

Article

Spatiotemporal Transition Characteristics and Influencing Factors of New-Quality Productive Forces Development in China Based on Random Forest Model

Yuanfeng Dai ^{1,2}, Huixia Li ^{1,*}, Hongyi Zhou ¹, Hanmei Dang ³, Jiaru Luo ¹ and Fei Yang ³

¹ School of Architecture and Planning, Foshan University, Foshan 528000, China; zhouhyfs@fosu.edu.cn (H.Z.); 2122358091@stu.fosu.edu.cn (J.L.)

² School of Environment and Chemical Engineering, Foshan University, Foshan 528000, China

³ School of Economics and Trade, Foshan University, Foshan 528000, China; 2112564019@stu.fosu.edu.cn (H.D.); 2112464035@stu.fosu.edu.cn (F.Y.)

* Correspondence: lihuixia@fosu.edu.cn

Abstract

New-quality productive forces provide an important conceptual lens for understanding how innovation-driven development, digital empowerment, and the green transition jointly support sustainable regional development. From a geographical perspective, this study develops a multidimensional evaluation system for new-quality productive forces based on the three elements of productive forces: laborers, means of labor, and objects of labor. Using panel data for 31 provincial-level administrative units in China from 2012 to 2022, we integrate the entropy weight method, standard deviation ellipse, exploratory spatiotemporal data analysis, the obstacle degree model, and the random forest model to examine the spatiotemporal evolution and influencing mechanisms of new-quality productive forces. The results show that: (1) China's new-quality productive forces increased steadily during the study period, but their overall level remained relatively low and regional disparities continued to widen. Spatially, they exhibited a pronounced "high in the east and low in the west" pattern, with South China and East China maintaining leading positions and Guangdong and Jiangsu forming a dual-core growth structure. (2) The spatial center of gravity remained southeast of the Hu Huanyong Line, and its expansion direction was broadly parallel to this line, indicating a relatively stable spatial configuration. The ESTDA results further reveal significant positive spatial autocorrelation, strong temporal inertia, and marked path dependence in local spatial transitions. (3) High-tech talent supply, innovation and entrepreneurship vitality, and ecological governance capacity constitute the main internal bottlenecks constraining the development of new-quality productive forces. The analysis of external factors indicates that economic scale and population size are the primary predictors of NQPF development, whereas government intervention, openness, urbanization, and industrial structure exhibit varying degrees of nonlinearity and regional heterogeneity. These findings enrich the geographical interpretation of new-quality productive forces and provide empirical evidence for formulating differentiated regional innovation policies and productivity transformation strategies.

Keywords: new quality productive forces; space-time transition characteristics; driving mechanism; exploratory spatiotemporal data analysis; random forest; green transition China



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1. Introduction

Against the backdrop of a global reconfiguration of economic growth drivers, the rapid diffusion of digital technologies, and the accelerating transition toward green and low-carbon development, transforming regional economies from conventional factor-driven growth to innovation-led, digitally enabled, green, and efficiency-oriented development has become a central concern in regional economics and economic geography. Conventional growth trajectories have relied largely on the extensive input of land, capital, and labor. Although these models supported economic expansion at particular stages of development, they also intensified resource depletion, environmental pressure, and uneven regional development. As the new round of technological revolution and industrial transformation deepens, regional competitive advantages increasingly depend on human capital, knowledge accumulation, R&D capability, digital infrastructure, and green governance. The capacity of regions to mobilize, integrate, and transform these factors has therefore become a key determinant of their position in the coordinated transition toward digitalization and green transformation [1].

From an international theoretical perspective, regional productivity upgrading cannot be explained solely by capital accumulation or industrial-scale expansion. Rather, it is closely shaped by innovation systems, knowledge spillovers, technology diffusion, and absorptive capacity. Endogenous growth theory emphasizes the central role of technological progress and human capital accumulation in sustaining long-term economic growth [2]. Regional innovation system theory further suggests that interactions among multiple innovation actors influence knowledge creation, technology commercialization, and the spatial diffusion of innovation [3]. Absorptive capacity theory indicates that the ability of regional actors to identify, assimilate, and apply external knowledge is a key condition for converting technology diffusion into productivity gains [4]. Taken together, these perspectives suggest that regional productivity transformation emerges from the co-evolution of technological innovation, knowledge flows, industrial carrying capacity, and institutional arrangements. Two additional strands of international literature provide useful reference points for understanding regional productivity transformation. Green total factor productivity evaluates productivity performance while accounting for resource inputs and undesirable environmental outputs [5]. Economic complexity, by contrast, emphasizes the knowledge, skills, and productive capabilities embedded in increasingly diversified and sophisticated economic structures [6]. These perspectives highlight the efficiency and capability dimensions of productivity upgrading, respectively. However, neither fully captures the broader regional foundations, industrial carriers, and application conditions involved in the formation of new-quality productive forces.

The concept of “new quality productive forces” (NQPFs) provides an analytical lens for understanding regional productivity transformation under these changing conditions. Its core proposition is that scientific and technological innovation acts as the leading force in moving beyond traditional modes of economic growth and in generating an advanced form of productive forces characterized by high technology, high efficiency, and high quality [7]. In international academic terms, new-quality productive forces can be interpreted as the regional capacity for productivity transformation driven by green–digital synergy. This capacity is embodied in the agglomeration of innovation-oriented laborers, the deployment of digitalized means of labor, and the expansion of green industrial application scenarios. Through these processes, regions reorganize new production factors, reshape production modes, upgrade industrial structures, and improve operational efficiency [8]. In this sense, new-quality productive forces not only summarize China’s innovation-driven development practice but also provide a conceptual bridge to endogenous growth theory, regional innovation system theory, and absorptive capacity

theory. Accordingly, this study defines new-quality productive forces as the comprehensive regional capacity to achieve productivity upgrading through the synergistic effects of innovation-driven development, digital empowerment, and green transition. Based on this understanding, existing studies on new-quality productive forces can be grouped into the following four strands:

① **Connotation and Concept:** Scholars first conduct theoretical interpretations of new-quality productive forces based on General Secretary Xi Jinping's important expositions and the classic Marxist definition of the three factors of productivity [9]. It is widely recognized that new-quality productive forces represent an advanced form of productivity driven by technological innovation, emerging from the leapfrogging development and optimal combination of laborers, instruments of labor, and subjects of labor. Further, researchers have deeply analyzed the connotation and extension of new-quality productive forces from multiple perspectives, including spatiotemporal dimensions, scientific and technological innovation, and production structures [10]. Scholars have comprehensively defined its conceptual scope from the perspectives of formation logic [11], operational mechanism [12], and realization paths [13], concluding that new-quality productive forces are a new form of productivity led by scientific and technological innovation and realized through breakthroughs in key technologies. ② **Measurement and Spatiotemporal Evolution:** From the perspective of Chinese-style modernization, researchers have conducted unique theoretical examinations of new-quality productive forces. Pioneeringly, they have constructed an analytical framework for the influencing factors of new-quality productive forces starting from the three core elements—laborers, instruments of labor, and subjects of labor—and further explored the interactive effects between substantive factors and permeable factors. Based on this theoretical framework, an indicator evaluation system for new-quality productive forces has been established to quantitatively assess its development status [14]. In terms of spatiotemporal characteristic analysis, various econometric models have been employed to measure new-quality productive forces and analyze its spatiotemporal distribution patterns. Findings indicate that the level of new-quality productive forces has been increasing year by year, yet it remains in a low-level development stage. Significant heterogeneity exists in the performance of new-quality productive forces across different regions, provinces, and municipalities, reflecting disparities in resource allocation and other aspects [15,16]. ③ **Influencing Factors:** Current empirical analyses of influencing factors are mainly based on multiple linear regression models. It has been found that institutional factors such as data marketization and fiscal and taxation policies are key engines driving the development of new-quality productive forces [17]. Empirical studies have also verified that factors including financial agglomeration, digital economy, urban scale, and industrial structure significantly promote the growth of new-quality productive forces [18–21]. ④ **Empowering Effects on Regions and Industries:** New-quality productive forces have triggered profound transformations in sectors such as agriculture [22], tourism [23], and sports industry [24]. These play a vital role in promoting high-quality economic development [25], urban–rural integration [26], industry–education integration [27], and Chinese-style modernization [28]. Practice has proven that new-quality productive forces not only demonstrate strong driving forces across various industries but also provide a sustainable source of impetus for promoting high-quality socio-economic development [29].

A review of the existing literature shows that preliminary progress has been made in clarifying the conceptual connotation, measurement and evaluation, spatiotemporal evolution, and influencing factors of NQPFs. However, several limitations remain. First, the theoretical connotation and conceptual boundaries of NQPFs require further clarification. Existing studies have been embedded primarily in domestic policy discourse, while insufficient attention has been paid to linking NQPFs with broader international theories of

innovation, regional transformation, and productivity upgrading. Moreover, the theoretical boundaries between NQPFs and related concepts, such as high-quality development, the digital economy, and industrial upgrading, have not been fully distinguished. Second, the geographical perspective and dynamic spatial analysis remain insufficient. Existing studies provide limited explanations of the spatial evolution patterns, regional coordination mechanisms, and local spatiotemporal transition processes of NQPFs. Third, existing methods tend to be relatively static and linear. Many studies rely on static spatial analysis or conventional regression models, which are limited in their ability to capture spatiotemporal coupling, path dependence, nonlinear associations, and threshold effects.

