Pol. J. Environ. Stud. Vol. 33, No. 5 (2024), 5381-5390
DOI: *10.15244/pjoes/183075* ONLINE PUBLICATION DATE: 2024-04-25

Original Research

Study on Measurement and Influencing Factors of Trade Embodied Carbon-Based on China-Russia Agricultural Products Trade

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Received: 29 October 2023
Accepted: 24 January 2024

Abstract

China and Russia are major agricultural countries with abundant agricultural resources, holding important global agricultural trade market positions. While the scale of China-Russia agricultural trade has maintained rapid growth, the embodied carbon emissions from agricultural products have also increased. This article first uses input-output data to construct a multi-regional input-output model under a total trade accounting method to calculate the carbon emission coefficients, trade value-added, and embodied carbon emissions of three categories of agricultural products traded between China and Russia from 2009 to 2019. Our results show that, from an industry perspective, Category C3 agricultural products have the highest carbon emission coefficients; Category C1 agricultural products have the highest export value-added. From the standpoint of imports and exports, Russia's export value-added to China has proliferated in recent years and is slightly higher than that of Chinese exports to Russia; the embodied carbon emissions from Chinese agricultural products are higher than those from Chinese exports to Russia. We further examined the impact of trade scale, trade structure, and carbon emission intensity on embodied carbon, finding that these three factors have heterogeneous effects on the embodied carbon of agricultural trade for different industries and countries.

Keywords: China-Russia; agricultural trade; embodied carbon measurement; LMDI index decomposition model; impact factor analysis

Introduction

As the ties between China and Russia deepen, their collaboration in trade, particularly in agriculture, has witnessed significant growth [1]. Both nations, being major players in the global agricultural market, have strengthened their trade relations due to factors like their entry into the World Trade Organization, the initiation of the Belt and Road Initiative, and economic sanctions imposed by Western countries on Russia [2]. This has led to a substantial increase in bilateral agricultural trade, reaching a total value of 5.5 billion USD in 2020, marking a sevenfold rise since 2001[1]. China has emerged as the largest importer of Russian agricultural products, while Russia holds the third position among importers of Chinese agricultural goods [3].

The traded agricultural products are diverse, with China exporting processed items like vegetables, fruits, fish, crustaceans, and mollusks to Russia, while Russia exports

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[1] https://www.statista.com/statistics/1003171/russia-value--of-trade-in-goods-with-china/

frozen fish, plant wood, soybeans, and edible oils to China. This comprehensive range of traded products showcases strong complementarity, positioning both nations as crucial partners in agricultural trade cooperation.

Amidst global economic growth, heightened environmental awareness has led to a focus on reducing carbon emissions to combat climate change [4]. Despite agriculture traditionally being considered a low-carbon industry, the IPCC assessment report highlights that carbon emissions from agricultural product trade contribute significantly, accounting for 23% of global emissions[2]. As Sino-Russian agricultural trade expands, the associated hidden carbon emissions and international carbon transfers have also increased [5]. This trend poses challenges such as the imposition of green barriers by developed nations under the guise of environmental protection, potentially hindering foreign trade development and impacting national economies [6, 7]. Therefore, this study aims to analyze and understand the hidden carbon emissions in Sino-Russian agricultural trade, calculate these emissions, and identify influencing factors to propose targeted carbon reduction strategies.

In the era of economic globalization, international trade cooperation intensifies, leading to a rise in cross-border intermediate goods [8]. Conventional statistical methods for international trade face challenges such as double counting of trade value and neglect of intermediate products [9, 10]. To address these issues and accurately estimate hidden carbon emissions, this study integrates the trade value-added method into a multi-regional input-output model, creating a bilateral trade hidden carbon model. This approach enhances the accuracy of results by avoiding the repetition of total carbon emissions and clarifying carbon emission responsibilities. Existing studies on embodied carbon emissions primarily focus on entire industries, lacking specific recommendations for targeted strategies [11]. This study, however, takes a sectoral perspective on agricultural products, leveraging China's status as a major agricultural nation and Russia's role in China's agricultural trade. By measuring the scale and proportion of hidden carbon emissions in Sino-Russian agricultural trade and exploring influencing factors, this research contributes to the theoretical development of this field.

