water

Article

Spatial–Temporal Evolution Characteristics and Influencing Factors of Agricultural Water Use Efficiency in Northwest China—Based on a Super-DEA Model and a Spatial Panel Econometric Model

Weinan Lu [1], Wenxin Liu [1], Mengyang Hou [1], Yuanjie Deng [1], Yue Deng [1], Boyang Zhou [2] and Kai Zhao [1,*]

[1] College of Economics and Management, Northwest A&F University, Taicheng Road, Yangling 712100, China; luweinan@nwafu.edu.cn (W.L.); liuwenxin@nwafu.edu.cn (W.L.); houmengyang@nwafu.edu.cn (M.H.); dengyuanjie@nwafu.edu.cn (Y.D.); dengyue@nwafu.edu.cn (Y.D.)

[2] College of International Relations, Xi'an International Studies University, Xi'an 710061, China; amado1988@163.com

* Correspondence: zhaokai@nwafu.edu.cn

Abstract: Improving agricultural water use efficiency (AWUE) is an important way to solve the shortage of water resources in arid and semi-arid regions. This study used the Super-DEA (data envelopment analysis) to measure the AWUE of 52 cities in Northwest China from 2000 to 2018. Based on spatial and temporal perspectives, it applied Exploratory Spatial Data Analysis (ESDA) to explore the dynamic evolution and regional differences of AWUE. A spatial econometric model was then used to analyze the main factors that influence the AWUE in Northwest China. The results showed firstly that the overall AWUE in Northwest China from 2000 to 2018 presented a steady upward trend. However, only a few cities achieved effective agricultural water usage by 2018, and the differences among cities were obvious. Secondly, AWUE showed an obvious spatial autocorrelation in Northwest China and showed significant high–high and low–low agglomeration characteristics. Thirdly, economic growth, urbanization development, and effective irrigation have significant, positive effects on AWUE, while per capita water resource has a significant, negative influence. Finally, when improving the AWUE in arid and semi-arid regions, plans should be formulated according to local conditions. The results of this study can provide new ideas on the study of AWUE in arid and semi-arid regions and provide references for the formulation of regional agricultural water resource utilization policies as well.

Keywords: agricultural water use efficiency; spatial–temporal evolution; influencing factors; Northwest China; spatial econometric model

Citation: Lu, W.; Liu, W.; Hou, M.; Deng, Y.; Deng, Y.; Zhou, B.; Zhao, K. Spatial–Temporal Evolution Characteristics and Influencing Factors of Agricultural Water Use Efficiency in Northwest China—Based on a Super-DEA Model and a Spatial Panel Econometric Model. *Water* **2021**, *13*, 632. https://doi.org/10.3390/w13050632

Academic Editor: Josue Medellin-Azuara

Received: 11 January 2021
Accepted: 22 February 2021
Published: 27 February 2021

1. Introduction

Water is an essential and vital natural resource for the survival of all life on Earth [1]. However, due to factors such as rapid population and economic growth, urbanization, and industrialization [2], the global demand for water is growing at a rate of 1% per year, and the growth in demand for water is coming mostly from developing countries and emerging economies. At the same time, climate change is accelerating the global water cycle, resulting in more rain in wet areas and drought in dry areas. The quantity and quality of water resources will be further reduced in the coming decades, with increasing threats to human health, the environment, and sustainable development [3].

China is the world's largest developing country and one of the 21 water-poor countries; its per capita water resources share is low, being less than 1/4 of the world per capita [4]. The contradiction between socio-economic development and water shortage is serious. As a traditionally agricultural country, agricultural production consumes 60–65% of China's total water use and feeds 22% of the world's population on 7% of the world's arable land [5]. However, China's agricultural base is weak, and the long-term crude production method relying on large-scale factor inputs makes the effective utilization coefficient of irrigation water and the water productivity of farmland only equivalent to 60% of the world's advanced level [6]. At the same time, with the accelerated industrialization and urbanization in China, the demand for industrial and domestic water resources is increasing, and the proportion of agricultural water consumption to total water consumption is on a decreasing trend, from 97.1% in 1949 to 61% in 2019 [7]. China's agricultural water resources are utilized in a crude manner and coupled with competition between different water use sectors, resulting in increasingly prominent agricultural water use efficiency (AWUE) problems and a structural scarcity of water resources [8], which have serious and far-reaching impacts on agricultural production and food security.

In the face of the increasingly serious problem of agricultural water resources, the Chinese government set the goal of saving water and increasing efficiency in agricultural development in the National Water-Saving Action Plan [9], released in 2019, so as to effectively improve the utilization efficiency of water resources and the capacity for water security. As an important grain base in China, Northwest China has extremely distinct characteristics of water resource formation and transformation, water cycle processes, and spatial–temporal distribution. It is a typical representative of arid and semi-arid regions in the world [10]. Therefore, taking Northwest China as the research area, this paper discusses the spatio-temporal evolution characteristics of AWUE and identifies the key factors influencing the improvement in AWUE. This not only will enable the Chinese government to propose a specific and feasible path to improve AWUE in Northwest China but will also have important implications for promoting the AWUE in arid and semi-arid regions around the world and for developing countries in terms of formulating policies related to the sustainable development of agricultural water resources.

The scientific evaluation of AWUE is a basic prerequisite for the overall improvement of AWUE. In general, the evaluation of AWUE is a multi-objective and multi-criterion synthetical problem in essence [11], and related evaluation studies have been developed and refined in the course of production and life, resulting in different types of AWUE. According to its development history, there has been a gradual shift from the study of engineering efficiency of irrigation water delivery and field utilization to various efficiency studies with water productivity as an indicator [12]. Hu et al. [13] measured water use efficiency (WUE) in the framework of total factor production by the "ratio of target water consumption to actual quantity". This measurement idea considers the contribution of various input factors on economic growth, so as to measure the macro-comprehensive economic benefits of a resource system more truly and objectively [14]. Since then, the total factor water use efficiency (TWUE) has gradually been recognized and applied by the academic community. On the basis of this evaluation, scholars have measured the AWUE by the stochastic frontier analysis (SFA) [15,16], data envelopment analysis (DEA) [17–19], and other methods.

Research on factors affecting the AWUE has been conducted in two main areas: on the one hand, AWUE studies were conducted based on farm household survey data. Based on the stochastic frontier analysis, Xu et al. [20] measured wheat irrigation AWUE and its influencing factors among farmers in Anhui Province. Geng [21] evaluated the AWUE and influencing factors of 806 cotton households in Xinjiang and found that differences in individual farmer characteristics and business practices can have a significant impact on the AWUE of cotton. Based on the survey data of 213 farmers' planting production in Northwest China, Yu [22] found that the AWUE of maize and sunflower varied greatly under different irrigation methods. On the other hand, AWUE studies were conducted based on national or provincial agricultural water use data [23–26]. Tong [27] used the Tobit model to analyze the influence of agricultural water use in China and found that annual precipitation, imports and exports of agricultural products, and the proportion of groundwater in the water supply structure have a significant, positive effect on AWUE, while per capita water resources and irrigation fees inhibit AWUE. Mu et al. [18] used grey system analysis technology to analyze the influencing factors and found that both financial status and agricultural water conservation technologies have a positive influence on AWUE. Veettil et al. [28] found that the construction and upgrading of irrigation facilities and the adoption of agricultural water-saving technologies contributed to the improvement of AWUE in the Krishna River basin in India.

Generally, the existing literature has laid a firm foundation for the in-depth study of AWUE, but many deficiencies still remain to be improved: Firstly, most of the traditional models use the input–output data of the current period of the decision unit to construct the production frontier surface, which leads to an inability to directly compare the efficiency values in different years and makes it difficult to accurately and scientifically reflect the variability of each decision unit. Secondly, existing studies often ignore the impact of geographical and spatial factors on the development of regional AWUE when using the traditional panel model for analysis. However, in the process of agricultural production, due to the similarity of natural resource endowment, economic development level, and agricultural water use mode in adjacent areas, the AWUE between different regions may have mutual spatial influence. Thirdly, fewer studies have been conducted on AWUE in Northwest China, and the limited research is only at a national level and analyzes the AWUE differences between provinces in Northwest China. However, the important role of local and municipal governments in coordinating the allocation of resources within cities makes the study of meso-geographic units necessary. Thus, the study at the local and municipal levels allows for a more in-depth examination of the characteristics and unevenness of AWUE development between regions.

Based on this, the current paper takes Northwest China as an example, using the global benchmark technology to construct an input-oriented Super-DEA to measure the AWUE of 52 cities in the region from 2000 to 2018. ESDA was used to analyze the spatial–temporal dynamic evolution and differentiation characteristics of AWUE, and a spatial panel econometric model was then constructed to examine the influencing factors of AWUE from the perspectives of resource conditions, agricultural modernization, and social and economic development. Qualitative analysis and empirical tests yield relevant policy implications.

2. Study Area

Northwest China encompasses the provinces of Shaanxi, Gansu, Qinghai, Ningxia, and Xinjiang (Figure 1). It has an arid and semi-arid climate. Located in the hinterland of the Eurasian continent, Northwest China represents approximately 30% of China's land area, 7.3% of its population, and 5.4% of its GDP. It has a scarce precipitation, has less than 500 mm of annual rainfall, and is characterized by arid, continental arid, semi-arid, and alpine climates [29].

Northwest China is rich in light, heat, and soil resources. It is an important reserve base for grain production in China and has an important agricultural value and strategic position [30]. However, the ecological environment in this region is generally arid and short of water. The total water resources are only 202.7 billion m^3, accounting for 7.25% of China's total water resources. After deducting the water resources that are difficult to use or cannot be used, the actual per capita water resources in the northwest region are approximately 990 m^3, less than 1/10 of the world average, and the average water resources per mu of cultivated land is less than half of China's average level [31]. It is one of the regions with the greatest shortage of water resources and the most prominent contradiction between human and water in China. Meanwhile, the social and economic development level and the degree of agricultural mechanization of Northwest China is relatively backward, and the agricultural development mode is relatively extensive [32]. In some areas, such as the Shiyang river basin, the utilization rate of water resource development exceeds 100% [33]. The irrational (i.e., inefficient, extensive, and wasteful) use of water resources further exacerbates the shortage of agricultural water resources.

