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Impact mechanisms and pathways of agricultural socialized services on agricultural green production in China under its dual-carbon goals

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KEYWORDS

Agricultural green production, agricultural green total factor productivity, agricultural socialized services, dual-carbon goals

HIGHLIGHTS

- Validates a positive effect of agricultural socialized services on household-level green production.
- Identifies resource endowment as a positive moderator and reveals non-linear threshold effects in service provision.
- Uncovers dual heterogeneity in impacts across regions and farm scales.
- Proposes a three-pillar policy framework integrating endowment empowerment, differentiated strategies and multiactor carbon governance.

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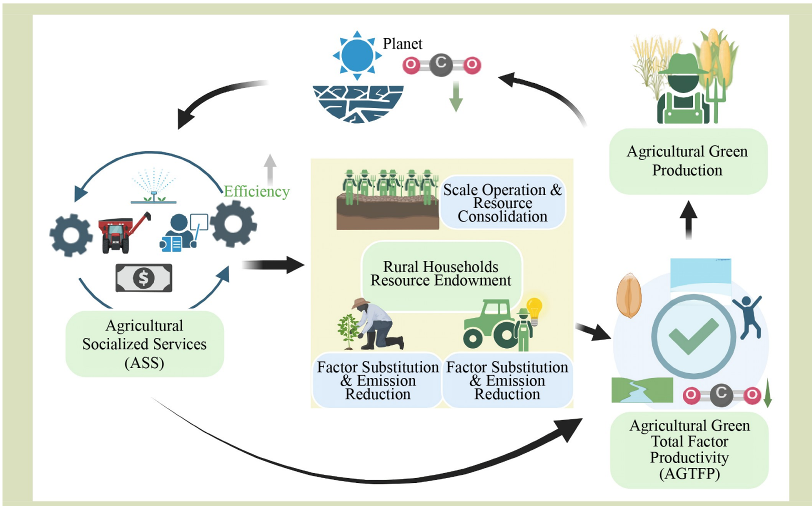
GRAPHICAL ABSTRACT



ABSTRACT

Agricultural socialized services (ASS) are essential for connecting smallholders with modern agriculture, enhancing agriculture productivity and driving sustainable green production. Therefore, these services constitute a fundamental pillar of contemporary agricultural frameworks. This study empirically analyzed how ASS drive agricultural green production under China's dual-carbon goals (carbon peaking and carbon neutrality) using an extended regression model with micro-macro panel data. This empirical analysis provided four key findings: (1) ASS exert a positive effect on agricultural green production on the household level; (2) rural household resource endowments serves as a positive moderator of this relationship; (3) ASS exert non-linear impacts on agricultural green production, with distinct threshold effects observed at critical service provision levels and (4) ASS exhibit dual heterogeneity-regional disparities and scale-dependent responsiveness. These findings highlight the dual environmental-rural development benefits of the services, prompting the three-pillar policy framework: (1) farmer endowment empowerment policy system establishment, (2) adoption of endowment-sensitive differentiation strategy, and (3) multi-actor carbon governance. This study contributes to sustainable agriculture theory while offering actionable strategies to advance green agricultural development and enhance the integration of agricultural socialization services with smallholder operations.

1 Introduction

As the world's largest carbon emitter since 2006[1], China faces significant climate challenges, with its CO_2 emissions reaching 12.6 Gt in 2023, a 4.7% annual increase driven primarily by a 5.2% surge in energy combustion emissions. Confronting both global climate pressures and domestic development needs, the Chinese Government has formulated the strategic dual-carbon goals of achieving carbon peaking by 2030 and carbon neutrality by 2060. These ambitious targets represent China's commitment to transitioning toward green, low-carbon development while addressing its substantial carbon footprint, particularly from the energy sector which remains the primary driver of emission growth. This dual-carbon strategy not only responds to global climate imperatives but also aligns with China's long-term sustainable development objectives, requiring comprehensive transformations across all economic sectors.

As its second-largest carbon emission source, the agricultural sector contributes approximately 25% of China's total greenhouse gas output[2], making its decarbonization essential for achieving both green agricultural production and China's dual-carbon targets[3]. Current mitigation strategies encompass four key dimensions: (1) technological innovations in precision agriculture and green production[4,5]; (2) structural optimization through land consolidation and sustainable cropping systems[6,7]; (3) policy instruments including environmental taxation and cooperative development[8,9]; and (4) input management through fertilizer optimization and service adoption[4,10].

Of these approaches, agricultural socialized services (ASS) represent a comprehensive value-chain approach that spans from pre-production planning to postharvest management[11]. These services simultaneously enhance productivity through resource integration[12] and promote sustainability via precision input management, effectively addressing the historical trade-off between agricultural output and environmental protection. Their demonstrated success in overcoming adoption barriers has elevated ASS to a cornerstone of China's green agricultural strategy, with the government actively promoting their implementation as a key policy instrument for low-carbon transition.

Operationalized through a tripartite network of agribusinesses, cooperatives and village collectives, ASS leverage institutional strengths to overcome three fundamental constraints: financial limitations, cost barriers and technical knowledge gaps[13,14]. By providing professional expertise, economies of scale and market linkages, these services have successfully mitigated the risk-triad that has hindered sustainable practice adoption among smallholders. This institutional innovation not only accelerates the adoption of green technologies but also maintains the viability of family farming, offering a distinctive Chinese model for sustainable agricultural intensification that balances productivity growth with ecological stewardship.

Current scholarship has established that ASS have a dual role in promoting sustainable farming practices and regulating chemical inputs. Empirical studies demonstrate that these services significantly enhance farmer willingness to adopt green production methods[15], foster pro-environmental behaviors[16,17] and contribute to lower agricultural carbon emissions[18,19], thereby facilitating a shift toward sustainable agriculture[20]. However, the empirical record reveals notable contradictions regarding fertilizer use mitigation, with studies reporting: (1) crop-specific reductions of 0.055%–0.443% per service expenditure unit[21]; (2) only reduced application disparities without aggregate decreases[22]; and (3) limited effectiveness for part-time farmers[23].