Literature Review

In terms of methods for calculating trade-embodied carbon, there are primarily two categories: one involves recording the entire lifecycle process of a product from production to finished goods, tracing the carbon emissions footprint, and subsequently calculating the carbon emissions, known as the Life Cycle Assessment (LCA) method [12-15]. The other category involves calculating the carbon emissions of a product during the production process based on the input-output relationships of different economic sectors. This method is called the Input-Output Analysis, and input-output models include single-region and multi-region input-output models [16-18]. With the clarification of the international division of labor, the total trade accounting method under multi-region input-output models has gradually become the primary approach for studying embodied carbon emissions.

When decomposing the influencing factors of embodied carbon, scholars commonly utilize decomposition models such as the Structural Decomposition Analysis (SDA) and the Logarithmic Mean Divisia Index (LMDI) model. The LMDI model is currently the most widely adopted decomposition method compared to the SDA structural decomposition model. It allows for a comprehensive analysis of the influencing factors of embodied carbon emissions from the perspectives of scale, structure, and intensity [19]. Meng et al. [20] constructed an LMDI model to decompose the specific impact structure of carbon emissions. Their analysis revealed that economic growth propels the growth of embodied carbon, and a decrease in energy intensity can effectively reduce carbon emissions. The study recommended a rational response to the relationship between economic development and carbon emissions, advocating for adjustments to the energy structure.

Material and Methods

Date and Sectoral Division of Agricultural Products

This paper focuses on China-Russia agricultural trade, necessitating standardized industry categorizations due to variations in input-output tables and energy consumption statistics. The study primarily relies on Asian Development Bank (ADB) data supplemented by the World Input-Output Database (WIOD), classifying the entire industry into 35 sectors. The study aligns input-output, energy consumption, and trade data classifications following adjustment methods proposed by Chen Si et al. [21] and Liu Chang et al. [22]. The study consolidates eight specific sectors into three major agricultural product industries (C1, C2, and C3) to address discrepancies between customs HS codes and input-output categories, enhancing clarity and consistency (see Table 1).

Research Methodology

Direct Carbon Emission Factor for Agricultural Products

This paper utilizes the reference methods and parameters provided by the IPCC Guidelines for National Greenhouse Gas Inventories and, at the same time, draws on the concept and calculation method of the direct consumption coefficient in the input-output coefficients to propose the concept of the natural carbon emission coefficient [23-25]. It is expressed as the carbon dioxide emission from the energy consumed for each unit of product produced.

2 https://news.climate.columbia.edu/2022/09/19/the-growing--awareness-and-prominence-of-environmental-sustainability/

Table 1. Adjusted sectoral classification of agricultural products

code	Adjusted sectoral classification of agricultural products	Classification of agricultural products under the input-output table	Corresponds to Customs Export Chapter 24 Agricultural Products (01-24)
C1	Agriculture	Agriculture	06,07,08,09,10,12,15
C1	Livestock	Livestock	01
C1	Forestry	Forestry	13,14,23,20
C1	Fisheries	Fisheries	03
C2	Food Industry	Food Processing Manufacturing	17,04,21,19
C2	Beverage & Alcohol & Tobacco Industry	Beverage and Alcohol Manufacturing	18,22
C2	Tobacco	Tobacco Manufacturing	24
C3	Plant & Wood Industry	Plant and Wood Manufacturing	06,13,14,20

Source: Based on input-output tables and customs product tables.

Calculate the direct carbon emission coefficient of an industry i: the carbon dioxide emissions directly caused by the production of one unit of product in industry i, denoted as , is calculated by the following formula:

$$r_i = \sum_{i=1}^{7} \theta_i \times h_i / g_i \quad (1)$$

Where $\sum_{i=1}^{7} \theta_i \times h_i$ denotes the carbon emissions generated by energy consumption in the manufacturing process of products in industry i, and g_i is the total output value of that industry; θ_i is the energy consumption coefficient of industry i, and h_i is the actual energy consumption of industry i.

