

Article

Analysis of the Interactive Response Relationships Between Agricultural Pollution Reduction and Carbon Emission Mitigation and Agricultural Economic Development: A Case Study of Henan Province, China

Hanghang Fan ^{1,2}, Ling Li ^{1,2,*}, Xingming Li ^{1,2}, Yongjie Yu ^{1,2}, Yong Wu ^{1,2}, Donghao Li ^{1,2}, Jianwei Liu ^{1,2} and Xiuli Wang ^{1,2}

¹ College of Resources and Environment, Henan Agricultural University, Zhengzhou 450046, China; fhh@stu.henau.edu.cn (H.F.); lxm01@stu.henau.edu.cn (X.L.); 17335621513@163.com (Y.Y.); yong.wu@henau.edu.cn (Y.W.); lidonghao@henau.edu.cn (D.L.); liujianwei@henau.edu.cn (J.L.); wangxiuli@henau.edu.cn (X.W.)

² Henan Engineering Research Center of Land Consolidation and Ecological Restoration, Zhengzhou 450046, China

* Correspondence: liling@henau.edu.cn

Abstract: Ensuring the synergistic advancement of agricultural pollution reduction and carbon emission mitigation, along with sustainable development, is crucial for achieving the ‘dual carbon’ target and modernizing agriculture. To ensure sustainable agricultural development, this study employs a coupling coordination model to explore the synergistic effects of pollution reduction and carbon emission mitigation in Henan Province, considering the agricultural carbon emissions (ACEs), agricultural non-point source pollution (ANP), and the gross value of agricultural output (GVAO) of 18 cities in Henan from 2010 to 2022 as endogenous variables. A panel vector autoregression (PVAR) model is utilized to analyze the interactive responses between agricultural pollution reduction and carbon emission mitigation and agricultural economic development. The results indicate that the degree of synergy between ACE and ANP in Henan Province has shown a trend towards higher values and a diminishing polarization phenomenon between 2010 and 2022, with most regions having degrees of synergy at higher levels. Furthermore, the interactive response relationships between agricultural pollution reduction and carbon emission mitigation and agricultural economic development reveals that the GVAO in Henan Province has a significant positive impact on both ACE and ANP, and that agricultural pollution reduction and carbon emission mitigation are constrained by agricultural economic development, with no significant bidirectional causal relationship observed overall and a lack of positive interaction in the long term. Finally, ACE, ANP, and GVAO in Henan Province exhibit a strong self-reinforcing mechanism, particularly ACE and GVAO, which show a pronounced self-growth trend. Overall, Henan Province should fully utilize the synergistic effects of agricultural pollution reduction and carbon emission mitigation to achieve coordinated progress in agricultural pollution reduction and carbon emission mitigation, as well as green and sustainable development of the agricultural economy.

Keywords: agricultural; pollution reduction; carbon emission mitigation; agricultural economy; PVAR model; synergistic effects



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1. Introduction

The construction of an ecological civilization has always been a strategic goal and long-term plan for China, concerning the future and destiny of the nation and its people, and is an essential guarantee for China to achieve sustainable development and promote the well-being of its citizens [1]. Agriculture, as the foundation of human survival and development, is an integral part of ecological civilization in terms of environmental sustainability [2]. As a populous agricultural country, China bears the responsibility of meeting the food needs of its population of 1.4 billion people while also being tasked with environmental protection and governance in the process of food production [3]. As major carbon emitters, agricultural carbon emissions account for 17% of China's total carbon emissions [4]; thus, in the context of China's large carbon footprint, agricultural carbon emissions cannot be overlooked. Moreover, China's agricultural environment is also affected by non-point source pollution [5,6], and both factors hinder the sustainable development of agriculture in China. Since the Chinese government proposed the "dual carbon" target in 2020, various climate and environmental issues have been actively addressed in an attempt to achieve a carbon peak and carbon neutrality [7,8], providing fundamental policy support for the synergistic governance of pollution reduction and carbon emission mitigation in agriculture. Against this backdrop, constructing a green and sustainable agricultural development system and promoting high-quality growth of the agricultural economy have significant practical importance.

"Pollution reduction" and "carbon emission reduction" have long been promoted as two separate environmental management measures. It was not until the end of the 20th century that some scholars discovered that a reduction in greenhouse gas emissions would lead to a corresponding decrease in environmental pollutants [9]. Following the "co-benefit" concept proposed in the Third Assessment Report of the Intergovernmental Panel on Climate Change (IPCC), scholars began to consider combining pollution reduction and carbon emission reduction and re-examined their relationship [10]. On the basis of the national conditions of China, research has shown that the synergistic control of the two is reflected mainly in the following: on the one hand, measures to reduce greenhouse gas emissions also reduce the emissions of environmental pollutants; on the other hand, the reduction in environmental pollutants also leads to a weakening of greenhouse gas emissions [11]. On this basis, researchers have reported that "same root, same source, and synchronous" characteristics exist in the emission of greenhouse gases and pollutants. For example, the use of fertilizers and pesticides, and the manure produced by the growth of livestock and poultry, not only produce pollutants such as ammonia and nitrogen but also produce greenhouse gases such as CO₂ and CH₄ [12,13]. The synergistic control of the two has a reliable theoretical and practical basis, and the comprehensive management of both can achieve maximum benefits [14]. Scholars, on the basis of the above characteristics, have conducted research on pollution reduction and carbon emission reduction in various fields and industries, such as the synergistic reduction in carbon dioxide and atmospheric pollutants in China's transportation industry [15]; the synergistic effect of pollution reduction and carbon emission reduction measures in the power industry on a national scale [16]; the synergistic enhancement of sponge city source facilities in construction [17]; the synergistic impact mechanism of emissions trading on pollution reduction and carbon emission reduction [18]; and the empirical analysis of the synergistic effect and its influencing mechanism of pollution reduction and carbon emission reduction in Chinese agriculture through the dual fixed-effects regression model [19]. With respect to the research on the synergistic effect of pollution reduction and carbon emission reduction, most scholars choose the coupling coordination model, and this research theory is widely used to study the coordination issues of hot projects [20]. From a multidimensional system

perspective, coupling coordination is an orderly development trend where various subsystems within a system promote and influence each other, and it is a consistent expression of the composite of subsystems to the outside world [21]. “Pollution reduction” and “carbon emission reduction” are two systems that have the same root and source and influence each other. The coupling coordination of pollution reduction and carbon emission reduction is based on the mechanism of mutual promotion and shared prosperity among subsystems within the system, and it is characterized by the significant effects of one party stimulating and promoting the effective benefits of the other [22]. On the basis of the same root and source characteristics of agricultural carbon emissions (ACEs) and agricultural non-point source (ANP) pollution, treating the two as common goals for governance and accelerating the synergistic promotion of pollution reduction and carbon emission reduction will significantly improve governance benefits and reduce costs [12,13].

At present, ecological and environmental governance has entered a new phase. To ensure the sustainable advancement of pollution reduction and carbon emission reduction in agriculture, it is necessary to promote synergistic enhancement with economic growth [23]. In the new development stage, pollution reduction and carbon emission reduction need to be integrated into economic development to ensure high-quality sustainable economic development and achieve the transformation and upgrading of the agricultural economy [24]. Research on the relationships between pollution reduction and carbon emission reduction and economic development is relatively rich, including the application of models and methods such as the Tapio decoupling model [25], the environmental Kuznets curve (EKC) [26,27], and the panel vector autoregression (PVAR) model [28,29]. Among them, EKC research covers multiple scales and fields, including national [30,31], provincial [32–34], and transnational levels [35,36], and discusses and analyzes sectors such as agriculture [34], industry [37,38], and tourism [39]. The Tapio decoupling model is mainly used to analyze the decoupling status of environmental pollution under economic changes [8,40,41], spatiotemporal changes and differences [42], and driving factor analyses [43], and is used to comprehensively analyze the asynchronous changes and interrelationships between economic development and environmental pollution [25,44]. The PVAR model interprets the interactive and coordinated relationship between pollution reduction and carbon emission reduction and economic development from a bidirectional causal perspective [1]. Some scholars have proposed that there is an inverse “U”-shaped linear relationship between carbon emissions and the economy [45], testing that there is a Granger causal relationship between carbon emissions and economic growth [46,47] and analyzing the interactive response relationship of influencing factors on the basis of the coupling coordination model [48]. As an important carrier of economic development, some scholars have combined the Tapio decoupling model with the PVAR model to explore the dynamic relationships and influencing mechanisms among transportation infrastructure, carbon emissions, and economic growth [25]. In addition, some scholars have added the variable income inequality to explore the path of green and healthy economic development in China [46], improve the income gap, and promote common prosperity. Other scholars have focused on the three major urban agglomerations in China. As an important source of China’s economic development, the study of the response relationships between pollution reduction and carbon emission reduction and high-quality economic development in urban agglomerations is important for exploring the green and low-carbon transformation of China’s economic development. The above research and exploration indicate that the connections between pollution reduction and carbon emission reduction and economic growth are close, and the research is very mature, with a relatively perfect method system. Selecting typical areas and mature research methods to study the relationships between pollution reduction and carbon emission reduction and economic growth can accelerate

the high-quality sustainable development of pollution reduction and carbon emission reduction and the economy, forming a green development pattern.

