

Article

High-Standard Farmland Construction Policy, Agricultural New-Quality Productivity, and Greenhouse Gas Emissions from Crop Cultivation: Evidence from China

Ying Wang *, Jiaqi Li, Yiqi Fan and Wanling Chen

School of Public Administration, China University of Geosciences, Wuhan 430074, China; 1202311086@cug.edu.cn (J.L.); fanyiqi@cug.edu.cn (Y.F.); cwling@cug.edu.cn (W.C.)

* Correspondence: yingwang@cug.edu.cn

Abstract: China faces the dual challenges of mitigating greenhouse gas emissions and ensuring food security. Given that crop cultivation constitutes a major source of agricultural greenhouse gas emissions, analyzing the emission reduction impact of China's high-standard farmland construction (HSFC) policy, a crucial food security initiative, holds significant importance. This study calculates greenhouse gas emissions from crop cultivation (CGHGE) from a life cycle assessment (LCA) perspective and evaluates the agricultural new-quality productivity level across 31 regions in China from 2005 to 2022. Subsequently, this study utilizes the continuous difference-in-differences (DID) model to examine the impact of the HSFC policy on CGHGE per unit area. Furthermore, the mediating role of agricultural new-quality productivity in the relationship between HSFC policies and CGHGE per unit area was examined. The results show that HSFC can significantly mitigate the growth of CGHGE per unit area, with an average annual reduction of 62.88%. The regional heterogeneity analysis indicates that HSFC exerts statistically significant negative effects on CGHGE per unit area across both western and eastern China. Furthermore, heterogeneity tests demonstrate that HSFC's emission reduction effects are particularly pronounced in major grain-producing regions. HSFC contributes to emission reductions by enhancing agricultural new-quality productive forces, which subsequently lead to lower CGHGE. The findings of this study suggest that governments should implement differentiated and targeted policies for HSFC, with particular emphasis on the crucial role of new-quality agricultural productivity in reducing CGHGE.

Keywords: high-standard farmland construction; greenhouse gas emissions; crop cultivation; agricultural new-quality productivity; continuous difference-in-differences



Academic Editor: Francisco Manzano Agugliaro

Received: 16 April 2025

Revised: 13 May 2025

Accepted: 22 May 2025

Published: 27 May 2025

Citation: Wang, Y.; Li, J.; Fan, Y.; Chen, W. High-Standard Farmland Construction Policy, Agricultural New-Quality Productivity, and Greenhouse Gas Emissions from Crop Cultivation: Evidence from China. *Land* **2025**, *14*, 1157. <https://doi.org/10.3390/land14061157>

Copyright: © 2025 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (<https://creativecommons.org/licenses/by/4.0/>).

1. Introduction

Climate change, predominantly characterized by global warming, has emerged as a critical threat to the sustainability of natural ecosystems and human societies [1]. As one of the sectors most susceptible to climate change, agriculture faces mounting pressures from the growing occurrence of extreme weather events, which in turn heighten threats to global food security [2]. Concurrently, agricultural activities represent a significant source of greenhouse gas emissions (GHGE), contributing approximately 30% to the global total [3]. In recent years, China has achieved remarkable progress in agricultural development, particularly in enhancing the comprehensive production capacity of its grain sector [4]. However, the persistent reliance on extensive agricultural practices has led to pressing issues, including excessive resource depletion and a steady increase in greenhouse gas

emissions. According to the First Biennial Transparency Report on Climate Change of the People's Republic of China [5], China's total greenhouse gas emissions in 2021 reached approximately 12.99 billion tons of CO₂eq, with agricultural activities accounting for 6.5% of the national total. Within the agricultural sector, crop cultivation represented 47.63% of the sector's emissions. Within crop production activities, nitrous oxide (N₂O), methane (CH₄), and carbon dioxide (CO₂) accounted for approximately 22.9%, 14.7%, and 10.03% of emissions, respectively [5]. Among these, nitrous oxide (N₂O) and methane (CH₄) exhibit significantly higher global warming potentials compared to carbon dioxide (CO₂), making their role in driving climate change particularly critical [6].

High-standard farmland construction (HSFC) is a key measure to ensure both the preservation and enhancement of farmland quantity and quality. The objective of HSFC is to upgrade existing farmland into uniformly leveled and consolidated plots, supported by modern infrastructure such as efficient irrigation facilities, precision farming technologies, and stable agricultural energy provision [7]. The idea of prioritizing the development of stable and high-yield basic farmland was first proposed in China's Central Document No. 1 in 2004, laying the groundwork for the formal rollout of the HSFC policy in 2011. In the 2025 edition of Central Document No. 1, entitled Opinions of the Central Committee of the Communist Party of China and the State Council on Further Deepening Rural Reform and Advancing Comprehensive Rural Revitalization, the importance of promoting high-quality development of HSFC is clearly reaffirmed [8]. Additionally, the "National High-Standard Farmland Construction Plan (2021–2030)", issued by the State Council in 2021, identifies promoting green agricultural development as a key objective [9]. The plan also sets an ambitious target of establishing 80 million hectares of HSFC by 2030. Historical experiences from other countries offer valuable insights into the potential efficiency gains and environmental consequences of land consolidation, providing context for evaluating the HSFC initiative. In Europe, for example, land consolidation programs implemented in countries like the Netherlands, Germany, and France throughout the 20th century significantly enhanced agricultural productivity by reducing land fragmentation, improving infrastructure, and facilitating mechanized farming [10,11]. These programs often led to increased yields and better land use efficiency, but they also triggered concerns regarding biodiversity loss, soil degradation, and wetland reduction, particularly when environmental safeguards were weak or absent [12,13]. In contrast, more recent approaches in Nordic countries have integrated ecological considerations into consolidation planning, promoting multifunctional land use and sustainable agricultural landscapes [10,11]. Japan placed great emphasis on ecological protection and the coordination of rural landscapes during the implementation of land consolidation. Under the guidance of the "multifunctional agriculture" concept, project planning was refined to achieve synergy between improving agricultural infrastructure and preserving natural ecosystems [14,15]. These international cases underscore that while land consolidation can lead to considerable efficiency gains, it may also bring unintended ecological trade-offs if not guided by strong environmental governance. Thus, drawing on these experiences can inform the design and assessment of HSFC policies to balance agricultural productivity with ecological sustainability.

Current research on the green effectiveness of the HSFC policy primarily focuses on its impact on the green efficiency of farmland use [16,17], ecological environmental quality [18–20], and carbon emissions [21,22]. For instance, Guo et al. conducted long-term monitoring of the ecological impacts of land consolidation projects in China's Chaohu Lake Basin. Their findings demonstrate that while the implementation phase of land consolidation projects causes significant disturbance to the ecological environment, the ecosystem shows remarkable resilience, typically recovering within 3–5 years post-implementation. Moreover, the study reveals that the ecological environment quality in project areas not only

recovers, but continues to show sustained improvement after this restoration period [23]. Sun et al. examined the impact of land consolidation initiatives on ecological environmental quality in Yan'an, China. Their research indicated that interventions like "mountain flattening for land creation" initially led to a decline in the ecological environment quality of the targeted areas. However, over time, these efforts began to yield positive effects on the ecological environmental quality level of the consolidated area, ultimately leading to an overall improvement in the ecological environmental quality level of the consolidated area [18]. Liu and Lin measured agricultural carbon emissions per unit area by considering the carbon emissions generated from energy consumption during agricultural production [24,25]. Using a difference-in-differences (DID) model, they demonstrated that the implementation of the HSFC policy significantly reduces carbon emissions per unit area of cultivation. Similarly, Li et al. investigated the impact of the HSFC policy on agricultural carbon emission intensity based on emissions from fertilizers, pesticides, diesel, irrigation, plastic film, and tillage [26]. However, these studies' reliance on uniform emission factors without regional differentiation limited the accuracy of the results. Greenhouse gas emissions from crop cultivation encompass multiple stages, including the input of production materials, farmland management practices, and crop growth, each contributing to greenhouse gas emissions. Previous research examining the relationship between HSFC and carbon emissions from agricultural activities has overlooked two key dimensions: first, in the scope of emissions considered, and second, in the types of gases accounted for, particularly neglecting N_2O and CH_4 , which are major contributors to agricultural greenhouse gases. Therefore, adopting a life cycle assessment approach (LCA) is essential to comprehensively account for greenhouse gas emissions from crop cultivation across all stages, including production material input, farmland management practices, and crop growth. This holistic approach will provide a more accurate and nuanced understanding of the environmental impacts of HSFC and inform more effective policy interventions.

Agricultural new-quality productivity refers to the transformative effects brought about by advancements in technology, improved resource utilization, and the upgrading of agricultural industries [27,28]. According to Cao et al., technologies such as precision agriculture, digital tools, and smart farming systems constitute the core components of agricultural new-quality productivity [29]. These forces are characterized by cutting-edge technologies, enhanced efficiency, and superior output quality, driving modernization in the sector. Current studies mainly focus on defining and analyzing the formation logic of agricultural new-quality productivity [30–32], exploring practical pathways for its development, evaluating agricultural new-quality productivity [33], and examining how it can empower high-quality development in economic and agricultural sectors [34]. As the agricultural manifestation of new-quality productivity, agricultural new-quality productivity breaks away from traditional agriculture's high-input, high-consumption development model through technological innovation. By integrating technological, green, and digital elements, they provide new momentum for sustainable development in crop cultivation. Precision agriculture leverages technologies like GPS, remote sensing, and data analytics to manage inputs such as fertilizers and pesticides more efficiently. This method enhances crop yields while also significantly reducing N_2O emissions by minimizing excess nitrogen use [35,36]. Intelligent irrigation systems, supported by the development of digital infrastructure, integrate IoT sensors and AI algorithms to dynamically adjust irrigation schedules based on soil moisture and weather data. This optimizes water use efficiency, lowers energy consumption for water pumping, and mitigates emissions associated with over-irrigation [37,38]. Theoretically, these technologies contribute to emission reduction through mechanisms such as input-use efficiency, energy saving, and enhanced carbon sequestration in soils, aligning with the principles of ecological modernization

and sustainable intensification [39,40]. However, the potential of agricultural new-quality productivity to contribute to CGHGE reductions through HSFC development remains a critically understudied area in the current literature.

To address these research gaps, this study uses an LCA approach to quantify CGHGE in 31 regions across China from 2000 to 2022. Based on the quantification of CGHGE, this study adopts a DID model to explore how HSFC policies affect CGHGE and investigates the mediating role of agricultural new-quality productivity in this relationship. The main innovations of this study are as follows: (1) This study calculates CGHGE based on the life cycle concept, covering three key stages: production material input, farmland management practices, and crop growth. This enhances the comprehensiveness and accuracy of CGHGE measurements. (2) This study examines the mediating role of agricultural new-quality productivity between high-standard farmland construction and CGHGE by introducing agricultural new-quality productivity as a mediating indicator.

