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Measurement, Regional Differences, and Dynamic Evolution of Agricultural New-Quality Productive Forces

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Abstract: Agricultural new quality productive forces constitute a key driver for advancing high-quality agricultural development and represent an essential pathway toward realizing Chinese-style agricultural modernization. Based on a balanced panel dataset comprising 284 prefecture-level cities in China from 2008 to 2023, this study constructs a comprehensive evaluation framework of ANQPF from the dimensions of new laborers, new objects of labor, and new means of labor. A vertical–horizontal differentiation method, fixed-base efficacy coefficient method, and linear weighted aggregation method are applied to measure the level of ANQPF. Furthermore, Dagum Gini coefficient decomposition, kernel density estimation, traditional Markov chain, and spatial Markov chain models are employed to investigate regional disparities and dynamic evolution characteristics. The empirical results reveal the following: (1) The national average level of ANQPF shows a steady upward trend. Although the levels and contribution rates of new laborers, new objects of labor, and new means of labor all exhibit continuous growth, heterogeneity across dimensions remains. (2) The Dagum Gini coefficient indicates that overall disparities remain stable, while intra-regional, inter-regional, and transvariation density differences are all significant, with inter-regional disparities playing a dominant role. (3) Kernel density estimation shows that the national distribution exhibits a multi-modal and complex pattern, with evolving characteristics over time. The eastern region demonstrates leading and concentrated advantages, the central region shows stable improvement, the western region remains relatively lagging and dispersed, and the northeastern region displays a unique pattern with greater volatility. (4) Traditional and spatial Markov chains reveal system stability, club convergence, and transition rules shaped by spatial dependence. Based on the above findings, this study proposes some policy implications.

Keywords: Agricultural New Quality Productive Forces; Vertical–Horizontal Differentiation Method; Dagum Gini Coefficient; Regional Disparities; Dynamic Evolution.

1. Introduction

With the acceleration of the global technological revolution and industrial transformation, the concept of "new quality productive forces" has emerged as a central theme in China's development strategy. Since President Xi Jinping first articulated the concept during an inspection tour in Heilongjiang in September 2023, new quality productive forces have been widely recognized as a fundamental driver for reshaping industrial structures, fostering innovation-led growth, and supporting the construction of a modern economic system. The 2024 Government Work Report explicitly incorporated this concept into national development planning, underscoring its strategic significance in guiding future industrial and technological advancement.

As the foundation of the national economy, agriculture plays an irreplaceable role in ensuring food security, promoting rural revitalization, and advancing agricultural modernization. However, China's agricultural sector currently faces multiple challenges, including constraints associated with traditional production methods, persistent tight balance between grain supply and demand, increasing resource and environmental pressures, and growing international competition in agricultural markets. Developing agricultural new quality productive forces (ANQPF) has thus become an essential strategic choice. It enables agriculture to achieve self-driven transformation, improve production efficiency, enhance sustainability, and strengthen resilience against risks related to food and agricultural product supplies.

ANQPF is a comprehensive concept rooted in classical Marxist productive force theory, which traditionally includes laborers, objects of labor, and means of labor. In the context of modern agriculture, these components are endowed with new characteristics. New laborers represent high-quality human capital equipped with advanced knowledge, digital literacy, innovative capabilities, and the ability to adapt to smart agricultural environments. New objects of labor reflect the transformation of agricultural production targets toward ecological, diversified, and green development, including strategic emerging agricultural industries, improved agricultural varieties, ecological restoration, and new rural digital business models. New means of labor encompass both physical tools—such as modern equipment and infrastructure—and intangible means, including digital technologies, information platforms, and intelligent management systems. Together, these elements form an integrated system that fosters innovation-driven, green-oriented, and technology-intensive agricultural development.

Despite the growing academic attention to new quality productive forces, existing research has primarily focused on macroeconomic or industrial sectors, with relatively limited exploration of the agricultural domain. Most relevant studies emphasize conceptual discussions, theoretical interpretations, or qualitative analysis, lacking unified measurement standards and systematic empirical evaluation. Moreover, research specifically examining spatial disparities and dynamic evolution patterns of ANQPF across China's regions remains insufficient. As agriculture is highly heterogeneous across regions, characterized by varied resource endowments, technological capacities, industrial structures, and environmental conditions, understanding the regional differentiation and evolution of ANQPF is crucial for formulating targeted policies and promoting coordinated regional development.

In this context, the present study aims to fill this gap by providing a comprehensive empirical analysis of ANQPF in China. From the dimensions of new laborers, new objects of labor, and new means of labor, this study constructs a multidimensional evaluation indicator system. Using panel data from 284 prefecture-level cities from 2008 to 2023, we measure ANQPF levels and examine their spatial disparities and dynamic transitions through a combination of the vertical–horizontal differentiation method, fixed-base efficacy coefficient method, linear weighted aggregation method, Dagum Gini coefficient decomposition, kernel density estimation, and both traditional and spatial Markov chain models.

The contributions of this study are threefold. First, it enriches the theoretical understanding of ANQPF by integrating classical productive force theory with sector-specific characteristics of modern agriculture. Second, it constructs a systematic, multi-level indicator system that captures the complexity of ANQPF and provides an objective measurement approach for long-term cross-regional comparison. Third, it offers empirical evidence on regional disparities, distributional dynamics, and spatial dependence patterns of ANQPF, thereby generating policy-relevant insights for enhancing coordinated regional development and accelerating agricultural modernization.

Overall, this study provides a comprehensive analytical framework for understanding the formation, measurement, and evolution of ANQPF, offering important implications for promoting high-quality agricultural development and safeguarding national food security in the new era.

2. Literature Review

As new quality productive forces have become a focal concept in China's economic governance and academic discourse, scholars have conducted extensive research from multiple perspectives, including theoretical interpretation, measurement methodology, and influencing mechanisms. Existing studies provide a foundation for understanding the conceptual evolution and practical significance of new quality productive forces, yet research specifically addressing their agricultural dimension remains relatively limited.

2.1. Theoretical Foundations of New Quality Productive Forces

A growing body of research has examined the conceptual connotation and theoretical logic underlying new quality productive forces. Several scholars argue that the concept derives from Marx's productive force theory while embedding China's historical experience in socialist development and the modernization of its economic system [1-3]. This framework emphasizes the central role of technological innovation and highlights the need for upgrading production structures and fostering new forms of productivity that align with high-quality development goals. Studies also underscore that new quality productive forces represent a shift from traditional factor-driven growth to innovation-driven development, playing a transformative role in promoting strategic emerging industries and future industries [4].

In the field of agriculture, researchers have begun exploring how digital technologies reshape agricultural production modes and how new labor elements contribute to high-quality agricultural development. For instance, digital agriculture is found to accelerate structural upgrading, improve production efficiency, and enhance rural revitalization. Some scholars emphasize the key role of disruptive technologies—such as intelligent equipment, digital breeding, and precision agriculture—in building modern agricultural production systems. These studies collectively highlight that agriculture, like other sectors, is undergoing a profound transformation driven by innovation, digitalization, and green development [5-7].