When calculating energy consumption intensity (θ), we adhere to the 2006 IPCC Guidelines, using data from the Energy Statistical Yearbook for eight types of energy in the agricultural production process. We focus on direct energy consumption, excluding electric power, and compute carbon emission coefficients using the Energy Carbon Emission Factor (ECEF) formula from the IPCC 2006 version of Energy (Chapter 6).

$$\theta_k = NVC_k + CEF_k * COF_k * (44/12)(k = 1,2, \dots 7) \quad (2)$$

Where θ_k is the CO_2 emission factor (energy carbon emission factor) for a particular energy source k. NVC_k does China's 2018 Energy Statistical Yearbook express the average single energy heat generation. CEF_k the value of the carbon emission factor provided by the IPCC expresses the amount of carbon contained in one unit of energy heat. COF_k is the oxidation rate of the carbon factor when the energy source is burned.

Calculation of Value Added in Agricultural Trade Based on the Gross Trade Accounting Approach

Based on the entire trade accounting method, this paper calculates the values of DVA and RDV of different agricultural industries in China and Russia and sums them up to derive the export value added of three agricultural products in China and Russia as follows [26-29].

According to the multiregional input-output table, the tripartite input-output model composed of China, Russia, and the third country can be expressed as:

$$\begin{bmatrix} A_{cc} & A_{cu} & A_{ct} \\ A_{uc} & A_{uu} & A_{ut} \\ A_{tc} & A_{tu} & A_{tt} \end{bmatrix} \begin{bmatrix} X_c \\ X_u \\ X_t \end{bmatrix} + \begin{bmatrix} Y_{cc} & Y_{cu} & Y_{ct} \\ Y_{uc} & Y_{uu} & Y_{ut} \\ Y_{tc} & Y_{tu} & Y_{tt} \end{bmatrix} = \begin{bmatrix} X_c \\ X_u \\ X_t \end{bmatrix} \quad (3)$$

Where subscripts c, u, and t denote China, Russia, and third countries, respectively; A is the input coefficient; X denotes output; and Y is the final demand product.

Table 2. Implications of GTAA decomposition

Component	Symbol	Decomposition Content	Symbol	Code
Domestic value added absorbed abroad	DVA	Domestic value added of final product exports	DVA-FIN DVA-INT DVA-INTREX	T1 T2 T3+T4+T5
Domestic value added returned to and absorbed by country	RDV	Direct intermediate exports absorbed by importing countries	/	T6+T7+T8
Value added abroad	FVA	Direct intermediate exports resulting from production in importing country absorbed by other countries	MVA OVA	T11+T12 T14+T15
Purely double-counted components	PDC	/	DDC FDC	T9+T10 T13+T16

According to the WWZ (total trade accounting method) decomposition formula, the total exports from China to Russia are decomposed into the following 16 components, and the same is true for Russian exports to China. In turn, the vector T1-T16 can be expressed as:

$$Ecu=T1+T2+\cdots\cdots+T16=\ \Sigma Tn \tag{4}$$

The meaning of its specific decomposition is shown in Table 2.

Measurement of Embodied Carbon Emissions

Based on the measurement and decomposition methodology of the total trade accounting method above, the embodied carbon emissions from country C's exports to country U are divided into three components:

Carbon emissions from value added in the exporting country are expressed using the product of DVA_{cu} and RDV_{cu} with the whole carbon emission factor of the exporting country (the product of the direct carbon emission factor and the Leontief inverse matrix).

$$EC = f_c L_{cc}(DVA_{cu} + RDV_{cu}) \tag{5}$$

To accurately measure embodied carbon emissions in China-Russia agricultural trade, we follow the approach suggested by Gao et al. [30] and Dissanayake et al. [31]. This involves multiplying the full carbon emission coefficients with the value added. We calculate complete carbon emission coefficients for three agricultural product types in China and Russia, combining direct emission coefficients with World Input-Output Database data. Multiplying these coefficients by the trade's value added provides the data for embodied carbon emissions in the China-Russia agricultural trade.

Decomposition Analysis of Implicit Carbon Emission Influencing Factor Effects of China-Russia Agricultural Products Trade Based on LMDI Modeling

Many scholars explore the impact of embodied carbon emissions from the scale effect [32, 33], structural effect [34, 35], and intensity influence of products [36, 37]. Accordingly, this paper mainly explores the impact of embodied carbon emissions from three aspects: the scale of China-Russia agricultural trade, trade structure, and technological progress.

