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Spatial Differences and Influencing Factors of Urban Water Utilization Efficiency in China

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The purpose of urban water management is to improve urban water utilization efficiency (UWUE), which in turn addresses water shortages in urban areas. The present study aimed to evaluate the UWUE of 284 cities at the prefecture level in China between 2003 and 2018 by the slacks-based measure of super-efficiency, explore its spatial differences through exploratory spatial data analysis, and analyze the influencing factors using the statistical tool Geodetector. The results showed that the average value of UWUE in China was generally low but tended to rise gradually. There were significant spatial differences in UWUE across China, with considerable global and local spatial autocorrelation, and local spatial autocorrelation was characterized primarily by high-high and low-low regions. Industrial structure and urban population were the main influencing factors for UWUE. Finally, based on these findings, we offered policy implications for improving UWUE and coordinated development between cities.

Keywords: urban water utilization efficiency, spatial difference, influencing factor, slacksbased measure of super-efficiency, exploratory spatial data analysis, geodetector

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1 INTRODUCTION

According to a report by the Food and Agriculture Organization of the United Nations, with the rapid growth of the global population, the per capita supply of freshwater resources has decreased by over 20% in the past 20 years (Cazcarro and Steenge 2021). Global water consumption has increased sixfold in the past 100 years and has grown at an annual rate of about 1%. It is estimated that by 2050, more than half of the world's population will face water shortages (Liao et al., 2021). Affected by natural conditions and continued economic development, China also sustains a severe shortage of water resources (Deng et al., 2021). On the one hand, uneven spatial and temporal distributions, mismatches between supply and demand, the lack of public awareness of water conservation, and extensive use of water resources pose a massive challenge to the "ecological civilization" and sustainable development (Liu et al., 2022). On the other hand, China *per se* is extremely short of urban water resources, as evidenced by water shortages in nearly all provincial capitals. More than 400 out of the 660 cities in China are short of water, of which 110 are facing grievous situations (Huang Y. et al., 2021). Water utilization efficiency (WUE) refers to the ratio of the optimal input of water resources to their actual input required by economic and social demands, namely, the economic value of products manufactured per unit of water consumption (Sileshi et al., 2020). In the situation of water shortage, improving the WUE is of great significance in two aspects. First, the improvement of WUE means improving the intensive and economical utilization of water resources, which helps to reduce the waste of water resources and realize the sustainable utilization of water resources. Second, the improvement of WUE means increasing the economic output per unit of water consumption, which is helpful to further improve economic benefits. Therefore, improving China's urban water utilization efficiency (UWUE) may be a pivotal solution to water shortages in cities.

Most previous studies have focused on WUE, while little attention has been directed to UWUE. These studies favor industry sectors and regions as the object of WUE evaluation, especially agriculture and industry. Since water plays a crucial role in maintaining agricultural security, improving agricultural WUE becomes an important means of promoting sustainable agricultural development (Namaalwa et al., 2020; Liu et al., 2021). The consumption of water resources has been increasing with industrialization, and improving WUE may play an essential part in developing a system of green industrial production. For this reason, researchers have made efforts to find a way to increase industrial WUE (Shang et al., 2017; Liu et al., 2020a; Liu et al., 2020b). Previous studies on the spatial differences in WUE have focused on provincial administrative units or the overall situation across China. In addition, attention has also been paid to the WUE in strategic regions, such as the Yellow River Basin (Guan et al., 2016), the Yangtze River Basin (Pan et al., 2020), and the Tibetan Plateau (Cheng et al., 2021).

Four methods have been used to calculate WUE in previous studies: 1) water footprint (Cao et al., 2021); 2) comprehensive indicator evaluation (Zhang et al., 2019; Song et al., 2020); 3) single factors (Li et al., 2008); and 4) the total factor of WUE (Hu et al., 2006; Shi et al., 2021; Liu et al., 2022), such as stochastic frontier analysis (SFA) and data envelopment analysis (DEA). The first three simple methods cannot reflect the dependency of the output of the production process on multiple factors. It is vital to take into consideration the inputs of factors other than investment in water resources when calculating WUE. Compared with SFA, DEA does not require the basic functional form and gives consideration to a variety of inputs and outputs. It thus has significant advantages in the measurement of efficiency.

WUE is the result of multiple factors. Some researchers have been concerned with single factors, such as environmental regulation (Wang and Wang 2021), the fattening period in animal husbandry (Huong et al., 2020), and national policies on WUE (Zhang et al., 2020; Zhang et al., 2021). Other researchers have examined the effects of multiple factors. According to them, positive factors included dependence on exports (Deng et al., 2016), technical progress and educational value (Wang G. et al., 2018), government behavior (Yang et al., 2020), economic growth, urbanization, and effective irrigation (Lu et al., 2021). Conversely, negative factors were agricultural added value, per capita water consumption, and unit output of sewage (Deng et al., 2016), industrial structure (Wang S. et al., 2018), population pressure (Yang et al., 2021), and per capita water resources (Lu et al., 2021). Some studies focused on the agricultural sector for resources utilization (Elahi et al., 2021a; Elahi et al. 2021b; Elahi et al.2022a; Elahi et al.2022b).

