water

MDPI

Article

Understanding the Mechanism of Urbanization Affect Agricultural Water Efficiency: Evidence from China

Deyang Li [1], Hongxu Shi [1,*], Peihua Ma [2], Shuning Zhu [1] and Hao Xu [1]

[1] School of Agricultural Economics and Rural Development, Renmin University of China, Beijing 100872, China; lideyang@ruc.edu.cn (D.L.); zhushuning@ruc.edu.cn (S.Z.); xhao1110@ruc.edu.cn (H.X.)
[2] Department of Nutrition and Food Science, College of Agriculture and Natural Resources, University of Maryland, College Park, MD 20740, USA; peihua@umd.edu
* Correspondence: shihongxu@ruc.edu.cn

Abstract: Concerns regarding food security and sustainable development have been highlighted as a result of water scarcity and growing urbanization. It is imperative to look into their relationship. This study examines the impact of urbanization on agricultural water efficiency (AWE) in China utilizing China province-level panel data from 2002 to 2019. The findings indicate that urbanization has a U-shaped relationship with AWE, meaning that urbanization first had a detrimental effect on AWE before reversing course. These findings are robust to the inclusion of three measures of urbanization and the estimation of the instrumental variable method. Structural equation modeling of the underlying mechanisms demonstrates that, at higher levels of urbanization, planting structure and irrigation facilities partially mediate the urbanization-AWE relationship; the mediate effects account for between 27.3% and 100% of total effects, depending on the urbanization measurement used. China should continue investing in rural irrigation infrastructure as it urbanizes, as this would improve water efficiency.

Keywords: agricultural water efficiency; urbanization; U-shape curve; structural equation modeling; supper efficiency DEA method

check for updates

Citation: Li, D.; Shi, H.; Ma, P.; Zhu, S.; Xu, H. Understanding the Mechanism of Urbanization Affect Agricultural Water Efficiency: Evidence from China. *Water* **2022**, *14*, 2176. https://doi.org/10.3390/w14142176

Academic Editor: Pilar Montesinos

Received: 6 May 2022
Accepted: 7 July 2022
Published: 9 July 2022

1. Introduction

Urbanization is an unavoidable trend in China's development. Policymakers in China have also identified urbanization as a critical factor in sustaining socioeconomic growth. It is widely acknowledged that urbanization has the potential to significantly increase consumer and investment demand while also creating a plethora of job opportunities [1,2]. Given the importance of urbanization in economic growth and environmental sustainability, there is growing concern about the effects of rapid urbanization on the diversion of water supplies away from agriculture and the potential impact on agricultural sustainability [3]. Water resource overuse has been a side effect of increasing urbanization and industrialization, resulting in dwindling supplies [4]. Improving the efficiency with which water resources are used is a critical issue that must be addressed immediately in order to maintain economic and social growth in the face of climate change [5–7]. China is not endowed with an abundance of water; water is the primary constraint on China's future development; and water issues are a top priority for Chinese policymakers [8]. Food security is a fundamental concern in urban growth since it is hampered by water scarcity. Without agricultural stability, there can be no progress or prosperity, rendering industrialization and urbanization projects ineffective [9].

According to a review of the literature, the majority of recent research has concentrated on the effects of urbanization on food security, agricultural production, and land use [10–15]. Growing urbanization creates a constraint on water allocation between rural and urban regions. There is far less water available for agricultural production owing to urbanization. Improving agricultural water efficiency (AWE) is of considerable relevance in the context of water shortages due to urbanization [16]. One of the United Nations' Sustainable Development Goals (SDGs) is to significantly increase water efficiency [17]. Furthermore, the irrigation water consumption indicator for agriculture is based on a single agricultural input. Agricultural water efficiency, on the other hand, takes into account all agricultural inputs and outputs and thus more accurately measures technological progress and characterizes agricultural water use. Examining the impact of urbanization on agricultural water use using the AWE indicator is thus both practical and instructive. AWE expansion is essential for food security and water conservation. Improving AWE faces a number of challenges, such as land fragmentation [8], lack of collective action in rural areas [18], and limited access to water-saving technologies [19]. Interestingly, despite the fact that water is scarce and improving AWE is critical for achieving sustainable agricultural production, little research has been conducted on the effects of urbanization on AWE.

There are at least three significant negative consequences of urbanization on AWE. To begin with, the loss of productive farmland has the potential to damage the local agricultural support sector [10], such as water-saving technology, due to a lack of demand. Second, the young and middle-aged rural labor force seeks non-agricultural jobs in cities [20], leaving an increasing number of women, children, and the elderly in rural regions, deteriorating the quality of human capital in rural areas [21]. They have a more difficult time adopting and mastering water-saving devices. Thirdly, irrigation facilities and water infrastructure in rural areas are deteriorating or have already deteriorated as a result of a lack of collective action to maintain them; urbanization is one of the reasons that rural regions lack collective action [22]. As smallholder farmers who take off-farm work lose their reliance on agriculture as a source of income owing to increasing urbanization, rural infrastructure investment dwindles and collective action vanishes. Due to decentralized smallholder farming in China, the irrigation water use efficiency is poor. Without collective action, successful water-saving irrigation facility usage is impossible in the case of smallholder agriculture.

While urbanization has been shown to have a detrimental effect on agricultural water efficiency [23], little attention has been paid to the fact that urbanization may also have a beneficial effect on AWE [24]. Urbanization encourages large-scale intensive use of rural land [25]. And large-scale rural land is easier to adopt community-based water-saving technologies, which could improve AWE [8]. Urbanization has the potential to increase agricultural technology levels [16], resulting in an increase in AWE. Urbanization could support agriculture by establishing industry. China's government has made significant investments in rural development and developed a 'rural revitalization strategy' [26]. This strategy will benefit the promotion of irrigation facilities in rural areas and will result in an increase in the AWE [19]. Additionally, urbanization has resulted in a shift in food consumption patterns, with an increase in the consumption of cash crops such as vegetables [27,28]. Growing cash crops such as vegetables requires more modern management and may use less water, lowering production costs [29,30].

Is urbanization beneficial or detrimental to agricultural water efficiency in China? A few pieces of literature clearly explain the relationship between urbanization and AWE. As a result, there is a gap in knowledge regarding how urbanization affects AWE. Investigating the relationship is critical for sustainable development in order to achieve the goal of food security and water conservation. This is the first study that we are aware of that examines the relationship between urbanization and AWE. The study makes use of panel data from China's National Bureau of Statistics for 31 provinces from 2002 to 2019. This research makes several significant contributions to the literature on urbanization-AWE relationships. To begin, this study is unique in that it is the first of its kind in that our paper's urbanization and AWE measures, combined with nationally representative longitudinal data, provide a much broader picture of related issues. Second, this study makes extensive use of China's provincial panel data to examine the impact of urbanization on AWE. Three indicators were used to proxy urbanization in this study, and IV estimations were used to address the possibility of endogeneity, ensuring that the estimated results are robust and reliable.

Third, in order to gain a more complete understanding of the urbanization-AWE nexus, we examine potential mediators using a structural equation modeling (SEM) approach that incorporates planting structure adjustment and irrigation facility supply as channel variables. Thus, this study sheds light on the potential mechanisms by which urbanization affects AWE.

The rest of the paper is divided into the following sections: Section 2 introduces the indicator measures and empirical approach; Section 3 summarizes the findings and elucidates the heuristic processes through which urbanization affects AWE in China; and Section 4 closes the research with a discussion of the primary findings and their policy implications.

2. Materials and Methods

2.1. Measuring Agricultural Water Efficiency

Currently, data envelopment analysis (DEA) is a widely used technique to assess effectiveness. The two primary DEA model types are CCR (named after Charnes, Cooper, and Rhodes, 1978) and BCC (named after Banker, Charness, and Cooper, 1984). In contrast to the BCC model, which assumes that activities have variable returns to scale, the CCR model posits that activities have constant returns to scale [31]. Three criteria are used by DEA to define efficiency: scale efficiency, overall technical efficiency (derived by the CCR model), and pure technical efficiency (determined by the BCC model). This study tries to determine *AWE*, which evaluates the ability to create a certain output with the least amount of water inputs. As a result, the input-oriented CCR model is put into practice.

In this study, agricultural water efficiency (AWE) is defined as the ratio of the ideal irrigation water input to the actual irrigation water input, using the following formula:

$$AWE_{i,t} = \frac{OAWI_{i,t}}{AAWI_{i,t}} \tag{1}$$

where $AWE_{i,t}$ denotes province i at time t in terms of agricultural water efficiency. $AAWI_{i,t}$ is the actual agricultural water input of province i at time t, $OAWI_{i,t}$ is the optimal agricultural water input of province i at time t.

