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Study on the Mechanism of Agricultural Greenhouse Gas Emission Reduction Under Macro Emission Reduction Measures

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Abstract: Clarifying the impact of macro emission reduction measures on the mechanism of agricultural greenhouse gas emission reduction is of great significance in promoting climate change governance and the construction of a carbon emission reduction policy system. This paper explores the mechanism of important macro emission reduction measures based on a multi-level progressive factor decomposition perspective and designs a coupled model of computable general equilibrium and structural path decomposition to identify the key emission reduction paths of major macro emission reduction measures and to decompose the drivers that promote emission reduction in each path. This study found that: (1) The emission reduction effect of the combination of carbon tax, carbon sink and carbon capture, utilization, and storage macro emission reduction measures is dominated by the indirect emission reduction triggered by the industrial chain, accounting for 95.67% of the total agricultural GHG emission reduction, and the emission reduction effect is gradually weakened with the increase in the production level. (2) The emission intensity effect and the industrial structure effect are the main drivers of the macro emission reduction portfolio measures to promote emission reduction, but there are differences in the roles of the different drivers on the various production levels and different emission reduction pathways. (3) Vegetables, fertilizers, the light industry, and other key industries are the main agricultural greenhouse gas emission reduction contributing industries, of which the emission reduction contribution from citizen consumption is the largest, and the emission reduction is mainly achieved by influencing the demand path of the vegetable industry and the light industry to the upstream high-energy-consuming or high-emission industries. Therefore, there is a need to fully utilize the mechanisms that drive emission reduction at different production levels and pathways by each key factor and to take targeted measures to promote synergistic emission reduction among industries. In the short term, focus on enhancing the role of the emission intensity effect, while in the medium and long term, pay much attention to the positive role of the industrial structure effect on agricultural greenhouse gas emissions.

Keywords: macro abatement; agricultural greenhouse gases; computable general equilibrium model; structure path decomposition; emission reduction measures

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1. Introduction

As a basic industry, agriculture is most vulnerable to climate change, and its production and operation activities are closely related to greenhouse gas (GHG) emissions, making it one of the major sources of GHG emissions [1,2]. Agricultural GHG emissions in 2020 will be second only to the energy and industrial sectors, accounting for about 18% of anthropogenic carbon emissions [Climate Change 2021: The Physical Science Basis]. At this stage, agricultural sources of non-CO_2 GHG account for 10–12% of total global anthropogenic GHG emissions, with nitrous oxide (N_2O) accounting for about 60% and methane (CH_4) for about 40% of the global emission structure from agricultural activities [3]. How to mitigate agricultural greenhouse gas (GHG) emissions has become a common global concern. China's agricultural GHG emissions account for about 17% of the total emissions and continue to grow at an annual rate of 5% [4]. Therefore, agricultural GHG emission reduction is of great significance for China to realize the goal of "carbon peaking and carbon neutrality".

In order to gradually realize "dual control" over the total volume and intensity of carbon emissions, and to reach the goal of "carbon peaking and carbon neutrality" on schedule, China has implemented a series of measures to promote carbon emission reduction. The combined configuration of different emission reduction policy instruments has played an important role in China's green and low-carbon development process [5,6]. Academics have also widely discussed the design of China's emission reduction system under the "dual-carbon" goal, which mainly includes macro emission reduction measures such as administrative orders, carbon tax, carbon trading, carbon sinks, CCUS, and so on [7,8]. Except for carbon tax measures, all of the above emission reduction measures have been implemented in China.

The relevant literature on emission reduction measures is very fruitful. Nordhaus, using the Dynamic Integrated Climate Economy (DICE) model, found that administrative orders to regulate carbon emissions would bring about huge economic costs, while a moderate carbon tax is an effective way to promote emission reduction [9]. Jia and Lin used the CEEEA model to re-analyze the difference between carbon tax and carbon trading and discussed the different impacts of the carbon tax mechanism and carbon trading mechanism on the environment, energy, and economy [10]. Academic research on carbon sinks mainly focuses on total amount measurement and carbon storage potential assessment [11–13]. For example, Piao Shilong et al. explored the evolution of carbon sinks in China's terrestrial ecosystems, providing a scientific basis for the formulation of measures to increase sinks in China's afforestation [14]. CCUS is a carbon capture, sequestration, and reuse technology, which can support the effective initiative of carbon emission reduction from the technical dimension. DOU et al.'s study systematically reviewed the development trend of the CCUS industry at home and abroad and concluded that at this stage, China is in a critical period of transition from field trials to industrialization and should focus on improving the recovery rate [15].

The existing academic research on macro emission reduction measures focuses on the effect of carbon emission reduction and lacks research on the impact of agricultural greenhouse gases. These studies usually focus only on individual industries to analyze the emission reduction effects of macro emission reduction measures, with slightly less attention paid to the interactions between industries and no in-depth exploration of the factors through which macro emission reduction measures affect changes in greenhouse gas emissions in industries, i.e., the mechanism of emission reduction belongs to the "black box".

The methods to study emission reduction pathways and drivers include models such as complex networks, CGE, SPD, SDA, etc. Based on the complex network theory, Hu et al. established a carbon emission control industry selection model for selecting China's carbon emission control industry [16]. Zhao et al. used the improved CGE model to evaluate the impact of carbon pricing policy on carbon emission and carbon emission intensity [17]. Wen and Zhang used a non-competitive input–output table combined with structural path analysis (SPA) to analyze the situation of intersectoral carbon emission transfer in China [18]. Yang et al. used structural decomposition analysis (SPD) to study structural emission reductions in China's industrial and energy systems [19].

However, these methods used alone are unable to clearly identify the specific transmission process and key emission reduction pathways of emission reduction measures to promote inter-industry carbon emission reduction. Wood and Lenzen designed a structural path decomposition (SPD) model based on the integration of the advantages of SPA and SDA, which can systematically analyze the transmission process and drivers of emission reduction measures based on the industrial chain perspective [20]. However, the existing literature has not coupled the CGE model with SPD to explore the mechanism of macro emission reduction measures to promote the reduction in agricultural GHG emissions.

The existing literature lacks research on the mechanism of reducing agricultural greenhouse gas emissions through macro emission reduction measures. Therefore, this paper explores the emission reduction mechanism by constructing a coupling model of CGE and SPD. That is the novelty of the issue.

The objectives of this paper are as follows. This paper explores the transmission mechanism and driving factors of the macro emission reduction portfolio measures including carbon tax, carbon sinks, and CCUS to promote agricultural GHG emission reduction based on the perspective of progressive drivers and constructs a dynamic CGE and SPD coupling model. Furthermore, this paper aims to grasp the reasons why emission reduction portfolio measures promote emission reduction on a macro level, decompose the drivers of emission reduction from the level of total emission reduction, production stage, and industrial chain, and dig deeper into the emission reduction mechanism of macro emission reduction portfolio measures of carbon tax, carbon sinks, and CCUS.

