authors'.

Consent to Participate All authors gave explicit consent to participate in this study.

Consent to Publish All authors gave explicit consent to publish this manuscript.

Authors Contributions All authors contributed to and collaborated in this research. Wencong Yue, Meirong Su, and Yanpeng Cai developed the methods. Wencong Yue, Meng Xu, Qiangqiang Rong, and Chao Xu provided the case study for application of the methods. Zhenkun Tan, Zhongqi Liu, Xuming Jiang, and Zhixin Su collected and analysed the data.

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Competing Interests The authors declare that there are no conflicts of interest.

Availability of data and materials Detailed data and figures are provided as supplementary information.

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Figures

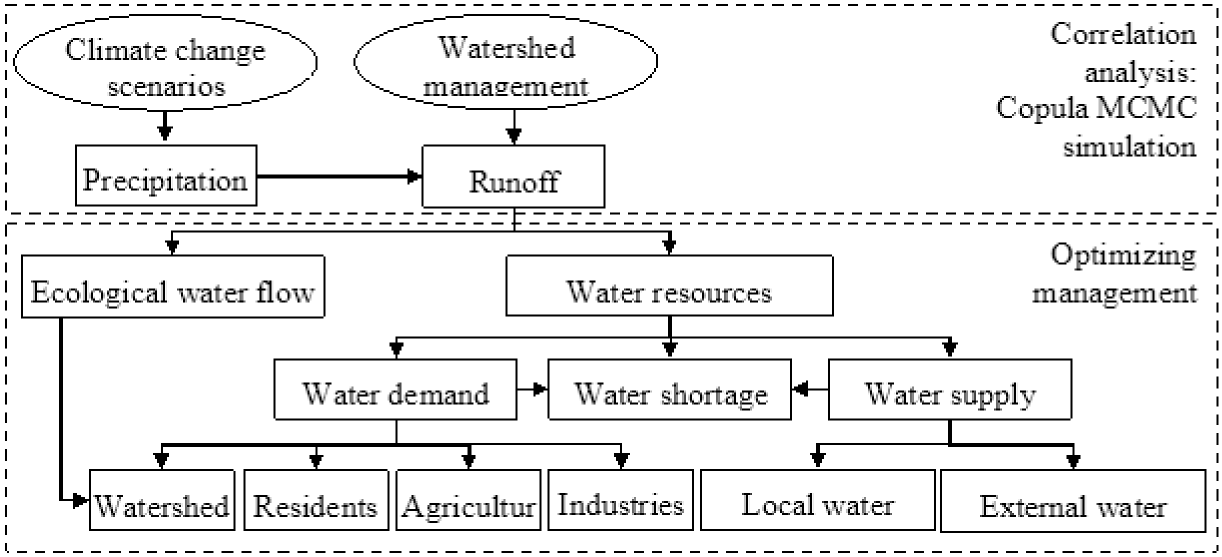

Figure 1

Framework for water resources management under climate change conditions

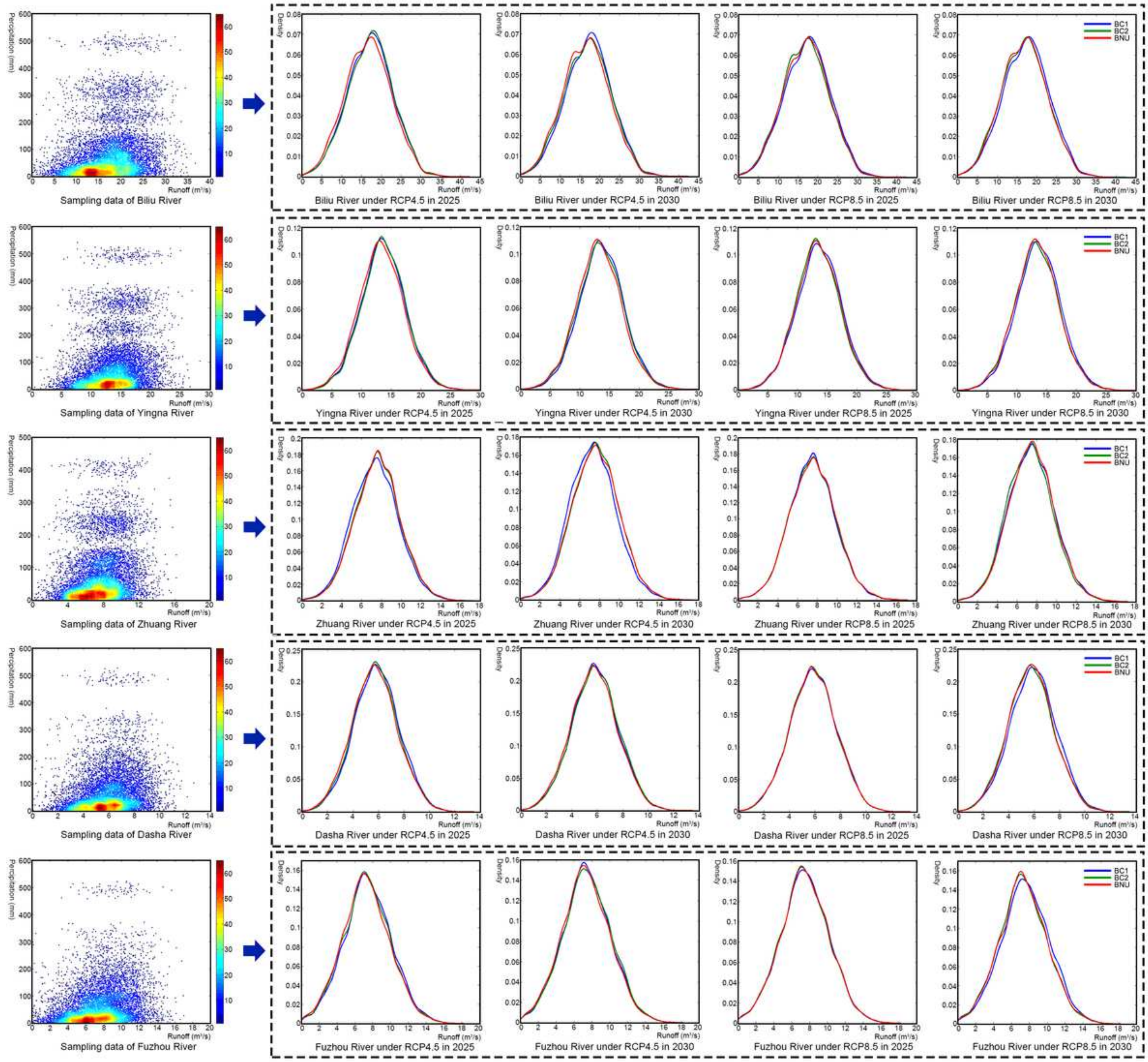

Figure 2

Distributions of runoff velocity in Dalian’s watersheds under multiple climate change scenarios based on the copula sampling method.

