

Article

Agricultural New-Quality Productive Forces and Carbon Efficiency: Empirical Evidence from China

Liudi Li ¹, Yuming Li ¹, Bingbing Wei ¹, Jing Zhang ² and Xiuguang Bai ^{1,*} 

¹ College of Economics and Management, Northwest A&F University, Yangling 712100, China; 18891610415@sina.cn (L.L.); li666@nwfau.edu.cn (Y.L.); bingbingwei@nwfau.edu.cn (B.W.)

² School of Civil Engineering and Architecture, Shaanxi University of Technology, Hanzhong 723001, China; zhangjing@snut.edu.cn

* Correspondence: baixg960@nwsuaf.edu.cn

Abstract

Enhancing agricultural carbon emission efficiency (ACEE) is a pivotal pathway for advancing environmentally sustainable transformation in agriculture and achieving the ‘dual carbon’ targets. However, empirical evidence on whether and how new-quality productive forces in agriculture contribute to improvements in ACEE remains limited. Using a super-efficiency slack-based measure (SBM) model, this study estimates the performance of carbon emissions from agricultural activities for 30 Chinese provinces from 2011 to 2022. Based on provincial panel data, fixed-effects, mediation, and threshold-effect models are combined within a panel data framework to investigate the impact of agricultural new-quality productive forces (ANQPF) on ACEE and its underlying mechanisms. The results indicate that: (1) ANQPF exerts a significant positive effect on ACEE. (2) Land transfer and the level of agricultural socialized services serve as important transmission channels through which ANQPF improves ACEE. (3) The relationship between ANQPF and ACEE exhibits a pronounced threshold effect. Below the threshold, the positive impact is significantly strengthened; however, as population density increases, the marginal effect of ANQPF on ACEE gradually declines. (4) Heterogeneity analysis indicates that the enhancing effect of ANQPF on ACEE is more pronounced in non-resource-based provinces and major grain-producing regions. In light of these findings, the results suggest that ANQPF should be positioned as a core policy lever. Simultaneously, land transfer should be optimized, the development of agricultural socialized services should be strengthened, and region-specific policies should be formulated to achieve synergistic outcomes in agricultural carbon reduction, efficiency improvement, and green growth.

Keywords: new-quality productive forces; agricultural carbon emission efficiency; land transfer; the level of agricultural socialized services; threshold effect; heterogeneity



Academic Editor: Giuseppe Timpanaro

Received: 24 January 2026

Revised: 22 February 2026

Accepted: 26 February 2026

Published: 27 February 2026

Copyright: © 2026 by the authors.

Licensee MDPI, Basel, Switzerland.

This article is an open access article distributed under the terms and conditions of the [Creative Commons Attribution \(CC BY\)](https://creativecommons.org/licenses/by/4.0/) license.

1. Introduction

Under the dual challenges of climate change at the global scale and food security, the greening and decarbonization of agriculture are not only central to global climate governance but also a critical issue for advancing sustainable and environmentally responsible development. According to data from the IPCC [1], agriculture, forestry, and other land-use activities account for approximately 23% of net anthropogenic greenhouse gas emissions. More critically, without effective policy interventions, agricultural greenhouse gas emissions are projected to increase by 58% by 2050, potentially becoming one of the

most challenging and pivotal carbon sources in global climate governance [2]. Alongside high-input and resource-intensive practices involving pesticides, plastic mulch, and chemical fertilizers, carbon emission pressures in the agricultural sector have become increasingly pronounced [3]. As a global leader in agricultural production, China has long relied on traditional extensive production practices, which have intensified efficiency losses and ecological imbalances, thereby constraining progress in agricultural modernization and regional economic coordination [4]. Consequently, improving ACEE has become a central policy goal and a key indicator of green agricultural transition.

In response to these pressures, China has recently advanced the concept of ANQPF. ANQPF refers to a productivity paradigm driven by scientific and technological breakthroughs, characterized by the intelligent and green reconfiguration of laborers, means of labor, and objects of labor [5]. Grounded in endogenous growth theory [6] and green growth theory [7], ANQPF shifts agriculture from a factor-intensive to an innovation-intensive model. By integrating biotechnology, digital monitoring, and precision equipment [8], ANQPF has the potential to simultaneously raise output and enhance ACEE.

Despite this theoretical promise, empirical evidence on the ANQPF–ACEE nexus is scarce. Prior studies have focused on the measurement [9] and determinants of ACEE [10,11] or on the economic outcomes of ANQPF [12], yet the two strands remain disconnected. Although potential mechanisms such as land consolidation and socialized services are conceptually plausible pathways through which ANQPF could enhance carbon efficiency, these channels have not been systematically theorized, nor have they been empirically tested in the existing literature. Moreover, whether this effect is heterogeneous across regions with different resource endowments remains unclear.

This study addresses these gaps by empirically examining the impact of ANQPF on ACEE using provincial panel data from China for 2011–2022. It contributes to the literature in four ways. First, it refines the ANQPF measurement framework by incorporating digital, green, and technological indicators within the Marxist three-element structure, offering a more comprehensive and replicable index. Second, unlike existing studies that focus primarily on total carbon emissions or emission intensity, this paper evaluates carbon performance from an efficiency perspective using a super-efficiency SBM framework that incorporates undesirable outputs. Carbon emission efficiency captures the joint optimization of multiple inputs and outputs and better reflects changes in green total factor productivity than single-ratio indicators. Third, this study integrates land transfer and agricultural socialized services into a unified mediation framework, identifying how factor reallocation and organizational restructuring transmit the impact of ANQPF to ACEE. By uncovering these specific transmission channels, the paper moves beyond models that examine only direct effects and deepens the understanding of how ANQPF drives green transformation. Fourth, by introducing population density as a threshold variable, this paper incorporates spatial-demographic constraints into the analysis of green productivity transformation. Population density reflects land resource pressure, the feasibility of large-scale operation, and ecological carrying capacity. Identifying a demographic threshold reveals that the carbon-efficiency effect of ANQPF is conditional rather than uniformly linear, thereby providing a clearer basis for differentiated regional policy design.

2. Literature Review

A substantial body of literature has measured ACEE using data envelopment analysis (DEA) and stochastic frontier analysis (SFA). Wang et al. [13] employed a DEA model to measure ACEE in China and found pronounced interprovincial heterogeneity in efficiency levels. Xia et al. [14] adopted a SBM model accounting for undesirable outputs to estimate China's ACEE, and found that it generally demonstrates an upward trajectory, but the

carbon emission efficiency level in the eastern region exceeds the national average. At the micro level, research on factors affecting ACEE mainly focuses on farmers' production behavior, including the adoption of green technologies such as conservation tillage [15], input of production factors [16], and utilization of productive services [17]. Macro-level determinants including agricultural modernization [18], urbanization [19], and environmental regulations [14] have also been examined. Despite these advances, the potential role of ANQPF in enhancing ACEE remains largely unexplored.

The concept of ANQPF, though rooted in Marxist productivity theory, has been reinterpreted in the context of the fourth industrial revolution [20]. Scholars generally define ANQPF as a higher-order productivity form propelled by technological innovation and factor reconfiguration [21,22]. Measurement approaches vary. Cao et al. [23] and Wu et al. [24] constructed indices from the three-element perspective using entropy weighting. Luo et al. [25] and Jiang [26] emphasized technological, green, and digital attributes, developing multi-dimensional frameworks. Empirically, ANQPF has been shown to foster rural–urban integration [27], agricultural high-quality development [28], and income growth [29]. However, its environmental performance, particularly in terms of carbon efficiency, remains underexplored. A few recent studies suggest that ANQPF reduces agricultural carbon emissions [30] and manufacturing emission intensity [31], yet none have directly examined ACEE, leaving a critical gap.

In summary, while the literature on ACEE and ANQPF has progressed in parallel, the intersection of the two fields is largely uncharted. No study has systematically quantified how ANQPF affects ACEE or explored the underlying mechanisms. This paper aims to fill this void by integrating ANQPF and ACEE into a unified analytical framework, thereby advancing both theoretical understanding and empirical evidence on low-carbon agricultural transformation.

3. Theoretical Analysis and Research Hypotheses

3.1. Theoretical Analysis of the Impact of ANQPF on ACEE

ACEE is a core indicator for evaluating green agricultural production. Specifically, it refers to the comprehensive capacity of an agricultural production system to maximize desirable output and minimize undesirable output (agricultural carbon emissions) under a given set of production factor inputs [32]. Compared with single-indicator measurements, total factor carbon emission efficiency better captures the complex characteristics of agricultural production involving multiple inputs and outputs. Accordingly, this study adopts a total factor perspective to measure ACEE by constructing a comprehensive indicator system that incorporates inputs such as labor, land, and machinery, including both desirable and undesirable outputs.

Existing studies conceptualize ANQPF as an advanced form of productivity driven by scientific and technological innovation under tightening resource and environmental constraints [33]. Its essence lies in achieving efficient coordination and deep optimization among laborers, means of labor, and objects of labor. From the perspective of green total factor productivity and low-carbon transition theory, productivity upgrading is not solely reflected in output expansion but also in improvements in resource-use efficiency and reductions in carbon intensity [34,35]. Technological progress under environmental constraints induces cleaner production processes and promotes the substitution of high-carbon inputs with energy-efficient and low-emission technologies [36].