2. Theoretical Analysis and Research Hypothesis

High-standard farmland development entails the scientifically guided reorganization and enhancement of agricultural land resources, incorporating modern construction methods, land grading, and supporting infrastructure improvements. These activities are designed to enhance production efficiency and improve the ecological environment [41]. A review of existing research indicates that HSFC policies contribute to large-scale agricultural operations, improvements in crop planting structures, and the advancement of agricultural technologies [24,42,43]. These changes in external conditions are anticipated to exert a suppressive effect on carbon emissions in crop cultivation. From a scale-effect perspective, under specific technological conditions, appropriately increasing the scale of cultivation can optimize the allocation of input factors, thereby reducing production costs or enhancing yields. The construction of high-standard farmland involves land leveling, consolidation of fragmented plots, and optimization of ditch and road layouts, all of which help concentrate land parcels and mitigate the issue of fragmented farmland. By enhancing the scale of land management, it is possible to reduce labor costs effectively, promote the intensive use of input factors, decrease agricultural inputs, and enhance agricultural productivity, thus playing a role in lowering carbon emissions from the agricultural sector [44]. From a structural-effect standpoint, HSFC promote a shift towards a “grain-centered” planting structure through mechanisms like land transfer, agricultural mechanization, and the specialization of grain production [45]. On one hand, shifts in planting structure are strongly tied to investments in agricultural inputs. By encouraging the large-scale, centralized cultivation of specific crop varieties, these adjustments foster continuous, specialized production models, thereby improving the allocation of resources. Existing studies indicate that food crops, in contrast to cash crops, tend to result in lower soil erosion and contribute more effectively to soil carbon sequestration. This reduces the reliance on agricultural inputs such as chemical fertilizers, pesticides, and plastic mulch [46]. Additionally, food crop cultivation often employs higher levels of mechanization and integrated service systems, which not only facilitate specialized agricultural practices, but also substantially improve production efficiency. These improvements lead to higher output, better production efficiency, and a reduction in carbon emissions. Technological advancements driven by HSFC policies significantly improve the conditions for agricultural production. Through measures like land consolidation, improved field roads, and machine-accessible pathways, these policies facilitate agricultural mechanization, reduce labor inputs, and boost productivity. Furthermore, HSFC enables large-scale operations such as mechanical soil tilling and straw return, which contribute to the adoption of low-carbon farming practices. The theoretical

mechanism of HSFC on GHGE is shown in Figure 1. Based on the above, we propose the following hypothesis:

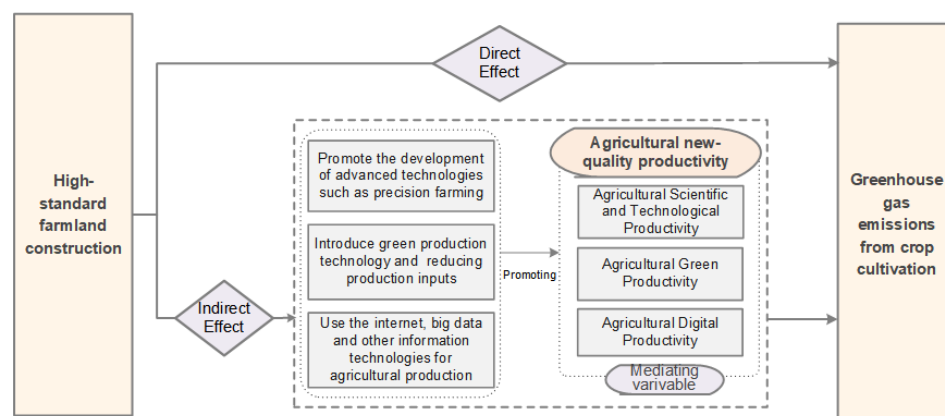


Figure 1. The theoretical mechanism of HSFC on GHGE.

Hypothesis 1: *High-standard farmland construction exerts a negative impact on GHGE from crop cultivation.*

Agricultural new-type productivity relies on technological innovation to break away from the traditional high-input, high-consumption model, and represents a form of productivity more aligned with the goals of high-quality agricultural development [33]. HSFC and greenhouse gas emissions from crop cultivation are linked through the mediating role of agricultural new-type productivity, which operates in several key ways.

Firstly, HSFC reduces CGHGEs by improving agricultural technological productivity. HSFC enhances agricultural productivity through technological advancements, such as the adoption of smart irrigation systems. These systems make use of soil moisture sensors and real-time weather information to enhance irrigation efficiency, thereby reducing water waste and lowering carbon emissions from pump operations [47]. Additionally, precision fertilization technology tailors fertilizer application based on soil type and climatic conditions, effectively curbing greenhouse gas emissions caused by excessive chemical fertilizer use [48].

Secondly, HSFC reduces CGHGEs by enhancing agricultural green productivity. As a model for green agricultural development, HSFC promotes a shift toward sustainable production practices that emphasize clean energy and environmentally friendly farming. The application of cutting-edge technologies, such as IoT, big data, mobile internet, smart control, and satellite positioning, makes it possible to monitor crop growth with precision and in real time [26]. Furthermore, it improves the efficiency of land and water resource allocation through scientific planning and management, fostering intensive and efficient land use while minimizing resource waste and environmental degradation [44]. HSFC also supports the development and adoption of low-carbon crop varieties, such as stress-tolerant and low-methane-emitting rice cultivars. Combined with integrated pest management techniques, this approach reduces pesticide usage and further mitigates greenhouse gas emissions [49].

Thirdly, HSFC reduces CGHGE by enhancing agricultural digital productivity. HSFC provides robust infrastructure support for the development of agricultural digitalization. By incorporating cutting-edge information technologies like the Internet of Things, big data, mobile internet, smart control systems, and satellite positioning, it allows for real-time, accurate monitoring of crop growth conditions. This facilitates refined management across various stages including planting, fertilizing, irrigation, and harvesting, thereby improving energy use efficiency and reducing carbon emissions [50,51]. Moreover, digital technologies

help break down “information silos”, enhance farmers’ awareness of green agriculture and environmental protection, and promote the adoption of sustainable farming practices, thus offering strong technical support for emission reduction in crop cultivation [52,53]. By integrating advanced digital agriculture technologies, HSFC elevates the quality of productive forces in agriculture, drives the transformation of crop production models, and opens new avenues for reducing agricultural GHGE. Given the above discussion, this study proposes the following hypothesis:

Hypothesis 2: HSFC promotes CGHGE reduction by enhancing agricultural new-quality productivity, with agricultural new-quality productivity serving as a mediator in reducing CGHGE through HSFC.

3. Methods and Materials

3.1. Methods

3.1.1. Calculation of CGHGEs

The CGHGEs in this study include three types of GHGEs, CH₄, N₂O, and CO₂. According to the global warming potential (GWP) in the sixth assessment of the IPCC, this article converts CH₄ (GWP₁₀₀ = 27) and N₂O (GWP₁₀₀ = 273) into an equivalent amount of CO₂ [6]. Drawing on the research ideas of the LCA method [54], this study divides the life cycle of crop cultivation into several stages, production materials input, planting management, and crop growth (Figure 2), and calculates the carbon emissions generated by the entire process of crops. Since the research data in this article belong to the macro level, the IPCC emission coefficient method is more suitable for use [55,56]. The emissions are shown in Appendix A. The calculation steps are as follows:

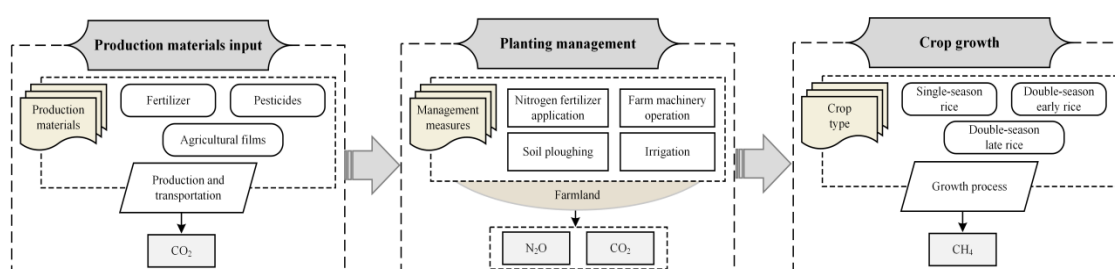


Figure 2. Greenhouse gas emissions from crop cultivation.

(1) In the production materials input phase, we calculated CO₂ emissions during production and transportation, caused by energy consumption during the production and transportation of fertilizers, pesticides, and agricultural films. The calculation formula is as follows:

$$A_k(t) = \sum_{j=1}^3 (I_{tj} \times EFI_j \times 44/12) \quad (1)$$

where $A_k(t)$ represents CO₂ emissions of factor inputs in region k in year t ; I_{tj} denotes the inputs of factor category j in year t ; EFI_j denotes the carbon (C) emission factor of agricultural materials in category j (Table A1) [57–60]; and 44/12 is the conversion factor, i.e., C equivalent to CO₂ equivalent [61,62].

(2) At the planting management phase, we calculated GHGEs (CO₂, N₂O, and CH₄ emissions) caused by crop planting management by drawing on the study of He et al. [63]. The calculation formula is as follows:

$$B_k(t) = B_k^1(t) + B_k^2(t) \quad (2)$$

$$B_k^1(t) = \left(\begin{array}{l} (X_{1k} + X_{2k} \div 3) \times R_{2k} + \\ (X_{1k} + X_{2k} \div 3) \times X \times R_3^v + \\ (X_{1k} + X_{2k} \div 3) \times R_{4k} \times R_3^w \end{array} \right) \times 44/28 \times GWP_{N_2O} \quad (3)$$

$$B_k^2(t) = \sum_{j=1}^3 (G_{tj} \times EFG_j \times 44/12) \quad (4)$$

where $B_k(t)$ represents GHGEs emissions during the crop management phase in region k during year t . $B_k^1(t)$ denotes N_2O emissions from nitrogen-containing fertilizer application in region k during year t , where X_{1k} and X_{2k} represent the input quantities of nitrogen fertilizer and compound fertilizer in region k , respectively. R_{2k} is the direct N_2O emission coefficient for fertilizer application in region k (Table A2). X is the volatilization rate of compound fertilizer (10%). R_3^v and R_3^w represent the indirect N_2O emission coefficients induced by nitrogen deposition and nitrogen leaching/runoff, with values of 0.01 and 0.0075, respectively [64]. R_{4k} is the ratio of nitrogen leaching and runoff, calculated as 5.9/12.2 [65]; 44/28 is the ratio of the molecular weights of N_2O to N_2O-N ; GWP_{N_2O} is the coefficient for converting N_2O to CO_2 equivalent, and its value is 273. $B_k^2(t)$ indicates other CO_2 emissions during the crop management phase in region k during year t , where G_{tj} represents the input quantity of type j management practices (including diesel usage, soil tillage, and effective irrigation) in year t , and EFG_j denotes C emission factor for input element j in the crop management phase (Table A1).

(3) In the crop growth phase, we quantified CH_4 emission converted to CO_2 equivalent from paddy fields due to flooded anaerobic fermentation. The calculation methodology is described below:

$$C_k(t) = \sum_{j=1}^3 (S_{tj} \times EFU_j \times GWP_{CH_4}) \quad (5)$$

where $C_k(t)$ denotes CH_4 emission converted to CO_2 equivalent from the growing chain of rice in area k in year t ; S_{tj} denotes the sown area of rice type j in year t ; EFU_j denotes CH_4 emission factors of rice type j (Table A3); GWP_{CH_4} is the coefficient for converting CH_4 to CO_2 equivalent, and its value is 27 (IPCC, 2021) [6].

(4) Finally, we calculated GHGEs from crop cultivation and GHGEs from crop cultivation per unit area with the following formula:

$$CGHGE_{kt} = A_k(t) + B_k(t) + C_k(t) \quad (6)$$

$$CGHGE_{kt} \text{ per unit area} = \frac{CGHGE_{kt}}{L_k(t)} \quad (7)$$

where $CGHGE_{kt}$ and $CGHGE_{kt}$ per unit area denote GHGEs from crop cultivation and GHGEs from crop cultivation per unit area of region k in year t , respectively. $L_k(t)$ denotes the crop sown area in region k in year t .

3.1.2. Continuous DID

The National Land Consolidation Plan (2011–2015), officially launched by the Ministry of Land and Resources of China and related agencies in 2011 [66], marked the nationwide implementation of the high-standard farmland policy [24]. In this paper, the National Land Consolidation Plan (2011–2015) is treated as a quasi-natural experiment, and a DID approach is employed to assess the impact of the HSFC policy on CGHGE. Since all regions were simultaneously affected by the policy implementation, it is not feasible to divide them into control and treatment groups based on whether they were exposed to the policy. However, there were variations in the target numbers set for policy execution across regions,

meaning that the intensity of policy impact differed. This provides a basis for applying the continuous DID model.

In the traditional DID model, both the regional treatment indicator (treat) and the time indicator (period) are specified as binary dummy variables. The coefficient of their interaction term (treat $\times$ period) captures the estimated policy impact by comparing changes over time between the treatment and control groups, before and after the policy implementation. However, this setup only captures the binary distinction of whether a region was exposed to the policy or not, and fails to account for variations in intensity. In some cases, different units are affected by the policy to varying degrees, so the regional policy grouping dummy variable can be replaced with a continuous variable.