To address these gaps and respond to the practical need for place-based development of NQPFs, this study takes 31 provincial-level administrative units in China as the research sample and constructs a multidimensional analytical framework to examine the spatiotemporal evolution and influencing mechanisms of NQPFs. First, based on the three-element theory of productive forces, namely laborers, means of labor, and objects of labor, this study constructs an evaluation system for NQPFs using the entropy weight method and further conducts robustness tests. Second, standard deviation ellipse analysis and exploratory spatiotemporal data analysis are employed to reveal the spatial migration, local spatial association, and spatiotemporal transition characteristics of provincial NQPFs in China. Third, the obstacle degree model and random forest model are used to identify internal constraints and external determinants, with particular attention to nonlinear relationships and threshold effects.

The contributions of this study are threefold. First, theoretically, this study clarifies the conceptual boundaries between NQPFs and related concepts, including high-quality development, the digital economy, and industrial upgrading, thereby strengthening the theoretical basis for interpreting regional productivity transformation. Second, empirically, this study constructs a three-dimensional evaluation system consisting of new-quality laborers, new-quality means of labor, and new-quality objects of labor, and further identifies the spatial migration, local association, and spatiotemporal transition processes of NQPFs. Third, methodologically, this study introduces a random forest model to capture the nonlinear associations between external determinants and NQPFs, and improves the reliability of the interpretation through model validation. The findings deepen the understanding of the spatial differentiation and dynamic evolution of provincial NQPFs in China, and provide empirical evidence for regional productivity transformation, innovation resource allocation, and differentiated policy formulation.

2. Research Methods and Data Sources

2.1. Research Methods

2.1.1. Conceptual Definition of New-Quality Productive Forces and Construction of the Indicator System

NQPFs refer to an advanced form of productive forces led by scientific and technological innovation. They promote transformations in production modes, industrial organization, and resource allocation through the systematic upgrading and optimized combination of laborers, means of labor, and objects of labor [14–16]. Unlike traditional productive forces, which rely mainly on the extensive input of capital, labor, and natural resources, NQPFs emphasize the transformative role of knowledge, data, technology, and green factors in reshaping the production process. Their core meaning therefore lies not merely in the improvement in individual production factors, but in the restructuring of factor composition and factor combinations within the productive-force system.

Drawing on the classical three-element theory of productive forces in Marxian political economy, this study regards NQPFs not as a concept detached from traditional productive

forces, but as a new stage of productive-force development generated by the qualitative upgrading of laborers, means of labor, and objects of labor in the context of digitalization, intelligent transformation, and green transition. Accordingly, this study constructs an evaluation system from three dimensions: new-quality laborers, new-quality means of labor, and new-type objects of labor. Specifically, new-quality laborers represent the human actors involved in knowledge creation, technology absorption, and innovation application. New-quality means of labor refer to the technological and infrastructural carriers through which innovation achievements are embedded in the production process. New-type objects of labor denote the industrial and environmental application scenarios shaped by new technologies, new industries, and green development principles [30,31]. These three dimensions correspond to the productive-force logic of “innovation actors–technological carriers–application scenarios” and jointly constitute the formation basis of regional NQPFs.

NQPFs are closely related to high-quality development, innovation capacity, the digital economy, and green development, but they differ from these concepts in analytical focus. High-quality development emphasizes the quality and outcomes of economic development, whereas NQPFs focus on the productivity foundation and driving mechanisms that support these outcomes [14]. Innovation capacity mainly concerns knowledge creation and technological R&D, while NQPFs place greater emphasis on the transformation of innovation outputs into actual productive capacity [15]. The digital economy centers on data factors and the application of digital technologies, whereas NQPFs also incorporate green transition, optimized factor allocation, and production-mode innovation [32,33]. Green development emphasizes resource conservation and ecological protection, whereas NQPFs further require the coordinated improvement in ecological benefits and production efficiency [34]. Therefore, the indicator system constructed in this study is not a simple aggregation of related concepts. Rather, it is designed to characterize the comprehensive capacity of a region to reorganize productivity factors through scientific and technological innovation and thereby generate new development momentum. This capacity encompasses both the scale foundation created by high-skilled talent, innovation infrastructure, and industrial platforms, and qualitative attributes such as factor structure, investment intensity, resource efficiency, and green development performance. To distinguish scale effects from quality-related attributes, this study further normalized aggregate indicators by population or GDP. The recalculated results were then used for robustness testing.

In selecting indicators, this study follows the principles of scientific validity, data availability, representativeness, and comparability. Drawing on existing studies on the measurement of new-quality productive forces (NQPFs), as well as related research on regional innovation, the digital economy, and green development, this study constructs an evaluation system comprising 20 indicators [14–20,30,31]. The specific dimensions and indicators are as follows:

New-quality laborers. New-quality laborers constitute the fundamental basis for the development of NQPFs. They reflect the transformation of traditional labor structures through higher levels of knowledge, advanced skills, and stronger innovation capabilities. According to endogenous growth theory and absorptive capacity theory, human capital accumulation and knowledge creation are key drivers of technological progress and sustained economic growth [2,4] while entrepreneurial activity serves as an important carrier of technology diffusion and industrial innovation [35]. Accordingly, this study measures new-quality laborers from four aspects: talent reserves, entrepreneurship support, market vitality, and output efficiency. The annual average number of high-tech employees reflects the stock of innovation-oriented labor. The number of people served by entrepreneurship services in the current year captures the supporting capacity of innova-

tion and entrepreneurship service systems. The number of newly established enterprises per 100 people reflects market vitality and the intensity of innovation and entrepreneurship. Per capita GDP represents the output efficiency generated by the coordinated operation of production factors. Considering that per capita GDP has certain outcome-oriented characteristics, this study removes this indicator and recalculates the index in the robustness test to examine whether the main conclusions remain stable.

New-quality means of labor. New-quality means of labor are the key carriers through which innovation achievements are transformed into actual productive capacity. They reflect the upgrading of production tools toward digitalization, networking, and technological advancement. Regional innovation system theory suggests that innovation actors, infrastructure, and institutional environments jointly shape knowledge production and technology diffusion [36]. Studies on knowledge spillovers further indicate that transport connectivity and information networks influence the spatial circulation of innovation factors [37]. Based on the innovation value chain, this study evaluates new-quality means of labor from six aspects: factor mobility, digital connectivity, innovation input, knowledge output, technology transformation, and industrial application. Road mileage and railway mileage reflect the basic conditions for factor mobility. The number of Internet broadband access users, the number of computers used per 100 people, and the total volume of telecommunications services characterize the level of information and communication infrastructure. R&D expenditure reflects the intensity of innovation input. The number of invention patents granted captures knowledge output capacity. Technology market turnover represents the capacity for transforming scientific and technological achievements. Software business revenue reflects the industrial application level of digital technologies. Together, these indicators correspond to the input, output, transformation, and application stages of the innovation chain. In addition, digital infrastructure can facilitate information flows, technological innovation, and more efficient resource allocation, thereby promoting green innovation and the improvement in green total factor productivity [38–40].

New-type objects of labor refer to the industrial and environmental application scenarios formed under the influence of new technologies, new industries, and green development principles. They reflect the extension of production activities toward high-tech industries and green development fields. NQPFs depend not only on scientific and technological innovation and the upgrading of production tools, but also on industrial structural transformation and the shift toward greener development modes [31]. This study measures new-type objects of labor from six aspects: industrial carriers, policy support, pollution constraints, resource recycling, environmental governance, and ecological foundations. The number of high-tech enterprises reflects the carrier capacity of high-tech industries. The share of energy conservation and environmental protection expenditure in general public budget expenditure captures policy support for green transformation. Chemical oxygen demand emissions per unit of GDP and sulfur dioxide emissions per unit of GDP characterize pollution intensity. The comprehensive utilization of general industrial solid waste reflects resource recycling capacity. The number of industrial wastewater treatment facilities per unit land area captures environmental governance capacity. Forest coverage reflects the ecological foundation for green development. Research on environmental regulation and green innovation suggests that appropriate environmental governance can enhance productivity through the innovation compensation effect [34]. These indicators therefore capture the green attributes and industrial application scenarios of NQPFs.

This study adopts the entropy weight method to construct the comprehensive evaluation index of NQPFs. First, the subindices of new-quality laborers, new-quality means of labor, and new-type objects of labor are calculated separately. The same method is then used to determine the weights of the three dimensions (Table 1). Finally, after data

standardization and weighted summation, the comprehensive NQPF index is obtained. The entropy weight method is a widely used non-parametric multi-criteria decision-making method. It determines objective weights by measuring the information entropy of indicator data, thereby reducing the influence of subjective judgment. The calculation formulas are provided in previous studies [41,42].

Table 1. Evaluation indicator system of new-quality productivity forces.

