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The Green Productivity Effect of Agricultural New Quality Productive Forces—Evidence from Provincial Panel Data and Farm Household Surveys

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Abstract

Developing agricultural new quality productive forces (NQP) is an important pathway to promoting the green transformation of agriculture. This study constructs an evaluation indicator system for NQP from three dimensions: new quality workers (NQW), new quality means of labor (NQML), and new quality objects of labor (NQOL). Using panel data from 30 provinces in China for 2011–2023 and survey data from 533 farm households in Sichuan Province in 2024, it employs a two-way fixed effects model, a spatial Durbin model (SDM), and a threshold model to examine the relationships between NQP and agricultural green total factor productivity (AGTFP), and between farm-level new quality productive forces (FNQP) and green production behavior (GB), respectively. The findings show that NQP are significantly positively associated with AGTFP and exhibit certain spatial associations; FNQP are significantly positively associated with GB, indicating that production factor quality is closely associated with farmers' green production practices; the threshold analysis suggests a stronger positive association between FNQP and GB among farmers with higher digital information analysis ability (DIAA). The study reveals the links between production factor quality and agricultural green development (AGD) at the levels of regional productivity and farmer behavior, providing empirical evidence for coordinating the development of knowledge and skills, technological equipment, and production conditions, and for providing targeted training in information ability.

Keywords: agricultural new quality productive forces; agricultural green total factor productivity; spatial spillovers; farmers' green production behavior; digital information analysis ability

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1. Introduction

AGTFP is a key indicator of the degree of coordination between economic output and resource and environmental costs in agricultural production, and an important basis for evaluating the level of agricultural sustainable development. Against the backdrop of global population growth, tightening resource and environmental constraints, and increasing climate change risks, improving resource use efficiency and reducing environmental burdens while ensuring agricultural output has become a common issue in sustainable agricultural development [1]. Agricultural activities and nitrogen fertilizer use can also contribute to nitrogen pollution in water bodies [2]. The OECD places agricultural productivity, sustainability, and resilience within a coordinated framework, emphasizing that innovation and improvements in resource use efficiency are important foundations for

sustainable agricultural productivity growth [3]. The FAO further points out that agricultural automation, particularly digital automation, has the potential to improve productivity, resilience, and resource use efficiency, and enhance environmental sustainability [4]. Recent studies also show that digital agricultural technologies can improve production efficiency through precision inputs, intelligent operations, and data-driven decision-making, and demonstrate considerable potential for saving inputs such as fertilizers, pesticides, water, and energy [5]. In this context, China's green transformation of agriculture also faces multiple requirements: stabilizing agricultural output, improving resource use efficiency, and reducing environmental costs. Existing studies show that China's AGTFP grew at an average annual rate of 5.66% during 2011–2022 [6], and that technological progress, carbon dioxide productivity, total nitrogen productivity, and other factors jointly contributed to improvements in China's AGTFP [7]. However, under increasingly stringent resource and environmental constraints, sustained improvements in agricultural productivity cannot rely solely on additional traditional factor inputs; new momentum for productive forces must also be generated through technological progress, improvements in factor quality, and changes in production methods [8]. Therefore, further improving AGTFP through advanced production factors and their optimized combinations has become an important issue to be addressed in the green transformation of agriculture.

Agricultural new quality productive forces (NQP) provide a new perspective for understanding this issue. As a new round of scientific and technological revolution and industrial transformation increasingly penetrates agriculture, digital technologies, biotechnology, and intelligent equipment are continuously entering agricultural production, accompanied by changes in agricultural workers' knowledge and skills, the technological content of the means of production, and agricultural production conditions. The 2024 Central No. 1 Document further strengthened agricultural science and technology support in agricultural scientific and technological innovation, biological breeding, agricultural machinery and equipment, and a high-quality production and management workforce [9]. The 2025 Central No. 1 Document further explicitly proposed "using scientific and technological innovation to guide the concentration of advanced production factors and developing NQP according to local conditions" [10]. NQP are led by scientific and technological innovation and characterized by improvements in production factor quality and innovative allocation. Their development can change input methods and resource allocation in agricultural production through improvements in workers' quality, innovations in the means of production, and improvements in production conditions, providing a new productive foundation for reducing resource consumption and environmental costs and improving agricultural production efficiency [11]. Agricultural production has clear regional linkages, and new technologies, knowledge, and production methods may extend to surrounding areas through interregional production links and factor flows. It is therefore necessary to further examine the relationship between NQP and AGTFP and its spatial characteristics.

On this basis, this study examines the relationship between NQP and agricultural green development (AGD) at regional and farm household scales. At the regional level, panel data from 30 provinces in China for 2011–2023 are used to analyze the relationship between NQP and AGTFP and its spatial associations. At the farm household level, survey data from 533 farm households in Sichuan Province in 2024 are used to examine the relationship between FNQP and GB and to analyze the threshold role of DIAA. The provincial analysis focuses on cumulative productivity changes under resource and environmental constraints, whereas the farm household survey focuses on the implementation of selected green production practices. The two sets of results provide complementary empirical evidence at different levels.

2. Literature Review

Existing research has established a foundation for examining the relationship between NQP and agricultural green performance. Relevant studies mainly examine AGTFP, green cultivated land use efficiency, agricultural eco-efficiency, and green development efficiency, and generally find that NQP can improve agricultural green performance through green technological progress, optimized factor allocation, and industrial structure upgrading [12]. Related research on agricultural green and sustainable productivity pays considerable attention to technological progress and the application of advanced production factors, while food system research has gradually focused on the effects of synergies among different adaptation measures on agricultural system resilience and sustainability [13]. Existing studies find that technological progress is an important driver of AGTFP growth, whereas misallocation of agricultural capital, labor, land, and other factors reduces agricultural green production efficiency [14]. Regarding specific technology applications, Huck et al. systematically reviewed research on the environmental impacts of digital agricultural technologies and identified precision agriculture and digital crop management as the main current application areas in the environmental assessment of digital agriculture [15]. Atia et al. summarized the applications of CRISPR and other biotechnologies in improving crop stress resistance and sustainable production capacity from the perspective of crop gene editing [16]. Liu further found that anthropogenic adaptation measures, such as variety improvement and adjustments to sowing dates, can improve the adaptation of highland barley to climatic conditions and expand suitable planting areas [17]. Based on life cycle assessments of Italian dairy farms, Lovarelli et al. found that precision livestock technologies, such as automated milking, can reduce environmental impacts per unit of product by improving production efficiency [18].

Some studies further examine the spatial characteristics of NQP and agricultural green performance, suggesting that knowledge dissemination, technology diffusion, and spatial links may extend the relevant effects to neighboring regions [19,20]. Using spatial econometric models to study agricultural factor misallocation and green production efficiency, Lei et al. found that capital, labor, and land misallocation not only reduces local agricultural green production efficiency but also has spatial effects on neighboring regions [14]. Based on panel data from 1602 counties in China during 2011–2020, Lu et al. found that rural digitalization can improve AGTFP and exhibits spatial spillover effects under different spatial weight matrices [21].

At the farm household level, existing research more often explains farmers' technology applications and GB through factors such as access to digital information, technology cognition, and production conditions [22]. In their analysis of research on the adoption of precision agriculture and agricultural digitalization technologies, Kroupová et al. found that operating scale, education, and technological literacy are important factors affecting farmers' adoption of these technologies; information on technological benefits, advisory services, and technical support also influence their technology choices [23]. Research on agricultural human capital also finds that practical education and agricultural skill development can strengthen the capacity foundations for individual participation in agricultural production and operations [24]. Following a systematic review of research on the adoption of sustainable agricultural innovations, Rizzo et al. found that innovation characteristics, operators' psychological cognition, socioeconomic characteristics, and the operating environment all affect farmers' adoption of sustainable agricultural innovations [25]. Thompson et al.'s systematic mapping of research on farmers' adoption of ecological production practices further shows that individual farmer characteristics, farm operating structures, and different types of ecological practices constitute the main research topics in this field [26].

Overall, existing research examines the green performance of NQP through AGTFP, agricultural eco-efficiency, and other measures, and further considers their spatial effects. It also analyzes farmers' technology adoption and GB through access to digital information, technology cognition, resource endowments, and production conditions. These studies provide an important foundation for understanding the relationship between NQP and AGD. However, existing research on NQP remains concentrated mainly at the regional level, with relatively few studies analyzing the relationship between NQP and farmers' GB at the farm household level.