Previous studies on pollution reduction and carbon emission reduction in relation to the economy have focused predominantly on high-value industries, with relatively few investigations dedicated to agriculture. First, most existing studies have primarily conducted analyses from a unidirectional perspective, lacking a comprehensive framework that incorporates ACE, ANP, and the agricultural economy to analyse their mutual responses over multiple directions and long periods. This has led to inaccuracies in the analysis of the response outcomes among these variables. Second, the agricultural economy and the agricultural environment constitute an inseparable, integrated open system, where changes in any element can potentially trigger responses across time in the entire system or the other component. However, past research has often concentrated on static time perspectives, neglecting long-term dynamic analyses of the system's inherent and interrelated lag effects. Third, existing studies tend to be limited to national and provincial scales, resulting in a singular and inflexible approach that does not account for local conditions. Based on these issues, this study selects the Panel Vector Autoregression (PVAR) model, which can incorporate agricultural carbon emissions (ACEs), agricultural non-point source pollution (ANP), and gross value of agricultural output (GVAO) as endogenous variables, to investigate their long-term interactive response relationships. Henan Province, one of China's major grain-producing regions, is chosen as the study area. Considering the availability and timeliness of data, the study period is set from 2010 to 2022. As a populous and industrially diverse province in central China, Henan features both northern winter wheat and southern rice cultivation, as well as a large number of terraced fields in its western regions. Compared with other provinces in China, Henan is more typical and comprehensive in the agricultural sector and thus has representative significance. In terms of research scale, this study employs the coupling coordination model to conduct spatiotemporal heterogeneous synergy analysis of ACE and ANP in counties and districts of Henan Province. Meanwhile, the PVAR model is used to dynamically analyze the agricultural pollution reduction and carbon emission mitigation, as well as agricultural economic development in different cities of Henan. This includes Granger causality tests to explore causal relationships, multi-period impulse response analysis, and variance decomposition. By examining the possibilities of sustainable development from multiple scales and over a long period, this study aims to achieve coordinated improvement and efficiency enhancement in agricultural pollution reduction and carbon emission mitigation, as well as agricultural economic development. It also seeks to accelerate the realization of the "dual carbon" goals and agricultural modernization, providing theoretical support and suggestions for agricultural transformation and green sustainable development in grain-producing regions like Henan Province.

2. Materials and Methods

2.1. Study Area Profile and Data Sources

As shown in Figure 1, Henan Province is located in the central and eastern parts of mainland China and consists of 18 prefecture-level cities and 158 counties and districts. The terrain is relatively high in the east and low in the west, with vast plains and a large population. The province has well-developed agriculture and animal husbandry industries, making it an important grain-producing region in China. In 2022, Henan Province had an employed population of 47.82 million, 13.2 million of whom were employed in the primary sector, which is truly a major agricultural province. As a major producer and exporter of agricultural products in China, the total output value of agriculture, forestry, animal husbandry, and fisheries in 2022 was CNY 1095.224 billion, with an agricultural

output value of CNY 694.83 billion, accounting for 63.4% of the total output value. In terms of grain production, Henan Province produced 67.8937 million tons of grain in 2022, accounting for 9.9% of the national total and ranking 2nd in the country, while also increasing production by 3.7% compared with 2021, maintaining a continuous state of increased production. In the animal husbandry sector, Henan Province produced a total of 6.732 million tons of pork, beef, mutton, and poultry meat in 2022, with pork production reaching 4.6533 million tons, accounting for 69.1% of the total output. Henan Province, while being a major grain-producing province, is also the leading province in the country for pig breeding and supply, with both pig inventory and output ranking at the forefront nationwide. With its large scale of agriculture and animal husbandry industries, Henan Province also faces significant environmental pollution issues resulting from agricultural production. Therefore, it is essential for each region to adopt localized agricultural pollution reduction and carbon emission mitigation measures, accelerate the transformation and upgrading from “traditional agriculture” to “smart agriculture”, and promote the green and sustainable development of agriculture.

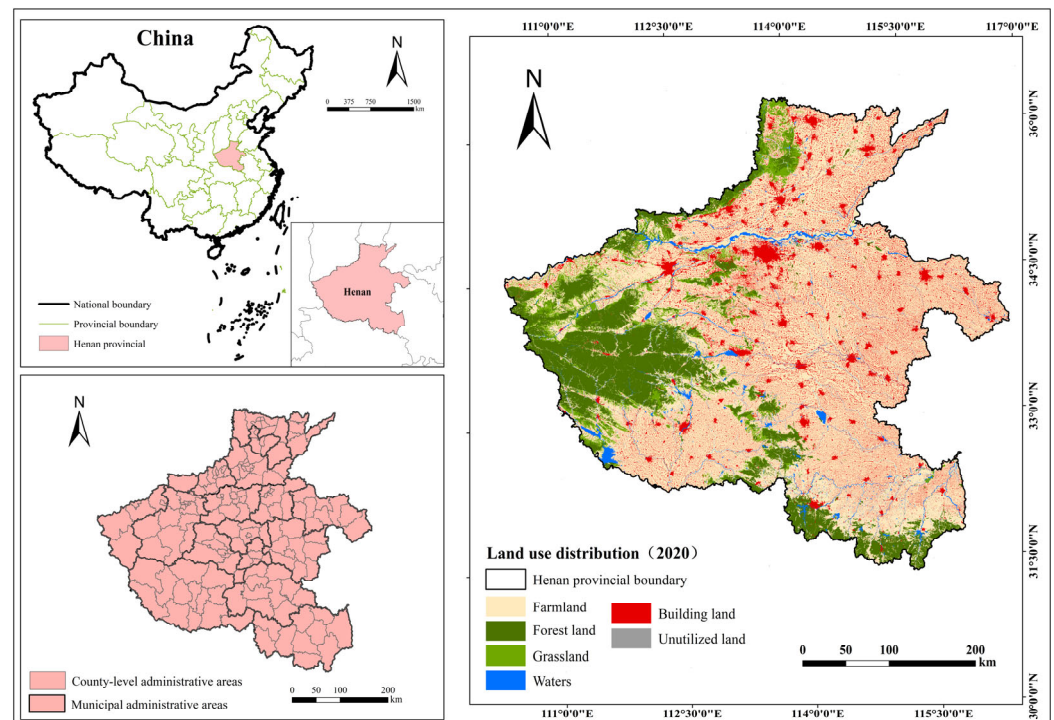


Figure 1. Study area.

This study focuses primarily on counties and prefecture-level cities in Henan Province. The original data for calculating agricultural carbon emissions (ACEs) and agricultural non-point source pollution (ANP) are mainly from the “Henan Provincial Statistical Yearbook” and statistical data reported by local bureaus of statistics from 2010 to 2022. To address the issue of data availability and ensure the timeliness of the data, a small number of missing data points were estimated and supplemented using linear interpolation with StataMP 18 software. The gross value of agricultural output (GVAO) of each city in Henan Province from 2010 to 2022 was selected as the economic development indicator. To eliminate the impact of price factors, the total output value for each year is deflated to a base year, which is set as 2010 in this study.

2.2. Coordination and Interaction Mechanism

The agricultural economy serves as the driving force for the sustainable development of agriculture, and it maintains a complex relationship of continuous interaction and dynamic adjustment with agricultural development [49,50]. On the one hand, the rapid development of the agricultural economy has stimulated the scaling up and marketization of the agricultural industry. On the other hand, the healthy development of the agricultural industry ensures the sustained and steady growth of the agricultural economy. As shown in Figure 2, agricultural production activities result in ACE and ANP, which can damage the agricultural production environment and are detrimental to the achievement of the “dual carbon” target. On the basis of the study of the dynamic equilibrium relationships between agricultural pollution reduction and carbon emission mitigation and the agricultural economy, constructing a green and low-carbon agricultural development model is essential to ensure the continued growth of the agricultural economy, create new advantages for the green development of agriculture, and lay a foundation for the sound and healthy development of grain-producing regions such as Henan Province.