Existing research indicates that, compared with the binary DID approach, the continuous DID model preserves its fundamental characteristics while capturing more nuanced sample heterogeneity, thereby reducing potential biases associated with arbitrary group classifications [67]. The continuous DID model has been widely applied by scholars in policy evaluation and causal identification [68–70]. In this study, the continuous variable “proportion of land consolidation area” is used to reflect the intensity of the HSFC policy’s impact across different regions.

To credibly estimate the impact of HSFC on CGHGEs per unit area using a continuous DID model, our identification strategy relies on several key assumptions. Firstly, the core identifying assumption is that, in the absence of differential changes in treatment intensity, regions would have experienced similar trends in the outcome variable. This is a generalization of the parallel trends assumption used in binary DID designs. We assess this by conducting pre-trend tests and plotting the dynamic treatment effects. Secondly, there may have been farmland cultivation equivalent to the HSFC practices present before the HSFC was formalized. Thus, we implemented a placebo test by assigning “pseudo” HSFC treatment values to years prior to the actual policy implementation. In addition, to further mitigate the concern of implicit treatment, we excluded regions with high levels of farmland scale operations prior to the HSFC launch. Thirdly, the variation in treatment intensity should not be systematically driven by other concurrent policies that also affect the outcome. To address this, we include year and region fixed effects as well as time-varying controls that capture the effects of other policies. According to previous research [16], we have excluded the impact of the Action Plan for Zero Growth in Fertilizer Use by 2020 and the Action Plan for Zero Growth in Pesticide Use by 2020. To examine whether the treatment intensity in one region exerts spillover effects on others, which would indicate a potential violation of the Stable Unit Treatment Value Assumption, we conduct the following robustness checks: firstly, we exclude regions that are geographically adjacent to high-treatment areas (defined as those in the top quartile of the treatment variable distribution during the treatment period) and re-estimate the baseline continuous DID model. This helps to eliminate the potential influence of demonstration or spillover effects from neighboring high-intensity regions.

$$CGHGE_{kt} \text{ per unit area} = \alpha_0 + \beta_{1kt} LH_{kt} \times I_t^{post} + \sum_{l=2}^L \beta_{lkt} X_{lkt} + \delta_k + \theta_t + \varepsilon_{kt} \quad (8)$$

where LH_{kt} represents the proportion of high-standard farmland area; I_t^{post} represents the dummy variable of the policy implementation time point, where post is the policy implementation year 2011, t is the year of policy implementation, and when $t \geq 2011$, I_t^{post} takes the value of 1, otherwise it is 0; X_{lkt} represents the control variable; δ_k represents the province fixed effect; θ_t represents the year fixed effect; ε_{kt} is the random error term; α_0 is the constant term; and β_{lkt} are the parameters to be estimated.

3.1.3. Parallel Trends Assumption and Dynamic Effect Test

The parallel trends test is an essential prerequisite for using the DID model. Therefore, prior to conducting baseline regressions, we first adopt an event study approach to examine pre-treatment differences between groups and perform a policy timing uniqueness test. This ensures no policy effects existed prior to 2011. This study uses the initial year of the sample period (2005) as the baseline and replaces the $Treat \times Post$ term with a series of interaction terms between year dummies and the $Treat$ variable. The regression results show that all coefficients of $Treat \times Before$ are statistically insignificant in the pre-policy years, while the $Treat \times After$ terms generally show significantly positive coefficients in the post-policy period. These findings confirm that the parallel trends assumption is satisfied. The following parallel trend and dynamic effect model is constructed:

$$CGHGE_{kt} \text{ per unit area} = \alpha_0 + \sum_{i=2005}^{2022} \beta_{1kt} LH_{it} \times D_t + \sum_{l=2}^L \beta_{lkt} X_{lkt} + \delta_k + \theta_t + \varepsilon_{kt} \quad (9)$$

where D_t represents the year dummy variable, and other variables remain consistent with Formula (8).

3.1.4. Mediating Effect Test

According to the theoretical analysis of the intermediary mechanism in Section 2 above, the path of how HSFC affects agricultural new-quality productivity and then reduces CGHGE per unit area is tested. This paper uses a two-stage method to verify the internal mechanism of the HSFC policy affecting CGHGE per unit area. The first stage verifies the impact of the HSFC policy on agricultural new-quality productivity. The second stage verifies the impact of agricultural new-quality productivity on CGHGE per unit area. The intermediary effect test model of this paper is as follows:

$$ANQP_{kt} = \alpha_0 + \alpha_{1kt} LH_{kt} \times I_t^{post} + \sum_{l=2}^L \varphi_{lkt} X_{lkt} + \delta_k + \theta_t + \varepsilon_{kt} \quad (10)$$

$$CGHGE_{kt} \text{ per unit area} = \alpha_0 + \alpha_{1kt} LH_{kt} \times I_t^{post} + \sum_{l=2}^L \varphi_{lkt} X_{lkt} + \alpha_{kt} ANQP_{kt} + \delta_k + \theta_t + \varepsilon_{kt} \quad (11)$$

where $ANQP_{kt}$ represents the mediating variable agricultural new-quality productivity; α_0 is the constant term; α_{1kt} and α_{kt} denote to the parameters to be estimated; φ_{lkt} represents the estimated coefficient for the control variable; and other variables remain consistent with Formula (8).

3.2. Data and Variable

3.2.1. Data Sources

This study employs panel data from 31 provincial-level regions in China (excluding Hong Kong, Macao, and Taiwan) spanning 2005 to 2022 to assess the impact of HSFC policies on greenhouse gas emissions from crop cultivation and to examine the mediating role of agricultural new-quality productivity. Among them, the construction area of high-standard farmland from 2005 to 2017 comes from the China Fiscal Yearbook of previous years, and the construction area of high-standard farmland from 2017 to 2022 comes from the work reports of local governments.

For calculating CGHGE per unit area, the specific indicators comprise fertilizer application quantity, pesticide usage, agricultural plastic film consumption, diesel fuel consumption, effective irrigation area, crop sown area, and cultivated land area. These data came from the China Fiscal Yearbook and China Agricultural Statistical Yearbook. Emission

factor data were obtained from various literature sources, with detailed references provided in the methodology section.

For indicators related to agricultural new-quality productivity, expenditure on agriculture, forestry, and water conservancy projects as well as general budget outlays were sourced from the China Fiscal Statistical Yearbook. Internal R&D expenditure and research personnel data came from the China Statistical Yearbook on Science and Technology. Employment figures in the primary industry were derived from the China Population and Employment Statistical Yearbook. Rural electricity consumption data came from the China Rural Statistical Yearbook. Indicators including broadband internet subscribers, broadband access ports, rural telephone subscribers, long-distance optical cable length, and forest coverage rate were collected from the China Statistical Yearbook. Soil erosion control area data were cross-referenced from both the China Statistical Yearbook and China Agricultural Machinery Industry Yearbook.

Concerning control variables, expenditure on agriculture, forestry, and water affairs, secondary industry value-added, total import–export volume, and urban and rural population figures were all acquired from the China Statistical Yearbook. Crop disaster-affected area and irrigation area data came from the China Rural Statistical Yearbook. Education levels of primary industry workers were obtained from the China Population and Employment Statistical Yearbook. Rural labor force data were compiled from both the China Rural Management Statistical Yearbook and China Rural Policy. In addition, the missing values of the data are supplemented by linear interpolation methods. The descriptive statistics of the main variables are shown in Table 1.

Table 1. Descriptive statistical analysis results.

Variable	Abbreviation	Units	Obs	Mean	SD	Min	Max
Greenhouse gas emissions per unit area from crop cultivation	CGHGE per unit area	t CO ₂ eq/ha	558	4.6819	1.9372	2.0817	8.7288
The interaction term between the scale of HSFC and the timing of HSFC policy implementation	LA_ I_{2011}^{post}	/	558	0.3282	0.3191	0.0000	1.0571
Agricultural new-quality productivity	ANQP	/	558	0.2071	0.1257	0.0339	0.7413
The level of financial support for agriculture	FIN	%	558	0.1107	0.0612	0.0103	0.2924
The disaster area of cultivated land	AL	%	558	6.3176	1.7086	2.4849	9.6256
The level of urbanization	UR	%	558	0.5554	0.1398	0.3300	0.8639
The level of rural education	RE	%	558	7.5287	0.6767	5.9486	8.5664
The percentage of irrigated area	IR	%	558	0.6478	0.3105	0.2618	1.3302
The plastic film per unit area	PF	10 t/ha	558	0.0022	0.0015	0.0004	0.0061
The fertilizer use per unit area	FE	10 t/ha	558	0.0465	0.0222	0.0136	0.0904
The percentage of rural labor force	LAB	%	558	0.8541	0.2309	0.4407	1.2784

3.2.2. Variable Selection

(1) Explained variables

The explained variable is greenhouse gas emissions per unit area from crop cultivation.

(2) Core explanatory variables

The core explanatory variable is the interaction term between the scale of HSFC and the timing of HSFC policy implementation. Among them, the scale of HSFC is characterized by the ratio of HSFC area to cultivated land area, and since the HSFC policy was standardized and implemented in 2011, the implementation time of the HSFC policy in 2011 and later is assigned a value of 1, and the opposite is assigned a value of 0.

(3) Control variables

In addition to the HSFC policy that will affect crop cultivation, other factors will also have an impact on it. According to the existing research [42,71–75], the following indicators were selected as control variables:

The level of financial support for agriculture refers to the proportion of expenditure on agriculture, forestry, and water affairs to general budget expenditure. The disaster area of cultivated land is measured by the ratio of disaster area to cultivated land. The level of urbanization is measured by the proportion of urban population to total population. The level of rural education is measured by the number of years of education per capita in rural areas. The percentage of irrigated area is measured by the ratio of irrigated area to cultivated land. The plastic film per unit area is measured by the amount of plastic film used on cultivated land. The fertilizer use per unit area is measured by fertilizer application on cultivated land. The percentage of rural labor force is measured by the ratio of rural labor force to rural population.

(4) Mediating variable

Agricultural new-quality productivity is a breakthrough to the traditional agricultural productivity, which is conducive to providing new dynamic energy for the high-quality development of agriculture; this study selected new-quality productive forces as the mediating variable. Based on the existing research [34,76,77], the evaluation index system is structured around three dimensions, including agricultural scientific and technological productivity, agricultural green productivity, and agricultural digital productivity. This study applies the entropy method to calculate the weights of each indicator, which are then used to evaluate the level of agricultural new-quality productivity. The indicator system is shown in Table 2:

Table 2. The evaluation index system of agricultural new-quality productivity.

Primary Indicators	Secondary Indicators	Tertiary Indicators	Measurement Method	Indicator Attributes
Agricultural scientific and technological productivity	Financial support	Agricultural R&D investment level	/	+
		Agricultural financial investment	Financial expenditure on agriculture, forestry and water/General financial expenditure	+
	Talent support	Number of people engaged in agricultural science and technology activities	Number of R&D × Coefficient A	+
		Agricultural labor force population	Number of employees in the primary sector × Coefficient A	+
Agricultural green productivity	Resource consumption	Fertilizer input	Fertilizer application/Crop sown area	-
		Rural electricity consumption	/	-
	Environmental governance	Area treated for soil erosion per unit Forest cover	Area of soil erosion control/Cultivated land	-
Agricultural digital productivity	Information services	Rural internet user counts	/	+
		Rural internet access ports	Internet broadband access port	+
	Mobile communication	Rural telephone user counts	Average number of cell phones per 100 rural households	+
		Length of long-haul optical cable	/	+

Note: Coefficient A is the ratio of the gross value of agricultural output to the gross value of agricultural, forestry, animal husbandry, and fishery output, and the separation of agricultural factors is accomplished by calculating the product of the relevant indicator and the coefficient A.

