

# A Two-stage Approach to Basin-scale Water Demand Prediction

Yanhu He<sup>1</sup> · Jie Yang<sup>1</sup> · Xiaohong Chen<sup>1</sup> ·  
Kairong Lin<sup>1</sup> · Yanhui Zheng<sup>1</sup> · Zhaoli Wang<sup>2</sup>

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**Abstract** Water demand prediction (WDP) is the basis for water allocation. However, traditional methods in WDP, such as statistical modeling, system dynamics modeling, and the water quota method have a critical disadvantage in that they do not consider any constraints, such as available water resources and ecological water demand. This study proposes a two-stage approach to basin-scale WDP under the constraints of total water use and ecological WD, aiming to flexibly respond to a dynamic environment. The prediction method was divided into two stages: (i) stage 1, which is the prediction of the constrained total WD of the whole basin ( $T_w$ ) under the constraints of available water resources and total water use quota released by the local government and (ii) stage 2, which is the allocation of  $T_w$  to its subregions by applying game theory. The WD of each subregion ( $T_s$ ) was predicted by calculating its weight based on selected indicators that cover regional socio-economic development and water use for different industries. The proposed approach was applied in the Dongjiang River (DjR) basin in South China. According to its constrained total water use quota and ecological WD,  $T_w$  data were 7.92, 7.3, and 5.96 billion  $m^3$  at the precipitation frequencies of 50%, 90%, and 95%, respectively (in stage 1). Industrial WDs in the domestic, primary, secondary, tertiary, and environment sectors are 1.08, 2.26, 2.02, 0.44, and 0.16 billion  $m^3$ , respectively, in extreme dry years (in stage 2).  $T_w$  and  $T_s$  exhibit structures similar to that of observed water use, mainly in the upstream and midstream regions. A larger difference is observed between  $T_s$  and its total observed water use, owing to some uncertainties in calculating  $T_w$ . This study provides useful insights into adaptive basin-scale water allocation under climate change and the strict policy of water resource management.

**Keywords** Water demand prediction · Two-stage approach · Game theory · Dongjiang River basin, South China

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✉ Xiaohong Chen  
eescxh@mail.sysu.edu.cn

<sup>1</sup> Department of Water Resources and Environment, SunYat-sen University, Guangzhou 510275, China

<sup>2</sup> School of Civil Engineering and Transportation, South China University of Technology, Guangzhou 510641, China

## 1 Introduction

Water demand prediction (WDP) provides a basis for water allocation (Chen and Boccelli 2014; Romano and Kapelan 2014). Understanding the effects of administrative intervention and socioeconomic development on water demand is necessary to develop effective policies on water supply management. In recent years, research on WDP has received increased attention under a changing environment (Wada et al. 2013; Babel et al. 2014; Elliott et al. 2014; Wang et al. 2016; Mohtar and Daher 2016).

According to the prediction horizon and periodicity, WDP can be mainly categorized as long-term (i.e., spanning more than 2 years) (Rinaudo 2015), medium-term WDP (i.e., spanning from 3 months to 2 years) (Mombeni et al. 2013), and short-term (i.e. spanning less than 3 months) (Zhou et al. 2000; Bai et al. 2014; Mouatadid and Adamowski 2016). Various WDP models and methods can be broadly classified into time-series and multiple factor correlation analysis (Adamowski and Karapataki 2010; Campisi-Pinto et al. 2012; Zhai et al. 2012), or linear and nonlinear (Zhang et al. 2012; Chen 2011; Adamowski et al. 2012). Time-series methods can indicate the relationship between WD and time series by building the time series prediction model, which is preferable for short-term WDP; however, time-series techniques cannot reflect the inherent mechanism of WD and cannot easily present an objective illustration of the complex water demand system. Multiple factor correlation analysis methods can usually provide more reasonable WDP results by establishing the relationship between WD (as output) and its variables (as input), but they cannot easily provide an accurate forecast of each variable as an input. Linear methods (e.g., exponential smoothing models, autoregressive integrated moving average models, linear regression models, etc.) have been widely used because they are simple to understand and interpret. However, linear methods cannot handle the varying degrees of nonlinearity in WD data, which can be improved by nonlinear methods (e.g., ANNs, fuzzy logic, model trees, etc.). The performances of the models can be evaluated according to statistical criteria such as, average absolute relative error (AARE), normalized root mean square error (NRMSE) and threshold statistic ( $T_s$ ). Each of the typical statistical models has its own characteristic, for example, the ANNs has the ability to learn from input and output and adapt to it in an interactive manner (Al-Zahrani and Abo-Monasar 2015); the FISs, as an inference mechanism, is used to establish a relationship between a series of input and output using fuzzy sets theory (Firat et al. 2009). The aforementioned WDP methods were demonstrated as useful tools in providing foundation for adjusting industrial structures, controlling pump constructions, scheduling urban water facilities, and making water supply management decisions by providing different prediction horizons of water demand, largely based on historical water use data.

These WDP methods typically focus on the performance of applied mathematical simulation models, which largely depend on the high quality of observed water use data or significant variables of WD as inputs. In fact, some constraints as inputs are considered in many developed statistical models, these constraints are usually parts of the model itself and have different functions. For example, the constrained orthogonal least-squares method is used to identify the structure and the parameters of the TSK fuzzy models (Mastorocostas et al. 2001); the linear constraints are used to incorporate weak supervision into the learning procedure and improve the performance of this procedure (Pathak et al. 2015); the use of inequality constraints in the linear regression models is to guarantee the mathematical coherence between the predicted values (Neto et al., de A Lima Neto et al. 2005). However, as to WDP models, several constraints, including available water resources, ecological water demand, and constrained total water use in countries (e.g., China) that largely contribute to water resource exploitation, are not properly considered, particularly for long-term WDP (Qin et al. 2015).

Moreover, subregions in a basin are usually bundled with economy–population interactions, leading to water use competition (Liu and Wang 2003). Sustainable water exploitation has to be kept at the basin scale by treating each subregion as an individual stakeholder of water use. Expansion of WD for each subregion should be inhibited to improve water use efficiency and maintain a healthy ecosystem under constrained water use. Meanwhile, the role of each subregion, determined by its population, economy, location, and even political status, should be differentiated in WDP, which has received relatively less attention.

