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Interactions between Economic Growth and Environmental Degradation toward Sustainable Development

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Abstract: Ongoing environmental issues and degradation provoke the implementation of relevant incentives to overcome them without restrictions of economic growth. Considering the Chinese sustainable development policy, each province should provide the effective ecological regulations that consider the dynamic changes of the economic and ecological indicators of the province's development. In this case, the paper aims to analyze the relationship between economic growth and environmental quality. The object of the investigation is the Henan provinces of China from 1994 to 2020. The study applied a vector autoregression model between the one-way and two-way relationship analysis, Granger causality test, cointegration test, and impulse response function. The findings confirm that GDP growth causes exhaust gas production and that SO_2 will also influence wastewater. The results of the co-consolidation analysis showed that if the production of industrial solid waste gas and SO_2 volume increased by 1% each, GDP per capita would increase by 0.22% and 0.35%, respectively. The findings of the variance decomposition of the GDP per capita in the first phase are all due to their perturbation term. The other influencing factors have no influence. Over time, GDP per capita is less and less affected and significantly enhanced by wastewater, exhaust gas, and SO_2.

Keywords: economic growth; environmental quality; VAR model; sustainable development; innovation

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1. Introduction

Chinese sustainable development policy defined that all provinces should implement the coherent policy that considers the dynamic changes of the country. At the same time, to reach these goals the local authorities should provide active policy in environmental regulations, green investment, green education, etc. [1]. Moreover, the implemented policies should not limit the country's economic growth [2]. With the development practice, environmental protection and economic growth are greatly related, which provokes the controversial discussion on the role of each in the country's development among world experts. The scholars [3–7] confirmed that economic growth attracts additional financial resources to the country and generates added value for society. From the other side, the priory studies empirically justified that economic growth without effective regulations provokes environmental degradation. However, past studies [8,9] have shown that economic growth with effective environmental policy could bring the economic benefits in long-term.

It should be noted that the Henan provinces are the leader of coal production in China. Moreover, the Henan provinces occupied the fifth place on petroleum and natural gas production [10]. Consequently, it has caused the overpollution of the provinces and the declining well-being of the people. Thus, the government should implement relevant and effective mechanisms to reduce nature degradation without restricting economic growth. Moreover, it necessary to consider the interconnection between the changes of the ecological and economic indicators of the country's development. In this case, the paper contributes to the development of a scientific approach (based on vector autoregression model) to detect the intertwined dynamics of the indicators that revealed the economic growth and environmental quality for the Henan provinces of China.

Paper has the following structure: literature review—analysis of the theoretical framework of the relationship between economic growth and environmental pollution as core indicators of environmental quality; materials and methods—explaining the methods and instruments to check the interconnection between economic growth and environmental pollution; results—explaining the core findings of the investigation; discussion and conclusions—comparison analysis of the obtained data with the previous investigation; policy implications, study limitations and direction for future investigations.

2. Literature Review

The world scientific community and experts have already aggreged that economic development should not increase the eco-destructive impact on the environment. Thus, Dasgupta and Heal [11] suggested that economic and ecological development could coexist progress together. Economic development did not necessarily mean that the economy and the environment could be in a mutually coordinated relationship at the cost of large energy consumption. At the same time, Hettige and Mani [12] confirmed that environmental pollution could be reduced by implementing strict management mechanisms to improve the ecological environment. The study [13] confirmed the strong relationship between factors of economic growth, public health, and environmental quality for central EU countries for 2005–2018 years. Based on EKC theory, the papers [14,15] proved a similar conclusion for China on linking economic growth and environmental pollution. Hence, the study [14] applied a regression model to check the hypothesis of the investigation. In addition, Bildirici and Gökmenoğlu [16] analyzed the link between economic development, environmental pollution, and renewable energy. Applying the MS-VAR and MS-Granger Causality, they confirmed the bidirectional causality between CO2 and economic growth for G7 countries for 1961–2013.

The paper [17] analyzed the ethical aspects of the relationship between economic growth, CO_2 emissions, and energy consumption among 106 countries for 1971–2011. Using the panel vector autoregression and impulse response function analyses, the study [17] proved the bidirectional causality between energy consumption and economic growth. At the same time, they did not confirm that renewable energy consumption was conducive to economic growth. The paper [18] showed the long-term link between environmental and economic development. Moreover, they analyzed the role of energy consumption from the transport sector (as the biggest energy consumer in Asia countries) in environmental and economic development. Considering the findings [18] concluded that increasing the energy consumption of the transport sector and GDP growth by 1% provoked the degradation of the environmental quality by 0.57% i 0.46, respectively.

Furthermore, they highlighted that extending green innovation in the transport sector allowed increasing economic growth without environmental degradation. The study [19] confirmed that spreading energy innovations allowed declining greenhouse gas emissions and boosted economic growth in 17 OECD countries. It should be noted that the study [19] also based investigations on EKC theory. The past study [20] applies the dynamic ARDL model to prove the linking among environmental degradation and economic growth for Pakistan. Their findings confirmed the EKC curve for the case. However, the results [21] for the USA case have the controversial conclusions for decomposed and undecomposed. Thus, the composed model did not confirm the EKC theory for the USA case but the composed model did confirm the EKC theory for USA.

