

Article

Efficiency and Driving Factors of Agricultural Carbon Emissions: A Study in Chinese State Farms

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Abstract: Promoting low-carbon agriculture is vital for climate action and food security. State farms serve as crucial agricultural production bases in China and are essential in reducing China's carbon emissions and boosting emission efficiency. This study calculates the carbon emissions of state farms across 29 Chinese provinces using the IPCC method from 2010 to 2022. It also evaluates emission efficiency with the Super-Slack-Based Measure (Super-SBM model) and analyzes influencing factors using the Logarithmic Mean Divisia Index (LMDI) method. The findings suggest that the three largest carbon sources are rice planting, chemical fertilizers, and land tillage. Secondly, agricultural carbon emissions in state farms initially surge, stabilize with fluctuations, and ultimately decline, with higher emissions observed in northern and eastern China. Thirdly, the rise of agricultural carbon emission efficiency is driven primarily by technological progress. Lastly, economic development and industry structure promote agricultural carbon emissions, while production efficiency and labor scale reduce them. To reduce carbon emissions from state farms in China and improve agricultural carbon emission efficiency, the following measures can be taken: (1) Improve agricultural production efficiency and reduce carbon emissions in all links; (2) Optimize the agricultural industrial structure and promote the coordinated development of agriculture; (3) Reduce the agricultural labor scale and promote the specialization, professionalization, and high-quality development of agricultural labor; (4) Accelerate agricultural green technology innovation and guide the green transformation of state farms. This study enriches the theoretical foundation of low-carbon agriculture and develops a framework for assessing carbon emissions in Chinese state farms, offering guidance for future research and policy development in sustainable agriculture.

Keywords: state farms; agricultural carbon emission; agricultural carbon emission efficiency; IPCC method; Super-SBM model; LMDI method; sustainable agriculture



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1. Introduction

Global warming has triggered many adverse effects, including rising sea levels, extreme weather, increased disease spread, less biodiversity, and profound threats to global agricultural productivity [1–3]. Given the indispensable role of agriculture in ensuring food security and human prosperity, the imperative to curtail carbon emissions has emerged as a universal obligation and collective endeavor [4]. China has taken proactive measures to engage in climate governance in light of the escalating global climate crisis. In 2020, China committed to the international community, aiming to peak its carbon dioxide emissions by 2030 and achieve carbon neutrality by 2060 [5]. Embracing a sustainable and low-carbon approach is not merely an option but a necessity, serving as a crucial pathway toward realizing these dual carbon goals and ensuring high-quality development while smoothly transitioning between old and new economic patterns [6]. The agricultural sector, necessary for low-carbon transformation, has witnessed rapid growth in recent years. However, this growth has generated concerns regarding escalating energy consumption and carbon

emissions. Notably, China's agricultural carbon emissions presently amount to roughly 16–17% of the total carbon emissions [7]. Consequently, expediting the transition to low-carbon agricultural farming practices is critical. Given specified input factors, achieving low-carbon agricultural development necessitates optimizing output while concurrently minimizing redundant carbon emissions [8]. Therefore, it is of paramount importance to evaluate the efficiency of agricultural carbon emissions. This evaluation paves the way for a more sustainable agrarian landscape [9].

State farms are a unique form of agricultural economy in China. In the early years of the People's Republic of China, the government leveraged the military to advance agriculture. It established a vast network of state farms nationwide, consolidating China's farmland resources [10]. The respective provincial administrations uniformly and centrally govern the 1799 farms within each province. Today, they have become the backbone of Chinese agriculture [11], driving the modernization of agriculture, safeguarding food security, and making consistent supplies of vital farm products in China [12]. These state farms operate relatively independently as highly organized, large-scale, industrialized agricultural production units [13]. Through large-scale production practices, they have substantial impacts on carbon emissions. With the rise of low-carbon agriculture, state farms' relatively autonomous and closed-loop system is also undergoing a green transformation. However, it grapples with inactive mechanisms and poor management [12]. Therefore, this paper aims to quantify and evaluate the carbon emission efficiency in agricultural practices within state farms and explore the impact of emissions.

Researchers [11].

Agricultural carbon emissions quantify agriculture's environmental impact, especially carbon emissions, using three main methods: the IPCC approach, which utilizes carbon emission coefficients; the life cycle method [14,15], evaluating emissions and sequestration within set boundaries using emission coefficients [16]; and the input–output method [17,18], which calculates energy demands and emissions from input–output tables and energy factors. In addition, agriculture is a crucial sector for improving carbon emission efficiency [19]. Many scholars have researched Chinese agricultural carbon emission efficiency [20,21]. Most noticed an upward trend in overall efficiency, but there were differences between regions. For example, Zhang et al. [22] found an aggregation phenomenon of agricultural carbon emission efficiency between southern and northern China. Zhang et al. [23] found that the carbon emission efficiency along the Maritime Silk Road was higher than that of other provinces along the Belt and Road. A study on state farms in the Heilongjiang Province proved that adjusting cropping structures and optimizing irrigation and fertilization techniques helped reduce emissions and enhance efficiency are influenced by agricultural production efficiency, agricultural industry structure, agricultural economic development level, and agricultural labor scale [24]. Yasmeen et al. [25] found that the impact of agricultural production efficiency on emissions varied among 17 major agricultural countries, with China's efficiency lagging behind developed countries. Xiong et al. [9] noted that a 1% increase in efficiency led to a 0.33% decrease in emissions. Zhu and Huo [26] observed an inverted U-shaped relationship between efficiency and emissions. Agricultural industry structure also plays a crucial role; Yang et al. [27] and Chen et al. [28] highlighted its influence, with unreasonable structures hindering carbon reduction. Shi and Chang [29] noted that upgrading the industry structure reduced emissions. Agricultural economic development is another primary driver of increased emissions [30], with a higher coupling effect between economic growth and emissions in central China compared to the western region [31]. The agricultural labor scale can inhibit emissions, as shown by Yao et al. [32] and Liu et al. [30] in Hunan and Jiangxi provinces, respectively.

Despite the attention given to agricultural carbon emissions, there remains a gap in the existing literature regarding the specific context of Chinese state farms. Firstly, most studies on agrarian carbon emissions in China focus on national, provincial, or important grain-producing regions, with minimal attention to state farms. However, state farms, serving as a leader in ensuring food security and promoting high-quality

agricultural development, hold strategic importance for China. This oversight represents a critical research gap the present study aims to address. Secondly, the previous literature usually utilizes the traditional Data Envelopment Analysis (DEA) model or the Slack-Based Measure (SBM) model with undesirable outputs. However, the DEA model has limitations in terms of involving non-desirable outputs, and the SBM model with undesirable outputs cannot compare multiple decision-making units (DMUs) with the efficiency values of one. Recognizing these shortcomings, this research employs the Super-SBM model with undesirable outputs to rank multiple DMUs with efficiency value one and analyzes the spatiotemporal evolution of carbon emissions. It also uses the Malmquist–Luenberger (ML) index to assess carbon emission efficiency dynamically. Thirdly, although previous research has examined the efficiency and driving factors of carbon emissions separately, it is imperative to investigate them in conjunction due to the observed correlation between agricultural carbon emission efficiency and emission levels [26]. Since a core of enhancing agricultural carbon emission efficiency lies in controlling emission levels, this paper adopts the Logarithmic Mean Divisia Index (LMDI) method to analyze influencing factors on carbon emissions in Chinese state farms.

Thus, the present study aims to answer the following questions:

1. What is the current status of agricultural carbon emissions and carbon emission efficiency in Chinese state farms?
2. How have the agricultural carbon emissions and the carbon emission efficiency evolved spatiotemporally?
3. What are the key factors influencing carbon emissions in Chinese state farms, and how can these factors be decomposed to inform the development of low-carbon strategies?

By addressing these research questions, this paper endeavors to bridge the existing research gap and contribute to advancing low-carbon agriculture in China.

This research advances the understanding of agricultural carbon emissions in Chinese state farms by introducing several innovations that distinguish it from previous research. Firstly, it fills a gap in the literature by focusing on state farms, which have been overlooked in previous studies despite their strategic importance in food security and agricultural development. Secondly, adopting the Super-SBM model with undesirable outputs and the ML index represents a methodological advancement, overcoming the limitations of the traditional DEA and SBM models in the existing literature. Lastly, by integrating the analysis of carbon emission efficiency and influencing factors through the LMDI method, this study presents a holistic view of the carbon emissions landscape in Chinese state farms. Based on the contribution of various impacting factors, decomposition aids in advancing low-carbon strategies and achieving sustainable agricultural development. This innovative approach reveals the dynamic efficiency trends and disentangles the underlying drivers of carbon emissions, thereby offering valuable insights for designing and implementing effective low-carbon agriculture policies and strategies.

