

Spatial econometric analysis on influencing factors of water consumption efficiency in urbanizing China

BAO Chao^{1,2,3}, CHEN Xiaojie^{1,2,3,4}

1. Institute of Geographic Sciences and Natural Resource Research, CAS, Beijing 100101, China;

2. Key Laboratory of Regional Sustainable Development Modeling, CAS, Beijing 100101, China;

3. College of Resources and Environment, University of Chinese Academy of Sciences, Beijing 100049, China;

4. China Urban Construction Design & Research Institute CO.LTD, Beijing 100120, China

Abstract: Due to the limitation of total amount of water resources, it is necessary to enhance water consumption efficiency to meet the increasing water demand of urbanizing China. Based on the panel data of 31 provinces in China in 1997–2013, we analyze the influencing factors of water consumption efficiency by spatial econometric models. Results show that, 1) Due to the notable spatial autocorrelation characteristics of water consumption efficiency among different provinces in China, general panel data regression model which previous studies often used may be improper to reveal its influencing factors. However, spatial Durbin model may best estimate their relationship. 2) Water consumption efficiency of a certain province may be influenced not only by its socio-economic and eco-environmental indicators, but also by water consumption efficiency in its neighboring provinces. Moreover, it may be influenced by the neighboring provinces' socio-economic and eco-environmental indicators. 3) For the macro average case of the 31 provinces in China, if water consumption efficiency in neighboring provinces increased 1%, water consumption efficiency of the local province would increase 0.34%. 4) Among the ten specific indicators we selected, per capita GDP and urbanization level of itself and its neighboring provinces have the most prominent positive effects on water consumption efficiency, and the indirect effects of neighboring provinces are much larger. Therefore, the spatial spillover effects of the economic development level and urbanization level are the primary influencing factors for improving China's water consumption efficiency. 5) Policy implications indicate that, to improve water consumption efficiency, each province should properly consider potential influences caused by its neighboring provinces, especially needs to enhance the economic cooperation and urbanization interaction with neighboring provinces.

Keywords: water consumption efficiency; water resources management; urbanization; spatial spillover effects; spatial Durbin model

Received: 2017-03-04 **Accepted:** 2017-06-13

Foundation: Major Projects of the National Natural Science Foundation of China, No.41590844; National Natural Science Foundation of China, No.41571156; Service Project on the Cultivation and Construction for the Characteristic Research Institute of the Chinese Academy of Sciences, No.TSYJS02

Author: Bao Chao (1978–), PhD and Associate Professor, specialized in urbanization and urban sustainable development.
E-mail: baoc@igsrr.ac.cn

1 Introduction

During rapid urbanization, China has confronted steady increase of water consumption in the past few decades (Bao and He, 2015). However, China's available water resources are limited and unevenly distributed (Jiang, 2009). Water scarcity and related eco-environmental degeneration have significantly hindered China's socio-economic development (Bao and Fang, 2007; Fang *et al.*, 2007; Li and Ma, 2014). Constrained by total water resources and increasingly difficult cross-regional water diversion, it is necessary to improve water consumption efficiency for the decoupling of economic growth and water resources utilization in China, especially in water scarce regions and urbanizing areas (Cai, 2008; Bao and Fang, 2012; Bao and Chen, 2015).

Chinese government has set up "The Most Stringent Water Management System" in January 2012 and established "red lines" of water consumption efficiency for each province. The growth rate of water consumption efficiency in China and each province should be larger than the standard which the Ministry of Water Resources of China has planned (Huang, 2015; Zang *et al.*, 2016). Many scholars have studied China's water consumption efficiency and relevant influencing factors by various methods, including stochastic frontier analysis (SFA), data envelopment analysis (DEA), slacks-based measure (SBM) model, undesirable and meta-frontier model, directional distance function, etc. (Kaneko *et al.*, 2004; Li and Ma, 2014; Sun *et al.*, 2014; Wang *et al.*, 2015; Ma *et al.*, 2016; Deng *et al.*, 2016). They have estimated the absolute or relative value of water consumption efficiency for China's provinces, and revealed the main influencing factors, including water resources endowment, water consumption structure, industrial structure, technical progress, economic development level, per capita education expense, etc.