Building on this theoretical foundation, ANQPF embeds frontier technologies such as information technology, biotechnology, and digital platforms into agricultural production systems, thereby promoting the evolution of agriculture toward precision, circularity, and greenness. For example, smart agricultural machinery and Internet of Things technologies

enable the precise application of water and fertilizers, effectively reducing resource waste and input redundancy [3]. The substitution of chemical inputs with clean energy and biotechnologies reduces reliance on high-carbon factors, including pesticides, and enhances production efficiency under environmental constraints [37]. Circular agriculture models convert straw and livestock manure into organic fertilizers and bioenergy, increasing desirable outputs while reducing both input use and carbon emissions [38]. In addition, policy instruments such as carbon trading schemes, ecological compensation mechanisms, and region-specific differentiated strategies strengthen emission-reduction incentives and further promote improvements in ACEE [39]. Through these technological and institutional adjustments, ANQPF contributes to simultaneous gains in total factor productivity and environmental performance, forming the direct theoretical basis for improved carbon emission efficiency. Accordingly, Hypothesis 1 is formulated.

H1. *ACEE is significantly improved by the development of ANQPF.*

Land fragmentation and lagging labor skills have resulted in low utilization efficiency of traditional agricultural factors. In the absence of advanced technologies and equipment, agricultural products are less competitive in the market, and the economic value of land is difficult to fully realize, resulting in low willingness among farmers to participate in land transfer [40]. By introducing advanced production factors such as intelligent agricultural machinery, Internet of Things monitoring devices, and biotechnological breeding technologies, ANQPF fundamentally transforms traditional agriculture heavily dependent on natural conditions [33]. This transformation substantially enhances land output efficiency and the value creation of agricultural products, increases the investment value of land resources, and consequently attracts new types of diversified agricultural business entities to participate in land transfer [41]. Existing studies suggest that larger operational scales improve technical efficiency and reduce factor misallocation in agriculture [42]. As land is consolidated through transfer, mechanization rates increase and input use becomes more standardized, which reduces excessive application of fertilizers and pesticides and lowers carbon emission intensity per unit of output [43].

Moreover, the development of ANQPF is premised on the realization of economies of scale. The intrinsic requirement for large-scale land management has driven innovation and expansion of the land transfer system, thereby enlarging the scale of land transfer and improving its efficiency [44]. Empirical evidence shows that land transfer facilitates resource reallocation toward more productive and technologically advanced operators, promotes specialized production, and enhances total factor productivity in agriculture [45].

From an environmental perspective, scale management enables the adoption of precision farming and conservation tillage, which improve input-use efficiency relative to fragmented smallholder production [46]. Land transfer further optimizes land resource allocation through the growth of modern agricultural business organizations, enabling adjustments in planting and breeding structures based on market demand and local resource endowments and enhancing land-use efficiency [47]. These changes ultimately contribute to improvements in ACEE. Accordingly, we propose Hypothesis 2.

H2. *ACEE is enhanced by ANQPF through increased land transfer.*

By embedding intelligent equipment, biotechnological breeding, and digital technologies, ANQPF drives the transformation of agricultural socialized services from traditional agricultural extension toward intelligent and systematic services covering the entire agricultural value chain [48]. In this process, agricultural operators integrate key service resources such as agricultural input supply, machinery operations, and agricultural product sales,

and rely on specialized service organizations to provide farmers with trusteeship or semi-trusteeship services, thereby mitigating land fragmentation and promoting the centralized management of cultivated land [49].

From the perspective of production economics, agricultural socialized services reduce transaction costs, alleviate information asymmetry, and enable smallholders to access scale economies that would otherwise be unattainable under fragmented operations [50]. By promoting the adoption of standardized production practices and mechanized operations, service providers improve input allocation efficiency and reduce excessive or redundant input use, particularly of fertilizers, pesticides, and diesel fuel [51]. Through the promotion of smart services such as soil monitoring and precision irrigation, resource redundancy in inefficient production stages is reduced, thereby enhancing total factor productivity and lowering carbon intensity [52,53]. Moreover, through technological penetration and the optimization of service resource allocation, ANQPF expands the service coverage radius and reduces marginal service costs [40]. Specialized service organizations gradually replace smallholders' experience-based and extensive management practices. By curbing the application of chemical inputs, these organizations respond to market demand for green agricultural products, thereby achieving a synergistic improvement in economic and ecological benefits and ultimately enhancing ACEE [54]. Accordingly, we propose Hypothesis 3.

H3. *ANQPF promotes improvements in ACEE by enhancing the level of agricultural socialized services.*

3.2. Threshold Effects of ANQPF on ACEE

Differences in population density across regions are associated with heterogeneity in resource endowments and levels of economic development, which may give rise to nonlinear effects of ANQPF on ACEE [55]. Population density is a key structural variable reflecting land scarcity, production scale constraints, and factor competition intensity, all of which shape the marginal effectiveness of technological progress and organizational innovation in agriculture [45].

In regions with relatively low population density, agricultural production is often characterized by weak infrastructure, limited access to agricultural socialized services, slow diffusion of advanced technologies, and small-scale or fragmented operations. Under such conditions, the application costs of ANQPF tend to be relatively high, which may constrain their immediate efficiency-enhancing effects [56]. Nevertheless, even in low-density areas, ANQPF can still improve ACEE by optimizing agricultural production structures and enhancing the efficiency of agricultural resource allocation, although the marginal improvement may be limited.

As population density increases, moderate agglomeration of labor, capital, and service providers facilitates the optimal reallocation of production factors and improves resource allocation efficiency [57]. This process is consistent with the induced innovation and agricultural intensification hypothesis, whereby rising population pressure stimulates technological adoption, organizational upgrading, and the expansion of agricultural socialized services, thereby amplifying the positive impact of ANQPF on ACEE [58]. However, when population density exceeds a certain level, excessive population concentration may intensify land scarcity and exacerbate land fragmentation, thereby compressing agricultural production space and constraining large-scale and intensive agricultural operations. These constraints can raise the marginal cost of green technology adoption and weaken the efficiency-enhancing effects of ANQPF. Moreover, densely populated regions are often accompanied by higher levels of domestic wastewater and solid waste emissions, which increase the complexity and cost of agricultural carbon emission governance and may offset part of the low-carbon benefits generated by ANQPF [59,60]. Therefore, selecting popula-

tion density as a threshold variable can effectively illuminate non-linear characteristics of ANQPF on ACEE as population concentration changes, and it captures the structural transition from agglomeration-driven efficiency gains to congestion- and land-scarcity-induced constraints. Based on this reasoning, this study proposes Hypothesis 4.

H4. *Population density has a threshold effect on improving ACEE through ANQPF.*

4. Materials and Methods

4.1. Model Setting

To examine the impact of ANQPF on ACEE, this study constructs the following baseline panel econometric model:

$$ACEE_{it} = \alpha_0 + \alpha_1 ANQPF_{it} + \lambda Controls_{it} + \mu_i + \sigma_t + \varepsilon_{it} \quad (1)$$

In Equation (1), $ACEE_{it}$ is the dependent variable, representing ACEE in province i at year t . $ANQPF_{it}$ is the core explanatory variable, indicating the development level of ANQPF. $Controls_{it}$ is a set of control variables. i and t indicate province and year, respectively. μ_i represents province fixed effects, which control for unobserved, time-invariant regional characteristics such as natural resource endowments, agro-climatic conditions, and long-standing institutional factors. σ_t is the time fixed effects, capturing common shocks and macro-level changes that affect all provinces in a given year, including national policies and macroeconomic fluctuations. ε_{it} is the idiosyncratic error term, reflecting time-varying unobserved factors that are not captured by the explanatory variables or fixed effects. α_0 is the constant term, and α_1 is the coefficient to be estimated.

Theoretical analysis indicates that ANQPF influences ACEE through two primary channels: promoting land transfer and enhancing the level of agricultural socialized services. To empirically test the existence of these mechanisms, this study follows the existing literature [61] and sets the following econometric model.

$$Med_{it} = \gamma_0 + \gamma_1 ANQPF_{it} + \lambda Controls_{it} + \mu_i + \sigma_t + \varepsilon_{it} \quad (2)$$

In Equation (2), Med is the mediating variable. γ_0 is the constant term, γ_1 is the coefficient to be estimated, and the definitions of the remaining variables correspond to those specified in Equation (1).

To explore the nonlinear characteristics of the influence of ANQPF on ACEE, this study employs population density as the threshold variable and constructs the following panel threshold model.

$$ACEE_{it} = \beta_0 + \beta_1 ANQPF_{it} \cdot I(Ia \leq \eta_1) + \beta_2 ANQPF_{it} \cdot I(\eta_1 < Ia \leq \eta_2) + \beta_3 ANQPF_{it} \cdot I(Ia > \eta_2) + \lambda Controls_{it} + \mu_i + \sigma_t + \varepsilon_{it} \quad (3)$$

In Equation (3), Ia is the threshold variable, η_1 and η_2 represent the threshold values. $I(\cdot)$ is the indicator function. β_0 is the constant term, and β_1 , β_2 and β_3 are the coefficients to be estimated. The definitions of the remaining variables are the same as in Equation (1).

To analyze the heterogeneity in the impact of ANQPF on ACEE, this study builds on the baseline regression model and further examines the heterogeneous impacts of ANQPF on ACEE across regions with different resource endowments and agricultural production functions.

4.2. Variable Selection and Measurement

4.2.1. Dependent Variable

ACEE. Following the extant literature [62], this study constructs an index system for ACEE, as presented in Table 1. The input variables include fertilizer input, inputs of pesticides, agricultural plastic film, agricultural labor, fixed capital stock in the agricultural sector, crop planting area, and agricultural machinery inputs. In terms of outputs, total agricultural output value is considered the desirable output, whereas agricultural carbon emissions are treated as the undesirable output.