2. Methodology

2.1. Study Area

State farms serve as crucial agricultural production bases in China, producing essential agricultural commodities, including rice, wheat, and corn. The formation and development of these areas are deeply intertwined with China's specific historical background. In 1956, the government established the Ministry of Agriculture and Reclamation and numerous state farms to address the national food shortage [13]. State farms harnessed state-owned lands and employed methods like military reclamation and immigrant settlement to cultivate barren lands, thereby developing agricultural resources on a large scale and forming an agrarian production model unique to China [33]. State farms have transformed vast stretches of wilderness into grain cultivation bases. Since the founding of China, these state farms have played a pivotal role in safeguarding national food security, advancing agricultural modernization, and fostering regional economic growth.

The distribution of China's state farms is extensive, spanning vast territories in 31 provinces in mainland China, from the northeast to the southwest and from the eastern coast to inland zones. Each province manages its own state farms, which are collectively referred to by the name of their respective province. For example, "Heilongjiang state farms" refers to all the 113 state farms within the Heilongjiang Province. The 29 provinces encompass 1766 state farms. Figure 1 illustrates the distribution of major state farms. Blue areas in the figure represent the counties that host the top three farms with agricultural gross outputs exceeding CNY 100 million in each province.

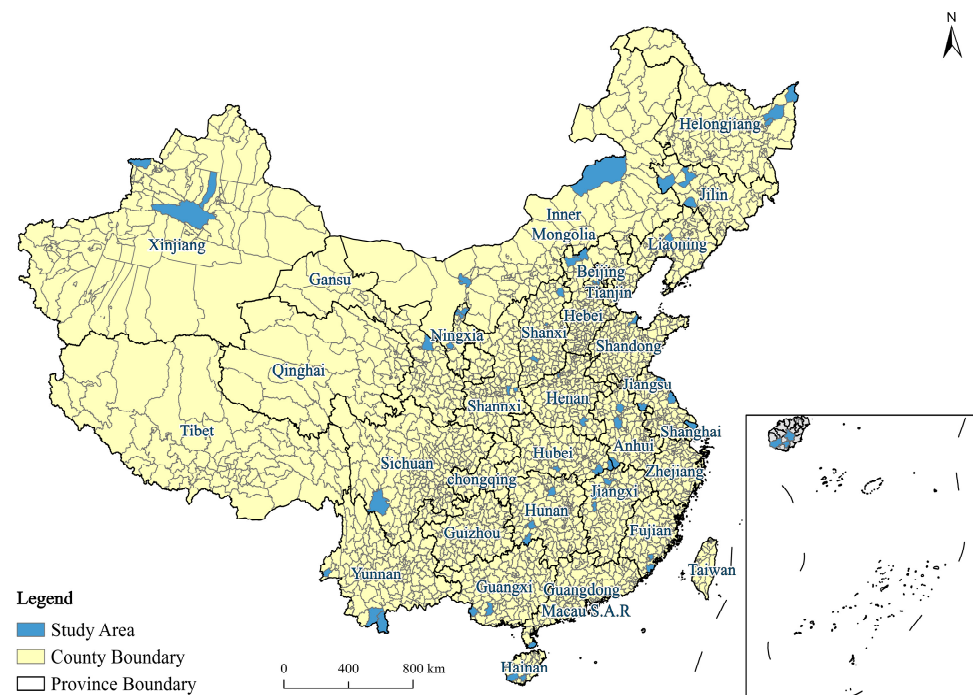


Figure 1. The counties of major state farms in each province of China.

This study focuses on state farms across 29 provinces primarily engaging in agricultural cultivation activities. Most state farms cultivate rice, with only Inner Mongolia, Jilin, Hebei, Gansu, Qinghai, Ningxia, and Shanxi specializing in corn. In addition, Heilongjiang, Xinjiang, Jiangsu, Anhui, Henan, Shandong, and Shaanxi simultaneously cultivate rice and wheat or corn and wheat. Tibet and Chongqing state farms were excluded from the sample. Tibet has been excluded due to its serious lack of data. Additionally, since the focus of this paper is specifically on crop farming, and given that the state farms in Chongqing are primarily involved in animal husbandry and fishery activities, which do not align with the scope of this research, Chongqing was excluded from the analysis. Table 1 shows the areas of state farms in the 29 provinces, sorted by average size, from 2010 to 2022.

As shown in Table 1, there existed a pronounced disparity in the areas of state farms across various provinces in China. Heilongjiang emerged as the leader with the most extensive area for its state farms, significantly surpassing all other provinces. Xinjiang followed with an area of over 1.4 million square hectares over the 12 years. The result is consistent with the previous literature, which regarded the state farms in Heilongjiang and Xinjiang as major agricultural bases [22,34]. Then, the areas of state farms in Inner Mongolia, Liaoning, Hubei, and Jilin consistently maintained an area exceeding 100,000 square hectares. Conversely, the cultivated areas of state-owned farms in Shanxi, Zhejiang, Tianjin, Guizhou, Beijing, and Sichuan remained below 10,000 square hectares.

Table 1. The areas of state farms (unit: hm²).

State Farms	2010	2012	2014	2016	2018	2020	2022
Heilongjiang	2,800,938	2,879,660	2,892,305	2,908,927	2,956,354	2,972,109	3,121,274
Xinjiang	1,470,835	1,512,900	1,555,603	1,605,949	1,630,039	1,658,270	1,978,867
Inner Mongolia	648,530	654,136	660,308	669,128	694,576	748,202	756,670
Liaoning	146,551	154,932	154,835	157,661	158,165	161,369	161,905
Hubei	136,640	137,617	135,880	131,993	142,551	143,851	144,109
Jilin	114,346	117,478	123,752	130,138	103,739	108,780	109,590
Hebei	89,095	92,820	98,017	96,726	95,797	98,236	101,001
Jiangxi	52,116	52,580	83,154	83,360	84,384	79,462	83,877
Hunan	67,271	67,216	67,146	67,141	76,187	77,860	79,137
Jiangsu	73,112	71,428	71,084	65,526	64,577	64,053	64,044
Gansu	56,952	59,270	65,202	67,288	68,921	70,594	72,415
Qinghai	26,220	26,492	25,866	152,267	38,063	31,762	29,237
Ningxia	39,708	39,613	42,346	43,283	41,201	43,231	48,443
Guangdong	37,500	37,836	37,921	37,866	38,052	46,460	54,133
Hainan	39,178	37,568	34,201	35,798	35,492	34,266	34,576
Guangxi	32,647	32,805	33,846	33,959	33,624	34,660	35,613
Shanghai	29,450	29,447	35,763	35,763	38,238	38,101	29,497
Anhui	34,746	29,356	30,104	30,167	30,215	29,291	32,925
Henan	26,843	27,605	30,009	29,623	28,084	21,874	21,772
Yunnan	12,709	12,194	12,380	13,122	12,014	13,539	13,368
Shandong	10,165	12,290	14,613	14,022	12,814	5,669	5,849
Shaanxi	9081	8948	9217	9559	10,844	11,179	11,197
Fujian	11,101	10,957	10,799	9359	8347	7079	6693
Shanxi	6440	6683	6752	6588	6485	6405	6275
Zhejiang	4102	4070	4045	3787	4260	3416	3539
Tianjin	3191	2760	2612	2917	2727	2739	2289
Guizhou	2014	1722	1701	1763	1145	1023	2800
Beijing	1483	1454	1434	1439	1396	1410	1278
Sichuan	849	899	898	873	850	1040	1054
Total	5,983,813	6,122,736	6,241,793	6,445,992	6,419,139	6,515,930	6,613,427

The cultivated areas of state farms in over half of the provinces exhibited an upward trend. However, notable declines were observed in Jiangsu, Shandong, Fujian, and Tianjin. From the national perspective, the area of state farms has substantially expanded, increasing from 5,983,813 square hectares in 2010 to 6,613,427 square hectares in 2022, at an average annual growth rate of 0.84%. This trend underscores the development of agricultural land use patterns in China and highlights the importance of ongoing monitoring and policy interventions to ensure sustainable agricultural development.

