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Water demand predictions for megacities: system dynamics modeling and implications

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Abstract

Sustaining the water supply in megacities is an enormous challenge. To address this challenge, it is especially important to predict water demand changes in megacities. This paper presents a system dynamics model to predict the future water demands of different sectors considering multiple factors, including population, structure of the economy, and water supply and use technologies. Compared with traditional methods such as the time series method and structure analysis method, the proposed model takes into account the interconnections, non-linear relationships and feedbacks between the various factors in a systems context. The model is applied to Beijing, a megacity with a population over 20 million and very limited water availability. It is found that the total water demand is likely to increase by at least 36.1% (up to 62.5%) by 2030 compared with that in 2011, and the water deficits vary from -0.36×10^9 to 1.80×10^9 m^3 in 2030. In addition, scenarios are designed to account for impacts associated with economic development, climate change and inter-basin water transfers. It is shown that climate change may have a large impact on the water supply reliability in Beijing. The water shortage problems can be alleviated via inter-basin water transfers.

Keywords: Beijing; Climate change; Megacities; Scenario analysis; System dynamics; Water demand prediction

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1. Introduction

A megacity is usually defined as a metropolitan area with a total population in excess of 10 million. As of 2016, there are 36 megacities in the world and 8 in the developing world. Megacities are increasingly a phenomenon of the developing world that will affect the future prosperity and stability of the entire world (Bugliarello, 1999); meanwhile, the developed world also needs to pay attention to this phenomenon because of globalization. Characteristics of megacities are their size, their complexity in terms of administration and infrastructure, and their environmental impact. Most megacities around the world are experiencing water shortages driven by population, land use, urbanization and industrial development. Water shortages and their associated impacts will extend well beyond the administrative boundaries of megacities because of cascading effects on regional water supplies and the profound influence that these cities have globally.

To manage the water shortages and ensure water sustainability in megacities, it is important and urgent that we determine the amount of water that a megacity needs over a given period of time in the future, based on which water conservation measures and policies can be developed to deal with the possible water shortages via optimal planning of investment for expanding and/or updating water supply systems and institutional reform for water demand management. Reasonable predictions of future water demands in megacities will play a decisive role in this planning.

Water demand predictions in megacities involve complex economic, social, technological and engineering factors, such as population, structure of the economy, residential water users' behaviors, water conservation technologies, and others. Interaction and feedback relationships generally exist between these factors. An integrated and systemic approach is needed to assess the interactions and feedback among the various factors. Reasonable water demand predictions cannot be obtained based on only one of these factors or a linear superposition of the results from individual analyses. These factors should be systematically considered in an integrated framework.

However, most water demand studies have either been fragmented or have not effectively captured the interactive and synergetic effects of the coupled socioeconomic and physical processes (Yang *et al.*, 2016). The methods commonly used in water demand predictions include statistical methods (e.g. time series methods and structural analysis methods (Zhang *et al.*, 2003; Msiza *et al.*, 2008; Zhai *et al.*, 2012; Tiwari & Adamowski, 2013) and systems simulation methods (He, 2009)). Statistical methods generally rely on historical data to establish relationships between the water demand and relevant factors (Shao *et al.*, 2012). However, statistical methods often neglect the interactions and interconnectedness among various factors, thereby failing to capture the systematic behavior of water demands in megacities.

System simulation methods are supposed to overcome the deficiency of statistical methods. In this study, we develop a simulation model using the system dynamic (SD) approach. This choice is based on several justifications. First, multiple studies have proved that the SD approach can effectively address water shortage problems using both interactive and non-linear relationships in megacities (Winz *et al.*, 2009; Mirchi *et al.*, 2012). The complex factors associated with water demand predictions in megacities can be integrated into a holistic model to conduct water demand analysis of multiple sectors in a region (Sehlke & Jacobson, 2005; Qin *et al.*, 2012). Second, the SD approach allows users to easily understand the relationships and feedback among the various factors associated with water demand predictions in megacities. Finally, the SD approach allows the incorporation of hydrologic, agronomic and behavioral factors and processes into the simulation of water demand predictions.

We develop a SD model in this study for water demand prediction in megacities. The Beijing municipality in China is selected as a case study to illustrate the functionality of the proposed SD model. Beijing is a typical megacity that has faced severe water shortages over the past several decades. The study on water demand in Beijing can provide an example for other megacities in the world to deal with existing or potential water shortage.

2. Methods

2.1. SD methodology

SD was first introduced by Forrester in the 1950s (Forrester, 1961). The method was originally used to analyze complex industrial processes, such as production management and inventory management (Qin *et al*., 2012). However, SD gradually became a modeling framework in systems theory and has been applied to various disciplines to understand the dynamic behaviors of diverse complex systems. SD models are causal mathematical models (Barlas, 1996) based on the fundamental premise that the structure of a system causes observable and predictable behavior. SD modeling starts with determining the structure of the system. This process consists of identifying the interactions and relationships among different components of the system. These relationships are represented in both qualitative (i.e. causal loop diagrams) and quantitative (i.e. stock-and-flow models) forms and are followed by mathematical formulation. Ultimately, scenario analyses are conducted to project the future state of the system. SD models are typically developed as user-friendly softwares with graphical user interfaces, such as PD-plus, VENSIM, STELLA and POWERSIM.

2.2. Water demand calculations

The water demand calculation is the main component of the methods used in this study. Total water demand (*TWD*) is the sum of domestic water demand (*DWD*), industrial water demand (*IWD*), agricultural water demand (*AWD*) and environmental water use (*EWU*). *AWD* can be further divided into irrigation water demand (*IrriWD*), livestock water demand (*LWD*) and forestry and fishery water demand (*FFWD*). *FFWD* and *EWU* are given as inputs while the other terms are intermediate variables that are calculated based on the methods presented in the following sections. The calculation methods involve socioeconomic, hydrologic and agronomic factors that affect the water demands.

2.2.1. Domestic water demand. *DWD* is mainly related to the total population and economic development. Economic development would significantly affect the water use habits among residential water consumers. Furthermore, water scarcity issues can impact the water consumption of domestic water users. The factors used to determine the *DWD* quantity include the total population growth rate (ϕ_{pop}), resident income growth rate (ϕ_{gdpc}), income elasticity of *DWD* (η_{gdpc}), domestic water price (P_{dw}), domestic water price elasticity (η_p) and water deficit index (*WDI*). Therefore, *DWD* at time *t* can be calculated using Equation (1) (Cai & Rosegrant, 2002; Rosegrant & Cai, 2002):

$$DWD(t) = DWD(t - \Delta t) + \{\phi_{dwd}(t) \times [P_{dw}(t)]^{\eta_P} \times f(WDI)\} \times dt \tag{1a}$$

$$\phi_{dwd}(t) = \phi_{pop}(t) + \eta_{gdpc}(t) \times \phi_{gdpc}(t) \tag{1b}$$

$$f(WDI) = \begin{cases} 1 & \text{if } WDI(t) \leq 0; \\ WDI(t)^{\eta_{WDI}} & \text{if } WDI(t) > 0; \end{cases} \tag{1c}$$

$$WDI(t) = \begin{cases} 0 & \text{if } WD(t) < 0 \\ \dfrac{WD(t)}{TWD(t)} = \dfrac{TWD(t) - TWS(t)}{TWD(t)} & \text{else} \end{cases} \tag{1d}$$

where Δt is the time step; $f(WDI)$ is a function of *WDI*; η_{WDI} is the *WDI* elasticity of *DWD*; and $WD(t)$, $TWD(t)$ and $TWS(t)$ are the water deficit, total water demand and supply at time t, respectively.

WDI is a quantitative indicator determined by the total water supply and demand. It considers both the supply and demand aspects of the complex water utilization system. Larger values of *WDI* correspond to more serious water shortage problems in a region.

2.2.2. Industrial water demand. *IWD* is calculated based on several factors, such as the gross domestic product (GDP), income (GDP per capita, *GDPC*), water use technology improvement and industrial water price (P_{IW}). Improvements to water use technologies can promote water conservation in the industrial sector and decrease the water demand. Water price plays a modulatory role in the industrial sector. We estimate an overall *IWD* rather than specific water demands in different industrial sectors.

