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Water Resource Utilization Assessment in China Based on the Dynamic Relationship between Economic Growth and Water Use

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Abstract: Water scarcity has significantly hampered China's economic, social, and environmental development. Ensuring sustainable water utilization is crucial given the mounting water stress accompanying continuous economic growth. A quantitative water resource forewarning model was constructed using the vector autoregressive (VAR) model. By analyzing the key indicators related to water systems and GDP data from 2001 to 2022, the VAR model revealed the long-term dynamic correlation between water consumption and economic growth using generalized impulse response, co-integration, and predictive variance decomposition analyses. The results revealed the presence of a long-term equilibrium between water consumption and economic growth, with a stable co-integration relationship and an optimal lag period of one year. The positive impact of water consumption on economic development increased during the 2001–2022 period, indicating a rising dependence of GDP on water resources. Water usage rose with economic development, while the water resource carrying capacity remained high and continued to grow. Based on the generalized impulse response, co-integration, and predictive variance decomposition analyses, this study predicted water-use-related indicators, providing vital early warnings for China's water environment carrying capacity from 2023 to 2050. This enabled informed decision-making and fostered sustainable water management practices for the future.

Keywords: water consumption; water resource carrying capacity; economic growth; dynamic relationship; VAR model

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1. Introduction

With swift population increase and economic growth, the increasing water demand placed immense pressure on the water system [1,2]. Over the last several decades, China's Gross Domestic Product (GDP) has experienced significant growth, with a staggering increase of more than 330% at constant prices from 1978 (CNY 365 billion) to 2022 (CNY 1210.20 billion) [3]. This tremendous growth has led to resource security challenges, positioning China as one of the largest economies and resource consumers in the world [4]. However, this growth also exacerbates the issue of water scarcity, with total water use surging from 103 trillion liters in 1950 to 599.82 trillion liters in 2022. Meanwhile, the total available water resources remain relatively stable and unevenly distributed, with the south accounting for more than 80% of the total, while the north only accounted for around 20%. Therefore, China is classified as a 'water-scarce' country according to the United Nations Environment Programme [5].

Statistics reveal that China's per capita water consumption is expected to reach only 425 m^3 in 2022, less than half of the global average [6]. Moreover, an estimated 440 out of 669 Chinese cities experience water shortages, with 110 of them facing 'serious' scarcity [7]. Additionally, a nationwide survey of 1935 sampling sites at China's rivers, lakes, and reservoirs in 2018 revealed that 29% of them had poor water quality [8]. And around 300 million rural inhabitants lack access to safe drinking water [9]. These water shortages and related environmental issues are becoming a significant impediment to China's economic sustainable development [7,10].

Understanding the relationship between water resources and economic growth is crucial for exploring pathways to achieve sustainable water utilization and sustainable economic development [11–13]. Sustainable water utilization represents water consumption practices that do not deplete water stocks and impair water ecosystems [14]. It has been discovered that the interaction between water resources and economic growth is bidirectional: On one hand, economic growth is paired with a rise in water consumption. However, when economic growth surpasses a certain critical value, and with advancements in technology, the optimization of industrial structure, and changes in economic growth patterns, the speed of increase in water usage starts to decline [15,16]. On the other hand, water usage also affects economic growth, as the limited nature of water resources inevitably impacts investment and the economic growth speed in subsequent stages [17,18]. Many scholars have concurred that economic growth led to a rise in total water use [19–21]. Similarly, studies have indicated that water resources played a crucial role in driving economic growth. For instance, Alrwis et al. [22] assessed the effect of water scarcity on Saudi Arabia's national economic growth and concluded that water scarcity affected GDP by reducing crop areas and agricultural output.

Furthermore, researchers have explored the implications of economic growth on water resources. Zhao et al. [23] found a significant inverted U-shaped relationship between water consumption and economic growth across different regions in China for the period 2003 to 2014. Zhang et al. [24] demonstrated a curved, inverted U-shaped correlation between per capita industrial water usage and GDP across different regions in China using the triple reduction model. Using a simultaneous equation model, Hao et al. [25] analyzed the correlation between water consumption and economic growth in 29 Chinese provinces from 1999 to 2014 and discovered an N-shaped relationship between per capita water use and per capita GDP in China.

