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Synergistic effects of agricultural dual-scale management on carbon reduction in China

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The dual-scale agricultural management, namely farmland-scale management and service-scale management, offers a solution for achieving a balance between ensuring food security and reducing carbon emissions. Based on panel data of 30 Chinese provinces between 2005 and 2021, we use two-way fixed effects model and mediating effect model to explore the impact of dual-scale agricultural managements on agricultural carbon emission intensity. It was found that: Dual-scale agricultural managements have a significant negative correlation with agricultural carbon emission intensity; They have a synergistic effect on reducing carbon emission intensity through industrial agglomeration effect, technological progress effect, and machinery service effect; Farmland-scale management correlate more significantly with reduced agricultural carbon emission intensity in regions with balanced food production and sales, regions with high degree of agricultural mechanization, and the eastern regions, while service-scale management correlate more significantly in the main food sales regions, high degree of agricultural mechanization regions and the central regions.

Environmental problems, such as global warming and extreme weather phenomena are caused by excessive greenhouse gas emissions[1,2], exacerbating the challenges associated with climate response and seriously threating the development and survival of humankind[3]. China, as the largest emitter of greenhouse gases in the world[4], has resolved to achieve peak carbon emissions by 2030 and carbon neutrality by 2060. However, the widespread use of fertilizers and pesticides has led to a large increase in agricultural output, it has also negatively impacted the environment. China's agricultural sector accounts for 20% of the country's total greenhouse gas emissions and 13% of its total carbon emissions[5,6], which are significantly higher than for more developed countries. The previous model of crude and high-emission agriculture is no longer able to facilitate high-quality, sustainable agricultural development in China[7]. It is therefore essential to transition from high-carbon agriculture to low-carbon, green agriculture[8]. Since food security relies on high agricultural inputs and outputs, agriculture is the main source of carbon emissions in China[9,10], mainly due to China's large population and limited arable land and water resources per capita[11]. Therefore, balancing food security and carbon reduction represents a major constraint in China's agricultural development. In this context, it is crucial to explore the mechanisms that drive agricultural carbon emissions and potential strategies to reduce these emissions to promote sustainable agricultural development and address global climate change.

As a modern production and management model, agricultural land management on an appropriate scale is an important means of governance. The objective is to optimize the allocation of rural land resources and enhance agricultural production[12]. It plays an important role in safeguarding farmers' income and guaranteeing food security[13–15] while also facilitating low-carbon agricultural development[16,17]. The farmland-scale management theory[18] and the service-scale management theory[19] stand as the two predominant approaches to managing agriculture on an appropriate scale. Farmland-scale management (FSM) refers to large-scale agricultural management through the transfer and concentration of agricultural land[20,21], while service-scale management (SSM) involves large-scale agricultural management through the specialized division of labor and the purchasing of productive services by farmers[22–25]. These two approaches not only increase agricultural production, but also provide basic support for the green transformation of the agricultural sector[26,27].

It is important to note that most studies in this field have analyzed the impacts of FSM or SSM on agricultural production and carbon emissions from a single perspective[28–33]. Few studies have incorporated both FSM and SSM into a dual-scale framework to analyze their synergistic effect. In fact, FSM and SSM are not isolated from each other in modern agricultural systems, but have strong synergies. The lack of systematic research conducted from a dual-scale perspective to explore this synergistic effect has led

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to an incomplete understanding of the complex relationship between agricultural operation modes and carbon emissions. This makes it is difficult to accurately grasp the key approaches necessary to achieve low-carbon agricultural development through the optimization of the operational scale of farmland and agricultural services.

Accordingly, this study theoretically analyzes how FSM and SSM influence ACEI through a "dual-scale" management mode that combines the "land-scale management" and "service-scale management" as defined by Zheng et al.[34]. The theoretical analysis framework is illustrated below in Fig. 1.

The upper and lower branches in Fig. 1 respectively illustrate the action pathways of SFM and SSM on ACEI. The "Three Rights Separation" policy for agricultural land separates the ownership, contracting and management rights of rural land, of which the contracting and management rights belong to farmers, and farmers can transfer the contracting rights to others. The promulgation of this policy improves farmers' enthusiasm for the transfer of agricultural land[35], which lays a solid foundation for large-scale agricultural management[36]. The agricultural production services introduced by new management approaches involve all the different aspects of agricultural production directly or indirectly by providing a series of specialized and organized services[23], which provide feasible means for small-scale farmers to participate in large-scale modern agricultural systems[24]. The combination of agricultural land management and socialized services constitutes a synergistic, dual-scale management strategy for promoting sustainable agricultural production. Large-scale agricultural operations can significantly optimize the allocation of production factors and promote the efficient utilization of agricultural resources compared to that of dispersed small-scale farmers[37,38]. Large-scale operations also reduce agricultural pollution and reliance on chemical fertilizers through the implementation of ecological protection technologies, thereby reducing agricultural carbon emissions[30,33,39] and promoting green agricultural development[40,41]. Thus, Hypotheses 1 and 2 are proposed as follows:

H1: The expansion of FSM reduces ACEI.

H2: The expansion of SSM reduces ACEI.

The expansion of farmland scale management can increase demand for mechanization and production services[42], while the provision of agricultural production services can promote the outsourcing of labor- and technology-intensive segments. This alleviates labor constraints and other confounding factors associated with the expansion of farmland scale operations and promotes its continued adoption[43,44]. Therefore, FSM and SSM contribute synergistically to reducing agricultural carbon emissions by complementing and facilitating each other through horizontal and vertical agricultural labor division, this is depicted in the Fig.1 through the double sided arrows.

As farmland and service management continue to expand and agricultural production gradually becomes more centralized, the trend of industrial agglomeration becomes increasingly apparent[45]. As farmers adopt more advanced agricultural technologies and machinery[30,46–49], labor productivity improves and agricultural energy consumption and carbon emissions are directly reduced[32,50,51]. As shown in Fig. 1, this indicates that the industrial agglomeration effect, the technological progress effect, and the machinery service effect generated by a dual-scale management strategy jointly promote low-carbon and high-efficiency agriculture. Therefore, this study proposes Hypotheses 3 and 4:

H3: FSM and SSM have a synergistic effect on the reduction of ACEI.

H4: FSM and SSM reduces ACEI through the industrial agglomeration effect, the technological progress effect and the machinery service effect.

Based on the above theoretical analysis, this study uses panel data of 30 provinces in China and employs various empirical models to verify the synergistic effects of FSM and SSM on reducing ACEI. We will also explore the mediating role of industrial agglomeration, technological progress, and machinery service in this effect. We then propose corresponding countermeasures as evidence-based support for the promotion of low-carbon agricultural development and the formulation of effective regional policies in China. We also aim to provide anecdotal reference and practical recommendations for developing countries with large populations and limited land resources that face challenges in balancing food security and agricultural carbon emission reduction, so as to promote green transformation and the sustainable development of global agriculture.

Results

Measurement results of ACEI

Figure 2 shows the temporal evolution of FSM, SSM1, and ACEI in China from 2005 to 2021. Overall, FSM and SSM1 showed an upward trend. FSM increased from 0.588 hectares per person in 2005 to 0.708 in 2021, with an average annual growth rate of about 1.167%. SSM1 increased from 3.916×10^9 yuan in 2005 to 25.804×10^9 yuan in 2021, with an average annual growth rate of about 12.507%. The growth rate of FSM has slowed, owing to current challenges associated with agricultural land transfer and the vigorous promotion of agricultural socialization services in China. ACEI showed a decreasing trend at the national level, from 0.541 tons per ten thousand yuan in 2005 to 0.163 in 2021, with an average annual decrease of about 7.224%. This might be due to China's promotion of green agricultural development and large-scale operations, new management bodies, and research and development into green technologies. These initiatives kick-started the green agricultural transformation with a focus on reducing carbon emissions and carbon sequestration.