The intensity of the industrial water demand (*IWDI*) is based on the *IWD* amount. A linear relationship between *IWDI*, GDP per capita (*GDPC*) and a time variable (T) can be estimated using a regression analysis based on historical records, as described by Equation (2b) (Cai & Rosegrant, 2002; Rosegrant & Cai, 2002):

$$IWD(t) = GDP(t) \times IWDI(t) \times [P_{IW}(\mathrm{t})]^{\eta_{\mathrm{IWD}}} \tag{2a}$$

$$IWDI(t) = \alpha + \beta_{IWD}(t) \times GDPC(t) + \gamma(t) \times T(t) \tag{2b}$$

$$T(t) = (t - 2{,}000) + 100 \tag{2c}$$

$$\alpha > 0,\ \frac{\partial IWDI}{\partial GDPC} = \beta_{IWD} < 0,\ \frac{\partial IWDI}{\partial T} = \gamma < 0 \tag{2d}$$

where α is the intercept and is constant during the simulation period; $\beta_{IWD}(t)$ is the income coefficient of *IWD* at time t, reflecting how industrial water use intensity changes with *GDPC*; $\gamma(t)$ is the time coefficient at time t, reflecting the water use technology changes that occur with social technology changes; and η_{IWD} is the industrial water price elasticity. Equation (2c) quantitatively describes the technology change over time, given an initial $T(t)$ value of 100 and a later value larger than 100. The expression in Equation (2d) always holds for Equation (2b) (Cai & Rosegrant, 2002).

2.2.3. Irrigation water demand. *IrriWD* represents the crop water requirements based on hydrologic and agronomic characteristics. This variable is the sum of the water demands of all the crops considered in the model. The water demand of each crop is determined by meteorological, hydrological and agronomic conditions. *IrriWD* can be calculated by Equation (3) (Cai & Rosegrant, 2002; Rosegrant & Cai, 2002):

$$IrriWD = \frac{NIrWD}{BE} \tag{3a}$$

$$NIrWD = \sum_{cp} \{A_{cp} \times \left[\sum_{st} (kc^{cp,st} \times ET_0^{st} - ER^{cp,st}) \right] \} \times (1 + LR) \tag{3b}$$

where *cp* is the crop index based on 12 crop types (wheat, corn, cotton, rice, forage, tubers, vegetables, oil-bearing crops, melons and strawberries, soybean, drugs, and flowers), which encompass all types of crop in the study site; *ct* is the index that represents the crop growth stage (four growth stages are considered for all the crops); *A* is the crop planting area; *kc* is the crop coefficient, which is used to predict evapotranspiration (*ET*; appendix Table A1, available with the online version of this paper); ET_0 is the reference *ET*; *LR* is the salt leaching factor, which is characterized by the soil salinity and irrigation water salinity and is always 10–15% of the total *IrriWD*; *BE* is the basin efficiency; *ER* is the effective rainfall; and *NIrWD* is the net irrigation water demand.

Effective rainfall (*ER*) is the rainfall that infiltrates into the root zone and becomes available for crop use. *ER* depends on total rainfall (*TR*), soil moisture content (*Z*), ET_0, and soil characteristics (hydraulic conductivity *K*, moisture content at field capacity *Zs*, etc.). *ER* can be calculated using Equation (4):

$$\begin{cases} ER^* = \max\,[0, (1.253 \times TR^{0.824} - 2.935) \times 10^{0.001 \times ET_c}](\text{mm}) \\ ER = \min\,(ER^*, TR, ET_c) \\ If\ TR = 12\ mm/month,\ ER \sim TR \end{cases} \tag{4}$$

2.2.4. Livestock water demand. *LWD* is estimated based on the amount of livestock and the associated water use quota. We assume that the water use quota is constant during the simulation period. We consider four types of livestock: large animals (including cows, horses and other animals with large somatotypes), pigs, sheep, and poultry. Other animals in the study site are not considered because they have negligible water demands or lack corresponding data. *LWD* can be calculated using Equation (5) (Qin *et al.*, 2012):

$$LWD(t) = \sum_{i=1}^{4} Quota_i \times N_i(t) \tag{5}$$

where $Quota_i$ refers to the water use quota of livestock *i*; $N_i(t)$ is the amount of livestock *i* at time *t*; and $i = 1$, 2, 3 or 4 refers to large animals, pigs, sheep or poultry, respectively.

3. Case study: Beijing, the capital of China

3.1. Study site

The city of Beijing is located on the northernmost portion of the North China Plain (NCP) (Figure 1). Specifically, the city is situated in the transition zone between the Mongolian Plateau and the NCP. The city is located within Hebei Province and neighbored by the city of Tianjin. Beijing is the center of China's political, economic and cultural development. The total population of the city in 2014 was approximately 21.5 million (population density was 1,311 persons/km^2 and urbanization rate was 86.3%). The transient population became an important driving factor in the increase in urbanization rate in Beijing. Agricultural land use accounted for about 67.5% of the total land area in 2014. In the past 30 years, the land use and land cover of Beijing have undergone huge change. A large area of agricultural land, such as cultivated land, forest land, grassland, wetland and other land cover types, has gradually become urban land, forming an obvious transition structure from the urban core zone, rural–urban fringe zone to suburb area zone. Since the 11th five-year plan, the energy development situation in Beijing has been good. In 2009, the energy consumption per 10^4 RMB GDP fell by 3.8% on a year-on-year basis; the ratio of energy growth and economic growth is 1:2.65, supporting rapid economic development with a relatively low energy growth rate (Guo, 2011). However, there are four challenges in the energy development of Beijing. First, the general situation of clean energy supply remains constrained by the prominent supply–demand contradiction in natural gas and high-quality coal. Second, heating is facing restrictions from available resources, the environment and economy. Third, the difficulty of energy conservation and emissions' reduction increases with time. Fourth, regulating energy supply and utilization is harder than before because of the complex operating environment.

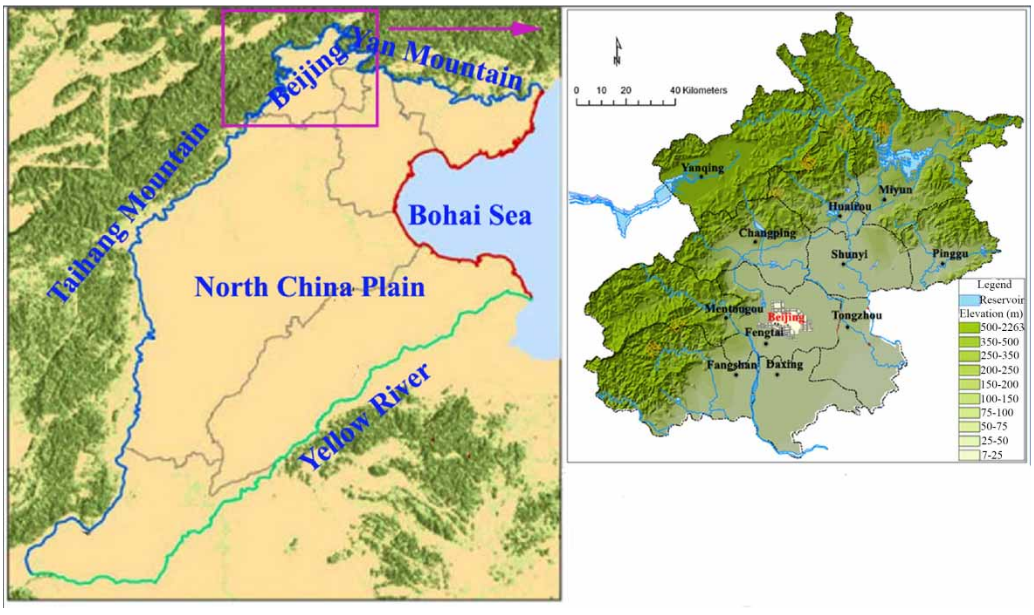

Fig. 1. The terrain elevation graph of Beijing Municipality and its location in the North China Plain (NCP).

Beijing belongs to the warm, temperate and semi-humid continental monsoon climate zone. The long-term annual average rainfall is 603 mm (1956–2003); however, rainfall often exhibits significant inter-annual variations. Recently, Beijing experienced a severe drought event that lasted five years (1999–2003). Furthermore, the seasonal rainfall distribution is uneven, with approximately 60–80% of the rainfall occurring throughout the summer flood season (i.e. from June to September) (Sun *et al.*, 2007). The surface water evaporation is 1,500–2,200 mm and has increased over time. As part of the NCP, Beijing relies heavily on groundwater, especially within the agricultural water consumption sector. The water deficit problem in Beijing is closely related to the dependence upon groundwater supply and the large *AWD* (Yang *et al.*, 2016). Given a limited total water supply, an increasing water demand may worsen the water shortage problem.