The vector autoregression (VAR) model, introduced by Sims [26], provides a new macro-econometric framework to capture complex dynamic interrelationships among macroeconomic variables over flexible time series. Traditional univariate autoregression is characterized by a linear model with single equation and single variable, whereas the VAR model is a linear model with multiple equations and variables. In the VAR model, each variable is explained both by its lagged values and by the current and past values of the other variables. This provides a methodical approach of capturing the diverse dynamics across multiple time series. VAR models allow for the analysis of interactions between several variables through impulse response. Scholars have utilized the VAR model in various studies related to renewable energy consumption, greenhouse gases emission, economic growth, and other factors influencing economies and environmental outcomes [27–29].

The prediction and warning of the overloading status of the water environment carrying capacity involves assessing the deviation of water quality and quantity from the ideal state. It comprises three main components: water use assessment, water use change prediction, and regulation. An effective approach to water use assessment is the comprehensive warning index system [5,30]. When constructing the early warning indicator system, it is beneficial to refer to the evaluation index system for the water environment carrying capacity [31]. This system incorporates the general principles of water environment assessment while considering the complex characteristics of regional water resources systems. A comprehensive regional early warning indicator system for sustainable water resource utilization encompasses not only indicators related to the water resources system but also social, economic, and ecological indicators.

In this paper, we employed water and economic data from the 2001–2022 period and utilized the VAR model to explore the dynamic correlation of economic growth and water consumption. Based on the relationship results, we have predicted China's water use changes during 2023–2050. Additionally, we proposed an early warning system to assess water utilization sustainability for analyzing the overloading status of water resources carrying capacity during 2023–2050. By analyzing the internal dependence and causal relationship between water consumption and economic growth, the paper aims to offer guidance for assessing the sustainability of water resources and early warning for potential water overload in the future, serving as a foundation for policymaking to ensure water sustainability.

2. Methodology

2.1. VAR Model

2.1.1. The Establishment of the VAR Model

By formulating a model where each endogenous variable (a variable explained by the equations) is considered as a function of the lagged values of all endogenous variables, the VAR method avoids the necessity for a structured model. The following equation shows the VAR(p) model:

$$f_t = \alpha_1 f_{t-1} + \alpha_2 f_{t-2} + \ldots + \alpha_p f_{t-p} + \beta g_t + \varepsilon_t \tag{1}$$

where the f_t is an $n \times 1$ vector of the endogenous variables; $f_{t-1}, f_{t-2}, f_{t-p}$ are the lag periods of the f_t; $\alpha_1, \alpha_2, \alpha_p$ represent the matrices of suitable dimensions containing the model's unknown parameters of the f_t; g_t is the exogenous variable (a variable not explained within the model); β refers to the expected coefficient of the g_t; and ε_t is an $n \times 1$ vector of exogenous shocks.

The VAR model can be transformed into a matrix:

$$\begin{bmatrix} f_{1t} \\ f_{2t} \\ \cdots \\ f_{kt} \end{bmatrix} = \alpha_1 \begin{bmatrix} f_{1t-1} \\ f_{2t-1} \\ \cdots \\ f_{kt-1} \end{bmatrix} + \alpha_2 \begin{bmatrix} f_{1t-2} \\ f_{2t-2} \\ \cdots \\ f_{kt-2} \end{bmatrix} + \cdots + \alpha_p \begin{bmatrix} f_{1t-p} \\ f_{2t-p} \\ \cdots \\ f_{kt-p} \end{bmatrix} + \beta \begin{bmatrix} g_{1t} \\ g_{2t} \\ \cdots \\ g_{kt} \end{bmatrix} + \begin{bmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \\ \cdots \\ \varepsilon_{kt} \end{bmatrix} \tag{2}$$

where $f_{1t}, f_{2t}, \ldots, f_{kt}$ are endogenous variables, and they are associated with the same period. They are calculated by their lagged variables, exogenous variables, and exogenous shocks. We convert the equation into a matrix for the convenience of observing the calculation results of each variable.

2.1.2. Time Difference Correlation Analysis (TDCA)

The TDCA method utilizes the time difference correlation coefficient (TDCC) to determine the average relationship between two or more sequences in the entire time series. The TDCC ranges from −1 to 1, where 0 indicates no correlation, −1 indicates complete negative correlation, and 1 indicates complete positive correlation. The correlation coefficient reflects the degree of linear relationship between economic growth and water use. By quantifying the temporal relationship, it is judged whether a sequence is preceded or delayed relative to another sequence [32].

The process is as follows: Firstly, a warning indicator that comprehensively reflects the current sustainable utilization of water resources is used as a benchmark indicator J, and the benchmark indicator is fixed, and other selected indicators I are moved forward or backward in time relative to the benchmark indicator for several years. Then, the TDCC between the benchmark and the moved sequence is calculated. The maximum number of years of movement corresponding to the resulting maximum correlation coefficient is considered as the lead or delay of the indicator. At the same time, based on this, the index of the selected indicators is divided into the leading and lag periods. The TDCA method has characteristics such as quantitative calculation, high precision, and low sequence length requirement.

