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Promoting inclusive water governance and forecasting the structure of water consumption based on compositional data: A case study of Beijing

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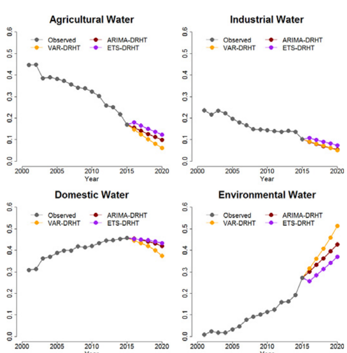
HIGHLIGHTS

- Governance of water use is critical for relieving water use conflicts.
- Models are used to forecast the structure of water usage.
- VAR-DRHT is the best performing model in this study.

GRAPHICAL ABSTRACT



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ABSTRACT

Water is centrally important for agricultural security, environment, people's livelihoods, and socio-economic development, particularly in the face of extreme climate changes. Due to water shortages in many cities, the conflicts between various stakeholders and sectors over water use and allocation are becoming more common and intense. Effective inclusive governance of water use is critical for relieving water use conflicts. In addition, reliable forecasting of the structure of water usage among different sectors is a basic need for effective water governance planning. Although a large number of studies have attempted to forecast water use, little is known about the forecasted structure and trends of water use in the future. This paper aims to develop a forecasting model for the structure of water usage based on compositional data. Compositional data analysis is an effective approach for investigating the internal structure of a system. A host of data transformation methods and forecasting models were adopted and compared in order to derive the best-performing model. According to mean absolute percent error for compositional data (CoMAPE), a hyperspherical-transformation-based vector autoregression model for compositional data (VAR-DRHT) is the best-performing model. The proportions of the agricultural, industrial, domestic and environmental water will be 6.11%, 5.01%, 37.48% and 51.4% by 2020. Several recommendations for water inclusive development are provided to give a better account for the optimization of the water use structure, alleviation of water shortages, and improving stake holders' wellbeing. Overall, although we focus on groundwater, this study presents a powerful framework broadly applicable to resource management.

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1. Introduction

With the rapid and continuous progress of urbanization, industrialization and modernization, contradictions between substantial water demands and the increasing shortage of water resources have become even more prominent. Water resources have gradually become a restricting factor for regional socio-economic and environmental development. The water consumption structure is the result of water resources distribution in each sector of industry and civil life, and its characteristics reflect the status of the sustainable development of water resources (Zhai, 2011). Water consumption structure is an embodiment or yardstick of urban sustainability and social inclusiveness. Adjusting the water consumption structure is the first step in achieving optimal allocation of water resources and solving the contradictions involved in water resources utilization.

Without considering the conflicts surrounding resources endowment and consumption, the objectives of developing society would no longer be plausible (Kooy et al., 2016). In the face of common and intense contradictions between social demands and resource endowments, ecological sustainability is widely recognized as a goal of utmost importance for human socio-economic development. How to integrate ecological sustainability with social inclusion and do it well is also a challenging mission for the development of society in the present and the future. Looking at developed countries with hindsight indicates the progress of sustainable development often makes a trade-off to propel economic growth at the cost of social inclusions (Gupta et al., 2015). Some large institutions are criticized for their so-called sustainability wisdom and practices by scarifying inclusiveness. For example, they usually reconcile economic goals with ecological conservation, but neglect or aggravate social inequalities (Atkisson, 2013).

Inclusive development is defined by Gupta et al. (2015) as "development that includes marginalized people, sectors and countries in social, political and economic processes for increased human well-being, social and environmental sustainability, and empowerment." (p. 546). Inclusive development emphasizes the mutual development of different levels and different types of economic sectors in order to meet the needs of various classes of production and lifestyles. An inclusive development strategy and practice will be concerned with social justice, equity, and the wide participation of all stakeholders in social development, addressing the common issues of being excluded from development, unfairness, and marginalization (Beall and Fox, 2007; Sachs, 2012).

As the capital of China, Beijing's rapid economic development has attracted a large number of immigrants in recent years. According to the Beijing Statistics Bureau, the resident population of Beijing was 21,729,000 at the end of 2016 (Beijing Municipal Bureau of Statistics, 2016). The rapid increase of population and the limited carrying capacity of the environment indicate that the issue of water shortage in Beijing has become increasingly prominent (Wei et al., 2015a, 2015b). A shortage of water resources and unbalanced utilization has become an important factor restricting the sustainable development of Beijing for a long time into the future (Wei et al., 2016). Therefore, an accurate analysis and scientific prediction of the water consumption structure of Beijing is the premise and basis for making scientific plans for water resources utilization, and the main basis for adjusting and optimizing the structure of industry in the city, which will be important and of significance for the coordinated development of the socio-economy and resource environment in Beijing.

Water related literature has traditionally been focused on forecasts of the absolute volume of water consumption, which has received huge concern from practitioners and academia. Many forecasting methods for time series data have been widely used, including the Moving Average (Reghunath et al., 2005; Kang et al., 2014; Boubaker, 2017), Exponential Smoothing (Kang et al., 2014; Caiado, 2009), Regression Analysis (Maidment and Miaou, 1986; Fildes et al., 1997; Jain et al., 2001; Bougadis et al., 2010), the Artificial Neural Network (Jain and Kumar, 2007; Coulibaly and Baldwin, 2005; Liu et al., 2001; Bennett et al., 2013; Liu et al., 2003a, 2003b), Grey Forecasting (Fang and Tao, 2014; Hou, 2015; Wang et al., 2014), and System Dynamics (Sun et al., 2016; Ghasemi et al., 2017; Chhipi-Shrestha et al., 2017). These methods are good for ease of understanding and verifiability. The shortcomings are also remarkable, including things such as a high number of errors, and susceptibility to random factors, etc.

