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China's Agricultural Water-Use Efficiency and Its Influencing Factors under the Constraint of Pollution Emission

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ABSTRACT

To ensure the sustainability of agriculture in China, it is critical to improve the agricultural water-use efficiency (AWE) under the constraint of pollution emission. Based on the 2011-2015 panel data of the inputs and outputs of provincial AWE in China, this paper measures the AWE of each provincial administrative region (hereinafter referred to as province) in China under the constraint of pollution emission, using the minimum distance to strong efficient frontier (MinDS) model, and analyzes the main factors affecting China's AWE under the constraint of pollution emission with a self-designed panel Tobit model. The results show that: (1) Under the constraint of pollution emission, the AWE in China generally remained on high levels, but with significant inter- and intra-regional differences; (2) Under the said constraint, there was a great gap between Chinese regions and provinces in pure technical water use and large-scale water use; (3) the scarcity of water resources and the level of economic development have significant positive impacts on the AWE; the development of crop farming, the development of animal husbandry, the construction of farmland water conservancy, crop planting structure, and drought have significant negative impacts on the AWE. On this basis, several policy suggestions were presented to improve China's AWE under the constraint of pollution emission.

1. INTRODUCTION

Water resources and agricultural production are closely related. On the one hand, the scarcity of water resources will restrict the sustainability of agriculture to a certain extent; on the other hand, some undesirable outputs that inevitably exist in agricultural production during the water resource utilization will pollute the environment, damages the ecosystem to a certain extent, and exacerbates the shortage of agricultural water resources, thus inhibiting the improvement of the AWE. For a long time, China's agricultural water use accounts for about 60% of the total water use, indicating a very tense supply-demand relationship [1, 2]. China's agricultural non-point source pollution is an important source of water pollution. In 2015, agricultural chemical oxygen demand (COD) and ammonia nitrogen emissions accounted for 48.06% and 31.58% of the total respectively. Also, the temporal and spatial distribution of water resources in China is extremely uneven. Despite of the huge amount of total water resources, the per capita water resources are relatively small, with a moderate water shortage in China. Natural factors such as climate change affect precipitation and temperature [3, 4], and further the total amount of water resources, while human factors such as economic growth, population increase, urbanization, and the development of secondary and tertiary industries, etc. influence water resources consumption and exacerbate water pollution problems [5], which both have combined to aggravate the shortage of water resources [6]. There is a contradiction between the sustainable development of agriculture and the scarcity of water resources. The latter has an inhibitory effect on the former [7]. Therefore, to ensure the sustainable development of China's agriculture, it's crucial to improve the AWE. In addition, China is a major agricultural country in the world, and its improvement in AWE plays an important role in the sustainability of world agriculture [8].

Many researches have been conducted on water-use efficiency in China. Deng et al. [9]; Lu and Xu [10]; Yang et al. [11] respectively adopted the SBM-DEA model and three-stage DEA-Malmquist index model, and the CRS-SBM-DEA model to study the water-use efficiency in China and achieve some useful results, but there is the lack of sufficient research on the AWE. The research on China's AWE originated from Wang et al. [12]. The measurement of water-use efficiency under the total-factor framework was first made by Hu et al. [13], i.e., the use of the ratio of target water consumption to actual water consumption for measurement with the value of water-use efficiency between 0-1. The amount of slack is positively correlated with the potential for improving water-use efficiency. If the slack value is 0, it means that the water-use efficiency is 1 at the production frontier. Using data envelopment analysis (DEA) and stochastic frontier approach (SFA), Speelman et al. [14]; Frijia et al. [15]; Njuki et al. [16] conducted research on the AWE of different farm types in the northwest regions of South Africa, unheated greenhouse farms in Tunisia, and major U.S. counties. In addition, lots of Chinese scholars, Yang and Jiang [17]; Wang et al. [18] respectively adopted DEA-Malmquist method and SFA to evaluate and analyze China's inter-provincial AWE. Tang et al.

[19]; Wang et al. [20] studied regional AWE by taking Guanzhong Plain and Heihe River Basin in China as research objects. The researches above have all achieved beneficial results, without considering the undesirable output produced by agricultural water use, i.e., agricultural pollution emission. In recent years, a few scholars have begun to consider it in the AWE measurement. For example, Yang and Liu [21] applied the DEA method to measure China's AWE under the constraint of agricultural pollution emissions based on the data of 2011 and 2012, but the sample data wasn't sufficient.