As shown in Fig. 3, we map the spatial and temporal evolution of ACEI at the provincial level in 2005, 2010, 2015, and 2021 using ArcGIS software, and partition them into five zones. Among the 30 provinces (excluding the Tibet Autonomous Region), there are none in low-value zones in 2005 and 2010, and only Guizhou, Beijing, and Qinghai are in low-value zones in 2015, whereas there are already 20 provinces in low value zones in 2021, such as Guizhou and Qinghai. There are several provinces in high-value

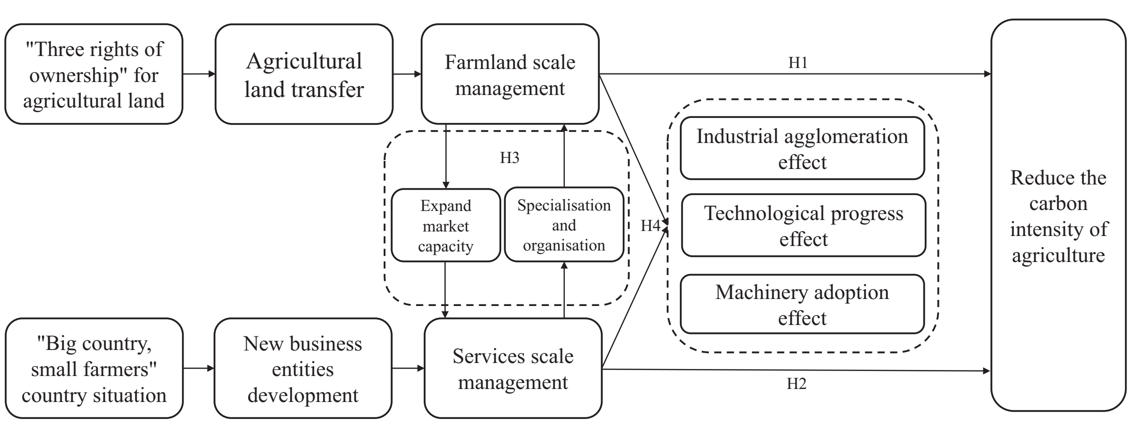

Fig. 1 | Theoretical analysis of the impact of FSM and SSM on ACEI.

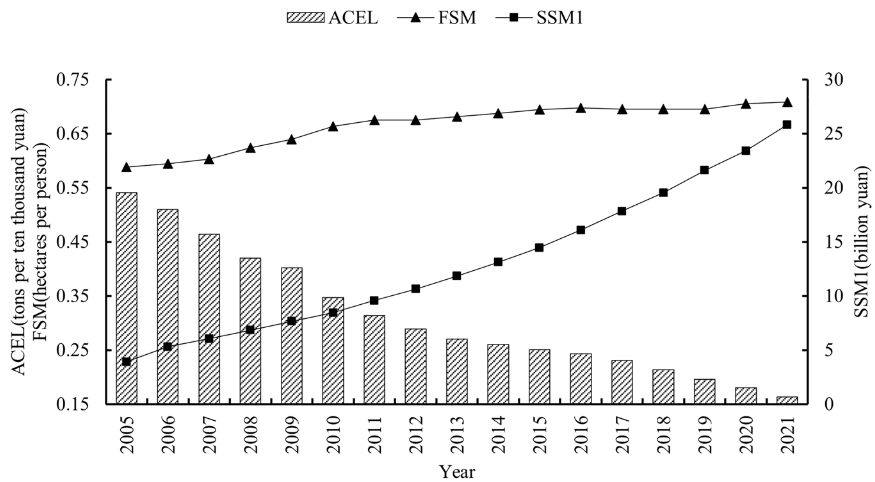

Fig. 2 | Temporal evolution of FSM, SSM1 and ACEI from 2005 to 2021. Note: FSM is farmland scale management; SSM1 is the exponential value of service scale management (SSM); ACEI is agricultural carbon emission intensity. The data of FSM and SSM1 are sourced from China Rural Statistical Yearbook, the data of ACEI is sourced from China Statistical Yearbook and IPCC. The same as the table below.

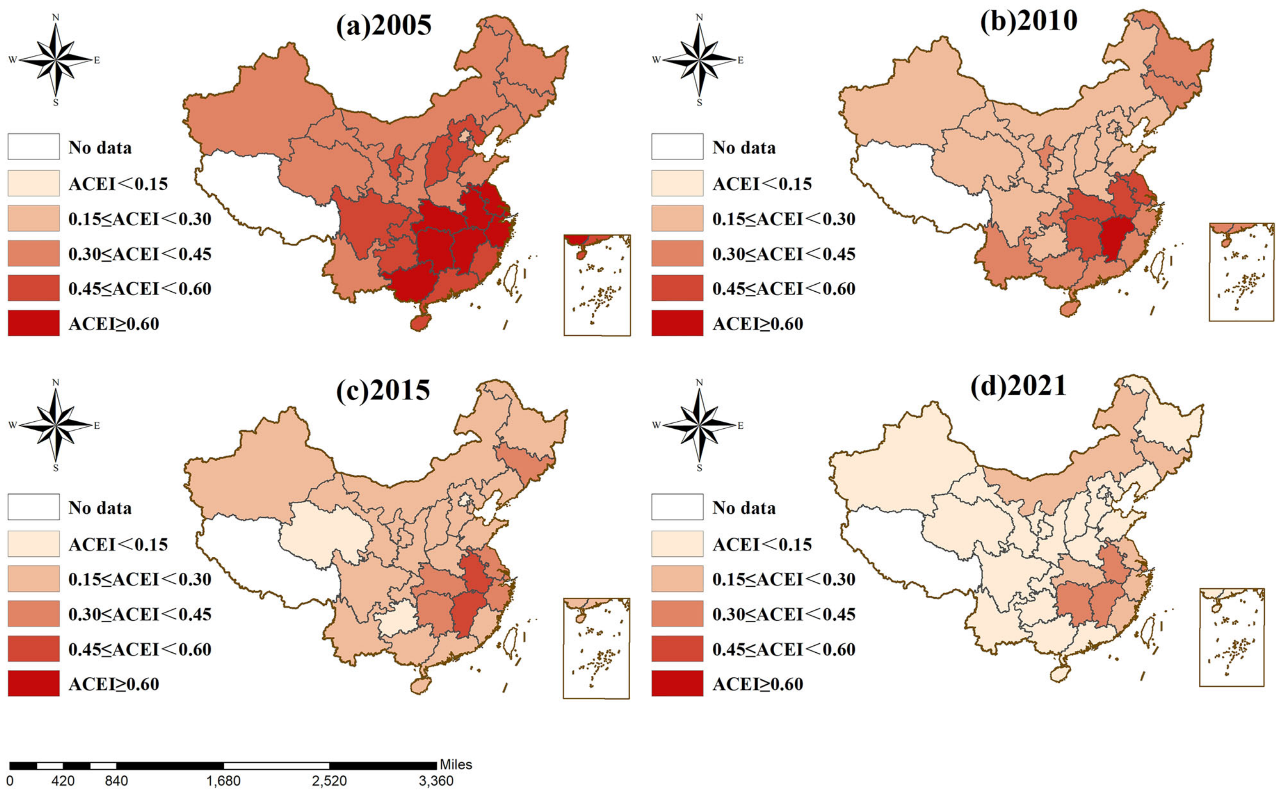

Fig. 3 | ACEI in various provinces of China in 2005, 2010, 2015 and 2021. Based on the standard map GS (2023) 2767 from Standard Map Service website of the Ministry of Natural Resources, PRC, with no modifications to the base map boundaries. **a** China's ACEI by province in 2005. **b** China's ACEI by province in 2010. **c** China's ACEI by province in 2015. **d** China's ACEI by province in 2021.

zones in 2005, such as Jiangxi and Hubei, and Jiangxi is the only province in a high-value zone in 2010. There are no provinces in high-value zones in 2015 and 2021, indicating that ACEI show a decreasing trend at the provincial level, which is consistent with the national level.