3. Theoretical Analysis and Research Hypotheses

3.1. Theoretical Analysis of NQP and AGTFP

NQP are an advanced form of productive forces led by scientific and technological innovation and characterized by improvements in production factor quality and optimized combinations [27]. Compared with agricultural growth that mainly relies on increased traditional factor inputs, NQP place greater emphasis on improving production efficiency through technological progress and optimized factor allocation [28]. AGTFP emphasizes productivity improvements under resource and environmental constraints. The two are internally consistent in improving production efficiency, improving resource use, and promoting changes in agricultural production methods [29]. With the development of NQP, agricultural workers' knowledge and skills, advanced technological equipment, and production conditions continuously improve, supporting optimized agricultural factor allocation and the application of green production methods. Combining improvements in knowledge and skills with the application of technological equipment helps improve the precision of production decisions and operational management and reduce unreasonable production factor inputs. Existing research points out that the productivity and environmental benefits of advanced technologies require joint support from knowledge and skills and infrastructure conditions [4]. Meanwhile, technological progress and improvements in production conditions help improve resource use efficiency and reduce resource consumption and environmental burdens in agricultural production. Therefore, by promoting the application and optimized allocation of advanced production factors, NQP improve input–output relationships under resource and environmental constraints, supporting AGTFP growth [30]. Based on this analysis, the following research hypothesis is proposed:

H1. *NQP are positively associated with AGTFP.*

3.2. Theoretical Analysis of Spatial Spillover Effects of NQP

Agricultural production has clear spatial associations. Geographically neighboring regions often share certain similarities in natural conditions, cropping systems, factor markets, and technological needs, and agricultural technologies, production experience, and production services may flow across administrative boundaries. Existing research finds that agricultural factor allocation is associated not only with local green production efficiency but also with certain spatial associations [14]. New technologies, equipment, and production organization methods generated by improvements in NQP may improve local resource allocation and production efficiency and also influence AGTFP in surrounding regions through interregional technological links, market links, and production cooperation. Related research also finds positive spatial spillover relationships between rural digitalization and AGTFP [21]. Thus, the green productivity effects of NQP may extend across regions. Based on this analysis, the following research hypothesis is proposed:

H2. *NQP have positive spatial spillover effects on AGTFP.*

3.3. Theoretical Analysis of FNQP and GB

Farmers are the direct decision-makers in the choice of agricultural inputs and production methods [31]. From the perspective of the productive factor structure, farmers' human capital and technological learning ability, intelligent means of production, and improved land and production conditions jointly constitute the capacity foundation for organizing production and applying new technologies. When these conditions improve, farmers have more technological choices in variety selection, nutrient management, pest and disease control, and water use, and are better positioned to adopt resource-saving and environmentally friendly production methods [32,33]. Relevant research shows that operators' education, technological literacy, and information on benefits are closely associated with technology choices, while different types of practices and operating environments also influence farmers' ecological production practices [23,26]. Therefore, this study incorporates knowledge and skills, technological equipment, and production conditions into the same factor framework to examine their links with green production practices. On this basis, the following research hypothesis is proposed:

H3. *FNQP are positively associated with GB.*

3.4. Threshold Role of DIAA

Whether FNQP are reflected in green production methods at the farm household level also depends on whether farmers can effectively identify and process information entering production decisions. Intelligent equipment, technical training, and modern production conditions expand the information and technologies available to farmers, but an increase in the amount of information does not mean that it automatically translates into production decisions. Agricultural technology information is highly context-dependent. Farmers need to assess its authenticity, extract key information, and distinguish useful from useless content to match external technological knowledge to their own production conditions [34–36]. DIAA focuses on content identification and processing and can help farmers match acquired information to their own technological needs and production conditions. When DIAA is weak, additional technologies and production conditions may not yet provide a stable basis for green production decisions. Once analysis ability reaches a higher level, farmers are better able to identify suitable technologies, compare input plans, and form actionable production judgments, allowing the positive association between FNQP and GB to emerge more fully. On this basis, the following research hypothesis is proposed:

H4. *The association between FNQP and GB exhibits threshold characteristics based on DIAA; the positive association is stronger when DIAA is higher.*

4. Data and Methods

4.1. Variable Selection and Description

4.1.1. Regional-Level Variables

(1) Dependent variable: AGTFP. A global non-radial slacks-based directional distance function with variable returns to scale (VRS), accounting for undesirable outputs, is combined with the global Malmquist–Luenberger (GML) index to measure AGTFP [37,38]. Input indicators include agricultural employment, crop sown area, total agricultural machinery power, a composite agricultural input index, a composite energy input index, and effective irrigated area. The desirable output is gross agricultural output at constant prices, and the undesirable output is agricultural carbon emissions. Using 2010 as the base year, annual GML indices are cumulatively multiplied to obtain cu-

mulative GML levels for each province during 2011–2023, denoted as AGTFP. Details of the measurement settings are provided in Appendix B.1.

(2) Core explanatory variable: NQP. Unlike agricultural modernization, which focuses on the overall transformation of the agricultural production system, agricultural digitalization, which focuses on information technology applications, and human capital, which emphasizes workers' knowledge and skills, NQP comprehensively examine production factor quality and allocation through three dimensions: NQW, NQML, and NQOL. They emphasize the coordination of knowledge and skills, advanced technologies, and production conditions. Accordingly, this study selects 11 indicators to construct a composite index of NQP. NQW reflect the foundations of human capital and technological learning; NQML reflect technological research and development, digital access, and professional service conditions; and NQOL reflect land production conditions and public observation services. Specifically, mobile phone ownership represents digital access conditions, the irrigation assurance ratio reflects water supply conditions, the disaster resistance indicator reflects the ability of agricultural production to withstand natural disasters, and the total number of meteorological stations represents the scale of public observation service provision. Each of the three primary dimensions receives a weight of 1/3, with equal weights within dimensions. The indicators are shown in Table 1 and Appendix A Table A3; data preprocessing and sensitivity weighting schemes are provided in Appendix B.2.

(3) Control variables. To control for the common effects of regional socioeconomic conditions on AGTFP, this study selects four control variables: urbanization rate, the share of primary industry value added in gross domestic product (GDP), per capita GDP, and environmental protection expenditure intensity. Urbanization rate reflects urban–rural population and factor flows; the share of primary industry value added in GDP reflects the regional industrial structure; per capita GDP controls for the level of regional economic development; and environmental protection expenditure intensity reflects local investment in environmental governance. Per capita GDP is entered in natural logarithms in the regressions.

Table 1. Indicator system of NQP.

Primary Indicator	Secondary Indicator	Definition and Proxy Meaning
NQW	Average years of education per rural worker	Educational and knowledge foundations
	Proportion of rural adults receiving technical training	Technological learning foundations
	Density of agricultural science and technology personnel	Science and technology personnel/agricultural employment
NQML	Agricultural research and development (R&D) input density	R&D stock × 10/sown area
	Density of agricultural science and technology patents	Number of patents × 10/sown area
	Rural broadband access rate	Digital access conditions
	Rural mobile phone ownership	Mobile phones owned per 100 households
	Intensity of agricultural socialized services	Intensity of agricultural professional and auxiliary services (standardized)
NQOL	Irrigation assurance ratio	Effective irrigated area/sown area
	Disaster resistance indicator	1 − disaster-affected area/sown area (standardized)
	Number of agricultural meteorological observation stations	Scale of public observation service provision

4.1.2. Micro-Level Variables

(1) Dependent variable: Farmers' GB. It is constructed from six practices: improved varieties, organic fertilizer and farmyard manure, soil testing and formula fertilization, physical pest control, biological pest control, and water-saving irrigation. Water-saving

irrigation was selected in place of deep tillage because it directly reflects agricultural water conservation and complements the indicators of variety selection, fertilizer management, and pest control, strengthening the coverage of green production practices. Each practice is assigned 1 or 0 according to whether it is implemented, and their equally weighted average forms a GB index ranging from 0 to 1. Each additional practice implemented increases the index by 1/6. The indicators are shown in Table 2, and alternative measurement schemes are provided in Appendix B.3.