While ASS have received increasing scholarly attention, three critical research gaps persist in understanding their role in agricultural green production. First, the current literature remains predominantly theoretical, lacking robust empirical validation of service impacts. Second, researchers have yet to systematically examine the underlying mechanisms through which these services facilitate green production transitions. Third, important contextual factors including threshold effects and regional heterogeneity remain largely unexplored. This study addressed these limitations through four key methodological innovations: (1) longitudinal panel data analysis to strengthen empirical validity, (2) application of the slack-based measure global Malmquist-Luenberger (SBM-GML) index for precise household-level green performance measurement, (3) comprehensive assessment of rural household resource endowments using entropy weight method, and (4) systematic investigation of mechanism of ASS impact including the moderating role of resource endowments, non-linear threshold effects of ASS on green production, and regional heterogeneity and households operational scale heterogeneity in service impacts. The resulting framework advances both theoretical knowledge of agricultural service systems and provides actionable policy insights for optimizing service delivery under China's dual-carbon strategy, effectively bridging the research-practice divide in sustainable agricultural transformation. The research framework and core mechanisms proposed in this study are given in Fig. 1. This framework provides a systematic elaboration of the theoretical pathways and empirical logic governing how ASS affect agricultural green production under China's dual-carbon goals.

2 Theoretical analysis and research hypothesis

2.1 Agricultural socialized services and agricultural green production

The theoretical foundations of scale economy, classical specialization and induced technological innovation collectively provide a comprehensive framework for understanding how ASS drive the green transformation of agriculture. Initially, scale economy theory elucidates the dual synergistic pathways through which these services enhance agricultural productivity: by addressing factor constraints in land transfer markets, they consolidate fragmented land parcels, facilitating more efficient resource management and reducing chemical input reliance[24]; and by leveraging service-scale externalities, they dismantle barriers to green technology adoption through procurement economies of scale for ecofriendly inputs[25], enhancing collective bargaining power to drive down unit costs[26] and minimizing information search costs for sustainable practice dissemination. These innovations overcome the limitations of household farming models, reconfiguring China's smallholder production systems and yielding substantial improvements in agricultural green total factor productivity (AGTFP).

Drawing on established specialization theory[27] and contemporary empirical evidence[28], ASS further enhance production efficiency through complementary specialization pathways: horizontal specialization enables land consolidation and rural household resource endowment accumulation for green technology adoption, while vertical specialization facilitates production segment outsourcing via knowledge spillovers and risk sharing. This institutional arrangement optimizes resource allocation via comparative advantage, effectively overcoming smallholder scale constraints and generating dual benefits of improved technical efficiency and reduced environmental externalities, thereby elevating AGTFP.

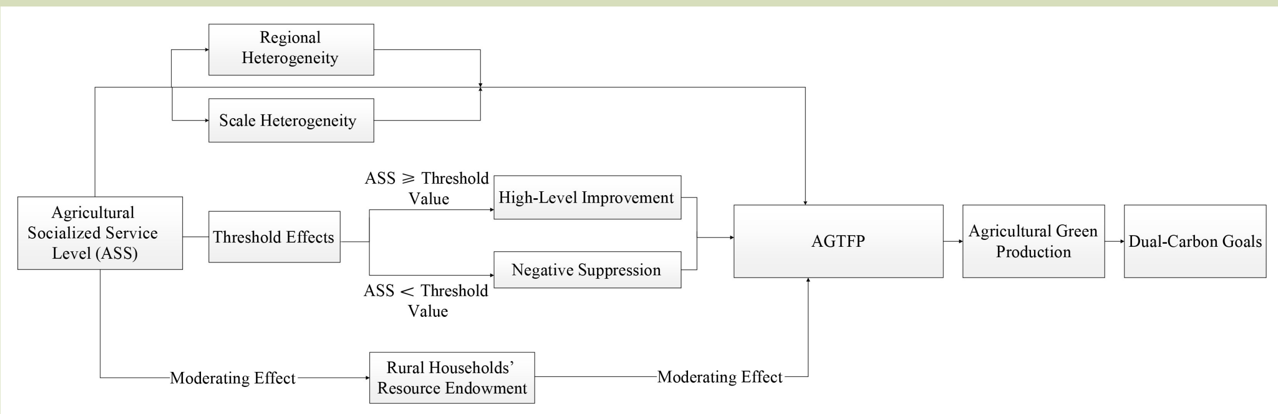


Fig. 1 Research framework and core mechanistic pathways.

The theory of induced technological innovation posits that ASS act as institutional platforms lowering sustainable technology adoption barriers through two synergistic mechanisms: input substitution via green alternatives (e.g., organic fertilizers and biopesticides) decoupling production from pollution[29] and knowledge intermediation bridging smallholder capacity gaps through specialized service provision[30]. By externalizing technological complexity to professional providers, this arrangement creates an evolutionary pathway for sustainable intensification, achieving immediate environmental gains through cleaner inputs while building long-term adaptive capacity for continuous green technology upgrading in smallholder systems.

Finally, empirical evidence has revealed significant spatial dependence in ASS, generating productivity spillovers through macro-level knowledge diffusion via interregional service clusters enhancing AGTFP through technology transfer and demonstration effects[31,32] and micro-level network externalities where localized adoption patterns create spatial autocorrelation in sustainable practice implementation[33]. The mobility of these knowledge-intensive services facilitates cross-boundary technological spillovers through mechanized operations and digital extension systems[34], transforming geographic proximity into a determinant of regional green development trajectories. Collectively, these theories and empirical findings underscore the pivotal role of ASS in propelling the green transformation of agriculture.

Based on an integrated analytical framework, this study proposed that:

Hypothesis 1: *Agricultural socialized services demonstrate a statistically significant and positive impact on the progression of agricultural green production.*

2.2 Moderating effect of rural household resource endowments

Building on the Hayami-Ruttan induced innovation theory[35] that identifies labor-saving mechanization and land-saving biochemical technological progress as two core pathways of agricultural technological evolution, this study extended this theoretical framework to the field of sustainable agriculture, with a particular focus on the intrinsic dynamics of agricultural green transformation. The core proposition of the theory is that regional heterogeneity in resource endowments induces differentiated technological innovation directions and development trajectories by influencing relative price signals, a claim that has been extensively and empirically supported through comparative studies of agricultural modernization initially in the USA[36] and later Japan[37].

In this paper, it is argued that the same logic of factor-induced innovation applies to the transition toward green production practices. Specifically, variations in environmental constraints, resource availability and green policy incentives across regions can be viewed as shifts in the implicit *price* of ecological factors, thereby inducing distinct green innovation responses. For example, regions facing severe environmental pressures or stringent regulation may be more inclined to adopt pollution-reducing and resource-conserving technologies, whereas areas with abundant ecological endowments might prioritize productivity, enhancing low-impact innovations.

