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Agricultural low-carbon transformation driven by the integration of agriculture and tourism: empirical evidence from China

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Introduction: Agricultural carbon emissions are a major source of global climate change. The new form of agricultural economy resulting from the deep integration of agriculture and tourism (IAT) provides an innovative solution for the low-carbon transformation of agriculture (LCTA).

Methods: This study took the historical data of 30 provinces in China from 2010 to 2022 as the observation sample, and used methods such as the two-way fixed effects model and the quantile model to examine the impact effect and mechanism path of IAT on agricultural carbon reduction. To synthesize the IAT index, we also employ gray relational degree, factor analysis method and entropy weight method.

Results: The research results show that the technological effect, labor substitution and green environmental protection awareness of IAT are conducive to improving the green productivity of agriculture and leading to LCTA. This result still holds true after eliminating endogeneity and conducting multiple robustness tests. However, the positive effect of IAT on carbon emission reduction is heterogeneous. The results of the nonlinear test show that in areas with low agricultural carbon emissions, IAT will play a stronger positive role, while the positive role it can play in areas with high carbon emissions is limited. The results of the mechanism test show that IAT will indirectly promote LCTA through channels that facilitate land transfer and the aggregation of agricultural labor force.

Discussion: This research is a beneficial exploration of agricultural carbon reduction in the context of addressing climate change. The results of this study are of guiding significance for accelerating the realization of sustainable development goal 13 (SDGs 13).

KEYWORDS

integration of agriculture and tourism, agricultural carbon emissions, agricultural socialized services, land transfer, industrial integration

1 Introduction

Recent years have witnessed an intensifying trend of global warming, characterized by increasingly frequent extreme climate events. These phenomena pose significant threats to human health and jeopardize the sustainable development of economies and societies globally (Wang et al., 2024a; Wang Z. et al., 2025; Nian et al., 2025). Mitigating carbon emissions is therefore imperative to avert a climate crisis. Within this context, agricultural carbon emissions constitute a primary driver accelerating global climate change. Empirical studies indicate that greenhouse gas emissions from China's

agricultural sector account for approximately 20% of national totals (Ning et al., 2024). To address this challenge, China has established ambitious strategic objectives: achieving peak carbon emissions by 2030 and carbon neutrality by 2060. Notably, the *2024 Report on Low-Carbon Development of China's Agriculture and Rural Areas* suggests that agricultural greenhouse gas emissions likely peaked between 2015–2017 and are now in a phase of gradual decline. Nevertheless, substantial decarbonization potential remains—particularly within crop cultivation, livestock production, and rural energy consumption systems. As the world's largest developing economy and carbon emitter, China faces significant challenges in reconciling agricultural decarbonization with its mandate to ensure food security and stable supplies of essential agricultural products. Key constraints include: (1) Incomplete sectoral peaking. Certain agricultural and rural subsystems have yet to achieve emission peaks, with insufficient time remaining for phased transitions; (2) Unrealized mitigation potential. Systematic pathways for sustained agricultural emission reduction require further exploration, lacking established long-term economic models; (3) Production system trade-offs. Decarbonization necessitates transforming production methods, potentially compromising food security and farm income stability; (4) Economic implications. Transition costs may increase consumer prices for low-carbon agricultural products, reduce purchasing power, and escalate governmental expenditures for environmental services (such as afforestation subsidies), thereby straining public finances. Consequently, addressing these multifaceted challenges necessitates accelerated development of low-carbon agricultural systems and the rapid decarbonization of both agricultural production and rural energy infrastructures.

With the continuous advancement of the rural revitalization strategy, the integration of the three industries in rural areas has risen to become the core task of the “agriculture, rural areas and farmers” work of governments at all levels. As a key area for the development of modern tourism, the integration of agriculture and tourism holds strategic value in enhancing the ecological efficiency of rural areas, driving the coordinated development of industries, optimizing the agricultural industrial pattern, and promoting the modernization transformation of agriculture (Qiu et al., 2021). More importantly, the integrated development of agriculture and tourism is a significant driving force for rural residents to change their livelihood strategies. It not only effectively enhances farmers' economic benefits but also serves as a crucial link in promoting green agricultural development and fair social progress, as well as achieving green emission reduction in agriculture (Huang et al., 2022). At present, the integrated development of agriculture and typical service industries is increasingly becoming a new driving force for rural development. Among them, developing rural leisure tourism based on local conditions and relying on local characteristic agriculture and culture has become an important means to achieve green development in rural areas. The allocation effect of the integration of agriculture and tourism on the endowment of factors such as labor, land, capital and technology required for the green development of agriculture has given rise to the rapid development of rural tourism, making the integration of agriculture and tourism an important means to achieve green emission reduction in agriculture. The Intergovernmental Panel on Climate Change (IPCC) pointed out in its sixth assessment report that global warming will make the adverse effects of climate change on food security and water security even more severe. How

to reduce carbon emissions from agriculture and actively respond to climate change is an urgent current issues that needs to be addressed. This research aims to explore how the integration of rural industries can influence the intensity of agricultural carbon emissions, and to deeply analyze the relationship and mechanism of action between the two, providing valuable inspirations for promoting high-quality agricultural development and achieving the “dual carbon” goals. The scientific goals that this research needs to achieve are: (1) From a theoretical perspective, this paper analyzes why IAT can reduce carbon emissions in agriculture and achieve a low-carbon transformation of agriculture (LCTA). Then, historical data from China is used to verify the positive effect of IAT on LCTA. (2) The impact of IAT on the agricultural sector is extensive and profound.. If there are positive effects, then through what channels does IAT achieve its goals? (3) Is there any heterogeneity in this positive effect?

2 Literature review

2.1 Agricultural carbon emissions

From the perspective of agricultural carbon reduction, measuring agricultural greenhouse gas emissions and analyzing the basic current situation are the basic prerequisites for achieving low-carbon agriculture. Research related to agricultural carbon emissions can be classified into the following three categories:

- (1) Analysis of the sources of agricultural carbon emissions. The diversity of agricultural production determines the multi-source characteristics of agricultural carbon emissions. Determining the sources of agricultural carbon emissions is the prerequisite for measurement and analysis. Some literature holds that agricultural carbon emissions mainly result from the direct input of agricultural materials, the use of chemical fertilizers, pesticides, agricultural diesel and agricultural films, as well as the energy and fuel consumed in agricultural irrigation (Zhang and Shen, 2025; Huang et al., 2024). From the perspective of actual production, due to the differences in geographical environment and production processes among various regions, the use of agricultural fertilizers varies in different areas, and the agricultural carbon emissions brought about by different types of fertilizers also differ (Cai et al., 2025; Fan et al., 2022). During the process of animal husbandry, the carbon emissions produced by agriculture mainly come from gases such as nitrous oxide and methane released during the treatment of manure and the fermentation of animal intestines (Luo et al., 2025; Du et al., 2024). There are also literatures suggesting that greenhouse gas emissions are produced during the cultivation and growth of crops (Wang et al., 2023b; Wang M. et al., 2024). This is jointly determined by plant respiration, farmland environment and soil organic matter content.
- (2) Measurement of agricultural carbon emissions. After calculating the agricultural CO₂ emissions, it is possible to conduct research on the spatio-temporal evolution and dynamic evolution characteristics of the total agricultural carbon emissions and the inter-provincial agricultural carbon emissions. Published literatures have explored the measurement indicators and calculation systems of

agricultural carbon emissions, and proposed the emission coefficient method, model simulation method, and field measurement method (Hu et al., 2023; Lokupitiya and Paustian, 2006; Vleeshouwers and Verhagen, 2002). In terms of total volume and intensity, China's agricultural carbon emissions and carbon emission intensity have experienced an inverted U-shaped trend of growth followed by decline (Wen et al., 2022; Huan et al., 2024; Su et al., 2023; Wu et al., 2024). The current carbon emission behavior is mainly survival-oriented carbon emissions. Between 2015 and 2017, agricultural carbon emissions reached a turning point of decline. In terms of spatial form, there is a relatively obvious spatial agglomeration effect of agricultural carbon emissions in China, and the inter-provincial spatial correlation shows the characteristics of "high-high" agglomeration and "low-low" agglomeration (Wen et al., 2024). The regional heterogeneity of agricultural carbon emissions in China is very obvious, and the main carbon sources in different regions also vary (Tian et al., 2014).

- (3) Analysis of external factors promoting carbon emission reduction in agriculture. Based on the precise calculation of agricultural carbon emissions in China, scholars mainly explored the impacts of the advancement of urban-rural integration techniques, agricultural mechanization, digital inclusive finance, agricultural industrial agglomeration, land transfer and large-scale operation, and agricultural product trade on agricultural carbon emissions (Peng et al., 2025; Tang and Chen, 2022; Shen et al., 2023). Regarding the issue of carbon emission reduction in agriculture, existing research mainly unfolds from two dimensions. First, from the theoretical level, explore the concept definition, practical predicaments and emission reduction paths of agricultural carbon reduction, conduct corresponding research on the characteristics and influencing factors of agricultural carbon emissions in China, and expand the research boundaries based on sub-fields such as emission reduction potential measurement, optimization of emission reduction policies and improvement of emission reduction technologies (Franks and Hadingham, 2012; You and Wu, 2014; Guo and Zhang, 2023). However, existing studies on the drivers of reduction have predominantly focused on technological while largely neglecting the potential role of cross-sectoral, such as the synergy between agriculture and tourism (Chen et al., 2024; Li et al., 2023; Leung and Lau, 2021; Liu et al., 2021).