Beijing has required additional water to support the expanding economic development, thereby worsening the water resources situation in the city. The ever-growing demand for water poses a major challenge to sustainable development in megacities such as Beijing. The annual average *TWD* in Beijing reached 3.91×10^9 m^3 during the period 1988–2012 (Figure 2), with large inter-annual variations during these years. However, the multi-year (1956–2000) average water availability (i.e. maximum water supply) of Beijing is 3.73×10^9 m^3 (Zhang *et al.*, 2012). In individual years, the total water availability fluctuates and is often significantly less than the *TWD*. This situation results in groundwater overexploitation and the depletion of rivers and reservoir storage. Beijing currently faces a severe water shortage problem. The water resource availability per capita in Beijing is approximately 300 m^3 per year, which is significantly less than national and world averages and is far below the internationally recognized water shortage standard (i.e. 1,000 m^3 per capita) (Zhang, 2002). Agricultural and domestic demands accounted for 45% and 31% of water consumption in 2001 and 26% and 44% of consumption in 2012, respectively.

Since 1980, the water price has been used as an economic tool to adjust the balance between water supply and demand in Beijing. The water price in Beijing includes water resource fees, water engineering fees and sewage disposal fees. Beijing has implemented nine water price adjustments since 1992.

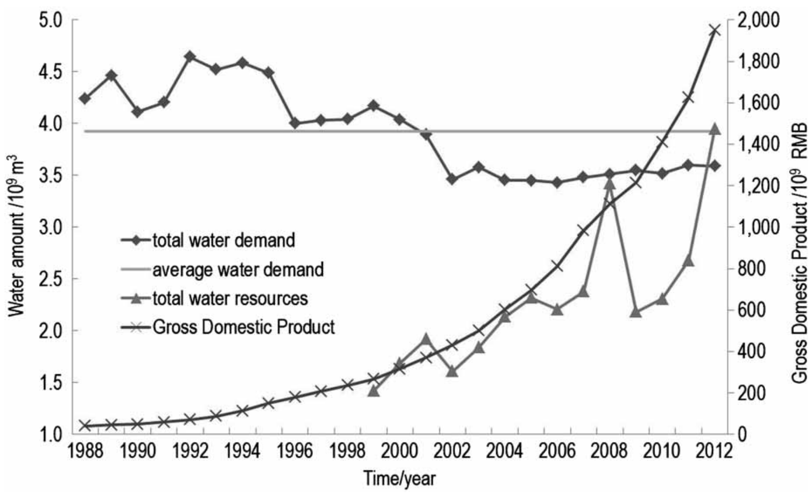

Fig. 2. The annual and average TWD, total water resources, and GDP of Beijing. *Data sources*: Beijing Water Resources Bulletin (BWA, 2001–2012), Haihe River Basin Water Resources Bulletin (WRPBHRB, 1998–2005), Beijing Statistical Yearbook (BMBS, 1989–2013) and Song *et al*. (2010).

Subsequently, the water prices for different industries have increased between threefold and eightfold (Shen *et al.*, 2009). The domestic water price is 4 RMB/m^3, while the non-domestic water price ranges from 5.8 RMB/m^3 for administrative purposes to 81.68 RMB/m^3 in the leisure spa industry. The Beijing Government has announced that it will gradually increase the domestic water price and reasonably adjust the urban domestic water price. In addition, the government will enforce over-utilization surcharges associated with water use in the industry and service sectors and will continue to strictly implement different water price policies in high water-consumption industries to promote adjustments within the industrial and water use structures.

3.2. Model construction

3.2.1. Model structure. Figure 3 illustrates the causal loop diagram (CLD) (i.e. conceptual model) of the water demand simulation model in Beijing. This diagram provides valuable system information, including feedback loops, loop dominance and time delays (Mirchi *et al.*, 2012). CLD development is the first step in developing the SD model. This step identifies the elements of the model and the causal relationships among them. The water demand component includes *DWD*, *IWD*, *AWD* (*IrriWD*, *LWD* and *FFWD*) and *EWU*. Furthermore, the water supply component accounts for groundwater, surface water, water from the South-to-North Water Diversion Project (SNWDP) (a multi-decade infrastructure mega-project in China, which ultimately seeks to channel 4.48×10^{10} m^3 of fresh

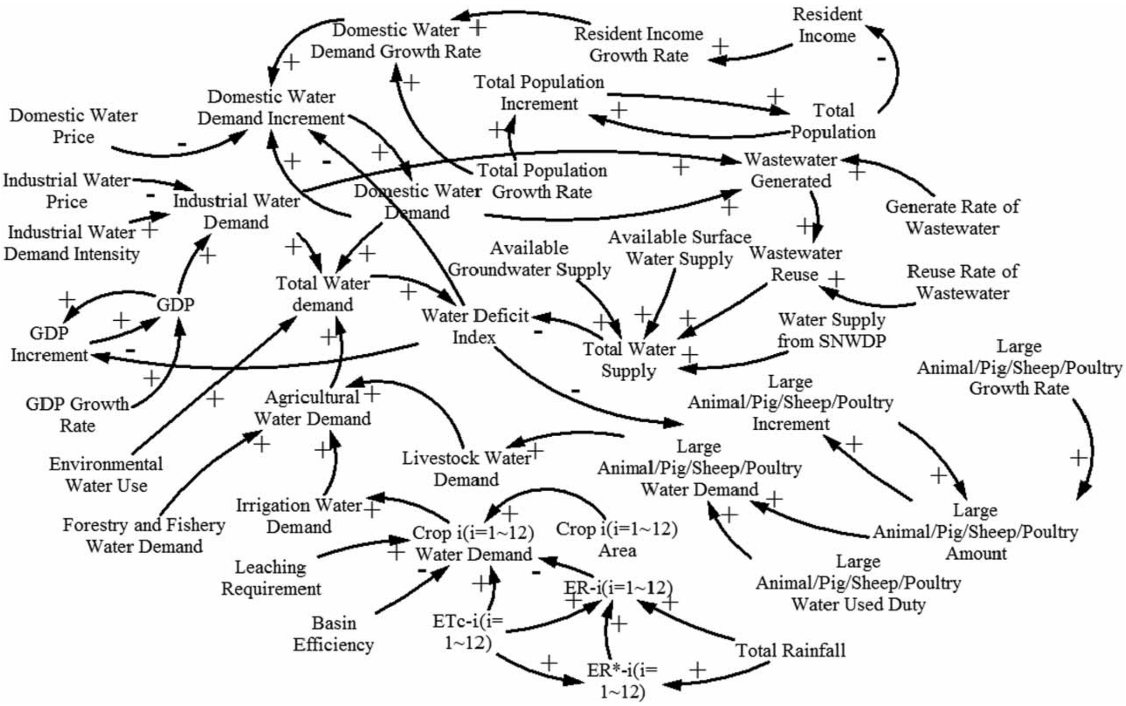

Fig. 3. The CLD of the water demand simulation model in Beijing, where each arrow is a cause and effect relationship and the polarity on the link (+ / −) represents the change direction produced by a cause. ‘ + ’ means the same direction while ‘ − ’ means the reverse direction.

water annually from the Yangtze River in southern China to the more arid and industrialized north using three canal systems: the eastern route, central route, and western route; Feng *et al.*, 2007) and reused water. According to different water consumption sectors and environmental and supply principles, the SD model is divided into five sub-systems: socioeconomic (population growth), agricultural, industrial, water reuse, and water resources. The name of each sub-system describes the main component of that sub-system. The main socioeconomic, technological, hydrological and agronomic factors that influence each sub-system are considered and presented in the CLD. Each sub-system is also interrelated and mutually influenced by other sub- systems (Qin *et al.*, 2012). The *WDI* plays an important role in the connections between sub-systems by reinforcing (positive) effects or balancing (negative) effects associated with stable sub-system variables. The CLD demonstrates the qualitative relationships among various factors and serves as the framework for the quantitative construction of the model.

The second step in SD model construction develops a stock-flow diagram (SFD) based on the CLD. The SFD describes the quantitative relationships among variables using equations and input data (Figure 4) and represents the system in terms of stocks and flows. Stocks (levels) are calculated at one specific time and represent any variable that accumulates or depletes over time. Flows (rates) are calculated over an interval of time and indicate activities or variables that cause the stock to change (Mirchi *et al.*, 2012). The SFD can characterize the system processes graphically using a series of quantitative relationships and the associated equations, providing the foundation for model calibration, validation and prediction under different scenarios.

Socioeconomic (population growth) sub-system. The state variables in this sub-system include the total population and the *DWD*. The natural population growth rate has an impact on the total population (Figure 4(a)), while the *DWD* is calculated using Equation (1), which considers various socioeconomic factors that affect the *DWD*. The population serves as a driver of the *DWD*. The more rapid the population growth is, the higher the *DWD* is.

Industrial sub-system. The state variable in this sub-system is GDP, which is determined by the GDP growth rate and the *WDI* (Figure 4(b)). The *IWD* intensity is calculated using Equation (2), which considers the economic and technological factors that affect the *IWD*. GDP is the main driver exerting a positive effect on the *IWD*.