Le and Sarkodie [22] analyzed the developing economies to check the hypothesis on the relationship between energy consumption (renewable and traditional energy) and environmental and economic development. Considering the findings, [22] outlined the necessity to implement policy on extending green energy and restructuring the economy. Moreover, it allowed reducing CO_2 emissions.

The research [23] analyzed the panel data of Artic region for 1990–2017 years. They analyzed the following indicators to check the relationship between economic growth and environmental degradation: financial development, natural resources, globalization, consumption of non-renewable and renewable energy, greenhouse gas emissions, GDP per capita. Based on the empirical findings, the scholars concluded the dynamic interconnections between consumption of non-renewable and renewable energy, greenhouse gas emissions, and economic growth.

The paper [24] confirmed the link between waste, economic growth, and greenhouse gas emission in the Danish case. Thus, the findings of Machine Learning allowed concluding that economic growth provoked the increase in waste that polluted the environment. Namlis and Komilis [25] proved a similar conclusion on the significant correlation between municipal waste and economic growth in the case of EU countries. However, the paper [26] applied the Waste Kuznets curve to check the hypothesis on the relationship between waste and socioeconomic indicators of the Australian state of New South Wales. The empirical findings confirmed that regions with high socioeconomic indicators had a more effective waste management system, which minimizes the negative impact on the environment. In China's example, scholars [27] confirmed that increasing SO_2 emissions led to declining indicators of economic growth. The findings of [28] justified the inverted U-shape EKC between economic growth and SO_2 emissions. At the same time, the studies [28,29] concluded that innovations and trade openness provoked the increasing SO_2 emissions. However, urbanization reduced SO_2 emissions in emerging Asian economies in the long-run perspective. Thus, the unidirectional relation causality was from urbanization to SO_2 emissions and from SO_2 emissions to economic growth in the short run.

Considering the research results of experts and scholars, the relationship between the economy and the environment in Henan Province was studied using the VAR model.

3. Materials and Methods

3.1. Data

The GDP per capita (GDP), wastewater (WW), waste gas (WG), and SO_2 from Henan Province from 1994 to 2020 were selected for analysis, and the secondary data were obtained from the National Bureau of Statistics of China [30]. In order to avoid possible heterovariance and drastic fluctuations in the data and easy to obtain stable series that does not change the characteristics of the time-series data based on the actual data, the various time-series variables were log-normalized, and finally, the new series data were obtained.

The Henan Province of China is located in the middle of China (Figure 1). The terrain runs from north to south and connects east to west, and it is composed of plain and basin, mountain, hilly, and water surface, across the Haihe River, Yellow River, Huaihe River, and Yangtze River. Most of the provinces are in the warm temperate zone, in the south across the subtropical, and have a continental monsoon climate from the northern subtropical to the warm temperate zone. Henan, which is located in the junction of coastal open area and the central and western regions, is the middle of China's economy from east to west.

Henan Province adheres to economic construction as the center, promotes agricultural modernization in the province, accelerates industrialization development, and constantly enhances its economic strength. By 2000, Henan Province achieved a GDP of 5499.707 billion yuan, up 1.3% over the previous year (Figure 2). Among them, the added value of the primary industry was 535.374 billion yuan, up 2.2%. The secondary industry's added value was 2287.533 billion yuan, up 0.7%; the added value of the tertiary industry was 26,676.801 billion yuan, up 1.6%. The permanent resident population of the province is 9,9365,519, an increase of 5,341,952 and 5.68% from 2010.