A two-stage approach to WDP is developed to support the management of WD under different frequencies at the basin scale and is applied in the Dongjiang River (DjR) basin in South China for a case study. Stage 1 aims to determine the total amount of water in a whole basin, with the consideration of available water resources under variable precipitation frequencies, constrained total water use, and ecological water demand, among others. Stage 2 aims to provide WDP results for each subregion and its industries by using the calculated weight based on the selected indicators and the WD capacity of each industry from the observed water use data, according to game theory. The main advantage of the proposed WDP approach over previous methods is its ability to reflect change in available water resources and the impact of government policy (e.g., the frequency of inflow, constrained total water use). Government policy is important because water use conflict—particularly between the upper-middle and downstream regions of a river basin—may occur, owing to increasing water demand intensified by fast industrialization and urbanization (Li et al. 2015). The second advantage relates to the consideration of the economic and political role of each subregion in the proposed WDP by selecting the indicators covering regional socioeconomic development and water use; this provides a basis for subregional WD in the basin under a changing environment. The third advantage includes its simple calculation and less dependence on the high quality of observed water use data.

This paper is organized as follows. The new proposed WDP approach will be described in the next section. The case study of the DjR basin is explained in section 3, followed by the application of the proposed approach in section 4. In section 5, we compare the proposed approach with typical WDP methods to clarify its characteristic. Finally, the conclusions are drawn in Section 6.

## 2 Methodology

The proposed WDP approach for a river basin in this study consists of two stages: constrained total WD of the whole basin ( $T_w$ ) (stage 1) and total WD ( $T_s$ ) and industrial WD for each subregion (stage 2). Detailed descriptions of the fundamental assumption and the two stages of the proposed WDP approach are presented in Fig. 1 and are explained in the following paragraphs.

### 2.1 Fundamental Assumptions of the Two-Stage WDP Approach

The proposed WDP is based on two assumptions: 1) Given the constrained total WD of a whole basin, each subregion has fully grasped the WD information of other subregions, and 2) for each subregion, industrial WD is chosen to maximize its efficiency within the capacity of industrial water use of the subregion—that is,  $T_s$  and the industrial WD of each subregion in a basin can be considered in a multi-stage complete information static game model. In the game model, each subregion and industry is taken as an individual stakeholder, who is allocated WD in a cooperative way under the constrained total WD of a whole basin; Specifically,

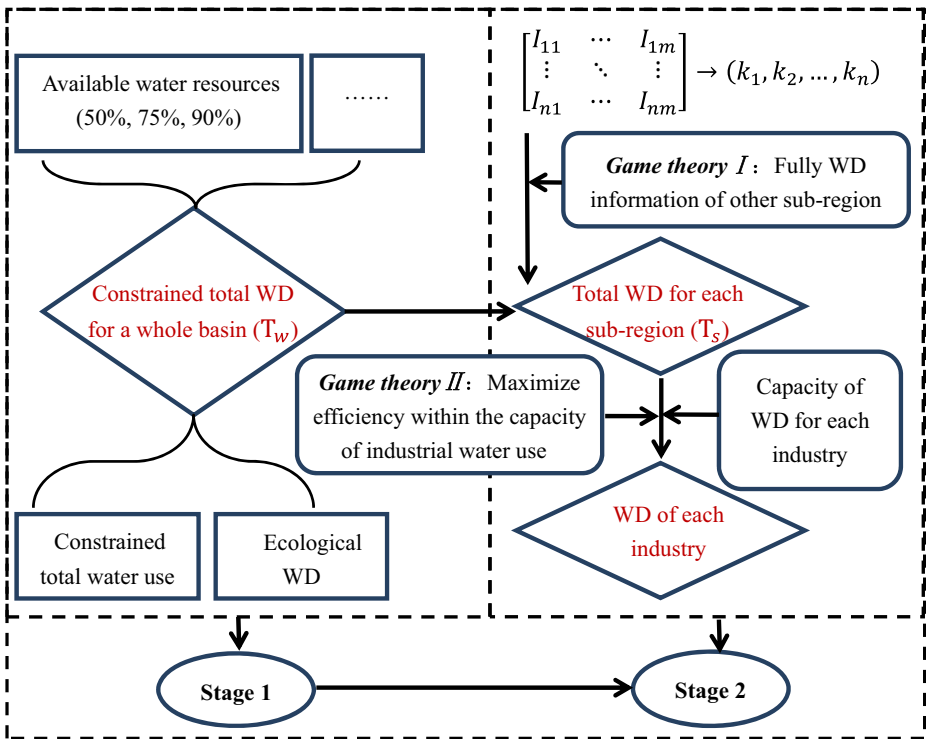


Fig. 1 Diagram of the proposed two-stage WDP approach

assumption 1 illustrates that for a given constrained total WD of the whole basin,  $T_s$  varies and is predicted by its socioeconomic development level and location in the cooperative game model, which provides a basis for industrial WD in a subregion. Water use efficiency for each industry is optimal when a Nash equilibrium of WD exists for all subregions and industries in the whole basin. If the water use efficiency of industry A is lower than that of others, the WD of industry A would be restricted and partly moved to an industry with higher water use efficiency. This effect prompts industry A to improve its water use efficiency. Finally, a new Nash equilibrium of WD for each industry is achieved. The cooperative game model in the study is applied just because it fits the situation of basin-scale WD conflict more easily and is convenient in practical use.

**2.2 Constrained Total WD of a Whole Basin-Stage 1**

For any basin, we assume that limited water resources are available for human and ecosystem development in a certain space–time range. In this study, the limited water resources are referred to as the constrained total WD of the whole basin, which is affected by both natural (e.g., variation of available water resources, climate change, and ecosystem change, etc.) and socioeconomic factors (e.g., national or regional policy, regional development plan, etc.). The water demand of a basin consists of off-stream WD for socioeconomic development and instream WD mainly for ecological conservation. Ecological WD is essential in maintaining a sustainable ecosystem for a basin, which should be deducted from the total water resources. Thus, the total available water ( $T_a$ ) is calculated as

$$T_a = T_g - WD_e \quad (1)$$

Where  $T_g$  is the total water resources of the whole basin,  $WD_e$  is the ecological WD of the basin.