Given that this study concentrates on agriculture in the narrow sense, namely crop farming, agricultural carbon emissions are quantified from three dimensions. First, carbon dioxide emissions associated with farmland utilization are calculated, primarily covering five major emission sources: chemical fertilizers application, pesticide use, agricultural plastic film, diesel, and tillage activities (see Table 2). Second, carbon emissions generated from crop straw burning are taken into account. This study focuses on four major grain crops: rice, wheat, maize, and soybean. The corresponding emission coefficients are adopted from He et al. [63] (Table 3). Third, methane (CH₄) emissions from rice cultivation are incorporated. Given that CH₄ emission rates during the rice growing period vary across provinces due to differences in temperature, climate, and other conditions, this study follows Min and Hu [64] to estimate carbon emissions from rice cultivation in each province. The specific emission coefficients for rice cultivation by province are reported in Table 4. Agricultural carbon emissions are calculated according to the following equation.

$$\sum Ace = \sum Ace_c = \sum T_C \cdot \delta_C \quad (4)$$

In Equation (4), Ace is total carbon emissions, c represents different types of agricultural carbon sources, and T_C and δ_C indicate the amount of each emission source and its associated carbon emission coefficient, respectively.

Traditional DEA models are typically based on radial measures and often ignore input slacks and output shortfalls, which may lead to biased efficiency estimates in the presence of input redundancy or undesirable outputs [65,66]. By contrast, SFA relies on explicit functional form and distributional assumptions for the inefficiency term [67], which may potentially limit its applicability in multi-input–multi-output settings. Given the complex production structure of agriculture and the inclusion of undesirable outputs such as carbon emissions, these approaches may be less suitable for measuring ACEE.

Table 1. Index system of ACEE.

Index	Variable	Unit
Input	Fertilizer input	10 ⁴ t
	Pesticide input	10 ⁴ t
	Agricultural plastic film input	10 ⁴ t
	Agricultural fixed capital stock	CNY 10 ⁸
	Crop sown area	10 ³ hm ²
	Agricultural labor	10 ⁴ people
	Agricultural machinery input	10 ⁴ kWh
Desirable Output	Total agricultural output value	CNY 10 ⁸
Undesirable Output	Agricultural carbon emissions	10 ⁴ t

Table 2. Carbon emission sources and coefficients of farmland use.

Carbon Source	Carbon Emission Coefficient	Reference Source
Chemical fertilizers	0.8956 kg C·kg ⁻¹	Oak Ridge National Laboratory, USA
Pesticides	4.9341 kg C·kg ⁻¹	Oak Ridge National Laboratory, USA
Agricultural plastic film	5.18 kg C·kg ⁻¹	Institute of Agricultural Resources and Ecological Environment, Nanjing Agricultural University
Diesel	0.5927 kg C·kg ⁻¹	Intergovernmental Panel on Climate Change (IPCC)
Tillage	312.6 kg C·km ⁻²	College of Biological and Agricultural Engineering, China Agricultural University

Table 3. Carbon emission sources and coefficients of straw burning.

Grain Crops	Carbon Emission Coefficient
Rice	0.18 kg C·kg ⁻¹
Wheat	0.16 kg C·kg ⁻¹
Maize	0.17 kg C·kg ⁻¹
Soybean	0.15 kg C·kg ⁻¹

Table 4. Emission coefficients of rice cultivation by province.

Region	Coefficient	Region	Coefficient	Region	Coefficient
Beijing	13.23	Tianjin	11.34	Hebei	15.33
Liaoning	9.24	Jilin	5.57	Heilongjiang	8.31
Zhejiang	35.6	Anhui	31.9	Fujian	34.6
Henan	17.85	Hubei	38.2	Hunan	35
Hainan	38.4	Chongqing	16.9	Sichuan	16.9
Shaanxi	12.51	Gansu	6.83	Qinghai	0
Inner Mongolia	8.93	Jiangsu	32.4	Shandong	21
Xinjiang	10.5	Yunnan	5.7	Shanxi	6.62
Shanghai	31.26	Jiangxi	42.2	Guangdong	41.2
Guizhou	16.1	Ningxia	7.35	Guangxi	36.4

Following Zhu et al. [3], this study employs an input-oriented super-efficiency SBM model to measure ACEE, as specified in Equation (5). Unlike traditional DEA, the SBM model directly incorporates slack variables into the efficiency measure, thereby capturing input redundancy, desirable output shortfalls, and excess undesirable outputs within a non-radial framework. The super-efficiency extension further allows efficiency scores greater than unity, enabling the discrimination and ranking of decision-making units (DMUs). An

input-oriented specification is employed to reflect the policy objective of reducing excessive input use and associated carbon emissions while maintaining output levels.

$$\rho = \min \frac{1 - \frac{1}{m} \sum_{i=1}^m \bar{s}_i}{1 + \frac{1}{s_1 + s_2} \left(\sum_{r=1}^{s_1} \frac{s_r^g}{y_{r0}^g} + \sum_{k=1}^{s_2} \frac{s_k^b}{y_{k0}^b} \right)}$$

$$s.t. \begin{cases} \sum_{j=1}^n \lambda_j x_{xj} + \bar{s}_i = x_{i0}, i = 1, 2, \dots, m \\ \sum_{j=1}^n \lambda_j y_{rj}^g + s_r^g = y_{r0}^g, r = 1, 2, \dots, s_1 \\ \sum_{j=1}^n \lambda_j y_{kj}^b + s_k^b = y_{k0}^b, r = 1, 2, \dots, s_2 \\ \lambda_j \geq 0, \\ \bar{s}_i \geq 0, s_r^g \geq 0, s_k^b \geq 0 \end{cases} \quad (5)$$

In Equation (5), ρ is ACEE. $\bar{s}_i$ is designated as the slack variable for the i -th input, indicating input redundancy. s_r^g is the slack variable for the r -th desirable output, reflecting a shortfall in desirable output. s_k^b is the slack variable for the k -th undesirable output, indicating excess undesirable output. x_{i0} , y_{r0}^g and y_{k0}^b are the inputs, desirable outputs, and undesirable outputs of the target DMU, respectively. λ_j is the weight coefficient of the DMUs.

4.2.2. Core Explanatory Variable

ANQPF. According to Marxist theory of productive forces, which identifies laborers, the objects of labor, and the means of labor as the three fundamental elements, productivity is determined by the combination of these elements and their respective qualities [68]. Distinct from traditional forms of productivity, ANQPF is a sophisticated iteration of productive powers underpinned by scientific and technological breakthroughs as the primary catalyst. It restructures the allocation of agricultural production factors and organizational modes, thereby promoting the transition of agriculture from a traditional “factor-dependent” model to an “innovation-driven” paradigm.

Building on this three-element framework, this study constructs an integrated evaluation system for ANQPF encompassing agricultural laborers, objects of labor, and means of labor (Table 5). Within each primary dimension, indicators reflecting digitalization, greening, and technological advancement are incorporated [69]. Specifically, the labor dimension captures human capital, digital literacy, and productivity attributes; the objects-of-labor dimension reflects environmentally friendly practices and industrial integration; and the means-of-labor dimension measures both tangible infrastructure and intangible innovation capacity.

Since all indicators selected in this study are positive indicators, the data are standardized as follows:

$$X'_{ij} = \frac{[x_{ij} - \min(x_j)]}{[\max(x_j) - \min(x_j)]} + 0.0001 \quad (6)$$

where X'_{ij} denotes the standardized value of indicator j for province i .

In the second step, the proportion of province i under indicator j is calculated as:

$$y_{ij} = \frac{X'_{ij}}{\sum_{i=1}^{30} X'_{ij}} \quad (7)$$

Table 5. Evaluation index system of ANQPF.

Primary Indicator	Secondary Indicator	Tertiary Indicator	Explanation	Attribution	Weights
Agricultural laborers	Labor skills	Education level	Per capita years of formal education in rural areas	+	0.0020
		Training ratio	Number of graduates from rural adult education and technical training institutions/rural population	+	0.0482
		Agricultural science and technology	Number of provincial R&D personnel $\times$ (number of agricultural R&D personnel/total national R&D personnel)	+	0.0335
	Labor productivity	Economic income	Rural per capita disposable earnings	+	0.0251
		Economic efficiency	Total output value of agriculture, forestry, animal husbandry and fishery/primary industry workers	+	0.0136
		Agricultural output	Grain output/total output value of agriculture, forestry, animal husbandry, and fishery	+	0.0264
	Digital literacy of laborers	Digital equipment	Number of rural broadband access users/number of rural households	+	0.0211
		Digital communication	Mobile internet data traffic $\times$ (rural population/total population at year-end)	+	0.0683
		Digital payment	E-commerce sales/rural population	+	0.1129
Agricultural objects of labor	Environment friendly practices	Conservation tillage	Area under conservation tillage/cultivated land area	+	0.0517
		Soil and water conservation	Area of soil erosion control/area affected by soil erosion	+	0.1503
		Renewable energy	Solar energy utilization rate (use of solar water heaters)	+	0.0354
	Industrial integration	Industrial value enhancement	Value added of agriculture, forestry, animal husbandry, and fishery services/total output value of agriculture, forestry, animal husbandry, and fishery	+	0.0052
		Industrial diversification	Revenue from forestry tourism and leisure services/total output value of agriculture, forestry, animal husbandry, and fishery services	+	0.0427

Table 5. Cont.