The main contributions of this paper include, firstly, exploring the impacts of macroemission reduction measures on agricultural GHG emissions. Secondly, fully considering the inter-industry correlation and inter-industry transmission mechanism of macro emission reduction measures and analyzing the "black box of pathways" of macro emission reduction combinations in terms of multileveled progressive drivers. Thirdly, combining the advantages of a dynamic CGE model in policy assessment and SPD in path decomposition, we constructed a coupled model of the two, decomposed the emission reduction role of macro emission reduction combination measures based on the industrial chain level, and designed a model for evaluating macro emission reduction measures. The findings of this paper will help optimize the construction of China's emission reduction system and provide policy support for inter-industry synergistic emission reduction.

The target audience of this paper is primarily researchers and policymakers concerned with climate change issues.

2. Model and Data

2.1. A Dynamic Computable General Equilibrium Model of Chinese Agriculture

The computable general equilibrium (CGE) model is based on the theory of general equilibrium with mathematical equations modeled to reflect the economic activities of the society as a whole. The model depicts the interactions between various sectors and variables in an economic system by means of a system of linked equations, focusing on how the supply and demand of various commodities and factors of production in an economic system are regulated by the price adjustment mechanism in order to reach an equilibrium state. This paper constructs a CGE model based on the CEEEA2.0 [21] and CHINAGEM-E models, with the basic modules including a production module, an income–expenditure module, a trade module, an equilibrium and macro closure module, and an energy–environment module.

In the production module, this paper employs seven levels of nested production technologies (Figure 1), where Leontief's production technology is treated as a synthetic intermediate input and all other input components are considered as CES production technologies. The model divides the input factors into labor, capital, and land and breaks down the agricultural sector into rice, wheat, corn, soybeans, potatoes, oilseed crops, cotton, sugar crops, vegetables, melons and fruits, other crops, forest products, livestock products, and fishery products, for a total of 14 subsectors. The energy sector consists of coal, oil, natural gas, refined oil, and refined natural gas, and the power sector includes five renewable energy subsectors: thermal and hydropower, wind power, nuclear power, solar power, and biomass power. Referring to CEEEA2.0, the model introduces a mechanism for firms to respond to energy price changes by spontaneously regulating production efficiency in response to energy–environmental policies and energy price shocks.

The income–expenditure module focuses on describing cash flows between residents, businesses, governments, and internationally. Residents receive remuneration for their labor and returns on investment from factor markets, receive transfers from the government, and spend their income on consumption, savings, and taxes. Business income is derived from sales in the product market, capital gains in the factor market, and government transfers. Capital gains go abroad, except to firms and residents. The income earned by firms is mainly used to pay for labor, return on capital, and taxes. Government revenues are derived from a variety of taxes, including direct taxes on residents, indirect taxes on businesses, carbon taxes, and customs duties. The rest of the world derives its revenues from domestic imports and capital gains, and its expenditures include domestic exports and capital repayments. In the revenue–expenditure module, the LES demand function is used to simulate residential demand over time in order to reflect changes in the structure of residential consumption.

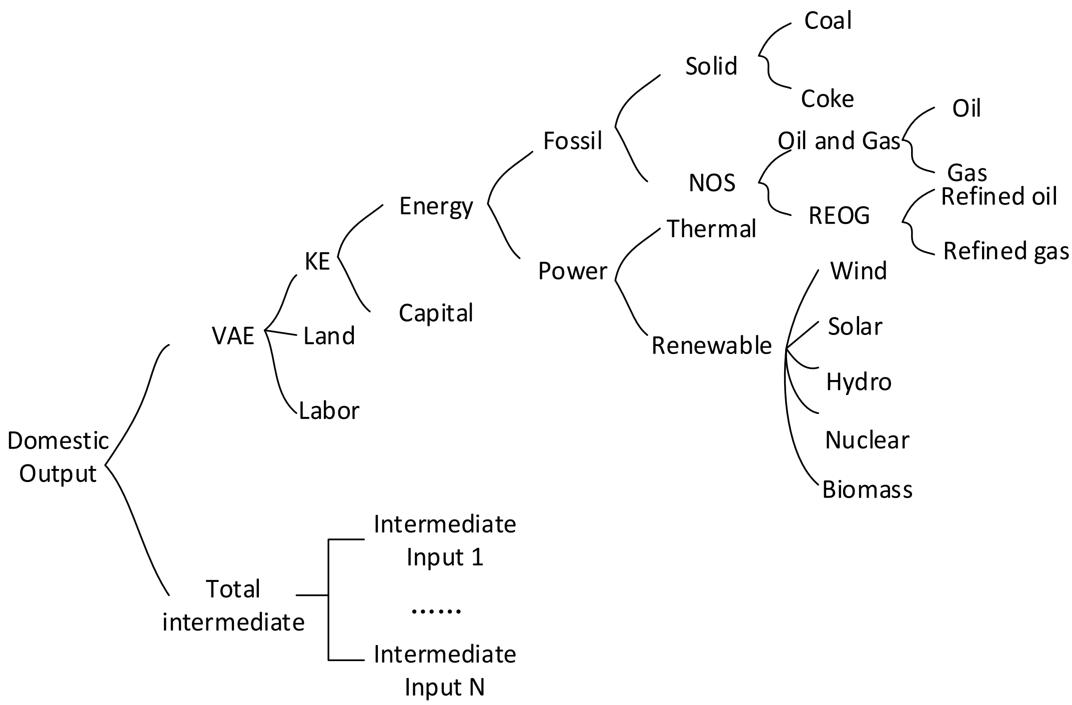

Figure 1. Nested structure of production functions (referring to Jia et al. [21]).

The trade module follows the "Armington assumption" and describes the imperfect substitutability between domestically produced and imported goods in the form of a CES function. In modeling the allocation decision of domestically produced goods in the face of export and domestic sales, it is portrayed in the form of the CET function.

In the equilibrium and macro closure module, it is assumed that the demand for each factor is equal to the supply to ensure that the market is cleared. Given that the simulations in this paper are designed based on a long-run scenario, the macro closure thus satisfies the neoclassical closure condition.

The energy–environment module portrays GHG emissions. As shown in Figure 2, agricultural GHG emissions are mainly designed with reference to Zhang et al. [22] and CHINAGEM-E. Cultivation emissions include three components: first, carbon emissions triggered by agricultural inputs, specifically: ① fertilizers, pesticides, and agricultural films at the intermediate input end; ② energy elements: the main energy inputs in the agricultural sector include coal, oil, natural gas, and electricity; and ③ arable land. The second is methane emissions from paddy cultivation. The third is nitrous oxide emissions triggered by nitrogen fertilizers at the intermediate input end. Livestock emissions mainly include ① CO_2 from energy inputs; ② CH_4 emissions from gastrointestinal fermentation of livestock and poultry; and ③ CH_4 and N_2O emissions from manure management systems. The rest of the industries have only considered carbon emissions due to energy inputs.

