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Quantitative Analysis of Agricultural Carbon Emissions and Absorption from Agricultural Land Resources in Shaanxi Province from 2010 to 2022

Qingqing Liang [1,*] and Fang Yin [2]

[1] School of Earth Science and Resources, Chang'an University, Xi'an 710054, China
[2] Shaanxi Key Laboratory of Land Consolidation, School of Land Engineering, Chang'an University, Xi'an 710054, China; yinf@chd.edu.cn
* Correspondence: lqq2013@chd.edu.cn; Tel.: +86-29-82339083

Abstract: Agriculture is not only a significant source of greenhouse gas emissions but also a vast carbon sink system. Achieving the "dual carbon" goals—carbon peaking and carbon neutrality—is a major strategic objective for China in the near future. This study focuses on agricultural data from 2010 to 2022 in Shaanxi Province. It begins by analyzing the current economic and environmental conditions of the province and its resource endowment. This study then quantitatively assesses carbon absorption, carbon emissions, and the net carbon sink in agriculture over this period. Additionally, a vector autoregression (VAR) model is used to empirically analyze the relationship between agricultural carbon emissions and their influencing factors in Shaanxi Province. Key findings include the following: (1) From 2010 to 2022, the total carbon emissions from agriculture in Shaanxi Province were controlled to around 3 million tons, showing an overall trend of "growth-slow decline" with fluctuations. The carbon emissions from fertilizer application accounted for approximately 60% of the total carbon emissions from agriculture in Shaanxi Province, with a total volume ranging from 1.623 to 2.164 million tons. The total carbon absorption from agriculture in Shaanxi Province showed an increasing trend with fluctuations year by year from 2010 to 2022, with an average annual increase of 1.367%. (2) Fertilizers, pesticides, agricultural films, and agricultural diesel are the primary contributors to agricultural carbon emissions. (3) Results from the Johansen cointegration test reveal a long-term equilibrium relationship between agricultural carbon emissions in Shaanxi Province and influencing factors such as fertilizers and pesticides in the short term. The contributions of fertilizers, pesticides, agricultural films, and agricultural diesel to agricultural carbon emissions are 1.351%, 1.888%, 10.663%, and 0.258%, respectively. (4) The long-term contributions of fertilizers and pesticides to agricultural carbon emissions initially increased before undergoing a gradual attenuation, with average attenuation rates of 1.351% and 1.888%, respectively.

Keywords: Shaanxi Province; agricultural land resources; carbon emissions; spatio-temporal characteristics; decoupling effects; sustainability; economic development

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1. Introduction

Climate change is the most significant global environmental issue of this century. Tackling the challenge of climate change is a complex systemic task, primarily focused on reducing greenhouse gas emissions such as carbon dioxide and adapting to broader climate trends [1,2]. Energy conservation and emission reduction have become shared global responsibilities [3,4]. Transitioning to a low-carbon economy is an unavoidable step for the global economy to move from the high-carbon era to the low-carbon era. This transition is crucial for addressing global warming, ensuring energy security, and protecting resources and the environment [5].

"Low-carbon agriculture", as a subset of the "low-carbon economy" and a strategy for combating climate change, is gaining increasing attention. According to the United

Nations Food and Agriculture Organization, agriculture contributes approximately 21% of global greenhouse gas emissions. In the context of advancing a low-carbon economy, developing low-carbon agriculture is a vital pathway for promoting sustainable agricultural development. Agriculture is an industry that interacts bidirectionally with the natural environment [6,7]. It is directly affected by global climate warming while simultaneously contributing to climate change through the continuous emission of greenhouse gases. Agriculture is both a significant source of greenhouse gas emissions and a major carbon sink [8]. Achieving green and low-carbon development in agriculture is crucial for advancing the goals of carbon peaking and carbon neutrality. Reducing agricultural emissions and enhancing carbon sequestration are vital strategies with substantial potential [9]. Therefore, researching and developing low-carbon agriculture has significant theoretical and practical importance. It is an essential choice for mitigating global climate warming, addressing the energy crisis, and solving environmental issues associated with traditional agricultural practices [10,11]. Developing low-carbon agriculture is also a requirement for achieving sustainable agricultural development. It has been demonstrated that developing low-carbon agriculture is the most effective strategy for addressing environmental pollution caused by chemical-based farming, reducing energy consumption, and lowering greenhouse gas emissions. In low-carbon agricultural practices, only biological organic fertilizers and plant protectants are used, eliminating the need for chemical fertilizers and pesticides. These practices alone can reduce current energy consumption by more than 80%. For instance, in nitrogen fertilizer production alone, it is possible to save between 100 and 150 million tons of standard coal and 100 billion kilowatt-hours of electricity. When including the savings from phosphorus fertilizers, potassium fertilizers, and pesticides, the total conservation of energy resources and electricity would be even greater.

Existing data show that greenhouse gas emissions in the agricultural production sector have been reduced by 854 million tons of carbon dioxide equivalent, accounting for 23.4% of China's total emissions.

In summary, low-carbon agriculture represents a complex agricultural economic model. It is a strategically designed system that requires a multi-faceted approach to achieve effective results.

As a major agricultural country, China's efforts in reducing agricultural emissions and enhancing carbon sequestration will be crucial for achieving its carbon peaking and carbon neutrality goals. The success of these efforts will significantly impact global greenhouse gas reduction targets. China aims to peak its carbon emissions before 2030 and achieve carbon neutrality by 2060. Building a socialist ecological civilization with carbon reduction as a key component requires contributions from all industries. Agriculture, being a significant source of greenhouse gas emissions [11,12], plays a critical role in these goals. Therefore, emission reduction and carbon sequestration in the agricultural and rural sectors are essential components of China's carbon peak and carbon neutrality targets. This area is also highly promising [13–15]. Many studies focus on specific regions or countries, such as China, Europe, and the United States. Within China, research often targets provinces like Shaanxi, Jiangsu, and regions with significant agricultural activity [16]. Methods of quantitative analysis include the following: (1) Life Cycle Assessment (LCA), which evaluates the environmental impacts of agricultural processes from production to disposal; (2) Carbon Footprint Analysis, which measures the total greenhouse gas emissions caused by agricultural activities; and (3) Input–Output Analysis, which assesses the relationship between agricultural inputs (fertilizers, pesticides) and outputs (crop yield, emissions).

A review of the domestic literature reveals that current research by Chinese scholars on agricultural carbon emissions primarily focuses on the national level and provinces and cities in the eastern and southern regions. However, there is a notable scarcity of studies on the western regions, particularly Shaanxi Province. Shaanxi Province is a key agricultural region in China and is also ecologically fragile. The low-carbon development of agriculture is a crucial strategic choice for Shaanxi to mitigate resource and environmental constraints and achieve the nation's "dual carbon" goals. Over the years, Shaanxi Province has prioritized food security as a fundamental task. To ensure food security, the province has implemented various measures, including strengthening policy support, enhancing disaster prevention and reduction, stabilizing arable land, and improving agricultural technology [17]. It is crucial to promote the high-quality development of ecological protection and green, low-carbon agriculture in Shaanxi Province [18–22]. By advancing these initiatives, Shaanxi Province can make significant contributions to ecological protection and the development of green, low-carbon agriculture.

Therefore, accurately assessing the carbon emissions and carbon sequestration potential of agricultural land resources in Shaanxi Province is beneficial for research on carbon neutrality and for regional ecological conservation and high-quality development [23]. This study aims to empirically analyze the relationship between agricultural carbon emissions and influencing factors in Shaanxi Province using the VAR model, based on scientific calculations of carbon emissions from six types of carbon sources in Shaanxi Province from 2010 to 2022 [22]. This research could provide scientific basis and policy recommendations for achieving agricultural carbon reduction goals in Shaanxi Province. It will support the adjustment of agricultural development methods and industrial structure, ultimately contributing to the realization of Shaanxi Province's agricultural carbon reduction targets.