2.2. Measurement of New Quality Productive Forces

Regarding measurement approaches, prior studies have proposed several indicator systems to quantify new quality productive forces at various scales. Many scholars construct multi-dimensional evaluation systems centered on new technologies, new industries, and new business formats. Common quantitative methods include entropy weighting, composite index construction, and panel-data-based objective weighting mechanisms[8]. Building on these approaches, researchers also incorporate spatial metrics such as the Dagum Gini coefficient, spatial correlation tests, and kernel density estimation to examine spatial disparities and temporal evolution.

However, existing measurement systems are predominantly macro-oriented and focus mainly on national or regional economic structures. Few studies tailor evaluation frameworks specifically to the agricultural sector, where production characteristics, technology adoption patterns, and regional heterogeneity significantly differ from manufacturing or service industries. This gap highlights the need for a sector-specific and theoretically grounded measurement system for agricultural new quality productive forces.

2.3. Influencing Factors of New Quality Productive Forces

Another strand of literature investigates the determinants of new quality productive forces. Digital transformation has been shown to significantly enhance productivity by improving information flows, optimizing resource allocation, and enabling technological upgrading. Studies also confirm the positive impacts of digital finance, enterprise ESG performance, and innovation capability on the development of new quality productive forces. These findings collectively indicate that technological advancements, institutional arrangements, and financial innovation are important drivers of new productive forces[9-10].

Nevertheless, the influencing mechanisms within the agricultural domain remain insufficiently explored. Current studies often generalize from non-agricultural sectors, overlooking agriculture's unique production environment—characterized by seasonal variability, ecological constraints, and high dependence on natural resources. As a result, there is limited understanding of how agricultural labor forces, production technologies, ecological assets, and digital infrastructure interact to shape agricultural new quality productive forces [11].

2.4. Research Gaps

Despite valuable insights from existing studies, several important research gaps remain:

Lack of sector-specific theoretical interpretation. Current research seldom elaborates on how Marxist productive force theory can be systematically extended to the agricultural context under modern technological conditions.

Absence of unified measurement standards for ANQPF. Existing evaluation frameworks vary widely and lack a comprehensive, multi-dimensional system specifically designed for agriculture.

Insufficient empirical evidence on regional disparities. Although spatial differences in economic development are well documented, few studies analyze the spatial distribution and inequality of ANQPF across China's prefecture-level cities.

Limited understanding of dynamic evolution. Research incorporating kernel density estimation, traditional Markov chains, and spatial Markov chains to examine the dynamic transitions of ANQPF is scarce.

To address these gaps, this study constructs an integrated theoretical, measurement, and empirical analysis framework for agricultural new quality productive forces. By combining multi-dimensional indicators with spatial and temporal analytical tools, this research contributes to a more comprehensive understanding of the formation, development, and evolution of ANQPF in China.

3. Theoretical Framework, Indicator System, and Measurement Approaches for Agricultural New Quality Productive Forces

Agricultural new quality productive forces (ANQPF) constitute a comprehensive concept that reflects the overall upgrading and transformation of agricultural productivity driven by technological innovation. Rooted in Marxist productive force theory—which emphasizes laborers, objects of labor, and means of labor—ANQPF assign new attributes and functions to these components under the context of digitalization, green transformation, and modernization. This section elaborates the theoretical foundations of ANQPF, constructs a multi-dimensional indicator system, and introduces the measurement methods used in this study.

3.1. Theoretical Connotation of Agricultural New Quality Productive Forces

ANQPF represent an innovation-driven and technology-empowered advancement of agricultural productive forces. Their theoretical connotation is reflected in the redefinition and upgrading of traditional productive force elements.

New laborers form the central subject of ANQPF. They possess advanced knowledge, technical skills, digital literacy, and strong innovative capacities. Improvements in educational attainment, professional training, and employment structure contribute to enhancing laborers' overall competency. Equipped with modern agricultural management concepts and the ability to operate intelligent technologies, new laborers drive the transformation from traditional labor-intensive agriculture toward knowledge-intensive and technology-intensive production.

New objects of labor constitute the material basis of ANQPF. Compared with traditional agricultural production relying primarily on land, forests, and biological resources, ANQPF emphasize ecological consciousness, industrial transformation, and diversified agricultural development[12-13]. This includes: strategic emerging agricultural industries, ecological and environmental improvement, enhanced agricultural variety breeding and application, development of rural e-commerce and new business models.

These changes promote resource efficiency, environmental sustainability, and modernization of agricultural production structures.

New means of labor serve as the key driver of ANQPF. They incorporate both tangible means-such as agricultural machinery, infrastructure, irrigation systems, and digital communication networks—and intangible means, including digital technologies, data platforms, smart agricultural systems, and innovative management tools. Technological innovation enables qualitative improvements in agricultural production efficiency, resource allocation, and industrial upgrading, providing strong technical support for ANQPF.

The essential features of ANQPF include: Enhanced human capital and improved labor quality; Technological and disruptive innovation as the core driving force; Deep integration of multiple production factors and collaborative optimization; Industrial extension and boundary expansion through cross-sectoral integration; Digital and green transformation as the dominant developmental trend.

Thus, ANQPF represent a holistic, modernized productivity system led by innovation, supported by new laborers and labor means, and manifested in structural, ecological, and technological upgrading.

3.2. Indicator System Construction and Data Sources

Based on the theoretical connotation of ANQPF and existing literature, this study develops a comprehensive evaluation indicator system covering three major dimensions: new laborers, new objects of labor, and new means of labor. The system aims to capture both quantitative and qualitative reflections of agricultural modernization.

All data used in this study are derived from authoritative national statistical yearbooks and official databases, including: National Bureau of Statistics of China, China Statistical Yearbook, China Rural Statistical Yearbook, China Fiscal Yearbook, China Environmental Statistical Yearbook, China Social Statistical Yearbook, China Energy Statistical Yearbook, China Management Statistical Yearbook, China Rural Cooperative Economy Statistical Yearbook, China Rural Policy and Reform Yearbook, Digital Finance Research Center at Peking University.

The dataset covers 284 prefecture-level cities across China from 2008 to 2023. Missing data are supplemented using the moving-average interpolation method to ensure completeness and accuracy.