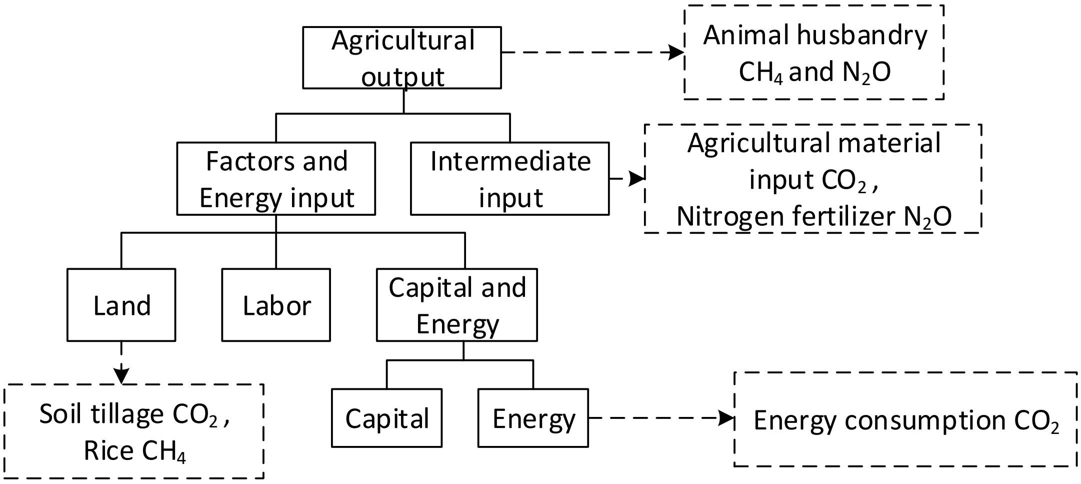

Figure 2. Structure of agricultural GHG emissions (referring to Zhang et al. [22]).

To ensure that real physical accounts of GHG emissions are embedded in the CGE model, this paper assumes that the growth rate of emissions for each product is equal to the growth rate of demand for that product, drawing on the studies of CHINAGEM-E and Zhao Minjuan et al. [2]. The details are as follows: ① growth rate of factor-induced emissions = growth rate of factor demand; ② growth rate of intermediate input-induced emissions = growth rate of intermediate input demand; and ③ growth rate of output-induced emissions = growth rate of output demand.

We refer to Jia et al. [21] to set the baseline scenario, i.e., there is no intervention of the three macro emission reduction measures, namely, carbon tax, carbon sinks, and CCUS. In the macro abatement portfolio intervention scenario, three emission reduction measures are included: carbon tax, carbon sinks, and CCUS. The carbon sink pathway is based on the research of Piao Shilong et al. [14,23], and the CCUS pathway is based on the research results of Everbright Securities Research Institute. In addition, the carbon sink measures in this paper exist as early as 2020, and it is assumed that the CCUS and carbon tax measures begin to be implemented in 2024. This paper assumes a carbon tax only on non-agricultural sectors.

2.2. Structural Decomposition Analysis (SDA)

SDA is a comparative static analysis method that can decompose changes in target variables in an economic system into changes in their respective variables and measure the contribution of each variable to the changes in the target variables, and based on input–output table data, it is able to reveal the impact of inter-industry correlations on agricultural GHG emissions [24–26]. With reference to Yao and Liu [26], this paper expands SDA in order to decompose and analyze the emission reduction mechanism and influencing factors of carbon tax, carbon sink, and CCUS emission reduction combination measures at different levels and decompose the agricultural GHG emission reduction generated by the emission reduction combination measures into the emission intensity effect, the industrial structure effect, the demand structure effect, and the demand scale effect, to reveal the effect of the four effects working together. According to the characteristics of the input–output table, the following equilibrium relationship exists:

$$A \cdot X + Y = X \tag{1}$$

In Equation (1), A is the matrix of direct consumption coefficients; X is the column vector of total output; and Y is the column vector of final domestic demand. After shifting the terms, X can be expressed as:

$$X = (I - A)^{-1} \cdot Y = L \cdot Y \tag{2}$$

In Equation (2), I is the unit matrix; $L = (I - A)^{-1}$ is the Leontief inverse matrix; and the total GHG emissions TM generated during agricultural production are:

$$TM = M \cdot X = M \cdot L \cdot Y \tag{3}$$

In Equation (3), M is the agricultural GHG emission intensity, i.e., the agricultural GHG emissions per unit of output of each industry. Referring to the decomposition method of Lin et al. [27] for total carbon emissions, total agricultural GHG emissions TM can also be expressed as:

$$TM = M \cdot L \cdot U \cdot H \tag{4}$$

In Equation (4), M is the row vector of agricultural GHG emission coefficients of each industry and L, U, and H are the industrial structure effect, the demand structure effect, and the demand scale effect, respectively. The amount of changes in agricultural GHG emissions before and after the implementation of emission reduction combination measures is expressed as:

$$\begin{aligned} \Delta TM &= TM_t - TM_0 \\ &= \Delta M \cdot L_t \cdot U_t \cdot H_t + M_0 \cdot \Delta L \cdot U_t \cdot H_t \\ &+ M_0 \cdot L_0 \cdot \Delta U \cdot H_t + M_0 \cdot L_0 \cdot U_0 \cdot \Delta H \end{aligned} \tag{5}$$

In Equation (5), ΔTM is the change in agricultural GHG emission reduction from the implementation of the combination of carbon tax, carbon sinks, and CCUS emission reduction measures, where subscript t indicates the scenario of the implementation of the combination of emission reduction measures and subscript 0 indicates the baseline scenario in which the combination of emission reduction measures is not implemented. TM_0 and TM_t are the total agricultural GHG emissions before and after the implementation of the mitigation package, respectively. ΔM, ΔL, ΔU, and ΔH are the changes in the drivers before and after the implementation of the combination of measures to reduce emissions. Using the "polar decomposition method", the ΔTM decomposition equation can be obtained:

$$\Delta TM = f(\Delta M) + f(\Delta L) + f(\Delta U) + f(\Delta H) \tag{6}$$

In Equation (6), $f(\Delta M)$, $f(\Delta L)$, $f(\Delta U)$, and $f(\Delta H)$ are the agricultural GHG emission reduction due to the emission intensity effect, the industrial structure effect, the demand structure effect, and the demand scale effect, respectively. Under the assumption that one type of demand changes and other types of demand remain unchanged, the effects of different demand types on agricultural GHG emission reduction can be analyzed.