efficiency, the transformation and application of agricultural scientific and technological innovation, and the upgrading of consumer demand, providing a new model for the coordinated development of rural revitalization and ecological civilization (Ye and Jiang, 2025; Qin et al., 2022; Zhang and Zhang, 2024; Shi and Liao, 2025). (2) Some scholars believe that although the modernization of production conditions driven by industrial integration has strengthened the market driving force, it may trigger extensive production expansion and induce the risk of agricultural non-point source pollution (Lai et al., 2023; Zhang et al., 2021). Furthermore, some studies suggest that under the background of the unbalanced development of rural industrial integration, there are significant differences in the level of industrial integration, the scale of cultivation of integration entities, and the degree of extension of industrial chains among various regions, which may lead to stage heterogeneity in the impact of rural industrial integration on the ecological environment (Li et al., 2023; Wang R. et al., 2023; Shen et al., 2024). (3). Previous studies directly related to this research explored the green development effects of ATI. In the process of integrating agriculture and tourism, with the increase of disposable income, farmers are willing to improve their living environment. In the process of rural revitalization, farmers have injected new vitality into tourism development by opening homestays, developing local specialties, and promoting the humanistic stories and local products of their hometowns through live streaming. This process has imperceptibly strengthened the development and protection of traditional villages, promoted the improvement of the rural ecological environment, and thus achieved green development (Liu et al., 2023; Chen et al., 2023). Under the traditional agricultural production and operation mode, the allocation efficiency of agricultural production factors is relatively low. The new business forms formed by ATI have provided non-agricultural employment and entrepreneurship opportunities for the surplus rural labor force, attracted some labor force to separate from traditional agricultural production activities, promoted the moderate-scale and intensive operation of agricultural land resources, and thereby formed a certain scale effect. ATI enables the market-based flow and interaction of elements such as talents, information, capital, technology and management in the two industries, thereby promoting the optimal allocation of production factors, improving the allocation efficiency of agricultural factors and driving the green development of agriculture (Zhou et al., 2021; Wang et al., 2023a; Chen et al., 2025).

2.2 The impact of IAT on the economy and society

With the continuous deepening of the integration of agriculture and tourism, its development effect has attracted the attention of scholars. Literature review reveals that scholars' research on the impact of the integration of agriculture and tourism on rural development mostly focuses on the analysis of economic and social effects (Li and Yan, 2023). (1) Some scholars emphasize that the integration of rural industries forms an ecological benefit effect through three mechanisms: the improvement of governance

2.3 Research gap

The existing literature has fully analyzed the external factors influencing agricultural carbon emission reduction and the positive role of IAT in the ecological environment. However, the above-mentioned literature has not directly analyzed the impact of IAT on carbon emissions, resulting in it being unclear whether IAT has led to a reduction in agricultural carbon emissions (ACE). If the answer is affirmative, then how does IAT achieve carbon reduction? What is their mechanism of action? These problems have not been completely solved at present. To sum up, the

possible boundary contributions of this paper are as follows: (1) Based on the concept of industrial integration, we regard the deep integration of agriculture and tourism as a whole, revealing the positive effect of IAT on LCTA. (2) From the perspective of the path mechanism, this paper builds a brand-new research framework. From the summary of the literature, the existing literature has not yet explored the role played by land transfer and agricultural socialized services in the influence of IAT on LCTA. Therefore, this study incorporates LT and ASS into the research framework, and the conclusions obtained enrich the relevant research on rural tourism promoting agricultural carbon emission reduction. (3) This study also employed panel quantile technology to examine the nonlinear relationship between IAT and LCTA. It reveals the heterogeneous results of the N-shaped pattern.

3 Theoretical mechanism and research hypothesis

3.1 Direct influence mechanism

IAT is a new form of industrial integration based on agriculture, blurring the original boundaries between agriculture and tourism. The two intersect and permeate each other, eventually integrating into one, thereby achieving the development of agriculture driven by tourism. The integration of agriculture and tourism not only reconstructs the economic form of rural areas, but also forms carbon reduction efficiency through a triple transmission path of technological penetration, factor reset and industrial reconstruction. This impact is mainly reflected in the following aspects:

- (1) Technical effect. The integration of agriculture and tourism promotes the substitution effect of low-carbon technologies. The integration and coordinated development of agriculture and tourism have given rise to the research and development, integration and application of technologies between agricultural business entities and tourism enterprises. The demand for standardized services in the tourism industry has driven the introduction of green technological equipment such as precise fertilization systems and intelligent irrigation devices at the production end in agriculture (Lu et al., 2022; Liu Y. et al., 2025). Meanwhile, the digital management experience formed in the operation of cultural and tourism projects will directly accelerate the penetration of agricultural Internet of Things technology. Through the clean substitution effect of input factors, it will directly reduce carbon emissions in agricultural production and operation activities (Li and Wang, 2025).
- (2) Green awareness effect. The integration of agriculture and tourism has enhanced the ecological awareness of agricultural producers and rural residents. Rural tourism relies heavily on a good ecological environment and organic agricultural products. To promote the sustainable development of the tourism industry and increase operating income, local residents are willing to adopt green and low-carbon production technologies. Rural tourism operation companies will also require their employees to enhance

their ecological and environmental protection awareness. This is not only achieved by enhancing the human capital of the industry, but also by strengthening the education of new professional farmers through cultural and tourism project management training, and incorporating the awareness of ecological environment protection into agricultural production decisions (Yang et al., 2025). It is even more important to make good use of the structural carbon reduction brought about by the intensive land system. The composite development of leisure agricultural land will further enhance the carbon carrying capacity of the land and achieve the driving effect of green and low-carbon elements (Xiao et al., 2022). By leveraging the consumption scenarios of rural tourism to enhance the value of low-carbon agricultural products, we can not only increase farmers' income but also promote the green and sustainable development of the agricultural industry.

- (3) The improvement of the comprehensive quality of workers. The intensification of agricultural labor force, as an important manifestation of the upgrading of agricultural human capital, has always been regarded as an important strategic fulcrum for alleviating agricultural carbon emissions (Han et al., 2024). The development of IAT will not only promote non-agricultural employment for farmers, but also attract "new farmers" to flock to the agricultural sector, generating a labor substitution effect. With the deepening of the integration of agriculture and tourism and the reconstruction of the division of labor system, new types of agricultural business entities can transform and upgrade through management strategies such as agricultural skills training and job optimization, enhance the comprehensive quality and collaboration ability of workers, further reduce agricultural production costs and energy consumption, and thereby break through the inefficient cycle in the traditional agricultural production process, ultimately reducing carbon emissions in agricultural production (Cao, 2024). The suction effect generated by the service positions derived from the new forms of integration of agriculture and tourism may lead to: on the one hand, the transfer of young and middle-aged labor force to jobs such as dormitory management and tourism reception, which prompts the surplus rural power to enhance labor productivity by borrowing agricultural machinery. On the other hand, due to the seasonality of rural tourism, although it may lead to fluctuations in employment, it will instead increase the utilization rate of positions integrating agriculture and tourism. Moreover, the integration of agriculture and tourism can promote the development of rural tourism training bases, precisely match industrial positions with the application of smart agricultural technologies, and based on the actual demands of the agricultural and tourism market, promote the green development of agriculture and tourism, effectively reducing carbon emissions (Gu et al., 2025; Cheng et al., 2025). Based on this, this paper proposes the first hypothesis:

Hypothesis 1 (H1): The technological effects, green awareness and improvement of the quality of workers generated by IAT will promote LCTA.

3.2 Analysis of indirect mechanism

3.2.1 Analysis of the role of land transfer

According to the new economic growth theory, to achieve LCTA, it is necessary to adopt efficient and rational utilization of agricultural resources and reduce the negative externalities of pollution in the process of intensive production (Hou et al., 2023).

Land transfer (LT) will generate a scale effect. The contiguous land has endowed farmers with the possibility of large-scale production (Lu H. et al., 2025; Ke et al., 2022). According to the theory of returns to scale, as the production scale expands, the cost per unit output will decrease. Due to the limitations in terms of land, capital and management, small-scale agricultural operations are not conducive to the application of advanced agricultural technologies and equipment, hindering the improvement of agricultural production efficiency and LCTA (Zhou C. et al., 2024). The expansion of the scale of agricultural land operation will prompt operators to adopt more advanced production tools and technologies, such as improving the level of mechanization and intensively using agricultural chemicals. LT enables agricultural operators to adjust the scale of agricultural operations more appropriately according to the actual situation, achieve optimal scale operation, thereby making more effective use of various production factors, reducing resource waste and the input of agricultural chemicals, and lowering agricultural carbon emissions (Bai et al., 2025). In terms of agricultural operation models, with the acceleration of LT and the expansion of operation scale, agricultural producers can conduct refined management of agricultural production and operation activities. For instance, with the assistance of modern digital technology, farmers can precisely plan the uses of their existing land and optimize the density and spatial layout of agricultural factor input. This process will reduce energy consumption and environmental pollution in agricultural output, thereby reversing the inefficient state of decentralized operation in traditional agriculture and ultimately achieving LCTA (Zeng et al., 2022).

LT enhances the stability of agricultural property rights. Different types of farmers will have differentiated agricultural land investment behaviors due to the differences in their business goals (Wang S. et al., 2025). New types of business entities, due to their larger scale of operation and stronger dependence on agriculture, pay more attention to the sustainability of agricultural production and value the long-term benefits of agricultural production. They tend to adopt production technologies with longer payback periods such as straw returning to the field. Small-scale farmers, on the other hand, tend to focus on short-term production benefits, thus developing differentiated long-term investment behaviors in agricultural land. With the advancement of land transfer reform, the state's recognition of the trading of agricultural land management rights has increased. The standardized determination of land management rights and property rights will prompt the agricultural operation behaviors of new land contractors to tend toward long-term strategies. To maximize long-term transfer-in benefits, transferees will pay more attention to the sustainable use of land, reduce the input of agricultural chemicals that are harmful to the long-term development of land, and enhance the adoption of green and low-carbon technologies, thereby helping to reduce agricultural carbon emissions (Huang et al., 2023).