4. Results

4.1. Spatio-Temporal Evolution of CGHGE

During the study period, CGHGE exhibited fluctuating trends. From 2005 to 2015, emissions increased from 644.42 Mt. CO₂eq to 756.90 Mt. CO₂eq. After 2015, CGHGE showed a declining trend, decreasing to 669.52 Mt. CO₂eq by 2022. Overall, the average annual growth

rate of CGHGE during the study period was 0.23%. In terms of the structure of CGHGEs, between 2005 and 2022, the planting management phase held the largest proportion of CGHGE, with an average of 38%. This was followed by the production materials input segment at 33%, while the crop growth segment held the smallest share of CGHGE, at only 29%. Notably, the planting management phase demonstrated a consistent decline in its emission share, decreasing from 40.34% to 38.39%, with an average annual decrease rate of 0.29%. In contrast, the crop growth phase exhibited a gradual but fluctuating increase, rising from 26.08% to 26.75% during the study period. The production materials phase also showed a fluctuating upward trend, growing from 33.58% to 34.86% of total emissions between 2005 and 2022.

From a spatial distribution perspective, regional differences in CGHGE are evident (Figure 3). At the provincial level, the Inner Mongolia Autonomous Region, Heilongjiang Province, and Xinjiang Uygur Autonomous Region experienced increasing emissions, growing at 3.54%, 4.31%, and 4.38% annually, respectively. Conversely, Shandong, Fujian, Zhejiang, Jiangsu, and the Ningxia saw declining emissions, with annual reductions of 1.57%, 1.72%, 1.90%, 0.52%, and 1.29%, respectively. Major agricultural provinces, including Heilongjiang, Henan, Hunan, Jiangsu, and Anhui, consistently high in emissions, accounting for over 30% of the total in 2022. Meanwhile, Beijing, Tianjin, and Shanghai maintained consistently low emissions, remaining below 3 Mt. CO₂eq throughout the study period.

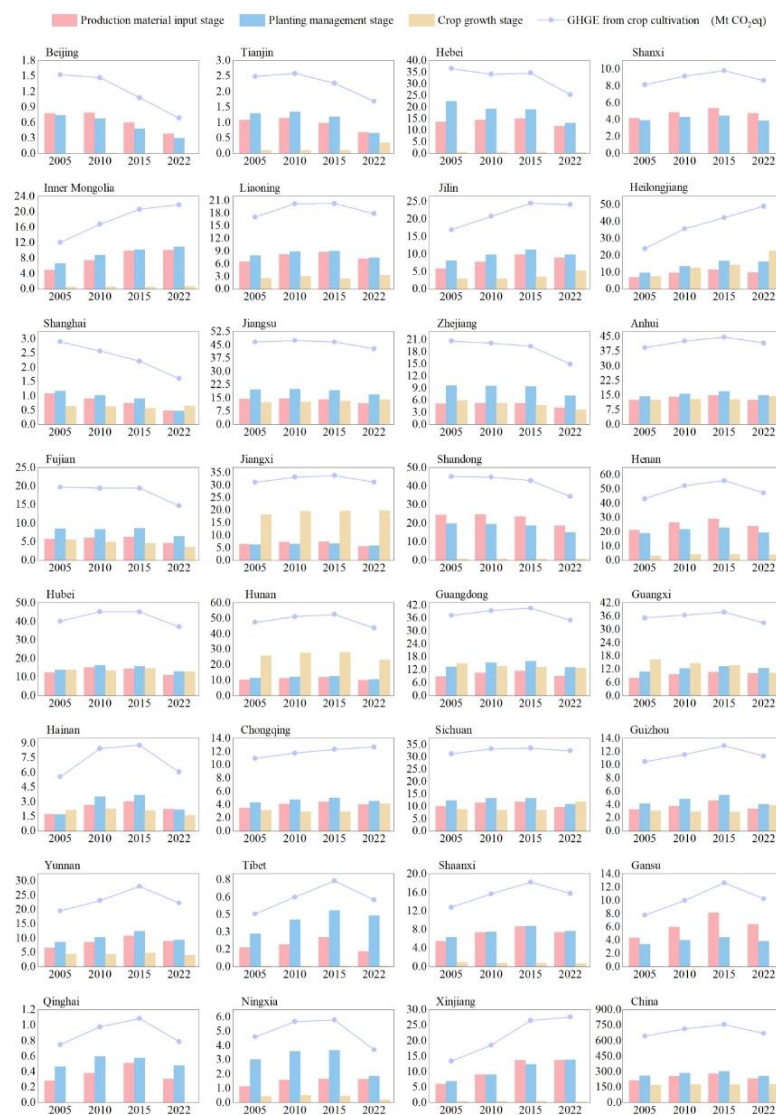


Figure 3. Greenhouse gas emissions from crop cultivation of 31 regions in China from 2005 to 2022.

Greenhouse gas emissions per unit area from crop cultivation also exhibited distinct phased evolution characteristics (Figure 4). During the study period, the overall trend followed an inverted “U” curve, with the turning point occurring in 2015. Specifically, from 2005 to 2015, PCGE showed a steady rise, increasing from 4.33 t CO₂eq/ha to 4.91 t CO₂eq/ha. However, between 2015 and 2022, emissions declined significantly, falling to 4.27 t CO₂eq/ha by 2022, representing an average annual decrease of 1.93%. At the provincial level, CGHGE per unit area in eastern coastal provinces such as Guangdong, Hainan, and Fujian was relatively high, all exceeding 7 t CO₂eq/ha. Additionally, CGHGE per unit area in Qinghai, Tibet, and Gansu provinces has remained consistently low, at 2.23, 2.21, and 1.66 t CO₂eq/ha, respectively, in 2022.

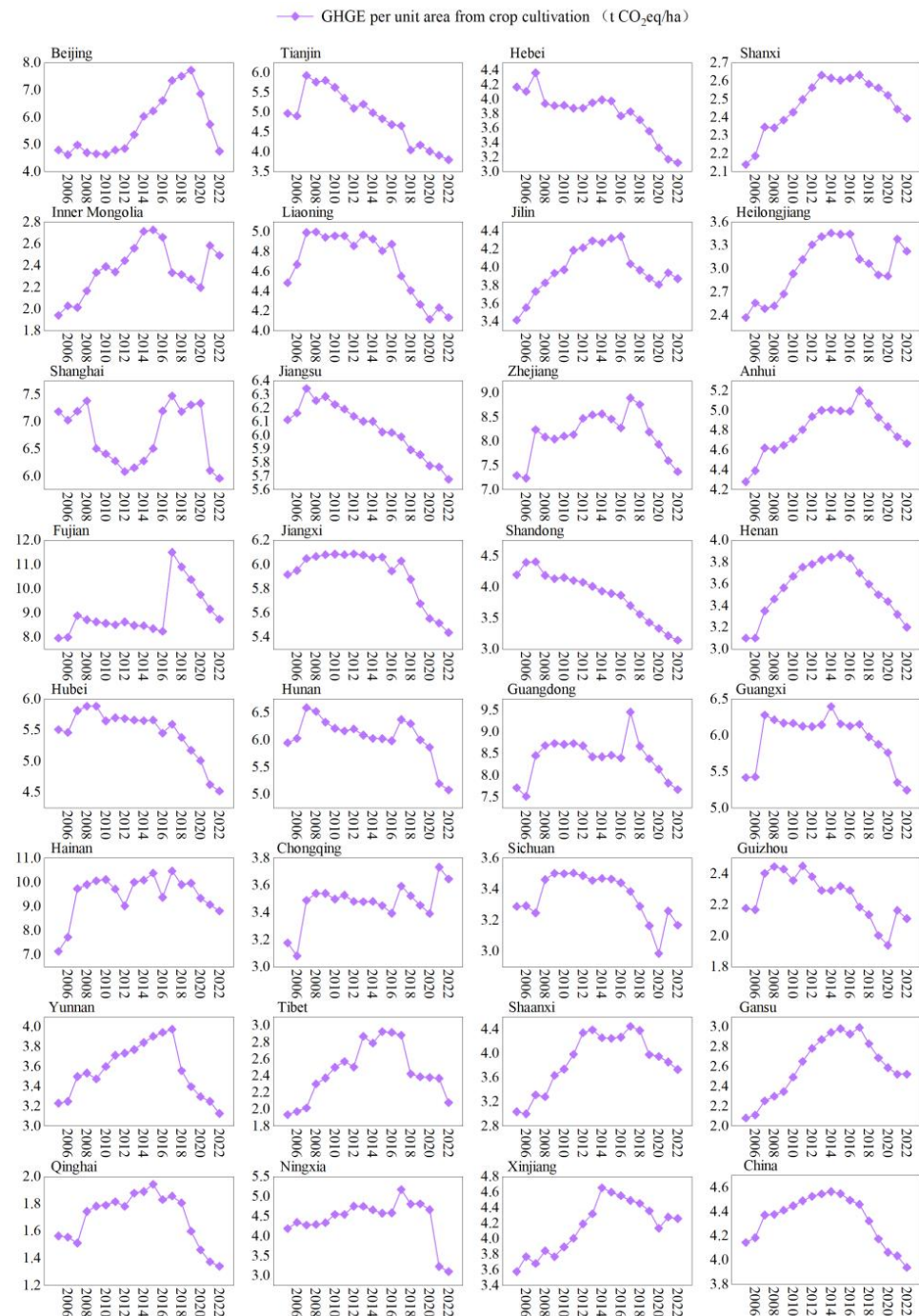


Figure 4. Greenhouse gas emissions per unit area from crop cultivation of 31 regions in China from 2005 to 2022.

4.2. The Impact of HSFC on CGHGEs

4.2.1. Benchmark Regression Result

The benchmark regression results presented in Table 3 reveal consistent evidence that HSFC significantly reduces CGHGEs per unit area across alternative model specifications. Column (1) reports the uncontrolled estimation, showing a statistically significant negative coefficient of -0.6929 ($p < 0.01$), indicating that HSFC implementation is associated with substantial emission reductions. The results in Column (2) demonstrate that, after incorporating provincial fixed effects and adding control variables, the coefficient is -0.7514 ($p < 0.01$). The results in Column (3) includes both provincial and year fixed effects, yielding a highly significant HSFC coefficient of -0.6288 ($p < 0.01$). Consequently, it can be inferred that the HSFC has a negative impact on CGHGEs per unit area, thereby providing empirical support for hypothesis H1.

Table 3. Benchmark regression results.

	(1) CGHGE Per Unit Area	(2) CGHGE Per Unit Area	(3) CGHGE Per Unit Area
LA_2011 ^{post}	-0.6929^{***} (0.1356)	-0.7514^{***} (0.1411)	-0.6288^{***} (0.1396)
FIN	—	1.5113^{***} (0.4897)	1.4713^* (0.8797)
AL	—	-0.1081^{***} (0.0187)	-0.0656^{***} (0.0235)
UR	—	-2.1046^{***} (0.5897)	-1.4592^* (0.8064)
RE	—	0.1410^* (0.0786)	0.1187 (0.0888)
IR	—	-1.3361^{***} (0.2128)	-1.0274^{***} (0.2224)
PF	—	143.3952^{***} (47.9487)	96.1250^{**} (47.9262)
FE	—	5.4093^* (3.1546)	5.5362^* (3.1754)
LAB	—	-0.1438 (0.1943)	-0.1054 (0.2063)
Cons	4.5528^{***} (0.0504)	5.4485^{***} (0.5919)	5.0061^{***} (0.7400)
Province	YES	YES	YES
Year	YES	NO	YES
N	558	558	558
R ²	0.973	0.973	0.975

Note: *, **, and *** denote significance at the 10%, 5%, and 1% significance level, respectively. Standard errors in parentheses.

4.2.2. Parallel Test and Dynamic Policy Effect

The parallel test was applied to test the effectiveness of the estimation results of the continuous DID model. Figure 5 depicts the changes in the estimated coefficients of the policy interaction term, which capture the temporal dynamics of the policy's effect on CGHGE per unit area. As shown in the figure, the estimated coefficients of the policy-related variables near zero and lack statistical significance prior to the policy's implementation. This suggests that there were no notable differences between the treatment and control groups before the policy took effect. Consequently, the policy impact of HSFC on CGHGE per unit area was negligible during this pre-implementation period. Following the formal enactment of the policy in 2011, the policy's influence on CGHGE per unit area displayed a consistent downward trend, thereby supporting the parallel trend assumption. This finding not only confirms that the policy significantly reduced CGHGE per unit area after

its implementation, but also underscores the appropriateness and validity of applying a continuous DID analysis.