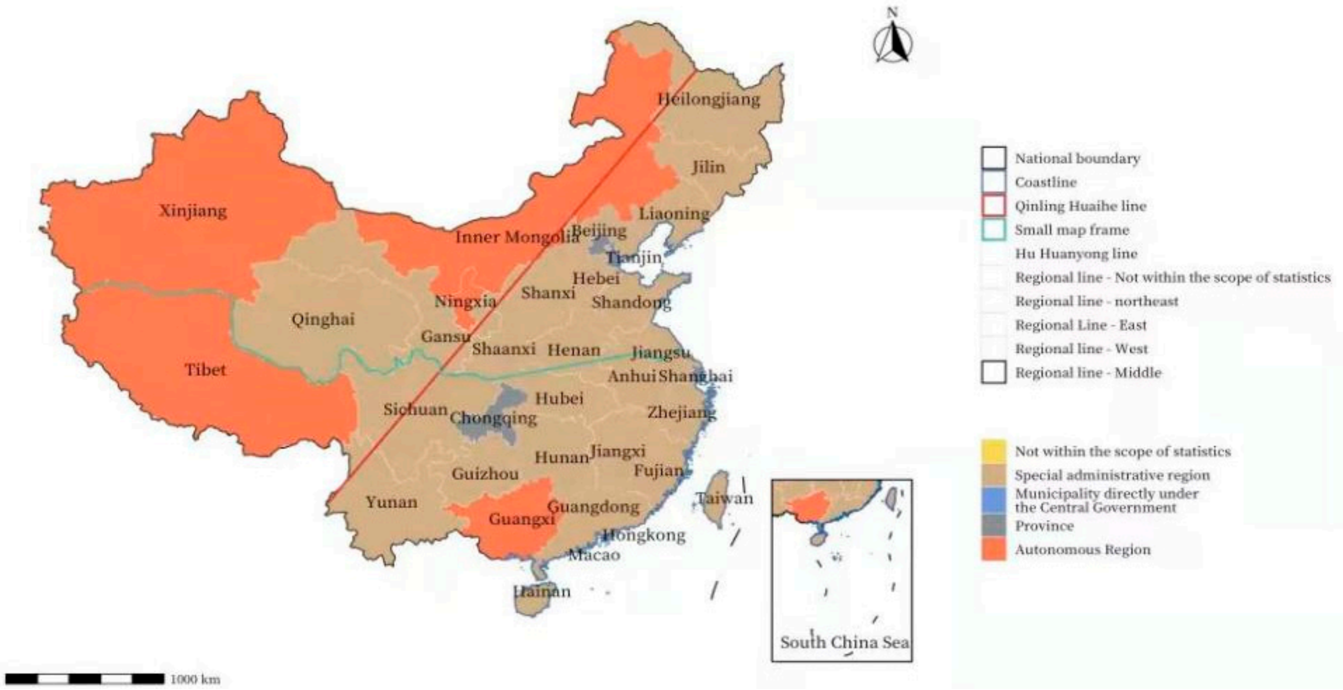


Figure 1. Map of China.

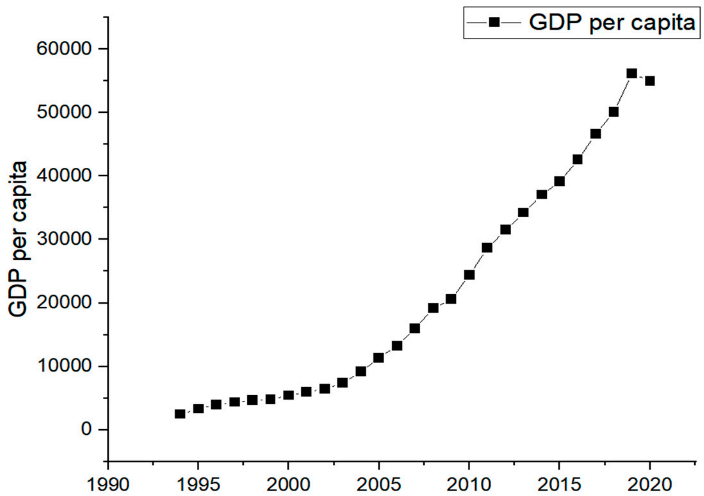


Figure 2. GDP per capita in Henan Province from 1994 to 2020.

From the figure above, we can see that the GDP per capita in Henan Province is in a period of rapid development, and its economic level is constantly improving, from 247.6 billion yuan in 1994 to 2444 to 6 billion yuan in 2010. After 2010, the GDP per capita reached 5099 by 2020.707 billion yuan.

From Figure 3, we can see that wastewater and exhaust emissions have been in a gentle trend, declining after 2015 but very slowly. SO_2 was on an upward trend from 1994 to 2007 and reached its highest point in 2007.

From 2007–2020, the downward trend is obvious, indicating that environmental pollution is serious. Thus, the state began to take corresponding measures to achieve sustainable development.

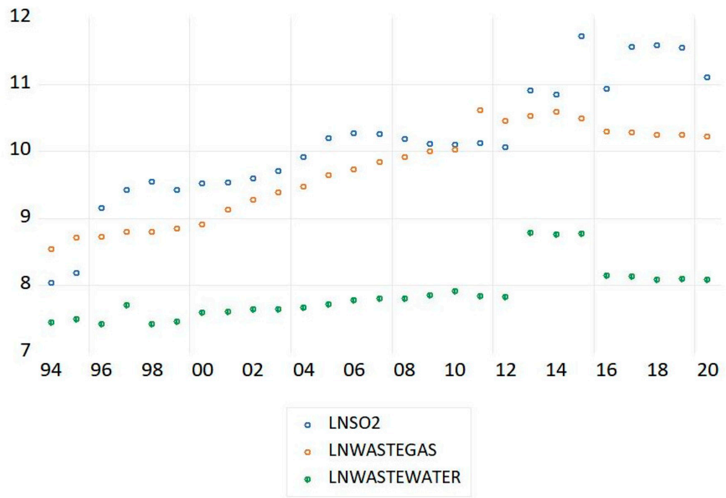


Figure 3. Wastewater, waste gas, and SO_2 emissions of Henan Province from 1994 to 2020.