2. Materials and Data

2.1. Study Area

Shaanxi Province is located between latitudes 31°42′ N and 39°35′ N and longitudes 105°29′ E and 111°15′ E. It serves as a transitional zone between China's warm southeastern region and the arid northwestern region, characterized by a continental climate. The province features a diverse terrain, with mountains and rivers crisscrossing the landscape. In the south, there are the Daba Mountains; in the central region, the Qinling Mountains; and in the north, the Baiyu, Liang, and Lao Mountains. The Qinling Mountains serve as a natural boundary, with the area to the north belonging to the Yellow River Basin and the area to the south belonging to the Yangtze River Basin. Due to the complex terrain, there are significant climate differences and ecological conditions between the northern and southern regions, resulting in the formation of distinct agricultural zones.

Shaanxi has a complex terrain and diverse land types. The Qinba mountainous region is characterized by its numerous mountains and limited arable land, often described as "eight parts mountain, one part water, and one part farmland". The Han River valley predominantly consists of low mountain hills and basins, making it a treasure trove of subtropical resources for the entire province. The renowned Hanzhong Basin, an alluvial plain of the Han River, has abundant water resources and is a prolific producer of rice, earning it the nickname "Little Jiangnan". The Guanzhong Plain is an alluvial plain formed by river deposition and less accumulation. The Wei River runs through it, creating a flat terrain with fertile soil, making it the primary base for grain and cotton production in Shaanxi.

From 1978 to 2022, the grain-sown area in Shaanxi Province decreased from 4.488 million hectares to 3000 hectares. Efforts have been focused on ensuring the planting areas for the three main grains: wheat, corn, and rice. The province faces a shortage of reserve arable land, with limited land available for cultivation. Additionally, the growing population and the continuous reduction of arable land, coupled with frequent natural disasters such as droughts, floods, hail, and windstorms, have become major constraints on agricultural development.

2.2. Measurement Items and Methods

2.2.1. Agricultural Carbon Emission Indicators and Calculations

(1) Sources and Estimation Methods of Agricultural Carbon Emissions

The most common method for estimating carbon emissions is based on agricultural land use. Agricultural carbon emissions primarily stem from six aspects of agricultural production [24,25]: (1) fertilizer application; (2) pesticide use; (3) agricultural film usage; (4) agricultural machinery operations; (5) land tillage practices; and (6) irrigated agriculture.

The carbon emission estimation formula is as follows [22,23,26]:

$$E = \sum E_i = \sum T_i \times \delta_i$$

where E represents the total agricultural carbon emissions, E_i represents the carbon emissions from various carbon sources, T_i represents the quantity of each carbon emission source, and, as shown in Table 1 [22,23,27], δ_i represents the carbon emission coefficient of each carbon emission source.

Table 1. Carbon emission coefficients of agricultural energy and reference sources.

Carbon Sources	Carbon Emission Coefficients	Unit	Reference Sources
Fertilizer	0.896	kg/kg	"West" and "Oak Ridge National Laboratory, United States"
Pesticides	4.934	kg/kg	Oak Ridge National Laboratory, United States
Agricultural plastic film	5.183	kg/kg	Institute of Resource, Ecosystem, and Environment of Nanjing Agricultural University (IREEA)
Diesel	0.593	kg/kg	Intergovernmental Panel on Climate Change (IPCC)
Tillage	3.126	kg/hm^2	College of Biological Sciences and Biotechnology, China Agricultural University
Agricultural irrigation	20.476	kg/hm^2	Dubey

Note: The carbon emission factor for agricultural irrigation is 25 kg/hm^2. However, since only the fossil fuel consumption from thermal power generation contributes to indirect carbon emissions, this factor should be adjusted by the thermal power coefficient, which represents the proportion of thermal power in China's total electricity generation. Based on statistical data from the China Yearbook (2000–2018), the average thermal power coefficient was calculated to be 0.819. As a result, the adjusted carbon emission factor for agricultural irrigation is 20.476 kg/hm^2.

The main data sources are from the "Shaanxi Statistical Yearbook" and the "China Rural Statistical Yearbook" from 2010 to 2022.

(2) Measurement of Carbon Emission Scale, Intensity, and Structure

Carbon sources in the agricultural system include CO_2 emissions from energy consumption, soil respiration, livestock breeding, and land use changes in agricultural production. Energy consumption is the most significant source of CO_2 emissions. Therefore, in this paper, we use the total amount and scale of carbon emissions from agricultural energy consumption to represent the greenhouse gas emissions in the development of low-carbon agriculture in Shaanxi Province.

(3) Per Capita Agricultural Carbon Emissions

Per capita agricultural carbon emissions = Total agricultural carbon emissions/Total rural population.

(4) Carbon Emission Intensity per Unit Arable Land Area

The carbon emission intensity per unit arable land area is calculated as the total agricultural carbon emissions divided by the arable land area. Here, the arable land area does not consider the actual production capacity of arable land resources.

(5) Agricultural Carbon Emission Intensity

Agricultural carbon emission intensity is an important indicator for measuring the quality and efficiency of agricultural economic growth. Agricultural carbon emission intensity = Agricultural carbon emissions/Agricultural Gross Domestic Product (GDP), reflecting the amount of carbon emissions produced per unit of agricultural GDP output.

2.2.2. Sources and Calculation Methods of Agricultural Carbon Absorption

Agricultural carbon sink refers to the process of absorbing carbon dioxide from the atmosphere through agricultural planting, vegetation restoration, and other measures, thereby reducing greenhouse gas concentrations [27]. Under the "dual carbon" goal, continuously increasing the net carbon sink capacity of agriculture will become an important objective for agricultural development, thereby accelerating the transformation of traditional agriculture into green, low-carbon agriculture [28,29].

Carbon absorption in arable land is mainly based on crop yield data from cultivated land, combined with the types of crops planted on arable land in China (grain crops, cash crops, and fruits and vegetables), economic coefficients, and carbon absorption rates determined in practice in China. For specific estimation methods, please refer to other relevant literature [30].

2.2.3. Current Situation of Net Carbon Sink in Agriculture

The net carbon sink represents the difference between the total carbon sink and the total carbon source, calculated as total carbon absorption minus total carbon emissions [31,32]. A higher positive value of the net carbon sink indicates a stronger ecological function of agriculture, highlighting its role as a significant carbon sink system. Increasing the net carbon sink in agriculture will be a key objective for agricultural development, driving the transition from traditional practices to green, low-carbon agriculture [33].

3. Results

3.1. Agricultural Carbon Emissions

3.1.1. Total Agricultural Carbon Emissions

Based on the carbon emission formula and relevant data, this paper calculates the total agricultural carbon emissions in Shaanxi Province from 2010 to 2022. The fluctuation trends are described below.

Based on Table 2 and Figure 1, it can be observed that from 2010 to 2022, the total agricultural carbon emissions in Shaanxi Province remained around 3 million tons, following a fluctuating pattern of "growth followed by slow decline". In 2010, carbon emissions totaled 2.738 million tons, rising to 3.369 million tons in 2013. Emissions then decreased slightly to 3.286 million tons in 2015, increased again to 3.338 million tons in 2017, and ultimately declined to 3.042 million tons in 2022.

Table 2. Total agricultural carbon emissions in Shaanxi Province from 2010 to 2022 (10,000 tons).