The specific calculation method is as follows:

Assume that the benchmark is $J = (j_1, j_2, \ldots, j_n)$, the selected indicator is $I = (i_1, i_2, \ldots, i_n)$, the TDCC is R_l:

$$R_l = \frac{\sum_{l=1}^{kt} \left(i_{t+l} - \bar{i}\right)\left(j_t - \bar{j}\right)}{\sqrt{\sum_{l=1}^{kt} \left(i_{t+l} - \bar{i}\right)^2 \sum_{l=1}^{kt} \left(j_t - \bar{j}\right)^2}} \tag{3}$$

$$l = \begin{cases} 1 & t \geq 0 \\ 1 - t & t < 0 \end{cases}, t = 0, \pm 1, \pm 2, \ldots, \pm MB \tag{4}$$

Here, $t = 0$ means the indicators are synchronized. When taking a negative value, it means moving forward or pre-emption; when it is positive, it means hysteresis, which is called lag number or time difference number. $\bar{i}$ and $\bar{j}$ refer to the mean value of indicator I and J. MB refers to the years of movement. kt represents the data volume after the I and J indicators are aligned. In the calculation of the index, the TDCC under various delay numbers is computed. Among these R_l values, the maximum value R'_l after taking the absolute value is selected, and the corresponding delay number $'l$ signifies either the leading or lagging period. During the inspection process, the closer R'_l is to 1, the more ideal it is, and the fluctuation of I and J is closer. If R_l is the largest at $t = 0$, the index I is the synchronization index of the reference index J; if it is the largest when $t < 0$, then I is the hysteresis index of the reference index J.

2.2. Water Sustainable Utilization Assessment Index System

2.2.1. Indicator Selection

In this study, a representative index variable was selected for economic growth and water resource utilization for quantitative analysis. GDP represents the production results of all resident economic units in a country or region and covers all industries of the national economy. It is a measure of the total economic activity between countries and regions [33]. Therefore, in this study, GDP is utilized as an economic growth indicator, measured in units of CNY 100 million.

Based on the water usage structure, water resources are categorized into four types: domestic water, agricultural water, industrial water, and ecological water. Considering the ecological water consumption is small and ecological water use has been used as a separate indicator for statistics in recent years, for the convenience of research, this paper classifies it into domestic water. Therefore, this paper selects total water consumption (TWC), domestic water usage, industrial water usage, and agricultural water usage as water use indicators (unit: 100 million m^3).

In addition, indicators such as the ratio of sewage treatment facilities (STFs) per capita of GDP, the amount of STFs, and the total amount of water resources were chosen to evaluate both water resources carrying capacity and water environmental carrying capacity.

2.2.2. Early Warning Indicators for Sustainable Use of Water Resources

In the early warning indicator system, the indicator's impact on the sustainability of regional water consumption is not consistent over time. Some indicators have an impact on current water use, while others take some time to have an impact on it. Based on many studies, this paper uses water resources status, economic, and social indicators to reflect the characteristics, development, and consumption of regional water resources, and ultimately the status of regional water sustainability is measured.

Therefore, based on the selected 26 indicators (Table 1), it is necessary to further distinguish the order in which these indicators influence the sustainable utilization of water resources. These indicators were categorized into three types: leading, synchronous, and lagging indicators. This paper screened the early warning indicators for the sustainable utilization of water resources based on their categorization [34–36].

Table 1. Early warning indicator system construction.

Number	Indicator	Indicator Classification	Number	Indicator	Indicator Classification
T1	Total water resources/100 million m^3	Internal system	T14	NOx emissions/tons	Internal system
T2	Total water consumption/100 million m^3	Internal system	T15	Ammonia nitrogen emissions/tons	Internal system
T3	Industrial water consumption/100 million m^3	Internal system	T16	Total industrial exhaust emissions/billion m^3	Internal system
T4	Per capita GDP/CNY 10,000	External system	T17	Population/million	Internal system
T5	water consumption of CNY 10,000 GDP/m^3	Internal and external system	T18	Exhaust gas treatment facilities/Tai	Internal system
T6	Per capita living water consumption/m^3	Internal system	T19	CNY 10,000 industrial output COD emissions/tons	Internal and external system
T7	COD emissions/tons	Internal system	T20	Power generation/billion kWh	External system
T8	Ammonia nitrogen emissions/tons	Internal system	T21	The difference in the number of units of STFs per unit/Tai	Internal system
T9	Sewage discharge/tons	Internal system	T22	Forest cover rate/%	Internal system
T10	CNY 10,000 GDP sewage discharge/tons	Internal and external system	T23	The difference in the unit GDP exhaust gas treatment facilities/Tai	Internal system
T11	Sewage treatment facilities/Tai	Internal system	T24	Power generation difference/billion kwh	Internal system
T12	Urban sewage treatment rate/%	Internal and external system	T25	CNY 10,000 industrial output value ammonia nitrogen emissions/tons	Internal and external system
T13	Sulfur dioxide emissions/tons	Internal system	T26	Average annual precipitation/mm	External system