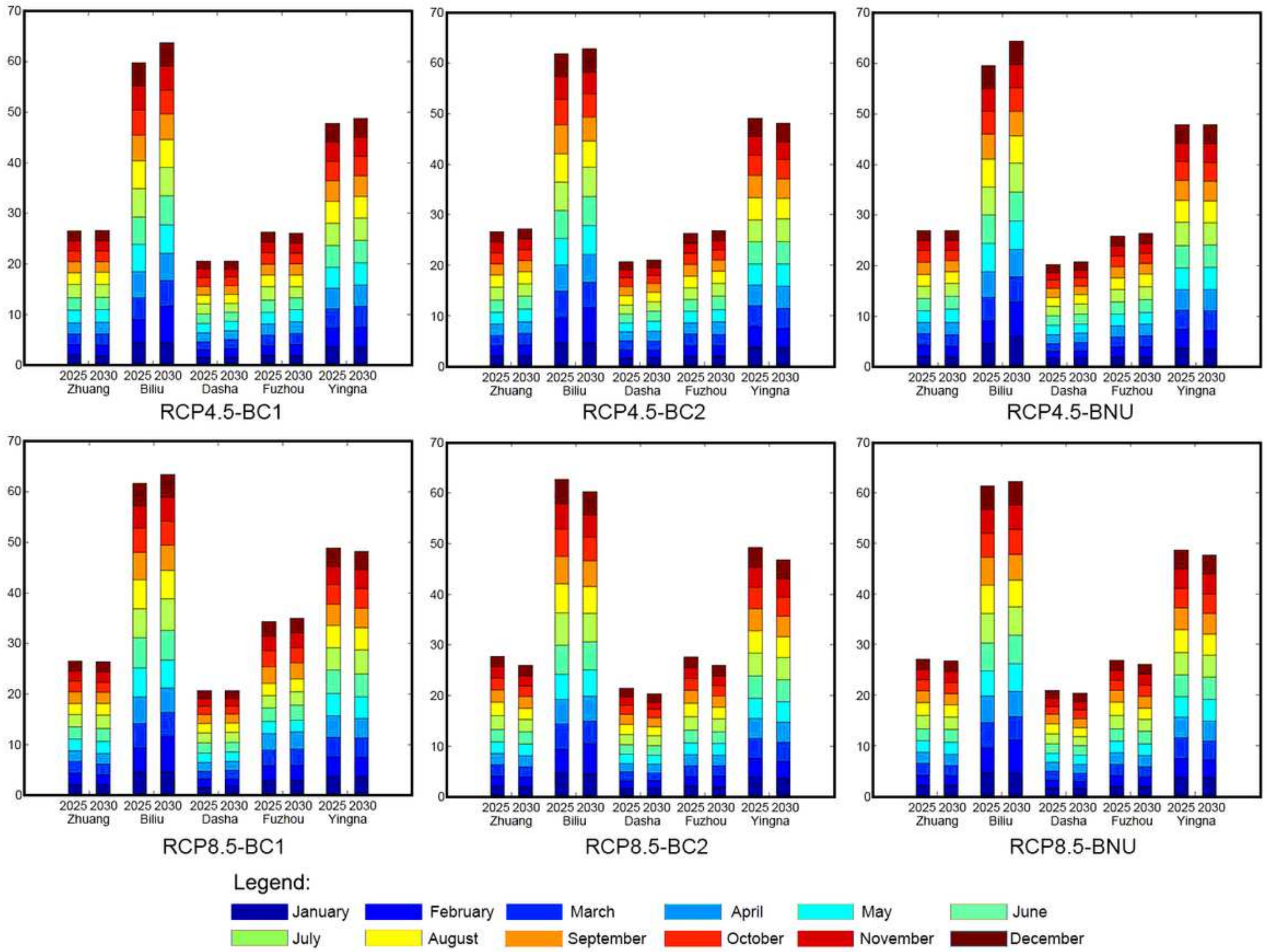

Figure 3

Monthly ecological water requirement in Dalian (mean values) in 2025 and 2030. Unit: m3/s.

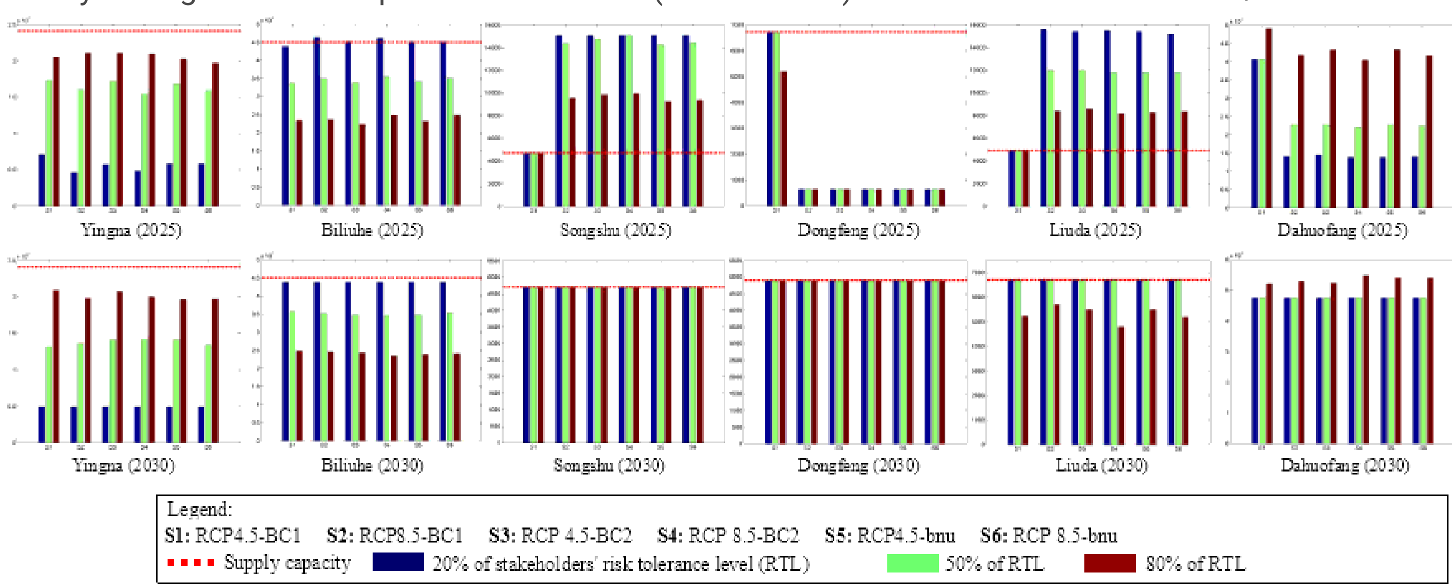

Figure 4

The allocation of water resources under multiple climate change scenarios in consideration of reservoir supply capacity.

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