2.2. Data and Sample

This study defines agriculture as crop farming because input factors related to carbon emission efficiency, such as pesticides, agricultural film, and chemical fertilizer, are primarily used in crop production. Data were sourced from the China State Farms Statistical Yearbook and the China Rural Statistical Yearbook. Specifically, data concerning six carbon sources used for agricultural carbon emission calculation, which are chemical fertilizers, pesticides, agricultural films, land tillage, irrigation, and rice planting, were derived from the China State Farms Statistical Yearbook. Data for another carbon source, diesel fuel, were sourced from the China Rural Statistical Yearbook. Inputs for land, machinery, labor, agricultural materials, and agricultural output used in calculating carbon emission efficiency came from the China State Farms Statistical Yearbook. Factors influencing agricultural carbon emissions, such as production efficiency, industrial structure, economic development level, and labor scale, were also sourced from the China State Farms Statistical Yearbook. To mitigate the effects of price variations across years, the annual values were normalized to prices comparable to those of the 2010 level.

2.3. IPCC Method

This study calculated the level of agricultural carbon emissions using the IPCC method [35]. Its principle involves calculating the emissions of specific carbon sources by multiplying the data for a particular carbon source by its corresponding emission coefficient [36]. The IPCC method is the most widely used approach that relies on carbon emission coefficients from the Intergovernmental Panel on Climate Change (IPCC), providing a standardized approach aligned with international climate policies [37,38]. To facilitate the subsequent analysis, all calculations were converted into a unified standard of carbon [39]. Equation (1) illustrates agricultural carbon emissions.

$$CE = \sum E_i = \sum T_i Q_i \quad (1)$$

In Equation (1), CE represents the total agricultural carbon emissions, whereas E_i signifies the emission quantity associated with the carbon source i . T_i and Q_i represent the quantity and the carbon emission coefficient of that particular carbon source, respectively. Referencing Charnes et al. [40], Table 2 presents the carbon sources and their corresponding emission coefficient.

Table 2. Carbon sources and emission coefficients.

Carbon Source	Measurement	Coefficient
Chemical fertilizer (kg)	Chemical fertilizer usage	0.8956 kg (CO ₂ eq)·kg ^{−1}
Pesticide (kg)	Pesticide usage	4.9341 kg (CO ₂ eq)·kg ^{−1}
Agricultural film (kg)	Agricultural plastic film usage	5.18 kg (CO ₂ eq)·kg ^{−1}
Diesel fuel (kg)	Agricultural diesel consumption	0.5927 kg (CO ₂ eq)·kg ^{−1}
Land tillage (hm ²)	Crop sown area	312.6 kg (CO ₂ eq)·hm ^{−2}
Irrigation (hm ²)	Effective irrigated area	266.48 kg (CO ₂ eq)·hm ^{−2}
Rice planting (hm ²)	CH ₄ emissions from rice	338 kg (CH ₄ eq)·hm ^{−2}

As shown in Table 2, agricultural carbon emissions contained two sources in this research: first, agricultural material inputs, including emissions from chemical fertilizers, pesticides, agricultural film, diesel fuel, irrigation, and land tillage; second, CH₄ generated from organic substances from rice roots by methanogens in paddy fields during cultivation.

2.4. Super-SBM Model and Malmquist–Luenberger Index

Charnes and Cooper established the traditional DEA model in 1978 [41]. It has been extensively utilized in research on agricultural carbon emissions and CO₂ efficiency measurement [42,43]. However, neither the CCR nor the BCC model in the DEA methodology considers the impact of slack variables, leading to inaccurate evaluations of carbon emission efficiency [44]. Furthermore, the traditional DEA model cannot consider undesirable outputs, which restricts the normativity of the research and the objectivity of the results. Tone [45] introduced slack variables, establishing a comprehensive undesirable input–output SBM model. Later, Tone [46] built upon the SBM model by revising the treatment of slack variables. This modification addressed the issue in both the SBM and traditional DEA models, where multiple DMUs simultaneously achieve one score, making it impossible to rank them accurately. The Super-SBM model offers three advantages that enhance its applicability in evaluating carbon emission efficiency. Firstly, it addresses the limitation of traditional DEA models by differentiating and ranking decision units even when multiple units achieve total efficiency simultaneously. Secondly, the Super-SBM model handles issues related to variable slackness. Incorporating slack variables into the analysis captures inefficiencies that may otherwise be overlooked in conventional DEA models. Lastly, in contrast to traditional DEA methods that often struggle to incorporate negative externalities into their analysis, the Super-SBM model treats undesirable outputs as part of the efficiency assessment process. This enables its efficiency to reflect the status of agricultural carbon emission efficiency.

The agricultural sector faces the dual challenge of increasing total output value while reducing carbon emissions. Thus, it is necessary to simultaneously consider both economic benefits and negative environmental effects in studies related to agricultural carbon emissions. This requires a balance among inputs, desirable outputs, and undesirable outputs. In this context, the Super-SBM model measures agricultural carbon emission efficiency in state farms. Assuming m input factors, e desirable output factors, and f undesirable output factors, the input, desirable output, and undesirable output indicators can be expressed as vectors: $x^t \in R^m$, $y^a \in R^e$, and $y^b \in R^f$. R denotes the set of real numbers. Thus, the production possibility set is represented as Equation (2):

$$P = \left\{ (x, y^a, y^b) \mid x \geq X\lambda; y^a \leq Y^a\lambda; y^b \geq Y^b\lambda; \lambda \geq 0 \right\} \quad (2)$$

In Equation (2), X and Y represent the input and output of a DMU, while λ is the adjustment matrix. $X\lambda$ and $Y\lambda$ are the input and output of the frontier, respectively. Equation (3) is the established Super-SBM model with undesirable outputs, and Equation (4) describes its constraint condition:

$$\rho^* = \min \frac{1 - \frac{1}{m} \sum_{i=1}^m \frac{s_i^-}{x_{it}}}{1 + \frac{1}{e+f} \left(\sum_{j=1}^e \frac{s_j^a}{y_{r0}^a} + \sum_{k=1}^f \frac{s_k^b}{y_{h0}^b} \right)} \quad (3)$$

$$s.t. \begin{cases} \sum_{j=1, j \neq t}^n \mu_j x_{ij} - s_i^- \leq x_{it} \\ \sum_{j=1, j \neq t}^n \mu_j y_{kj}^a + s_i^- \geq y_{r0}^a \\ \sum_{j=1, j \neq t}^n \mu_j y_{hj}^b - s_h^b \leq s_h^b \\ 1 + \frac{1}{e+f} \left(\sum_{k=1}^e \frac{s_k^a}{y_{r0}^a} + \sum_{h=1}^f \frac{s_h^b}{y_{h0}^b} \right) > 0 \\ \mu, s^-, s^a, s^b \geq 0 \end{cases} \quad (4)$$

In the above equations, ρ^* represents the efficiency of a DMU, i represents the input indicator i , $j(t)$ represents the DMU $j(t)$, μ represents the non-negative weight vector, s^- represents the slack variable for inputs, s^a represents the slack variable for desirable outputs, and s^b represents the slack variable for undesirable outputs.

This research established an indicator system for agricultural carbon emission efficiency. Table 3 presents the input and output variables, their measurement methods, and the corresponding units in the indicator system. Input indicators contain land, machine, labor, chemical fertilizer, pesticide, and agricultural film. The desirable output indicators include economic and ecological output, whereas the undesirable output indicator is the environmental cost.

Table 3. Indicators of agricultural carbon emission efficiency.

Layer	Indicator	Measurement	Unit
Input	Land	Cropland area	hm ²
	Machine	Total power of agricultural machinery	kW
	Labor	Quantity of agricultural employees	persons
	Chemical fertilizer	Total fertilizer application	tons
	Pesticide	Total pesticide application	tons
	Agricultural film	Total film application	tons
Desirable output	Economic output	Total agricultural output	CNY
	Ecological output	Agricultural carbon sequestration	tons
Undesirable output	Environmental cost	Agricultural carbon emissions	tons

The Super-SBM model is limited to single-period efficiency analysis for DMUs. Thus, this study employs the ML index for dynamic analysis to delve deeper into how agricultural carbon emission efficiency in state farms varies over time. Chung et al. [47] introduced the directional distance function to enhance desirable outputs while reducing undesirable ones.