Given the constrained factors of WD for a basin and based on  $T_a$ , its constrained total WD should be the minimum value of the constraints and is expressed as

$$T_w = \min(T_a, \text{cons } 1, \text{cons } 2, \dots, \text{cons } n) \quad (2)$$

Where  $T_w$  is the constrained total WD of the whole basin; cons 1, cons 2, ..., cons n are the amounts of water resources corresponding to the n constrained factors.

### 2.3 $T_s$ and industrial WD of each Subregion -Stage 2

In this stage, indicators covering socioeconomic development, water use, and water use efficiency are first selected to calculate the weight of each subregion used for allocating the constrained total WD of the whole basin ( $T_w$ ). Industrial WD is then determined by the capacity of observed industrial water use and subregional total WD.

The indicator selection is mainly based on the three principles as follows:

- (1) To response well to the changing environment

The indicators should fully reflect the changing environment, such as climate change, human activity, and government policy and so on.

- (2) A comprehensive and representative combination

The water demand system is complicated and the indicators should fully cover the influencing factors of the system. Meanwhile, the indicators should also be representative due to the difficult collection and great amount of calculation. In case of data redundancy, key indicators should be selected and focus on the aspects of socioeconomic development, water use, and water use efficiency.

- (3) A greater operability

Data of the indicators should be easily accessible and available, and the calculation of the indicators should be simple and clear.

In case of data redundancy, the final indicators can be chosen by using analytic hierarchy process (AHP) or principal components analysis (PCA) method from the selected indicators.

The indicator matrix A is listed as:

$$A = \begin{bmatrix} I_{11} & \cdots & I_{1m} \\ \vdots & I_{ij} & \vdots \\ I_{n1} & \cdots & I_{nm} \end{bmatrix} \quad (3)$$

Where n is the number of subregions, m is the number of the chosen indicator,  $I_{ij}$  is the value of the  $j_{th}$  indicator in the  $i_{th}$  subregion.

The values of the chosen indicators have to be standardized because their dimensions are inconsistent. For each column in the above matrix, the difference between the value of each

variable and the minimum value in the column is divided by the difference between the maximum and the minimum value of the column, which is the standardized series. The standardized indicator matrix B is listed as:

$$B = \begin{bmatrix} i_{11} & \cdots & i_{1m} \\ \vdots & i_{ij} & \vdots \\ i_{n1} & \cdots & i_{nm} \end{bmatrix} \tag{4}$$

For instance,  $i_{ij}$  in the standardized series of the  $j_{th}$  column is calculated as

$$i_{ij} = \frac{I_{ij} - I_{min,j}}{I_{max,j} - I_{min,j}} \tag{5}$$

Where  $I_{min,j}$  and  $I_{max,j}$  are the minimum and the maximum value of the  $j_{th}$  indicator,  $i_{ij}$  is the standardized value of the  $j_{th}$  indicator in the  $i_{th}$  subregion.

From Eq. (5),  $i_{ij} \in [0, 1]$ . The weight of the  $i_{th}$  subregion is equal to the sum of all elements in the  $i_{th}$  row of the standardized indicator matrix. The weight matrix K is given as follow:

$$K = \begin{bmatrix} k_1 \\ \vdots \\ k_i \\ \vdots \\ k_n \end{bmatrix} = \begin{bmatrix} i_{11} + i_{12} + \cdots + i_{1m} \\ \vdots \\ i_{i1} + i_{i2} + \cdots + i_{im} \\ \vdots \\ i_{n1} + i_{n2} + \cdots + i_{nm} \end{bmatrix} \tag{6}$$

Where  $k_i$  is the weight of the  $i_{th}$  subregion.

According to game theory, the total WD of each subregion can be allocated by using its weight from  $T_w$ ,

$$T_i = T_w \times \frac{k_i}{\sum k_i} \tag{7}$$

where  $T_i$  is the total WD of the  $i_{th}$  subregion.

Industrial WD in a subregion can be calculated as follows:

$$industrial\ WD_{it} = T_i \times \frac{C_{it}}{\sum_{l=1}^l C_{it}} \tag{8}$$

Where industrial  $WD_{it}$  is the WD of the  $t_{th}$  industry in the  $i_{th}$  subregion,  $l$  is the number of industries, and  $C_{it}$  is the capacity of the  $t_{th}$  observed industrial water use in the  $i_{th}$  subregion.

### 3 Case Study

Originating from Xunwu County in Jiangxi Province, flowing southwest to Guangdong Province and running into the Pearl River estuary, the Dongjiang River (DjR) is one of the three branches of the Pearl River in southern China (Fig. 2). Its mainstream has a total length of 562 km, and the total basin has a drainage area of 35,340 km<sup>2</sup> (He et al. 2015). The annual rainfall over the basin varies between 1500 mm in the dry season from October to March and 2400 mm in the wet or monsoon season from April to September (He et al. 2013). The DjR flows across Meizhou, Shaoguan, and Heyuan in the upstream region, Huizhou and Guangzhou in the midstream region, and Dongguan and Shenzhen in the downstream region. The river is the major water source for Hong Kong outside the basin.