Primary Indicator	Secondary Indicator	Tertiary Indicator	Explanation	Attribution	Weights
Agricultural means of labor	Tangible means of production	Traditional infrastructure	Effective irrigated area/cultivated land area	+	0.0160
		Digital infrastructure	Number of rural cable radio and television users/total number of households	+	0.0195
			Length of optical fiber cables per square meter of land		0.0983
		Resource conservation	Electricity consumption per unit of rural output value	+	0.0774
			Water consumption per unit of agricultural output value		0.0286
	Intangible means of production	Scientific and technological achievements	Number of applications for new agricultural plant varieties	+	0.0437
			Number of regional scientific papers indexed $\times$ (number of national agricultural, forestry, animal husbandry, and fishery scientific papers indexed/total number of national scientific papers indexed) (SCI + EI + CPCI)		0.0406
			Intramural R&D expenditure $\times$ (ratio of agricultural sector output/regional GDP)	+	0.0310
		Research and innovation	Local fiscal outlays for agriculture, forestry, and water affairs		0.0085

In the third step, the entropy value of indicator j is computed as:

$$e_j = -k \sum_{i=1}^{30} y_{ij} \ln(y_{ij}) \quad (8)$$

where $k = 1 / \ln 30, 0 \leq e \leq 1$.

In the fourth step, the weight of indicator j is determined as:

$$w_j = \frac{1 - e_j}{\sum_{j=1}^{23} (1 - e_j)} \quad (9)$$

Finally, the composite score is calculated as:

$$score = \sum_{j=1}^{23} w_j y_{ij} \quad (10)$$

Equation (10) indicates that the development level of ANQPF is obtained by summing the weighted contributions of all indicators, that is, the products of each indicator's weight w_j and its corresponding proportion y_{ij} .

Among all tertiary indicators, the largest weights are assigned to soil and water conservation (0.1503), digital payment (0.1129), and optical fiber density (0.0983). Under

the entropy-weight framework, higher weights reflect greater cross-provincial dispersion. This indicates that differences in environmental governance and digital infrastructure account for the largest share of inter-provincial variation in the ANQPF index. In contrast, local fiscal outlays for agriculture, forestry, and water affairs (0.0085) receive comparatively smaller weights, reflecting limited cross-regional dispersion.

4.2.3. Control Variables

Beyond ANQPF, drivers including planting structure, the scale of agricultural economic development, and fiscal support may also affect ACEE. Drawing on existing studies [3,28], the current inquiry incorporates the subsequent covariates. Planting structure (PS) denotes the ratio of non-grain crop area to total sown area. Agricultural mechanization level (Mech) is defined as agricultural machinery power per capita. Regional economic development level (Rgdp) is proxied by per capita GDP. Agricultural economic development level (Adl) is signified by the value added of agriculture, forestry, animal husbandry, and fishery divided by the corresponding sectoral employment. Trade openness (Open) is measured as the proportion of total agricultural imports and exports to the gross output value of agriculture, forestry, animal husbandry, and fishery. Agricultural fiscal support is delineated by the share of public budgetary outlays allocated to agrarian and water conservancy endeavors within the total gross output value of the agriculture-related industries. The level of crop damage (Lcd) is calculated as the share of disaster-affected cropland in total cultivated area. Human capital level (Hcl) is proxied by the concentration of higher education students to the overall population.

4.2.4. Mediating Variables

To investigate the mechanisms through which ANQPF affects ACEE, this study selects the level of agricultural socialized services and land transfer as mediating variables. Land transfer is characterized from the perspectives of participation rate and occurrence rate. Specifically, the former measures the percentage of households that have transferred their contracted land among all households under the household contract system, whereas the latter captures the share of transferred contracted land area in the total contracted land area [47]. In light of this study's focus on the repercussions of land tenure circulation for agricultural output, the occurrence rate metric is deemed more pertinent. Among them, the transferred area includes the area of transfer, exchange, lease, and the area of shareholding and other forms of transfer. The level of agricultural socialized services is operationalized as the quotient between the total output value of agricultural services and the headcount of agricultural practitioners. The aggregate production value of agricultural services is derived by the gross agrarian production normalized against the total output value of agriculture, forestry, animal husbandry, and fishery, factored by the output value of primary sector domains. The number of agricultural employees is calculated as the total agricultural output value divided by the total output value of agriculture, forestry, animal husbandry, and fishery, multiplied by the number of employees in the primary industry.

4.2.5. Threshold Variable

The impact of ANQPF on ACEE is closely related to population density. Population density reflects the degree of human capital agglomeration in a region. Differences in population density are associated with variations in agricultural production scale, technology adoption, and patterns of resource utilization, thereby affecting the effectiveness of ANQPF in enhancing ACEE. Accordingly, this study employs population density as the threshold variable, measured as the ratio of year-end resident population to land area [70].

4.3. Data Sources and Descriptive Statistics

This investigation adopts panel data for 30 provinces in China from 2011–2022. The primary data sources include the China Statistical Yearbook, China Energy Statistical Yearbook, China Social Statistical Yearbook, China Population and Employment Statistical Yearbook, China Environmental Statistical Yearbook, and provincial statistical yearbooks. Information on green patent applications and authorizations is obtained from the China Research Data Services Platform (CRNDS). Data on fertilizer, pesticide, agricultural plastic film, and diesel use are drawn from the China Rural Statistical Yearbook and are based on actual annual usage. Tillage data are based on the annual crop sown area. Missing observations for certain years are supplemented using linear interpolation. Descriptive statistics of the variables are reported in Table 6.

Table 6. Descriptive statistics of variables.

Variable Type	Variable	N	Mean	SD	Min	Max
Dependent variable	ACEE	360	0.578	0.265	0.194	2.082
	Agricultural carbon emissions (10 ⁶ t)	360	3.377	2.293	0.144	10.001
Core explanatory variable	ANQPF	360	0.109	0.055	0.035	0.313
Control variables	PS	360	34.994	14.479	2.925	64.687
	Mech	360	1.797	0.984	0.326	6.773
	Rgdp	360	6.057	3.060	1.641	19.031
	Adl	360	3.398	1.772	0.632	11.808
	Open	360	0.272	0.281	0.008	1.464
	Fiscal	360	0.259	0.111	0.105	0.758
	Lcd	360	0.139	0.113	0.004	0.695
	Hcl	360	0.021	0.008	0.006	0.114
Mediating variables	Land transfer	360	0.333	0.171	0.034	0.922
	level of agricultural socialized services	360	0.270	0.191	0.026	1.136
Threshold variable	Population density (people/km ²)	360	471.120	708.542	7.864	3950.794

5. Empirical Results and Analysis

5.1. Baseline Regression

Preparatory to regression analysis, this study conducts a multicollinearity test within a panel data analysis framework. The empirical results indicate that the variance inflation factor (VIF) is 2.33 (<10), suggesting the absence of serious multicollinearity among the explanatory variables. Based on the results of the LM test, F test, and Hausman test, a two-way fixed effects panel data model incorporating both individual and time effects is employed for the empirical analysis. Robust standard errors are employed to mitigate potential heteroskedasticity. To further consolidate the robustness of the quantitative findings, control variables are progressively incorporated into the fundamental estimation. The corresponding results are reported in Table 7. Estimates suggest that, irrespective of the inclusion of control variables, ANQPF maintains a robust positive association with ACEE at the 1% significance level, demonstrating that ANQPF can substantially enhance ACEE. Specifically, a 0.1-unit increase in ANQPF (approximately two standard deviations) is associated with a 0.127 increase in ACEE, equivalent to 22% of the sample mean (0.578). Accordingly, H1 is supported.

Table 7. Baseline regression results.

Variable	(1)	(2)	(3)	(4)
ANQPF	1.350 *** (0.325)	1.202 *** (0.317)	1.234 *** (0.316)	1.274 *** (0.346)
PS		0.004 ** (0.002)	0.004 * (0.002)	0.004 * (0.002)
Mech		−0.043 *** (0.011)	−0.036 *** (0.010)	−0.034 *** (0.010)
Rgdp			−0.005 (0.007)	−0.006 (0.007)
Adl			0.026 *** (0.007)	0.026 *** (0.007)
Open				−0.032 (0.066)
Fiscal				−0.243 (0.275)
Constant	0.431 *** (0.037)	0.395 *** (0.070)	0.314 *** (0.072)	0.390 *** (0.108)
Province FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Observation	360	360	360	360
R ²	0.890	0.896	0.900	0.900

Note: ***, **, and * indicate empirical significance at the 1%, 5%, and 10% levels, respectively. Robust standard errors are documented within parentheses, and the same applies hereinafter.

The estimated effects of the control variables are broadly in accordance with theoretical expectations. Planting structure and the level of agricultural economic development exert significantly positive effects on ACEE. In contrast, the level of agricultural mechanization is found to reduce ACEE. A plausible explanation is that the current agricultural machinery system, which relies primarily on fossil fuels, raises energy consumption and carbon emissions while intensifying and expanding cultivation, thereby lowering ACEE.

5.2. Endogeneity Test

To ensure the integrity of the baseline results and to alleviate endogeneity concerns arising from reciprocal causation, this study follows Tang et al. [71] by utilizing an instrumental variable constructed as the interaction between terrain ruggedness and the one-period lag of ANQPF. The reason is that terrain flatness constitutes an inherent natural condition for agricultural production. Flatter terrain facilitates the application of extensive intelligent agricultural machinery, the installation of irrigation facilities, and the consolidation of production oversight, thereby promoting the development of ANQPF and fulfilling the relevance criterion. Moreover, terrain ruggedness is primarily associated with natural geographical characteristics and remains decoupled from ACEE, thereby complying with the exogeneity postulate.