The early warning indicator system hierarchy structure consists of three levels (see Figure 1): target layer (A), criterion layer (S), and indicator layer (R).

2.2.3. Early Warning Indicator Hierarchy Model

In this paper, Eviews 5.1 was utilized for calculating the TDCC between the police index and the above-mentioned 26 warning indicators. Then, according to the calculated TDCC, the selection of index was determined, and the finally selected indicators were classified. The effective TDCC of each index should generally be greater than 0.5, and the time difference between the leading and lag indicators is usually more than three years.

Classification of indicators: If the maximum correlation coefficient corresponding to the indicator is obtained in the lead period of the indicator, then the indicator is classified as the leading indicator. On the other hand, if the maximum correlation coefficient corresponding to the indicator is obtained in the delay period of the indicator, then the indicator is classified as the lagging indicator. From the results, the nature category of each indicator was determined by examining both the indicator itself and the absolute value of the TDCC of the water resource availability index.

Based on the above results, 16 indicators were classified as the leading indicators, and there were 3 synchronous indicators (population, per capita GDP, and total water resources), while the remaining 13 were lagging indicators.

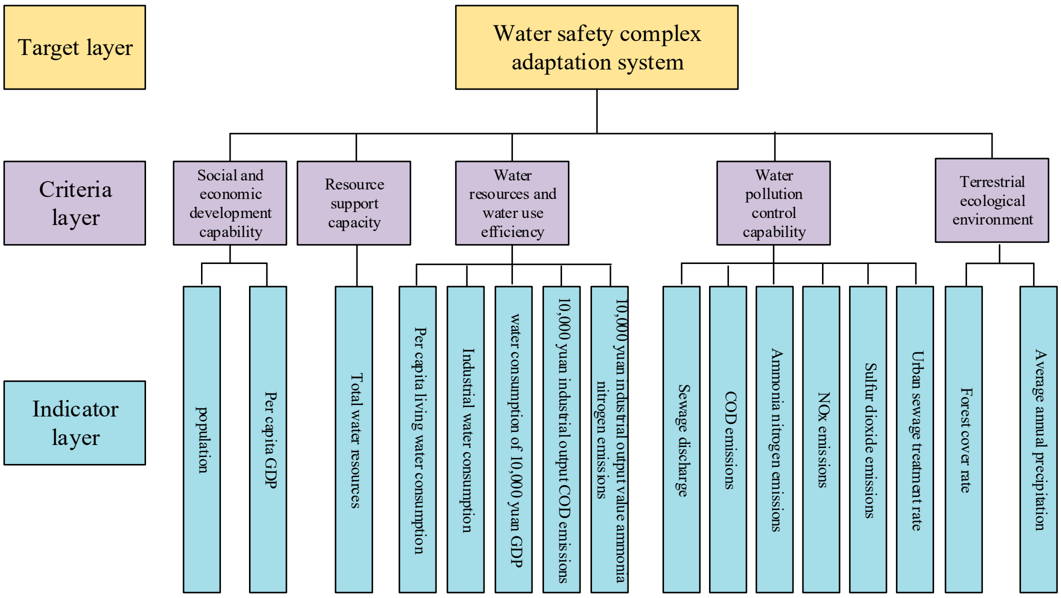

Figure 1. Early warning indicator hierarchy model.

2.3. Data Sources

The indicators mentioned above were obtained directly or indirectly from sources such as the China Water Resources Bulletin [37] and the China Statistical Yearbook (CSY) [3]. And the data include major provinces and cities in China. However, it is worth noting that the population data obtained from the CSY, including data from the past six Chinese population censuses, showed limited comparability across various periods and regions [38]. To address this issue, some scholars adjusted both the urban and the total population data for the period 2001 to 2022 in China [39]. Regarding the economic data, we calculated the growth rates in comparison to the previous year and then adjusted the China's GDP figures from 2001 to 2022 into constant prices in 1997.