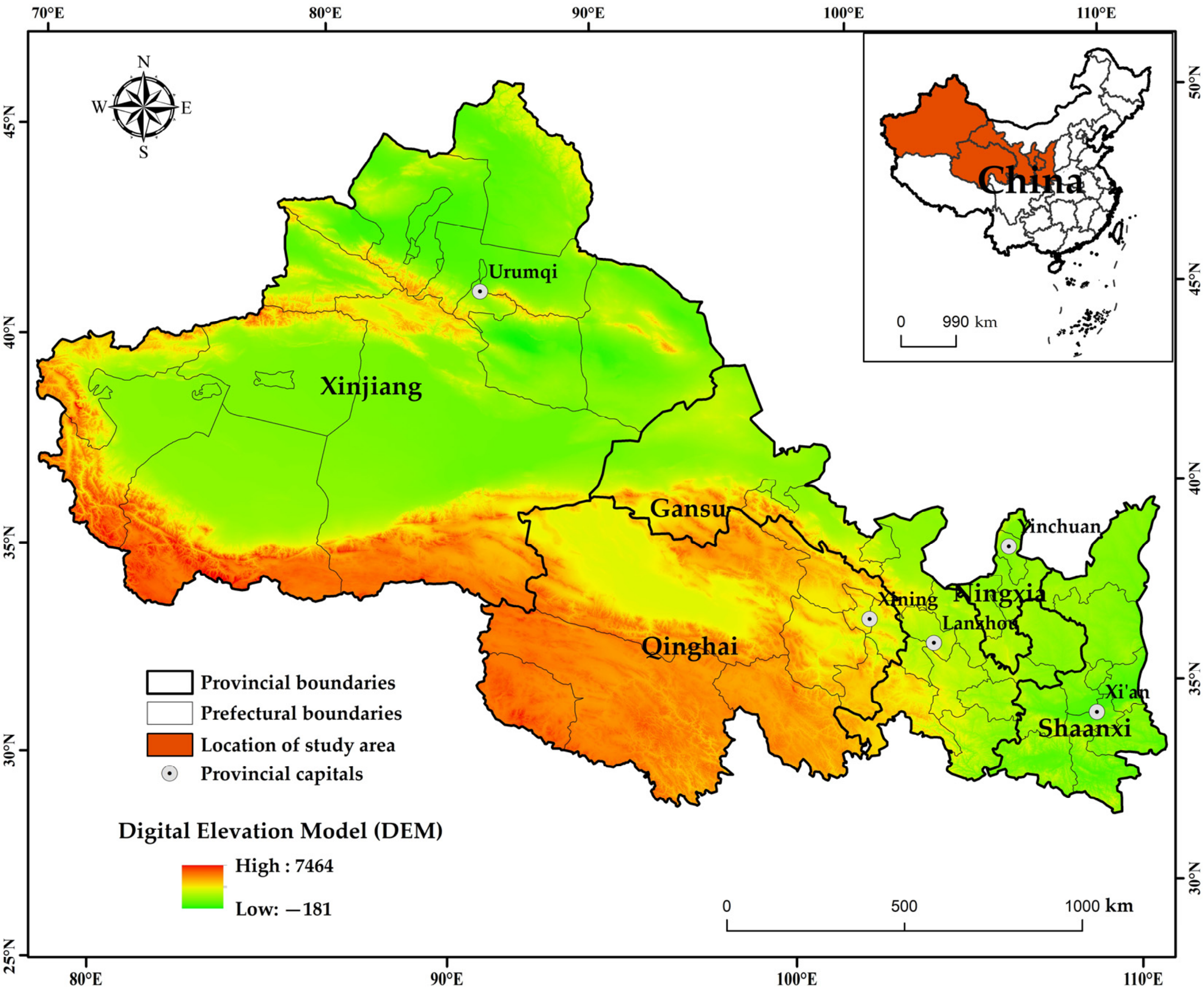

Figure 1. Study area in Northwest China.

3. Materials and Methods

3.1. AWUE Evaluation Indicator System

This paper uses global benchmark technology to construct the input-oriented Super-DEA model and measure the AWUE in Northwest China, which effectively solves the problem that multiple decision-making units cannot be compared across periods. Under the constant returns to scale (CRS) assumption, the input–output factors are evaluated in the Super-DEA model to obtain the optimal input of agricultural water resources. On this basis, the ratio of the optimal water consumption to the actual water consumption is used to obtain the value of AWUE. The efficiency value of the ith decision making units (DMU) is

$$P^{Global} = P^1 \cup P^2 \cup \ldots \cup P^t \quad (1)$$

$$\min_{\theta,z} \theta$$

$$s.t\begin{cases} \sum\limits_{t=1}^{T}\sum\limits_{n=1,n\neq 1}^{N} z_n^t x_{aq}^t \ll \theta \overline{x}_{aq}^t, q = 1, 2 \ldots, Q \\ \sum\limits_{t=1}^{T}\sum\limits_{n=1,n\neq 1}^{N} z_n^t y_{nj}^t \gg \overline{y}_{nj}^t, j = 1, 2 \ldots, J \\ z_n^t \gg 0, n = 1, 2, \ldots N, n \neq i, t = 1, 2 \ldots, T \\ x_q \gg x_{qi}, q = 1, 2 \ldots, Q \\ y_j \gg 0, y_j \ll y_{ji}, j = 1, 2 \ldots, J \end{cases} \tag{2}$$

where P^t represents the production reference set constructed based on the input–output data of the current section DMU, and P^{Global} represents the production reference set constructed based on the input–output data of the global benchmark.

Compared to traditional single-factor indicators, the AWUE will consider agricultural water inputs and other agricultural input factors in an integrated manner. In the process of agricultural production, input factors such as water, land, capital, labor, and technology are required. Referring to the existing literature [17,23], in this study, agricultural water consumption represents the input of water factor, the total sown area of crops represents the land input, the total power of agricultural machinery represents the capital input, the total number of primary industry employees represents the labor input, and the application amount of agricultural chemical fertilizer represents the technical input. Total agricultural output value represents the output index, which builds this study's index system of AWUE in Northwest China (Table 1).

Table 1. Evaluation index system of AWUE (agricultural water use efficiency).

	Variable	Unit	Variable Definition
Inputs	Land input	khm^2	Total sown area of crop
	Labor input	10^4 labor	Total number of primary industry employees
	Capital input	10^4 kW	Total power of agricultural machinery
	Water input	10^4 m^3	Total agricultural water consumption
	Technical input	10^4 t	Total application amount of agricultural chemical fertilizer
Outputs	Agricultural output value	Hundred million yuan	Total agricultural output value

3.2. *Exploratory Spatial Data Analysis (ESDA)*

Exploratory Spatial Data Analysis (ESDA) is a collection of spatial data analysis methods and techniques. Its core function is to test spatial homogeneity or heterogeneity through global and local spatial autocorrelation measurements.

3.2.1. Global Spatial Autocorrelation

In this paper, global Moran's I index is adopted to explore the spatial correlation and spatial difference of AWUE among 52 prefecture-level cities in Northwest China. The calculation formula is as follows:

$$I = \frac{n\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}(x_i - \overline{x})(x_j - \overline{x})}{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}\sum_{i=1}^{n}(x_i - \overline{x})^2} \tag{3}$$

where n is the sample size, x_i and x_j are the observation quantities of space positions i and j, and w_{ij} represents the proximity relationship between spatial positions i and j. When i and j are adjacent, w_{ij} = 1; otherwise, w_{ij} = 0. The value range of global Moran's I index is [−1, 1]. If the value of I is greater than 0 and significant, there is a positive spatial correlation between regions, showing the characteristics of spatial agglomeration. If the value of I is less than 0 and is significant, there is a negative spatial correlation between regions, which shows the spatial dispersion feature.

3.2.2. Local Spatial Autocorrelation (LISA)

In this paper, LISA was used to further measure the local spatial variation of AWUE in Northwest China, and the difference degree and significance level of local spatial agglomeration were analyzed. The calculation formula is as follows:

$$I_i = z_i \sum_j w_{ij} z_j, z_i = \frac{n(x_i - \overline{x})^2}{\sum_i (x_i - \overline{x})}, \ z_j = \left(x_j - \overline{x}\right) \tag{4}$$

where z_i and z_j are the standardization of observed values on region i and region j, respectively.

3.3. Spatial Econometric Model

Combining the factors of AWUE change, the spatial weight matrix is introduced to construct the spatial panel measurement model, which is mainly divided into a spatial lag model (SLM) and a spatial error model (SEM).

3.3.1. SLM Model

The SLM model is used to study whether the spatial correlation of AWUE between neighboring regions is caused by the spatial dependence between variables, and the expression is

$$Y = \rho WY + X\beta + \varepsilon \tag{5}$$

where W is the space weight matrix, X is the independent variable matrix, β is the regression coefficient of all variables, and ρ is the spatial regression coefficient, which reflects the direction and degree of spatial dependence.

3.3.2. SEM Model

The SEM model is used to study whether the spatial correlation of adjacent regions is caused by the error term. The expression is

$$Y = X\beta + (1 - \lambda W)^{-1} \quad \mu \quad \mu \ \sim \left(0, \sigma^2\right) \tag{6}$$

where the parameter λ is the magnitude of the spatial dependence between the perturbation error terms of the observation unit, reflecting the extent and direction of the influence of the dependent variable errors of the neighboring cities on the observed values in the region.