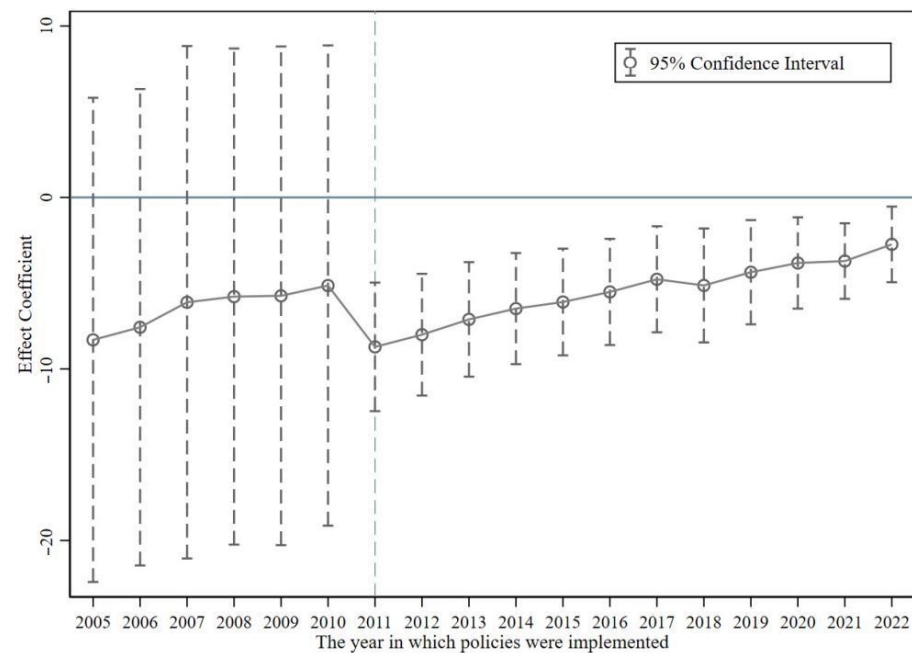


Figure 5. Parallel trend test.

4.2.3. Robustness Test

To ensure robustness, this study performs checks by replacing the dependent variable, switching from CGHGE per unit area to total CGHGE. The regression results in Column (1) of Table 4 indicate that HSFC significantly reduces CGHGEs, with a coefficient of -0.0642 , statistically significant at the 1% level. There may have been farmland cultivation equivalent to the HSFC practices present before the HSFC was formalized. Thus, we conduct two tests to ensure the robustness of our results. We conducted a placebo test by advancing the HSFC policy implementation date to 2007. The regression results are shown in Column (2) of Table 4. However, the regression result (-0.0100) shows no significant impacts, supporting the validity of our identification strategy. In addition, we further excluded regions that had relatively high levels of farmland-scale operations before the HSFC policy, including Heilongjiang, Henan, Hubei, Sichuan, and Jiangsu, as these areas were more likely to have implemented similar land consolidation measures independently. The results in Column (3) of Table 4 remained robust even after this exclusion. To assess whether the treatment intensity in one region generates spillover effects on neighboring regions, which would suggest a potential violation of the Stable Unit Treatment Value Assumption, we conduct the following robustness check. Specifically, we exclude regions that are geographically adjacent to high-treatment areas, defined as those falling within the top quartile of the treatment variable distribution during the treatment period. These regions including Jilin, Hubei, Jiangxi, Yunnan, Shanxi, Guizhou, Qinghai, and Inner Mongolia. The findings presented in Column (4) of Table 4 remained consistent and reliable even after this exclusion. The impact of HSFC on CGHGE per unit area may be subject to interference from geographical location factors. Specifically, municipalities directly under the central government such as Beijing, Tianjin, Shanghai, and Chongqing, which prioritize economic development in urban planning, may demonstrate shortcomings in HSFC. Therefore, this study excludes these four municipalities to verify the robustness of the baseline regression results. The regression results presented in Column (5) of Table 4 demonstrate that after excluding municipalities directly under the central government, the HSFC maintains a

statistically significant negative effect on CGHGE per unit area, with a coefficient of -0.5427 that remains significant at the 1% level. These findings are consistent with the benchmark regression results, confirming the robustness of the HSFC's promoting effect on CGHGE reduction even after the exclusion of special administrative regions.

Table 4. The results of robustness analysis.

	(1)	(2)	(3)	(4)	(5)	(6)
	Replace Explained Variable	Move the Policy Implementation Year to 2007	Excluding Regions with Prior High Levels of Farmland-Scale Operations	Excluding Regions That Are Geographically Adjacent to High-Treatment Areas	Excluding Municipalities Directly Under the Central Government	Remove Other Policy Distractions
LA_ I_{2011}^{post}	−0.0642 *** (0.0083)		−0.5927 *** (0.1519)	−0.6301 *** (0.1689)	−0.5427 *** (0.1565)	−2.254 *** (0.619)
LA_ I_{2007}^{post}		−0.0100 (0.2550)				
FIN	0.1717 *** (0.0521)	1.9671 ** (0.8942)	0.8954 (0.9965)	2.4780 ** (1.0845)	−0.3578 (0.7275)	0.833 *** (0.117)
AL	0.0029 ** (0.0014)	−0.0672 *** (0.0241)	−0.0647 ** (0.0268)	−0.0574 * (0.0295)	−0.0228 (0.0198)	−0.010 (0.007)
UR	−0.2466 *** (0.0477)	−1.5377 * (0.8233)	0.2774 (0.9966)	−0.6333 (1.0263)	−2.2468 *** (0.6566)	−1.5863 * (0.8198)
RE	0.0044 (0.0053)	0.1203 (0.0907)	0.1633 * (0.0986)	0.1516 (0.1124)	0.0711 (0.0761)	−0.005 (0.024)
IR	−0.0182 (0.0132)	−1.0974 *** (0.2268)	−1.0587 *** (0.2583)	−1.0666 *** (0.2794)	−0.0569 (0.1977)	−1.0639 *** (0.2262)
PF	2.1902 (2.8369)	70.8416 (49.3302)	96.3890 * (52.1329)	107.5381 * (56.2282)	252.5142 *** (41.6625)	38.366 *** (14.004)
FE	1.1566 *** (0.1880)	9.4605 *** (3.3423)	1.6505 (3.6589)	2.9524 (3.9111)	4.5002 * (2.5766)	11.8684 *** (3.3365)
LAB	−0.0043 (0.0122)	−0.0208 (0.2097)	−0.4557 * (0.2724)	−0.1394 (0.2474)	0.1567 (0.1667)	−0.0159 (0.2088)
Cons	0.2829 *** (0.0438)	4.7503 *** (0.7550)	4.2665 *** (0.8263)	4.6340 *** (0.9349)	4.9973 *** (0.5994)	1.567 * (0.942)
Province	YES	YES	YES	YES	YES	YES
Year	YES	YES	YES	YES	YES	YES
N	558	558	468	414	486	310
R ²	0.987	0.974	0.975	0.969	0.987	0.974

Note: *, **, and *** denote significance at the 10%, 5%, and 1% significance level, respectively. Standard errors in parentheses.

During the implementation of the HSFC policy, the existence of other policies affecting CGHGE per unit area may interfere with the estimation results. In 2015, the Ministry of Agriculture issued the Action Plan for Zero Growth in Fertilizer Use by 2020 and the Action Plan for Zero Growth in Pesticide Use by 2020. Since their introduction, China's agricultural fertilizer and pesticide usage has significantly declined. Given that fertilizer and pesticide application are major sources of agricultural carbon emissions, these policies would inevitably influence CGHGE per unit area. Therefore, to isolate the impact of the HSFC policy, samples from 2015 onward were excluded to mitigate interference from the zero-growth fertilizer and pesticide policies. The regression results presented in Column (6) of Table 4 demonstrate that HSFC maintains a negative effect on CGHGE per unit area at the 1% significance level.

4.2.4. Heterogeneity Test

This study examines the regional heterogeneity of HSFC policy impacts on CGHGE per unit area by categorizing provincial data into eastern, central, and western regions for empirical testing using fixed-effects models. The results in Columns (1)–(3) of Table 5 show that HSFC in eastern China has a statistically significant negative effect on agricultural carbon emissions with a coefficient of -0.0187 at the 1% significance level. In central China,

the HSFC coefficient is 0.0777, but statistically insignificant, indicating no discernible impact on CGHGE per unit area. The western region demonstrates a significant negative coefficient of -0.046 at the 10% significance level. These findings collectively reveal that HSFC's emission-reducing effects exhibit distinct regional variations, being most pronounced in western China, followed by eastern regions, while showing no significant effect in central China, thereby confirming the existence of regional heterogeneity in the policy's emission-reducing effects.

Table 5. The results of heterogeneity analysis.

	(1)	(2)	(3)	(4)	(5)
	Eastern Region	Central Region	Western Region	Major Grain-Producing Region	Non-Major Grain-Producing Region
LA_ I_{2011}^{post}	−0.0187 *** (0.0071)	0.0777 (0.0527)	−0.0460 * (0.0264)	−0.1726 *** (0.0436)	−0.0439 *** (0.0056)
FIN	0.0178 (0.0506)	0.6011 *** (0.1648)	−0.0334 (0.0725)	0.2095 * (0.1184)	0.0232 (0.0393)
AL	0.0019 (0.0013)	−0.0016 (0.0040)	0.0076 *** (0.0018)	−0.0005 (0.0030)	0.0027 ** (0.0011)
UR	−0.3568 *** (0.0502)	−0.6434 *** (0.1821)	0.0767 (0.0602)	−0.6973 *** (0.1090)	0.0947 ** (0.0424)
RE	0.0163 *** (0.0051)	−0.0502 *** (0.0141)	0.0029 (0.0061)	0.0257 ** (0.0106)	0.0003 (0.0040)
IR	0.0064 (0.0131)	0.0870 * (0.0509)	−0.0148 (0.0192)	0.0665 ** (0.0325)	−0.0280 *** (0.0101)
PF	4.4109 * (2.2789)	18.9013 (23.4160)	0.9953 (4.5368)	63.8527 *** (9.1547)	−3.7047 * (2.0377)
FE	0.2409 (0.2045)	1.0790 ** (0.5375)	1.1720 *** (0.2230)	0.4123 (0.4427)	0.7949 *** (0.1431)
LAB	0.0068 (0.0088)	0.2003 *** (0.0608)	−0.0800 *** (0.0184)	0.0931 *** (0.0209)	−0.0587 *** (0.0109)
Cons	0.2707 *** (0.0514)	0.8605 *** (0.1247)	0.1451 *** (0.0420)	0.3511 *** (0.0988)	0.1178 *** (0.0341)
Province	YES	YES	YES	YES	YES
Year	YES	YES	YES	YES	YES
N	198	144	216	234	324
R ²	0.996	0.987	0.989	0.975	0.990

Note: *, **, and *** denote significance at the 10%, 5%, and 1% significance level, respectively. Standard errors in parentheses.

To further examine potential heterogeneity in the effects of HSFC on CGHGE per unit areas across different functional regions in China, this study conducts subgroup analyses by categorizing provincial panel data into major grain-producing areas and non-major grain-producing areas based on regional grain production capacity. The empirical results presented in Column 4 of Table 5 demonstrate that HSFC in major grain-producing regions has a statistically significant negative impact on CGHGE per unit area, with a coefficient of -0.1726 at the 1% significance level. Meanwhile, Column 5 of Table 5 reveals that HSFC in non-major grain-producing regions also shows a significant negative effect, though smaller in magnitude (coefficient = -0.0439 , significant at 1% level). These findings provide clear evidence of functional heterogeneity in the emission-reducing effects of HSFC, with stronger impacts observed in grain-producing regions compared to non-grain-producing areas.