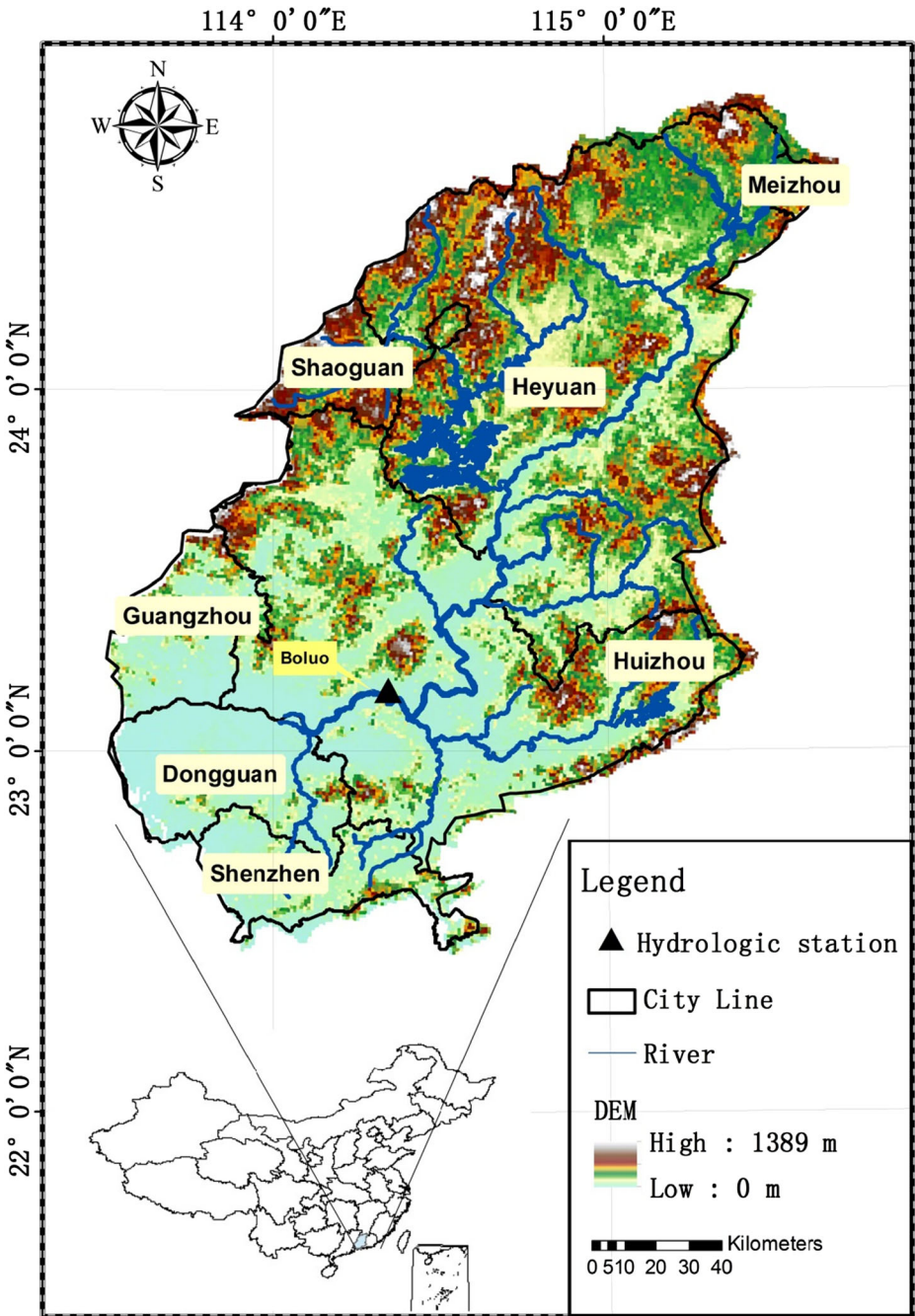


Fig. 2 Sketch map of the DjR basin in South China

The population and economy in the DjR basin have kept a rapid and persistent development because of China's reform and opening-up policy. Up to 2015, total population and gross domestic product (GDP) in the whole basin increased to \$27.8 million and \$222 billion,

respectively, which prompts large amounts of off-stream water demand. Meanwhile, the competition for water among subregions and water use sectors in the basin rise because of the unbalanced socioeconomic development in the upstream and downstream regions, as well as the uneven spatiotemporal distribution of water resources. The minimum, suitable, and maximum ecological instream flows of the Boluo station, which is the control hydrological station of the whole basin, are 187.4, 678.5, and 2091.5 m<sup>3</sup>/s, respectively (Zhang et al. 2012). Ecological instream flow is often occupied, particularly in extreme dry years (Lin et al. 2014a, b). Thus, the proposed two-stage WPD approach was applied in the prediction of  $T_w$  and the industrial WD of the entire DjR basin and its seven subregions (Table 1).

In the current study, total water resources as well as ecological instream water demand under variable precipitation frequencies (50%, 90%, and 95%) were obtained from the daily streamflow data of the Boluo station, covering the 1959–2010 period (Fig. 3). Hydrological data were released by the Guangdong Hydrological Bureau of China, with no missing data. The domestic, primary, secondary, tertiary and environmental (off stream) water use data of the seven subregions for the 1980–2015 period are summarized in Fig. 4. The socioeconomic development data of the subregions (e.g., population, GDP, water consumption) were obtained from Guangdong Water Resource Bulletin and Guangdong Statistical Yearbook. Since 2011, the Chinese government has put forward a water resource management policy concerning total water use, water use efficiency, and water quality, commonly referred to as “three red lines”; a specified control target for total water use has been set. For the subregions in the DjR, the control targets for total water use are 8.38, 8.75, and 8.29 billion m<sup>3</sup> under the frequencies of 50%, 90%, and 95%, respectively (Guangdong Provincial Water Resources Department 2012).

## 4 Results

### 4.1 Constrained Total WD of the DjR Basin

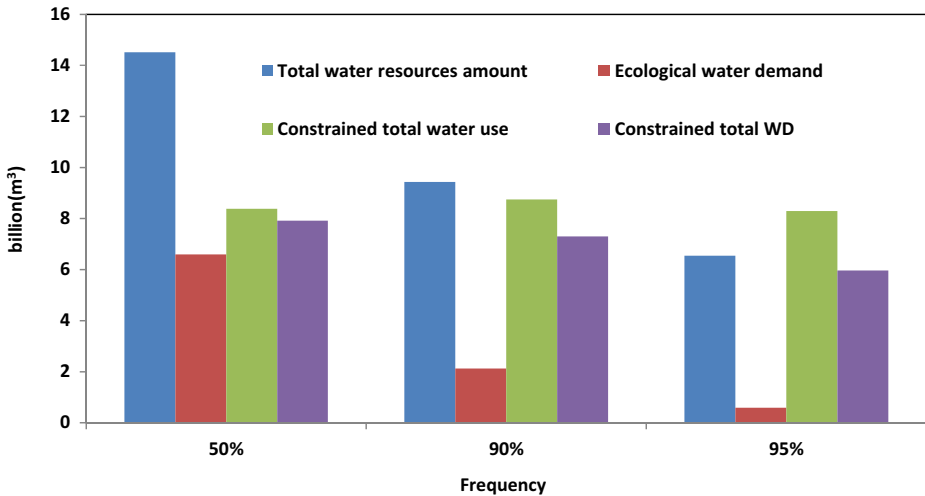
The total water resources and ecological WD of the DjR basin under the frequencies of 50%, 90%, and 95% were calculated based on the observed daily streamflow data of the Boluo station. The calculated ecological WD is also compared with the ecological instream flow of the Boluo station proposed by Zhang et al. (2012). In the present study, the constrained total water use quota released by the local government was used to calculate  $T_w$  (stage 1, Fig. 1). According to Eqs. (1)–(2), the constrained total WDs of the DjR basin under the frequencies of 50%, 90%, and 95% are 7.92, 7.3, and 5.96 billion m<sup>3</sup>, respectively (Fig. 3). With extreme dry years as an example,  $T_w$  should be restricted to 5.96 billion m<sup>3</sup>, which not only ensures the