Year	Fertilizer	Pesticides	Agricultural Film	Agricultural Diesel	Effective Irrigated Area	Tillage	Total
2010	162.372	6.488	19.068	44.716	40.429	0.655	273.728
2011	176.254	6.123	19.638	47.398	40.166	0.644	290.224
2012	185.658	8.664	20.242	48.696	39.835	0.645	303.739
2013	214.765	6.413	21.159	53.954	39.925	0.632	336.848
2014	216.467	6.312	21.486	54.060	37.822	0.620	336.767
2015	206.167	6.460	22.309	54.718	38.340	0.618	328.613
2016	207.690	6.508	22.645	54.985	38.662	0.644	331.134
2017	208.764	6.580	22.768	55.969	39.119	0.618	333.818
2018	207.869	6.192	22.868	54.872	39.485	0.616	331.901
2019	181.359	6.039	23.196	55.595	40.174	0.614	306.978
2020	180.822	5.897	23.167	55.358	39.856	0.615	305.714
2021	180.822	5.897	23.167	55.358	40.086	0.659	305.989
2022	179.747	5.745	22.944	54.469	40.622	0.678	304.205

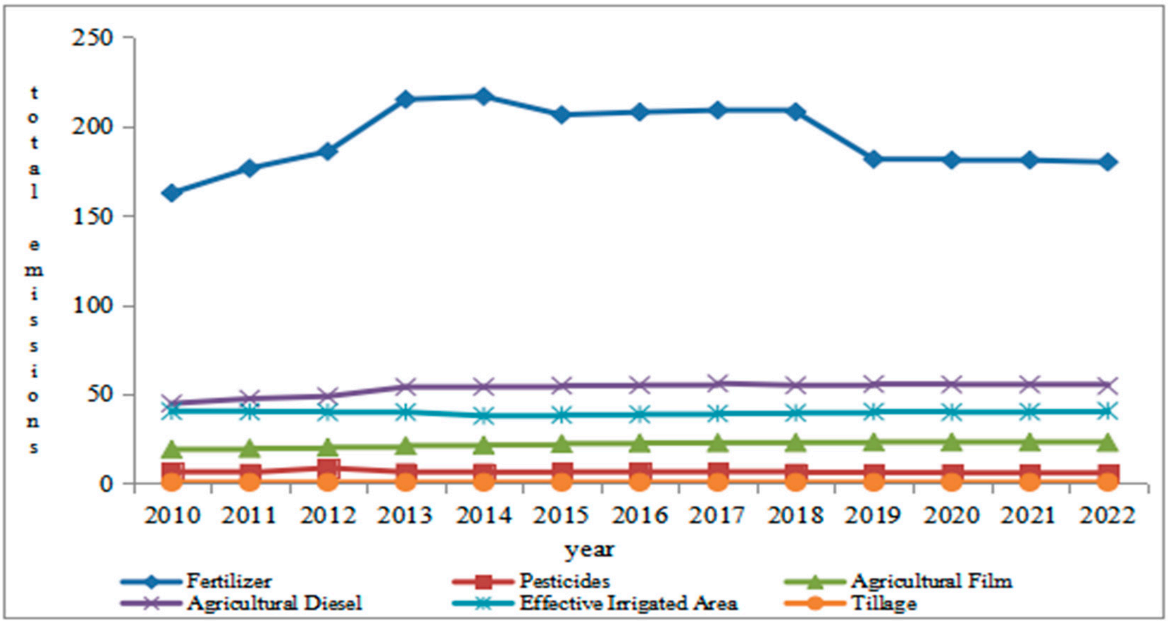

Figure 1. Total agricultural carbon emissions in Shaanxi Province from 2010 to 2022.

Fertilizer application accounts for approximately 60% of total agricultural carbon emissions in Shaanxi Province, with emissions ranging from 1.623 to 2.164 million tons. The highest value was 2.165 million tons in 2014, while the lowest was 1.624 million tons in 2010. Following fertilizers, agricultural diesel and effective irrigated areas contributed around 500,000 tons and 400,000 tons of carbon emissions, respectively.

3.1.2. Per Capita Agricultural Carbon Emissions

As shown in Figure 2, the data indicate that the per capita agricultural carbon emissions in Shaanxi Province have been increasing steadily, with a relatively low growth rate and increment. It increased from 0.135 tons per person in 2010 to 0.214 tons per person in 2022. The primary reason for this increase is the sharp decline in the rural population of Shaanxi since 2010, with a particularly significant drop in 2016, marking the start of a rapid decline. In 2010, the rural population was 20.28 million, falling to under 17 million by 2016 and plummeting to 14.24 million by 2022. This steep decline in the rural population has contributed to the rise in per capita agricultural carbon emissions in Shaanxi Province.

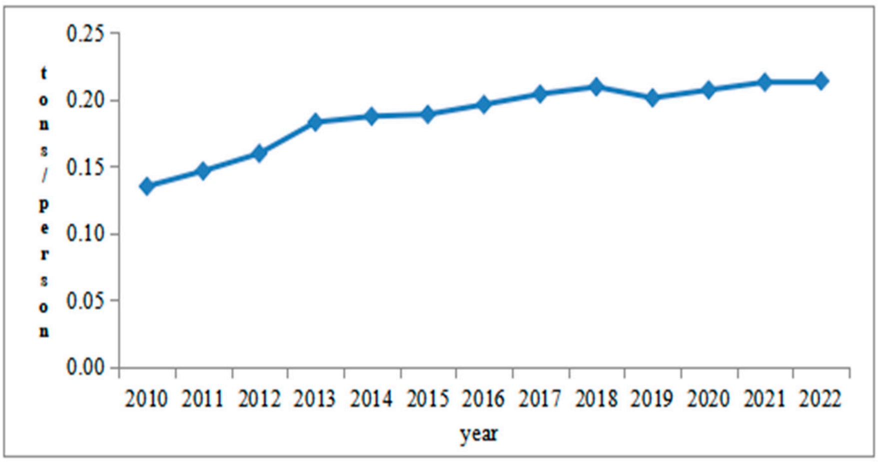

Figure 2. Agricultural carbon emissions per capita (tons/person) in Shaanxi Province, 2010–2022.

3.1.3. Carbon Emission Intensity Per Unit Arable Land Area

The data show that from 2010 to 2022, the carbon emission intensity per unit arable land area in Shaanxi Province remained generally stable, with a slow upward trend. It increased from 0.957 tons per hectare in 2010 to 1.037 tons per hectare in 2022.

3.1.4. Agricultural Carbon Emission Structure

According to data from Table 3, from 2010 to 2022, fertilizer remained the largest contributor to agricultural carbon emissions in Shaanxi Province, accounting for an average of 61.250% of total emissions. However, its overall proportion has been declining, decreasing to 59.087% in 2022.

Table 3. Agricultural carbon emission structure (%) in Shaanxi Province from 2010 to 2022.

Year	Fertilizer	Pesticides	Agricultural Film	Agricultural Diesel	Effective Irrigated Area	Tillage
2010	59.319	2.370	6.966	16.336	14.770	0.239
2011	60.730	2.110	6.767	16.332	13.840	0.222
2012	61.124	2.853	6.664	16.032	13.115	0.212
2013	63.757	1.904	6.281	16.017	11.853	0.188
2014	64.278	1.874	6.380	16.053	11.231	0.184
2015	62.739	1.966	6.789	16.651	11.667	0.188
2016	62.721	1.965	6.839	16.605	11.676	0.194
2017	62.538	1.971	6.821	16.766	11.719	0.185
2018	62.630	1.866	6.890	16.533	11.896	0.185
2019	59.079	1.967	7.556	18.111	13.087	0.200
2020	59.147	1.929	7.578	18.108	13.037	0.201
2021	59.094	1.927	7.571	18.092	13.100	0.215
2022	59.087	1.888	7.542	17.905	13.353	0.223
mean	61.250	2.045	6.973	16.888	12.642	0.203

As shown in Figure 3, the next highest proportions are agricultural diesel and effective irrigated area, with average proportions of 16.888% and 12.642%, respectively. The proportion of agricultural diesel shows a trend of fluctuating growth, mainly due to the continuous advancement of agricultural mechanization and the increasing consumption of diesel fuel as a result of the increasing power demand for agricultural machinery.

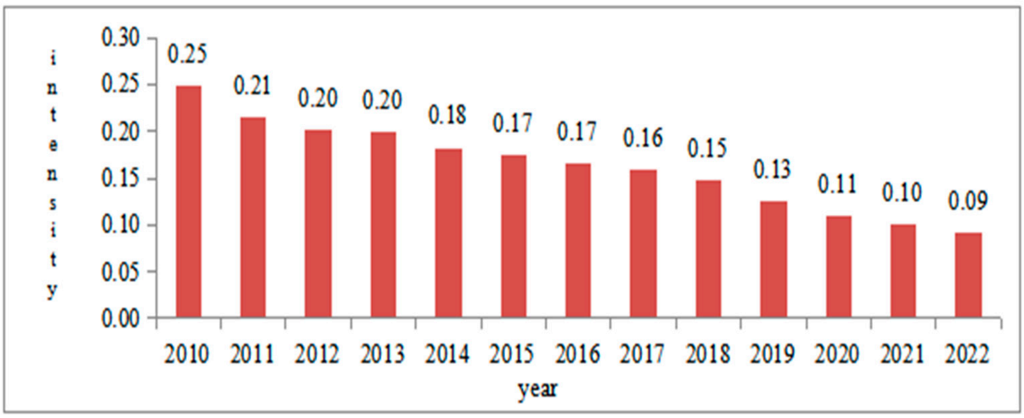

Figure 3. Trend chart of agricultural carbon emission intensity in Shaanxi Province from 2010 to 2022.