4.3. Mechanism Analysis

The results in Column (1) of Table 6 show that the coefficient for HSFC on agricultural new-quality productivity is 0.0614, with a 1% significance level. This indicates that HSFC

contributes to the advancement of agricultural new-quality productivity. In Column (2) of Table 6, the coefficient for agricultural new-quality productivity on CGHGE per unit area is -0.8849 , significant at the 5% level. This result indicates that agricultural new-quality productivity can effectively reduce CGHGE per unit area. After incorporating agricultural new-quality productivity into the equation, HSFC still has a significant negative impact on reducing CGHGE per unit area. After adding the mediating variable, the absolute value of the coefficient HSFC policy on CGHGE per unit area decreased from 0.6288 in Column (1) of Table 3 to 0.5744 in Column (2) of Table 6. This result confirms that HSFC can reduce CGHGE per unit area by promoting the development of agricultural new-quality productivity.

Table 6. Mechanism analysis.

	(1)	(2)
	ANQP	CGHGEs Per Unit Area
$LA\_I_{2011}^{post}$	0.0614 *** (0.0175)	-0.5744 *** (0.1405)
ANQP	—	-0.8849 ** (0.3558)
FIN	0.0047 (0.1100)	1.4755 * (0.8751)
AL	-0.0091 *** (0.0029)	-0.0737 *** (0.0236)
UR	0.5116 *** (0.1008)	-1.0065 (0.8226)
RE	-0.0091 (0.0111)	0.1107 (0.0884)
IR	0.1673 *** (0.0278)	-0.8793 *** (0.2291)
PF	-11.8240 ** (5.9933)	85.6621 * (47.8648)
FE	-0.9320 ** (0.3971)	4.7115 (3.1764)
LAB	0.0346 (0.0258)	-0.0748 (0.2056)
Cons	-0.0335 (0.0925)	4.9764 *** (0.7363)
Province	YES	YES
Year	YES	YES
N	558	558
R ²	0.907	0.975

Note: *, **, and *** denote significance at the 10%, 5%, and 1% significance level, respectively. Standard errors in parentheses.

5. Discussion

In March 2025, the General Office of the Central Committee of the Communist Party of China and the General Office of the State Council jointly issued the Implementation Plan for Gradually Converting Permanent Basic Farmland into High-Standard Farmland [78]. The plan sets ambitious targets: by 2030, China aims to cumulatively develop 90 million hectares of high-standard farmland, including upgrading 18.67 million hectares while simultaneously implementing efficient water-saving irrigation on an additional 5.33 million hectares. These targets underscore the Chinese government's strong commitment to HSFC. Many countries introduced farmland utilization and protection policies relatively early. For example, the United States' Conservation Reserve Program aims to promote ecological restoration and conservation-oriented land use by retiring environmentally sensitive land from agricultural

production [79]. Under the European Union's Common Agricultural Policy, Ecological Focus Areas are designed to preserve biodiversity and improve the sustainability of farmland systems [80]. In Japan, farmland consolidation programs address the challenge of fragmented land through structural adjustments and infrastructure investments, thereby enhancing land-use efficiency and long-term sustainability [81,82]. In comparison, China's high-standard farmland development policy exhibits distinctive characteristics in the coordinated advancement of food security, ecological protection, and rural revitalization [70,73]. Against this background, examining the impact of HSFC on CGHGE and exploring the mediating role of agricultural new-quality productivity on the relationship of HSFC and CGHGE holds significant practical and strategic importance for advancing agricultural modernization.

Our study demonstrates that HSFC can effectively reduce CGHGE per unit area, which aligns with existing research findings [24,41]. Based on the construction target for HSFC by 2030 outlined in the Implementation Plan for Gradually Converting Permanent Basic Farmland into High-Standard Farmland, and combined with the projection results of China's future carbon emissions from Mi et al. [83], we estimate that HSFC could reduce carbon emissions by 72.71 Mt. CO₂eq by 2030, accounting for approximately 0.67% of China's total carbon emissions in 2030.

The heterogeneity test results reveal that HSFC demonstrates stronger emission reduction effects in major grain-producing regions, which may be attributed to two key factors. First, these regions typically feature more concentrated farmland resources, enabling large-scale land consolidation (such as field merging and standardized irrigation systems) through HSFC implementation. This significantly reduces machinery operation intensity per unit area, directly lowering fossil fuel carbon emissions. Second, compared to non-major producing areas, major grain-producing regions benefit from greater government investment density in both funding and technology, facilitating more effective adoption of green technologies. Consequently, the natural endowments, policy advantages, and technology spillover effects in major grain-producing regions collectively amplify HSFC's emission reduction performance. This finding holds significant implications for formulating regionally differentiated emission reduction policies.

The regional heterogeneity analysis reveals that HSFC exerts statistically significant negative effects on CGHGE per unit area in both western and eastern China. This finding is consistent with previous research [24]. The eastern region, with its strong economic foundation and leading technological development, has formed a significant technology agglomeration effect, particularly in the Pearl River Delta and Yangtze River Delta regions. According to the sub-indicators of ANQP, the region excels in agricultural technology (0.1919) and digital productivity (0.2403), reflecting its advanced agricultural technological level and more developed digital infrastructure. These advantages enable the eastern region to effectively optimize agricultural resource allocation efficiency through smart farming technologies and digital precision management, while successfully promoting low-carbon farming practices such as soil testing, formula fertilization, and straw returning. Consequently, these measures have significantly enhanced the emission reduction effectiveness of HSFC. Meanwhile, although the western region lags behind in economic development, its HSFC has also achieved remarkable emission reduction results. This can be attributed to two main factors: the extensive implementation of HSFC in the region and its high agricultural green productivity. By utilizing abundant renewable energy resources like solar and wind power, the western region keeps energy consumption in rural areas relatively low, offering distinct regional advantages for reducing agricultural emissions.

More importantly, this study reveals that HSFC enhances agricultural new-quality productivity, which leads to emission reductions. This suggests that the implementation of HSFC facilitates the transition of farmland operators toward agricultural new-quality

productivity. By relying on agricultural technological innovation, it helps break away from the traditional high-input, high-consumption mode of productivity development. Through the integration of technology, green practices, and digitalization, it reduces CGHGE—such as by promoting the adoption of green production technologies like integrated water–fertilizer systems, smart irrigation, and climate-smart agricultural monitoring. Therefore, it is imperative to accelerate the development of agricultural new-quality productivity by enhancing investments in technological innovation, green and low-carbon solutions, and digital transformation. This will catalyze new emission-reduction drivers in crop cultivation and ultimately facilitate the transition toward sustainable agricultural development. Our research findings provide scientific evidence and policy support for the government to better leverage advanced agricultural productivity factors in guiding HSFC.

There are several limitations in this study. First, when selecting specific quantitative indicators for HSFC projects, this study chose the proportion of land consolidation area as the quantitative indicator, considering factors such as data availability, continuity, and references from related studies. However, this indicator may have certain limitations in fully reflecting the effects of HSFC on CGHGE per unit area. Therefore, future research on the quantification of core explanatory variables could consider the influence of other relevant factors and attempt to quantify them to provide a more comprehensive analysis of the impact of HSFC on CGHGE per unit area. Second, this study does not take carbon sequestration from crop cultivation into account, primarily because changes in soil carbon sequestration occur over a long period, and soil carbon pool changes are slow and require long-term field monitoring. Due to the lack of field monitoring data, carbon sequestration from crop cultivation was not included in the calculations. In future research, we will incorporate carbon sink effects into the calculation of CGHGE to enhance measurement accuracy, and further investigate the impact of HSFC policy on CGHGE.

6. Conclusions

Based on comprehensive measurements of GHGE from crop cultivation and evaluations of new-quality agricultural productivity across 31 Chinese provinces from 2005 to 2022, this study employs the difference-in-differences (DID) model and mediation effect model to investigate the impact of HSFC policy on CGHGE per unit area, with particular focus on the mediating role of agricultural new-quality productivity. The main findings are as follows:

From 2005 to 2022, CGHGE in China showed a fluctuating but overall increasing trend, rising from 644.4183 Mt. CO₂eq to 669.5152 Mt. CO₂eq, representing an average annual growth rate of 0.23%. The planting management phase constituted the largest emission source, accounting for 38% of total CGHGE. CGHGE per unit area followed an inverted U-shaped trajectory, peaking at 4.9090 t CO₂eq/ha in 2015 after increasing from 4.3321 t CO₂eq/ha in 2005, then decreasing to 4.2705 t CO₂eq/ha by 2022. Regionally, CGHGE per unit area were relatively high in South and East China, while North China, Northeast China, and Southwest China showed comparatively lower values.

The empirical results demonstrate that HSFC can significantly mitigate the growth of CGHGE per unit area, with an average annual reduction of 62.88%. This inhibitory effect remains statistically robust across multiple sensitivity analyses, confirming that the HSFC policy effectively contributes to lowering CGHGE per unit area.

The regional heterogeneity analysis indicates that HSFC exerts statistically significant negative effects on CGHGE per unit area across both western and eastern China. Furthermore, heterogeneity tests demonstrate that HSFC's emission reduction effects are particularly pronounced in major grain-producing regions.

The mediation analysis reveals that agricultural new-quality productive forces play a significant mediating role in the process whereby HSFC reduces CGHGE per unit area.

Specifically, the results demonstrate that HSFC contributes to emission reductions by enhancing agricultural new-quality productive forces, which subsequently lead to lower CGHGE per unit area.

Author Contributions: Conceptualization, Y.W.; methodology, Y.W. and J.L.; software, Y.W.; formal analysis, Y.F.; resources, Y.F. and J.L.; data curation, Y.F. and W.C.; writing—original draft preparation, Y.W.; writing—review and editing, Y.F. and Y.W.; visualization, Y.F. and J.L.; supervision, Y.W.; project administration, Y.W.; funding acquisition, Y.W. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by the Youth Foundation of the School of Public Administration, China University of Geosciences (CUGGG--2301). The APC was funded by the “CUG Scholar” Scientific Research Funds at the China University of Geosciences (Wuhan) (2022128).

Data Availability Statement: The data presented in this study are available on request from the author. The data are not publicly available due to privacy restrictions.

Conflicts of Interest: The authors declare no conflicts of interest.

Appendix A

Table A1. Carbon emission factors for various types of agricultural inputs.

Source	Coefficient (C)	Unit	Reference
Fertilizer	0.8956	kg·kg ^{−1}	West [84]
Pesticides	4.9341	kg·kg ^{−1}	Guan et al. [85]
Agricultural Films	5.18	kg·kg ^{−1}	Guan et al. [85]
Diesel	0.5927	kg·kg ^{−1}	Guan et al. [85]
Soil Tilling	312.6	kg·km ^{−1}	Guan et al. [85]
Irrigation	266.48	kg·ha ^{−1}	West [84]

Table A2. Default values of N₂O direct emission factors from agricultural land in different regions [55].

Region	N ₂ O Direct Emission Factor (kg N ₂ O-N/kg N Input)	Range
Zone I (Inner Mongolia, Xinjiang, Gansu, Qinghai, Xizang, Shaanxi, Shanxi, Ningxia)	0.0056	0.0015–0.0085
Zone II (Heilongjiang, Jilin, Liaoning)	0.0114	0.0021–0.0258
Zone III (Beijing, Tianjing, Hebei, Henan, Shandong)	0.0057	0.0014–0.0081
Zone IV (Zhejiang, Shanghai, Jiangsu, Anhui, Jiangxi, Hunan, Hubei, Sichuan, Chongqing)	0.0109	0.0026–0.022
Zone V (Guangdong, Guangxi, Hainan, Fujian)	0.0178	0.0046–0.0228
Zone VI (Yunnan, Guizhou)	0.0106	0.0025–0.0218

Table A3. Carbon emission factors in the crop growth chain (kg/ha) [55].