(1) Trade scale: The trade scale effect in agriculture, under constant structure and technology, shows that increased trade scale leads to higher embodied carbon emissions. This study explores this by examining the value added of agricultural product industries in China and Russia in relation to changes in embodied carbon emissions [38].

(2) Trade structure: The trade structure effect highlights that, with a constant scale of agricultural product trade, a higher proportion of product trade structure corresponds to increased embodied carbon emissions. This study examines the balance of value-added scale for agricultural products by industry in China and Russia [39].

(3) Technological progress: The intensity effect, linked to energy consumption and utilization, influences embodied carbon emissions. Technological progress enhances energy efficiency, lowering the complete carbon emission coefficient of agricultural products and reducing embodied carbon emissions [40]. This study uses China's and Russia's emission coefficients to explore the correlation between intensity effects and embodied carbon emissions.

This paper adopts the LMDI model to decompose and analyze the factors affecting embodied carbon emissions and further examines the main factors affecting the change of embodied carbon in the bilateral trade of agricultural products between China and Russia [41, 42].

$$EC = \sum_{i=1}^{n} E \times \frac{e_i}{E} \times \frac{q_i}{e_i} = \sum_{i=1}^{n} E \times S_i \times I_i \tag{5}$$

In equation (5): EC denotes the total embodied carbon emissions from trade in a country or region; E denotes the whole scale of transfers out of region s; e_i denotes the scale of transfers out of sector i in region s; q_i denotes the carbon emissions from sector i in region s; S_i denotes the proportion of the size of sector i to the total size in region s; and I_i denotes the embodied carbon intensity of sector i in region s. The total scale of transfer is still referred to as the decomposition part under the total trade accounting method.

The difference in trade-embodied carbon emission transfers between the two years based on the LMDI can be decomposed as follows:

$$\Delta Q = \Delta Q(t) - \Delta Q(0) = \Delta Q_{size} + \Delta Q_{str} + \Delta Q_{int} \tag{6}$$

$$\Delta Q_{size} = \sum_{i=1}^{n} L(q_i(t), q_i(0)) \times Ln(\frac{E(t)}{E(0)}) \tag{7}$$

$$\Delta Q_{str} = \sum_{i=1}^{n} L(q_i(t), q_i(0)) \times Ln(\frac{S_i(t)}{S_i(0)}) \tag{8}$$

$$\Delta Q_{int} = \sum_{i=1}^{n} L(q_i(t), q_i(0)) \times Ln(\frac{I_i(t)}{I_i(0)}) \tag{9}$$

$$Ln(a,b)\frac{a-b}{Lna - Lnb}, a \neq b \tag{10}$$

where ΔQ denotes the difference in embodied carbon emissions between two-year segments; ΔQ_{size} denotes the amount of change in embodied carbon emissions pulled by the scale effect; ΔQ_{str} denotes the amount of change in embodied carbon emissions pulled by the structural effect; ΔQ_{int} denotes the amount of change in embodied carbon emissions pulled by the intensity effect; $q_i(t)$ denotes the embodied carbon emissions of sector i in year t; $q_i(0)$ denotes the embodied carbon emissions of sector i in the embodied carbon emissions in the base year; E(t) denotes the scale of transfer out in year t; E(0) denotes the scale of transfer out in the base year; $S_i(t)$ denotes the share of the scale of transfer out in year t of sector i; $S_i(0)$ denotes the share of the scale of transfer out in the base year of sector i; $I_i(t)$ denotes the embodied carbon emission intensity in year t of sector i; $I_i(0)$ denotes the embodied carbon emission intensity in the base year of sector i, which is expressed by the total carbon emission coefficient. In this paper, when analyzing the decomposition of the three types of agricultural products' impact factors, the scale of redeployment used is based on the scale of agricultural products' value added. Since 2009 is the base period calculation year, the decomposition results of each part start from 2010.

Results and Discussion

Direct Carbon Emission Factor for Agricultural Products

This paper measures the carbon emission coefficients of different energy sources using Model (1). According to the energy index data in Table 3, the carbon emission coefficients of kerosene, diesel oil, and fuel oil are high, above 3.0, and fuel oil reaches more than 3.20, while the carbon emission coefficient of coal is the smallest, typically less than 2.0; and the carbon emission coefficients of coke, gasoline, and natural gas are in the range of 2.0-3.0.