Agricultural sub-system. Four *LWDs* and the *IrriWDs* of 12 crops are the main components of this sub-system (Figures 4(c) and 4(d)). The *FFWD* is treated as an input variable in this model. The *IrriWD* is calculated using Equation (3), which considers the hydrological and agronomic factors affecting the *IrriWD*. The *LWDs* are calculated using the water quota method in Equation (4). The drivers of *IrriWD* include the crop characteristics, irrigation areas and meteorological conditions, while the drivers of *LWDs* include the livestock quantities and associated quotas.

Water reuse sub-system. This sub-system considers wastewater reuse (Figure 4(e)). Wastewater is generated by domestic and industrial activities. However, these wastewaters have been increasingly reused as a result of technological improvements, including water treatment and reuse technologies. The reused wastewaters are added to the water supply sector and help to reduce the water shortages in megacities.

Water resources sub-system. The water supply sector in this sub-system includes the groundwater supply, surface water supply and water supply from SNWDP. The water demand sector includes the aforementioned water demands as well as *EWU*, which is treated as an input variable in this SD model (Figure 4(f)). The balance of the water supply and demand determines the sustainability of water resources in megacities. In return, the *WDI* affects the water demands. This impact is generally negative.

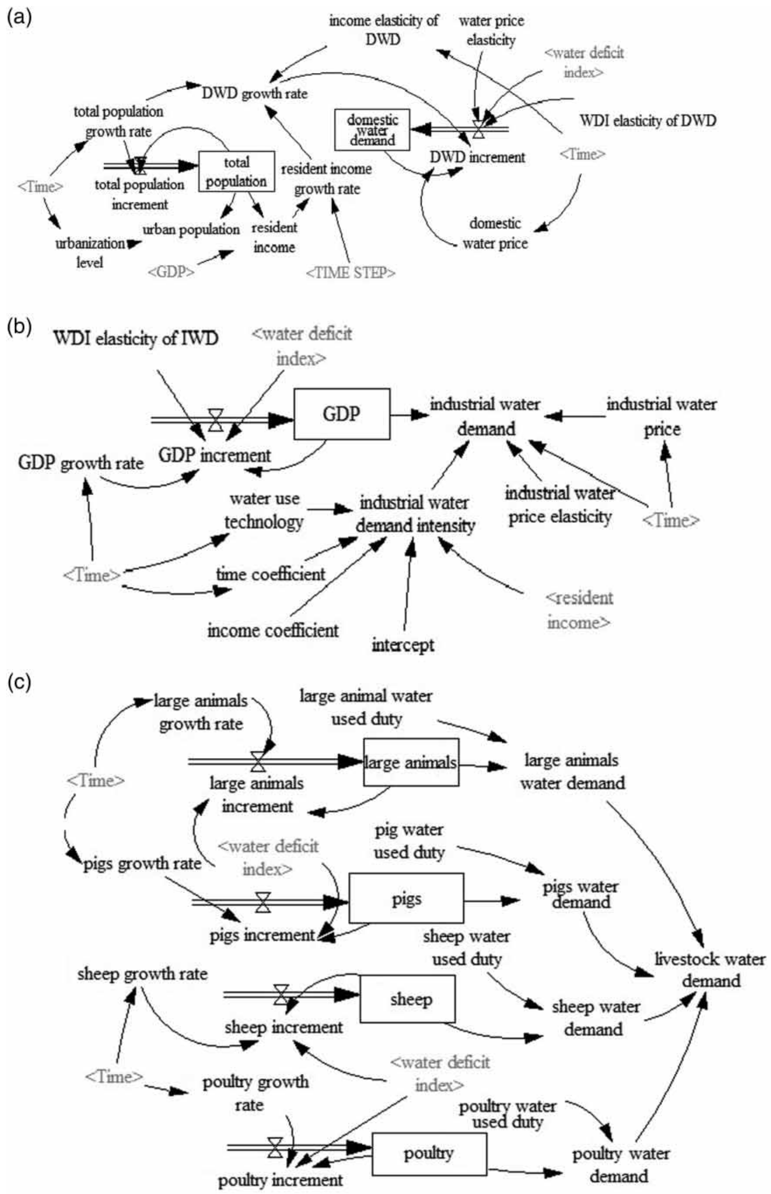

Fig. 4. Stock-flow diagram describing the detailed quantitative relationships among the variables of Beijing's SD model: (a) domestic water demand; (b) industrial water demand; (c) livestock water demand; (d) irrigation water demand; (e) water reuse; (f) total water supply and WDI. (*Continued*.)

3.2.2. Input data and simulation period. Three types of input data are used in the simulation model: table functions, constant values, and initial values. A table function is a time series variable used to express the non-linear relationship between variables in a model, which cannot be expressed in the form of an equation. A constant value does not change over time or within a time interval. An initial value refers to the initial value of a level variable, which reflects the cumulative effects of that variable. The input

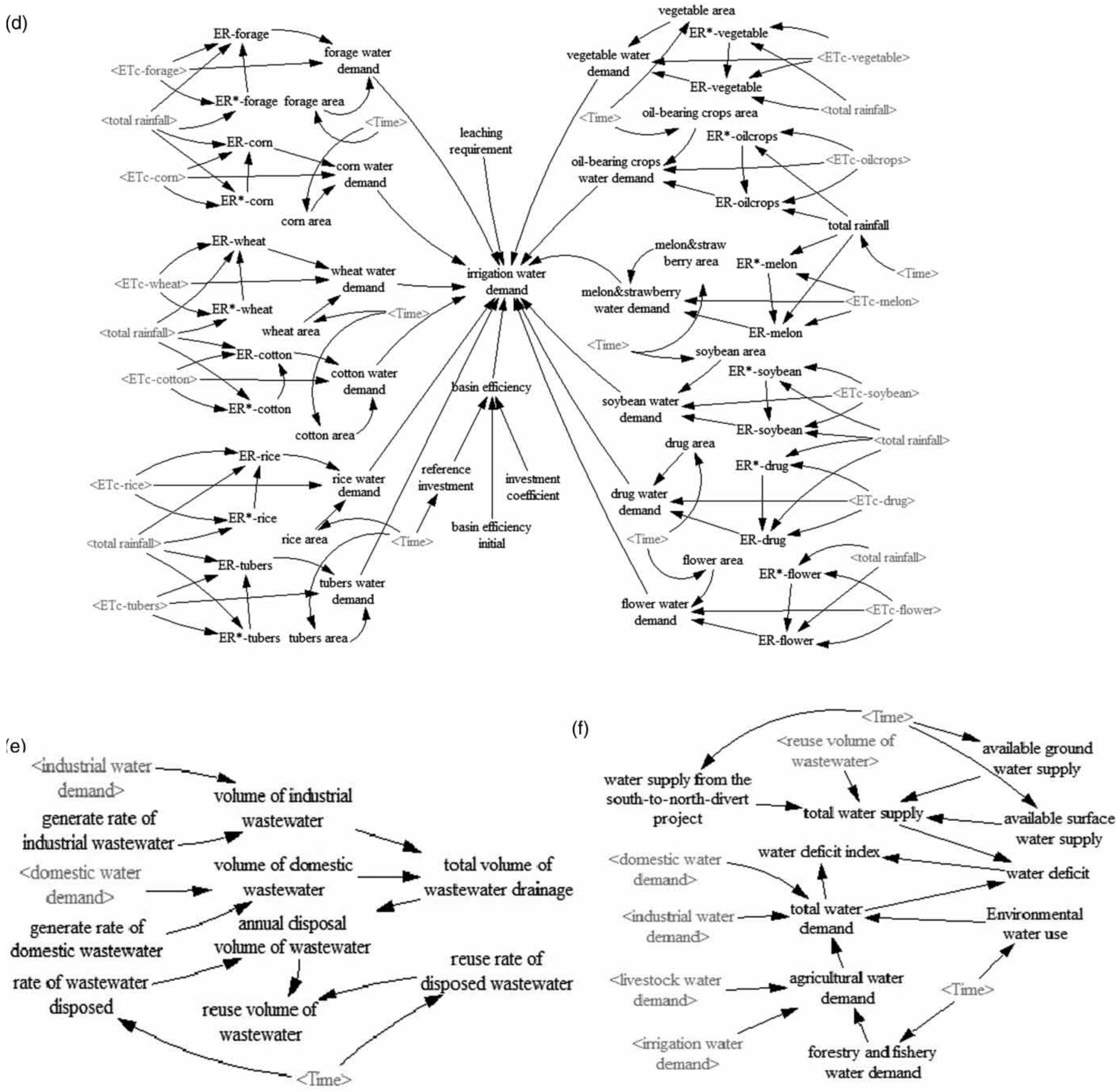

Fig. 4. Continued.

data used in the model are listed in Table 1, while the constant values used in the model are listed in Table 2, excluding the crop coefficients (kc; listed in appendix Table A1, available with the online version of this paper). These constant values were obtained using calibration processes. They fall within a reasonable range based on literature values.