It is hard to create a hierarchy for successful DMUs since the DEA gives all of them a score of 1. Thus, ranking is only feasible for DMUs that are ineffective. As a result, the DEA is less effective as a tool for estimating efficiency. The concept of "super efficiency" was first suggested by Andersen and Petersen in 1993 as a means of creating a hierarchy among DMUs [32]. The super-efficiency evaluation approach's fundamental tenet is to exclude the effective evaluation unit from the set and reconsider; this maintains the original non-effective value assessment and allows for comparison if the original effective value evaluation is larger than 1. We use a DEA with excellent efficiency for AWE measuring. Think of a situation where there are n DMUs, m input indexes, and q output indexes. The AWE is computed using the following model:

$$\min\left(\theta - \varepsilon\left(\sum_{i=1}^{m} s_i^- + \sum_{j=1}^{q} s_j^+\right)\right)$$
$$\text{s.t.}\begin{cases} \sum\limits_{\substack{k=1\\k\neq j}}^{n} \lambda_k x_{ik} + s_i^- = \theta x_i & i = 1,2,\ldots,m \\ \sum\limits_{\substack{k=1\\k\neq j}}^{n} \lambda_k y_{jk} - s_j^+ = y_j & j = 1,2,\ldots,q \\ \lambda_k \geq 0, & k = 1,\ldots,n \\ s_i^- \geq 0,\ s_j^+ \geq 0 & \end{cases} \tag{2}$$

x_{ik} denotes the i th input indicator, whereas y_{jk} is the j th output indication for the k th DMU. Where s_i^- and s_j^+ are slack variables at the input and output, respectively. The weight coefficient is denoted by λ_k. When *AWE* is calculated for, θ is obtained. θ is the comprehensive production efficiency.

Additionally, the following variables are included in the DEA model: fertilizer input is calculated using the quantity of nitrogen and phosphate fertilizer applied to agricultural produce. The amount of pesticide used to agricultural produce is used to quantify pesticide input. Diesel consumption is used as indicator for energy input in agricultural output. The total amount of agricultural water consumed is used as a proxy for the amount of water input. Total planted area is used as a proxy for land input. And the yield value of the agricultural planting business is utilized as a proxy for output value. Additionally, output numbers are deflated using 2002 as the base year to account for inflationary effects. Figure 1 depicts the regional distribution of agricultural water efficiency in China for four chosen years (2003; 2008; 2013; and 2018).

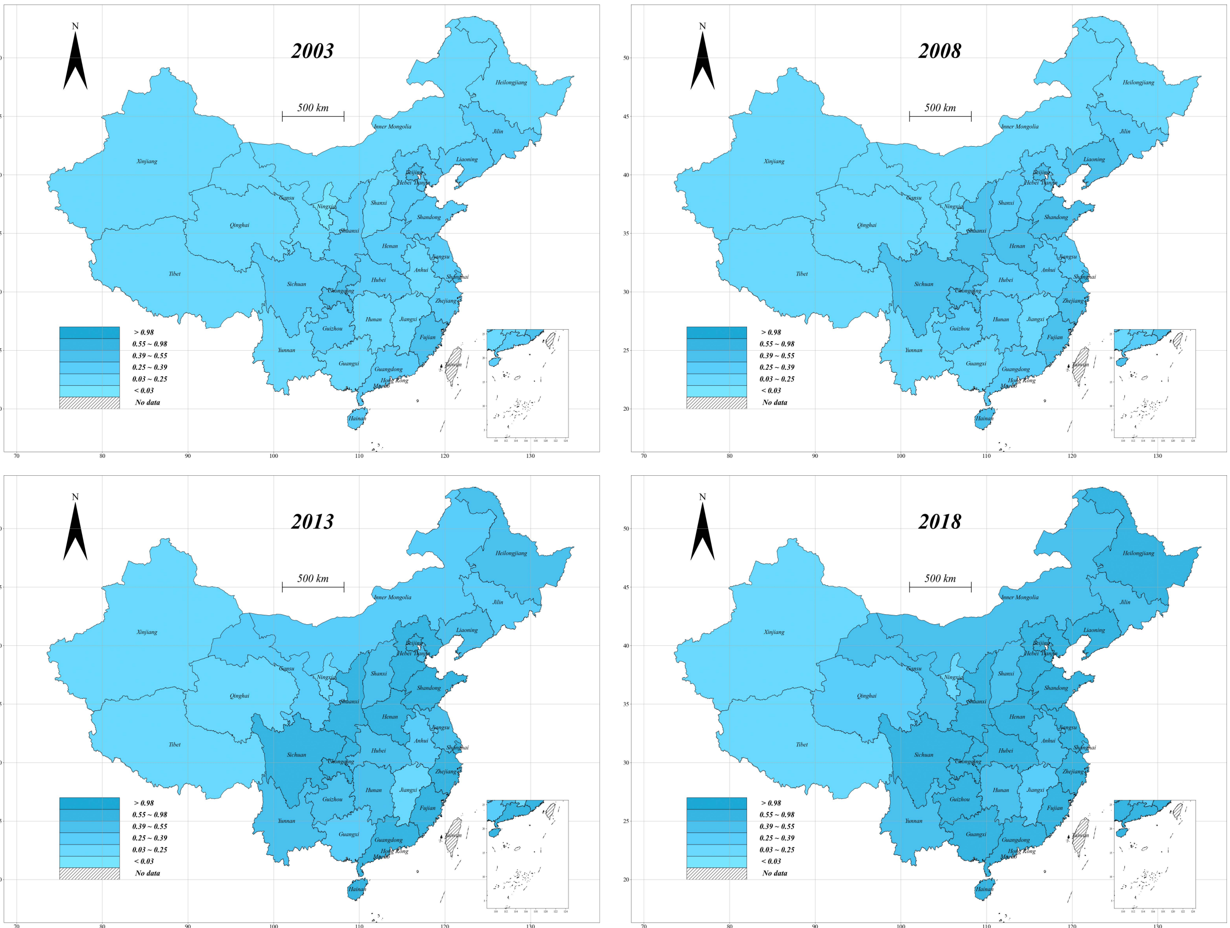

Figure 1. Spatial distribution of population urbanization for selected year (2003, 2008, 2013, and 2018).

2.2. Measuring Urbanization

In economics, urbanization refers to the process by which people migrate from rural to urban areas, which is typically quantified by the percentage of the permanent urban population in the total population (population urbanization). Using this indicator as the sole proxy for urbanization may skew research findings. Additionally, this study employs employment and land to represent urbanization in order to reach robust conclusions. Employment urbanization is quantified in terms of the percentage of people employed in secondary and tertiary industries. Land urbanization is proxied by the ratio of urban built-up area to provincial administrative area. Three indicators serve as proxies for urbanization in this study (population urbanization; employment urbanization; land urbanization).

Figure 2 shows the spatial distribution of population urbanization; Figure 3 shows the spatial distribution of employment urbanization; and Figure 4 shows the spatial distribution of land urbanization. Figures 2–4 show that China has some spatial unevenness in the development of urbanization levels. The level of urbanization in China has been increasing over time. The different levels of urbanization in China are reflected in three indicators as mention above. Further investigation reveals that, as shown in Figure 2, regional variations in population urbanization indicators are at their lowest point in recent years, with eastern and central China both exhibiting smaller variations. On the other hand, employment urbanization exhibits a significant inter-regional variation, with the southeast coast exhibiting a significantly higher level of employment urbanization (Figure 3). The developed secondary and tertiary industries in each province along the southeast coast are also somewhat reflected in this. To close the income gap and advance equality, a balanced economic development and a decline in regional disparities in urban employment are essential. In some ways, the degree of resources invested in urbanization is reflected in the degree to which land is urbanized. The strongest regional heterogeneity is demonstrated by this indicator (Figure 4). The first-tier Chinese megacities with this indicator have extremely high levels. Beijing, Shanghai, and Guangdong in particular. It is important to ease the strain on land resources in megacities. Ant it is urgent to make use of the vast land resources in the western region.