As Equations (5) and (6) illustrate, the ML index is decomposed into technical efficiency change (EC) and technological progress rate change (TC). The technical efficiency change index represents the growth in output resulting from production efficiency from period t to $t + 1$, reflecting whether resources are optimally allocated. The technological progress rate change index captures the impact of innovation or the introduction of new technologies from period t to $t + 1$, reflecting advancements in technological research and development capabilities [48]. Specifically, an ML index greater than 1 indicates an increase in agricultural carbon emission efficiency, an EC greater than 1 signifies an improvement in technical efficiency, and a TC greater than 1 indicates technological progress. Conversely, a negative value indicates a decline or lack of progress in the respective areas.

$$ML_t^{t+1} = \left[\frac{1 + \vec{D}_0^t(x^t, y^t, b^t; y^t, -b^t)}{1 + \vec{D}_0^t(x^{t+1}, y^{t+1}, b^{t+1}; y^{t+1}, -b^{t+1})} \times \frac{1 + \vec{D}_0^{t+1}(x^t, y^t, b^t; y^t, -b^t)}{1 + \vec{D}_0^{t+1}(x^{t+1}, y^{t+1}, b^{t+1}; y^{t+1}, -b^{t+1})} \right]^{1/2} \quad (5)$$

$$ML_t^{t+1} = EC_t^{t+1} \times TC_t^{t+1} \quad (6)$$

2.5. LMDI Method

Following the work by Chen et al. [49] and Hossain and Chen [50], this study adopted the LMDI method to decompose the driving elements of carbon emissions in state farms. It is a deterministic decomposition approach that precisely breaks down the total change into the contributions of various influencing factors [51]. The LMDI method offers several advantages. Firstly, it enables a precise, residual-free decomposition of the total change, ensuring that the identified factors fully explain the variation, leaving no unexplained portion. Secondly, LMDI results indicate the contribution of each factor to changes in carbon emissions, making the outcomes straightforward to interpret. Additionally, the LMDI method does not depend on statistical assumptions, such as normal distribution or linear relationships, which makes it more flexible in practical applications and less constrained by the type of data used. This study decomposes the factors influencing agricultural carbon emissions into four aspects: agricultural production efficiency, agricultural industry structure, agricultural economic development level, and agricultural labor scale. Equations (7) and (8) represent the LMDI decomposition for the factors influencing agricultural carbon emissions:

$$CE = \frac{CE}{AGDP} \times \frac{AGDP}{PIGDP} \times \frac{PIGDP}{P} \times P \quad (7)$$

$$BI = \frac{CE}{AGDP}, AI = \frac{AGDP}{PIGDP}, EI = \frac{PIGDP}{P} \quad (8)$$

where CE represents agricultural carbon emissions, AGDP represents the total agricultural output value, PIGDP represents the total output value of agriculture, forestry, animal husbandry, and fishery. P denotes the agricultural labor scale, which is the number representing the agricultural population; BI is agricultural production efficiency, which is the ratio of agricultural carbon emissions to total agricultural output; AI stands for agricultural industry structure, which is the ratio of agricultural output to the total output of agriculture, forestry, animal husbandry, and fishery industries; EI represents the agricultural economic development level, which is per capita agricultural output. Then, the decomposition can be expressed as Equation (9).

$$CE = BI \times AI \times EI \times P \quad (9)$$

By taking the logarithm of both sides of Equation (9) and applying the additive decomposition method, this study obtains the contribution of each factor by Equations (10) to (14).

$$\Delta BI = \frac{CE_t - CE_0}{\ln CE_t - \ln CE_0} \times (\ln BI_t - \ln BI_0) \quad (10)$$

$$\Delta AI = \frac{CE_t - CE_0}{\ln CE_t - \ln CE_0} \times (\ln AI_t - \ln AI_0) \quad (11)$$

$$\Delta EI = \frac{CE_t - CE_0}{\ln CE_t - \ln CE_0} \times (\ln EI_t - \ln EI_0) \quad (12)$$

$$\Delta P = \frac{CE_t - CE_0}{\ln CE_t - \ln CE_0} \times (\ln P_t - \ln P_0) \quad (13)$$

$$\Delta CE = \Delta BI + \Delta AI + \Delta EI + \Delta P \quad (14)$$

In the equations, ΔBI , ΔAI , ΔEI , and ΔP denote the influences of agricultural production efficiency, agricultural industry structure, agricultural economic development level, and agricultural labor scale on agricultural carbon emissions, respectively, when comparing year t with the base period. ΔCE represents the change in agricultural carbon emissions from the base period to year t .

3. Results

This section analyses agricultural carbon emissions, encompassing their spatiotemporal evolution, carbon emission efficiency, and the decomposition of influencing factors. This analysis aims to identify key trends, drivers, and opportunities for reducing emissions and promoting agricultural sustainability.

3.1. Temporal Evolution of Agricultural Carbon Emissions

Figure 2 displays the temporal evolution of carbon emissions in state farms from 2010 to 2022. It represents the changes in carbon emissions generated by seven carbon sources in state-owned farms, namely chemical fertilizer, pesticide, agricultural film, agricultural diesel oil, land tillage, irrigation, and rice planting. The emissions increased from 21,300.78 thousand tons in 2010 to 24,415.54 thousand tons in 2022, exhibiting a fluctuating upward trend at a 1.14% annual growth rate. Specifically, the trend can be segmented into three stages. In the first stage (2010 to 2013), emissions sharply increased due to the response to constructing national modern agricultural demonstration zones. This led to expanding cultivation areas and increased farming inputs such as machinery, fertilizers, agricultural films, and pesticides. The findings of this phase are consistent with those of Huang et al. [52], who observed a correlation between the escalation of agricultural carbon emissions and the increase in emissions stemming from diverse carbon sources.

Between 2014 and 2017, the second phase, carbon emissions fluctuated moderately, with a decline around 2015. This was attributed to the Ministry of Agriculture and Rural Affairs' initiative to achieve zero growth in fertilizer usage [53], to which state farms across China responded positively, gradually reducing the usage of agricultural inputs. However, in the initial stages of this action, state farms still heavily relied on fertilizers and pesticides, and traditional mindsets had not entirely changed, resulting in a rebound in emissions from 2016 to 2017, peaking at 25,386.03 thousand tons in 2017.

During the third stage, between 2018 and 2022, agricultural carbon emissions in state farms declined. This was closely related to policies aimed at stabilizing food production and specialized actions for emission reduction and carbon sequestration implemented in recent years [54].

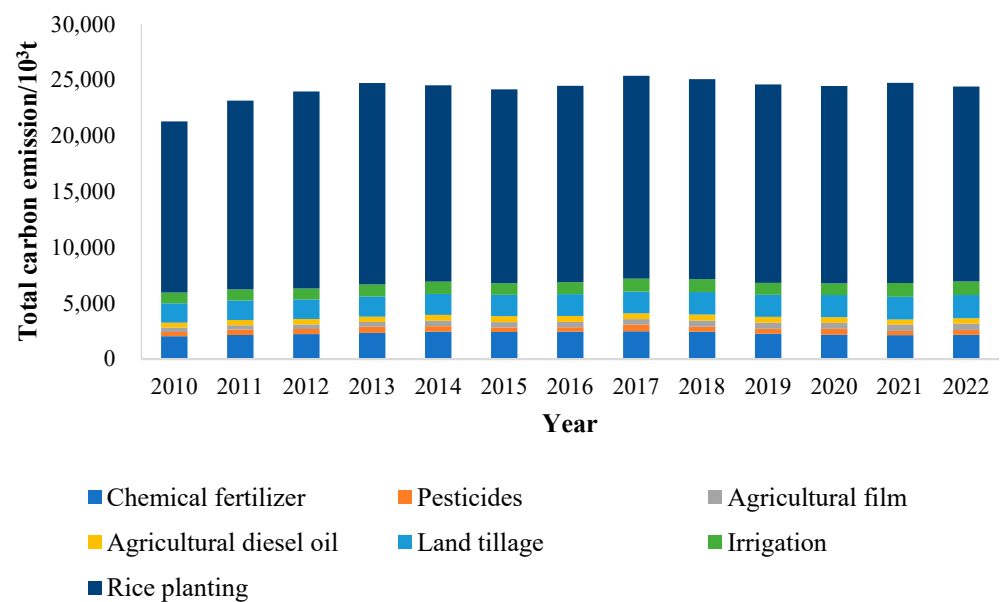


Figure 2. The temporal evolution of agricultural carbon emissions from 2010 to 2022.

Moreover, the seven types of carbon emissions from chemical fertilizers, pesticides, agricultural films, diesel fuel, land tillage, irrigation, and rice planting exhibit variability in state farms. As shown in Figure 2, rice planting contributed the most to agricultural carbon emissions from 2010 to 2022, accounting for over half of the total emissions, while pesticides and agricultural films accounted for a minor proportion. These findings contrast with those of Tian et al. [40], who identified chemical fertilizers, pesticides, and agricultural films as the primary contributors to agricultural carbon emissions, followed by rice planting, from 1995 to 2010. The disparity arises due to the temporal difference, as the current study focuses on emissions between 2010 and 2022. Since 2015, China has prioritized reducing the usage of chemical fertilizers and pesticides while enhancing their efficiency, leading to a decline in agricultural inputs and a corresponding decrease in the proportion of carbon emissions generated. Furthermore, the present research specifically targets state farms, which prioritize food security and hence have extensive rice cultivation, contributing to a higher proportion of rice planting-related carbon emissions.