Table 8 reports the impact of ANQPF on ACEE by using the instrumental variable method. The two-stage least squares (2SLS) estimation results show that the LM statistic significantly rejects the null hypothesis of under-identification. In the weak-instrument test, the Wald F statistic exceeds the critical value at the 10% significance level, indicating that the model does not suffer from a weak instrument problem. Accordingly, after addressing endogeneity concerns, the positive effect of ANQPF on ACEE remains statistically significant.

Table 8. Endogeneity test results.

Variable	(1) First Stage IV-ANQPF	(2) Second Stage ANQPF-ACEE
IV	0.206 *** (0.040)	
ANQPF		3.330 ** (1.555)
Kleibergen-Paap rk LM		13.552 ***
Kleibergen-Paap rk Wald F		26.259 [16.380]
Control Variable	YES	YES
Province FE	YES	YES
Year FE	YES	YES
Observation	330	330

Note: ***, **, and * indicate empirical significance at the 1%, 5%, and 10% levels, respectively. The value in brackets [] denotes the critical value at the 10% significance level of the Stock–Yogo weak identification test.

5.3. Robustness Tests

A series of robustness checks are conducted by winsorization, replacing the dependent variable, removing municipalities, and adding additional control variables. The results are reported in Table 9. Considering that outliers in the regression sample may bias the estimation results, column (1) applies 1% winsorization to the data. The results indicate that the effect of ANQPF on ACEE remains significantly positive. Column (2) substitutes the outcome variable by adopting agricultural carbon emissions as a surrogate for ACEE. Empirical evidence indicates ANQPF markedly curtails agricultural carbon emissions, thereby reinforcing its fundamental essence as a form of green productivity. Column (3) reports the regression results after removing Beijing, Shanghai, Tianjin, and Chongqing, which likewise demonstrate a significantly positive effect of ANQPF on ACEE. Column (4) incorporates the level of crop damage and human capital level as additional control variables. The findings confirm that ANQPF continues to exert a strong positive influence on ACEE.

Table 9. Robustness test results.

Variable	(1) Winsorization	(2) Alternative Dependent Variable	(3) Removing Municipali- ties	(4) Additional Controls
ANQPF	1.274 *** (0.346)	−3.150 *** (1.136)	1.537 *** (0.505)	1.260 *** (0.347)
Lcd				0.006 (0.072)
Hcl				0.776 (0.657)
Constant	0.390 *** (0.108)	3.080 *** (0.246)	0.237 (0.144)	0.374 *** (0.106)
Control Variable	YES	YES	YES	YES
Province FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Observation	360	360	312	360
R ²	0.900	0.993	0.894	0.900

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

5.4. Mechanism Test

In this section, land transfer and the level of agricultural socialized services are sequentially introduced as mediating variables into the regression models to examine whether they serve as transmission channels through which ANQPF affects ACEE. The estimation results are reported in Table 10.

Table 10. Mechanism test results.

Variable	(1) Land Transfer	(2) The Level of Agricultural Socialized Services
ANQPF	0.397 ** (0.167)	0.569 * (0.329)
Constant	0.467 (0.044)	−0.087 (0.073)
Control Variable	YES	YES
Province FE	YES	YES
Year FE	YES	YES
Observation	360	360
R ²	0.945	0.917

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

Column (1) shows that the regression coefficient of land transfer stands at 0.397, attaining significance at the 5% threshold, suggesting that ANQPF significantly promotes land transfer, thereby supporting Hypothesis H2. By facilitating large-scale land management, ANQPF dilutes the fixed costs of digital infrastructure, intelligent equipment, and green technologies, which consequently amplifies the vibrancy of the farmland transfer market and reduces transaction costs associated with land transfer. Existing studies indicate that land transfer lowers land management costs and improves land use efficiency through scale operations [72]. At the same time, land transfer encourages large-scale operators to behave more closely as ‘rational economic agents,’ motivating them to adopt green production technologies encompassing organic fertilizers, water-saving irrigation systems, and conservation tillage, thereby enhancing ACEE [73].

Outcomes delineated in Column (2) demonstrate that ANQPF significantly enhances the level of agricultural socialized services, thereby supporting Hypothesis H3. By leveraging intelligent with particular reference to the Internet of Things and big data, ANQPF restructures the agricultural service system through intelligent technologies exemplified by the Internet of Things and big data, promoting its transformation from traditional decentralized services to full-chain intelligent transformation. It optimizes the allocation of production factors and the large-scale application of green technologies through large-scale and professional models, thereby improving the level of agricultural socialized services. Existing research shows that the level of agricultural socialized services take the centralized and contiguous land trusteeship service as the carrier, promote carbon-mitigation technologies as exemplified by precision irrigation and intelligent fertilization, and improve resource utilization efficiency while reducing fertilizer, pesticide and energy consumption per unit of output [49]. In addition, socialized service organizations provided farmers with operational guidance and technical training, standardized the use of agricultural chemicals, and to some extent improved AECC [48].

5.5. Threshold Effect Test

The impact of ANQPF on agricultural carbon reduction may vary with population density. The estimated threshold can be interpreted as a critical point at which the marginal effect of ANQPF on ACEE changes significantly, reflecting a structural shift in production

conditions and environmental governance pressure rather than a simple division of the sample. Accordingly, this study employs population density as a threshold variable for empirical testing. The empirical results, reported in Table 11, indicate that the impact of ANQPF on ACEE follows a single-threshold specification with respect to population density, with an estimated threshold value of 15.875.

Table 11. Threshold effect test results.

Threshold Factor	Model	F-Statistic	<i>p</i> -Value	Bootstrap Replications	Crit10	Critical Threshold Crit5	Crit1
Population density	Single threshold	37.940	0.048	500	32.787	37.360	58.948
	Double threshold	25.040	0.268	500	37.699	53.133	100.473
	Threshold Model	Threshold Value	95% Confidence Lower Bound		95% Confidence Upper Bound		
	Single-threshold model	15.875	15.685		20.414		

After determining the population density threshold, a regression analysis was performed on the threshold effect of ANQPF on ACEE. The corresponding results are presented in Table 12. When population density is less than or equal to 15.875, ANQPF exerts a significantly positive effect on ACEE, with an estimated coefficient of 2.928. When population density exceeds 15.875, the enhancing effect of ANQPF on ACEE weakens. Overall, the positive effect of ANQPF on ACEE persists across different population density regimes. However, as population density increases, the emission-reduction effect of ANQPF gradually diminishes. This reflects that in relatively low-density regions, land constraints are weaker and the scope for scale expansion is larger. Under such conditions, technological upgrading and organizational restructuring embedded in ANQPF can more effectively translate into efficiency gains. In contrast, higher-density regions experience infrastructure congestion and intensified factor competition, with concentrated agricultural production limiting the diffusion and application of ANQPF, increasing coordination costs, and reducing the marginal productivity of technological inputs. Moreover, environmental carrying capacity pressures become more binding as density rises, constraining efficiency gains from production expansion. Therefore, population density captures structural heterogeneity in resource endowments and environmental pressures, resulting in heterogeneous returns to ANQPF. Taken together, these findings provide empirical support for Hypothesis H5.

Table 12. Single threshold regression results.

Variable	ACEE
ANQPF (Population density) $\leq$ 15.875	2.928 ** (1.183)
ANQPF (Population density) $>$ 15.875	1.212 ** (0.439)
Constant	0.299 ** (0.120)
Control variables	YES
Province FE	YES
Year FE	YES
Observation	360
R ²	0.722

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

In lower-density regions, land fragmentation is less severe, enabling technological upgrading and scale expansion embedded in ANQPF to translate more effectively into efficiency gains. In contrast, higher-density regions experience infrastructure congestion and intensified factor competition, with concentrated agricultural production limiting the diffusion and application of ANQPF, increasing coordination costs, and reducing the marginal productivity of technological inputs. Moreover, environmental carrying capacity pressures become more binding as density rises, constraining efficiency gains from production expansion. Therefore, population density captures structural heterogeneity in resource endowments and environmental pressures, resulting in heterogeneous returns to ANQPF. Taken together, these findings provide empirical support for Hypothesis H5.

5.6. Heterogeneity Test

5.6.1. Heterogeneity Test Based on Resource Endowment Levels

Based on differences in resource endowments [74], this study classifies provinces into resource-based and non-resource-based groups and conducts grouped regressions to examine whether the effect of ANQPF on ACEE exhibits heterogeneity. The regression results are reported in Table 13. The results indicate that the promoting effect of ANQPF on ACEE is statistically significant in non-resource-based provinces, while it is insignificant in resource-based provinces. A plausible explanation is that non-resource-based provinces face stronger resource and environmental constraints, leading factor allocation to be more inclined toward high-technology and innovation-oriented sectors. As a technology-intensive production paradigm, ANQPF is therefore more readily accepted and diffused in these regions. In contrast, resource-based provinces have long relied on the exploitation of traditional resources such as minerals and energy, resulting in an industrial structure dominated by high-carbon industries. The green technological innovation factors required for the development of ANQPF find it difficult to break through entrenched resource-dependent development paths, causing its emission-reduction effects to be diluted by the structural model of traditional high-carbon industries.

Table 13. Heterogeneity test results.