3.4. Variable Selection

The explained variable of this study is AWUE, which is calculated by Super-DEA.

The explanatory variables were selected from water resource conditions, the agricultural modernization level, and the social and economic development levels (Table 2). The AWUE in different cities is influenced by internal factors such as agricultural technical conditions, the popularization of mechanized services, and the popularization of water-saving technologies, which lead to changes in farmers' water use in agricultural production. Furthermore, the diversification of natural conditions, economic growth, urbanization, and other factors causes AWUE to change constantly. Referring to existing studies and considering the availability of data, water resource endowment (per capita water resources and annual precipitation), the agricultural modernization level (mechanization degree and effective irrigation degree), and the economic and social development level (urbanization level and per capita GDP) were selected as explanatory variables.

Water resource endowment: There is a negative effect of resource endowment on resource utilization efficiency. The two water resources most directly related to the effect of regional AWUE are irrigation water and precipitation. In regions where water resources are relatively abundant, farmers may have a poor awareness of water conservation. An unnecessary waste of water resources may occur in agricultural production, which increases the redundancy of agricultural water input and thus reduces the AWUE. Referring to existing studies [18–21], water resources per capita and annual precipitation were used to represent water resource endowment.

Agricultural modernization level: Agricultural modernization is an effective way to realize the efficient development of agricultural water use. The degree of mechanization can represent the application degree of machinery in farming, irrigation, drainage, etc. The effective irrigation area refers to the area of land equipped with irrigation equipment capable of normal irrigation. Both of them are important indexes reflecting the development level of agricultural modernization. Improving the level of agricultural equipment can create an efficient agricultural production system, further enhance the comprehensive production capacity, and promote the improvement of AWUE. Referring to existing studies [18–21], the degree of mechanization and effective irrigation were used to represent the level of agricultural modernization.

Economic and social development level: Economic and social development is the driving force to improve AWUE. Urbanization level and per capita GDP are important indicators to measure the level of economic and social development of a region. The higher the level of economic and social development is, the more farmers will be able to purchase and adopt efficient water-saving technologies and facilities, so as to improve the AWUE. Referring to existing studies [18–21], the urbanization rate and per capita GDP were adopted to represent the level of economic and social development.

Table 2. Variable selections and definitions. DEA: data envelopment analysis.

Variable/Unit			Variable Definition
Explained Variable		**AWUE**	**Calculated by Super-DEA**
Explanatory variables	water resource conditions	per capita water resources(PCW)/%	Total regional water resources/Total population of each region
		precipitation (PRE)/mm	The depth at which rainfall accumulates on the horizontal plane without evaporation, infiltration and loss
	agricultural modernization	mechanization degree (MECH)/%	Total power of agricultural machinery in various regions/Total planting area of crops
		effective irrigation degree(EIG)/%	Effective irrigation area in each region/Total planting area of crops
	Socio-economic development	economic growth (pGDP)/yuan RMB	GDP per capita
		urbanization (URBAN)/%	Urbanization rate of the resident population

3.5. Data Sources

In this paper, panel data on the provinces of Shaanxi, Ningxia, Xinjiang, Gansu, and Qinghai from 2000 to 2018 are used as the research sample. The data of the variables are derived from the China Rural Statistical Yearbook, the China Agricultural Statistical Report, the China Water Resources Bulletin, and the statistical yearbooks of all cities. There are missing data in individual years, and the adjacent year interpolation method is used to smooth the data.

4. Results and Discussion

4.1. Calculation of AWUE in Northwest China

MaxDEA software was used to calculate the AWUE of cities in Northwest China from 2000 to 2018 based on the total factor method, as shown in Appendix A. The average AWUE of 52 cities in Northwest China was ranked (Table 3). The mean AWUE values of different provinces were compared and analyzed (Figure 2).

Table 3. AWUE and ranking by region from 2000 to 2018.

City	2000	2009	2018	Mean	Ranking	City	2000	2009	2018	Mean	Ranking
Xi'an	0.13	0.36	1.27	0.46	19	Wuzhong	0.06	0.25	0.34	0.23	43
Tongchuan	0.29	0.48	0.78	0.50	14	Guyuan	0.09	0.29	0.58	0.30	33
Baoji	0.13	0.41	0.81	0.44	20	Zhongwei	0.06	0.26	0.59	0.25	42
Xianyang	0.07	0.31	0.98	0.50	15	Xining	0.09	0.23	0.61	0.28	34
Weinan	0.09	0.22	0.50	0.26	40	Haidong	0.10	0.24	0.45	0.26	39
Yan'an	0.20	0.48	1.06	0.57	11	Haibei	0.30	0.50	0.99	0.53	12
Hanzhong	0.01	0.08	0.98	0.35	28	Huangnan	0.46	0.74	1.01	0.73	5
Yulin	0.08	0.32	0.88	0.40	23	Hainan	0.32	0.41	0.88	0.49	16
Ankang	0.09	0.20	0.29	0.22	44	Golog	1.00	0.91	2.14	0.97	2
Shangluo	0.19	0.35	1.07	0.47	18	Yushu	0.51	0.76	2.67	0.87	4
Lanzhou	0.13	0.26	0.69	0.31	30	Haixi	0.24	0.30	0.79	0.43	21
Jiayuguan	1.05	1.01	0.93	0.94	3	Urumqi	0.21	0.51	0.99	0.61	8
Jinchang	0.16	0.24	0.53	0.26	36	Kelamayi	1.01	1.03	1.20	1.00	1
Baiyin	0.10	0.23	0.51	0.26	38	Shihezi	0.03	0.11	0.61	0.25	41
Tianshui	0.11	0.25	0.63	0.26	35	Tulufan	0.08	0.17	0.43	0.22	45
Wuwei	0.11	0.26	0.73	0.32	29	Hami	0.15	0.48	1.05	0.48	17
Zhangye	0.22	0.36	0.68	0.39	24	Changji	0.28	0.67	1.10	0.66	6
Pingliang	0.24	0.26	0.84	0.39	25	Ili	0.16	0.58	1.00	0.58	10
Jiuquan	0.07	0.38	0.66	0.37	26	Tarbagatay	0.28	0.67	0.97	0.63	7
Qingyang	0.10	0.27	0.58	0.35	27	Altay	0.14	0.21	0.31	0.21	46
Dingxi	0.16	0.21	0.43	0.26	37	Bortala	0.28	0.53	0.64	0.59	9
Longnan	0.14	0.21	0.73	0.31	31	Bayingol	0.15	0.43	1.00	0.52	13
Linxia	0.11	0.16	0.43	0.21	47	Aksu	0.05	0.13	0.24	0.13	50
Gannan	0.26	0.38	0.74	0.43	22	Kizilsu	0.17	0.20	0.25	0.21	48
Yinchuan	0.15	0.24	0.57	0.30	32	Kashgar	0.00	0.05	0.23	0.08	51
Shizuishan	0.06	0.05	0.45	0.17	49	Hoton	0.05	0.04	0.04	0.03	52

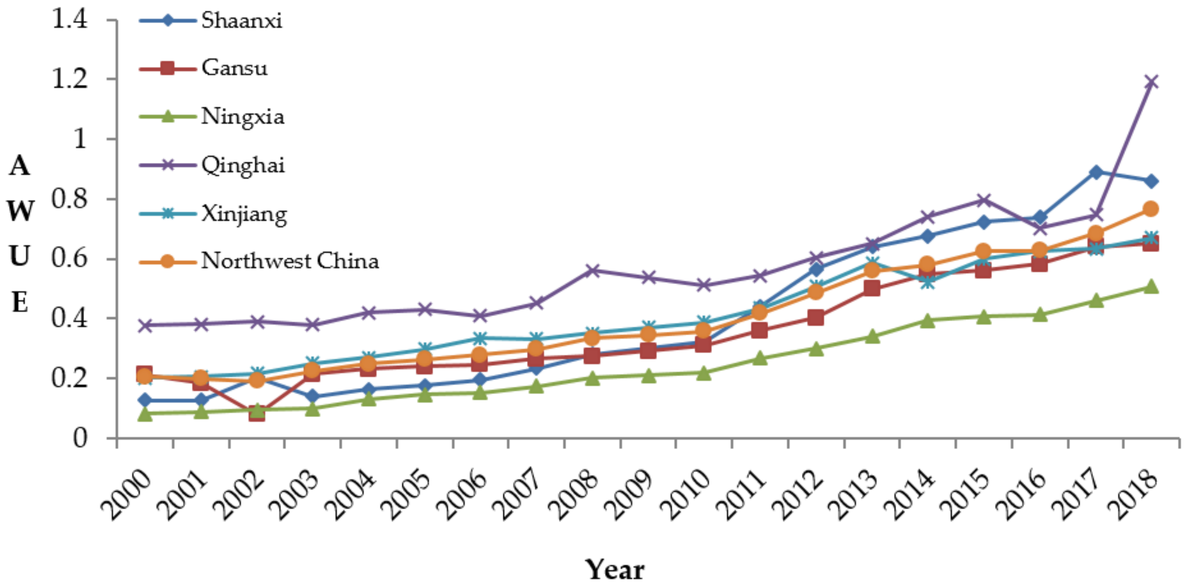

Figure 2. Evolution trend of agricultural water use efficiency (AWUE) in Northwest China from 2000 to 2018.

From the overall perspective of Northwest China, by observing the trend of Figure 2, the AWUE showed a steady upward trend from 2000 to 2018. The average efficiency increased from 0.21 in 2000 to 0.77 in 2018, with an average growth rate of 3.11%. However, the average AWUE in each year is below 0.8, which is still far from the effective frontier, indicating that there is still large room for improvement in AWUE in Northwest China.