Applying this theory to the context of China's agricultural green production, three key mechanisms were identified: (1) eco-innovation is not exogenously given but endogenously emerges from the dynamic interaction between regional resource conditions and innovation capacity; (2) spatial variation in factor proportions significantly shapes regional willingness and patterns to adopt sustainable technologies, resulting in a regional-factor adaptive characteristic of technological pathways; and (3) heterogeneity in household-level endowments not only positively moderates the effectiveness of ASS but also acts as a micro-level driver of environmentally friendly technological change. Based on these theoretical deductions and empirical insights, the following hypothesis was proposed:

Hypothesis 2: *The resource endowments of rural households exerts a significant positive moderating effect on the pathway through which agricultural socialized services drive agricultural green production.*

2.3 Threshold effects of agricultural socialized services on agricultural green total factor productivity

ASS represent an emerging production factor integrated into agricultural systems, strategically bridging smallholders and modern agricultural development. The efficacy of this integration, however, is fundamentally contingent on farmer cognitive reception and behavioral adoption of such services.

Structural disparities in resource endowments generate significant heterogeneity among farmers in terms of production goal formulation and factor allocation capacity. This heterogeneity manifests through three distinct mechanisms: graded variations in farmer ability to decode information about green agricultural technologies; stratified risk preferences and utility evaluations in technology adoption decisions; and differential patterns in the emulation of production management practices. These divergences ultimately materialize in two forms: persistent adherence to standard farming methods among some farmers, versus deep integration of innovative technologies among others, resulting in systematic differences in green technology efficiency across farmer groups.

Agricultural production activities are a profoundly coupled with natural factor endowments such as topography, landforms and plot size. When farmers possess relatively abundant factor endowments, particularly when managing large-scale, contiguous and flat farmland, they create uniquely favorable conditions for the efficient application of agricultural mechanization; scaled operations significantly reduce the frequency of machinery transfers per unit area, while regular plots effectively enhance the operational stability and working accuracy of agricultural machinery, thereby optimizing the operational efficiency and quality output of machinery services as a whole. In contrast, resource-constrained farmers managing small, fragmented plots face compounded techno-economic constraints during service implementation. Field fragmentation necessitates frequent equipment repositioning and idle running, accelerating fuel consumption and mechanical wear while creating extensive service gaps that diminish operational coverage. Also, dispersed plot configurations substantially increase labor inputs[38] through extended operational routes and repeated field-edge processing. These location-driven production costs collectively form significant barriers to service adoption, ultimately impeding improvements in green technology efficiency through elevated implementation costs and reduced service availability.

This study demonstrates that the effectiveness of ASS follow a non-linear pattern, substantially mediated by the inherent endowment characteristics of farmers. Accordingly, the following hypothesis was proposed:

Hypothesis 3: *Agricultural socialized services demonstrate threshold effects on promoting agricultural green production*

3 Data and variables

3.1 Data source

This study used two complementary data sources to ensure comprehensive analysis. The China Family Panel Studies (CFPS) provides nationally representative micro-level data. This dataset offers detailed socioeconomic and production characteristics at the household level, with its extensive geographical coverage guaranteeing robust representativeness. Based on the consistency of core variable expressions, 7794 agricultural households engaged in farming activities during all five survey years (2014, 2016, 2018, 2020 and 2022) were selected. This sample covered 24 provinces (autonomous regions/municipalities), excluding Beijing, Hainan, Hong Kong, Inner Mongolia, Macao, Ningxia, Qinghai, Xizang and Xinjiang. A total of 127 county-level administrative units were represented, ensuring strong geographical and demographic representativeness (attrition data are given in Table S1). For macro-level environmental context, the authoritative China Statistical Yearbook on Environment, jointly published by the National Bureau of Statistics and Ministry of Ecology and Environment, was used. The systematic framework of the yearbook includes: (1) environmental quality indicators (air, soil and water); (2) pollutant emission sources (agricultural, domestic and industrial); (3) ecological conservation measures; and (4) environmental governance strategies. This dual-data approach facilitated a thorough multiscale analysis bridging household-level agricultural practices with regional environmental dynamics.

3.2 Variable descriptions

3.2.1 Dependent variable

AGTFP was used as a metric for assessing agricultural green production. As a multidimensional performance metric, AGTFP serves as a powerful analytical tool for sustainable agriculture research, simultaneously fulfilling three critical functions: (1) precise quantification of input utilization efficiency, (2) holistic evaluation of green production performance, and (3) objective benchmarking of agricultural modernization trajectories[39]. The academic measurement of AGTFP has undergone significant methodological evolution, progressing through three principal analytical frameworks: data envelopment analysis (DEA), the Malmquist-Luenberger index and its sophisticated successor, the SBM-GML index. The SBM-GML approach constitutes a substantial methodological breakthrough by effectively overcoming two persistent limitations of standard productivity measurement: integrating slack variables to comprehensively account for input-output inefficiencies and eliminating directional bias in productivity estimation.

Recent productivity research has predominantly focused on the enterprise level, often relying on intermediate inputs as instrumental variables to address endogeneity and selection bias. In contrast, methodologies for analyzing rural household productivity has remained underdeveloped, typically limited to standard approaches including Olley-Pakes, Levinsohn-Petrin and basic DEA[40] This study advances the field by using a nationally representative sample from the CFPS to measure AGTFP at the household level. The analytical complexity of integrating multiple inputs with both desirable and undesirable outputs necessitates an innovative non-parametric framework, moving beyond the constraints of established production functions.

Contemporary productivity research predominantly focuses on enterprise-level studies, using intermediate inputs as instrumental variables to address endogeneity and sample selection bias, whereas rural household productivity analysis remains methodologically underdeveloped being largely confined to standard approaches such as Olley-Pakes, Levinsohn-Petrin and basic DEA. To bridge this gap, this study develops an innovative measurement framework for AGTFP using nationally representative household-level data from the CFPS. By integrating multiple inputs with both desirable and undesirable outputs within an enhanced DEA framework and incorporating a technically refined Malmquist-Luenberger index[41], the approach used in this study overcame the limitations of established parametric production functions and significantly improved the characterization of undesirable outputs, thereby offering a more robust methodological foundation for micro-level analysis of agricultural green productivity (Table S2). Details of calculating AGTFP using the Malmquist-Luenberger index are provided in supplementary materials.

3.2.2 Core explanatory variable

This study developed a novel input-output dimensional outsourcing framework to systematically evaluate ASS, with particular focus on assessing service responsiveness and quantifying household-level service provision. Based on the data structure of the CFPS, this study focused on two empirically measurable dimensions of agricultural outsourcing services: hired labor and machinery rental. These production phase services constitute the most critical and concentrated segment of the agricultural social service system, representing the area of highest demand among rural households compared to pre- or post-production alternatives. Methodologically, ASS were quantified using two continuous variables: expenditures on hired labor and agricultural machinery rentals. These two expenditure measures are subsequently integrated through the entropy method to construct a composite index reflecting the overall level of service provision.