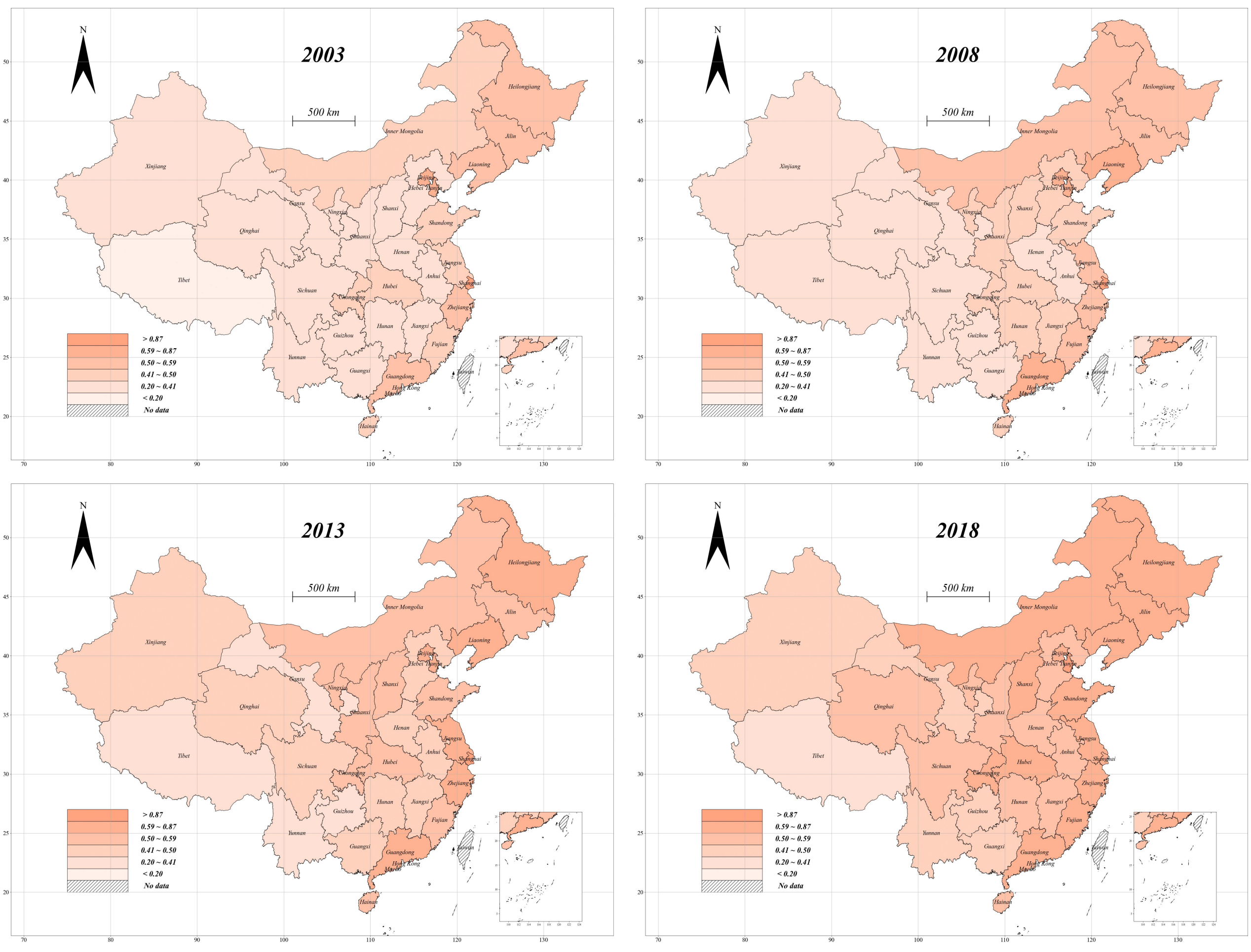

Figure 2. Spatial distribution of population urbanization for selected year (2003, 2008, 2013, and 2018).

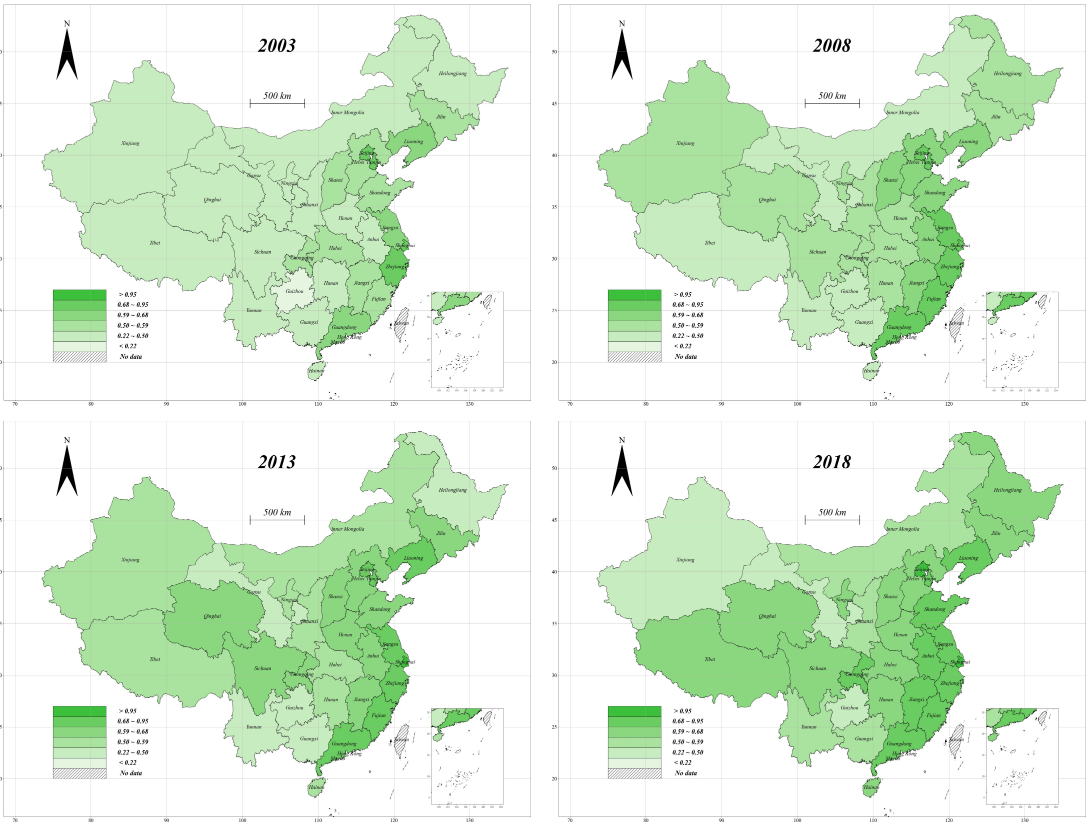

Figure 3. Spatial distribution of employment urbanization for selected year (2003, 2008, 2013, and 2018).

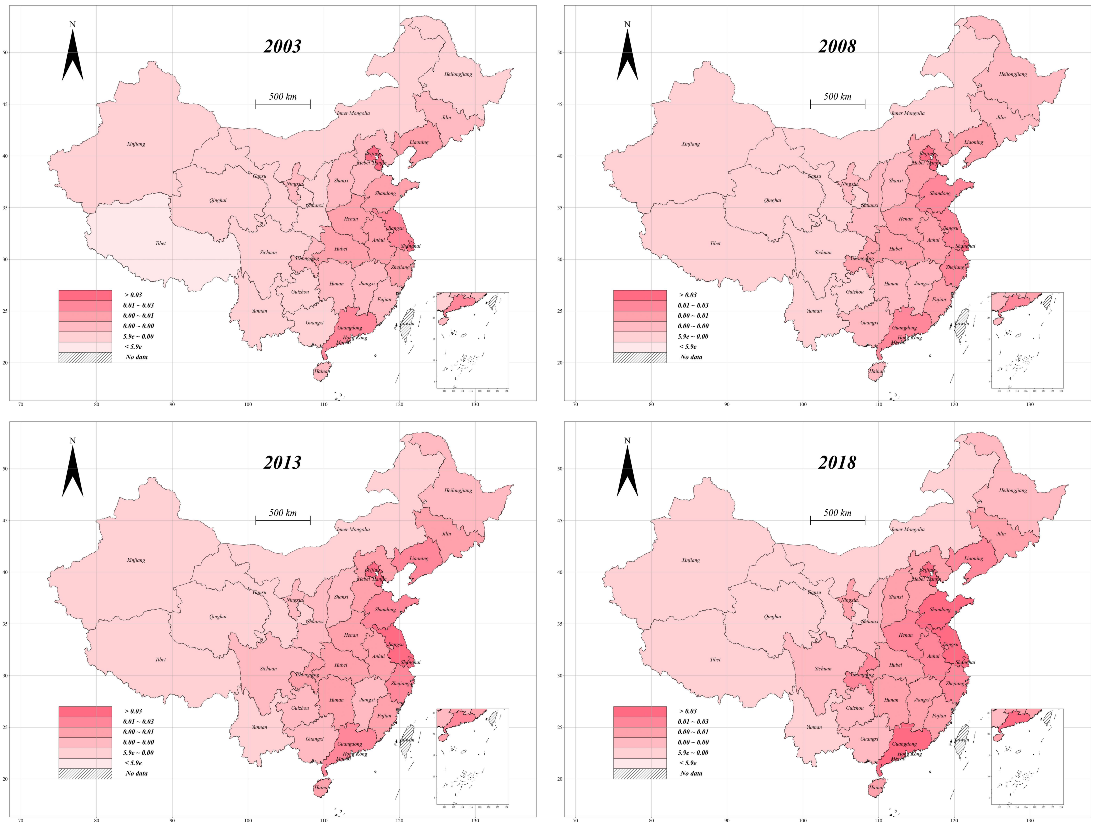

Figure 4. Spatial distribution of land urbanization for selected year (2003, 2008, 2013 and 2018).