From the provincial level (Figure 2), the average AWUE of the five northwest provinces was close to and at a low level at the beginning of the investigated period. By 2018, only Qinghai had achieved an effective AWUE of 1.19, followed by Shaanxi (0.86), Xinjiang (0.67), and Gansu (0.65). Ningxia had the lowest AWUE (0.51), and the inter-provincial difference was constantly expanding. During the investigation period, the AWUE of Qinghai was significantly higher than the average level of the other four provinces, but it also showed a trend of fluctuation and rise. The AWUE of Qinghai has significantly increased from 0.75 in 2017 to 1.19 in 2018, reaching the frontier of efficiency. The AWUE of Shaanxi rose steadily from 2000 to 2018, but after reaching its peak (0.89) in 2017, it declined slightly in 2018. From the perspective of the value of AWUE in Xinjiang, it showed a trend of steady fluctuation and progress during the investigated period. It only declined in 2014 and then began to rise slowly. The AWUE of Gansu dropped from 0.21 in 2000 to 0.08 in 2003, quickly recovered to the initial level of 0.22 in 2004, and then showed a steady upward trend. The AWUE of Ningxia kept rising steadily. However, due to the low initial efficiency and slow rise, the AWUE of Ningxia remained at the lowest level from 2000 to 2018.

From the city level (Tables A1 and A2), the AWUE in Hoton and Jiayuguan was reduced, and the AWUE in the other 50 cities increased to varying degrees during the investigation period. From 2000 to 2010, the AWUE of various cities showed a trend of rising fluctuation, but the change range was small, and the overall AWUE was still at a low level. Since 2011, when the Chinese government called for the implementation of the strictest water resource management system, the AWUE in cities has increased significantly, which shows the government's determination to save water, improve efficiency, and promote the improvement of AWUE. The AWUE in Hanzhong, Kashgar, Shihezi, Xianyang, and Yulin increased greatly, with an average growth rate of more than 10%. Altay, Bortala, Kizilsu, and Kelamayi had the smallest increase in AWUE with an average growth rate of less than 5%. According to the ranking results of the average AWUE from 2000 to 2018, the average AWUE in Kashgar and Hoton was the lowest, both below 0.01. The AWUE of Kelamayi, Golog, and Jiayuguan were the three highest, with an AWUE above 0.9.

4.2. Spatial Pattern and Differentiation Characteristics of AWUE in Northwest China

The time series analysis of AWUE in Northwest China can only describe the change trend and agglomeration difference of AWUE in time and cannot reflect the evolution law of the combination of time and space. Thus, the spatial pattern and differentiation characteristics of AWUE in Northwest China were explored based on the ESDA, an exploratory spatial data analysis method in GIS. According to the minimum AWUE value of 0.0026 and the maximum value of 2.6736 in Northwest China from 2000 to 2018, with an effective value of 1 in the Super-DEA model as the boundary, the values with an efficiency value of less than 1 were divided according to intervals of 0.3 and 0.6, and the AWUE in Northwest China was finally divided into four different intervals: (0.0026, 0.3), (0.3,0.6), (0.6, 1), and (1, 2.6736). Spatial distribution maps were produced showing typical time points in 2000, 2006, 2012, and 2018 (Figure 3).

It can be concluded from the spatial distribution diagram that, similar to the time series analysis above, the AWUE in Northwest China shows an obvious rising trend on the whole; however, it also reflects the fact that the efficiency of agricultural water use in cities of Northwest China has been low for a long time. In 2018, only individual cities in the provinces of Shaanxi, Qinghai, and Xinjiang were efficient in agricultural water use. Specifically, only Xi'an, Shangluo, Yan'an, Golog, Yushu, Huangnan, Kelamayi, Changji, Ili, Hami, and Bayingol achieved an effective AWUE of more than 1. Xi'an, Shangluo, and Yan'an are representative cities of Shaanxi. Compared with other cities in the same province, Xi'an, Shangluo, and Yan'an have a relatively high economic strength, a high agricultural technology level, and relatively high policy support. Qinghai is short of water all year. Therefore, the AWUE of these three cities is relatively high. Guoluo, Yushu, and Huangnan are located in the south of Qinghai, and in the range of the Sanjiangyuan Nature Reserve. They are important ecological barriers and water conservation areas. The scale of agriculture and animal husbandry is small, and they can produce more output with less input. The cities of Kelamay, Changji, Ili, and Hami are all located in Northern Xinjiang. They are not blocked by the Tianshan mountains and are affected by the moisture from the Atlantic Ocean and the Iberian airflow. As a result, the climate in Northern Xinjiang is wetter, and the water resources are more abundant. The optimal allocation of input and output can be achieved so as to realize the effective use of agricultural water.

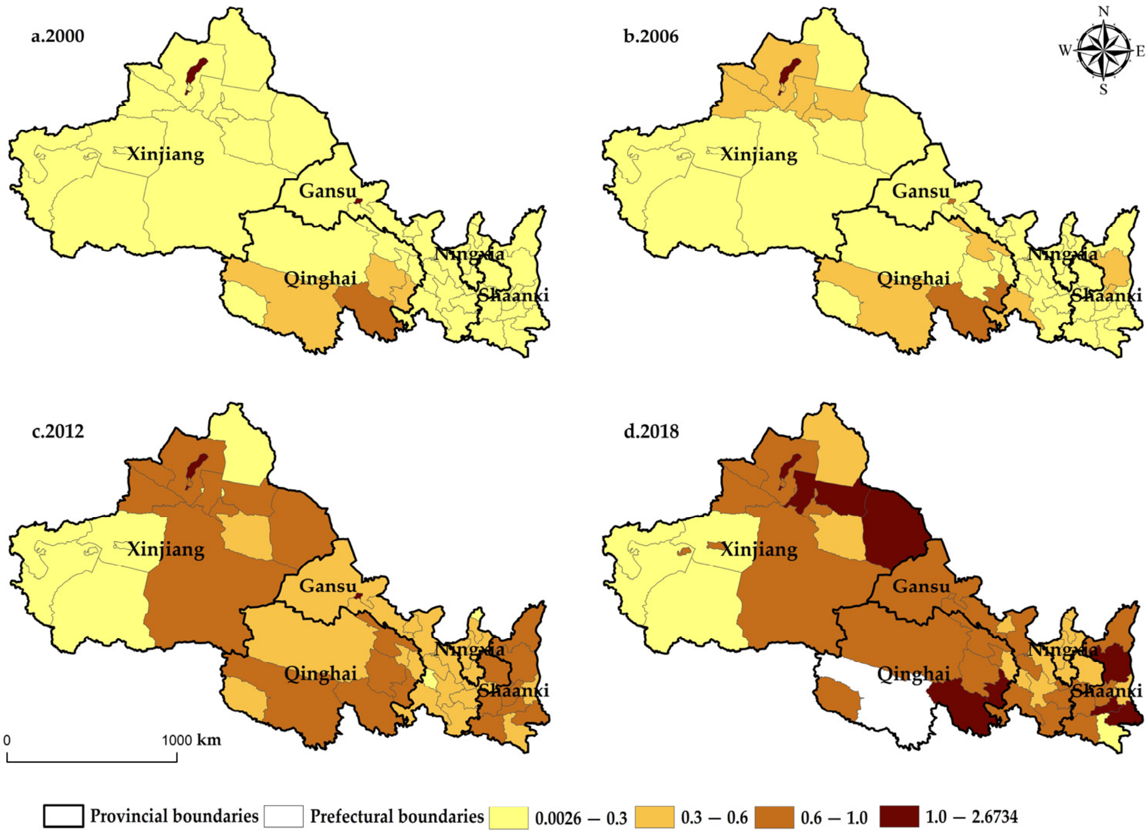

Figure 3. Spatial distribution of AWUE in Northwest China.

In order to further reveal the spatial variation and differentiation characteristics of AWUE in Northwest China, based on the support of ArcGIS and GeoDa software, the global Moran's I index, LISA agglomeration, and hotspot analysis under ESDA were used to analyze the spatial evolution characteristics, so as to characterize the spatial relationship between AWUE and its adjacent cities in Northwest China. The global Moran's I index conceptualizes the spatial relationship between cities based on the born-adjacent principle and standardizes the row to obtain the Moran's I of AWUE in Northwest China from 2000 to 2018. Moran's I was located in the interval of AWUE during the study period (0.1688, 0.3459), and all of them passed the significance test, indicating that there was a significant, positive correlation between AWUE in Northwest China, that is, a significant, positive agglomeration and dependency feature. However, the positive correlation of agglomeration characteristics experienced a "rise–fall–rise" similar to the N-type change process, i.e., an overall enhancement (Figure 4).

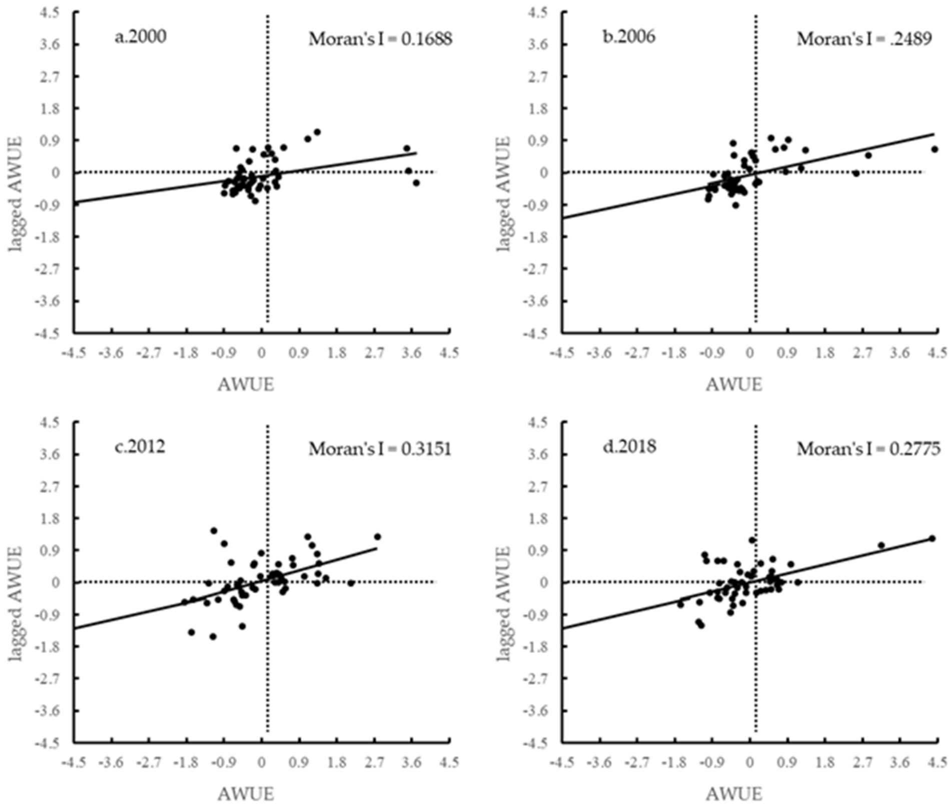

Figure 4. The Moran scatter map of AWUE in Northwest China from 2000 to 2018.