(2) Core explanatory variable: FNQP. FNQP are constructed from three dimensions: NQW, NQML, and NQOL. The provincial indicators reflect regional science and technology supply, public services, and production foundations, while the farm household indicators reflect operators' knowledge and skills, equipment applications, and the conditions of operated land. Both follow the same factor framework and correspond to regional and micro-level farm household decision-making, respectively. Equal dimension weights give the three types of factors equal status in the composite indicator, while entropy and mixed weighting are used to examine the effects of weighting based on sample differences. Sensitivity tests use entropy weighting across all indicators and 1:1 mixed weighting of equal and entropy weights. Specific indicators and weights are shown in Table 3 and Appendix A Table A3, and indicator standardization and alternative weighting methods are provided in Appendix B.4.

(3) Threshold variable: DIAA. It is constructed as the mean of three items scored on a 1–5 scale: assessing the authenticity and reliability of forwarded information, extracting the main meaning from large amounts of online information, and distinguishing useful from useless information. Higher values indicate stronger analysis ability, and Cronbach's α is 0.883. After excluding one household with missing item responses, the threshold analysis uses a complete sample of 532 households. DIAA is selected as the primary threshold variable because it captures the evaluation and interpretation of digital information relevant to green production decisions. Digital information sharing ability (DISA) reflects online information interaction and dissemination and is retained for supplementary analysis (Appendix B.5).

(4) Instrumental variable. The instrumental variable is an innovator indicator, assigned 1 for farmers who adopted digital technologies relatively early and 0 otherwise, and is used in two-stage least squares (2SLS) estimation of FNQP. Risk preference is scored on a 1–5 scale, with higher values indicating stronger risk preference, and is used in supplementary regression analysis.

(5) Operator characteristics include gender, age, age squared, and years of farming. Age and its squared term are included together to control for a possible nonlinear relationship between age and GB. Increasing age is accompanied by accumulated production experience and may also change learning and adaptation ability and operating decisions. Production and operating characteristics include registered capital, the number of people engaged in agricultural operations, total days of agricultural operations, and cultivated land area. Production and operating conditions include land terrain, the degree of financial constraints, and ease of access to credit. Specific variable transformations and coding are provided in Appendix B.5.

Table 2. Indicator system and final weights of farmers' GB.

Primary Dimension	Secondary Indicator	Indicator Description
GB	Improved varieties	Whether implemented (1 = Yes, 0 = No)
GB	Organic fertilizer and farmyard manure	Whether implemented (1 = Yes, 0 = No)
GB	Soil testing and formula fertilization	Whether implemented (1 = Yes, 0 = No)

Table 2. *Cont.*

Primary Dimension	Secondary Indicator	Indicator Description
GB	Physical pest control	Physical pest control using yellow sticky traps, insecticidal lamps, etc. (1 = Yes, 0 = No)
GB	Biological pest control	Whether implemented (1 = Yes, 0 = No)
GB	Water-saving irrigation	Whether implemented (1 = Yes, 0 = No)

Note: Each of the six practices has a weight of 1/6 in the baseline index. In the order shown in the table, the weights for the entropy-weighted alternative measure are 0.1512, 0.0742, 0.1656, 0.1198, 0.1936, and 0.2956, calculated from the sample of 533 farm households. Straw incorporation is used to test an alternative combination.

Table 3. Indicator system and final weights of FNQP.

Primary Indicator	Secondary Indicator	Specific Indicator Definition
NQW	Years of education	Years of education of the farm household operator (years)
NQW	Number of production technology training sessions	Number of production technology training sessions attended in 2023
NQML	Drones	Whether used
NQML	Intelligent rice transplanters	Whether used
NQML	Intelligent harvesters	Whether used
NQOL	High-standard farmland	Whether the cultivated land used for planting is high-standard farmland
NQOL	Soil quality	Farmers' assessment of overall soil quality
NQOL	Completeness of drainage and irrigation systems	Farmers' assessment of the completeness of the farm's drainage and irrigation systems

Note: Each primary dimension has a weight of 1/3, with equal weights within dimensions. Continuous indicators are winsorized at both tails at 1% and standardized to 0–1; binary indicators retain their 0–1 values.

4.1.3. Descriptive Statistics of the Main Variables

Table 4 reports descriptive statistics of the main farm-level variables. The mean values of the GB index and the FNQP index are 0.492 and 0.392, respectively, and the mean DIAA is 3.617. Sample sizes, standard deviations, and ranges for each variable are shown in Table 4; descriptive statistics of the main provincial variables are provided in Appendix A Table A1.

Table 4. Descriptive statistics of the main farm-level variables.

Variable	*N*	Mean	Standard Deviation	Minimum	Maximum
GB index	533	0.492	0.268	0.000	1.000
FNQP	533	0.392	0.134	0.103	0.823
NQW	533	0.432	0.161	0.000	0.964
NQML	533	0.285	0.298	0.000	1.000
NQOL	533	0.460	0.191	0.000	0.917
DIAA	532	3.617	0.823	1.000	5.000
Innovator indicator	533	0.143	0.350	0.000	1.000
Risk preference	533	2.437	1.084	1.000	5.000
Gender	533	0.878	0.328	0.000	1.000
Age	533	48.685	8.914	21.000	72.000
Years of farming	533	16.099	12.325	0.000	50.000
ln(1 + registered capital)	533	2.362	1.842	0.000	8.517
Number of people engaged in agricultural operations	533	2.482	1.290	0.000	9.000
ln(total days of agricultural operations)	533	5.523	0.454	3.401	5.900
ln(cultivated land area)	533	5.334	0.987	3.401	9.210
Terrain	533	1.702	0.458	1.000	2.000
Financial constraints	533	2.683	1.107	1.000	5.000
Ease of access to credit	533	3.568	0.879	1.000	5.000

4.2. Model Specification

(1) Two-way fixed effects model

To test the relationship between NQP and AGTFP, a two-way fixed effects model is constructed, controlling for time-invariant provincial characteristics and common shocks in each year:

$$\mathrm{AGTFP}_{it} = \alpha_0 + \alpha_1 \mathrm{NQP}_{it} + \alpha_2 X_{it} + \mu_i + \lambda_t + \varepsilon_{it}$$

where AGTFP_{it} denotes AGTFP in province i in year t; NQP_{it} denotes the NQP index; X_{it} denotes regional-level control variables; μ_i and λ_t denote province and year fixed effects, respectively; and ε_{it} is the random disturbance term. Standard errors are clustered by province.

(2) SDM

Cross-regional links in agricultural technologies and production services provide a theoretical basis for examining conditional spatial interactions. Annual Moran's I describes the unconditional spatial clustering of productivity in each year, while the two-way fixed effects SDM estimates spatial links after controlling for regional and year factors [39]. The baseline spatial weights use an inverse squared distance matrix between provincial capitals. Alternative spatial matrices and a sample excluding 2018–2020 are used to test the robustness of spatial links. The SDM is estimated by maximum likelihood and specified as follows:

$$\mathrm{AGTFP}_{it} = \rho W \mathrm{AGTFP}_{it} + \beta \mathrm{NQP}_{it} + \theta W \mathrm{NQP}_{it} + \gamma X_{it} + \eta W X_{it} + \mu_i + \lambda_t + \varepsilon_{it}$$

where W is the spatial weight matrix; ρ is the spatial lag coefficient; WNQP_{it} denotes the spatially weighted value of NQP in surrounding regions; and WX_{it} denotes the spatial lags of the control variables. Model restriction tests compare the specifications of the SDM with the non-spatial model, spatial autoregressive model (SAR), and spatial error model (SEM), and direct, indirect, and total effects are reported. Details of spatial matrix construction, standard errors, and effect decomposition are provided in Appendix B.6.

(3) Ordinary least squares (OLS) model. At the farm household level, an OLS model controls for county/district fixed effects to estimate conditional associations after controlling for observable farm household operating characteristics. Standard errors are clustered by township; details of the finite-sample adjustment are provided in Appendix B.7.

$$\mathrm{GB}_i = \beta_0 + \beta_1 \mathrm{FNQP}_i + \beta_2 Z_i + \delta_c + \varepsilon_i$$

where GB_i denotes the GB index for farm household i, namely the equally weighted proportion of the six practices implemented; FNQP_i denotes the FNQP index; Z_i denotes the control variables; and δ_c denotes county/district fixed effects.