2.3. Structure Path Decomposition (SPD)

SPD is a combination of SPA and SDA, and the drivers can be decomposed from an industry chain perspective [24,25]. The agricultural GHG abatement effect from the implementation of abatement portfolio measures varies as the inputs of each industry to other intermediate products are transmitted across the industrial chain, and the structural path analysis method based on the input–output table is able to create linkage pathways between industries at different production levels and quantify the contribution of each industrial chain to the abatement of agricultural GHG emissions. Taylor expansion of the Leontief inverse matrix L in Equation (3) allows for the total agricultural GHG emissions TM to be expressed as the sum of agricultural GHG emissions at different production levels:

$$\begin{aligned} TM &= M \cdot (I - A)^{-1} \cdot Y \\ &= M \cdot (I + A + A^2 + A^3 + \ldots\ldots) \cdot Y \\ &= M \cdot I \cdot Y + M \cdot A \cdot Y + M \cdot A^2 \cdot Y + M \cdot A^3 \cdot Y + \ldots\ldots \end{aligned} \tag{7}$$

In Equation (7), $M \cdot I \cdot Y$ is the direct agricultural GHG emissions due to the final demand of each industry; $M \cdot A^t \cdot Y$ is the indirect agricultural GHG emissions of each industry at different production levels. Further disaggregation of agricultural GHG issions by industry at each level yields the transmission pathways among industries:

$$\begin{aligned} TM &= M \cdot I \cdot Y + M \cdot A \cdot Y + M \cdot A^2 \cdot Y + M \cdot A^3 \cdot Y + \ldots\ldots \\ &= \begin{bmatrix} c_1 \cdot y_1 \\ c_2 \cdot y_2 \\ \vdots \\ c_n \cdot y_n \end{bmatrix} + \begin{bmatrix} \sum_{i=1}^{n} m_1 \cdot a_{1,i} \cdot y_i \\ \sum_{i=1}^{n} m_2 \cdot a_{2,i} \cdot y_i \\ \vdots \\ \sum_{i=1}^{n} m_n \cdot a_{n_i} \cdot y_i \end{bmatrix} + \begin{bmatrix} \sum_{i,j=1}^{n} m_1 \cdot a_{1,j} \cdot a_{j,i} \cdot y_i \\ \sum_{i,j=1}^{n} m_2 \cdot a_{2,j} \cdot a_{j,i} \cdot y_i \\ \vdots \\ \sum_{ij=1}^{n} m_n \cdot a_{n,j} \cdot a_{j,i} \cdot y_i \end{bmatrix} + \ldots\ldots \end{aligned} \tag{8}$$

In Equation (8), i, j, and k are different industries in the economic system. At level 1, $c_n \cdot y_n$ is the direct agricultural GHG emissions from each industry due to final demand, and the transmission path is "final demand $\rightarrow$ n-th industry". At level 2, $\sum_{i=1}^{n} m_n \cdot a_{n_i} \cdot y_i$ is the indirect agricultural GHG emissions generated by the first industry to satisfy the factor inputs of the i-th industry, and its transmission path is "final demand $\rightarrow$ the i-th industry $\rightarrow$ the first industry" and so forth. The indirect agricultural GHG emissions due to changes in final demand are thus decomposed into transmission paths between different production levels and different industrial chains. The final demand involved in this study includes five types: citizen consumption (CU), farmer consumption (CR), government consumption (CG), investment (IV), and export (EX), and by substituting the data of different final demands into the above equations, the agricultural GHG emissions driven by different types of demand can be obtained.

The decomposition of L by combining Equation (4) yields the contribution of the above four effects to agricultural GHG emissions at each production level, and TM can be expressed as the sum of agricultural GHG emissions at each level:

$$\begin{aligned} TM &= M \cdot (I + A + A^2 + \ldots) \cdot U \cdot H \\ &= M \cdot I \cdot U \cdot H + M \cdot A \cdot U \cdot H + \ldots + M \cdot A^t \cdot U \cdot H + \ldots \end{aligned} \tag{9}$$

In Equation (9), $M \cdot A^t \cdot U \cdot H$ is the agricultural GHG emissions of the (t + 1) level. According to Equation (8), TM can be disassembled into the sum of agricultural GHG emissions of different industrial chains. Through the structural decomposition analysis of the total emission reduction effect of the implementation of emission reduction combination measures, and through the structural decomposition analysis of the emission reduction effect of each production level and industrial chain, the contribution of different demand types and different driving factors to the emission reduction effect of emission reduction combination measures can be obtained.

In order to realize the coupling of CGE and SPD, SPD is incorporated into the CGE model as a module in this paper. SPD and the CGE model are linked through common variables such as agricultural greenhouse gas emission, total agricultural output value, and so on.

2.4. Data

The SAM table in this paper is expanded on the basis of "China's competitive input–output table" in 2020, which integrates and splits the 153 industrial sectors into 39 industrial sectors (Table 1). In order to study the emissions of various agricultural industries in detail, the agricultural sector is split in this paper. And in order to distinguish between clean energy and traditional energy, this paper splits the electricity sector. The methodology for splitting the agriculture and electricity sectors is based on the GTAP database construction methodology. Due to inconsistencies in the caliber of data sources, adjustments need to be made using the RAS method. The agricultural data involved are from the China Rural

Statistical Yearbook (2021), the import data for each product are from the official website of the General Administration of Customs of China, and the electricity data are from the China Electricity Statistical Yearbook (2021). The GHG physical account data for the base period 2020 are obtained from the emission factor method, which involves carbon emission factors with specific reference to Wei Yuqiong et al. and Li Bo et al., and CH_4- and N_2O-related emission factors with specific reference to Tian Yun et al. [28–30].

Table 1. Industry division of the computable general equilibrium (CGE) model.

No.	Industry	IO Table Number (2020)	No.	Industry	IO Table Number (2020)
I1	Rice	1	I21	Refined gas	99
I2	Wheat	1	I22	Thermal power	98
I3	Corn	1	I23	Hydro power	98
I4	Soybean	1	I24	Wind power	98
I5	Potato	1	I25	Nuclear power	98
I6	Oil crops	1	I26	Solar power	98
I7	Cotton	1	I27	Biomass power	98
I8	Sugar crop	1	I28	Chemicals	43, 46–52
I9	Vegetable	1	I29	Fertilizer products	44
I10	Fruit	1	I30	Pesticide products	45
I11	Other crops	1	I31	Plastic products	53
I12	Forestry	2	I32	Other mining products	8–11
I13	Husbandry	3	I33	Light industry	12–40
I14	Fishery	4	I34	Building materials	54–60
I15	Agricultural services	5	I35	Metal and products	61–66
I16	Coal production	6	I36	Manufacturing	67–97, 100
I17	Coal processing	42	I37	Construction	101–104
I18	Oil	7	I38	Transportation	107–117
I19	Gas	7	I39	Service	105–106, 118–149
I20	Refined oil	41			

3. Results

3.1. Analysis of Emission Reduction Effects and Factors at the Macro Level

According to the simulation results, in the next year after the implementation of the combination of carbon tax, carbon sinks, and CCUS macro emission reduction measures, the agricultural greenhouse gas emissions can be reduced by 276,637,400 t. The structural decomposition of the agricultural greenhouse gas emission reduction is shown in Table 2.

Table 2. Structural decomposition of agricultural GHG emission reduction under scenarios of emission reduction measures (%).