Baseline regression analysis

This paper employs a two-way fixed effects model to estimate the effects of FSM and SSM on ACEI, and the model is set as shown in Eqs. (1)–(3). We estimate the influence of FSM on ACEI using Eq. (1). Models 1–3 in Table 1 show the regression results when we gradually introduce the control variables. The coefficients of FSM in Models 2-3 are always significantly negative at the 1% statistical level, indicating that FSM can significantly reduce ACEI, thus confirming Hypothesis 1. Increased farmland management scale facilitates the precise allocation of water, fertilizer, and medicines, thereby improving resource utilization, reducing the use of pesticides and chemical fertilizers, effectively mitigating agricultural pollution, and ultimately reducing ACEI.

We estimate the influence of SSM on ACEI using Eq. (2). Models 4–6 in Table 1 show the regression results when we gradually introduce the control variables. The coefficients of SSM are always significantly negative at the 1% statistical level, indicating that SSM can significantly reduce ACEI by providing training to farmers on the use of agricultural technology, soil testing, formula fertilization, intelligent water-saving irrigation, and other technologies, and reducing resource waste and environmental pollution. This confirms Hypothesis 2.

Table 1 | Baseline regression results

Variables	Model 1 ACEI	Model 2 ACEI	Model 3 ACEI	Model 4 ACEI	Model 5 ACEI	Model 6 ACEI
FSM	−0.0931*	−0.161***	−0.144***			
	(0.037)	(0.040)	(0.034)			
SSM				−0.056***	−0.066***	−0.060***
				(0.015)	(0.015)	(0.014)
ER		−0.012***	−0.018***		−0.008**	−0.015***
		(0.003)	(0.003)		(0.003)	(0.003)
AIS		−0.004***	−0.005***		−0.004***	−0.005***
		(0.001)	(0.001)		(0.001)	(0.001)
FSA		0.009***	0.007***		0.009***	0.008***
		(0.002)	(0.002)		(0.002)	(0.001)
RHC			−0.254*			−0.251**
			(0.100)			(0.094)
IL			−0.064***			−0.064***
			(0.007)			(0.007)
Constant	0.374***	0.578***	1.722***	0.420***	0.595***	1.727***
	(0.025)	(0.055)	(0.212)	(0.030)	(0.051)	(0.209)
Province fixed	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed	Yes	Yes	Yes	Yes	Yes	Yes
Observations	510	510	510	510	510	510
R-squared	0.917	0.928	0.941	0.920	0.930	0.943

Note: The values in parentheses indicate the robust standard error of each coefficient. *, **, and *** represent significant levels of 10%, 5%, and 1%, respectively. ER is environmental regulation, AIS is agricultural industry structure, FSA is financial support to agriculture, RHL is rural human capital, and IL is innovation capacity.

In Models 3 and 6, the coefficients of environmental regulation (ER), agricultural industry structure (AIS), and innovation capacity (IL) are significantly negative at the 1% statistical level. The coefficient of rural human capital (RHC) is significantly negative at the 5% or 1% statistical level, it has a significant negative effect on ACEI. ER constitutes a region's influence on environmental protection and can effectively reduce ACEI. AIS shows a negative coefficient, possibly due to the fact that the use of advanced technologies and increased awareness of the importance of low-carbon practices in planting and animal husbandry effectively reduce ACEI. Improvements in innovation facilitate research and development and the popularization of low-carbon agricultural technologies, which also reduces ACEI. Improved RHC indicates an increase in farmers' education levels. This makes farmers more likely to pay attention to ecological protection, and is also conducive to innovation and the application of agricultural technologies, thus reducing ACEI. Financial support to agriculture (FSA) has a significant positive impact on ACEI at the 1% statistical level. Although FSA has increased agricultural output to a certain extent, it has also increased the input of fertilizers and pesticides, which are polluting elements in agriculture that effectively increase ACEI.

Table 2 | Robustness test: the impact of FSM on ACEI

Variables	Endogeneity test	Fixed effects model	Winsorized treatment	Excluding municipalities
FSM	−0.171***	−0.144***	−0.144***	−0.091***
	(0.036)	(0.031)	(0.034)	(0.043)
Constant		2.1283***	1.7220***	1.5344***
		(0.166)	(0.212)	(0.245)
Control variables	Yes	Yes	Yes	
Province fixed	Yes	Yes	Yes	
Year fixed	Yes	Yes	Yes	
Observations	480	510	510	442
R-squared		0.925	0.941	0.944

Note: The values in parentheses indicate the robust standard error of each coefficient. *, **, and *** represent significant levels of 10%, 5%, and 1%, respectively.

Robustness test

Although the baseline regression controls for year-fixed effects and province-fixed effects to mitigate endogeneity caused by omitted variables to a certain extent, the endogeneity test still needs to be performed due to miss variables. Table 2 shows the results of the robustness test of FSM's effect on ACEI. Firstly, the lagged one period of FSM is selected as the instrumental variable, and instrumental variable method is used. The F statistic value of the weak instrumental variable test is greater than 10, indicating the validity of the instrumental variable selection. The LM value is significant at the 1% statistical level, passing the non-identifiable test. The regression results of the second stage show that the coefficient for FSM remains significantly negative at the 1% statistical level, indicating that FSM can significantly reduce ACEI. In addition, a robustness test was also conducted via three methods, namely, fixed-effects regression, shrinking the data at the 99% level, and excluding any municipalities (Beijing, Tianjin, Shanghai, and Chongqing). The coefficients for the agricultural land operation scale were all significantly negative at the 1% statistical level, thereby verifying the robustness of the model. Similarly, Table 3 shows the results of the four robustness tests, indicating that SSM can significantly reduce ACEI, thus verifying the robustness of the model.

Synergistic effect analysis

Model 7 in Table 4 shows that the estimated coefficient of the impact of FSM on SSM is significantly positive at the 1% statistical level. This indicates that expanding farmland management scale encourages agricultural production and mechanization, which increases farmers' demand for services related to the operation of machinery and agricultural supplies, thereby promoting the development of agricultural production services. The results in Model 8 show that the estimated coefficient of the impact of SSM on FSM is significantly positive at the 1% statistical level, indicating that agricultural production services are conducive to increasing farmland operational scale by providing farmers with training in agricultural technologies and enhancing their ability to manage their operations. The results in Model 9 show that the estimated coefficients of FSM and SSM are significantly negative at the 5% statistical level, suggesting that they have a significant negative impact on ACEI. Overall, FSM and SSM are interrelated, mutually reinforcing, and have synergistic effects that are conducive to reducing ACEI.

According to the regression results of the threshold effect (supplementary information's Tables 5–7 and Method 2), we choose the threshold value of FSM as the critical point for group regression, in order to evaluate the effect of FSM×SSM on ACEI across three ranges (FSM ≤ 0.6962, 0.6962 < FSM < 0.9819, and FSM ≥ 0.9819). As shown in Eq. (3), we add the interaction terms for SSM and FSM to the regression (Models 7-9 in Table 5). With FMS ≤ 0.6962, the coefficient of FSM×SSM is significantly positive at the 1% statistical level, showing that FSM and SSM are substitutes for each other in reducing ACEI. With 0.6962 < FSM < 0.9819, the coefficient for FSM × SSM is significantly negative at the 10% statistical level, indicating that FSM and SSM synergistically reduce ACEI, and the two promote each other in reducing ACEI. When FSM ≥ 0.9819, the coefficient for FSM × SSM was significantly negative at the 1% statistical level. However, the absolute value became smaller, i.e., the synergistic relationship between FSM and SSM was weakened. Overall, when FSM is low (i.e., limited by resources and costs), farmers must weigh the trade-off between input factors and external services, resulting in a substitutional relationship between FSM and SSM. As FSM expands, large-scale operations break the scale threshold for the application of services, and FSM and SSM synergistically reduce ACEI through the division of specialized labor, technological synergy, and cost-sharing.