In the contrast, there is a dearth of studies concerned with water use structure, and the forecasts remain mainly qualitatively based. The main statistical approaches include Information Entropy (Ma et al., 2012; Liu and Liu, 2014; Su et al., 2008), Ecological Niche (Jiao et al., 2011), Grey System (Lv and Du, 2012; Bao and Fang, 2006; Chen et al., 2008), Linear Regression, (Bao and Fang, 2006; Chen et al., 2008; Gu and Wang, 2012), Water Footprint (Zhang et al., 2014; Mekonnen and Hoekstra, 2011; Mekonnen and Hoekstra, 2012; Gerbens-Leenes and Hoekstra, 2011; Xu et al., 2017), System Dynamics, (Zhang et al., 2015; Zarghami and Akbariyeh, 2012; Winz et al., 2009; Qi and Chang, 2011), and Gini Coefficients (Wang et al., 2012; Hu et al., 2016; Wang et al., 2011). However, the performance of these forecasting techniques is highly conditional, dependent on the data and the presumptions made, and a lack of insight into temporal-geographic changes.

Compositional data are usually used to describe the internal structure of a system, such as an investment structure, industrial structure, or a consumption structure, etc. The objective of a forecasting model using compositional data is to derive the forecasted water consumption structure based on historical data and evolutionary trends. The traditional solution is to derive the forecasted proportion of each component, respectively. However, this may cause difficulty understanding the results and the untenable result that the sum of the forecasted proportions is not equal to 1. In contrast, compositional data is good at understanding and predicting internal structure of a system.

The aim of this paper is to forecast the dynamic changes expected in Beijing's water use structure during the period from 2016 to 2020. A host of forecasting models based on compositional data has been developed. To achieve reliable forecasting results, estimation results of different models are compared according to their precision to derive the best performing model. Concrete and tenable solutions are recommended to promote inclusive water governance.

This study has rich and important implications. Applying the concept of inclusive development to water resources utilization offers an opportunity to consider relations between ecological sustainability and the utilization of water. On one hand, the inclusive development of water resources utilization is an important component of socio-economic sustainable development strategy. On the other hand, inclusive water governance for sustainable development is one of the top goals in a global agenda. Consumption of water should consider a trade-off between competing or even conflicting benefits. By means of inclusive water governance, potential competition can be avoided given an appropriate inclusion of an interests sharing mechanism. The concept of inclusive development reduces the uncertainty of water governance. For example, local governance elites and policy makers used to have an incomplete understanding of the changes in water resources and variations in water consumptions, and thus had limited control over the determinants of effective water governance. This uncertainty creates an impressive need for adaptability, viable alternative choices, and the capability of governments and planners to carry out appropriate policies and action plans for successful water governance. In view of the present water shortage and conflicts in Beijing, it is necessarily important to scientifically investigate the water consumption structure and predict its development trends. The research results provide valuable hints for effective utilization and conversation of water resources. The findings will be conducive to the efficient allocation of water resources and the implementation of an inclusive water development strategy.

2. Background of the water consumption structure of Beijing

Beijing is a typical city in China with a serious shortage of water resources. The per capita water resource in Beijing is less than 300 m^3, contributing to only 1/8 of the per capita water resources in China or 1/30 of the per capita water resources of the world (Zhai, 2011). The annual average amount of groundwater in Beijing is 2.521 billion m^3, but the water consumption in 2016 was about 3.880 million m^3 (Beijing Municipal Bureau of Statistics, 2016). The huge water shortfall can only be met by the over extraction of groundwater and input from neighboring provinces to maintain the balance between supply and demand. Over the past 30 years, the average annual precipitation and total water resources in Beijing have been reduced by 6.89% and 31.37%, respectively, while the total water consumption has reached the highest peak in history. The shortage of water resources has become the major bottleneck factor restricting the sustainable development of Beijing. Therefore, a reasonable prediction and governance of the water consumption structure is an important means to alleviate the overall water shortage in Beijing. According to water use activities, water consumption structure is mainly classified into four parts: agricultural water, industrial water, domestic water and environmental water. The historical change in the water consumption structure in Beijing during 2001–2015 is summarized and shown in Fig. 1.

As shown in Fig. 1, great structural changes have taken place in the Beijing water consumption structure during the 2001–2015 period, mainly as follows.

(1) During the past 15 years, the proportion of water consumed by agricultural decreased continuously and significantly, from 44.7% in 2001 to 17% in 2015, indicating a decrease up to 162.9%. After a short period of increase in 2004, the proportion water consumption attributed to agriculture continued to decline, and the rate of decline has increased year by year. It is perhaps related to decreases in the area used for farming due to rapid urbanization, or increases water used for residential living, or the introduction of advanced water-saving technology. In general, the decreased proportion of agricultural water consumption is conducive to the development of a water-saving agriculture structure in Beijing.

(2) Except for the period between 2001 and 2004, industrial water consumption generally shows a downward trend. Specifically, apart from a slight increase in 2013, the proportion of industrial water consumption continued to shrink, reduced from 23.7% in 2001 to 10.2% in 2015, a decrease of up to 132.4%. The rapid decline of industrial water consumption in Beijing shows that the optimization of the industrial structure in Beijing has achieved an initial success, and the industrial wastewater treatment and reuse technology has been improved.

(3) Domestic water, which occupies a large proportion of the water consumption structure, is an important component of the total water consumption in Beijing, and shows a steady upward trend. It accounted for the lowest proportion in 2001, but still accounted for 30.8%, and it exceeded the proportion of agricultural water consumption for the first time in 2005, placing it in the first rank. The rapid development of urbanization and the rapid increase of population are the causes of this phenomenon, which also reveals the key points of water saving strategy in Beijing.

(4) During the years 2001–2015, environmental water consumption increased sharply, from 0.8% in 2001 to 27.2% in 2015, which demonstrates the enhancement of public awareness of environmental amenities and ecology.

In conclusion, the rising proportion of environmental water consumption is pronounced, while agricultural water consumption and industrial water consumption decreased year by year. Domestic water remains the largest water-consuming sector. Especially in recent years, the pressure of domestic water consumption has become increasingly prominent, which means the optimization of the total water consumption structure in Beijing still has a long way to go in the future.