	$f(\Delta M)$	$f(\Delta L)$	$f(\Delta U)$	$f(\Delta H)$	Total
Citizens' Consumption	6.75	11.40	0.85	0.39	19.39
Farmers' Consumption	1.97	3.14	0.11	0.09	5.31
Government Consumption	2.00	4.81	0.01	−0.79	6.03
Investment	21.36	33.43	0.12	−0.45	54.46
Export	4.42	7.27	0.99	2.13	14.81
Total	36.50	60.06	2.07	1.37	100.00

From the viewpoint of the driving factors of agricultural GHG emission reduction, since the implementation of the combination of carbon tax, carbon sinks, and CCUS macro emission reduction measures, the emission intensity effect, the industrial structure effect, the demand structure effect, and the demand scale effect have all played a positive role in promoting agricultural GHG emission reduction. Among them, the emission reduction contribution of the industrial structure effect accounts for 60.06% of the total agricultural GHG emission reduction, indicating that the combination of carbon tax, carbon sinks, and CCUS macro emission reduction measures mainly realizes agricultural GHG emission reduction by changing the input–output structure of each industry and choosing cleaner intermediate inputs. The emission reduction contribution of the emission intensity effect accounts for 36.50% of the total agricultural GHG emission reduction and is an important driver of emission reduction.

According to Lin and Teng [27], the emission intensity effect contains the energy structure effect and the energy efficiency effect. Therefore, the combination of carbon tax, carbon sinks, and CCUS macro emission reduction measures may achieve agricultural GHG emission reduction by promoting the use of clean energy or improving energy efficiency. The emission reduction contribution rates of the demand structure effect and the demand scale effect are 2.07% and 1.37%, respectively, which are small in proportion, but indicate that the emission reduction combination measures can also promote agricultural GHG emission reduction by changing the demand structure and demand scale.

Judging from the role of different demand types on agricultural GHG emission reduction, all five types of final demand have a positive effect on agricultural GHG emission reduction in the scenario of implementing a combination of carbon tax, carbon sinks, and CCUS macro emission reduction measures. Among them, investment contributes the most to agricultural GHG emission reduction, with a contribution rate of 54.46%. Citizen consumption makes a significant contribution to emission reduction, with a contribution rate of 19.39%. However, the contribution of farmers' consumption and government consumption to agricultural GHG emission reduction is weak, with their contribution rates of only 5.31% and 6.03%, respectively.

Combining the impacts of different demand types and drivers, the industry structure effect is the most important factor in the reduction in agricultural GHG under the pull of various types of final demand. It shows that for agricultural GHG emissions caused by different demand types, the combination of carbon tax, carbon sinks, and CCUS macro emission reduction measures mainly realize agricultural GHG emission reduction by changing the input–output structure of each industry and increasing the input of low-carbon products.

Emission intensity effects also contribute to lower agricultural GHG emissions, driven by various types of final demand, suggesting that the implementation of a combination of mitigation measures may cause industries to favor cleaner energy use or strive to improve energy efficiency in order to reduce the intensity of agricultural GHG emissions from the industry, which will, in turn, contribute to the reduction in agricultural GHG emissions. The demand structure effect also leads to agricultural GHG emission reduction but with a lower contribution rate.

It is worth noting that the demand scale effect causes an increase in agricultural GHG emissions due to both government consumption and investment, suggesting that the combination of carbon tax, carbon sinks, and CCUS macro emission reduction measures needs to be innovated and improved.

3.2. Analysis of Emission Reduction Effects and Factors at the Production Hierarchy Level

According to the contribution of carbon emission reduction at different production levels under the implementation of the combination of carbon tax, carbon sinks, and CCUS macro emission reduction measures (Figure 3), the GHG emission reductions caused by the emission reduction measures are mainly concentrated at production levels 1 to 5.

Among them, level 1 indicates the direct emission reduction of the emission reduction measures, which only accounts for 4.33% of the total emission reduction, indicating that the direct emission reduction generated by the emission reduction combination measures is relatively small, while the indirect emission reduction caused by the input–output relationship between industries is the most important reason for the emission reduction promotion of emission reduction by the emission reduction combination measures. Level 3 has the largest share of emission reduction at 24.86%. However, indirect carbon emission reduction diminishes with the increase in the production level because, with the extension of the industrial chain, the agricultural GHG emissions and the space for emission reduction in the downstream production link of the industrial chain caused by final demand are smaller, and the effect of emission reduction combination measures diminishes with the extension of the industrial chain [26]. The emission reduction contribution of emission reduction combination measures is more limited after level 5.

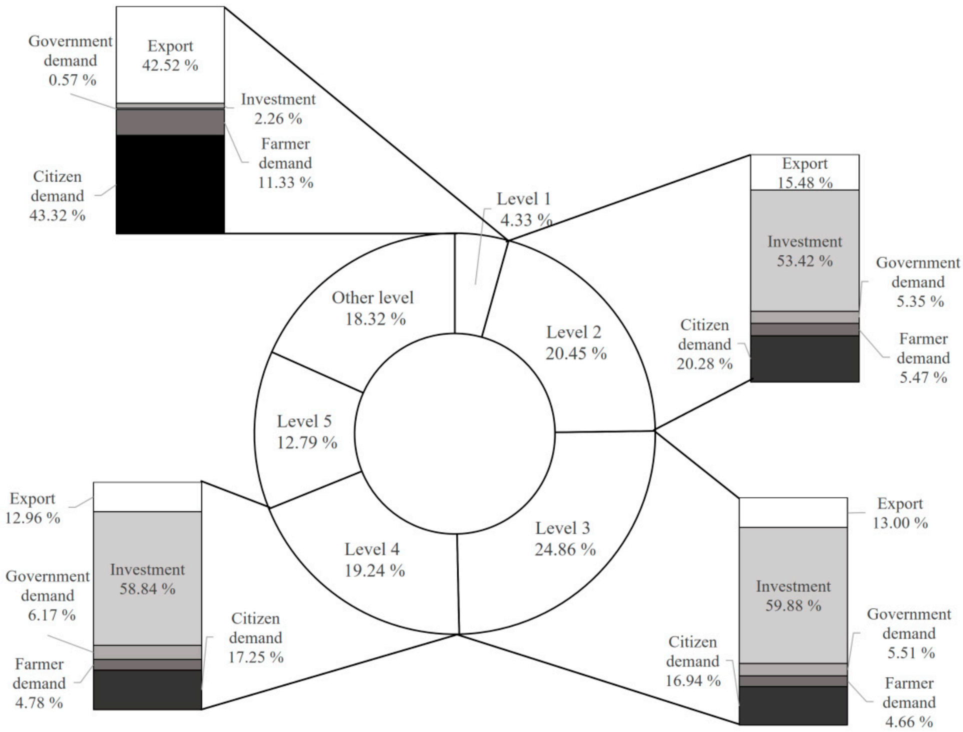

Figure 3. Decomposition of emission reduction contributions and types of demand at different production levels in scenarios of emission reduction measures.

3.2.1. Decomposition of Emission Reduction Factors at the Production Level

As can be seen in Figure 3, the contribution of agricultural GHG emission reduction at each production level is decomposed according to different demand types. More than 40% of the agricultural GHG reduction at production level 1 is due to citizen consumption and exports, suggesting that these two types of final consumption-induced GHG emissions are more likely to meet reduction targets.

