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Sustainable agricultural development in the context of low carbon economy: exploring the energy carbon Nexus and green transition in agricultural sector

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This study examines the coupling coordination between energy consumption and carbon emissions in China's agricultural sector and explores its implications for the low carbon transition. Using a coupling coordination model and provincial panel data from 2012 to 2021, the study assesses the level of energy carbon coordination in China's agricultural sector and analyzes its key determinants. Fixed effects models evaluate the impact of terminal energy structure, while mediation analysis tests whether agricultural carbon emission intensity transmits these effects. Additionally, out of sample validation and short term scenario projections are used to examine temporal stability. The results show that energy carbon coordination in China's agricultural sector is generally at a moderate to good level, indicating progress toward green transformation, although substantial regional disparities remain. Terminal energy structure is a key determinant, higher coal and diesel shares significantly reduce coordination, whereas a higher natural gas share improves it. Mediation analysis further shows that agricultural carbon emission intensity partly transmits these effects. Regional heterogeneity is observed, low GDP provinces are mainly constrained by coal dependence, while high GDP provinces face stronger diesel and electricity related emission pressures. The out of sample validation and short term scenario projections provide additional support for the temporal stability of these findings. These findings highlight the need for region specific decarbonization strategies in China's agricultural sector, including accelerated clean energy substitution, power sector decarbonization, stronger carbon monitoring, and improved cross sector policy coordination.

KEYWORDS
agricultural carbon emissions, agricultural low carbon transition, energy carbon coupling, energy consumption structure, regional disparities

1 Introduction

Climate change is a quintessential global public goods problem. As climate related risks intensify, carbon emission control and reduction have become pressing global challenges. Extreme weather events such as droughts, heavy rainfall, and heatwaves driven by global warming severely impact ecosystems, economic development, and social stability. A growing international consensus has emerged around long term goals and collaborative action to mitigate climate change through carbon emission reductions. However, carbon mitigation is far from a quick fix endeavor, as it involves multiple sectors and diverging pathways across nations. As the largest developing economy, China has pledged to peak its carbon emissions by 2030 and achieve carbon neutrality by 2060. This commitment demonstrates a sense of responsibility in global climate governance.

At the same time, with the advancement of urban rural integration and changes in rural factor structures, the economic behavior of energy consumption in agriculture is undergoing a profound transformation. Understanding the carbon emission mechanism in this context requires integrating the evolution of industrial structures and regional differences in resource endowments, thereby crafting green transition strategies that balance equity and efficiency. Furthermore, carbon reduction involves dimensions of transaction costs, incentive design, and institutional configuration. Effective policy implementation thus hinges on multi objective optimization strategies. Given agriculture's high energy intensity, its carbon emissions play a central role in the structural reform of environmental supply systems. Historically, China's rural energy consumption has been characterized by a path dependence on traditional high carbon energy, creating an "energy lock in effect" that hinders the marginal gains from low carbon transitions.

Therefore, achieving the dual carbon goals necessitates targeting rural carbon emissions alongside urban and industrial sectors(Guo and Guo, 2024; Wei et al., 2022), aiming for a balanced development and emission profile in rural China (Xu et al., 2024). As rural economic development accelerates, substantial changes in socioeconomic structures have occurred (Gao et al., 2024). Compared with urban areas, rural regions exhibit distinct energy consumption patterns and carbon emission characteristics, making them an increasingly critical focus of mitigation strategies (Wu et al., 2023; Xinfa et al., 2023). Particularly, the patterns of agricultural production and rural energy use profoundly affect rural carbon emissions, posing intricate challenges to emission control efforts (Wu et al., 2025). These challenges are compounded by factors like land use, energy consumption behavior, and transportation development (Han and Wu, 2018). China's rural energy transition has been marked by increasing energy intensity and shifts in energy policy focus (Wu and Han, 2022). Consequently, the energy carbon relationship in rural areas has become a hotspot in academic research (Wu, 2020; Yan, 2025).

2 Literature review

2.1 Energy use, emissions reduction pressure, and green transition in agricultural systems

Research on rural and agricultural decarbonization increasingly emphasizes that energy use patterns shape emission outcomes and, ultimately the feasibility of green transition pathways. A common starting point is to identify the main emission sources and their connections to energy consumption in rural areas, where agricultural production, household energy use, and transportation are often highlighted as dominant contributors (Li and Zhang, 2024; Yang et al., 2024). Building on this perspective, studies focusing on energy structure optimization argue that shifting the composition of energy use and improving end use efficiency are critical for reducing emission pressure while sustaining rural development (Jin et al., 2024; Li W. et al., 2024).

Within agriculture, low carbon transition is not only a technical issue but also a structural and organizational one. The structure and organization of smallholders can influence agricultural carbon emissions through production practices, input choices, and adoption of cleaner technologies (Yi and Gu, 2022). In parallel, the diffusion of new energy technologies in rural areas has been discussed as a practical route for unlocking agricultural carbon reduction potential (Li et al., 2014) and supporting emerging low carbon energy systems under new market or policy environments (Yang et al., 2025). Beyond energy emission trade off alone, recent work has extended the agricultural low carbon transition discussion to multi objective coordination with food security. Using coupling coordination analysis for Chinese provinces, He and Wei (2026) report an improving yet spatially uneven coordination between food security and agricultural carbon reduction and sequestration, highlighting the roles of technology, mechanization and input use. Complementary evidence further suggests that high coordination can be achieved through multiple sufficient pathways, with grain sown area and unit yield acting as core conditions in configurational analysis (He H. H. et al., 2024). Collectively, these studies suggest a coherent conceptual chain energy input and structural change to emission pressure and carbon intensity to transition performance which motivates integrated measurement of "energy carbon interaction" rather than examining energy and emissions in isolation.

2.2 Methodological evolution

Methodologically, existing work spans (i) emission accounting and source decomposition, (ii) efficiency measurement and driver identification, and (iii) integrated system nexus assessments. At the accounting stage, rural combustion related pollution and black carbon have been examined to reveal how solid fuel use and biomass or coal burning contribute to rural emission burdens (Zhang et al., 2018). At the efficiency stage, scholars estimate rural energy carbon emission efficiency and explore its determinants using provincial panel data or related empirical designs (Tian et al., 2023), while studies at the agricultural level further investigate drivers, spillover effects, and efficiency differences across provinces (Chen et al., 2020; Li et al., 2022; Xiaobing and Shiqi, 2022).

More recently, research has moved toward nexus or system based frameworks to capture interactions among resource, energy, and carbon subsystems. Representative examples include water energy carbon coupling assessments and multi system coordination analyses, which provide tools to quantify cross system synergy and constraints (Cao et al., 2023; Cheng et al., 2023; He, 2023). This methodological shift underpins the logic of using composite indicators and coupling coordination metrics to evaluate whether energy transition and emission reduction evolve synergistically an approach that aligns with this manuscript's focus on the energy carbon nexus within the agricultural sector. Coupling studies in agriculture also adopt richer spatial temporal and configurational designs. For example, He H. et al. (2024) develop a spatio temporal coupling framework to examine the bidirectional linkage between agricultural emission reduction and carbon sequestration and food security, documenting dynamic interactions, spatial correlations, and a "north south" clustering pattern in China. Such advances complement regression based driver identification by emphasizing both interaction mechanisms and potential developmental lags across regions.

2.3 Divergent findings and regional heterogeneity

A robust theme in the literature is the existence of pronounced regional disparities in rural energy use and carbon emissions. Differences in economic development, agricultural practices, and energy infrastructure can lead to heterogeneous emission patterns across provinces. Spatial spillover effects further complicate policy design, emission behaviors or inequalities may diffuse across neighboring regions and contribute to clustered patterns of rural or urban rural emission outcomes (Wei et al., 2024; Zhang and Li, 2022). Meanwhile, even when energy structure optimization is emphasized as a general strategy (Jin et al., 2024; Li W. et al., 2024), empirical findings may differ across contexts because the feasibility of substitution, technology adoption and organizational change varies by region (Yi and Gu, 2022). These divergences suggest the need for research designs that can support interprovincial comparison and explicitly examine "system coordination" under heterogeneous regional conditions. Methodological choices increasingly reflect heterogeneity concerns. Geographically and temporally weighted regression has been applied to show that the determinants of coordination between food security and carbon reduction sequestration vary markedly across space and time (He and Wei, 2026). Relatedly, combining social network analysis with GTWR indicates that the emissions impact of technological progress is spatially heterogeneous and is moderated by regions' positions in agricultural carbon emission networks (He and Ding, 2023).