3.1.5. Agricultural Carbon Emission Intensity

In 2010, total agricultural carbon emissions in Shaanxi Province were 2.737 million tons, with agricultural GDP at CNY 110.071 billion, resulting in an agricultural carbon emission intensity of 0.25 tons per CNY 10,000. By 2022, total agricultural carbon emissions had risen to 3.042 million tons, while agricultural GDP had increased to CNY 331.0428 billion, reducing the carbon emission intensity to 0.09 tons per CNY 10,000. From 2010 to 2022, agricultural carbon emission intensity in Shaanxi Province decreased annually, from 0.25 tons per CNY 10,000 in 2010 to 0.09 tons per CNY 10,000 in 2022. This trend indicates continuous improvements in the quality and efficiency of agricultural economic growth in Shaanxi Province, with a steady reduction in carbon emissions per unit of output.

3.2. Agricultural Carbon Absorption

3.2.1. Scale of Agricultural Carbon Absorption

Based on the yield data of some grain crops, cash crops, and fruits and vegetables in Shaanxi Province from 2010 to 2022, we can determine the total carbon absorption and carbon absorption of different crops used in cultivated land in Shaanxi Province during this period (Table 4).

Table 4. Total agricultural carbon sink in Shaanxi Province during 2010–2022 (10,000 tons).

Year	Rice	Wheat	Corn	Soybeans	Cotton	Rapeseed	Peanut	Tobacco	Vegetables	Fruits	Total
2010	86.409	477.471	666.489	59.366	23.670	63.738	9.952	4.721	61.318	307.302	1760.436
2011	88.940	477.719	689.657	57.562	21.330	65.412	10.570	5.146	63.602	327.730	1807.669
2012	90.724	505.465	709.945	56.644	19.980	66.798	11.323	5.883	66.906	350.426	1884.094
2013	94.527	441.332	726.269	40.869	15.975	65.754	11.124	5.277	70.371	359.303	1830.801
2014	90.022	467.757	667.894	30.582	10.935	67.626	12.140	4.296	73.713	371.747	1796.710
2015	90.416	513.294	668.465	20.893	9.315	70.236	11.857	4.140	76.427	386.944	1851.987
2016	90.528	489.152	749.138	32.179	7.605	67.482	12.862	3.698	78.960	403.104	1934.708
2017	90.641	493.077	648.979	31.646	5.400	68.994	13.040	3.126	82.136	427.062	1864.100
2018	90.776	486.926	688.202	31.672	4.455	66.618	13.186	2.749	85.663	402.690	1872.936
2019	90.416	463.510	717.781	30.957	3.420	67.068	12.872	4.320	89.876	445.723	1925.943
2020	90.586	501.374	730.240	31.286	0.315	67.518	12.966	4.328	92.731	464.922	1996.266
2021	81.956	515.146	708.490	33.221	0.135	70.146	11.815	4.165	95.344	487.662	2008.080
2022	82.496	521.431	726.294	40.421	0.090	64.656	12.234	4.394	98.628	512.607	2063.249

Based on Table 4 and Figure 4, from 2010 to 2022, the total carbon absorption in agriculture in Shaanxi Province showed an increasing trend with fluctuations, with an average annual increase of 1.367%. The peak of total agricultural carbon absorption in Shaanxi Province occurred in 2022, reaching 20.632 million tons. This increase is largely attributed to Shaanxi Province's steadfast implementation of General Secretary Xi Jinping's directives on farmland protection and food security. The province has enforced stringent farmland protection measures, effectively curbing the "non-agriculturalization" of farmland and preventing its conversion to non-grain uses. The government has issued various documents, including the "Implementation Plan for the Comprehensive Establishment of the Farmland Protection System in Shaanxi Province," which emphasizes prioritizing the protection of cultivated land and permanent basic farmland and upholding the red line for farmland protection and food security. These efforts have reinforced the significance of food security and farmland protection and fostered a supportive social environment for widespread participation in these initiatives.

3.2.2. Structure of Carbon Absorption in Arable Land

The proportion of agricultural carbon absorption structure in Shaanxi Province from 2010 to 2022 is detailed in Table 5 and illustrated in Figure 5. In terms of the structure of carbon absorption in arable land, corn and wheat in grain crops as well as rapeseed and fruits in cash crops are the primary contributors to carbon absorption in Shaanxi Province.

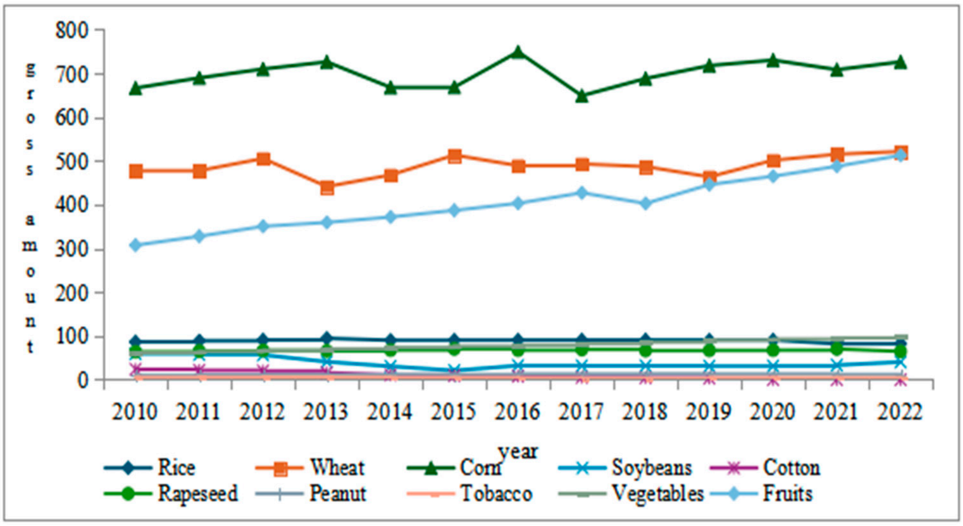

Figure 4. Structure and total amount of agricultural carbon sink in Shaanxi Province during 2010–2022.

Table 5. Proportion of agricultural carbon absorption structure in Shaanxi Province during 2010–2022 (%).

Year	Rice	Wheat	Corn	Soybeans	Cotton	Rapeseed	Peanut	Tobacco	Vegetables	Fruits
2010	4.908	27.122	37.859	3.372	1.345	3.621	0.565	0.268	3.483	17.456
2011	4.920	26.427	38.152	3.184	1.180	3.619	0.585	0.285	3.518	18.130
2012	4.815	26.828	37.681	3.006	1.060	3.545	0.601	0.312	3.551	18.599
2013	5.163	24.106	39.669	2.232	0.873	3.592	0.608	0.288	3.844	19.625
2014	5.010	26.034	37.173	1.702	0.609	3.764	0.676	0.239	4.103	20.690
2015	4.882	27.716	36.094	1.128	0.503	3.792	0.640	0.224	4.127	20.893
2016	4.679	25.283	38.721	1.663	0.393	3.488	0.665	0.191	4.081	20.835
2017	4.862	26.451	34.815	1.698	0.290	3.701	0.700	0.168	4.406	22.910
2018	4.847	25.998	36.745	1.691	0.238	3.557	0.704	0.147	4.574	21.500
2019	4.695	24.067	37.269	1.607	0.178	3.482	0.668	0.224	4.667	23.143
2020	4.538	25.116	36.580	1.567	0.016	3.382	0.650	0.217	4.645	23.290
2021	4.081	25.654	35.282	1.654	0.007	3.493	0.588	0.207	4.748	24.285
2022	3.998	25.272	35.201	1.959	0.004	3.134	0.593	0.213	4.780	24.845
Mean	4.723	25.852	37.019	2.036	0.515	3.552	0.634	0.229	4.194	21.246