However, the variation of China's water consumption efficiency is complex and the dominant influencing factors vary in different regions and development stages. Current studies seldom take the spatial interactions of water consumption efficiency and relevant influencing factors into consideration (Li and Ma, 2015). Most of them ignored the spatial spillover effects (Sun *et al.*, 2014). For example, we used "water consumption efficiency" (or "water use efficiency" or "water resources utilization efficiency") and "spatial spillover effect" (or "spatial effect" or "spatial interaction" or "spatial econometric") as topics (including Title, Abstracts and Keywords) to search literatures based on Web of Science - Science Citation Index Expanded (1900 to present) and Web of Science - Social Sciences Citation Index (1996 to present). There are only 20 results and two of them are related to China. In fact, water consumption efficiency of a certain province might be influenced not only by its socio-economic and eco-environmental indicators, but also by water consumption efficiency in its neighboring provinces. Moreover, it might be influenced by the neighboring provinces' socio-economic and eco-environmental indicators (Sun *et al.*, 2014; Li and Ma, 2015).

To address the above gaps and verify the above viewpoint, this paper explained spatial econometric models in Section 2, and applied them to investigate the spatial interactions between water consumption efficiency and its relevant influencing factors. Our empirical analysis used the panel data of 31 provinces in China during the period of 1997–2013 to examine the best appropriate model. Results and outcomes were presented in Section 3. Conclusions and implications were put forward in Section 4. It might help to thoroughly

understand the influencing factors of China's water consumption efficiency from a geographical perspective, and promote a more efficient use of water resources in urbanizing China.

2 Methodology and data sources

2.1 Spatial econometric methodology

Spatial econometric model emerged when econometrics turned to focus on spatial characters (Elhorst, 2010; Halleck and Elhorst, 2015). It originates general panel data regression model. However, the general panel data regression model can only reveal the relationship between the explained variable and the explanatory variable without considering the spatial spillover effects of the explained variable. When the explained variable has significant spatial spillover effects, if we use the general panel data regression model, the parameter estimated by ordinary least squares will be biased and inconsistent (Lesage and Pace, 2009). That's to say, the regression equation cannot pass the validity test. Under this circumstance, we may use spatial econometric model to resolve the problem.

Before constructing a spatial econometric model, we may judge the spatial dependence of the explained variable by spatial autocorrelation analysis preliminarily. If spatial dependence exists, we can use Lagrange Multiplier (LM) to test whether a model without any spatial interaction effect is better to describe the data than the spatial lag model or spatial error model. If the model without any spatial interaction effect is rejected, we can use Wald test or Likelihood Ratio (LR) test to judge whether spatial Durbin model can be simplified to spatial lag model or spatial error model. If it can't be simplified, it indicates that spatial Durbin model best describes the data, and we can use Hausman test or Likelihood Ratio (LR) test to judge whether a spatial Durbin model with spatial and/or time fixed or random effects is more appropriate (Lesage and Pace, 2009). The specific methods go as follows:

2.1.1 General panel data regression model

As for panel data, if they are stationary and cointegrated, a general panel data regression model can be used to reveal the relationship between the explained and explanatory variable, regardless of the spatial dependence. The general form is as follows:

$$y_{it} = \varphi + x_{it}\beta + c_i + \alpha_t + \varepsilon_{it} \quad (1)$$

where y_{it} is the explained variable in region i and period t ; x_{it} is the explanatory variable in region i and period t ; β is the regression coefficient of the explanatory variable, representing the influence of x_{it} on y_{it} ; φ is the constant term; c_i and α_t are the intercept term in region i and period t respectively; ε_{it} is the error term; $\varepsilon_{it} \sim N(\mu, \sigma^2)$. In spatial (or time) fixed effects model, c_i (or α_t) and ε_{it} are dependent. However, they are independent in spatial (or time) random effects model.