The above-referenced studies contribute knowledge to the spatial pattern and genesis of WUE at the provincial scale and provide a reference for policymaking. However, little attention has been paid to the WUE of cities (UWUE). Cities are highly populated and economically concentrated areas that consume large water volumes for both domestic and industrial purposes. In other words, the research on UWUE is of great significance. In the present study, we evaluated the UWUE of 284 cities at the prefecture level in China using the slacks-based measure (SBM) of super-efficiency based on unexpected output. On this basis, we also explored the spatial differences in UWUE by exploratory spatial data analysis (ESDA) as well as the influencing factors with the statistical tool Geodetector. The contributions of this study to the existing literature include: 1) The research object of cities rather than provinces can enrich the research content of WUE. 2) Cities are smaller than provinces, and the spatial differences in UWUE between them can reflect the spatial pattern of WUE more accurately. 3) The influencing factors of UWUE at the prefecture level can provide more empirical evidence for UWUE and offer a reference for policymaking.

2 METHODS AND DATA

Methods

2.1.1 Slacks-Based Measure of Super-efficiency

Since DEA focuses only on the expected output of economic activities and ignores unexpected output, its results may be biased (Liu et al., 2010). As such, SBM based on unexpected output was used to calculate UWUE in China, which took into consideration the unexpected output in the production process (Tone 2001). The specific procedures are described as follows:

Suppose there are n decision-making units (DMUs) in the production system. Each unit is composed of three input–output vectors: 1) input, 2) an expected output, and 3) an unexpected output. The three input–output vectors can be expressed as:

$$\mathrm{X} = [x_1,\ x_2,\ \ldots, x_n] \in R^{m\times n} \tag{1}$$

$$Y^g = \left[y_1^g, y_2^g,\ \ldots, y_n^g\right] \in R^{s_1\times n} \tag{2}$$

$$Y^b = \left[y_1^b, y_2^b,\ \ldots, y_n^b\right] \in R^{s_2\times n} \tag{3}$$

Suppose $X > 0$, $Y^g > 0$, and $Y^b > 0$. Then, the set of possibilities of production can be defined as:

$$P = \left\{\left(x, y^g, y^b\right) \middle| x \geq X\theta,\ y^g \geq Y^g\theta,\ y^b \leq Y^b\theta,\ \theta \geq 0\right\} \tag{4}$$

The actual expected output is lower than the ideal expected output of the frontier, while the actual unexpected output is higher than the unexpected output. Based on the set of production possibilities, the SBM model that considers the unexpected output in the DMU of evaluation $(x_0,\ y_0^g,\ y_0^b)$ is as follows:

$$\rho = \min \frac{1 - \frac{1}{m}\sum_{i=1}^{m} S_i^- / x_{i0}}{1 + \frac{1}{S_1 + S_2}\left(\sum_{r=1}^{S_1} S_r^g / y_{r0}^g + \sum_{r=1}^{S_2} S_r^b / y_{r0}^b\right)}\ s.t. \begin{cases} x_0 = X\theta + S^- \\ y_0^g = Y^g\theta - S^g \\ y_0^b = Y^b\theta - S^b \\ S^- \geq 0,\ S^g \geq 0,\ S^b \geq 0,\ \theta \geq 0 \end{cases} \tag{5}$$

In the formula, $S = (S^-, S^g, S^b)$ = the slacks in input, expected output, and unexpected output, respectively; ρ = the efficiency of the DMU (0-1). For a given DMU (x_0, y_0^g, y_0^b), if and only if $\rho = 1$, that is, when $S^- = S^g = S^b = 0$, it is effective; if $0 \le \rho < 1$, the evaluated unit is inefficient, and the input and output need to be improved. This nonlinear model is not conducive to the calculation of efficiency. Therefore, it was transformed into a linear model by the Charnes-Cooper transformation:

$$\tau = \min t - \frac{1}{m}\sum_{i=1}^{m}\frac{S_i^-}{x_{i0}},\ \text{s.t.}\begin{cases} 1 = t + \dfrac{1}{S_1 + S_2}\left(\sum_{r=1}^{S_1}\dfrac{S_r^g}{y_{r0}^g} + \sum_{r=1}^{S_2}\dfrac{S_r^b}{y_{r0}^b}\right) \\ x_0 t = X\mu + S^- \\ y_0^g t = Y^g\mu - S^g \\ y_0^b t = Y^b\mu - S^b \\ S^- \ge 0,\ S^g \ge 0,\ S^b \ge 0,\ \mu \ge 0,\ t > 0 \end{cases} \tag{6}$$

Most indicators used to assess efficiency involve a common phenomenon that the DMUs have 100% efficiency. It is necessary to distinguish these DMUs and the factors affecting the efficiency ranking. To ensure that the efficiency analysis yields reasonable values, SBM of super-efficiency was used for calculation in the present study:

$$\rho^* = \min \frac{\frac{1}{m}\sum_{i=1}^{m}\frac{\overline{x_i}}{x_{i0}}}{\frac{1}{S_1 + S_2}\left(\sum_{r=1}^{S_1}\bar{y}_r^g/y_{r^0}^g + \sum_{r=1}^{S_2}\bar{y}_r^b/y_{r^0}^b\right)}$$

$$s.t.\begin{cases} \bar{x} \ge \sum_{j=1,\ne k}^{n}\theta_j x_j \\ \bar{y}^g \le \sum_{j=1,\ne k}^{n}\theta_j y_j^g \\ \bar{y}^b \ge \sum_{j=1,\ne k}^{n}\theta_j y_j^b \\ \bar{x} \ge x_0,\ \bar{y}^g \le y_0^g,\ \bar{y}^b \ge y_0^b,\ \bar{y}^g \ge 0,\ \theta \ge 0 \end{cases} \tag{7}$$

The value of the objective function ρ^* represents the efficiency of the DMU. The definitions of the other variables are the same as those used in **Eq. 6**. The above models are based on the assumption that the scale is constant.