Type	Emission	Region					
		North China	East China	Central/South China	Southwest China	Northeast China	Northwest China
Single-season rice	CH ₄	234	215.5	236.7	156.2	168	231.2
	N ₂ O	0.24	0.24	0.24	0.24	0.24	0.24
Early double-season rice	CH ₄	—	211.4	241	156.2	—	—
	N ₂ O	0.24	0.24	0.24	0.24	0.24	0.24
Dual-season late rice	CH ₄	—	224	273.2	171.7	—	—
	N ₂ O	0.24	0.24	0.24	0.24	0.24	0.24
Spring wheat	N ₂ O	0.4	0.4	0.4	0.4	0.4	0.4
Winter wheat	N ₂ O	1.75	1.75	1.75	1.75	1.75	1.75
Corn	N ₂ O	2.532	2.532	2.532	2.532	2.532	2.532

Note: North China: Beijing, Tianjin, Hebei, Shanxi, Inner Mongolia; East China: Shanghai, Jiangsu, Zhejiang, Anhui, Fujian, Jiangxi, Shandong; Central South China: Henan, Hubei, Hunan, Guangdong, Guangxi, Hainan; Southwest China: Chongqing, Sichuan, Guizhou, Yunnan, Tibet; Northeast China: Liaoning, Jilin, Heilongjiang; Northwest China: Shaanxi, Gansu, Qinghai, Ningxia, Xinjiang.

References

1. Intergovernmental Panel on Climate Change (IPCC). Climate Change 2013: The Physical Science Basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change. Available online: <https://www.ipcc.ch/report/ar5/wg1/> (accessed on 9 March 2024).
2. Godfray, H.C.J.; Beddington, J.R.; Crute, I.R.; Haddad, L.; Lawrence, D.; Muir, J.F.; Pretty, J.; Robinson, S.; Thomas, S.M.; Toulmin, C. Food security: The challenge of feeding 9 billion people. *Science* **2010**, *327*, 812–818. [CrossRef] [PubMed]
3. Food and Agriculture Organization of the United Nations (FAO). FAOSTAT Emissions Totals Database. Available online: <http://www.fao.org/faostat/en/#data/GT> (accessed on 12 January 2025).
4. Xue, S.; Fang, Z.; van Riper, C.; He, W.; Li, X.; Zhang, F.; Wang, T.; Cheng, C.; Zhou, Q.; Huang, Z. Ensuring China's food security in a geographical shift of its grain production: Driving factors, threats, and solutions. *Resour. Conserv. Recycl.* **2024**, *210*, 107845. [CrossRef]
5. Ministry of Ecology and Environment of the People's Republic of China (MEEPRC). First Biennial Transparency Report on Climate Change of the People's Republic of China and Fourth Biennial Update Report on Climate Change of the People's Republic of China. Available online: https://www.mee.gov.cn/ywgz/ydqhbh/qhbhlf/202501/t20250110_1100393.shtml (accessed on 1 March 2025).
6. Intergovernmental Panel on Climate Change (IPCC). Climate Change 2021: The Physical Science Basis. Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change. Available online: <https://www.ipcc.ch/report/ar6/wg1/> (accessed on 9 March 2024).
7. Hao, S.; Wang, G.; Yang, Y.; Zhao, S.; Huang, S.; Liu, L.; Zhang, H. Promoting grain production through high-standard farmland construction: Evidence in China. *J. Integr. Agric.* **2024**, *23*, 324–335. [CrossRef]
8. Central People's Government of the People's Republic of China (CPGPRC). Opinions of the Central Committee of the Communist Party of China and the State Council on Further Deepening Rural Reform and Solidly Advancing Comprehensive Rural Revitalization. Available online: https://www.gov.cn/gongbao/2025/issue_11906/202503/content_7011166.html (accessed on 1 March 2025).
9. Central People's Government of the People's Republic of China (CPGPRC). National High-Standard Farmland Construction Plan (2021–2030). 2021. Available online: https://www.gov.cn/gongbao/content/2021/content_5639831.htm (accessed on 9 September 2024).
10. Jiang, Y.; Tang, Y.-T.; Long, H.; Deng, W. Land consolidation: A comparative research between Europe and China. *Land Use Policy* **2022**, *112*, 105790. [CrossRef]
11. Pašakarnis, G.; Maliene, V. Towards sustainable rural development in Central and Eastern Europe: Applying land consolidation. *Land Use Policy* **2010**, *27*, 545–549. [CrossRef]
12. Sikor, T.; Müller, D.; Stahl, J. Land Fragmentation and Cropland Abandonment in Albania: Implications for the Roles of State and Community in Post-Socialist Land Consolidation. *World Dev.* **2009**, *37*, 1411–1423. [CrossRef]
13. Janečková Molnárová, K.; Sklenička, P.; Bohnet, I.C.; Lowther-Harris, F.; van den Brink, A.; Movahhed Moghaddam, S.; Fanta, V.; Zástěra, V.; Azadi, H. Impacts of land consolidation on land degradation: A systematic review. *J. Environ. Manag.* **2023**, *329*, 117026. [CrossRef]
14. Hashimoto, S.; Nishi, M. Policy evolution of land consolidation and rural development in postwar Japan. *Geomat. Landmanag. Landsc.* **2016**, *3*, 57–75. [CrossRef]
15. Yoshida, T. Comparative Analysis on Land Consolidation Projects Between Indonesia and Japan. *J. Asian Archit. Build. Eng.* **2003**, *2*, b111–b116. [CrossRef]
16. Tang, W.; Huang, K.; Zhou, F. Can High-Standard Farmland Construction Policy Promote Agricultural Green Development? Evidence from Quasi Natural Experiments in Hunan, China. *Pol. J. Environ. Stud.* **2023**, *32*, 5333–5346. [CrossRef]
17. Fan, Y.; Wang, Y.; Han, R.; Li, X. Spatial-temporal dynamics of carbon budgets and carbon balance zoning: A case study of the middle reaches of the Yangtze River Urban Agglomerations, China. *Land* **2024**, *13*, 297. [CrossRef]
18. Sun, Z.H.; Han, J.C.; Li, Y.N.; Yang, L.Y.; Shi, L.; Yan, J.K. Effects of large-scale land consolidation projects on ecological environment quality: A case study of a land creation project in Yan'an, China. *Environ. Int.* **2024**, *183*, 108392.
19. Yu, Q.; Zeng, Q.; Yu, G. The Influence of Land Consolidation on Biomass and Ecological Environment. *Res. J. Appl. Sci. Eng. Technol.* **2014**, *7*, 3656–3662. [CrossRef]
20. Shan, W.; Jin, X.; Ren, J.; Wang, Y.; Xu, Z.; Fan, Y.; Gu, Z.; Hong, C.; Lin, J.; Zhou, Y. Ecological environment quality assessment based on remote sensing data for land consolidation. *J. Clean. Prod.* **2019**, *239*, 118126. [CrossRef]
21. Lu, H.; Ding, Y.; Zhang, J.; Wu, W.; Xu, D. Carbon reduction effect of comprehensive land consolidation and its configuration paths at the township level: A case study of Zhejiang Province, China. *J. Environ. Manag.* **2025**, *373*, 123855. [CrossRef]
22. Janus, J.; Ertunç, E. Impact of land consolidation on agricultural decarbonization: Estimation of changes in carbon dioxide emissions due to farm transport. *Sci. Total Environ.* **2023**, *873*, 162391. [CrossRef]

23. Guo, B.; Fang, Y.; Jin, X.; Zhou, Y. Monitoring the effects of land consolidation on the ecological environmental quality based on remote sensing: A case study of Chaohu Lake Basin, China. *Land Use Policy* **2020**, *95*, 104569. [\[CrossRef\]](#)
24. Liu, F.; Lin, J. The impact of high-standard farmland construction policies on the carbon emissions from agricultural land use (CEALU). *Land* **2024**, *13*, 672. [\[CrossRef\]](#)
25. Zhang, X.; Xiao, G.; Li, H.; Wang, L.; Wu, S.; Wu, W.; Meng, F. Mitigation of greenhouse gas emissions through optimized irrigation and nitrogen fertilization in intensively managed wheat–maize production. *Sci. Rep.* **2020**, *10*, 5907. [\[CrossRef\]](#)
26. Li, L.; Han, J.; Zhu, Y. Does environmental regulation in the form of resource agglomeration decrease agricultural carbon emissions? Quasi-natural experimental on high-standard farmland construction policy. *J. Clean. Prod.* **2023**, *420*, 138342. [\[CrossRef\]](#)
27. Huang, H.; Sheng, F. New quality productivity system: Factor characteristics, structural bearing and functional orientation. *Reform* **2024**, *2*, 15–24. (In Chinese)
28. Yue, S.; Bajuri, N.H.; Khatib, S.F.; Lee, Y. New quality productivity and environmental innovation: The hostile moderating roles of managerial empowerment and board centralization. *J. Environ. Manag.* **2024**, *370*, 122423. [\[CrossRef\]](#) [\[PubMed\]](#)
29. Cao, X.; Lei, J.; Shi, D.; Yu, W.; Tao, T.; Zhang, X.; Wang, A. New Quality Productivity of Agriculture and Rural Areas at the Provincial Scale in China: Indicator Construction and Spatiotemporal Evolution. *ISPRS Int. J. Geo-Inf.* **2025**, *14*, 104. [\[CrossRef\]](#)
30. Wang, K.; Liu, H. The development of new quality productivity of agriculture and the guarantee of food security in big countries: On “how to grow food”, “how to grow food” and “who will grow food”. *Reform* **2024**, *6*, 70–82. (In Chinese)
31. Luo, W.; Zuo, S.; Tang, S.; Li, C. The Formation of New Quality Productivity of Agriculture Under the Perspectives of Digitalization and Innovation: A Dynamic Qualitative Comparative Analysis Based on the “Technology-Organization-Environment” Framework. *Sustainability* **2025**, *17*, 597. [\[CrossRef\]](#)
32. Luo, B. On the new quality productivity of agriculture. *Reform* **2024**, *4*, 19–30.
33. Song, Z.; Leng, M.; Zhou, B.; Gao, X. New quality productivity of agriculture in China: Evaluation system construction, dynamic evolution and policy implications. *J. Agro-For. Econ. Manag.* **2024**, *23*, 425–434.
34. Lin, L.; Gu, T.; Shi, Y. The influence of new quality productive forces on high-quality agricultural development in China: Mechanisms and empirical testing. *Agriculture* **2024**, *14*, 1022. [\[CrossRef\]](#)
35. Balafoutis, A.; Beck, B.; Fountas, S.; Vangeyte, J.; Wal, T.V.; Soto, I.; Gómez-Barbero, M.; Barnes, A.; Eory, V. Precision Agriculture Technologies Positively Contributing to GHG Emissions Mitigation, Farm Productivity and Economics. *Sustainability* **2017**, *9*, 1339. [\[CrossRef\]](#)
36. Qayyum, M.; Zhang, Y.; Wang, M.; Yu, Y.; Li, S.; Ahmad, W.; Maodaa, S.N.; Sayed, S.R.M.; Gan, J. Advancements in technology and innovation for sustainable agriculture: Understanding and mitigating greenhouse gas emissions from agricultural soils. *J. Environ. Manag.* **2023**, *347*, 119147. [\[CrossRef\]](#)
37. Cillis, D.; Maestrini, B.; Pezzuolo, A.; Marinello, F.; Sartori, L. Modeling soil organic carbon and carbon dioxide emissions in different tillage systems supported by precision agriculture technologies under current climatic conditions. *Soil Tillage Res.* **2018**, *183*, 51–59. [\[CrossRef\]](#)
38. Medel-Jiménez, F.; Piringer, G.; Gronauer, A.; Barta, N.; Neugschwandtner, R.W.; Krexner, T.; Kral, I. Modelling soil emissions and precision agriculture in fertilization life cycle assessment—A case study of wheat production in Austria. *J. Clean. Prod.* **2022**, *380*, 134841. [\[CrossRef\]](#)
39. Han, Y.; Qi, Z.; Chen, P.; Zhang, Z.; Zhou, X.; Li, T.; Du, S.; Xue, L. Water-saving irrigation mitigates methane emissions from paddy fields: The role of iron. *Agric. Water Manag.* **2024**, *298*, 108839. [\[CrossRef\]](#)
40. Parvathi Sangeetha, B.; Kumar, N.; Ambalgi, A.P.; Abdul Haleem, S.L.; Thilagam, K.; Vijayakumar, P. IOT based smart irrigation management system for environmental sustainability in India. *Sustain. Energy Technol. Assess.* **2022**, *52*, 101973. [\[CrossRef\]](#)
41. Li, S.; Li, M.; Chen, J.; Shao, S.; Tian, Y. Impacts and Internal Mechanisms of High-Standard Farmland Construction on the Reduction of Agricultural Carbon Emission in China. *Agriculture* **2025**, *15*, 105. [\[CrossRef\]](#)
42. Zhou, Y.; Hu, Q.; Li, S.; Wang, M. Carbon sequestration effects of agricultural high-quality development: Evidence from China’s high-standard farmland construction. *Environ. Res. Commun.* **2024**, *6*, 125030. [\[CrossRef\]](#)
43. Zeng, S.; Zhu, F.; Chen, F.; Yu, M.; Zhang, S.; Yang, Y. Assessing the impacts of land consolidation on agricultural technical efficiency of producers: A survey from Jiangsu Province, China. *Sustainability* **2018**, *10*, 2490. [\[CrossRef\]](#)
44. Liu, Y.; Liao, W.; Zhang, X.; Qiu, H. Impact of high standard farmland construction policy on chemical fertilizer reduction: A case study of China. *Front. Environ. Sci.* **2023**, *11*, 1256028. [\[CrossRef\]](#)
45. Qian, L.; Liu, C.; Zheng, L.; Qian, W. How does high-standard farmland construction affect farmland transfer. *Chin. Land Sci.* **2023**, *37*, 62–70. (In Chinese)
46. Mathew, I.; Shimelis, H.; Mutema, M.; Minasny, B.; Chaplot, V. Crops for increasing soil organic carbon stocks—A global meta analysis. *Geoderma* **2020**, *367*, 114230. [\[CrossRef\]](#)
47. Zhao, C.; Qiu, R.; Zhang, T.; Luo, Y.; Agathokleous, E. Effects of Alternate Wetting and Drying Irrigation on Methane and Nitrous Oxide Emissions from Rice Fields: A Meta-Analysis. *Glob. Change. Biol.* **2024**, *30*, e17581. [\[CrossRef\]](#) [\[PubMed\]](#)