2.3. Control Variables

Our models incorporate provincial natural resource and socioeconomic characteristics, such as water resource sufficiency, industrial output, traffic, grain size per capita, rural income, and rural human capital. Water resource adequacy is determined by the total amount of water available per unit of cultivated land area. Industrial output value is the value of secondary industry output after price fluctuations are removed. The secondary highway mileage ratio of arable land area was used to estimate the development level of traffic. Crop sown area divided by the number of people employed in primary industry yields grain size per capita. Rural income refers to the per capita income of rural residents after price fluctuations are taken into account. We measure human capital in rural China by the proportion of people with a high school education or higher. Irrigation facility supply is quantified in terms of the number of irrigation devices per capita per unit of cultivated land area. This study uses the proportion of vegetable sown area as a proxy for planting structure.

2.4. Empirical Strategy

2.4.1. Two-Way Fixed Effects Model (FE)

Given the possibility of bias due to time-invariant un-observables, this study examines the urbanization-AWE relationship using the following two-way FE model:

$$AWE_{it} = \alpha + \beta_0 Urban_{it} + \beta_1 (Urban_{it})^2 + \beta_2 X_{it} + \beta_3 Z_i + \beta_4 T_t + \mu_i + \varepsilon_{it} \quad (3)$$

where AWE_{it} signifies individual i at time t in terms of AWE measured by DEA method. $Urban_{it}$ denotes the urbanization of individual i at time t. X_{it} denotes a collection of time-variant controls, Z_i and T_t respectively, denote time-invariant controls and time dummies, and ε_{it} is the error term. The unobservable time-invariant individual effects are captured by μ_i.

2.4.2. Instrumental Variable Estimation

The application of FE estimators in urbanization raises the risk of endogeneity, which includes omitted variable bias, measurement error, and reverse causation. The estimated coefficient of the core independent variable will be skewed due to the bias of the omitted factors. The FE estimate has a significant weakness in that it cannot rule out any time-varying unobserved variables that may affect both urbanization and AWE concurrently. Some unobservable factors, such as policy formulation, may influence urbanization and agricultural productivity in relation to AWE. To address endogeneity concerns, we perform 2SLS estimates with the first order lag term of urbanization as IV instruments, implicitly assuming that factors in the present cannot influence variables in the past.

2.4.3. Structural Equation Modeling

To investigate the channels via which urbanization may enhance AWE, this research used structural equation modeling (SEM) to analyze the effects of two hypothesized channel variables: irrigation facility supplies and planting structure. We investigated the mediation of channel factors on the EP-AWE relationship by controlling for water resource adequacy, industrial output, traffic, grain size per capita, rural income, and rural human capital. The comparative fit index (CFI), the standardized root mean square residual (SRMR), and the root mean square error of approximation (RMSEA) were used to assess the goodness-of-fit of our SEM estimates, with criteria of $\geq$0.9, =0.1, and =0.08, respectively [33].

3. Results

3.1. Descriptive Statistics

Figure 1 depicts the dynamic process of increasing urbanization from 2002 to 2019, using three indicators. Population urbanization grows at an average rate of 2.53 percent;

employment urbanization grows at an average rate of 1.62 percent; and land urbanization grows at an average rate of 4.77 percent.

The variables used in the DEA model and variables in the econometric mode are presented in in Table 1. The data in Table 1 are entirely derived from secondary sources, which include the China Statistical Yearbook, the China Rural Statistical Yearbook, the China Agriculture Yearbook, the China Agricultural Machinery Industry Yearbook, and the China Agriculture Yearbook. The research period is limited to 2002–2019 due to data availability. Table 1 contains the details and measures for the control and channel variables.

Table 1. Summary Statistics.

VarName	Unit/Measure	Mean	SD
Dependent Variable			
AWE	The results of DEA	0.420	0.243
Agricultural Production Input and Output			
Pesticide input	10 thousand ton	5.165	4.264
Fertilizer input	10 thousand ton	173.443	140.696
Energy input	10 thousand ton	63.562	65.914
Water input	100 million m^3	119.801	101.188
Land input	thousand hectare	4201.223	3038.830
Output Value	100 million CNY	899.265	787.222
Indicator of Urbanization			
Population Urbanization	Proportion of permanent urban population in the total population	0.447	0.238
Employment Urbanization	Proportion of people employed in the secondary and tertiary industries	0.610	0.160
Land Urbanization	Proportion of urban built-up area to provincial administrative area	0.017	0.030
Control Variable			
Natural disaster	Proportion of the affected area to the cultivated area	0.221	0.151
Industry Output Value	100 million CNY	5232.700	5303.610
Grain size per capital	Thousand hectare/10 thousand people	5.931	3.222
Water Resource Adequacy	100 million m^3/Thousand hectare	0.601	1.897
Rural income	Log (CNY per Person)	8.761	0.700
Traffic	km^3/ Thousand hectare	3.702	3.502
Human Capital	proportion of people with a high school education or above	0.111	0.052
Channel Variable			
Irrigation Facility	Number of irrigation equipment per capita per unit of land	3.531	9.723
Planting Structure	Proportion of vegetable sown area	0.148	0.123

3.2. Impact of Urbanization on AWE: Fixed Effect Estimates

Table 2 summarizes the results of the fixed effect (FE) regression. Urbanization is significantly associated with AWE and exhibits a U-shaped relationship, according to the estimation results. With population urbanization as the primary indicator, Figure 5 depicts the relationship between AWE and urbanization. Whether or not control variables are included, the results are significant across three different indicators of urbanization, implying that our findings are robust.

Table 2. Fix effect regression results.

	Population Urbanization		Employment Urbanization		Land Urbanization	
	(1) Without Controls	**(2) With Controls**	**(3) Without Controls**	**(4) With Controls**	**(5) Without Controls**	**(6) With Controls**
Urban	−0.213 **	−0.456 **	−0.174	−1.419 ***	−23.34 ***	−9.974 ***
	(0.0888)	(0.180)	(0.347)	(0.351)	(1.467)	(2.005)
$Urban^2$	1.121 ***	0.452 **	1.333 ***	1.168 ***	90.30 ***	45.18 ***
	(0.137)	(0.178)	(0.298)	(0.342)	(7.514)	(8.064)
Natural disaster		−0.0239		−0.0333		−0.0131
		(0.0351)		(0.0347)		(0.0344)
Water Resource Adequacy		−0.0938		−0.245 ***		−0.101
		(0.0852)		(0.0876)		(0.0829)
Industrial Output		9.75×10^{-6} ***		1.30×10^{-5} ***		3.69×10^{-6}
		(2.27×10^{-6})		(2.60×10^{-6})		(2.54×10^{-6})
Traffic		−0.0139 ***		−0.00569		−0.00200
		(0.00422)		(0.00401)		(0.00466)
Grain size per capita		0.00740 *		0.0110 ***		0.0102 **
		(0.00419)		(0.00408)		(0.00399)
Rural income		0.0567 ***		0.0563 ***		0.0510 ***
		(0.0167)		(0.0162)		(0.0160)
Rural Human Capital		0.131		0.302		−0.128
		−0.366 **		(0.230)		(0.234)
Constant	0.227 ***	1.275 *	−0.216 **	2.191 ***	0.130 ***	0.818
	(0.0324)	(0.740)	(0.104)	(0.745)	(0.0371)	(0.740)
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.288	0.887	0.262	0.889	0.224	0.893

Note: Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Furthermore, the natural disaster decreased AWE statistically but not significantly. Disasters may change the allocation of agricultural production factors, necessitating an increase in labor and water resources to mitigate the disaster's effects, lowering the AWE. Water resource sufficiency is associated with a lower AWE in Model4, but only statistically. Water-stressed areas must develop water-saving irrigation infrastructure as soon as possible, substitute capital for water resources, and accelerate the implementation of water-saving technological change. Although the value of industrial output increases AWE, only models 2 and 3 are statistically significant. To some extent, industrial output contributes to the provision of water-saving irrigation facilities, reflecting the region's technological level. The level of traffic development has a negative relationship with irrigation efficiency. The relationship between grain size per capita and AWE is positive and statistically significant, implying that scale production helps to improve AWE. AWE is positively influenced by both rural income and rural human capital. Increased income enables irrigation infrastructure investment, and increased education enables mastery of advanced water-saving irrigation techniques.