2.1.2 Exploratory Spatial Data Analysis

ESDA is a collection of spatial data analysis techniques used to describe the spatial distribution of data and express it visually. It can explain spatial differences in data and reveal the mechanism of spatial interaction between phenomena (Messner et al., 1999; Dong et al., 2021). ESDA takes use of global Moran's I and local Moran's I, and the former can express the spatial distribution of UWUE in an entire region. If global Moran's I is >0, the research object has a positive spatial autocorrelation, and the larger the value, the stronger the spatial agglomeration. It was calculated as follows:

$$I = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n}W_{ij}(x_i - \bar{x})(x_j - \bar{x})}{S^2\sum_{i=1}^{n}\sum_{j=1}^{n}W_{ij}} \tag{8}$$

$$S = \frac{1}{n}\sum_{i=1}^{n}(x_i - \bar{x})^2 \tag{9}$$

In the formula, n = the number of units in the research area; x_i and y_j = the UWUEs of units i and j; $\bar{x}$ = the average of all units; Wij = the spatial weight matrix of units i and j. If i and j have a boundary in common, $Wij = 1$; otherwise, $Wij = 0$. The standardized statistic was used to test the significance as follows:

$$Z(I) = \frac{[1 - E(I)]}{\sqrt{Var(I)}} \tag{10}$$

Wherein, $Z(I)$ = significance; $E(I)$ = mathematical expectation; $Var(I)$ = variance.

Local Moran's I expresses the spatial heterogeneity of UWUE in subregions of a given region. Combined with the scatter diagram and local Moran's I, the local indicators of spatial association (LISA) clustering map can directly show the types of clustering and significance levels of different elements, as given in **Eq. 11**:

$$I_i = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n}W_{ij}(x_i - \bar{x})(x_j - \bar{x})}{S^2} \tag{11}$$

The significance of local Moran's I is given in **Eq. 11**. By comparing the signs of $Z(I)$ and the significance levels of I_i, the research area whose significance levels reach a certain threshold ($p = 0.05$) can be divided into four types of spatial autocorrelation. If I_i is significantly positive and $Z(I) > 0$, it is a "high-high" type, which means that the UWUEs of the given city and its adjacent cities are high, and they are designated as "hot spots". If I_i is significantly positive and $Z(I) < 0$, it is a "low-low" type, which means that the UWUEs of the given city and adjacent cities are low, and they are "cold spots". If I_i is significantly negative and $Z(I) > 0$, it is a "high-low" type, suggesting that cities with high UWUE are surrounded by cities with low UWUE. If I_i is significantly negative and $Z(I) < 0$, it is a "low-high" type, indicating that cities with low UWUE are surrounded by cities with high UWUE. If I_i is significantly positive, this illustrates a significant local spatial positive correlation, reflecting spatial aggregation. If I_i is significantly negative, this indicates a significant local spatial negative correlation, reflecting spatial dispersion.

2.1.3 Geodetector

The Geodetector makes no linear hypothesis and has an elegant form and a clear physical meaning (Wang et al., 2010). The q-statistic can be used to measure spatial differentiation, detect explanatory factors, and analyze the interaction between variables. It has been widely used to explore the influencing factors for resources and the environment (Zhou et al., 2019; Huang C. et al., 2021; Wei et al., 2021). In the present study, it was calculated as follows:

$$P_{D,UWUE} = 1 - \frac{1}{n\sigma_{UWUE}^2}\sum_{i=1}^{m}n_{D,i}\sigma_{UWUE_{D,i}}^2 \tag{12}$$

In the formula, $P_{D,UWUE}$ = the driving force of UWUE; D = the factor driving UWUE; n = sample size; σ^2 = the variance of the research objects; m = the number of categories of a factor; $n_{D,i}$ =

TABLE 1 | Descriptive statistics of the indicators of UWUE.

Indicator	Variable	Units	Sample Size	Mean	Median	Standard Deviation	Maximum	Minimum
Input	Investment in fixed assets	10,000 yuan	4544	10,811,319.65	5983936	14,631,539.37	186,614,099	165,672
	Total water supply	10,000 tons	4544	16,227.79	7043.5	31,166.22	320,400	349
	Number of employees in urban areas	10,000 persons	4544	31.93	14.135	65.90	819.3	1.02
Expected output	GDP	10,000 yuan	4544	16,356,025.63	8533802.5	26,162,615.89	326,798,700	317,731
Unexpected output	Wastewater discharge	10,000 tons	4544	7530.26	5617.5	6552.85	30,081	88

the samples size of indicator D in class i. The range of values of $P_{D,UWUE}$ is [0, 1]. The larger the value, the stronger the explanatory power of this factor for UWUE. A value of zero indicates that the given factor has nothing to do with UWUE, and a value of one means that the relevant factor can fully explain UWUE.