Based on the 2011-2015 input-output panel data of China's provincial AWE, the authors applied the MinDS model to measure the AWE of China's provinces under the constraint of pollution emission, and established a panel Tobit model to analyze the key factors affecting the AWE of China under the said constraint. Meanwhile, the relationship between China's AWE and agricultural economic growth under the constraint of pollution emissions was also analyzed. On this basis. relevant policy suggestions were proposed accordingly to improve China's AWE.

2. MEASUREMENT AND ANALYSIS

2.1 Measurement method and data description

2.1.1 Measurement method: MinDS model

Aparicio et al. [22] introduced the programming equation of the MinDS model and its solution method. This method can limit all the evaluated DMU reference standards to the same hyperplane by adding constraint conditions with no need of determining the hyperplanes of all frontiers. After determining all the effective DMUs through the SBM model, the planning model can use the effective subset as its reference set for solving. Aparicio et al. solved the MinDS model as follows: (1) Supposing that there are n DMUs, the set of DMUs judged to be effective by the SBM model is *E*, each DMU has m kinds of inputs (*i*=1, 2, ..., *m*), *q* types of desirable output (*r*=1, 2, ..., *q*), and n types of undesirable output (*t*=1, 2, ..., *n*); (2) Solve the following mixed Integer linear programming to obtain the MinDS efficiency value:

$$\max\ \rho_k = \frac{\frac{1}{m}\sum_{i=1}^{m}(1-s_i^-/x_{ik})}{\frac{1}{q}\sum_{r=1}^{q}(1+s_r^+/y_{rk})+\frac{1}{\mathrm{n}}\sum_{t=1}^{n}(1+s_t^-/z_{tk})}$$

$$\begin{aligned} s.t. & \sum_{j\in E} x_{ij}\lambda_j + s_i^- = x_{ik}, i=1,2,\ldots,m \\ & \sum_{j\in E} y_{rj}\lambda_j - s_r^+ = y_{rk}, r=1,2,\ldots,q \\ & \sum_{\mathrm{j}\in E} \mathrm{z}_{\mathrm{tj}}\lambda_{\mathrm{j}} + \mathrm{s}_{\mathrm{t}}^- = z_{tk}, t=1,2,\ldots,n \end{aligned} \tag{1}$$

$$\begin{aligned} & s_i^- \geq 0, i=1,2,\cdots,m \\ & s_r^+ \geq 0, r=1,2\cdots,q \\ & s_t^- \geq 0, t=1,2,\cdots,n \\ & \lambda_j \geq 0,\ j\in E \end{aligned} \tag{2}$$

$$\begin{aligned} & -\sum_{i=1}^{m} v_i x_{ij} + \sum_{r=1}^{q} \mu_r y_{rj} - \sum_{t=1}^{\mathrm{n}} \beta_t z_{tj} + d_j = 0,\ j \in E \\ & v_i \geq 1, i = 1, 2, \cdots, m \\ & \mu_r \geq 1, r = 1, 2, \cdots, q \\ & \beta_t \geq 1, t = 1, 2, \cdots, n \end{aligned} \tag{3}$$

$$\begin{aligned} & \mathrm{d}_{\mathrm{j}} \leq M\mathrm{b}_j,\ j\in E \\ & \lambda_j \leq M(1-b_j),\ j\in E \\ & b_j \in \{0,1\},\ j\in E \\ & d_j \geq 0,\ j\in E \end{aligned} \tag{4}$$

In the equations above, *M* is a sufficiently large integer; only when all the slack variables are 0, can the evaluated DMU achieve the best efficiency; *p* is the provincial AWE under the constraint of pollution emission; for *K* provinces, the input, the desirable output, and undesirable output vectors can be denoted as x_k, y_k, and z_k, respectively; λ is the linear combination coefficient of DMU; s_i^- is the slack variable of input; s_r^+ is the slack variable of desirable output; s_t^- is the slack variable of undesirable output. At b_j=0, d_j=0, $\lambda_j \leq$M, and then DMU_j is the reference standard of DMU_k; at b_j=1, then $d_j \leq$ M, λ_j=0, and DMU_j is not the reference standard of DMU_k. Another very important advantage of the MinDS model is that the input or output index can reach the most efficient consensus at the least cost while analyzing undesirable output index.