Future water demand predictions were conducted for the period spanning 2012 to 2030 at a one-year time step. Data from the period 2000–2011 are used to calibrate the model. The goal of the calibration process is to provide a satisfactory match between simulation results and historical observations. Four

Table 1. Input data of the SD model of Beijing Municipality.

Table function	Abbr.	Constant	Abbr.
Total population growth rate	TPGR	Water price elasticity	WPE
Income elasticity of DWD	IEDWD	WDI elasticity of DWD	WDIEDWD
Domestic water price	DWP	Intercept	I
GDP growth rate	GDPGR	Time coefficient	TC
Industrial water price	IWP	Income coefficient	IncC
Large animals growth rate	LAGR	WDI elasticity of IWD	WDIEIWD
Pigs growth rate	PGR	Basin efficiency initial	BEI
Sheep growth rate	SGR	Investment coefficient	InvC
Poultry growth rate	PouGR	Leaching requirement	LR
Crop(i) area (i = 1–12)	CA-i	kc of crop (k) (k = 1–12)	kc-C-k
Total rainfall	TR	Pigs water used duty	PWUD
ET0-j (j = 1–12)	ET0-j	Sheep water used duty	SWUD
Rate of wastewater disposed	RWD	Poultry water used duty	PouWUD
Environmental water use	EWU	Industry wastewater fraction	IWF
Reuse rate of disposed wastewater	RRDW	Domestic wastewater fraction	DWF
Forestry and fishery water demand	FFWD	Industrial water price elasticity	IWPE
Water supply from the SNWDP	WSSNWDP	Large animals water used duty	LAWUD
Available surface water supply	ASWS	Available groundwater supply	AGWS
Initial value	**Abbr.**	**Initial value**	**Abbr.**
Total population	TP	Pigs	Ps
Domestic water demand	DWD	Sheep	Ss
GDP	GDP	Poultry	Pous
Large animals	LA		

Full names of all variables are presented in appendix Table A2 (available with the online version of this paper).

Table 2. Constant parameters obtained from the calibration processes in the SD model.

Parameter	Abbr.	Unit	Calibrated value
Domestic water price elasticity	DWPE	–	−0.6497
WDI elasticity of DWD	WDIEDWD	–	−0.0060
Income elasticity of DWD	IEDWD	–	0.3033
Time coefficient	TC	–	−0.19
Income coefficient	IncC	–	−0.05125
Intercept	I	$m^3/(10^4$ RMB)	30.1359
Industrial water price elasticity	IWPE	–	−0.3679
WDI elasticity of IWD	WDIEIWD	–	−0.0762
Basin efficiency initial	BEI	–	0.6106
Investment coefficient	InvC	–	0.0235
Leaching requirement	LR	–	0.15
Large animal water used duty	LAWUD	m^3/head/year	14.6
Pigs water used duty	PWUD	m^3/head/year	14.6
Sheep water used duty	SWUD	m^3/head/year	2.92
Poultry water used duty	PouWUD	m^3/head/year	1.46

different water demand variables in the model are used in the verification process. Historical annual water demands data were collected from the Beijing Water Resources Bulletin, which is released yearly by the Beijing Water Authority (BWA, 2001–2012).

3.3. Scenario design

Scenarios can be used to assess the rationalities and uncertainties associated with potential events during a given time period, which is often a future period. A scenario analysis provides an interesting and practical method for comparing the future states of a system based on different projections. A scenario analysis method is used in this study to select a set of scenarios that can help to solve or diminish the water scarcity problems in Beijing. Such an analysis can potentially be used by policy makers to design sustainable policies for the future.

Ten scenarios are designed to predict the future water demand of Beijing under different climatic and socio-economic conditions (Table 3). These scenarios include business-as-usual (BAU) scenario, climate change (CC) scenario, high economic development (HED) scenario, SNWDP scenario, livestock water conservation (LWC) scenario and combined scenario. The climate change scenario includes three scenarios that represent wet climate (CC_wet), normal climate (CC_normal) and dry climate (CC_dry). Additionally, the combined scenario includes three scenarios. The HED_SNWDP scenario considers both economic development and SNWDP. Additionally, the HED_LWC scenario considers both economic development and LWC. Finally, the HED_SNWDP_LWC scenario considers economic development, SNWDP and LWC simultaneously.

3.3.1. BAU scenario. The BAU scenario, which serves as our baseline, assumes that the system structure and development policies do not markedly vary during the prediction period, maintaining the present development trends into the future. Historical climate data from 2001 to 2011 are used to generate a 22-year time series and to represent climate conditions from 2012 to 2030 (a total of 19 years). Therefore, we obtain the climate data required for this scenario and other non-climate-change scenarios. According to the real-world scenario and the authors' knowledge, the economic development rate will be 8% in 2020 and 10% in 2030. Table 4 provides a summary of the table function parameters used in the BAU scenario.

Table 3. Summary of scenarios designed to simulate future water demand of Beijing.

Scenario name	Abbreviation	Scenario description
Business as usual	BAU	Status quo of Beijing
Climate change	CC_wet	GCM UKMO_HADCM3 (wet climate)
	CC_normal	GCM CSIRO_MK3 (normal climate)
	CC_dry	GCM CNRM_CM3 (dry climate)
High economic development	HED	BAU + emphasize economic development
South-to-North Water Diversion Project	SNWDP	BAU + consider the SNWDP as water supply
Livestock water conservation	LWC	BAU + consider LWC
Combined	HED_SNWDP	HED_SNWDP = HED + SNWDP
	HED_LWC	HED_LWC = HED + LWC
	HED_SNWDP_LWC	HED_SNWDP_LWC = HED + SNWDP + LWC

Note: climate change data from IPCC AR4, all climate scenarios are under A1B emission scenarios.

Table 4. Table function parameters used in the SD model under the BAU scenario.

Parameter	Abbr.	Unit	Parameter value		
			2012	2020	2030
Total population growth rate	TPGR	%	2.0	2.5	3.0
Domestic water price	DWP	RMB/m^3	4	6	8
GDP growth rate	GDPGR	%	6	8	10
Industrial water price	IWP	RMB/m^3	6.21	8	10
Large animals growth rate	LAWP	%	0.8	1.0	1.5
Pigs growth rate	PGR	%	−1	0	5
Sheep growth rate	SGR	%	−5	0	5
Poultry growth rate	PouGR	%	−1	0	3
Rate of wastewater disposed	RWD	%	82	85	90
Reuse rate of disposed wastewater	RRDW	%	60	65	70
Forestry and fishery water demand	FFWD	10^8 m^3	2.3	5.0	6.5
Environmental water use	EWU	10^8 m^3	4.5	7.5	9.5
Available surface water supply	ASWS	10^8 m^3	6.03	6.15	6.27
Available groundwater supply	AGWS	10^8 m^3	16.5	17.1	17.9

3.3.2. Climate change scenario. The rainfall data used in the climate change scenarios (i.e. CC_wet, CC_normal and CC_dry) are based on three general circulation model (GCM) projections for the A1B CO_2 emissions scenario. The data were downscaled and bias corrected for the NCP using the delta change method proposed by Qin *et al.* (in preparation). Because the study site is a typical region in the NCP, the method described by Equation (6) is used to calculate the average total rainfall in Beijing. This method is a simple but reasonable approach for generating total rainfall data in Beijing using both historical data and GCM projection data.

$$TR_{BJ} = TR_{NCP} \times \frac{TR_{BJ-base}}{TR_{NCP-base}} \tag{6}$$

where TR_{BJ} and TR_{NCP} are the average total rainfall values in Beijing and the NCP in the future, respectively. $TR_{BJ\text{-}base}$ and $TR_{NCP\text{-}base}$ are the average total rainfall values in Beijing and the NCP currently, respectively. The three GCMs considered in this study represent wet (UKMO_HADCM3), normal (CSIRO_MK3) and dry (CNRM_CM3) climate conditions. The monthly reference ET data for the prediction period (2012–2030) are adopted from the Beijing meteorological station.

Appendix Table A3 (available with the online version of this paper) shows the annual rainfall and reference ET values for the prediction period under three different climate change scenarios.

3.3.3. High economic development scenario. The HED scenario is designed based on the BAU scenario (Table 3). However, it differs in assuming higher economic development based on development rates (GDP growth rate) of 15% and 20% in 2020 and 2030, respectively. The other parameters are similar to those of the BAU scenario.