Under a 95% confidence interval, the relationship between the AWUE of a city in Northwest China and its neighboring cities was further explored based on a Moran's I scatter plot, taking 2000, 2006, 2012, and 2018 as typical time points (Figure 4). The range of Moran's I slope value is $(-1, 1)$. The closer it is to -1, the stronger the negative correlation will be. The closer it is to 1, the stronger the positive correlation will be. The I, III quadrants in the four quadrants represent H–H (high–high) agglomeration and L–L (low–low) agglomeration, and the II, IV quadrants represent a H–L (high–low) anomaly and an L–H (low–high) anomaly. The scatter plot shows most cities in the first study period in the I, III quadrant, and it can be said that the agricultural water use efficiency in Northwest China presents the agglomeration characteristics of H–H and L–L, i.e., the spatial distribution characteristics of AWUE cities and adjacent high efficiency cities, inefficient cities, and adjacent low efficiency cities. Fewer cities fall into quadrant II and IV, indicating that there are fewer obvious anomalies in their AWUE and adjacent cities.

In order to further determine the agglomeration or abnormal distribution of AWUE in the local space in Northwest China, the LISA agglomeration method under local Moran's I was used to analyze this. Similar to Moran's I scatter plot, the LISA cluster plot divides AWUE into four different types: (1) high–high agglomeration (H–H), meaning the AWUE of a city and its neighboring cities is high; (2) low–low agglomeration (L–L), meaning the AWUE of a city and its neighboring cities is low; (3) high–low agglomeration (H–L), meaning a city has a high AWUE, but that of its neighboring cities are low; and (4) low–high agglomeration (L–H), meaning a city's own AWUE is low, but that of its neighboring cities are higher. In addition, hot spot analysis can further detect the key location and local correlation of spatial agglomeration and identify the contribution of specific regions to a global autocorrelation. The Getis-OrdGi hotspot analysis of AWUE can be divided into hot, sub-hot, sub-cool, and cold spot areas, and can be combined with LISA agglomeration results (Figure 5), so that we can clearly explore, from a space perspective, Northwest China's AWUE in terms of agglomeration characteristics and spatial correlation.

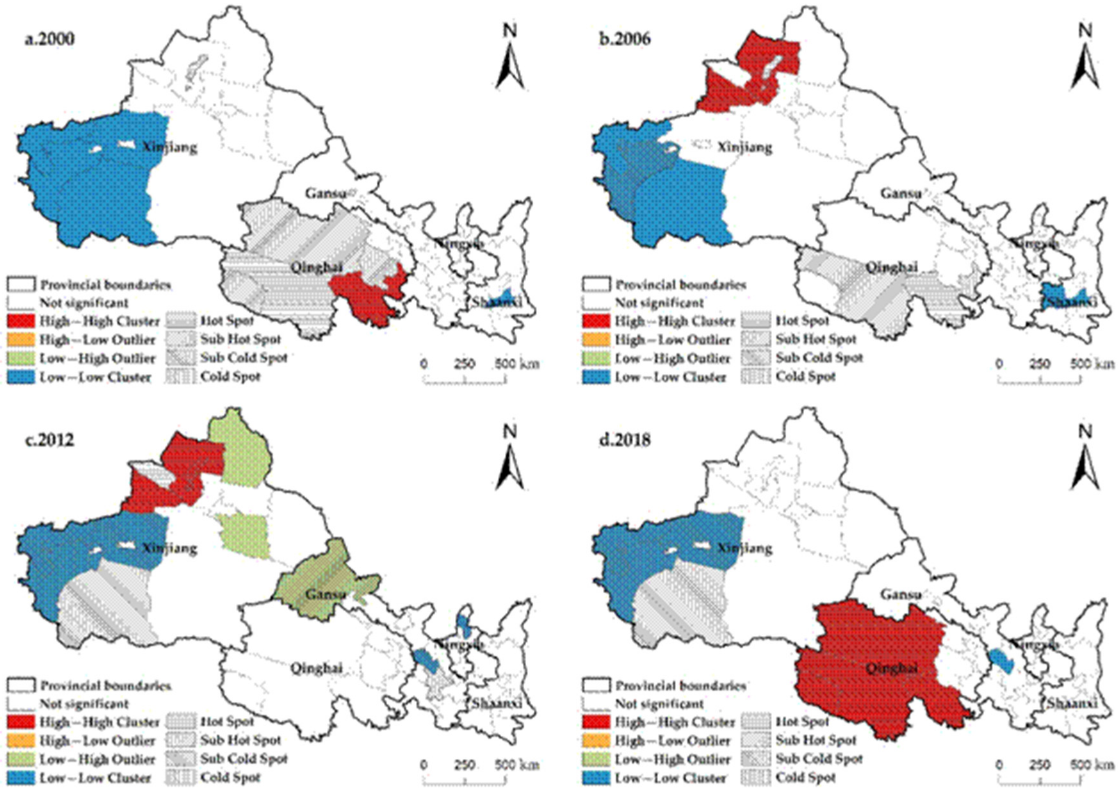

Figure 5. The LISA aggregation and hotspots of AWUE in Northwest China.

According to the distribution characteristics of local autocorrelation and hot spots, the distribution of high-value and low-value areas does not show obvious spatial trend characteristics, nor does it show consistent rules with the level of urban economic development. However, the following conclusions can be drawn from the figure: (1) The H–H type basically coincides with hot spot areas, but the change in a H–H area is more volatile from 2000 to 2018. It is distributed from Golog and Huangnan in Eastern Qinghai in 2000 to Ili and Tacheng in Northwestern Xinjiang in 2006 and 2012, and then to Haixi and Yushu in Western and Southern Qinghai in 2018. These cities and their neighboring cities are rich in water resources and have high AWUE, and the cities have significant, positive impacts on neighboring cities. (2) There is no cold point area with agricultural water use efficiency in Northwest China from 2000 to 2018, while the L–L type is more often in secondary cold point areas, and the change in L–L type is stable. These areas are basically located in the southwest of Xinjiang Kizilsu, Kashgar, Aksu, and other cities. Lanzhou is the only provincial capital city of the L–L type, which does not drive the surrounding cities to develop into an agricultural mode of high-efficiency water use. Lanzhou is the only provincial capital city in the L–L model that has not promoted the development of the surrounding cities to an agricultural model of high-efficiency water consumption. The AWUE of the low-concentration cities in Shaanxi and Ningxia have gradually improved, so they no longer exemplify an L–L model. (3) L–H and H–L are rarely distributed and sporadic over the years. In 2012, Altay, Tulufan, and Jiuquan were characterized mainly by low–high agglomeration and consisted mainly of sub-hot spots. The AWUE in these areas is low, and the agricultural production base is weak; however, the efficiency of the neighboring cities is relatively high. From 2000 to 2018, the scope agglomeration of H–L and L–H has changed from nothing, to existence, and then to nothing. The AWUE of those cities basically showed a gradual improvement, with room for further improvement.

4.3. Analysis on the Influencing Factors of AWUE

The change in AWUE in a region may influence the AWUE of neighboring regions. This spatial effect can be generated through the reconfiguration of production factors within the region and the flow of production factors between regions. This section mainly addresses the influencing factors of AWUE from the perspective of a spatial econometric model.

The premise of spatial econometric model construction is a spatial weight matrix. Two forms of spatial weight matrix are constructed here. One of them is the Rook adjacency weight matrix, W1, with a common boundary. When two cities have a common boundary, the elements in the matrix are set to 1; otherwise, they are set to 0. The other is the geographical distance weight matrix, W2. The elements in the matrix are constructed based on the square of the reciprocal of the latitude and longitude distance of the geometric center of the region.

Moran's I analysis in the previous article has confirmed that there is a spatial autocorrelation in the distribution of AWUE in Northwest China. Therefore, it is difficult for traditional regression models to accurately analyze the influencing factors of AWUE distribution. It is appropriate to use a spatial econometric model to analyze the influencing factors. The construction of the matrix is consistent with Moran's I index analysis. The test results show that the Moran index of AWUE under the two different spatial weight matrices is significantly positive, which indicates that the development of AWUE between cities exhibits a significant, positive spatial autocorrelation.

This paper identifies the specific form of the spatial econometric model through two Lagrange multipliers (LM-lag and LM-error) and their robust forms (Robust LM-lag and Robust LM-error). The results in Table 4 show that, under the two weight matrices, both LM-lag and LM-error passed the significance test. Robust LM-lag and Robust LM-error also passed the significance test. In general, the SLM is better than the SEM, so the SLM was chosen as the test model for spatial effect analysis. In addition, combined with Hausman's test, a fixed effect spatial measurement model was selected.

Table 4. The selection and definition of variables.