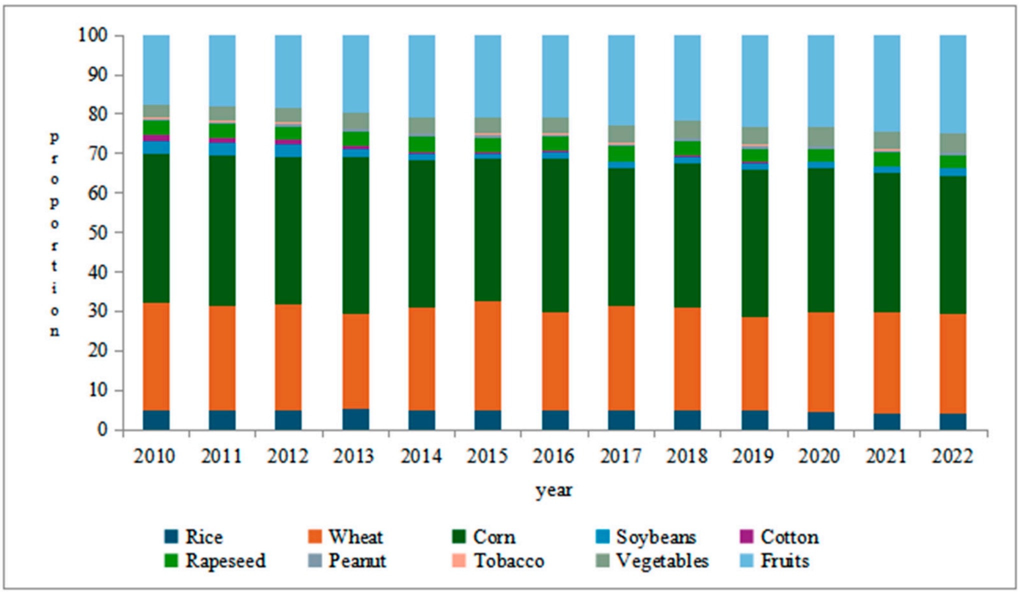

Figure 5. Carbon absorption structure of cultivated land in Shaanxi Province during 2010–2022.

1. In grain crops, although maize, wheat, and rice account for a large proportion of carbon absorption, their share of total carbon absorption is decreasing. The proportion of carbon absorption for maize, wheat, and rice decreased from 37.859%, 27.122%, and 4.908% in 2010 to 35.201%, 25.272%, and 3.998%, respectively. This decline is primarily due to reductions in the sown areas of these crops. Two main factors contribute to this decrease: First, sustained low prices in the grain market have led to relatively lower comparative benefits of growing grain crops compared to economic crops like vegetables and cotton, resulting in diminished enthusiasm among farmers for grain cultivation. Second, there is a trend toward transforming the planting structure to focus on high-quality and high-efficiency crops, with the sown area of economic crops increasing annually.
2. Among cash crops, cotton has experienced the most significant decrease in its proportion of carbon absorption, while the proportions for rapeseed, peanuts, and tobacco have remained relatively stable.
3. The proportion of carbon absorption contributed by fruits and vegetables is increasing, with a more pronounced growth trend. The proportion of fruits increased from 17.456% in 2010 to 24.845% in 2022. The proportion of vegetables increased from 3.483% in 2010 to 4.780% in 2022. Since the implementation of the "Vegetable Basket Project" in the 1980s, the demand for vegetables has continued to increase. At the same time, vegetable production yields high economic returns. With the continuous expansion of vegetable planting areas in China, vegetables have become the second-largest category of crops in agriculture, following only grains. The vegetable industry has become a pillar industry driving the development of agriculture and rural economy in China.

3.3. Agricultural Net Carbon Sinks

3.3.1. Overall Situation of Net Carbon Sink

As shown in Figure 6, total agricultural carbon emissions in Shaanxi Province increased from 14.867 million tons in 2010 to 17.590 million tons by 2022. China has set ambitious targets to peak carbon emissions before 2030 and achieve carbon neutrality by 2060. To meet these goals, China plans to implement comprehensive measures to reduce carbon emissions, establish clear peak targets, develop road maps and action plans for key regions and industries, and enhance supervision and assessment. This approach aims to fundamentally transform the economic, industrial, and energy structures at their core, ensuring the achievement of peak carbon emissions before 2030. Accelerating the development of low-carbon agriculture will be crucial to achieving these "dual carbon" objectives.

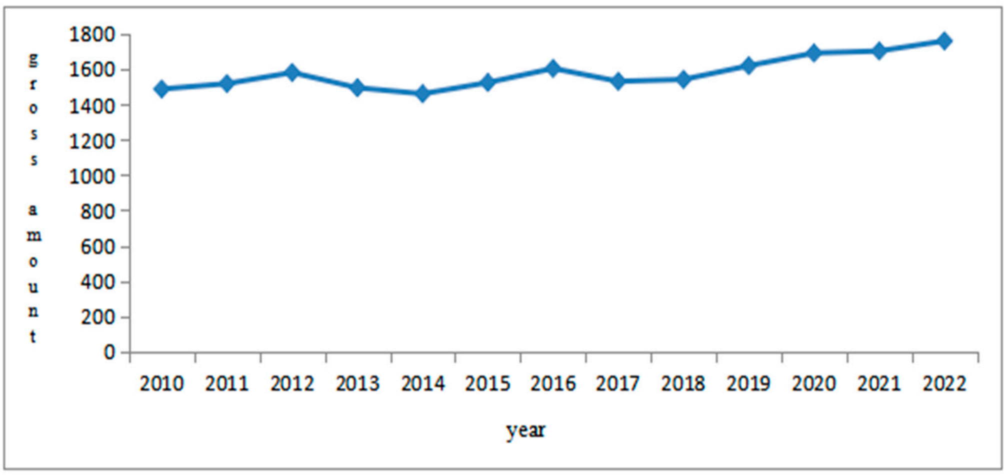

Figure 6. Trend of agricultural net carbon sink in Shaanxi Province from 2010 to 2022.

The overall net carbon sink in agriculture in Shaanxi Province reflects the balance between carbon absorption and carbon emissions across various agricultural activities. This analysis provides insights into the ecological performance of agriculture in the region and its contribution to mitigating climate change [31,33].

To conduct this analysis, data on carbon absorption and carbon emissions from key agricultural activities—including crop cultivation, livestock rearing, and land management practices—are collected and quantified. The net carbon sink value is determined by subtracting the total carbon emissions from the total carbon absorbed.

Understanding the overall net carbon sink in agriculture in Shaanxi Province is crucial for evaluating the environmental sustainability of agricultural practices and informing policy decisions aimed at promoting carbon-neutral or carbon-negative farming methods.

3.3.2. Analysis of Factors Affecting the Scale of Agricultural Net Carbon Sink

Factors influencing the net agricultural carbon sink in Shaanxi Province include carbon emissions and carbon absorption. Key contributors to carbon emissions from agricultural land resources are fertilizers, agricultural diesel, and the extent of effective irrigation areas. Conversely, the main factors affecting carbon absorption are the cultivated areas and yields of grain crops, economic crops, and fruits and vegetables. Additionally, the intensity of the agricultural net carbon sink and the scale of the rural population play a crucial role in shaping the net carbon sink. To enhance the agricultural net carbon sink, it is essential to adopt farming practices such as no-till, ridge tillage, reduced tillage, mulching, and straw return to the field, in addition to reducing carbon sources.

4. VAR Analysis

Currently, there are three common methods for studying the influencing factors of agricultural carbon emissions: the IPAT equation (Impact, Population, Affluence, and Technology), the Kaya identity, and the Logarithmic Mean Divisia Index (LMDI) method [28,29]. Other approaches include the Driving-force, Pressure, Status, Impact, and Risk (DPSIR) model and resource utilization regression models. This paper employs the weighted least squares method and vector autoregressive (VAR) analysis to develop an empirical model examining the relationship between agricultural carbon emissions and influencing factors in Shaanxi Province. Additionally, pulse response functions and variance decomposition techniques are used to analyze the magnitude and temporal variation patterns of the coefficients.