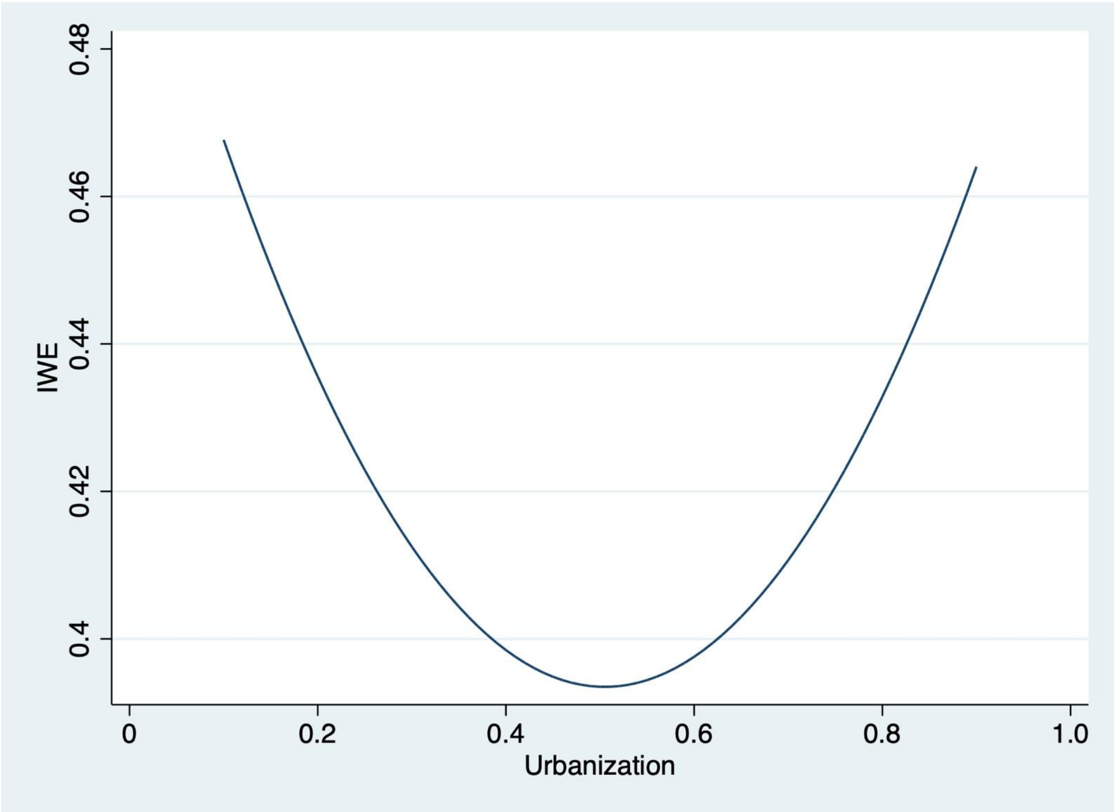

Figure 5. The relationship between population urbanization and AWE.

3.3. Two-Stage Least Squares Estimates

Given the possibility for urbanization endogeneity, this research use two-stage least squares (2SLS) approach (see Table 3). The first-stage of F statistic significantly bigger than 10, implying no weak IV instrumentation. After correcting for endogeneity issues, the association between urbanization and AWE remains U-shape. The findings reveal that the influence of urbanization on AWE is statistically significant, which are usually in accordance with FE result provided above demonstrating that the study conclusion is robust across three urbanization assessments. The bias-corrected estimates from the 2SLS model specification are greater than our baseline estimates across all urbanization. This means that our baseline estimations are downward biased. Not addressing endogeneity leads to underestimating the degree to which urbanization influences AWE.

Table 3. Two-stage least squares estimates.

	Population Urbanization	Employment Urbanization	Land Urbanization
	(1)	(2)	(3)
Urban	−0.548 **	−1.820 ***	−17.20 ***
	(0.260)	(0.461)	(2.380)
Urban^2	0.722 ***	1.262 ***	56.00 ***
(squared)	(0.244)	(0.407)	(7.457)
Controls	Yes	Yes	Yes
F statistic	61.21 ***	60.59 ***	64.09 ***

Note: Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

3.4. Potential Mechanisms

Urbanization levels greater than 0.5 were classified as high-level urbanization, while levels less than 0.5 were classified as low-level urbanization, based on an approximately calculated inflection point value of 0.5.

At low levels of urbanization, urbanization has a statistically significant negative effect on AWE (Table 4). A goodness-of-fit test confirms the models' suitability (Table 5). Channel variables become relevant only at high levels of urbanization. The mediating effect is statistically significant positive across three urbanization indicators at a high level of urbanization (Table 6). Mediate effects account for 27.3 percent to 100 percent of total effects, depending on the urbanization measurement used (Table 6). Depending on the type of urbanization indicator used, the proportion of total effects accounted for by mediating effects varies (Table 6).

Table 4. The structural model with controls (standardized coefficients).

Urbanization	AWE	Planting Structure	Irrigation Facilities
Population Urbanization			
Panel A: High urbanization			
Urbanization	0.283 ***	0.361 ***	0.481 ***
	(0.0766)	(0.0459)	(0.0395)
Planting Structure	0.122 **		
	(0.0527)		
Irrigation Facilities	0.129 **		
	(0.0564)		
Panel B: Low urbanization			
Urbanization	−0.0982 *	0.0551	−0.0259
	(0.0551)	(0.0677)	(0.0679)
Planting Structure	0.143 **		
	(0.0642)		
Irrigation Facilities	−0.112 **		
	(0.050)		
Employment Urbanization			
Panel C: High urbanization			
Urbanization	0.0485	0.461 ***	0.420 ***
	(0.0764)	(0.0401)	(0.0430)
Planting Structure	0.174 **		
	(0.0522)		
Irrigation Facilities	0.107 *		
	(0.0581)		
Panel D: Low urbanization			
Urbanization	−0.378 ***	0.0301	0.0182
	(0.0702)	(0.0604)	(0.0679)
Planting Structure	0.178 **		
	(0.0627)		
Irrigation Facilities	−0.125 **		
	(0.0517)		
Land Urbanization			
Panel E: High urbanization			
Urbanization	0.240 **	0.409 ***	0.749 ***
	(0.104)	(0.0408)	(0.0191)
Planting Structure	0.152 ***		
	(0.0484)		
Irrigation Facilities	0.572 ***		
	(0.0621)		
Panel F: Low urbanization			
Urbanization	−0.344 ***	0.0478	0.0509
	(0.0614)	(0.0556)	(0.0764)
Planting Structure	0.376 ***		
	(0.0657)		
Irrigation Facilities	−0.103 *		
	(0.0547)		

Note: Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 5. Goodness-of-fit statistic.

	Population Urbanization		Employment Urbanization		Land Urbanization	
	Panel A	**Panel B**	**Panel A**	**Panel B**	**Panel A**	**Panel B**
RMSEA	0.022	0.025	0.022	0.021	0.018	0.021
SRMR	0.009	0.013	0.075	0.012	0.080	0.0102
CFI	0.957	0.953	0.956	0.961	0.978	0.971

Note: root mean square error of approximation (RMSEA); standardized root mean square residual (SRMR); comparative fit index (CFI).

Table 6. Estimated Indirect effects and Total effects (standardized coefficients).

	Population Urbanization		Employment Urbanization		Land Urbanization	
	High	**Low**	**High**	**Low**	**High**	**Low**
Direct effects	0.283 ***	−0.0982 *	0.0485	−0.378 ***	0.240 **	−0.344 ***
	(0.0766)	(0.0551)	(0.0764)	(0.0702)	(0.104)	(0.0614)
Indirect effects	0.106 ***	0.0109	0.125 **	0.0031	0.490 *	−0.003
	(0.0315)	(0.0132)	(0.0321)	(0.0025)	(0.259)	(0.009)
Total effects	0.388 ***	−0.0982 *	0.125 **	−0.378 ***	0.730 **	−0.344 ***
	(0.0788)	(0.0551)	(0.0321)	(0.0702)	(0.410)	(0.0614)
Indirect effects/ Total effects	0.273	0	1	0	0.671	0

Note: Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Vegetable and other cash crop consumption has risen in tandem with people's pursuit of a high quality of life through urbanization. Cash crops could significantly boost farmers' income. Irrigation management is being prioritized in order to cut costs. Improving cash crop irrigation efficiency is thus profitable. As a result of urbanization, planting structure is a channel variable that improves AWE. As urbanization has progressed, regional economic strength has grown. Local governments now have more resources to support rural development initiatives such as irrigation. High levels of urbanization have improved irrigation efficiency as a result of bringing capital and technology into agricultural production.

4. Discussion

Water efficiency has grown into a worldwide concern. The Sustainable Development Goals (SDG 6) established by the United Nations is to significantly boost water efficiency across all sectors [17]. Agriculture is the primary user of fresh water, accounting for 70% of total withdrawals from bodies of water and up to 90% in developing nations. With climate change and rising urbanization, achieving sustainable agricultural growth, food security, and water conservation is a major challenge. China is experiencing a conflict between its large population and the scarcity of arable land [34]. The scarcity and unbalanced distribution of water resources has reinforced the importance of increasing water efficiency in agriculture. Given the critical nature of AWE improvement, more investigation of its different causes is necessary. Despite widespread focus to urbanization's implications on sustainable development and social welfare, empirical research offers scant insights into the relationship between AWE and urbanization, particularly in China. The analysis of national longitudinal province panel data in this research is intended to gain insight not only on the urbanization-AWE relationship in China, but also on the degree to which urbanization affects AWE through two channels: planting structure adjustment and irrigation facility supply. There may be two such routes in the midst of ongoing urbanization that could improve the effectiveness of agricultural water use. This is the area on which this essay focuses. This advances our knowledge of the mechanisms through which urbanization improves the efficiency of agricultural water use and has major implications for those regions that are experiencing rapid urbanization and water scarcity.