2.4 Research gaps and the marginal contribution of this study

Despite substantial progress, two gaps remain salient for understanding agricultural low carbon transition. First, existing studies often examine either energy structure or consumption or emission or efficiency outcomes separately, which may overlook whether improvements in energy use actually translate into coordinated reductions in emission pressure and better green transition performance (Li et al., 2022; Tian et al., 2023; Yang et al., 2024). Second, while nexus and coupling approaches have expanded rapidly (Cao et al., 2023; Cheng et al., 2023; He, 2023), applications that explicitly target the agricultural energy carbon nexus and link it to transition interpretation across provinces remain relatively limited, especially when regional heterogeneity and spillover contexts are recognized (Wei et al., 2024; Zhang and Li, 2022). Moreover, while food security oriented coupling studies integrate emission reduction and sequestration with agricultural output objectives, they rarely connect these objectives to the terminal energy consumption structure and upstream power mix that shape agricultural indirect emissions. This leaves room for energy carbon nexus analyses to complement multi objective coupling evidence by identifying energy structure levers and supply side constraints in the agricultural transition (He H. et al., 2024; He and Wei, 2026; He H. H. et al., 2024).

Against this background, this study contributes by (1) conceptually organizing the agricultural low carbon transition as an energy carbon nexus problem that connects energy structure change, emission pressure, and transition performance (Jin et al., 2024; Li W. et al., 2024; Yi and Gu, 2022); (2) adopting an integrated measurement approach consistent with coupling nexus research to quantify coordination dynamics rather than relying on single dimension indicators (Cao et al., 2023; Cheng et al., 2023; He, 2023); and (3) moving beyond a purely descriptive provincial comparison by combining mediation analysis with heterogeneity tests to identify stage dependent structural mechanisms how fuel mix changes transmit through carbon intensity channels to shape coupling coordination outcomes, thereby providing clearer levers for differentiated low carbon transition policies (Wei et al., 2024; Zhang et al., 2022), thereby offering a clearer empirical basis for discussing differentiated transition pathways.

2.5 Research hypotheses

Building on the literature reviewed above, a coherent conceptual chain has been emphasized. Energy input and structural change shape emission pressure and carbon intensity, which further affect transition performance. Consistent with this logic, this paper uses the coupling coordination degree to capture the overall coordination between the energy system and the agricultural carbon emission system, and formulates the following testable hypotheses.

The literature suggests that optimizing energy structure and improving end use patterns are central to reducing emission pressure while supporting green transition. Accordingly, different terminal energy shares are expected to exert heterogeneous impacts on the energy carbon coordination outcome.

> *H1*: High carbon energy shares hinder coordination

Holding other factors constant, a higher share of terminal coal consumption and a higher share of terminal diesel consumption are associated with a lower coupling coordination degree.

> *H2*: Clean fuel substitution improves coordination

Holding other factors constant, a higher share of terminal natural gas consumption is associated with a higher coupling coordination degree, reflecting the coordination gains from cleaner energy substitution.

> *H3*: Electrification may not raise coordination under a carbon intensive power mix

Given that the climate benefit of electrification depends on the upstream power generation mix, a higher share of terminal electricity consumption is expected to have a non positive association with in the current stage if electricity related indirect emissions remain high.

> *H4*: Agricultural carbon emission intensity mediates the relationship between energy structure variables and the coupling coordination degree

The above conceptual chain also implies that energy structure may influence coordination not only directly but also indirectly through changes in emission pressure and carbon intensity. To operationalize this mechanism, this study defines the mediator M as agricultural carbon emissions per unit of GDP, and examines whether M transmits the effect of energy structure variables X to the coupling coordination degree.

3 Construction of the evaluation index system and model selection

3.1 Data sources

To better reflect the level of coordination between energy and carbon systems in China's agriculture and accurately reflect the energy carbon relationship in Chinese agriculture, this study utilizes data from 2012 to 2023, sourced from the China Statistical Yearbook, China Agricultural Yearbook, China Rural Statistical Yearbook, China

Energy Statistical Yearbook, and the National Bureau of Statistics. This data encompasses the 31 provinces, municipalities, and autonomous regions in mainland China, and serves as the basis for constructing a comprehensive evaluation index system. The benchmark regressions and robustness tests are based on the provincial panel for 2012–2021. To provide supplementary evidence on temporal stability, observations for 2022–2023 are subsequently used as hold out data for out of sample validation, while the 2024–2025 values are generated only for scenario based short term projection rather than for model estimation.

3.2 Evaluation index system

Based on existing research on energy carbon relationships (He, 2023; Qi et al., 2021; Wang et al., 2024), this study develops an evaluation index system for China's energy carbon relationship. A total of 16 specific indicators are included to form a complete evaluation index system for China's agricultural energy carbon relationship. The specific indicators are detailed in Table 1.

Clarification on electricity related indicators. In this study, electricity is explicitly treated under two analytically distinct concepts. Electricity consumption refers to the amount of electricity used in agricultural production activities and is included in the energy subsystem as an energy input variable. By contrast, electricity related carbon emissions are included in the carbon subsystem as indirect emissions associated with agricultural electricity use. These emissions are measured on a consumption based accounting boundary and are converted from agricultural electricity consumption using the emission factors consistent with the adopted statistical sources. Importantly, emissions from electricity generation in the power sector are not separately added to the agricultural carbon emission subsystem, thereby avoiding double counting. This distinction ensures conceptual clarity between energy inputs and emission outcomes and allows the energy carbon coupling relationship to be evaluated in a consistent manner.

Following the assessment of the coupling and coordination between China's agricultural energy and carbon systems, this study identifies the factors influencing their synergistic development. Based on existing research findings (Li W. et al., 2024; Xiaobing and Shiqi, 2022; Xiong et al., 2016), a framework of influencing factors for the coupling and coordination of China's agricultural energy and carbon systems has been established, as detailed in Table 2.

ECS_a–ECS_d are energy structure variables entered as shares. Control variables follow the manuscript's original definitions; whenever variables appear with the "ln_" prefix in the text or tables, they are in natural logarithms. When multiple energy shares are included simultaneously, they should be interpreted as conditional associations holding other included shares constant; the specification does not impose a mechanical "sum to one" constraint in a way that forces perfect collinearity in estimation under the manuscript's variable construction and sample.

3.3 Model selection

3.3.1 Entropy method and coupling coordination model

This study employs the entropy method to process data, derive the weights of each evaluation indicator, and calculate the scores for each system. Subsequently, a coupling coordination model is applied for quantitative analysis to assess the coupling coordination levels of agricultural energy carbon systems across Chinese provinces and municipalities. The computational steps and model are as follows.

TABLE 1 Evaluation index system for China's agricultural energy carbon relationship.

Primary indicator		Secondary indicator	Unit positive or negative impact
Energy	Energy production	Coal production volume	(10,000 tons) (Negative)
		Diesel production volume	(10,000 tons) (Negative)
		Natural gas production volume	(Billion cubic meters) (Positive)
		Hydroelectric power generation	(Billion kWh) (Positive)
		Thermal power generation	(Billion kWh) (Negative)
	Energy consumption	Energy consumption volume	(10,000 tons of standard coal) (Negative)
		Coal consumption volume	(10,000 tons) (Negative)
		Diesel consumption volume	(10,000 tons) (Negative)
		Natural gas consumption volume	(Billion cubic meters) (Positive)
		Electricity consumption volume	(Billion kWh) (Negative)
Agricultural carbon emissions	Direct carbon emissions	Electricity related carbon emissions	(10,000 tons CO_2) (Negative)
		Diesel carbon emissions	(10,000 tons) (Negative)
		Tillage carbon emissions	(10,000 tons) (Negative)
	Indirect carbon emissions	Pesticide carbon emissions	(10,000 tons) (Negative)
		Fertilizer carbon emissions	(10,000 tons) (Negative)
		Agricultural film carbon emissions	(10,000 tons) (Negative)

Electricity consumption (energy subsystem), Electricity related carbon emissions (carbon subsystem, consumption based).

TABLE 2 Variable settings.

Variable properties	Variable name
Dependent variable	D (Energy Carbon System Coupling Coordination Level)
Core explanatory variable	ECS_a (Share of coal consumption in total energy consumption)
	ECS_b (Share of diesel consumption in total energy consumption)
	ECS_c (Share of natural gas consumption in total energy consumption)
	ECS_d (Share of electricity consumption in total energy consumption)
Control variables	Control_a (Scale of Energy Consumption)
	Control_b (Agricultural Carbon Emissions Scale Control)
	Control_c (Share of fossil fuels in energy production)
	Control_d (Share of clean energy in energy production)

Reference Equation 1 for the calculation of positive indicators:

$$X_{ij} = \frac{a_{ij} - \min\{a_{ij}\}}{\max\{a_{ij}\} - \min\{a_{ij}\}}, (i = 1,2,\ldots, m; j = 1,2,\ldots, n) \quad (1)$$

Reference Equation 2 for the calculation of negative indicators:

$$X_{ij} = \frac{\max\{a_{ij}\} - a_{ij}}{\max\{a_{ij}\} - \min\{a_{ij}\}}, (i = 1,2,\ldots, m; j = 1,2,\ldots, n) \quad (2)$$

Among them, i represents the year; j represents the specific indicator;$\{a_{ij}\}$is the original indicator,that is the specific value j of the indicator in the year i; $\min\{a_{ij}\}$ and $\max\{a_{ij}\}$ respectively represent the maximum or minimum value of a certain indicator in a certain year.