**Table 1** Seven subregions of the DjR basin

Subregion	Area (km <sup>2</sup> )	Location	ALAWA (billion m <sup>3</sup> )
Heyuan	13,646	Upstream	13.53
Meizhou	272		0.26
Shaoguan	1232	Middle stream	1.28
Huizhou	10,328		10.97
Zengcheng	1744		1.90
Dongguan	2465	Downstream	2.31
Shenzhen	1864		1.99

ALAWA represents Annual local average water resources amount





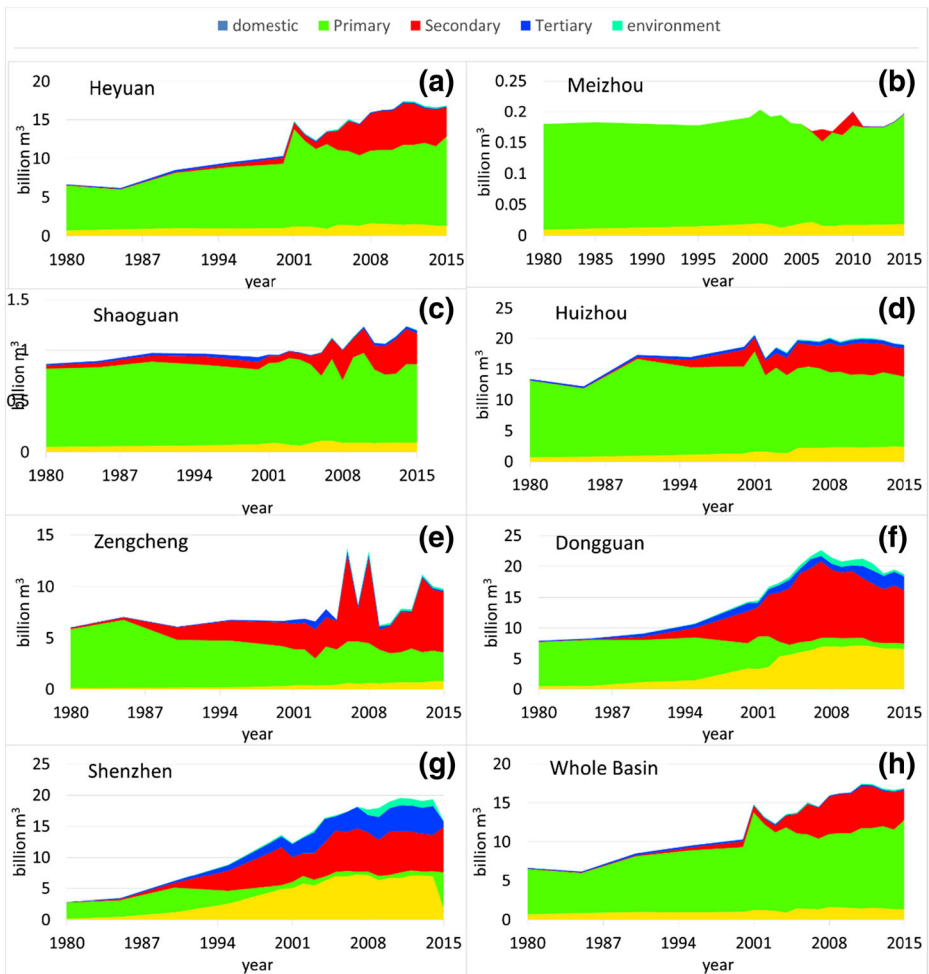
**Fig. 3** Total water resources, ecological water demand, constrained total water use, and WD at frequencies of 50%, 90%, and 95% in the DjR basin in South China

ecological WD but also complies with the policy of constrained total water use. In an extreme dry year,  $T_w$  is determined by the available water in the whole basin.

#### 4.2 $T_s$ and Industrial WD of each Subregion in the DjR Basin

$T_s$  and the industrial WD of each subregion in the DjR basin were calculated in stage 2. First, eleven indicators (Table 2) covering regional water use amounts, the socioeconomic development and water use efficiency of the DjR basin were selected according to the three principles described in section 2.3, and the weight of each subregion for determining its total WD were calculated based on Eqs. (4)–(6). The final weight matrix of the seven subregions (Table 1) from the upstream to the downstream is  $K = [0.126, 0.04, 0.063, 0.16, 0.151, 0.225, 0.234]$ . Second,  $T_s$  was calculated in accordance with Eq. (7) on the basis of  $T_w$  and the weight of each subregion. Last, the industrial WD of each subregion was calculated based on Eq. (8), considering the capacity of observed industrial water use in the 1985–2015 period (Fig. 4).

Subregions such as Shenzhen and Dongguan in the downstream region, which exhibit high levels of socioeconomic development and water use efficiency, have larger weights for being allocated subregional total WD (0.225 for Dongguan and 0.234 for Shenzhen); meanwhile, Meizhou and Shaoguan in the upstream region, have weights equal to 0.04 and 0.06, respectively. The weights of the subregions in the midstream region, including Heyuan, Huizhou and Zengcheng, are smaller than those in the downstream region but larger than those upstream regions. This difference can be largely attributed to the observed water use, local water resources, socioeconomic development, and water use efficiency of each subregion in the basin (Fig. 5). For instance, Shenzhen in the downstream region has the largest population and GDP and exhibits the highest water use efficiency; it requires larger amounts of water, particularly for domestic water use, and should be allocated the highest weight. Huizhou and Heyuan in the midstream region have a smaller population and GDP; in addition, they have lower irrigation rates of agricultural water but have more effective irrigated areas (0.109 and 0.075 billion hectares in Huizhou and Heyuan, respectively) than Shenzhen (0.003



**Fig. 4** Industrial WD of each subregion from 1980 to 2015 in the DjR basin in South China

billion hectares), which accounts for the most agriculture water use and should be allocated with a higher weight of subregional total WD.