2.1.2 Data description

This paper selects the input-output panel data of AWE in 31 provinces in China from 2011 to 2015. The relevant data were from the 2012-2016 *China Statistical Yearbook*, *China Water Resources Bulletin*, and *China Environmental Statistical Yearbook*. Among them, the added value of the primary industry was reduced to a constant price in 2010. Table 1 lists the descriptive statistics of input and output index of the AWE.

2.2 Analysis for measurement results

Using MaxDEA software, the AWE of 31 provinces in China was measured according to the 2011-2015 input-output indices. The results are shown in Table 2.

In this paper, 31 provinces were classified into 7 regions, as shown in Table 2. It can be clearly seen from the table that the AWE is significantly different between various regions and between provinces in China. In general, the AWE in different regions was ranked from large to small: Qinghai-Tibet region>Southwest region>Southern coastal region>Yangtze River Basin>Yellow River Basin>Northwest region>Northeast region. The Qinghai-Tibet region had the highest AWE and the Northeast region had the lowest AWE, with a difference of 0.229; the AWE of the southwestern region, the southern coastal region, and the Yangtze River Basin was higher than the national average, while that of the Yellow River Basin and the Northwest region was lower than the national average.

In addition to the inter-regional differences in China's AWE, there are also significant intra-regional differences in AWE. The AWE in Northeast China was lower than the national average, except Liaoning; that of the Yellow River Basin was lower than the national average, except Shandong and Shaanxi;

that of the Yangtze River Basin was higher than the national average, except 4 of the 7 provinces, namely Hunan, Anhui, Shanghai, and Jiangxi; that of southern coastal areas was higher than the national average, except Guangdong; that of Southwest China was higher than the national average, and within the region, the AWE in Sichuan and Guizhou was relatively low; that of Northwest China was lower than the national average, except Inner Mongolia.

Table 1. Descriptive statistics of inputs and outputs

DMU	Index type	Description	Observed value	Average	Standard deviation	Minimum	Maximum
31 provinces in China	Desirable output	Added value of primary industry (100 million yuan)	155	1558.58	1094.80	72.02	4204.16
	Non-desirable output	Agricultural COD emissions (t)	155	363657.7	328809	3855	1379733
		Agricultural ammonia nitrogen emissions (t)	155	25119.07	20407.86	457	75800
	Input indices	Total agricultural water (100 million m^3)	155	124.45	108.88	6.5	561.7
		Number of employees in the primary industry (10,000 people)	155	908.35	663.69	37.28	2670
		Total sown area of crops (ten thousand m^3)	155	5304.17	3704.68	173.7	14425
		Total power of agricultural machinery (ten thousand KW)	155	3381.20	3109.01	105.7	13353