3. Results and Discussion

3.1. VAR Model Establishment and Basic Test

3.1.1. Unit Root Test

Aiming at avoiding spurious regression and ensuring the stability of all sequences [40,41], we conducted an Augmented Dickey–Fuller (ADF) test for GDP (LOGJ) and TWC (LOGI). The findings (Table 2) indicated that both variables were second-order single-stationary sequences (DDLOGI and DDLOGJ).

Table 2. Variable ADF test results.

Variables	ADF Statistics	(*c*, *t*, *k*)	Significant	Conclusions
I	−1.4173	(c, 0, 0)	0.5542	unstable
LOGI	−1.4190	(c, 0, 0)	0.5534	unstable
DLOGI	−4.3906	(c, 0, 0)	0.0029	stable
DDLOGI	−8.6653	(c, 0, 0)	0.0000	stable
J	3.6281	(c, 0, 0)	1.0000	unstable
LOGJ	−3.2498	(c, 0, 0)	0.0311	stable
DLOGJ	−2.4218	(c, 0, 0)	0.1486	unstable
DDLOGJ	−5.7211	(c, 0, 0)	0.0002	stable

3.1.2. Cointegration Test

Given that the original variables were in an unstable state, it was essential to conduct further cointegration tests to ascertain whether a long-term equilibrium relationship existed among these variables. The cointegration test results (see Table 3) revealed the existence of a cointegration relationship among these variables.

Table 3. Cointegration test results.

Rank	Params	LL	Eigenvalue	Trace Statistic	Critical Value
0	2	−370.9920		18.9219	15.4100
1	5	−361.8070	0.5830	0.5510 *	3.7600
2	6	−361.5310	0.0259		

Note: * Refers to the existence of a cointegration relationship.

3.1.3. Choice of Lag Period

Choosing the lag period was essential for establishing the VAR model. We adjusted the total water consumption (TWC) and lag period of GDP using six inspection criteria (LogL, HQ, SC, FPE, LR, AIC). Following the rule of choosing the minimum values of HQ, SC, FPE, and AIC, we determined that the optimal lag order for GDP and TWC was 1 (Table 4).

Table 4. Results of lag order selection for the VAR model.

Categories	Lag Phase	LogL	HQ	SC	FPE	LR	AIC
GDP and TWC	0	31.7167	−3.4863	−3.3980	0.0001	NA	−3.496090
	1	89.9609	−9.8485 *	−9.5836 *	1.77×10^{-7} *	95.9316 *	−9.877761 *
	2	91.9565	−9.5932	−9.1518	2.31×10^{-7}	2.8173	−9.6419
	3	94.5015	−9.4025	−8.7846	2.93×10^{-7}	2.9941	−9.4707
	4	99.2552	−9.4717	−8.6772	3.07×10^{-7}	4.4740	−9.5594
	5	99.9781	−9.0667	−8.0956	5.82×10^{-7}	0.5102	−9.1738

Note: * represents the optimal lag order.

3.1.4. The Parameters Result in VAR

Based on the results of unit root test and lag period selection mentioned above, the VAR model was formulated as (5), which represented the relationship between GDP and TWC. The stationary sequences obtained from the tests were used as inputs to the model, and the model's parameters were estimated using the least squares method.

$$DLOGJ_1 = 0.2153C + 0.0452LOGI_1(t-1) + 0.9618LOGJ_1(t-1) \quad (5)$$

Table 5 illustrated that the test results for the VAR model were highly significant. The AIC and SC values were very low, and the fitting effect was better.

Table 5. Overall test results of the VAR model.

Statistics Value	Equation (5) Results
Residual Covariance (+degrees of freedom)	3.14×10^{-7}
Residual Covariance	2.30×10^{-7}
Log—Likelihood Estimation	100.8821
Akaike Information Criterion	−9.0363
Schwarz Criterion	−8.7379

3.1.5. The Test of Model Stability

After conducting the tests, it was found that all root moduli were below 1, indicating that the established VAR model of GDP and TWC was stable. As a result, various tests based on the VAR model proved to be effective (Table 6 and Figure 2).

Table 6. Stability test results.