LT is conducive to strengthening the technological investment in agricultural land. After the transfer, the scale operation entities, in order to obtain long-term investment returns, are more willing to adopt green technologies that can effectively improve soil moisture and reduce the carbon emission output in the production and operation process of the planting industry (Shen and Luo, 2025). In most cases, land is transferred from small-scale farmers to efficient agricultural business entities with advanced agricultural technologies and financial strength. These new types of entities can apply more advanced technologies, thereby reducing carbon emissions in the agricultural production process and leading to a low-carbon transformation of the entire agricultural economic sector (Li et al., 2024).

Based on this, land transfer promotes the low-carbon development of agriculture through three paths: scale effect, technological innovation and stable property rights, ultimately leading to LCTA. Based on this, Hypothesis 2 of this paper is proposed:

Hypothesis 2 (H2): IAT will promote the realization of LCTA through the channel of accelerating LT.

3.2.2 The role of agricultural socialized services

According to Smith's theorem, the expansion of the market scale can significantly enhance the overall production efficiency through deepening the division of labor and specialized production. In the agricultural sector, ASS integrate environmentally friendly inputs (such as fertilizers, pesticides, and agricultural films) with green production factors (such as capital, technology, and machinery), becoming a key link connecting small-scale farmers with green production methods and an important measure to promote small-scale farmers' integration into the modern agricultural system (Jiang et al., 2025). The core of it is manifested as follows: By purchasing third-party services, farmers entrust part or all of the production links (from cultivation to harvest) to professional service organizations for completion. Essentially, ASS is the concrete practice of the specialization of agricultural production processes. At the level of production methods, ASS, with their advantages of mechanization, specialization, technology and precision, have effectively changed the factor input model of farmers based on empirical inertia. ASS helps farmers reduce the use of chemical fertilizers and pesticides by promoting technologies such as reduced application of agricultural chemicals and precise irrigation, and promotes the transformation of agricultural production methods toward intensive operation (Lu Y. et al., 2025).

At the level of factor input, the promoting effect of ASS on the LCTA is mainly reflected in the reconstruction of the combination of agricultural production factors, that is, the introduction of green technologies and environmental factors. Green technology innovation and application are the core driving forces for achieving the LCTA. There are usually two paths for farmers to adopt green technologies: independent production or purchasing socialized services. Independent production often requires the purchase of agricultural machinery and equipment by oneself. However, due to the high purchase cost of agricultural machinery and the sunk cost caused by the low utilization rate, farmers' willingness to purchase agricultural machinery by themselves is generally low. By contrast,

adopting ASS has become a more economical option. Professional service organizations possess advanced agricultural machinery and equipment as well as specialized production management capabilities, which can effectively break through the “technical barriers” faced by small-scale farmers (Zhu et al., 2025). For instance, by introducing technologies such as soil testing and formula fertilization, green control with plant protection drones, collection of fertilizer efficiency information and soil nutrient detection, service providers empower farmers to achieve precise fertilization (enhancing nutrient utilization efficiency), apply deep plowing and deep loosening services (improving farmland quality), and adopt green control services (significantly reducing the use of chemical pesticides). In addition, service providers have controlled the use of agricultural chemicals from the source by optimizing the allocation of input materials (such as organic fertilizers replacing chemical fertilizers, biological pesticides replacing traditional pesticides, and promoting green integrated pest and disease control technologies). The reduced reliance of farmers on agricultural films, pesticides and fertilizers will lead producers to cut down on product production, ultimately facilitating the LCTA. At the level of the labor factor, ASS, by exerting the accumulation and spillover effects of human capital, effectively reduce the search and supervision costs for farmers in the employment process, make up for the problems of quantity shortage, quality decline and insufficient skills caused by the non-agricultural transfer of family labor force, thereby helping to alleviate the tendency of extensive operation caused by labor constraints. It provides an important labor force support for the green transformation of agriculture (Liu Z. et al., 2025). Therefore, this study puts forward research hypothesis 3:

Hypothesis 3 (H3): The IAT will achieve LCTA by promoting ASS.

3.3 The heterogeneity of the influence effect

Due to the significant differences in economic development, resource distribution, ecological environment and policy implementation capacity among different regions in China, as well as the varying degrees of emphasis placed on the integration of agriculture and tourism and the intensity of agricultural carbon emissions in different regions of China. Therefore, the actual effects of the integration of IAT and the intensity of agricultural carbon emissions will also vary among different regions and at different levels (Zhou Q. et al., 2024).

(1) In economically developed regions, the government departments attach great importance to the supportive policies for the integration of agriculture and tourism as well as agricultural ecological environment issues. The implementation cost of these supportive policies for industrial integration is relatively low, and there are relatively fewer obstacles in policy implementation. This can better protect the agricultural ecological environment and also help alleviate the problem of agricultural carbon emissions.

(2) In economically backward regions, due to external factors such as relatively backward agricultural technology and relatively poor ecological environment, the difficulty of implementing policies that promote the integration of agriculture and tourism

has increased and the problem of agricultural carbon emissions cannot be effectively alleviated. However, in the long term, economically backward regions may experience a “learning effect”, learning from economically developed regions and drawing on the development experience of the integration of agriculture and tourism in developed regions, thereby promoting the integration of agriculture and tourism to alleviate the problem of agricultural carbon emissions. In China, the economically backward regions are mainly the central and western regions. Due to factors such as backward technology, underdeveloped infrastructure and immature operational experience, these regions can achieve a lower carbon reduction effect from the IAT than the eastern regions.

(3) All the excellent natural resources and cultural landscapes in the western regions of China. As rural tourism projects rely heavily on natural resource endowments, this makes the IAT in the western region have excellent natural conditions. In these areas, humans do not need to make excessive modifications to the natural landscapes to create high-quality tourist attractions. This advantage makes the industrial chain and supporting facilities related to IAT very complete, creating favorable conditions for LCTA. What's important is that the ecology in the western region is extremely fragile. There are a large number of ecological reserves in these places. People are not allowed to carry out large-scale economic activities. Therefore, IAT in the western region will pay more attention to the protection of the ecological environment. However, in the western regions of China, there are a large number of resource-based cities and heavy industrial bases. For instance, Anhui and Henan provinces are highly dependent on coal and aluminum. Importantly, the central region remains an important grain-producing area in China. This area undertakes the main function of China's grain production. Therefore, agricultural production in these regions also accounts for a very large share. The input of production factors such as pesticides, agricultural films and agricultural machinery required for agricultural production is also very large. Combining the existing agricultural production technologies and the extensive production mode, the carbon reduction benefits that the central region can enjoy in the IAT are limited.

(4) In regions with lower ACEI, the basic ecological environment is better, which can better leverage the advantages of green agriculture, have a higher capacity to curb agricultural carbon emissions, and be more capable of integrating green technologies, thereby achieving green and high-quality agricultural development. In China, the main grain-producing areas are located in the central region. The eastern region mainly focuses on foreign trade and modern service industries, while the main industrial development models in the western region are characteristic agriculture and tourism, as well as primary processing and resource-dependent industries. Therefore, in the central region, due to the large amount of carbon emissions from agriculture, the economic and production models mainly lean toward the secondary industry, and the proportion of agriculture is very high. This limits the carbon reduction role that IAT can play.

Based on this, this paper proposes the fourth hypothesis:

Hypothesis 4 (H4): The influence of IAT on LCTA shows regional heterogeneity. Its specific manifestation is that the eastern region fully enjoys the carbon reduction effect of IAT, while the central region can enjoy relatively lower benefits.

4 Research design and data sources

4.1 Empirical model

Due to the inherent characteristics of each province that do not change over time (such as geographical conditions, historical agricultural structure, and policy traditions), these factors simultaneously affect the IAT and LCTA. The two-way fixed-effect (TWFE) model adopts the intra-group mean removal approach to eliminate the influence of unobstructed variables on the explained variables, and has a good advantage when eliminating the endogeneity problem caused by omitted variables. Combining theoretical analysis and research hypotheses, to verify the impact of IAT on LCTA, this study constructed the following panel data model:

$$LCTA_{it} = a_0 + a_1 IAT_{it} + a_2 \sum CV_{it} + \lambda_i + V_t + \varepsilon_{it} \quad (1)$$

In Equation 1, *LCTA* is the explained variable. In this study, it mainly represents the low-carbon transformation of agriculture; *IAT* is the core explanatory variable. In this study, it mainly represents the integration of agriculture and tourism; *CV* is a collection that contains all the control variables; *i* is the individual, *t* is the time, and ε_{it} is the random disturbance term that follows the white noise process; λ_i is the individual fixed effect and V_t is the time fixed effect; a_0 is a constant term, and a_1 and a_2 are the regression coefficients to be calculated.

The traditional three-stage mediating effect model requires modifying multiple equations to explain the statistical relationships among variables. It observes whether the regression coefficients of each model of the system of equations are in line with expectations. However, this method simply regards the causal relationship between the judgment variables as the change of regression coefficients and significance. Accidental relationships among variables can lead to serious endogeneity. Based on the theoretical analysis given in the existing literature and the implemented testing procedures, this study uses a two-stage mediating effect model to carry out the mechanism test (Jiang, 2022; Shen, 2024; Shen and Zhang, 2023). The practical approach of this theory is to focus on explaining the impact of mechanism variables on LCTA in the theoretical analysis and research hypothesis sections, while in the empirical analysis section, it is necessary to clarify the influence effect of IAT on mechanism variables and use relevant research results or cases to support it. At this stage, it is regarded as having a good advantage in dealing with endogeneity problems arising from multiple models. To analyze the potential pathways through which IAT affects LCTA, based on research hypotheses 2 and 3, the following panel data model was constructed in this study:

$$MV_{it} = b_0 + b_1 IAT_{it} + b_2 \sum CV_{it} + \lambda_i + V_t + \varepsilon_{it} \quad (2)$$

In Equation 2, *MV* is a mechanism variable. In this study, it mainly represents labor force agglomeration and land transfer; b_0 is constant term, and b_1 and b_2 are the regression coefficients to be calculated. The meanings represented by other symbols are consistent with Equation 1.