Variable	(1) Resource-Based Provinces	(2) Non-Resource- Based Provinces	(3) Major Grain- Producing Regions	(4) Major Grain- Consuming Regions	(5) Production- Consumption Balance Regions
ANQPF	0.471 (0.616)	1.415 *** (0.421)	4.021 *** (0.836)	0.985 ** (0.403)	1.018 (1.045)
Constant	−0.031 (0.154)	0.560 *** (0.126)	0.037 (0.149)	0.676 *** (0.234)	−0.250 (0.278)
Control Variable	YES	YES	YES	YES	YES
Province FE	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES
Observation	108	252	156	84	120
R ²	0.899	0.885	0.911	0.839	0.908

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

5.6.2. Heterogeneity Test Based on Agricultural Production Functions

Based on functional heterogeneity in agricultural production, provinces are divided into grain-producing, grain-consuming, and production–consumption balance groups for analysis. The results show that ANQPF significantly enhances ACEE in grain-producing regions, with a weaker effect in grain-consuming regions and no significant effect in balance regions. One possible reason is that major grain-producing regions shoulder the primary responsibility for national food security, characterized by concentrated agricultural inputs

and large-scale production. As a result, both the total volume and intensity of agricultural carbon emissions are inherently more prominent in these regions. Consequently, any efficiency-enhancing form of ANQPF such as intelligent irrigation and precision fertilization generates the largest marginal emission-reduction effects when applied in these areas. Although major grain-consuming regions have a relatively smaller agricultural sector, they are economically more developed and possess advantages in capital, technology, and human resources. Driven by consumer demand for environmentally friendly and high-quality agricultural products, these regions are both capable of and willing to take the lead in adopting high-cost green technologies. Therefore, while the emission-reduction effect of ANQPF is statistically significant in major grain-consuming regions, its significance is slightly lower than that observed in major grain-producing regions when accounting for agriculture's smaller share in overall economic output. In contrast, production–consumption balance regions, which are neither core food security bases nor market frontiers, tend to face relatively low levels of policy attention and market competitiveness. This dual constraint weakens the incentives for the diffusion and application of ANQPF in these regions, resulting in an insignificant emission-reduction effect.

6. Discussion

This study contributes to the literature on green agricultural transformation by examining the role of ANQPF in improving ACEE and situating the findings within existing research.

First, the empirical results indicate that ANQPF significantly enhances ACEE. This finding is consistent with evidence from the manufacturing sector showing that new quality productive forces reduce carbon emission intensity [33]. However, unlike existing studies that focus on industrial carbon intensity, this study extends the analysis to the agricultural sector and evaluates carbon efficiency under a super-efficiency SBM framework that incorporates undesirable outputs, thereby providing a more comprehensive assessment of green performance.

Second, the mechanism analysis demonstrates that ANQPF promotes ACEE through land transfer and agricultural socialized services, with land transfer exhibiting a stronger mediating role. This finding is consistent with previous studies showing that farm size expansion and land consolidation improve technical efficiency and reduce carbon emission intensity in agriculture [75,76]. Agricultural socialized services reduce transaction costs, standardize production practices, and facilitate the adoption of precision and low-carbon technologies. These results complement existing research on farm size expansion, mechanization services, and green production transformation [77,78] by explicitly identifying the transmission channels linking new productive forces to carbon efficiency.

Third, the nonlinear analysis reveals a significant single-threshold effect of population density. As population density increases, the marginal effect of ANQPF gradually weakens, reflecting a structural shift from agglomeration-driven efficiency gains to congestion and land-scarcity constraints. This pattern aligns with the literature on population pressure and agricultural intensification [58], while revealing the nonlinear interaction between demographic structure and green productivity transformation.

Fourth, the regional heterogeneity analysis shows that the positive effect of ANQPF on ACEE is more pronounced in major grain-producing regions and non-resource-based provinces. Compared with studies that primarily report spatial disparities in carbon emissions, this study highlights differences in carbon efficiency responsiveness to new productive forces.

Overall, these findings deepen the understanding of how new productive forces drive green agricultural transformation and clarify the mechanisms, nonlinear dynamics, and regional differences underlying this process.

7. Conclusions

ANQPF constitutes a critical driver of green agricultural transformation. Using provincial panel data for 2011–2022, this study examines the impact of ANQPF on ACEE, along with its mechanisms, threshold effects, and regional heterogeneity.

First, ANQPF significantly improves ACEE, and the result remains stable after addressing endogeneity and performing a series of robustness tests.

Second, ANQPF enhances ACEE through land transfer and agricultural socialized services, with land transfer exhibiting a stronger mediating effect.

Third, the relationship between ANQPF and ACEE exhibits a significant single-threshold effect based on population density, indicating that the marginal effect of ANQPF gradually weakens as density increases.

Fourth, the positive effect of ANQPF on ACEE is more pronounced in major grain-producing regions and non-resource-based provinces.

7.1. Policy Implications

Based on the conclusions, the following policy implications are proposed to promote the development of ANQPF and accelerate the low-carbon transformation of agriculture.

First, promote the ecological upgrading of agricultural production factors. Strengthen digital and low-carbon skill training for agricultural laborers, including professional farmer development programs and targeted green skill subsidies. Improve resource recycling systems by integrating livestock waste treatment, biogas utilization, and organic fertilizer substitution. Accelerate the replacement of energy-intensive machinery with energy-efficient equipment and promote renewable energy-integrated agricultural production models.

Second, enhance coordination between land transfer and agricultural service systems. Improve land transfer information platforms to increase transparency and matching efficiency, while strengthening legal safeguards for land-use rights. Expand fiscal and tax incentives to encourage diversified agricultural service providers and promote scale management, standardized production, and precision agriculture.

Third, optimize population–resource allocation under differentiated density conditions. Establish mechanisms to facilitate the interregional allocation of land, capital, and technology. In low-density areas, prioritize land consolidation and large-scale operations. In high-density areas, promote intensive and technology-driven production models to improve land-use efficiency and mitigate congestion effects.

Fourth, implement regionally differentiated development strategies. Construct high-standard farmland in major grain-producing regions and promote water-saving technologies. Strengthen cooperation between major grain-producing regions and major consumption areas, and implement market access for ‘carbon-labeled agricultural products.’ Carry out low-carbon agricultural development projects in production–consumption balance regions, and develop alternative industries such as the ‘non-timber forest-based economy’ and ecological breeding. Strengthen ecological restoration in resource-based provinces, and guide non-resource-based provinces to develop agricultural product processing, rural e-commerce, and related industries to extend the agricultural value chain and foster new growth points for ANQPF.

7.2. Limitations

This study has two primary limitations. First, due to the release cycle of official statistics, the empirical analysis covers data only up to 2022. Although this time span captures medium- to long-term trends, it does not incorporate the most recent dynamics, thereby constraining the timeliness of the conclusions. In addition, while the use of provincial-level

panel data ensures a sufficient sample size and estimation efficiency, it cannot fully capture micro-level behavioral mechanisms. Specifically, in the mediation analysis, land transfer is proxied by the share of transferred contracted land, and agricultural socialized services are measured by service output value per agricultural practitioner. These proxies capture scale expansion and service intensity but may not fully reflect contract stability, tenure security, or service quality heterogeneity. Second, the analytical framework and indicator system are constructed within China's specific institutional context and developmental stage. Although the findings provide meaningful policy insights, their external validity and broader generalizability require further verification through cross-national comparative analysis or contextualized replication in other major agricultural economies.

In light of these limitations, future research may proceed in two directions. First, extending the study period and incorporating micro-level survey data from farmers and agricultural enterprises would help uncover the behavioral foundations and heterogeneous effects underlying the observed macro-level relationships, including more nuanced measures of land tenure arrangements and service quality. Second, conducting international comparative studies by selecting representative agricultural countries or regions for replication analysis would facilitate the identification of more generalizable theoretical insights and policy implications.

Author Contributions: L.L.: Conceptualization, data curation, software, methodology, formal analysis, visualization, writing—original draft. Y.L.: Funding acquisition, formal analysis. B.W.: Formal analysis, resources. J.Z.: Supervision, formal analysis. X.B.: Funding acquisition, conceptualization, project administration, writing—review and editing, supervision. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by the Special project of scientific and technological innovation of Xinjiang Research Institute of Arid Area Agriculture (XJHQNY-2025-8), the Science and Technology Project of Yulin (2024-CXY-187) and Ministry of Education of Humanities and Social Science Foundation (22YJA790001).

Institutional Review Board Statement: Not applicable.

Data Availability Statement: The data presented in this study are openly available in the China Research Data Services Platform (CRNDS) at <https://www.cnrds.com/Home/Index#/> (accessed on 6 September 2025) and the statistical database of the China National Knowledge Infrastructure (CNKI) at <https://data.cnki.net/> (accessed on 15 September 2025).

