RESEARCH ARTICLE

Evolution and the drivers of water use efficiency in the water-deficient regions: a case study on Ω-shaped Region along the Yellow River, China

Gang Liu[1,2] · Omaid Najmuddin[3] · Fan Zhang[1]

Abstract

Enhancement of water use efficiency (WUE) is considered highly important to cope with the water scarcity challenges in dry regions. Therefore, this study evaluated spatiotemporal characteristics of WUE and its related drivers in the Ω-shaped Region along the Yellow River aiming to provide decision support information for alleviating water shortages in this region. We employed the SBM-DEA (slacks-based measure-data envelopment analysis) model to calculate the WUE considering undesired outputs, analyze temporal and spatial variation based on GIS and statistical methods, and investigate the various factors that influence WUE based on the generalized method of moment (GMM) model. The results are as follows. (1) The WUE followed an increasing–decreasing-increasing trend, suggesting that the expanding agricultural and the second industrial structures are largely dominated by water-intensive activities which add further pressure on the water resources. (2) The spatial discrepancy of WUE among the cities is significant; however, the spatial pattern changes were stable during 2010 to 2019. (3) Analysis of influencing factors provides solutions for improving WUE in the Ω-shaped Region. Irrigation system and water conservancy infrastructure development and the acceleration of industrial transformation are necessary for improving the WUE in the Ω-shaped Region.

Keywords Water use efficiency · Environmental economics · GMM · Water resource management · SBM-DEA · Regional development

Introduction

In the recent past, the development of the Yellow River basin (YRB), an ecologically important region, has gotten the particular attention of the Chinese national strategy by launching the ecological conservation and high-quality development of this region. The Ω-shaped Region, located in the upstream and midstream reaches of the YRB and extending from east to west (Sun et al. 2016), is one of the strongest bases of the second industry in Eurasia that is rich in energy resources and playing a vital role in the development of YRB (Xiang et al. 2017). However, despite having a large number of energy clusters, this region is extremely scarce of water resources and characterized with the fragile ecology. The problem of water scarcity is inherently a major challenge for the development of the Ω-shaped Region (Yang et al. 2020). Additionally, the rapid urbanization and industrialization further added to the problem and increased the gap between the supply and demand of water (Yan et al. 2020). As the economy grows, the water demand increases due to

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additional consumption by booming or new industries, thus leaving lesser water for environmental needs. Therefore, economic development on the one hand provides the necessary employment for the growing population; on the other hand, it leads to serious environmental consequences (Chen et al. 2020). As water supply is not fixed and accurate prediction is also challenging, enhancement of water use efficiency (WUE), therefore, is essential to cope with the water scarcity challenges. However, the water supply is limited by water allocation policy and natural precipitation. Facing the multiplying demand of water, it is an essential to enhance WUE.

The agricultural sector accounts for more than 60% of total water consumption in China (Li et al. 2020). A number of researchers have reported the positive impact of improved irrigation efficiency on agricultural development (Berbel et al. 2018, 2019; Cao et al. 2021). The given studies reported that improved efficiency had significantly reduced water scarcity and increased agricultural productivity. Similarly, many other studies investigated WUE of the secondary industry in China. Through these studies, researchers have attempted to explore the coupling relationship between WUE and the industrial structures (H. Wang et al. 2019a,b; Liu et al. 2020). The researchers also identified several factors that influence industrial WUE. For instance, the study of Hong et al. (2019) revealed that industrial WUE is significantly affected by industrial scale and technology. A number of cross-sectional studies also suggested the association of WUE and economic indicators (Wang and Wang 2017; Li and Long 2019; Shi et al. 2020). However, the so far conducted studies on industrial WUE have (1) ignored the services industry, and (2) the research were mainly focused on industry-level WUE rather than city-level WUE.

Current methods of estimating WUE mainly rely on data envelopment analysis (DEA) and stochastic frontier approach (SFA). DEA, a nonparametric method, has been widely utilized by many WUE studies (Shabanpour et al. 2017; Li et al. 2018; X. Wang et al. 2019a, b; Álvarez-Rodríguez et al. 2020; Xie et al. 2021). On the hand, SFA is generally applicable to a single output scenario, and the estimation of parameters is needed in this method (Carvalho and Marques 2016). Compared to SFA, DEA is widely adopted because it does not require the functional relationship between input and output and hence easier in applicability. Later in another work, Deng et al. (2016) developed a new modified framework for measuring regional WUE. Upon its introduction, the framework was adopted by many researchers and estimated WUE of different regions using the modified DEA model. In another study, Song et al. (2018) applied the undesirable output–based Malmquist-Luenberger productivity index to measure province-level WUE in China and to investigate the influencing factors of WUE by establishing a panel Tobit model. Ding et al. (2019) employed SE-SBM, a DEA model, to evaluate the

WUE of the economic belt in Yangtze river basin. Another study based on DEA model measured WUE of the hybrid network structure of water systems (Chen et al. 2021). This study also used the difference-in-differences (DID) model to evaluate the impact of various water rights policies on water resource utilization efficiency. Although many researchers have used DEA to assess WUE, there is still very little scientific understanding of undesired output. In China, understandably, the overexploitation of natural resources is the dominant driver of the rapid economic growth. The rapid and excessive consumption of natural resources such as water has not only led to economic inefficiency but also resulted in environmental pollution and the deterioration of the ecosystem. Therefore, there is a dire need to improve the current framework of natural resource utilization by identifying the undesired outputs to achieve desirable economic growth without further harming the resource environment and productivity. Also, knowledge and understanding of the spatiotemporal variation of the resource utilization efficiencies and the related drivers associated with given variation are vital for providing research-based policies to cope with the aforesaid challenges.

This study, firstly, estimated city-level WUE of the Ω-shaped Region from 2010 to 2019, and then, the spatiotemporal characteristics of WUE were discussed. Furthermore, generalized method of moment (GMM), a panel model, is applied to analyze the drivers of WUE in the study area. The results of this study provide a scientific reference for enhancing the regional WUE and improving the coordinated management of water resources in the study area.

The rest of this paper is organized as follows. Section 2 explains the natural and social-economic conditions of the Ω-shaped Region. Section 3 details our accounting approach and the data that we use. Section 4 discusses the results. Finally, we present our conclusions and discussions on the issue.