To eliminate the impact of human subjectivity in the process of determining indicator weights, this paper adopts the entropy method to determine the weights of each indicator. The weight of each indicator is determined by calculating its entropy value, and the specific calculation formula is as follows (Equations 3–7).

$$P_{ij} = \frac{X_{ij}}{\sum_{i=1}^{m} X_{ij}} \quad (3)$$

$$e_j = -k \sum_{i=1}^{m} P_{ij} \ \ln P_{ij},\ k = \frac{1}{\ln m} \quad (4)$$

$$g_j = 1 - e_j \quad (5)$$

$$W_j = \frac{g_j}{\sum_{j=1}^{n} g_j} \quad (6)$$

$$Z_i = \sum_{j=1}^{n} W_j X_{ij} \quad (7)$$

After determining the weights of each evaluation index using the entropy method, this paper quantitatively measures the coupling coordination effect of China's agricultural energy carbon system by applying the coupling coordination degree model. The specific formulas are as follows (Equations 8–10).

$$C = 2 \times \left[\frac{f(x) \cdot g(x)}{\left(f(x) + g(x)\right)^2} \right]^{\frac{1}{2}} \quad (8)$$

$$T = \alpha f(x) + \beta g(x) \quad (9)$$

$$D = \sqrt{C \cdot T} \quad (10)$$

C represents the coupling degree of China's agricultural energy carbon two systems, with a value range of [0.1], $f(x)$, and $g(x)$ respectively represent the development levels of the energy system and the agricultural carbon emission system. C The larger the value, the higher the coupling degree between the energy system and the agricultural carbon emission system. T is the comprehensive development index, that is, the comprehensive evaluation index of the two systems of energy and agricultural carbon emissions. α and β it is an undetermined coefficient. This paper holds that the energy system and the agricultural carbon emission system are equally important, so α and β is $\alpha = \beta = 0.5$, D it is the coupling coordination degree of the energy system and the agricultural carbon emission system.

3.3.2 Fixed effects model

To investigate the factors influencing the coordinated development of energy and carbon systems across Chinese provinces, this study employs a fixed effects model incorporating multiple variables. Specific details are provided in Equation 11. It should be noted that the fixed effects regressions are not intended to model the data generating process of the coupling coordination index itself, but rather to examine conditional associations between energy structure variables and variations in the measured coordination level across provinces and over time.

$$\begin{aligned} Dit = {} & \alpha + \beta 1ECS\_ait + \beta 2ECS\_bit + \beta 3ECS\_cit \\ & + \beta 4ECS\_dit + \gamma 1Control\_ait + \gamma 2Control\_bit \\ & + \gamma 3Control\_cit + \gamma 4Control\_dit + \mu i + \lambda t + \varepsilon it \end{aligned} \quad (11)$$

To ensure model robustness, this paper replaces the coupling coordination degree between the two systems with $lnDit$ for details, see the Equation 12.

$$\begin{aligned} LnDit &= \alpha + \beta 1ECS\_ait + \beta 2ECS\_bit + \beta 3ECS\_cit \\ &+ \beta 4ECS\_dit + \gamma 1Control\_ait + \gamma 2Control\_bit \\ &+ \gamma 3Control\_cit + \gamma 4Control\_dit + \mu i + \lambda t + \varepsilon it \end{aligned} \tag{12}$$

4 Coupling coordination level of China's agricultural energy carbon system

According to the classification criteria of coupling coordination degree, the coupling coordination level can be divided into 6 levels, namely extremely uncoordinated, relatively uncoordinated, critically coordinated, primary coordinated, intermediate coordinated and advanced coordinated. For the specific classification, please refer to Table 3.

Based on Table 4, the coupling coordination degree between China's agricultural energy system and agricultural carbon emission system shows an overall moderate to good level during 2012–2021, but with clear temporal fluctuations and widening interprovincial gaps. For most years, provincial values cluster mainly in the 0.6–0.8 interval, suggesting that the agricultural green transition and carbon mitigation efforts have generated positive coordination effects in many regions. Nevertheless, the table also reveals a growing tail of low coordination provinces in the later period several regions fall below 0.5 in certain years, including Inner Mongolia (2019–2020), Xizang (2019 and 2021), Guizhou (2019), Jiangxi (2020–2021), Hubei (2021), Hunan (2021), and Sichuan (2020–2021). By 2021, provincial values span roughly 0.3322 to 0.8105, indicating substantial divergence in coordinated development capacity.

Jiangxi shows a clear reversal in coupling coordination, reaching a high level in 2012 and declining to a low level by 2021. This change follows directly from the way energy structure determines the carbon intensity embedded in agricultural energy use, and hence shapes the relative evolution of the agricultural energy subsystem and the carbon emission subsystem. First, when the diesel share in agricultural energy consumption rises, agricultural energy use becomes more closely tied to direct fossil fuel combustion in field operations and agricultural logistics. Diesel use has a high and immediate emission consequence, so an increasing diesel share strengthens the transmission from energy input to carbon output. Under such a fuel structure, improvements in energy utilization are not matched by proportional reductions on the emission side; instead, the emission subsystem deteriorates relative to the energy subsystem, which mechanically lowers the coupling coordination level. Second, an increase in the electricity share does not, by itself, improve coupling coordination. Electricity affects emissions through the upstream power sector. When the power mix is not sufficiently low carbon, higher electricity consumption in irrigation, processing, drying, and other agricultural activities enlarges indirect emissions. In that case, electrification shifts emissions from on farm direct sources to off farm generation rather than eliminating them, so the carbon emission subsystem does not improve in step with the modernization of energy use. This structural feature produces an asynchronous evolution, the energy subsystem appears to upgrade, while the emission subsystem remains constrained by the carbon intensity of power supply. Third, when the energy transition is characterized by a rising diesel share and a rising electricity share under a carbon intensive power mix, the fuel structure effect dominates the coordination outcome. The agricultural energy subsystem expands and restructures toward fuels and energy carriers that still embed substantial carbon content, so the carbon emission subsystem cannot realize a commensurate improvement. As a result, the joint system moves away from coordinated development, which is reflected in Jiangxi's sharp decline in coupling coordination from 2012 to 2021.

In sum, Jiangxi's trajectory demonstrates that coupling coordination improves only when changes in the energy structure reduce the effective carbon intensity of agricultural energy use, when diesel dependence increases and electrification proceeds without sufficiently clean electricity, the energy and emission subsystems evolve out of sync, leading to a marked deterioration in the coupling coordination degree.

5 Analysis of factors influencing the coordination level of coupling between agricultural energy and carbon Systems in China

Based on diagnostic tests, the fixed effects (FE) model is the appropriate specification. The F test is highly significant, rejecting the pooled OLS model. The BP test is also significant, indicating that the random effects (RE) model outperforms the pooled OLS model. The Hausman test strongly rejects the random effects model. Therefore, the fixed effects model is superior, as detailed in Table 5.

TABLE 3 Classification criteria for coupling coordination degree.

Coupling coordination degree	Coordination type	Coordination level
$D < 0.3$	Extremely uncoordinated	Extremely low coordination level
$0.3 \leq D < 0.5$	Relatively uncoordinated	Low coordination level
$0.5 \leq D < 0.6$	Critically coordinated	Medium low coordination level
$0.6 \leq D < 0.7$	Primary coordinated	Medium coordination level
$0.7 \leq D < 0.8$	Intermediate coordinated	Medium high coordination level
$0.8 \leq D \leq 1$	Highly coordinated	High coordination level

TABLE 4 Coupling coordination degree of China's agricultural energy carbon system.