Equation (5)	
Root	**Module**
0.9631	0.9631
0.8017	0.8017

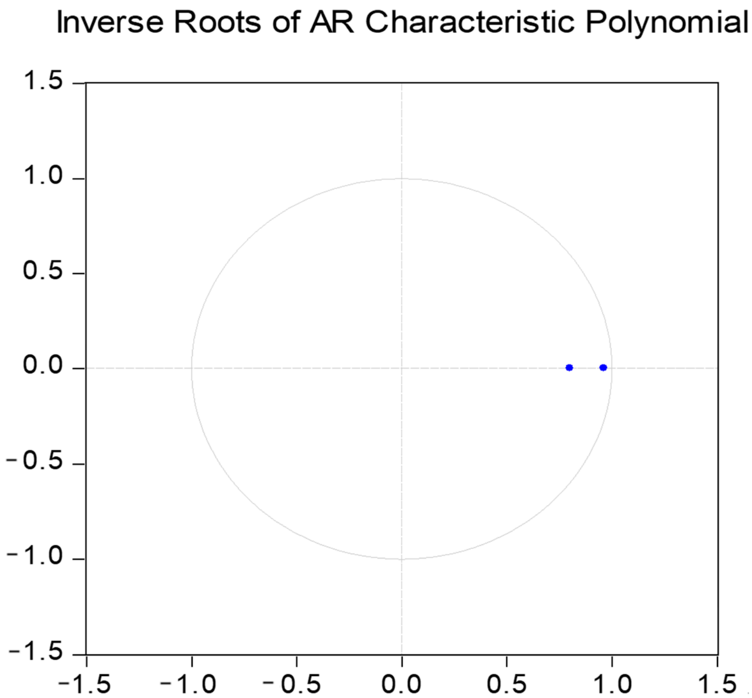

Figure 2. Unit circle test diagram.

3.1.6. Granger Causality Test (GCT)

The GCT was employed to determine the chronological order between economic variables. However, it does not necessarily indicate a causal relationship, which necessitates comprehensive judgment based on theory, experience, and the model. We conducted the Granger Causality Test between GDP and total water consumption (Table 7). By combining the principle of the Granger Causal Analysis, a one-way causal relationship between GDP and TWC was clearly established.

Table 7. Results of GCT.

Null Hypothesis	Samples	F Statistic	*p* Values	Yes/No
LNJ does not Granger Cause LNI	16	0.45248	0.8123	No
LNI does not Granger Cause LNJ	16	5.33224	0.0989	Yes

3.2. Pulse Effect Analysis

Figure 3 illustrated the mutual influence and interactions between GDP and TWC. Regarding how GDP responded to TWC, the DDLOGI value was 0 during the initial period. However, it exhibited positive values that gradually decreased in magnitude in the subsequent second, third, fourth, and fifth periods. This indicated that a decreasing dependence of GDP on TWC over time.

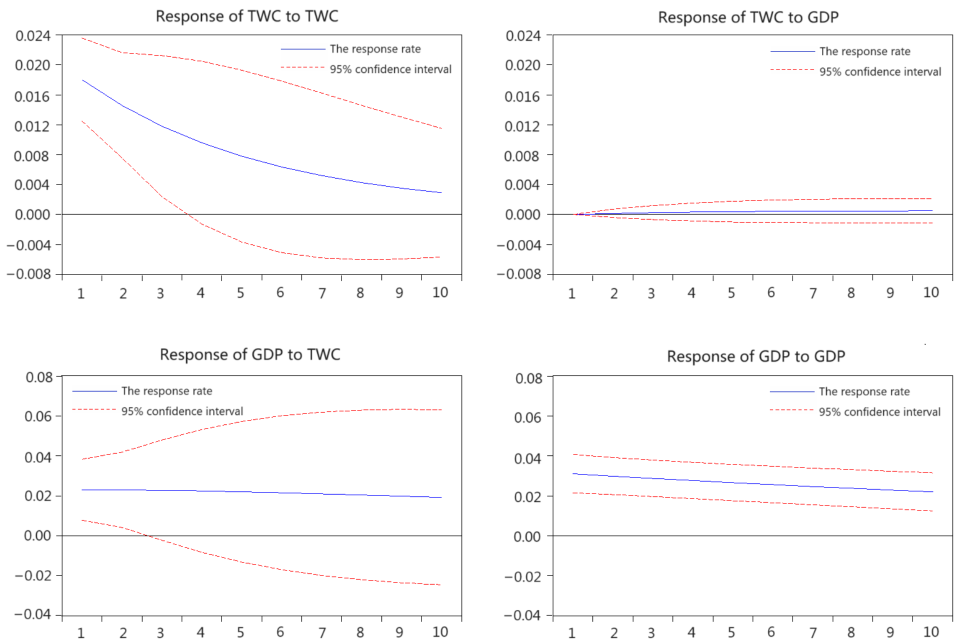

Figure 3. Impulse response function graph of GDP and TWC.