3.3.4. SNWDP scenario. The SNWDP scenario considers the impact of the SNWDP on the water resources balance and the water demand projection of Beijing. The water from the SNWDP is considered a surface water supply in the SD model. This supply will increase the total water supply to Beijing and potentially alleviate or solve water shortage problems in the future. According to the SNWDP plan, water was first supplied to Beijing from 27 December 2014 at a diversion rate of 12×10^8 m^3 per year. This diversion process is implemented in the model using 'IF THEN ELSE' statement. The model structure and the other parameters are similar to those of the BAU scenario.

3.3.5. LWC scenario. The LWC scenario attempts to save water associated with the livestock sector during the prediction period. Because the *LWD* is calculated using the water use quota method, reducing the water use quota directly would likely provide a practical water conservation strategy. Specifically, this scenario reduces the water use quota of all four livestock groups by 30%. The other parameters are similar to those of the BAU scenario.

3.3.6. Combined scenario. Three scenarios (HED_SNWDP, HED_LWC and HED_SNWDP_LWC) are included in this scenario, which considers both economic development and the water diversion project (Table 3). Each combined scenario is the combination of two or three scenarios; thus, the parameters of these scenarios are used in this combined scenario.

3.4. Results

This section provides the results of the water demand simulations for the period of 2012–2030 under different climatic, socioeconomic and development scenarios. Comparing the results under different scenarios can provide useful insights regarding Beijing's social and water resources development in the future. This comparison can benefit local governments and policy makers.

Figure 5 compares the simulation model results and historical data. Overall, the *DWD*, *IWD*, *AWD* and *TWD* simulations all adequately reflect historical trends. The domestic and industrial water demands generally agree with the historical data, while discrepancies exist between the agricultural and total water demands and the associated historical data. These discrepancies are mainly due to the *IrriWD* simulation. In reality, farmers may use substantially more water for irrigation than what is simulated in this model. Overwatering is a common practice of many farmers, as they believe that increasing irrigation will increase crop yields. This relationship is difficult to simulate because the model cannot accurately reflect or simulate the irrigation behaviors of all the farmers in a megacity such as Beijing.

Table 5 shows the total water demand, total water supply and water deficit values in 2012, 2020 and 2030, respectively, under different scenarios. Due to the increased reuse of wastewater, the total water supply continually increases in all scenarios, including those without SNWDP and those with dry climates. By 2030, the *TWD* is likely to increase by at least 36.1% (up to 62.5%) compared with the historical *TWD* in 2011. However, different prediction scenarios suggest different reasons for these increases. The *TWDs* increase dramatically under climate change scenarios due to vastly increased *IrriWDs*. Population growth and industrial development also contribute to demand increases in scenarios related to high economic development, water conservation and the water diversion project. Scenarios that consider economic development require more water than the BAU scenario. CC_dry and LWC exhibit the largest and smallest *TWDs*, respectively, in 2030. The results imply that further economic development and climate change would increase the water demand and water deficit. If economic development continues to be the top priority in Beijing (scenario HED), water users will require 5.18×10^9 m^3 of water in 2030;

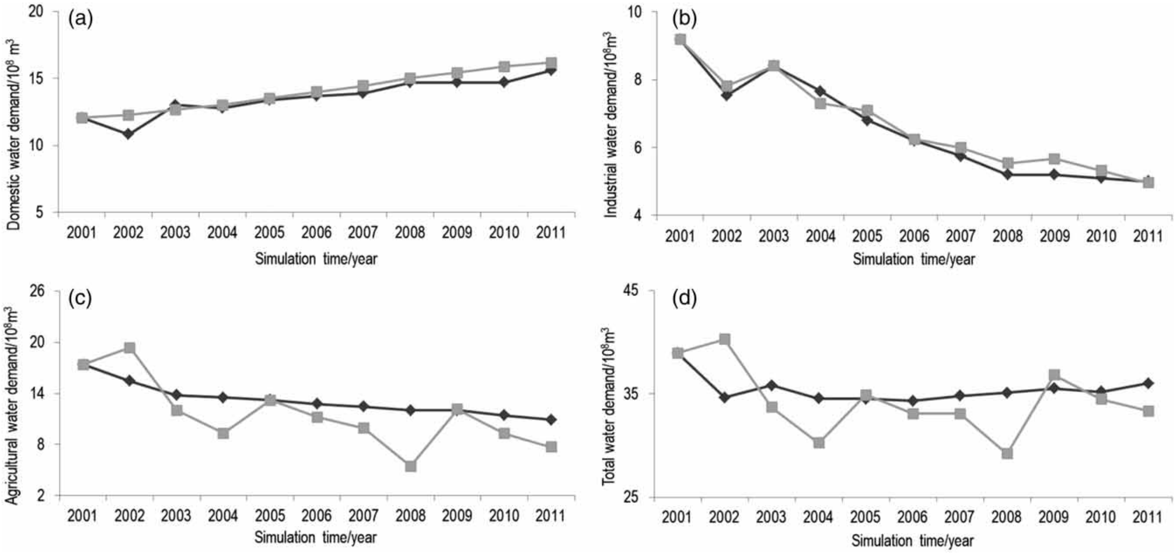

Fig. 5. Comparison plot between simulation results and historical data for the calibration period (2001 to 2011) for: (a) domestic water demand; (b) industrial water demand; (c) agricultural water demand; and (d) total water demand.

Table 5. Total water demand, total water supply and water deficit in 2012, 2020 and 2030 under different scenarios.

	Total water demand (10^8 m^3)			Total water supply (10^8 m^3)			Water deficit (10^8 m^3)		
Scenario	2012	2020	2030	2012	2020	2030	2012	2020	2030
BAU	37.3	45.9	49.1	31.5	34.9	40.7	5.8	11.0	8.4
CC_wet	29.7	45.9	52.9	31.5	35.0	40.7	−1.8	11.0	12.1
CC_normal	31.0	46.3	54.2	31.5	34.9	40.6	−0.4	11.4	13.6
CC_dry	35.3	50.9	58.5	31.5	34.9	40.5	3.8	16.0	18.0
HED	37.3	48.0	51.8	31.5	36.0	42.1	5.8	12.0	9.7
SNWDP	37.3	45.5	49.0	31.5	46.8	52.6	5.8	−1.3	−3.6
LWC	36.9	45.6	48.7	31.5	35.0	40.7	5.5	10.6	8.0
HED_SNWDP	37.3	47.3	51.2	31.5	47.6	53.8	5.8	−0.3	−2.6
HED_LWC	36.9	47.7	51.3	31.5	36.0	42.1	5.5	11.7	9.2
HED_SNWDP_LWC	36.9	47.0	50.4	31.5	47.6	53.6	5.5	−0.7	−3.2

however, the water demand will be approximately 5×10^9 m^3 of water in 2030 if economic development, water conservation and water diversion are all considered in the future (scenario HED_SNWDP_LWC). Therefore, water deficit problems will continue to exist for all scenarios except SNWDP, HED_SNWDP and HED_SNWDP_LWC (Table 5).

Figure 6 shows the maximum, minimum and mean values of *TWD* under all scenarios. The maximum value is approximately 6×10^9 m^3, while the minimum value is approximately 3.7×10^9 m^3. The values vary widely based on the scenario. The scenarios that consider economic development exhibit the largest maximum *TWDs*, while the scenarios that include water diversion or water conservation exhibit the smallest maximum *TWDs*.

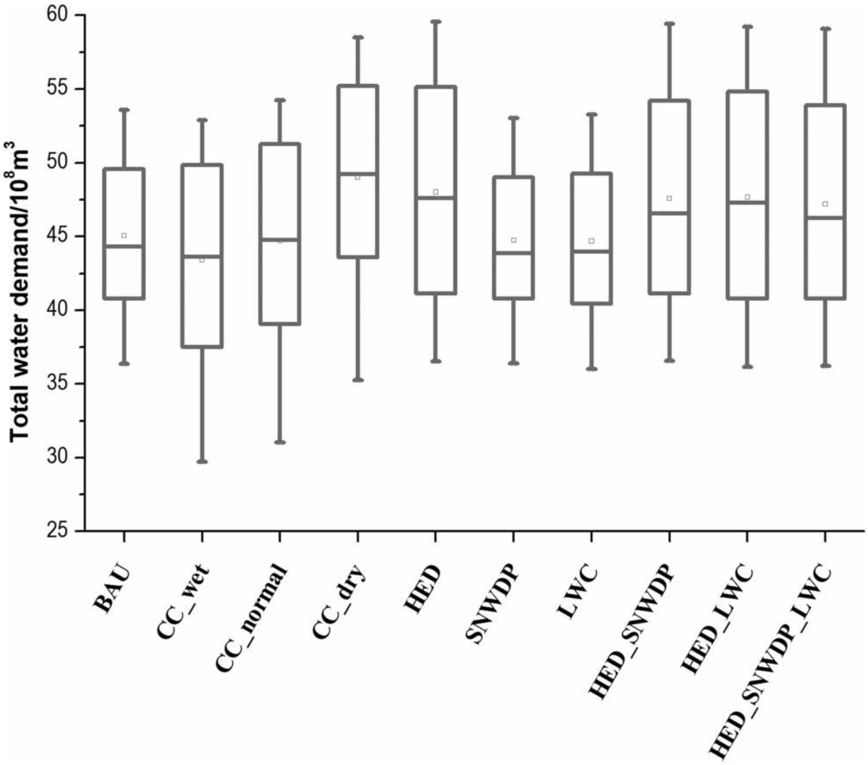

Fig. 6. Box chart of TWD under different scenarios, where the center horizontal line marks the median of the sample; the upper and lower edges of the box (the hinges) mark the 25th and 75th percentiles (i.e. the central 50% of the values fall within the box); the upper and lower vertical lines represent the maximum and minimum of the sample; and the square in the box marks the mean value of the sample.