3. Research method and data

The key procedures for developing a forecasting model with the use of a compositional data series can be summarized into three key steps. Firstly, the constraints of the compositional data should be eliminated by transforming the original compositional data into a group of independent variables. Secondly, based on these transformed new data, an array of traditional forecasting models can be adopted to obtain the forecasted values without any constraints. Finally, these forecasted values are retransformed into compositional data. Both the data transformation methods and forecasting models are introduced as follows.

3.1. Compositional data

The term compositional data was originally proposed by Aitchison (1982), and was expressed as a vector $\boldsymbol{x} = [x_1, x_2, \ldots, x_D]$ with all the components having values between 0 and 1 (nonnegative constraint) and summing up to be 1, i.e., $\sum_{i=1}^{D} x_i = 1$ (constant-sum constraint). Compositional data are usually used to describe the internal structure of a system, such as, investment structure, industrial structure, consumption structure, etc.

Consider a time series of compositional data $\{\boldsymbol{x}^{(k)}, k = 1, 2, \ldots, T\}$, where the observed compositional data at time k is expressed as $\boldsymbol{x}^{(k)} = [x_1^{(k)}, x_2^{(k)}, \ldots, x_D^{(k)}]$. The objective of a forecasting model using compositional data observations is to derive the forecasted compositional value at time $T + t$, denoted by $\boldsymbol{x}^{(T+t)}$.

Owing to the constraints of compositional data, most of the traditional forecasting models cannot be used directly for compositional data. Accordingly, the following data transformation methods are introduced to deal with the constraints of the compositional data before adopting a forecasting model.

3.1.1. Linear combination component (LCC) method

The LCC method assumes one of the components to be a linear combination of the others (Pawlowsky-Glahn et al., 2015). For example, we select $x_D^{(k)}$, construct the model for the rest of the $D - 1$ components (i.e., $x_1^{(k)}$, …, $x_{D-1}^{(k)}$), and then derive the forecasted values of $x_i^{(T+t)}$ for $i = 1, 2, \ldots, D - 1$. Thus, $x_D^{(T+t)}$ can be expressed as

$$x_D^{(T+t)} = 1 - \sum_{i=1}^{D-1} x_i^{(T+t)}. \tag{1}$$

3.1.2. Isometric logratio (ILR) transformation

Constructing a forecasting model by means of a certain ILR transformation (Egozcue et al., 2003; Egozcue and Pawlowsky-Glahn, 2005; Wang et al., 2013) can be described as follows:

1) For each time k in $\{1, 2, \ldots, T\}$, obtain the vector $\boldsymbol{u}^{(k)} = (u_1^{(k)}, u_2^{(k)}, \ldots, u_{D-1}^{(k)})$ from $\boldsymbol{x}^{(k)}$, where

$$u_i^{(k)} = \sqrt{\frac{i}{i+1}} \log \frac{\sqrt[i]{\prod_{j=1}^{i} x_j^{(k)}}}{x_{i+1}^{(k)}}, i = 1, 2, \cdots, D-1. \tag{2}$$

2) For each i in $\{1, 2, \ldots, D - 1\}$, conduct the forecasting model using the time series $\{u_i^{(k)}, k = 1, 2, \ldots, T\}$, respectively, and obtain the forecasted component value $u_i^{(T+t)}$. Thus, the whole vector $\boldsymbol{u}^{(T+t)}$ can be expressed as

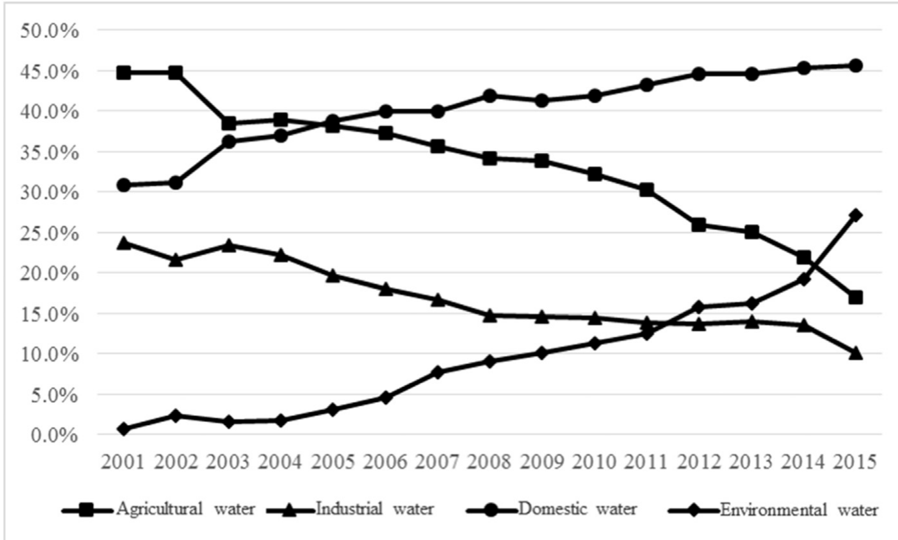

Fig. 1. Beijing water consumption structure during 2001–2015.
Source: Beijing statistical yearbook 2016.

$$\boldsymbol{u}^{(T+t)} = \left(u_1^{(T+t)}, u_2^{(T+t)}, \ldots, u_{D-1}^{(T+t)}\right). \tag{3}$$

3) Obtain the vector $\boldsymbol{v}^{(T+t)} = (v_1^{(T+t)}, v_2^{(T+t)}, \ldots, v_D^{(T+t)})$ from $\boldsymbol{u}^{(T+t)}$ as

$$v_i^{(T+t)} = \sum_{j=i}^{D} \frac{u_j^{(T+t)}}{\sqrt{j(j+1)}} - \sqrt{\frac{i-1}{i}} u_{i-1}^{(T+t)}, i = 1, 2, \ldots, D, \tag{4}$$

with $u_0^{(T+t)} = u_D^{(T+t)} = 0$.