Chemical fertilizers and land tillage were the second and third largest carbon sources. Fertilizer use led to greenhouse gas emissions during application and throughout their production and transportation processes, making them vital contributors to agriculture's overall carbon footprint. The proportion of carbon emissions from chemical fertilizer slightly declined from 10.01% to 8.84%, showing an initial increase and subsequent decrease. According to Wang et al. [53], the reason for this is attributed to the Zero Growth Action Plan for Chemical Fertilizer and Pesticide Usage implemented by the Ministry of Agriculture and Rural Affairs of China in 2015. Additionally, the relatively high contribution of land tillage to carbon emissions was influenced by metabolism and the consumption of organic matter. Carbon emissions from land tillage accounted for 7.31% to 8.53% of the total emissions during the study period. This stability indicates a consistent land use pattern, which mitigates emission level variations from this source.

3.2. Spatial Evolution of Agricultural Carbon Emissions

This study sorted cases for even-numbered years to more intuitively display the distribution of agricultural carbon emissions in state farms, as shown in Table 4.

Table 4 shows that the agricultural carbon emissions of state farms vary greatly in different provinces. Among the top three provinces regarding state farms' emissions, Heilongjiang and Xinjiang state farms achieved growth rates of 1.31% and 3.23%, respectively. For instance, emissions in Heilongjiang rose from 12,758.25 thousand tons

in 2010 to 14,921.04 thousand tons in 2022. Xinjiang state farms' emissions grew from 1948.78 thousand tons to 2764.25 thousand tons, reflecting a more substantial increase. In contrast, Liaoning state farms witnessed a slight decrease in emissions, with an annual growth rate of -0.40% , decreasing from 1000.03 thousand tons to 952.73 thousand tons. In the last three regions, namely Guizhou, Beijing, and Sichuan, the agricultural carbon emissions were significantly lower than in other regions. Among them, the carbon emissions of Guizhou and Sichuan showed a declining trend, while that of Beijing increased from 4.69 thousand tons in 2010 to 15.45 thousand tons in 2022.

Table 4. Agricultural carbon emission cases in even-numbered years (Unit: 10^3 t).

State Farms	2010	2012	2014	2016	2018	2020	2022
Heilongjiang	12,758.25	15,194.59	14,849.48	14,645.47	15,288.60	15,010.13	14,921.04
Xinjiang	1948.78	2032.07	2479.68	2381.51	2806.80	2706.74	2764.25
Liaoning	1000.03	973.47	1019.56	1044.85	946.56	967.26	952.73
Jiangxi	721.95	730.44	958.27	950.66	928.62	963.60	947.54
Hunan	867.19	886.81	892.27	902.77	688.69	745.35	789.21
Hubei	657.17	688.33	762.55	778.93	788.39	739.80	730.73
Jiangsu	627.61	629.58	675.23	759.32	775.73	739.19	706.34
Inner Mongolia	387.74	412.08	457.20	493.05	508.22	514.22	519.72
Jilin	396.15	444.12	471.63	456.52	327.33	355.21	343.54
Hainan	373.07	456.71	335.74	401.50	367.51	214.71	198.08
Hebei	233.17	260.88	269.76	305.03	389.52	323.47	301.67
Shanghai	268.25	266.80	274.98	259.04	262.81	263.34	219.94
Anhui	198.03	153.95	155.60	168.38	191.09	194.09	194.96
Ningxia	162.20	170.04	165.50	153.97	157.22	150.32	147.22
Guangdong	141.13	150.35	155.23	151.93	133.59	138.77	135.30
Yunnan	119.32	101.26	109.70	119.78	68.08	80.51	75.16
Guangxi	86.29	91.08	94.12	99.20	93.81	80.25	147.13
Fujian	125.60	113.38	109.59	97.59	66.34	59.07	54.72
Gansu	62.99	78.42	96.71	93.89	92.94	90.28	111.58
Henan	53.45	48.30	59.38	57.43	53.67	42.79	42.82
Shandong	19.56	22.33	59.68	48.46	67.26	11.21	11.31
Qinghai	18.21	10.64	11.72	50.23	23.48	22.97	22.15
Shaanxi	14.75	17.10	17.20	19.65	15.09	13.76	17.07
Zhejiang	25.19	20.06	16.01	13.58	11.41	7.03	11.38
Tianjin	9.36	9.38	10.42	10.35	9.68	18.96	18.36
Shanxi	7.38	7.76	8.60	8.47	7.61	12.01	11.71
Guizhou	7.58	7.82	7.97	8.64	2.23	3.64	3.67
Beijing	4.69	4.72	3.73	4.74	4.88	3.41	15.45
Sichuan	5.68	2.59	2.33	1.25	0.91	1.42	0.76
Total	21,300.78	23,985.06	24,529.84	24,486.19	25,078.04	24,473.51	24,415.54

Simultaneously, to enhance the comprehension and facilitate the visualization of Table 4, which outlines agricultural carbon emissions, and to enable a side-by-side comparison of the disparities in these emissions among state farms, a three-dimensional map was crafted and presented in Figure 3.

The notable divergence in agricultural carbon emissions across state farms aligns with Wang et al.'s findings [55], which highlighted regional disparities in China's agricultural carbon emissions. This variation can be attributed to differences in cropping patterns, farm areas, and agricultural resource endowments [52]. Firstly, state farms that primarily cultivate rice had higher carbon emissions, as rice planting was the largest carbon source. For instance, Jiangxi, Hunan, and Jiangsu state farms mainly focused on rice farming and generated significant CH₄ emissions, leading to higher carbon emissions. In contrast, Qinghai, Shanxi, and Sichuan state farms' minimal rice cultivation made their carbon emissions lower than in other regions. Secondly, larger state farms have greater total carbon emissions. For example, Heilongjiang, Xinjiang, and Liaoning state farms exhibited higher emissions due to the expansion of their farm areas, which accelerates soil respiration and increases

agricultural carbon emissions. Thirdly, the expansion of farm areas and the intensification of agriculture led to a substantial rise in the use of fertilizers, pesticides, agricultural films, and machinery, all contributing to increased agricultural carbon emissions.

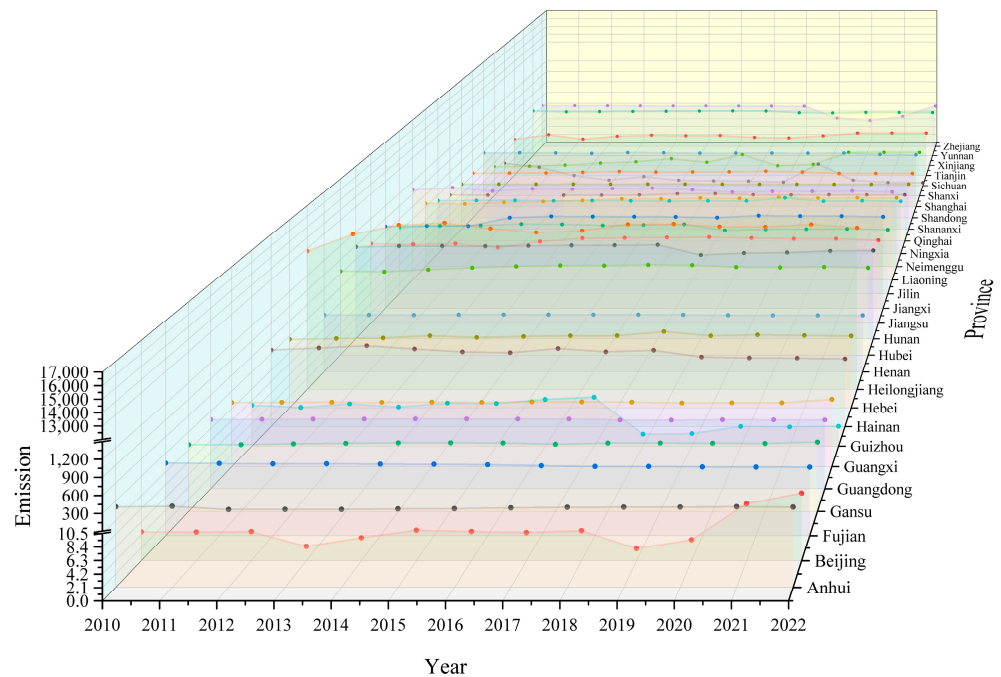


Figure 3. The spatial distribution of agricultural carbon emission (Unit: 10^3 t).