$T_s$  and the industrial WD of each subregion in the DjR basin under the frequencies of 50%, 90%, and 95% are presented in Fig. 6. Shenzhen, Dongguan, Huizhou, Zengcheng, Heyuan, Shaoguan, and Meizhou have  $T_s$  rates of 23%, 22%, 16%, 15%, 13%, 6%, and 4% of  $T_{in}$ , respectively; each rate corresponds to the calculated weight of each subregion. As to the whole basin, the WD of the domestic, primary, secondary, tertiary, and urban environment are 1.08, 2.26, 2.02, 0.44, and 0.16 billion  $m^3$ , respectively, in extreme dry years. Regarding the industrial WD of each subregion, Shenzhen has the most balanced WD structure; the secondary WDs of Dongguan and Zengcheng account for the most, and the primary WDs of Heyuan and Huizhou account for 60% and 64% of its total subregional WD, respectively, which is determined by the industrial structure of the subregions. From the upstream to the downstream regions of the DjR basin, the proportion of primary WD decreases, whereas that of secondary WD increases until a balanced WD structure is achieved in the most developed region.

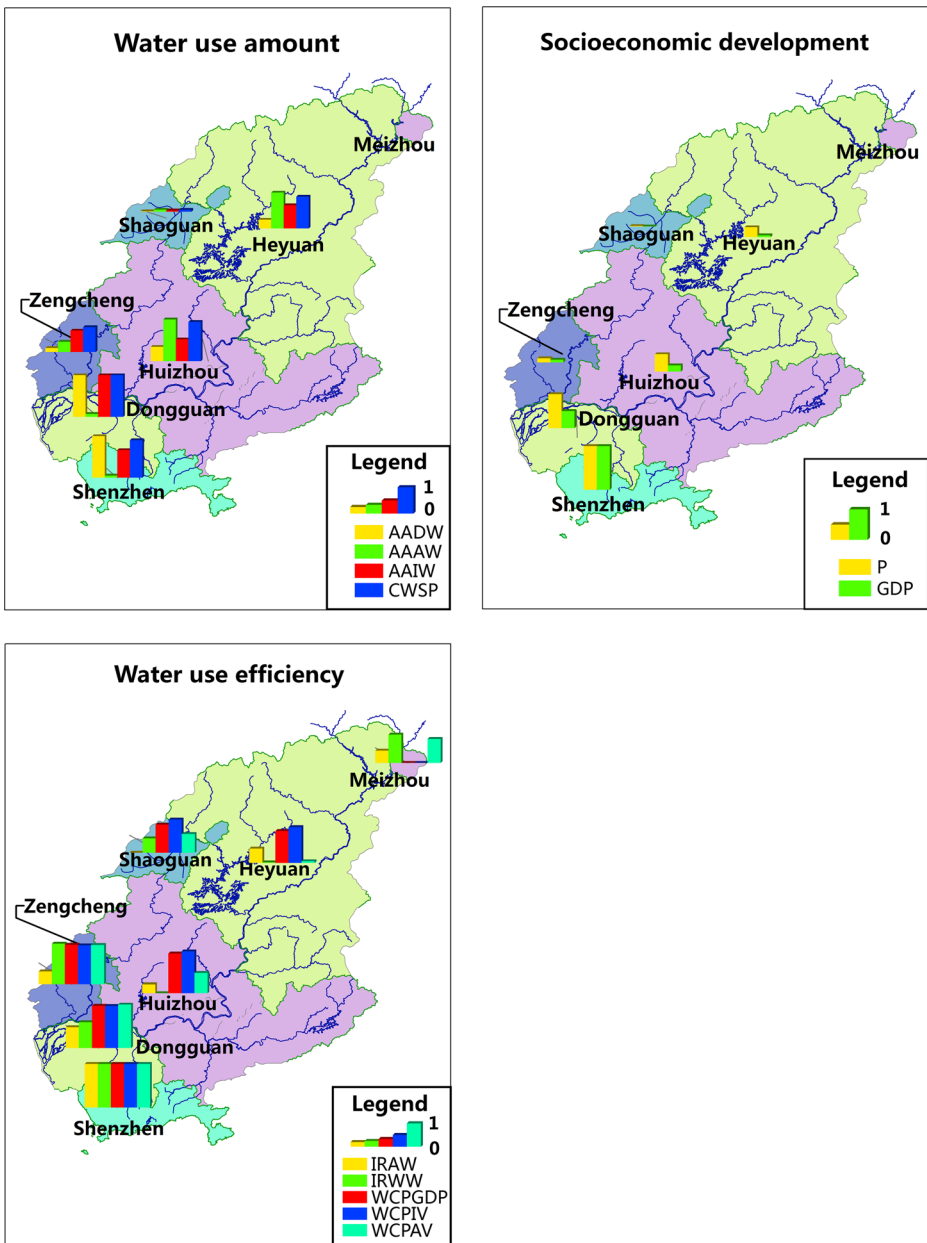
**Table 2** Selected indicators for calculating the weight of each subregion in the DjR basin

Class	Indicator	Abbreviation	Unit
Water use	Average annual domestic water use	AADW	million m <sup>3</sup>
	Average annual agricultural water use	AAAW	million m <sup>3</sup>
	Average annual industrial water use	AAIW	million m <sup>3</sup>
	Capacity of current water supply project	CWSP	million m <sup>3</sup>
Socioeconomic development	Population	P	thousand persons
	Gross domestic product	GDP	billion yuan
Water use efficiency	Irrigation rate of agricultural water	IRAW	–
	Industrial water reuse rate	IRWW	%
	Water consumption per unit of 10,000 gross domestic product	WCPGDP	m <sup>3</sup>
	Water consumption of per unit of 10,000 industrial output value	WCPIV	m <sup>3</sup>
	Water consumption of per unit of 10,000 agricultural output value	WCPAV	m <sup>3</sup>