The distribution of water resources in China is shown in Figure 6. It can be seen that there is a large spatial heterogeneity in the distribution of water resources in China.

Water resources are more abundant in the southeastern coastal region. Looking further at Figures 7 and 8, there are also large differences in the way water resources are supplied in China. The southeastern coastal region is rich in surface water resources due to its humid climate and abundant precipitation, which ranks among the highest in the country. Groundwater water resources are supplied mainly in the northern regions of China. It is useful to study the efficiency of agricultural irrigation while further considering the sources of water resources supply. Nevertheless, this study has some flaws and is not fully thought through. The eastern region experiences a humid monsoon climate, which means there will probably be more natural precipitation and water vapor there [35]. In this case, it is likely that the level of urban development will have little impact on agricultural water resources. In order to deal with water scarcity, irrigation facilities must be adopted in accordance with local conditions since China is a vast country with widely divergent natural environments [36,37]. The three urbanization indicators that were used in this study may have some shortcomings, and future research can create an urbanization indicator that is more comprehensive and wide ranging [38].

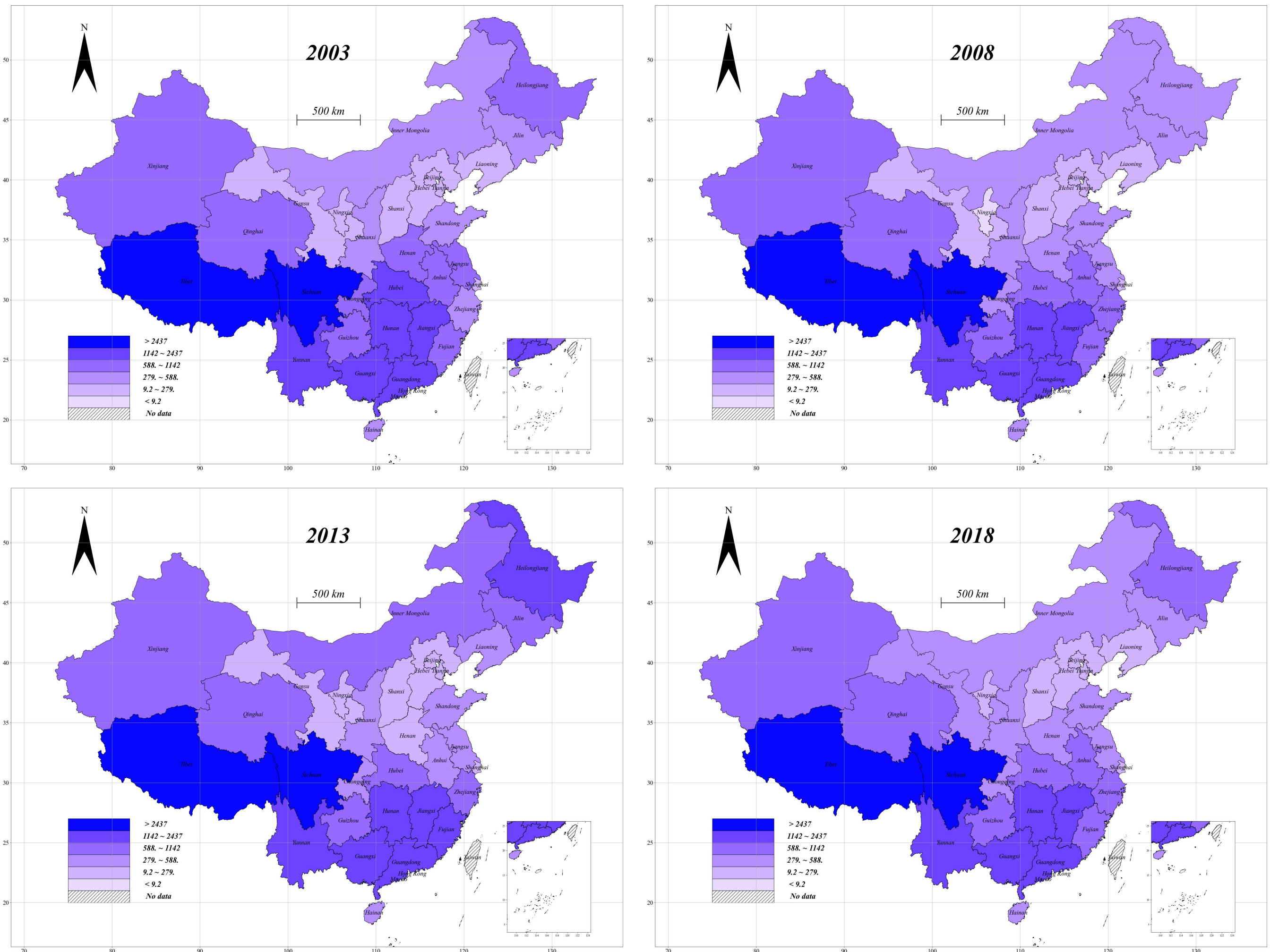

Figure 6. Geographical distribution of China's annual total water resources (billion cubic meters) for selected years (2003, 2008, 2013 and 2018).

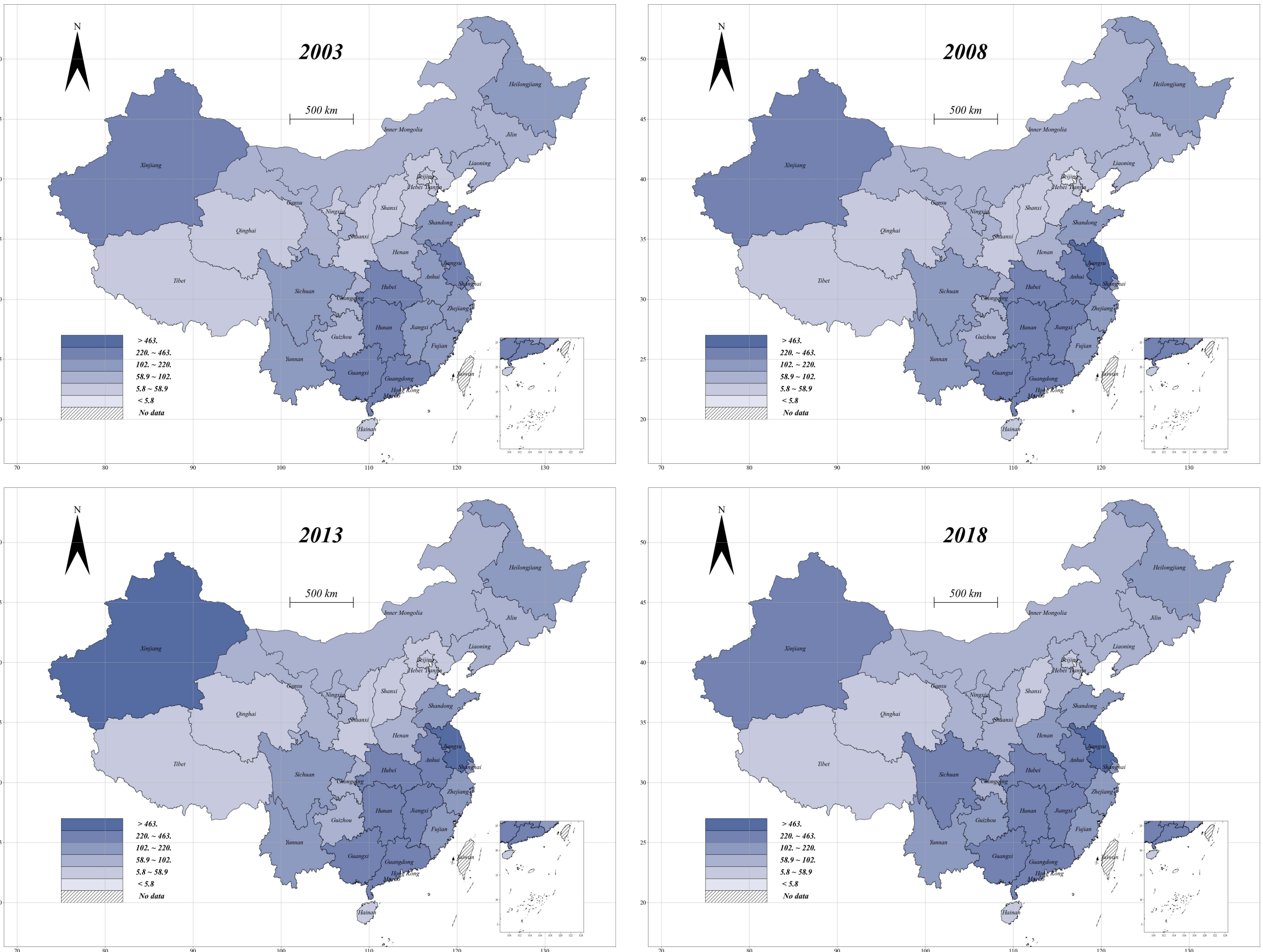

Figure 7. Geographical distribution of China's annual surface water supply (billion cubic meters) for selected years (2003, 2008, 2013 and 2018).