3.2. Model Construction

In 1890, Sims proposed the vector autoregression model (VAR) as a macroeconomic analysis, which described the dynamic structure and data rules between multiple variables, and then analyzed their interactive relationship [31,32]. The model regards all analytic variables as endogenous, which explains Sims' criticism of the traditional joint cubic equation model: the assumption that some variables are exogenous is very inappropriate and often not supported by mature economic theory. The VAR model not only makes the current values of a set of variables explained by the past values of these variables but also applies to the analysis of economic problems as they describe a variable joint mechanism of action. Furthermore, one of the advantages of the VAR model is the option to detect the intertwined dynamics of the country's indicators changes. In general, the analysis process of the VAR model is divided into the following steps: first, to estimate a simplified form of the VAR model. The second is to test the correctness of the simplified model. The model's defects are tested in the final stage and solved by the modification and adjustment of the model. If the simplified form model passes the starting test phase, the simplified VAR model may be used for prediction and structural analysis. The specific manifestations are as follows:

3.2.1. The Form of the Vector Autoregressive (VAR) Model

Suppose the K time-series variables to be studied:

$$y_t = (y_{1t} + y_{2t} + y_{3t} + \ldots + y_{kt}) \tag{1}$$

Economic variable data will have certain terms μ_t, and random terms during generation $y_t = \mu_t + x_t$, In the context of prediction, it is difficult to propose a compelling explanatory meaning. Therefore, the addition of determining trend terms is not recommended in practical applied VAR models. The pure random part x_t, may contain random trends and consolidation relations; it has a zero mean and can be represented by a VAR process. Suppose the random part X is a P order VAR process with the expression:

$$x_t = A_i x_{t-1} + \ldots + A_p x_{t-p} + \mu_t \tag{2}$$

The A_i (i = 1, …, P) is a parameter matrix of K*K, the random perturbation term $\mu_t = (\mu_{1t},\ \mu_{2t})\ (\mu_{1t}, \mu_{2t}, \ldots, \mu_{Kt})'$ is a K dimension with a zero mean, with a variance matrix of $\sum$ the white noise process, μ_t~N(0, $\sum$). The use lag operator and matrix polynomials defined by it are:

$$\mathrm{A(L)} = I_K - A_1\mathrm{L} - \ldots - A_p L_p \tag{3}$$

If for the arbitrary:

$$z \subset C, but|z| \leq 1, detA(Z) = det(I_k) - A_1 z - \ldots - A_P Z_P) \neq 0 \tag{4}$$

That is, if all the roots of the determinant polynomial $detA(Z)$ fall outside the complex unit root circle, then x_t is stationary. Under the general assumption, a stable process x_t has a time-invariant mean, variance, and covariance structure and is a stationary process. However, if det$A(Z)$= 0 at Z = 1 and all other roots of the matrix polynomial fall outside the complex unit circle, some or all of the variables are single-integral. Thus, the process x_t is non-stationary. Furthermore, the x_t, mentioned earlier, represents the random part, which is generally unobservable, while the y_t representation is the vector composed of all observable variables. The equation, on both sides simultaneously by $A(L)$, is expressed as:

$$A(L)y_t = A(L)\mu_t + A(L)x_t \tag{5}$$

$$\text{If } \mu_t = \mu_0 + \mu_{1t} \tag{6}$$

$$\text{then } A(L)y_t = v_0 + v_{1t} + \mu_t, \text{or } y_t = v_0 + v_{1t} + A_1 y_{t-1} + \ldots + A_p y_{t-p} + \mu_t \tag{7}$$

$$V_0 = \left(I_K - \sum_{j=1}^{p} A_j\right)\mu_0 + \left(\sum_{j=1}^{p} jA_j\right)\mu_1,\ V_1 = (I_K - \sum_{j=1}^{p} A_j)\mu_1 \tag{8}$$

3.2.2. Estimation of the VAR Model

Considering the standard VAR (P) model, the simplified form can be expressed as:

$$y_t = [v_0, v_1, A_1 \ldots A_p] Z_{t-1} + \mu_t \tag{9}$$

For each equation, the least squares estimation (OLS).

3.2.3. Selection of the Lag Order of the VAR Model

The number of parameters in the VAR model is the square of the VAR order. The fewer constraints on the parameter matrix, the better. Sequence tests or model selection criteria generally determine the order of the VAR model. The lag order obtained by sequence tests or model selection criteria depends heavily on the selection of K. The chosen K is too small, the order of an appropriate model may not be in these possible sets, and the chosen K has a pseudo-lag order.

The test procedure for the sequence is performed first by setting a maximum, reasonable lag order for K and then in the null hypothesis:

$$H_0 :\ A_k = 0 \tag{10}$$

$$H_0 :\ A_{k-1} = 0 \tag{11}$$

After conducting multiple tests, the tests will not stop until the null hypothesis is rejected and the final lag order can be determined. Determine the standard order of the model, and we usually choose the following formula:

$$c(m) = \text{logdet}(\sum\nolimits^{\wedge} m) + ct\phi(m) \tag{12}$$

The main model selection criteria are the Chi Pool Information Criterion (AIC) [33], expressed as:

$$AIC(m) = \text{logdet}\left(\sum\nolimits^{\wedge} m\right) + \frac{2m}{T}K^2, CT = \frac{2}{T} \tag{13}$$

For the Q test [34], the expression is:

$$HQ(m) = \text{logdet}\left(\sum\nolimits^{\wedge} m\right) + \frac{2\text{loglog}T}{T}MK^2 \tag{14}$$

$$CT = \frac{\text{loglog}(T)}{T} \tag{15}$$

The Schwarz criterion (SC) [35] is expressed as:

$$SC(m) = \text{logdet}\left(\sum\nolimits^{\wedge} m\right) + \frac{\log T}{T} MK^2 \tag{16}$$

$$CT = \frac{\log(T)}{T} \tag{17}$$

In all these methods of judgment, $\phi(m) = mK^2$. It is the number of parameters in the VAR model with the order m. The selection criteria for the VAR model order are found in all possible orders m = 0... the order minimizing the above statistics k. Of these three tests, the order found by the AIC criterion is often the largest, with SC choosing the smallest order.