First-Level Indicator (Weight/%)	Second-Level Indicator	Third-Level Indicator	Indicator Code	Weight/%	Attribute
Laborers (47.52)	Economic contribution of laborers	Per capita GDP (yuan)	A ₁	6.53	+
	Quality structure of laborers	Average annual number of high—tech employees (persons)	A ₂	25.00	+
	Innovation and entrepreneurship vitality	Number of entrepreneurship service personnel in the current year (persons)	A ₃	15.42	+
		Number of newly—established enterprises per hundred people	A ₄	0.57	+
Instruments of Labor (34.05)	Transportation and Logistics Facilities	Highway mileage (kilometers)	B ₁	1.23	+
		Railway mileage (km)	B ₂	1.55	+
	Information and communication facilities	Internet broadband access users (10,000 households)	B ₃	1.91	+
		Number of computers in use per 100 people (units)	B ₄	1.14	+
		Total volume of telecommunications business (10,000 yuan)	B ₅	4.38	+
		Software business revenue (100 million yuan)	B ₆	5.74	+
	Technology capital and application	Turnover in the technology market	B ₇	5.68	+
		Number of invention patents granted	B ₈	4.47	+
		R&D expenditure	B ₉	7.95	+
Subjects of Labor (18.43)	Industrial structure and energy level	Number of high—tech enterprises (units)	C ₁	4.61	+
		Expenditure on energy conservation and environmental protection/General public budget expenditure	C ₂	0.83	+
	Resource efficiency and emissions	Total chemical oxygen demand emissions/GDP (tons/10,000 yuan)	C ₃	0.05	—
		Total sulfur dioxide emissions/GDP (tons/10,000 yuan)	C ₄	0.12	—

Table 1. Cont.

First-Level Indicator (Weight/%)	Second-Level Indicator	Third-Level Indicator	Indicator Code	Weight/%	Attribute
Subjects of Labor (18.43)	Resource efficiency and emissions	Comprehensive utilization volume of general industrial solid waste (10,000 tons)	C ₅	1.77	+
	Ecological Foundation and Governance	Number of industrial waste water treatment facilities/Land area (sets/10,000 square kilometers)	C ₆	9.88	+
		Forest coverage rate (%)	C ₇	1.18	+

Note: “+” indicates a positive effect, whereas “−” indicates a negative effect.

2.1.2. Methods for Spatiotemporal Distribution Analysis

The standard deviational ellipse (SDE) was used to characterize the spatial distribution and directional evolution of new-quality productive forces (NQPFs). By estimating the mean center, major axis, minor axis, and rotation angle of the ellipse, the SDE can reveal the central tendency, dispersion range, and dominant orientation of spatial elements [43,44]. In this study, the geometric centroid of each provincial-level administrative unit was used as the spatial coordinate point. Provincial boundary data were obtained from the Standard Map Service System of the Ministry of Natural Resources, and the centroid coordinates of each province were extracted using ArcGIS Desktop 10.7. The weight (w_i) was defined as the NQPF index of province (i) in a given year. This setting allows the SDE to reflect the contribution of each province’s NQPF development level to the spatial mean center and directional expansion pattern. Therefore, the SDE results represent the weighted spatial mean center, directional orientation, and spatial dispersion of provincial NQPFs, rather than the geometric distribution of provincial administrative units alone. This weighted approach provides a more accurate characterization of the spatial evolution of NQPFs across China’s provinces. The calculation formulas are as follows:

$$\text{Centroid coordinates : } \bar{X}_W = \frac{\sum_{i=1}^n w_i x_i}{\sum_{i=1}^n w_i}, \quad \bar{Y}_W = \frac{\sum_{i=1}^n w_i y_i}{\sum_{i=1}^n w_i} \quad (1)$$

$$\text{Azimuth : } \tan \theta = \frac{(\sum_{i=1}^n w_i^2 \hat{x}_i^2 - \sum_{i=1}^n w_i^2 \hat{y}_i^2) + \sqrt{(\sum_{i=1}^n w_i^2 \hat{x}_i^2 - \sum_{i=1}^n w_i^2 \hat{y}_i^2)^2 + 4 \sum_{i=1}^n w_i^2 \hat{x}_i^2 \hat{y}_i^2}}{2 \sum_{i=1}^n w_i^2 \hat{x}_i \hat{y}_i} \quad (2)$$

$$\text{Standard deviation of the } x\text{-axis : } \sigma_x = \sqrt{\frac{\sum_{i=1}^n (w_i \hat{x}_i \cos \theta - w_i \hat{y}_i \sin \theta)^2}{\sum_{i=1}^n w_i^2}} \quad (3)$$

$$\text{Standard deviation of the } y\text{-axis : } \sigma_y = \sqrt{\frac{\sum_{i=1}^n (w_i \hat{x}_i \sin \theta - w_i \hat{y}_i \cos \theta)^2}{\sum_{i=1}^n w_i^2}} \quad (4)$$

In Equations (1)–(4), (x_i, y_i) denotes the spatial coordinate; w_i denotes the spatial weight; $(\bar{X}_w, \bar{Y}_w)$ denotes the weighted mean center of each observation variable; θ is the azimuth of the standard deviational ellipse; and $\hat{x}_i$ and $\hat{y}_i$ represent the coordinate deviations of each observation variable from the weighted mean center, respectively.

2.1.3. Methods for Spatiotemporal Correlation Analysis

This study employed exploratory spatiotemporal data analysis (ESTDA) to examine the spatiotemporal association characteristics of new-quality productive forces (NQPFs) in China. ESTDA extends traditional exploratory spatial data analysis (ESDA) by incorporat-

ing the temporal dimension, thereby overcoming the static limitations of conventional spatial association analysis. It characterizes the spatiotemporal interaction patterns of attribute values across spatial units and is mainly implemented through LISA time-path analysis and LISA space-time transition analysis. In this study, a first-order Queen contiguity matrix was used as the baseline spatial weight matrix. Two provincial-level administrative units were defined as spatially adjacent and assigned a value of 1 if they shared either a common boundary or a common vertex; otherwise, the value was set to 0. To reduce the influence of differences in the number of neighboring provinces on the spatial lag term, the spatial weight matrix was row-standardized. The Queen contiguity matrix was selected because this study focuses on local spatial associations and spatiotemporal transitions of NQPFs among geographically adjacent provincial units. This matrix can effectively capture direct proximity relationships between provinces. The significance of global Moran's I and local spatial associations was tested using 999 random permutations, with the significance level set at 5%.

LISA time path: The LISA time path reflects the temporal stability and dynamic evolution of local spatial association patterns by tracing the movement of each spatial unit's coordinates in the Moran scatter plot over time [45]. In this study, the relative length, trajectory tortuosity, and migration direction of the LISA time path were calculated to characterize the evolution intensity of the spatial structure, the dynamic stability of spatial dependence, and the direction of coordinated spatial movement of NQPFs, respectively. This method provides a quantitative tool for identifying the spatiotemporal association patterns and local evolutionary trajectories of NQPFs across China's provinces. The relevant calculation formulas are as follows:

$$\text{Relative Length: } l_i = \frac{N \times \sum_{t=1}^{T-1} d(L_{i,t}, L_{i,t+1})}{\sum_{j=1}^N \sum_{t=1}^{T-1} d(L_{j,t}, L_{j,t+1})} \quad (5)$$

$$\text{Tortuosity: } \varphi_i = \frac{\sum_{t=1}^{T-1} d(L_{i,t}, L_{i,t+1})}{d(L_{i,1}, L_{i,T})} \quad (6)$$

In Equations (5) and (6), $N = 31$; T is the time length; $L_{i,t}$ denotes the coordinate location of province i in year t ; and $d(L_{j,t}, L_{j,t+1})$ represents the movement distance of province j from year t to year $t + 1$. Referring to relevant studies [46,47], based on the average movement level of LISA coordinate points, the movement directions of each provincial unit are classified into four categories: positive synergy type ($0-90^\circ$); negative-positive type ($90-180^\circ$); negative synergy type ($180-270^\circ$); positive-negative type ($270-360^\circ$).

LISA Spatiotemporal Transition. Rey et al. [48] incorporated the dynamic properties of the LISA time path into the classic Markov chain, constructed the spatiotemporal transition probability matrix and spatiotemporal transition theory, and divided four types of transitions (Table 2). This can further quantify the evolutionary patterns of spatial correlation of the LISA index of new-quality productive forces among different types.

Table 2. Types of spatiotemporal transition.

Type	Specific Type	Specific Characteristics
Type I	$LH_t \rightarrow LH_{t+1}, HL_t \rightarrow HL_{t+1}, HH_t \rightarrow HH_{t+1}, LL_t \rightarrow LL_{t+1}$	Both itself and its neighborhood are stable
Type II	$LH_t \rightarrow HH_{t+1}, HL_t \rightarrow LL_{t+1}, HH_t \rightarrow LH_{t+1}, LL_t \rightarrow HL_{t+1}$	Itself undergoes transition while its neighborhood remains stable
Type III	$LH_t \rightarrow LL_{t+1}, HL_t \rightarrow HH_{t+1}, HH_t \rightarrow HL_{t+1}, LL_t \rightarrow LH_{t+1}$	Itself is stable while its neighborhood undergoes transition
Type IV	$HL_t \rightarrow LH_{t+1}, LH_t \rightarrow HL_{t+1}, LL_t \rightarrow HH_{t+1}, HH_t \rightarrow LL_{t+1}$	Both itself and its neighborhood undergo transition

2.1.4. Analysis Method of Influencing Factors

Clarifying the key internal constraints, external determinants, and dynamic evolution mechanisms of new-quality productive forces (NQPFs) is essential for formulating place-based optimization strategies and improving the spatial allocation of NQPFs across regions.