4.1. Model Construction

$$Y_1 = f(X_1, X_2, X_3, X_4 \ldots X_{10}) Y_1 = f(X_1, X_2, X_3, X_4 \ldots X_{10}) \quad (1)$$

To effectively address heteroscedasticity, we employ the double-logarithmic form of the Cobb–Douglas (C-D) function model. The model is established as follows [30]:

$$\begin{aligned} \ln Y_1 = C + \beta_1 \ln X_1 + \beta_2 \ln X_2 + \beta_3 \ln X_3 + \beta_4 \ln X_4 + \beta_5 \ln X_5 + \beta_6 \ln X_6 \\ + \beta_7 \ln X_7 + \beta_8 \ln X_8 + \beta_9 \ln X_9 + \beta_{10} \ln X_{10} + \mu \end{aligned} \quad (2)$$

In Equation (2), u represents the random error term, Y_1 denotes agricultural carbon emissions, and $X_1 X_2 \ldots X_{10}$ represent the quantities of fertilizer application, compound fertilizer application, nitrogen fertilizer application, phosphate fertilizer application, potassium fertilizer application, pesticide usage, agricultural plastic film usage, agricultural diesel usage, effective irrigation area, and plowing area, respectively. (Unit: ten thousand tons/thousand hectares.)

4.2. Results Analysis

4.2.1. Analysis of Weighted Least Squares (WLS) Regression

The regression analysis yields the following regression equation:

$$\ln Y_1 = 1.3358 + 0.7166 \ln X_1 + 0.0907 \ln X_6 + 0.0985 \ln X_7 + 0.1458 \ln X_8$$

$$\ln Y_1 = 1.3358 + 0.7166 \ln X_1 + 0.0907 \ln X_6 + 0.0985 \ln X_7 + 0.1458 \ln X_8$$

$$(0.138)\ (0.060)\ (0.005)\ (0.005)\ (0.005)$$
$$\mathrm{t} = (9.664)\ (12.033)\ (16.606)\ (20.743)\ (28.119)$$

$\ln X_2$, $\ln X_3$, $\ln X_4$, $\ln X_5$, $\ln X_9$, $\ln X_{10}$ do not pass the 5% significance level test, indicating that the influence of these factors on the dependent variable is relatively small. Therefore, these variables are excluded. $\ln X_1$, $\ln X_6$, $\ln X_7$, $\ln X_8$ passed the 5% significance level test, indicating that the impact of fertilizer application, pesticide use, agricultural plastic film usage, and diesel use on agricultural carbon emissions is the most significant.

The statistical results from the model indicate that, holding other variables constant, an increase of 10,000 tons in fertilizer application would result in an increase of 0.717 million tons in agricultural carbon emissions. Similarly, for every additional 10,000 tons of pesticide use, agricultural carbon emissions would rise by 0.0907 million tons, assuming other variables remain constant. Additionally, an increase of 10,000 tons in agricultural plastic film usage would lead to a 0.098-million-ton increase in agricultural carbon emissions, with other variables held constant.

4.2.2. Vector Autoregression (VAR) Estimation

Based on five selection criteria, the optimal lag order was determined to be one. To perform a cointegration test on the relevant variables, the optimal lag order for the cointegration testing was established by first determining the optimal lag order of a VAR model. According to the computational results and considering five information criteria—Likelihood Ratio (LR), Final Prediction Error (FPE), Akaike Information Criterion (AIC), Schwarz Information Criterion (SC), and Hannan–Quinn Criterion (HQ)—the optimal lag order for the VAR model is found to be two. Therefore, a lag order of one should be selected for the cointegration testing.

The Granger causality joint test produced p values below 5%, indicating that agricultural carbon emissions, along with the four influencing factors—fertilizer, pesticide, agricultural plastic film, and diesel fuel—are all endogenous variables. The results of the final VAR model are presented in Table 6. As shown in Table 6, the coefficient of determination (R-squared) for each equation exceeds 95%, demonstrating a strong fit of the equations to the explained variables.

Table 6. Results of vector autoregressive estimation of agricultural carbon emissions.

	LNY1	**LNX1**	**LNX6**	**LNX7**	**LNX8**
LNY1(−1)	−5.529 −11.763 [−0.470]	−6.478 −8.096 [−0.800]	−21.340 −12.732 [−1.676]	7.691 −27.629 [0.278]	−3.678 −33.094 [−0.111]
LNY1(−2)	6.298 −8.166 [0.771]	10.502 −5.620 [1.869]	12.834 −8.839 [1.452]	−16.176 −19.181 [−0.843]	−3.743 −22.975 [−0.163]
LNX1(−1)	4.699 −7.815 [0.601]	5.277 −5.379 [0.981]	15.789 −8.459 [1.867]	−3.594 −18.356 [−0.196]	3.144 −21.987 [0.143]
LNX1(−2)	−4.444 −5.356 [−0.830]	−7.370 −3.686 [−1.999]	−7.989 −5.796 [−1.378]	9.297 −12.579 [0.739]	3.167 −15.067 [0.210]

Table 6. *Cont.*

	LNY1	LNX1	LNX6	LNX7	LNX8
LNX6(−1)	0.581 −1.073 [0.542]	0.795 −0.738 [1.077]	2.047 −1.161 [1.762]	−0.575 −2.520 [−0.228]	−0.243 −3.019 [−0.080]
LNX6(−2)	−0.733 −0.773 [−0.949]	−1.024 −0.532 [−1.924]	−1.734 −0.837 [−2.073]	1.503 −1.816 [0.828]	−0.166 −2.175 [−0.076]
LNX7(−1)	0.695 −1.153 [0.603]	0.763 −0.793 [0.962]	1.786 −1.248 [1.431]	−0.512 −2.707 [−0.189]	0.877 −3.243 [0.271]
LNX7(−2)	−0.559 −0.816 [−0.685]	−1.015 −0.562 [−1.808]	−1.431 −0.883 [−1.621]	2.188 −1.916 [1.142]	0.376 −2.295 [0.164]
LNX8(−1)	0.768 −1.628 [0.472]	0.854 −1.120 [0.762]	3.020 −1.761 [1.714]	−1.206 −3.823 [−0.316]	0.763 −4.579 [0.167]
LNX8(−2)	−0.823 −1.102 [−0.747]	−1.437 −0.758 [−1.895]	−1.508 −1.192 [−1.264]	2.364 −2.587 [0.914]	0.545 −3.099 [0.176]
C	0.378 −8.757 [0.043]	−2.673 −6.027 [−0.443]	−0.278 −9.478 [−0.029]	10.217 −20.568 [0.497]	5.673 −24.636 [0.230]

Therefore, see Table 7 for details, since all these points lie within the unit circle, it indicates that the estimated VAR model is stable.

Table 7. Test data of each equation of VAR model.

Indicators	LNY1	LNX1	LNX6	LNX7	LNX8
The coefficients of determination	0.996	0.998	0.996	0.993	0.985
Adjusted coefficients of determination	0.991	0.994	0.990	0.983	0.963
Residual sum of squares	0.002	0.001	0.003	0.013	0.018
Standard deviation	0.018	0.012	0.020	0.042	0.051
F-statistic	193.388	286.198	168.734	98.146	45.002
Maximum likelihood estimation	55.215	61.941	53.791	39.845	36.597
Information criteria	−4.913	−5.660	−4.755	−3.205	−2.844
Schwarz criterion	−4.369	−5.116	−4.210	−2.661	−2.300
Mean of dependent variable	8.749	8.373	4.881	4.949	7.301
Standard deviation of dependent variable	0.193	0.161	0.195	0.323	0.263

4.3. Basic Tests

4.3.1. Augmented Dickey–Fuller (ADF) Unit Root Test

From the test results, the ADF test statistic is −4.027, which is below the corresponding critical value. Therefore, we reject the null hypothesis, indicating that the difference series of agricultural carbon emissions (LNY1) does not have a unit root and is stationary. In other words, LNY1 is first-order integrated, denoted as LNY1~I (1).