Area	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021
Beijing	0.6904	0.7345	0.7210	0.7260	0.7608	0.7398	0.7022	0.6748	0.6736	0.6609
Tianjin	0.6104	0.6494	0.6507	0.6274	0.6723	0.6760	0.7949	0.7998	0.7701	0.7793
Hebei	0.6434	0.7144	0.7517	0.7066	0.7741	0.7119	0.6559	0.6525	0.6878	0.7089
Shaanxi	0.6903	0.6935	0.6944	0.6825	0.7495	0.7260	0.6836	0.6845	0.6914	0.6362
Inner Mongolia	0.7131	0.7356	0.7019	0.6650	0.5639	0.5717	0.5070	0.4946	0.4593	0.5842
Liaoning	0.5156	0.5896	0.5571	0.5416	0.6395	0.6742	0.7128	0.7529	0.7746	0.7912
Jilin	0.5718	0.7873	0.7159	0.7044	0.6780	0.6161	0.5750	0.5573	0.5583	0.5572
Heilongjiang	0.6428	0.7598	0.7200	0.7191	0.6489	0.6460	0.6107	0.6187	0.5947	0.5749
Shanghai	0.6005	0.6251	0.6496	0.6435	0.6202	0.5960	0.6678	0.6252	0.6609	0.8105
Jiangsu	0.7204	0.6767	0.6626	0.6069	0.5964	0.6189	0.6395	0.6108	0.5809	0.6247
Zhejiang	0.5919	0.6223	0.6488	0.6578	0.7322	0.6815	0.6918	0.7716	0.7482	0.7980
Anhui	0.8602	0.7351	0.7037	0.6209	0.6580	0.6311	0.5910	0.5932	0.5425	0.5234
Fujian	0.7025	0.6180	0.5871	0.6778	0.8131	0.7995	0.7295	0.7129	0.7042	0.6737
Jiangxi	0.8787	0.7654	0.7624	0.7329	0.6666	0.6243	0.5804	0.5599	0.4271	0.3810
Shandong	0.7530	0.8194	0.7351	0.6556	0.6146	0.5644	0.5769	0.5814	0.6142	0.6041
Henan	0.7683	0.7894	0.7504	0.7317	0.6412	0.6417	0.6340	0.6762	0.6600	0.6210
Hubei	0.7362	0.6813	0.6371	0.7017	0.7054	0.6753	0.7273	0.6326	0.5776	0.4670
Hunan	0.7953	0.6947	0.6968	0.6987	0.7251	0.7210	0.6898	0.6305	0.5612	0.3865
Guangdong	0.7323	0.7687	0.7736	0.8114	0.8245	0.7960	0.6482	0.6724	0.6183	0.5298
Guangxi	0.7739	0.6509	0.6587	0.6181	0.5857	0.6299	0.6602	0.6261	0.6090	0.6297
Hainan	0.7103	0.7359	0.7098	0.6701	0.6394	0.6808	0.5746	0.6040	0.5672	0.7266
Chongqing	0.5769	0.5763	0.5869	0.6297	0.6670	0.6647	0.6419	0.5871	0.6841	0.5139
Sichuan	0.7207	0.7285	0.6790	0.7391	0.7520	0.7578	0.6702	0.6093	0.4388	0.3322
Guizhou	0.5735	0.5570	0.5869	0.6058	0.5960	0.5642	0.6427	0.4781	0.6660	0.5299
Yunnan	0.6658	0.6563	0.6709	0.6921	0.7747	0.7709	0.8078	0.7581	0.6951	0.6763
Xizang	0.6329	0.6989	0.7583	0.6312	0.6131	0.5434	0.5677	0.4759	0.6373	0.4261
Shaanxi	0.7616	0.7222	0.6814	0.7102	0.7432	0.7590	0.7296	0.6446	0.5787	0.5339
Gansu	0.6931	0.6810	0.6456	0.6850	0.7468	0.6754	0.6265	0.6463	0.6445	0.6212
Qinghai	0.7550	0.7909	0.7975	0.7831	0.7704	0.7412	0.7989	0.7152	0.6463	0.5054
Ningxia	0.7989	0.7909	0.6730	0.6977	0.7707	0.6801	0.5994	0.6115	0.5870	0.5874
Xinjiang	0.8265	0.7034	0.7434	0.6700	0.6564	0.6392	0.6028	0.5645	0.5585	0.5087

TABLE 5 Summary of test results (n = 310).

Inspection type	Purpose of inspection	Inspection value	Inspection conclusion
F inspection	Comparison and selection of FE model and POOL model	F (30,271) = 9.142, p = 0.000	FE model
BP inspection	Comparison and selection of RE model and POOL model	$\chi^2(1) = 8.357$, p = 0.002	RE model
Hausman inspection	Comparison and selection of FE and RE models	$\chi^2(7) = 267.924$, p = 0.000	FE model

5.1 Baseline regression results

The core explanatory variables are four terminal energy consumption structure indicators the proportions of coal, diesel, natural gas, and electricity consumption, corresponding, respectively, to the categories ECS_a, ECS_b, ECS_c, ECS_d. The results of the two way fixed effects model are as follows.

The coefficient on the coal consumption share is −0.164 and is significantly negative at the 5% level. Holding other factors constant, an increase in the share of coal in final energy consumption significantly reduces the coupling coordination level of the energy carbon system. This implies that an energy consumption structure heavily reliant on coal hampers the synergistic optimization of the energy and carbon emission systems, and may induce a "high energy, high carbon" lock in effect.

The coefficient on the diesel consumption share is −3.213 and is significantly negative at the 1% level, indicating a pronounced adverse impact. An increase in the proportion of diesel in terminal energy consumption markedly deteriorates the coordination level of energy carbon coupling. Since diesel use is largely concentrated in sectors such as transportation and agricultural machinery where emission factors are relatively high and emission abatement is difficult an expansion in its share substantially lowers the overall coordination level of the system.

By contrast, the coefficient on the natural gas consumption share is 5.920 and is significantly positive at the 5% level. This suggests that increasing the proportion of natural gas in terminal energy consumption can significantly enhance the coordination between the energy system and the carbon emission system. As a relatively clean fossil fuel, a higher share of natural gas helps to reduce the carbon emission intensity per unit of energy, thereby promoting a more coordinated evolution of the energy and carbon systems.

The coefficient on the electricity consumption share is −1.450 and is significantly negative at the 1% level, indicating a robust negative association between a higher electricity share and the coupling coordination degree D in the current sample. This negative association is consistent with the manuscript's accounting boundary that separates electricity consumption from electricity related carbon emissions, under which electrification can coincide with higher indirect emission pressure when the upstream power mix remains carbon intensive; we interpret this as a structural consistency rather than a causal identification. This interpretation is consistent with the paper's reported negative and significant coefficient on the thermal power share in the production side structure Control_c in the same baseline specification Table 6, but we do not claim the causal transmission channel is identified in this manuscript.

Overall, the findings for the core explanatory variables clearly demonstrate that shifting the terminal energy consumption structure away from high carbon energy sources toward relatively cleaner energy sources is a key pathway to enhancing the coordination of the energy carbon system. However, in the absence of sufficient decarbonization of the power sector, simply increasing the share of electricity consumption is unlikely to substantially improve the coupling coordination level. For details, see Table 6.

Regarding the control variables, the key factors include the scale of energy consumption, total carbon emissions, and the share of thermal power and natural gas in the energy production structure.

The coefficient for the energy consumption scale is −0.234, which is significantly negative at the 1% level. This indicates that, after controlling for structural factors, a higher total energy consumption is associated with lower energy carbon coupling coordination. This result suggests that, under existing technological and structural constraints, large scale energy consumption continues to depend primarily on high carbon energy sources. As a result, this dependency exerts substantial pressure on carbon emissions and impedes improvements in systemic coordination.

The coefficient for the total carbon emissions scale is −0.139, which is significantly negative at the 5% level. This reflects a significant negative correlation between the scale of carbon emissions and the level of energy carbon coupling coordination. Higher total carbon emissions imply greater challenges for the energy carbon system in achieving the objectives of "low carbon, high efficiency, and coordination," leading to a corresponding decline in coupling coordination. This finding aligns with theoretical expectations and underscores the critical role of carbon emission reductions in improving system coordination.

The coefficient for the share of thermal power generation is −0.263, which is significantly negative at the 1% level. This indicates that a higher proportion of thermal power in the energy production

TABLE 6 Summary of panel model results.

Item	POOL model	FE model	RE model	Two way fixed effects
Intercept	0.690** (7.036)	4.704** (7.601)	0.823** (5.618)	4.116** (6.136)
ECS_a	−0.020 (−1.407)	−0.141* (−2.078)	−0.020 (−0.885)	−0.164* (−2.216)
ECS_b	−0.072 (−0.176)	−3.507** (−5.010)	−0.087 (−0.161)	−3.213** (−4.480)
ECS_c	0.773 (0.676)	6.550** (2.625)	1.947 (1.217)	5.920* (2.353)
ECS_d	0.021 (0.124)	−2.081** (−5.792)	−0.616* (−2.586)	−1.450** (−2.841)
Control_a	−0.007 (−0.524)	−0.333** (−6.180)	−0.018 (−0.946)	−0.234** (−3.533)
Control_b	0.008 (1.036)	−0.061 (−1.067)	0.019 (1.565)	−0.139* (−2.045)
Control_c	−0.010 (−0.417)	−0.268** (−3.960)	−0.028 (−0.800)	−0.263** (−3.863)
Control_d	0.066 (1.265)	0.047 (0.451)	0.069 (0.945)	0.070 (0.674)
Adjusted R^2	0.027	−17.828	−0.057	−18.909
Within R^2	0.009	0.407	0.125	0.345
Sample size	310	310	310	310
Inspection	$F\,(8,301) = 1.063, p = 0.389$	$F\,(8,271) = 23.251, p = 0.000$	$\chi^2(8) = 18.369, p = 0.021$	$F\,(8,262) = 12.752, p = 0.000$

Dependent variable = D.
*$p < 0.05$; **$p < 0.01$. The text in parentheses is t-value.

structure corresponds to lower coordination between the energy and carbon systems. Even if the end use consumption structure is optimized, the overall energy carbon system coordination remains significantly constrained if thermal power continues to dominate in upstream power generation.