4) The designed forecasted compositional data $\boldsymbol{x}^{(T+t)}$ can be obtained from $\boldsymbol{v}^{(T+t)}$ as

$$\boldsymbol{x}^{(T+t)} = \left[\frac{v_1^{(T+t)}}{\sum_{j=1}^{D} v_j^{(T+t)}}, \frac{v_2^{(T+t)}}{\sum_{j=1}^{D} v_j^{(T+t)}}, \ldots, \frac{v_D^{(T+t)}}{\sum_{j=1}^{D} v_j^{(T+t)}}\right]. \tag{5}$$

3.1.3. Dimension-reduction approach through a hyperspherical transformation (DRHT)

The main procedures for using the DRHT method to forecast a compositional data series can be described as follows (Wang et al., 2007):

1) For each time k in $\{1,2,\ldots,T\}$, obtain the vector $\boldsymbol{\theta}^{(k)} = (\theta_2^{(k)}, \theta_3^{(k)}, \cdots, \theta_D^{(k)})$ from $\boldsymbol{x}^{(k)}$ as

$$\theta_i^{(k)} = \left\{ arccos\sqrt{x_i^{(k)}}, i = D,\ arccos\left(\frac{\sqrt{x_i^{(k)}}}{\prod_{j=i+1}^{D} sin}\theta_j^{(k)}\right), i = D-1, D-2, \cdots, 2. \right. \tag{6}$$

2) For each i in $\{2,3,\ldots,D\}$, conduct the forecasting model based on the time series $\{\theta_i^{(k)}, k = 1,2,\ldots,T\}$, and derive the forecasted component value $\theta_i^{(T+t)}$. Thus, the whole vector $\boldsymbol{\theta}^{(T+t)}$ can be expressed as

$$\boldsymbol{\theta}^{(T+T)} = \left(\theta_2^{(T+t)}, \theta_3^{(T+t)}, \cdots, \theta_D^{(T+t)}\right). \tag{7}$$

3) The desired forecasted compositional data $\boldsymbol{x}^{(T+t)}$ can be obtained from $\boldsymbol{\theta}^{(T+t)}$ as $\boldsymbol{x}^{(T+t)} = [x_1^{(T+t)}, x_2^{(T+t)}, \cdots, x_D^{(T+t)}]$, where

$$x_i^{(T+t)} = \begin{cases} \left(\prod_{j=2}^{D} sin\theta_j^{(T+t)}\right)^2, i = 1, \\ \left(cos\theta_i^{(T+t)} \cdot \prod_{j=i+1}^{D} sin\theta_j^{(T+t)}\right)^2, i = 2, 3, \cdots, D-1, \\ \left(cos\theta_D^{(T+t)}\right)^2, i = D. \end{cases} \tag{8}$$

The above-mentioned sections have introduced the main procedures for transforming compositional data. The advantages and shortcomings of these methods for transforming compositional data are summarized as follows.

a. One of the main advantages of the LCC method is that it is theoretically straightforward and easy to use. However, owing to accumulative errors, the disadvantages are also obvious in that the result is often less understandable and even contradictory. For example, Pawlowsky-Glahn et al. (2015) pointed out that sometimes the forecasted value will exceed the value range.
b. The ILR transformation method offers a good alternative for coping with the constraints problem of compositional data. However, the presumption of the estimation seems rather rigid and restrictive: that is, all components are supposed to be positive (Wang et al., 2007).
c. The DRHT method is one of high flexibility as it allows some components to be zero, however, it still does not allow for the existence of a certain component with the value of 1. Another major shortcoming is that the nonlinear transformation in the DRHT method may not be consistent with the Aitchison geometry in compositional data analysis (Aitchison, 1982).

3.2. Forecasting models

After transforming the original compositional data, several traditional methods can be used for the next procedure in the data forecasting, such as for instance, the autoregressive integrated moving average model (ARIMA), the exponential smoothing model (ETS), the Theta function expansion method (Theta), the vector autoregression model (VAR), the additive nonlinear autoregressive model (AAR) and the neural network nonlinear autoregressive model (NNET). The main forecasting models for a time series are illustrated as follows.

3.2.1. Autoregressive integrated moving average

The ARIMA model is a classical and common forecasting technique for time series data (Box and Pierce, 1970; Jenkins, 2004). It assumes that observations follow a pattern of a random consequence in a *temporal* order. Then, the forecasted value can be obtained by using a constructed model, which can perfectly capture the features of the latent random consequence.

3.2.2. Exponential smoothing

The ETS model developed by Brown et al. (1961) is another popular method for time series prediction, which assumes the trend of the time series to be stable and regular. In the ETS model, the forecasted values can be obtained by a weighted average of the previous observations. Moreover, the weights reduce gradually when the related observations move gradually away from the point to be forecasted. The traditional ETS models include the single, second and cubic models.

3.2.3. Theta function expansion

The Theta function expansion (Theta) method, which was first proposed by Assimakopoulos and Nikolopoulos (2000), has been demonstrated to be equivalent to the simple exponential smoothing method with drift (Hyndman and Billah, 2003).

3.2.4. Vector autoregression

The VAR model is one of the most popular methods for dealing with several relevant economic indicators together (Lütkepohl, 2005). The VAR model is constructed as a function of the lagged time series values of all the endogenous variables, which expands the univariate autoregression model into a multivariate time series.

3.2.5. Additive nonlinear autoregressive model

The AAR model assumes the time series to be the combination of the nonparametric univariate functions of the lagged time series values (Chen and Tsay, 1993). The functions are usually represented by cubic regression splines. Moreover, the rolling machine is adopted to improve the prediction accuracy.

3.2.6. Neural network nonlinear autoregressive model

The NNET model regards the time series as an input-output system that is determined by a nonlinear mechanism (Janacek, 2003). The NNETS model can better reveal the correlation of a nonlinear time series in the delay state space. The rolling machine is also introduced.