3.2.3 Moderating variable

Drawing on established scientific principles and building on the methodological framework of Cheng et al.[38], this study constructed a robust multidimensional evaluation framework using the entropy weighting method to quantify and analyze rural household resource endowments. The analytical framework comprises five distinct dimensions: (1) natural endowment, (2) economic endowment, (3) human capital endowment, (4) physical capital endowment, and (5) social endowment, operationalized via 21 empirically validated indicators (Table 1).

The main analytical steps for measuring rural household resource endowments using the entropy weighing method were:

Data standardization - normalize raw indicators to [0,1] range as:

$$Z_{ij} = \frac{X_{ij} - X^{j}_{min}}{X^{j}_{max} - X^{j}_{min}}\ (i = 1,2,\ldots,n;\ j = 1,2,\ldots,m) \tag{1}$$

$$Z_{ij} = \frac{X^{j}_{max} - X_{ij}}{X^{j}_{max} - X^{j}_{min}}\ (i = 1,2,\ldots,n;\ j = 1,2,\ldots,m) \tag{2}$$

where, Z_{ij} is the standardized value of the original indicator data, X_{ij} is the raw data value for the j-th indicator across 7794 rural households. X^{j}_{max} and X^{j}_{min} are the maximum and minimum values, respectively, for the j-th indicator among all 7794 rural households.

Proportion calculation - compute the proportion for each observation as:

Table 1 Variable definitions and coding for rural household resource endowments

Dimension	Variable indicator	Operational definition and coding	Attribute
Natural endowment	Settlement type	Plain/grassland = 2, hilly/mountainous = 1, others = 0	+
	Land expropriation	Whether experienced land expropriation: yes = 1, no = 0	+
	Waste disposal	Public trash bins/special collection = 1, others = 0	+
	Local transportation cost (yuan)	Monthly expenses including public transit, car and motorcycle fuel	+
Economic endowment	Non-mortgage debt (yuan)	Outstanding non-housing bank loans	–
	Cash and deposits (yuan)	Total liquid assets of household members	+
	Business income	Net profit from self-employment in past 12 months (CFPS): yes = 1, others = 0	+
	Commercial insurance	Commercial insurance expenditure: yes = 1, others = 0	+
Human capital endowment	Female ratio (%)	Proportion of female household members	–
	Average education	Average years of schooling in household	+
	Elderly count (⩾65 years)	Number of elderly members (CFPS-derived)	–
	Medical expenses (yuan)	Healthcare spending in past 12 months: yes = 1, others = 0	–
	Book collection (vol.)	Number of owned books (excluding periodicals/e-books)	+
Physical capital endowment	Productive assets (yuan)	Value of productive equipment/facilities with >12 month lifespan (CFPS)	+
	Real estate value (yuan)	Total market value of all owned properties	+
	Vehicle ownership	Owns automobile: yes = 1, no = 0 (CFPS-derived)	+
	Durable goods value (yuan)	Total value of appliances, electronics, vehicles, etc.	+
Social endowment	Social support	Donations to relatives/others: yes = 1, no = 0	+
	Gift expenditures (yuan)	Monetary/real gift expenses in the previous 12 months	+
	Happiness score	Self-rated happiness (0 = worst, 10 = best)	+
	Genealogy record	Has family genealogy (2010 data): yes = 1, no = 0	+

$$p_{ij} = \frac{Z_{ij}}{\sum_{i=1}^{7794} Z_{ij}} \quad (3)$$

Entropy value determination - calculate entropy for each indicator as:

$$e_j = -k \sum_{i=1}^{7794} p_{ij} \ln(p_{ij}), k = \frac{1}{\ln(7794)} \quad (4)$$

Redundancy degree calculation - calculate the redundancy degree (i.e., divergence coefficient) of the information entropy of each indicator as:

$$d_j = 1 - e_j \ (j = 1, 2 \ldots\ldots m) \quad (5)$$

Weight assignment - derive objective weights as:

$$w_j = \frac{1 - e_j}{\sum_{j=1}^{m} (1 - e_j)} \quad (6)$$

Composite scoring - compute rural household resource endowments index as:

$$S_i = \sum_{j=1}^{m} w_j \cdot Z_{ij} \quad (7)$$

3.2.4 Control variables

This study used four key variables as controls including village to county distance, village economic condition, village per capita income and presence of polluting enterprises, as detailed in Table 2.

4 Model specification and empirical results

4.1 Benchmark regression results analysis

The empirical analysis examining the impact of ASS on agricultural green production was performed using a panel

Table 2 Variable definition and descriptive statistics

Variable type	Variable name	Measurement/Calculation method	Mean	SD
Dependent	Agricultural green total factor productivity	Measured using global Malmquist-Luenberger index model	1.74	0.573
Explanatory	Agricultural socialized service	Measured using the entropy method and logarithmically transformed	7.17	0.651
Moderating	Household resource endowments	Computed via entropy method	1.34	0.963
Control	Distance	Village to county distance (km)	28	23.0
	Economy	Village economic condition (level 1–7)	3.8	1.47
	Income	Village per capita income (10,000 yuan)	2.9	2.14
	Pollution	Presence of polluting enterprises (yes = 1, no = 0)	0.30	0.418

fixed-effects model:

$$G_{it} = \alpha_0 + \beta ASS_{it} + \varphi CV_{it} + \alpha_i + \gamma_t + \varepsilon_{it} \quad (8)$$

where, the dependent variable G_{it} is the AGTFP of province i in year t, the core explanatory variable ASS_{it} is the level of ASS in province i during year t, CV_{it} is a series of control variables, α_0 is the intercept term, β and φ are the estimated coefficients of the core explanatory variable and control variables, respectively, ε_{it} is the random error term, and α_i and γ_t are individual fixed effects (province-level) and time fixed effects, respectively.