Conversely, when concerning how TWC responded to GDP, DDLOGJ was 0 in the first period. It turned positive in the second period and remained positive in the third period. Subsequently, the response showed increasing convergence, implying that the continued economic growth had a diminishing impact on the further development of water resources.

3.3. *Analysis of Variance Decomposition*

3.3.1. Analysis of Variance Decomposition of GDP and TWC

In Figure 4, the variance decomposition of GDP and TWC was presented. It was observed that TWC contributed less to the variance of GDP, which was consistently maintained below 5%. The variation in GDP was mainly influenced by its own dynamics.

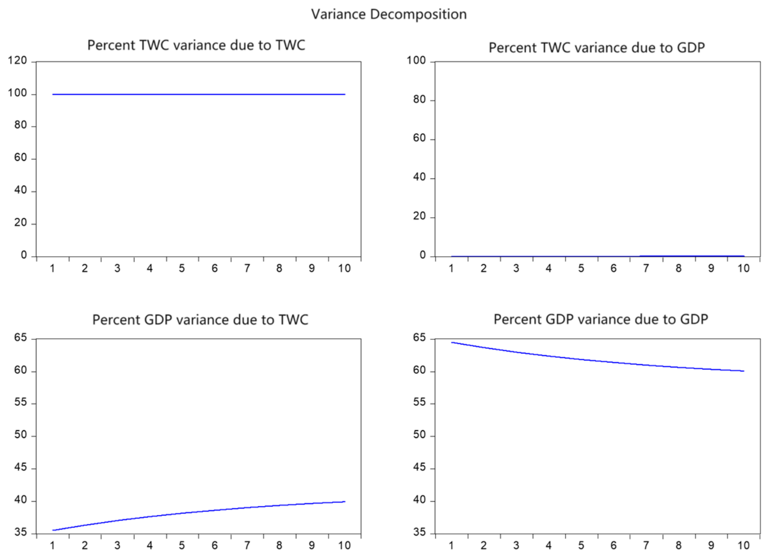

Figure 4. Variance decomposition.

On the other hand, the contribution of GDP to TWC was notably high. Except for the first two periods, where it was less than 30%, the contribution increased over time and gradually exceeded 30%. After the fifth period, it experienced a slight increment and then stabilized. Ultimately, it approached and reached close to 40%, indicating that the growth of the economy had a significant impact on water consumption.

3.3.2. Forecast the TWC and GDP Changes of 2023–2050

The VAR model predicted the changes in GDP and TWC of 2023–2050 (see Figure 5). From 2023 to 2050, TWC exhibited a gradual upward trend. Similarly, GDP followed a similar trend, showing continuous growth, albeit at a slower pace.

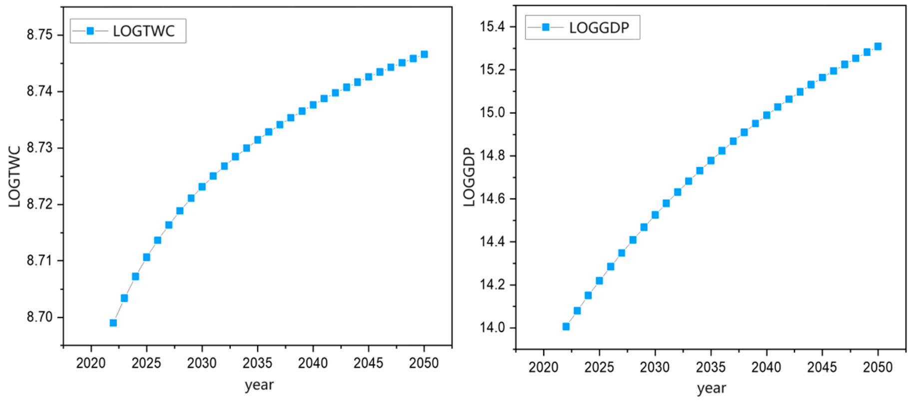

Figure 5. Prediction of 2023–2050 based on the VAR model.

3.4. Water Overload Status Results

Considering the sustainable water resources management, we calculated the water environmental pressure index and the pressure index of water resources. By combining these indices, we derived the comprehensive water overload state index.

Figure 6 illustrates that the overload index displays a nearly linear decrease starting from the year 2023. The water pressure index was calculated by TWC and population. The water environmental index was calculated by TWC and the environmental indicators. Both the water environment pressure and water resources pressure indices exhibited similar trends, indicating that the status of China's water resources was not optimistic, considering both the total amount and the development of the water environment.