The pros and cons of these six forecasting methods are summarized as follows:

a. The ARIMA is based on a consolidated theoretical underpinning. Thus, the predicted results are reliable in general. The shortcomings of the method are that the ARIMA has a strong requirement that the original data should carry information rich enough for modeling.
b. One advantage of the exponential smoothing model is that it has a relaxed requirement for data. For example, the forecasting model can be performed with just a few observations. The disadvantages are also evident in that the ETS method is more suitable for short or medium-term predictions, as predicted values are virtually the weighted averages of the historical data and are greatly affected by the impact of the most recent data in the time order.
c. As a derivation of the ETS model, the Theta function expansion method inherits the major advantages of the ETS models and is easy to perform. However, the downsides are evident in that the flexibility of the forecasting model and its scope of application are limited.

(2) The vector autoregressive model considers the relationship between different time series, which contributes to capturing well the features of the times series. However, it makes strong model assumptions and usually needs a large-size data sample.
(3) The additive nonlinear autoregressive model allows the lagged times series values to contain *a* nonparametric form in the autoregressive (AR) model, which expands the use of the traditional AR model. Since the process of regression splines, the AAR model is also not suitable for long-term prediction.
(4) Numerous studies have shown that the neural network nonlinear autoregressive model has high prediction accuracy in nonlinear time series analysis. The downsides are that the NNETS model takes a longer time to conduct, and only applies to recurring predictions.

In forecasting compositional data, two special processes are of the highest significance: removing the constraints of the compositional data before modeling, and transforming the forecasted values back to compositional data after forecasting. These procedures take into account the constraints of the compositional data in the modeling, and ensure the final forecasted results will be embodied with compositional structure. After the data are transformed, most of the traditional forecasting methods can be used with compositional data.

3.3. Developing a forecasting model

To evaluate the forecasting performance of the alterative models, we divided the observed compositional data into two sets, i.e., the training set $\{\boldsymbol{x}^{(k)}, k=1,2,\ldots,M\}$ and the forecasting set $\{\boldsymbol{x}^{(k)}, k=M+1, M+2,\ldots,N\}$. The forecasting set consists of the latest data, and the rest data are included in the training set. The data in training set are used to build up the forecasting model and thus predict the data in forecasting set. These forecasted values are then used to select the final forecasting model from all the alternatives by comparing with the real observed data in forecasting set. The best-performed model will be selected and used to forecast Beijing's water use structures by 2020.

To measure forecasting precision, we introduce mean absolute percent error for compositional data (CoMAPE), which is defined as

$$\text{CoMAPE} = \frac{1}{N-M}\sum_{k=M+1}^{N}\frac{d_A\left(\boldsymbol{x}^{(k)},\hat{\boldsymbol{x}}^{(k)}\right)}{\left\|\boldsymbol{x}^{(k)}\right\|_A}\times 100\%, \tag{9}$$

where $d_A(\boldsymbol{x}^{(k)},\hat{\boldsymbol{x}}^{(k)})$ and $\|\boldsymbol{x}^{(k)}\|_A$ are defined by Aitchison (1982) as

$$d_A\left(\boldsymbol{x}^{(k)},\hat{\boldsymbol{x}}^{(k)}\right) = \sqrt{\sum_{i=1}^{D}\left(\log\frac{x_i^{(k)}}{g_m\left(\boldsymbol{x}^{(k)}\right)} - \log\frac{\hat{x}_i^{(k)}}{g_m\left(\hat{\boldsymbol{x}}^{(k)}\right)}\right)^2}, \tag{10}$$

$$\left\|\boldsymbol{x}^{(k)}\right\|_A = \sqrt{\sum_{i=1}^{D}\left(\log\frac{x_i^{(k)}}{g_m\left(\boldsymbol{x}^{(k)}\right)}\right)^2} \tag{11}$$

and g_m denotes the geometric mean operation, e.g., $\mathrm{g_m}(\mathbf{x}^{(\mathrm{k})}) = \left(\prod_{\mathrm{i}=1}^{\mathrm{D}} \mathrm{x_i^{(k)}}\right)^{1/D}$.

Table 1
Description on the methods for transforming compositional data and forecasting modeling.

Process methods for transforming compositional data	
LCC.A	LCC method regarding "Agriculture" as the linear combination
LCC.I	LCC method regarding "Industry" as the linear combination
LCC.L	LCC method regarding "Life" as the linear combination
LCC.E	LCC method regarding "Environment" as the linear combination
ILR	Isometric logratio transformation
DRHT	Dimension-reduction approach through a hyperspherical transformation

Forecasting models	
ARIMA	Autoregressive integrated moving average model
ETS	Exponential smoothing model
Theta	Theta function expansion method
AAR	Additive nonlinear autoregressive model
Rolling-AAR	The AAR model with rolling machine
VAR	Vector autoregressive model
NNET-1	Neural network model with 1 hidden layer
NNET-2	Neural network model with 2 hidden layer
NNET-3	Neural network model with 3 hidden layer
Rolling-NNET-1	Neural network model with 1 hidden layer and rolling machine
Rolling-NNET-2	Neural network model with 2 hidden layer and rolling machine
Rolling-NNET-3	Neural network model with 3 hidden layer and rolling machine

Compared with the traditional MAPE (mean absolute percent error) measure for testing model effectiveness (Makridakis et al., 1979), CoMAPE gives an analogous definition for compositional data. Specifically, $d_A(x^{(k)}, \hat{x}^{(k)})$ measures the difference between the observed and forecasted compositional data, $\boldsymbol{x}^{(k)}$ and $\hat{\boldsymbol{x}}^{(k)}$, and $\|\boldsymbol{x}^{(k)}\|_A$ measures the magnitude of the observation, $\boldsymbol{x}^{(t)}$. A lower CoMAPE value indicates a more reliable forecasting model for the compositional data, with lower forecasting errors. This study selected the model with the lowest CoMAPE as the best performing forecast model for compositional data.

3.4. Data

This study used Beijing's water consumption data from 2001 to 2015, sourced from the Beijing Statistical Yearbook 2016. Based on the sectorial classification, there are four major water use areas i.e. agricultural, industrial, domestic, and environmental. Historical data for Beijing water use structure is illustrated in Fig. 1 and the main characteristics of Beijing's water consumption are summarized in Section 2.