Using the same method, we can obtain the following test results: LNX1~I (1), LNX6~I (1), LNX7~I (1), and LNX8~I (1).

4.3.2. Johansen Cointegration Test

According to the Johansen cointegration test results in Table 8, the trace statistics are all greater than the 5% critical value level, indicating the presence of a long-term equilibrium relationship between agricultural carbon emissions in Shaanxi Province and the influencing factors such as fertilizers and pesticides.

Table 8. Non-standardized cointegration coefficients.

LNY1	LNX1	LNX6	LNX7	LNX8
280.258	−298.173	43.264	−7.005	−44.478
584.443	−423.526	−40.390	−51.258	−76.490
−851.055	577.962	65.872	58.335	154.446
381.772	−245.239	−19.464	−70.981	−33.537
−1091.464	665.445	101.926	129.220	160.812

Table 9 provides the estimates of non-standardized cointegration coefficients, while Table 10 presents the estimates of standardized cointegration coefficients, including the coefficients for the three cointegration relationships. The first cointegration relationship is expressed as the cointegration vector:

$$\beta = (1\ -1.064\ 0.154\ -0.025\ -0.159)$$

Table 9. Standardized cointegration coefficients.

Cointegration Equation		Maximum Likelihood Estimation
LNY1	LNX1	LNX6
1.000	−1.064	0.154
	(0.024)	(0.013)
D(LNY1)	−0.946 −1.035	
D(LNX1)	0.074 −0.928	
D(LNX6)	−6.179 −1.218	
D(LNX7)	0.705 −2.917	
D(LNX8)	−3.932 −3.335	

Table 10. Granger causality test.

The Null Hypothesis	F-Value	*p* Value
LNX1 does not Granger cause LNY1	1.147	0.048
LNX6 does not Granger cause LNY1	0.766	0.085
LNX7 does not Granger cause LNY1	0.215	0.009
LNX8 does not Granger cause LNY1	0.949	0.012

4.3.3. Granger Causality Test

Next, we perform the Granger causality test. At a significance level of 10%, the results indicate that X Granger causes variations in LNY1. In other words, fertilizers, pesticides, agricultural films, and agricultural diesel are Granger causes of agricultural carbon emissions.

4.4. Impulse Response Functions and Variance Decomposition

Figure 7, based on the VAR model using the orthogonalization method and the Cholesky decomposition technique, displays the impulse response paths to shocks of variables. The horizontal axis represents the lag periods of the impulse effect (in months), while the vertical axis represents the degree of response of the dependent variable to the explanatory variable. The "----" line represents the 95% confidence interval of the trajectory of the response variable to shock changes. In this model, the lag of the impulse effect is set to 10 periods.

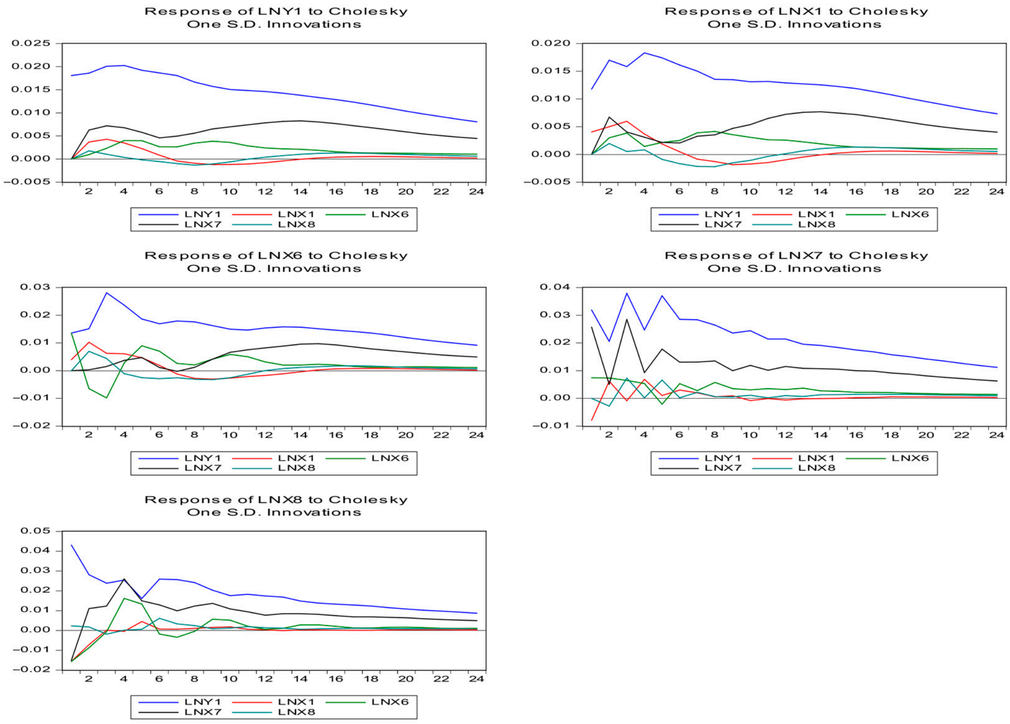

Figure 7. Impulse response analysis of agricultural carbon emissions and influencing factors in Shaanxi Province.

From Figure 7, it is evident that a positive shock to rice (LNX1) during this period positively impacts agricultural carbon emissions (LNY1) for the first 10 periods. The positive effect peaks in the second period at 0.02059 standard deviations. After reaching this peak, the impact gradually declines and turns negative between the fifth and ninth periods. The negative impact reaches its minimum in the sixth and seventh periods, then gradually approaches zero around the tenth period before stabilizing. This suggests that fertilizer use significantly affects agricultural carbon emissions. This finding supports the "Implementation Plan for Agricultural and Rural Emissions Reduction and Carbon Sequestration" jointly issued by the Ministry of Agriculture and Rural Affairs and the National Development and Reform Commission in June 2022. The plan advocates for reducing fertilizer use, enhancing efficiency, and improving carbon sequestration in farmland. Similar principles apply when a one-standard-deviation positive shock is given to LNX6 and LNX8.

To more effectively assess the importance of different factor shocks, we further utilize variance decomposition to analyze the contribution of each structural shock of carbon emission factors to the changes in agricultural carbon emissions in Shaanxi Province. The results are presented in Table 11.

Table 11. Variance decomposition results of influencing factors of agricultural carbon emissions.

Forecast Period	Standard Deviation	LNY1	LNX1	LNX6	LNX7	LNX8
1	0.018	100.000	0.000	0.000	0.000	0.000
2	0.027	92.178	1.870	0.124	5.398	0.430
3	0.035	88.940	2.652	0.518	7.543	0.347
4	0.041	87.710	2.608	1.319	8.107	0.255

Table 11. *Cont.*

Forecast Period	Standard Deviation	LNY1	LNX1	LNX6	LNX7	LNX8
5	0.046	87.602	2.328	1.806	8.059	0.205
6	0.050	88.310	2.005	1.816	7.682	0.187
7	0.053	88.636	1.758	1.832	7.577	0.197
8	0.056	88.346	1.606	2.021	7.795	0.232
9	0.059	87.653	1.505	2.270	8.326	0.245
10	0.061	86.921	1.427	2.439	8.976	0.237
11	0.064	86.257	1.355	2.469	9.697	0.221
12	0.066	85.585	1.282	2.441	10.482	0.210
13	0.068	84.885	1.209	2.401	11.295	0.210
14	0.070	84.195	1.144	2.362	12.080	0.220
15	0.072	83.599	1.090	2.317	12.757	0.237
16	0.073	83.118	1.046	2.265	13.311	0.260
17	0.075	82.741	1.012	2.215	13.752	0.280
18	0.076	82.441	0.984	2.173	14.105	0.297
19	0.077	82.201	0.961	2.140	14.388	0.309
20	0.078	82.013	0.942	2.115	14.611	0.318
21	0.079	81.868	0.926	2.095	14.788	0.324
22	0.079	81.752	0.911	2.078	14.932	0.328
23	0.080	81.655	0.898	2.064	15.053	0.330
24	0.080	81.570	0.887	2.054	15.158	0.332
mean	0.062	85.842	1.351	1.888	10.663	0.258

Table 11 includes seven columns. The first column denotes the forecast period, and the second column represents the standard deviation of the predicted values of variable LNY1 for each period. The following five columns are percentages, representing the contributions of equations with LNY1, LNX1, LNX6, LNX7, and LNX8 as dependent variables to the standard deviation of predicted values of LNY1 for each period. The sum of each row equals 100%. Taking t = 3 as an example, the predicted standard deviation of LNY1 is 0.034753. Out of this, 88.94046% is attributed to its own residual shock, 2.652% to the residual shock of LNX1, 0.518% to the residual shock of LNX2, 7.543% to the residual shock of LNX7, and 0.347% to the residual shock of LNX8.