2.1.2 Spatial autocorrelation analysis

Spatial autocorrelation analysis is a useful method to describe the spatial dependence and spatial heterogeneity by panel data. If the variable has spatial autocorrelation characteristics, it indicates that a spatial econometric model is better to describe the data than a general panel data regression model. In 1950, Moran proposed Global Moran's I indicator based on spatial stochastic distribution phenomenon (Moran, 1950), which is widely used as an index to measure spatial autocorrelation (Lin and Wang, 2016). The specific calculation formula is as follows:

$$I_t = \frac{n}{\sum_{i=1}^n \sum_{j=1}^n w_{ijt}} \times \frac{\sum_{i=1}^n \sum_{j=1}^n w_{ijt} (x_{it} - \bar{x}_t)(x_{jt} - \bar{x}_t)}{\sum_{i=1}^n (x_{it} - \bar{x}_t)^2} \quad (2)$$

where I_t is the Global Moran's I index of the whole region in period t ; x_{it} is the research variable in region i and period t ; \bar{x}_t is the mean value of the research variable in period t ; n is the number of spatial units; w_{ijt} is the spatial weights matrix of region i and region j in period t , and if the i th and j th spatial units are neighboring, $w_{ijt} = 1$; if not, $w_{ijt} = 0$. I_t varies from -1 to 1. If it is above zero, it indicates a positive spatial autocorrelation. If it is less than zero, it indicates a negative spatial autocorrelation. If it is close to zero, it indicates that the research variable is randomly distributed. Furthermore, the bigger the absolute value of I_t is, the greater the spatial autocorrelation is.

2.1.3 Spatial econometric model

Spatial econometric models comprise spatial lag model (SLM), spatial error model (SEM) and spatial Durbin model (SDM) (Lesage and Pace, 2009; Lee and Yu, 2010). Specifically, spatial lag model contains the spatial lag term of the explained variable in general panel data regression model, which indicates the interaction effect of the explained variable in neighboring units on the explained variable in a specific unit. Spatial error model contains a spatial error term, which indicates the interaction effect of the explanatory variables in neighboring units on the explained variable in a specific unit. However, spatial Durbin model is a comprehensive form of them, and contains the spatial lag term of the explained variable and the spatial error term of the explanatory variables. The three kinds of spatial econometric models are expressed as follows (Elhorst, 2003, 2014):

$$y_{it} = \lambda \sum_{j=1}^N W_{ij} y_{jt} + \phi + x_{it} \beta + c_i + \alpha_t + \varepsilon_{it} \quad (3)$$

$$y_{it} = \phi + x_{it} \beta + c_i + \alpha_t + u_{it}, \quad u_{it} = \rho \sum_{j=1}^N W_{ij} u_{jt} + \varepsilon_{it} \quad (4)$$

$$y_{it} = \lambda \sum_{j=1}^N W_{ij} y_{jt} + \phi + x_{it} \beta + \sum_{j=1}^N W_{ij} x_{ijt} \theta + c_i + \alpha_t + \varepsilon_{it} \quad (5)$$

where λ is the spatial regression coefficient, which indicates the influence of the explained variable in neighboring spatial units (marked as y_n) on the explained variable in the local spatial unit (marked as y_s). If λ is significantly positive, it indicates that the improvement of the explained variable in a spatial unit may correspond with the improvement of this variable in other spatial units in the study area. u_{it} is the spatial autocorrelation error term; ρ is the spatial error coefficient, which indicates the influence of the spatial error term in neighboring spatial units (marked as u_n) on the spatial error term in the local spatial unit (marked as u_s); θ is the spatial lag term coefficient of the explanatory variable, which indicates the influence of the explanatory variables in neighboring spatial units (marked as x_n) on y_s ; N is number of spatial units; W_{ij} is spatial weights matrix, and if the i, j th spatial unit is neighboring, $W_{ij} = 1$; if not, $W_{ij} = 0$; the rest items are of the same as those noted in the general panel data regression model.

To judge whether the spatial lag model or spatial error model is better to describe the data, we may use LM test to examine the significance of the spatial lag effect and the spatial error effect. If one of them is significant while the other is not, we can choose the significant model. However, if both of them are significant or insignificant, we need apply the spatial Durbin model. Then we can use Wald test or LR test to test the hypotheses $H_0: \theta = 0$ and $H_0: \theta + \lambda\beta = 0$. From the first hypothesis, we can decide whether it can be simplified to the spatial lag model. From the second hypothesis, we can decide whether it can be simplified to the spatial error model. If both hypotheses are rejected, it cannot be simplified and we should use spatial Durbin model itself (Burridge, 1981; Elhorst, 2014).

