

Article

An Empirical Research on Influence Factors of Industrial Water Use

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Abstract: The contradiction between increasing demand and current supply has affected the healthy development of industry. Investigating the key influence factors of industrial water use change has important practical significance for water resource management. In this study, the authors propose the vector autoregression model to analyze the dynamic influences of industrial development, technological progress, and environmental protection on industrial water use change, and take Jiangsu Province, China as a case study. Results show that each of the factors had different effects during 2001–2015, in which industrial development was the greatest contributor to the change of industrial water use and showed a positive effect in the forecast period; technological progress played a major role in reducing industrial water use, but the negative effect weakened periodically over time; environmental protection also had a positive influence in the early forecast period, and then showed a marginal effect with time. Results of this study could assist the relevant authorities to formulate appropriate industrial development planning and water saving policies, and to reasonably control the industrial water demand.

Keywords: industrial water use; influence factors; Jiangsu Province; vector autoregression model

1. Introduction

Water plays a crucial role in different production processes. According to its function and purpose, industrial water use can be classified as production water use, cooling and thermal water use, and miscellaneous water use [1,2]. Compared to agriculture and domestic water use, water for industrial use is more complex, and it is more easily affected by changes in the external environment such as industrial development, production level upgrading, environmental protection requirements, and climate change [3–7].

With the rapid progress of industrialization and urbanization, water shortage has become the bottleneck restricting sustainable industrial development in China, especially for the water-intensive industry [8,9]. In addition, over the recent decades, multi-purpose water management has reflected the different functions provided by rivers, which can be complementary or conflicting [10]. This calls for more integrated water resource management. The implementation of various effective measures of integrated water resource management, to alleviate the constraints of water shortages on economic and social development, can be categorized as structural measures (water conservancy projects, such as building dams and water transfers) and non-structural measures (water resource management, such as formulating water saving regulation). Due to financial and environmental restrictions, a water shortage crisis is more likely to be solved through water resource management strategy than by building water

conservancy projects [11]. The Chinese government has set up “three red lines” to promote economic and social development and adapt to water resource carrying capacity, which put forward clear requirements and targets for the amount of water withdrawal, water usage efficiency, and quantity of pollution discharge; preliminary results have been achieved [12]. In view of the process and characteristics of water utilization, the purposes of water resource management for industry are to decrease fresh water withdrawal and effluent discharge, and to improve the utilization rate of water resources.

Steady growth of economic development continues to drive water demand for industry [8,13]; it is projected that water withdrawal and water consumption will both show an increasing trend in the future, and that the industrial water demand of China in the 2050s will be twice that of the 2010s under a sustainability scenario [6,14]. In addition, the decrease of water resources availability and increased use of cooling water caused by climate change exacerbate the degree of water resource constraints on industrial development [7,15,16]. Researchers have begun to pay more attention to water network optimization based on substance flow analysis and pinch analysis under multiple objectives and scales to achieve efficient utilization of water resources [17–19]. Additionally, integrated water management strategies covering different segments have been proposed, which include water monitoring, water system optimization, and wastewater reuse, to assess water conservation potential [2]. From the macro level, there are relatively few studies on the influence of external environmental factors on the change of industrial water use. Moreover, the existing studies have emphasized the analysis of the impacts of economic development and technical innovation on water use [20,21]. Usually, the influence factors of industrial water use are complex, including industrial development, water-saving technologies, environmental protection, and climate change [22,23]. In particular, industrial production is accompanied by wastewater and exhaust emissions. Under strict requirements of ecological and environmental protection in China, the high standards regulating discharge of industrial wastewater and emission of industrial waste gas have been set up and implemented, with higher requirements being put on the manufacturing sector. Discharge of industrial wastewater and exhaust gas up to the allowed standard have an impact on industrial water demand [24]. Thus, environmental protection should be included among the main influence factors for further analysis regarding their impact on the change of industrial water use.

Various methods have been applied to quantify the promotion or inhibition effects of various factors on water use. The representative models include the Structural Decomposition Analysis (SDA) method, STIRPAT model, Laspeyres method, Input–output method, and Logarithmic Mean Divisia Index (LMDI) method [25,26]. Applying the factor decomposition model, Sun and Wang [27] measured the economic growth effect, industrial structure effect, water intensity effect, and mixing effect of the driving force of water utilization change. Cazcarro et al. [28] explored the impacts of technology, the input substitution process, and the changes in final demand on water consumption for the years 1980–2007 using the input–output model. Yang et al. [29] adopted the dynamic SDA method to investigate the influence of socioeconomic determinants on water footprint evolution. Shang et al. [30] decomposed the driving forces of industrial water use by the LMDI and the refined Laspeyres models. The above-mentioned quantitative analysis methods have static problems and cannot reflect the dynamic relationship between influencing factors and water use. In fact, the change of industrial water use is a dynamic process. The vector autoregression (VAR) model, as a simultaneous equation model, can not only reveal the interdependencies among variables, but can also forecast the dynamic relationship between variables. As it is easy to understand and operate, it has been adopted for analysis in various fields, especially in the economic and environmental fields [31–35]. Nevertheless, there is still a lack of studies that adopt the VAR model to investigate the relationship between influence factors and industrial water use.