3.2.4. The Granger Causality Test for the VAR Model

Based on the priory study [36–38], this paper adopted the methodology for the Granger causality test. It should be noted that Granger proposed the concept of a Granger causality relationship in 1969 [39]. If the information contained in the y_{2t} in the variable is helpful for the variable y_{1t} prediction, the y_{2t} is called the Granger reason of the y_{1t} variable. It assumes that variables y_{1t} and y_{2t} are generated by binary VAR (P), in the following form:

$$\begin{bmatrix} y_{1t} \\ y_{2t} \end{bmatrix} = \sum\nolimits_{i=1}^{p} \begin{bmatrix} a1_{1j} & a1_{2j} \\ a2_{1j} & a2_{2j} \end{bmatrix} \begin{bmatrix} y_{1t-i} \\ y_{2t-i} \end{bmatrix} \mu_t \tag{18}$$

If and only if $a_{1,2,i} = 0$, I = 1,2, . . . , p when the Granger reasons. Varivariable y_{2t} is not the Granger reason for y_{1t}.

3.2.5. Johansson Cointegration Test

Based on the prior research [40–43], this study applied the Johansen cointegration test. It is judged by computational statistics versus the maximum eigenvalue statistic [40–42]. The inspection method of statistics is relatively special, and the circular inspection method is adopted. The first null hypothesis of the statistic indicates that there is no co-consolidation relationship. If the confidence level with the corresponding probability p-value is greater than 5%, it indicates the original hypothesis and thus indicates that there is no co-consolidation relationship; if the confidence level with the corresponding probability p-value is less than 5% or the trace statistic value is greater than the critical value, then the original hypothesis is rejected, indicating at least one co-consolidation relationship, then the next original hypothesis is continued. The second null hypothesis of the trace statistic at most indicates a co-consolidation relationship; it indicates the confidence level where the corresponding probability p-value is greater than 5%, accepts the original hypothesis, indicates a co-consolidation relationship, and ends the confidence level where the corresponding probability p-value is less than 5%. Or, if the trace statistic is greater than the threshold, then it rejects the original hypothesis and indicates at least two co-consolidation relationships, and then cycles to the next original hypothesis. The maximum eigenvalue statistic test has the same circular test rule as the trace statistic test. There are, at most, K-1 co-consolidation relationships among the K variables.

3.2.6. Impulse Response Analysis of the VAR

The pulse response analysis of the model could be written as follows:

$$\begin{cases} y_{1t} = \mu_1 + \pi 11.1y1, t-1 + \pi 12.1y2, t-1 + \mu_{1t} \\ y_{2t} = \mu_2 + \pi 21.1y1, t-1 + \pi 22.1y2, t-1 + \mu_{2t} \end{cases} \tag{19}$$

where y_{1t} is the GDP of Henan province, y_{2t} indicates that the amount of industrial solid waste production is the error term of y_{1t} and the error term of y_{2t}.

If unrelated, it is easy to explain the impact of the current solid waste production volume on the current and future period values of the GDP and solid waste production stock, respectively. The pulse response function is a predictive analysis of the relationship between the studied VAR variables and the correct model form after the VAR model.

3.3. Variance Decomposition

Variance decomposition is also a tool used to analyze the impact in the VAR model after the model test and determine the correct model form [44]. Methods to evaluate the resulting VAR model system, studying the influence of a certain variable on each variable in the VAR model, are usually measured by the relative variance contribution (relative variance contribution, RVC). It measures that in a VAR model system, a certain variable produces an impact based on the relative contribution of the orthogonal variance to the variance of the other variables in the VAR model system.

4. Results

The first step in modeling the time series is to test for stationarity, which is adopted from the past studies [45]. The test for stationarity is a commonly used ADF test, with the test results in Table 1.

Table 1. ADF test results.

Variable	Inspection Type (c,t,p)	ADF	*p*-Value	Criticality Value 1%	5%	10%	Stationariness
GDP	(c,0,0)	−1.678	0.73	−4.374	−3.603	−3.238	non-stationary
lnGDP	(c,0,1)	−3.019	0.0468	−3.724	−2.986	−2.633	stationary
WW	(c,0,0)	−1.222	0.8846	−4.356	−3.595	−3.233	non-stationary
lnWW	(c,0,1)	−6.301	0.0001	−4.374	−3.603	−3.238	stationary
WG	(c,0,0)	−1.479	0.8108	−4.356	−3.595	−3.233	non-stationary
lnWG	(c,0,1)	−5.819	0.0004	−4.374	−3.603	−3.238	stationary
SO_2	(c,0,0)	−0.908	0.9393	−4.374	−3.603	−3.238	non-stationary
$lnSO_2$	(c,0,1)	−4.769	0.0042	−4.374	−3.603	−3.238	stationary

Note: In the test type, c, t, p represent the intercept, the time trend term, and the number of lag periods, respectively; GDP—GDP per capita; WW—wastewater; WG—waste gas.