Table 3 systematically presents the empirical results through a progressively specified regression framework, with all models

Table 3 Regression result of ASS on AGTFP

Variable	AGTFP			
	Step 1	Step 2	Step 3	Step 4
ASS	0.0463***	0.0426***	0.0391***	0.0367***
	(0.0152)	(0.0121)	(0.0132)	(0.0114)
Distance		−0.2954***		−0.274***
		(0.0782)		(0.0917)
Economy		0.422**		0.434**
		(0.197)		(0.215)
Income		0.0363***		0.0299***
		(0.0122)		(0.0079)
Pollution		0.375**		0.694**
		(0.184)		(0.344)
Time effect	No	No	Yes	Yes
Individual effect	No	No	Yes	Yes
Constant	Yes	Yes	Yes	Yes
R^2	0.294	0.324	0.287	0.319
Observations	7794	7794	7794	7794

Note: ASS, agricultural socialized service; FE, fixed effect; and *, ** and *** indicate significance at 10%, 5% and 1% levels, respectively. Two-way clustered standard errors are reported in parentheses; the same applies to the following tables. Specifications for Steps 1 and 2 did not control for time or individual fixed effects, whereas those in Steps 3 and 4 incorporate both, respectively.

estimated using STATA 18.0 using two-way clustered standard errors. The analysis adopts a stepwise approach: Step 1 obtained the baseline ordinary least squares estimates including only the core explanatory variable. Step 2 expanded the model by incorporating the full set of control variables (Table 2). To address potential omitted variable bias arising from unobserved heterogeneity, Step 3 used a two-way fixed-effects estimator that accounts for both individual-specific and temporal variations. Finally, Step 4 obtained the most complete specification, integrating all control variables with individual and year fixed effects to yield the most reliable estimation results. This progressive modeling approach served two key purposes: (1) it demonstrates the robustness of the core findings across different specifications, and (2) it systematically addresses potential omitted variable bias through the sequential inclusion of controls and fixed effects. All models maintain consistent coefficient interpretation while progressively strengthening the identification strategy.

These regression analyses yielded consistently positive and statistically significant coefficients ($p < 0.01$) for ASS across all model specifications. These robust findings quantitatively establish that ASS contribute significantly to the enhancement of AGTFP. These empirical results substantiate the theoretical framework used in this study, demonstrating that ASS are a critical for advancing agricultural green production. Collectively, this evidence provides compelling support for Hypothesis 1.

4.2 Endogeneity test

Potential endogeneity may also stem from unobserved time- or individual-varying omitted variables. To mitigate such concerns and verify the robustness of the baseline estimates, this study adopted an instrumental variable strategy. Drawing on the methodology proposed by Lewbel[42], an instrumental variable (IV_ASS) was constructed for ASS, defined as the cube of the deviation between an individual household level ASS and the mean level ASS of their province. The estimation results are shown in Table 4.

The diagnostic statistics support the validity of the instrument: the Kleibergen-Paap rk LM statistic rejects under-identification, and the Cragg-Donald Wald F statistic exceeds conventional thresholds, ruling out weak instrument concerns. In the first-stage regression, IV_ASS had a coefficient of 0.0482, significant at the 1% level, confirming a strong positive association with ASS. The second-stage gave an ASS coefficient of 0.0356, also significant at the 1% level, indicating that the core finding of a positive treatment effect remains robust after accounting for endogeneity.

4.3 Moderation effect model

Building on the baseline regression, this study investigated the moderating effect of ASS on agricultural green production using a moderation effect analysis framework to systematically

Table 4 Endogeneity test results for agricultural socialized services (ASS) and agricultural green total factor productivity (AGTFP)

Variable	ASS	AGTFP
IV_ASS	0.0482***	
	(0.0154)	
ASS		0.0356***
		(0.0117)
Controls	Yes	Yes
Time FE	Yes	Yes
Individual FE	Yes	Yes
Kleibergen-Paap rk LM statistic		132.5
Cragg-Donald Wald F statistic		379
R^2	0.258	0.230
Observations	7794	7794

Note: This analysis used the same control variable specification as Table 3.

examine the boundary conditions under which rural human influence the impact of ASS on AGTFP. Specifically, a moderation model was constructed by incorporating an interaction term between ASS and HRE (ASS × HRE), with the model specification rigorously following the classical moderation effect testing paradigm established by Baron and Kenny[43]. The moderation effect model is constructed as:

$$G_{it} = \alpha_0 + \beta_1 ASS_{it} + \beta_2 (ASS_{it} \times HRE_{it}) + \varphi CV_{it} + \alpha_i + \gamma_t + \varepsilon_{it} \quad (9)$$

To ensure precise estimation of moderation effects and mitigate multicollinearity concerns, mean-centering procedures were implemented for all key variables. Specifically, both the core explanatory variable (ASS) and the moderator variable (rural household resource endowments, HRE) were centered by subtracting their respective sample means, yielding transformed variables c_ASS and c_HRE.

This centering procedure yielded three significant methodological benefits: (1) it substantially reduced the correlation between interaction terms and their constituent main effects, (2) it improved the stability and reliability of coefficient estimates, and (3) it maintained the original economic interpretation of all model variables. These advantages were formally operationalized through the moderation effect model specification, which used the centered variables to ensure robust estimation of the ASS-HRE interaction dynamics.

Using these centered variables, the moderation effect model is:

$$G_{it} = \alpha_0 + \beta_1 ASS_{it} + \beta_2 (c\_ASS_{it} \times c\_HRE_{it}) + \varphi CV_{it} + \alpha_i + \gamma_t + \varepsilon_{it} \quad (10)$$

Diagnostic analyses revealed that variable centering significantly improves model properties: post-centering variance inflation factors gave an average reduction of 42% compared to the original specification, while coefficient standard errors decreased by 28%–35%. Crucially, these improvements were achieved without compromising model fit or altering substantive conclusions.

The robustness of this approach was further verified through collinearity diagnostics, which confirm that condition indices remain well below conventional thresholds. These comprehensive validation procedures establish a solid statistical foundation for the moderation analysis while ensuring the reliability of subsequent inferences.

The regression results of the moderating effects before and after centering are given in Table 5.

The data given in Table 5 provides robust evidence that rural household resource endowments significantly moderates the impact of agricultural services, with both the original (ASS × HRE) and centered (c_ASS × c_HRE) interaction terms showing statistically significant coefficients (0.0094 and 0.0125, respectively). These consistent results across alternative specifications confirm that household resource endowments has a significant moderating influence in the pathway through which ASS influence agricultural green production, thus supporting Hypothesis 2.