The obstacle degree model was used to diagnose and rank the core internal factors restricting the development of NQPFs. By quantifying the contribution and constraint intensity of each indicator, this model can identify the dominant obstacle factors within a complex system and clarify their relative restrictive effects on system development [49]. The specific calculation formulas are as follows [50]:

$$T_{ij} = 1 - y_{ij} \quad (7)$$

$$O_{ij} = \frac{T_{ij}W_i}{\sum_{k=1}^n T_{ik}W_k} \times 100\% \quad (8)$$

In Equations (7) and (8), T_{ij} is the deviation degree; W_i is the contribution degree; y_{ij} is the standardized value; and O_{ij} is the obstacle degree of the influencing factor.

In addition, machine learning methods are increasingly used in sustainability research to identify nonlinear relationships, complex interactions, and heterogeneous responses in multidimensional systems [51]. In this study, random forest is used as an interpretable tool for identifying nonlinear associations rather than for establishing causal effects. The random forest model was employed to identify nonlinear associations between external factors and NQPFs. While the preceding spatial analyses focused on spatial dependence and spatiotemporal evolutionary structures, the random forest model was used to characterize nonlinear response relationships between external determinants and the NQPF index. These approaches are therefore complementary. Random forest is a non-parametric machine learning algorithm based on ensemble learning. By integrating multiple weak learners, it improves predictive stability and generalization performance for unseen data, and has the advantages of high accuracy, strong robustness, and broad applicability [52,53]. It has been widely applied in geography, ecology, environmental science, and related fields [54]. Following previous studies [19–21], this study used the NQPF index as the response variable. Six external factors were selected as predictors: urbanization rate (X1), openness level (X2), degree of government intervention (X3), total economic output (X4), population size (X5), and industrial structure (X6). The sample consisted of 341 observations from 31 provincial-level administrative units in China during 2012–2022. Province and year were used only for grouping and cross-validation and were not included as predictors in the model. The number of trees was set to 1500, with ($mtry = 2$), while ($nodesize$) was kept at the default value of the randomForest package (version 4.7.1.2).

Model performance was evaluated using out-of-bag validation and leave-one-province-out cross-validation (LOPO-CV). In each LOPO-CV iteration, all annual observations for one province were assigned to the test set, while observations from the remaining provinces were used for model training, thereby reducing potential information leakage associated with province-specific dependence. Predictive performance was assessed using the root mean squared error (RMSE), mean absolute error (MAE), squared Pearson's correlation between observed and predicted values (R^2_{cor}), and the Nash–Sutcliffe efficiency-based coefficient of determination (R^2_{NSE}). Variable importance was measured using permutation importance, expressed as the percentage increase in mean squared error (%IncMSE), and its statistical significance was assessed using 999 permutation tests implemented in the rfPermute package (version 2.5.4). To quantify uncertainty in the importance estimates, 95% confidence intervals were calculated from 200 bootstrap resamples. Partial dependence plots were used to characterize the marginal nonlinear associations between each predictor and the NQPF index, with uncertainty bands estimated from 100 bootstrap resamples.

To further evaluate the robustness, residual spatial structure, temporal associations, and interpretability of the random forest results, five supplementary analyses were conducted. First, annual Moran's I statistics were calculated for the LOPO-CV prediction residuals using the same row-standardized Queen-contiguity matrix adopted in the preceding spatial analyses and 999 random permutations. Second, TreeSHAP was employed to characterize the direction, magnitude, and observation-level heterogeneity of each predictor's contribution to the model predictions. Their nonlinear transition points were then identified by fitting two-segment piecewise linear models to 100 bootstrap partial dependence curves, and the median transition point and corresponding 95% bootstrap interval were reported. Third, XGBoost and support vector regression were introduced as alternative machine learning algorithms using the same predictors and LOPO-CV framework. Fourth, two-way fixed-effect spatial autoregressive and spatial error models were estimated using the same spatial-weight matrix to account for spatial dependence and unobserved province- and year-specific heterogeneity. Fifth, all explanatory variables were lagged by one year, and the random forest model was re-estimated using 310 observations for 2013–2022 to examine potential delayed associations. These supplementary analyses were intended to assess predictive robustness, residual spatial dependence, temporal ordering, and model interpretability, rather than to establish strict causal relationships.

The relevant formulas are presented below.

$$\hat{y}_i = \frac{1}{B} \sum_{b=1}^B T_b(x_i) \quad (9)$$

where B is the number of regression trees, which was set to 1500 in this study; T denotes the prediction generated by the (b)-th regression tree; and x is the feature vector composed of the six external influencing factors. The final random forest prediction is obtained by averaging the predictions of all regression trees.

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2} \quad (10)$$

$$MAE = \frac{1}{n} \sum_{i=1}^n |y_i - \hat{y}_i| \quad (11)$$

$$R^2_{cor} = \left[\frac{\sum_{i=1}^n (y_i - \bar{y})(\hat{y}_i - \bar{\hat{y}})}{\sqrt{\sum_{i=1}^n (y_i - \bar{y})^2} \sqrt{\sum_{i=1}^n (\hat{y}_i - \bar{\hat{y}})^2}} \right]^2 \quad (12)$$

$$R^2_{NSE} = 1 - \frac{\sum_{i=1}^n (y_i - \hat{y}_i)^2}{\sum_{i=1}^n (y_i - \bar{y})^2} \quad (13)$$

Here, n is the number of validation observations; y is the observed NQPF value; $\hat{y}$ is the corresponding predicted value; $RMSE$ is more sensitive to large prediction errors, whereas MAE represents the average absolute magnitude of prediction errors. Lower $RMSE$ and MAE values indicate greater predictive accuracy.

R^2_{cor} metric primarily measures the consistency between variations in the observed and predicted values. A value closer to 1 indicates stronger linear agreement. However, this metric is relatively insensitive to systematic overprediction or underprediction. By contrast, R^2_{NSE} accounts for both prediction errors and systematic deviations.

To improve the interpretability of the random forest model, this study employed the SHapley Additive exPlanations (SHAP) method. SHAP decomposes the prediction for each observation into a baseline prediction and the marginal contributions of individual

explanatory variables. Derived from the Shapley value in cooperative game theory, SHAP considers the marginal contribution of each variable across different feature combinations. It can therefore identify variable importance, effect direction, and heterogeneity across observations.

For the (j)-th explanatory variable, its SHAP value for observation is calculated as follows:

$$\phi_j(f, x) = \sum_{S \subseteq N_j} \frac{|S|!(M-|S|-1)!}{M!} [f_x(S \cup j) - f_x(S)] \quad (14)$$

where $\phi_j(f, x)$ is the SHAP value of the (j)-th variable for observation x ; N is the set of all explanatory variables; M is the total number of variables; S is a subset of variables that does not contain variable j ; and $|S|$ is the number of variables in subset S . The terms $f_x(S)$ and $f_x(S \cup j) - f_x(S)$ denote the expected model predictions based on subset S and on subset S after variable j is added, respectively. Their difference represents the marginal contribution of variable j .

SHAP satisfies the additive explanation property. Thus, the prediction for an individual observation can be decomposed as follows:

$$f(x_i) = \phi_0 + \sum_{j=1}^M \phi_{ij} \quad (15)$$

The global importance of each variable was further measured using its mean absolute SHAP value:

$$I_j = \frac{1}{n} \sum_{i=1}^n |\phi_{ij}| \quad (16)$$

where I_j denotes the global importance of the j -th variable. A larger I_j indicates a stronger overall contribution to the model predictions. Compared with conventional variable-importance measures, SHAP not only ranks the explanatory variables but also reveals their effect directions, nonlinear relationships, and potential threshold ranges. It therefore provides a more comprehensive interpretation of the factors influencing NQPF development.

2.2. Data Sources

Constrained by data availability, this study selected data from 2012 to 2022 to measure the level of new-quality productive forces in 31 provincial-level administrative units in China, excluding Hong Kong, Macao, and Taiwan. The data were obtained from the official website of the National Bureau of Statistics of China, the *China Statistical Yearbook*, the *China Environmental Statistics Yearbook*, the *China Industrial Statistical Yearbook*, the *China Population and Employment Statistics Yearbook*, and provincial statistical yearbooks and statistical bulletins. Missing values were supplemented using linear interpolation. Missing values accounted for 1.60% of all indicator observations and were mainly scattered across the annual series of a small number of provinces. Linear interpolation was used in the baseline analysis, while multiple imputation was applied as a robustness check. All indicators were normalized using global min–max scaling based on the complete set of observations for the 31 provincial-level administrative units from 2012 to 2022. Indicators related to monetary values or regional scale were further tested using alternative specifications expressed in constant prices, per capita terms, or per unit of GDP.

3. Results

3.1. Data Preprocessing and Robustness Checks of the Composite NQPF Index

To assess whether data preprocessing and index construction affected the composite NQPF index, a series of robustness tests were conducted. These tests considered price ad-

justments, scale heterogeneity, missing-value treatment, normalization methods, weighting schemes, and indicator overlap.

First, all monetary indicators were converted to constant prices, and the index was recalculated using the baseline global normalization and hierarchical entropy-weighting procedures. The resulting index was highly consistent with the baseline index, with a Pearson's correlation of 0.9982, a Spearman correlation of 0.9973, and a normalized RMSE of 1.42%. Replacing linear interpolation with multiple imputation also produced closely comparable results. These findings indicate that neither price adjustment nor missing-value treatment materially affected the index.