Indicator System Overview

The indicator system is constructed according to Table 1 of the original Chinese manuscript and fully incorporates the following structures:

Table 1. Indicator System of Agricultural New Quality Productive Forces

Target Layer	Guideline Layer	Primary indicator	Secondary Indicators	Level 3 Indicators	Measurement Method	Attribute
New Quality Productivity	New Workers	Worker Skills	Level of education	Average Years of Education per Capita in Rural Areas	Average years of schooling per capita in rural areas	Correct
				Intensity of Education Expenditures	Education Expenditure* (Gross Output Value of Agriculture, Forestry, Animal Husbandry, and Fisheries / Regional Gross Domestic Product) / Total Fiscal Expenditure	Correct
		Labor productivity	Per capita output value	Per capita agricultural value added	Added Value of Agriculture, Forestry, Animal Husbandry, and Fisheries / Rural Population	Correct
			Per capita income	Farmers' disposable income	Per capita disposable income of farmers	Correct
		Worker consciousness	Employment Philosophy	Proportion of employees in the industry	The proportion of employment in the tertiary sector relative to total employment	Correct
	New labor object	New-quality industries	Strategic Emerging Industries	Status of High-Tech Industry Development	Number of R&D Researchers* (Gross Output Value of Agriculture, Forestry, Animal Husbandry, and Fisheries / Regional Gross Domestic Product)	Correct
					Water-saving irrigation area / Effective irrigation area	Correct
					Internal R&D Expenditure* (Gross Output Value of Agriculture, Forestry, Animal Husbandry, and Fisheries / Regional Gross Domestic Product)	Correct
					Contribution of Technological Progress to Annual Average Growth Rate of Total Agricultural Output Value	Correct
					Number of Agricultural Plant Variety Rights Applications per Provincial Land Area	Correct
					Number of Authorized Agricultural Plant Variety Rights / Provincial Land Area	Correct
					Number of Taobao Villages / Provincial Land Area	Correct
				Environmental Governance Level	Area Treated for Soil Erosion Control / Provincial Land Area	negative
					Value of Ecosystem Services / Total Land Area of the Region	Correct
		Ecological Environment	Green and eco-friendly	Forest coverage rate	Forest coverage rate	Correct
				Environmental protection efforts	Environmental Protection Expenditures/Government Public Finance Expenditures	Correct
				Green Technology Innovation	Green Patent Applications / Total Patent Applications	Correct
			Pollution Reduction	Pollutant emissions	Fertilizer Application Rate / Crops Sown Area	negative
					Pesticide Application Rate / Crop Planting Area	negative
					Agricultural plastic film usage/Crop planting area	negative
					Agriculture, Forestry, and Water Resources Expenditures / Fiscal Expenditures	Correct
	New Means of Production	Means of material production	Facilities and Equipment	Traditional infrastructure	Highway mileage	Correct
					Production Equipment Investment / Fixed Asset Investment	Correct
					Total Agricultural Machinery Power	Correct
					Number of Rural Hydropower Stations	Correct
					Number of Rural Internet Access Ports	Correct
				Digital Infrastructure	Number of Rural Broadband Access Users	Correct
					Mobile phone penetration rate	Correct
					Actual number of rural cable TV subscribers / Total number of households	Correct

3.3. Measurement Methods

When measuring agricultural new-quality productive forces, to ensure the objectivity of the evaluation results and the transparency of the evaluation process, this study also draws on and adopts the series of scientific methods proposed by Nie Changfei and Jian Xinhua, with appropriate adjustments and optimizations based on the characteristics of agricultural new-quality productive forces. The detailed explanations of these methods are as follows:

3.3.1. Indicator Weighting: Vertical–Horizontal Grading Method

The vertical–horizontal grading method is an objective weighting technique that captures the dynamic differences among evaluation objects based on panel data. Assume the set of evaluation objects is $\{s_1,s_2,\ldots,s_n\}$, and the vector of indicator weights is $w=\{w_1,w_2,\ldots,w_m\}^T$. Let z_{ij},t_k denote the original value of indicator j for province i in year t_k, and let z_{ij}^*,t_k denote the value obtained after dimensionless normalization.

The comprehensive evaluation function at time t_k is given by:

$$y_j,t_k=\sum_{(j=1,2,3,\cdots m)}^{j} w_j{*}z{*}i_j,t_k \tag{1}$$

To accurately characterize the differences among the evaluation objects, we use the total squared deviation as the measurement metric:

$$\sigma^2 = \sum_{k=1,2,3\cdots N}\sum_{i=1,2,3,\cdots n}\left(y_i,t_k - y\right)^2 \tag{2}$$

Where, y represents the average comprehensive evaluation score of all evaluation objects across all years. To apply min–max normalization to the data, the total squared deviation can be adjusted as follows:

$$\sigma^2 = wT * H * w \tag{3}$$

Where, H is a $m \times m$ symmetric matrix, obtained by multiplying AT_k and A_k, which are constructed from the indicator data of each year, resulting in matrix $H_k = AT_k * A_k$. Furthermore, after setting $w^T w = 1$, the value of w reaches its maximum when w is the eigenvector corresponding to the largest eigenvalue of matrix H. To ensure that all indicator weights remain positive, we impose the constraint $w > 0$.

3.3.2. Data Standardization: Fixed-Base Efficacy Coefficient Method

To ensure that the agricultural new-quality productive forces are comparable across years, we adopt the fixed-base efficacy coefficient method using the initial sample year (2012) as the reference period. The standardization formula is as follows:

For positive indicators:

$$s_{ij},t_k = 10\times\left[\left(maxz_j,t_1 - z_{ij},t_k\right)/\left(maxz_j,t_1 - minz_j,t_1\right)\right] \tag{4}$$

For negative indicators:

$$s_{ij},t_k = 10\times\left[\left(z_{ij},t_k - minz_j,t_1\right)/\left(maxz_j,t_1 - minz_j,t_1\right)\right] \tag{5}$$

Where, z_{ij},t_k and s_{ij},t_k represent the original value and the standardized value of indicator j for province i in year t_k, respectively. $\max[z_j,t_1]$ and $\min[z_j,t_1]$ refer to the maximum and minimum values of the indicator in the base period.

3.3.3. Comprehensive Measurement: Linear Weighting Method

After obtaining the standardized indicator values and the corresponding weight vector, we adopt the linear weighting method to calculate the level of agricultural new-quality productive forces for province i in year t_k, denoted as X_i,t_k. The calculation formula is as follows:

$$X_i,t_k = \sum_{j=1,2,3,\cdots m} w_j * s_{ij},t_k \tag{6}$$

3.3.4. Gini Coefficient

The Gini coefficient is an important indicator used to measure the degree of inequality. In this study, we adopt the Dagum Gini coefficient decomposition method to assess the spatial disparities in China's agricultural new-quality productive forces. The overall Gini coefficient (G) is calculated using Equation (7):

$$G = \frac{\sum_{j=1}^{k}\sum_{h=1}^{k}\sum_{i=1}^{n_j}\sum_{r=1}^{n_h}|y_{ji} - y_{hr}|}{2n^2\overline{y}} \tag{7}$$