When calculating the mean within the forecast period of 24 periods, the contribution of LNY1's own residual shock to the standard deviation of predicted values reaches 85.842%, while the contributions of other variables are relatively small. Specifically, 1.351% is attributed to the residual shock of LNX1, 1.888% to the residual shock of LNX2, 10.663% to the residual shock of LNX7, and 0.258% to the residual shock of LNX8.

It can be observed that the long-term contributions of fertilizers and pesticides to agricultural carbon emissions exhibit a trend of initially increasing and then decreasing, experiencing a gradual attenuation process, with mean attenuation levels of 1.35083% and 1.8883%, respectively.

The long-term contribution of agricultural diesel to agricultural carbon emissions remains relatively stable. Meanwhile, the long-term contribution of agricultural film to agricultural carbon emissions shows a continuous increasing trend, rising from 5.398% in the second period to 15.158% in the twenty-fourth period.

4.5. Cointegration Test Results

The cointegration tests indicate the presence of a long-term stable equilibrium relationship between fertilizers, pesticides, agricultural film, and agricultural diesel with agricultural carbon emissions. Variance decomposition analysis further reveals that over a forecast period of 24 periods, the majority of the variability in the standard deviation of predicted values for agricultural carbon emissions (LNY1) is attributed to its own shock, accounting for 85.84167%. Conversely, the contributions from other variables are relatively minor. Specifically, fertilizers (LNX1) contribute 1.351%, pesticides (LNX6) contribute

1.888%, agricultural film (LNX7) contributes 10.663%, and agricultural diesel (LNX8) contributes 0.258%.

5. Discussion, Limitations, and Future Research Directions

5.1. Discussion

In the context of the "dual carbon" target, advancing green and low-carbon agricultural development is both an immediate necessity and a crucial pathway for future sustainable development. The empirical analysis of agricultural carbon emissions in Shaanxi Province offers valuable insights into the factors driving these emissions and highlights potential strategies for achieving low-carbon agricultural practices.

Given the context of Shaanxi Province and China, the development of low-carbon agriculture should adhere to three key prerequisites: it must integrate reasonable technical measures from traditional agriculture, it should not compromise economic development and food security, and it should not entirely eliminate the use of agricultural production materials. While pursuing environmental goals, it is crucial to also achieve yield and income targets.

Firstly, the development of low-carbon agriculture is inherently linked to the implementation of reasonable technical measures from traditional agriculture. The technologies used in low-carbon agriculture cannot be divorced from both traditional and modern agricultural practices; they must be grounded in the principles of both. Low-carbon agriculture has emerged as a significant trend and direction in global agricultural development. It largely integrates the core elements of existing conventional and modern agricultural models, thus demonstrating considerable vitality and promising prospects.

Secondly, the development of low-carbon agriculture should not compromise economic development or food security. Managing the balance between energy, environmental goals, and economic growth while ensuring agricultural productivity and food security is crucial. Effectively leveraging agriculture's role in reducing greenhouse gas emissions and advancing low-carbon agriculture within a low-carbon economy presents a significant challenge for the Chinese government.

Thirdly, the development of low-carbon agriculture does not necessitate the complete exclusion of agricultural production materials. While advancing low-carbon practices, it is important to maintain investment in capital and agricultural inputs, such as fertilizers and pesticides. Instead of eliminating these inputs, the focus should be on reducing their usage while improving fertilization techniques. This includes adopting biodiversity-based agricultural practices, conducting soil testing for optimized fertilization, enhancing nutrient management, and increasing the effectiveness of input use. Concurrently, promoting the use of organic fertilizers, combining organic and inorganic fertilizers, ensuring product safety from the source, and advancing ecological environmental protection are essential steps in developing low-carbon agriculture.

5.2. Limitations and Future Research Directions

(1) In terms of research scope, the development of low-carbon agriculture should embrace the concept of "big agriculture," which includes five sectors: crop farming, forestry, animal husbandry, fishery, and ancillary industries. Among these, animal husbandry is the primary source of carbon emissions, while forestry plays the leading role in carbon absorption. However, this paper focuses primarily on crop farming, which is a subset of "small agriculture." Therefore, future research should emphasize the broader concept of "big agriculture."
(2) When calculating agricultural GDP, the impact of inflation was not taken into account.

6. Conclusions and Recommendations

6.1. Conclusions

Choosing an appropriate low-carbon agricultural development model based on resource endowments and development stages is crucial. While the concept of low-carbon agriculture is widely accepted worldwide, its interpretation varies according to national conditions and contexts. Unlike developed countries, which may have more resources and advanced technologies, developing nations focus on balancing development with environmental protection. As a result, there are significant differences in how sustainable agricultural development models are implemented across countries.

At China's current stage, the development of low-carbon agriculture should not compromise economic growth or food security. Efforts must ensure that the "dual carbon" goals and food security advance simultaneously.

(1) Expanding agricultural land area is an important means of increasing carbon sinks in farmland. The key is to continuously optimize agricultural practices, adjusting cropping systems according to local conditions and seasons to increase cropping intensity, which effectively amounts to expanding sowing areas.
(2) From 2010 to 2022, the overall trend of agricultural carbon emissions in Shaanxi Province showed fluctuations, with a general pattern of "increase followed by a gradual decline". In 2013, agricultural carbon emissions in Shaanxi Province reached their peak, with the primary sources of carbon being fertilizers, pesticides, and agricultural films used in land utilization. This effectively implements the key objectives outlined in China's 2014 agricultural planting guidelines, focusing on goals such as water control, fertilizer control, and pesticide control. It aims to gradually achieve low-carbon and high-yield production.
(3) The level of economic development is a crucial factor affecting the intensity of agricultural carbon emissions.

6.2. Recommendation

1. Strengthening low-carbon technological innovation in agriculture and controlling carbon emissions from major sources are essential. This includes reducing the use of agricultural inputs such as fertilizers and pesticides to achieve emission reduction goals.

The amount of diesel used in agriculture is a key factor influencing carbon emissions. Irrigation of farmland and the use of agricultural machinery are the main contributors to carbon emissions from diesel use in agriculture. In the future, there is a need to explore new types of green energy with lower carbon emissions to replace polluting energy sources.

Vigorously promote and disseminate technologies for reducing and increasing the efficiency of chemical fertilizers and pesticides. Specifically, this can be achieved by implementing reduced fertilizer application, rational use of water-soluble fertilizers, and controlled-release fertilizers to enhance fertilizer utilization efficiency. Control the use of pesticides and promote new methods such as the use of biological pesticides. Additionally, advance the development of agricultural waste recycling technologies and enhance the recycling and reuse of materials such as agricultural films and pesticide packaging.

2. While ensuring food security, it is crucial to make rational adjustments to the rural industrial structure, promote low-carbon planting techniques, and enhance the green production level of agriculture comprehensively.

In summary, during the "14th Five-Year Plan" period, Shaanxi Province should establish a development concept for green and low-carbon agriculture that prioritizes ecology, emphasizes green principles, adopts long-term strategies, and focuses on industry. This includes exploring advanced technologies in "clean production, green transformation, and low-carbon emission reduction", promoting the utilization of agricultural waste biomass resources, advancing the green and low-carbon cleaning of agricultural production, optimizing agricultural ecological environments, and improving the livelihoods of farmers.

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