According to the model Settings and variable Settings, the flowchart of this study is shown in Figure 1.

4.2 Variable setting

4.2.1 Explained variable

Low-carbon transformation of agriculture (LCTA). Low-carbon agriculture refers to an agricultural production mode that aims to lower carbon emissions by reducing greenhouse gas emissions, improving resource utilization efficiency and protecting the ecological environment during the process of agricultural production and rural development. Promoting low-carbon agriculture can reduce the negative impact of agriculture on climate change, enhance the sustainable development level of agriculture, and facilitate the green transformation of the rural economy. Adhering to the principles of “reduction”, “reuse” and “resource utilization” in a low-carbon economy, low-carbon agriculture is regarded as a new model of agricultural development that changes the original pursuit of economic output as the sole purpose. It requires minimizing the carbon footprint generated by agricultural economic activities as much as possible on the basis of resource recycling, and achieving the minimization of production factor input and the maximization of economic output (Mrówczyńska-Kamińska et al., 2021). Overall, promoting LCTA means reducing greenhouse gas emissions from agricultural activities and achieving good economic effects. Achieving LCTA reflects a balance between environmental protection and economic benefits. Therefore, based on the endogenous relationship between agricultural input and output, this study used super slacks-based measurement (SBM) model to calculate agricultural production efficiency to measure LCTA. When setting the production feasibility set, in order to achieve the cross-period comparability of the measurement results, global production technology was used in this study. Since data enveloping analysis (DEA) and SBM models have been widely used, this study does not present the production technology set and the computational equations for solving linear programming. Their basic principles and mathematical concepts can be found in the published literature (Wang et al., 2024b).

Based on the factor theory of agricultural economic growth and the practice of existing literature (Zhao et al., 2025; Wang et al., 2024d; Hamid et al., 2025), this study constructed the input-output evaluation system of LCTA on the basis of the narrow concept of agriculture. The evaluation system for the low-carbon transformation of agriculture is mainly developed from the perspective of input and output. In the input indicators, we mainly rely on the production factors that are essential for agricultural production, such as land, irrigation, chemical fertilizers and necessary agricultural technologies.

Table 1 reports the specific information of the LCTA evaluation system.

According to the basic characteristics of the planting industry and human activities, the sources of carbon emissions in the agricultural sector can be classified into the following seven categories: chemical fertilizers, pesticides, cultivation, the use of agricultural machinery, irrigation, agricultural films and energy

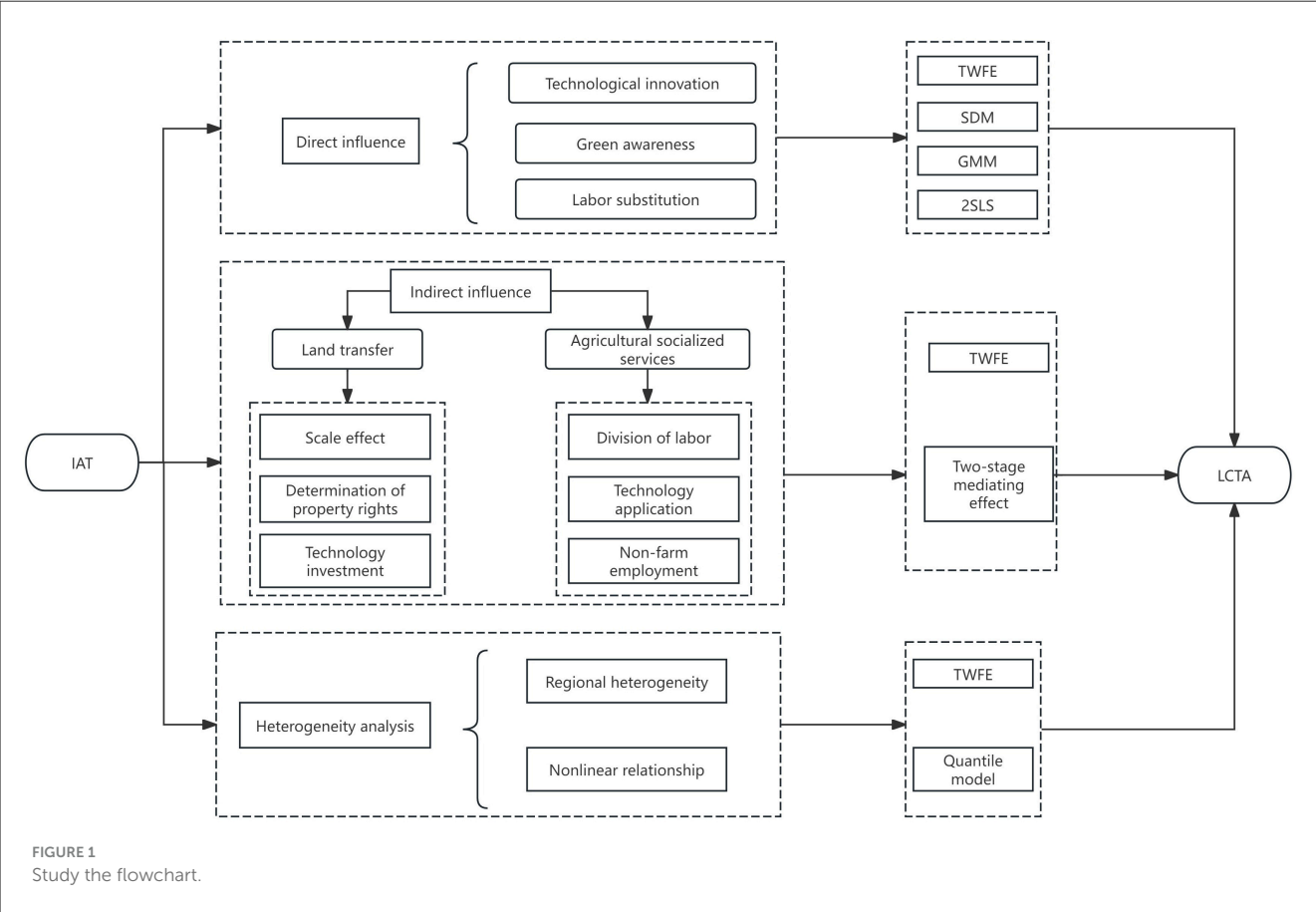


TABLE 1 The input and output evaluation system of LCTA.

Indicator type	Primary indicator	Specific explanations of the indicators
Input variable	Labor force	The number of practitioners in the primary industry
	Material input	Agricultural films, chemical fertilizers, pesticides; irrigation
	Land	The total sown area of crops
	Technology	Total power of agricultural machinery
Output variable	Expected output	The actual added value of the primary industry
	Unexpected output	Agricultural carbon emissions

(Alhashim et al., 2021). The calculation process of carbon emissions in the planting industry can refer to the published literature (Guo et al., 2023; Li and Wang, 2023; Tang et al., 2025; Zhang and Shen, 2025). Since the National Bureau of Statistics of China did not calculate in detail the usage of fossil energy in rural areas, this study used the electricity consumption of rural residents to measure energy consumption. The calculation equation for carbon emissions generated by electricity is $C_E = ES \times F$, among them, ES represents electricity consumption, F is a factor of carbon emissions in the power grid, and C_E is the carbon emission volume of the power grid. Thanks to the existing literature's research on soil, this study incorporated the carbon emissions from agricultural land use when calculating agricultural carbon emissions (Jul et al., 2025). They mainly involve CH_4 and N_2O produced during the growth of crops due to photosynthesis and respiration.

4.2.2 Core explanatory variable

Integration of agriculture and tourism (IAT) as an important support for the modernization of agriculture, is a significant indicator for achieving sustainable agricultural development. The aim is to provide significant impetus for the high-quality development of agriculture by integrating the resource and technological advantages of agriculture and tourism.

4.2.2.1 Indicator system

Based on the methods and research frameworks provided in the published literature (Zhou et al., 2021, 2022a), this study constructed the evaluation system in Table 2. The construction includes agriculture-tourism correlation, new integrated industry form, economic and social effects of integrated development. Unlike most studies, this research particularly takes the input-output ratio of the agricultural industry and the tourism

TABLE 2 index system for the integration of IAT.

Criteria	Indicators	
Industrial correlation degree	Gray correlation degree of agriculture and tourism industry	Domestic agricultural added value
		Domestic tourism revenue
		The total number of tourists received upon entry
		Domestic tourism revenue
		Regional foreign exchange tourism revenue
New integrated industry form	The number of demonstration counties for leisure agriculture and rural tourism in each province	
	The number of national demonstration sites for leisure agriculture and rural tourism in each province	
Economic and social effects of integrated development of agriculture and tourism	Investment	Investment in fixed assets of rural households
		New fixed asset investment in the agricultural sector
		Orchard area
	Employment	The number of individual employees in rural areas
		The number of employees in private enterprises in rural areas
	Industrial development	The ratio of total tourism revenue to economic growth in each province
		The ratio of the added value of the primary industry to the GDP of each province

industry as important indicators to measure the integration of IAT, and conducts an overall assessment of the synergy and integration of agriculture and tourism. This not only helps to improve the environment of the agricultural industry, but also provides a development direction for achieving sustainable development of the agricultural industry and promoting green agricultural development.