Indicators

Indicators need to be determined to assess UWUE in China from the perspectives of input, expected output, and unexpected output. Capital, resources, and labor force required in economic production yield not only expected outputs such as economic growth and income but also unexpected outputs such as resource consumption and environmental pollution. Some researchers have investigated the characteristics of water resources utilization in economic production (He et al., 2020). In light of the availability and comparability of data, capital, water resource, and labor force were taken into consideration as the input-related indicators of UWUE and were expressed as the investment in fixed assets, total water supply, and the number of employees in urban areas, respectively. Economic growth was regarded as an indicator of the expected output of UWUE and expressed as the gross domestic product (GDP). Wastewater discharge was deemed as an indicator of the undesirable outputs of UWUE and expressed as industrial wastewater discharge. **Table 1** shows the descriptive statistics of the UWUE indicators.

Source of Data

The data of the five indicators were all derived from China's Economic and Social Big Data Research Platform (https://data.cnki.net/). There are totally 333 cities above the prefecture level in China. Since the data of some cities in central and western China were unavailable, 284 of them were finally included in this study.

3 RESULTS

The Evolution of UWUE in China

SBM of super-efficiency was employed to assess UWUE in China between 2003 and 2018, as shown in **Figure 1**, which showed two prominent characteristics. First, the overall UWUE of Chinese cities during this period was low. As previously described in Wang et al. (2020), 0.6 was used as the standard to gauge efficiency. The year of 2018 saw the maximum number of cities (82) with a UWUE >0.6, accounting for 28.9% of the 284 cities. 2006 and 2007 witnessed the minimum number of cities (10) with a UWUE >0.6, accounting for only 3% of the total. Only a few cities in China had high UWUEs, suggesting that there is considerable room for improvement in UWUE. This result was consistent with the results of other research on WUE efficiency (Liu et al., 2022). The fundamental reason for this is that the long-term rapid economic growth in China depends on the traditional growth model featuring extensive investment of resources, labor, and other factors. This inefficient model consumes huge water resources and produces large volumes of wastewater discharge, thereby resulting in a low overall UWUE in China.

Second, the overall UWUE appeared to be on the rise during the research period. This phenomenon can be described more concisely and directly by dividing the cities into regions and scales. China's regional economic layout can be divided into four regions: eastern China, central China, western China, and Northeastern China (**Table 2**.) (Li and Liu 2020). The evolution of the average UWUEs in China and its four regions is illustrated in **Figure 2**, which shows a fluctuating upward trend from 2003 to 2015, with slight declines in some years. After 2015, UWUE rose significantly, possibly because the government decided to promote the "ecological civilization" ever since for resource conservation and environmental protection. According to the scale type of the resident population, Chinese cities can be divided into five types: super megacity, megacity, large-scale city, medium-scale city, and small-scale city (Qi et al., 2016). The city-size classification standard in China is listed in **Table 3**. The average UWUEs of different scales are illustrated in **Figure 3**, indicating that the UWUEs of different scales tended to increase. Since 2008, the UWUE in super megacities has maintained the highest level for a long time. The possible reasons are as follows: First, the developed technology of super megacities is conducive to improving the level of economical and intensive utilization of water resources; Second, super megacities have a higher degree of population and economic agglomeration, which can bring significant agglomeration benefits in the process of water resources utilization. The UWUE in large-scale cities has remained at the lowest level in recent years. The possible reason is that there is a high demand for water resources due to the large population and economic scale, but the technical level and agglomeration effect have not been brought into play, resulting in the low level of UWUE.

ArcGIS 10.2 was used to test global spatial agglomeration, which demonstrated that global Moran's I was positive and