Table 2. The AWE of 31 provinces in China from 2011-2015

Regions		2011	2012	2013	2014	2015	Mean value	No.
Northeast China	Liaoning	1.0000	1.0000	1.0000	1.0000	0.8031	0.9606	1
	Jilin	0.7418	0.7329	0.7806	0.7069	0.6342	0.7193	2
	Heilongjiang	0.7373	0.6709	0.6485	0.6413	0.5585	0.6513	3
	Regional average	0.8264	0.8013	0.8097	0.7827	0.6653	0.7771	7
Yellow River Basin	Beijing	0.6843	0.7355	0.7108	1.0000	1.0000	0.8261	4
	Tianjin	0.6256	0.6134	0.6154	0.6691	0.6274	0.6302	7
	Hebei	0.6627	0.6773	1.0000	0.6836	0.6751	0.7397	5
	Shanxi	0.7067	0.7004	0.7250	0.7103	0.6341	0.6953	6
	Shandong	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1
	Henan	0.8769	0.8650	0.8679	0.8481	0.8404	0.8569	3
	Shaanxi	1.0000	1.0000	1.0000	1.0000	0.8297	0.9659	2
	Regional average	0.7937	0.7988	0.8456	0.8444	0.8010	0.8167	5
Yangtze River Basin	Shanghai	1.0000	0.5789	1.0000	0.6082	0.6541	0.7683	6
	Jiangsu	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1
	Zhejiang	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1
	Anhui	0.7678	0.8043	0.8065	0.7595	0.7098	0.7696	5
	Jiangxi	0.7790	0.7581	0.7560	0.7645	0.7738	0.7663	7
	Hubei	0.9210	0.8956	0.9139	0.8952	0.8799	0.9011	3
	Hunan	0.8671	0.8827	0.8593	0.8439	0.8411	0.8588	4
	Regional average	0.9050	0.8457	0.9051	0.8388	0.8370	0.8663	4
South coastal region	Fujian	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1
	Guangdong	0.8065	0.7858	0.7976	0.7966	0.8223	0.8018	4
	Guangxi	0.9086	0.8843	0.8672	0.8615	0.8318	0.8707	3
	Hainan	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1
	Regional average	0.9288	0.9175	0.9162	0.9145	0.9135	0.9181	3
Southwest region	Chongqing	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1
	Sichuan	0.8836	0.9119	0.8991	0.9012	0.9062	0.9004	4
	Guizhou	0.8037	0.7768	1.0000	1.0000	1.0000	0.9161	3
	Yunnan	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1
	Regional average	0.9218	0.9222	0.9748	0.9753	0.9766	0.9543	2
Northwest region	Inner Mongolia	1.0000	1.0000	1.0000	1.0000	0.6329	0.9266	1
	Gansu	0.8259	0.8092	0.7401	0.7724	0.7692	0.7834	2
	Ningxia	0.7516	0.6986	0.6964	0.6719	0.5901	0.6817	4
	Xinjiang	1.0000	0.6369	0.7261	0.7378	0.5723	0.7346	3
	Regional average	0.8944	0.7862	0.7907	0.7955	0.6411	0.7816	6
Qinghai-Tibet region	Tibet	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1
	Qinghai	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1
	Regional average	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1
National average		0.8823	0.8522	0.8842	0.8668	0.8254	0.8622	-

Table 3 shows that the national AWE from 2011 to 2015 was 0.8622, the agricultural pure technical water use was 0.9126, and the large-scale water use was 0.9489. From the regional perspective, the AWE, the agricultural pure technical water use, and the large-scale water use in the Qinghai-Tibet region were all 1, reaching the highest level. The AWE in Northeast and Northwest China was lower mainly due to the drag of pure technical water use. The Yellow River Basin, the Yangtze River Basin, the southern coastal region, and the southwestern region were mainly dragged down by the agricultural large-scale water use. From the perspective of provinces, in addition to Qinghai and Tibet, the AWE, pure technical water use, and large-scale water use of the five provinces of Shandong, Jiangsu, Zhejiang, Fujian and Chongqing, were all 1, on the highest level. The AWE of the 11 provinces such as Tianjin, Shanxi, Jilin, Heilongjiang, Anhui, Jiangxi, Hunan, Guangxi, Gansu, Ningxia, and Xinjiang were mainly dragged down by the pure technical water use. The AWE of the remaining 13 provinces WAS mainly dragged down by the large-scale water use (Note: The agricultural pure technical water use and large-scale water use data of each province are omitted).

Table 3. Average value of agricultural water-use efficiency in various regions in China from 2011 to 2015

Regions	CRS Agricultural water-use efficiency	Ranking	VRS Pure technical water use	Ranking	Large-scale water-use	Ranking
Northeast China	0.7771	7	0.7882	7	0.9931	2
Yellow River Basin	0.8167	5	0.9041	5	0.9082	7
Yangtze River Basin	0.8663	4	0.9267	4	0.9370	6
South coastal region	0.9181	3	0.9704	3	0.9480	5
Southwest region	0.9541	2	1.0000	1	0.9541	4
Northwest region	0.7816	6	0.8075	6	0.9779	3
Qinghai-Tibet region	1.0000	1	1.0000	1	1.0000	1
National average	0.8622	-	0.9126	-	0.9489	-

3. ANALYSIS FOR INFLUENCING FACTORS

3.1 Model setting and variable interpretation

The random-effects Tobit models were established as:

Model 1: $E_{it} = C + \sum_b x_{b,it} + u_i + z_{it}$

Model 2: $E_{it} = C + \sum_b x_{b,it} + \sum_j \beta_{j,it} + u_i + z_{it}$

In the above equations, E_{it} is the AWE in the i-th province of China's agriculture in year *t*; *C* is a constant term; *x* is the control variable; u_i is the standard deviation of individual effects (individual error); z_{it} is standard deviation of random interference item (random error), *i*=1, 2, ..., 31, representing 31 provinces, and *t* representing the year; *b*=1, 2, ..., 4, representing 4 core explanatory variables; *j*=1, 2, ..., 8, representing 8 control variables. $x_{b,it}$ represents the set of core explanatory variables: (1) The level of agricultural economic development (x_1), expressed by the per capita income of rural residents in China (thousand yuan), to verify the Environmental Kuznets Curve (EKC) theory [23]; (2) The square of the per capita income of rural residents (thousand yuan) (x_2), also be recorded as (x_1^2); (3) Water scarcity (x_3), expressed by the amount of water resources per capita in each province (thousand m^3). (4) Economic development level (x_4), expressed by per capita GDP (ten thousand yuan). $\beta_{j,it}$ represents the set of control variables: (1) Overall industrial structure (β_1), expressed by the proportion of the added value of the primary industry in the GNP; (2) Development of crop farming (β_2), expressed by the proportion of crop farming industry's added value in the primary industry; (3) Development of animal husbandry (β_3) expressed by the proportion of the added value of animal husbandry in the primary industry; (4) construction of farmland water conservancy (β_4) expressed as the ratio of effective irrigation area to the total sown area of crops; (5) Popularity of water-saving agriculture (β_5) expressed by the proportion of water-saving irrigation area to the total sown area of crops; (6) Crop planting structure (β_6) expressed by the proportion of rice sown area to the total crops; (7) Drought (β_7) by the proportion of drought-affected area to the total sown area of crops; (8) Flood disaster (β_8), expressed by the proportion of flood disaster area to the total sown area of crops.

3.2 Analysis for influencing factors of China's AWE

The regression results of Tobit panel data are shown in Table 4.

Table 4. Regression results of panel Tobit data

Variable	Model 1 Factor	Model 1 z value	Model 2 Factor	Model 2 z value
x_1	-4.3759*	-2.39	-1.4271	-0.77
$x_2(x_1^2)$	0.3766	0.55	-0.2160	-0.33
x_3	4.3114**	2.42	3.3067**	2.19
x_4	7.4892**	2.41	3.6095	1.12
β_1			0.8622	0.94
β_2			-1.6875***	-3.94
β_3			-1.7129***	-3.35
β_4			-0.7909***	-3.03
β_5			0.3005	1.48
β_6			-0.5813**	-2.15
β_7			-0.2841*	-1.80
β_8			-0.3320	-1.16
C	87.7999***	7.36	258.62206***	6.08
sigma-*u*	19.4349***	5.52	14.0709***	5.30
Sigma-*e*	10.4626***	11.51	9.6835***	11.47
p	0.4367		0.6786	
wald	12.74		42.95	
LR	91.52		60.05	

Note: ***, **, * are significant at the level of 1%, 5%, and 10% respectively

(1) The results analysis of core explanatory variables in Table 4 found that the regression coefficient of rural residents' per capita income was -4.3759, passing the 10% significance level test; meanwhile, the regression coefficient of rural residents' income squared was positive, indicating a consistency with the EKC theory, that is, China's AWE and agricultural economic growth under the constraint of pollution emissions present a U-shaped relationship, but the square of rural residents' income didn't pass the significance level test. This is possibly because the proportion of non-agricultural income in the income of rural residents is increasing, while the proportion of agricultural operating income in the income of rural residents is decreasing. The changes in income structure have caused more rural young and middle-aged labor force to be no longer engaged in agricultural operations, and the elderly to become the main laborer. However, the elderly is not good at water-saving concepts and the corresponding water-saving technologies, or have certain misunderstandings in the agricultural water use. With the further growth of rural residents' non-agricultural income, a large number of farmers may abandon their own farming and transfer the farm lands to

large households engaged in agricultural production, which will help to improve the AWE. Besides, regression coefficient of water scarcity was 4.3114 and passed the 5% significance level test, indicating that the scarcer the water resources, the lower the AWE, which is mainly because China is a country with a shortage of water resources, and in years with scarce water resources, the priority is given to residential water and industrial water, and sometimes the agricultural water isn't available, which will affect the normal production of agriculture, and then decrease the AWS. The regression coefficient of the economic development level was 7.4892, and passed the 5% significance level test, which indicates that the higher the level of economic development, the higher the AWE. The reason may be that with the continuous development of the economic level, the secondary industry and the tertiary industry will give more feedback to agriculture, e.g., the agricultural infrastructure, etc. have been continuously improved, and the level of agricultural science and technology has been continuously improved, thereby promoting the improvement of the AWE. When considering the control variables, the rural residents' per capita income, the square of rural residents' per capita income, the degree of water scarcity and the level of economic development have a decreased impact on the AWE, and only the degree of water scarcity passed the significance level test.