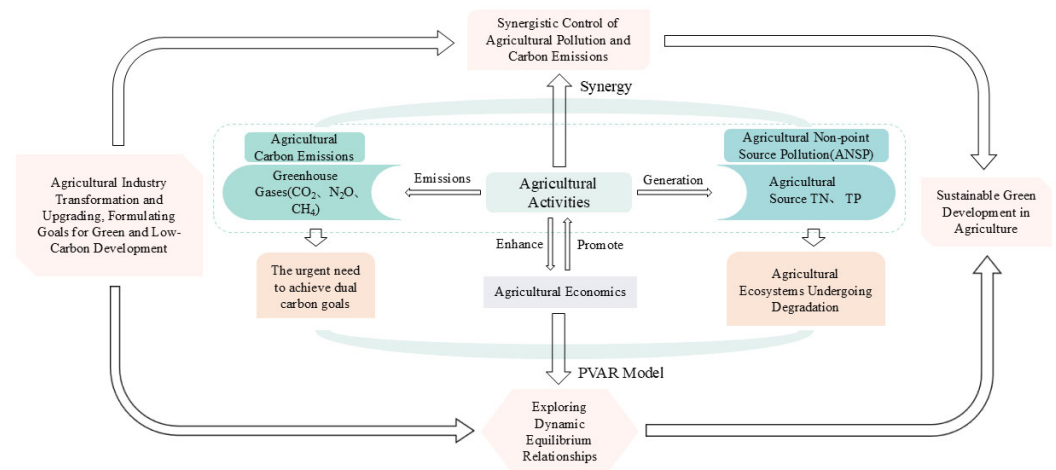


Figure 2. Interactive mechanism of agricultural pollution reduction and carbon emission mitigation with agricultural economic development.

2.3. Methods

2.3.1. Accounting for Agricultural Carbon Emissions and Non-Point Source Pollution

Taking ACE and ANP as the objects of accounting, and selecting indicators such as CO₂, total nitrogen (TN), and total phosphorus (TP), this study calculates the emissions of pollution reduction and carbon emission mitigation in Henan Province’s counties, districts, and prefecture-level cities from 2010 to 2022.

The accounting for ACE primarily employs the emission factor method [51–55]. As shown in Table 1, there are four main aspects: agricultural production input materials, crop cultivation, livestock and poultry breeding, and open burning of crop residues [56,57]. In the calculations, carbon emissions from agricultural production are converted into standard CO₂, with a conversion factor of 44/12. Furthermore, based on the 100-year global warming potential values published in the Fourth Assessment Report of the IPCC, CH₄ and N₂O are converted. The global warming potential values are 1 for CO₂, 25 for CH₄, and 298 for N₂O [58].

Table 1. Carbon accounting for agriculture.

Types of Carbon Sources	Calculation Formula	Correlation Coefficient Values
Agricultural production input materials	$E_1 = \sum [T_i \times \alpha_i \times (44/12)]$ In the equation, E_1 represents the carbon emissions from agricultural inputs; T_i is the amount of the i-th type of carbon source used; α_i is the emission coefficient of the i-th type of carbon source.	The carbon sources include chemical fertilizers, pesticides, agricultural films, diesel consumption, crop sowing area, and effective irrigation area, with coefficients of 0.8956 kg(C)/kg, 4.934 kg(C)/kg, 5.18 kg(C)/kg, 0.5927 kg(C)/kg, 312.6 kg(C)/km ² , and 266.48 kg(C)/ha, respectively.
Crop cultivation	$E_2 = \sum (S_i \times \tau_i)$ In the equation, E_2 represents the N₂O emissions produced during the planting process of crops; S_i is the sowing area of the i-th type of crop; τ_i is the N₂O emission coefficient of the i-th type of crop.	The carbon sources selected are wheat, corn, beans, oil crops, and vegetables, with coefficients of 1.75 kg(N ₂ O)/ha, 2.532 kg(N ₂ O)/ha, 2.29 kg(N ₂ O)/ha, 0.95 kg(N ₂ O)/ha, and 4.944 kg(N ₂ O)/ha, respectively.
Livestock and poultry breeding	$E_3 = E_{CH_4} + E_{NO_2}$ $E_{CH_4} = \sum B_i \times (D_i + G_i)$ $E_{NO_2} = \sum (B_i \times G_i)$ In the equation, E_3 represents the N₂O emissions produced during the process of livestock breeding, while E_{CH_4} and E_{NO_2} respectively represent the CH₄ and N₂O emissions generated by livestock breeding; B_i is the number of the i-th type of animal raised; D_i is the CH₄ produced by enteric fermentation; G_i is the CH₄ or N₂O produced by manure management.	The carbon sources selected are cattle, sheep, and poultry, with their coefficients being the CH ₄ and N ₂ O emission coefficients generated by enteric fermentation and manure management, respectively. The coefficients are referenced from the research by Hu Xiangdong [53].
Open burning of crop residues	$E_4 = \sum (Q_k \times M_k \times N_k \times P_k \times L_k)$ In the equation, E_4 represents the greenhouse gas emissions from straw burning; Q_k is the yield of crop k; M_k is the straw-to-grain ratio of crop k; N_k is the open burning ratio of crop k; P_k is the burning efficiency of crop k; L_k is the emission factor of crop k.	Open burning of wheat and maize stover was used as the carbon source to account for its crop-grass-to-grain ratio, open burning ratio, combustion efficiency, and emission factors with reference to the study by Cheng Linlin and other scholars [51].

Considering the current state of agricultural production in Henan Province, the inventory analysis method [59,60] is used to calculate the emissions of ANP. As shown in Table 2, the pollution sources include four aspects: agricultural fertilizers, livestock and poultry farming, rural living, and solid waste from farmlands [61], totalling 15 pollution units. The emissions are accounted for using the loss coefficients [62] and pollution generation coefficients [63] of the pollution units.

Table 2. Emission factors for agricultural non-point source pollution.

Types of Pollution Sources	Pollution Units	Pollution Emission Factor Formula	Correlation Coefficient Values
Agricultural fertilizers	Nitrogen fertilizer, phosphorus fertilizer, and compound fertilizer	Pollution emission coefficient = pollutant generation rate $\times$ loss rate	In the pollution units, the nitrogen pollutant generation rate for compound fertilizers is 31, and the phosphorus pollutant generation rate is 0.15. The nitrogen pollutant generation rate for nitrogen fertilizers is 1, while the phosphorus pollutant generation rate for phosphorus fertilizers is 0.44. The loss rates of nitrogen and phosphorus are 0.1 and 0.07, respectively. The TN (total nitrogen) pollutant generation rates per head for cattle, pigs, sheep, and poultry are 61.1, 4.51, 2.28, and 0.275 kg, respectively. The TP (total phosphorus) pollutant generation rates per head are 10.07, 1.7, 0.45, and 0.115 kg, respectively. The loss rates for TN and TP are 0.208 and 0.1715, respectively.
Livestock and Poultry farming	Cattle, pigs, sheep, and poultry	Pollution emission coefficient = pollutant generation rate $\times$ loss rate	
Solid waste from Rural living	Wheat, corn, legumes, oilseeds, and vegetables	Pollution emission coefficient = stubble generation coefficient $\times$ (stubble utilization structure proportion $\times$ pollutant generation rate) $\times$ loss rate	The straw coefficient, straw utilization structure proportion, pollutant generation rate, and loss rate for paddy, wheat, corn, legumes, tubers, oil crops, and vegetables are derived from the research by Lai Siyun [62].
Solid waste from Rural living	The pollution emission coefficients for TN (Total Nitrogen) and TP (Total Phosphorus) per capita per year in rural areas are 0.89 kg and 0.2 kg.		

2.3.2. Coupling Coordination Model

The coupling coordination model is a conceptual model used to describe the interactions and synergistic relationships among different components within a system. It is commonly employed to investigate the degree of coordination among these components. This study employs the coupling coordination model [22,64–66] to obtain the synergistic effects of agricultural pollution reduction and carbon emission mitigation. The specific formula is as follows:

$$C = \frac{2\sqrt{U_1 U_2}}{U_1 + U_2} = \sqrt{[1 - (U_2 - U_1)] \frac{U_1}{U_2}} \quad (1)$$

$$T = \beta_1 U_1 + \beta_2 U_2 \quad (2)$$

$$D = \sqrt{C \times T} \quad (3)$$

In the formula, U_1 and U_2 represent the evaluation indices of ACE and ANP, respectively, after being normalized by the range standardization method; C is the calculated coupling degree; T is the comprehensive synergy index of the two subsystems; β_1 and β_2 are the undetermined coefficients of the two subsystems, which are set to 0.5 according to their importance; and D is the calculated coupling coordination degree of the two subsystems, with a value range of [0, 1], where a higher value indicates better synergy between the two subsystems, and a lower value indicates worse synergy.

2.3.3. Non-Parametric Kernel Density Estimation

Agricultural carbon emissions (ACEs) and agricultural non-point source pollution (ANP) exhibit certain temporal variation trends. To specifically investigate these trends over time, this study employs kernel density estimation to illustrate the temporal changes in the synergy degree between ACE and ANP. The three-dimensional kernel density curves representing their temporal variations are constructed using MATLAB R2022a software [13].