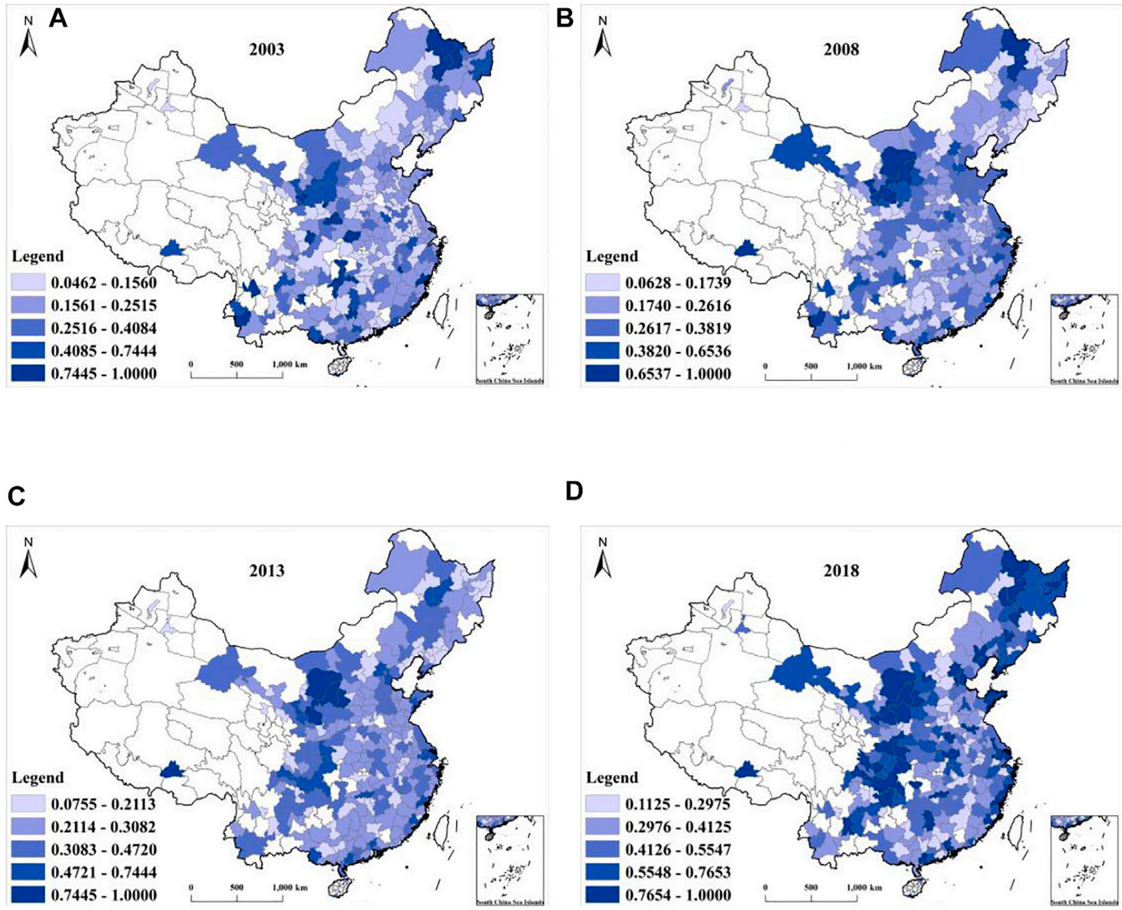

FIGURE 1 | China's UWUEs between 2003 and 2018. **(A)** 2003; **(B)** 2008; **(C)** 2013; **(D)** 2018. Note: This figure shows only the results of 4 years, and the others can be seen in **Supplemental Materials**.

TABLE 2 | Four regions in China.

Regions	Provinces (Municipality Directly under the Central Government, Autonomous Region)
Eastern China	Beijing, Tianjin, Hebei, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong, and Hainan
Central China	Shanxi, Anhui, Jiangxi, Henan, Hubei, and Hunan
Western China	Inner Mongolia, Guangxi, Chongqing, Sichuan, Guizhou, Yunnan, Tibet, Shaanxi, Gansu, Qinghai, Ningxia, and Xinjiang
Northeastern China	Liaoning, Jilin, and Heilongjiang

passed the 1% significance test (**Table 4**). The UWUE across China was similarly characterized by spatial agglomeration, which could be used to identify hot and cold spots. The overall global Moran's I increased, indicating that spatial agglomeration of UWUE in China was becoming increasingly prominent.

ArcGIS 10.2 also demonstrated that UWUE was characterized by remarkable local spatial autocorrelation (**Figure 4**). This result was also consistent with the findings of other research on WUE efficiency (Liu et al., 2022). The relevant regions can be divided into the four types mentioned above. Together, the high-high and low-low regions accounted for more than 60% of all cities in each year and more than 70% throughout the research period. The high-high cities were distributed mainly in northwestern, northeastern, and southwestern China, while the urban agglomerations of Beijing-Tianjin-Hebei, the Yangtze River Delta, and the Pearl River Delta were scattered in individual years. The low-low cities were distributed mainly in northeastern and central China. The results of both global and local spatial autocorrelation showed that there were significant spatial differences in UWUE across China.

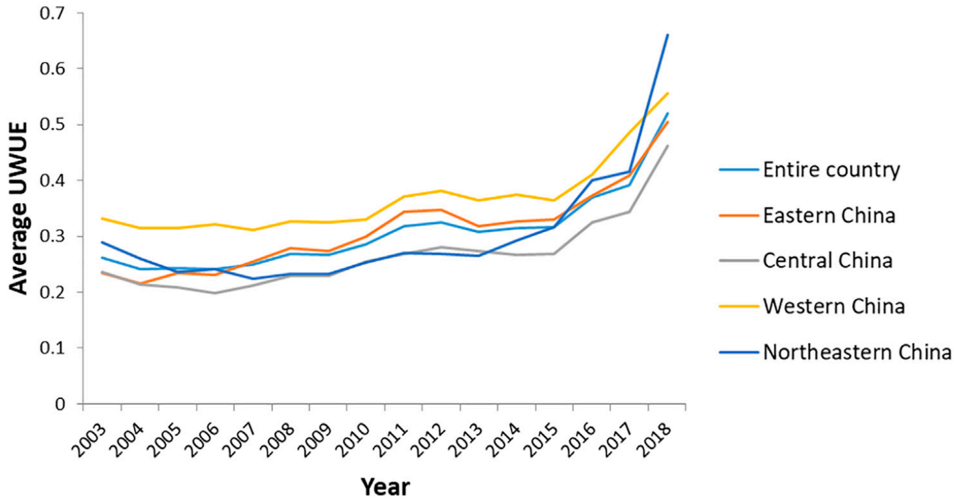

FIGURE 2 | Average UWUEs in China and its four regions.