2.1.4 Estimation of direct and indirect effect

From the formula of spatial Durbin model, we can see that the explained variable in the local spatial unit (marked as y_s) is mainly influenced by three factors. One is the explained variable in neighboring spatial units (marked as y_n). The second is the explanatory variables in the local spatial unit (marked as x_s). The third is the explanatory variables in neighboring spatial units (marked as x_n). Obviously, x_s can have direct influence on y_s ($x_s \rightarrow y_s$). It also can influence y_n and then influence y_s through spatial autocorrelation of y_n ($x_s \rightarrow y_n \rightarrow y_s$). These two kinds of combined effects which x_s has on y_s are named direct effect of the explanatory variables. Similarly, x_s can have direct influence on y_n ($x_s \rightarrow y_n$). It also can influence y_s and then influence y_n through spatial autocorrelation of y_s ($x_s \rightarrow y_s \rightarrow y_n$). These two kinds of combined effects which x_s has on y_n are named indirect effect of the explanatory variables, or spatial spillover effect of the explanatory variables.

In fact, direct and indirect effects are combined influences which the explanatory variables have on the explained variable through complex interaction. They are different from the regression coefficient of the explanatory variable $\beta(x_s \rightarrow y_s)$ and the spatial lag term coefficient $\theta(x_n \rightarrow y_s)$ in formula (5). Furthermore, spatial Durbin model can be adapted into the following formula (Lesage and Pace, 2009; Elhorst, 2014):

$$Y_t = (I - \lambda W)^{-1} \phi t_N + (I - \lambda W)^{-1} (X_t \beta + W X_t \theta) + (I - \lambda W)^{-1} \nu_t^* \quad (6)$$

where ϕt_N is the spatial error term; ν_t^* is the time error term with time and spatial effects. Thus, the partial derivative of the explained variable with respect to the k th explanatory variable at a particular point in time is as follows:

$$\left[\frac{\partial Y}{\partial x_{1k}} \quad \frac{\partial Y}{\partial x_{Nk}} \right] = (I - \lambda W)^{-1} \begin{bmatrix} \beta_k & w_{12}\theta_k & \cdot & w_{1N}\theta_k \\ w_{21}\theta_k & \beta_k & \cdot & w_{2N}\theta_k \\ \cdot & \cdot & \cdot & \cdot \\ w_{N1}\theta_k & w_{N2}\theta_k & \cdot & \beta_k \end{bmatrix} \quad (7)$$

In the above equation, the average of the diagonal elements of the matrix on the right-hand side is defined as the direct effect, and the average of either the row sums or the column sums of the off-diagonal elements of that matrix is defined as the indirect effect (Lesage and Pace, 2009; Elhorst, 2014).

2.2 Data sources and descriptive statistics

According to literature review and data availability, we use frequently used statistical indicators to represent water consumption efficiency and its influencing factors (Table 1). Spe-

cifically, water consumption efficiency is the explained variable. It is usually indicated by the economic output of per cubic meter water consumption, or the water consumption of per economic output. Normally, Chinese used to use water consumption per ten thousand yuan GDP to measure it. According to *China Water Resources Bulletin*, total water consumption is divided into four categories, such as water consumption for agriculture, water consumption for industry, water consumption for residents, and water consumption for eco-environment provided by artificial measures. Among them, water consumption for agriculture includes water consumption for farmland irrigation, water consumption for forestry, fishery and animal husbandry. Water consumption for residents includes domestic water for rural and urban residents. The influencing factors are the explanatory variables, including water resources endowment, water resources development level, economic development level, urbanization level, industrial structure optimization level, investment level, social consumption level, urban and rural income level, and agricultural development level, which are indicated by ten specific indicators (Table 1). It should be pointed out that water consumption per ten thousand yuan GDP is a negative indicator while others are positive indicators.