This paper has three aspects of innovation and contribution that differ from previous studies. Firstly, we introduce environmental protection, which has a close connection with industrial water use, as an influence factor to analyze the impact on industrial water use. Previous studies seldom

considered this factor. Secondly, compared to static analysis of previous studies, the VAR model was employed to reveal the dynamic relationship between selected influence factors and industrial water use. This could give more comprehensive information for policy makers. Thirdly, the majority of existing studies emphasized the analysis of the influence of water use change on a regional scale. We focus on the impact analysis of changes in sectoral water use within the region; Jiangsu Province is selected as the study area, which is the largest industrial province of China and faces environmental protection problems. This is an ideal representative to carry out the analysis of industrial water use change. The location of Jiangsu Province is shown in Figure 1.

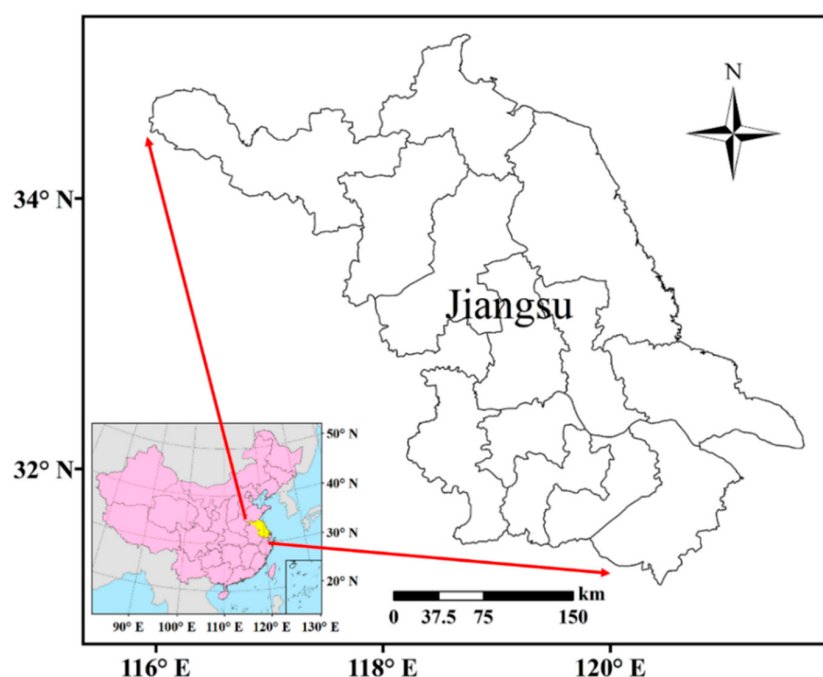


Figure 1. The location of Jiangsu Province in China.

2. Materials and Methods

2.1. Data

All data reflect the actual situation of Jiangsu Province from 2001 to 2015. The annual amount of industrial water use (W_t) and water use per unit of industrial output (I_t) were acquired from Jiangsu Water Resources Bulletin. Data of industrial output (G_t) were obtained from Jiangsu Statistical Yearbook. In order to eliminate the effect of rising prices and inflation, industrial output was calculated at constant prices (Year 2000 = 100). The annual discharge (emission) of industrial wastewater, sulfur dioxide, and dust were extracted from China Environmental Statistics Yearbook and Jiangsu Statistical Yearbook. The statistical summary of all variables in this research is shown in Table 1.

Table 1. The statistical summary of all variables in this research.

Variable		Mean	Maximum	Minimum	Standard Deviation
W_t		177.14	225.3	125.1	34.07
I_t		159.76	335.22	44.68	94.99
G_t		13,171.48	25,305.37	4291.10	6888.49
E_t	Wastewater discharge intensity	21.22	45.36	8.86	11.95
	SO ₂ emission intensity	0.0050	0.0115	0.0012	0.0036
	Dust emission intensity	0.0029	0.0072	0.0008	0.0023

2.2. VAR Model

The VAR model is widely used for time series analysis, which was first proposed by Sims [36]. The model constructed by the function described by each endogenous variable is the lag value of all endogenous variables in the system. Additionally, the model, without any prior constraints, is based on time series data to determine dynamic relationship of endogenous variables instead of theory. Thus, the VAR model is applied to analyze the dynamic connection between industrial water use and its influencing factors.

The model consists of multiple simultaneous equations, where the endogenous variable is located on the left of the equation, and the right is its own hysteresis and the lag of other endogenous variables. The general simplified form of the VAR (p) model with lag order p can be expressed as:

$$Y_t = u + A_1 \cdot Y_{t-1} + \cdots + A_p \cdot Y_{t-p} + \varepsilon_t \quad (t = 1, 2, \cdots, T), \quad (1)$$

where Y_t is a $K \times 1$ endogenous variable vector, p is lag order, u is a vector of constant terms, $A_1, \cdots, A_p$ are $K \times K$ parameter matrices, and ε_t represents a $K \times 1$ random error column vector.