This study relies on energy carbon emission data, industry-specific energy consumption, and the gross output value of agricultural products by sector to determine the direct carbon emission coefficients of agricultural products by sector. The carbon emission coefficients for Russian agricultural products are derived from the Russian Statistical Yearbook, utilizing information on gross output value and energy consumption. In cases where output value and energy consumption data are missing for specific years, calculations are based on forecasts related to the input-output scale, exports, and outputs of agricultural products in China and Russia (refer to Tables 4). Notably, C1 agricultural products exhibit the second-highest coefficients, ranging between 0.265-0.335 and 0.200-1.822, compared to C3 agricultural products. C2 food, beverage, alcohol, and tobacco industries display the lowest coefficients, indicating lower CO2 emissions in the direct production process for this category, with values ranging from 0.056 to 0.2138 and 0.0138 to 0.141, respectively.

Analysis of Embodied Carbon Emissions from China-Russia Agricultural Trade

Analysis of Total Embodied Carbon Emissions from China-Russia Agricultural Trade

Figure 1 illustrates the fluctuation in China-Russia agricultural trade's total embodied carbon volume (2009-2019). China's embodied carbon emissions from agricultural exports to Russia varied between 2.06 million

Table 3. Various energy consumption coefficients

Energy type	NCV (kJ/M3)	CEF (kJ/106 kJ)	COF	Energy Carbon Emission Factor θ_k
Coal	20908	26 4	0 93	1 8822
Coke	28435	29.5	0.93	2.8604
Gasoline	43070	19.1	0.98	2.9560
Kerosene	43070	19.5	0.99	3.0487
Diesel oil	42652	20.2	0.98	3.0959
Fuel Oil	41816	21.1	0.99	3.2028
Natural gas	38931	15.3	0.99	2.1622

Table 4. Direct carbon emission coefficient (in tons)

Year	Direct carbon emission coefficient of Classified agricultural products in China(unit: million tons/billion dollars)			Direct carbon emission coefficient of Classified agricultural products in Russia (Unit: tons/billion dollars)		
	C1	C2	C3	C1	C2	C3
2009	0.2963	0.2138	11.8912	0.2007	0.0721	19.8286
2010	0.2838	0.2220	12.0186	0.2175	0.0912	20.1064
2011	0.2653	0.1768	10.2191	0.2242	0.0638	16.6291
2012	0.2662	0.1403	9.3383	0.3056	0.0532	9.5556
2013	0.2661	0.1314	8.4638	0.1563	0.0503	8.5551
2014	0.2772	0.1074	8.0759	0.3596	0.0300	10.3623
2015	0.3036	0.0928	7.9889	0.4203	0.0277	11.1507
2016	0.3217	0.0875	7.6133	0.4188	0.0203	10.9432
2017	0.3253	0.0720	7.3620	0.5089	0.0172	11.3277
2018	0.3357	0.0679	7.0159	1.8227	0.1408	12.9761
2019	0.2943	0.0559	6.7843	1.7862	0.0704	9.8695

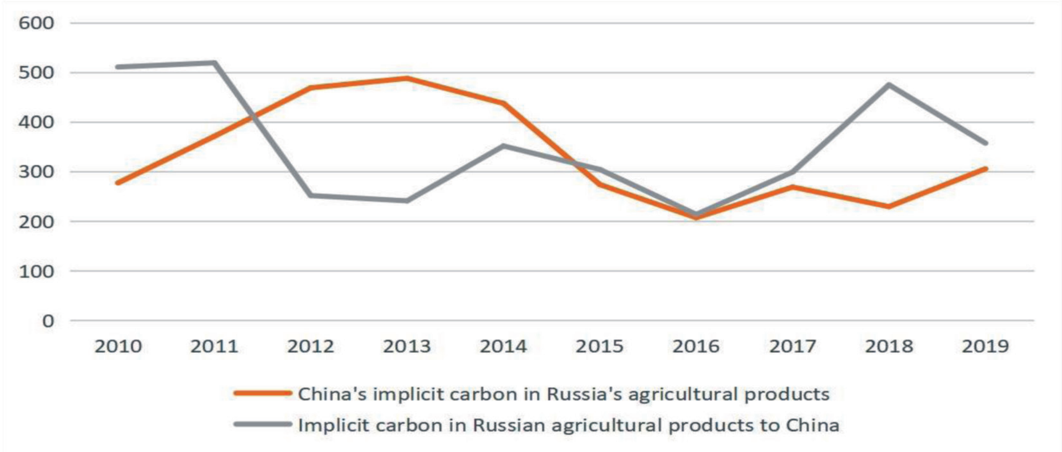

Fig. 1. Embodied Carbon Emissions from Overall Agricultural Trade between Russia and China (in tons)