Table 1 The description or calculation of variables used in the present study

Variable	Description or calculation
Water consumption efficiency	Total water consumption / GDP
Per capita water resources	Total water resources / Total population
Utilization ratio of water resources	Total water consumption / Total water resources
Per capita GDP	GDP / Total population
Urbanization level	Urban population / Total population
Ratio of value added of the tertiary industry in GDP	Value added of the tertiary industry / GDP
Per capita total investment in fixed assets	Total investment in fixed assets / Total population
Per capita social retail sales of consumer goods	Social retail sales of consumer goods / Total population
Urban per capita disposable income	National sample survey data
Rural per capita net income	National sample survey data
Per capita grain yield	Total grain yield / Total population

Data of the above variables in 1997–2013 can be directly obtained or calculated based on *China Statistic Yearbook* and *China Water Resources Bulletin*. However, China’s population data have poor comparability among different periods and regions (Zhou and Yu, 2002). For higher comparability, we use the population data in China and its 31 provinces which were modified and forecasted by Shen (2006) and Fang *et al.* (2009). In addition, we use economic data in China and its 31 provinces at constant price in 1997.

3 Empirical results and outcomes

3.1 Confusing information of general panel data regression model

Before constructing the general panel data regression model, we use unit root test to check the stationarity of the panel data series (Dickey and Fuller, 1979). Results show that such indicators as water consumption per ten thousand yuan GDP, per capita water resources, utilization ratio of water resources, ratio of value added of the tertiary industry in GDP are

stationary series. Other indicators, including per capita GDP, urbanization level, per capita total investment in fixed assets, per capita social retail sales of consumer goods, urban and rural per capita disposable income, and per capita grain yield are non-stationary series. However, they are all stationary after being expressed in natural logs. Therefore, these indicators are all expressed in natural logs. Subsequently, we use cointegration test to check the cointegration relationship (Johansen and Juselius, 1990). Results show that there are cointegration relationships among these variables.

For a general panel data regression model, the selection of time or spatial form may have a strong effect on the simulation results. In the perspective of mathematic, unobserved effects in fixed effects model (c_i or α_i) are related to the error term (ε_{it}) because there are still unknown factors that influence the explained variable besides the observed ones. Consequently, the fixed effects model can only be used to describe the observed objects. The results cannot be expanded in spatial or time series. In contrast, unobserved effects in random effects model are independent to the error term because there are no other factors that influence the explained variable besides the observed ones. Consequently, the random effects model can be expanded in spatial or time series. Due to the particularity of each geographic unit, spatial fixed effects model tends to work better in spatial sequence. However, due to the continuity of socio-economic development in time series, time random effects model tends to work better. Therefore, we use the spatial fixed and time random form in the general panel data regression model.

The results of the general panel data regression model are listed in Table 2. It shows that, per capita water resources, utilization ratio of water resources and per capita social retail sales of consumer goods have significant positive effects on water consumption per ten thousand yuan GDP. However, urbanization level, per capita total investment in fixed assets and urban per capita disposable income have significant negative effects. Other indicators, including per capita GDP, ratio of value added of the tertiary industry in GDP, rural per capita net income and per capita grain production have no significant effects on water consumption efficiency.

Table 2 Results of general panel data regression model for water consumption efficiency in China

Variable	Regression coefficient	<i>t</i>
Intercept term	6934.39	5.85(0.0000)***
Per capita water resources	0.02	4.69(0.0000)***
Utilization ratio of water resources	0.86	5.01(0.0000)***
Per capita GDP	257.05	1.37(0.1698)
Urbanization level	-605.77	-2.52(0.0119)**
Ratio of value added of the tertiary industry in GDP	-2.68	-0.63(0.5316)
Per capita total investment in fixed assets	-183.01	-2.62(0.0090)***
Per capita social retail sales of consumer goods	199.55	2.21(0.0273)**
Urban per capita disposable income	-712.97	-3.79(0.0002)***
Rural per capita net income	46.32	0.29(0.7709)
Per capita grain yield	-108.18	-1.41(0.1606)

Note: *p* is listed in the bracket; ***, **, * denote level of significance at 1%, 5% and 10% respectively.

The above results are inconsistent with our qualitative cognition. In general, per capita GDP, which is positively correlated to urbanization level, per capita total investment in fixed

assets and per capita social retail sales of consumer goods, should have a significant positive effect on water consumption efficiency. However, when we used spatio-temporal mixed data, the results may be confusing and misleading because per capita GDP might be positively correlated to water consumption efficiency in time series while negatively correlated to water consumption efficiency in spatial series.