Model Selection	W1		W2	
	$\chi 2$	P	$\chi 2$	P
LM test no spatial lag	15.996	0.000	1.489	0.222
Robust LM test no spatial lag	7.469	0.006	16.017	0.000
LM test no spatial error	8.528	0.003	4.633	0.031
Robust LM test no spatial error	0.001	0.980	19.159	0.000

Table 5 reports the model estimation results under different weight matrices. To facilitate comparative analysis, it also reports the measurement results of the one-period lagged spatial panel models (Models 2 and 4) and the traditional ordinary least squares (OLS) model (Model 5). From the regression estimation results, the influence of various factors on AWUE under two spatial weight matrices is significant and consistent in direction. It has good robustness. At the same time, the coefficients of the time lag effect l.lnAWUE and the spatial spillover effect ρ are both significantly positive, indicating that the AWUE between cities has significant path dependence and spatial spillover effects. On the one hand, path dependence means that the changes in AWUE in the current period are positively affected by the previous period of AWUE, which shows that the AWUE of various regions has certain dynamics and related characteristics in time. Past agricultural production and water-saving methods will influence the subsequent agricultural activities and thus affect the improvement of the region AWUE. In addition, spatial spillover means that the AWUE of this region will have a strong demonstration effect and radiant driving effect on the AWUE of neighboring regions. The similarity of resource endowment, production conditions, and irrigation tradition between adjacent areas will strengthen the demonstration effect and the mutual influence of agricultural production water in adjacent areas.

Table 5. Model estimation results.

Variables	W1		W2		Model 5
	Model 1	Model 2	Model 3	Model 4	
l.lnAWUE		0.755 *** (14.28)		0.751 *** (16.31)	
lnPCW	−0.058 *** (−3.14)	−0.033 *** (−3.16)	−0.058 *** (−2.87)	−0.024 ** (−2.48)	−0.459 *** (−2.63)
lnPRE	−0.002 (0.06)	−0.006 (−0.23)	−0.020 (−0.44)	−0.026 (−1.05)	0.016 (0.36)
lnURBAN	0.223 ** (2.17)	0.071 * (1.72)	0.268 *** (3.27)	0.073 ** (1.98)	0.129 *** (4.19)
lnpGDP	0.663 *** (6.07)	0.200 *** (2.87)	0.565 *** (7.27)	0.198 *** (2.68)	0.835 *** (28.13)
lnMECH	0.075 (0.75)	0.039 (0.73)	0.092 (1.17)	0.016 (0.31)	0.074 ** (1.70)
lnEIG	0.258 ** (2.19)	0.160 *** (3.18)	0.254 *** (2.57)	0.176 *** (3.24)	0.180 *** (2.61)
ρ	0.163 ** (2.11)	0.031 (0.74)	0.129 ** (2.29)	0.073 * (1.74)	
sigma2	0.136 *** (4.44)	0.074 *** (4.67)	0.162 *** (4.16)	0.055 *** (6.99)	0.419
Adj-R2	0.687	0.828	0.655	0.854	0.649
LogL	−79.701	−90.369	−132.883	39.9647	271.310
N	936	936	936	936	936

Notes: *, **, *** represent significance at 10%, 5%, and 1%, respectively; value in the bracket is Z-test value.

In terms of water resource endowment, both per capita water resources and annual precipitation have a negative influence on AWUE, but only per capita water resources passed the significance test. This might be because people in areas with high per capita water resources are less aware of water conservation. People in these areas have behaviors that lead to wasted agricultural water, thereby reducing AWUE. There is a positive relationship between annual precipitation and AWUE, which is different from the conclusion drawn by other scholars from a national perspective, but it accords with the fact of drought and water shortage in Northwest China. The annual water volume in Northwest China, the region with the least rainfall in the country, is 15–910 mm. Under the predicament of drought and water shortage, relatively abundant rainfall will reduce the amount of agricultural irrigation water to a certain extent, and relatively ease the tension between water supply and demand in agricultural production. However, scarce rainfall is still difficult to meet the needs of production development and has no significant impact on AWUE.

In terms of economic and social development levels, per capita GDP and the urbanization level both have a significant, positive impact on AWUE. The impact of economic and social development on AWUE may have two effects. On the one hand, in areas with higher levels of economic and social development, farmers are more likely to accept advanced agricultural technology concepts and have the ability to purchase and adopt efficient water-saving technologies and facilities in agricultural production. On the other hand, the higher the level of urbanization, the stronger the effect of absorption and radiation, which can provide a solid guarantee for regional industrial agglomeration and technological innovation and is conducive to the development of local production equipment, water-saving technology, and water conservancy facilities, thus contributing to the improvement of AWUE.

In terms of the agricultural modernization level, the effective irrigation level has a positive and significant influence on the AWUE; that is, the improvement of the effective irrigation level can improve the AWUE. The improvement of the effective irrigation level can improve the extensive irrigation methods in Northwest China, reduce the amount of agricultural water consumption, and reduce the redundant input of water resources, which will increase the AWUE. The level of mechanization did not have a positive impact on the AWUE. It may be because of the blind planning and construction of water conservancy facilities in Northwest China that the introduced technology and equipment are not effective and cannot easily play their due role.

5. Conclusions

In this study, cities in Northwest China from 2000 to 2018 were considered as research objects, and the Super-DEA model was adopted to measure the AWUE of 52 cities in Northwest China. The spatial and temporal dynamic evolution and divergence characteristics of AWUE were explored through the global Moran's I index and LISA agglomerative maps, and a spatial panel econometric model was then constructed to analyze the influencing factors of AWUE. The main conclusions are as follows:

From the trend of time evolution, the AWUE in Northwest China shows a trend of a steady rise, yet it is still far from the effective frontier. There is still a large space for improvement. According to the analysis results of the broken line diagram, the AWUE of various cities showed a trend of fluctuation and increase, but the range of change was small, and the overall efficiency was still at a low level. After 2011, the rising degree increased and then in 2018 reached 0.77. The AWUE values of Kelamayi, Golog, and Jiayuguan were the three highest. The average AWUE in Kashgar and Hoton was the lowest.

From the spatial evolution pattern, the spatial distribution of AWUE in Northwest China has a significant, positive correlation. According to ESDA analysis, the AWUE values of 52 cities in Northwest China show significant, positive agglomeration and dependency characteristics. The high–high and low–low agglomeration effects are significant, and the distribution is concentrated.

The change in AWUE is influenced by factors such as resource endowment, socio-economic development, and agricultural modernization development, and there is a significant spatial dependence. Per capita GDP, the urbanization level, and the effective irrigation degree have a significant, positive impact on AWUE, and per capita water resources have a significant, negative impact on AWUE.

Based on the above analysis, some policy implications for improving AWUE in Northwest China can be made: First, on the basis of the implementation of measures such as the development of economies of scale, it is necessary to develop agricultural water conservation strategies and countermeasures according to local conditions based on the water resource endowment, the degree of agricultural development, the level of technology, and other factors in each city to avoid the implementation of uniform policies. Second, in order to achieve the coordinated development of AWUE in various cities, the radiating role of areas with high AWUE should be brought into play, the free flow of agricultural production factors should be promoted, and the cooperation and exchange of agricultural water conservation strategies between municipalities should be expanded. Third, it is necessary to further change the water-saving production mode and strengthen the innovation and promotion of agricultural science and technology, so that agricultural water resources can be effectively managed and fully utilized. At the same time, in areas with relatively abundant water resources, publicity on water conservation should be strengthened to improve farmers' awareness of water conservation.

Improving AWUE is not only important for solving the shortage of water resources, but also a necessary way to realize the construction of agricultural ecological civilization. The Super-DEA solves the problem of comparing efficiency values across periods, but it does not fully consider water resource input constraints, surface source pollution emissions, or the various influencing factors that lead to the loss of AWUE. Future research could measure AWUE by incorporating agricultural carbon emissions and agricultural surface pollution into the non-desired output. At the same time, natural and socio-economic factors, such as different crop types, irrigation technology, climatic conditions and population density, can be introduced to explore in depth the influencing factors of AWUE.

Author Contributions: Data curation, Y.D. (Yue Deng) and Y.D. (Yuanjie Deng); funding acquisition, W.L. (Weinan Lu); methodology, W.L. (Wenxin Liu); resources, M.H. and B.Z.; writing—review and editing, W.L. (Weinan Lu) and K.Z. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by the Major Research Projects of the National Social Science Fund of China (15ZDA052); Soft Science Program of National Forestry and Grassland Administration (20200131023); Science and Technology Plan Project, Yulin Science and Technology Bureau (CXY−2020-073); Graduate Student Science and Technology Innovation Program of College of Economics and Management, Northwest A&F University (JGYJSCXXM2020002).

Institutional Review Board Statement: This study mainly focused on models and data analysis and did not involve human factors considered dangerous. Therefore, ethical review and approval were waived for this study.

Informed Consent Statement: Not applicable.

Data Availability Statement: Data are available on request due to restrictions, e.g., privacy or ethical. The data presented in this study are available on request from the corresponding author. The data are not publicly available due to the strict management of various data and technical resources within the research teams.

Acknowledgments: We would like to thank the American journal experts who edited this paper. We also appreciate the constructive suggestions and comments on the manuscript from the reviewer(s) and editor(s).

Conflicts of Interest: The authors declare no conflict of interest.

Disclosure Statement: The authors report that there is no potential conflict of interest.

Appendix A

Table A1. The AWUE in China from 2000 to 2018.