and 4.88 million tons. Emissions increased from 2009 to 2013, declined to 2.07 million tons from 2013 to 2016, and fluctuated after that, reaching 3.05 million tons in 2019 (a 24.9% YoY increase). Russia's emissions to China ranged from 2.4 million to 5.19 million tons, peaking in 2011. Stability followed until a sharp increase to 4.74 million tons in 2018 (a 58.8% YoY rise), emphasizing the need for an improved trade environment.

Classification and Analysis of Embodied Carbon Emissions from Agricultural Products Trade Between China and Russia

Table 5 shows the changes in embodied carbon emissions of the three categories of agricultural products exported from China and Russia in 2009-2019, and through the statistical values in the table, we can intuitively find that in the trade of the three categories of agricultural products, due to the characteristics of the production of the products, the C3 category of agricultural products produces the most embodied carbon emissions, followed by the C1 category of traditional agricultural products, and the C2 category of farm products, the natural gas, gasoline and other energy consumption inputs in the production process, C2 agrarian products, in the production process of natural gas, gasoline, coal and other energy consumption is low, resulting in its own direct carbon emission coefficient is low, as well as in the trade volume and the scale of trade value added generated by China and Russia accounted for a small proportion, so this category of agricultural products in the three categories of agricultural products of the lowest embodied carbon emissions.

Summary Analysis

The analysis of embodied carbon emissions from China-Russia agricultural trade reveals distinctive trends. China's exports to Russia initially increase, then decrease, while Russia's exports to China show a reduction

Table 5. Embodied carbon emissions from China-Russia classified agricultural exports (in tons)

Year	China-Russia embodied carbon in three categories of agricultural products			Russia-China embodied carbon in three categories of agricultural products		
	C1	C2	C3	C1	C2	C3
2009	34.21	10.99	231.7	16.36	0.77	327.24
2010	35.08	13.4	322.41	18.4	1.17	490.85
2011	32.78	13.19	356.09	21.04	0.84	497.01
2012	17.04	9.87	441.61	13.06	0.76	237.53
2013	25.17	10.22	452.29	9.75	0.88	230.17
2014	12.94	9.68	414.49	10	0.53	340.81
2015	10 76	6 99	255 82	14 62	0 58	288 78
2016	9.55	6.51	190.78	10.7	0.29	202.43
2017	14.01	7.24	247.3	20.97	0.41	277.41
2018	9.04	3.27	216.82	154	13.61	306.82
2019	31.56	3.48	270.22	132.26	5.14	219.68

Source: Based on the embodied carbon emissions formula.

followed by an increase. Overall, Russian exports exhibit slightly higher carbon emissions.

In sub-sectors, C3 plant and timber products, with higher energy consumption, lead to significant carbon emissions, topping the list. Traditional C1 agrarian products, despite high trade turnover, rank second due to lower energy consumption. C2 products follow with minor carbon emissions.

Trends in embodied carbon correlate with shifts in overall trade volume, influenced by key events like the 2008 financial crisis, Russia's WTO accession in 2012, the "Belt and Road" initiative in 2013, Western sanctions in 2014, and U.S.-China trade relations in 2018. Critical change nodes include the 2008 financial crisis, Russia's WTO accession in 2012, the "Belt and Road" initiative in 2013, Western sanctions in 2014, U.S.-China trade friction in 2018, and trade fluctuations from the Russian-Ukrainian conflict in 2022.