The water demands predicted by our model are comparable to predictions in the literature (Table 6). Most of these studies conducted water demand predictions under different scenarios, which allow them to be compared with our study. Although these models adopted different methods and prediction periods, they obtained similar prediction results given these inherent differences. For the year 2020, the *TWD* predicted by Zhai *et al*. (2012) and Huang *et al*. (2009) are 34.24–46.53 × 10^8 m³ and 28.38–52.83 × 10^8 m³, respectively, which are similar to the prediction results of this study (45.89–50.89 × 10^8 m³), while the result of Cheng *et al*. (2013) (36.32 × 10^8 m³) is smaller and Fan *et al*. (2006) (48.72–56.41 × 10^8 m³) is larger than those of this study. As the method, model structure, assumptions and designed scenarios are very different among these studies, the prediction results cannot be exactly the same. This comparison demonstrates that the SD methodology and model developed in this study can be used to predict water demands in Beijing. Note that not only macroeconomic factors but also hydrological and agronomic factors are included in water demand simulations in our model, while other studies mainly considered macroeconomic factors alone. This is the biggest difference between our study and other studies. This is also the reason why there are studies that have predicted larger or smaller water demands than ours. However, the addition of non-economic factors likely reduces the uncertainty of the model and provides more realistic water demand predictions, as more realistic factors that affect the water demands are considered and modeled in this study.

Table 6. Comparison of future water demand predictions in Beijing under different study cases.

Case	Prediction method	Prediction period	Prediction target	Result at end of prediction period (10^8 m^3)
Zhai *et al*. (2012)	Time series forecasting method	2010–2020	TWD	34.24–46.53
Cheng *et al*. (2013)	Gray system model	2012–2020	TWD	36.32
Zhang *et al*. (2003)	Multivariate linear regression analysis	2001–2010	DWD	8.08
Shao *et al*. (2012)	Methods based on statistical law	2007–2014	IWD DWD	IWD: 4.37–5.09 DWD: 15.48–20.60
Fan *et al*. (2006)	System dynamics	2005–2010	TWD	48.72–56.41
Huang *et al*. (2009)	System dynamics	2005–2020	TWD	28.38–52.83
This study	System dynamics	2012–2030	TWD	45.89–50.89 at 2020 48.73–58.50 at 2030

The range of prediction results represents water demands under different scenarios in each study case.

WDI is an indicator of the degree of water shortage in a system. A positive *WDI* value indicates that a water shortage problem exists in that system. Figure 7 illustrates the *WDI* of Beijing during the prediction period. For scenarios BAU, CC_wet, CC_normal, CC_dry, HED, LWC and HED_LWC, the *WDI* values are always positive, suggesting that water shortage problems exist throughout the entire prediction period. The other three scenarios (i.e. scenarios including SNWDP) include *WDI* values of zero in many years, implying that no water shortage problems exist in those years. Although the water demand will increase due to societal development, the water diversion project can potentially solve water shortage problems by increasing the water supply in Beijing. However, water shortages appear towards the end of the prediction period under these scenarios due to societal development and crop irrigation. Figure 7 shows that water conservation in the livestock sector can partially help to solve water shortage problems in Beijing. Conversely, climate change may worsen the water shortage issue, which may

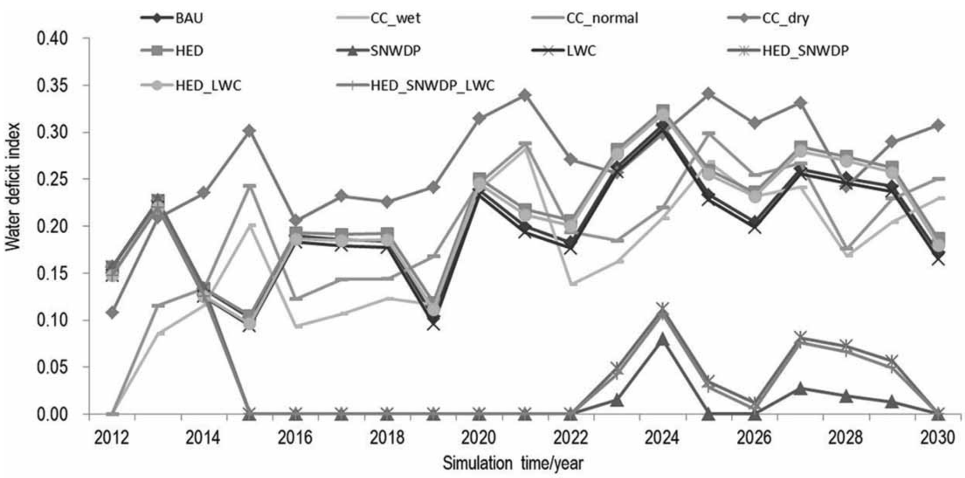

Fig. 7. WDI of all scenarios for the prediction period 2012–2030.

require proper adaptation strategies. Predictably, drier climates resulted in larger *WDI* values and more serious water shortage problems.

Figure 8 shows the variations in water demand shares in each sector compared with the *TWD* under different scenarios. The shares of different sectors under different scenarios do not exhibit substantial variations. The *AWD* percentages are relatively constant and exhibit decreasing trends under all scenarios. This is due to the stable *IrriWD*. The *DWD* percentages also display decreasing trends under all scenarios. The *IWD* and *EWU* percentages both show increasing trends during the prediction period because economic development and environmental protection are considered very important in Beijing. Among different sectors, *DWD* contributes the most to *TWD*. This is mainly because of the dense population and the high urbanization rate in the city.

Wastewater drainage is a water quality variable in this study that indicates the water environment and water recycling of the study site. The reuse of wastewater has a positive effect on the water utilization of Beijing. Figure 9 shows the average volume of wastewater drainage and wastewater reuse for all ten scenarios. From this figure we can see that the wastewater drainage increases with the development of the economy, which means that the water environment becomes worse. On average, the wastewater reuse rate is about 0.5 for all scenarios. This indicates that there is huge potential for Beijing to increase the wastewater reuse rate through the advances in technology, in order to increase the water supply and hence to alleviate the water deficit problems. Meanwhile, the water quality will be better with more wastewater being reused.

According to the simulation results, scenarios HED_SNWDP and HED_ SNWDP_LWC represent the best options for alleviating water shortage problems in Beijing. Scenario SNWDP can also effectively solve water shortage problems by increasing the water supply through the water diversion project. Climate change may largely impact the water balance in the future due to the direct influence on the water supply and *AWD*.

4. Discussion

4.1. Model use to support water resources planning in megacities

As demonstrated by the modeling scenarios, the SD model can be used as a tool for 'what-if' analysis under the various conditions in the future, and thus provide recommendations for effective solutions to address existing or potential water shortage problems. The model can be used as a communication tool between water resources modelers and managers or planners to estimate the range of water demand in the future under both natural and socioeconomic conditions and explore strategies to mitigate water shortage risk in a megacity. The managers' and planners' knowledge and justification are often helpful to quantify model parameters, justify the results, and provide feedback to modify the model.

The SD model can also be used together with other models for more detailed and comprehensive analysis. For example, the IWR-MAIN (Institute for Water Resources-Municipal And Industrial Needs) model is a decision-support package for projecting municipal and industrial water demands at a finer spatial and temporal scale (Sellers & Hatcher, 1991; Mohamed & Al-Mualla, 2010a, 2010b). However, IWR-MAIN does not relate water demand to hydroclimatic, socioeconomic and technological factors. Using both the SD model proposed in this paper and IWR-MAIN can provide complementary information for city managers and planners.