3.3. The Distribution of Agricultural Carbon Emission Efficiency

A Super-SBM model was constructed based on the input and output indicators in Table 1 by the software MATLAB version R2020a. Table 5 presents the changes in agricultural carbon emission efficiency of state farms across 29 provinces over even-numbered years in 12 years. The national average agricultural carbon emission efficiency in state farms across 29 provinces from 2010 to 2022 was 0.92, indicating a high emission level. Then, the efficiency showed a downward trend from 2010 to 2014 and a fluctuating upward pattern from 2015 to 2019, followed by a slight dip in 2020, and subsequently maintained a high level. This signifies progress in China's agricultural carbon reduction efforts.

The average annual carbon emission efficiency of 13 state farms surpasses the mean of the 29 state farms. Among them, Heilongjiang and Xinjiang state farms have large-scale farming operations, concentrated land use, and diverse crop varieties, which lead to higher carbon absorption through photosynthesis and abundant net carbon sinks [56]. Their exceptional endowment of natural resources and soil carbon sequestration capacity resulted in efficient carbon emissions. Moreover, the high emission efficiency of Guangxi, Qinghai, and Ningxia state farms was due to their lower rice cultivation and outputs, resulting in lower overall agricultural carbon emissions [57]. With its developed economy, Shanghai can support agricultural modernization and ecological development [58]. Thus, it achieved high agricultural carbon emission efficiency through technological support and an emphasis on sustainable agriculture. Similarly, Jiangsu, Tianjin, Guangdong, Beijing, Hainan, and Shaanxi state farms surpassed the national average in agricultural carbon emission efficiency. Their proficiency in green technology brought high efficiency. Moreover, the high carbon emission efficiency of Jilin was attributed to the government's guidance in adopting low-carbon production methods through agricultural subsidy policies [59].

Table 5. Agricultural carbon emission efficiency cases in even-numbered years.

State Farms	2010	2012	2014	2016	2018	2020	2022	Mean
Heilongjiang	1.92	2.08	2.15	2.34	2.15	1.94	1.94	2.12
Xinjiang	1.41	1.28	1.24	1.89	1.18	1.55	1.74	1.45
Guangxi	1.43	1.38	1.40	1.41	1.13	1.37	1.08	1.29
Shanghai	1.18	1.17	1.23	1.20	1.33	1.24	1.51	1.28
Jiangsu	0.91	0.86	1.18	1.40	1.50	1.55	1.32	1.25
Tianjin	1.26	1.44	1.21	1.22	1.24	1.01	0.58	1.20
Qinghai	1.19	1.14	1.00	1.20	1.04	1.13	1.16	1.14
Ningxia	1.18	1.05	1.07	1.19	1.08	1.14	1.17	1.14
Guangdong	1.04	1.10	0.61	1.16	1.21	0.74	1.29	1.07
Beijing	0.70	1.36	1.35	1.12	1.01	1.17	1.34	1.06
Hainan	1.02	0.41	0.72	1.29	1.34	1.05	1.25	1.05
Shaanxi	0.77	0.56	1.10	1.17	1.28	1.27	1.21	1.04
Jilin	1.09	0.56	1.31	1.28	0.88	0.58	1.24	0.94
Fujian	1.05	1.09	0.28	1.12	0.64	1.03	1.16	0.90
Sichuan	1.04	1.22	0.30	1.13	1.35	0.70	0.39	0.86
Inner Mongolia	1.13	1.13	1.07	0.73	0.52	0.45	0.62	0.82
Zhejiang	1.05	0.24	0.28	1.14	1.08	0.25	1.01	0.77
Guizhou	0.36	0.17	0.22	1.07	1.32	1.19	1.30	0.75
Anhui	1.10	0.61	0.45	0.50	1.08	0.60	0.74	0.75
Liaoning	0.87	0.69	0.72	0.73	0.47	0.46	0.43	0.68
Shandong	0.60	0.59	0.44	0.65	0.61	0.59	1.13	0.64
Gansu	0.81	0.57	0.44	0.49	0.43	0.39	1.01	0.63
Yunnan	0.62	0.35	0.40	0.58	0.49	0.34	1.04	0.62
Shanxi	0.48	1.04	1.07	0.40	1.02	0.18	0.17	0.58
Hunan	0.34	0.31	0.28	0.31	0.53	0.50	1.17	0.57
Hebei	0.59	0.62	0.51	0.68	0.44	0.38	0.50	0.54
Henan	0.55	0.63	0.42	1.02	0.47	0.30	0.38	0.53
Hubei	0.66	0.64	0.34	0.69	0.39	0.31	0.41	0.51
Jiangxi	0.54	0.45	0.32	0.47	0.41	0.31	0.34	0.45
Mean	0.93	0.85	0.80	1.02	0.95	0.82	0.99	0.92

Other state farms, with carbon emission efficiency values ranging from 0.45 to 0.90, had the potential for enhancing emission efficiency. The results reveal that state farms with lower efficiency tend to be those in the midland, such as Jiangxi, Hubei, Henan, Hebei, and Hunan. This was due to their fragmented land use, which in turn led to high inputs and a large-scale demand for labor in agricultural production processes. This is aligned with the findings of Xia et al. [60], who identified that agricultural carbon emission efficiency in central China was the lowest nationwide. In contrast, the eastern region demonstrated efficiency levels surpassing the national average. Similarly, Cheng et al. [61] corroborated lower efficiency in the central region and higher efficiency in the eastern and northeastern provinces. Inner Mongolia, Anhui, and Liaoning state farms were also classified as low-efficiency regions due to their relatively low level of agricultural modernization and lower intensification compared to other major agricultural areas [62].

Figure 4 further virtualizes the differences in agricultural carbon emission efficiency among state farms across provinces.

Considering Figures 3 and 4, China's state farms can be categorized into distinct groups based on their agricultural carbon emissions and efficiency levels. Provinces such as Jiangxi and Hunan were characterized by high emissions and low efficiency. In contrast, regions like Heilongjiang and Xinjiang, while exhibiting high emissions, achieved high efficiency. Meanwhile, Shanghai, Beijing, and Tianjin stood out as low-emission, high-efficiency areas. On the other hand, provinces like Inner Mongolia and Qinghai were identified as low-emission but low-efficiency. Lastly, provinces such as Anhui and Henan were characterized by below-average efficiency and small planting areas.

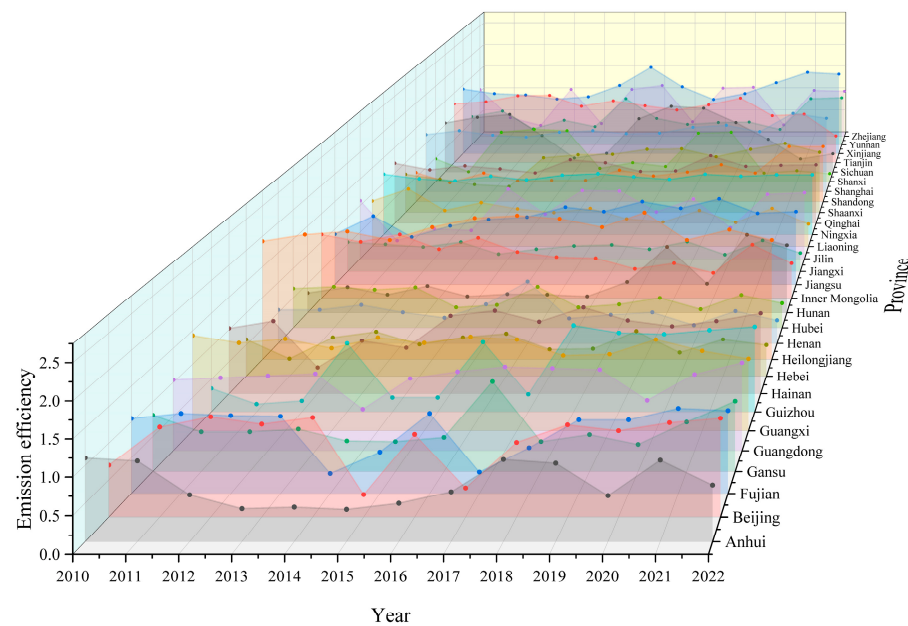


Figure 4. Agricultural carbon emission efficiency of state farms.

This study used the ML index for decomposition analysis to further analyze the dynamic changes in the carbon emission efficiency of state farms. Figure 5 shows the changes in the ML Index, the Efficiency Change Index (EC), and the Technological Change Index (TC) of state farms by year.