4.4 Threshold Effect Model

To ensure the validity of model estimation, this study first conducted first-order lag unit root tests on all variables (including the dependent variable, core explanatory variables, control variables and threshold variable) to verify data stationarity. This preliminary testing procedure serves as a critical foundation for avoiding spurious regression problems and ensuring the reliability of subsequent analytical results. Based on data that passed the stationarity tests, the dynamic panel threshold model constructed in this study is specified as:

Since the static panel threshold model failed to account for the path dependence and dynamic persistence of the dependent variable, while also requiring strict exogeneity of independent variables-conditions that were often difficult to satisfy in real-world economic contexts, the threshold effect model was extended into a dynamic threshold model.

$$G_{it} = \alpha_0 + \varphi_0 G_{it-1} + \beta_1 ASS_{it} \times I(ASS < \theta) + \beta_2 ASS_{it} \times I(ASS \geqslant \theta) + \varphi CV_{it} + \alpha_i + \gamma_t + \varepsilon_{it} \quad (11)$$

where, G_{it-1} is the one-period lagged term of the dependent variable, the threshold variable is *ASS*, and θ is the threshold value.

This analysis revealed that ASS has a positive linear relationship with AGTFP. This finding prompts a critical methodological question, could this apparent linearity obscure more complex, underlying non-linear patterns. To systematically investigate this possibility, this study implemented a threshold regression model (Eq. 11) to precisely identify critical adoption thresholds and regime-dependent effects of ASS on AGTFP.

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Table 5 The moderating effect of HRE on the impact of ASS on AGTFP

Variable	AGTFP	
	Model (1)	Model (2)
ASS	0.0087***	0.0062***
	(0.0028)	(0.0021)
HRE	0.0726**	0.0734*
	(0.0441)	(0.0397)
ASS × HRE	0.0094***	
	(0.0030)	
c_ASS × c_HRE		0.0125**
		(0.0059)
Distance	–0.277***	–0.285**
	(0.0808)	(0.1265)
Economy	0.378**	0.397**
	(0.172)	(0.182)
Income	0.0379**	0.0318**
	(0.0192)	(0.0134)
Pollution	0.378**	0.693**
	(0.190)	(0.347)
Time FE	Yes	Yes
Individual FE	Yes	Yes
Constant	Yes	Yes
R^2	0.275	0.283
Observations	7794	7794

Note: *, ** and *** denote significance at 10%, 5%, and 1% levels, respectively.

The integrity of any panel data estimation hinges on the stationarity of the variables. Non-stationary data can lead to spurious regression, invalidating statistical inference. Therefore, the first step was to conduct a diagnostic check for unit roots using the Levin-Lin-Chu test. As shown in Table 6, the results confirmed that ASS, AGTFP and all control variables are stationary, as the null hypothesis of a unit root is rejected for each at the 1% significance level. Having confirmed the stationarity of the data, the threshold model was estimated.

The threshold number test results revealed a statistically significant single threshold at the 1% significance level. In contrast, potential second and third thresholds failed to meet conventional significance standards even at the 10% level. Following the principle of statistical parsimony and based on rigorous hypothesis testing criteria, the single-threshold specification was selected for subsequent econometric analysis, as it provided the most robust model configuration.

The results of the threshold regression are given in Table 7. To address the issues of path dependence in the dependent variable and potential endogeneity in the model, this study used both the first-differenced generalized method of moments (FD-GMM) and system generalized method of moments (SYS-GMM) approaches to estimate the model (Eq. 11). The single-threshold regression results, estimated via FD-GMM with a one-period lag of the dependent variable (L.AGTFP) and the results of the threshold regression estimated via the SYS-GMM method are given Table 7.

Table 6 Stationarity test (Levin-Lin-Chu test) results

Variable	Test statistic	*P* value	Unit root test passed
ASS	–25.6	0.0000	Yes
AGTFP	–24.3	0.0002	Yes
Distance	–25.6	0.0000	Yes
Economy	–25.5	0.0001	Yes
Income	–26.7	0.0000	Yes
Pollution	–26.4	0.0002	Yes

Table 7 Threshold effect regression results

Variable	FD-GMM	SYS-GMM
L.AGTFP	0.0315^{***} (0.0096)	0.0339^{***} (0.0107)
Regime 1 (ASS < threshold)	-0.0124^{*} (0.0065)	-0.0165^{**} (0.0077)
Regime 2 (ASS ⩾ threshold)	0.0156^{***} (0.0053)	0.0218^{***} (0.0068)
Threshold value	27.8	29.3
AR(1)		0.0082
AR(2)		0.574
Hansen Test		0.305
Controls	Yes	Yes
Time FE	Yes	Yes
Individual FE	Yes	Yes
Constant	Included	Included
Observations	7794	7794

Note: FD-GMM, first-differenced generalized method of moments; SYS-GMM, system generalized method of moments; ***, ** and * represent statistical significance at the 1%, 5% and 10% levels, respectively.

As shown in Table 7, the panel threshold effect in the model is statistically significant. Regarding to FD-GMM result, when the level of ASS is below the threshold, its impact on AGTFP had a coefficient of –0.0124. However, once the level of ASS exceeded the threshold, the coefficient was positive, at 0.0156. This indicates that ASS has statistically significant asymmetric effects on AGTFP across distinct threshold regimes, thereby providing robust support for Hypothesis 3. With the system GMM threshold regression, the Hansen test results (P = 0.305) supported the validity of the instrument set. Also, the Arellano-Bond tests for autocorrelation gave p-values of 0.0082 for AR(1) and 0.574 for AR(2), indicating that the error term had first-order but not second-order serial correlation. These diagnostics confirm the appropriateness of the SYS-GMM estimator in this work.

4.5 Heterogeneity analysis

4.5.1 Heterogeneity analysis of rural households in different regions

According to the latest economic zone classification standards (GB/T 4754-2022) issued by the National Bureau of Statistics, the 24 provincial-level administrative units considered in this study (excluding Beijing, Hainan, Hong Kong, Inner Mongolia, Macao, Ningxia, Qinghai, Xizang and Xinjiang) are classified into four major economic regions (Table 8).

A two-way fixed-effects model was used with reference to the economic zone classification standards established by the National Bureau of Statistics. The analysis systematically investigated regional heterogeneity patterns with results are given in Table 9.