2.3.4. PVAR Model

To further investigate the dynamic response relationships between agricultural pollution reduction and carbon emission mitigation and the agricultural economy, a PVAR model is constructed for empirical analysis on the basis of an analysis of the coupling coordination model. The PVAR model, which is based on the vector autoregression (VAR) model, optimizes the panel data without setting causal relationships between variables, treating all variables as endogenous [67,68]. It can simultaneously consider both time effects and individual effects [69], and combines impulse response analysis and variance decomposition to explore the dynamic response relationships between variables [1,70]. The formula for the PVAR model is as follows:

$$Y_{it} = \gamma_0 + \sum_{j=1}^n \gamma_j Y_{it-j} + \alpha_i + \beta_i + \varepsilon_i \quad (4)$$

In the formula, Y_{it} is a three-dimensional column vector that includes three endogenous variables: agricultural carbon emissions (ACEs) (t), agricultural non-point source pollution (ANP) (t), and gross value of agricultural output (GVAO) (in billion CNY). Here, i represents the prefecture-level city, t represents the year, γ_0 is the intercept term, j is the order of lag, γ_j is the parameter matrix for the j -th lag, α_i is the individual fixed effect, β_i is the individual time effect, and ε_{it} is the stochastic disturbance term.

3. Results and Analysis

3.1. Temporal Analysis of Agricultural Carbon Emissions and Non-Point Source Pollution in Agriculture

Based on the data collection and collation conducted in the early stage, the agricultural carbon emissions (ACEs) and agricultural non-point source pollution (ANP) emissions in Henan Province from 2010 to 2022 were calculated. As shown in Figure 3, both ACE and ANP in Henan Province reached their peaks in 2015 and then showed a gradual downward trend over time, with consistent changes between the two. This is consistent with the results of relevant studies [12,71]. Among the 18 prefecture-level cities in Henan Province, Nanyang, Zhumadian, Zhoukou, and Shangqiu have relatively high proportions, and their distributions in both ACE and ANP are consistent. This is related to the scale of the agricultural industry in these cities. For a long time, Nanyang, Zhumadian, Zhoukou, and Shangqiu have been important sources of agricultural products, supporting the agricultural development of Henan Province. Since 2015, China has proposed a green and low-carbon transformation and development of agriculture. Various regions have actively carried out large-scale planting, improved the recycling technology of livestock manure, and reduced the use of agricultural inputs. Efforts have been made to improve pollutant emissions and reduce agricultural carbon emissions from the source and through technological means, achieving green, circular, and low-carbon agricultural development.

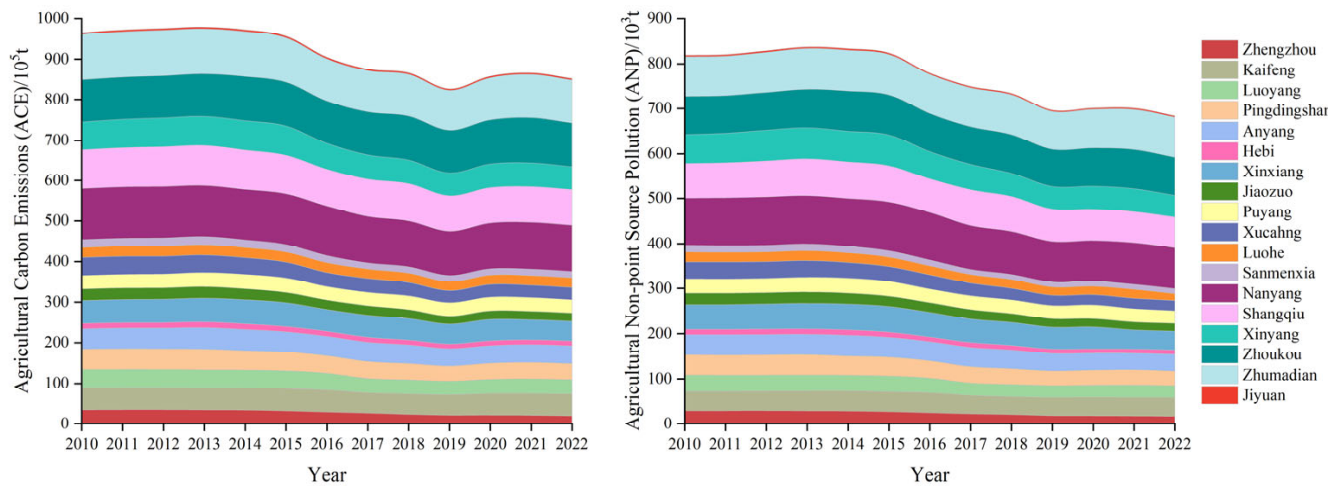


Figure 3. Temporal characteristics of agricultural carbon emissions and agricultural non-point source pollution in Henan Province from 2010 to 2022.

3.2. Spatio-Temporal Analysis of the Degree of Synergy of Agricultural Pollution Reduction and Carbon Emission Mitigation

To more specifically and vividly present the development and changes in the degree of synergy between pollution reduction and carbon emission mitigation in Henan Province, this study employs the non-parametric kernel density estimation method [12] to plot the three-dimensional curves of the degree of synergy between ACE and ANP from 2010 to 2022 for various prefecture-level cities in Henan Province using MATLAB R2022a software, as shown in Figure 4. The figure shows that the peaks of the three-dimensional kernel density curves are distributed mainly between 0.7 and 0.9. Overall, there is a rightward tilt in the centre of the curves, indicating that the degree of synergy between pollution reduction and carbon emission mitigation in Henan Province's agriculture is relatively high and has been increasing overall. First, regarding the overall characteristics of the peaks, the peaks of the degree of synergy distribution show an increasing trend, with the wave peak shape changing from a broad peak to a sharp peak, indicating that the differences in the degree of synergy among various cities are gradually decreasing. Second, in terms of the number of peaks, from 2010 to 2017, the kernel density curve has only one distinct peak, suggesting that the polarization phenomenon of the degree of synergy was weak during this period. From 2018 to 2022, the distribution curve of the degree of synergy clearly shows a double-peak state and a left-tail phenomenon, indicating that some areas in Henan Province have a degree of synergy lower than the overall level, indicating polarization. Between 2021 and 2022, the double-peak characteristic of the curve weakens, and the range of polarization phenomena gradually narrows, but there are still some areas with a degree of synergy that differs from the overall level. In summary, the overall degree of synergy between pollution reduction and carbon emission mitigation in various cities in Henan Province has continued to improve, and there has been a noticeable polarization phenomenon that has gradually weakened in recent years. The differences in the degree of synergy between cities have gradually decreased, with the number of areas with lower values increasing and then decreasing, evolving towards areas with higher values.

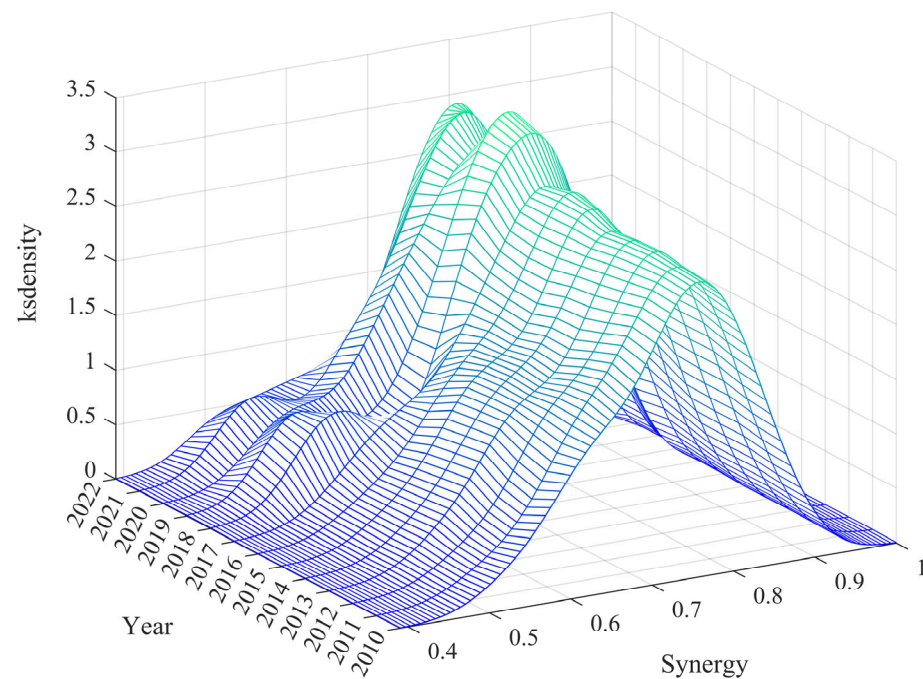


Figure 4. Kernel density estimation curve of the synergistic degree of agricultural pollution reduction and carbon emission mitigation.