The dynamic nexus between industrial water use (W_t) and industrial development (G_t), technological progress (I_t), and environmental protection (E_t) needs to be explored, and the four variables mentioned above were selected to construct the VAR system. The industrial output was used to reflect the industrial development variable. The water use per unit of industrial output was selected to represent technological progress. The discharge or emission intensity of industrial wastewater discharge, sulfur dioxide emissions, and dust emissions was used to comprehensively reflect the environmental protection variable. However, three environmental protection variables may cause the analysis of the relationship between environmental protection and industrial water use change to be more complex. In order to solve this problem, the integrated index method was adopted for conversion of multiple variables of environment protection into an environmental regulation strength (ERS) indicator, and the ERS indicator was used to reflect environmental protection, which is expressed by E_t . The specific process of the comprehensive index method follows that of Fu and Li [37]. The definitions of all variables are shown in Table 2.

Table 2. Definition of all variables in this research.

Variable	Definition	Units of Measure
W_t	The annual amount of industrial water use	10^8 m^3
I_t	Water use per unit of industrial output	$\text{m}^3 \cdot 10^{-4} \text{ yuan}$
G_t	Industrial output	10^8 yuan
E_t	Integrated indicator of industrial wastewater discharge, industrial sulfur dioxide emission, and dust emission intensities	$\text{tons} \cdot 10^{-4} \text{ yuan}$

Tables 1 and 2 show that the dimensions of the four variables are different and there are orders of magnitude differences. Logarithmic treatment is an effective method which could avoid the sharp fluctuation of data and eliminate the possible heteroscedasticity, and not change the characteristics of the time series data [38]. It has been commonly used in VAR model variable time series stationarity testing in previous studies [31,39]. Therefore, natural logarithm treatment was performed on the original data sets, and the data sets are expressed as $\ln W_t$, $\ln G_t$, $\ln I_t$, and $\ln E_t$, where W_t , G_t , I_t , and E_t refer the industrial water use, industrial development, technological progress and environmental protection, respectively.

As mentioned above, the VAR system consists of the following four variables: Industrial water use (W_t), industrial development (G_t), technological progress (I_t), and environmental protection (E_t). According to Equation (1), the specific form of VAR (p) is as follows:

$$\begin{aligned} \ln W_t &= u_{10} + \sum_{i=1}^p \alpha_{11,i} \ln W_{t-i} + \sum_{i=1}^p \alpha_{12,i} \ln G_{t-i} + \sum_{i=1}^p \alpha_{13,i} \ln I_{t-i} + \sum_{i=1}^p \alpha_{14,i} \ln E_{t-i} + \varepsilon_{Wt} (t = 1, 2, \dots, T) \\ \ln G_t &= u_{20} + \sum_{i=1}^p \alpha_{21,i} \ln W_{t-i} + \sum_{i=1}^p \alpha_{22,i} \ln G_{t-i} + \sum_{i=1}^p \alpha_{23,i} \ln I_{t-i} + \sum_{i=1}^p \alpha_{24,i} \ln E_{t-i} + \varepsilon_{Gt} (t = 1, 2, \dots, T) \\ \ln I_t &= u_{30} + \sum_{i=1}^p \alpha_{31,i} \ln W_{t-i} + \sum_{i=1}^p \alpha_{32,i} \ln G_{t-i} + \sum_{i=1}^p \alpha_{33,i} \ln I_{t-i} + \sum_{i=1}^p \alpha_{34,i} \ln E_{t-i} + \varepsilon_{It} (t = 1, 2, \dots, T) \\ \ln E_t &= u_{40} + \sum_{i=1}^p \alpha_{41,i} \ln W_{t-i} + \sum_{i=1}^p \alpha_{42,i} \ln G_{t-i} + \sum_{i=1}^p \alpha_{43,i} \ln I_{t-i} + \sum_{i=1}^p \alpha_{44,i} \ln E_{t-i} + \varepsilon_{Et} (t = 1, 2, \dots, T). \end{aligned} \quad (2)$$

It should be noted that Equation (2) is the embodiment of the specific form of the original model, and no modifications have been made to the original model.

Testing the stationarity of the time series of each variable is the premise of applying the VAR model, which could avoid the phenomenon of pseudo-regression caused by the instability of variables. Thus, a stationarity test should be performed on the time series before build the model. Many methods have been developed for the stationarity test, and unit root test is the most commonly used method [40]. Three common unit root test methods were applied: The Augmented Dickey–Fuller test (ADF) test, the Kwiatkowski Phillips Schmidt Shin (KPSS) test, and the Phillips Perron (PP) test [41–43]. The ADF test is a widely considered and chosen method. However, in small samples, it has its own insurmountable defects, and the validity of the test results is affected [44]. The PP test was selected to supplement the ADF test. The principle of the KPSS test is different from the above two methods, having the null hypothesis that the time series is stationary rather than having a unit root as hypothesized by the ADF test and PP test. It can make up for the defects of ADF and PP test methods [42,45]. These three methods are complementary to each other in verifying the unit root test process, which makes the test result more comprehensive and persuasive.