The coefficient for the natural gas production share is 0.070, but it is not statistically significant. While the coefficient is positive, its lack of statistical significance suggests that, within the current sample period, changes in the proportion of natural gas production have not yet had a stable and significant impact on energy carbon coupling coordination. Potential explanations for this include considerable variation in natural gas resource endowments, infrastructure constraints, and the phased nature of natural gas development during the sample period. These factors warrant further exploration in future analyses. For details, see Table 6.

These baseline results are broadly consistent with the hypotheses formulated in Section 2.5. The negative associations of coal and diesel shares with the coupling coordination degree support the expectation that high carbon terminal energy dependence undermines coordination (Hypothesis H1), while the positive association of natural gas share supports the clean substitution hypothesis (Hypothesis H2). In addition, the observed non positive role of electricity consumption is consistent with the view that electrification does not automatically improve coordination when upstream power decarbonization is insufficient (Hypothesis H3).

5.2 Robustness test results

As shown in Table 7, the choice of the fixed effects (FE) model is primarily based on two reasons. First, the F test comparing the FE model with the pooled OLS model is highly significant. Second, the Hausman test strongly rejects the null hypothesis of consistency for the RE estimator, rendering the RE model unsuitable. Therefore, the FE model is the most reasonable choice both theoretically and empirically.

In the two way fixed effects model with ln_D as the dependent variable, the joint explanatory power of the explanatory variables on ln_D remains significant after controlling for regional and time effects. This indicates that even after applying a logarithmic transformation to the coordination index to address scale differences and potential heteroscedasticity, the model retains strong explanatory power and statistical significance, validating the robustness of the benchmark regression results. See Table 8 for details.

The share of coal consumption remains negatively correlated and approaches statistical significance. In the two way fixed effects model, its coefficient is −0.236 with a t value of −1.965. Compared to the benchmark regression using D as the dependent variable, the sign remains negative. Although the significance slightly weakens, the negative trend persists. This indicates that regardless of the econometric method employed, the conclusion that an increase in coal consumption share weakens the coordination of the energy carbon system holds true. While the logarithmic transformation slightly reduces the statistical strength of the effect, its direction remains unchanged.

The share of diesel consumption consistently exhibits a significant and strong negative effect. In the two way fixed effects model, the coefficient for diesel consumption ranged from −3.213 to −5.145, both showing significant negative values at the 1% significance level. This effect is more pronounced than the coefficient in the benchmark regression, indicating that regardless of whether D or ln_D is used as the dependent variable, the share of diesel consumption consistently acts as a key high carbon factor significantly inhibiting the coordination of the energy carbon system.

The share of natural gas consumption exhibits a stable and significant positive impact. In the benchmark regression, the coefficient for natural gas consumption is 5.920, significantly positive. In the robust regression, this coefficient reached 10.138, remaining positive at the 5% significance level with a larger absolute value. This indicates that increasing natural gas's share in final energy consumption significantly enhances the coordination of the energy carbon system.

The share of electricity consumption continues to exert a negative influence. In the two way fixed effects model, when the dependent variable is D, the coefficient for the share of electricity consumption is −1.450, showing a significant negative correlation. When the dependent variable is ln_D, the coefficient is −2.299, indicating a significantly negative correlation with a larger absolute value at the 1% significance level. This suggests that under the current power supply structure, which still exhibits strong "high carbon attributes," simply increasing the share of terminal electricity consumption will not automatically improve energy carbon coordination in the short term. See Table 8 for details.

Energy Consumption Scale, exhibits a stable and significant negative impact. The benchmark regression yields a coefficient of approximately −0.234, which is significantly negative. In the robustness regression, the coefficient is −0.361, showing a significant negative correlation at the 1% significance level. These results indicate that under current structural and technological conditions, higher total energy consumption actually weakens the coordination between energy and carbon systems. This demonstrates that "high energy consumption expansionary growth" undermines energy carbon coordination mechanisms, a conclusion consistent across different measurement methods.

Total carbon emissions remain negatively correlated with energy carbon coordination, though the significance level slightly

TABLE 7 Summary of inspection results (n = 310).

Inspection type	Purpose of inspection	Inspection value	Inspection conclusion
F inspection	Comparison and selection of FE model and POOL model	$F(30,271) = 8.742$, $p = 0.000$	FE model
BP inspection	Comparison and SELECTION of RE model and POOL model	$\chi^2(1) = 7.777$, $p = 0.003$	RE model
Hausman inspection	Comparison and selection of FE and RE models	$\chi^2(7) = 236.851$, $p = 0.000$	FE model

TABLE 8 Summary of panel model results.

Item	POOL model	FE model	RE model	Two way fixed effects
Intercept	−0.367* (−2.320)	5.798** (5.745)	−0.157 (−0.673)	4.838** (4.443)
ECS_a	−0.029 (−1.262)	−0.213 (−1.922)	−0.028 (−0.788)	−0.236 (−1.965)
ECS_b	−0.189 (−0.286)	−5.754** (−5.040)	−0.213 (−0.247)	−5.145** (−4.419)
ECS_c	1.624 (0.881)	11.315** (2.781)	3.342 (1.308)	10.138* (2.482)
ECS_d	0.013 (0.046)	−3.299** (−5.632)	−0.964* (−2.535)	−2.299** (−2.773)
Control_a	−0.012 (−0.569)	−0.531** (−6.042)	−0.030 (−0.985)	−0.361** (−3.349)
Control_b	0.013 (1.056)	−0 08 (−0.620)	−0.030 (−1.567)	−0.204 (−1.843)
Control_c	−0.011 (−0.289)	−0.415** (−3.760)	−0.038 (−0.678)	−0.407** (−3.682)
Control_d	0.070 (0.832)	0.010 (0.060)	0.069 (0.584)	0.047 (0.276)
Adjusted R^2	0.023	−15.290	−0.054	−16.619
Within R^2	0.008	0.395	0.118	0.330
Sample size	310	310	310	310
Inspection	F (8,301) = 0.884, p = 0.531	F (8,271) = 22.086, p = 0.000	$\chi^2(8)$ = 16.617, p = 0.038	F (8,262) = 11.385, p = 0.000

Dependent variable = Ln_D.
*$p < 0.05$; **$p < 0.01$. The text in parentheses is t-value.

decreased while the direction remained consistent. In the ln_D model, the coefficient is −0.204 with a t value of 1.843. In contrast, the D model coefficient is −0.139, significant at the 5% level. Despite slightly reduced significance, the negative correlation trend persists, corroborating the overall conclusion. See Table 8 for details.

Robustness tests yield consistent findings. An increase in the share of high carbon energy sources weakens coupling coordination, while an increase in the share of clean natural gas significantly strengthens it. Furthermore, before power decarbonization, electricity consumption exerts a negative impact on coupling coordination. Both economies of scale and structural effects yield stable results. Total energy consumption and carbon emission expansion exert negative effects on D or ln_D. An increase in the share of thermal power generation further weakens energy carbon coupling coordination. When the dependent variable is transformed to ln_D, the signs and significance levels of core explanatory variables and control variables remain largely consistent. Notably, the absolute values of some coefficients have increased, reinforcing the robustness of the conclusions and indicating that the findings are not dependent on specific indicator forms. See Table 8 for details.

The robustness evidence strengthens the interpretation that the baseline findings are not specification driven. In particular, the direction of the estimated effects remains aligned with the hypotheses, high carbon energy shares are associated with lower coordination (Hypothesis H1), clean substitution via natural gas is associated with higher coordination (Hypothesis H2), and the electricity share effect remains non positive in the sample period (Hypothesis H3).

While the robustness tests confirm that the main findings are not sensitive to alternative variable specifications, an additional question remains as to whether the identified structural relationships retain explanatory relevance beyond the original estimation period. To address this issue, the following section supplements the in sample evidence with an out of sample validation and a short term scenario analysis.