This study further analyzed the synergy degree of agricultural carbon emissions (ACEs) and agricultural non-point source pollution (ANP) in 158 counties and districts of Henan Province, selecting the years 2010, 2014, 2018, and 2022 as the investigation years. To analyze the spatial distribution patterns from a small-scale perspective, using ArcMap 10.8 software, the degree of synergy is divided into five relative levels, from low to high, designated as the low value area, next low value area, medium value area, next high value area, and high value area, corresponding to levels 1, 2, 3, 4, and 5 in Table 3. In Figure 5, overall, the level 5 areas in Henan Province are distributed mainly in the west, north, and south, where the proportion of forest land is relatively high compared with that in other areas; arable land is distributed mostly in patches; the agricultural industry structure is rational; and the synergy level is high [72]. The remaining areas are mostly level 4, with the fewest areas being level 1 and level 2. First, in 2010, the level 5 synergy regions were distributed mainly in the south and northwest, with a concentrated distribution and accounted for the highest proportion, 67.72%, of all counties and districts in Henan Province, followed by the level 4 regions, which accounted for 27.85%. Second, in 2014, the number of level 5 synergy regions increased, with the proportion increasing to 71.52%, and the number of level 4 regions decreased. In 2018, the number of level 5 synergy regions increased by two, with the proportion increasing to 72.78%, whereas the number of level 4 regions decreased, accounting for 20.89%, which was a decrease of 6.96% compared with that in 2010; one outlier region changed from level 5 to level 1, indicating significant fluctuations in degree of synergy in that area. Finally, in 2022, the number of level 5 synergy regions increased by two again, with the proportion reaching 74.05%, an increase of 6.33% compared with that in 2010, whereas the number of level 4 regions remained the same as that in 2018. There was one level 1 region in the southwest, where the degree of synergy has been below 0.1 for a long time, mainly because the values of ACE and ANP in that region are high, far exceeding the levels of surrounding areas [71,73]. In summary, the degree of synergy between pollution reduction and carbon emission mitigation in Henan Province is mostly concentrated at levels 5 and 4, with few areas having lower degrees of synergy due to high emission levels. Overall, there is a trend of convergence towards higher

values over time, with regional differences diminishing. As a major agricultural province, Henan Province, in line with sustainable development strategies, can effectively achieve the synergistic enhancement of pollution reduction and carbon emission mitigation.

Table 3. Synergy degree levels.

Synergy Level	Synergy Degree	Categories
1	(0.00, 0.20]	Low value area
2	(0.20, 0.40]	Next medium value area
3	(0.40, 0.60]	Medium value area
4	(0.60, 0.80]	Next high value area
5	(0.80, 1.00]	High value area

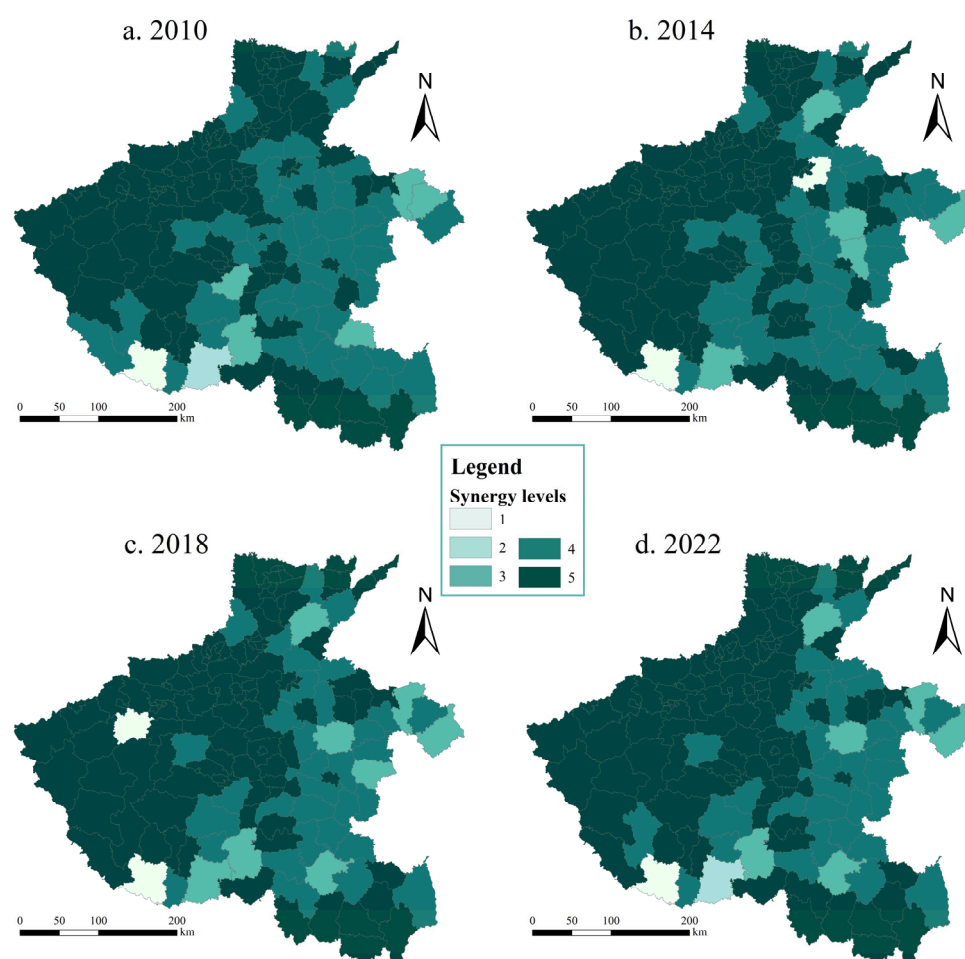


Figure 5. Spatio-temporal distribution of the synergistic degree of agricultural pollution reduction and carbon emission mitigation.

3.3. Empirical Analysis of the PVAR Model

3.3.1. Descriptive Statistics of the Variables

To ensure that the model is not affected by heteroscedasticity, the three variables of agricultural carbon emissions (ACEs), agricultural non-point source pollution (ANP), and gross value of agricultural output (GVAO) are logarithmically transformed to generate new variables: $\ln ACE$, $\ln ANP$, and $\ln GVAO$. According to Table 4, descriptive statistics are obtained for the mean, standard deviation, maximum, and minimum values of these three new variables. The relatively low standard deviations of the variables $\ln ACE$, $\ln ANP$, and $\ln GVAO$ in Henan Province indicate that there is regional synergy in agricultural carbon

emissions, agricultural non-point source pollution, and the total value of agricultural output. As shown by the spatiotemporal evolution of the three variables in Figure 6, $\ln\text{ACE}$ and $\ln\text{ANP}$ exhibit a declining trend, whereas $\ln\text{GVAO}$ shows an increasing trend over time, suggesting that efforts in pollution reduction and carbon emission mitigation are continuously achieving results and that the agricultural economy is continually growing.

Table 4. Statistical characteristics of variables $\ln\text{ACE}$, $\ln\text{ANP}$, and $\ln\text{GVAO}$.

Variables	Mean	Std. Dev	Max	Min	Observations
$\ln\text{ACE}$	5.956868	0.8223884	3.607756	7.144036	N = 234
$\ln\text{ANP}$	10.38476	0.8452691	7.966314	11.58799	N = 234
$\ln\text{GVAO}$	5.282085	0.9216374	2.48409	6.8343905	N = 234

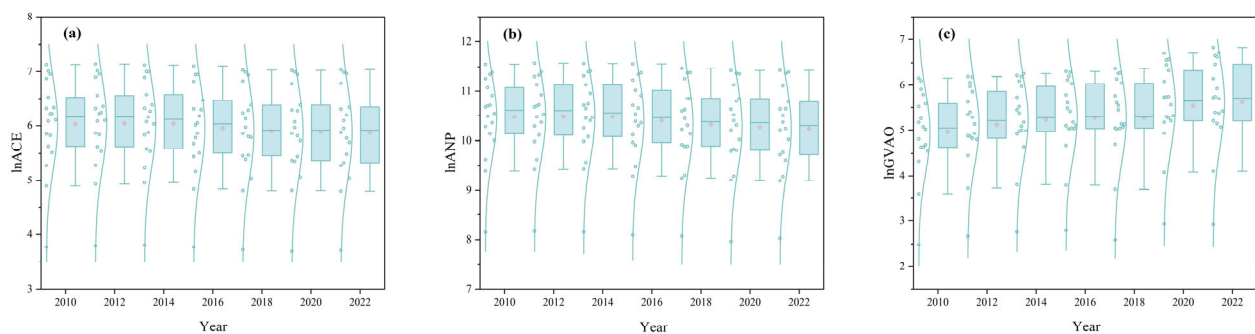


Figure 6. Spatio-temporal evolution of variables $\ln\text{ACE}$, $\ln\text{ANP}$, and $\ln\text{GVAO}$. (a–c) are the statistical distributions of the variables $\ln\text{ACE}$, $\ln\text{ANP}$ and $\ln\text{GVAO}$ for 2010–2022, respectively.