(4) Cross-sectional threshold model

Following Hansen's [40] sample-splitting approach, a single-threshold model is constructed to test whether the conditional association between FNQP and GB varies with DIAA. The model also controls for the linear term of the threshold variable and is specified as follows:

$$\mathrm{GB}_i = \beta_0 + \beta_{\mathrm{L}}\, \mathrm{FNQP}_i \mathrm{I}(\mathrm{Analysis}_i \le \gamma) + \beta_{\mathrm{H}}\, \mathrm{FNQP}_i \mathrm{I}(\mathrm{Analysis}_i > \gamma) + \varphi \mathrm{Analysis}_i + \beta_2 Z_i + \delta_c + \varepsilon_i$$

where $\mathrm{Analysis}_i$ denotes DIAA; γ is the threshold value; and β_{L} and β_{H} are the FNQP coefficients on the two sides of the threshold, respectively. The threshold value is determined by grid search, and threshold existence and regime differences are assessed using township-clustered inference. Candidate thresholds, bootstrap procedures, and test settings are provided in Appendix B.8.

4.3. Data Sources

At the regional level, the measurement period is 2010–2023 and the baseline regression period is 2011–2023, covering 30 provinces excluding Tibet, with 390 province–year observations. Hong Kong, Macao, and Taiwan are not included. The data mainly come from annual editions of the China Statistical Yearbook, China Rural Statistical Yearbook, provincial statistical yearbooks, and materials compiled by the research team. Farm-level data come from a stratified sampling survey conducted by the research team in Sichuan Province from July to August 2024. A total of 560 questionnaires were distributed, yielding 533 valid questionnaires, with a valid response rate of 95.18%, covering 9 cities (prefectures) and 12 counties (county-level cities, districts). The regressions form 53 township groups based on county/district and township identifiers for clustered inference. The two datasets correspond to regional productivity and Sichuan farmers' behavior, respectively, and are standardized and estimated within their respective sample ranges.

5. Results

Using panel data from 30 provinces during 2011–2023 and survey data from 533 farm households in Sichuan Province in 2024, this study examines the relationship between NQP and AGTFP and its spatial links. At the farm household level, it analyzes the association between FNQP and GB and the conditions associated with DIAA. At both the regional and farm household levels, productive conditions are characterized through three dimensions—NQW, NQML, and NQOL—providing complementary evidence on regional productivity and farmers' production methods.

5.1. Empirical Analysis of the Relationship Between NQP and AGTFP

Table 5 shows a positive association between NQP and cumulative AGTFP. The coefficient in the full model is 0.422 ($p = 0.0299$), meaning that, within the same province, after controlling for common year shocks and socioeconomic conditions, a 0.1 increase in the NQP index corresponds to an increase of approximately 0.042 in cumulative GML. This quantitative relationship reflects cumulative productivity differences relative to the 2010 base year and has a different meaning from changes in annual growth rates. As control variables are added progressively, the core coefficient remains positive and receives statistical support, consistent with the theoretical expectation of H1. Joint improvements in knowledge and skills, R&D and service conditions, and land production foundations help apply suitable technologies and coordinate production inputs. The estimation results are consistent with this interpretation of factor coordination. Descriptive statistics and correlation coefficients of the main regional variables are provided in Appendix A Tables A1 and A2.

Table 6 and Appendix A Table A4 examine the baseline association in terms of weighting, timing, outcome measurement, and indicator composition. The core coefficients for mixed weighting, the explanatory variable lagged by one period, and the log GML model are 0.397, 0.445, and 0.371, respectively, all significant at the 5% level. The lagged model shows that prior factor conditions remain positively associated with subsequent productivity, consistent with the interpretation that knowledge and skills, equipment investments, and production conditions gradually take effect in actual production. After excluding 2018–2020, the coefficient is 0.430 ($p = 0.0452$), indicating that the positive regional association is not formed solely by observations from these three years. After removing digital access proxy indicators or the objects of labor dimension, the coefficients are 0.410 and 0.400, respectively, both significant at the 5% level, indicating that the association is also supported by other factor indicators. Different weighting methods and functional forms change the coefficient scales; these tests mainly compare estimation directions and statistical support.

Table 5. Baseline regression results for NQP and AGTFP.

Variable	(1)	(2)	(3)	(4)
NQP	0.342 *	0.374 **	0.367 **	0.422 **
	(0.175)	(0.167)	(0.165)	(0.185)
Urbanization rate	—	−0.394	−0.391	−0.329
		(0.274)	(0.273)	(0.243)
Environmental protection expenditure intensity	—	—	0.327	0.369
			(0.513)	(0.492)
Share of primary industry value added in GDP	—	—	—	0.369
				(0.476)
ln(per capita GDP)	—	—	—	−0.078
				(0.087)
Province fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Sample size	390	390	390	390
Adjusted R^2	0.842	0.847	0.847	0.848

Note: The dependent variable is the cumulative GML level with 2010 as the base year. Province-clustered robust standard errors for 30 provinces are in parentheses, and two-sided *p*-values use a t-distribution with 29 degrees of freedom. *, ** indicate significance at the 10%, 5% levels, respectively.

Table 6. Robustness tests for NQP and AGTFP.

Variable	(1) Baseline	(2) Mixed Weighting	(3) One-Period Lag	(4) Log GML
NQP	0.422 **	0.397 **	—	0.371 **
	(0.185)	(0.190)		(0.155)
NQP lagged by one period	—	—	0.445 **	—
			(0.174)	
Control variables	Yes	Yes	Yes	Yes
Province fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Sample size	390	390	360	390
Adjusted R^2	0.848	0.849	0.852	0.869

Note: Mixed weighting assigns 1/2 each to baseline equal weights and entropy weights across all indicators. The one-period lag regression covers 2012–2023. Column (4) uses the natural logarithm of cumulative GML as the dependent variable. All models use province-clustered standard errors. ** $p < 0.05$.

5.2. Spatial Spillover Effects of NQP: Empirical Results

Table 7 shows that positive spatial correlation in AGTFP mainly reaches statistical significance during 2018–2020, and is significant at the 10% level in 2014, indicating annual differences in its spatial clustering characteristics. An SDM is further used to examine spatial links after controlling for regional characteristics and common year shocks.

Table 7. Annual global Moran's I for AGTFP.

Year	2011	2012	2013	2014	2015	2016	2017
Moran's I	0.007	−0.013	0.043	0.082 *	0.048	0.031	0.069
p-value	0.1073	0.4893	0.1336	0.0838	0.2097	0.3613	0.1953
Year	2018	2019	2020	2021	2022	2023	
Moran's I	0.269 ***	0.279 ***	0.230 ***	0.093	0.053	0.019	
p-value	0.0046	0.0025	0.0057	0.1590	0.3375	0.5577	

Note: The inverse squared distance matrix is row-standardized. * $p < 0.10$; *** $p < 0.01$.

Spatial model restriction tests show that the spatial terms are jointly significant and that the restrictions simplifying the SDM to SAR or SEM are both rejected, providing statistical grounds for using the SDM (see Appendix A Table A8). Table 8 reports the

baseline SDM and spatial effect decomposition. The spatial coefficient ρ is 0.404 ($p < 0.001$). The direct effect of NQP is 0.281 ($p = 0.0007$), the indirect effect is 0.572 ($p = 0.0661$), and the total effect is 0.853 ($p = 0.0069$). The local direct association has strong statistical support, while the positive cross-regional association reaches significance at the 10% level under the baseline matrix.

Table 8. SDM estimates and spatial effect decomposition.

Variable	Basic SDM Estimates	Direct Effect	Indirect Effect	Total Effect
NQP	0.254 *** (0.086)	0.281 *** (0.083)	0.572 * (0.311)	0.853 *** (0.316)
NQP in surrounding regions	0.255 (0.198)	—	—	—
Spatial lag term (ρ)	0.404 *** (0.089)	—	—	—
Control variables	Yes	Yes	Yes	Yes
Spatial lags of control variables	Yes	Yes	Yes	Yes
Province fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Sample size	390	390	390	390

Note: The SDM is estimated by maximum likelihood with two-way fixed effects. Standard errors of the basic coefficients are derived from the likelihood Hessian matrix; effect standard errors use the Delta method and account for parameter covariances. *p*-values use a normal approximation, which differs from province-clustered inference in the non-spatial regressions. * $p < 0.10$; *** $p < 0.01$.

Table 9 and Appendix A Table A5 report robustness tests using different spatial weight matrices and sample periods. Direct effects generally remain positive and receive statistical support under different matrix specifications and after excluding 2018–2020. Indirect effects, however, are more sensitive to the spatial weight matrix and sample period and do not reach statistical significance under the economic–geographic matrices and some specifications excluding years. The results indicate that the local positive association is relatively stable, while statistical support for cross-regional spatial associations depends on the specific specification.