4.2.2.2 Measurement method

According to the index system, this paper comprehensively used the gray correlation degree and factor analysis method to calculate the IAT. This paper first conducts a gray correlation degree analysis on the input-output levels of agriculture and tourism. Then, based on the results of the gray relational degree analysis, this study uses the factor analysis method and entropy weight method with objective performance to measure IAT (Ren et al., 2020; Yang et al., 2020). Its calculation process mainly consists of the following steps. (1) Measure the industrial correlation between agriculture and tourism. As reported in Table 2, this study used four indicators, namely agricultural added value, tourism revenue, number of tourists and foreign exchange income from tourism in each region, to conduct a gray correlation analysis. In the actual operation process, we set the agricultural added value as the reference sequence and the other three indicators as characteristic variables. Then, the correlation coefficients of each feature sequence are summed up and the average value is taken to finally obtain the industrial correlation degree. The equation for calculating the mean of the characteristic coefficients is:

$$GCD = \sum_{i=1}^3 \frac{\gamma_i}{3} \quad (3)$$

In Equation 3, GCD is the industrial correlation degree that this research needs to calculate, γ is the correlation coefficient of each characteristic variable. The calculation process of the correlation coefficients of each characteristic variables are as follows:

The first step is to process the indicators by using the initialization method.

$$f(x_k) = \frac{x_k}{x_1} = y_k, x \neq 0 \quad (4)$$

In Equation 4, x_1 is the first array, and x_k is the k_{th} data. The meaning of this equation is that each indicator is divided by the first data. Then, the mathematical model of gray relational degree is used for calculation.

$$\psi[x_0(k), x_1(k)] = \frac{\Delta min + \rho \Delta max}{\Delta ik + \rho \Delta max} \quad (5)$$

$$\Delta min = \min_i \min_k |x_0(k) - x_i(k)| \quad (6)$$

$$\Delta max = \max_i \max_k |x_0(k) - x_i(k)| \quad (7)$$

$$\Delta ik = |x_0(k) - x_i(k)| \quad (8)$$

In Equations 5–8, ρ is the resolution coefficient, $x_i(k)$ is the k_{th} value to be initialized, $x_0(k)$ is the value of the k_{th} comparison sequence. Δmax and Δmin are the maximum and minimum values respectively. Finally, we need to calculate the

weighted average of the correlation coefficients between each of its indicators and the corresponding elements of the reference sequence respectively to reflect the correlation relationship between each control device object and the reference sequence.

$$\gamma_i = \frac{1}{m} \sum_{k=1}^m \psi[x_0(k), x_1(k)] \quad (9)$$

The result of Equation 9 is the correlation coefficient of each characteristic variable. After calculating the degree of industrial correlation, we need to integrate it with other indicators to obtain a comprehensive score. As the evaluation system involves multiple indicators, to avoid the trap of high-dimensional data, we used factor molecules to extract the common factors with a higher cumulative variance contribution rate. Suppose Y_{ij} is the score of the j th factor in the i th sample, z is the total number of samples, and c is the total number of factors. Then, by using the entropy weight method to assign weights to each factor, we can obtain:

$$Y_{ij} = \frac{y_{ij} - \min(y_{1j}, y_{2j}, \dots, y_{zj})}{\max(y_{1j}, y_{2j}, \dots, y_{zj}) - \min(y_{1j}, y_{2j}, \dots, y_{zj})} \quad (10)$$

Equation 10 represents the standardization processing of the original index using the range method. Then, we need to calculate the information entropy of each indicator.

$$P_{ij} = \frac{Y_{ij}1}{\sum_{i=1}^z Y_{ij}} \quad (11)$$

$$e_j = \frac{1}{1nz} \sum_{i=1}^z P_{ij} \ln P_{ij} \quad (12)$$

In Equations 11, 12, P_{ij} represents the weight of each indicator to all indicators, and e_j is the information entropy. Then the weight of each factor is:

$$W_j = \frac{1 - e_j}{\sum_{i=1}^z (1 - e_j)} \quad (13)$$

In Equation 13, W is the weight coefficient. Then, multiplying the values of the weight coefficients and the common factors can yield the result of ITA. Its calculation process is shown in Equation 14.

$$IAT = \sum_{i=1}^c Y_{ij} W_j \quad (14)$$

4.2.3 Control variables

Because there are many external factors affecting LCTA, in order to reduce the negative impact of omitted variables on the model estimation results, this study selected six variables as control

variables based on the published literature (Feng et al., 2025; Zhou et al., 2022b). Urbanization rate (UR) is measured by the ratio of the urban population to the total population. Population density (PD) is measured by the ratio of the total urban population to the administrative area. Planting structure (PS) is measured by the ratio of the sown area of grain to the total sown area of crops. Fiscal support for agriculture (FSA) is measured by the government's public fiscal budget expenditure in the agricultural and forestry sectors. Local climate (LC) is measured by the average annual rainfall. Level of economic development (LED) is measured by per capita gross domestic product (GDP). Industrial structure (IS) is measured by the ratio of the added value of the primary industry to the GDP.

4.2.4 Mechanism variables

Land transfer (LT) This study uses the total area of household contracted cultivated LT in each province announced by the Ministry of Agriculture and Rural Affairs of China as a proxy indicator for the transfer of agricultural land. It includes the quantity of land transferred out by all farmers. Agricultural socialized services (ASS). This study measures it by using the ratio of the output value of agriculture, forestry, animal husbandry and fishery services to the total output value of agriculture, forestry, animal husbandry and fishery.

4.3 Data sources and descriptive statistics

To reflect the availability and comparability of relevant indicators, the original data of relevant variables are from *China Statistical Yearbook*, *China Rural Statistical Yearbook*, *China Environmental Statistical Yearbook*, *China Tourism Statistical Yearbook*, the statistics bureaus of each province and express professional superior (EPS) data platform. Based on the availability of the data, this study selected panel data from 30 provinces in China from 2010 to 2022 as the observation samples. The data of power grid emission factors are sourced from the Ministry of Ecology and Environment of China. For a very small number of missing values, this study used the linear interpolation method to calculate them. Table 3 reports the descriptive statistical results and representative symbols of each variable.

5 Analysis of empirical results

5.1 Benchmark regression results

Based on the results of the F-test and Hausman test, this study selected the two-way fixed-effect model to calculate the results of the Equation 1. Furthermore, in order to eliminate the negative impact of heteroscedasticity and autocorrelation on the regression results, this study employed robust standard errors.

The results of columns (1) and (3) in Table 4 show that in the case of adding any control variables, the regression coefficients of IAT for LCTA are 0.402 and 0.163 respectively, and are significant at the 1% and 5% levels respectively. This result initially confirms that IAT has a positive effect on LCTA. To eliminate the negative

TABLE 3 Descriptive statistics of variables.

Variable	Code	N	Mean	Sd	Min	Max
Low-carbon transformation of agriculture	LCTA	390	−1.044	0.533	−2.329	0.204
Integration of agriculture and tourism	IAT	390	0.389	0.606	−1.833	2.032
Urbanization rate	UR	390	4.065	0.205	3.521	4.495
Financial support for agriculture	FSA	390	6.149	0.611	4.207	7.215
Industrial structure	IS	390	2.013	0.936	−1.609	3.262
Population density	PD	390	7.901	0.407	6.639	8.669
Economic development level	LED	390	10.864	0.478	9.482	12.156
Agricultural socialized services	ASS	390	−3.282	0.670	−5.141	−0.951
Land transfer	LT	390	15.964	1.188	11.865	18.049
Local climate	LC	390	6.703	0.647	4.951	7.825
Planting structure	PS	390	−0.457	0.223	−1.035	−0.029

TABLE 4 Benchmark regression result.

Variable	(1)	(2)	(3)	(4)
	OLS	OLS	TWFE	TEFE
IAT	0.402*** (9.82)	0.161*** (2.75)	0.163** (2.90)	0.059** (2.34)
PD		0.305*** (7.87)		0.140*** (6.52)
IS		0.253*** (8.60)		0.441*** (6.75)
PS		−0.971*** (−9.97)		−0.310** (−2.53)
FSA		−0.042 (−0.75)		−0.078 (−0.95)
UR		0.990*** (3.97)		0.504*** (4.27)
LED		0.425*** (3.42)		0.739*** (8.83)
LC		0.091*** (3.20)		−0.047 (−0.57)
Individual-fixed effect	No	No	Yes	Yes
Time-fixed effect	No	No	Yes	Yes
R-square	0.2087	0.6018	0.8047	0.8626
F-statistic			94.05***	463.90***
Hausman test			18.85***	29.91***

The t-statistic is in parentheses.

*** and ** indicate significance at the 1% and 5% levels, respectively.

impact of individual differences on the regression results. This study incorporated all control variables into the model. The results of columns (2) and (4) in Table 4 show that the regression coefficients of IAT for LCTA are 0.161 and 0.059 respectively, and are significant at the 1% and 5% levels respectively. This result once again confirms the positive effect of IAT on LCTA. Research Hypothesis 1 was tested. By comparing the regression results of ordinary least square (OLS) and TWFE, it can be known that in TWFE, the regression coefficient of IAT is smaller than that of OLS, and its significance is also lower. This result implies that external factors that do not change with individuals and do not

change over time have an impact on LCTA. Adopting TWFE can eliminate the endogeneity problem caused by omitted variables to a certain extent.

5.2 Robustness test

To better prove the robustness of the baseline regression results, this paper adapts the following four methods for verification. Furthermore, to avoid the endogeneity problems that may occur in regression, this paper first conduct endogeneity tests. The specific

methods are as follows:

(1) Change the measurement method of LCTA. In the benchmark regression model, this study used the super SBM model to measure LCTA. However, this method can only calculate the static efficiency value at a certain point in time and cannot directly analyze the changing trend of efficiency over time. Its major flaws are also reflected in the inability to analyze the cross-temporal evolution of efficiency and the inability to distinguish between technological progress and the contribution of technological efficiency. To eliminate this defect, this study used the SBM-GML method to recalculate LCTA. This method quantifies the growth rate of green total factor productivity by constructing an intertemporal distance function, revealing the long-term evolution state of production efficiency. Under the global reference framework, it resolves the issues of cross-period comparison, decomposition of technological progress, and quantification of green productivity that super SBM model cannot handle, providing a more comprehensive temporal insight for policy-making. It can be known from column (1) of Table 5 that the regression coefficient of IAT is 0.171 and significant at the 1% level. Compared with the result of the benchmark regression, in this method, the sign and significance of IAT have not changed significantly, indicating that the result of LCTA promoted by IAT is robust.