The conclusions drawn from the above table show that, for between 90% and 99% of confidence, the ADF value of each variable is greater than its critical value. It confirms that the time-series data are non-stationary, and the resulting test results cannot reject the null hypothesis of the unit root. The new series obtained after the first-order difference of the above variables all have ADF values less than their cutoff at 90% confidence and $p < 0.05$. Hence, the time-series data have been stationary after the first-order difference.

In judging the best lag order, the principle selected here is the AIC, SC minimum criterion. The best lag period results of the VAR model are shown in Table 2.

Table 2. VAR model lag period results.

Lag	LogL	LR	FPE	AIC	SC	HQ
0	−16.657	-	7.08×10^{-5}	1.796	1.994	1.846
1	87.894	163.645	3.30×10^{-8}	−5.904	−4.916	−5.656
2	112.803	30.323	1.76×10^{-8}	−6.678	−4.901	−6.231
3	140.177	23.804	1.00×10^{-8}	−7.668	−5.100	−7.022

According to Table 2, the VAR model has the smallest AIC, SC value at the first-order lag, and thus the optimal lag period is 3.

Since the time-series data are non-stationary in most cases, if the non-stationary time-series data are single-integrated of the same order, then there may be a specific equilibrium relationship between the data. The Granger causality test was conducted to examine causality among the variables in Table 3.

Table 3. Granger causality action test.

Null Hypothesis	F-Statistics	Prob.	Result
LnSO_2 does not Granger Cause LnGDP	0.211	0.887	accept
LnGDP does not Granger Cause LnSO_2	2.324	0.111	accept
LnWG does not Granger Cause LnGDP	0.914	0.455	accept
LnGDP does not Granger Cause LnWG	3.471	0.039	reject
LnWW does not Granger Cause LnGDP	0.968	0.431	accept
LnGDP does not Granger Cause LnWW	2.428	0.101	accept
LnWG does not Granger Cause LnSO_2	0.945	0.441	accept
LnSO_2 does not Granger Cause LnWG	1.000	0.417	accept
LnWW does not Granger Cause LnSO_2	0.408	0.749	accept
LnSO_2 does not Granger Cause LnWW	4.064	0.024	reject
LnWW does not Granger Cause LnWG	0.751	0.537	accept
LnWG does not Granger Cause LnWW	2.404	0.103	accept

From the Granger causality test (Table 3), $p > 0.05$ accepts the null hypothesis. It indicates that there is no Granger causal relationship between the two variables. The value of $p < 0.05$ rejected the null hypothesis that Granger is causal between the two variables [36–39]. The findings confirmed that GDP growth causes exhaust gas production and that SO_2 will also influence wastewater.

According to the cointegration theory [40,41], the three endogenous variables are first-order single consolidation variables, so there may be a consolidation relationship. The following co-consolidation analysis considered industrial wastewater discharge, industrial waste gas discharge, and SO_2 discharge. The results are shown in Table 4.

Table 4. Johansson cointegration test results [40,41].

Hypothesized Number of CE (S)	Eigenvalue	Trace Statistic	Critical Value	Prob.
None	0.803	66.690	47.856	0.0003
At most 1	0.495	27.735	29.787	0.085
At most 2	0.319	11.333	15.495	0.192
At most 3	0.084	2.112	3.841	0.146

The results from the maximum feature root test in Table 4 show that at 95% confidence, the null hypothesis is not rejected. Hence, there is indeed a long-term equilibrium relationship between human resident GDP and industrial wastewater, industrial non-completeness, and SO_2. The co-integral equation is:

$$In\ GDP = -0.5152 Inww + 0.2199 Inwg + 0.3467 InSO_2 \tag{20}$$

The above co-integer equation treats it logarithmically for all the variables, and then the coefficients in this co-consolidation equation are expressed as elasticity. When the production of industrial solid waste gas and SO_2 volume increased by 1% each, GDP per capita increased by 0.2199% and 0.3467%, respectively. Declining the emission of industrial waste by 1% led to decreasing GDP per capita by 0.5152%.

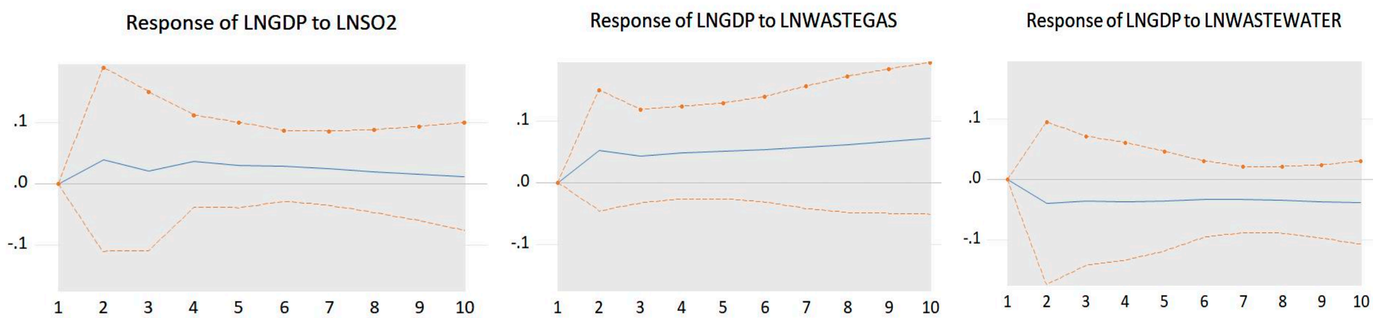
For the pulse response analysis, it is beneficial to explore further the relationship between GDP per capita and related factors. Take the pulse response first step to ensure the model's stability. The AR root icon could be tested with the following results (Table 5).