Regions	2000 Year	2001 Year	2002 Year	2003 Year	2004 Year	2005 Year	2006 Year	2007 Year	2008 Year	2009 Year
Xi'an	0.13	0.14	0.14	0.15	0.18	0.20	0.21	0.25	0.34	0.36
Tongchuan	0.29	0.28	0.29	0.29	0.29	0.30	0.32	0.36	0.45	0.48
Baoji	0.13	0.14	0.17	0.15	0.19	0.21	0.24	0.28	0.33	0.42
Xianyang	0.07	0.08	0.20	0.11	0.16	0.19	0.20	0.25	0.29	0.29
Weinan	0.09	0.09	0.11	0.10	0.12	0.13	0.14	0.17	0.19	0.28
Yan'an	0.20	0.23	0.25	0.23	0.25	0.28	0.31	0.36	0.49	0.48
Hanzhong	0.01	0.01	0.22	0.01	0.02	0.03	0.04	0.05	0.08	0.08
Yulin	0.08	0.07	0.10	0.09	0.12	0.13	0.17	0.22	0.33	0.32
Ankang	0.09	0.10	0.23	0.16	0.10	0.06	0.07	0.09	0.11	0.20
Shangluo	0.19	0.14	0.32	0.10	0.20	0.23	0.25	0.29	0.23	0.35
Lanzhou	0.13	0.14	0.04	0.15	0.17	0.18	0.18	0.22	0.26	0.26
Jiayuguan	1.05	0.91	0.35	1.04	1.01	0.95	0.90	0.87	0.72	1.01
Jinchang	0.16	0.15	0.07	0.15	0.15	0.16	0.18	0.21	0.24	0.24
Baiyin	0.10	0.10	0.05	0.10	0.13	0.14	0.15	0.18	0.19	0.23
Tianshui	0.11	0.12	0.04	0.12	0.13	0.14	0.13	0.05	0.11	0.11
Wuwei	0.11	0.11	0.05	0.13	0.16	0.18	0.19	0.22	0.21	0.26
Zhangye	0.22	0.09	0.07	0.19	0.28	0.23	0.25	0.28	0.33	0.36
Pingliang	0.24	0.10	0.06	0.17	0.27	0.21	0.23	0.27	0.29	0.26
Jiuquan	0.07	0.04	0.08	0.20	0.08	0.26	0.30	0.32	0.37	0.38
Qingyang	0.10	0.11	0.05	0.14	0.13	0.17	0.18	0.20	0.24	0.27
Dingxi	0.16	0.20	0.05	0.14	0.17	0.15	0.15	0.19	0.22	0.21
Longnan	0.14	0.13	0.03	0.11	0.15	0.14	0.15	0.18	0.22	0.21
Linxia	0.11	0.12	0.06	0.12	0.13	0.14	0.15	0.17	0.17	0.16

Table A1. *Cont.*

Regions	2000 Year	2001 Year	2002 Year	2003 Year	2004 Year	2005 Year	2006 Year	2007 Year	2008 Year	2009 Year
Gannan	0.26	0.26	0.10	0.27	0.28	0.29	0.31	0.33	0.36	0.38
Yinchuan	0.15	0.15	0.12	0.12	0.14	0.16	0.17	0.20	0.22	0.24
Shizuishan	0.06	0.06	0.10	0.11	0.07	0.07	0.07	0.07	0.07	0.05
Wuzhong	0.06	0.07	0.08	0.09	0.18	0.19	0.20	0.21	0.22	0.25
Guyuan	0.09	0.09	0.10	0.10	0.13	0.15	0.16	0.21	0.22	0.29
Zhongwei	0.06	0.06	0.06	0.06	0.13	0.17	0.17	0.19	0.23	0.26
Xining	0.09	0.09	0.10	0.10	0.10	0.12	0.13	0.17	0.21	0.23
Haidong	0.10	0.10	0.10	0.11	0.12	0.14	0.15	0.20	0.24	0.24
Haibei	0.30	0.30	0.31	0.32	0.32	0.34	0.33	0.31	0.45	0.50
Huangnan	0.46	0.46	0.45	0.46	0.50	0.60	0.60	0.58	0.71	0.74
Hainan	0.32	0.32	0.34	0.24	0.40	0.28	0.29	0.34	0.42	0.41
Golog	1.00	1.00	1.00	0.99	0.98	1.05	0.98	0.99	1.05	0.91
Yushu	0.51	0.51	0.55	0.55	0.66	0.62	0.50	0.73	1.11	0.76
Haixi	0.24	0.25	0.27	0.28	0.28	0.29	0.28	0.30	0.30	0.30
Urumqi	0.21	0.23	0.31	0.49	0.61	0.62	0.58	0.54	0.52	0.51
Kelamayi	1.01	1.00	1.00	1.00	1.00	0.99	1.36	0.91	0.98	1.03
Shihezi	0.03	0.02	0.03	0.03	0.03	0.06	0.06	0.07	0.11	0.11
Tulufan	0.08	0.08	0.10	0.11	0.13	0.15	0.18	0.19	0.19	0.17
Hami	0.15	0.15	0.12	0.17	0.18	0.23	0.28	0.41	0.42	0.48
Changji	0.28	0.28	0.30	0.34	0.38	0.46	0.49	0.51	0.55	0.67
Ili	0.16	0.16	0.18	0.26	0.30	0.37	0.40	0.48	0.49	0.58
Tarbagatay	0.28	0.30	0.33	0.37	0.37	0.43	0.48	0.52	0.53	0.67
Altay	0.14	0.14	0.15	0.15	0.16	0.17	0.18	0.17	0.19	0.21
Bortala	0.28	0.29	0.30	0.36	0.39	0.41	0.43	0.46	0.45	0.53
Bayingol	0.15	0.16	0.17	0.20	0.22	0.25	0.25	0.35	0.39	0.43
Aksu	0.05	0.05	0.05	0.05	0.06	0.07	0.07	0.09	0.11	0.13
Kizilsu	0.17	0.17	0.18	0.18	0.18	0.20	0.20	0.21	0.20	0.20
Kashgar	0.00	0.00	0.00	0.00	0.01	0.02	0.03	0.02	0.04	0.05
Hoton	0.05	0.05	0.05	0.05	0.04	0.04	0.04	0.03	0.03	0.04

Table A2. The AWUE in China from 2000 to 2018 (continued from Table A1).

Regions	2010 Year	2011 Year	2012 Year	2013 Year	2014 Year	2015 Year	2016 Year	2017 Year	2018 Year
Xi'an	0.45	0.48	0.60	0.69	0.73	0.76	0.81	0.87	1.27
Tongchuan	0.49	0.55	0.64	0.68	0.72	0.76	0.75	0.76	0.78
Baoji	0.47	0.48	0.60	0.65	0.72	0.74	0.77	0.79	0.81
Xianyang	0.45	0.54	0.61	0.66	0.76	0.84	0.87	1.89	0.98
Weinan	0.28	0.26	0.34	0.35	0.40	0.43	0.46	0.48	0.50
Yan'an	0.54	0.62	0.76	0.84	0.89	1.01	0.95	1.01	1.06
Hanzhong	0.15	0.40	0.49	0.67	0.85	0.79	0.88	0.96	0.98
Yulin	0.38	0.44	0.54	0.63	0.70	0.77	0.77	0.89	0.88
Ankang	0.25	0.41	0.45	0.50	0.26	0.27	0.28	0.30	0.29
Shangluo	0.43	0.49	0.62	0.72	0.74	0.85	0.84	0.95	1.07
Lanzhou	0.29	0.30	0.35	0.41	0.44	0.51	0.55	0.66	0.69
Jiayuguan	0.86	1.02	0.99	1.16	1.02	0.96	1.00	1.03	0.93
Jinchang	0.25	0.27	0.29	0.31	0.35	0.39	0.41	0.52	0.53
Baiyin	0.28	0.27	0.31	0.37	0.42	0.44	0.46	0.49	0.51
Tianshui	0.23	0.27	0.30	0.42	0.47	0.45	0.60	0.59	0.63
Wuwei	0.28	0.30	0.38	0.43	0.49	0.52	0.55	0.69	0.73
Zhangye	0.38	0.42	0.47	0.55	0.62	0.61	0.61	0.68	0.68
Pingliang	0.35	0.36	0.44	0.50	0.60	0.63	0.72	0.81	0.84
Jiuquan	0.40	0.43	0.47	0.55	0.59	0.64	0.63	0.61	0.66
Qingyang	0.33	0.33	0.44	0.71	0.83	0.76	0.56	0.56	0.58
Dingxi	0.26	0.25	0.30	0.38	0.44	0.41	0.42	0.43	0.43
Longnan	0.26	0.24	0.32	0.41	0.49	0.58	0.66	0.71	0.73
Linxia	0.20	0.19	0.21	0.27	0.29	0.31	0.33	0.41	0.43
Gannan	0.46	0.40	0.46	0.52	0.63	0.63	0.67	0.74	0.74