Further Analysis: Decomposition Analysis of Factors Affecting Embodied Carbon Emissions from China-Russia Agricultural Trade

Analysis of Implicit Carbon Decomposition in China's Classified Agricultural Exports to Russia

(1) Trade scale: C1 product emissions from China to Russia initially decrease then increase, closely tied to trade scale changes. C2 emissions follow the same pattern as trade scales, decreasing with reduced trade. C3 emissions correlate positively with scale but decrease from 2014 to 2018 as the scale drops. However, C3's positive impact on emissions diminishes as the scale decreases.

(2) Structural effects: C1's structural changes increased emissions after 2017. C2's primarily positive structural effect increases emissions, turning negative after 2018. C3's structural effect initially promotes emissions, then turns negative, driving reduction.

(3) Intensity effect: C1's low energy efficiency increased emissions from 2014-2018, improving in 2019. C2 and C3 show consistently harmful intensity effects from 2010-2019, indicating that progress in energy efficiency drives emission reduction. Table 6 shows the specific results.

Analysis of Implicit Carbon Decomposition in Russia's Classified Agricultural Exports to China

(1) C1 product emissions to China from Russia had varying scale effects, positive in 2010-2011 and 2017-2018 but negative in 2019. C2 emissions had minimal and steady scale effects, peaking in 2017. C3 scale effects fluctuated, causing emission growth in 2010-2011 and 2017-2018 but a decline in 2019.

(2) C1 structural effects were adverse in 2010-2015, turning positive in 2019. C2 had a positive structural effect in 2010-2015, turning negative in 2017-2019, aligning with emission decline. C3 showed positive structural effects in 2010-2015, turning negative in 2017-2019, consistent with emission reduction. The structural effect of C3 was positive in 2010-2016, turning significantly negative in 2017-2018, especially in 2018, and becoming positive again in 2019.

(3) C1 intensity effects were adverse in 2010-2014, turning positive after 2015, leading to increased emissions. Improved energy efficiency in 2019 resulted in a negative intensity effect and emission reduction. C2 consistently had a negative intensity effect, significantly reducing emissions, especially in 2018-2019. C3 had a negative intensity effect in 2011-2013, turning positive in 2014-2018, but became negative again in 2019, the main factor in emission reduction. Table 7 shows the specific results.

Table 6. Results of embodied carbon decomposition of China's exports of three types of agricultural products to Russia (in tons)

Type	decomposition of effect	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019
C1	Embodied carbon credits	0.87	-2.3	-15.7 5	8.14	-12.2 3	-2.18	-1.21	4.46	-4.97	22.52
	Scale effect	4.76	3.9	-5.33	4.09	-2.19	-2.61	-1.12	3.93	-5.95	9.15
	Structural effect	-1.68	-3.08	-10.9 3	4.54	-10.8 0	-0.11	-0.75	0.05	0.72	15.21
	Intensity effect	-2.21	-3.12	0.51	-0.49	0.76	0.54	0.66	0.48	0.26	-1.84
C2	Embodied carbon credits	2.41	-0.21	-3.32	0.35	-0.54	-2.69	-0.49	0.73	-3.98	0.22
	Scale effect	1.67	1.53	-2.54	1.97	-1.19	-1.82	-0.75	2.32	-3.36	1.71
	Structural effect	0.04	0.93	2.04	-1.03	2.57	0.12	0.43	0.1	-0.74	-1.44
	Intensity effect	0.7	-2.67	-2.82	-0.59	-1.92	-0.99	-0.17	-1.68	-0.62	-0.82
C3	Embodied carbon credits	90.71	33.69	85.52	10.68	-37.8 0	-158. 67	-65.0 4	56.52	-30.4 8	53.4
	Scale effect	37.71	39	-88.1	87.67	-51.6	-72.5	-24.5	73.58	-121. 58	123.1
	Structural effect	67.12	39.13	199.4	-43.65	41.46	-12.5	-34.1	-13.9 9	97.74	-66.3
	Intensity effect	-14.1 3	-44.45	25.8	-33.34	-27.6 7	-73.59	-6.36	-3.07	-6.64	-3.41

Source: Calculations based on the LMDI decomposition method

Table 7. Results of embodied carbon decomposition of Russian exports of three types of agricultural products to China (in tons)