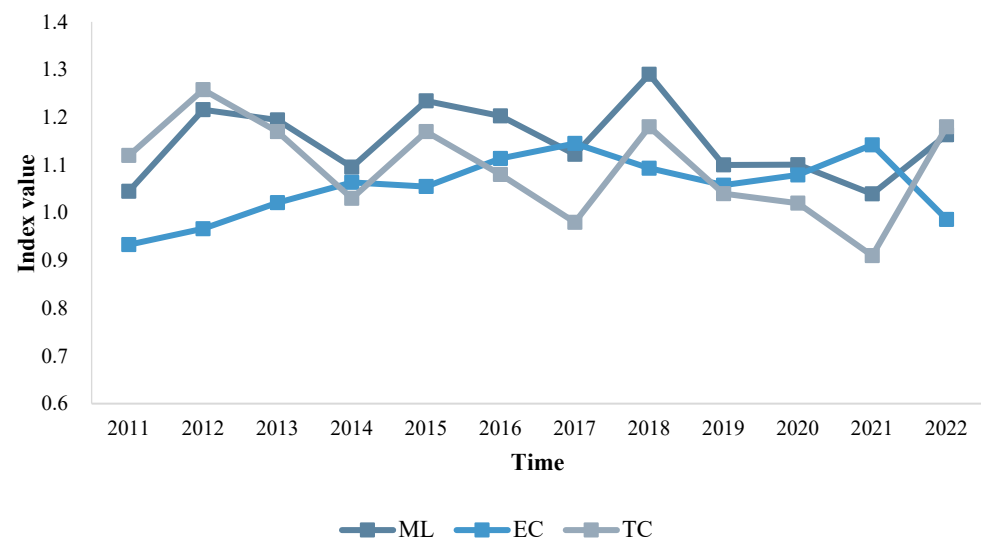


Figure 5. ML index and its decomposition.

From 2010 to 2022, the ML, EC, and TC indices for agricultural carbon emission efficiency were 1.15, 1.05, and 1.09, respectively. This indicates that, when the agricultural carbon emission efficiency in state farms increased by an average of 15% annually, the technical efficiency increased by 5%, while the technological progress rate increased by 9%. Therefore, technological progress was the primary driver behind improving efficiency in state farms. During the research period, the trend in the ML index was generally consistent with the technological progress index, further indicating that technological progress is the primary element contributing to the improvement in efficiency in China's state farms.

3.4. Influencing Factors of Agricultural Carbon Emission

The contributions of agricultural production efficiency, agricultural industry structure, agricultural economic development level, and agricultural labor scale to carbon emissions, calculated by the LMDI method, are broken down annually, as Table 6 shows.

Table 6. Decomposition of factors influencing agricultural carbon emissions in state farms (Unit: 10^3 t).

Year	Agricultural Production Efficiency (ΔBI)	Agricultural Industry Structure (ΔAI)	Agricultural Economic Development Level (ΔEI)	Agricultural Labor Scale (ΔP)	Total Effect (ΔCE)
2010–2011	−1708.90	−428.51	4249.42	−248.60	1863.35
2011–2012	6179.10	−7710.64	2830.68	−478.32	820.92
2012–2013	−10,917.83	9740.51	−1258.81	3188.85	752.66
2013–2014	−840.74	217.21	5175.89	−4760.28	−207.88
2014–2015	−1204.14	603.41	222.12	14.78	−363.79
2015–2016	165.63	114.01	−105.41	145.98	320.14
2016–2017	−416.05	−1275.95	2041.20	550.52	899.84
2017–2018	−632.46	422.95	8027.58	−8126.07	−307.99
2018–2019	465.34	−1125.34	755.11	−500.56	−405.49
2019–2020	−2934.64	549.55	2300.12	−54.38	−139.45
2020–2021	−2600.58	563.20	1946.44	317.69	226.76
2021–2022	−167.46	−907.73	1363.31	−632.44	−344.33
Cumulative effect	−14,612.73	762.66	27,547.63	−10,582.82	3114.76
Contribution rate/%	−469.15	24.49	884.42	−339.76	100

Table 6 reveals the distinct contributions of various factors to agricultural carbon emissions in state farms. The agricultural economic development level has a significant cumulative contribution, increasing carbon emissions by 27,547.63 thousand tons, corresponding to a remarkable contribution rate of 884.42%. Statistical analysis confirms that this factor consistently remained above zero, indicating a persistent stimulatory effect on carbon emissions. The positive correlation suggests that emissions increase as the agricultural economy develops.

In addition, the agricultural industrial structure contributes an additional 762.66 thousand tons to carbon emissions, accounting for 24.49% of the total increment. On the one hand, statistical analysis verifies the positive relationship between agricultural industrial structure and carbon emissions. As the agricultural industrial structure is measured by the ratio of agricultural output to the total output of agriculture, forestry, animal husbandry, and fishery industries, the result suggests that shifts in the agricultural industrial structure toward more intensive agricultural activities lead to higher carbon emissions. On the other hand, the variability observed in the agricultural industrial structure reflects its higher sensitivity to external factors, such as government policies and market demands. This sensitivity introduces fluctuations in the carbon emission levels, making the structure less stable than the economic development level.

In contrast, agricultural production efficiency and agricultural labor scale demonstrate negative contributions to carbon emissions. Agricultural production efficiency cumulatively reduced emissions by 14,612.73 thousand tons, with a negative contribution rate of −469.15%. This reduction indicates that improvements in production efficiency led to more sustainable farming practices, reducing overall emissions. Similarly, the agricultural labor scale reduces carbon emissions by 10,582.82 thousand tons, with a negative contribution rate of −339.76%. This statistical inverse relationship suggests that reductions in labor intensity contribute to lower emissions.

Figure 6 further visualizes the evolution of driving factors on carbon emissions.

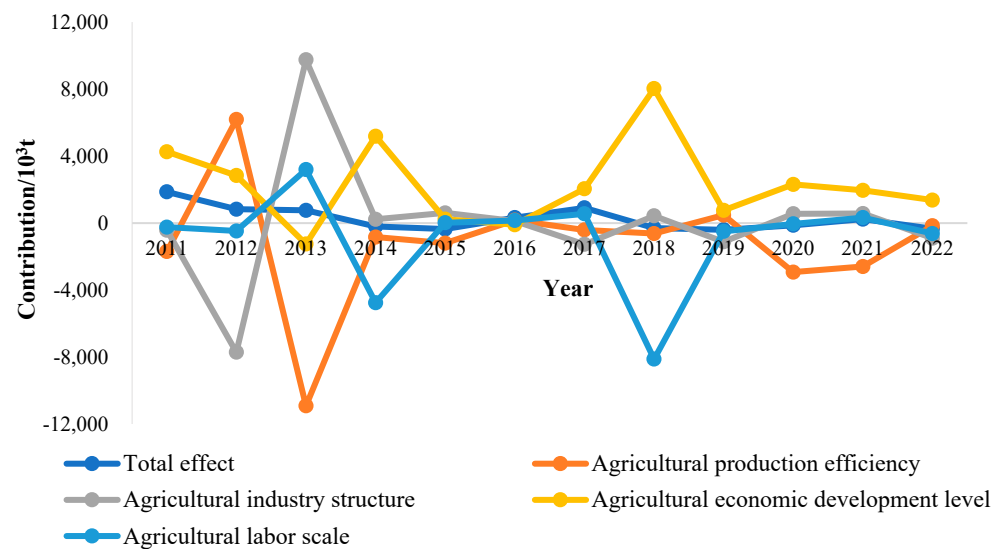


Figure 6. The trend in factors influencing carbon emissions in state farms.

4. Discussion

The development of the agricultural economy, adjustments in the agricultural industry structure, improvements in agricultural production efficiency, and changes in the scale of agricultural labor profoundly impact carbon emissions. Therefore, exploring the effects of these influencing factors is of great importance for achieving sustainable agricultural development and addressing climate change.

Agricultural economic development was the principal reason for the rise in state farm carbon emissions, aligning with Sui and Lv's findings [63]. The scale of agricultural production was expanded to achieve higher levels of agricultural economic development, and more resources were utilized [64]. These increased inputs and intensified farming practices boosted agricultural productivity and income. However, the expanding production scales to meet growing market demands and enhance economic returns necessitated the introduction of more machinery, fertilizers, and pesticides. These inputs released CO₂ during their production and application processes. Additionally, Zhao et al. [65] found that inadequate environmental protection measures exacerbated soil erosion and loss of biodiversity and increased the risk of carbon release from soils and vegetation, thus leading to a rise in agricultural carbon emissions. Consequently, enhancing economic development has spurred increased carbon emissions. As key players in agricultural production, state farms must strike a balance between economic development and carbon emissions. Farms can ensure agricultural output while reducing carbon emissions by using clean fertilizers, improving fertilizer utilization, and adopting degradable agricultural films. The government can increase subsidies for clean agricultural products to increase their market share in the planting industry.