Table 9. Robustness tests of spatial effects under different spatial weight matrices.

Variable	Inverse Squared Distance	Inverse Distance	4 Nearest Neighbors
Spatial lag term (ρ)	0.404 *** (0.089)	0.871 *** (0.242)	0.010 (0.091)
Direct effect	0.281 *** (0.083)	0.416 * (0.234)	0.366 *** (0.082)
Indirect effect	0.572 * (0.311)	2.935 (6.826)	0.110 (0.162)
Total effect	0.853 *** (0.316)	3.351 (7.045)	0.476 *** (0.164)
Control variables and spatial lags	Yes	Yes	Yes
Province fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
Sample size	390	390	390

Note: All three models control for province and year fixed effects, control variables, and their corresponding spatial lags. Standard errors are in parentheses. * $p < 0.10$; *** $p < 0.01$.

5.3. Empirical Results on the Relationship Between FNQP and GB

At the farm household level, 533 valid observations are used to examine the conditional association between FNQP and GB; correlation coefficients are provided in Appendix A Table A9. The Pearson correlation coefficient between FNQP and the GB index

is 0.123, and that between DIAA and the GB index is 0.130, both significant at the 1% level. Correlation coefficients of the main variables are shown in Appendix A Table A9, and conditional associations are subsequently estimated by controlling for operators and operating conditions. Table 10 reports the baseline regression results for FNQP and GB. The core variable coefficient in the full model is 0.223 ($p = 0.0153$), significant at the 5% level. A 0.1 increase in the FNQP index corresponds to an increase of approximately 2.23 percentage points in the equally weighted implementation proportion of the six practices, supporting the positive conditional relationship expected by H3. As control variables are added progressively, the core coefficient remains positive.

Table 10. Baseline regression results for FNQP and GB.

Variable	(1)	(2)	(3)	(4)
FNQP	0.292 ***	0.317 ***	0.203 **	0.223 **
	(0.102)	(0.111)	(0.099)	(0.089)
Gender	—	−0.077 **	−0.085 **	−0.078 *
		(0.037)	(0.038)	(0.040)
Age	—	0.007	0.004	−0.001
		(0.011)	(0.011)	(0.011)
Age squared	—	-5.22×10^{-5}	-3.23×10^{-5}	1.57×10^{-5}
		(1.17×10^{-4})	(1.10×10^{-4})	(1.08×10^{-4})
Years of farming	—	0.000	0.001	0.001
		(0.001)	(0.001)	(0.001)
ln(1 + registered capital)	—	—	0.008	0.007
			(0.007)	(0.006)
Number of people engaged in agricultural operations	—	—	−0.010	−0.010
			(0.012)	(0.012)
ln(total days of agricultural operations)	—	—	0.096 ***	0.079 **
			(0.032)	(0.033)
ln(cultivated land area)	—	—	0.032 **	0.032 **
			(0.014)	(0.014)
Terrain	—	—	—	0.114 **
				(0.045)
Financial constraints	—	—	—	−0.009
				(0.012)
Ease of access to credit	—	—	—	0.053 ***
				(0.014)
County/district fixed effects	Yes	Yes	Yes	Yes
Township-clustered standard errors	Yes	Yes	Yes	Yes
Number of township clusters	53	53	53	53
Sample size	533	533	533	533
R^2	0.071	0.082	0.117	0.158
Adjusted R^2	0.049	0.054	0.083	0.120

Note: The dependent variable is the equally weighted GB index for the six practices. Township-clustered robust standard errors for 53 townships are in parentheses, with a finite-sample adjustment; two-sided p-values use a t-distribution with 52 degrees of freedom. Age squared is expressed in scientific notation. * $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$.

Under different weighting methods, the estimated coefficients for FNQP are all significantly positive, indicating that the baseline results are somewhat robust to adjustments in index weighting (see Appendix A Table A10). Table 11 tests the robustness of GB measurement in terms of weighting, model form, and practice combinations. The coefficient for the entropy-weighted GB index is 0.171 ($p = 0.0652$); when the number of the six practices adopted is used as the outcome variable, the Poisson coefficient is 0.451 ($p = 0.0159$); and the equally weighted index coefficient for the alternative combination involving straw incorporation is 0.282 ($p = 0.0005$). Neither the estimated age coefficient nor its squared term reaches statistical significance. The estimation directions are consistent across different

measures, indicating that the baseline results are somewhat robust to adjustments in the GB indicators.

Table 11. Robustness tests using alternative indicators for FNQP and GB.

Variable	Entropy-Weighted GB Index OLS	Number of Green Production Behaviors Adopted Poisson	Equally Weighted Straw Incorporation Alternative OLS
FNQP	0.171 * (0.091)	0.451 ** (0.181)	0.282 *** (0.076)
Control variables	Yes	Yes	Yes
County/district fixed effects	Yes	Yes	Yes
Township-clustered standard errors	Yes	Yes	Yes
Number of township clusters	53	53	53
Sample size	533	533	533

Note: Models use OLS/Poisson with baseline controls and county/district fixed effects. Township-clustered standard errors (53 clusters) are in parentheses. * $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$.

Supplementary instrumental variable estimation shows that the innovator indicator is significantly associated with FNQP, and the 2SLS results remain positive under different risk preference control specifications (see Appendix A Table A11). This estimation relies on the exclusion assumption that early digital technology adoption experience is not directly associated with GB through other channels. Therefore, this study mainly relies on OLS and alternative measurement tests to interpret conditional associations.

5.4. Analysis of the Threshold Role of DIAA

Table 12 reports the threshold test results for DIAA. The estimated threshold is 3.667, the Sup-*F* statistic is 6.409, and the bootstrap test is significant at the 10% level, suggesting a threshold pattern in the relationship between FNQP and GB. The 95% confidence candidate set is {3.333, 3.667}.

Table 12. Threshold estimation results for DIAA.

Threshold Variable	Threshold Value	Sup-*F*	Bootstrap *p*-Value	Sample Size
DIAA	3.667	6.409	0.0596	532

Note: The candidate points are {3.000, 3.333, 3.667}, and the 95% confidence candidate set is {3.333, 3.667}. The low and high regimes each contain 266 households, involving 46 and 44 townships, respectively. Some townships contain observations in both regimes; the complete sample contains 53 townships. The confidence set uses a cluster wild bootstrap under the estimated threshold model to calibrate the profile likelihood ratio (LR), with a critical value of 2.864.

Table 13 reports the regression results for different DIAA regimes. The FNQP coefficient in the low-ability regime is 0.139 and does not reach statistical significance; the coefficient in the high-ability regime is 0.327, significant at the 1% level. The coefficient difference between the two regimes is significant at the 5% level under a fixed cutoff. The results suggest a stronger positive association between FNQP and GB among farmers with higher DIAA. This may be because higher information analysis ability helps farmers identify suitable technologies, compare input plans, and make green production decisions in light of their own production conditions. The supplementary DISA analysis shows a similar high-regime pattern (Appendix A Table A7). Overall, these findings provide suggestive support for H4.

Table 13. FNQP estimates across DIAA regimes.

Regime-Specific Effects	Equally Weighted GB Index OLS	Entropy-Weighted GB Index 'OLS	Number of Green Production Behaviors Adopted Poisson
FNQP × I (Analysis ≤ γ)	0.139	0.081	0.275
	(0.090)	(0.095)	(0.193)
FNQP × I (Analysis > γ)	0.327 ***	0.284 ***	0.642 ***
	(0.096)	(0.095)	(0.188)
High regime − low regime	0.187 ** $p = 0.0273$	0.203 ** $p = 0.0169$	0.367 ** $p = 0.0301$
Control variables	Yes	Yes	Yes
County/district fixed effects	Yes	Yes	Yes
Township-clustered standard errors	Yes	Yes	Yes
Number of township clusters	53	53	53
Sample size	532	532	532

Note: $\gamma = 11/3$. Regimes are determined using the unrounded three-item mean and threshold value. Each model controls for the linear term of analysis ability, all baseline control variables, and county/district fixed effects. Table 12 reports the threshold existence test that searches again for the cutoff using the equally weighted behavior index; the corresponding test for the entropy-weighted behavior measure gives $p = 0.0388$. Regime differences are assessed using clustered Wald tests at the fixed estimated cutoff. ** $p < 0.05$; *** $p < 0.01$.