In practical application, a key issue is the optimal lag order selection. Generally, the selection principle of lag order tends to choose a larger value to take full advantage of variable information of the constructed model. However, the greater the lag order, the more parameters need to be estimated, and degrees of freedom of the model are reduced correspondingly [46]. Therefore, balancing lag order selection and degrees of freedom of the model needs to be taken into consideration.

3. Results

3.1. Variable Description

According to the annual data of the variables, we depict the trends of industrial water use, industrial output, water use per unit of industrial output, and environmental regulation strength. As shown in Figure 2, industrial water use increased rapidly from 2001 to 2007, then showed a declining trend, especially after 2012. This is mainly due to the establishment of water-saving society and implementation of the strictest water resources management system. Industrial output showed a significant upward trend with an average annual growth rate of 13.0%. Water use per unit of industrial output reflected a gradual decreasing trend, which suggests that industrial water use efficiency has been gradually improved. Environmental regulation strength generally presented a fluctuating downward trend, which indicates that environmental protection has achieved remarkable results, and that the wastewater and waste gas emissions have been effectively controlled.

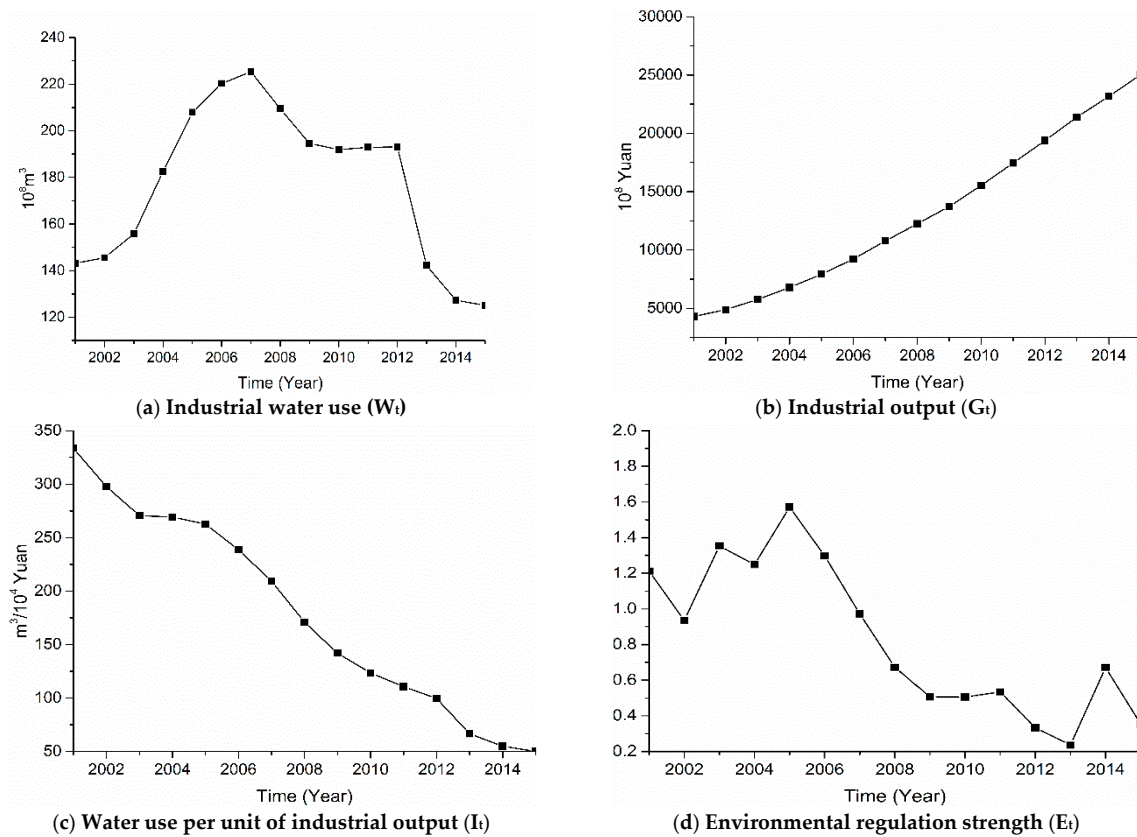


Figure 2. Change trends of variables from 2001 to 2015.

3.2. The Unit Root Test Analysis

ADF, KPSS, and PP methods were selected to verify the stationarity of time series of variables. The results of unit root test of each variable are shown in Table 3.

Table 3. Unit root test results.

Variable		ADF		PP		KPSS
LnW_t	(c, 0, 1)	0.3886	(0, 0, 2)	−0.2799	(c, t, 2)	0.1608 **
$DLnW_t$	(0, 0, 0)	−2.0363 **	(0, 0, 2)	−2.0363 **	(c, t, 2)	0.0814
LnG_t	(c, 0, 0)	−5.9871 ***	(c, 0, 0)	−5.9871 ***	(c, t, 2)	0.1683 **
$DLnG_t$	(c, t, 0)	−5.4543 ***	(c, t, 2)	−6.9820 ***	(c, t, 2)	0.1315 *
LnI_t	(c, t, 0)	−1.2753	(c, t, 2)	−1.1784	(c, t, 2)	0.1559 **
$DLnI_t$	(c, t, 1)	−3.9786 **	(c, t, 12)	−3.7376 *	(c, t, 2)	0.0847
LnE_t	(c, t, 0)	−2.8113	(c, t, 3)	−2.7236	(c, 0, 2)	0.5080 **
$DLnE_t$	(c, t, 0)	−4.8098 ***	(c, 0, 2)	−4.9289 ***	(c, 0, 2)	0.1192

(c, t, p), c = constant, t = trend, p = lag length. * Denote significance at 10%. ** Denote significance at 5%. *** Denote significance at 1%.