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

References

1. IPCC. *Climate Change and Land: An IPCC Special Report on Climate Change, Desertification, Land Degradation, Sustainable Land Management, Food Security, and Greenhouse Gas Fluxes in Terrestrial Ecosystems*; Intergovernmental Panel on Climate Change: Geneva, Switzerland, 2019.
2. Aleksandra Arcipowska, E.M.Y.L. 5 Questions About Agricultural Emissions, Answered. Available online: <https://www.wri.org/insights/5-questions-about-agricultural-emissions-answered> (accessed on 19 November 2025).
3. Zhu, Y.; Huo, C. The impact of agricultural production efficiency on agricultural carbon emissions in China. *Energies* **2022**, *15*, 4464. [CrossRef]
4. Liu, L.; Hu, X.; Li, L.; Sun, Z.; Zhang, Q. Understanding China's agricultural non-carbon-dioxide greenhouse gas emissions: Subnational insights and global trade dynamics. *Environ. Impact Assess. Rev.* **2024**, *106*, 107487. [CrossRef]
5. Huang, Q.; Guo, W.; Wang, Y. A study of the impact of new quality productive forces on agricultural modernization: Empirical evidence from China. *Agriculture* **2024**, *14*, 1935. [CrossRef]
6. Ma, Z.; Liu, T.; Li, J.; Liu, Z.; Chen, W. Spatial effect analysis of forestry technology innovation on forestry industry economic growth. *Forests* **2023**, *14*, 557. [CrossRef]
7. Yu, D.S.; Liu, L.X.; Gao, S.H.; Yuan, S.Y.; Shen, Q.L.; Chen, H.P. Impact of carbon trading on agricultural green total factor productivity in China. *J. Clean. Prod.* **2022**, *367*, 132789. [CrossRef]

8. Jia, X.M.; Zhang, W.T.; Zhu, T.T. Agricultural new productive forces driving sustainable agricultural development: Evidence from Anhui province, China. *Sustainability* **2026**, *18*, 792. [[CrossRef](#)]
9. Zhang, X.; Zhou, X.; Liao, K. Regional differences and dynamic evolution of China's agricultural carbon emission efficiency. *Int. J. Environ. Sci. Technol.* **2023**, *20*, 4307–4324. [[CrossRef](#)]
10. Xiong, C.; Yang, D.; Xia, F.; Huo, J. Changes in agricultural carbon emissions and factors that influence agricultural carbon emissions based on different stages in Xinjiang, China. *Sci. Rep.* **2016**, *6*, 36912. [[CrossRef](#)] [[PubMed](#)]
11. Shan, T.; Xia, Y.; Hu, C.; Zhang, S.; Zhang, J.; Xiao, Y.; Dan, F. Analysis of regional agricultural carbon emission efficiency and influencing factors: Case study of Hubei province in China. *PLoS ONE* **2022**, *17*, e266172. [[CrossRef](#)]
12. Gang, H.; Zhao, F.Y. Research on the coupling and harmonization degree of new productive force and high-quality economic development. *Financ. Res. Lett.* **2025**, *84*, 107684. [[CrossRef](#)]
13. Wang, R.; Feng, Y. Research on China's agricultural carbon emission efficiency evaluation and regional differentiation based on Dea and Theil models. *Int. J. Environ. Sci. Technol.* **2021**, *18*, 1453–1464. [[CrossRef](#)]
14. Xia, Y.; Guo, H.; Xu, S.; Pan, C. Environmental regulations and agricultural carbon emissions efficiency: Evidence from rural China. *Heliyon* **2024**, *10*, e25677. [[CrossRef](#)] [[PubMed](#)]
15. Huang, B.; Kong, H.; Yu, J.; Zhang, X. A study on the impact of low-carbon technology application in agriculture on the returns of large-scale farmers. *Int. J. Environ. Res. Public Health* **2022**, *19*, 10177. [[CrossRef](#)]
16. Dong, G.; Wang, Z.; Mao, X. Production efficiency and ghg emissions reduction potential evaluation in the crop production system based on emergy synthesis and nonseparable undesirable output dea: A case study in Zhejiang province, China. *PLoS ONE* **2018**, *13*, e0206680. [[CrossRef](#)] [[PubMed](#)]
17. Sun, X.Y.; Guang, S.Y.; Cao, J.J.; Zhu, F.Y.; Liu, J.X.; Sriboonchitta, S. Effect of agricultural production trusteeship on agricultural carbon emission reduction. *Agriculture* **2023**, *13*, 1457. [[CrossRef](#)]
18. Zhang, S.; Li, X.; Nie, Z.; Wang, Y.; Li, D.; Chen, X.; Liu, Y.; Pang, J. The significance of agricultural modernization development for agricultural carbon emission efficiency in China. *Agriculture* **2024**, *14*, 939. [[CrossRef](#)]
19. Li, J.J.; Li, S.W.; Liu, Q.; Ding, J.L. Agricultural carbon emission efficiency evaluation and influencing factors in Zhejiang province, China. *Front. Environ. Sci.* **2022**, *10*, 1005251. [[CrossRef](#)]
20. Venturini, F. Intelligent technologies and productivity spillovers: Evidence from the fourth industrial revolution. *J. Econ. Behav. Organ.* **2022**, *194*, 220–243. [[CrossRef](#)]
21. Yang, R.; Jin, X.L.; Huang, W.H.; Wang, S.K. Evolutionary game analysis of the driving mechanism for green technology innovation in enterprises: A new quality productive forces perspective. *Financ. Res. Lett.* **2025**, *85*, 108115. [[CrossRef](#)]
22. Li, S.; Liu, J.; Guo, W. Empowered or negative? Research on the impact of industrial agglomeration on the development of agricultural new quality productive forces: Evidence from Shandong province, China. *Sustainability* **2025**, *17*, 3348. [[CrossRef](#)]
23. Cao, X.; Lei, J.; Shi, D.; Yu, W.; Tao, T.; Zhang, X.; Wang, A. New quality productivity of agriculture and rural areas at the provincial scale in China: Indicator construction and spatiotemporal evolution. *ISPRS Int. J. Geo-Inf.* **2025**, *14*, 104. [[CrossRef](#)]
24. Wu, H.L.; Yang, H.F.; Yan, J.L. Level measurement, regional difference decomposition and dynamic evolution of China's agricultural new quality productive forces. *J. Nonlinear Convex Anal.* **2025**, *26*, 1887–1898.
25. Luo, W.; Zuo, S.; Tang, S.; Li, C. The formation of new quality productivity of agriculture under the perspectives of digitalization and innovation: A dynamic qualitative comparative analysis based on the “technology-organization-environment” framework. *Sustainability* **2025**, *17*, 597. [[CrossRef](#)]
26. Jiang, S. Evaluation of new quality productive forces in Henan province based on improved entropy weight-topsis method and deep learning. *Sci. Rep. (Nat. Publ. Group)* **2025**, *15*, 35434. [[CrossRef](#)] [[PubMed](#)]
27. Cui, J.; Du, D.S. New quality productive forces, urban-rural integration and industrial chain resilience. *Int. Rev. Econ. Financ.* **2025**, *102*, 104245. [[CrossRef](#)]
28. Li, L.; Gu, T.; Shi, Y. The influence of new quality productive forces on high-quality agricultural development in China: Mechanisms and empirical testing. *Agriculture* **2024**, *14*, 1022. [[CrossRef](#)]
29. Qiu, L.N.; Liu, X.; Zhou, T.F. Impact of new quality productive forces on the share of enterprise labor income. *Financ. Res. Lett.* **2025**, *86*, 108523. [[CrossRef](#)]
30. Ye, F.; Zhang, Q. Impact of agricultural new-quality productivity forces on agricultural resilience and environmental sustainability in China: From the perspective of carbon emissions. *Sustainability* **2025**, *17*, 9630. [[CrossRef](#)]
31. Zhang, J.H.; Wang, X.D.; Zhang, W.H.; Wang, L.Z. Can the carbon emissions trading policy promote the development of new quality productive forces in manufacturing enterprises? *Financ. Res. Lett.* **2025**, *83*, 107617. [[CrossRef](#)]
32. Han, G.; Xu, J.; Zhang, X.; Pan, X. Efficiency and driving factors of agricultural carbon emissions: A study in chinese state farms. *Agriculture* **2024**, *14*, 1454. [[CrossRef](#)]
33. Li, J.; Lin, Y.; Dai, M.; Chen, H. New quality productive forces, technological innovations, and the carbon emission intensity of the manufacturing industry: Empirical evidence from Chinese provincial panel data. *Sustainability* **2025**, *17*, 9641. [[CrossRef](#)]