Study Area

The Ω-shaped Region is a concentrated area of five provinces which are Gansu, Ningxia, Inner Mongolia, Shaanxi, and Shanxi along the Yellow River. It covers 19 cities of Taiyuan, Datong, Shuozhou, Xinzhou, Linfen, Lvliang, Hohhot, Baotou, Wuhai, Ordos, Bayan Nur, Yanan, Yulin, Baiyin, Qingyang, Yinchuan, Shizuihan, Wuzhong, and Zhongwei (Fig. 1). The population of the Ω-shaped Region is 134.8 million in 2019 that consumes 53.8 billion m^3 of freshwater resources (National Bureau of Statistics of the People's Republic of China 2020). The total water resource in this area is about 137.9 billion m^3 including 55.2 billion m^3 of freshwater, accounting only 4.7% of China's water resources. Surface water is the main source of water in this area (Omer et al.
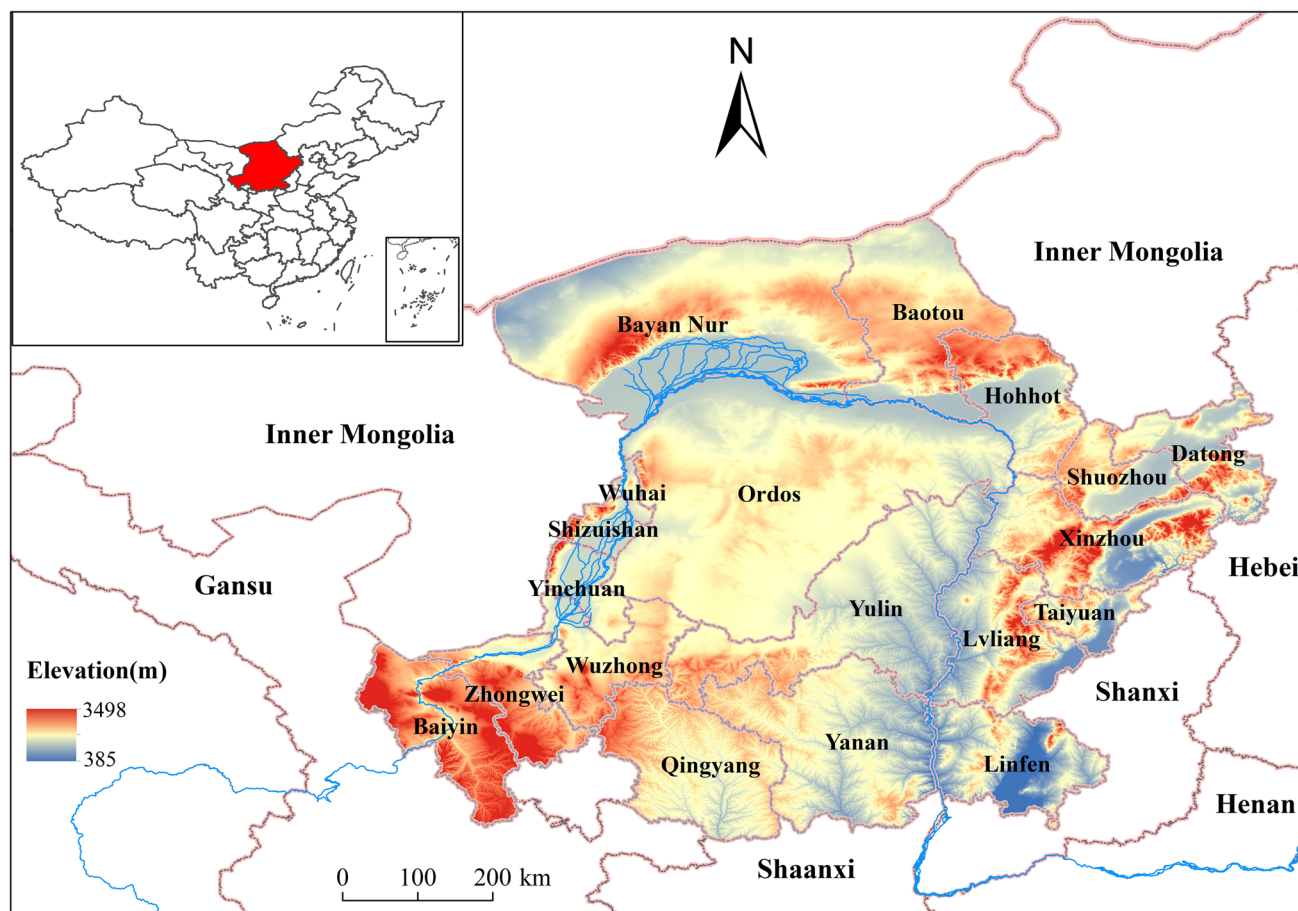
Fig.1 Geographic distribution map of research area

2021). The water resources distribution is also significantly uneven between different regions (Yang et al. 2021). For instance, comparing the two similar sized provinces, Shaanxi has 198.12 billion m^3 of water resources, while Shanxi only has about 3.892 billion m^3 of water resources. The areas with abundant groundwater resources, such as Lvliang and Linfen in Shanxi province, are mainly located along the riverbed. Inner Mongolia and Ningxia are relatively water-scarce regions. Ningxia's available water resources in 2019 reached to only 504 million m^3. Therefore, traditionally, water access has been the major concern in achieving long-term high-quality development of the Ω-shaped Region.

Methodology and materials

Data source

The data required in this paper includes input–output data that were needed to be used for measuring the urban WUE by employing the SBM-DEA, the data concerning different factors of WUE. For SBM-DEA modeling, the relevant

datasets of labor, capital, and water resources were used. The number of employed persons in each urban units was used to denote labor, the social fixed investments were used as proxy to capital, and "urban water supply" was used to represent water resources. Undesirable output indicators were represented by the total amount of wastewater discharged annually and amount of industrial wastewater discharged, while, for desirable output, the study used gross domestic product (GDP) per capita of each region. Environmental regulation, the rate of economic development, industrial structure, technology, irrigation and water conservancy facilities, and urbanization were considered as the influencing factors of WUE. The study used the ratio of industrial value added to the amount of industrial wastewater as the proxy to environmental regulation. Per capita GDP is used to represent economic development. Similarly, the ratio of primary industry upon total industry can denote industrial structure. The number of patent applications was used as proxy to the technology and innovation levels. The percentage of irrigated area from the total cultivated area was considered to represent irrigation and water conservancy facilities. Lastly, proportion of urban population in the total population was

used as proxy to urbanization. Table 1 shows the information of various datasets that were used in this study and covers the period from 2010 to 2019.