Table 8 Regional classification

Region	Provincial-level administrative units	Type
Northeast	Heilongjiang, Jilin, Liaoning	3 provinces
Eastern	Fujian, Guangdong, Hebei, Jiangsu, Shandong, Shanghai, Tianjin, Zhejiang	6 provinces and 2 municipalities
Western	Chongqing, Gansu, Guangxi, Guizhou, Shaanxi, Sichuan, Yunnan	5 provinces, 1 municipality and 1 autonomous region
Central	Anhui, Henan, Hubei, Hunan, Jiangxi, Shanxi	6 provinces

Table 9 Heterogeneity analysis results of rural households in four regions of China

Variable	Northeast		Eastern		Western		Central	
ASS	0.0381^{***} (0.0132)	0.0397^{***} (0.0122)	0.0335^{***} (0.0114)	0.0349^{***} (0.0162)	0.0323^{***} (0.0097)	0.0338^{***} (0.0118)	0.0236^{*} (0.0082)	0.0257^{*} (0.0090)
Controls	No	Yes	No	Yes	No	Yes	No	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.287	0.297	0.263	0.289	0.275	0.288	0.297	0.302
Observations	2468	2468	1960	1960	1103	1103	2263	2263

Note: *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

This empirical analysis revealed three key findings concerning the geographically heterogeneous effects of ASS on China's agricultural green production. First there was a statistically significant performance gradient across regions: the Northeast region had the highest service system effectiveness, followed by the Eastern, Central and Western regions. Three key factors could explain these regional disparities: (1) the Northeast region has distinctive agricultural advantages through its industry-leading mechanization rate (98.2%) and pivotal role as the China's primary grain base (producing about 25.7% of China's total output); (2) the Eastern region capitalizing on its advanced economic advantages and infrastructure has established a relatively mature agricultural socialized service system characterized by digitally-led approaches, professional organization support, and market-oriented operations; and (3) the underdeveloped economic foundation, insufficient factor allocation and weak market demand in Central and Western regions create systemic constraints.

4.5.2 Heterogeneous effects analysis of rural holdings with different labor characteristics and operational scales

In addition to analyzing the regional heterogeneity effects of ASS on AGTFP, this study also conducted an in-depth investigation into the heterogeneity analysis of rural holdings with different cultivation scales. Regarding the classification and treatment of agricultural scale operations, Huo et al.[44] defined rural holdings with cultivated land areas of 0.2 ha or less, 0.267–0.533 ha and 0.6 ha or more as small-, medium- and large-scale farms, respectively. Rao[45] defined small-scale rural holdings more broadly as those cultivating less than 1 ha. While, Xu et al.[46] defined rural holdings with cultivated land areas more than 5 times China's average household cultivated land area as large-scale farms, while the rest were classified as small-scale farms.

Based on established classification standards in the literature and the specific characteristics of the sample used, this study defined rural holdings operating cultivated land areas below 0.4 ha as small-scale farms and those cultivating more than 1 ha as large-scale farms. Within the full sample, small-scale farms (n = 4947) constitute 63.5% of the total, while large-scale farms (n = 2847) account for the remaining 36.5%.

As shown in Table 10, the empirical regression results revealed a clear divergence in the impact of ASS on agricultural green production based on rural household operational scale; while

Table 10 Heterogeneity analysis results of rural holdings with different operational scales

Variable	AGTFP			
	Small farms (< 0.4 ha)		Large farms (⩾ 0.4 ha)	
	Model (1)	Model (2)	Model (3)	Model (4)
ASS	0.0214 (0.0147)	0.0265 (0.0173)	0.0346*** 0.0120)	0.0374*** (0.0129)
Controls	No	Yes	No	Yes
Time FE	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes
R^2	0.0872	0.124	0.104	0.223
Observations	4947	4947	2847	2847

Note: *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

service participation of small-scale farms exhibits a positive yet statistically insignificant association with AGTFP, large-scale farms show a strongly significant and positive relationship. These results indicate that participation in ASS fails to significantly improve green production efficiency among small-scale rural holdings, whereas it contributes substantially to productivity and sustainability gains in large-scale operations. These findings are consistent with existing literature: Zheng and Zhang[47] observed that large-scale farms had lower overuse of chemical inputs and higher adoption of green production practices compared to small-scale farms; similarly, Yang et al.[25] reported significantly greater technical efficiency gains from ASS among larger-scale operators. Thus, this study corroborates the conclusion that service-based interventions produce differentiated effects across farm scales, with meaningful improvements concentrated primarily among large-scale farms.

The observed heterogeneity in farm scale can be attributed to one or more of the following mechanisms. First, disparities in green input intensity. Stronger capital capacity and risk tolerance of large-scale farms facilitate their sustained adoption of high-cost green inputs, an advantage amplified by ASS through economies of scale and efficient application. In contrast, small-scale farms, constrained by limited budgets, rely more on standard inputs and exhibit lower use-efficiency of green services. Second, divergent patterns in technology adoption. Large-scale farms have a stronger propensity and capacity to adopt advanced green production technologies, which often require high initial investment but yield long-term returns. This advantage is further amplified by ASS, which lower the adoption threshold for technologies such as precision fertilization and smart irrigation systems. In contrast, small-scale farms have constrained marginal returns due to limited landholdings, leading them to rely predominantly on basic standard services and demonstrating considerably narrower scope for technological upgrading. Third, fundamental differences in production objectives and behavioral logic. Small-scale holdings are primarily used for self-sufficient production, with goals centered on household food consumption rather than efficiency or sustainability. Consequently, ASS exhibit limited effects on improving their green production efficiency. Conversely, large-scale farms operate under a profit-driven, market-oriented logic, strategically leveraging these services to enhance yields, improve quality, and access premium markets. This results in significantly stronger outcomes in both sustainability and productivity.

4.6 Robustness test and placebo test

4.6.1 Robustness test

To further validate the causal relationship between ASS and AGTFP, this study used four robustness checks. These included substituting the dependent variable, incorporating a lagged core explanatory variable, adopting an alternative measure of farm-level green productivity and winsorizing all variables. The relationship between ASS and AGTFP was re-estimated under each specification to ensure the findings are empirically robust.

Replacement of the explained variable. In the benchmark regression analysis, this study used the SBM-GML index model to measure AGTFP as the explained variable. Considering that this method originates from the Malmquist-Luenberger index model and that earlier literature predominantly used this approach, this study recalculated a new total factor productivity indicator (*n*_AGTFP) using that index model while maintaining the same input and output indicators to enhance the comparability of the research conclusions. The regression results (Table 11) indicated that after replacing the explained variable, the core explanatory variable remains statistically significant, and the coefficient direction aligned with the benchmark regression results. This further confirms the robustness of the research conclusions.

Lagged term of the core explanatory variable. Given that total factor productivity is a dynamic indicator with sequential growth characteristics, this study lagged the core explanatory variable (ASS) by one period (L.ASS) and re-conducted the fixed-effects regression analysis to examine the persistence of its impact on AGTFP. The lagged core explanatory variable remained statistical significance and the coefficient sign remained consistent with the benchmark regression results (Table 11). This suggests that the previous research conclusions are not affected by the temporal relationship of variables and exhibit strong robustness.