Table A2. *Cont.*

Regions	2010 Year	2011 Year	2012 Year	2013 Year	2014 Year	2015 Year	2016 Year	2017 Year	2018 Year
Yinchuan	0.31	0.33	0.39	0.43	0.46	0.48	0.52	0.54	0.57
Shizuishan	0.10	0.11	0.10	0.14	0.37	0.38	0.41	0.43	0.45
Wuzhong	0.22	0.28	0.29	0.33	0.34	0.35	0.36	0.26	0.34
Guyuan	0.32	0.36	0.39	0.45	0.53	0.49	0.47	0.54	0.58
Zhongwei	0.26	0.28	0.34	0.39	0.26	0.33	0.31	0.54	0.59
Xining	0.30	0.31	0.35	0.42	0.49	0.49	0.52	0.57	0.61
Haidong	0.25	0.34	0.38	0.40	0.38	0.44	0.38	0.39	0.45
Haibei	0.52	0.54	0.60	0.70	0.92	0.95	0.76	0.66	0.99
Huangnan	0.75	0.78	0.80	0.93	1.01	0.96	1.02	1.01	1.01
Hainan	0.47	0.47	0.54	0.62	0.72	0.76	0.79	0.79	0.88
Golog	0.92	0.79	0.88	0.67	0.76	1.03	0.44	0.87	2.14
Yushu	0.89	0.81	0.87	0.94	1.02	1.02	0.94	0.94	2.67
Haixi	0.37	0.38	0.39	0.51	0.63	0.72	0.76	0.75	0.79
Urumqi	0.59	0.59	0.67	0.76	0.75	0.84	0.89	0.89	0.99
Kelamayi	0.97	0.87	0.97	1.34	0.46	0.87	0.99	0.98	1.20
Shihezi	0.13	0.13	0.18	0.32	0.41	0.79	0.79	0.79	0.61
Tulufan	0.21	0.20	0.22	0.31	0.32	0.36	0.37	0.37	0.43
Hami	0.52	0.46	0.65	0.77	0.65	0.74	0.85	0.91	1.05
Changji	0.71	0.78	0.90	0.99	0.96	0.91	0.98	0.90	1.10
Ili	0.60	0.68	0.78	0.90	0.95	0.94	0.83	0.92	1.00
Tarbagatay	0.69	0.73	0.98	0.94	0.81	0.79	0.88	0.96	0.97
Altay	0.20	0.21	0.21	0.24	0.29	0.29	0.31	0.32	0.31
Bortala	0.62	0.82	0.82	0.87	0.87	0.84	0.89	0.93	0.64
Bayingol	0.50	0.58	0.76	0.94	0.71	0.99	0.91	0.84	1.00
Aksu	0.13	0.15	0.14	0.19	0.20	0.22	0.22	0.21	0.24
Kizilsu	0.21	0.20	0.22	0.23	0.26	0.22	0.24	0.24	0.25
Kashgar	0.08	0.08	0.07	0.08	0.15	0.21	0.22	0.21	0.23
Hoton	0.03	0.04	0.04	0.04	0.02	0.01	0.01	0.01	0.04

References

1. Richey, A.S.; Thomas, B.F.; Lo, M.L.; Famiglietti, J.S.; Swenson, S.; Rodell, M. Uncertainty in global groundwater storage estimates in a total groundwater stress framework. *Water Resour. Res.* **2015**, *51*, 5198–5216. [CrossRef]
2. Voeroesmarty, C.J.; Mcintyre, P.B.; Gessner, M.O.; Dudgeon, D.; Prusevich, A.; Green, P. Global threats to human water security and river biodiversity. *Nature* **2010**, *467*, 555–561. [CrossRef] [PubMed]
3. The United Nations World Water Development Report 2018: Nature-Based Solutions for Water. Available online: https://www.unwater.org/publications/world-water-development-report-2018/ (accessed on 19 March 2018).
4. Deng, X.P.; Shan, L.; Zhang, H.; Turner, N.C. Improving agricultural water use efficiency in arid and semiarid areas of China. *Agric. Water Manag.* **2006**, *80*, 23–40. [CrossRef]
5. Geng, Q.; Ren, Q.; Nolan, R.H.; Wu, P.; Yu, Q. Assessing china's agricultural water use efficiency in a green-blue water perspective: A study based on data envelopment analysis. *Ecol. Indic.* **2019**, *96*, 329–335. [CrossRef]
6. Peng, S. Water resources strategy and agricultural development in china. *J. Exp. Bot.* **2011**, *62*, 1709–1713. [CrossRef]
7. Song, P.; Wang, X.; Wang, C.; Lu, M.; Wang, H. Analysis of agricultural water use efficiency based on analytic hierarchy process and fuzzy comprehensive evaluation in Xinjiang, China. *Water* **2020**, *12*, 3266. [CrossRef]
8. Sun, S.K.; Liu, J.; Wu, P.T.; Wang, Y.B.; Zhao, X.N.; Zhang, X.H. Comprehensive evaluation of water use in agricultural production: A case study in Hetao irrigation district, China. *J. Clean Prod.* **2011**, *112*, 4569–4575. [CrossRef]
9. National Water-Saving Action Plan. Available online: http://www.mwr.gov.cn/xw/slyw/201910/t20191016_1365357.html (accessed on 16 October 2019).
10. Chen, Y.; Li, B.; Li, Z.; Li, W. Water resource formation and conversion and water security in arid region of northwest china. *J. Geogr. Sci.* **2016**, *26*, 939–952. [CrossRef]
11. Tan, Q.; Zhang, T.Z. Robust fractional programming approach for improving agricultural water-use efficiency under uncertainty. *J. Hydrol.* **2018**, *564*, 1110–1119. [CrossRef]
12. Halsema, G.E.V.; Vincent, L. Efficiency and productivity terms for water management: A matter of contextual relativism versus general absolutism. *Agric. Water Manag.* **2012**, *108*, 9–15. [CrossRef]
13. Hu, J.L.; Wang, S.C.; Yeh, F.Y. Total-factor water efficiency of regions in China. *Resour. Policy* **2006**, *31*, 217–230. [CrossRef]
14. Cao, X.; Zeng, W.; Wu, M.; Guo, X.; Wang, W. Hybrid analytical framework for regional agricultural water resource utilization and efficiency evaluation. *Agric. Water Manag.* **2020**, *231*, 106027. [CrossRef]

15. Liu, X.; Shi, L.; Qian, H.; Sun, S.; Wu, P.; Zhao, X. New problems of food security in northwest china: A sustainability perspective. *Land Degrad. Dev.* **2020**, *31*, 975–989. [CrossRef]
16. Kaneko, S.; Tanaka, K.; Toyota, T.; Managi, S. Water efficiency of agricultural production in china: Regional comparison from 1999 to 2002. *Int. J. Agric. Res. Gov. Ecol.* **2004**, *3*, 231–251. [CrossRef]
17. Azad, M.A.; Ancev, T.; Hernández-Sancho, F. Efficient water use for sustainable irrigation industry. *Water Res. Manag.* **2015**, *29*, 1683–1696. [CrossRef]
18. Mu, L.; Fang, L.; Wang, H.; Chen, L.; Yang, Y.; Qu, X.J. Exploring northwest china's agricultural water-saving strategy: Analysis of water use efficiency based on an SE-DEA model conducted in Xi'an, Shaanxi province. *Water Sci. Technol.* **2016**, *74*, 1106–1115. [CrossRef]
19. Liu, Y.; Hu, X.; Zhang, Q.; Zheng, M. Improving agricultural water use efficiency: A quantitative study of zhangye city using the static CGE model with a CES water−land resources account. *Sustainability* **2017**, *9*, 308. [CrossRef]
20. Xu, L.; Huang, Y. Measurement of Irrigation Water Efficiency and Analysis of Influential Factors: An Empirical Study of Mengcheng County in Anhui Province. *Res. Sci.* **2012**, *34*, 105–113.
21. Geng, X.H.; Zhang, X.H.; Song, Y.L. Measurement of Irrigation Water Efficiency and Analysis of Influential Factors: An Empirical Study based on stochastic production frontier and cotton farmers' data in Xinjiang. *J. Nat. Resour.* **2014**, *29*, 934–943.
22. Yu, Z.Y.; Liang, S.M. Analysis of irrigation water using efficiency in arid and semi-arid areas in Northwest China based on Miami model. *J. Arid. Land Res. Environ.* **2017**, *31*, 49–55.
23. Wang, Y. Urban land and sustainable resource use: Unpacking the countervailing effects of urbanization on water use in china, 1990–2014. *Land Use Policy* **2020**, *9*, 104307. [CrossRef]
24. Zhang, X.D.; Zhu, S. Spatial differences and influencing factors of regional agricultural water use efficiency in Heilongjiang province, China. *Water Supply* **2019**, *19*, 545–552.
25. Wang, G.F.; Chen, J.C.; Wu, F.; Li, Z.H. An integrated analysis of agricultural water-use efficiency: A case study in the Heihe river basin in northwest china. *Phys. Chem. Earth Parts A/B/C* **2015**, *89*, 3–9. [CrossRef]
26. Azad, M.A.; Ancev, T. Measuring environmental efficiency of agricultural wateruse: A Luenberger environmental indicator. *J. Environ. Manag.* **2014**, *145*, 314–320. [CrossRef]
27. Tong, J.P.; Ma, J.F.; Wang, H.M. Agricultural Water Use Efficiency and Technical Progress in China Based on Agricultural Panel Data. *Res. Sci.* **2014**, *36*, 1765–1772.
28. Veettil, P.C.; Speelman, S.; Huylenbroeck, G.V. Estimating the impact of water pricing on water use efficiency in semi-arid cropping system: An application of probabilistically constrained nonparametric efficiency analysis. *Water Res. Manag.* **2013**, *27*, 55–73. [CrossRef]
29. Guo, B.; Kong, W.H.; Jiang, L. Dynamic monitoring of vulnerability and quantitative analysis of driving factors in northwest arid desert ecosystem. *J. Nat. Resour.* **2018**, *33*, 412–424.
30. Deng, M.J. "Three Water Lines" strategy: Its spatial patterns and effects on water resources allocation in Northwest China. *Acta Geogr. Sin.* **2018**, *73*, 1189–1203.
31. Huang, Y.J.; Su, Y.; Li, R.L.; He, H.Q.; Liu, H.Y. Study of the spatio-temporal differentiation of factors influencing carbon emission of the planting industry in arid and vulnerable areas in northwest china. *Int. J. Environ. Res. Public Health* **2019**, *17*, 187. [CrossRef]
32. Wang, G.F.; Lin, N.; Zhou, X.X.; Li, Z.H.; Deng, X.Z. Three-stage data envelopment analysis of agricultural water use efficiency: A case study of the Heihe river basin. *Sustainability* **2018**, *10*, 568. [CrossRef]
33. Ma, J.Z.; Wang, X.S.; Edmunds, W.M. The characteristics of ground-water resources and their changes under the impacts of human activity in the arid northwest china—A case study of the Shiyang river basin. *J. Arid Environ.* **2005**, *61*, 277–295. [CrossRef]