(2) Control the spatial spillover effect. According to the new economic geography theory, there exist spatial spillover effects of mutual imitation, mutual influence and mutual connection among economic variables. For rural tourism, individuals with geographical proximity imitate the business experience of advanced individuals and then develop projects with similar functions based on the local natural endowment, thereby generating a competitive effect. Under the background of rural revitalization, the Chinese government will also organize leading village organizations and agricultural enterprises in the industry to hold experience-sharing sessions for other market entities that do not have advantages, and provide necessary technical assistance. In this mode, the spatial spillover effect among individuals needs to be paid attention to. For LCTA, advanced experience will also affect the agricultural production models in neighboring areas. To eliminate the bias caused by not considering the spatial spillover effect, this study uses the geographical distances between provincial capital cities to construct the spatial weight matrix and employs the spatial Durbin model (SDM) to calculate the equation. It can be known from column (2) of Table 5 that the regression coefficient of IAT is 0.231 and significant at the 10% level. Although all the significance decreased, there was still statistical significance. This result implies that the conclusion that IAT promotes LCTA still holds.

(3) Changing the model. Because economic growth is related to the existing production methods and business models. In the agricultural sector, LCTA is also closely related to past low-carbon behaviors. To fully reflect the path dependence of economic variables, this study incorporates the time lag term of LCTA into

TABLE 5 Result of the robustness.

Variable	SBM-GML	SDM	SYS-GMM
	(1)	(2)	(3)
ATI	0.171*** (3.52)	0.231* (1.89)	0.481*** (3.91)
CV	Yes	Yes	Yes
Individual-fixed effect	Yes	Yes	Yes
Time-fixed effect	Yes	Yes	Yes
AR(1)			0.002
AR(2)			0.256
Hansen			0.223
N	390	390	360

*** and * indicate significance at the 1% and 10% levels. The t-statistic is reported in parentheses.

the model and employs the system GMM model to eliminate potential endogeneity. It is notable that the p -value of AR (1) is less than 1, while the result of AR (2) is greater than 1, indicating that there is no sequence correlation in the model. It can be known from column (3) of Table 5 that in the GMM model, the regression coefficient of IAT is 0.481 and significant at the 1% level. This result indicates that the positive effect of IAT on LCTA still holds true.

5.3 Identification of causal relationship

Considering that the traditional bidirectional fixed effect evaluation model may have estimation bias and endogeneity problems, terrain undulation degree is selected as the instrumental variable (IV) of this paper (Xu et al., 2025a,b). The influence of terrain on IAT is very significant. The endowment of natural resources directly affects the presentation form of this rural tourism project. The terrain of China is characterized by being higher in the west and lower in the east, distributed in a stepped pattern. The terrain of high mountains and river valleys in the west is particularly common. Due to the limitations of terrain, the development of agriculture and tourism in mountainous and river valley areas often has shortcomings in transportation, land and other aspects, making it difficult to exert the advantages of scale and clustering like in plain areas. Therefore, the process of ITA is mostly slow and difficult. From the perspective of economic benefits, the influence of terrain also has a double-edged sword phenomenon. Landscape scarcity and the development of experience economy projects are important sources of positive revenue. Undulating terrain is prone to form unique visual assets, providing natural conditions for creating distinctive tourism projects and creating core selling points for enhancing the tourism appeal of agricultural landscapes. The slope resources can be developed into experience projects such as hiking, grass sliding and mountain biking, creating secondary consumption scenarios and increasing the per capita consumption of tourists. For example, the photography tourism in the terraced fields of Yuanyang, Yunnan. High-value economic crops can be laid out in steep slope areas. Meanwhile, viewing

platforms can be built by taking advantage of the slope views to achieve land reuse of “agricultural production + landscape consumption”. Its negative impact is reflected in the construction cost and large-scale development. The agricultural mechanization rate in steep slope areas is low and relies on human labor. Fragmented plots of land hinder large-scale agricultural projects and make it difficult to form supply chain advantages. The cost of laying roads and water and electricity pipelines is 30% to 50% higher than that on flat land, and the maintenance cost increases with the slope. Since the terrain undulation is a fixed constant value and does not change over time, it will be eliminated by the mean removal method of TWFE. Therefore, based on the practical methods in the existing literature (Angrist and Krueger, 1991), this study interacts it with the temporal dummy variable to form a new variable.

5.3.1 The traditional instrumental variable method

Under the strict exogenous assumption, the two-stage least squares (2SLS) method is applied to test the causal relationship between IAT and LCTA. The specific test results are shown in column (1) of Table 6. As can be seen, the value of LM statistic is 40.678 and is significant at the 1% level. This indicates that there is no obvious problem of weak instrumental variables in the benchmark regression of this paper. Furthermore, the coefficient value of Wald F statistic is 44.124, which is much greater than the critical value of the 10% significance level. It rejects the null hypothesis that the selected instrumental variable is unrecognizable, proves that the selection of the instrumental variable is scientific and reasonable. It can also be found from column (1) that in the first stage of 2SLS, the regression coefficient of the instrumental variable to IAT is -2.453 and is significant at the 1% level. This result implies that the steep terrain is not conducive to the development of rural tourism projects. The principle of correlation of instrumental variables has been verified. The results in column (2) of Table 5 show that in the second stage of 2SLS, the regression coefficient of IAT is 0.374 and significant at the 5% level. This result is consistent with the result of the benchmark regression, indicating that after eliminating the endogeneity problem, the conclusion that IAT promotes LCTA still holds.

5.3.2 Relax the exogenous constraints of instrumental variables

Although instrumental variables selected from a natural perspective have effectively addressed the issue of endogeneity to a certain extent, complete exogeneity of instrumental variables is merely an ideal state. In recent years, an increasing number of econometricians have begun to relax the model Settings of traditional IV estimation and discuss robust inference methods under approximately exogenous instrumental variables. To address concerns over the exogeneity constraints of instrumental variables, this paper employs plausibly exogenous (PE) estimates to conduct causal inferences again. Conely et al. (2012) proposed that replacing strict exclusivity constraints with instrumental variables would have a certain impact on the explained variables. Therefore, confidence

intervals for regression coefficients were constructed based on the prior information of the parameters to test the robustness of the estimation results when the instrumental variables were not completely exogenous. In this paper, the local to zero (LTZ) is used to test the robustness of the estimation results when the instrumental variables are not completely exogenous. Since it is only weakly endogenous, the deviation of the IV estimator is still smaller than that of OLS, so the IV estimator still has its value. At present, this method has been widely applied in supplementary tests for causal inference (Zheng and Jin, 2024; Liu et al., 2024; Li and He, 2025).

From the results in column (3) of Table 6, the regression coefficient of IAT is 0.572 and is significant at the 5% level. This result implies that, in the case of relaxing the exogeneity assumption of the instrumental variable, in other words, we assume that IV has a slight endogeneity, and the causality of IAT promoting LCTA still holds. This result reinforces the causal relationship obtained by using the 2SLS model.

5.3.3 Heteroskedasticity based instrumental variable

Linear regression models with endogenous variables are typically identified using external information such as exogenous external tools or parameter distribution assumptions. However, at present, some studies have obtained recognition results by taking advantage of the properties of heteroscedasticity without exogenous tools. The Heteroskedasticity based instrumental variables (HBIV) method proposed by Lewbel (2012) is an important innovation in econometrics. It constructs instrumental variables by taking advantage of the heteroskedasticity within the model. It has solved the problem of scarcity of traditional instrumental variables. The advantages of this method are as follows: (1) It does not rely on external instrumental variables. It does not need to search for external instrumental variables but directly generates instrumental variables from heteroscedasticity within the model. (2) Relax the exclusivity constraint requirements. Instrumental variables are constructed from the higher-order moments of endogenous variables, avoiding the direct causal path problem that may exist with external tools. The revolutionary advantage of this method lies in: shifting the source of instrumental variables from “external search” to “internal generation”, which greatly expands the application boundaries of causal inference. At present, a large number of literatures have used this method for causal inference (Zhou and Chen, 2020; Qi and Zhang, 2022; Liu et al., 2024).

The P -value of the Breusch-Pagan test shows that at the 1% level, the null hypothesis that the data have homoscedasticity is strongly rejected, and it is considered that the data in this paper have heteroscedasticity. Therefore, the prerequisite for using HBIV is met. It can be found from the results in column (4) of Table 6 that the regression coefficient of IAT is 0.455 and is significant at the 1% level. This means that the results estimated by using the instrumental variables constructed with the model residuals confirm the causal relationship between the two. This result once again reinforces the reliability of the 2SLS estimation results.

TABLE 6 The result of the endogeneity test.