Where, n represents the total number of samples, k denotes the number of regions, and y_{ji} and y_{hr} refer to the indicator values of city i in region j and city r in region h, respectively. The term represents the mean value. The within-group Gini coefficient (G_{jj}) is determined by Equation (8):

$$G_{jj} = \frac{1}{2\overline{y}}\sum_{i=1}^{n_j}\sum_{r=1}^{n_j}\frac{|y_{ji} - y_{jr}|}{n_j^2} \tag{8}$$

This coefficient reflects the degree of inequality within region j. The between-group Gini coefficient (G_{jh}) is calculated using Equation (9):

$$G_{jh} = \frac{\sum_{i=1}^{n_j}\sum_{r=1}^{n_h}|y_{ji} - y_{hr}|}{n_j n_h(\overline{y_j} + \overline{y_h})} \tag{9}$$

Here, y_j and y_h represent the mean values of regions j and h, respectively. Furthermore, the Dagum Gini coefficient, which reflects the overall level of agricultural new-quality productive forces, can be decomposed into three components: the within-group difference (G_W), the between-group difference (G_{nb}), and the transvariation intensity (G_t).

$$G_\omega = \sum_{j=1}^{k} G_{jj} P_j S_j \tag{10}$$

$$G_{nb} = \sum_{j=2}^{k}\sum_{h=1}^{j-1} G_{jh} D_{jh}(P_j S_h + P_h S_j) \tag{11}$$

$$G_t = \sum_{j=2}^{k}\sum_{h=1}^{j-1} G_{jh}(P_j S_h + P_h S_j)(1 - D_{jh}) \tag{12}$$

3.3.5. Kernel Density Estimation

In this study, the Gaussian kernel function is selected to perform kernel density estimation. The kernel density function is defined as follows:

$$f(x) = \frac{1}{Nh}\sum_{i=1}^{N} K\left(\frac{X_i - \overline{X}}{h}\right) \tag{13}$$

Where, N denotes the total number of samples, h is the bandwidth, and X_i represents the independently and identically distributed observations, while the term refers to their mean. The kernel function is expressed as follows:

$$K(x) = \frac{1}{\sqrt{2\pi}} e^{-\frac{y^2}{2}} \tag{14}$$

3.3.6. Traditional and Spatial Markov Chain Models

The Markov chain is an important type of stochastic process model whose defining feature is the Markov property. This property indicates that for a stochastic process described as X_n over a time set T, the probability distribution of the next state X_{t+1} depends solely on the current state X_t. It does not rely on any previous sequence of states, such as X_1, X_2, …, X_{t-1}. In other words, the future state is determined only by the present state and is independent of the path taken to reach it.

$$P\left\{X(t+1) = j \mid X(t) = i, X(t-1) = i_{t-1}, \ldots, X(0) = i_0\right\} = P\left\{X(t+1) = j \mid X(t) = i\right\} \tag{15}$$

Here, P represents the probability that the agricultural new-quality productive forces of a given province shift from type i in year t to type j in year $_{t+1}$.

$$P = \frac{n_{ij}}{n_i} \tag{16}$$

4. Measurement Results of Agricultural New-Quality Productive Forces

4.1. Overall Trend Analysis

From a time-series perspective, the national average level of agricultural new-quality productive forces shows a steady upward trend. As presented in Table 2, the value increased from 0.2593 in 2008 to 0.4031 in 2023, indicating continuous progress and development over this extended period.

This upward trajectory may be attributed to several factors. First, sustained investment and innovation in agricultural science and technology have accelerated the transformation of agricultural production toward modernization and intelligence. Second, the optimization of the agricultural industrial structure has facilitated more efficient resource allocation, thereby enhancing overall productivity. Third, the strengthened policy support for agricultural development—such as subsidies and investments in agricultural infrastructure—has created a favorable environment for improving agricultural new-quality productive forces.

4.2. Regional Comparative Analysis

Based on the regional division of the National Bureau of Statistics, the 284 prefecture-level cities are classified into four major regions: the eastern, central, western, and northeastern regions. According to Table 2, the eastern region's average value is consistently and significantly higher than the national average across all years, with a clear upward trend.

This indicates that the eastern region is at the forefront of developing agricultural new-quality productive forces, likely benefiting from its solid economic foundation, advanced technological capabilities, and well-developed agricultural industrial system. The region is more capable of attracting high-quality talent and advanced agricultural technologies, while its agricultural enterprises possess stronger innovation capabilities and market competitiveness. Consequently, agricultural new-quality productive forces in the eastern region have risen rapidly. For example, the region generally leads in agricultural informatization and the application of precision agricultural technologies, resulting in substantial improvements in production efficiency and, therefore, higher levels of new-quality productivity.

The central region's average value is lower than that of the eastern region but demonstrates a stable upward trend, with a relatively consistent gap compared to the national average. As an important agricultural production base, the central region holds resource advantages; however, it may lag slightly behind the eastern region in technological application and industrial development. Nonetheless, with the implementation of strategies promoting the rise of central China, increased investment in agricultural infrastructure and agricultural technology diffusion has gradually improved agricultural new-quality productive forces, narrowing the gap with the eastern region.

The western region exhibits relatively lower average values among the four regions, with a slower growth rate. This can be primarily attributed to constraints such as natural conditions and relatively lagging economic development, which slow the pace of agricultural modernization. However, in recent years, with the deepening of the Western Development Strategy, progress has been made in areas such as ecological conservation, agricultural ecological construction, and the development of characteristic agriculture. These efforts have gradually raised the region's agricultural new-quality productive forces. For instance, some western areas have leveraged modern technology to improve production efficiency and added value by promoting characteristic industries such as specialty fruit production and animal husbandry.

The northeastern region has also experienced growth from 2008 to 2023, with its average value approaching that of the eastern region in certain years. As China's key grain-producing base, the northeastern region has abundant arable land and agricultural resources and enjoys advantages in agricultural mechanization. In recent years, the region has actively advanced supply-side structural reforms, strengthened agricultural technological innovation, and promoted industrial upgrading. These efforts have further enhanced agricultural new-quality productive forces, reinforcing its crucial role in safeguarding national food security.