In the same way, we continue to select the threshold value for SSM as the critical point (Supplementary information's Tables 5–6), and conduct group regression across three intervals (SSM ≤ 2.8781, 2.8781 < SSM < 3.8444, and SSM ≥ 3.8444) to analyze the effect of FSM×SSM on ACEI. The coefficient for FSM × SSM is significantly positive at the 1% statistical level when SSM ≤ 2.8781, i.e., FSM and SSM are substitutes for each other in reducing ACEI. The coefficient for FSM × SSM is significantly negative at the 5% statistical level when 2.8781 < SSM < 3.8444, indicating that FSM and SSM synergistically reduce ACEI. When SSM ≥ 3.8444, the coefficient for FSM×SSM was not significant, demonstrating that FSM and SSM do not affect each other in reducing ACEI. Overall, when SSM is low, the socialized agricultural service delivery system is not yet mature, and service supply is fragmented, i.e., there is a substitutional relationship between FSM and SSM. When SSM is expanded, low-carbon technologies are provided to large-scale farming operations, and a market demand is created for services, resulting in a synergistic relationship between FSM and SSM. In summary, when the values for FSM or SSM are high, they

Table 3 | Robustness test: the impact of SSM on ACEI

Variables	Endogeneity test	Fixed effects model	Winsorized treatment	Excluding municipalities
SSM	−0.073***	−0.075***	−0.060***	−0.039***
	(0.023)	(0.012)	(0.014)	(0.016)
Constant		1.917***	1.727***	1.580***
		(0.155)	(0.209)	(0.250)
Control variables	Yes	Yes	Yes	
Province fixed	Yes	Yes	Yes	
Year fixed	Yes	Yes	Yes	
Observations	480	510	510	442
R-squared		0.933	0.943	0.945

Note: The values in parentheses indicate the robust standard error of each coefficient. *, **, and *** represent significant levels of 10%, 5%, and 1%, respectively.

Table 4 | Synergistic effect results

Variables	Model 7 SSM	Model 8 FSM	Model 9 ACEI
FSM	0.898***		−0.091**
	(0.191)		(0.032)
SSM		0.095***	−0.049**
	(0.019)	(0.015)	(0.019)
Constant	1.256	0.595	1.786***
	(1.016)	(0.305)	(0.209)
Control variables	Yes	Yes	Yes
Province fixed	Yes	Yes	Yes
Year fixed	Yes	Yes	Yes
Observations	510	510	510
R-squared	0.973	0.968	0.945

Note: The values in parentheses indicate the robust standard error of each coefficient. *, **, and *** represent significant levels of 10%, 5%, and 1%, respectively.

Table 5 | Synergistic effect results: interaction terms of FSM×SSM

Variables	Model 10 ACEI	Model 11 ACEI	Model 12 ACEI	Model 13 ACEI	Model 14 ACEI	Model 15 ACEI
Threshold range	FSM ≤ 0.6962	0.6962 <FSM <0.9819	FSM ≥ 0.9819	SSM ≤ 2.8781	2.8781 <SSM <3.8444	SSM ≥ 3.8444
FSM×SSM	0.1418***	−0.0960*	−0.0526***	0.0326***	−0.1440**	−0.1338
	(0.028)	(0.052)	(0.012)	(0.010)	(0.056)	(0.136)
Constant	0.8225***	1.6982***	1.7667***	1.5320***	1.4321***	1.6982
	(0.210)	(0.305)	(0.385)	(0.245)	(0.386)	(0.750)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Province fixed	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed	Yes	Yes	Yes	Yes	Yes	Yes
Observations	367	65	76	367	65	76
R-squared	0.969	0.993	0.975	0.953	0.989	0.999

Note: The values in parentheses indicate the robust standard error of each coefficient. *, **, and *** represent significant levels of 10%, 5%, and 1%, respectively.

Table 6 | Mediating effect analysis (two-step method)

Variables	Model 16 AIA	Model 17 AIA	Model 18 ATP	Model 19 ATP	Model 20 AMA	Model 21 AMA
FSM	0.566***		0.195***		1.638***	
	(0.190)		(0.061)		(0.314)	
SSM		0.151***		0.046***		0.114**
		(0.049)		(0.015)		(0.056)
Constant	1.594**	1.739**	0.489	0.552*	0.420	1.475
	(0.679)	(0.701)	(0.308)	(0.306)	(1.294)	(1.182)
Control variables	YES	YES	YES	YES	YES	YES
Province fixed	YES	YES	YES	YES	YES	YES
Year fixed	YES	YES	YES	YES	YES	YES
Observations	510	510	510	510	510	510
R-squared	0.937	0.936	0.891	0.889	0.757	0.736

Note: The values in parentheses indicate the robust standard error of each coefficient. *, **, and *** represent significant levels of 10%, 5%, and 1%, respectively. AIA is agricultural industrial agglomeration, ATP is agricultural technological progress, and AMS is agricultural machinery services.

tend to have a synergistic effect in reducing ACEI, which verifies Hypothesis 3.

Mediating effect analysis

This paper follows Jiang Ting's[52] two-step method and combines Eqs. (4)-(5). It selects agricultural industrial agglomeration (AIA), agricultural technological progress (ATP), and agricultural machinery services (AMS) as mediating variables to further analyze the mechanism of FSM and SSM on ACEI. Model 16 shows that the regression coefficient for FSM on AIA is significantly positive at the 1% statistical level, meaning that increasing the scale of agricultural land operations is favorable to AIA. On the one hand, large-scale agricultural land operations facilitate the large-scale purchasing of agricultural production materials, thus attracting more agricultural production entities to the cluster. On the other hand, large-scale agricultural production increases market supply, which helps build a regional brand and improves market competitiveness and influence, thereby promoting AIA.

Model 17 shows that the coefficient for the regression of SSM on AIA is significantly positive at the 1% statistical level, meaning that the expansion of SSM is beneficial to AIA. SSM promotes agricultural production specialization and drives the development of related upstream and downstream industries such as agricultural supply, product processing, logistics and transportation, and marketing. These industries center around the core industry of agricultural production and are increasingly crucial to the development of AIA. As AIA expands, the flow and reallocation of resource factors become more active, which facilitates the sharing of knowledge and resources among stakeholders in the agglomeration area. This is conducive to the formation of economies of scale and the utilization of production factors, creating a carbon-reducing effect.

Model 18 in Table 6 shows that the expansion of FSM promotes ATP, with the coefficient for FSM being significantly positive at the 1% statistical level. On the one hand, the expansion of the FSM reduces the costs of agricultural production, improves farmers' economic returns, and promotes investment in new technologies and equipment among farmers which improves production efficiency. On the other hand, the expansion of FSM also provides a better platform for the introduction and promotion of new technologies and equipment and makes it easier for large-scale stakeholders to obtain policy and financial support from the government, which further promotes ATP.

Model 19 in Table 6 indicates that SSM can also effectively promote ATP, with the coefficient for SSM being significantly positive at the 1% statistical level. SSM brings advanced agricultural technologies and equipment into farmers' production processes through outsourcing, hosting, and other means. Since it increases the application and promotion of technology, it increases farmers' production potential and continuously promotes ATP through the sharing of pertinent information on the state of the industry and problems relevant to agricultural production. We measure ATP using the DEA-Malmquist index and confirmed that ATP significantly inhibits ACEI. Therefore, we can conclude that FSM and SSM reduce ACEI through the promotion of ATP.