The observed water use in the three typical years (2000, 2002, and 2004) correspond to the frequencies of 50%, 90%, and 95% are chosen and compared to verify  $T_s$  and the industrial WD of each subregion in the DjR basin (Fig. 7). Overall, the structure of total WD is similar to that of the observed water use in the whole basin and its subregions in the upstream and midstream regions under the three precipitation frequencies. Moreover, for each subregion, the proportion of  $T_s$  in  $T_w$  is in accordance with the proportion of its total observed water use in the whole basin; a greater difference between  $T_s$  and the total observed water use is observed. This difference may be partly attributed to uncertainties in calculating  $T_w$  (Eqs. (1) to (2)), including the total available water, ecological WD, and constraints. One of these constrained factors is the total water use quota released by the government, which leads to increased differences in the total amount; another reason is the capacity of each industrial water use (from the series of observed data) when calculating industrial WD (Eq. (8)), which results in a similar structure of WD and observed water use for each subregion. An increased significant difference is observed between the structures of WD and observed water use in Shenzhen, the most developed region in the downstream region. For example, WD of the primary is larger than that of observed water use, which leads to a smaller WD of other industries, compared with that of the observed water use. The proposed method performs well in allocating  $T_w$  to its subregions, but more actions should be taken to reduce the uncertainty in calculating  $T_w$ .

## 5 Discussion

The two-stage WDP approach proposed in this study differs from previous WDP methods (e.g., artificial neural networks, time-series models, auto-regressive models) in that first, it intends to predict the constrained total and industrial WD of a basin and its subregions under variable frequencies of the total water resources and has no specific predict horizon, which is different from the hourly, daily, weekly, monthly, or annual WDP of an urban city or just a subregion by using time-series, statistical, or artificial models. Second, the proposed method gives  $T_w$  considering the available water resources, ecological WD, and policy regulation (e.g., constrained total water use quota), and based on  $T_w$ ,  $T_s$  and the industrial WD of each subregion are allocated using the weight calculated by socioeconomic development and water use indicators, according to game theory; meanwhile, in previous WDP methods, WD with



**Fig. 5** Standardized value of 11 selected indicators covering average annual observed water use, socioeconomic development, and water use efficiency of each subregion from 1980 to 2015 in the DjR basin in South China

different prediction horizons are simulated using the time-series model or the artificial model based on the available water consumption and climatic data, and the WDP models are built largely relying on the identification of major variables negatively or positively affecting WD (Ghimire et al. 2016), which requires large amounts of high-quality observed water use data.

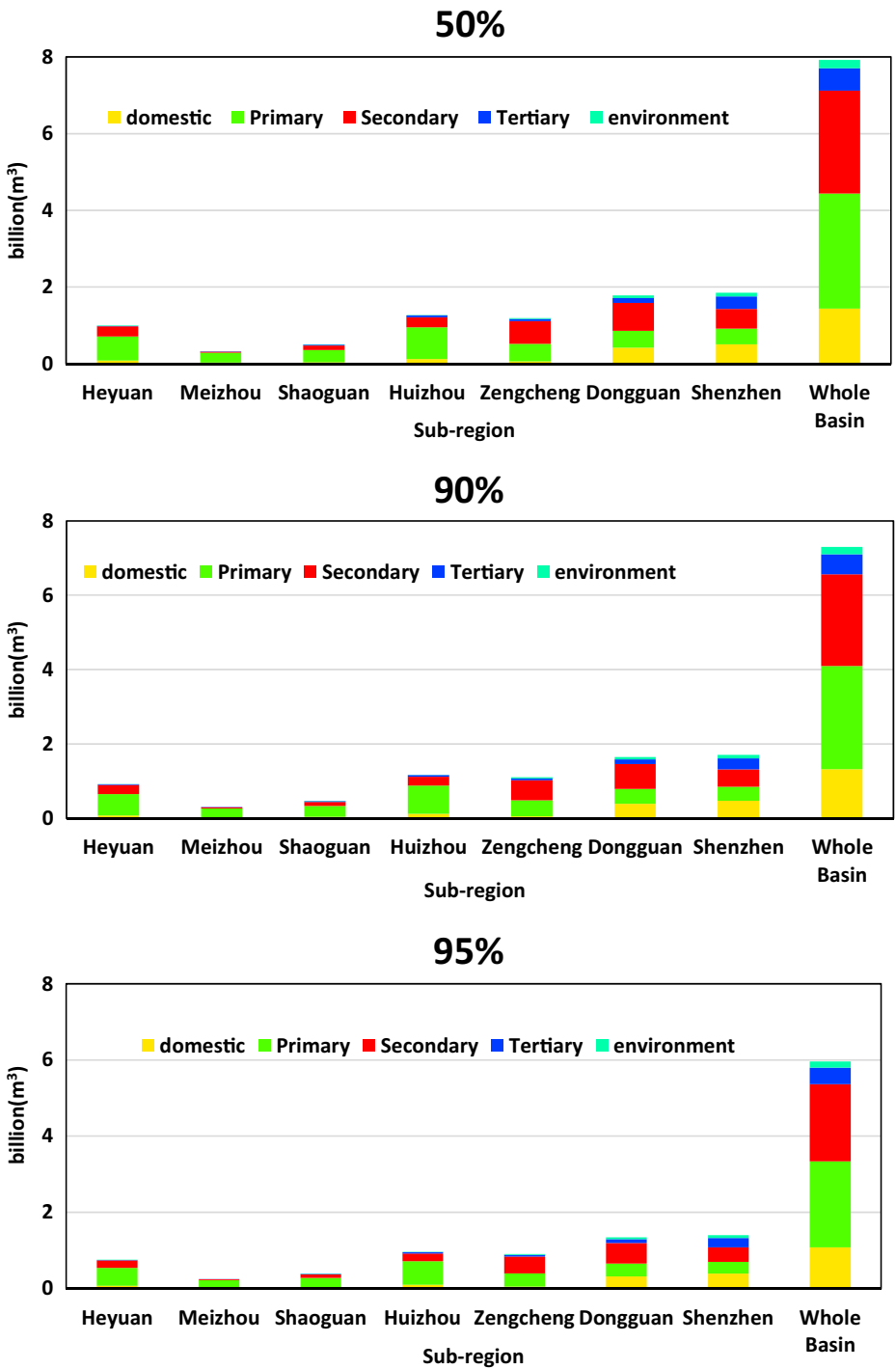
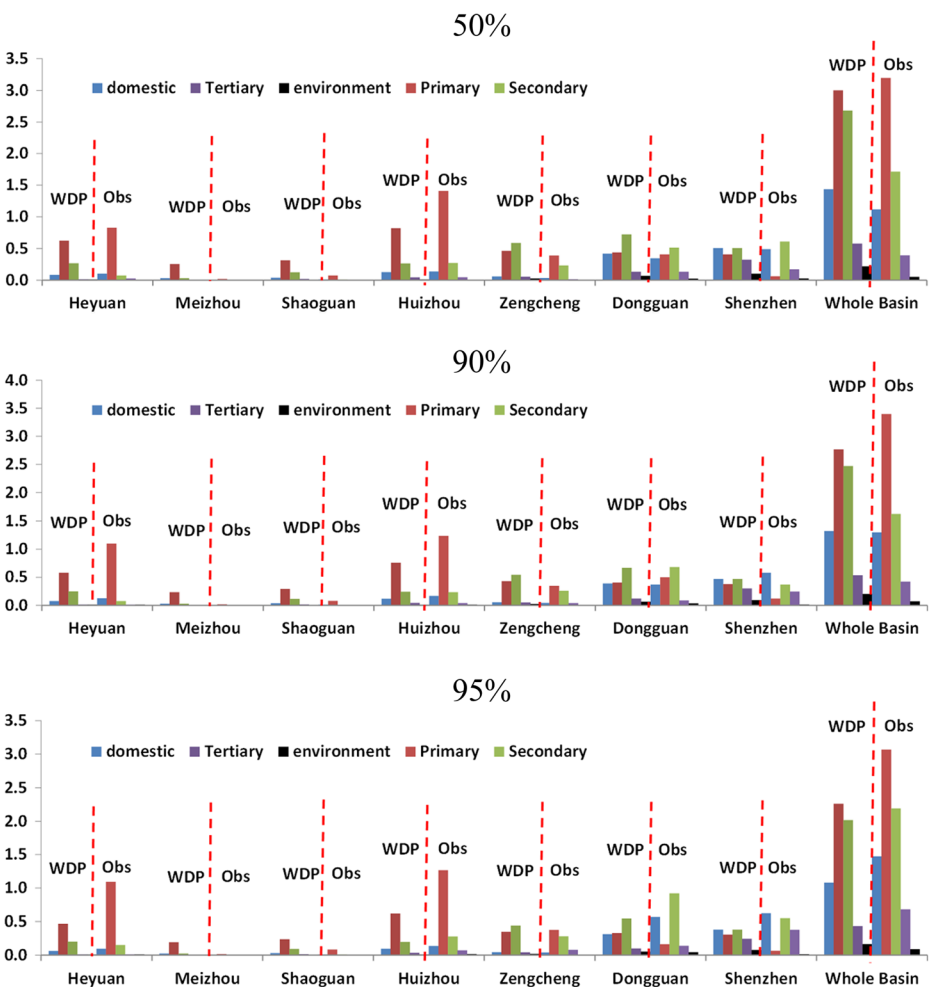