Type	decomposition of effect	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019
C1	Embodied carbon credits	0.87	-2.30	-15.7 5	8.14	-12.2 3	-2.18	-1.21	4.46	-4.97	22.52
	Scale effect	4.76	3.90	-5.33	4.09	-2.19	-2.61	-1.12	3.93	-5.95	9.15
	Structural effect	-1.68	-3.08	-10.9 3	4.54	-10.80	-0.11	-0.75	0.05	0.72	15.21
	Intensity effect	-2.21	-3.12	0.51	-0.49	0.76	0.54	0.66	0.48	0.26	-1.84
C2	Embodied carbon credits	2.41	-0.21	-3.32	0.35	-0.54	-2.69	-0.49	0.73	-3.98	0.22
	Scale effect	1.67	1.53	-2.54	1.97	-1.19	-1.82	-0.75	2.32	-2.62	1.71
	Structural effect	0.04	0.93	2.04	-1.03	2.57	0.12	0.43	0.10	-0.74	-1.44
	Intensity effect	0.70	-2.67	-2.82	-0.59	-1.92	-0.99	-0.17	-1.68	-0.62	-0.82
C3	Embodied carbon credits	90.71	33.69	85.52	10.68	-37.80	-158. 67	-65.04	56.52	-30.48	53.40
	Scale effect	37.71	39.00	-88.10	87.67	-51.60	-72.50	-24.55	73.58	-121. 58	123.15
	Structural effect	67.12	39.13	199.42	-43.65	41.46	-12.58	-34.13	-13.9 9	97.74	-66.33
	Intensity effect	-14.13	-44.45	-25.80	-33.34	-27.67	-73.59	-6.36	-3.07	-6.64	-3.41

Source: Calculations based on the LMDI decomposition method

Conclusions

Utilizing input-output data, a multi-regional model computes carbon emission coefficients, trade value-added, and embodied carbon emissions for three China-Russia agricultural product categories (C1, C2, C3) from 2009 to 2019. Findings reveal: (1) C3 has the highest carbon coefficients, followed by C1 and C2. (2) Despite high carbon coefficients for C3, Russian agricultural exports to China surpass China's in value-added, with C1 leading, followed by C2 and C3. (3) Russia's embodied carbon emissions to China exceed China's to Russia, showing a declining trend for China and fluctuations followed by an increase for Russia; C3 products contribute the highest, followed by C1 and C2 with the lowest emissions.

Employing an LMDI index decomposition model from 2010 to 2019, influencing factors, including trade scale, structure, and carbon emission intensity, are examined. Results indicate: (1) Export scale is the primary factor increasing embodied carbon emissions for both countries, with structural effects playing a secondary role for China and intensity effects being the smallest. Russia exhibits intensity effects as the second-most significant factor. (2) By industry, the intensity effect minimally promotes embodied carbon emissions for C1 products in both countries, while mainly restraining emissions for the other categories. Structural effects shift from restraint to promotion in the export trade of all three categories. Below are some policy recommendations:

Mitigating the scale effect is key to reducing embodied carbon in Sino-Russian agricultural trade. Instead of cutting trade scale, prioritize carbon emission reduction. For low-carbon trade, Chinese exporters should enhance energy efficiency, embrace clean energy, and receive government support. Global knowledge transfer in clean energy technologies is crucial.

To tackle rising carbon emissions from expanding trade, focus on agricultural decarbonization. Implement low-carbon technologies, raise awareness, and support government-led initiatives for sustainable practices in China.

For reduced embodied carbon in China's agricultural exports to Russia, improve the trade structure. Diversify markets, leverage opportunities like RCEP, FTA, and "Belt and Road", and enhance trade infrastructure for stability.

Fostering a sustainable, low-carbon model requires policy alignment, adoption of international emission standards, and refined carbon accounting. Expanding Sino-Russian agricultural trade is vital amid the Russia-Ukraine conflict for stability and effective carbon management.

Although this paper provides a detailed empirical analysis of the embodied carbon in Sino-Russian trade in agricultural products, the years studied are relatively limited due to data constraints, and future studies can further increase the sample size.

Conflict of Interest

The authors declare no conflict of interest.

Data Availability Statement

The data used to support the findings of this study is included within the article, and further inquiries can be directed to the corresponding author.

Acknowledgements

This study was supported by Laboratory of Transport Pollution Control and Monitoring Technology (No. Z2209-030).

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