Table 5. Characteristic root results test.

Root	Modulus
0.916098 − 0.07988i	0.919574
0.916098 + 0.07988i	0.919574
0.505716 − 0.401883i	0.645956
0.505716 + 0.401883i	0.645956
−0.438022	0.438022
−0.322500	0.322500
0.153822 − 0.149650i	0.214607
0.153822 + 0.149650i	0.214607

The VAR model established in this paper is 2, the number of variables is 4, and the number of characteristic roots equals 8. The results in Table 5 show that the inversion of the above 8 roots is less than 1, and 8 points fall in the unit circle, proving that the VAR model is stable. If at least one feature root is equal to 1 or greater than 1, some points are on or outside the unit circle, which shows that the VAR model is unstable. Therefore, the VAR model established above could pass the stability test, and the established model could be considered stable. That is, the next pulse response analysis could be performed.

The following impulse response analysis included the three established environmental pollution indicators and economic growth index VAR model. The results are shown in Figure 4.



(**a**) (**b**) (**c**)

Figure 4. InGDP to $LNSO_2$ impulse response results. Notes: dashed line (orange)—standard deviation measures with 95% confidence interval; blue line—orthogonalized impulse response function.

The horizontal axis represents the lag of the impact period (years), and the vertical axis represents the response to the impact. The model information impact lag period is set to 10 years. The dashed line indicates the standard deviation band, and the meaning of the impulse response may occur.

As can be seen from Figure 4a, after a positive impact of SO_2, GDP per capita began to increase during phase 2, declined during phase 2 to 3, from phase 3 experienced a continuous decline later in phase 4, and achieved stability after phase 6 (response value of 0.005). Figure 4b reveals that after a positive impact of industrial wastewater discharge, the GDP per capita began to increase in the second phase and has grown slowly since the third phase (response value of 0.05). Figure 4c demonstrate that after a negative impact on industrial wastewater discharge, the GDP per capita dropped during periods 1 and 2 and grew slowly after phase 2 and remained in a steady state (response value of −0.03).

Given a positive impact on GDP per capita, the response map of each environmental pollution index can be obtained (Figure 5).

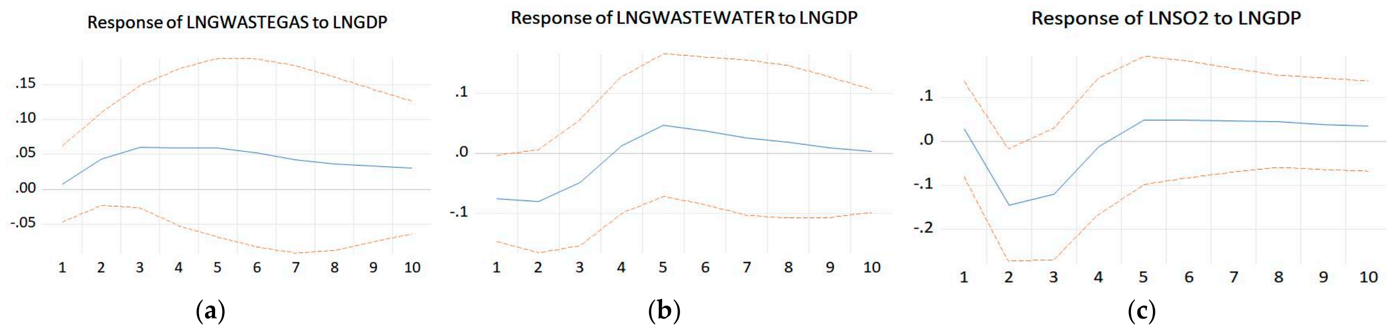


Figure 5. LnWASTEGAS to LnGDP impulse response results. Notes: dashed line (orange)—standard deviation measures with 95% confidence interval; blue line—orthogonalized impulse response function.

There was a positive increase in industrial waste gas emissions during phase 1, reaching the maximum in phase 3 (response value 0.051), while phase 3 began to decline slowly and stabilized after phase 7 (response value 0.026) (Figure 5a). Industrial emissions grew negative during phase 1, rising to positive at phase 4 (0.002), the maximum (response 0.05) and a slow decline after phase 68, and finally stabilizing (response 0.001) (Figure 5b). SO_2 production decreased from phase 1 to 2; phase 2 was at the lowest point (response value-0.15) and rose after phase 2, while it experienced a straight end period at a positive and stable state after phase 5 (response value 0.05) (Figure 5c).

The GDP per capita immediately responded to the impact of a standard deviation. Moreover, the response is positive and has been in a slowly rising trend. Later, it demonstrated that China's economy is growing. The GDP per capita responds to the decline immediately after a standard deviation impact of SO_2, and we can see the slow declining trend from Figure 1. It indicates that the relationship between the two is weak. GDP per capita also positively impacts wastewater and waste gas emissions, which have been rising, further showing a positive correlation.