The ADF test and PP test suggest that time series of $\ln W_t$, $\ln I_t$, and $\ln E_t$ are integrated of order one (I(1)), whereas the first-order differences of the time series are integrated of order zero (I(0)), which confirms the hypothesis that the time series of $\ln W_t$, $\ln I_t$, and $\ln E_t$ have a unit root. The KPSS test shows different results compared to the ADF and PP tests, because the null hypothesis is the opposite of the other two methods, so it also shows that the time series of $\ln W_t$, $\ln I_t$ and $\ln E_t$ have a unit root. For the variable $\ln W_t$, the ADF and PP tests suggest stationarity; the KPSS test shows that it

is not stationary. The industrial output, which expressed in terms of $\ln W_t$, is a macroeconomic index. Generally speaking, macroeconomic data will be stable after first-order difference. Therefore, through comprehensive analysis of the test results and based on previous research [47], we deem the time series of the four variables are all I (1).

As mentioned above, the four variables are all integrated of order one, meaning that the model might be unstable and the impulse response function might be not convergent if the VAR model is established directly, therefore, the VAR model was established by first order difference of each variable, and it is also agreed that the difference of variables is still expressed by the names of $\ln W_t$, $\ln G_t$, $\ln I_t$, and $\ln E_t$ without affecting the understanding of the following contents.

3.3. The Optimal Lag Order Analysis

It is particularly important to choose the lag order while building a VAR model. The selected optimal lag order could maximize the fitness of the forecast process with statistical time series and minimize the measure of forecast precision. The most common procedure for VAR order selection is application of model selection criteria. In this paper, the sequential modified LR test statistic (LR), Final prediction error (FPE), Akaike information criterion (AIC), Schwarz information criterion (SC), and Hannan–Quinn information criterion (HQ) criteria are exploited to jointly determine the optimal order. As shown in Table 4, the results are all in agreement that $p = 1$ is the optimal lag order.

Table 4. Lag length criteria.

Lag	LogL	LR	FRE	AIC	SC	HQ
0	139.2350	NA	1.08×10^{-14}	−20.80538	−20.63155	−20.84111
1	170.8913	38.96,165 *	1.15×10^{-15} *	−23.21405 *	−22.34489 *	−23.39270 *

* indicates lag order selected by the criterion.

3.4. Model Stability Test

The stability of the model directly affects the validity of the variance decomposition and impulse response analysis results. Therefore, the stability test must be formulated to verify whether the model is stable or not. The necessary and sufficient condition for the stability of the VAR model is that all the eigenvalues of the model characteristic equation are outside the unit circle, that is to say, the inverse eigenvalues of the model characteristic equation are within the unit circle [38]. The results are reflected in Figure 3, and it serves to show that all the inverse eigenvalues of the model's characteristic equation are within the unit circle, which indicates that the built VAR model is stable.

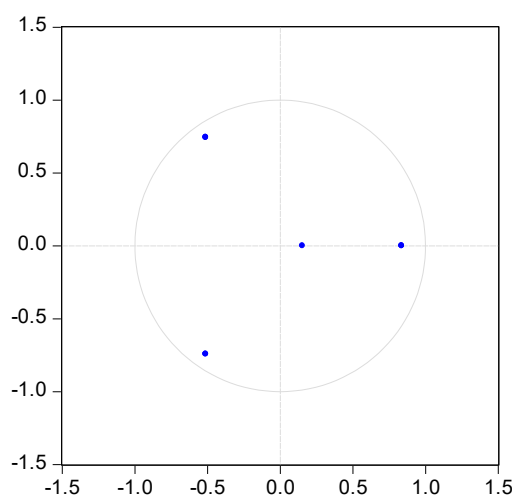


Figure 3. Inverse roots of AR characteristic polynomial.

3.5. Variance Decomposition Analysis

Variance decomposition analysis is normally a method that explores the relative effects of variables [48]. It is used to analyze the contribution degree measured by forecast variance of a specific shock to the endogenous variables of model and gives the relative importance information of each structural shock that affects the variable in the VAR model. Hence, it is able to clearly tell us the proportion of forecast variance produced by all variables with specific shocks on a specified variable at a specified time horizon [31,39].