3.2 Spatial autocorrelation, spatial lag and spatial error effects test

We use Global Moran's *I* indictor to test spatial autocorrelation of water consumption efficiency for provincial China. Results show that Global Moran's *I* of China's water consumption efficiency fluctuated around 0.5. It indicates that water consumption efficiency has significant positive spatial autocorrelation among different provinces in 1997–2013, and water consumption efficiency in neighboring provinces may have a positive effect on itself. Therefore, it's necessary to build spatial econometric model to improve the accuracy of the general panel data regression model.

We use LM test and Robustness LM test to examine the spatial lag effects and the spatial error effects in four different forms, including time and spatial random effects, time random and spatial fixed effects, spatial random and time fixed effects, time and spatial fixed effects. The results are listed in Table 3. It shows that only the spatial error effects in the form of time and spatial random effects, spatial random and time fixed effects fail to pass the Robustness LM test. The spatial error and spatial lag effects in other forms all pass the LM test and Robustness LM test. Besides, the spatial lag effects are more significant than spatial error effects. Therefore, it's necessary to further propose a spatial Dubin model.

Table 3 Results of LM test with different spatial-specific and time-specific effects in China

Item	Time and spatial random effects	Time random and spatial fixed effects	Spatial random and time fixed effects	Time and spatial fixed effects
Spatial lag effect	41.11	71.73	30.43	16.33
LM test	(0.000)***	(0.000)***	(0.000)***	(0.000)***
Spatial lag effect	13.98	33.8	10.29	27.74
Robustness LM test	(0.000)***	(0.000)***	(0.001)***	(0.000)***
Spatial error effect	27.38	50.19	20.48	6.23
LM test	(0.000)***	(0.000)***	(0.000)***	(0.013)**
Spatial error effect	0.24	12.26	0.34	17.65
Robustness LM test	(0.621)	(0.000)***	(0.560)	(0.000)***

Note: *p* is listed in the bracket; ***, **, * denote level of significance at 1%, 5% and 10% respectively.

3.3 Best estimation of spatial Dubin model

We use Hausman test to examine the spatial Dubin model in four different forms, including time and spatial random effects, time random and spatial fixed effects, spatial random and time fixed effects, and time and spatial fixed effects. The results show that, spatial Dubin model with time and spatial random effects is rejected while spatial Dubin model with time and spatial fixed effects is acceptable. Spatial Dubin model with spatial random and time fixed effects is rejected while spatial Dubin model with time random and spatial fixed effects is acceptable. According to the results of Hausman test and empirical experience, we finally choose spatial Dubin model with time random and spatial fixed effects to estimate the

relationship between water consumption efficiency and relevant influencing factors. Subsequently, we use Wald test to examine the spatial Dubin model with time random and spatial fixed effects. Results show that it can't be simplified to spatial lag or spatial error model. Therefore, the spatial Dubin model with time random and spatial fixed effects best describes the data. The results are listed in Table 4.

Table 4 Results of spatial Dubin model with time random and spatial fixed effects in China

Variable	Regression coefficient		Lag term coefficient	
	β	t	θ	t
Spatial regression coefficient λ	0.34	6.20 (0.0000)***	—	—
Per capita water resources	0.01	3.35 (0.0008)***	0.01	0.81 (0.4152)
Utilization ratio of water resources	1.00	6.10 (0.0000)***	-1.65	-4.26 (0.0000)***
Per capita GDP	-456.17	-2.48 (0.0132)**	-2044.96	-5.75 (0.0000)***
Urbanization level	-186.48	-0.75 (0.0045)***	-976.51	-1.94 (0.0520)*
Ratio of value added of tertiary industry in GDP	-4.23	-1.01 (0.3114)	-24.1	-2.49 (0.0130)**
Per capita total investment in fixed assets	-115.88	-1.77 (0.0772)*	19.9	0.15 (0.8793)
Per capita social retail sales of consumer goods	-255.41	-3.05 (0.0023)***	79.76	0.46 (0.6488)
Urban per capita disposable income	-45.23	-0.17 (0.8640)	467.9	1.20 (0.2311)
Rural per capita net income	-117.76	-0.50 (0.6171)	1479.13	4.31 (0.0000)***
Per capita grain yield	-106.05	-1.25 (0.2104)	-431.69	-2.61 (0.0090)***

Note: p is listed in the bracket; ***, **, * denote level of significance at 1%, 5% and 10% respectively.