5.3 Out of sample validation and short term transition scenario analysis

To further strengthen the empirical interpretation of the agricultural energy carbon nexus, this study supplements the baseline and robustness regressions with an out of sample validation and a short term transition scenario analysis.

First, an out of sample validation is conducted to examine whether the relationships identified in the benchmark model remain informative when applied to more recent observations outside the original estimation period. Using the xtoos_t procedure in Stata, the model estimated from the original sample is evaluated against the hold out observations for the most recent years. This step is not intended to transform the study into a pure forecasting exercise; rather, it serves as an additional assessment of whether the structural relationship between terminal energy consumption structure and agricultural energy carbon coordination remains temporally stable under potentially evolving economic and policy conditions.

The validation results suggest that the model retains a certain degree of short term predictive relevance, especially for one step ahead prediction, while prediction errors increase notably as the forecast horizon expands. Specifically, for the fixed effects model using D as the dependent variable, the out of sample prediction for 2023 based on the last in sample year of 2022 yields an RMSE_oos of 0.3004 and a U-Theil statistic of 24.3682, whereas the longer horizon prediction for 2022–2023 based on the last in sample year of 2021 produces a much larger RMSE_oos of 6896.8480 and a U-Theil statistic of 40349.6300. A similar pattern is found for the alternative specification using ln_D, the one step ahead prediction based on 2022 gives an RMSE_oos of 0.4654 and a U-Theil statistic of 19.5302, while the two period out of sample validation based on 2021 yields substantially larger values, with RMSE_oos reaching 10981.1400 and U-Theil rising to 36853.0900. These results indicate that the model captures a meaningful part of the structural relationship governing the coordination between the agricultural energy system and the agricultural carbon emission system, but its extrapolation capacity becomes weaker when the prediction window is extended. Therefore, the out of sample exercise provides supportive rather than definitive evidence for temporal stability, the model is informative for short term assessment, yet caution is still required when interpreting longer horizon projections.

Second, to connect the empirical findings more directly to the discussion of agricultural low carbon transition, a short term scenario analysis is conducted for 2024–2025 (Elsawah et al., 2020). Since the future values of explanatory variables are not directly observable, a moderate growth scenario is constructed in which the explanatory variables are assumed to increase by 2% annually relative to their 2023 levels. On this basis, the fixed effects model estimated with the 2012–2023 sample is used to generate scenario based projections of the coordination indicator for each province.

The scenario results are broadly consistent with the central findings of the paper. Provinces with more favorable structural conditions in the energy system continue to exhibit relatively higher projected coordination levels, while regions facing stronger fossil fuel dependence or structural pressure remain at comparatively lower levels. In particular, Yunnan (0.7122 in 2024; 0.7124 in 2025), Chongqing (0.6970; 0.6969), Qinghai (0.6690; 0.6684), and Sichuan (0.6459; 0.6448) show relatively high projected values, whereas Shandong (0.3637; 0.3569), Liaoning (0.4195; 0.4139), Guangdong (0.4155; 0.4098), and Shanghai (0.4360; 0.4307) remain at comparatively lower levels. More importantly, the projected interprovincial differences are not random numerical outcomes; rather, they reflect the persistence of the energy structure mechanisms identified in the baseline regressions, namely, that high carbon terminal energy dependence constrains coordination improvement, while cleaner substitution supports the green transition of the agricultural energy carbon system.

Taken together, the out of sample validation and scenario based projection reinforce the article's core argument that the quality of agricultural low carbon transition depends not only on energy input expansion, but more fundamentally on how the terminal energy mix evolves and whether cleaner substitution is sufficient to weaken carbon emission pressure. These additional results therefore extend the baseline and robustness analysis by showing that the estimated structural relationships are not confined to the in sample period alone, and that under a moderate growth scenario, the short term evolution of agricultural energy carbon coordination remains closely linked to the regional energy transition pathway.

It should be emphasized that the 2024–2025 results are scenario based projections rather than verified forecasts. Their value lies mainly in illustrating the possible short term trajectory of agricultural energy carbon coordination under a specified structural assumption, thereby providing a complementary perspective for discussing sustainable agricultural development and differentiated transition policies. For details, see Tables 9, 10.

5.4 Heterogeneity analysis

To examine regional differences in energy carbon system responses based on economic development, this study divides the sample into high GDP and low GDP groups, based on the median provincial GDP. For details, see Tables 11, 12. A two way fixed effects model is applied to each group, with coupling coordination degree as the dependent variable. The sample sizes for the two groups are 160 and 150, respectively. Results show significant differences in how energy consumption structure, energy scale, carbon emission scale, and energy production structure affect coupling coordination, reflecting regional economic heterogeneity.

In the high GDP group, the fuel structure channel becomes the dominant constraint on the coupling coordination outcome. Consistent with Hypothesis H1 and H3, the two way fixed effects estimates show that both the diesel consumption share ECS_b and the electricity consumption share ECS_d are significantly negative, indicating that coordination deteriorates when agricultural energy use is increasingly concentrated in diesel intensive operations and in electricity consumption under a power system that has not yet fully decarbonized. This result aligns with the paper's accounting boundary that treats electricity consumption as an energy input in the energy subsystem while separately capturing electricity related indirect emissions in the carbon subsystem, so electrification can weaken coordination when upstream carbon intensity remains high. Overall, high GDP provinces exhibit a "transition quality" constraint, modernization through mechanization and electrification does not translate into coordinated improvement unless end use fuel switching away from diesel and power sector decarbonization progress sufficiently fast. For details, see Table 13.

In the low GDP group, the heterogeneity pattern shifts toward a classic "coal lock in versus clean substitution" mechanism. In line with Hypothesis H1 and H2, the coal consumption share ECS_a is significantly negative while the natural gas consumption share ECS_c is significantly positive in the two way fixed effects specification, demonstrating that reducing coal dependence and expanding cleaner fuel substitution directly improves the coordination between the agricultural energy and emission subsystems. Compared with the high GDP group, the electricity share does not deliver a stable coordination gain once both province and year effects are controlled, which reinforces the paper's central message that electrification is not a universal pathway to higher coordination without parallel improvements in the upstream electricity mix. Taken together, the subgroup results reveal stage dependent transition levers, low GDP provinces benefit most from initial fuel substitution away from coal, whereas high GDP provinces face stronger constraints from diesel reliance and electricity related indirect emissions. For details, see Table 14.

TABLE 9 Out of sample validation of the agricultural energy carbon coordination model.

Model	Last in sample year	Validation period	RMSE_oos	U-Theil
FE model (D)	2021	2022–2023	6896.8480	40349.6300
FE model (D)	2022	2023	0.3004	24.3682
FE model (ln_D)	2021	2022–2023	10981.1400	36853.0900
FE model (ln_D)	2022	2023	0.4654	19.5302

This table reports the out of sample validation results obtained from the xtoos_t procedure in Stata. Lower values of RMSE_oos and U-Theil indicate better predictive performance. The results show that the model performs relatively better in one step ahead prediction than in longer horizon extrapolation.

TABLE 10 Scenario based projection of agricultural energy carbon coordination in 2024–2025.

Province	2024	2025
Beijing	0.5697	0.5671
Tianjin	0.5225	0.5189
Hebei	0.5636	0.5608
Shaanxi	0.5167	0.5130
Inner Mongolia	0.4988	0.4948
Liaoning	0.4195	0.4139
Jilin	0.6192	0.6176
Heilongjiang	0.5785	0.5760
Shanghai	0.4360	0.4307
Jiangsu	0.5002	0.4962
Zhejiang	0.4391	0.4339
Anhui	0.5721	0.5695
Fujian	0.5042	0.5003
Jiangxi	0.5971	0.5950
Shandong	0.3637	0.3569
Henan	0.5734	0.5708
Hubei	0.5454	0.5423
Hunan	0.5227	0.5191
Guangdong	0.4155	0.4098
Guangxi	0.5919	0.5896
Hainan	0.5551	0.5521
Chongqing	0.6970	0.6969
Sichuan	0.6459	0.6448
Guizhou	0.5008	0.4967
Yunnan	0.7122	0.7124
Tibet	0.6240	0.6224
Shaanxi	0.6102	0.6083
Gansu	0.5889	0.5866
Qinghai	0.6690	0.6684
Ningxia	0.5746	0.5721
Xinjiang	0.5960	0.5938

This table presents the scenario based projection results for 2024–2025. The explanatory variables are assumed to grow by 2% annually from their 2023 levels. Therefore, the reported values should be interpreted as short term transition projections under a moderate growth scenario rather than precise forecasts.

TABLE 11 Summary of inspection results (n = 160).