Alternative measurement of farmer-level green productivity. As outlined in supplementary materials, AGTFP_a was used as an alternative proxy for AGTFP to verify the robustness of ASS effect on agricultural green production. The alternative measure AGTFP_a remained statistically significant (Table 11), confirming that ASS significantly improve household-level green productivity.

Winsorization of variables. To mitigate the potential influence of extreme observations on causal inference, all variables including ASS, agricultural green total factor productivity and the control variables were winsorized at the 1% level. The model was then re-estimated using the winsorized ASS. The estimated coefficients (Table 11) for both the core ASS index and its intensity remained significantly positive at the 1% level. This confirms that the positive effect of ASS on AGTFP is robust and not driven by extreme values or outliers.

4.6.2 Placebo test

The preceding analyses indicated that ASS significantly promote agricultural green total factor productivity. Although the baseline regression incorporated a wide range of control variables and accounted for regional fixed effects, there may

Table 11 Robustness test results

Variable	AGTFP			
	Model (1)	Model (2)	Model (3)	Model (4)
*n*_AGTFP	0.0338***			
	(0.0104)			
L.ASS		0.0346**		
		(0.0114)		
AGTFP_a			0.0323***	
			(0.0109)	
W_ASS				0.0415***
				(0.0131)
Controls	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes
Constant	Yes	Yes	Yes	Yes
R^2	0.209	0.186	0.222	0.314
Observations	7794	5138	7794	7794

Note: *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively.

still be certain unobservable random factors that interfere with the identification of the causal relationship between the two, potentially leading to estimation bias. To address this possibility, this study drew on the approaches of Li et al.[48] and He et al.[49] to conduct a placebo test on the causal relationship between ASS and AGTFP.

Accordingly, this study used a bootstrap method to conduct 500 random samplings, generating a simulated treatment group and re-estimating the impact of ASS on AGTFP based on the randomly generated data. The estimated coefficients of ASS in the random samples follow a normal distribution, indicating the reasonableness of the 500 bootstrap resamplings and the validity of the placebo test. Also, the mean of the estimated coefficients for ASS in the randomly generated samples were distributed around zero, significantly deviating from the estimated coefficient of 0.0367 in the benchmark regression. This suggests that unobservable random factors do not drive the promoting effect of ASS on AGTFP. Thus, the results passed the placebo test, confirming that the conclusion that ASS contribute to the enhancement of agricultural green production is robust (Fig. S1).

5 Conclusions and policy implications

5.1 Conclusions

The empirical results confirm that ASS significantly improve AGTFP by enhancing technological efficiency, with rural household resource endowments acting as a critical moderating factor. In addition, these effects have non-linear dynamics characterized by threshold effects and substantial regional heterogeneity-most pronounced in northeast China, where advantages in operational scale and mechanization infrastructure amplify the benefits. These findings collectively elucidate a viable pathway toward sustainable agricultural intensification and offer actionable evidence for designing spatially differentiated policy interventions.

5.2 Policy implications

Drawing on the empirical findings, this study proposes three targeted policy recommendations to facilitate agricultural green transformation.

First, to systematically overcome barriers to applying agricultural socialization services in green production, a comprehensive policy system centered on farmer endowment empowerment should be established. This system would provide a multi-path synergistic approach targeting four key elements: implementing mechanization-adapted land improvement and virtual contiguity plans to enhance farmland compatibility and operational continuity; introducing green service vouchers and service order pledge loans to boost purchasing power and activate static assets; establishing a demonstration farmer network with on-site training to strengthen technical capabilities; and reinforcing village collectives as service integrators to enhance smallholder market position through unified negotiations and supervision. These interconnected measures would form a virtuous endowment empowerment-service adoption-green efficiency cycle that could systematically optimize rural household endowments, reduce adoption thresholds, and lay the institutional foundation for continuous improvement in agricultural green total factor productivity.

Second, an endowment-sensitive differentiated strategy should be adopted to promote agricultural socialization services. The core of this approach would involve the precise identification of rural holdings with larger operational scales, higher educational attainment and stronger financial capacity, and prioritizing their access to high-level service packages. By leveraging their inherent resource and managerial advantages, this strategy could facilitate the scaled and efficient adoption of services, thereby establishing replicable demonstration models. Meanwhile, region-specific policies should be carefully aligned with local conditions: in areas experiencing significant labor outmigration, emphasis should be placed on enhancing subsidies for mechanization services, while in capital-scarce regions, integrated support programs that combine financial services with production inputs should be established. Such targeted interventions have the potential to systematically address deficits in key resource endowments across diverse regions, ultimately improving the overall effectiveness of agricultural socialization services and strengthening their contribution to green transformation outcomes.

Third, to effectively implement China's agricultural dual-carbon strategy (carbon peaking and carbon neutrality), a collaborative government-society effort should establish a multidimensional evaluation framework encompassing three critical dimensions of sustainability: (1) environmental - using quantitative indicators like carbon emissions per unit of agricultural output and agricultural non-point source pollution treatment rates to accurately assess ecological carrying capacity; (2) economic - using dynamic parameters including green agriculture output share and eco-agricultural product premium rates to systematically evaluate low-carbon transition benefits; and (3) social - incorporating farmer green income growth and rural living environment satisfaction to ensure inclusive development. This integrated environment-economy-livelihood assessment mechanism enables both nationwide dynamic monitoring of agricultural green transition progress and provides data-driven support for region-specific policy packages, thereby synergizing carbon goals with rural revitalization.

While this study has provided valuable insights, it has some potential limitations that warrant attention in future research. (1) The analysis is constrained to the 2014–2022 period, and expanding the temporal scope could yield more robust and generalizable empirical findings. (2) The heterogeneity analysis focused solely on regional variations, overlooking potentially significant differences based on grain production levels. Incorporating production-scale heterogeneity would offer a more nuanced understanding of how ASS differentially impact green production across various farming operation sizes. (3) Data constraints in the CFPS database precluded the use of household-level pesticide and fertilizer application intensity as an undesired output in the measurement of AGTFP. Addressing these limitations in subsequent studies could substantially enhance the comprehensiveness and practical relevance of the research outcomes.

Supplementary materials

The online version of this article at https://doi.org/10.15302/J-FASE-2026676 contains supplementary materials (Fig. S1; Tables S1–S2; Eq. S1–S3).

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Compliance with ethics guidelines

Tingyi Yang declare that she has no conflicts of interest or financial conflicts to disclose. This article does not contain any studies with human or animal subjects performed by any of the authors.

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