(2) The results analysis of control variables in Table 4 found that the regression coefficient of crop farming development was -1.6875, and it has passed the 1% significance level test. This indicates that the proportion of the added value of the crop farming is negatively correlated with the AWE, which is mainly because the water use per unit value added of the crop farming is higher than that of forestry, animal husbandry and fishery (e.g., in 2014, the water use of crop farming in Anhui occupied 94.39% of the total agricultural water use, while the added value of farming only accounted for 52.66%). The regression coefficient of the development of animal husbandry was -1.7129, and passed the 1% significance level test, indicating that the greater the proportion of the added value of animal husbandry, the lower the AWE. The reason may be that despite of the low water use of the unit value added in animal husbandry (for example, in 2014, the proportion of water use of animal husbandry in the total water use of Anhui Province was far lower than 5.61%, while the value added of animal husbandry accounted for 23.58%), the development of animal husbandry will still cause serious environmental pollution [24], thereby reducing the AWE under the constraint of pollution emissions. The regression coefficient of farmland water conservancy construction was -0.7909, and passed the 1% significance level test, which indicates that it does not significantly promote the AWE. This may be that the main purpose of constructing the farmland water conservancy infrastructure is to alleviate the problem of agricultural water shortage, but it also produces a certain amount of waste of agricultural water resources, thus reducing the AWE. The regression coefficient of the crop planting structure was -0.5813, and passed the 5% significance level test. This indicates that the proportion of rice sown area to total crop sown area has a significantly negative impact on the AWE, because rice is a crop that consumes a lot of water, and the unit value-added water consumption of rice is large. The regression coefficient of drought was -0.2841, and it has passed the 10% significance level test. This shows that drought has a significant negative impact on the AWE. The reason is that the lack of water for crops has a certain degree of impact on the yield and quality of crops, and then reduce the added value of crops or require more irrigation water due to drought, resulting in a decrease in the AWE, which is consistent with the research findings of Song and Oxley [25].

4. CONCLUSIONS AND SUGGESTIONS

4.1 Main conclusions

In this paper, the MinDS model was applied to estimate China's AWE under the constraints of pollution emissions from 2011 to 2015, and a random-effect panel Tobit model was used to analyze the factors affecting China's AWE. The main conclusions are drawn as follows: (1) The average AWE in China was 0.8622 on a high level; (2) There were significant inter- and intra- regional differences in the AWE; (3) Under the constraint of pollution emissions, China's AWE and agricultural economic growth presented a u-shaped curve relationship, conforming to the EKC theory, but this conclusion is not robust; (4) The scarcity of water resources and the level of economic development have a significant role in the improvement of China's AWE; development of animal husbandry, construction of farmland water conservancy, crop planting structure, and drought have a significant negative impact on China's AWE.

4.2 Policy suggestions

Based on the above research conclusions, the suggestions were proposed to improve the AWE under the constraints of pollution emissions: (1) Strengthen the intra-regional exchange of experiences in agricultural water saving, and focus on the provinces with low AWE; (2) Emphasize on increasing the income of rural residents and promoting economic development, and try to reach the inflection point of the EKC as soon as possible; (3) The construction of farmland water conservancy should focus on water-saving infrastructure, and the alleviation of water use and water conservation problems in drought-prone areas; (4) Vigorously promote the green development of agriculture, encourage the development of combined agriculture and animal husbandry and recycling agriculture while controlling the use of pesticides and fertilizers, etc., take multiple measures to treat livestock and poultry manure in a harmless manner, and strive to achieve zero discharge of manure; (5) Optimize the variety structure and production model of the crop farming; it is necessary to actively cultivate water-saving and high-efficiency crop varieties, as well as rationally and appropriately promote the co-cultivation mode of rice and fishery, which can not only increase the agricultural added value per unit of arable land, but also reduce the COD and ammonia nitrogen etc. [26].

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