6. Discussion

This study examines the relationship between NQP and AGD from the perspective of production factor quality and allocation. The productivity and environmental benefits of agricultural automation depend not only on advanced technological equipment but also on conditions such as workers' knowledge and skills, infrastructure, and technological accessibility [4]. Technological literacy, information on benefits, and operating conditions are also closely associated with agricultural technology adoption [23]. The NQP framework incorporates knowledge and skills, advanced equipment, and production conditions into a unified analytical system, providing an integrated production factor perspective for understanding AGD. The provincial and farm-level empirical results show that NQP are positively associated with AGTFP and farmers' GB, respectively. The former reflects productivity performance under resource and environmental constraints, while the latter reflects the implementation of specific green production practices. The two types of evidence reveal links between production factor quality and AGD at different levels. The threshold analysis suggests a stronger positive association between FNQP and GB among farmers with higher DIAA. Farmers' adoption of ecological production practices is influenced by operator characteristics and the operating environment [26], while information analysis ability helps operators identify suitable technologies and make production decisions in light of production conditions. Therefore, the green transformation of agriculture requires improvements in technological equipment and production conditions, improvements in operators' information analysis and technology application abilities, and attention to the actual environmental performance of green production practices.

Spatial econometric analysis shows a relatively stable positive association between NQP and local AGTFP, while cross-regional indirect effects are more sensitive to the spatial weight matrix and sample period. The geographical specificity of agricultural production creates regional differences in technological needs, production conditions, and socialized service provision, potentially affecting the scope and extent of the effects of cross-regional flows of advanced technologies and production factors. Technology dissemination, cross-regional agricultural machinery services, and production cooperation may form channels for interregional spatial links, but their roles are influenced by technological suitability and regional economic connections. These findings indicate that the development of NQP should emphasize matching local production conditions with technological application needs and promote agricultural technology extension and socialized service cooperation in

light of interregional production links. The specific mechanisms forming cross-regional spatial links require further examination using data on technology and service flows.

This study has several limitations. The provincial panel and Sichuan farm household survey differ in study period, spatial scope, and outcome measurement, so the two types of evidence cannot yet directly identify the mechanisms through which farmers' GB translates into regional green productivity. The farm household cross-sectional data cannot fully rule out reverse causality and self-selection, and the exclusion restriction of the existing instrumental variable requires further verification. Subjective assessments and reported behaviors may be affected by common method bias and recall error, while the sampling scope and implementation methods also affect the external applicability of the conclusions. In addition, the spatial model mainly reflects average spatial links during the sample period and does not yet directly identify differences in parameters across stages or specific transmission channels. Future research could combine longitudinal farm household surveys across multiple regions, actual input–output records, and interregional technology service data to further identify the causal relationship between NQP and green development, the conditional role of DIAA, and the mechanisms forming spatial links.

7. Conclusions and Policy Implications

7.1. Conclusions

Based on panel data from 30 provinces during 2011–2023 and a survey of 533 farm households in Sichuan in 2024, this study reaches the following conclusions. First, NQP are significantly positively associated with cumulative AGTFP. Alternative weighting, lagged explanatory variables, log productivity, exclusion of 2018–2020, and indicator group adjustments all provide evidence in the same direction. Second, the spatial extension reveals a relatively stable local direct association, while cross-regional indirect associations vary with spatial weights and sample periods. Third, FNQP have a positive conditional association with green practices, with the full baseline model significant at the 5% level; the entropy-weighted behavior measure, the number of practices adopted, and the equally weighted alternative combination provide statistical support in the same direction. Fourth, the threshold analysis suggests that the positive association between FNQP and GB is stronger among farmers with higher DIAA. These findings indicate that AGD requires coordinated attention to production factor quality and farmers' information application ability.

7.2. Policy Implications

First, coordinate the development of NQP and production factor allocation. Combine improvements in agricultural workers' knowledge and skills, the application of advanced technological equipment, and improvements in production conditions; strengthen assessments of technological application outcomes, resource use efficiency, and green production performance; improve technology extension and agricultural machinery service systems; and improve the efficiency of advanced production factor use. Second, strengthen the development of farmers' DIAA. Provide targeted training on judging information authenticity, comparing technological benefits, and screening useful information. Provide differentiated technological advisory and application services according to differences in farmers' information processing abilities and operating conditions, and improve their ability to use digital information in production decisions. Third, strengthen cooperation in regional agricultural technology extension and production services. Conduct joint technology trials, extension exchanges, and cross-regional agricultural machinery services in light of regional natural conditions, cropping systems, and technological needs. Strengthen assessments of technological application outcomes and resource and environmental performance, and improve the effectiveness of agricultural technology extension and green production services.

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Institutional Review Board Statement: This study was a non-interventional social science questionnaire survey that fell outside the scope of China's Measures for the Ethical Review of Life Science and Medical Research Involving Humans (2023). At the time of data collection, prior ethics committee approval was not explicitly required by the institution. The ethical review status was subsequently verified by the College of Management, Sichuan Agricultural University.

Informed Consent Statement: Verbal informed consent was obtained from all participants before the interviews. Oral consent was adopted because the study involved non-interventional, face-to-face questionnaire interviews. All participants were informed of the research purpose, the voluntary nature of participation, confidentiality measures, and their right to decline questions or withdraw.

Data Availability Statement: The data supporting the findings of this study are available from the corresponding author upon reasonable request. The data are not publicly available to protect the privacy of survey respondents.

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

Appendix A. Supplementary Statistics and Sensitivity Tests

Table A1. Descriptive statistics of the main regional-level variables.

Variable	*N*	Mean	Standard Deviation	Minimum	Maximum
Cumulative global Malmquist–Luenberger (GML)	390	1.095	0.105	0.821	1.448
Agricultural new quality productive forces (NQP)	390	0.381	0.113	0.122	0.739
Urbanization rate	390	0.600	0.118	0.344	0.895
Share of primary industry value added in gross domestic product (GDP)	390	0.095	0.052	0.002	0.252
ln(per capita GDP)	390	10.920	0.475	9.688	12.286
Environmental protection expenditure intensity	390	0.029	0.010	0.010	0.068

Table A2. Correlation coefficients of the main regional-level variables.

Variable	1	2	3	4	5	6
1 Cumulative GML	1.000					
2 NQP	0.526 ***	1.000				
3 Urbanization rate	0.418 ***	0.621 ***	1.000			
4 Share of primary industry value added in GDP	−0.231 ***	−0.498 ***	−0.635 ***	1.000		
5 ln(per capita GDP)	0.566 ***	0.780 ***	0.860 ***	−0.663 ***	1.000	
6 Environmental protection expenditure intensity	−0.168 ***	−0.138 ***	−0.013	−0.032	−0.105 **	1.000

Note: Correlation coefficients are based on observations without fixed effects adjustment, and significance is assessed using conventional Pearson tests. Variables with missing values are calculated using pairwise complete observations. ** $p < 0.05$; *** $p < 0.01$.

Table A3. Final weights of NQP under different weighting methods.

Indicator	Equal Weights Across and Within Dimensions	Entropy Weights Across All Indicators	1:1 Mixed Weighting
Regional: Years of education	0.1111	0.0244	0.0677
Regional: Adult training proportion	0.1111	0.1844	0.1478

Table A3. *Cont.*

Indicator	Equal Weights Across and Within Dimensions	Entropy Weights Across All Indicators	1:1 Mixed Weighting
Regional: Science and technology personnel as a proportion of the agricultural labor force	0.1111	0.2134	0.1623
Regional: research and development (R&D) input density	0.0667	0.1968	0.1318
Regional: Agricultural patent density	0.0667	0.0737	0.0702
Regional: Broadband access rate	0.0667	0.0794	0.0731
Regional: Mobile phone ownership	0.0667	0.0281	0.0474
Regional: Socialized service intensity	0.0667	0.0742	0.0704
Regional: Irrigation assurance ratio	0.1111	0.0684	0.0898
Regional: Disaster resistance indicator	0.1111	0.0154	0.0633
Regional: Meteorological stations	0.1111	0.0417	0.0764
Farm household: Years of education	0.1667	0.0117	0.0892
Farm household: Number of training sessions	0.1667	0.0647	0.1157
Farm household: Drones	0.1111	0.0933	0.1022
Farm household: Intelligent rice transplanters	0.1111	0.3431	0.2271
Farm household: Intelligent harvesters	0.1111	0.2718	0.1914
Farm household: High-standard farmland	0.1111	0.1851	0.1481
Farm household: Soil quality	0.1111	0.0099	0.0605
Farm household: Drainage and irrigation systems	0.1111	0.0204	0.0658

Note: The two scales are standardized and entropy weights are calculated within their respective samples, and index interpretations correspond to their respective reference ranges. The unrounded weights in each group sum to 1.