Aggregate indicators were then converted into per capita or GDP-normalized measures according to their substantive meanings. The scale-adjusted index remained strongly correlated with the baseline index, with Pearson's $r = 0.8907$, Spearman's $\rho = 0.8613$, and a normalized RMSE of 9.69%. Although the scores and rankings of some provinces changed, the overall temporal pattern and interprovincial ordering remained broadly consistent. This suggests that population and economic size do not solely determine the index. However, the actual scale of high-skilled labor, innovation infrastructure, and industrial carriers remains an important component of regional NQPF capacity.

Second, the index was recalculated using winsorized, rank-based, and year-specific normalization, as well as equal weighting, CRITIC weighting, single-level entropy weighting, and the exclusion of A1 (per capita GDP). All alternative specifications remained highly consistent with the baseline index (Supplementary Figures S1 and S2; Table S1). The winsorized specification showed the strongest agreement, with Pearson's $r = 0.991$ and Spearman's $\rho = 0.995$. After excluding A1, the corresponding coefficients remained 0.985 and 0.981, respectively. Even under CRITIC weighting, which produced the largest deviation, Spearman's ρ remained 0.892.

Finally, indicator redundancy was examined using within-dimension correlations, variance inflation factors, and leave-one-indicator-out tests. Correlations were generally weak in dimensions A and C, while stronger associations were observed among B6, B7, and B8. These indicators nevertheless represent different stages of the innovation chain. In addition, all first-level VIF values were below 5, and deleting individual indicators caused only limited changes in provincial rankings (Supplementary Figures S3–S5).

Overall, the results confirm that the composite NQPF index is robust to alternative preprocessing and construction choices. Because scale adjustment altered the scores and rankings of some provinces, the index should be interpreted as a measure of comprehensive regional NQPF capacity. It reflects scale foundations, structural characteristics, and quality- and efficiency-related attributes, rather than quality and efficiency alone.

3.2. Spatiotemporal Characteristics of the Evolution of New-Quality Productive Forces

3.2.1. Evolution Characteristics of the Spatiotemporal Pattern of New-Quality Productive Forces Development

Temporal evolution (Table 3 and Figure 1): ① At the national level, China's new-quality productive force (NQPF) index increased from 0.109 in 2012 to 0.227 in 2022, with an average value of 0.164. The index showed steady growth throughout the study period, but its overall level remained relatively low, suggesting that the potential for productivity transformation and upgrading in China has not yet been fully released. This pattern may be associated with two aspects. On the one hand, China has made continuous progress in scientific and technological innovation, and the growing output of innovation activities has provided important support for the development of NQPFs. On the other hand, the transformation of scientific and technological achievements into actual productive capacity remains constrained by the path dependence of traditional industrial structures and factor allocation patterns. In addition, the scale effects of the domestic market have not been

fully realized, and new forms of production relations have not yet fully adapted to the development requirements of NQPFs [55]. ② At the regional level, the NQPF index showed a steady upward trend across all regions. South China recorded the highest average value (0.259), followed by East China (0.251) and Central China (0.199). The average values of the remaining regions were all below the national average, with Northwest China recording the lowest value, at only 0.071. Moreover, the interregional range gradually widened from 0.152 in 2012 to 0.267 in 2022, indicating an intensification of regional imbalance in the development of NQPFs. This widening divergence may reflect the stronger agglomeration and siphon effects of developed regions, such as South China, relative to their diffusion effects on less-developed regions, such as Northwest China. ③ At the provincial level, Guangdong Province had the highest average NQPF value (0.629), followed by Jiangsu Province (0.540), Shandong Province (0.287), and Beijing Municipality (0.280). The lowest average values were observed in Xizang (0.035), Ningxia (0.035), and Qinghai (0.045). Overall, the NQPF index increased in all provinces during the study period. Beijing recorded the largest increase, at 0.352, followed by Guangdong (0.341) and Jiangsu (0.330). By contrast, Jilin and Liaoning showed the smallest increases, at 0.014 and 0.023, respectively. The provincial range of the NQPF index expanded from 0.472 in 2012 to 0.778 in 2022. This suggests that innovation-driven momentum has not been evenly diffused across provinces. Instead, it has been further concentrated in leading provinces such as Guangdong, thereby contributing to widening provincial disparities in the development of NQPFs.

Table 3. Development level index of new-quality productivity forces in China (2012–2022).

Region	Province	2012	2014	2016	2018	2020	2022	Average
East China	Shanghai	0.202	0.167	0.185	0.211	0.245	0.306	0.213
	Jiangsu Province	0.409	0.575	0.485	0.543	0.610	0.739	0.540
	Zhejiang Province	0.156	0.180	0.252	0.373	0.354	0.392	0.275
	Anhui Province	0.085	0.097	0.121	0.153	0.195	0.246	0.151
	Fujian Province	0.101	0.125	0.126	0.162	0.170	0.195	0.145
	Jiangxi Province	0.080	0.168	0.113	0.138	0.178	0.207	0.148
	Shandong Province	0.205	0.239	0.267	0.281	0.309	0.468	0.287
	Average	0.177	0.222	0.221	0.266	0.294	0.365	0.251
South China	Guangdong Province	0.475	0.572	0.565	0.635	0.726	0.816	0.629
	Guangxi	0.071	0.063	0.077	0.134	0.146	0.130	0.099
	Hainan Province	0.031	0.033	0.044	0.059	0.054	0.071	0.048
	Average	0.192	0.223	0.229	0.276	0.309	0.339	0.259
North China	Beijing	0.156	0.188	0.227	0.284	0.349	0.508	0.280
	Tianjin	0.069	0.088	0.092	0.103	0.117	0.145	0.108
	Shanxi Province	0.067	0.076	0.087	0.095	0.178	0.119	0.100
	Hebei Province	0.090	0.102	0.128	0.153	0.232	0.177	0.159
	Inner Mongolia	0.075	0.094	0.101	0.112	0.109	0.143	0.104
	Average	0.091	0.110	0.127	0.149	0.197	0.218	0.150
Central China	Henan Province	0.127	0.310	0.196	0.190	0.231	0.263	0.205
	Hubei Province	0.107	0.125	0.160	0.181	0.213	0.274	0.180
	Hunan Province	0.106	0.214	0.223	0.255	0.201	0.268	0.212
	Average	0.113	0.216	0.193	0.208	0.215	0.268	0.199

Table 3. Cont.

Region	Province	2012	2014	2016	2018	2020	2022	Average
Southwest China	Sichuan Province	0.124	0.137	0.185	0.208	0.251	0.276	0.195
	Guizhou Province	0.033	0.052	0.169	0.089	0.117	0.128	0.090
	Yunnan Province	0.062	0.064	0.082	0.097	0.129	0.134	0.094
	Chongqing	0.081	0.079	0.103	0.121	0.128	0.145	0.113
	Tibet	0.003	0.013	0.018	0.041	0.028	0.038	0.035
	Average	0.061	0.069	0.111	0.111	0.131	0.144	0.105
Northwest China	Shaanxi Province	0.084	0.106	0.129	0.141	0.183	0.193	0.151
	Gansu Province	0.025	0.033	0.051	0.055	0.075	0.076	0.053
	Qinghai Province	0.020	0.044	0.043	0.046	0.051	0.064	0.045
	Ningxia	0.015	0.023	0.027	0.043	0.043	0.067	0.035
	Xinjiang	0.053	0.044	0.056	0.068	0.114	0.090	0.070
	Average	0.040	0.050	0.062	0.071	0.093	0.098	0.071
North east China	Heilongjiang Province	0.064	0.197	0.078	0.085	0.101	0.111	0.096
	Jilin Province	0.068	0.078	0.078	0.082	0.083	0.082	0.079
	Liaoning Province	0.128	0.129	0.130	0.139	0.159	0.151	0.143
	Average	0.087	0.135	0.095	0.102	0.114	0.115	0.106
National Average		0.109	0.142	0.148	0.170	0.196	0.227	0.164