To select the best performing forecast model for compositional data, this study used Beijing's water consumption data from 2001 to 2012 as training set, and the data from 2013 to 2015 the forecasting set. Then, the CoMAPE value of the period from 2013 to 2015 is used to select the best performing forecast model.

4. Results and discussion

Table 1 shows the abbreviations of both compositional data transforming methods and forecasting models. The forecasting set (i.e., from 2013 to 2015) was used to measure the accuracy of these alternative models. The forecasting performances, represented by CoMAPE values, are summarized in Table 2. To forecast compositional data, there exist two key processes. One is the transformation of compositional data, and the other is data forecasting. In Table 2, rows and columns denote the transformation methods for compositional data and the forecasting models, respectively.

What the forecasting study concerned most is the forecasting efficiency, i.e., the model's performance in the forecasting set. The CoMAPE is introduced as the key criterion for measuring the accuracy of each forecasting model. In the forecasting set, CoMAPE indicates the forecasting performance of the model. The performances of each forecasting model are determined by both data transformation methods for compositional data (by row) and forecasting models (by column). Regarding the processing methods for compositional data, the family of LCC methods generally has high uncertain volatility. For example, the CoMAPE value of the model together with the LCC.E and the AAR methods is 89.98%, which is several times larger than the other models' (i.e., LCC.A of 18.55%, LCC·I of 18.82% and LCC.L of 54.49%). In general, the DRHT method performs well having more stable CoMAPE values. Regarding the forecasting models, the CoMAPE values of the ARIMA, ETS and VAR models are small in general, ranging from 16.8% to 31.38%. Models with the lowest CoMAPE values can be recognized as being the best-performing forecast models, indicating the least prediction errors. Therefore, based on the lowest CoMAPE values, this study used combinations of the DRHT process method for compositional data with the three forecasting models, i.e., VAR, ARIMA and ETS, to forecast the water consumption structure from 2016 to 2020 (see Table 3 and Fig. 2). The combined use of the DRHT and the VAR gave the best-performing forecasting model having the lowest CMAPE value of 16.8% in the forecasting set (Table 2). The specified predicted proportions of each type of water consumption are given in Table 3.

Table 3 and Fig. 2 show forecasting results for Beijing water consumption structure from 2016 to 2020. The VAR-DRHT, ARIMA-DRHT and the ETS-DRHT are the top three performing models according to the CoMAPE values (Table 2). Forecasting trends are similar in these three models and they provide a range of structure changes. By 2020, the proportion of agricultural water will be reduced to between 6.1% and 12.31%, and the proportion of industrial water consumption will only vary from 5.01% to 7.39%. According to the current trend, the proportion of agricultural and industrial water consumption in the total water consumption structure will continue to decline, with the continuous optimization of the industrial structure in Beijing. At the same time, according to the Beijing population control plan of 2017, by

Table 2
CoMAPE comparisons of alternative forecasting models (unit: %).

	ARIMA	ETS	Theta	AAR	Rolling-AAR	VAR
LCC.A	21.11	25.43	25.73	18.55	18.55	20.53
LCC.I	21.11	27.55	25.73	18.82	18.82	20.53
LCC.L	21.11	27.09	25.73	54.49	54.06	20.53
LCC.E	21.11	29.05	25.73	89.98	46.89	20.53
ILR	27.13	21.73	22.14	22.65	21.49	31.38
DRHT	19.49	19.87	24.78	72.8	44.49	16.8[a]

	NNET-1	NNET-2	NNET-3	Rolling-NNET-1	Rolling-NNET-2	Rolling-NNET-3
LCC.A	16.84	16.83	17.68	17.44	17.47	16.64
LCC.I	18.78	91.64	27.98	19.31	40.69	20.83
LCC.L	17.05	78.22	22.38	16.76	28.62	16.4
LCC.E	17.95	87.13	28.95	16.94	33.26	22.46
ILR	63.34	63.3	61.07	61.65	58.69	62.51
DRHT	35.31	24.44	41.95	26.16	38.98	38.67

[a] Indicates the best-performed forecasting model with the lowest CoMAPE of 16.8% in the forecasting set.

Table 3
Forecasting results of Beijing's water consumption structure from 2016 to 2020 (unit: %).

Method	Year	Agricultural	Industrial	Domestic	Environmental
VAR-DRTH	2016	14.78	9.11	44.48	31.63
	2017	12.44	8.13	43.38	36.04
	2018	10.15	7.12	41.95	40.78
	2019	8.02	6.07	40	45.92
	2020	6.11	5.01	37.48	51.4
ARIMA-DRHT	2016	15.55	8.95	45.38	30.13
	2017	14.09	7.88	44.85	33.18
	2018	12.64	6.93	44.11	36.31
	2019	11.24	6.08	43.18	39.5
	2020	9.91	5.31	42.05	42.74
ETS-DRTH	2016	18.07	10.85	45.32	25.77
	2017	16.54	9.93	45.06	28.47
	2018	15.06	9.04	44.64	31.26
	2019	13.66	8.2	44.04	34.11
	2020	12.31	7.39	43.28	37.02

2020 the population of Beijing will be strictly controlled at 23 million. Hence, the proportion of domestic water consumption will continue to be maintained at a level of about 40%, with a slight downward trend. With the rapid implementation of "the construction of an ecology-friendly society" and the green economic strategy of Beijing, as well as increasing investment in environmental protection facilities, the proportion of water consumed by the environment will significantly increase year by year. It is expected to reach between 37.02% and 51.4% by 2020. According to the VAR-DRHT (the best performing model), the weight of agricultural and industrial water use shows significant reduction, dropping from 14.78% to 6.11%, and from 9.11% to 5.01% respectively during 2016 and 2000. The proportion of domestic water will maintain a mild reduction from 44.48% to 37.48%. The environmental water segment will rise remarkably from 31.63% to 51.4% in the same period. It will overtake domestic water as the largest water-consuming sector.