With the extension of the industrial chain, the GHG emissions caused by investment have a greater potential for emission reduction, and the contribution of agricultural GHG emission reduction at levels 2–4 is 53.42%, 59.88%, and 58.84%, respectively. This has similar characteristics to the structure of China's sectoral carbon emissions, with consumer spending and investment being the main causes of both China's CO_2 emissions and its agricultural GHG emissions. Therefore, there is a large scope for emission reduction in the scenario of implementing emission reduction combination measures.

Citizen consumption and export both contribute more than 15.00% and 12.00% to the reduction in emissions at the top 5 production levels, respectively, and have a large potential for emission reduction. The contribution of farmers' consumption emission reduction is concentrated in the direct emission reduction, with a contribution of 11.33%, but the potential of indirect emission reduction is small, with a contribution of less than 6.00% in all cases, decreasing with the increase in the production level.

According to the decomposition of the contribution of different drivers to agricultural GHG emission reduction at each production level (Figure 4), it is found that the influence of different factors on the effect of agricultural GHG emission reduction at each production level varies in degree and direction dimensions. Among them, the emission intensity effect dominates agricultural GHG emission reduction and contributes significantly to agricultural GHG emission reduction at all levels of production. Especially at level 1, the emission reduction contribution of the emission intensity effect accounts for 58.40%. The contribution of emission reduction decreases with the extension of the industrial chain but still occupies a major position. This shows that the implementation of the emission reduction portfolio measures will firstly affect the energy structure and energy efficiency of each sector and then realize GHG emission reduction by reducing the GHG emission intensity of the agricultural sector.

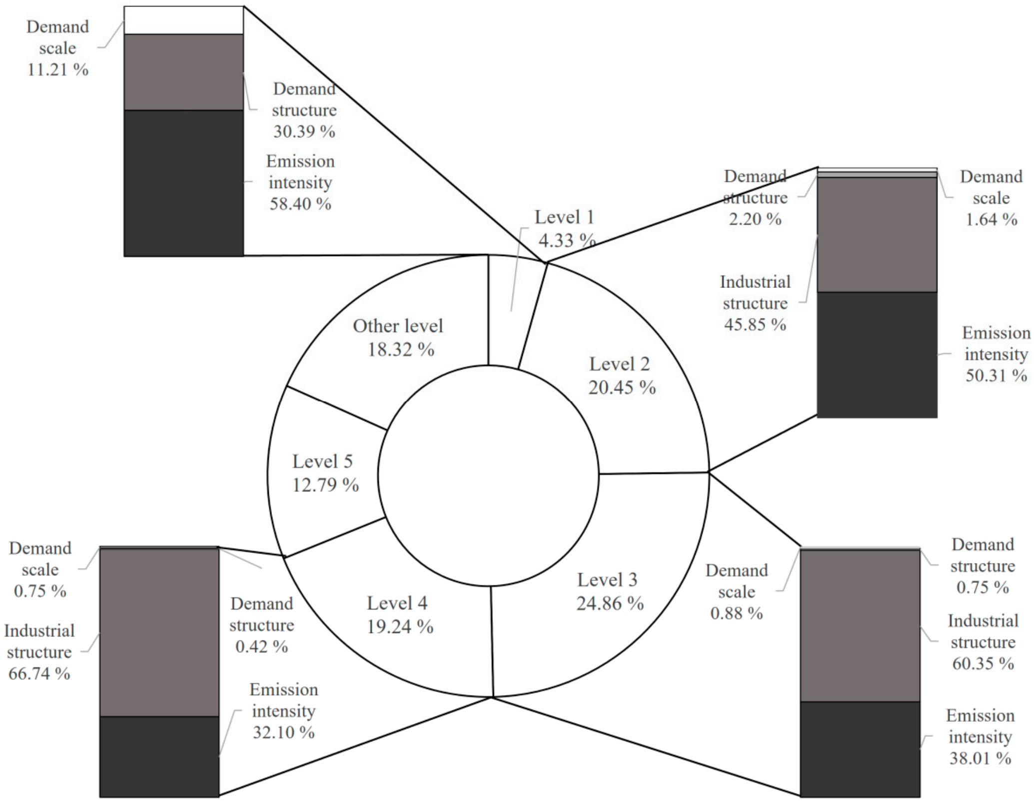

Figure 4. Decomposition of emission reduction contributions and influencing factors at different production levels in the scenarios of emission reduction measures.

The effect of industrial structure on agricultural GHG emission reduction is not significant at production level 1, but the effect of industrial structure on agricultural GHG emission reduction at levels 2–4 gradually increases with the extension of the industrial chain. The reason is that the emission reduction portfolio measures act directly on the first level of production, and industries are not able to adjust intermediate inputs in a timely manner. However, with the extension of the industrial chain, industries tend to choose relatively low-carbon and clean inputs as intermediate inputs, which promotes the development of the industrial structure in the direction of decarbonization and thus promotes the emission reduction in GHG in agriculture [26].

The demand scale effect and the demand structure effect mainly play a role in the direct emission link and have less influence on the indirect emission link. This shows that with the extension of the industrial chain, the final demand leads to the narrowing of the agricultural greenhouse gas emission base and the space for emission reduction in the downstream production link of the industrial chain.

3.2.2. Distribution of Emission Reduction Contributions by Sectors

Table 3 reflects the specific impacts of the implementation of the emission reduction portfolio measures on the agriculture-related sectors. Observations show that the implementation of emission reduction portfolio measures promotes different degrees of reduction in agricultural GHG emissions across industries, but there are differences in the sensitivity to emission reduction measures and the contribution of emission reduction among industries.

Table 3. Distribution of emission reduction contributions from different agriculture-related sectors under the emission reduction measures scenario.

No.	Industry	Emission Reduction (10^4 Tons)	Emission Reduction Contribution (%)	Share of Emission Reduction Contribution (%)	
				Direct Emission Reduction	Indirect Emission Reduction
I9	Vegetable	−55.99	33.80	24.12	75.88
I11	Other crops	−28.30	17.09	23.66	76.34
I13	Husbandry	−25.59	15.45	−5.00	105.00
I1	Rice	−18.30	11.05	22.73	77.27
I10	Fruit	−16.89	10.20	25.66	74.34
I3	Corn	−5.76	3.48	7.45	92.55
I2	Wheat	−3.86	2.33	11.83	88.17
I6	Oil crops	−2.51	1.52	16.29	83.71
I7	Cotton	−2.42	1.46	21.03	78.97
I15	Agricultural services	−1.90	1.15	18.00	82.00
I5	Potato	−1.20	0.72	9.25	90.75
I8	Sugar crop	−1.08	0.65	20.43	79.57
I14	Fishery	−1.03	0.62	44.05	55.95
I4	Soybean	−0.80	0.48	2.28	97.72

Among them, vegetables, livestock, rice, and fruits are the main contributors to the realization of agricultural GHG emission reduction in agriculture-related industries, accounting for 70.13% of the emission reduction in agriculture-related industries, with emission reduction contribution rates of 33.80%, 15.45%, 11.05%, and 10.20%, respectively. The contribution of the potato, sugar crop, fisheries, and soybean sectors to agricultural GHG emission reduction is significantly lower, with all contributing less than 1 percent to emission reduction.