Table 5 describes the percentage of forecast error variance of the $\ln W_t$ shocked by all variables for the ten-year period. For the industrial water use change, in addition to its own influence, industrial output shock accounts for the largest proportion of the change of industrial water use. It has an increasing effect on industrial water use change with time, from around 15.3% in the first period, increasing to 24.1% in the end, and shows a fluctuating upward trend, which indicates that industrial water use and industrial development have a strong positive correlation. The environmental protection shock ranks second to industrial development. The contribution of environmental protection has increased from 14.2% in the first period to 14.8% in the second period, then downward to the minimum 13.2%, and maintains an upward trend until the end period. The influence of technological progress on industrial water use is basically consistent with the trend of environmental protection, but the contribution degree is slightly lower than that of environmental protection. In summary, industrial development, technological progress, and environmental protection have increasing effects on industrial water use at a specified time period, however, the influence trend does not increase linearly, but fluctuates.

Table 5. Variance decomposition results.

Period	S.E.	$\ln W_t$	$\ln G_t$	$\ln I_t$	$\ln E_t$
1	0.080185	100.0000	0.000000	0.000000	0.000000
2	0.127087	58.90791	15.30284	11.59534	14.19392
3	0.136670	53.47121	19.58484	12.10484	14.83911
4	0.145645	58.69928	17.36662	10.77795	13.15616
5	0.158871	52.67770	19.75646	12.79561	14.77023
6	0.161609	51.40966	20.14291	12.57893	15.86850
7	0.165227	53.14265	19.36203	12.07962	15.41570
8	0.170317	50.70844	20.58523	13.01690	15.68943
9	0.171401	50.21471	20.45792	12.85544	16.47193
10	0.173073	50.83091	20.10459	12.61742	16.44708

3.6. Impulse Response Analysis

The impulse response functions (IRFs) were applied to analyze the dynamic response of the system. Particularly, they describe the dynamic response of applying a standard deviation on the random error term on all endogenous variables [48]. This method not only reflects the dynamic relationship between different variables, but also identifies the impact of all endogenous variables with a shock in the model at a specified time horizon and quantify the influence degree of the shock.

The IRFs were generated as shown in Figure 4. One standard deviation shock to industrial development ($\ln G_t$) promotes industrial water use directly for 2 years, reaches the maximum positive response at the second period, and then exhibits periodic fluctuation change with time. It reflects nearly a positive response within the whole specified time period, which implies that industrial development will continue to promote industrial water use over the forecast period, but the positive effect will decrease over time. As China's largest industrial province, the industrial output of Jiangsu

Province has increased considerably, at the average annual growth rate of 13.4% from 2001 to 2015 [49]. The corresponding industrial water use showed an increasing trend from 2001 to 2013. Although industrial development promotes the demand for industrial water, the promotion will not be always sustainable. With the promotion and strength of water resource management, industrial water-saving technology has been popularized and applied, and the growth trend of industrial water use has been effectively curbed. Industrial water use dropped significantly after 2013, which was a response to the implementation of the most stringent water resource management system. With orderly progress of industrialization and urbanization, the scale and output of Jiangsu Province industries in the future will be expected to maintain steady and sustained growth, and the demand for industrial water will increase further. Although integrated water resource management, which includes water-saving technology application, water resource management system implementation, and so on, could restrain the industrial water demand, technological progress has limited impact on reducing water use with time, and industrial development will still play the dominant role in promoting the industrial water demand [50]. Thus, adapting to the carrying capacity of water resources is a prerequisite for future industrial development [51].