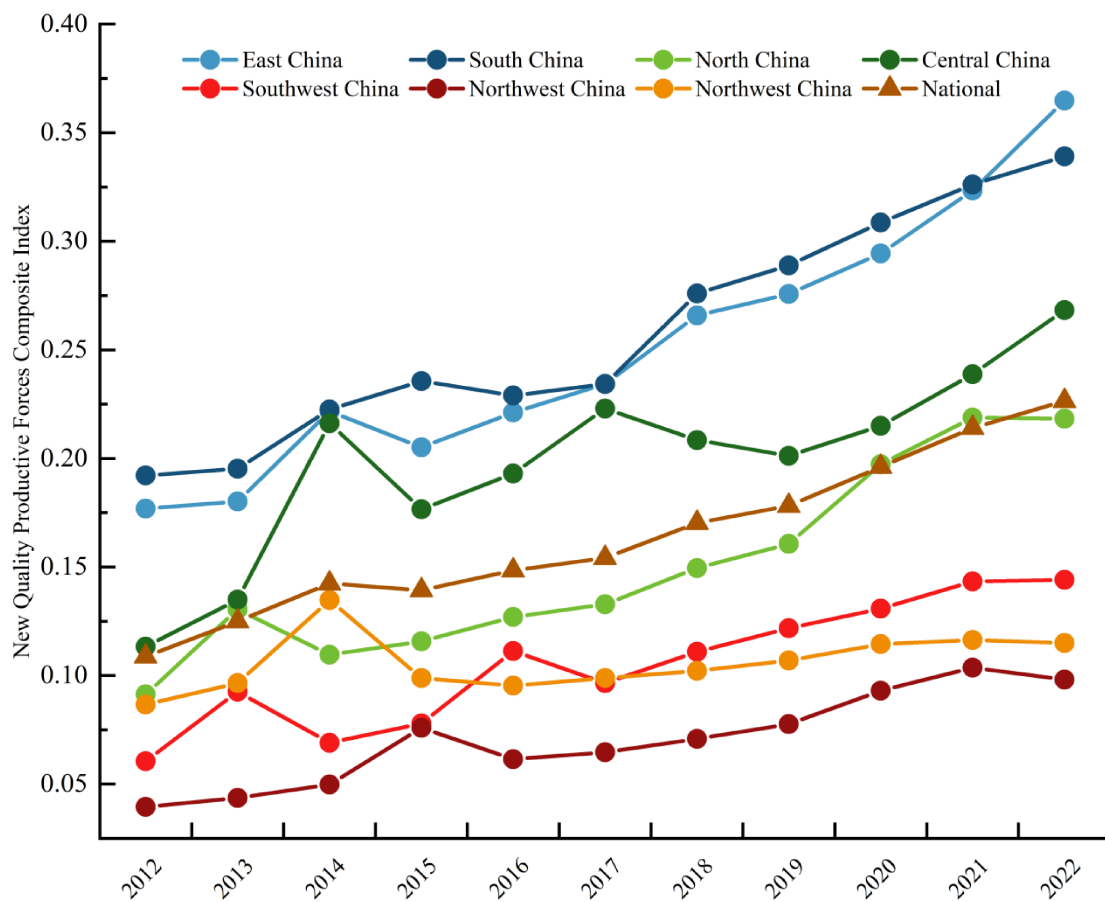


Figure 1. Trend chart of new-quality productivity forces development level in China (2012–2022).

Spatial patterns and evolution: ① In terms of spatial distribution (Figure 2), NQPFs exhibited a clear “high in the east and low in the west” pattern, with coastal provinces showing substantially higher levels than inland provinces. Overall, the spatial pattern indicated a gradual expansion from coastal regions toward inland areas. In 2012, only Guangdong and Jiangsu reached the medium level, while Shandong and Shanghai were classified as relatively low; all other provinces remained at the low level. This indicates that the development of NQPFs was still dispersed and concentrated mainly in coastal areas. By 2017, the number of coastal provinces at the relatively low level had increased, while Beijing, Zhejiang, and Hunan had also entered the relatively low category, suggesting an initial coastal-to-inland expansion. By 2022, this trend had become more pronounced. The NQPF levels of coastal provinces improved markedly: Guangdong reached the high level, Jiangsu reached the relatively high level, and Beijing and Shandong reached the medium level. In addition, several inland provinces, including Sichuan, Hubei, Jiangxi, Anhui, and Henan, gradually entered the relatively low level.

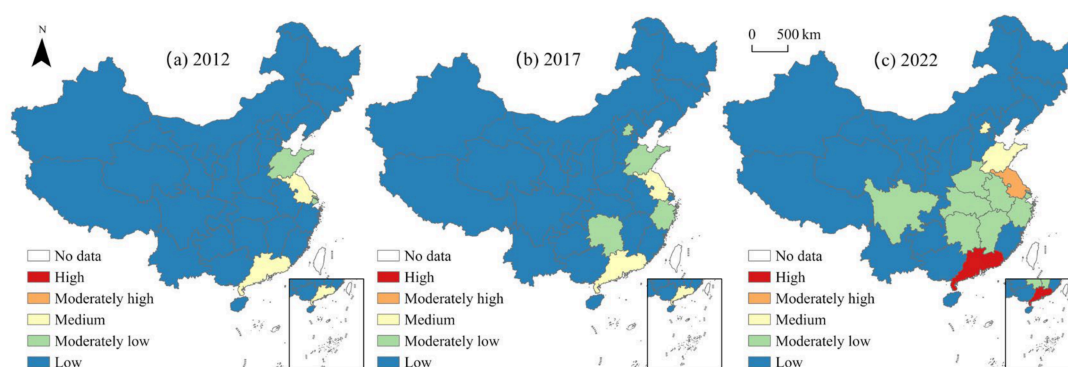


Figure 2. Spatial distribution pattern of new-quality productivity forces development level in China (2012–2022). Note: This map is created based on the standard map from the Standard Map Service of the Ministry of Natural Resources (No. GS (2024)0650), with no modifications to the base map boundaries.

② In terms of spatial evolution, the centroid movement trajectory (Figure 3) shows that the centroid of NQPFs was consistently located east of the Hu Huanyong Line during the study period, mainly near Xinyang City, Henan Province. The centroid showed alternating east–west movements, with fluctuating movement distances. This pattern further confirms that the spatial expansion of NQPFs was not a simple linear diffusion process, but a dynamic adjustment process extending from the eastern coastal areas toward the central and western inland regions. This spatial evolution may be partly explained by three mechanisms. First, geographical endowments and historical accumulation have generated strong path dependence. Eastern coastal regions have long benefited from favorable location conditions, early industrialization, stronger innovation foundations, and more developed market systems. Through circular cumulative causation, these advantages have been continuously reinforced. By contrast, the relative disadvantages of western regions in attracting innovation-oriented development factors are difficult to reverse in the short term. The resulting core–periphery structure has further consolidated regional disparities in NQPFs. Second, factor flows show clear spatial polarization. Key factors supporting NQPFs, including high-quality human capital, R&D resources, digital infrastructure, and innovation platforms, remain highly concentrated in eastern coastal regions. This concentration further activates regional innovation ecosystems in leading areas. Given the systemic and threshold effects of these driving factors, it is difficult for many western provinces to simultaneously reach the critical conditions required for leapfrog development. Third, institutional arrangements remain uneven across space. Excessive government intervention

may constrain market vitality, while inflexible policy environments may weaken the ability of lagging regions to attract key innovation factors. In addition, local protectionism and administrative barriers may hinder the cross-regional restructuring and efficient allocation of development factors.

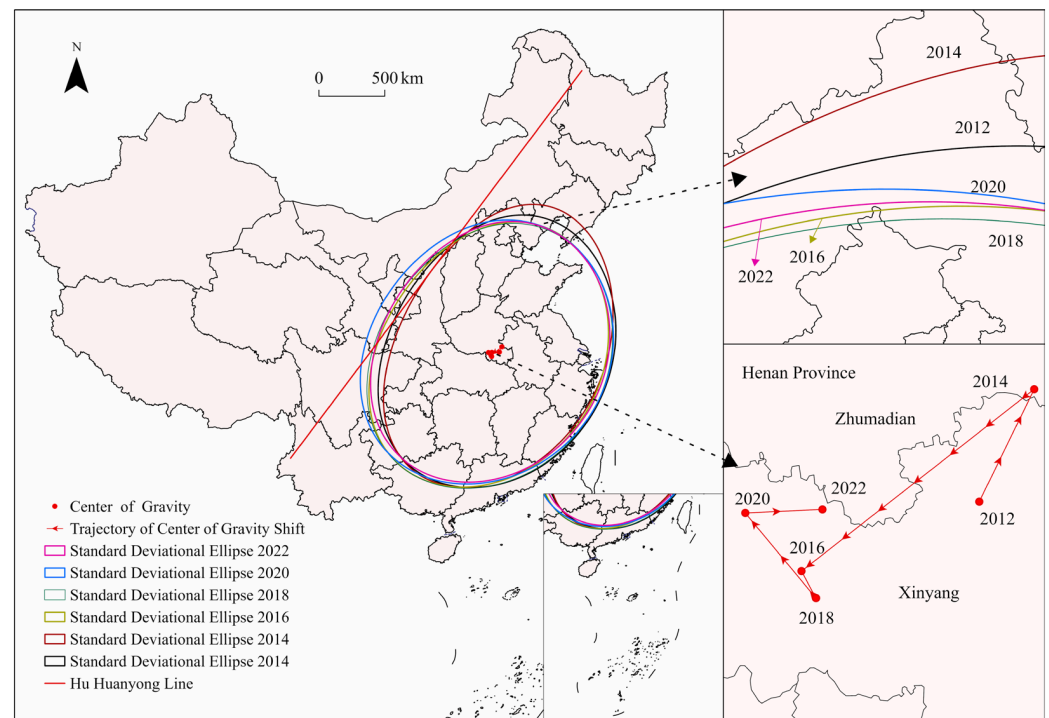


Figure 3. Standard deviation ellipse distribution and center of gravity shift trajectory of new-quality productivity forces. Note: This map is created based on the standard map from the Standard Map Service of the Ministry of Natural Resources (No. GS (2024)0650), with no modifications to the base map boundaries.

The directional characteristics of the spatial distribution further show that the rotation angle exhibited an overall fluctuating upward trend during the study period, increasing from 53.27° in 2012 to 59.91° in 2022. This indicates that the spatial expansion of new-quality productive forces (NQPFs) was mainly oriented along the southeast–northwest direction, broadly parallel to the Hu Huanyong Line, and that this directional tendency gradually strengthened over time. Meanwhile, the difference between the lengths of the major and minor axes declined slightly, suggesting a gradual increase in the spatial centripetal tendency of NQPFs. This pattern indicates that the spatial structure of NQPFs has gradually shifted from an initial pattern of scattered coastal distribution toward a zonal clustering pattern.