SBM-DEA

The use of DEA is a well-established approach in measuring the efficiency of various resources. It was originally developed to solve mathematics problems related to operational researches. Later, considering its usefulness and high accuracy in evaluation of resource utilization efficiency having multiple input–output indexes, it has been widely adopted by various disciplines covering topics such as carbon emission, resource utilization, technological innovation, and business management (Ahn et al. 2018; Chen and Jia 2017; Mardani et al. 2017).

However, the multidisciplinary applications of DEA are not without limitations. Upon the application of traditional DEA in resource use efficiency studies, the researchers identified two major limitations. Firstly, the traditional DEA could not explain the intermediate processes from input to output and, thus, ignores the impact of the intermediate processes on efficiency (Rebolledo-Leiva et al. 2019). Secondly, it does not incorporate the undesired outputs in the modeling process. To overcome the given shortcomings, instead of traditional DEA, this study applied a modified DEA model, i.e., SBM-DEA (slacks-based measure-data envelopment analysis model). On the one hand, SBM-DEA provides the flexibility to adjust the input–output scale as needed (Pishgar-Komleh et al. 2021), and on the other hand, the model incorporates undesired output, which both lead to more accurate measurement of efficiency as compared to the traditional model (Zhou et al. 2020). Therefore, following the available literature of Tian et al. (2020, Tone et al. (2020), and Guo et al. (2019), this study utilized the SBM-DEA model for estimating the WUE of the Ω-shaped metropolitan region along the Yellow River. Input information included labor, capital, and water resources, the undesired output indicators included sewage discharge and industrial wastewater discharge, and the expected output indicator was the gross regional product. The model mathematical formula and detail are as follows.

This model is suitable for estimating the WUE of a region with n DMU_j ($j = 1, \ldots, n$) and K nodes ($k = 1, \ldots, K$). m_k and r_k represent the number of different nodes and output variables, respectively. (k, h) denotes the relationship between different nodes k and node h. The variables of x_j^k, y_j^k, and $z_j^{(k,h)}$ represent input variables, output variables, and connecting variables, respectively. The production process is characterized by the following function.

$$\begin{cases} x^k \geq \sum_{j=1}^n x_j^k \lambda_j^k (k = 1, \ldots, K) \\ y^k \geq \sum_{j=1}^n y_j^k \lambda_j^k (k = 1, \ldots, K) \\ z^{(k,h)} \geq \sum_{j=1}^n z_j^{(k,h)} \lambda_j^k (\text{output in stage } k) \\ z^{(k,h)} \geq \sum_{j=1}^n z_j^{(k,h)} \lambda_j^h (\text{input in stage } h) \\ \lambda_j^h \geq 0 (\forall j, k) \end{cases} \quad (1)$$

where λ_j^h is the weight vector of k. The relaxation variables are introduced on the basis of Eq. (1), and the DMU_o ($o = 1, \ldots, n$) can be represented by the following equation.

$$x_o^k = X^k \lambda^k + s^{k-}, y_o^k = Y^k \lambda^k - s^{k+}, \lambda^k \geq 0, s^{k-} \geq 0, s^{k+} \geq 0, \forall k \quad (2)$$

Table 1 Data and sources

Code	Data	Source
1	Number of employed persons in urban units	Provincial statistical yearbook
2	Fixed investments	City statistical communiqué of economic and social development
3	Urban water supply	China City Statistical Yearbook
4	Annual wastewater discharged	China Urban Construction Statistical Yearbook
5	Industrial wastewater discharged	China City Statistical Yearbook
6	City GDP	China City Statistical Yearbook
7	Industrial value added	Provincial statistical yearbook
8	GDP/capita	Provincial statistical yearbook and China City Statistical Yearbook
9	Ratio of primary industry upon total industry	Provincial statistical yearbook
10	Number of patent applications	Provincial statistical yearbook and City statistical communiqué of economic and social development
11	Irrigated area	Provincial statistical yearbook and City statistical communiqué of economic and social development
12	Cultivated area	Provincial statistical yearbook
13	Proportion of urban population	Provincial statistical yearbook

where $X^k = (x^1, ..., x^k), Y^k = (y^1, ..., y^k)$, s^{k-} denotes input redundancy, and s^{k+} denotes the insufficient output. Connection variables are illustrated by the following equation.

$$Z^{(k,h)} \lambda^h = Z^{(k,h)} \lambda^k, \forall k, h \tag{3}$$

where $Z^{(k,h)} = (z_1^{(k,h)}, ..., z_n^{(k,h)})$.

Non-oriented efficiency is adopted in this paper to measure water resource utilization efficiency, as shown by Eq. (4) and Eq. (5).

$$\rho^0 = \min_{\lambda^k s^{k-} s^{k+}} \frac{\sum_{k=1}^{K} w^k [1 - \frac{1}{m_k} (\sum_{i=1}^{m_k} \frac{s_j^{k-}}{x_{io}})]}{\sum_{k=1}^{K} w^k [1 - \frac{1}{r_k} (\sum_{i=1}^{r_k} \frac{s_j^{k+}}{y_{io}})]} \tag{4}$$

$$\begin{cases} \sum_{k=1}^{K} w^k = 1 \\ w^k \geq 0 \end{cases} \tag{5}$$

where w^k is the weight of stage k and m^k and r^k represent the number of input–output variables, respectively. To simplify the equation, the nonlinear programming in Eqs. (4) and (5) were transformed into the linear programming as shown by Eqs. (6), (7), and (8).

$$\min_{\lambda^k, s^{k-} s^{k+}} \delta = t - \sum_{k=1}^{K} w^k (\frac{1}{m_k} \sum_{j=1}^{m_k} \frac{S_j^{k-}}{x_{jo}^k}) \tag{6}$$

$$s.t. 1 = t + \sum_{k=1}^{K} w^k [\frac{1}{r_k} (\sum_{j=1}^{r_k} \frac{S_j^{k+}}{y_{jo}^k})] \tag{7}$$

$$tx_{jo} = \sum_{j=1}^{m_k} \gamma_j x_j + S_j^{k-}, ty_{jo}^k = \sum_{j=1}^{r_k} \gamma_j y_j^k - S_j^{k+}, \gamma_j \geq 0, S_j^{k-} \geq 0, S_j^{k+} \geq 0 \tag{8}$$

where δ is WUE. Furthermore, several variables need to be explained by Eqs. (9)–(11).

$$\gamma_j = t\lambda_j \tag{9}$$

$$S_j^{k-} = ts^{k-} \tag{10}$$

$$S_j^{k+} = ts^{k+} \tag{11}$$

Econometrics model: GMM

WUE is determined by many factors, rather than by two or three factors. The so far conducted studies in different regions have investigated various area-specific drivers of WUE. Given the aim of this study and the knowledge gained

from the reviewed literature (Zhi et al. 2016; Vieira et al. 2017; Shi et al. 2021; Guo et al. 2021), the environmental regulation, economic development, technological level, and urbanization were selected as the independent variables to investigate their impact on WUE in the study area. Furthermore, apart from the traditional factors, this study also included irrigation and water conservancy infrastructure development in the list of independent variables because they are shaping the industrial structure in the study area.