48. Iqbal, S.; Xu, J.; Khan, S.; Worthy, F.R.; Khan, H.Z.; Nadir, S.; Ranjitkar, S. Regenerative fertilization strategies for climate-smart agriculture: Consequences for greenhouse gas emissions from global drylands. *J. Clean. Prod.* **2023**, *398*, 136650. [\[CrossRef\]](#)
49. Zhang, G.; Yang, Y.; Wei, Z.; Zhu, X.; Shen, W.; Ma, J.; Lv, S.; Xu, H. The low greenhouse gas emission intensity in water-saving and drought-resistance rice in a rainfed paddy field in Southwest China. *Field Crops Res.* **2023**, *302*, 109045. [\[CrossRef\]](#)
50. Sharma, V.; Tripathi, A.K.; Mittal, H. Technological revolutions in smart farming: Current trends, challenges & future directions. *Comput. Electron. Agric.* **2022**, *201*, 107217.
51. Chen, Y.; Li, M. How does the digital transformation of agriculture affect carbon emissions? Evidence from China's provincial panel data. *Humanit. Soc. Sci. Commun.* **2024**, *11*, 713. [\[CrossRef\]](#)
52. Zhong, R.; He, Q.; Qi, Y. Digital economy, agricultural technological progress, and agricultural carbon intensity: Evidence from China. *Int. J. Environ. Res. Public Health* **2022**, *19*, 6488. [\[CrossRef\]](#)
53. Ikram, M.; Ferasso, M.; Sroufe, R.; Zhang, Q. Assessing green technology indicators for cleaner production and sustainable investments in a developing country context. *J. Clean. Prod.* **2021**, *322*, 129090. [\[CrossRef\]](#)
54. Fan, J.; Liu, C.; Xie, J.; Han, L.; Zhang, C.; Guo, D.; Niu, J.; Jin, H.; McConkey, B.G. Life cycle assessment on agricultural production: A mini review on methodology, application, and challenges. *Int. J. Environ. Res. Public Health* **2022**, *19*, 9817. [\[CrossRef\]](#)
55. National Development and Reform Commission. Guidelines for the Preparation of Provincial Greenhouse Gas Inventories (Trial). Available online: <http://www.edcmep.org.cn/tzh/ptfb/zcbz/202106/P020210601177040314696.pdf> (accessed on 9 September 2024).
56. Wang, Y.; Fan, Y.; Li, H.; Shang, Z. Dynamic Simulation and Reduction Path of Carbon Emission in “Three-Zone Space”: A Case Study of a Rapidly Urbanizing City. *Land* **2025**, *14*, 245. [\[CrossRef\]](#)
57. Smith, P.; Reay, D.; Smith, J. Agricultural methane emissions and the potential for mitigation. *Philos. Trans. R. Soc. A* **2021**, *379*, 20200451. [\[CrossRef\]](#)
58. Bennetzen, E.H.; Smith, P.; Porter, J.R. Agricultural production and greenhouse gas emissions from world regions—The major trends over 40 years. *Glob. Environ. Change.* **2016**, *37*, 43–55. [\[CrossRef\]](#)
59. Bennetzen, E.H.; Smith, P.; Porter, J.R. Decoupling of greenhouse gas emissions from global agricultural production: 1970–2050. *Glob. Change. Biol.* **2016**, *22*, 763–781. [\[CrossRef\]](#) [\[PubMed\]](#)
60. Cui, Y.; Khan, S.U.; Deng, Y.; Zhao, M. Regional difference decomposition and its spatiotemporal dynamic evolution of Chinese agricultural carbon emission: Considering carbon sink effect. *Environ. Sci. Pollut. Res.* **2021**, *28*, 38909–38928. [\[CrossRef\]](#)
61. Chen, B.; Xu, C.; Wu, Y.; Li, Z.; Song, M.; Shen, Z. Spatiotemporal carbon emissions across the spectrum of Chinese cities: Insights from socioeconomic characteristics and ecological capacity. *J. Environ. Manag.* **2022**, *306*, 114510. [\[CrossRef\]](#)
62. Gao, B.; Huang, T.; Ju, X.; Gu, B.; Huang, W.; Xu, L.; Rees, R.M.; Powlson, D.S.; Smith, P.; Cui, S. Chinese cropping systems are a net source of greenhouse gases despite soil carbon sequestration. *Glob. Change. Biol.* **2018**, *24*, 5590–5606. [\[CrossRef\]](#)
63. He, D.; Deng, X.; Wang, X.; Zhang, F. Livestock greenhouse gas emission and mitigation potential in China. *J. Environ. Manag.* **2023**, *348*, 119494. [\[CrossRef\]](#)
64. IPCC's Task Force on National Greenhouse Gas Inventories. 2019 Refinement to the 2006 IPCC Guidelines for National Greenhouse Gas Inventories. Available online: <https://www.ipcc.ch/report/2019-refinement-to-the-2006-ipcc-guidelines-for-national-greenhouse-gas-inventories/> (accessed on 9 September 2024).
65. Gu, B.; Ju, X.; Chang, J.; Ge, Y.; Vitousek, P.M. Integrated reactive nitrogen budgets and future trends in China. *Proc. Natl. Acad. Sci. USA* **2015**, *112*, 8792–8797. [\[CrossRef\]](#)
66. Ministry of Natural Resources of the People's Republic of China (MNRPRC). *National Land Remediation Plan (Approved by the State Council)*; Ministry of Natural Resources of the People's Republic of China (MNRPRC): Beijing, China, 2011.
67. Qian, N. Missing women and the price of tea in China: The effect of sex-specific earnings on sex imbalance. *Q. J. Econ.* **2008**, *123*, 1251–1285. [\[CrossRef\]](#)
68. Stuart, E.A.; Huskamp, H.A.; Duckworth, K.; Simmons, J.; Song, Z.; Chernew, M.E.; Barry, C.L. Using propensity scores in difference-in-differences models to estimate the effects of a policy change. *Health Serv. Outcomes Res. Methodol.* **2014**, *14*, 166–182. [\[CrossRef\]](#)
69. Zheng, W.; Shen, G.Q.; Wang, H.; Hong, J.; Li, Z. Decision support for sustainable urban renewal: A multi-scale model. *Land Use Policy* **2017**, *69*, 361–371. [\[CrossRef\]](#)
70. Peng, J.; Zhao, Z.; Chen, L. The impact of high-standard farmland construction policy on rural poverty in China. *Land* **2022**, *11*, 1578. [\[CrossRef\]](#)
71. Ye, F.; Wang, L.; Razzaq, A.; Tong, T.; Zhang, Q.; Abbas, A. Policy impacts of high-standard farmland construction on agricultural sustainability: Total factor productivity-based analysis. *Land* **2023**, *12*, 283. [\[CrossRef\]](#)
72. Liu, H.; Zhang, W. Spatial and temporal variation and convergence in the efficiency of high-standard farmland construction: Evidence in China. *J. Clean. Prod.* **2024**, *452*, 142200. [\[CrossRef\]](#)
73. Gong, Y.; Zhang, Y.; Chen, Y. The impact of high-standard farmland construction policy on grain quality from the perspectives of technology adoption and cultivated land quality. *Agriculture* **2023**, *13*, 1702. [\[CrossRef\]](#)

74. Dong, H.; Han, J.; Zhang, Y.; Chen, T.; Fan, H.; Wang, C. Research on influencing factors of cultivated land productivity of high-standard farmland projects in Hanzhong city of China—an empirical study based on PLS-SEM. *Front. Sustain. Food Syst.* **2023**, *7*, 1176426. [\[CrossRef\]](#)
75. Huang, Q.; Guo, W.; Wang, Y. A Study of the Impact of New Quality Productive Forces on Agricultural Modernization: Empirical Evidence from China. *Agriculture* **2024**, *14*, 1935. [\[CrossRef\]](#)
76. Zhang, Z.; Gao, M.; Zhang, X. High-standard farmland construction, new agricultural productivity and grain production increase. *Southwest Financ.* **2024**, *10*, 17–29. (In Chinese)
77. Tian, H.; Zhu, Z. Analysis of China’s grain production efficiency and influencing factors—Based on DEA-Tobit two-step method. *Chin. Agric. Resour. Reg. Plan.* **2018**, *39*, 161–168. (In Chinese)
78. Central People’s Government of the People’s Republic of China (CPGPRC). Implementation Plan for Gradually Converting Permanent Basic Farmland into High-Standard Farmland. Available online: https://www.gov.cn/gongbao/2025/issue_11986/202504/content_7019259.html (accessed on 1 March 2025).
79. Hellerstein, D.M. The US Conservation Reserve Program: The evolution of an enrollment mechanism. *Land Use Policy* **2017**, *63*, 601–610. [\[CrossRef\]](#)
80. Keane, M.; Connor, D.; Wegren, S.K.; Graça, P.; Gregório, M.J.; Camolas, J. Agricultural Policy Schemes: European Union’s Common Agricultural Policy. *Agenda* **2000**, *4*, 688–695.
81. Jentzsch, H. Tracing the Local Origins of Farmland Policies in Japan—Local-National Policy Transfers and Endogenous Institutional Change. *Soc. Sci. Jpn. J.* **2017**, *20*, 243–260. [\[CrossRef\]](#)
82. Koshiyama, N. Influence of Field Water Management by Land Consolidation in Paddy Field Zone in Hokkaido, Japan. *Irrig. Drain.* **2019**, *68*, 103–108. [\[CrossRef\]](#)
83. Mi, Z.; Wei, Y.-M.; Wang, B.; Meng, J.; Liu, Z.; Shan, Y.; Liu, J.; Guan, D. Socioeconomic impact assessment of China’s CO₂ emissions peak prior to 2030. *J. Clean. Prod.* **2017**, *142*, 2227–2236. [\[CrossRef\]](#)
84. West, T.O.; Marland, G. A synthesis of carbon sequestration, carbon emissions, and net carbon flux in agriculture: Comparing tillage practices in the United States. *Agric. Ecosyst. Environ.* **2002**, *91*, 217–232. [\[CrossRef\]](#)
85. Guan, N.N.; Liu, L.Y.; Dong, K.; Xie, M.; Du, Y.J. Agricultural mechanization, large-scale operation and agricultural carbon emissions. *Cogent Food Agric.* **2023**, *9*, 2238430. [\[CrossRef\]](#)

Disclaimer/Publisher’s Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.