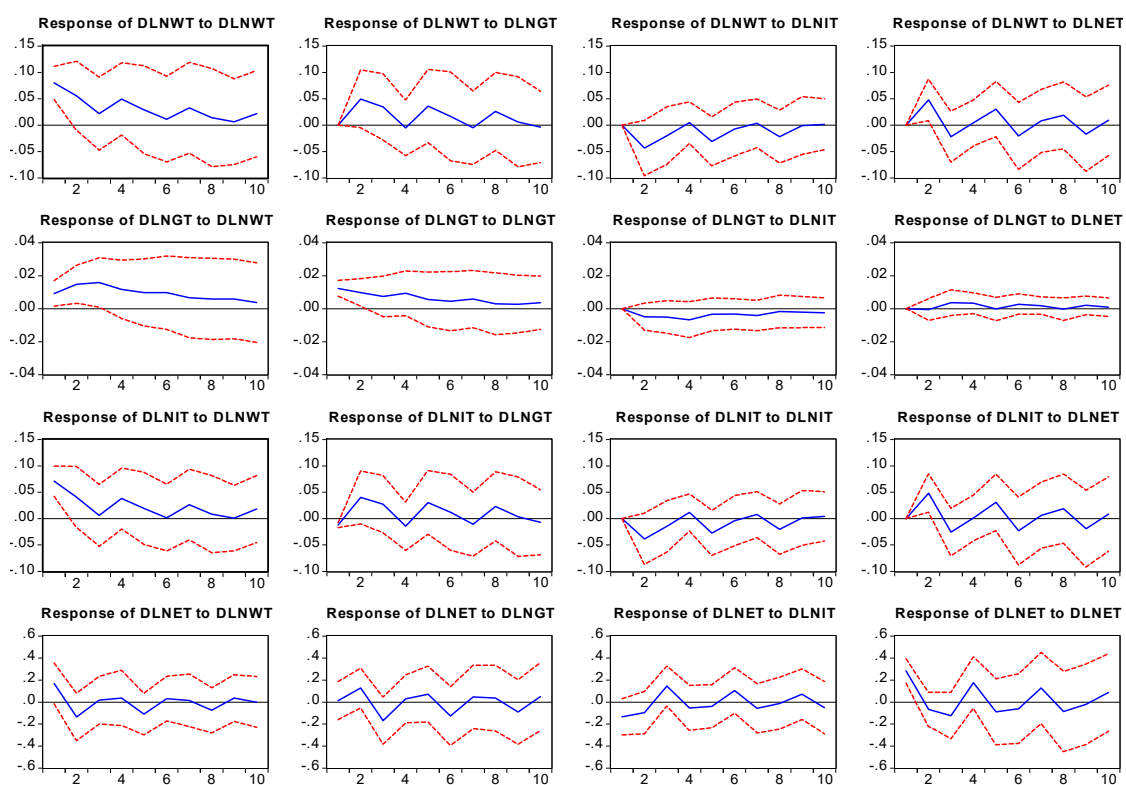


Figure 4. Responses of industrial water use to different influence factors. The blue solid lines indicate the mean responses to a one standard deviation shock, while the dotted lines represent ± 2 standard deviations of the responses. The x-axis is the forecast horizon (in years), and the y-axis is the forecasted response of the dependent variable to a unit shock in the corresponding error term.

The industrial water use indicates a significant negative response to technological progress ($\ln I_t$), which means that technological progress could inhibit industrial water use. As shown in Figure 4, the negative effect of technological progress on industrial water use reached its maximum in the second period and decreased periodically with time. Correspondingly, water use per unit of industrial output in Jiangsu Province dropped obviously from 333.64 m³/t in 2001 to 49.97 m³/t in 2015. Meanwhile, the recycling ratio of industrial water utilization in Jiangsu Province increased from 57% in 2005 to about 70% in 2015 [49] as the improvement of industrial water utilization level and efficiency reduced the demand for fresh water. Nevertheless, water use per unit of industrial output decreased slowly

and showed a steady trend from 2013 to 2015. That indicates that technological progress could not maintain a state of rapid innovation, as it has a certain periodicity, and that the water-saving effect of technological progress will be weakened with the passage of time and the increase of industrial scale, correspondingly [7]. Coupled with Jiangsu's continued industrial growth, the restraining effect of technological progress on industrial water demand is limited, which explains the failure of technological progress to sustain a significant negative effect over the whole forecast period, and presents a periodic decay trend. Besides, the response of technological progress to one standard deviation shock in industrial water use is positive over the forecast period, which implies the increasing of industrial water use will promote technological progress.

The industrial water use shows a positive response to environmental protection ($\ln E_t$) at the early time period, reaches its maximum in the second period, and then fluctuates near zero from the third period to the end period. This indicates that the strengthening of environmental protection will promote the increase of industrial water demand clearly in the short term, and that medium- and long-term effects are not significant. Environmental protection for industrial water use mainly involves the discharge of industrial wastewater and waste gas. The discharge or emission intensity of industrial wastewater discharge, sulfur dioxide emissions, and dust emissions in Jiangsu Province showed a significant downward trend, from 63.5 t/10⁴ yuan, 0.026 t/10⁴ yuan, and 0.016 t/10⁴ yuan in 2001, to 7.4 t/10⁴ yuan, 0.003 t/10⁴ yuan, and 0.002 t/10⁴ yuan in 2015, respectively. The reduction of industrial wastewater discharge intensity could improve the water resources utilization rate and decrease fresh water consumption, however, the reduction of industrial waste gas emission intensity needs more water consumption to reach environmental protection policy requirements. Thus, increasing the intensity of environmental protection will promote the growth of industrial water demand in the short-term. When coupled with improvement of wastewater reuse rate and application of water-saving technologies for industrial waste gas treatment, the impact of environmental protection on industrial water use is no longer significant in the long term. In addition, the environmental protection path is positive in response to a shock in industrial water use in the current period, and drifts around zero after the second period, which suggests that the increasing of industrial water use will strengthen the current environmental protection, and show a marginal effect over the forecast period.

4. Discussion

According to the results mentioned above, there are some different findings.

Industrial development is the greatest contributor to industrial water use changes, except for the impact of industrial water use itself, and shows a positive effect on industrial water use. Compared with previous studies, this result suggests that the promoting effect of industrial development on industrial water use is not always stable and continuous but weakens with time. One of the reasons for this phenomenon is that, restricted by water resource conditions, the available water resources could not fully meet the requirements of industrial development. In order to meet the requirement of industrial development be compatible with the regional water resource carrying capacity, the state strengthens the management of water resources by formulating macro-control policies, and further promotes rationalization of industrial distribution and structural adjustment. That is, the development scale and trend of the industry will be reasonably controlled through macro-control measures, and this will alleviate the demand and influence on industrial water use. Another reason is that the development of industry is accompanied by technological progress; the result in Figure 4 validates this view. Technological progress can improve the efficiency of industrial water use, which results in inhibiting the rapid growth of water consumption caused by industrial development. In a word, macro- and micro-control can effectively alleviate the demand for industrial water in industrial development, but the stable development of industry will still increase the demand for water resources.