Model 20 shows that the regression coefficient for FSM on AMS is significantly positive at the 1% statistical level, indicating that expanded farmland operational scale contributes to AMS. The demand for large-scale agricultural production services that results from the expansion of the scale of farmland operations provides market space for the specialization and technologization of AMS. This gives rise to many different specialized agricultural machinery service providers.

Model 21 demonstrates that the coefficient for the regression of SSM on AMS is significantly positive at the 5% statistical level. The promotion of SSM leads to a more detailed and specialized division of agricultural production. Agricultural production service organizations can provide specialized operational training for various types of agricultural machinery according to the operators' existing skills, which further increases AMS. In addition, AMS optimizes agricultural production by providing comprehensive machinery services for various stakeholders in the agricultural sector and promoting the development of large-scale, standardized operations, thereby reducing ACEI. To summarize, FSM and SSM reduce ACEI through AIA, ATP, and AMS, thereby confirming Hypothesis 4.

Heterogeneity analysis

Models 22–24 in Table 7 present the regression results concerning the effect of FSM on ACEI in the three regions of the main food production regions, main food sales regions, balanced food production and sales regions. The coefficients for FSM are all significantly negative at the 1% statistical level, indicating that FSM significantly reduces ACEI in these three main regions, of which the balanced food production and sales regions are the most pronounced. This is due to the land in these regions being more finely divided. The expansion of FSM improves the utilization of fertilizers and pesticides on finely divided land, which is more effective in reducing ACEI. Models 25–27 show the regression results of the effect of SSM on ACEI. SSM has the strongest effect on reducing ACEI in the main food sales regions and is significant at the 1% statistical level. The estimated coefficients for SSM in the main food-producing regions and balanced food production and sales regions are significant at the 5% and 10% statistical levels, respectively.

The level of agricultural mechanization was measured using the ratio of the total amount of power consumed by agricultural machinery to the total crop sown area. The sample was divided into three groups, namely, low-level, medium-level, and high-level. Models 28–30 and 31–33 in Table 8 show the regression results of the effect of FSM and SSM on ACEI, respectively. The reduction effect of FSM and SSM on ACEI is greatest in the high-level regions, and significant at the 1% statistical level. The improvement of agricultural mechanization strengthens the emission reduction effect of FSM and SSM through a combination of technological adoption and institutional innovation.

Models 34–36 in Table 9 present the regression results for the three major regions of eastern, central, and western, respectively. The coefficients for FSM are all significantly negative at the 1% statistical level, indicating that FSM in the three major regions significantly reduces ACEI. The greatest effect is observed in the western region, and the weakest in the central region. Although the western region is richer in land resources, topographical limitations, and other natural conditions contribute to lower utilization of agricultural land, making FSM more conducive to reducing ACEI. Models 37–39 in Table 9 show that the coefficients for SSM in the three major regions are significantly negative at the 5%, 1%, and 10% statistical levels, respectively. This indicates that SSM significantly reduces ACEI in the three major regions, with the greatest effect observed in the western region. The

Table 7 | Heterogeneity analysis of functional food areas

Variables	Model 22	Model 23	Model 24	Model 25	Model 26	Model 27
	Main food production regions	Main food sales regions	Balanced food production and sales regions	Main food production regions	Main food sales regions	Balanced food production and sales regions
FSM	−0.274***	−0.232***	−0.301***			
	(0.072)	(0.044)	(0.060)			
SSM				−0.0645**	−0.0967***	−0.0356*
				(0.021)	(0.024)	(0.014)
Constant	3.297***	2.528***	0.0603	3.165***	2.253***	0.313
	(0.394)	(0.239)	(0.238)	(0.408)	(0.261)	(0.241)
Control variables	YES	YES	YES	YES	YES	YES
Province fixed	YES	YES	YES	YES	YES	YES
Year fixed	YES	YES	YES	YES	YES	YES
Observations	221	119	170	221	119	170
R-squared	0.953	0.970	0.957	0.953	0.966	0.953

Note: The values in parentheses indicate the robust standard error of each coefficient. *, **, and *** represent significant levels of 10%, 5%, and 1%, respectively.

Table 8 | Heterogeneity analysis of agricultural mechanization level

Variables	Model 28	Model 29	Model 30	Model 31	Model 32	Model 33
	Low level	Medium level	High level	Low level	Medium level	High level
FSM	−0.1175***	−0.1423	−0.1932***			
	(0.036)	(0.137)	(0.060)			
SSM				−0.0472**	−0.0534**	−0.0795***
				(0.019)	(0.024)	(0.029)
Constant	2.3875***	1.3831***	1.2224***	2.4334***	1.3632***	1.1945***
	(0.373)	(0.405)	(0.352)	(0.353)	(0.410)	(0.329)
Control variables	YES	YES	YES	YES	YES	YES
Province fixed	YES	YES	YES	YES	YES	YES
Year fixed	YES	YES	YES	YES	YES	YES
Observations	170	170	170	170	170	170
R-squared	0.963	0.969	0.956	0.963	0.971	0.958

Note: The values in parentheses indicate the robust standard error of each coefficient. *, **, and *** represent significant levels of 10%, 5%, and 1%, respectively.

central region is an important food production base in China with a greater potential for the development of SSM. Policy support from the government has served to promote the development of SSM in the central region, which has a significant effect on the reduction of ACEI.

Discussion

This study systematically analyzes the synergistic effect of FSM and SSM on reducing ACEI and their internal mechanisms from both a theoretical and empirical standpoint. Against the background of the dual challenges associated with agricultural modernization and carbon emissions in China, this study provides a new perspective on agricultural sustainable development, as well as an empirical basis to support policymakers.

The key findings of this study show that: (1) FSM and SSM showed a growing trend, while ACEI showed a decreasing trend at the national and provincial levels from 2005 to 2021; (2) Both FSM and SSM have a significant negative correlation with ACEI: each unit increase in FSM decreased ACEI by 0.144 (tons per ten thousand yuan); for every one-unit increase in SSM, ACEI decreases by 0.06 (tons per ten thousand yuan). (3) Dual-scale management has a synergistic effect on reducing ACEI through the industrial agglomeration effect, the technological progress effect, and the machinery service effect; (4) FSM correlate more significantly with reduced ACEI in regions with balanced food production and sales, regions with high degree of agricultural mechanization, and the eastern regions, while SSM correlate more significantly with reduced ACEI in the main food sales regions, high degree of agricultural mechanization regions and the central regions.

Based on these findings, the following countermeasures are proposed to reduce the ACEI and promote green agricultural development:

First, strengthen the synergistic cooperation of dual-scale management subjects. It should fully recognize the synergistic effect the synergistic effect between moderate-scale farmland operations and agricultural production services, especially in regions with high degrees of agricultural mechanization. It is important to leverage this synergistic effect of dual-scale farmland- and service-scale management in terms of technological adoption, information sharing, the industrial chain, and capital, thereby jointly promoting low-carbon agricultural development.