(1) Agricultural water. According to the "13th Five-Year period for water development planning in Beijing" (13thWDPB), Beijing's total water consumption will be controlled to within 4.300 billion m^3 in 2020, of which agricultural water consumption will be controlled to within 500 million m^3, and agricultural water consumption will continue to decline. The decrease in cultivated land area and the increase in water saving irrigation methods are the main reasons for the decrease in agricultural water consumption. Vigorously implementing projects involving highly efficient agricultural water-saving irrigation methods and the realization of the full coverage of agricultural water-saving facilities, as well as agricultural pumping well metering facilities, will enhance the utilization coefficient of farmland irrigation water to reach 0.710 by 2020 (Beijing Municipal Government, 2016). At the same time, strengthening controls on agricultural pollution, continuing to promote agricultural water price reform, and establishing the agricultural subsidy system and an accurate

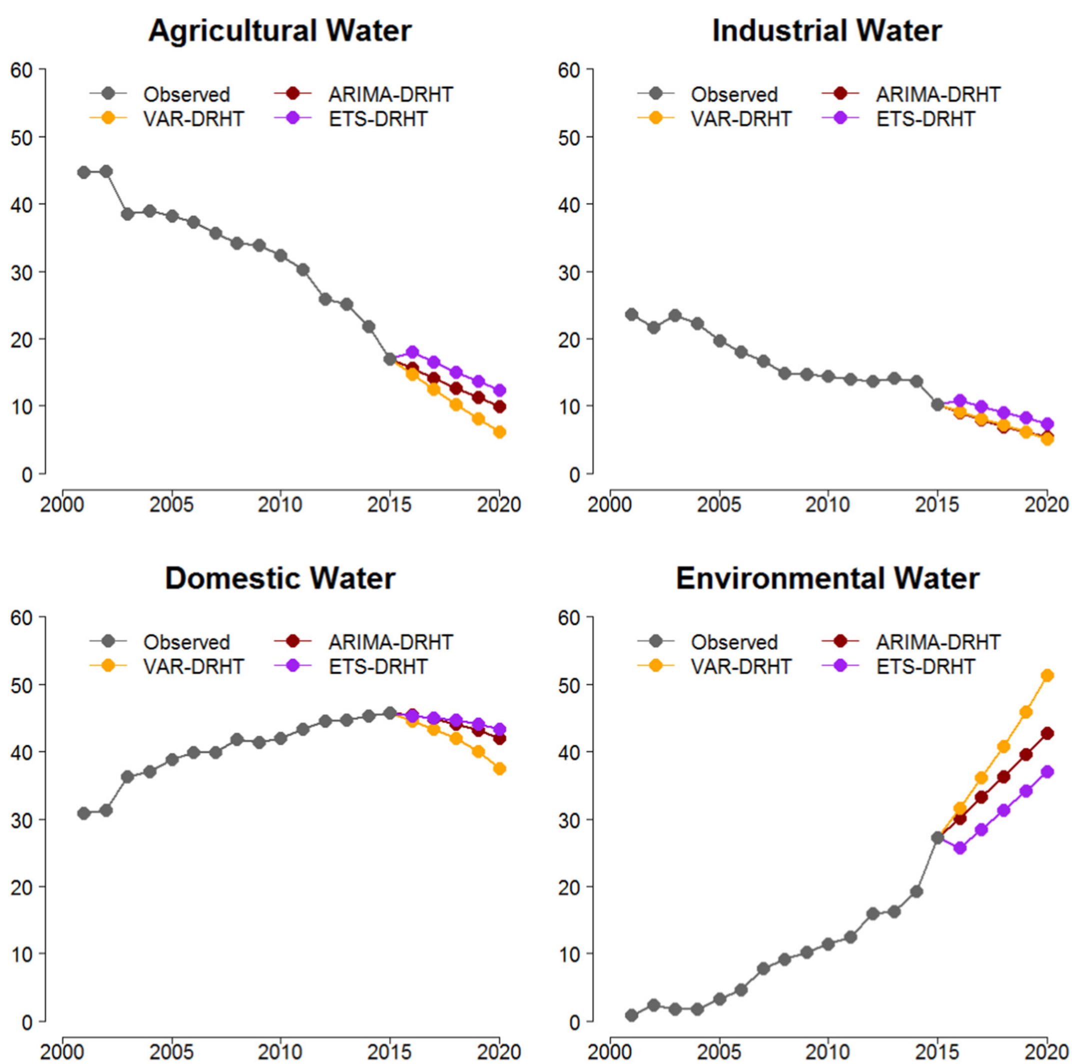

Fig. 2. Forecasting results for Beijing's water consumption structure from 2016 to 2020 (unit: %).

water-saving incentive mechanism will effectively reduce the proportion of water consumed by agriculture in the overall water consumption structure.

(2) Industrial water. According to the 13th WDPB, industrial water consumption will be controlled to within 510 million m^3 by 2020, in order to achieve zero growth in the total amount. On the one hand, with the constant adjustment and transformation of the economic structure of Beijing, industrial enterprises with high-energy consumption, high-pollution and high water consumption will be gradually phased out or diverted to other cities. The proportion allotted to the service sector in the overall economic structure of Beijing will be on the rise in the future. By 2020, the service sector will account for more than 80% of Beijing's whole GDP (Beijing Municipal Commission of Development and Reform, 2017), which will effectively reduce the consumption of water resources by traditional industries. On the other hand, in recent years, Beijing has vigorously promoted the investment and utilization of environmental protection facilities, and vigorously promoted the use of advanced water-saving technologies and equipment to increase the rate of water reuse, which means the industrial water consumption per million RMB output value will be reduced year by year.

(3) Domestic water. In accordance with the overall plan, by 2020, domestic water consumption will be controlled to within 1.820 billion m^3. The increasing population is the main reason for the relatively high proportion of domestic water consumption. Since the "green concept" has been institutionalized as the dominant mode of economic development in Beijing, promoting efficient water-saving domestic water appliances and the availability of recycled water in households will make Beijing's domestic water saving project see great potential. 3 years later, Beijing will realize the full use of efficient water saving appliances in governments, schools, and hospitals, which will also contributes to making the proportion of domestic water consumption relatively stable by 2020.