To investigate the significance of the selected factors on WUE, this study adopted the generalized method of moment (GMM) model. The model equation is given as following:

$$\begin{aligned} WUE_{it} &= \alpha_0 + \mu WUE_{i(t-1)} + \alpha_1 ER_{it} + \alpha_2 ED_{it} \\ &+ \alpha_3 IS_{it} + \alpha_4 TL_{it} + \alpha_5 UR_{it} + \alpha_6 WF_{it} + \varepsilon_{it} \end{aligned} \tag{12}$$

where i denotes various cities and t represents different years. ER indicates environmental regulation, calculated by dividing the total industrial output value by the amount of industrial wastewater discharged. ED represents economic development level, explained by per capital gross domestic product; IS shows industrial structure, estimated by the proportion of agricultural value added to gross domestic product. TL is the technology level, estimated by patent filings per unit of gross domestic product. UR denotes urbanization, expressed by the proportion of urban population to total population. WF represents the construction of irrigation and water conservancy facilities, denoted by the proportion of the irrigated area to the total cropped area. α_0 is constant. $\alpha_1 \sim \alpha_6$ are the regression coefficients of independent variables, respectively; μ is the coefficient of the spatial lag term; ε_{it} is disturbance.

Results

Temporal evolution of WUE from 2010 to 2019

Table 2 shows the values of WUE of different cities located in the Ω-shaped Region along the Yellow River from 2010 to 2019. The WUE of almost all the cities in the metropolitan area increased from 2010 to 2011. During this period, the average WUE increased from 0.5074 to 0.5751. Lvliang and Zhongwei cities showed the highest increase in WUE, i.e., more than 15%. From 2011 to 2013, most cities experienced a decrease in WUE. The average of WUE during this period declined from 0.5751 to 0.4946. From 2013 to 2019, the WUE of cities in the Ω-shaped Region showed a fluctuating upward trend, reaching the peak value of 0.5327 in 2019 and lowest value of 0.4894 in 2015. The overall trend of WUE during the study period in the Ω-shaped Region was increasing which can be associated with the suitable environmental

Table 2 WUE of the Ω-shaped Region along the Yellow River from 2010 to 2017

Cities	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019
Baiyin	0.3752	0.4069	0.3656	0.3466	0.3055	0.2816	0.3274	0.3342	0.3451	0.3102
Baotou	0.5236	0.5508	0.5595	0.4955	0.5234	0.6155	0.597	0.4833	0.4706	0.431
Bayan Nur	0.4435	0.4808	0.4864	0.4622	0.456	0.5614	0.5205	0.5177	0.4915	0.5241
Datong	0.3089	0.3241	0.3058	0.2715	0.2988	0.3023	0.2854	0.2335	0.2466	0.2641
Hohhot	0.9348	1	1	0.8553	0.7335	0.7181	0.6773	0.6536	0.6636	0.6089
Linfen	0.4752	0.553	0.4799	0.4277	0.4107	0.406	0.3889	0.4327	0.4874	0.4599
Lvliang	0.6303	1	0.6293	0.6496	0.5588	0.4827	0.5129	0.5414	0.5926	0.5776
Ordos	0.9691	1	1	0.9818	1	1	1	0.9659	1	0.9763
Qingyang	0.411	0.4647	0.4534	0.4291	0.4956	0.4405	0.3995	0.4848	0.5149	0.6012
Shizuishan	0.3222	0.3774	0.3481	0.3333	0.3485	0.4177	0.3852	0.2676	0.4114	0.457
Shuozhou	0.526	0.5645	0.5846	0.5015	0.5083	0.4356	0.5447	0.5873	0.642	0.6586
Taiyuan	0.4536	0.4987	0.421	0.3731	0.3601	0.3609	0.3946	0.4194	0.3481	0.3536
Wuhai	0.4761	0.5254	0.545	0.4668	0.5836	0.4894	0.5534	0.6163	0.6822	0.7079
Wuzhong	0.3097	0.3587	0.3228	0.2746	0.2822	0.2787	0.2794	0.2866	0.3219	0.3945
Xinzhou	0.3089	0.3474	0.3281	0.3034	0.3141	0.3477	0.3091	0.3159	0.3543	0.3206
Yanan	0.5159	0.5932	0.6212	0.5338	0.5331	0.4407	0.4024	0.4381	0.482	0.4705
Yinchuan	0.3241	0.3828	0.3798	0.3652	0.277	0.2787	0.3594	0.3415	0.3892	0.4211
Yulin	1	1	1	0.8989	1	1	1	0.9082	1	1
Zhongwei	0.3328	0.4989	0.4131	0.4271	0.4119	0.4413	0.4465	0.4844	0.5483	0.584

policies and government awareness campaigns in motivating private enterprises and local people to use water more efficiently. Since 2014, the Chinese government implemented stricter environment policies and developed the ecological protection plan pertaining to the 13th National Five-Year Plan. Also, the water pricing reforms and the increasing government efforts on water conservation education have paid off in improved WUE in China. However, WUE in the Ω-shaped Region restively remains lower. The agricultural WUE is particularly low as the irrigation techniques in the region are largely traditional which leads to high water wastage. Also, the disproportionate industrial structure is largely dominated by water-intensive industries exacerbating the existing water use dilemma in this region.

From the given cities in the table, the WUE of Ordos and Yulin were the highest. The average WUE of these cities during the study period was 0.9893 and 0.9807, respectively. On the contrary, the lowest mean WUE was estimated for Datong, i.e., 0.2841. The largest decline of WUE was found for the city of Hohhot, i.e., from 1 in 2011 to 0.6089 in 2019. Similarly, the county of Shuozhou presents the example of significant fluctuating trend where WUE at first declined (from 0.5260 in 2010 to 0.4356 in 2015) and then sharply increased upward (to 0.6586 in 2019).

To compare the relative status of WUE among cities, we adopted percentages to represent the values of WUE. As showed in Fig. 2, the percent varied between 0 and 3%. Most cities have stable status, while a few cities showed rising or declining trend. Hohhot presented a declining trend in this decade. Furthermore, the performance of almost all cities

have fluctuated. For example, the status of Baotou went up from 2010 to 2015 but descended from 2015 to 2019. The results indicate that the varying relative status of WUE in the Ω-shaped Region from 2010 to 2019 is less with time. The next subsection moves on to discuss the time series outliers.