3.3.2. Unit Root and Cointegration Tests of Variables

This study uses StataMP 18 statistical analysis software for data analysis and processing. To ensure the stationarity of the variables, multiple unit root tests are conducted on the data, including the Levin–Lin–Chu (LLC) test, Im–Pesaran–Shin (IPS) test, augmented Dickey–Fuller–Fisher (ADF–Fisher) test, and Phillips–Perron–Fisher (PP–Fisher) test. According to the results presented in Table 5, the variables $\ln\text{ACE}$ and $\ln\text{ANP}$ exhibit unit roots and fail the stationarity test. However, their first-differences, $d\ln\text{ACE}$, $d\ln\text{ANP}$, and $d\ln\text{GVAO}$ reject the null hypothesis, indicating that they are first-order integrated, forming stationary series without unit roots, and are suitable for PVAR model analysis.

Table 5. Unit root test results of the data. ** and *** indicate statistical significance at the 5% and 1% confidence levels, respectively, with the p -values enclosed in parentheses, as will be the case for the rest of the text; the variables $d\ln\text{ACE}$, $d\ln\text{ANP}$, and $d\ln\text{GVAO}$ are the first differences of the variables $\ln\text{ACE}$, $\ln\text{ANP}$, and $\ln\text{GVAO}$, respectively.

Variables	LLC Test	IPS Test	ADF–Fisher Test	PP–Fisher Test	Conclusion
$\ln\text{ACE}$	−4.959 *** (0.000)	−3.240 *** (0.001)	41.209 (0.252)	41.632 (0.239)	Non-stationary
$d\ln\text{ACE}$	−7.244 *** (0.000)	−6.064 *** (0.000)	71.984 *** (0.000)	128.240 *** (0.000)	Stationary
$\ln\text{ANP}$	−3.573 *** (0.000)	−2.829 *** (0.000)	42.434 (0.213)	52.719 ** (0.036)	Non-stationary
$d\ln\text{ANP}$	−4.496 *** (0.000)	−5.326 *** (0.000)	54.610 ** (0.024)	94.861 *** (0.000)	Stationary
$\ln\text{GVAO}$	−2.770 *** (0.003)	−3.399 *** (0.000)	62.288 *** (0.004)	202.916 *** (0.000)	Stationary
$d\ln\text{GVAO}$	−6.064 *** (0.000)	−7.012 *** (0.000)	115.298 *** (0.000)	351.501 *** (0.000)	Stationary

Further cointegration tests are conducted to verify the long-term equilibrium relationships among the variables [25]. The Pedroni test [74] and the Westerlund test [75] are used to investigate the cointegration relationships between $\ln\text{ACE}$, $\ln\text{ANP}$, and $\ln\text{GVAO}$. The results presented in Table 6 show that all test items significantly reject the null hypothesis,

which is the assumption that there is no cointegration relationship between the three variables. This confirms the existence of a long-term cointegration relationship between $\ln ACE$, $\ln ANP$, and $\ln GVAO$.

Table 6. Cointegration test results of the data. ** and *** denote statistical significance at the 5% and 1% confidence levels, respectively. The p -values are presented in parentheses.

Testing Method	Test Item	Statistical Value
Pedroni test	Modified Phillips–Perron	3.769 *** (0.000)
	Phillips–Perron	−4.031 *** (0.000)
	Augmented Dickey–Fuller	−3.925 *** (0.000)
Westerlund test	Variance ratio	1.769 ** (0.038)

3.3.3. Determination of the Optimal Lag Order and Stability Test

Before determining the optimal lag order of the variables, it is necessary to ensure the validity of the estimated parameters and the degrees of freedom. The model's optimal lag order is determined based on the Akaike Information Criterion (AIC), the Bayesian Information Criterion (BIC), and the Hannan–Quinn Information Criterion (HQIC). It is generally believed that the minimum value corresponding to each criterion represents the optimal lag order for that criterion [76]. When all three criteria yield their minimum values simultaneously, the lag order can be determined as the optimal lag order for the model. The results shown in Table 7 indicate that the minimum values for all three criteria occur at the first lag, thus confirming that the optimal lag order for the PVAR model is one.

Table 7. Optimal lag order test results of the PVAR model. * indicates the optimal lag order selected based on the AIC, BIC, and HQIC criteria.

Lag Order	AIC	BIC	HQIC
1	−9.278 *	−8.161 *	−8.825 *
2	−8.866	−7.494	−8.309
3	−8.221	−6.550	−7.542

To ensure the stability of the model, further stability tests are conducted on the PVAR model. As shown in Figure 7, all unit roots of the variables lie within the unit circle, demonstrating that the constructed PVAR model is robust and ready for further model estimation and analysis.

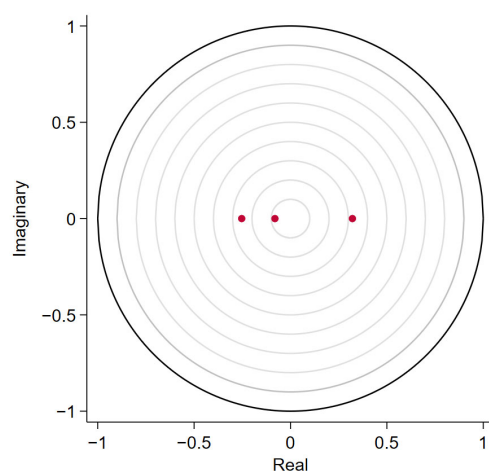


Figure 7. PVAR model stability test. The red dots represent the three variables $\ln ACE$, $\ln ANP$, and $\ln GVAO$. If all the red dots are within the unit circle, it indicates that the model is stable. If any red dot lies outside the unit circle, it suggests that the model is unstable.

3.3.4. Estimation Results of the PVAR Model

Granger causality tests are commonly used to determine whether there is a causal relationship between variables [28,64,77]. This study is used to preliminarily determine the relationships between agricultural carbon emissions (ACEs), agricultural non-point source pollution (ANP), and gross value of agricultural output (GVAO). The results in Table 8 indicate that GVAO is a Granger cause of both ACE and ANP, and that ANP is a Granger cause of ACE, whereas there are no significant bidirectional causal relationships between GVAO, agricultural pollution reduction, and carbon emission mitigation. The reason for this is that the agricultural economy is closely related to agricultural production, and the growth of the agricultural economy often comes with the generation of agricultural pollution. As a major agricultural province, Henan must leverage these interdependent relationships to achieve coordinated sustainable development in pollution reduction, carbon emission mitigation, and agricultural economic growth, in order to realize high-quality green development in agriculture.

Table 8. Granger causality test results.

Test Variable	chi ²	df	p-Value	Null Hypothesis	Conclusion
dlnANP	2.915	1	0.088	dlnANP is not a Granger cause of dlnACE	Reject
dlnGVAO	6.750	1	0.009	dlnGVAO is not a Granger cause of dlnACE	Reject
dlnACE	0.780	1	0.377	dlnACE is not a Granger cause of dlnANP	Accept
dlnGVAO	3.738	1	0.053	dlnGVAO is not a Granger cause of dlnANP	Reject
dlnACE	2.210	1	0.137	ddlnACE is not a Granger cause of dlnGVAO	Accept
dlnANP	2.455	1	0.117	dlnANP is not a Granger cause of dlnGVAO	Accept

Following the optimal lag order of one, as determined by our tests, we employ the Generalized Method of Moments (GMMs) to analyze the interactive relationships between the variables [25,29,67,78]. Table 9 shows that the lagged one-period GVAO has a significant positive effect on both ACE and ANP and that ANP also has a significant positive effect on ACE. The growth of the agricultural economy leads to an increase in ACE and ANP, which is consistent with the results of the Granger causality test. Overall, GVAO has a significantly negative effect on reducing agricultural pollution and mitigating carbon emissions, which is related to the traditional agricultural production model in Henan Province. Agricultural production in Henan often uses agricultural resources and tools that have a significant destructive impact on the environment and ecology, which is not conducive to the green and sustainable development of agriculture. It is necessary to accelerate the transformation of agricultural production and promote the green transformation and upgrading of the industry.

Table 9. GMM estimation results of the PVAR model. * and ** denote statistical significance at the 10% and 5% confidence levels, respectively, with the *p*-values reported in parentheses; L1. represents the variable lagged by one period, serving as the explanatory variable; h_ denotes the variable that has undergone forward mean differencing, serving as the dependent variable.