TABLE 3 | City-size classification standard in China.

Type of City	Super Megacity	Megacity	Large-Scale City	Medium-Scale City	Small-Scale City
Resident population	≥1 million	(5 million, 10 million)	(1 million, 5 million)	(0.5 million, 1 million)	<0.5 million

Spatial Differences in UWUE.

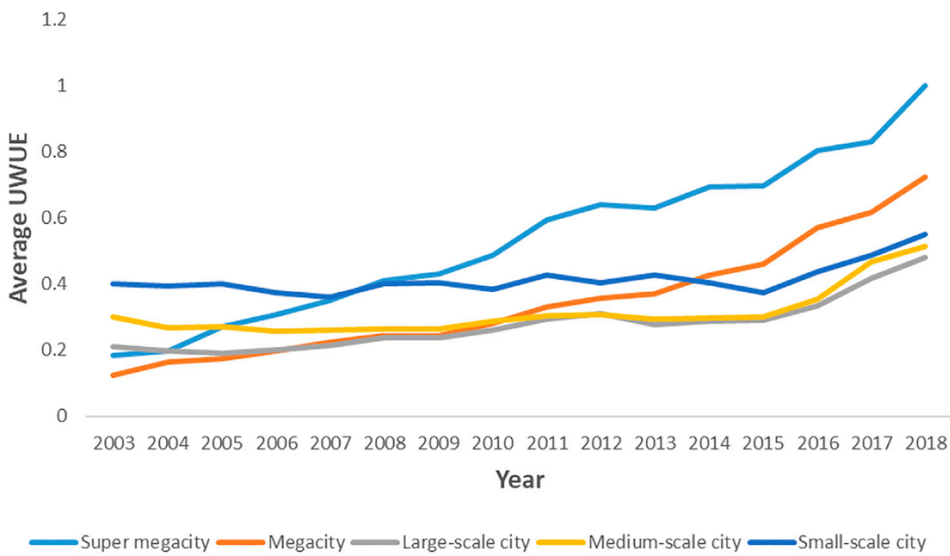

FIGURE 3 | Average UWUEs of different scales of cities.

Influencing Factors for UWUE

WUE is affected by various economic, social, and natural factors. With reference to a previous study (Babuna et al., 2020), in the present study, urban population, industrial structure, resident income, technological progress, the volume of surface water, and environmental regulation were selected as the potential influencing factors for UWUE and justified as follows.

1) Urban population. This is a frequently used indicator of urbanization. The larger the indicator, the higher it can drive the growth of urban consumption, which improves

TABLE 4 | Global spatial autocorrelation of UWUE in China.

Year	Moran's *I*	*Z*	*p* value
2003	0.151	6.45	0.000000
2004	0.158	7.85	0.000000
2005	0.146	8.59	0.000000
2006	0.174	8.40	0.000000
2007	0.205	7.66	0.000000
2008	0.226	7.87	0.000000
2009	0.186	9.21	0.000000
2010	0.208	8.29	0.000000
2011	0.301	7.55	0.000000
2012	0.324	8.98	0.000000
2013	0.284	7.60	0.000000
2014	0.255	8.94	0.000000
2015	0.303	7.71	0.000000
2016	0.205	6.39	0.000000
2017	0.234	7.47	0.000000
2018	0.298	6.70	0.000000

the input and output of the economy. However, a larger urban population also entails excessive consumption of water resources, which in turn affects UWUE (Meng et al., 2021). It is expressed as the number of people residing in a given urban area.

2) Industrial structure. The state of industrial structure is an important indicator of economic growth. Different industrial structures lead to significant differences in economic output, water consumption, and wastewater discharge, which in turn affect UWUE (Zhu and Zhang 2021). It is expressed as the share of the secondary industry.
3) Resident income. Resident income promotes the input and expected output of UWUE but may also impact the unexpected output. With increasing resident income, residents are more aware of the need to save water, which reduces the discharge of industrial wastewater. However, this also increases demand for products, which increases the discharge of industrial wastewater (Liu L. et al., 2020). Resident income is expressed as the per capita disposable income of urban residents.
4) Technological progress. This is not only the result of economic growth but also its cause, and affects the input and expected output of UWUE. Technological progress affects industrial wastewater discharge from two aspects: technological innovation in industrial production can reduce the amount