Table A4. Sample and indicator sensitivity of the regional model.

Specification	Coefficient	Province-Clustered Standard Error (SE)	*p*-Value	*N*
Excluding 2018–2020	0.430	0.205	0.0452	300
Removing digital access proxies	0.410	0.166	0.0196	390
Removing the objects of labor dimension	0.400	0.186	0.0397	390

Note: The digital access proxies are broadband and mobile phones. After indicators are removed, equal weights are recalculated across the retained dimensions and within dimensions. All specifications retain the same GML, control variables, and two-way fixed effects.

Table A5. Spatial results using economic–geographic matrices and excluding 2018–2020.

Matrix and Sample	ρ	Direct Effect	Indirect Effect	Total Effect
Geographic squared distance: Full sample	0.404 *** (0.089)	0.281 *** (0.083)	0.572 * (0.311)	0.853 *** (0.316)
Economic–geographic distance: Full sample	0.814 *** (0.206)	0.353 *** (0.106)	0.465 (2.236)	0.818 (2.303)
Economic–geographic squared distance: Full sample	0.393 *** (0.084)	0.292 *** (0.081)	0.360 (0.281)	0.652 ** (0.287)
Geographic squared distance: Excluding three years	0.215 * (0.113)	0.231 ** (0.099)	0.248 (0.293)	0.479 * (0.283)
Economic–geographic distance: Excluding three years	0.254 (0.279)	0.286 *** (0.098)	−0.413 (0.702)	−0.127 (0.701)
Economic–geographic squared distance: Excluding three years	0.185 * (0.112)	0.246 ** (0.098)	0.107 (0.272)	0.354 (0.261)

Note: $N = 390$ in the full sample and $N = 300$ after excluding three years. Economic weights use average per capita GDP for 2011–2023; matrices are not recalculated when years are excluded. Model or Delta-method standard errors are in parentheses. * $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$.

Table A6. OLS sensitivity to controls for risk preference and the innovator indicator.

Specification	Farm-Level New Quality Productive Forces (FNQP)	Risk Preference	Innovator Indicator	Core *p*-Value
Baseline 4	0.223 ** (0.089)	—	—	0.0153
Risk control	0.221 ** (0.091)	−0.032 *** (0.010)	—	0.0183

Table A6. *Cont.*

Specification	Farm-Level New Quality Productive Forces (FNQP)	Risk Preference	Innovator Indicator	Core *p*-Value
Risk category controls	0.230 ** (0.091)	Category controls	—	0.0150
Risk and innovator controls	0.163 * (0.097)	−0.031 *** (0.010)	0.050 (0.031)	0.0979

Note: $N = 533$. Standard errors are clustered by 53 townships, and the models include county/district fixed effects and all baseline control variables. Risk category controls use the low-risk group as the reference. * $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$.

Table A7. Supplementary threshold estimates for DISA.

Outcome Variable	Low Regime	High Regime	*p*-Value for Differences at a Fixed Cutoff
Equally weighted green production behavior (GB) index	−0.064 (0.156)	0.264 *** (0.088)	0.0050
Entropy-weighted GB index	−0.072 (0.160)	0.213 ** (0.091)	0.0191
Number of practices adopted	−0.190 (0.365)	0.512 *** (0.180)	0.0086

Note: Sharing ability is the mean of four items, and the estimated cutoff is 3.000; candidate points are {2.50, 2.75, 3.00, 3.25, 3.50, 3.75}. The low regime contains 148 households in 32 townships, and the high regime contains 385 households in 52 townships. The threshold existence Sup-*F* for the equally weighted behavior index is 11.287; the township wild-cluster bootstrap with 9999 replications gives $p = 0.0472$, with random seed 20,261,011. The 95% threshold confidence candidate set is {3.000}. The corresponding threshold test for the entropy-weighted behavior measure gives $p = 0.1204$. All three models control for the linear term of sharing ability, all baseline control variables, and county/district fixed effects; regime-difference *p*-values are calculated at the fixed estimated cutoff. ** $p < 0.05$; *** $p < 0.01$.

Table A8. Specification tests for the SDM.

Test	Null Hypothesis/Restriction	Likelihood Ratio (LR) Statistic, df, and *p*-Value	Conclusion
SDM → non-spatial model	ρ and the spatial lag coefficients of five explanatory variables are jointly 0	34.571 df = 6, $p < 0.001$	Reject restriction
SDM → spatial autoregressive model (SAR)	Spatial lags of explanatory variables are jointly 0	18.044 df = 5, $p = 0.0029$	Reject restriction
SDM → spatial error model (SEM)	The common factor restriction of the spatial error model is satisfied	18.249 df = 5, $p = 0.0026$	Reject restriction

Note: LR tests compare restricted and unrestricted models under the same two-way fixed effects orthogonal transformation and Gaussian likelihood. The SDM → non-spatial model test examines 6 joint restrictions, and each of the other tests examines 5 restrictions.

In Table A8, the LR statistic for jointly setting the spatially lagged dependent variable coefficient and the spatial lag coefficients of the five explanatory variables to zero is 34.571, with 6 degrees of freedom and $p < 0.001$. The LR statistics for simplifying the SDM to SAR and SEM are 18.044 and 18.249, respectively, both with 5 degrees of freedom, and *p*-values of 0.0029 and 0.0026, respectively. Under the current likelihood, fixed effects, and weight specifications, spatial terms improve overall model fit, and retaining the spatial lags of explanatory variables has statistical grounds. Therefore, the full-period SDM is used to identify average spatial links after controlling for other conditions, while annual Moran's I describes the clustering context of those links. Specific economic interpretations are based on the direct and indirect effects of NQP; model selection results do not substitute for effect tests.

Table A9. Correlation coefficients of the main farm-level variables.

Variable	1	2	3	4	5	6	7
1 GB index	1.000						
2 FNQP	0.123 ***	1.000					
3 New quality workers (NQW)	0.098 **	0.479 ***	1.000				
4 New quality means of labor (NQML)	0.148 ***	0.780 ***	0.098 **	1.000			
5 New quality objects of labor (NQOL)	−0.056	0.476 ***	0.008	−0.006	1.000		
6 Digital information analysis ability (DIAA)	0.130 ***	0.129 ***	0.203 ***	0.064	0.001	1.000	
7 Innovator indicator	0.115 ***	0.412 ***	0.068	0.510 ***	0.011	−0.023	1.000

Note: Pearson correlations use pairwise complete observations and conventional two-sided tests. $N = 532$ for correlations involving DIAA and 533 otherwise. ** $p < 0.05$; *** $p < 0.01$.

Table A10. Sensitivity tests for FNQP weighting methods.

Weighting Method	Coefficient	Clustered SE	*p*-Value	Assessment
Equal weights across and within dimensions	0.223	0.089	0.0153	Significant at 5%
Entropy weights across all indicators	0.160	0.054	0.0049	Significant at 1%
1:1 mixed equal and entropy weighting	0.203	0.070	0.0055	Significant at 1%

Note: $N = 533$. All OLS models include baseline controls and county/district fixed effects. Standard errors are clustered by township (53 clusters); two-sided *p*-values use a t-distribution with 52 degrees of freedom.

Table A11. Supplementary instrumental variable estimates for FNQP and GB.

Variable/Test	First Stage FNQP	Baseline Controls Two-Stage Least Squares (2SLS)	Risk Score Controls 2SLS	Risk Category Controls 2SLS
Innovator indicator	0.136 *** (0.015)	—	—	—
FNQP	—	0.578 ** (0.217)	0.528 ** (0.221)	0.510 ** (0.234)
Baseline control variables	Yes	Yes	Yes	Yes
Risk preference	No	No	Score	Categories
County/district fixed effects	Yes	Yes	Yes	Yes
Number of township clusters	53	53	53	53
Sample size	533	533	533	533
First-stage *F*	82.61	82.61	80.49	79.88
Anderson–Rubin (AR) test *p*-value ($\beta = 0$)	—	0.0100	0.0211	0.0344

Note: The second-stage dependent variable is the equally weighted GB index for the six practices, and the instrumental variable is an indicator for farmers who adopted digital technologies relatively early. The first-stage *F* is the township-clustered robust Wald statistic (t^2) for the single excluded instrument; the AR test examines the reduced form under the hypothesis $\beta = 0$. Standard errors are clustered by township, and *p*-values use a t-distribution with 52 degrees of freedom. ** $p < 0.05$; *** $p < 0.01$.