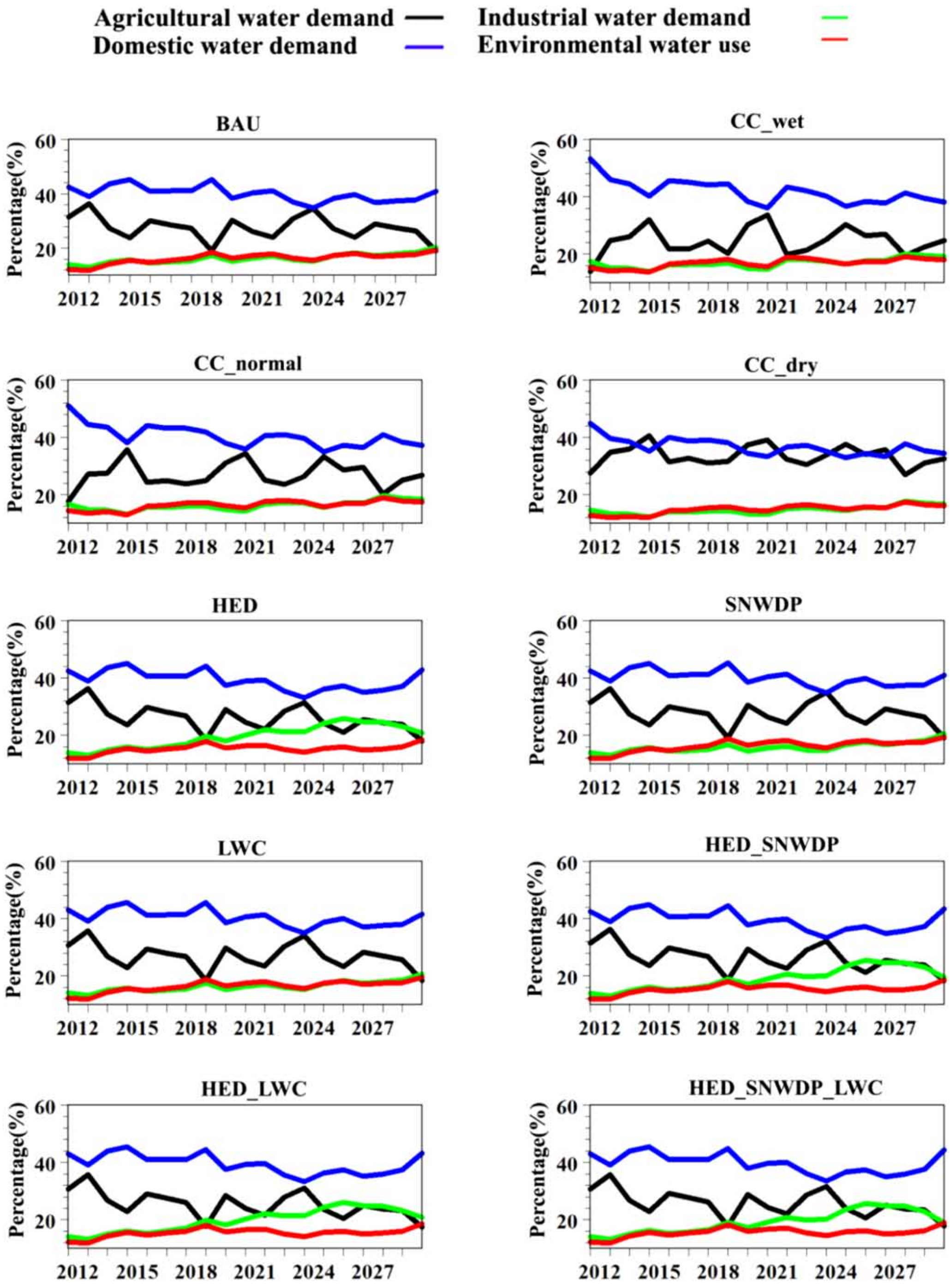

Fig. 8. Share of different sectors of TWD under different scenarios for the prediction period.

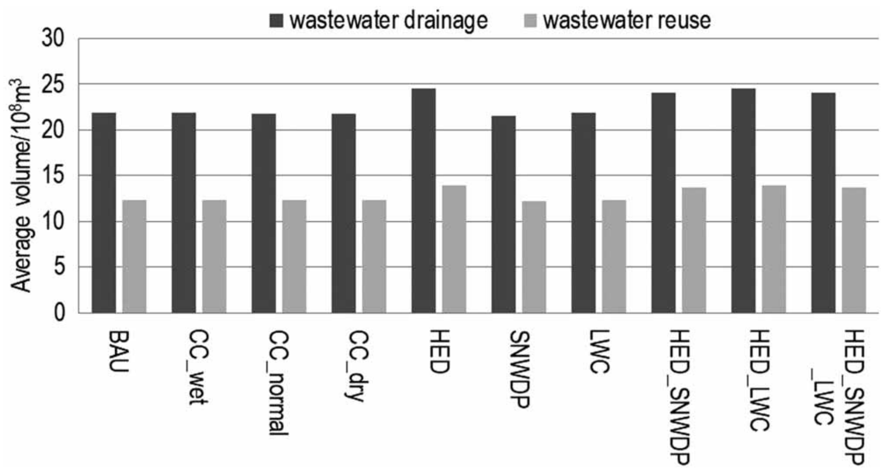

Fig. 9. Average volume of wastewater drainage and wastewater reuse for all ten scenarios.

In addition, the SD software can provide graphical user interfaces for model users to view model inputs and outputs under a modeling scenario, conduct sensitivity analysis of model parameters, and design multiple scenarios for 'what-if' analysis. This feature makes it convenient for modeler–user communications.

4.2. Extension of the SD model to other megacities

There were a total of 36 megacities in the world by 2016. Many megacities face water shortage threats due to high population growth and rapid economic development. The water demand prediction model based on systems dynamics may also be extended to other megacities for water demand prediction and water shortage assessment for the following reasons. First, the water demand calculation methods (Equations (1)–(5)) take into account the various hydroclimatic, agronomic, socioeconomic and technological factors and the interactions among these factors to calculate domestic, industrial, irrigation and livestock water demands. The methods are general and can be used for other megacities as long as the data are available for the calibration of the parameters.

Second, the SD model components and the connection between them (i.e. the model structure) developed for Beijing (Figure 4) can also be transformed to other megacities though the model components may need some modification according to data availability and specific water use conditions (e.g. some cities have negligible irrigation water use; some have large water use for recreation, etc.).

Additionally, the scenario design and analysis procedures for Beijing can be followed when the model is applied to other megacities. The SD model provides flexible interfaces to account for any change and impact of the various factors.

Finally, the trend of water demand change in Beijing that is identified from the scenario analysis in this study might occur in other megacities and thus the implications for Beijing can be informative for other cities. However, it should be noted that the SD model designed is empirical because the relationship and parameter quantifications more or less involve our knowledge, estimation and justification based on our long-term experiences of water resources management in the NCP and Beijing. When the SD model is extended to another city, the experiences of local modelers and water resources managers will also be important for the successful application of the model. Further extension and improvement of the model include using additional water use observations to develop more appropriate empirical relationships and quantify parameters, assessing the impact of new technologies such as those for water treatment, recycling and water storage (e.g. building a 'sponge' city; Yu *et al*., 2015) and considering the nexus relationship (trade-off and synergy) between the water and energy sectors.

5. Conclusions

This study adopts an integrated and systematic approach that takes into account many socioeconomic, agronomic, hydrological and technological factors and their feedback relationships associated with water demands in megacities in a consistent predictive model. The water demand calculations are undertaken for different water use sectors, including domestic, industrial and agricultural sectors. Beijing was selected as a case study to demonstrate the developed SD approach. Data from 2001 to 2011 were used to calibrate the model. Ten scenarios are designed to predict annual water demands from 2012 to 2030 using the calibrated model, considering economic development, climate change, inter-basin water transfer and water conservation technology. The predicted water demands by our model are comparable to those in the literature. The *TWD* is likely to increase by at least 36.1% (up to 62.5%) from 2011 to 2030. The corresponding water deficits range from 0.80 to 1.80 km^3. However, several scenarios end with water surplus ranging from 0.26 to 0.36 km^3 for the year 2030 (Table 5). Climate change may largely impact the water balance in Beijing, as indicated by the large water demands and water deficits under the three climate change scenarios. The inter-basin water transfer project (SNWDP) and water conservation technology play an important role in alleviating water shortage in the future, and three scenarios, HED_SNWDP, HED_SNWDP_LWC and SNWDP, are recommended for implementation. Beyond the case study of Beijing demonstrated in this paper, the proposed SD model is applicable to other megacities because of its generality in water demand calculation methods by sector and scenario design and analysis procedures. The model results are useful for city planners for infrastructure and technology investment and water demand management policy reform considering the various hydroclimatic and socioeconomic conditions.

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