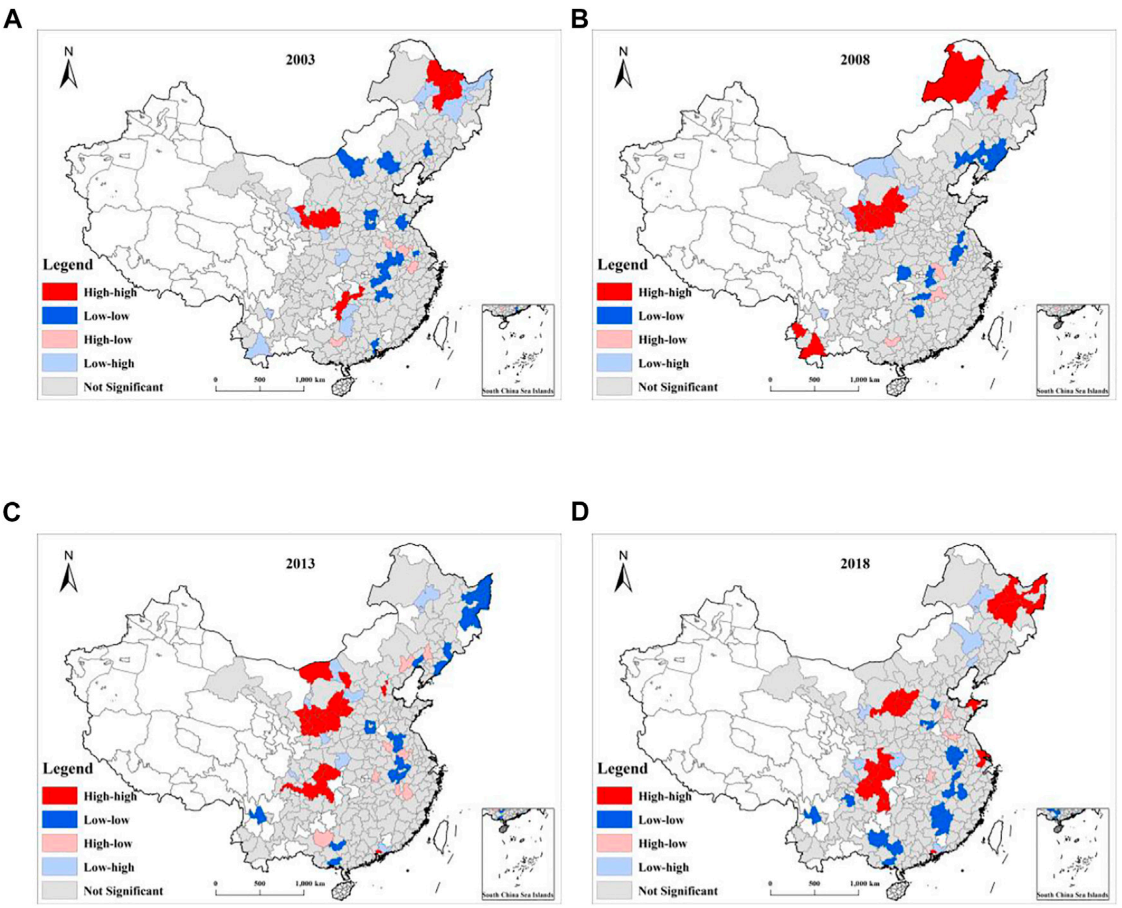

FIGURE 4 | Local spatial autocorrelation of UWUE in China between 2003 and 2018. **(A)** 2003; **(B)** 2008; **(C)** 2013; **(D)** 2018. Note: This figure shows only the results of 4 years, and the others can be seen in **Supplemental Materials**.

TABLE 5 | Analysis of UWUE using Geodetector.

Year	Urban Population	Industrial Structure	Resident Income	Technological Progress	Volume of Surface Water	Environmental Regulation
2003	0.2206	0.3111	0.0017	0.1242	0.0013	0.0022
2004	0.2331	0.4662	0.0012	0.1097	0.0012	0.0018
2005	0.2192	0.4563	0.0014**	0.1052	0.0004	0.0018
2006	0.2172	0.5030	0.0013	0.1124	0.0005	0.0012
2007	0.2533	0.5617	0.0012	0.1002	0.0003	0.0039**
2008	0.2512	0.5822	0.0012	0.0935	0.0016	0.0029
2009	0.2655	0.6406	0.0019	0.1005**	0.0012	0.0033**
2010	0.2824	0.6011	0.0018	0.1017**	0.0014	0.0028
2011	0.2811	0.6782	0.0017	0.0958**	0.0013	0.0037
2012	0.2316	0.6908	0.0004***	0.0870	0.0015	0.0041
2013	0.2582	0.7205	0.0003	0.0807	0.0012	0.0022
2014	0.2312	0.7536	0.0004	0.0924**	0.0008	0.0027
2015	0.2512	0.7779	0.0002	0.0967**	0.0013	0.0021
2016	0.2880	0.7705	0.0008	0.0877	0.0017	0.0030**
2017	0.2662	0.7834	0.0007	0.0855	0.0006	0.0034
2018	0.3436	0.7991	0.0011	0.0939	0.0011	0.0037

*Note: ** and ***represent significance at levels of 10 and 5%, respectively; the other values are significant at the 1% level.*

of discharged wastewater, and technological progress may lead to expansion of production and an increase in wastewater discharge (Chen Z. et al., 2021). In this study, the number of patent applications was used to represent technological progress.

5) The volume of surface water. This is a natural factor affecting UWUE. Under the same conditions, the greater the volume of surface water, the greater the total volume of water supply in a city (Song et al., 2021). It is expressed as the volume of surface water in a given urban area.
6) Environmental regulation. The purpose of environmental regulation is to protect the environment, improvements in which can save water and thus improve UWUE (Fu et al., 2021). It is expressed as the amount of investment in environmental pollution control.