Second, the three major effects that reduce agricultural carbon emissions should be leveraged further. The government should introduce differentiated policies to scientifically plan agricultural industrial parks to promote the clustering of enterprises according to agricultural resources and industrial base of each region. Investment in agricultural research and technological innovation should be increased, especially in low-carbon, environmentally friendly, and efficient agricultural technologies. In addition, the government should collaborate with farmers to develop a highly

Table 9 | Heterogeneity analysis of three major regions

Variables	Model 34 East	Model 35 Centre	Model 36 West	Model 37 East	Model 38 Centre	Model 39 West
FSM	−0.1918***	−0.1045	0.0124			
	(0.040)	(0.088)	(0.064)			
SSM				−0.0406*	−0.0469*	−0.0417***
				(0.023)	(0.025)	(0.014)
Constant	2.8389***	3.1212***	0.5940**	2.8251***	3.1808***	0.7318***
	(0.226)	(0.461)	(0.272)	(0.251)	(0.468)	(0.280)
Control variables	YES	YES	YES	YES	YES	YES
Province fixed	YES	YES	YES	YES	YES	YES
Year fixed	YES	YES	YES	YES	YES	YES
Observations	187	136	187	187	136	187
R-squared	0.964	0.953	0.944	0.958	0.955	0.948

Note: The values in parentheses indicate the robust standard error of each coefficient. *, **, and *** represent significant levels of 10%, 5%, and 1%, respectively.

efficient mechanized production system, and promote the adoption of advanced agricultural equipment and mechanical technologies. This would help reduce ACEI by comprehensively leveraging the industrial agglomeration effect, the technological adoption effect, and the machinery adoption effect.

Third, farmland-scale and service-scale management should be promoted in accordance with local conditions. With regard to farmland scale management in the balanced production and sales regions and the eastern regions, land transfer mechanisms should be improved and subsidies for large-scale operations should be provided to encourage large-scale farming and the creation of new agribusinesses and other agricultural management bodies. These measures would facilitate legal land management on an appropriate scale. However, it should be noted that there is a need to prevent the unchecked expansion of planting scale due to the one-sided pursuit of faster transfer speeds and larger operational scales. With regard to service-scale management in the major food-consumption regions and the central regions, the agricultural productive service industry should be vigorously developed through the creation of socialized service initiatives with a high degree of organization, efficiency, and service quality. Preferential policy incentives should also be introduced to guide these service organizations' adoption of low-carbon technologies.

The innovative contributions of this study are as follows: first, by incorporating FSM and SSM into a unified analytical framework and systematically analyzing their combined impact on ACEI, we provide new insights and theoretical support for agricultural carbon reduction. Second, this study reveals the synergistic effect of FSM and SSM, showing that the combination of land-scale management through continuous cultivation and service-scale management through the outsourcing of services is a feasible path to achieving agricultural modernization and green transformation. Third, this study innovatively identifies several mechanisms through which FSM and SSM jointly reduce ACEI, namely, the industrial agglomeration effect, the technological progress effect, and the machinery service effect, thereby enriching the theoretical understanding of green agricultural transformation. Finally, this study explores the differential impacts of FSM and SSM on ACEI across different regions in China through a regional heterogeneity analysis and provides practical references for different regions to formulate more precise and effective agricultural emission reduction policies according to each region's resource base and developmental level.

Nevertheless, this study has certain limitations. First, there may be other mechanisms by which to explain the synergistic effect of FSM and SSM on ACEI which should be further explored in the future. Second, this study uses macro-level provincial data and does not include data concerning smaller administrative units and family farmers due to data availability constraints. Due to the lack of micro-level farming data, we used the ratio of cultivated land area to the number of agricultural workers at the provincial level as a proxy for FSM. While this indicator has been widely used in the existing empirical literature, it is important to acknowledge that it may not fully capture detailed features of farmland management data, such as land fragmentation and small to average-sized farms. Finally, this study did not consider the spatial effects of dual-scale management and subsequent studies could use spatial econometric models to assess potential spillover effects.

Methods

Variables

Table 10 provides detailed descriptions and data sources for each variable, descriptive statistical analysis of variables can be found in the supplementary information's Table 4.

Explained variable. The explanatory variable is agricultural carbon emission intensity (ACEI), which is the ratio of agricultural carbon emissions to total agricultural output value. In this paper, "agriculture" refers to narrow-sense agriculture, which is specifically the crop farming industry. The carbon emission coefficient method was used to measure total agricultural carbon emissions, including CO_2 emissions caused by agricultural materials (e.g., fertilizers, pesticides, agricultural films, and diesel fuel) and electricity consumption for irrigation, N_2O emissions caused by soil tillage, and CH_4 emissions caused by the growing of paddy rice. The specific calculation methods (Supplementary Method 1) and coefficients (Supplementary Table 1–3) can be found in the supplementary information.

Core explanatory variables. The core explanatory variables used in this study are farmland scale management (FSM) and service scale management (SSM). Farmland-scale management is measured as the ratio of total crop sown area to the primary industry in each province, reflecting the per capita area of cultivated agricultural land. Service scale management is measured as the logarithmic value of the gross production value of agriculture, forestry, animal husbandry and fishery services, which is selected as a proxy variable referring Zhang et al. (2024)[53].

Control variables. Drawing upon existing studies[54,55], environmental regulation (ER), agricultural industry structure (AIS), financial support to agriculture (FSA), rural human capital (RHL), and innovation capacity (IL) were selected as control variables. ER reflects regional environmental regulation intensity, and regions with lower ER tend to exhibit higher levels of agricultural pollution and carbon emissions due to lax pollution regulations. AIS denotes the resource allocation mode and sustainable development capacity of agricultural production. Therefore, optimizing AIS can improve resource utilization and thereby reduce ACEI. FSA

Table 10 | Variable description

Variables		Description	Unit	Data sources
Explained variable	ACEI	Ratio of agricultural carbon emissions to total agricultural output	tons per ten thousand yuan	China Statistical Yearbook; IPCC
Core explanatory variable	FSM	The ratio of the area sown in crops to the number of people employed in agriculture, forestry and fisheries	hectares per person	China Rural Statistical Yearbook
	SSM	The logarithmic value of the gross production value of agriculture, forestry, animal husbandry and fishery services		China Rural Statistical Yearbook
Control variables	ER	Ratio of environmental protection and energy conservation expenditures to local general budget expenditures	%	China Statistical Yearbook
	AIS	Ratio of agricultural output to total agricultural, forestry, animal husbandry and fisheries output value	%	China Statistical Yearbook
	FSA	Ratio of local financial expenditures on agriculture, forestry and water to general budget expenditures	%	China Statistical Yearbook
	RHL	Average years of schooling in the primary sector	year	China Statistical Yearbook
	IL	Number of domestic patent applications granted	ten thousand pieces	China Science and Technology Statistical Yearbook
Mediating variable	AIA	Ratio of regional agricultural GDP in national GDP to regional GDP in national GDP		China Statistical Yearbook
	ATP	The results of the DEA-Malmquist decomposition		China Statistical Yearbook
	AMS	Number of farmers participating in agricultural machinery service organizations	$\times 10^5$ persons	China Agricultural Machinery Industry Yearbook

represents the sustainable governance capacity toward agricultural development and may increase inputs of polluting factors in agricultural production chains and operations, thereby increasing ACEI. RHL refers to a region's base of human capital resources, and IL refers to a region's innovation and technological transformation capacity. Therefore, enhancing RHL and LR can reduce ACEI by facilitating technological adoption and innovation.

Mediating variables. Agricultural industrial agglomeration (AIA), agricultural technological progress (ATP), and agricultural machinery services (AMS) were selected as mediating variables in the impact of FSM and SSM on ACEI. AIA is expressed as the ratio of regional agricultural GDP in national GDP to regional GDP in national GDP. ATP denotes the efficiency of technological progress as measured by the decomposition of total factor agricultural productivity, as proposed by Ma and Cui (2021)[56]. AMS represents the number of farmers participating in agricultural machinery service organizations.