Technological progress, which includes the improvement of manufacturing processes and utilization of water saving technologies, has a negative effect on industrial water use and restrains the industrial water demand. This consistent with the findings of Flörke et al. and Liu et al. [22,52].

In contrast to other studies, this result also shows that the restraining effect of technological progress on industrial water consumption is not stable and sustainable, but decreases periodically with time, which can be explained in two aspects. One is that the improvement of production technology has a certain periodicity, as investment in research and development takes time to translate, and this period is relatively long. On the other hand, the popularization and application of advanced water-saving technologies are susceptible to economic benefits; industrial enterprises are less active in the application of water-saving technologies from the perspective of economic efficiency. Currently, the application of water-saving technology mainly depends on policy requirements, as the popularity of water-saving technology restricts the effect of water-saving. Therefore, more efforts should be made in research and development to accelerate the promotion and application of water-saving technologies, and to realize the dynamic control of industrial water demand by technological progress.

Environmental protection has an effect on increasing industrial water use in the short term, and shows a margin effect on industrial water use in the long term. Moreover, the influence of environmental protection on industrial water use will also increase gradually with the increase of time. With the strengthening of ecological environment protection, Jiangsu Province has put forward higher requirements for industrial waste gas and wastewater discharge. In order to meet the demand of environmental protection requests, countermeasures, such as gas desulfurization and dust elimination, were implemented and promoted effectively. Meanwhile, gas desulfurization and dust elimination consume certain amounts of fresh water [24]. The strict requirements of environmental protection could significantly increase water demand in the short term. With the improvement of wastewater reuse technology and graded utilization of reclaimed water however, the use of unconventional water sources replaces fresh water in the process of gas desulfurization and dust elimination, which will alleviate the demand for industrial fresh water [2,53], and the effects of environmental protection on industrial water demand will be no longer obvious in the long term. In the future, environmental awareness may be further enhanced and the requirements for industrial environmental protection may also be deepened and more comprehensive, therefore, it is urgent to adopt technical and non-technical measures to reasonably control the demand environmental protection for water resources.

In a word, the VAR model could quantitatively reflect the degree of how industrial development, technological progress and environmental protection impact industrial water use, which is conducive for the authorities to propose targeted integrated water resource management measures to solve the problems faced by industrial water use caused by external environmental change. Meanwhile, it reveals the dynamic relationship among industrial water use and industrial development, technological progress, and environmental protection, which facilitates policy makers to appropriately adjust integrated water resource management measures and promote dynamic water resource management.

5. Conclusions

Exploring the dynamic relationship between influencing factors and water resources utilization is a significant prerequisite for strengthening water resource management. This paper selected Jiangsu Province of China as the typical study area to examine the dynamic relationship between industrial water use and its key influence factors by using the VAR model. Through empirical analysis, we quantitatively analyzed the contribution degrees of different influence factors on the change of industrial water use by variance decomposition analysis and applied impulse response analysis method to reveal the dynamic relationship between influence factors and industrial water use change.

The results demonstrate, in addition to the influence of industrial water use itself, industrial output shock accounts for the largest proportion and has a positive effect in the whole forecast period. Technological progress produces a negative effect in the whole forecast period, but the inhibition effect decreases with time. Compared with industrial development and technological progress, the impact of environmental protection on industrial water use shows a significant positive response in the early forecast period. Moreover, the influence degrees of the three factors on industrial water use increase over time; more attention should be paid to the dynamic changes of these three factors in the forecast

of industrial water demand in the future. These above-mentioned results are not only helpful to improve the analysis of influencing factors of water use but are also worthy of special attention from authorities in order to formulate industrial development programs and water resources protection planning for ensuring regional water security. Besides, they also suggest that application of VAR model can intuitively and clearly report the relationship of influencing factors and water resources utilization.

This research also has some limitations which need to be further improved. One is the size of the data sample. Due to the lack of statistics, only 15-year data samples are exposed for each variable. However, the time series passed the stationarity and model stability test, which indicates that the process of model construction is reasonable, and the output is credible. Of course, if the number of samples of the variable is large enough, the relationship between variables could be reflected more comprehensively. The other aspect is the selection of variables. We aim to clarify the impact of economic and social development on industrial water use in this paper, which is why we neglect to analyze the influence of climate change on industrial water use. In fact, climate change has direct and indirect effects on industrial water use [54,55]. On the one hand, cooling water is a major part of industry water use. Climate change causes temperature change, and temperature change directly affects cooling water consumption. On the other hand, industry is an important part of carbon emissions. Adaptation and mitigation measures of climate change will affect the development scale of industrial industry and indirectly affect industrial water use. The impact of climate change on industrial water use is complex and uncertain, and further in-depth research in this regard, based on the results of this work, needs to be conducted. Future work would employ reasonable methods to improve this data sample size, and the response mechanism of water use change to climate change should merit an in-depth examination.

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