However, this structural adjustment has not reversed regional imbalance. Instead, polarization has become more evident in some areas, further confirming the uneven development of NQPFs and the complex spatial associations among provinces. Eastern coastal areas, as major gateways of globalization, possess more mature supporting systems and have long acted as leading regions in innovation-driven development. Policy dividends, including national independent innovation demonstration zones, have also been concentrated in regions such as the Yangtze River Delta and the Pearl River Delta, reinforcing the scattered coastal distribution of NQPFs in the early stage. With the implementation of national strategies such as the Yangtze River Economic Belt, the Rise of Central China, and the Western Development Strategy, innovation factors and other key resources have gradually been guided toward central and western inland regions. Consequently, provinces

such as Hunan and Sichuan have shown accelerated development of NQPFs, contributing to the emergence of a zonal clustering pattern.

3.2.2. Spatiotemporal Correlation Characteristics of New-Quality Productive Forces Development

(1) LISA Time Path Analysis

To identify the spatial agglomeration characteristics of provincial new-quality productive forces (NQPFs) in China from 2012 to 2022, this study first calculated Global Moran's I using GeoDa 1.22.0.4. The results passed the significance test, indicating that provincial NQPFs exhibited significant positive spatial autocorrelation. The LISA time-path method was then used to characterize the dynamic evolution of local spatial associations by calculating the relative length, tortuosity, and migration direction of each provincial trajectory. These indicators were classified into four categories—low, relatively low, relatively high, and high—using the natural breaks method.

Overall, the relative length of the LISA time path displayed a spatial pattern of higher values in the east and lower values in the west (Figure 4a). This indicates that the local spatial association structure of NQPFs changed more markedly in eastern China, whereas the spatial dependence structure in western China remained relatively stable. From 2012 to 2022, the relative length of the LISA time path was below 1 in 51.61% of provincial units. Specifically, 11 provinces were classified into the relatively low category (0.432–0.690), and six provinces were classified into the low category (0.691–1.023), together accounting for 54.84% of all provincial units. This suggests that the local spatial association structure of NQPFs remained relatively stable in most provinces. By contrast, Hunan, Henan, and Hebei showed relatively long LISA time paths, indicating that the evolution of NQPFs in these provinces was less synchronized with that of their neighboring provinces and generated more complex spatial interaction patterns. Hebei Province, in particular, maintained close spatial and functional linkages with Beijing. On the one hand, Beijing continued to attract capital, technology, and talent from surrounding areas, thereby widening the development gap between Beijing and Hebei. On the other hand, under the Beijing–Tianjin–Hebei Coordinated Development Strategy, some non-capital functions of Beijing were transferred to Hebei. These dual processes jointly contributed to the instability of Hebei's local spatial association with its neighboring provinces.

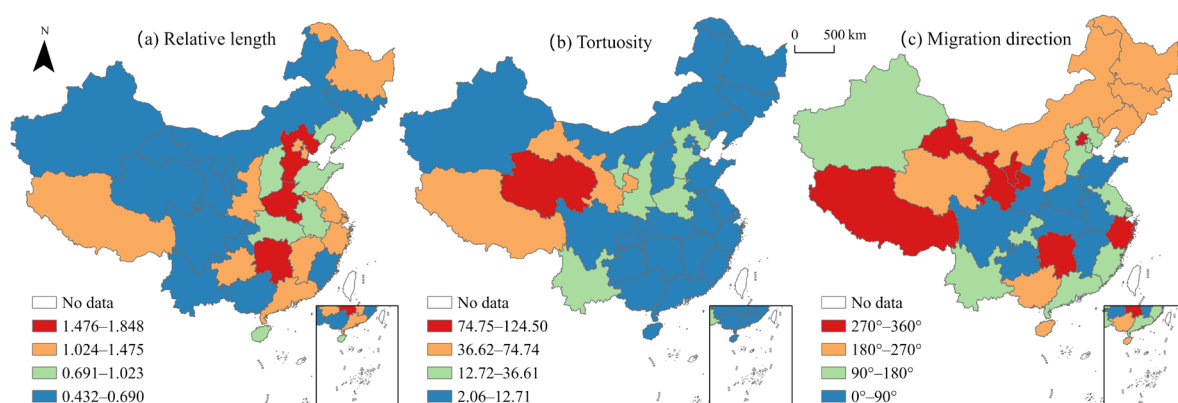


Figure 4. (a) Spatial characteristic distribution map of relative length of LISA time path; (b) Spatial characteristic distribution map of tortuosity of LISA time path; (c) Spatial characteristic distribution map of migration direction of LISA time path. Note: This map is created based on the standard map from the Standard Map Service of the Ministry of Natural Resources (No. GS (2024)0650), with no modifications to the base map boundaries.

Henan and Hunan are important national transportation hubs and maintain close interregional linkages with surrounding provinces. They are also major destinations for industrial transfer from the Yangtze River Delta and Pearl River Delta regions. Because such transfers are often accompanied by uncertainty in industrial selection, factor inflow, and local absorption capacity, these two provinces exhibited more complex spatial interaction trajectories during the study period.

The tortuosity values of the LISA time paths were greater than 1 for all provinces, indicating that the movement trajectories of local spatial associations exhibited nonlinear characteristics. This suggests that the evolution of new-quality productive forces (NQPFs) in all provincial units involved dynamic migration, particularly in the direction of local spatial dependence. Specifically, 23 provinces were classified into the low-tortuosity category (2.059–12.71), accounting for 74.19% of all provincial units, while five provinces were classified into the relatively low-tortuosity category (12.72–36.61), accounting for 16.13%. Together, provinces in the low and relatively low categories accounted for 90.32% of the total, indicating that most provinces showed relatively limited volatility in the direction of local spatial dependence and in the spatial growth process of NQPFs. Eight provinces had tortuosity values above the average level of 18.23, accounting for 25.81% of all provincial units. Among them, Qinghai recorded the highest tortuosity value, followed by Xizang and Gansu, with all three provinces far exceeding the threshold value of 1. This indicates that the LISA trajectories of NQPFs in these provinces were characterized by more complex temporal dynamics and more pronounced nonlinear changes. This pattern may be partly associated with their specific geographical and developmental conditions. Qinghai and Xizang are characterized by fragile ecological environments, where the development of NQPFs is constrained by ecological conservation redlines and environmental carrying capacity. Gansu, meanwhile, is undergoing a difficult transition from traditional growth drivers to new growth drivers. Under these conditions, these provinces need to continuously balance development demands with ecological constraints and adjust their industrial development directions according to local conditions, thereby generating more complex evolutionary paths and more frequent changes in the spatial dependence direction of NQPFs.

During the study period, 14 provinces, accounting for 45.16% of the total, exhibited coordinated movement in the migration direction of the LISA time paths of NQPFs. This indicates that the evolution of provincial NQPFs showed a certain degree of spatial integration (Figure 4c). Among these provinces, eight were classified as the positive synergy type, accounting for 57.14% of the coordinated provinces, and were mainly distributed in inland non-border areas. This pattern may be related to the implementation of national strategies such as the Rise of Central China, which have promoted integrated planning, interprovincial coordination, and regional cooperation among relevant provinces. Six provinces were classified as the negative synergy type, accounting for 42.86% of the coordinated provinces. These provinces were mainly distributed in North China and Northeast China, as well as in Guangxi and Hainan in southern China. The negative synergy pattern in North China and Northeast China may be associated with structural constraints, including relatively homogeneous industrial structures and the decline in traditional industries. Because the industrial systems of provinces within these regions are closely interconnected, local development difficulties may spread to neighboring provinces, resulting in negative spatial co-movement in the evolution of NQPFs. The remaining provinces were classified as either the negative–positive type or the positive–negative type, and were mainly distributed in coastal and border areas, indicating more complex and less synchronized local spatial transition processes.

(2) LISA Space–Time Transition Analysis

The LISA space–time transition matrix further reveals the dynamic transition process of local spatial association types. The results (Table 4) show that Type I transitions, indicating no change in local spatial association type, dominated the overall pattern, with a probability of 0.8516. This was followed by Type II (0.0774), Type III (0.0645), and Type IV (0.0065) transitions. These results indicate that the local spatial association structure of provincial new-quality productive forces (NQPFs) was characterized by strong transition inertia, whereas synchronous transitions occurred only rarely. Further examination of specific transition paths shows that the LH → HH transition had the highest probability within Type II transitions (0.0258), while the HL → HH transition recorded the highest probability within Type III transitions (0.0226). These patterns suggest that some provinces tended to shift toward high-level spatial association, reflecting a gradual strengthening of high-value clustering in the spatial evolution of NQPFs. However, the dominance of Type I transitions indicates that most provinces experienced no substantial change in local spatial association type during the study period. Overall, the LISA space–time transition results reveal clear transition inertia and path dependence in the spatial evolution of provincial NQPFs. Local spatial associations remained relatively stable in most cases, suggesting that the spatial structure of NQPFs was persistent and that interprovincial spatial restructuring remained limited from 2012 to 2022.

Table 4. Space–time transition probability matrix of new-quality productivity forces.