Firstly, the spatial regression coefficient λ is significantly positive. It indicates that water consumption efficiency in one province is obviously influenced by its neighboring provinces. At the same time, it also has obvious positive effects on water consumption efficiency in neighboring provinces. In other words, water consumption efficiency has obvious spatial spillover effects in provincial China. For the macro average case of the 31 provinces in China, if water consumption efficiency in neighboring provinces increased 1%, water consumption efficiency of the local province would increase 0.34%.

Secondly, the significant test of the regression coefficient β indicates that water consumption efficiency of each province in China is influenced by six indicators of itself, including per capita water resources, utilization ratio of water resources, per capita GDP, urbanization level, per capita total investment in fixed assets and per capita social retail sales of consumer goods. However, the other four indicators have no significant effect on water consumption efficiency in itself. From the values of the regression coefficient β of those six indicators which have significant effects, two indicators such as per capita water resources and utilization ratio of water resources have positive effects on water consumption per ten thousand yuan GDP, or have negative effects on water consumption efficiency. The other four indicators all have negative effects on water consumption per ten thousand yuan GDP, or have positive effects on water consumption efficiency.

Finally, the significant test of the lag term coefficient θ indicates that water consumption efficiency of each province in China is influenced by six indicators of its neighboring provinces, including utilization ratio of water resources, per capita GDP, urbanization level, ratio of value added of the tertiary industry in GDP, rural per capita net income and per capita grain yield. However, the other four indicators of its neighboring provinces have no signifi-

cant effect. From the values of the lag term coefficient θ of those six indicators which have significant effect, only rural per capita net income of its neighboring provinces has positive effects on water consumption per ten thousand yuan GDP, or has negative effects on water consumption efficiency. The other five indicators of its neighboring provinces all have negative effects on water consumption per ten thousand yuan GDP, or have positive effects on water consumption efficiency.

3.4 Direct and indirect effects of different influencing factors

To be mentioned, the regression coefficient β and the lag term coefficient θ only indicate the interaction effects which the observed indicators of the local province and its neighboring provinces have on water consumption efficiency of itself. The secondary interaction effects through spatial spillovers of water consumption efficiency are not considered. Therefore, based on the results of spatial Dubin model, we further calculate the direct and indirect effects of different influencing factors on China's water consumption efficiency. We listed the results in Table 5. From it, we can determine whether the direct and indirect effects are positive or negative according to the significance of their coefficients. We can also determine which kind of effects is larger according to their absolute values.

Table 5 Direct and indirect effects of different influencing factors on China's water consumption efficiency

Variable	Direct effects		Indirect effects	
	Coefficient	<i>t</i>	Coefficient	<i>t</i>
Per capita water resources	0.02	3.41 (0.0018)***	0.02	1.34 (0.1897)
Utilization ratio of water resources	1.23	5.41 (0.0000)***	-1.87	-3.32 (0.0023)***
Per capita GDP	-692.34	-1.56 (0.0012)***	-2701.77	-5.01 (0.0000)***
Urbanization level	-192.87	-1.08 (0.0028)***	-1513.65	-2.17 (0.0374)**
Ratio of value added of the tertiary industry in GDP	-12.12	-0.58 (0.5657)	-32.03	-2.19 (0.0362)**
Per capita total investment in fixed assets	-24.49	-1.67 (0.1042)	-25.68	-0.13 (0.8938)
Per capita social retail sales of consumer goods	-432.92	-3.1 (0.0041)***	-242.73	-0.98 (0.3358)
Urban per capita disposable income	-488.69	-0.09 (0.9266)	-656.44	1.28 (0.2092)
Rural per capita net income	448.58	0.02 (0.9863)	2052.82	4.81 (0.0000)***
Per capita grain yield	6.82	1.83 (0.0768)*	-679.06	-3.03 (0.0050)***

Note: *p* is listed in the bracket; ***, **, * denote level of significance at 1%, 5% and 10% respectively.