As can be seen from Table 3, the emission reduction contribution of the emission reduction combination measures to each industry is mainly concentrated in the indirect emission reduction link. The livestock industry has not achieved direct emission reduction, indicating that the emission reduction combination measures need to be optimized.

3.3. Analysis of Emission Reduction Effects and Factors at the Industrial Chain Level

By analyzing the main emission reduction pathways and drivers of the emission reduction combination measures at the industry chain level, it was found that there were 20 agriculture-related pathways with the largest emission reduction contribution in the scenarios of the implementation of the emission reduction combination measures, whose emission reduction contribution accounted for 44.28% of the total emission reduction in the agriculture-related industries (Table 4).

Table 4. Decomposition of the top 20 agriculture-related emission reduction pathways and their drivers under the mitigation measure scenario.

No.	Emission Reduction Pathways	Emission Reduction (10 k Tons)	Emission Reduction Contribution (%)	Percentage of Emission Reduction Contribution from Each Factor (%)			
				$f(\Delta M)$	$f(\Delta L)$	$f(\Delta U)$	$f(\Delta H)$
1	CU→9→29	−9.77	5.41	96.89	1.26	−1.00	2.86
2	CU→9	−5.68	3.15	86.36	0.00	−7.37	21.01
3	CR→9→29	−5.44	3.02	97.06	1.26	−0.76	2.44
4	EX→33→9	−5.23	2.90	30.88	3.01	−19.56	85.67
5	CU→11→29	−5.12	2.84	96.76	1.30	−0.92	2.86
6	EX→33→13	−5.04	2.79	5.06	4.13	−26.87	117.68

Table 4. *Cont.*

No.	Emission Reduction Pathways	Emission Reduction (10 k Tons)	Emission Reduction Contribution (%)	Percentage of Emission Reduction Contribution from Each Factor (%)			
				$f(\Delta M)$	$f(\Delta L)$	$f(\Delta U)$	$f(\Delta H)$
7	CU→33→9	−4.90	2.71	76.13	7.41	−2.06	18.52
8	CU→9→22	−4.31	2.39	14.08	85.24	−0.37	1.04
9	EX→9	−3.65	2.02	30.82	0.00	−16.33	85.51
10	CU→14→22	−3.43	1.90	14.30	85.50	−0.86	1.06
11	CR→9	−3.13	1.73	87.53	0.00	−5.67	18.14
12	CR→11→29	−2.86	1.58	96.97	1.31	−0.72	2.44
13	CG→15→22	−2.81	1.56	15.75	92.42	0.39	−8.56
14	EX→33→11	−2.79	1.55	27.42	3.16	−20.54	89.97
15	EX→9→29	−2.78	1.54	77.81	1.01	−5.00	26.19
16	CU→11	−2.77	1.54	83.65	0.00	−7.72	24.07
17	IV→9→29	−2.65	1.47	101.81	1.32	−1.38	−1.75
18	CG→15→20	−2.53	1.40	29.08	99.63	1.38	−30.09
19	CU→3→29	−2.48	1.38	97.37	1.17	−1.42	2.87
20	CU→33→11	−2.42	1.34	72.95	8.40	−2.34	20.99
Total		−79.82	44.23	64.23	16.46	−6.18	25.49

3.3.1. Major Agriculture-Related Emission Reduction Pathways

Based on the final demand perspective, there are nine agriculture-related emission reduction paths triggered by citizens' consumption, accounting for 22.66% of the emission reduction contribution of the agriculture-related sector, which has the largest emission reduction potential. The total number of export-induced agriculture-related emission reduction pathways is five, with an emission reduction contribution of 10.80%.

The total number of agriculture-related emission reduction paths triggered by farmers' consumption is three, with an emission reduction contribution of 6.33%. The government consumption-induced agriculture-related emission reduction paths total two, with an emission reduction contribution of 2.96%. There is only one agriculture-related emission reduction path caused by investment, with an emission reduction contribution of 1.47%, and the potential for emission reduction is relatively small.

Among the nine agriculture-related emission reduction pathways at the citizen consumption level, there are three industrial chains in which the vegetable industry is the production sector at level 1, indicating that under the scenario of implementing emission reduction portfolio measures, citizen consumption can achieve GHG emission reduction in agriculture mainly by influencing the vegetable industry's demand for upstream industries such as thermal power and chemical fertilizers.

The light industry, as a level 1 production sector, has a total of two industry chains, indicating that under the scenario of implementing a combination of emission reduction measures, citizen consumption mainly realizes agricultural GHG emission reduction by influencing the light industry's demand for upstream industries such as the vegetable industry and other crops.

Of the five agriculture-related emission reduction pathways induced by exports, two and three involve the vegetable industry and light industry, respectively, indicating that exports achieve agricultural GHG emission reduction mainly by influencing the demand of the light industry for upstream industries such as the vegetable industry, livestock, and other crops. At the same time, agricultural GHG emission reduction is achieved by influencing the vegetable industry's demand for upstream industries such as fertilizers.

At the industry level involved in agricultural emission reduction pathways, the above 20 emission reduction pathways mainly involve the vegetable, fertilizer, and light industries. The vegetable industry appears 10 times in the top 20 emission reduction pathways and is a major emission reduction contributing industry. The reason is that the vegetable industry belongs to the downstream of the industrial chain, and the emission reduction effects generated by emission reduction measures such as carbon tax on upstream industries such as thermal power and fertilizers will be passed downstream along the industrial chain, further enhancing the direct GHG emission reduction of agriculture in this industry.

The fertilizer industry appears seven times in the top 20 emission reduction pathways, with a large contribution to emission reduction. The reason for this is that the emission reduction effect of emission reduction measures such as the carbon tax levied on the fertilizer industry will be passed along the industrial chain to the downstream corn, vegetable, and other crop industries, strengthening the industry's indirect emission reduction in agricultural GHG.

This shows that the existing literature ignores the role of the light industry in agricultural GHG emission reduction, but according to the decomposition results of agriculture-related emission reduction pathways, it can be seen that 5 out of the top 20 emission reduction pathways involve the light industry, which has a high degree of influence in the key agriculture-related emission reduction pathways. The reason is that the light industry is highly dependent on high-emission upstream industries such as vegetables, other crops, and livestock, and when the emission reduction portfolio measures curb the scale of development of the light industry, the demand for vegetables, other crops and livestock will be reduced accordingly, which will reduce agricultural GHG emissions to a certain extent.

3.3.2. Driving Factors of Industrial Chain Emission Reduction

In the implementation of the mitigation portfolio measures scenario, this paper provides a structural decomposition of the top 20 agriculture-related mitigation pathways in order to reveal the impact and contribution of each driver to emission reduction. Overall, the emission intensity effect makes the greatest contribution to emission reduction. Among the top 20 emission reduction pathways, there are 12 emission reduction pathways in which the emission intensity effect plays a dominant role, and its emission reduction contribution accounts for 64.23% of the top 20 emission reduction pathways.