The findings of our study have important policy implications. They emphasize, above all, the critical importance of ensuring urban development and financial support for rural development, which is consistent with China's current 'rural revitalization' strategy. To achieve critical policy objectives such as food security and agricultural sustainability, the government has increased its efforts to improve AWE. Given that China's level of urbanization has now passed the inflection point identified in the preceding analysis, accelerating urbanization while developing water infrastructure in rural areas may be an effective way to increase AWE.

Many rural migrant workers leave rural areas and relocate to cities since a large labor force is required to promote urbanization during periods of low urbanization. As more women, children, and the elderly remain in rural areas, the quality of human capital in rural areas gradually deteriorates. Furthermore, as people's incomes have become more reliant on non-farm employment, investment in many rural infrastructure projects has decreased. As a result, rural irrigation infrastructure decline is common in rural areas. This decline is also due to the difficulty of forming effective collective action in rural areas as a result of migration, as well as the prevalent situation in which irrigation facilities are overlooked as a common pond resource. However, urbanization is the only solution to these problems. When people reach a high level of urbanization, their desire for a better quality of life causes changes in planting structure. Growing more cash crops, such as vegetables, promotes fine-grained management and thus increases agricultural water use efficiency. The Chinese government's 'rural revitalization' strategy of urban feedback to rural areas is also increasing investment in rural areas. The State Council, for example, issued the "National Water Saving Irrigation Plan", which stated that water-saving irrigation projects should account for 80 percent of the country's effective irrigation area by 2020. The policy encourages farmers to use water-saving technologies (such as sprinkler and micro irrigation). The financial viability of such a plan is, of course, dependent on the economic growth brought about by urbanization.

While this is negative for AWE in the early stages of urbanization, the development problem can only be solved through development. According to the above-mentioned research, China has reached the stage of urbanization that promotes AWE and should therefore continue to accelerate urbanization. China places a premium on urbanization's role in agricultural upgrading and takes measures such as urbanizing surplus rural labor, increasing agricultural financial support to accelerate agricultural modernization, and promoting large-scale agriculture to facilitate the coordination of urbanization and modern agriculture. Agriculture should benefit from city-based advanced research and technology, capital investment, and management experience. In order to ensure that AWE improves, agricultural irrigation infrastructure and agricultural irrigation machinery are built to the greatest extent possible.

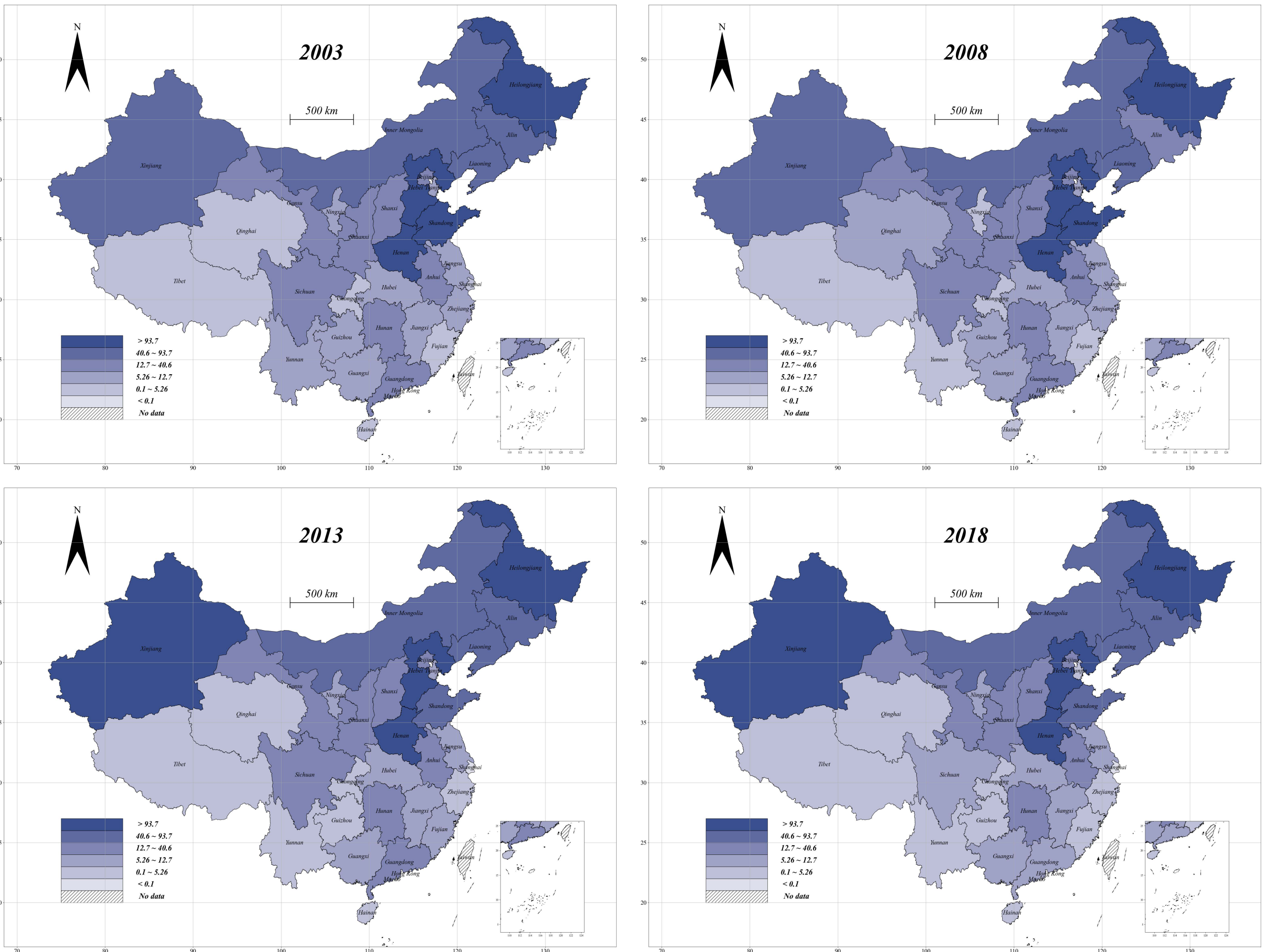

Figure 8. Geographical distribution of China's annual ground water supply (billion cubic meters) for selected years (2003, 2008, 2013 and 2018).

5. Conclusions

The study's findings are as follows. First, the distribution of water resources in China is spatially heterogeneous, with more abundant water resources in the southeast.

The north has a greater supply of groundwater resources, while the south has a greater supply of surface water resources. Second, agricultural water use efficiency varies by region in China, with the upper reaches of the Yangtze and Yellow River basins and the southeastern coastal areas having higher agricultural water use efficiency. China's agricultural water use efficiency has improved over time. Third, in China, the relationship between urbanization and agricultural water use efficiency has a U-shape, indicating a non-linear effect. Specifically, urbanization has a negative impact on agricultural water use efficiency at the low level of urbanization and a positive impact on agricultural water use efficiency at the high level of urbanization. After replacing the estimation method and urbanization measure, the findings remain robust. Fourth, in the high-level urbanization stage, irrigation facility supply and cropping structure are important channels through which urbanization contributes to agricultural water use efficiency. After the measurement indicators are replaced, the conclusions remain robust.

Author Contributions: D.L.: formal analysis, investigation, data curation, writing—original draft, writing—review and editing, supervision. H.S.: conceptualization, methodology, visualization, writing—original draft, writing—review and editing. P.M.: data curation, writing—review and editing. H.X.: investigation. S.Z.: investigation. All authors have read and agreed to the published version of the manuscript.

Funding: Acknowledged support from the School of Agricultural Economics and Rural Development, Renmin University of China's Student Research Training Program (Grant No. 21A03).

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: All data are from public databases, and the sources are described in the article.

Acknowledgments: Thanks for the help of Student Research Training Program (Relationship coordination, contractual norms and benefit distribution in agricultural quasi-integrated supply chains; Grant No. 21A03). The authors gratefully acknowledge the helpful reviews and comments from the Editor and anonymous reviewers, which improved this manuscript considerably.