Table 5 shows the analysis results of the six indicators pertaining to UWUE in China with Geodetector. Industrial structure and urban population made significantly greater contributions to UWUE than the other four factors, hence the primary influencing factors for UWUE. Technological progress played a role, while resident income, the volume of surface water, and environmental regulation had little impact on UWUE. This differed from the influencing factors of agricultural WUE, namely, technological progress and farmers' income (Liu et al., 2022).

With respect to urban industrial structure in China, 125 out of the 284 cities studied were dominated by secondary industry in 2018. The structure of urban industry had been dominated by secondary industry for a long time and was in the middle of rapid industrialization. An inverted U-shaped relationship was observed between water consumption and economic growth in different stages of industrialization, where this was commonly known as the environmental Kuznets curve. Rapid industrialization with respect to industrial structure led to increased consumption and rising demand for water resources. Moreover, a large volume of wastewater discharge was inevitably the result of industrial production. Therefore, the industrial structure was the biggest factor affecting UWUE in China.

A clue to the impact of urban population on UWUE could be seen from **Figure 3** mentioned above. UWUE in small-scale cities was highest between 2003 and 2007. This could be attributed to low water consumption and sewage discharge in small-scale cities, and therefore UWUE could be maintained at a high level compared with other types of cities. Since 2008, super megacities enjoyed the highest UWUE instead of small-scale cities. For a long time, there were only six super megacities in China: Beijing, Tianjin, Shanghai, Shenzhen, and Chongqing. The highest UWUE in these six cities could be attributed to the government's promotion of national economic and environmental protection policies as well as the agglomeration effect produced by these huge urban populations. With the gradual agglomeration of populations and economies to form super megacities, in addition to the effect of technological progress improving UWUE, the various elements of agglomeration helped to reduce the consumption and pollution of water resources, thereby improving their utilization efficiency as a result of the building and utilization of water resource infrastructure. Therefore, the agglomeration of large-scale urban populations could improve UWUE.

4 CONCLUSIONS AND POLICY IMPLICATIONS

Conclusions

This study attempted to evaluate UWUE and exploring its spatial differences and influencing factors. We evaluated the UWUE of 284 cities at the prefecture level in China between 2003 and 2018 by SBM of super-efficiency, explored its spatial differences through ESDA, and analyzed the influencing factors using

Geodetector. The findings were as follows: The average value of UWUE in China was generally low but tended to rise gradually. There were significant spatial differences in UWUE across China, with considerable global and local spatial autocorrelation, and local spatial autocorrelation was characterized primarily by high-high and low-low regions. Industrial structure and urban population were the main influencing factors for UWUE. This study has some limitations. We analyzed the spatial differences of UWUE by ESDA, which could reflect the spatial autocorrelation characteristics of UWUE but could not reflect the spatial differences of UWUE comprehensively. In the future, it is necessary to further study the spatial differences of UWUE using Dagum's decomposition of the Gini coefficient and kernel density estimation.

Policy Implications

In view of the overall low UWUE in China, it is necessary for urban managers to comprehensively understand the nature and dynamics of their water usage, increase investment in water resources in terms of capital, technology, and talent, and reduce wastewater and sewage discharge. It is also important for industrial enterprises to improve water-saving and pollution control technologies for the improvement of UWUE. Citizens are expected to become aware of the importance of saving water and reducing waste. Efforts should also be made to coordinate industrial production, living demands, and ecological water use between all cities and build "green systems" to secure water supplies.

As for the substantial impact of industrial structure on UWUE, it is important for cities to build a modern industrial structure to cater to the use of green water resources. The industrial upgrade is an important means of improving UWUE. It is necessary to transform labor-intensive industries into new industrial clusters based on innovations in capital and technology. Moreover, it is also essential to keep abreast of structural adjustments and technological progress and transform traditional industries that consume large amounts of water.

With regard to the impact of urban population on UWUE, it is crucial to strengthen the effect of the population agglomeration of megacities and large-scale cities. The populations of these two types of cities have accounted for a large proportion but they have yet witnessed an agglomeration effect. In particular, the UWUE of large-scale cities has become the lowest since 2013. It is necessary to make specific action plans to improve UWUE in these cities. In addition, it is also important to give full play to the radiation effect of super megacities, so that medium- and small-scale cities can enjoy the benefits of technology transfer, thereby improving their UWUE.

In terms of the spatial differences in UWUE, it is necessary to establish a coordinated mechanism to strengthen regional technical cooperation and form contiguous, highly efficient regions for water resource use to improve the UWUE of all cities. Regions with high UWUE are expected to rely on their advantages of capital and technology to explore more channels for spillover. Regions with low UWUE are supposed to invest in science and technology and strengthen environmental monitoring and government supervision. This includes a joint supervision system and information sharing mechanism between local tax departments and water conservation departments.

DATA AVAILABILITY STATEMENT

Publicly available datasets were analyzed in this study. This data can be found here: https://data.cnki.net/.

AUTHOR CONTRIBUTIONS

All authors contributed to the study conception and design. Conceptualization, KL and ZC; methodology, WL and JW; software, WL and JW; validation, KL, WZ; formal analysis, KL, WZ; investigation, JW; resources, KL; data curation, JW; writing—original draft preparation, KL; writing—review and editing, ZC, FL; supervision, ZC; project administration, KL, FL. All authors read and approved the final manuscript.

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SUPPLEMENTARY MATERIAL

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/fenvs.2022.890187/full#supplementary-material

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