Table 2. The Average Level of Agricultural New-Quality Productive Forces

	Eastern average	Central average	Western average	Northeastern average	National average
2008	0.3248	0.2249	0.2074	0.3028	0.2593
2009	0.3406	0.2337	0.2168	0.3086	0.2700
2010	0.3541	0.2438	0.2247	0.3213	0.2808
2011	0.3652	0.2572	0.2344	0.3372	0.2927
2012	0.3838	0.2613	0.2469	0.3430	0.3039
2013	0.3915	0.2724	0.2490	0.3560	0.3116
2014	0.4063	0.2790	0.2631	0.3761	0.3245
2015	0.4212	0.2920	0.2745	0.3759	0.3360
2016	0.4290	0.3030	0.2831	0.4014	0.3470
2017	0.4424	0.3092	0.2903	0.4045	0.3554
2018	0.4594	0.3184	0.2952	0.4285	0.3674
2019	0.4692	0.3309	0.3020	0.4361	0.3768
2020	0.4823	0.3369	0.3167	0.4440	0.3878
2021	0.4929	0.3423	0.3247	0.4545	0.3961
2022	0.5094	0.3573	0.3367	0.4627	0.4099
2023	0.5018	0.3483	0.3304	0.4626	0.4031

Overall, although China has made substantial progress in agricultural new-quality productive forces over the past decade, regional disparities remain significant. Moving forward, further cooperation and coordinated development among regions should be strengthened. Leveraging the eastern region's role as a growth engine can help elevate the levels in the central, western, and northeastern regions. Meanwhile, each region should tailor development strategies to its resource endowments and industrial foundations by increasing investment in agricultural technological innovation, strengthening talent cultivation, and optimizing industrial structures. These efforts will contribute to transforming and upgrading agricultural production methods, promoting balanced and sustainable improvements in agricultural new-quality productive forces nationwide, and laying a solid foundation for ensuring national food security and advancing agricultural modernization.

4.3. Levels of Agricultural New-Quality Productive Forces Across Dimensions

As shown in Figure 1, all three dimensions exhibit a steady upward trend from 2008 to 2023. The average level of new laborers rose from 0.2752 in 2008 to 0.4157 in 2023, displaying the most pronounced growth. This reflects China's continuous efforts and remarkable achievements in cultivating agricultural talent and improving the quality of agricultural practitioners. Increasing numbers of workers equipped with professional knowledge, innovative thinking, and modern management concepts have entered the agricultural sector. These individuals have strongly contributed to the innovation and development of agricultural production models, forming a solid human-capital foundation for enhancing agricultural new-quality productive forces.

The level of new labor means also increased steadily, rising from 0.2533 in 2008 to 0.3965 in 2023. This demonstrates the ongoing optimization and upgrading of production tools, infrastructure, and information technology in China's agricultural sector—for example, the widespread adoption of modern agricultural machinery and the promotion of smart agricultural management systems. However, its growth rate is slightly slower than that of new laborers, suggesting that the upgrading of labor means may face constraints such as high technology conversion costs or limited promotion coverage.

The level of new labor objects likewise increased year by year, growing from 0.2540 in 2008 to 0.4010 in 2023. This indicates continuous expansion and quality improvement of agricultural production objects in China, shifting from traditional planting and breeding toward diversified areas such as specialty agriculture and ecological agriculture. This diversification enriches agricultural value and content, further supporting the sector's transition toward high-quality development.

In terms of contribution rates, new laborers increased from 0.2500 in 2008 to 0.4000 in 2023, showing a stable upward trend and gradually becoming the most influential dimension among the three. This highlights the critical role of improving labor quality and optimizing talent structures in advancing agricultural new-quality productive forces. It suggests that human capital is becoming increasingly important in agricultural modernization, as high-quality laborers can better apply new technologies, explore new markets, and innovate production and management models, thereby facilitating industrial upgrading.

The contribution rate of new labor means rose from 0.2000 in 2008 to 0.3500 in 2023, maintaining steady growth. This indicates that with continuous progress in agricultural science and technology, new labor means play an increasingly vital role in improving production efficiency and quality. Although its contribution rate is slightly lower than that of new laborers, it remains an indispensable driving force, providing solid material and technological support for the enhancement of agricultural new-quality productive forces.

The contribution rate of new labor objects increased from 0.2200 in 2008 to 0.3700 in 2023, reflecting the growing importance of optimizing production objects in agricultural development. Expanding and improving production objects can effectively meet diversified market demands, increase agricultural value-added, and promote the extension and improvement of the agricultural industry chain.

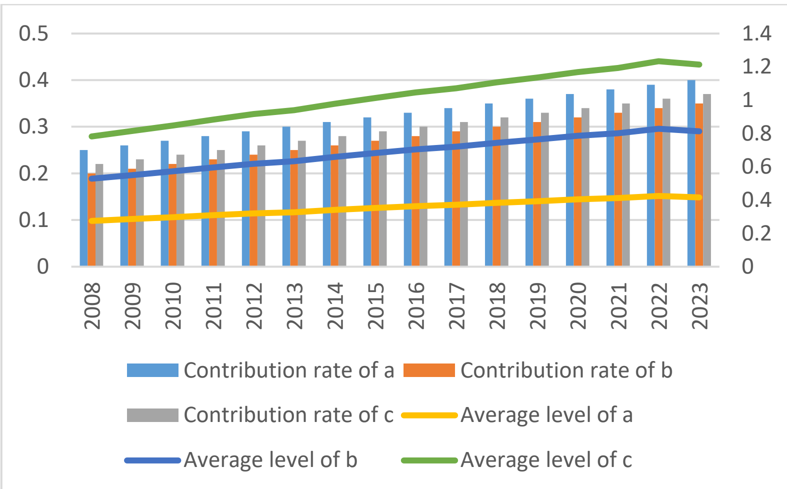


Figure 1. ANQPF levels by dimension

Overall, the simultaneous rise in the average levels and contribution rates across the three dimensions indicates a positive pattern of mutual reinforcement and coordinated development. New laborers, equipped with advanced labor means, work on increasingly optimized labor objects, jointly driving improvements in agricultural new-quality productive forces. Meanwhile, the upgrading of labor means requires the skills and knowledge of laborers, and the expansion of labor objects relies on support from both other dimensions.

However, the differences in contribution rates also suggest that achieving balanced development across dimensions will be crucial going forward. Enhancing coordination—such as improving the alignment between laborers and new labor means, or promoting tailored development of labor means based on the characteristics of labor objects—will help achieve more efficient and sustainable improvements in agricultural new-quality productive forces and support China's agricultural modernization at a higher level.

5. Analysis of Regional Differences and Sources of ANQPF

To further investigate the regional differences and underlying sources of agricultural new-quality productive forces, this study applies the Gini coefficient calculation and decomposition method proposed by Dagum and Yao et al., examining disparities within the "eastern– central– western–northeastern" regional pattern. The results are reported in Table 3.

The findings reveal the following:

(1) From 2008 to 2023, the overall Gini coefficient fluctuated within a narrow range of 0.188–0.199, indicating that the overall disparity in China's agricultural new-quality productive forces remained relatively stable. No signs of significant imbalance intensification or rapid convergence were observed, suggesting a steady macro-development pattern.

(2) The within-region difference contributed approximately 0.040–0.043, with a contribution rate oscillating around 21%. This suggests that although regions have made progress in enhancing agricultural new-quality productive forces, persistent internal disparities remain due to variations in natural conditions, resource endowments, and policy implementation. Nevertheless, the influence of within-region differences has stayed relatively stable.

(3) The between-region difference contributed 0.098–0.106, with a contribution rate of 51%–54%, making it the dominant source of overall disparity. Distinct differences in economic development, technological capabilities, and industrial foundations across regions lead to varying development speeds and levels of agricultural new-quality productive forces, resulting in pronounced interregional gaps.