Time series outliers analysis of WUE based on boxplot

Boxplot analysis is used to show the temporal characteristics of WUE of various cities in the Ω-shaped Region (Fig. 3). Boxplot is a statistical chart that can display information about the dispersion of a set of data. In this paper, it is used to reflect the characteristics of the distribution of WUE data and to conduct comparisons of characteristics of WUE among different cities. The shorter the box and line segments, the more concentrated the distribution of water resources efficiency is, and vice versa.

The lower and upper limits of each box line respectively represent the lowest and the highest values of WUE for each city. The upper and lower sides of the boxes respectively indicate the upper and lower quartiles, while the solid line in the middle denotes the median. The distribution of WUE in each city is explained by the length of the box. The lengthier boxes explain more inconsistency and dispersion of the temporal WUE values for the respective city. Some cities are labeled with 1–2 solid points and the year which indicate the outlier values of the given city in that particular year. The temporal distribution and consistency analysis of WUE may help in
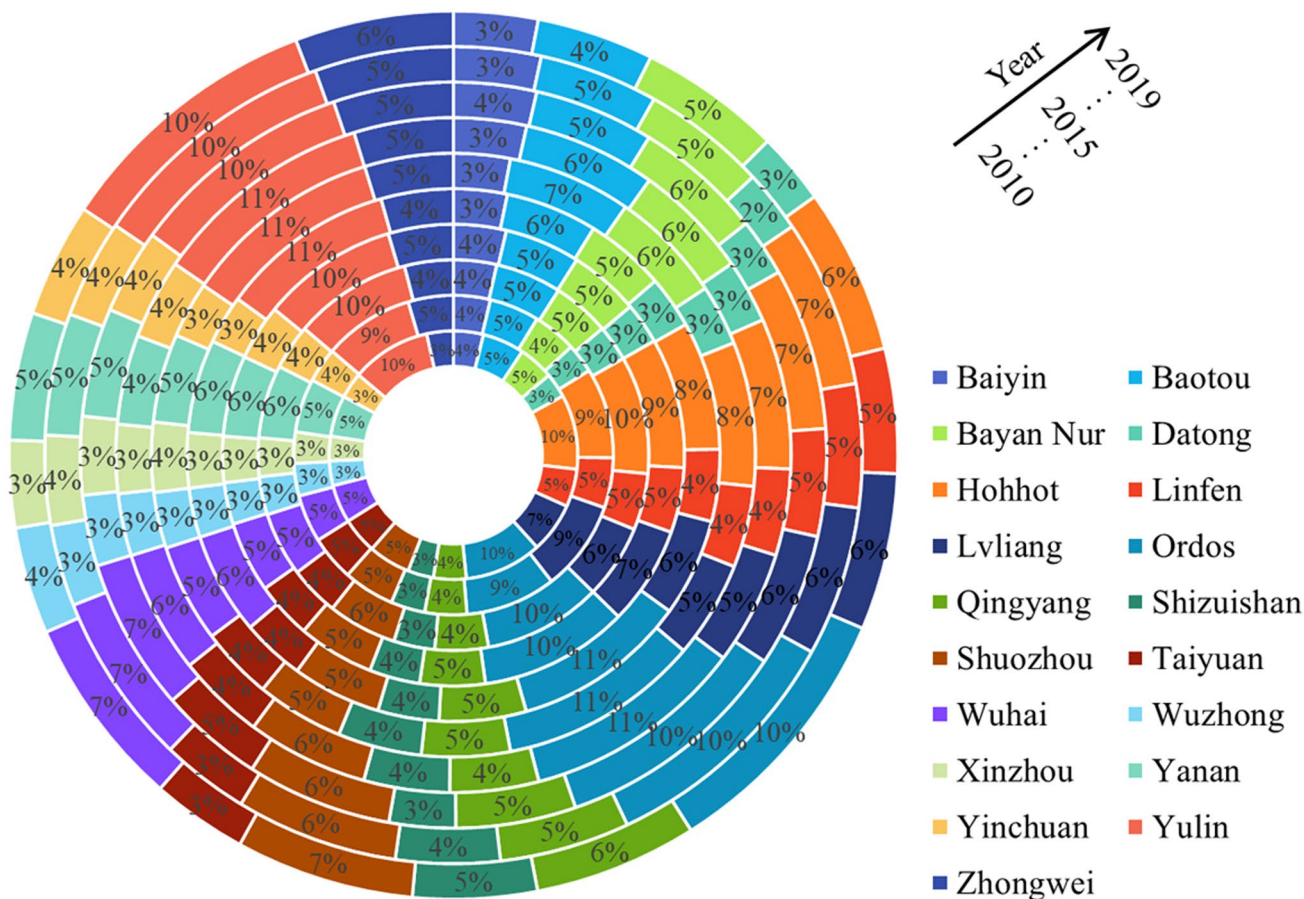
Fig.2 Relative status of WUE in the Ω-shaped Region from 2010 to 2019

understanding the impact of urban development strategies that serve to improve WUE. Hohhot was identified with the largest difference between the upper and lower bounds among the 19 cities in this region, indicating the highest temporal dispersion and inconsistent performance of WUE. On the other hand, the gap between upper and lower values of Datong, Ordos, Wuzhong, Xinzhou, and Yulin were the smallest, showing a more stable improvement of WUE in these cities. There are five outliers in four cities, one each in Lvliang, Qingyang, and Wuzhong and two in Yulin. The distribution of the outliers is also not concentrated in one year rather distributed between different years, i.e., 2011, 2019, and 2013. The reasons for the occurrence of outliers and inconsistencies could be associated with time- and place-specific reasons.

### The spatial pattern of WUE in the Ω-shaped Region

The spatial mapping of WUE efficiently provides the needed information that enables to compare the performance of different cities and to prioritize intervening regions (Fig. 4).

Natural breaks (NB) method is adopted to classify the spatial variation of WUE.

In general, the WUE varied significantly across the cities in the Ω-shaped Region. The WUE of the hinterland region was classified with high values; however, some cities in this region were relatively experiencing low WUE in 2011. However, in recent years, several cities in the northeast have significantly improved their WUE. Cities located in the north and south of the Ω-shaped Region were characterized with small spatial variations and relatively showed consistent values.