Variable	2SLS		LTZ	HBIV	DML	
	(1)	(2)	(3)	(4)	(5)	(6)
IAT		0.347** (2.22)	0.572** (2.13)	0.455*** (3.64)	0.328** (1.99)	0.625** (3.57)
IV	−2.453*** (−13.51)					
CV	Yes	Yes	Yes	Yes	Yes	Yes
Individual-fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Time-fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
LM statistics	40.678					
F statistics	44.124					
Breusch-Pagan test				0.001		

*** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

5.3.4 Policy evaluation

The concept of the rural complex originated from the implementation of the “Oriental Village” project in Yangshan Town, Wuxi City in 2012. The aim is to promote agricultural efficiency, increase farmers’ income and rural greening through the integration of rural industries. The rural complex is an important development model that has emerged under China’s rural revitalization strategy in recent years, integrating functions such as modern agriculture, leisure tourism, and rural communities (or rural communities). In June 2017, the Ministry of Finance issued the “Notice on Carrying Out Pilot Policies for Rural Complex Construction”. This document has identified the provinces in China that will implement rural complexes. It also mentioned that local governments need to determine the goals and long-term plans for the pilot areas of the complex based on the “foundation, advantages, characteristics, scale and potential” of villages and industries. The pilot project of rural complex construction aims to encourage local governments to make full use of rural resources and develop diversified industrial projects. By using the fiscal funds of the Ministry of Finance in the form of special funds, encourage relevant units to explore and implement a comprehensive rural development model that combines modern agriculture, leisure tourism and rural communities in accordance with local conditions. It has now become an important measure to promote the high-quality development of rural industries. As the integrated development model of rural areas also emphasizes industrial integration and calls for efficient agricultural production and livable rural living communities. This concept has a high degree of integration with IAT. Therefore, this study takes the policy issued by the Ministry of Finance in 2017 as a quasi-natural experiment and then uses dual machine learning (DML) for estimation. At present, DML has been widely used for causal inference in policy evaluation scenarios (Liu and Wei, 2025; Pan and Hua, 2024).

Columns (5) and (6) in Table 6 respectively report the estimation results of the random forest and the neural network algorithm with a sample segmentation ratio of 1:3. As can be seen from Table 6, the regression coefficients of IAT in the two DML algorithm cases are 0.328 and 0.625 respectively. They are significant at the 5% and 1% levels respectively. This result indicates that the implementation of the rural complex policy has significantly promoted LCTA.

TABLE 7 Result of the mechanism test.

Variable	ASS	LT
	(1)	(2)
IAT	0.571*** (3.29)	0.229** (2.69)
Control variables	Yes	Yes
Individual-fixed effect	Yes	Yes
Time-fixed effect	Yes	Yes

*** and ** respectively indicate significance at the 1% and 5% levels. The t-statistic is reported in parentheses.

6 Mechanism analysis and heterogeneity analysis

6.1 Mechanism analysis

To examine the mediating path of IAT promoting LCTA, combined with research hypotheses 2 and 3, this study once again used the TWFE model to calculate Equation 2.

6.1.1 Analysis of the mechanism of land transfer

It can be known from column (3) of Table 7 that the regression coefficient of IAT is 0.229 and significant at the 5% level. This result implies that IAT has a positive effect on LT. According to the two-stage mediating effect theory, the fact that the result of the second stage is in line with expectations means that IAT will achieve LCTA through the channel of accelerating LT. Research Hypothesis 2 was tested.

The core mechanism by which IAT promotes LT can be summarized as enhancing the marginal revenue of land and reducing the resistance of LT. From the perspective of land revenue, under the traditional small-scale farming operation model, the marginal revenue of land decreases, the transfer rent is lower than the non-agricultural opportunity cost, and farmers are reluctant to pay rent. With the assistance of IAT, the tourism function endows agricultural land with landscape value and experience value, and the revenue per unit area has expanded from a single agricultural product output to a compound revenue of “agricultural products +

services". For instance, the ticket revenue of the picking garden is 3 to 5 times that of the planting income. This will increase the value of the land. In a typical case in China, after developing a tea and tourism complex through land transfer in Ji'an County, Zhejiang Province, the land rent rose from 800 yuan per mu for pure planting to 3,000 yuan per mu. Therefore, IAT endows agricultural land with more economic value and will attract farmers' willingness to increase LT (Wang M. et al., 2024). From the perspective of rural tourism project development, IAT (such as homestay clusters and main farms) require contiguous land, and this practical demand forces the integration and transfer of scattered plots. The high returns of emerging tourism projects have driven agricultural and tourism enterprises, cooperatives, and urban capital to replace traditional farmers as tenants with a high willingness to pay. High-price acquisitions will prevent the existing land from being sold on the market, thereby reducing transaction costs and frictions, and most importantly, accelerating the process of LT. IAT also allows farmers to invest their assets as shares and enjoy dividend income from profits. For farmers, developing an IAT in rural areas increases their opportunities to seek non-agricultural jobs. For instance, farmers can work as service staff or tour guides in tourism projects, achieving employment that leaves the land but not their hometowns. As a result, the risk of unemployment decreases after the transfer. Meanwhile, some contracts stipulate that farmers contribute their land as shares to receive dividends and share the value-added benefits of tourism. Driven by multiple benefits, farmers are more willing to transfer their land.

6.1.2 Analysis of the mechanism of agricultural socialized services

It can be known from column (1) of Table 7 that the regression coefficient of IAT is 0.571 and is significant at the 1% level. This result implies that IAT will promote the development of ASS. According to the two-stage mediating effect theory, the significant regularity of the IAT result indicates that IAT can achieve LCTA by promoting the development of ASS. Research Hypothesis 3 was tested.

From the perspective of agricultural economics, the core mechanism by which IAT promotes the development of ASS can be summarized as: reshaping the demand structure and reconstructing the industrial organizational relationship. Generally speaking, the demand for third-party services in traditional agriculture includes the cultivation and harvesting of agricultural machinery, the sale of agricultural products, and the control of pests and diseases. From the perspective of agricultural production, the application of IAT means that a large number of rural residents flock to rural tourism projects to achieve non-agricultural employment. The reduction of human labor force has prompted large-scale agricultural machinery to be outsourced to third-party services. Therefore, the rapid development of ASS has been positively influenced by IAT. From the perspective of requirements, IAT has put forward more complex requirements for ASS. Under the development of IAT, market entities have increased new demands for landscape-based planting design, the development of interactive experience courses for tourists, and the creation of agricultural tourism brand Internet protocol (IP). This new demand has

promoted new types of socialized services such as agronomic landscape planning services and rural brand marketing services. This change has made the division of labor in the agricultural sector more explicit. Specialized social services have enhanced agricultural production efficiency and economic value. From the perspective of enterprise organizational relationships, the main characteristics of the demand for ASS in traditional agricultural applications are short-term service outsourcing and single-operation billing. However, the impact of IAT on ASS is manifested as long-term service equity investment sharing and full industrial chain service package payment. This service model and profit-sharing model help to reduce costs and achieve economies of scope. Therefore, IAT provides a market environment for the further development of ASS.

6.2 Heterogeneity analysis

To further clarify the impact of IAT on the LCTA, the heterogeneous effects of regression in different regions and quantiles were explored. This not only enriches the understanding of the IAT, but also provides a more refined perspective for the formulation of agricultural environmental policies and agricultural development policies in the future.

6.2.1 Geographical regional heterogeneity

Due to the differences in resource endowments and economic development stages among different regions in China, the mechanism of IAT on agricultural carbon emissions may show significant geographical heterogeneity (Chen et al., 2023). For this purpose, in this study, the samples were divided into three major regions: the east, the middle, and the west for group regression.

It can be known from the results of columns (1) to (3) in Table 8 that the regression coefficients of IAT on LCTA are 0.261, 0.053 and 0.146 respectively, and are significant at the 5%, 10% and 1% levels respectively. By comparing the magnitudes of the regression coefficients in the three regions, it can be known that the positive effect of IAT is the strongest in the eastern region, followed by the western region, and finally the central region. The reason for this result might be that the developed eastern regions have accelerated the transformation and upgrading of traditional agriculture to ecological service industries through IAT. The terrain in the eastern region is flatter, and the rainfall and climate are also suitable for agricultural production. The eastern region is also a densely populated area in China and has an exceptionally developed economy. This natural geographical location is conducive to the large-scale development of modern agriculture and promotes the development and growth of rural tourism. The developed economy has placed digital technology innovation in the eastern region at the forefront. Relevant enterprises utilize digital technologies to optimize agricultural production processes. Relying on the geographical advantage of being close to the suburbs, they better develop low-carbon leisure agriculture and achieve LCTA. Furthermore, as the clean energy and digital infrastructure in the eastern region are more developed than those in other regions, it is more capable of providing technical

TABLE 8 Result of regional heterogeneity.

Variable	Eastern	Central	Western
	(1)	(2)	(3)
IAT	0.261** (2.47)	0.093* (1.67)	0.146*** (3.17)
Control variable	Yes	Yes	Yes
Individual-fixed effect	Yes	Yes	Yes
Time-fixed effect	Yes	Yes	Yes

***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. The t-statistic is reported in parentheses.

support for green agricultural production methods, thereby further reducing the generation of agricultural carbon emissions. Although the IAT in the central region has a positive effect on LCTA, the effect is low and the significance is only 10%. This result implies that rural tourism resources in the central region are scarce, the development of IAT is relatively slow, and its impact on agricultural carbon emission reduction is weak. Although the utilization efficiency of some resources has been improved through industrial integration, the mechanism for the coordinated development of agricultural modernization and tourism has not yet been fully established. The insufficient depth of research and application of green and low-carbon agricultural technologies has led to the failure to fully unleash the green emission reduction effects of agriculture. Furthermore, the functional positioning of the central region as a major grain-producing area makes it face more constraints in the process of balancing food security and industrial transformation. It is notable that the IAT in the western region has a significant promoting effect on LCTA, and the influence coefficient is significantly positive at the 1% level. It means that the development of IAT in the western region is beneficial to LCTA. From the perspective of natural conditions, the western region of China has a large number of high mountains, rivers and plateaus, and natural conditions have a significant impact on economic development. The cultural resources in the western region are also exceptionally rich, as it is home to the largest number of ethnic minorities in China. Therefore, the western region has significant advantages in developing IAT.