(4) Environmental water. According to the 13th WDPB, environmental water consumption will reach 1.200 billion m^3 by 2020. Since 2001, the proportion of Beijing's water consumed by the environment has increased sharply, exceeding industrial water and agricultural water use and becoming the second largest use of water, which reflects the enhancement of public awareness of the need for an ecologically friendly environment. Greening, sprinkling roads and watering landscaping are the main uses of the environmental water. Because Beijing continues to increase environmental pollution controls, water demand for green area irrigation and sprinkling to lay dust will continue to increase, which will lead to the amount of environment water consumption maintaining second place in the total water consumption structure for the long term. However, with the continuous growth of Beijing's population and the increasing public demand for environmental improvement, there is still a big gap to fill in the demand for ecological water, and the use of ecological environment water is still at an initial stage.

In the water shortage areas, developing water-efficient industries and compressing high-consumption ones is the main strategy of the water consumption structure adjustments around the world. In recent years, the water consumption in the U.S., Japan and other developed countries has been stable and even tended to decline, which is closely related to the adjustment of the water consumption structure. For example, through the compression and elimination of some water consuming industries such as chemicals, paper making etc., these countries emphasize the development of water-saving industries such as the electronic information industry and service industry, optimize the structure of their water consumption, and improve water use efficiency and effectiveness. In addition, agriculture, as a major water consumer, is also the focus of water consumption structure adjustment. In order to solve the problem of the increasing cost of agricultural water consumption, many countries have made the necessary adjustments to their agricultural structure. On the one hand, they are reducing high water consumption crops, and increasing crops require less water; on the other hand, they are vigorously developing high value-added crops, thus increasing the cost pressures associated with high water consumption, and thereby; increasing agricultural economic benefits. For example, in the process of developing water-saving irrigation methods, Israel reduced the area used for grain crops, expanded the planting area of high output vegetables, fruits and flowers, and optimized the structure of its agricultural water consumption.

5. Conclusion

Water is an indispensable and precious resource for human beings, and it is in part a nonrenewable resource, especially if it comes from ancient subterranean aquifers that take hundreds or even thousands of years to recharge, if at all. The shortage of water resources is a key issue for Beijing, with its large population and high speed of economic development, which must be faced during the long period of development. The accurate analysis and scientific prediction of the water consumption structure of Beijing is not only the premise and basis for making a scientific plan for water resources utilization, but also the main basis for adjusting and optimizing its economic structure. It is of critical importance for the coordinated development of the socio-economic and resource environment of Beijing. Based on historical data, this paper conducted a quantitative analysis of the development rules and recent trends of the water consumption structure of Beijing, and predicted the water consumption structure of Beijing during the "13th five year plan" period (2015–2020).

According to the predicted results, the segments of agricultural, industrial, domestic, and environmental water use by 2020 will be in the range of between 6.11% and 12.31%, 5.01% and 7.39%, 37.48% and 43.28%, and 37.02% and 51.4% respectively. Forecasts based on forecast results, the VAR-DRHT give the most convincing results with the highest precision. According to the VAR-DRHT, the proportion of agricultural, industrial, domestic and of environmental water will be 6.11%, 5.01%, 37.48% and 51.4% by 2020.

This research found that agricultural and industrial water consumption will continue to decline as a proportion of the total water consumption structure of Beijing, while domestic water consumption will maintain at a stable level and the environmental water consumption proportion will significantly increase year by year to 2020. The transformation and upgrading of the city's economic structure as well as the further development of green environmental protection concepts are the main driving forces for the continuous optimization of the water consumption structure in Beijing. Meanwhile, the concept of inclusive development will further promote the coordination of Beijing's social development, economic development, environmental protection and utilization of water resources with each other, which will cause the water consumption structure in Beijing to be further optimized, narrowing the gap between it and advanced countries in the utilization of water resources. Concrete and viable policy recommendations are provided as follows to promote inclusive water governance.

(1) Improve the utilization rate of water resources and build a water recycling mechanism. Based on the concept of inclusive development, the development of a water resources saving society is per se to re-explore the new mechanism and new structure of social production from the perspective of recycling water resources. While gradually improving the allocation and delivery of water resources, Beijing should improve the potential for wastewater purification and reuse so that water resources can be utilized rationally and sustainably in the ongoing economic cycle.

(2) Improve the total amount of water consumption control and the quota management system. A monitoring and supervision mechanism should be established for water consumers who use more than 1000 m^3 in a year (Liu et al., 2003a, 2003b). This water control should be gradually implemented in districts, counties, towns, streets and at water consumers. Beijing should strictly control the total amount of water used, and guide the county to closely link the industrial layout with the total amount of water consumed, and promote the development of new and high technology to save water.

(3) Improving the macro-regulation and sectorial allocation of water resources. The rational use of water resources has a profound influence on economic development, social security and ecological reservations. In the face of the increasingly serious water crisis, many countries in the world are adopting water management to regulate and manage water demand, particularly for cities with a water scarcity (Stephenson, 1999). Beijing has conspicuously limited water resources, and the water supply has been overloaded for a long time. These government-led measures include mandatory standards for minimizing water use and water recycling efficiency, such as labeling for appliances, building codes etc. In addition, the government needs to integrate the water consumption indicators from various sectors into the macro-control system, and further optimize the allocation of water resources in different industries.

(4) Make water prices reasonable. Effective water demand management can be realized mainly through water price incentives. For a long time, due to the subsided low price of water, the "economic leverage" function of water pricing is absent in China. Therefore, it is imperative to establish a water pricing system that is adapted to the market economy mechanism. The government should set up market-oriented other than social welfare-based water prices to restrain the expansion of high water consumption industries, compress the use of agricultural irrigation water, promote the efficient utilization of environmental water, and ease the water contradictions among various sectors and stakeholders (Savenije and Van Der Zaag, 2002).

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