The WUE of Ordos and Yulin, located in the center of the Ω-shaped Region, was estimated with the highest values in the region. In the northern part of the Ω-shaped Region, Bayan Nur and Baotou were estimated with medium-level WUE in the whole region. In northeast of the Ω-shaped Region, the WUE of Hohhot, Shuozhou, and Datong was significantly different. From the given cities, Datong (belongs to Shanxi province) has a relatively low WUE, with a maximum value of 0.32 in 2011. Hohhot (belongs to Inner Mongolia) has a significantly higher WUE than the other two cities, with the highest value of 1 in 2011 and 2012.

Fig.3 Boxplot of WUE of the Ω-shaped Region from 2010 to 2019
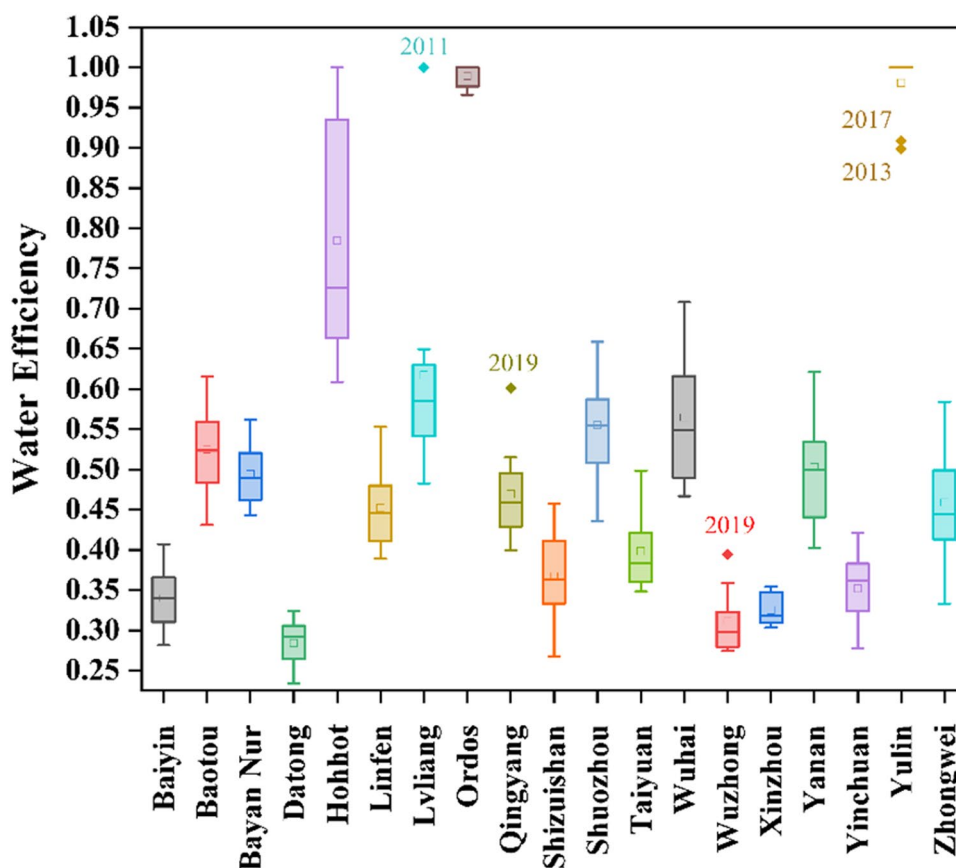
Even though the WUE of Hohhot declined in the latter years, it is still the highest in the whole region. Some other interesting observations can be derived from the remaining cities of the Ω-shaped Region. For instance, in the southern part where WUE is generally low, Yanan reached higher levels in 2011 and 2012.

## Migration of the gravity center and discrete trends

The gravity center and the standard deviation ellipse are employed to further analyze the spatial and temporal variation of WUE. In geography, the gravity center reflects the spatial distribution of a geographic element in a specific region, while the standard deviation ellipse illuminates the spatial dispersion of the geographic element. In this study, the gravity center was adopted to explain the spatial distribution of WUE in different years, and the standard deviation ellipse was used to explore the spatial dispersion of WUE over the years. The longer and shorter half-axes of the standard deviation ellipse indicate the direction and range of the data distribution, respectively. The greater differences between the longer and shorter half-axes increase the likelihood of the directionality of the data and vice versa.

During the study period, the gravity center of WUE in the Ω-shaped Region first, in 2010, shifted westward (Fig. 5),

with the gravity center in Yulin city, and then, it shifted northwestward to Ordos in 2015. The shift of gravity center to northwest was mainly due to significant improvement in WUE of Bayan Nur, Baotou in the north, and Zhongwei in the west. Finally, the gravity center shifted to the southwest in 2019, which can be associated with the improved WUE of western and southern cities. The distance of movement in the first 5 years (2010–2015) of the study period was 17.03 km and in the latter 5 years (2015–2019) was 21.52 km, indicating a faster movement in the latter 5 years. The gravity center of WUE was hovering in Ordos and Yulin, which suggests that the WUE of the given cities were notably higher than the other cities.