(4) The transvariation density—reflecting cross-regional overlapping differences—contributed 0.046–0.052, with a contribution rate of 24%–26%. Its stable contribution indicates its non-negligible role in shaping overall disparities, suggesting that complex cross-regional interactions exist in agricultural development.

Overall, the between-region difference is the primary driver of the total Gini coefficient, while within-region differences and transvariation density also make stable contributions, collectively forming the existing disparity pattern.

Table 3. Dagum Gini Decomposition Results

year	Overall Gini Coefficient	Within-Region Difference		Between-Region Difference		Transvariation Intensity	
		Contribution Value	Contribution Rate (%)	Contribution Value	Contribution Rate (%)	Contribution Value	Contribution Rate (%)
2008	0.199	0.043	21.542	0.105	52.653	0.051	25.804
2009	0.194	0.041	21.245	0.106	54.474	0.047	24.279
2010	0.196	0.042	21.258	0.106	54.301	0.048	24.439
2011	0.193	0.041	21.409	0.103	53.337	0.049	25.253
2012	0.193	0.041	21.246	0.104	53.797	0.048	24.956
2013	0.194	0.042	21.439	0.105	54.139	0.047	24.421
2014	0.195	0.041	21.306	0.102	52.821	0.050	25.871
2015	0.189	0.040	21.326	0.100	52.936	0.049	25.738
2016	0.188	0.041	21.670	0.098	51.909	0.049	26.419
2017	0.190	0.041	21.552	0.099	52.014	0.050	26.434
2018	0.192	0.040	21.023	0.104	54.027	0.048	24.949
2019	0.189	0.040	21.425	0.102	54.076	0.046	24.498
2020	0.188	0.040	21.442	0.099	52.546	0.049	26.011
2021	0.191	0.041	21.399	0.099	51.695	0.051	26.907
2022	0.189	0.041	21.576	0.097	51.466	0.051	26.957
2023	0.191	0.040	21.398	0.098	51.693	0.052	26.908

Therefore, in designing agricultural policies, efforts should focus on reducing interregional disparities, strengthening regional cooperation, and promoting resource complementarity to achieve coordinated development. At the same time, attention must be paid to intra-regional balance by optimizing resource allocation according to local conditions. Additionally, cross-regional overlapping influences should be appropriately addressed to effectively mitigate disparities. These measures will contribute to promoting balanced and high-quality agricultural development, advancing agricultural modernization, and ensuring the sustainable and stable growth of the agricultural sector.

Using the decomposition method of the Gini coefficient, this study further examines the sources of disparities in agricultural new-quality productive forces across the four major regions—eastern, central, western, and northeastern China. The decomposition results are presented in Table 4.

Table 4 shows that:

(1) Within-region Gini coefficients demonstrate that the eastern region maintains relatively balanced internal development, with values mostly ranging between 0.070 and 0.077. This balance can be attributed to its strong economic foundation, well-developed infrastructure, and highly efficient technology extension systems. The central region fluctuates between 0.136 and 0.146, indicating comparatively greater internal disparities, possibly related to differences in resource endowments, industrial structures, and policy effectiveness among its cities. The western region is similar to the central region, with values between 0.139 and 0.149, reflecting uneven development influenced by geographic

constraints and relatively weaker economic conditions. The northeastern region exhibits the largest internal disparities, with values between 0.281 and 0.307, which may be associated with its industrial restructuring, transitions in production modes, and varying policy emphases.

(2) Between-region Gini coefficients reveal that disparities between the eastern region and the other three regions are generally high. For example, the eastern–central coefficient ranges between 0.109 and 0.119, highlighting substantial differences between the east and the rest of the country. This reflects imbalances in agricultural development foundations, technological investment, and industrial upgrading across regions. The coefficients for central–western, central–northeastern, and western–northeastern regions also show fluctuations, indicating that disparities among these regions persist due to differences in development paths, resource utilization, and technological application.

In summary, significant disparities exist both within and between regions in terms of agricultural new-quality productive forces. Policy formulation should therefore address both dimensions. Within regions, policies should be tailored to local imbalances to promote internal equilibrium. Between regions, enhanced cooperation and strategic coordination are needed, along with increased support for the central, western, and northeastern regions to reduce gaps and promote sustainable and balanced national development. These efforts will strengthen China's overall agricultural competitiveness, support stable industrial development, and contribute to national food security.

Table 4. Within- and Between-Region Gini

year	Within-Region Gini				Between-Region Gini					
	Eastern	Central	Western	Northeastern	East–Central	East–West	East–Northeast	Central–West	Central–Northeast	West–Northeast
2008	0.077	0.146	0.149	0.307	0.118	0.196	0.242	0.197	0.257	0.252
2009	0.072	0.142	0.148	0.291	0.115	0.197	0.237	0.188	0.245	0.243
2010	0.074	0.136	0.141	0.300	0.113	0.195	0.244	0.183	0.249	0.246
2011	0.070	0.144	0.142	0.300	0.114	0.187	0.238	0.187	0.251	0.245
2012	0.076	0.141	0.139	0.287	0.117	0.198	0.236	0.186	0.240	0.238
2013	0.074	0.143	0.147	0.294	0.117	0.193	0.239	0.185	0.246	0.244
2014	0.070	0.144	0.152	0.291	0.114	0.197	0.233	0.197	0.247	0.244
2015	0.070	0.145	0.140	0.285	0.119	0.191	0.229	0.182	0.239	0.237
2016	0.076	0.139	0.144	0.281	0.113	0.187	0.228	0.184	0.240	0.235
2017	0.075	0.410	0.144	0.284	0.115	0.191	0.229	0.184	0.238	0.238
2018	0.068	0.138	0.142	0.293	0.109	0.191	0.237	0.193	0.250	0.242
2019	0.074	0.141	0.144	0.283	0.114	0.188	0.232	0.186	0.243	0.235
2020	0.073	0.140	0.139	0.283	0.113	0.190	0.227	0.187	0.238	0.235
2021	0.071	0.146	0.140	0.290	0.116	0.191	0.229	0.189	0.244	0.242
2022	0.071	0.145	0.144	0.283	0.116	0.189	0.227	0.185	0.238	0.236
2023	0.071	0.146	0.140	0.290	0.116	0.191	0.229	0.190	0.244	0.242