Specifically, we can see that only the direct and indirect effects of two indicators such as per capita GDP and urbanization level are significantly negative. It indicates that these two indicators have significantly positive effect on water consumption efficiency in both the local province and its neighboring provinces. Moreover, the absolute values of the indirect effects are much larger than that of the direct effects. On average, if the natural logs of per capita GDP in each province increased 1%, water consumption per ten thousand yuan GDP in the local province and its neighboring provinces would decrease 692.34% and 2701.77%, and that of the whole country would decrease 3394.11%. If the natural logs of urbanization level in each province increased 1%, water consumption per ten thousand yuan GDP in the local province and its neighboring provinces would decrease 192.87% and 1513.65%, and that of the whole country would decrease 1706.52%. It indicates that the spatial spillover

effects of these two indicators are primary influencing factors for the improvement of China's water consumption efficiency.

However, the direct and indirect effects of the other eight indicators are much different and complicated. The direct effect of per capita water resources is significantly positive while the indirect effect is insignificant. The direct effects of utilization ratio of water resources and per capita grain yield are significantly positive while the indirect effects are significantly negative. The direct effect of ratio of value added of the tertiary industry in GDP is insignificant while the indirect effect is significantly negative. The direct and indirect effects of per capita total investment in fixed assets and urban per capita disposable income are all insignificant. The direct effect of per capita social retail sales of consumer goods is significantly negative while the indirect effect is insignificant. The direct effect of rural per capita net income is insignificant while the indirect effect is significantly positive. Among these direct and indirect effects which are significant, the absolute values are all small. We can call these indicators as the secondary influencing factors.

4 Conclusions and implications

This study analyzes the influencing factors of water consumption efficiency in urbanizing China by spatial econometric models from the aspects of water resources endowment, water resources development level, economic development level, urbanization level, industrial structure optimization level, investment level, social consumption level, urban and rural income level and agricultural development level. We may get the following conclusions and policy implications:

(1) The spatial autocorrelation characteristics of water consumption efficiency among different provinces in China are significant. Therefore, the general panel data regression model which previous studies often used may be improper to reveal its influencing factors because it did not consider the spatial spillover effects of water consumption efficiency, and the results may be confusing and misleading. However, spatial econometric model may extract the significant factors more accurately because it considers the complicated spatial interaction effects. According to the results of LM test, Hausman test and Wald test, the spatial Dubin model with time random and spatial fixed effects can provide the optimal estimation on influencing factors of water consumption efficiency in urbanizing China.

(2) China's water consumption efficiency has obvious spatial spillover effect. In other words, water consumption efficiency in each province is significantly influenced by water consumption efficiency of its neighboring provinces. On the other hand, water consumption efficiency in each province may significantly influence the water consumption efficiency of its neighboring provinces. For the macro average case of the 31 provinces in China, if water consumption efficiency in neighboring provinces increased 1%, water consumption efficiency of the local province would increase 0.34%. Therefore, to control the "red line" of water consumption efficiency, each province should properly consider potential influence caused by its neighboring provinces, and a unified water resources management system among different provinces should be further strengthened.

(3) China's water consumption efficiency in local province is significantly influenced by some specific socio-economic and eco-environmental indicators of itself and its neighboring

provinces. Among the ten specific indicators we selected, per capita GDP and urbanization level of itself and its neighboring provinces have the most prominent positive effects on water consumption efficiency, and the indirect effects of neighboring provinces are much larger. Therefore, the spatial spillover effects of the economic development level and urbanization level are the primary influencing factors for improving China's water consumption efficiency. Moreover, though some of the direct or indirect effects of the other eight indicators are significant, the absolute values are all small. These indicators are the secondary influencing factors. On the whole, beyond water itself, a coordinated socio-economic development strategy among different provinces should also be strengthened. Especially, enhancing the economic cooperation and urbanization interaction with neighboring provinces may help to improve water consumption efficiency in each province.

However, though we have detected the positive/negative and direct/indirect effects of the influencing factors on water consumption efficiency in urbanizing China, we cannot reveal the essential reason behind it at present. The specific and practical interaction mechanism still remains to be studied in the future. Meanwhile, we just showed an application of spatial econometric model, and did not consider some technical matters such as elimination of the multicollinearity and endogeneity. Besides, due to the availability of data, some important indicators may be missing, such as agricultural modernization level, informatization level and education level. If data is available in the future, the influencing factors could be identified more accurately.

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