The demand scale effect is the second largest emission reduction driver in the agriculture-related emission reduction pathways, with its emission reduction contribution accounting for 25.49% of the top 20 emission reduction pathways.

There are four emission reduction pathways, numbered 8, 10, 13, and 18, in which the effects of the industrial structure play a major driving role. All four pathways contain two levels of industries, and the final production sector of the chain belongs to the refined petroleum and thermal power industries. In the implementation of the mitigation package scenario, energy-consuming industries will adjust their intermediate inputs and reduce their inputs of high-carbon energy sources, such as refined petroleum and thermal power, in order to reduce their carbon emissions.

The emission intensity effect and the industry structure effect have a positive contribution to agricultural GHG emission reduction in all industrial chains, but there are differences in the effects of the other two drivers on different industrial chains.

The demand structure effect has a negative impact on agricultural GHG emission reduction in most pathways. That is, under the scenario of implementing emission reduction portfolio measures, the demand structure effect causes the agricultural GHG emissions of each industry chain to increase. The reason is that the implementation of emission reduction portfolio measures changes its demand structure, i.e., the proportion of the industry chain that relies more on inputs of energy products or high-emission intermediate products increases, leading to an increase in agricultural GHG emissions.

The paths with higher impacts driven by the demand structure effect are 4, 6, 9, and 14, all of which are due to agricultural GHG emissions driven by the type of export demand. This shows that the negative demand structure effect is mainly due to the influence of the export demand-driven industry chain.

4. Discussion

At the macro level, the effect of industrial structure and the change in investment demand are the main reasons for the contribution of macro emission reduction portfolio measures. This suggests that promoting green investment, adjusting input–output structures across industries, and selecting cleaner intermediate inputs are more conducive to achieving greenhouse gas emission reductions in agriculture.

At the industrial chain level, the number of agriculture-related emission reduction paths caused by citizen consumption and export is the most, and the emission reduction potential is the largest. Thus, implementing macro emission reduction portfolio measures can effectively promote agricultural greenhouse gas emission reduction by actively encouraging green consumption and adjusting export structure.

The key industries involved in the path of agricultural emission reduction mainly include the vegetable, fertilizer, and light industries. Consequently, focusing on these industries is crucial when implementing macro emission reduction portfolio measures to promote the emission reduction of upstream and downstream industries.

The research findings of this paper effectively expand the study on the emission reduction mechanism of the influence of macro emission reduction measures on agricultural GHG. By understanding the emission reduction mechanisms, policymakers can make more precise and effective policies for agricultural greenhouse gas emission reduction.

5. Conclusions and Policy Implications

5.1. Conclusions

In this paper, a dynamic CGE and SPD coupling model is constructed to simulate the emission reduction scenario of implementing the macro emission reduction combination measures of carbon tax, carbon sinks, and CCUS. The emission reduction drivers of the combination of emission reduction measures are progressively decomposed at three levels: total emission reduction, production stage, and industrial chain. The main conclusions of this study are as follows:

(1) In terms of the structure of agricultural GHG emission reduction, the emission reduction effect of the combination of carbon tax, carbon sinks, and CCUS macro emission reduction measures is dominated by the indirect agricultural GHG emission reduction triggered by the integration of the industrial chain, which accounts for 95.67% of the total emission reduction, while the direct carbon emission reduction only accounts for 4.33%. The emission reduction effect reaches its maximum at the third production level, after which the emission reduction effect gradually decreases with the increase in the production level.

(2) In terms of the drivers of agricultural GHG emission reduction, the emission intensity effect is the most important driver of agricultural GHG emission reduction, and it has an obvious role in reducing agricultural GHG emissions at all levels. The industrial structure effect is the secondary driving factor for agricultural GHG emission reduction, and the promotion effect of the industrial structure effect on agricultural GHG emission reduction at levels 2–5 gradually increases with the extension of the industrial chain. The demand structure effect and the demand scale effect have obvious abatement effects only in direct abatement, and the promotion effect in indirect abatement is not significant. There are differences in the impacts of different drivers on various production levels and different emission reduction pathways. In the agriculture-related emission reduction pathway, in addition to the demand structure effect that leads to an increase in agricultural GHG emissions, the other three effects also contribute significantly to agricultural GHG emission reduction.

(3) In terms of emission reduction pathways, the emission reduction of the top 20 agriculture-related emission reduction pathways accounted for 44.23% of the total agricultural GHG emission reduction in agriculture-related industries. Agricultural GHG emissions triggered by citizen consumption have a greater abatement potential, and agricultural GHG emission reductions are achieved mainly through the path of reducing the demand for upstream energy-intensive or high-emission industries by the vegetable industry and the light industry. Key industries such as vegetables and fertilizers provide the main agricultural GHG emission reduction contribution, mainly through indirect emission reduction. The light industry has high participation in the main agriculture-related emission reduction pathway and is a key industry that pulls upstream high-emission industries to reduce emissions.

5.2. Policy Implications

Based on the above findings, the following insights are drawn regarding the optimization of China's agricultural GHG emission reduction policies and the better use of the emission reduction role of the combination of carbon tax, carbon sinks, and CCUS macro emission reduction measures:

(1) It is necessary to grasp and make use of the differences in the emission reduction effects of macro emission reduction combination measures at the production and industrial chain levels and optimize the implementation of differentiated emission reduction strategies. For industries that contribute significantly to direct emission reduction (such as the vegetable, livestock, rice, and fruit industries), technological improvement, efficiency enhancement, and energy innovation on the production side will promote emission reduction by the industries themselves. For industries with a large contribution to indirect emission reduction, attention should be paid to optimizing the structure of intermediate inputs and reducing inputs of high-energy-consuming and high-emission products.

(2) In the short term, we should focus on enhancing the role of the emission intensity effect as the mainstay in promoting greenhouse gas emission reduction in agriculture and reducing the emission intensity through the use of cleaner energy sources or improved energy efficiency, among other means. In the medium and long term, we should pay attention to the positive role of the industrial structure effect on agricultural greenhouse gas emissions, further accelerate the transformation and upgrading of the industrial structure, and accelerate the realization of agricultural greenhouse gas emission reduction through structural optimization.

(3) It is necessary to give full play to the role of macro emission reduction portfolio measures in driving inter-industry synergistic emission reduction through final demand and to stimulate the potential for demand-side emission reduction. For the consumption-driven emission reduction path, it is necessary to actively advocate low-carbon life and green consumption and expand the proportion of low-carbon product supply. For the export-driven emission reduction path, it is necessary to actively adjust the export structure and reduce the dependence on the industrial chain of high-energy-consuming and high-emission products.

The limitation of this paper is that it fails to identify the individual effects of each measure in the macro emission reduction combination of carbon tax, carbon sinks, and CCUS. In future research, the individual effects of each measure in the macro emission reduction package can be further explored through the decomposition simulation of the dynamic CGE model and other methods.

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