The long semiaxis of the standard deviation ellipse of the Ω-shaped Region from 2010 to 2019 varies between 341 and 349 km, while the short semiaxis varies from 213 to 221 km, and the directional angle increases from 74.02° to 75.88°. Given the changes of the standard deviation ellipse, the spatial distribution pattern of WUE in the Ω-shaped Region is stable and shows a northeast-southwest directional distribution. From 2010 to 2015, the long half-axis of the standard deviation ellipse became shorter, while the short half-axis became longer, and the distribution range expanded. The rotation angle increased by 0.26°. It indicates that the spatial distribution of WUE in this period has a non-concentrated
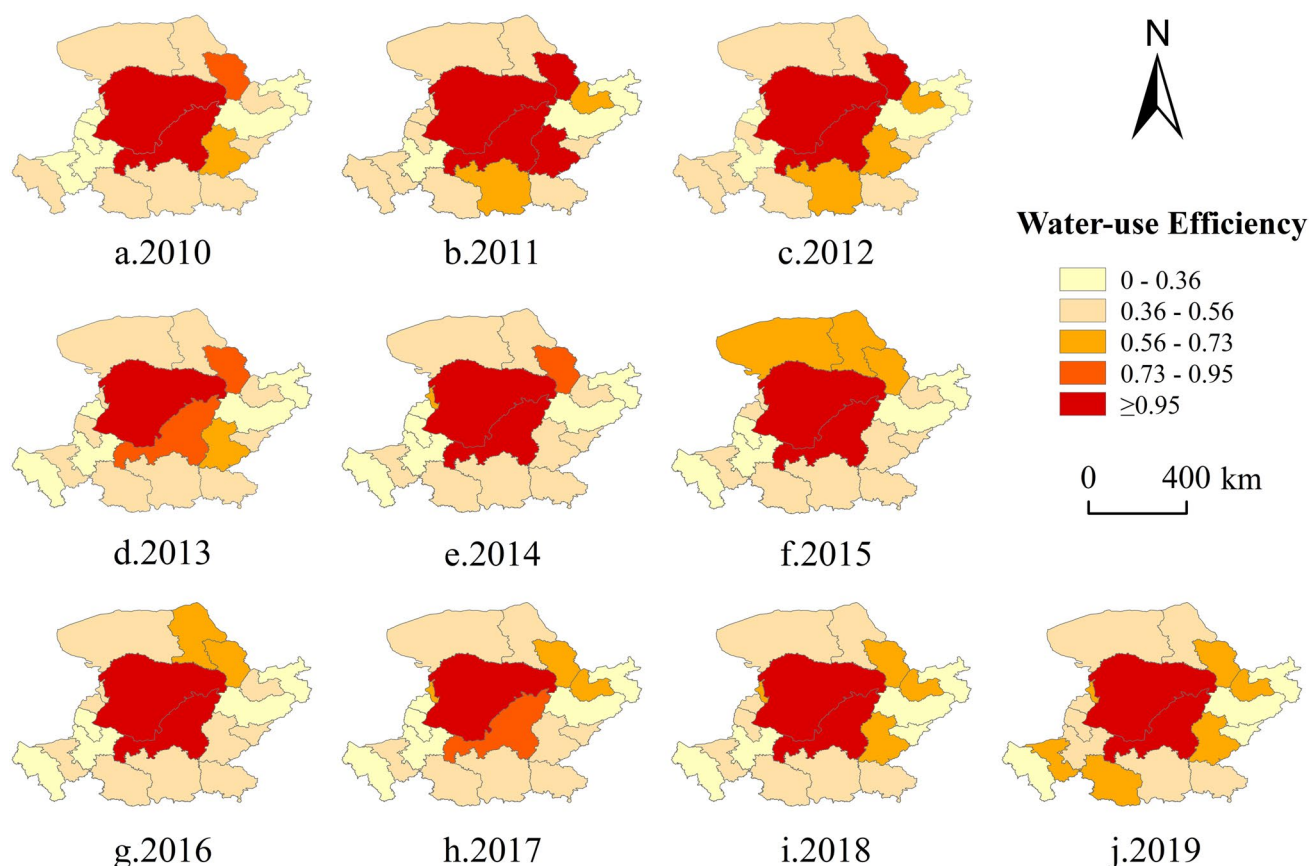
Fig.4 Spatial pattern of WUE of the Ω-shaped Region from 2010 to 2019

trend and its directional characteristics were more obvious. From 2015 to 2019, the long semiaxis of the standard deviation ellipse became longer, and the short semiaxis became shorter; the spatial distribution of WUE was more concentrated, the rotation angle continued to increase, and the directionality became more and more obvious.

Analysis of the influencing factors on WUE

The GMM model was employed to analyze the factors influencing the WUE in the Ω-shaped Region. The coefficient, standard error, z, $P > z$, and 95% confidence interval of each variable are listed in Table 3. In addition, the key test indicators, especially Sargan and AR (2), are also presented at the bottom of Table 3. Sargan is used to determine the validity of the model. The Sargan of the employed GMM model was greater than 0.1, indicating that the selected variables are suitable for this study. The p value of AR (2) was also greater than 0.1, implying that there is no second-order autocorrelation problem.

The coefficient of WUE_{t-1}, lagged variable, is $0.5098 > 0$, indicating that the improvement in WUE in the previous year

was favorable for the progress of WUE in the current year. It also suggests that the dynamic panel model was suitable for this study. The positive coefficient of the economic development (ED) implies that economically developed regions were able to use water more efficiently. The coefficient of industrial structure (IS) is negative. In this study, the industrial structure is represented by the share of agriculture in the total industries. Therefore, a large share of agriculture and a water-intensive industry actually have a negative impact on WUE. The application of traditional irrigation methods might be one of the main reasons of low agricultural WUE (Fang et al. 2017). Higher levels of technology (TL) will increase WUE. New technologies can enhance WUE both by reducing the water input and increasing the output per unit of water. The negative value of farmland water facility construction (WF) indicates that currently WF in the Ω-shaped Region is relatively weak and needs to be further improved in the future. The effect of urbanization (UR) on WUE is also negative. This might be due to the fact that urbanization leads to undesired output that reduces the WUE. Rudimentary industrial production mode with high pollution and emission is unconducive to WUE. In the context of

Fig.5 Standard deviation ellipse and center of gravity change of WUE of the Ω-shaped Region from 2010 to 2019
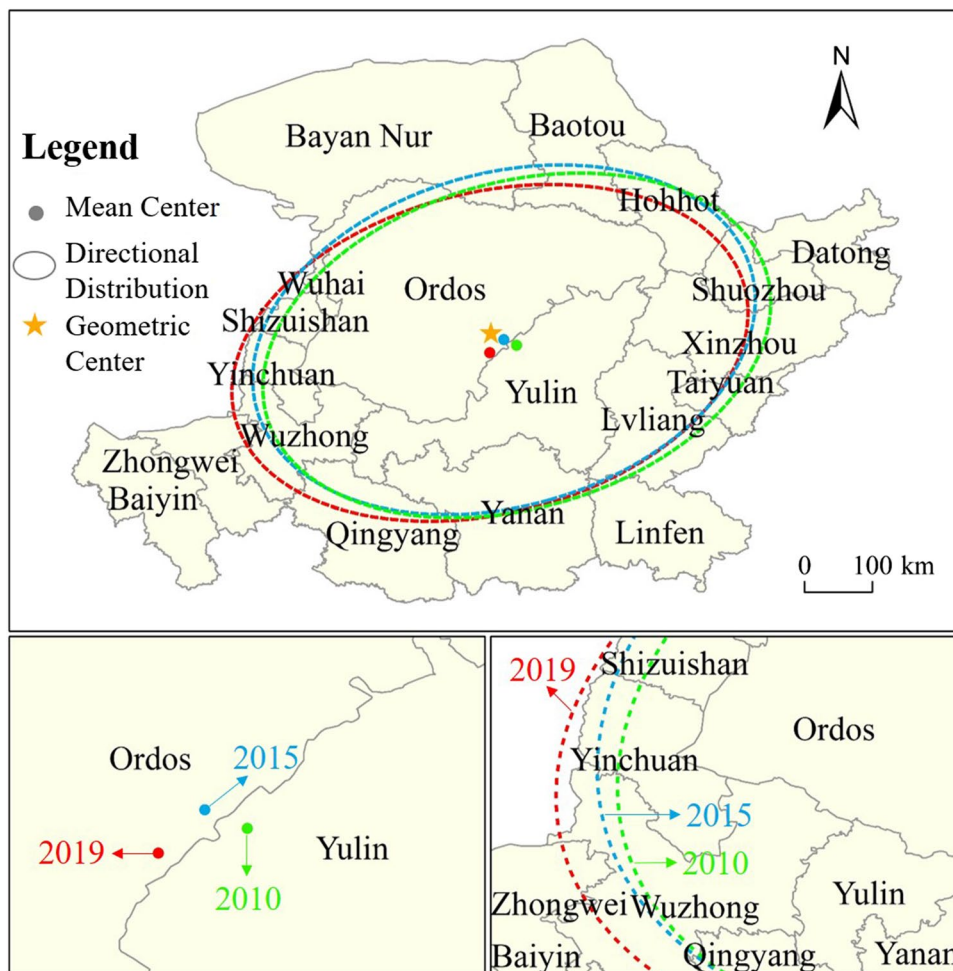
Table 3 Regression results of influencing factors of WUE of the Ω-shaped Region