Inspection type	Purpose of inspection	Inspection value	Inspection conclusion
F inspection	Comparison and selection of FE model and POOL model	F (15,136) = 11.369, p = 0.000	FE model
BP inspection	Comparison and selection of RE model and POOL model	$\chi^2(1) = 1.555$, p = 0.106	POOL model
Hausman inspection	Comparison and selection of FE and RE models	$\chi^2(7) = 125.622$, p = 0.000	FE model

The heterogeneity patterns further contextualize the hypotheses. In the high GDP group, the significantly negative effects of diesel ECS_b and electricity ECS_d indicate that coordination improvement is constrained by diesel intensive end use activities and electricity related emission pressure, supporting Hypothesis H1 and reinforcing the conditional nature of electrification emphasized in Hypothesis H3.

TABLE 12 Summary of Inspection Results (n = 150).

Inspection type	Purpose of inspection	Inspection value	Inspection conclusion
F inspection	Comparison and selection of FE model and POOL model	F (14,127) = 10.638, p = 0.000	FE model
BP inspection	Comparison and selection of RE model and POOL model	$\chi^2(1)$ = 23.521, p = 0.000	RE model
Hausman inspection	Comparison and selection of FE and RE models	$\chi^2(7)$ = 65.997, p = 0.000	FE model

TABLE 13 High GDP groups summary of panel model results.

Item	POOL model	FE model	RE model	Two way fixed effects
intercept	1.442** (5.684)	9.110** (6.256)	1.902** (5.294)	9.004** (5.877)
ECS_a	−0.009 (−0.247)	−0.397** (−3.345)	−0.053 (−1.040)	−0.236 (−1.715)
ECS_b	−3.071** (−3.676)	−8.682** (−6.451)	−4.282** (−4.046)	−7.379** (−5.091)
ECS_c	−7.430* (−2.346)	−10.906 (−1.852)	−7.944* (−1.997)	−11.330 (−1.883)
ECS_d	−0.417 (−1.099)	−2.082** (−3.356)	−1.042* (−2.228)	−3.669** (−4.257)
Control_a	−0.061* (−2.208)	−0.603** (−4.446)	−0.100* (−2.407)	−0.550** (−3.380)
Control_b	0.006 (0.363)	−0.240* (−2.335)	0.024 (1.031)	−0.295* (−2.370)
Control_c	0.042 (0.705)	−0.268** (−2.693)	0.022 (0.290)	−0.359** (−3.481)
Control_d	0.222 (1.922)	−0.393 (−1.903)	0.155 (1.019)	−0.552** (−2.619)
Adjusted R^2	0.104	−34.153	0.007	−36.561
Within R^2	0.153	0.562	0.283	0.396
Sample size	160	160	160	160
Inspection	F (8,151) = 2.196, p = 0.031	F (8,136) = 21.801, p = 0.000	$\chi^2(8)$ = 33.792, p = 0.000	F (8,127) = 16.288, p = 0.000

Dependent variable = D.
*p < 0.05; **p < 0.01. The text in parentheses is t-value.

TABLE 14 Low GDP groups summary of panel model results.

Item	POOL model	FE model	RE model	Two way fixed effects
Intercept	0.940** (5.881)	3.208** (5.374)	1.505** (5.746)	2.016** (3.369)
ECS_a	−0.007 (−0.426)	−0.109 (−1.496)	0.022 (0.668)	−0.163* (−2.244)
ECS_b	0.731 (1.402)	−0.857 (−1.151)	0.856 (1.306)	−0.501 (−0.723)
ECS_c	0.866 (0.663)	7.876** (3.159)	4.851* (2.445)	6.435** (2.758)
ECS_d	0.154 (0.766)	−1.504** (−3.833)	−0.796* (−2.567)	0.402 (0.768)
Control_a	−0.041* (−1.994)	−0.250** (−4.920)	−0.110** (−3.296)	−0.033 (−0.533)
Control_b	0.009 (0.802)	0.001 (0.023)	0.036 (1.854)	−0.198* (−2.381)
Control_c	−0.077* (−2.249)	−0.354** (−2.975)	0.225** (3.560)	−0.178 (−1.512)
Control_d	0.148* (2.254)	0.333** (3.041)	0.306** (3.242)	0.373** (3.701)
Adjusted R^2	0.155	−6.164	−0.180	−14.264
Within R^2	0.130	0.453	0.348	−0.052
Sample size	150	150	150	150
Inspection	F (8,141) = 3.232, p = 0.002	F (8,127) = 13.148, p = 0.000	$\chi^2(8)$ = 50.543, p = 0.000	F (8,118) = 11.867, p = 0.000

Dependent variable = Ln_D.
*p < 0.05; **p < 0.01. The text in parentheses is t-value.

In the low GDP group, the significantly negative coefficient on coal ECS_a together with the significantly positive coefficient on natural gas ECS_c supports Hypotheses H1 and H2, indicating that reducing coal dependence and promoting clean substitution constitute the primary structural levers for improving D. Taken together, the results confirm that electrification alone does not guarantee higher coordination and must be aligned with cleaner energy supply and fuel mix upgrading.

5.5 Mediation effect analysis

In this paper, the dependent variable is the level of coupling coordination between the energy system and the agricultural carbon emissions system. Existing research demonstrates that growth in per capita gross domestic product (GDP) is the primary driver accelerating the increase in agricultural carbon emissions (Chen et al., 2020). Therefore, this study sets the mediating variable as agricultural carbon emissions per unit of GDP (denoted as M). This aims to explore whether the level of economic development exerts a mediating effect on the coordinated development of the energy system. The independent variables encompass various energy production and consumption structure variables, along with total carbon emissions and total energy consumption scale (collectively denoted as X). The corresponding mediation effect model can be expressed as. For more details, please refer to Equation 13.

$$Mi = \alpha 0 + \alpha 1X1i + \alpha 2X2i + \alpha 3X3i + \alpha 4X4i + \alpha 5X5i + \alpha 6X6i + \alpha 7X7i + \alpha 8X8i + \varepsilon 1i \tag{13}$$

This is the equation for "the total effect of the energy structure on the degree of coupling coordination D, without considering intermediaries." For more details, please refer to Equation 14.

$$Di = \beta 0 + \beta 1X1i + \beta 2X2i + \beta 3X3i + \beta 4X4i + \beta 5X5i + \beta 6X6i + \beta 7X7i + \beta 8X8i + \varepsilon 2i \tag{14}$$

The equation after incorporating the intermediary term (path b and path c′) represents the core equation for "simultaneously considering the impact of energy structure and agricultural carbon emission intensity on the coupling coordination level D." For more details, please refer to Equation 15.

$$Di = \gamma 0 + \gamma 1X1i + \gamma 2X2i + \gamma 3X3i + \gamma 4X4i + \gamma 5X5i + \gamma 6X6i + \gamma 7X7i + \gamma 8X8i + bMi + \varepsilon 3i \tag{15}$$

This study applies a mediation framework to examine how energy production and consumption structure influence the coupling coordination degree, which measures the coordination between the energy system and the agricultural carbon emission system. After jointly controlling for energy structure variables, total carbon emissions in logarithmic form, and total energy consumption in logarithmic form, the mediator agricultural carbon emissions per unit of gross domestic product shows a positive and statistically significant association with the coupling coordination degree. The estimated coefficient is 1.612 and is significant at the 5 % level. This pattern implies that, during the sample period, higher agricultural carbon emission intensity is associated with a higher measured coordination level. Accordingly, the interprovincial coordination observed in the data can be described as a "high carbon coordination" pattern, meaning that improvements in measured coordination may coexist with elevated carbon intensity.

To situate this "high carbon coordination" result within the broader transition literature, it is useful to distinguish stages of agricultural low carbon transition. In an early stage, energy modernization often advances faster than deep decarbonization of end use fuels and upstream electricity. As a result, energy inputs and emissions increase in a more synchronized manner, so the two subsystems may exhibit a relatively high coupling coordination value even though carbon emission intensity remains elevated. This stage based interpretation is consistent with studies emphasizing rural energy transition path dependence and the "lock in" effect, where structural upgrading can initially raise energy intensity and emission pressure before clean substitution and efficiency improvements dominate (Wu, 2020; Wu and Han, 2022; Xiong et al., 2016).

In a later stage, as cleaner fuels diffuse in end use and the power sector decarbonizes, the coordination mechanism should evolve from "high carbon coordination" toward "low carbon synergy," where improvements in the energy subsystem are accompanied by declining emission intensity and weaker emission pressure per unit output. Within this lens, the positive association between carbon emission intensity and the coupling coordination index identifies provinces that remain in an earlier transition stage; it also motivates interpreting coupling coordination jointly with carbon intensity indicators when assessing green transition performance, as highlighted by integrated nexus and efficiency research that distinguishes system interaction metrics from decarbonization outcomes (Tian et al., 2023; Zhang and Li, 2022).