The variance decomposition is able to decompose the variance of each variable in the model to each perturbation term (Table 6). It provides the relative impact of the various variables within each perturbation term VAR model to further judge the relationship between economic growth and environmental pollution.

Table 6. The variance decomposition results.

Period	SE.	LnGDP	$LnSO_2$	LnWG	LnWW
1	0.052	100.000	0.000	0.000	0.000
2	0.096	97.042	0.396	0.443	2.119
3	0.131	93.313	0.221	2.328	4.137
4	0.161	87.932	0.151	4.493	7.424
5	0.188	81.815	0.233	6.776	11.176
6	0.215	75.426	1.089	8.515	14.970
7	0.246	69.330	3.110	9.371	18.188
8	0.279	64.096	5.850	9.482	20.572
9	0.313	59.954	8.652	9.188	22.206
10	0.347	56.798	11.124	8.760	23.319

As can be seen from the variance decomposition of the GDP per capita, in the first phase, the GDP per capita is all due to its own perturbation term. The other influencing factors have basically no influence. Over time, GDP per capita is less and less affected by itself and significantly enhanced by wastewater, exhaust gas, and SO_2.

5. Discussion

The results of this analysis empirically justify that economic growth provokes natural degradation. Thus, the Granger causality test allows concluding that an increase in GDP leads to the development of exhaust gas production. The obtained findings enrich the investigation undertaken by past studies for Chinese provinces [46–48]. Moreover, as in the past studies [49–55] the results confirm that SO_2 has an statistically significant effect on wastewater. The researchers [49,50] proved that the intensity of the SO_2 impact relates to the frequency of the GDP changes. The findings showed that 1% growth of SO_2 and industrial solid waste provoke the GDP per capita growth by 0.22% and 0.35%, respectively. At the same time, reducing industrial waste by 1% leads to falling GDP per capita by 0.52%.

Such tendencies could be explained by inefficient environmental system protection at the industrial companies in the energy sector [49,55–59]. Thus, they ignore environmental regulations and do not modernize with respect to ecofriendly technologies and green innovation. Moreover, the environmental regulation should be modernized and guarantee the transparency and accountability of ecological protection activities of the companies.

Moreover, the researchers [54–59] divided the two types of ecological regulations into command-and-control regulations and market-based incentive environmental regulations. Thus, the command-and-control regulations provide the strict control and obligatory consideration of indicated ecological norms and standards. They could cause the modernization of ecological equipment and limit the development eco-destructive projects. However, they will not be conducive to the development of green innovation in the country. The study [54] proves that implementation of new environmental protection legislations in China provoked the slowdown of industrial development. The market-based incentive environmental regulations focused voluntary implementation and incorporating of green factors in the business process. They allow attracting additional green investment to the companies due to the developing of a responsible and green image. Moreover, in the long-term, it leads to reducing the negative impact on the environment without the restriction of company's productivity. Moreover, market-based incentive environmental regulations are the basis of the green development of EU countries, which are the leader in green growth [54–62].

6. Conclusions

The study applied the long-term equilibrium equation between the economic growth and environmental pollution level and the impulse response analysis to check the dynamic action mechanism between economic growth and environmental pollution. The investigation is based on analyzing GDP per capita, industrial wastewater emission, and industrial exhaust emission in Henan Province from 1994 to 2020. The results show that economic growth exacerbates the pollution of the environment (especially the air environment), which is related to the development model of equal emphasis on the service industry and heavy industry in Henan Province. More enterprises ignore the protection of the environment to seek economic growth. Economic growth and SO_2 emissions have a positive interaction, strongly driving growth, and economic growth reduces SO_2 emissions to some extent.

Thus, considering the results of the analysis of the dynamic relationship between economic growth and environmental pollution in Henan Province, the following suggestions to promote sustainable development could be outlined.

It is necessary to strengthen environmental supervision and accelerate the adjustment of the energy structure and the utilization of new energy. Furthermore, the government should accelerate the research and application of emerging environmental protection technologies. It is necessary to encourage the development of environmental protection industries dominated by the comprehensive utilization of waste.

The development of Henan provinces mostly depends on the industrial sector. At the same time, industrial sector is one of the core generators of natural pollution. The obtained results confirmed the interconnection between GDP per capita (which is mostly generated by the industrial sector) and environmental degradation. In this case, the restructuring of the industrial sector could be conducive to the declining of natural pollution and promoting sustainable development. Scholars [2,63] have justified that the restructuring of the industrial sector requires the relevant innovative technologies, which appeared to be due to Industry 4.0. Furthermore, the innovative technologies make it possible to reduce the environmental costs [64,65]. Moreover, the effective way of restructuring the industrial sector should be based on the best practices. Thus, the authorities should share information about the best practices and develop the industrial network. In addition, it is necessary to develop light industry and promote clean production in the industry, including heavy industry.

Despite the actual findings, the investigation has several limitations. Thus, in further investigations, the object of investigation should be extended. Moreover, economic growth and green development depend on the vast range of indicators that could boost or limit the countries and regions' development. In this case, in further investigations, it is necessary to consider the quality of governance, the globalization process, urbanization, etc. Furthermore, future investigations must consider the linear and non-linear causal relationships between the mentioned indicators.

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