Fig. 6  $T_s$  and industrial WD for each subregion at precipitation frequencies of 50%, 90%, and 95% in the DjR basin in South China

WDP in the current study is conducted by using the two-stage WDP approach under the constraints of available water resources, ecological WD, and constrained total water use quota and so on, according to the game theory. Therefore, the proposed approach is simple and has a greater operability for the WDP of a river basin and its involved subregions, compared with the previous typical statistical models. In addition, the constraints for WD vary according to climate change, land use change, population growth, and government policy and so on. Hence, the proposed method can respond better to the changing environment. For example, in stage 1, the constrained total water use quota released by the government and the variability of water resources due to climate change can be reflected in the determination of  $T_w$  (Eq. (1)), which renders the WDP result close to actual results.

In the current study, only the constrained total water use quota released by the government was considered to reflect the impact of the policy on  $T_w$ ; however, factors affecting the WD of a basin are complex and dynamic (Yang et al. 2016). This finding suggests that more



**Fig. 7** Comparison of the observed water use and the predicted total and industrial WD of the entire DjR basin and its seven subregions at precipitation frequencies of 50%, 90%, and 95%. WDP represents water demand prediction, Obs represents observed water demand

constrained factors, such as stakeholder interests, water environmental capacity, and water quality should be incorporated into stage 1 when determining the constrained total WD of a whole basin under the changing environment. Overall, the proposed approach helps allocate water for subregions along the river under ecological and environmental protection, reduces water use conflicts in the upstream and downstream regions, and suggests adaptive measures for sustainable water resources management under the changing environment.

## 6 Conclusion

This study proposed a two-stage approach to predict the total and industrial WD of a basin and its subregions under variable frequencies. The DjR basin was chosen for a case study. Available water resources, ecological WD, and constrained total water use quota were considered in stage 1 to determine the constrained total WD of the DjR basin. Game theory was applied to allocate  $T_w$  to its seven subregions by calculating the weight of each subregion and to predict industrial WD by using the water use capacity of each industry. Eleven indicators covering historical water use and socioeconomic development were chosen to calculate the weight of each subregion. The observed and predicted  $T_w$  and industrial WD of the whole basin and its seven subregions were compared. The following conclusions were drawn:

- (1) The structure of the total WD predicted by the proposed method in this study is similar to that of the observed water use in the whole basin and its subregions, mainly in the upstream and midstream regions.
- (2) The proportion of  $T_s$  in  $T_w$  is in accordance with the proportion of the total observed water use for each subregion. Meanwhile, the difference between  $T_s$  and total observed water use is larger because of some uncertainties in calculating  $T_w$ .
- (3) The proposed method is simple and performs well in allocating  $T_w$  to the subregions and predicting industrial WD at the basin scale.

Further studies should focus on incorporating additional necessary constraints into stage 1 and reducing the uncertainty in determining  $T_w$  under a changing environment. Adaptive measures should also be taken to cope with the predicted  $T_s$  in the basin.

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