Along the transmission pathway from the explanatory variables to agricultural carbon emissions per unit of gross domestic product, energy structure significantly reshapes agricultural carbon emission intensity. The shares of natural gas production and coal consumption are positively related to the mediator, with coefficients of 0.012 and 0.006, both significant at the 1 % level. Total carbon emissions in logarithmic form also exert a significant positive effect on the mediator. By contrast, the shares of thermal power production, electricity consumption, and diesel consumption, as well as total energy consumption in logarithmic form, are all significantly negative, with coefficients of minus −0.004, minus −0.052, minus −0.183, and minus −0.013, respectively. Among these, diesel consumption has the largest absolute coefficient, indicating the strongest association with reductions in agricultural carbon emission intensity.

Combining these estimates with the mediation coefficient of 1.612, the results indicate that a higher share of natural gas production, a higher share of coal consumption, and a larger total carbon emission scale indirectly increase the coupling coordination degree by raising agricultural carbon emissions per unit of gross domestic product. In contrast, a higher share of thermal power generation, a higher share of electricity consumption, a higher share of diesel consumption, and a larger energy consumption scale indirectly reduce the coupling coordination degree by lowering agricultural carbon emission intensity. A notable case is coal consumption, which exhibits an inhibitory effect. In the model without the mediator, the coefficient of coal consumption share on the coupling coordination degree is minus −0.020 and not statistically significant. After including agricultural carbon emissions per unit of gross domestic product, the direct effect becomes minus −0.029 and is significant at the 5 % level. Together with the positive indirect effect through the mediator, this indicates offsetting direct and indirect pathways, which can mask coal's overall association with coordination when mediation is ignored.

The mediation equation achieves an R squared of 0.611, suggesting that agricultural carbon emissions per unit of gross domestic product are well explained by energy structure variables and energy consumption scale. Overall, the mediation results highlight agricultural carbon emission intensity as an important channel through which energy structure is associated with the observed coordination dynamics. Details are reported in Tables 15, 16.

The presence of a statistically detectable indirect pathway through agricultural carbon emissions per unit of gross domestic product is consistent with Hypothesis H4. Following the interpretation boundary adopted in this manuscript, we treat this as evidence of an indirect association channel within the mediation framework, rather than an absolute claim of complete mediation.

When the indirect effect is significant but the total effect is not, this may reflect offsetting direct and indirect components; we therefore avoid absolute claims and interpret the evidence as supporting a statistically detectable indirect pathway under the reported bootstrap inference.

6 Conclusions and recommendations

6.1 Conclusion

This study examines the coupling coordination between energy consumption and carbon emissions in China's agricultural sector, an important pillar of the national low carbon transition. The main findings are as follows.

First, China's provincial agricultural energy carbon systems display generally favorable coordination over 2012–2021. Results show that the coupling coordination degree between China's agricultural energy system and agricultural carbon emission system shows an overall moderate to good level during 2012–2021, suggesting an overall move toward coordinated green transformation, while substantial regional disparities persist.

Second, terminal energy consumption structure is a key determinant of coordination. Substituting high carbon fuels such as coal and diesel with cleaner alternatives, particularly natural gas, is associated with higher coordination. By contrast, greater electricity use does not automatically improve coordination, especially when the power generation mix remains carbon intensive, underscoring the importance of supply side decarbonization.

Third, the mediation results show that agricultural carbon emissions per unit of gross domestic product are statistically linked to the coupling coordination degree and constitute a detectable indirect pathway in the mediation framework. We therefore describe the observed pattern as "high carbon coordination" in a strictly descriptive sense provinces may exhibit relatively higher coordination while carbon intensity remains elevated within the sample distribution. This terminology does not imply a normative endorsement of high emissions; rather, it highlights that higher coordination does not necessarily guarantee lower emission pressure and should be interpreted jointly with carbon intensity indicators. Interpreted through a staged transition lens, this pattern reflects that some provinces are still in an early phase where

TABLE 15 Summary of mediator effect test results.

Item	C overall effect	A	B	A*B mediation effect value	A*B (Boot SE)	A*B (z-value)	A*B (p-value)	A*B (95% BootCI)	C′ direct effect	Inspection conclusion
X → M → D	0.008	0.009**	1.612*	0.015	0.077	0.195	0.845	0.048 ~ 0.349	−0.007	Indirect only effect
X → M → D	−0.007	−0.013**	1.612*	−0.020	0.063	−0.319	0.749	−0.285 ~ −0.036	0.014	Indirect only effect

*$p < 0.05$; **$p < 0.01$.
Bootstrap Type = Percentile Bootstrap Method.

TABLE 16 Mediation effect model testing simplified format.

Variables	*D*	*M*	*D*
Constant	0.690** (7.036)	0.094** (11.488)	0.538** (4.609)
ECS_a	−0.020 (−1.407)	0.006** (4.879)	−0.029* (−2.003)
ECS_b	−0.072 (−0.176)	−0.183** (−5.339)	0.223 (0.524)
ECS_c	0.773 (0.676)	−0.117 (−1.225)	0.962 (0.846)
ECS_d	0.021 (0.124)	−0.052** (−3.637)	0.105 (0.606)
Control_a	−0.007 (−0.524)	−0.013** (−11.885)	0.014 (0.897)
Control_b	0.008 (1.036)	0.009** (14.042)	−0.007 (−0.672)
Control_c	−0.010 (−0.417)	−0.004* (−2.014)	−0.003 (−0.145)
Control_d	0.066 (1.265)	0.012** (2.795)	0.047 (0.883)
M			1.612* (2.358)
Sample size	310	310	310
R^2	0.027	0.611	0.045
Adjust R^2	0.002	0.600	0.017
F-value	F (8,301) = 1.063, p = 0.389	F (8,301) = 58.978, p = 0.000	F (9,300) = 1.577, p = 0.121

*$p < 0.05$l; **$p < 0.01$. The text in parentheses is t-value.

modernization and energy substitution have not yet been accompanied by deep decarbonization of fuels and power supply; accordingly, improving coordination should be pursued together with explicit carbon intensity reduction targets (Wu and Han, 2022; Xiong et al., 2016).

Finally, energy structure effects are heterogeneous across development levels. In low GDP provinces, coordination is primarily constrained by coal dependence, while increasing the natural gas share yields significant coordination gains, indicating that 'coal to cleaner substitution remains the most effective structural lever. In high GDP provinces, coordination is more strongly constrained by diesel dependence and electricity related emission pressure, implying that improvements in D hinge on reducing diesel intensive activities and aligning electrification with upstream power sector decarbonization.

Additionally, the out of sample validation suggests that the model retains some short term predictive relevance, although forecasting errors increase substantially as the prediction horizon expands. The scenario based projection for 2024–2025 further indicates that under a moderate growth assumption, interprovincial disparities in agricultural energy carbon coordination are likely to persist in the short run, with the projected pattern remaining closely tied to regional energy transition pathways.

6.2 Recommendations

Based on these findings, several policy implications follow.

First, adopt region differentiated transition strategies. High GDP provinces should prioritize reducing diesel intensive energy use and coordinating agricultural electrification with upstream power sector decarbonization, whereas low GDP provinces should focus on phasing down coal dependence and expanding feasible clean substitution such as natural gas.

Second, accelerate terminal energy structure upgrading in agriculture by reducing coal and diesel reliance and expanding feasible clean alternatives, including natural gas and renewables where conditions permit including natural gas and renewables where conditions permit, with coal to gas substitution prioritized in low GDP regions and diesel reduction prioritized in high GDP regions.

Third, coordinate electrification with upstream power decarbonization. Expanding electricity use in agriculture should be coupled with a cleaner generation mix to ensure that indirect emissions decline alongside end use electrification.

Fourth, strengthen agricultural carbon monitoring, accounting, and reporting systems to support credible evaluation and policy adjustment, and scale up incentives for low carbon agricultural technologies through finance, research support, and capacity building.

Fifth, enhance cross sector policy coordination across energy, agriculture, and carbon governance so that policy objectives, instruments, and implementation mechanisms are aligned.

The scenario based projection further implies that without stronger structural adjustment in terminal energy use, interprovincial disparities are unlikely to narrow rapidly in the short run. Therefore, policy design should not only address current structural bottlenecks, but also anticipate their persistence under moderate growth conditions.

Together, these measures can improve the energy carbon coordination of China's agricultural sector and support progress toward the dual carbon goals and sustainable agricultural development.

Data availability statement

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

Author contributions

XW: Investigation, Software, Data curation, Methodology, Writing – review & editing, Conceptualization, Validation, Project administration, Formal analysis, Writing – original draft. ZW: Project administration, Investigation, Validation, Data curation, Conceptualization, Formal analysis, Methodology, Writing – original draft, Software, Writing – review & editing. WZ: Writing – review & editing, Writing – original draft.

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Conflict of interest

The author(s) declared that this work was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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