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

References

1. World Bank. *Urban China: Toward Efficient, Inclusive, and Sustainable Urbanization*; The World Bank: Washington, DC, USA, 2014; ISBN 978-1-4648-0206-5.
2. Friedmann, J. Four Theses in the Study of China's Urbanization. *Int. J. Urban Reg. Res.* **2006**, *30*, 440–451. [CrossRef]
3. Yan, T.; Wang, J.; Huang, J. Urbanization, Agricultural Water Use, and Regional and National Crop Production in China. *Ecol. Model.* **2015**, *318*, 226–235. [CrossRef]
4. Li, F.; Phillips, M.A. The Influence of the Regulatory Environment on Chinese Urban Water Utilities. *Water Resour. Manag.* **2017**, *31*, 205–218. [CrossRef]
5. Wang, J.; Hou, B.; Zhao, Y.; Xiao, W.; Lu, F. Research on Scale Demonstration Technology of Inter Basin Water Transfer Project in Agricultural Irrigation. *Water Resour. Manag.* **2021**, *35*, 5243–5258. [CrossRef]
6. García-Mollá, M.; Puertas, R.; Sanchis-Ibor, C. Application of Data Envelopment Analysis to Evaluate Investments in the Modernization of Collective Management Irrigation Systems in Valencia (Spain). *Water Resour. Manag.* **2021**, *35*, 5011–5027. [CrossRef]
7. Yue, W.; Liu, Z.; Su, M.; Xu, M.; Rong, Q.; Xu, C.; Tan, Z.; Jiang, X.; Su, Z.; Cai, Y. Inclusion of Ecological Water Requirements in Optimization of Water Resource Allocation Under Changing Climatic Conditions. *Water Resour. Manag.* **2022**, *36*, 551–570. [CrossRef]
8. Shi, H. Performance of Community-Based Water-Saving Technology under Land Fragmentation: Evidence from Groundwater Overexploitation in the North China Plain. *Water Policy* **2021**, *23*, 1542–1555. [CrossRef]
9. Shao, W.; Zhou, Z.; Liu, J.; Yang, G.; Wang, J.; Xiang, C.; Cao, X.; Liu, H. Changing Mechanisms of Agricultural Water Use in the Urbanization and Industrialization of China. *Water Policy* **2017**, *19*, 908–935. [CrossRef]
10. Oueslati, W.; Salanié, J.; Wu, J. Urbanization and Agricultural Productivity: Some Lessons from European Cities. *J. Econ. Geogr.* **2019**, *19*, 225–249. [CrossRef]

11. Liu, J.; Wang, M.; Yang, L.; Rahman, S.; Sriboonchitta, S. Agricultural Productivity Growth and Its Determinants in South and Southeast Asian Countries. *Sustainability* **2020**, *12*, 4981. [CrossRef]
12. Liu, X.; Xu, Y.; Engel, B.A.; Sun, S.; Zhao, X.; Wu, P.; Wang, Y. The Impact of Urbanization and Aging on Food Security in Developing Countries: The View from Northwest China. *J. Clean. Prod.* **2021**, *292*, 126067. [CrossRef]
13. Li, J.; Chen, J.; Liu, H. Sustainable Agricultural Total Factor Productivity and Its Spatial Relationship with Urbanization in China. *Sustainability* **2021**, *13*, 6773. [CrossRef]
14. Deng, Z.; Zhao, Q.; Bao, H.X.H. The Impact of Urbanization on Farmland Productivity: Implications for China's Requisition–Compensation Balance of Farmland Policy. *SSRN J.* **2020**, *9*, 311. [CrossRef]
15. Aneseyee, A.B.; Soromessa, T.; Elias, E.; Noszczyk, T.; Feyisa, G.L. Evaluation of Water Provision Ecosystem Services Associated with Land Use/Cover and Climate Variability in the Winike Watershed, Omo Gibe Basin of Ethiopia. *Environ. Manag.* **2022**, *69*, 367–383. [CrossRef] [PubMed]
16. Li, J.; Li, Y. Influence Measurement of Rapid Urbanization on Agricultural Production Factors Based on Provincial Panel Data. *Socio-Econ. Plan. Sci.* **2019**, *67*, 69–77. [CrossRef]
17. *The Sustainable Development Goals Report 2021*; The Department of Economic and Social Affairs, United Nations Publications: New York, NY, USA, 2021.
18. Wang, Y.; Zang, L.; Araral, E. The Impacts of Land Fragmentation on Irrigation Collective Action: Empirical Test of the Social-Ecological System Framework in China. *J. Rural Stud.* **2020**, *78*, 234–244. [CrossRef]
19. Wang, J.; Zhu, Y.; Sun, T.; Huang, J.; Zhang, L.; Guan, B.; Huang, Q. Forty Years of Irrigation Development and Reform in China. *Aust. J. Agric. Resour. Econ.* **2020**, *64*, 126–149. [CrossRef]
20. Gu, H.; Ling, Y.; Shen, T.; Yang, L. How Does Rural Homestead Influence the Hukou Transfer Intention of Rural-Urban Migrants in China? *Habitat Int.* **2020**, *105*, 102267. [CrossRef]
21. Yuan, Y.; Wang, M.; Zhu, Y.; Huang, X.; Xiong, X. Urbanization's Effects on the Urban-Rural Income Gap in China: A Meta-Regression Analysis. *Land Use Policy* **2020**, *99*, 104995. [CrossRef]
22. Wang, Y.; Chen, C.; Araral, E. The Effects of Migration on Collective Action in the Commons: Evidence from Rural China. *World Dev.* **2016**, *88*, 79–93. [CrossRef]
23. Zhang, X.; Kong, Y.; Ding, X. How High-Quality Urbanization Affects Utilization Efficiency of Agricultural Water Resources in the Yellow River Basin under Double Control Action? *Sustainability* **2020**, *12*, 2869. [CrossRef]
24. 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. [CrossRef]
25. Deng, J.S.; Qiu, L.F.; Wang, K.; Yang, H.; Shi, Y.Y. An Integrated Analysis of Urbanization-Triggered Cropland Loss Trajectory and Implications for Sustainable Land Management. *Cities* **2011**, *28*, 127–137. [CrossRef]
26. Chen, M.; Zhou, Y.; Huang, X.; Ye, C. The Integration of New-Type Urbanization and Rural Revitalization Strategies in China: Origin, Reality and Future Trends. *Land* **2021**, *10*, 207. [CrossRef]
27. Cheung, J.T.H.; Lok, J.; Gietel-Basten, S.; Koh, K. The Food Environments of Fruit and Vegetable Consumption in East and Southeast Asia: A Systematic Review. *Nutrients* **2021**, *13*, 148. [CrossRef] [PubMed]
28. Putra, A.S.; Tong, G.; Pribadi, D.O. Food Security Challenges in Rapidly Urbanizing Developing Countries: Insight from Indonesia. *Sustainability* **2020**, *12*, 9550. [CrossRef]
29. Kim, S.; Meki, M.N.; Kim, S.; Kiniry, J.R. Crop Modeling Application to Improve Irrigation Efficiency in Year-Round Vegetable Production in the Texas Winter Garden Region. *Agronomy* **2020**, *10*, 1525. [CrossRef]
30. Kapoor, R.; Kumar, A.; Sandal, S.K.; Sharma, A.; Raina, R.; Thakur, K.S. Water and Nutrient Economy in Vegetable Crops through Drip Fertigation and Mulching Techniques: A Review. *J. Plant Nutr.* **2022**, 1–15. [CrossRef]
31. Nabavi-Pelesaraei, A.; Abdi, R.; Rafiee, S.; Bagheri, I. Determination of Efficient and Inefficient Units for Watermelon Production-a Case Study: Guilan Province of Iran. *J. Saudi Soc. Agric. Sci.* **2016**, *15*, 162–170. [CrossRef]
32. Andersen, P.; Petersen, N.C. A Procedure for Ranking Efficient Units in Data Envelopment Analysis. *Manag. Sci.* **1993**, *39*, 1261–1264. [CrossRef]
33. Shi, H.; Ma, P.; Zeng, Y.; Sheng, J. Understanding the Interaction between Regulatory Focus and Message Framing in Determining Chinese Consumers' Attitudes toward Artificial Meat. *Int. J. Environ. Res. Public Health* **2022**, *19*, 4948. [CrossRef] [PubMed]
34. Dang, X.; Sui, B.; Gao, S.; Liu, G.; Wang, T.; Wang, B.; Ning, D.; Bi, W. Regions and Their Typical Paradigms for Soil and Water Conservation in China. *Chin. Geogr. Sci.* **2020**, *30*, 643–664. [CrossRef]
35. Hui, P.; Tang, J.; Wang, S.; Niu, X.; Zong, P.; Dong, X. Climate Change Projections over China Using Regional Climate Models Forced by Two CMIP5 Global Models. Part II: Projections of Future Climate: Projections of Climate Over China with Multi-RCM Driven by CMIP5 GCM. *Int. J. Climatol.* **2018**, *38*, e78–e94. [CrossRef]
36. Liu, J.; Jin, J.; Niu, G. Effects of Irrigation on Seasonal and Annual Temperature and Precipitation over China Simulated by the WRF Model. *J. Geophys. Res. Atmos.* **2021**, *126*, e2020JD034222. [CrossRef]
37. Zhang, S.; Yang, Y.; McVicar, T.R.; Yang, D. An Analytical Solution for the Impact of Vegetation Changes on Hydrological Partitioning Within the Budyko Framework. *Water Resour. Res.* **2018**, *54*, 519–537. [CrossRef]
38. Zhang, B.; Zhang, J.; Miao, C. Urbanization Level in Chinese Counties: Imbalance Pattern and Driving Force. *Remote Sens.* **2022**, *14*, 2268. [CrossRef]