Models

Two-way fixed effects model. This study constructs a two-way fixed effects model to examine the impact of FSM and SSM on the ACEI. Building upon the Hypothesis 1 and 2, the specific base model was set up as follows:

$$ACEI_{i,t} = \alpha_0 + \alpha_1 FSM_{i,t} + \sum_{k=2}^{6} \alpha_k Control_{i,t} + \sigma_i + \mu_t + \varepsilon_{i,t} \tag{1}$$

$$ACEI_{i,t} = \beta_0 + \beta_1 SSM_{i,t} + \sum_{k=2}^{6} \beta_k Control_{i,t} + \sigma_i + \mu_t + \varepsilon_{i,t} \tag{2}$$

$$\begin{aligned} ACEI_{i,t} =& \theta_0 + \theta_1 FSM_{i,t} + \theta_2 SSM_{i,t} + \theta_3 FSM_{i,t} \times SSM_{i,t} \\ &+ \sum_{k=4}^{8} \theta_k Control_{i,t} + \sigma_i + \mu_t + \varepsilon_{i,t} \end{aligned} \tag{3}$$

Where i and t represent the province and the year, respectively. $ACEI_{i,t}$, $FSM_{i,t}$ and $SSM_{i,t}$ represent the agricultural carbon emission intensity, farmland scale management and service scale management of province i in period t, respectively. α_1 and β_1 represent the estimated coefficient of FSM and SSM respectively; $FSM_{i,t} \times SSM_{i,t}$ is the interaction term of $FSM_{i,t}$ and $SSM_{i,t}$, and θ_3 is the estimated coefficient of the interaction term, when $\theta_3 > 0$, it means that FSM and SSM play synergistic effect in reducing ACEI, and both of them promote each other and reduce ACEI together; When $\theta_3 < 0$, it indicates that FSM and SSM play alternative roles in reducing ACEI and they complement each other. $Control_{i,t}$ denotes the control variables, σ_i and μ_t represent the individual province effect and time fixed effect, and $\varepsilon_{i,t}$ represents the random disturbance term.

Mediating effect model

In order to explore the mediating effect of AIA, ATP and AMA in the impact of FSM and SSM on ACEI, the two-step approach suggested was adopted referring to the study of Jiang (2022)[52], and the mediating effect model as follows:

$$M_{i,t} = \gamma_0 + \gamma_1 FSM_{i,t} + \sum_{k=2}^{6} \gamma_k Control_{i,t} + \sigma_i + \mu_t + \varepsilon_{i,t} \tag{4}$$

$$M_{i,t} = \delta_0 + \delta_1 SSM_{i,t} + \sum_{k=2}^{6} \delta_k Control_{i,t} + \sigma_i + \mu_t + \varepsilon_{i,t} \tag{5}$$

Where $M_{i,t}$ represents mediating variable: AIA, ATP and AMA. Equation 4 is to test the impact of FSM on mediating variables, γ_1 is the estimated coefficient of FSM; Eq. 5 is to test the impact of SSM on mediating variables, δ_1 is the estimated coefficient of SSM, and other variables are set as in Eq. 1.

Data availability

This study includes 30 provinces (cities and districts) in China, excluding Hong Kong, Macao, Taiwan and Tibet, and is conducted from 2005 to 2021. The data for calculating agricultural carbon emission intensity, core explanatory variables, control variables and mediating variables can be obtained from the China Statistical Yearbook (https://data.cnki.net/yearBook/single?id=N2023110024), the China Rural Statistical Yearbook (https://data.cnki.net/yearBook/single?id=N2024010048), the China Energy Statistics Yearbook (https://data.cnki.net/yearBook/single?id=N2023050100), the China Agricultural Machinery Industry Yearbook (https://data.cnki.net/yearBook/single?id=N2023060184). Source data required for reproducing the main figures is available at: https://doi.org/10.6084/m9.figshare.30121264.

Code availability

All computer codes generated during this study are available from the corresponding authors on request.

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References

1. Fischer, E. M. & Knutti, R. Anthropogenic contribution to global occurrence of heavy-precipitation and high-temperature extremes. *Nat. Clim. Change* **5**, 560–564 (2015).
2. Lashof, D. A. & Ahuja, D. R. Relative contributions of greenhouse gas emissions to global warming. *Nature* **344**, 529–531 (1990).
3. Mora, C. et al. Broad threat to humanity from cumulative climate hazards intensified by greenhouse gas emissions. *Nat. Clim. Change* **8**, 1062–1071 (2018).
4. Elzen, M. et al. Greenhouse gas emissions from current and enhanced policies of China until 2030: Can emissions peak before 2030?. *Energy Policy* **89**, 224–236 (2016).
5. Lin, J. et al. Opportunities to tackle short-lived climate pollutants and other greenhouse gases for China. *Sci. Total Environ.* **842**, 156842 (2022).
6. Yu, Z., Zhang, F., Gao, C., Mangi, E. & Ali, C. The potential for bioenergy generated on marginal land to offset agricultural greenhouse gas emissions in China. *Renew. Sustain. Energy Rev.* **189**, 113924 (2024).
7. Liu, D., Zhu, X. & Wang, Y. China's agricultural green total factor productivity based on carbon emission: an analysis of evolution trend and influencing factors. *J. Clean. Prod.* **278**, 123692 (2021).
8. Ji, M., Li, J. & Zhang, M. What drives the agricultural carbon emissions for low-carbon transition? Evidence from China. *Environ. Impact Assess. Rev.* **105**, 107440 (2024).
9. Fusuo, Z., Xinping, C. & Peter, V. Chinese agriculture: an experiment for the world. *Nature* **497**, 33–35 (2013).
10. Qi, X. et al. Ensuring food security with lower environmental costs under intensive agricultural land use patterns: a case study from China. *J. Environ. Manag.* **213**, 329–340 (2018).
11. Kang, S. et al. Improving agricultural water productivity to ensure food security in China under changing environment: From research to practice. *Agric. Water Manag.* **179**, 5–17 (2017).
12. Xu, Q., Yin, R. & Zhang, H. Economies of scale, returns to scale and the problem of optimum-scale farm management: an empirical study based on grain production in China. *Econ. Res. J.* **46**, 59–71 (2011).
13. Timmer, C. P. *Food Security and Scarcity* (University of Pennsylvania Press, 2014).
14. Xia, Y. & Kuang, Y. Multidimensional poverty reduction effects of farmland transfer: an analysis based on data collected from 1218 farm households in five provinces. *Chin. Rural Econ*. **9**, 44–61 (2017).
15. Yin, G., Xu, X., Piao, H. & Lyu, J. The synergy effect of agricultural dual-scale management on farmers' income: evidence from rural China. *China Agric. Econ. Rev*. **16**, 591–607 (2024).
16. Liu, Q. & Xiao, H. What is the logic of the scale of farmland operations affecting agricultural carbon emissions? The mediating role of factor inputs and the moderating role of cultural quality. *Rural Econ*. **5**, 10–17 (2020).
17. Xu, X., Li, C., Guo, J. & Zhang, L. Land transfer-in scale, land operation scale and carbon emissions from crop planting throughout the life cycle: evidence from China rural development survey. *Chin. Rural Econ.* **11**, 40–58 (2022).
18. Zhong, Z., Hu, J. & Cao, S. Land transfer and agricultural services: "route competition" or "mutual reinforcement"? An analysis based on cases from 12 villages in Linyi, Shandong province. *Chin. Rural Econ.* **10**, 52–70 (2020).
19. Chen, Y. & Zhong, F. Should China's agricultural development take the path of scale or socialization: discussion based on Smith's theorem of the division of labor. *Issues Agric. Econ.* **6**, 4–13 (2024).
20. Huo, C. & Chen, L. The impact of land transfer policy on sustainable agricultural development in China. *Sci. Rep.* **14**, 7064 (2024).
21. Yu, C. A. O. et al. Effect of land tenure fragmentation on the decision-making and scale of agricultural land transfer in China. *Land Use Policy* **99**, 104996 (2020).
22. Tang, L., Liu, Q., Yang, W. & Wang, J. Do agricultural services contribute to cost saving? Evidence from Chinese rice farmers. *China Agric. Econ. Rev.* **10**, 323–337 (2018).
23. Houssou, N. et al. Agricultural mechanization in Ghana: is specialized agricultural mechanization service provision a viable business model?. *Am. J. Agric. Econ.* **95**, 1237–1244 (2013).
24. Van Loon, J. et al. Scaling agricultural mechanization services in smallholder farming systems: case studies from sub-Saharan Africa, South Asia, and Latin America. *Agric. Syst.* **180**, 102792 (2020).
25. Zou, B. & Mishra, A. K. Modernizing smallholder agriculture and achieving food security: An exploration in machinery services and labor reallocation in China. *Appl. Econ. Perspect. Policy* **46**, 1662–1691 (2024).
26. Duan, J. et al. Consolidation of agricultural land can contribute to agricultural sustainability in China. *Nat. Food* **2**, 1014–1022 (2021).
27. Wang, S. et al. Urbanization can benefit agricultural production with large-scale farming in China. *Nat. Food* **2**, 183–191 (2021).
28. Cao, X. & Jin, T. Land transfer, Agricultural scale management and agricultural carbon emissions—Quasi-natural experiments based on land transfer policy. *J. Huazhong Agric. Univ.* **4**, 153–163 (2024).
29. Guan, N., Liu, L., Dong, K., Xie, M. & Du, Y. Agricultural mechanization, large-scale operation and agricultural carbon emissions. *Cogent Food Agric.* **9**, 2238430 (2023).
30. Lu, H., Duan, N. & Chen, Q. Impact of agricultural production outsourcing services on carbon emissions in China. *Environ. Sci. Pollut. Res.* **30**, 35985–35995 (2023).
31. Shi, R., Shen, Y., Du, R., Yao, L. & Zhao, M. The impact of agricultural productive service on agricultural carbon efficiency—from urbanization development heterogeneity. *Sci. Total Environ.* **906**, 167604 (2024).
32. Wang, H., Liu, C., Xiong, L. & Wang, F. The spatial spillover effect and impact paths of agricultural industry agglomeration on agricultural non-point source pollution: a case study in Yangtze River Delta, China. *J. Clean. Prod.* **401**, 136600 (2023).
33. Zhu, M., Wang, G., Xiang, W. & Shang, J. Effects and its spatial characteristics of socialized agriculture services on agricultural carbon emissions. *Chin. J. Eco-Agric.* **32**, 1288–1301 (2024).
34. Zheng, X., Lin, Q. & Zhou, L. An analysis of innovation, performance and spillover effects of "dual-scale" operation in China's agriculture. *Chin. Rural Econ.* **7**, 103–123 (2022).