Explanatory Variable	Dependent Variable		
	h_dlnACE	h_dlnANP	h_dlnGVAO
L1.h_dlnACE	−0.0316 (0.779)	0.2199 (0.192)	−0.5274 (0.185)
L1.h_dlnANP	0.1633 ** (0.039)	−0.2709 (0.895)	0.6194 (0.186)
L1.h_dlnGVAO	0.1029 ** (0.029)	0.1160 * (0.086)	0.0030 (0.986)

3.3.5. Impulse Response Analysis

This study, which is based on 200 simulations using the Monte Carlo method, sets the shock period to 10 periods to more comprehensively reflect the impulse response results [25]. On the basis of the results of the Granger causality tests and GMM estimations, this study only conducts impulse response analysis on variables with significant causal relationships. Figure 8 shows that, first, ANP exhibits a significant positive impulse response to ACE in the current period, with ACE reaching its maximum value under a one-standard-deviation shock in the first period, and the positive response gradually decreasing by the second period, returning to zero by the third period. Overall, ANP has a significant positive effect on ACE, which is related to their “same origin and source” characteristics. In the process of reducing agricultural pollution and carbon emissions, both can be achieved as a common goal. Second, the positive impact of GVAO on ACE reaches its maximum in the current period, decreases to zero by the second period, increases to a small peak value, and then gradually decreases, approaching zero by the third period. The positive impact of GVAO on ANP starts from zero, gradually increases, reaches a peak in the first period, then gradually decreases and becomes negative by the second period, showing a slightly negative impact by the third period, and approaches zero by the fourth period. Overall, the impact of agricultural economic development on pollution reduction and carbon emission mitigation in agriculture shows characteristics of volatility and time lag, indicating that agricultural economic growth has a negative effect not only on pollution reduction but also on carbon emission mitigation in agriculture. The two will gradually integrate and evolve into a good cooperative situation during their joint development. As a major province with a large population and a major grain-producing area, Henan cannot neglect the development of the agricultural economy, but the process of reducing pollution and carbon emissions in agriculture cannot stagnate. Only by transforming and upgrading agricultural production and exploring new models of green agricultural development can the dilemma of agricultural economic development be overcome, and green and sustainable agricultural development can be achieved.

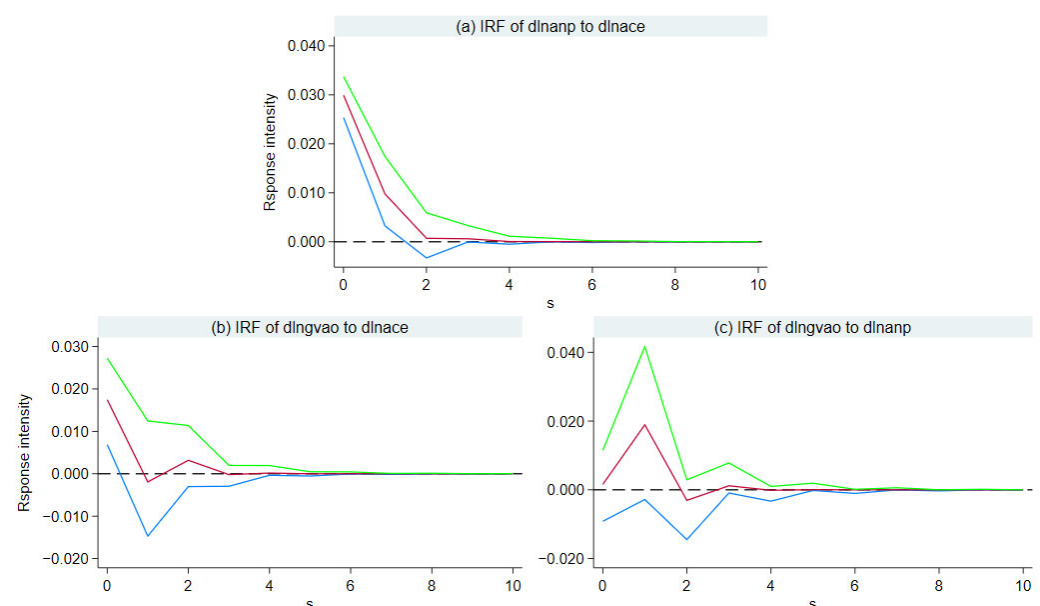


Figure 8. Impulse response results of the PVAR model. The horizontal axis represents the number of lags, the vertical axis represents the response of the variable. The green and blue lines represent the upper and lower bounds of the 95% confidence interval, respectively. The red line indicates the trend of the impulse response of the response variable after giving a standard deviation shock to a particular shock variable.

3.3.6. Variance Decomposition

Variance decomposition is often used to explore the extent to which endogenous variables are affected in different periods, that is, to quantify the contribution rates of different disturbance terms to the changes in endogenous variables [25,46,48], which can further explain the mutual influence relationships between GVAO, ACE, and ANP. According to the results in Table 10, first, the fluctuations of each variable are mainly influenced by themselves. In the 3rd period, the contribution rates of ACE, ANP, and GVAO to their own fluctuations are 93.9%, 46.6%, and 90.5%, respectively. Second, the influence of ANP on ACE stabilizes at 46.6% in the 3rd period, indicating that the impact between the two is long-term and significant and that synergistic control is the correct path to effectively promote the reduction of agricultural pollution and carbon emissions. Finally, the contribution rates of GVAO to agricultural carbon emissions and agricultural non-point source pollution stabilize at 4.3% and 5.1%, respectively, in the 3rd period, indicating long-term and stable impacts and that agricultural economic growth has a significant impact on the reduction of agricultural pollution and carbon emissions in the long term. This may be because the current agricultural production model in Henan Province often uses agricultural machinery and resources that are highly consumed and highly emitted. According to the current development model, the development of the agricultural economy in the future is mostly based on environmental damage. In summary, Henan Province urgently needs to take effective measures to develop a modern green agricultural development model, promote a virtuous cycle of agricultural economic development, and establish a new era development pattern that is tailored to local conditions.

Table 10. Variance decomposition results.

Period	dlnACE			dlnANP			dlnGVAO		
	dlnACE	dlnANP	dlnGVAO	dlnACE	dlnANP	dlnGVAO	dlnACE	dlnANP	dlnGVAO
1	1	0.49	0.044	0	0.51	0	0	0	0.955
2	0.941	0.493	0.043	0.016	0.463	0.05	0.042	0.044	0.908
3	0.939	0.489	0.044	0.018	0.466	0.051	0.043	0.045	0.905
4	0.939	0.489	0.044	0.018	0.466	0.051	0.043	0.045	0.905
5	0.939	0.489	0.044	0.018	0.466	0.051	0.043	0.045	0.905
6	0.939	0.489	0.044	0.018	0.466	0.051	0.043	0.045	0.905
7	0.939	0.489	0.044	0.018	0.466	0.051	0.043	0.045	0.905
8	0.939	0.489	0.044	0.018	0.466	0.051	0.043	0.045	0.905
9	0.939	0.489	0.044	0.018	0.466	0.051	0.043	0.045	0.905
10	0.939	0.489	0.044	0.018	0.466	0.051	0.043	0.045	0.905

4. Discussion

This paper explores the synergistic effects of agricultural carbon emissions (ACEs) and agricultural non-point source pollution (ANP) through a coupling coordination degree model. Building on this foundation, a PVAR model is utilized to analyze the interactive response relationships between pollution reduction, carbon emission reduction, and agricultural economic growth in Henan Province in detail, which holds reference value. First, as a major grain-producing area in the Central Plains of China, Henan Province focuses more on the production scale of agricultural production than other provinces do to ensure the task of grain production, and has a stronger dependence on agricultural chemicals [19]. However, it has a greater degree of coordination in terms of pollution and carbon reduction [12], with significant potential for synergistic emission reduction. Currently, agricultural investment in Henan Province is mostly limited to ensuring production scale and has not achieved the rational use of agricultural investment. Traditional environmental protection methods

have led to prominent agricultural environmental issues. Second, some scholars have reported that “pollution reduction” is more complex than “carbon reduction” when urban pollution and carbon reduction are explored, with diverse driving sources. Urban pollution and carbon reduction should be synergistically promoted with “carbon reduction” at the core [79]. Moreover, the random nature of ANP emissions in terms of agricultural pollution and carbon reduction, which are not easy to detect and control [63], indicates that urban and agricultural pollution and carbon reduction are homogeneous. This also suggests that agricultural pollution and carbon reduction should focus on ACE to maximize synergistic benefits [80]. The study also reveals that ACE has a strong self-reinforcing mechanism and that controlling it can achieve better governance benefits. Finally, the growth of the agricultural economy resulting from agricultural production largely depends on policies and government support. The low price of agricultural products makes the economic level of key agricultural production areas far lower than that of other areas, resulting in the loss of certain regional development rights. To achieve balanced regional development and sustainable agricultural development, a reasonable economic compensation system needs to be established to safeguard the development rights of major grain-producing areas [81]. In addition, due to limitations in the length of the article and the availability of data, while ensuring the timeliness of the research, this study was unable to explore the influencing factors of the interactive responses between agricultural pollution reduction and carbon emission mitigation and agricultural economic growth. These factors include economic factors, policy factors, and climatic factors, among others. Future research will strengthen questionnaire surveys as well as investigations into government policies and market dynamics to continue in-depth studies in this area.