6. Dynamic Evolution of Agricultural New-Quality Productive Forces

6.1. Kernel Density Estimation of Agricultural New-Quality Productive Forces

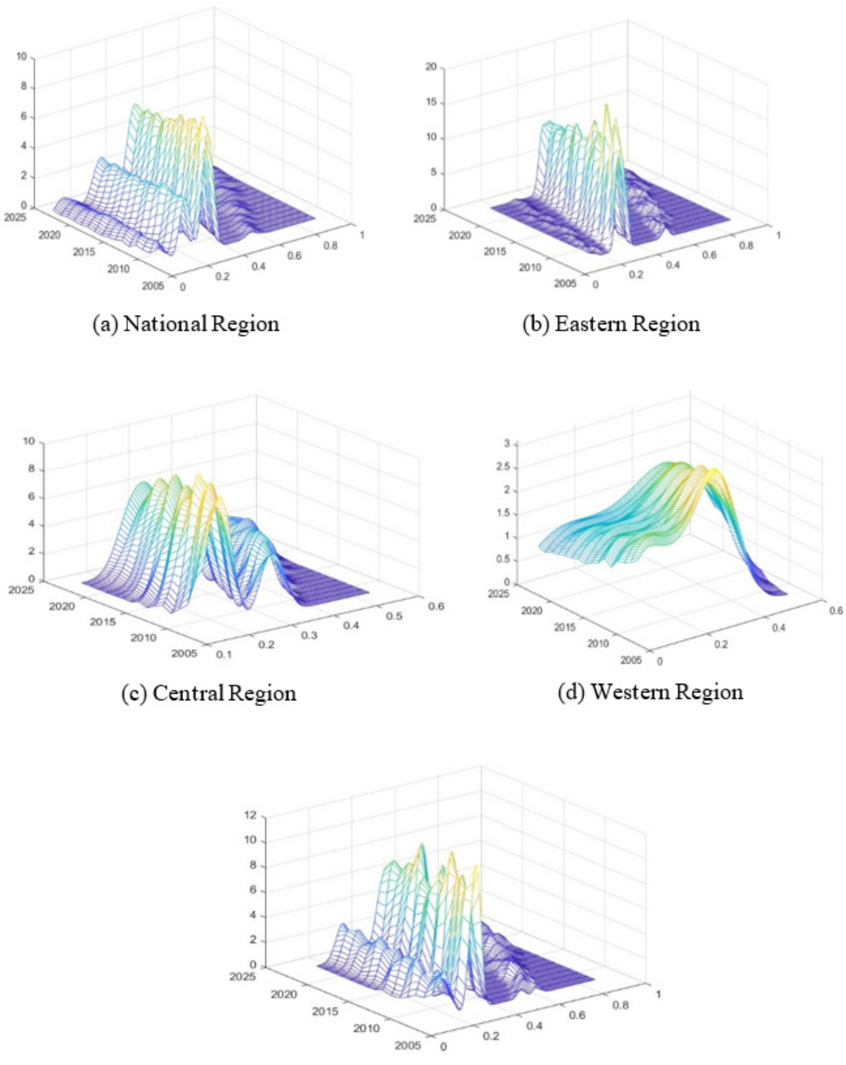
From the national kernel density curves of agricultural new-quality productive forces, the overall distribution exhibits a multimodal pattern with a relatively complex structure. Over time, from 2008 to 2023, the density curves show clear fluctuations and shifts. In the early years, the distribution is relatively flat, indicating a dispersed level of agricultural new-quality productive forces across regions. In the middle years, more pronounced peaks emerge, suggesting that during this period, a large number of regions concentrated around certain specific productivity levels. By 2023, both the shape and the location of the peaks shift again, reflecting the dynamic evolution of agricultural new-quality productive forces throughout the long-term development process.

The kernel density curves for the eastern region display relatively high and concentrated peaks. This indicates that agricultural new-quality productive forces in the east are clustered within higher-value intervals. Over time, the eastern region has shown a clear concentration trend even in earlier years, and this clustering becomes increasingly evident in higher-level intervals as time progresses. This pattern may be attributed to the region's strong economic foundation, advanced technological capabilities, and well-developed agricultural infrastructure, which together enable rapid improvement and sustained high levels of new-quality productive forces.

The kernel density distribution of the central region shows a moderate degree of concentration. Compared with the eastern region, the central region exhibits lower peak values and a slightly more dispersed distribution, although clear clustering areas remain. Over time, the agricultural new-quality productive forces in the central region gradually improve, with the peaks shifting toward higher levels. However, the magnitude of this shift is smaller than that of the eastern region. This implies that although the central region has made progress, certain constraints—such as limitations in technology adoption or structural conditions—have slowed its pace relative to the east.

The kernel density curves for the western region reveal a low and relatively dispersed distribution. In the early years, the western region shows low values with wide dispersion and no strong clustering. Over time, slight upward improvements are visible, but the overall distribution remains relatively scattered. This pattern may be linked to the region's natural constraints and relatively underdeveloped economic conditions, which restrict the rapid concentration and advancement of agricultural new-quality productive forces.

The northeastern region presents a unique kernel density pattern, characterized by relative concentration but also substantial fluctuations. The region demonstrates its own clustering interval, yet peak values vary considerably across different years. This volatility may be associated with the structural characteristics of the northeastern agricultural economy. As a major grain-producing base, the region's agricultural productivity is heavily influenced by policy shifts, market dynamics, and natural conditions. These factors contribute to the year-to-year variability in its agricultural new-quality productive forces.



(a) National Region

(b) Eastern Region

(c) Central Region

(d) Western Region

(e) Northeastern Region

Figure 2. Kernel density estimation of China's ANQPF

6.2. Traditional Markov Chain

To further explore the spatial mobility and correlation characteristics in the evolutionary process of agricultural new-quality productive forces, a traditional Markov chain model is introduced. Following the approach of Shi Yutang and others, the levels of agricultural new-quality productive forces are divided into four categories based on quartiles: high level (I), upper-middle level (II), lower-middle level (III), and low level (IV). As shown in Table 6:

(1) The probabilities of each category maintaining its current state after one year—83%, 64%, 65%, and 87%—indicate that all categories have a high likelihood of remaining in their existing state. This reflects a certain degree of stability within the system.

(2) The diagonal elements are consistently larger than the off-diagonal elements, suggesting the presence of club convergence. High-level regions demonstrate a strong self-reinforcing effect: supported by advanced agricultural technologies, well-developed industrial systems, high-quality agricultural labor, and sufficient capital investment, these regions continuously strengthen and enhance their productivity levels, forming a relatively stable and advantageous "club." Likewise, low-level regions—constrained by weak infrastructure, lagging technological adoption, shortages of skilled personnel, and limited funding—tend to remain within a relatively closed cycle of low development. This not only widens their gap with higher-level regions but also forms a distinct low-level "club."

(3) In terms of mobility patterns, transitions are more likely to occur between adjacent levels, whereas direct transitions between non-adjacent levels are rare. This suggests that improvements in agricultural new-quality productive forces are constrained by the current development level while still exhibiting strong interregional linkages. However, leapfrog transitions are difficult to realize. For example, high-level regions have some probability of moving to the upper-middle level, but no possibility exists for a direct transition to the lower-middle or low levels.