35. Wang, Q. & Zhang, X. Three Rights Separation: China's Proposed rural land rights reform and four types of local trials. *Land Use Policy* **63**, 111–121 (2017).
36. Rogers, S. et al. Scaling up agriculture? The dynamics of land transfer in inland China. *World Dev.* **146**, 105563 (2021).
37. Nigussie, Z. et al. Factors influencing small-scale farmers' adoption of sustainable land management technologies in north-western Ethiopia. *Land Use Policy* **67**, 57–64 (2017).
38. Qian, L., Lu, H., Gao, Q. & Lu, H. Household-owned farm machinery vs. outsourced machinery services: The impact of agricultural mechanization on the land leasing behavior of relatively large-scale farmers in China. *Land Use Policy* **115**, 106008 (2022).
39. Wang, R., Zhang, Y. & Zou, C. How does agricultural specialization affect carbon emissions in China?. *J. Clean. Prod.* **370**, 133463 (2022).
40. Chen, S., Zhong, Z. & Lu, H. Impact of agricultural production outsourcing service and land fragmentation on agricultural non-point source pollution in China: evidence from Jiangxi Province. *Front. Environ. Sci.* **10**, 1079709 (2023).
41. Yu, Y., Chi, Z., Yu, Y., Zhao, J. & Peng, L. Boosting agricultural green development: Does socialized service matter?. *Plos one* **19**, e0306055 (2024).
42. Zhang, Z., Hua, C., Ayyamperumal, R., Wang, M. & Wang, S. The impact of specialization and large-scale operation on the application of pesticides and chemical fertilizers: a spatial panel data analysis in China. *Environ. Impact Assess. Rev.* **106**, 107496 (2024).
43. Jiang, S. & Cao, Z. Impact of agricultural socialisation services on adequate scale land management and comparative study—empirical evidence based on CHIP micro data. *J. Agrotech. Econ.* **11**, 4–13 (2016). (in Chinese).
44. Yang, Z., Rao, F. & Zhu, P. The impact of specialized agricultural services on land scale management: an empirical analysis from the perspective of farmers' land transfer-in. Chin. Rural Econ. **3**, 82–95 (2019).
45. Zhang, H., Zhang, J. & Song, J. Analysis of the threshold effect of agricultural industrial agglomeration and industrial structure upgrading on sustainable agricultural development in China. *J. Clean. Prod.* **341**, 130818 (2022).
46. Luo, B. Rethinking and extension of the coase theorem: reform and choice of land circulation institutions in rural China. *Econ. Res. J.* **52**, 178–193 (2017).
47. Hu, Y., Li, B., Zhang, Z. & Wang, J. Farm size and agricultural technology progress: Evidence from China. *J. Rural Stud.* **93**, 417–429 (2022).
48. Luo, H., Hu, Z., Hao, X., Khan, N. & Liu, X. Assessment and comparison of agricultural technology development under different farmland management modes: a case study of grain production, China. *Land* **11**, 1895 (2022).
49. Xu, D., Liu, Y., Li, Y., Liu, S. & Liu, G. Effect of farmland scale on agricultural green production technology adoption: evidence from rice farmers in Jiangsu Province, China. *Land Use Policy* **147**, 107381 (2024).
50. Yang, H., Wang, X. & Bin, P. Agriculture carbon-emission reduction and changing factors behind agricultural eco-efficiency growth in China. *J. Clean. Prod.* **334**, 130193 (2022).
51. Zhang, L. et al. Impact of land circulation and agricultural socialized service on agricultural total factor productivity. *Econ. Geogr.* **44**, 181–189 (2024).
52. Jiang, T. Mediating effects and moderating effects in causal inference. *China Ind. Econ.* **05**, 110–120 (2022).
53. Zhang, S., Wen, X., Sun, Y. & Xiong, Y. Impact of agricultural product brands and agricultural industry agglomeration on agricultural carbon emissions. *J. Environ. Manag.* **369**, 122238 (2024).
54. Ji, X., Liu, H. & Zhang, Y. Study on the influence of rural land transfer on agricultural carbon emission intensity and its mechanism in China. *China Land Sci.* **37**, 51–61 (2023).
55. Pang, H., Liu, X., Gong, Y. & Wang, Z. Internet of things development, technological innovation and agricultural carbon intensity. *Econ. Probl.* **2**, 77–83 (2024).
56. Ma, J. & Cui, H. Effect and mechanism of agricultural insurance on agricultural carbon emission reduction. *China Popul. Resour. Environ.* **31**, 79–89 (2021).

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Qing Guo: data curation, formal analysis, investigation, methodology, writing original draft, writing-review and editing. Hanying Zhang: formal analysis, investigation, methodology, writing-original draft, writing-review and editing. Jing Liu: conceptualization, formal analysis, funding acquisition, project administration, supervision. Zhimin Wu: writing-original draft. Yinding Zhang: conceptualization, funding acquisition, project administration, supervision. Xiangdong Hu: conceptualization, funding acquisition, project administration, supervision.

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The authors declare no competing interests.

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