Variable	Coefficient	Std. err	z	P>z	[95% Conf. interval]	
WUE_{t-1}	0.5098	0.0891	5.7200	0.0000***	0.3351	0.6845
ER	0.1879	0.1311	1.4300	0.1520	–0.0691	0.4448
ED	0.3590	0.0752	4.7700	0.0000***	0.2117	0.5064
IS	–0.0661	0.0301	2.2000	0.0280**	0.0071	0.1252
TL	0.0458	0.0252	–1.8200	0.0690*	–0.0952	0.0035
WF	–0.1131	0.0352	–3.2200	0.0010***	–0.1820	–0.0442
UR	–0.3287	0.1823	–1.8000	0.0710*	–0.6861	0.0287
Constant	–0.0183	0.0238	–0.7700	0.4410	–0.0649	0.0283
Others	Sargan	0.114	Number of obs		171	
	AR (2)	0.13				

***, significant at 1%; **, significant at 5%; and *, significant at 10% level

ecological protection and high-quality development of the Yellow River basin, the Ω-shaped Region should focus on the construction of agricultural water conservancy facilities, accelerate the industrial transformation, and implement strict environmental protection management measures to enhance WUE.

Conclusion and discussions

Conclusion

This study aimed to conduct the spatiotemporal evolution and influencing factors of WUE in the Ω-shaped Region

which is one of the important metropolitan areas in the Yellow River basin. We adopted the SBM-DEA model to estimate city-level WUE, considering the undesired outputs. Then, we analyzed the spatial and temporal distribution characteristics and employed the gravity center and standard deviation ellipse to discuss the changes of gravity and spatial dispersion of WUE. Finally, GMM was applied to investigate the influencing factors of WUE in the Ω-shaped Region. The major finding of his study are as follows:

(1) The WUE of the Ω-shaped Region from 2010 to 2019 followed a fluctuating trend of first increasing–decreasing-increasing. From 2010 to 2011, the WUE first increased from 0.5074 to 0.5751; then from 2011 to 2013, it decreased again to 0.082; and since then, it was always increasing till it reached the maximum value of 0.5327 in 2019. In general, the WUE of the Ω-shaped Region is still very low. The type of agricultural irrigation (mainly flooded irrigation) with high water wastage and the industrial structure dominated by agriculture and other water-intensive industries have exacerbated the water use dilemma in this region.

(2) From spatial perspective, there is obvious spatial divergence characteristics for the WUE in the Ω-shaped Region during the decade. The WUE of the central area was the highest, while the cities with lower WUE were distributed in the northeast and southwest of the metropolitan region. From 2010 to 2019, the gravity center of WUE in the Ω-shaped Region shifted westward; however, the spatial distribution pattern of WUE did not change significantly.

(3) The analyses of the influencing factors of WUE denoted that impact of economic development level and technology level was significantly positive on WUE, while the impact of agricultural share in the industrial structure, construction of agricultural water conservancy facilities, and urbanization was significantly negative. To exercise ecological protection and high-quality development of the Yellow River basin, the focus in Ω-shaped Region should be given to the construction of water conservancy facilities and acceleration of the industrial transformation.

Discussions

Water is essential for industrial production and regional development, and improved WUE is a prerequisite need for ecological protection and high-quality development. This study analyzed the current status, trends, and drivers of WUE in the Ω-shaped Region and offers knowledge, helping the decision-makers to develop research-based policy tools in dealing with regional water scarcity.

In this study, discrepancy in the variation of WUE was observed. From 2000 to 2019, WUE in eight cities (Linfen, Datong, Yanan, Lvliang, Baiyin, Baotou, Taiyuan, and Hohhot) decreased by 3.22 to 34.86%. Urbanization should be responsible for the decline in WUE. On the one hand, high pollution and emission caused by urbanization were unconducive to WUE. On the other hand, the consumption of water increased due to more population and productions. Yulin's WUE remained same. This may be the result of trade-off among the driving factors of WUE. Furthermore, increase of WUE is witnessed in other cities. The cities with improved WUE are all in low urbanization, which means low pollution and emission. Meanwhile, the government has encouraged the construction of agricultural infrastructure in these years, accelerating the improvement of WUE.

Although efforts were focused to collect accurate data and utilize the most suitable econometric tools to carry this study, this study still has the following potential limitations that need to be considered in future researches. Firstly, the study period covered only 10 years due to the limitation of data. The data covering longer time period increases the accuracy and leads to better decision-making. Furthermore, the selection of influencing factors was also limited to fewer dependent variables due to lack of data. Several other factors, which are not considered here, may also significantly impact the WUE in the region. Upon the access of new datasets, future studies may consider a larger set of variables to conduct a more comprehensive investigation of the influencing factors of WUE in the study area.

Author contribution Gang Liu: methodology, data curation, writing—original draft, and software. Omaid Najmuddin: writing—review and editing. Fan Zhang: conceptualization, writing—review and editing, and supervision.

Data availability The total data and materials are available for applicants if needed.

Declarations

Ethical approval The authors approve principles of ethical and professional conduct.

Consent to participate The authors consent to participate in the preparation of this article.

Consent to publish The authors consent to publish this article in *Environmental Science and Pollution Research*.

Competing interests The authors have no conflicts of interest to declare that are relevant to the content of this article.

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