Table 5. Traditional Markov Transition Matrix

Type	I	II	III	IV	Observed Value
I	0.828804	0.171196	0	0	1104
II	0.107446	0.64279	0.249764	0	1061
III	0	0.089789	0.653169	0.257042	1136
IV	0	0	0.127216	0.872784	959

6.3. Spatial Markov Chain

To further examine how spatial factors influence the transition probabilities of agricultural new-quality productive forces, spatial lag conditions were incorporated into the traditional Markov transition matrix to construct a spatial Markov chain (see Table 6). As shown in Table 6:

(1) Differences in developmental inertia are reflected in the self-maintenance probabilities across levels under various spatial neighborhood types. The diagonal elements reveal that under their respective spatial lag environments, all levels of agricultural new-quality productive forces exhibit a tendency to maintain their current state. For example, within neighborhood Type I, the high-level (I) category has a state-retention probability as high as 92%. This indicates strong development inertia under a spatial environment consistent with its characteristics. High-level regions are likely to maintain their advantages due to established agricultural industrial systems, efficient agricultural technology innovation mechanisms, and strong resource integration capacity.

(2) The probability of upward transitions varies significantly across spatial neighborhood types, showing strong spatial dependence. For instance, for the upper-middle level (II), the probability of upgrading to the high level (I) is 28% under the neighborhood Type I spatial lag, but this probability rises sharply to 67% under neighborhood Type II. This demonstrates that surrounding spatial environments exert markedly different influences on upward mobility. A favorable and well-matched spatial context (e.g., neighborhood Type II) facilitates upward transitions by enabling technology diffusion, industrial cooperation, and resource synergy. Conversely, a relatively unfavorable spatial context (e.g., neighborhood Type I for the II level) limits such upward development.

Similarly, downward transitions are also highly sensitive to spatial lag. For example, the probability of the upper-middle level (II) dropping to the low level (IV) reaches 89% under the neighborhood Type IV environment. This suggests that when located in an adverse spatial environment, regions face substantial risks of decline, possibly due to spillover effects from surrounding low-level areas—such as outdated agricultural production concepts, insufficient infrastructure, and weak technological adoption—leading to regression in their own agricultural new-quality productive forces.

(3) The spatial Markov chain results highlight the critical role of spatial factors in the evolution of agricultural new-quality productive forces. Regional development is not isolated but is closely connected to and influenced by neighboring areas. Therefore, agricultural policy design should consider spatial linkages and synergistic effects across regions. Strengthening regional cooperation, optimizing resource allocation, and promoting factor mobility are essential to overcoming spatial constraints and fostering an environment conducive to improving agricultural new-quality productive forces. This will enable regions at different development levels to progress together, supporting agricultural transformation, upgrading, and sustainable development nationwide.

Table 6. Spatial Markov Chain Probability Matrix

Neighborhood Type	t/t+1	I	II	III	III	Observed Value
I	I	0.928685	0.071315	0	0	631
	II	0.278481	0.607595	0.113924	0	79
	III	0	0.083333	0.916667	0	12
	IV	0	0	0	1	1
II	I	0.669377	0.330623	0	0	369
	II	0.096995	0.693989	0.209016	0	732
	III	0	0.233333	0.677778	0.088889	270
	IV	0	0	0.113924	0.886076	79
III	I	0.653061	0.346939	0	0	49
	II	0.078261	0.5	0.421739	0	230
	III	0	0.056402	0.699695	0.243902	656
	IV	0	0	0.216561	0.783439	314
III	I	0.909091	0.090909	0	0	55
	II	0.15	0.55	0.3	0	20
	III	0	0.005051	0.449495	0.545455	198
	IV	0	0	0.079646	0.920354	565

7. Conclusion and Suggestions

Based on an in-depth analysis of agricultural new-quality productive forces across 284 prefecture-level cities in China from 2008 to 2023, this study provides a comprehensive understanding of development levels, regional disparities, and dynamic evolution, offering important insights for advancing China's agricultural modernization.

In terms of development levels, the national mean level of agricultural new-quality productive forces has steadily increased, driven by technological investment, industrial restructuring, and supportive policies. The levels and contribution rates of new laborers, new labor materials, and new labor objects all show synchronous growth, though with varying magnitudes. This indicates progress in improving labor quality, upgrading production tools, and diversifying agricultural production objects, while also highlighting the need for greater coordination among these dimensions.

Regarding regional disparities, the overall Gini coefficient remains relatively stable; however, significant differences persist within and between regions as well as in transvariation density. The eastern region exhibits strong internal balance, while internal disparities remain prominent in the central, western, and northeastern regions. Large gaps between the eastern region and the other regions make interregional differences the dominant source of overall disparity, underscoring the urgency of promoting coordinated regional development.

In terms of dynamic evolution, kernel density analysis reveals varied development trajectories nationwide and across regions, while traditional and spatial Markov chain results demonstrate system stability, club convergence, and spatially influenced transition patterns.

Based on these conclusions, the following policy recommendations are proposed:

(1) Strategies for coordinated regional development. Increase support for the central, western, and northeastern regions by establishing dedicated agricultural development funds focused on technological R&D, infrastructure improvement, and talent attraction to narrow regional gaps. For example, agricultural science and technology demonstration zones can be established in western China to promote advanced technologies. Encourage collaboration between developed eastern regions and other areas by forming cross-regional agricultural industrial alliances to facilitate resource sharing and knowledge exchange. For instance, eastern agricultural enterprises may partner with farmers in central and western regions to implement contract farming, thereby enhancing agricultural industrialization in these regions.

(2) Measures to promote coordinated factor development. Improve the agricultural education system by strengthening collaboration between agricultural universities and research institutions, designing interdisciplinary curricula aligned with the needs of agricultural new-quality productive forces, and cultivating talent capable of utilizing new production materials and engaging with new production objects. Increase investment in agricultural technology R&D and incentivize enterprise participation to overcome bottlenecks in upgrading production materials—such as developing affordable and easy-to-use intelligent agricultural equipment—and provide region-specific technical solutions based on local production objects.

(3) Region-specific development planning. The eastern region should consolidate its advantages by further advancing agricultural informatization and intelligent agriculture, building a hub for agricultural scientific innovation, and strengthening international cooperation to lead the development of agricultural new-quality productive forces. The central region should leverage its resource and geographical advantages, enhance the application of technological achievements, cultivate leading agricultural enterprises, and strengthen industrial clustering to accelerate productivity improvement. The western region should utilize its ecological and specialty agricultural resources to develop ecological and specialty agricultural belts—for example, promoting water-saving irrigation technologies and specialty horticulture in arid areas—while using technology to increase value-added and market competitiveness. The northeastern region should deepen supply-side structural reform, promote modernization and intelligent upgrading of agricultural machinery, stabilize grain production, extend the agricultural industrial chain, and improve overall agricultural efficiency to enhance the stability of its agricultural new-quality productive forces.

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