Appendix B. Variable Measurement and Model Calculation Details

Appendix B.1. Measurement of Agricultural Green Total Factor Productivity (AGTFP)

The global reference set covers 420 input–output observations from 30 provinces during 2010–2023. Inputs include agricultural employment (10,000 persons), crop sown area

(1000 hectares), total agricultural machinery power (10,000 kW), a composite agricultural input index, a composite energy input index, and effective irrigated area (1000 hectares). The desirable output is gross agricultural output at constant prices, and the undesirable output is agricultural carbon emissions (10,000 tonnes). Agricultural inputs and energy enter the measurement as composite input indices. The direction vector takes each observation's own input–output levels; the weights for mean input slack, desirable output slack, and undesirable output slack are 1/2, 1/4, and 1/4, respectively, and the intensity variables sum to 1. Interannual GML is calculated as the ratio of (1 + D) for the previous and current periods' global distance functions; for each province, annual indices are cumulatively multiplied, with 2010 set to 1.

The agricultural-input composite is the equal-weighted mean of fertilizer (nutrient-equivalent quantity), pesticide, and agricultural film; the energy-input composite is the equal-weighted mean of agricultural diesel and rural electricity consumption. Each component is winsorized at the pooled 1st and 99th percentiles, transformed using $\ln(1 + x)$, and min–max rescaled to 1–100 before averaging. Agricultural carbon emissions enter as the recorded province-year totals (10,000 tonnes) in the input–output dataset.

For an evaluated province-year observation o, the global non-radial directional distance function is defined as

$$D_o^G = \max_{\lambda,s} \left\{ \frac{1}{12} \sum_{k=1}^{6} \frac{s_k^x}{x_{ok}} + \frac{1}{4} \frac{s^y}{y_o} + \frac{1}{4} \frac{s^b}{b_o} \right\}.$$

subject to the following global VRS constraints:

$$\sum_{j=1}^{420} \lambda_j x_{jk} + s_k^x = x_{ok}, \qquad k = 1, \ldots, 6.$$

$$\sum_{j=1}^{420} \lambda_j y_j - s^y = y_o, \qquad \sum_{j=1}^{420} \lambda_j b_j + s^b = b_o.$$

$$\sum_{j=1}^{420} \lambda_j = 1, \qquad \lambda_j, s_k^x, s^y, s^b \geq 0.$$

Here, x denotes the six inputs, y the desirable output, b the undesirable output, λ the intensity variables, and s the associated slacks. The 420 observations jointly define the global production possibility set.

The interannual GML and cumulative AGTFP indices are computed as

$$\mathrm{GML}_{i,t-1,t} = \frac{1 + D_{i,t-1}^G}{1 + D_{i,t}^G}.$$

$$\mathrm{AGTFP}_{i,t} = \prod_{\tau=2011}^{t} \mathrm{GML}_{i,\tau-1,\tau} = \frac{1 + D_{i,2010}^G}{1 + D_{i,t}^G}, \qquad \mathrm{AGTFP}_{i,2010} = 1.$$

Appendix B.2. Measurement of the Provincial NQP Index

The 390 observations from 30 provinces during 2011–2023 serve as a common standardization reference. Each indicator is winsorized at both tails at 1%; science and technology personnel, R&D input, and patent density are transformed using $\ln(1 + x)$, followed by 0–1 min–max standardization. Each of the three primary dimensions receives a weight of 1/3, with equal weights within dimensions. The socialized service and disaster resistance indicators use standardized data, and the socialized service indicator uses a linear scale. Missing values are linearly interpolated by province, and endpoints are filled using the nearest valid observation. Sensitivity tests use entropy weights across all indicators, 1:1 mixed equal–entropy weighting, and the removal of selected indicators or dimensions. Final weights are shown in Appendix A Table A3.

Appendix B.3. Alternative Measures of Farmers' GB

Each of the six green production practices takes a value of 0 or 1, with baseline weights of 1/6 each. Robustness tests include an entropy-weighted index determined by differences in sample information, the number of the six practices adopted, and an alternative combination calculated as an equally weighted average of six practices after replacing water-saving irrigation with straw incorporation. In the order listed in Table 2, the entropy-weighted index weights are 0.1512, 0.0742, 0.1656, 0.1198, 0.1936, and 0.2956, calculated from the sample of 533 farm households.

Appendix B.4. Measurement of the FNQP Index

The 533 valid farm household observations serve as the standardization reference. Years of education and the number of production technology training sessions are winsorized at both tails at 1%; continuous and ordinal indicators undergo 0–1 min–max standardization, while binary indicators retain their original values. Each of the three primary dimensions receives a weight of 1/3, with equal weights within dimensions: years of education and the number of training sessions each receive a weight of 1/6, and the remaining six indicators each receive a weight of 1/9. Entropy weighting across all indicators and 1:1 mixed equal–entropy weighting are used for sensitivity tests. Final weights are shown in Appendix A Table A3.

Appendix B.5. Supplementary Threshold Indicator and Control Variable Coding

DISA is constructed as the mean of four items scored on a 1–5 scale: using Qzone or WeChat Moments, participating in online chat interactions, forwarding and sharing online information, and creating and uploading short agricultural videos. Higher values indicate stronger sharing ability. The innovator indicator is a 0–1 variable, and risk preference is coded from 1 to 5, from low to high risk. Among the micro-level control variables, registered capital uses $\ln(1 + \text{registered capital})$, and total days of agricultural operations and cultivated land area are entered in natural logarithms. Gender is a 0–1 variable, terrain is a 1–2 categorical variable, and financial constraints and ease of access to credit enter the model using the original 1–5 questionnaire coding. Provincial per capita GDP is entered in natural logarithms.

Appendix B.6. Spatial Weight Matrices and Effect Decomposition

The baseline matrix uses the inverse of squared geographic distances between provincial capitals, with diagonal elements set to 0 and row standardization applied. Robustness analysis further uses an inverse distance matrix and a 4-nearest-neighbor matrix. The inverse distance matrix reduces the rate of distance decay. The 4-nearest-neighbor matrix defines the 4 provinces whose capitals are closest to each province's capital as spatial neighbors, takes the union of neighbor relationships, and then applies row standardization. Economic–geographic matrices are also constructed, with unstandardized weights equal to neighboring provinces' average per capita GDP during 2011–2023 multiplied by the inverse geographic distance or inverse squared geographic distance, followed by row standardization. Matrices remain unchanged when years are excluded. SDM restriction tests examine whether the spatial terms are jointly zero and whether the model can be simplified to SAR or SEM. Spatial model standard errors come from the likelihood Hessian matrix; effect decomposition uses the Delta method and accounts for covariances among ρ, the local coefficient, and the spatial lag coefficient.

The spatial association of NQP is characterized by the partial derivative matrix $S = (I - \rho W)^{-1}(\beta I + \theta W)$. The direct effect is the average of the diagonal elements of S, including local links and spatial feedback; the indirect effect is the average of the row

sums of off-diagonal elements, representing the average association with other regions; and the total effect is the sum of the two [39].

Appendix B.7. Clustered Inference for Micro-Level OLS

Standard errors are clustered by the 53 townships identified through county/district and township combinations, with the finite-sample adjustment $G/(G-1) \times (N-1)/(N-K)$. Two-sided p-values are calculated using a t-distribution with $G-1$ degrees of freedom.

Appendix B.8. Threshold Search and Bootstrap Tests

Distinct values are retained if each of the two regimes contains at least 15% of the sample, yielding three candidate points: 3.000, 3.333, and 3.667. The threshold is selected by minimizing the residual sum of squares. The null hypothesis for the threshold existence test is $\beta_L = \beta_H$. The model is fitted under the null restriction, and Rademacher weights of -1 and 1 with equal probability are applied to residuals at the township level; all candidate points are searched again in each replication. The main test uses 19,999 replications and random seed 20,261,010. The threshold confidence candidate set is obtained by calibrating the profile LR critical value using a wild-cluster bootstrap under the estimated threshold model. Coefficients on both sides of the threshold use township-clustered standard errors and the same t-tests. Coefficient difference tests at a fixed cutoff and threshold existence tests are reported separately.

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