34. Färe, R.; Grosskopf, S.; Pasurka, C.A. Environmental production functions and environmental directional distance functions. *Energy* **2007**, *32*, 1055–1066. [\[CrossRef\]](#)
35. Li, K.; Lin, B. Measuring green productivity growth of Chinese industrial sectors during 1998–2011. *China Econ. Rev.* **2015**, *36*, 279–295. [\[CrossRef\]](#)
36. Li, X.; Qin, Q.; Yang, Y. The impact of green innovation on carbon emissions: Evidence from the construction sector in China. *Energies* **2023**, *16*, 4529. [\[CrossRef\]](#)
37. Zhao, L.J.; Liu, Y.; Shi, J.H. The environmental performance of agricultural production trusteeship from the perspective of planting carbon emissions. *China Agric. Econ. Rev.* **2023**, *15*, 853–870. [\[CrossRef\]](#)
38. Chen, Z.W.; Bi, G.D.; Guo, H.H. The effect of the level of digital agriculture development on agricultural carbon emission reduction in China: Mediating evidence based on agricultural labor productivity and production technical efficiency. *Sustainability* **2025**, *17*, 7669. [\[CrossRef\]](#)
39. Feng, X.C.; Zhao, Y.P.; Yan, R.Y. Does carbon emission trading policy has emission reduction effect?—An empirical study based on quasi-natural experiment method. *J. Environ. Manag.* **2024**, *351*, 119791. [\[CrossRef\]](#) [\[PubMed\]](#)
40. Wang, Z.F.; Wei, K.Y.; Wen, B.L.; You, K.J.; Wang, H.L.; Ye, C.X.; Ren, F.L. Research on the allocation level of land for agricultural facilities based on green and high-quality development: A case study of Zhejiang province. *Land* **2025**, *14*, 672. [\[CrossRef\]](#)
41. Li, Q.; Wang, Z.X. Impact of contract farming on green technological efficiency of farmers: A comparative study of two contract organizational models. *Front. Sustain. Food Syst.* **2024**, *8*, 1368997. [\[CrossRef\]](#)
42. Zhang, J.; Mishra, A.K.; Zhu, P.; Li, X. Land rental market and agricultural labor productivity in rural China: A mediation analysis. *World Dev.* **2020**, *135*, 105089. [\[CrossRef\]](#)
43. Zhu, W.; Qi, L.; Wang, R. The relationship between farm size and fertilizer use efficiency: Evidence from China. *J. Integr. Agric.* **2022**, *21*, 273–281. [\[CrossRef\]](#)
44. Zhou, Y.; Guo, Y.Z.; Liu, Y.S.; Wu, W.X.; Li, Y.R. Targeted poverty alleviation and land policy innovation: Some practice and policy implications from China. *Land Use Policy* **2018**, *74*, 53–65. [\[CrossRef\]](#)
45. Fei, R.; Lin, Z.; Chunga, J. How land transfer affects agricultural land use efficiency: Evidence from China’s agricultural sector. *Land Use Policy* **2021**, *103*, 105300. [\[CrossRef\]](#)
46. Luo, B.; Zhou, J.; Zang, H.; Sawut, A.; Feng, X.; Yang, Y.; Peixoto, L.; Wang, X.; Olesen, J.E.; Zeng, Z. Optimize farm size and agronomic practices to improve agricultural sustainability: A case of multi-indicator assessment from the north China plain. *Environ. Dev. Sustain.* **2025**, *27*, 6599–6618. [\[CrossRef\]](#)
47. Wang, M.S.; Zhang, X.; Guo, Z.X. The impact of farm structure on agricultural growth in China. *Land* **2024**, *13*, 1494. [\[CrossRef\]](#)
48. Yang, C.F.; Zeng, H.Y.; Zhang, Y.F. Are socialized services of agricultural green production conducive to the reduction in fertilizer input? Empirical evidence from rural China. *Int. J. Environ. Res. Public Health* **2022**, *19*, 14856. [\[CrossRef\]](#)
49. Chen, Z.W.; Tang, C.; Liu, B.; Liu, P.; Zhang, X.Y. Can socialized services reduce agricultural carbon emissions in the context of appropriate scale land management? *Front. Environ. Sci.* **2022**, *10*, 1039760. [\[CrossRef\]](#)
50. Manda, J.; Khonje, M.G.; Alene, A.D.; Tufa, A.H.; Abdoulaye, T.; Mutenje, M.; Setimela, P.; Manyong, V. Does cooperative membership increase and accelerate agricultural technology adoption? Empirical evidence from Zambia. *Technol. Forecast. Soc. Change* **2020**, *158*, 120160. [\[CrossRef\]](#)
51. Zhong, Z.; Jiang, W.; Yang, S. Does agricultural outsourcing improve technical efficiency? Evidence from farms of various scales in China. *J. Rural Stud.* **2025**, *117*, 103650. [\[CrossRef\]](#)
52. Cai, B.Z.; Shi, F.; Huang, Y.J.; Abatechane, M. The impact of agricultural socialized services to promote the farmland scale management behavior of smallholder farmers: Empirical evidence from the rice-growing region of southern China. *Sustainability* **2022**, *14*, 316. [\[CrossRef\]](#)
53. Lei, S.; Yang, X.; Qin, J. Does agricultural factor misallocation hinder agricultural green production efficiency? Evidence from China. *Sci. Total Environ.* **2023**, *891*, 164466. [\[CrossRef\]](#)
54. Xiong, C.H.; Chen, S.; Yang, D.G. Selecting counties to participate in agricultural carbon compensation in China. *Pol. J. Environ. Stud.* **2019**, *28*, 1443–1449. [\[CrossRef\]](#)
55. Yi, Y.C.; Wang, Y.J.; Li, Y.Q.; Qi, J. Impact of urban density on carbon emissions in China. *Appl. Econ.* **2021**, *53*, 6153–6165. [\[CrossRef\]](#)
56. Ribeiro, H.V.; Rybski, D.; Kropp, J.P. Effects of changing population or density on urban carbon dioxide emissions. *Nat. Commun.* **2019**, *10*, 3204. [\[CrossRef\]](#) [\[PubMed\]](#)
57. Bintz, J.; Lenhart, S. Optimal resource allocation for a diffusive population model. *J. Biol. Syst.* **2020**, *28*, 945–976. [\[CrossRef\]](#)
58. Ricker-Gilbert, J.; Jumbe, C.; Chamberlin, J. How does population density influence agricultural intensification and productivity? Evidence from Malawi. *Food Policy* **2014**, *48*, 114–128. [\[CrossRef\]](#)
59. Chang, S.C.; Li, M.H. Impacts of foreign direct investment and economic development on carbon dioxide emissions across different population regimes. *Environ. Resour. Econ.* **2018**, *72*, 583–607. [\[CrossRef\]](#)

60. Chen, J.; Wang, B.; Huang, S.; Song, M. The influence of increased population density in China on air pollution. *Sci. Total Environ.* **2020**, *735*, 139456. [[CrossRef](#)]
61. Carter, A.R.; Sanderson, E.; Hammerton, G.; Richmond, R.C.; Smith, G.D.; Heron, J.; Taylor, A.E.; Davies, N.M.; Howe, L.D. Mendelian randomisation for mediation analysis: Current methods and challenges for implementation. *Eur. J. Epidemiol.* **2021**, *36*, 465–478. [[CrossRef](#)]
62. Tian, Y.; Wang, R.; Yin, M.; Zhang, H. Study on the measurement and influencing factors of rural energy carbon emission efficiency in China: Evidence using the provincial panel data. *Agriculture* **2023**, *13*, 441. [[CrossRef](#)]
63. He, Y.; Cheng, X.; Wang, F. Regional spillover effects of agricultural carbon emissions from the perspective of technological diffusion. *J. Agrotech. Econ.* **2022**, *04*, 132–144. (In Chinese)
64. Min, J.; Hu, H. Measurement of greenhouse gas emissions from agricultural production in China. *CJPRE* **2012**, *22*, 21–27. (In Chinese)
65. Chang, T.; Tone, K.; Wu, C. Nested dynamic network data envelopment analysis models with infinitely many decision making units for portfolio evaluation. *Eur. J. Oper. Res.* **2021**, *291*, 766–781. [[CrossRef](#)] [[PubMed](#)]
66. Tone, K. A slacks-based measure of efficiency in data envelopment analysis. *Eur. J. Oper. Res.* **2001**, *130*, 498–509. [[CrossRef](#)]
67. Aigner, D.; Lovell, C.A.K.; Schmidt, P. Formulation and estimation of stochastic frontier production function models. *J. Econom.* **1977**, *6*, 21–37. [[CrossRef](#)]
68. Marx, K. *Capital: A Critique of Political Economy*, 1st ed.; Penguin Books: London, UK, 1990.
69. Jin, X.; Wang, Y.W.; Yin, K.D. Research on the measurement and spatiotemporal evolution characteristics of new quality productive forces in China's marine economy. *Front. Mar. Sci.* **2024**, *11*, 1497167. [[CrossRef](#)]
70. Guo, W.; Liu, J.; Zhao, X.; Hou, W.; Zhao, Y.; Li, Y.; Sun, W.; Fan, D. Spatiotemporal dynamics of population density in China using nighttime light and geographic weighted regression method. *Int. J. Digit. Earth* **2023**, *16*, 2704–2723. [[CrossRef](#)]
71. Tang, K.; Liu, X. Digital economy development and urban shrinkage: Evidence from nighttime light data. *J. Manag. Sci.* **2024**, *37*, 16–33. (In Chinese)
72. Jin, S.Q.; Jayne, T.S. Land rental markets in Kenya: Implications for efficiency, equity, household income, and poverty. *Land Econ.* **2013**, *89*, 246–271. [[CrossRef](#)]
73. Li, J.; Jiang, L.; Zhang, S. How land transfer affects agricultural carbon emissions: Evidence from China. *Land* **2024**, *13*, 1358. [[CrossRef](#)]
74. Dong, Q.Y.; Zhong, K.Y.; Liao, Y.J.; Xiong, R.L.; Wang, F.B.; Pang, M. Coupling coordination degree of environment, energy, and economic growth in resource-based provinces of China. *Resour. Policy* **2023**, *81*, 103308. [[CrossRef](#)]
75. Bai, J.; Liu, J.; Ma, L.; Zhang, W. The impact of farmland management scale on carbon emissions. *Land* **2023**, *12*, 1760. [[CrossRef](#)]
76. Hao, W.; Hu, X.; Wang, J.; Zhang, Z.; Shi, Z.; Zhou, H. The impact of farmland fragmentation in China on agricultural productivity. *J. Clean. Prod.* **2023**, *425*, 138962. [[CrossRef](#)]
77. Lu, F.; Meng, J.; Cheng, B. How does improving agricultural mechanization affect the green development of agriculture? Evidence from China. *J. Clean. Prod.* **2024**, *472*, 143298. [[CrossRef](#)]
78. Reardon, T.; Awokuse, T.; Belton, B.; Liverpool-Tasie, L.S.O.; Minten, B.; Nguyen, G.; Qanti, S.; Swinnen, J.; Vos, R.; Zilberman, D. Emerging outsource agricultural services enable farmer adaptation in agrifood value chains: A product cycle perspective. *Food Policy* **2024**, *127*, 102711. [[CrossRef](#)]

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