5. Conclusions and Recommendations

5.1. Research Conclusions

As a typical region for agricultural production in China and an internationally renowned producer of agricultural products, Henan Province’s synergy in agricultural pollution reduction and carbon emission mitigation, as well as the interactive response patterns with agricultural economy, serve as a typical reference for agricultural sustainability in other countries with similar climates. Through in-depth research and analysis, this study has reached the following conclusions:

(1) The synergy degree of agricultural carbon emissions (ACEs) and agricultural non-point source pollution (ANP) in different regions of Henan Province showed a trend of evolving towards higher values and a weakening of polarization phenomena during the period from 2010 to 2022. Overall, Henan Province has a high degree of synergy in terms of pollution and carbon reduction, with significant spatial heterogeneity. The western regions have higher degrees of synergy than the eastern regions do, and the degrees of synergy of all regions converge towards higher values, with polarization tendencies diminishing. ACE and ANP in each county and district of Henan Province have a good synergistic effect, with most regions having synergy degrees of level 4 and level 5.

(2) The gross value of agricultural output (GVAO) in Henan Province did not form a significant bidirectional response causal relationship with agricultural pollution reduction and carbon emission mitigation. The development of the agricultural economy has a significant positive effect on ACE and ANP, but the reverse effect is not significant. ANP also has a significant positive effect on ACE, but again, the reverse effect is not significant.

(3) The GVAO of Henan Province has a long-term positive effect on ACE and ANP. In terms of the interactive response relationships between agricultural economic development, agricultural pollution, and carbon reduction, pollution and carbon reduction are significantly negatively affected by agricultural economic development. There is a lack of positive

interactive relationships in the long term, with the growth of the agricultural economy often occurring at the expense of environmental pollution. Therefore, it is necessary to accelerate the transformation and upgrading of the agricultural industry structure and promote the quality and efficiency of resource allocation to achieve a virtuous cycle and sustainable development in agricultural production and the agricultural economy.

(4) Henan Province's ACE, ANP, and GVAO have strong self-reinforcing mechanisms, especially ACE and GVAO. Without intervention, the agricultural industry in Henan Province is growing well, but agricultural carbon emissions are still increasing strongly. This is because agriculture in Henan Province is still traditional and needs to accelerate transformation and upgrading. Combined with location-specific government policies, it is possible to achieve maximum agricultural sustainable development benefits by ensuring economic growth while coordinating pollution reduction and carbon emission reduction.

5.2. Policy Recommendations

Henan Province, as one of China's major grain-producing regions, must focus more on food security and strengthen agricultural environmental protection while seeking its own development to achieve a virtuous cycle of agricultural production and economic growth. To achieve sustainable development, it is necessary to start from multiple aspects, such as policy, regulation, technology, industrial structure, and public participation, on the basis of government support and emphasis and to promote the green and sustainable development of agriculture in Henan Province according to local conditions. The results of this study provide references and lessons for other provinces that are also major grain-producing areas in terms of sustainable agricultural development to ensure China's food security and to keep the Chinese people's food bowl firmly in their own hands.

(1) To fully capitalize on the synergistic effects of agricultural carbon emissions (ACEs) and agricultural non-point source pollution (ANP), proactive pollution reduction and carbon emission strategies should be implemented to transform the pressure of agricultural environmental governance into a new driving force for the sustainable development of the agricultural economy. Currently, China's agricultural pollution reduction and carbon emission strategies are primarily defensive, often in a state of stagnation or efficiency improvement, necessitating a shift towards proactive and innovative strategies to ensure the robust development of new quality agricultural productivity. Given the strong synergistic effects of ACE and ANP and their shared roots and origins, a dual approach to managing carbon emissions and non-point source pollution should be adopted to maximize the effectiveness of agricultural environmental governance. First, precision management of agricultural inputs should be initiated at the source of pollution, leveraging modern technologies such as remote sensing and the internet for precise control. This can be achieved by improving the efficiency of agricultural material use and recycling waste resources, thereby reducing nitrogen and phosphorus pollution from excessive application. Second, differentiated pollution reduction and carbon emission strategies should be formulated according to local conditions. Combining local realities, local governments should take the lead in increasing pollution control efforts in key grain-producing areas. Typical regions should create collaborative governance trading platforms for pollution reduction and carbon emission mitigation, similar to the near-zero carbon emission park pilot projects launched in Sichuan Province. By starting with these pilot zones and gradually expanding to broader areas, a mutually beneficial and multi-party collaborative governance pattern can be formed. This approach can effectively transform the pressure of agricultural environmental governance into a new driving force for sustainable agricultural economic development. Finally, a scientific and fair reward and punishment system should be established to strengthen accountability. From local governments to individual farmers, all

parties should work together to establish an efficient joint prevention and control model, effectively achieving sustainable and coordinated governance of pollution reduction and carbon emissions in agriculture.

(2) The self-reinforcing mechanisms of the agricultural economy should be leveraged, pathways for a virtuous cycle in agricultural development should be explored, and the dual benefits of pollution reduction and carbon emission reduction should be pursued along with economic growth in agriculture. For a long time, the agricultural economy has been thriving and growing. It is essential to fully utilize the self-reinforcing mechanisms of the agricultural economy to achieve diversified, coordinated, and comprehensive development in agricultural production. With the continuous advancement of rural revitalization, regions should integrate rural industries according to local conditions, cultivate and strengthen characteristic industries in rural areas, and allow the agricultural industry chain to continuously expand and extend. The synergy between agricultural production and the agricultural economy should be promoted. On the one hand, it is necessary to ensure a steady increase in grain output, adhere to the national strategic measures of “keeping grain in the land and keeping grain in technology,” and continuously enhance the comprehensive production capacity of grain, creating a new situation for grain production and further consolidating the foundation of food security. It is also important to coordinate and establish a regional production layout, including the optimization of the patterns of major producing areas, balanced areas, and major marketing areas. The government should strengthen policies that benefit and strengthen agriculture, establish a mechanism for compensating for the continuous development of major grain-producing areas, and increase the enthusiasm of farmers for production and local governments for ensuring food security, achieving a top-down, multi-level, integrated agricultural development system. On the other hand, China’s current pollution reduction and carbon emission mitigation efforts still focus primarily on carbon reduction. To further advance these goals, it is necessary to improve carbon regulation policies in agricultural production and establish rational and fair multi-level carbon trading platforms. For example, Shandong Province in China has successfully established a provincial carbon trading platform. By promoting carbon trading markets through local pilots and expanding them in various aspects and fields, resource misallocation in agricultural production can be corrected. This approach can also help achieve a virtuous cycle and sustainable development of agriculture in a coordinated manner.

(3) The upgrading of the agricultural industrial structure should be accelerated, breakthroughs in technological innovation should be promoted, and professional talent to drive the green and sustainable development of agriculture through innovation in pollution reduction and carbon emission reduction should be cultivated. The upgrading of the agricultural industry needs to shift traditional agriculture from high consumption and low efficiency towards green, low-carbon, and mechanized practices. For example, implementing agricultural technology demonstration projects similar to Shandong Province’s “Hydrogen for Every Home” initiative can help cultivate and enhance new agricultural productivity. This approach will contribute to the sustainable development of agriculture. First, the construction of agricultural water conservancy facilities should be accelerated to ensure the basic conditions for agricultural production and improve the disaster prevention and reduction capabilities of farmland. Second, the quantity of agricultural machinery should be increased, and the operational level of agricultural machinery should be improved to ensure the continuous enhancement of its social service capabilities, thereby increasing the labour efficiency and resource utilization rate in agricultural production. Third, the efficiency of agricultural fertilizers should be reduced to improve the comprehensive utilization efficiency of agricultural resources such as livestock manure, crop straw,

and discarded agricultural film, promoting the reuse of waste resources and effectively preventing and controlling “white pollution.” Fourth, cultivating high-quality crop varieties, strengthening resource allocation, ensuring the cultivation of professional talent and innovation-driven development, and guaranteeing the continuous and coordinated development of agricultural science and technology should be the focus to achieve true scientific and technological innovation to prosper and assist agriculture. Fifth, the training and education of farmers engaged in agricultural production should be strengthened, farmers’ conscious awareness of green and environmental protection should be established, and their participation in and understanding of green and low-carbon agriculture should be enhanced. Farmers should be allowed to personally experience the production benefits and efficiency improvements brought by green production, and their enthusiasm and potential to engage in green agricultural production should be stimulated. In summary, the digitalization and intelligentization of agriculture are the core and driving forces for the transformation and upgrading towards modernization. Ensuring the independence and strength of agricultural science and technology to achieve the green and sustainable development of agriculture through pollution reduction and carbon emission reduction is essential.

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