Agricultural industry structure was the secondary factor driving the increase in emissions, consistent with the work by Zhao et al. [66]. The agricultural industry structure in this paper is represented by the proportion of agricultural output within the total output value of agriculture, forestry, animal husbandry, and fishery. Therefore, the higher the value of the agricultural industry structure, the more incentive for agricultural activities. The state farms are primarily focused on farming, with higher intensification of agricultural mechanization and levels of inputs such as chemical fertilizers, pesticides, and machinery, leading to increased carbon emissions. However, Huang et al. [67] argue that the agricultural industry structure negatively drives agricultural carbon emissions. Different research areas cause this difference. Huang et al. conducted their research in Jiangxi Province, where the agriculture, forestry, animal husbandry, and fishery industries are relatively balanced, inhibiting carbon emissions. In contrast, this paper focuses on national state farms that are

primarily agricultural. As a result, optimizing the agricultural industry structure in state farms is vital. Without compromising the overall proportion of agriculture, policymakers and practitioners ought to refine its internal composition by nurturing endeavors focused on high-value, low-carbon crop cultivation. This encompasses promoting organic vegetable farming, boutique fruit cultivation, and sustainable medicinal herb production.

Agricultural production efficiency was a critical factor in curbing the growth of emissions in state farms, as also demonstrated by Yang et al. [68]. The rapid improvement in agricultural production efficiency, driven by technological advancements, promoted agricultural innovation and reduced agricultural losses, thereby inhibiting carbon emissions. Zhu et al. [26] also found that, in regions with high agricultural production efficiency, the improvement in efficiency can suppress the intensity of agricultural carbon emissions. Therefore, the government should evaluate the cost-effectiveness of various carbon-reducing agricultural technologies and promote the development of sustainable agricultural practices. To enhance agricultural production efficiency, the government should focus on transforming essential production elements, improving infrastructure, increasing land under large-scale management, and optimizing land resource allocation. Improving efficiency is inseparable from technological advancements; thus, farms should enhance agricultural production efficiency by introducing advanced technologies.

The scale of agricultural labor was the secondary driver in reducing agricultural carbon emissions in state farms. According to Hao et al. [69], improvements in planting efficiency and implementing national land transfer policies freed up rural labor, leading some laborers to transition to other industries, thereby mitigating emissions. Additionally, the workforce reduction compelled remaining workers to undergo more training and education, enhancing their professional skills and understanding of efficient, low-carbon technologies and methods. This talent improvement heightened agricultural production efficiency, reducing carbon emissions [70]. Thus, the state should effectively utilize surplus labor to curb carbon emissions by promoting the transformation of agricultural labor toward specialization and high-quality standards. This includes spreading awareness of low-carbon production practices and implementing automation technologies such as agricultural drones and autonomous machinery. Moreover, farms can ensure the continuity and scientific nature of low-carbon agricultural production by hiring professional farmers.

5. Conclusions

The study focused on state farms across 29 Chinese regions and calculated agricultural carbon emissions from 2010 to 2022 using the IPCC method. The Super-SBM model, ML index, and LMDI method were employed to analyze agricultural carbon emission efficiency and its driving factors, yielding the following conclusions. Firstly, the carbon emissions in agricultural state farms exhibited three stages: increase, fluctuation, and decline. Emissions from seven carbon sources showed varying degrees of increase. Spatially, agricultural carbon emissions were concentrated mainly in the northern and eastern regions. Secondly, the average agricultural carbon emission efficiency in China's state farms was 0.92, indicating a high agricultural output per unit of emissions. However, efficiency varied across different state farms. Technological progress was the primary factor enhancing agricultural carbon emission efficiency. Thirdly, the influence of various driving factors on carbon emissions was ranked in the following order: agricultural economic development level, agricultural production efficiency, agricultural labor scale, and agricultural industry structure. Improvements in agricultural economic development and uncoordinated industry structures increased carbon emissions, enhanced agricultural production efficiency, and reduced agricultural labor scale, which suppressed emissions.

This study developed and refined a framework to assess agricultural carbon emission efficiency tailored to the specific development conditions in Chinese state farms. This framework has theoretical value and can guide future research and policy development in sustainable agriculture. Exploring the development characteristics of carbon emissions in Chinese state farms enriches the theoretical foundation of eco-friendly and low-

carbon agriculture. Examining these characteristics broadens the scope of the research in sustainable agriculture.

Future researchers can use the models and methods developed in this study to assess agricultural carbon emission efficiency across different contexts. Furthermore, they could explore the driving factors identified in the research to understand their practical applications in different settings. For instance, investigating how technological progress enhances carbon emission efficiency can guide the adoption of similar technologies in agriculture. Researchers could also conduct cross-regional comparative analyses using this study's findings to identify best practices that can be scaled and adapted to other areas. This approach will help achieve carbon reduction goals and provide actionable insights for policymakers and practitioners.

This study underscores the importance of policymakers developing tailored policies. To harness the comparative advantages of state farms and address agricultural carbon emissions, policymakers should consider the following strategies based on different levels of agricultural carbon emissions and efficiency. Firstly, for provinces with high emissions and low efficiency (e.g., Jiangxi and Hunan), the government should incentivize investment in advanced agricultural green technologies, including methane reduction, conservation tillage, and organic fertilizers. Secondly, in regions with high emissions but high efficiency (e.g., Heilongjiang, Xinjiang), the government should encourage the optimization of the agricultural industry structure by promoting crops with higher carbon absorption capacity, like corn. Thirdly, for low-emission, high-efficiency areas (e.g., Shanghai, Beijing, Tianjin), the government should support green innovation and encourage the diffusion of best practices to surrounding regions. Fourthly, in low-emission, low-efficiency provinces (e.g., Inner Mongolia, Qinghai), the government should formulate economic support policies to boost agricultural infrastructure investment, enhancing farmers' incomes and production efficiency. Lastly, for farms with below-average efficiency and small planting areas (e.g., Anhui, Henan), the government should encourage land consolidation to improve machinery utilization and reduce labor force requirements, lowering carbon emissions.

State farms should adopt efficient use of natural resources and continuous innovation in sustainable and low-carbon agricultural technologies. Firstly, they should improve agricultural production efficiency to increase the use efficiency of carbon per unit. This can be achieved by adopting advanced farming practices such as precision agriculture and modern irrigation systems. Pesticides and chemical fertilizers should also be strictly regulated by integrated pest management promoting organic or bio-based alternatives. Secondly, leveraging the ML index decomposition results, state farms should invest in technological advancements that conserve and recycle agricultural inputs. Larger farms should support smaller ones with technology transfer, enhancing overall technological efficiency. Thirdly, state farms should establish a modern employment system to improve labor productivity. This involves attracting agricultural, technical, and management talent, nurturing professional farmers, minimizing redundant labor, and fostering labor specialization.

6. Limitations and Future Directions

This study still has several limitations that should be acknowledged. Firstly, this study does not include carbon emissions from straw burning due to the uncertainties in the amount of straw burned and the corresponding carbon emission coefficient. Moreover, agricultural carbon emissions are influenced by regional characteristics. However, this study focuses on China's state farms, failing to capture the distinct features of different areas, which could lead to varying carbon emission levels. Thirdly, due to the complexity of farming practices and the difficulty in obtaining data, it does not account for the impact of crop rotation on agricultural carbon emissions. Additionally, although this study covers the period from 2010 to 2022, changes in agricultural carbon emissions and efficiency are characterized by long-term and dynamic trends. The 12-year data may not fully capture long-term trends and potential cyclical variations. Finally, the research focuses solely on the agricultural carbon emissions from crop production activities without considering

emissions from livestock farming. Therefore, the results represent only a portion of the total agricultural carbon emissions.

Therefore, future efforts could be made to incorporate carbon emissions from straw burning by obtaining more precise data on the amount of straw burned and its carbon emission coefficient. This could involve enhanced field observations or the development of improved modeling techniques. Secondly, future studies could adopt a geographically differentiated approach by considering regional characteristics to delineate different state farms. This would allow for a more detailed analysis of how soil types, climatic conditions, and agricultural practices influence carbon emissions, thereby providing a more comprehensive understanding and enabling the development of targeted emission reduction strategies tailored to specific regions. Thirdly, various crop rotation methods could be investigated in the future, such as monoculture, wheat–corn rotation, and rice–soybean rotation, to more accurately evaluate agricultural carbon emissions and determine rotation strategies tailored to the specific conditions of different regions. Fourthly, future research should extend the study period, allowing for a better understanding of long-term trends and cyclical variations in agricultural carbon emissions and efficiency. Lastly, livestock farming metrics can be incorporated into the future studies. This will provide more comprehensive recommendations for the low-carbon development of state farms.

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