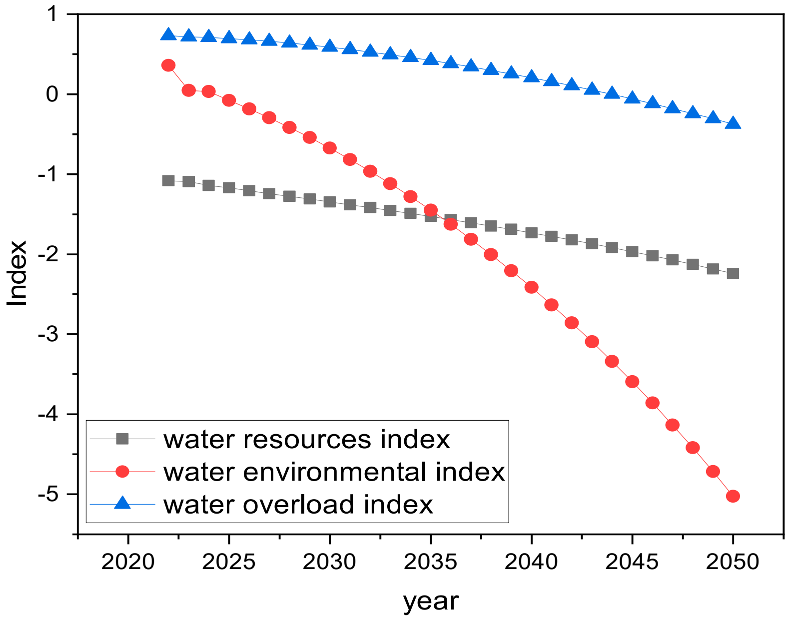

Figure 6. Prediction of water resources, water environment, and water overload pressure index: 2023–2050.

However, it can be observed that the water environment index declines at the fastest rate between 2023 and 2050, while the water overload index and water resources index decrease at a slower pace, maintaining consistent levels of decline.

4. Conclusions and Recommendations

Using the time series data of GDP and water consumption from 2001 to 2022, a VAR model was established between GDP and TWC, and their co-integration relationship was tested. The dynamic interaction between GDP and TWC was analyzed using the generalized impulse response function and predictive variance, and the VAR model was applied to forecast the water consumption trends from 2023 to 2050.

The findings are as follows: (1) Over the study period, there existed a cointegration between China's economic growth and TWC. However, TWC continued to demonstrate a notable increasing trend. The impact of GDP growth in curbing water resource consumption was not sufficiently evident. (2) The aggregated effect of GDP to TWC per capita was positive, and likewise, the aggregated effect of TWC to GDP was also positive. (3) GDP is a significant factor for predicting the variance of water resource use, whereas water use contributed less to the forecasted variance of economic growth. It is crucial to address the increase in TWC triggered by economic development and carefully consider the potential adverse effects of water shortages on economic growth. (4) According to the GCT results, the p-value of GDP to TWC was 0.0989. GDP did not serve as the granger cause of TWC, and the rapid growth of GDP significantly promoted the utilization of water resources, resulting in an increasing quantity of water use. (5) The water overload state index showed a declining trend between 2023 and 2050, implying a sustained improvement in China's water overload condition.

Based on the research findings, we recommend that the government adopt the following policy measures to achieve the sustainable management of water resources and the sustained economic prosperity.

Develop a comprehensive plan for the sustainable development of water resources: The government should carry out a comprehensive water resource management plan, with clear objectives and measures to ensure efficient use and equitable distribution of water resources.

Encourage the promotion of water-saving technologies and awareness: The government should encourage businesses and individuals to adopt water-saving technologies and measures while also raising public awareness about the importance of water conservation through education and campaigns.

Enhance water resource regulation and enforcement: The government ought to enhance water resources regulation and establish a sound enforcement system to crack down on illegal water extraction and water pollution.

In conclusion, prioritizing water resource management will lead to a win–win situation for both ecological balance and economic development. This approach will have a positive and extensive effects on China's environmental protection and economic growth.

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Abbreviations

In this manuscript, the following abbreviations are used:

VAR	Vector autoregressive
GDP	Gross Domestic Product
TDCA	Time difference correlation analysis
TDCC	Time difference correlation coefficient
OLS	Ordinary least square
STFs	Sewage treatment facilities
CSY	China Statistical Yearbook
ADF	Augmented Dickey–Fuller
TWC	Total water consumption
GCT	Granger Causality Test

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