6.2.2 Nonlinear analysis

The advantage of quantile regression lies in its ability to capture the structural differences of the ACEI conditional distribution by selecting the quantiles of different conditional distributions, reveal the heterogeneous influence of independent variables on dependent variables, especially focusing on extreme values, and thereby capture the potential nonlinear relationships among variables (Li et al., 2023; Koenker and Hallock, 2001; Che et al., 2023). To this end, this study selected four quantiles of 10%, 25%, 50%, 75%, and 90% to explore the dynamic characteristics of the intensity of the effect of IAT on ACE at different emission levels. To test the nonlinear relationship between IAT and LCTA, this study used the panel quantile model for calculation.

The results of the five regression junctions in Table 9 show that the positive impact of IAT on LCTA has always been valid. However, the role of IAT also shows heterogeneity. Its role in Q10 and Q25 is greater than that in Q50. Furthermore, the role played by IAT continues to increase after exceeding the 50% quantile. At Q75 and Q90, the regression coefficients of IAT were 0.303 and 0.402 respectively. This result implies that IAT plays a more positive role in provinces with a higher level of LCTA. Overall, the positive effect of IAT on LCTA shows an N-shaped evolution trend of first increasing, then decreasing and then increasing again. This nonlinear variation result indicates that the carbon reduction effect of IAT is closely related to the ACE between regions and the green production efficiency of agriculture (Yang and Wang, 2020). The agricultural ecological foundation in areas with low emissions is relatively good. IAT is more likely to optimize the production mode through the technology spillover effect. For instance, the combination of low-carbon tourism projects and precision agriculture can rapidly reduce marginal carbon emissions. In areas with medium emissions, large-scale agriculture coexists with tourism as the dominant sector. Improper allocation of resources leads to insufficient release of emission reduction potential. In high-emission regions, due to the high carbon lock-in effect, the role played by IAT in carbon reduction is weaker than that in low-emission regions.

7 Conclusions and policy recommendations

7.1 Conclusion and discussion

Based on the panel data of 30 provinces in China from 2010 to 2022, this study employed TWFE and a two-stage mediating effect model to verify the impact and mechanism of IAT on LCTA. The main conclusions of this study are:

- (1) IAT has a strong positive effect on LCTA. This conclusion still holds true after conducting robustness tests using multiple methods and eliminating endogeneity problems by applying the 2SLS model. This conclusion is consistent with the results of the existing literature (Wang et al., 2024c). This indicates that IAT promotes the transformation and upgrading of traditional agriculture to low-carbon service-oriented agriculture by reconfiguring factor allocation and upgrading business forms, providing a path reference for agricultural emission reduction in developing countries. It is particularly necessary to note that in order to strengthen the causal relationship between IAT and LCTA, this study also used 2SLS, approximate exogenous instrumental variables, heteroscedas-based instrumental variables, and policy evaluation for verification. In the policy assessment, we mainly employed dual machine learning. These results confirmed their causal relationship.
- (2) The results of the mechanism analysis show that LT and ASS are important mechanism paths for IAT to promote LCTA. This conclusion is consistent with the results of the existing literature (Yang et al., 2024) LT has promoted the

TABLE 9 The result of quantile regression.

Variable	Q10	Q25	Q50	Q75	Q90
	(1)	(2)	(3)	(4)	(5)
IAT	0.255*** (2.64)	0.289* (1.74)	0.253** (2.25)	0.303** (2.34)	0.402*** (3.78)
Control variable	Yes	Yes	Yes	Yes	Yes
Individual-fixed effect	Yes	Yes	Yes	Yes	Yes
Time-fixed effect	Yes	Yes	Yes	Yes	Yes

***, **, and * respectively indicate significance at the 1%, 5%, and 10% levels. The t-statistic is reported in parentheses.

determination of agricultural property rights and the large-scale development of production methods, and is conducive to the rise and development of modern agricultural production models. This change will significantly reduce high energy-consuming production factors and inputs as well as resource waste. Through land integration and precise management, the intensification of agricultural production has enhanced the efficiency of agricultural resource utilization. By embedding green technologies in the production process, it has reduced reliance on agricultural chemical pollutants and formed a low-carbon path of large-scale operation. Furthermore, LT has also promoted the adoption of low-carbon agricultural technologies. The development of ASS has promoted the specialization of agricultural production. This transformation has enhanced agricultural production efficiency and reduced the repeated purchase of agricultural machinery.

- (3) The results of the regional heterogeneity analysis indicate that the positive impact of IAT on LCTA is the strongest in the eastern region, followed by the western region, and finally the central region. The results calculated by the panel quantile model show that the influence of IAT on LCTA is nonlinear. It plays the most positive role in provinces with lower agricultural carbon emissions, corresponding to the two quantiles Q75 and Q90. It can also play a good and positive role in regions with a relatively low degree of LCTA, corresponding to the two quantiles Q10 and Q25. However, the positive role it can play at Q50 is limited. Overall, the influence of IAT on LCTA shows an N-shaped evolution trend.

By analyzing the impact and mechanism path of IAT on agricultural carbon reduction, the conclusions drawn in this article have significant practical significance for addressing climate change. Agriculture is not only a significant source of global greenhouse gas emissions but also a huge carbon sink system. The practical significance of this research lies in the discovery that the integrated development of agriculture and tourism plays a significant role in mitigating carbon reduction in the agricultural sector. It reveals that developing tourism in rural areas to enhance production efficiency and the value chain of agricultural products can effectively reduce greenhouse gas emissions from the production sector. Meanwhile, this study holds that labor division and large-scale production are important channels for reducing carbon emissions in the agricultural sector. However, the positive effects brought by these two factors can be achieved through the development of rural tourism projects. Through

this research, agricultural management departments, agricultural-related enterprises and farmers can gain management insights for balancing economic effects and environmental protection. The theoretical contribution of this research lies in that it has constructed a theoretical framework for the influence of IAT on LCTA. It reveals why ITA can reduce agricultural carbon emissions by establishing an analytical framework for land transfer and agricultural socialized services. This study also employed a quantile model to verify their nonlinear relationship. To some extent, it confirms the applicability of the environmental Kuznets curve in the greenhouse gas and control sectors.

7.2 Policy recommendations

To fully unleash the ecological benefits brought by industrial integration to agricultural carbon reduction, combined with the research results, the following management implications can be obtained:

(1) Strengthen regional differentiated infrastructure and collaborative models. Based on regional heterogeneity conclusions, eastern regions should leverage digital technology advantages to establish a collaborative development platform for “low-carbon agriculture + eco-tourism,” prioritizing the construction of an agricultural-tourism carbon accounting system covering the entire industrial chain. Carbon emission intensity indicators should be integrated into the rating system for demonstration parks, such as embedding carbon footprint tracking modules in smart greenhouses and homestay clusters. Central and western regions need to prioritize pilot agri-tourism integration projects in low-emission zones like ecological protection areas, strictly controlling the scale and energy consumption standards of tourism facilities to avoid farmland encroachment and ecological disturbances caused by overdevelopment. For example, lightweight ecological research programs should be promoted in karst landform regions to replace traditional energy-intensive agritainment models, mitigating carbon emission rebound effects in western regions.

(2) Deepen the Construction of Intermediary Mechanisms for Intensification Pathways. In response to the mediating effects of LT and ASS, special funds should be established to support large-scale application of green technologies such as precision fertilization and waste recycling systems. For instance, targeted subsidies from agri-tourism integration project funds could be

allocated for smart irrigation equipment procurement to reduce fertilizer use per unit output. Meanwhile, agri-tourism skill training centers should be established at the county level, incorporating mandatory courses on digital agricultural management and low-carbon tourism services to enhance labor force adaptability in ecological cultivation and green service domains. Virtual reality technology could simulate precision fertilization operations to strengthen technical proficiency among practitioners.

(3) Implement a tiered carbon emission intensity access system. Based on quantile regression results, a three-tier carbon emission intensity access standard should be established: low-emission zones may develop comprehensive tourism reception facilities but must construct biogas power generation and other circular systems; moderate-emission zones should be limited to light industries like eco-tourism, with mandatory implementation of cultivated land requisition-compensation balance and carbon sequestration compensation; high-emission zones, such as resource-based western provinces, should only permit scientific research and monitoring projects, with dynamic assessment mechanisms for ecological restoration and carbon emission offsets.

7.3 Future expectations

Future research can be deepened and expanded from the following two dimensions: (1) refine the observation scale and data dimensions. This study uses provincial panel data to reveal the macro impact of the integration of agriculture and tourism on ACEI, but the micro transmission mechanism still needs to be analyzed in depth. Subsequently, business data at the county and enterprise levels can be collected. By combining the scale of land transfer, the skills of the labor force, and the differences in the integration models of different business entities, the micro-path of the emission reduction effect of the integration of agriculture and tourism can be revealed. (2) Strengthen the research on the dynamic coupling between the policy environment and multiple factors. Further construct a dynamic system model including climate conditions, technological progress, and labor force structure, especially the nonlinear matching relationship between technology diffusion and the behavior of the main body. To further reveal the long-term mechanism and spatio-temporal heterogeneity characteristics of the integration of agriculture and tourism on ACEI, and to provide more precise theoretical support for improving the governance system of the integration of agriculture and tourism. (3) Although this study utilized the two-stage least square method to eliminate the endogeneity of the model, TWFE is not the mainstream method for causal identification. The research methods and results of this paper have certain limitations. In future research, the authors suggest conducting policy evaluation using the DID method based on the pilot policy of rural complex issued by the Ministry of Finance of China. This method can not only eliminate the

endogeneity of the model, but also alleviate the defects of the ATI evaluation system.

Data availability statement

Publicly available datasets were analyzed in this study. This data can be found here: The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

Author contributions

HW: Conceptualization, Investigation, Funding acquisition, Writing – original draft, Formal analysis, Data curation. DP: Visualization, Data curation, Resources, Validation, Writing – review & editing, Software, Methodology, Investigation.

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