$t \backslash t + 1$	HH	LH	LL	HL
HH	Type I (0.1677)	Type II (0.0161)	Type IV (0.0032)	Type III (0.0194)
LH	Type II (0.0258)	Type I (0.2097)	Type III (0.0097)	Type IV (0.0000)
LL	Type IV (0.0000)	Type III (0.0129)	Type I (0.3774)	Type II (0.0194)
HL	Type III (0.0226)	Type IV (0.0032)	Type II (0.0161)	Type I (0.0968)

3.3. Influencing Factor Analysis

3.3.1. Internal Influencing Factor Analysis

To further clarify the constraining effects of internal factors on the development of new-quality productive forces (NQPFs), this study used the obstacle degree model to diagnose major obstacle factors and identify key constraint variables. The results show that the main obstacle factors affecting NQPF development across China’s seven major regions exhibited a generally consistent pattern from 2012 to 2022. Owing to space limitations, only the top three obstacle factors in 2012, 2017, and 2022 are reported in Table 5.

Table 5. Main obstacle factors to new-quality productivity forces development in the seven major regions (2012–2022).

Region	Obstacle Factor	2012	2017	2022
Nationwide	The first obstacle factor	A_2 (0.2637)	A_2 (0.2597)	A_2 (0.2576)
	The second obstacle factor	C_6 (0.1975)	C_6 (0.2019)	C_6 (0.2041)
	The third obstacle factor	A_3 (0.1460)	A_3 (0.1455)	A_3 (0.1498)
East China	The first obstacle factor	A_2 (0.2774)	A_2 (0.2744)	A_2 (0.2709)
	The second obstacle factor	C_6 (0.1931)	C_6 (0.1906)	C_6 (0.1963)
	The third obstacle factor	A_3 (0.1346)	A_3 (0.1432)	A_3 (0.1371)
South China	The first obstacle factor	C_6 (0.2268)	C_6 (0.2304)	C_6 (0.2298)
	The second obstacle factor	A_2 (0.2112)	A_2 (0.2158)	A_2 (0.2098)
	The third obstacle factor	A_3 (0.1716)	A_3 (0.1572)	A_3 (0.1712)

Table 5. Cont.

Region	Obstacle Factor	2012	2017	2022
North China	The first obstacle factor	A ₂ (0.2782)	A ₂ (0.2756)	A ₂ (0.2798)
	The second obstacle factor	C ₆ (0.1799)	C ₆ (0.1872)	C ₆ (0.1925)
	The third obstacle factor	A ₃ (0.1663)	A ₃ (0.1651)	A ₃ (0.1663)
Central China	The first obstacle factor	A ₂ (0.2662)	A ₂ (0.2713)	A ₂ (0.2652)
	The second obstacle factor	C ₆ (0.2086)	C ₆ (0.2197)	C ₆ (0.2186)
	The third obstacle factor	A ₃ (0.1253)	A ₃ (0.0981)	A ₃ (0.1193)
Southwest China	The first obstacle factor	A ₂ (0.2597)	A ₂ (0.2584)	A ₂ (0.2561)
	The second obstacle factor	C ₆ (0.1978)	C ₆ (0.2003)	C ₆ (0.2021)
	The third obstacle factor	A ₃ (0.1420)	A ₃ (0.1457)	A ₃ (0.1493)
Northwest China	The first obstacle factor	A ₂ (0.2590)	A ₂ (0.2571)	A ₂ (0.2586)
	The second obstacle factor	C ₆ (0.1942)	C ₆ (0.1934)	C ₆ (0.1961)
	The third obstacle factor	A ₃ (0.1491)	A ₃ (0.1526)	A ₃ (0.1524)
Northeast China	The first obstacle factor	A ₂ (0.2725)	A ₂ (0.2626)	A ₂ (0.2606)
	The second obstacle factor	C ₆ (0.2030)	C ₆ (0.1962)	C ₆ (0.1967)
	The third obstacle factor	A ₃ (0.1345)	A ₃ (0.1536)	A ₃ (0.1518)

Although the rankings of the top three obstacle factors varied across China and its seven major regions, the core constraints were consistently concentrated in A₂, namely the annual average number of high-tech employees; C₆, namely the number of industrial wastewater treatment facilities per unit land area; and A₃, namely the number of people served by entrepreneurship services in the current year. Moreover, the rankings of these factors remained relatively stable over time. This suggests that the structure of high-quality labor supply, innovation and entrepreneurship vitality, and ecological governance capacity constitute the main internal constraints on NQPF development in China and its regions. Specifically, an insufficient supply of high-tech talent directly constrains innovation-driven development, industrial transformation, and upgrading, while weakening the competitiveness of emerging industries. These constraints may further impede the advancement of NQPFs [56]. Inadequate innovation and entrepreneurship vitality hinders the transformation of scientific and technological achievements, reduces market dynamism and industrial renewal efficiency, and weakens the capacity to cultivate new technologies, new models, and new business forms [57]. In addition, high-precision and high-end industries, such as semiconductors, impose stringent requirements on environmental conditions and pollution-control infrastructure. An insufficient supply of industrial wastewater treatment facilities may restrict the spatial layout of high-end industries and increase environmental governance costs, thereby crowding out resources for innovation and development. Furthermore, NQPFs are inherently green-oriented productive forces. Weak ecological foundations or inadequate environmental governance may deviate from the green and efficiency-oriented development logic of NQPFs [58].

3.3.2. External Influencing Factor Analysis

The random forest model demonstrated strong predictive performance. OOB validation yielded an RMSE of 0.0346, an MAE of 0.0221, an R²_cor of 0.9412, and an R²_NSE of 0.9389. Under the more stringent leave-one-province-out cross-validation, the corresponding values were 0.0675, 0.0419, 0.7828, and 0.7678, respectively. Although predictive

performance declined when entire provinces were excluded from model training, the model retained reasonable spatial generalization capacity.

The permutation and bootstrap importance results consistently identified total economic output (X4) and population size (X5) as the two leading predictors, whereas industrial structure (X6) showed the lowest additional predictive contribution (Figure 5). Urbanization, openness, and government intervention formed an intermediate group, and their overlapping bootstrap intervals suggest that minor differences in their rankings should not be overinterpreted. TreeSHAP analysis ranked the predictors as $X4 > X5 > X3 > X2 > X1 > X6$ (Figure 6). Higher values of X4 and X5 generally contributed positively to the predicted NQPF index, whereas higher values of X3 were predominantly associated with negative contributions. X1 and X2 showed more heterogeneous contribution patterns, while the SHAP contributions of X6 were concentrated mainly around zero.

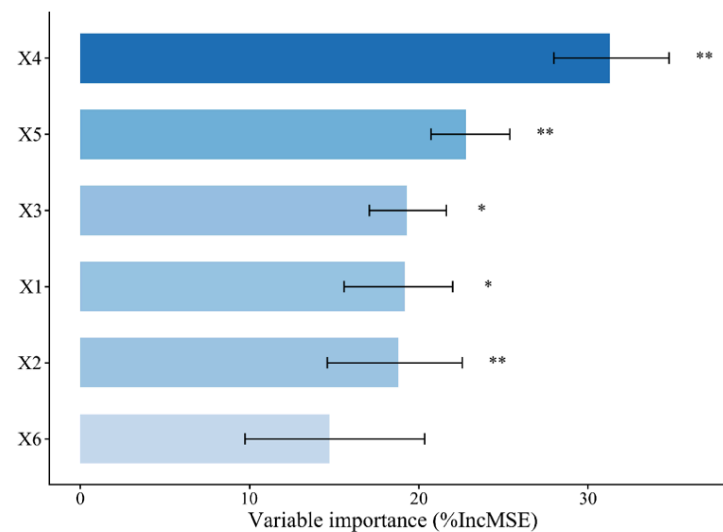


Figure 5. Importance ranking of influencing factors on new-quality productive forces. * $p < 0.05$, ** $p < 0.01$.

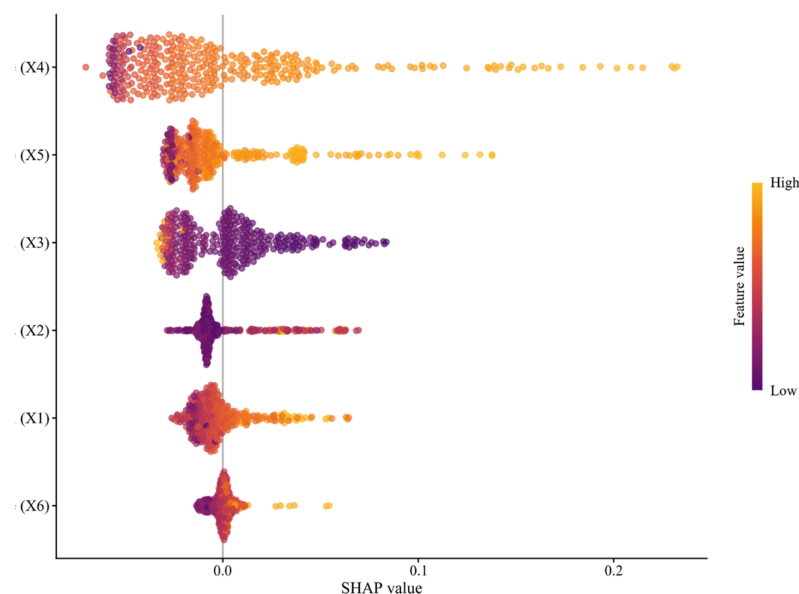


Figure 6. SHAP summary plot of the determinants of new-quality productive forces development.

The partial dependence plots further revealed the marginal nonlinear response patterns of the six external factors (Figure 7).

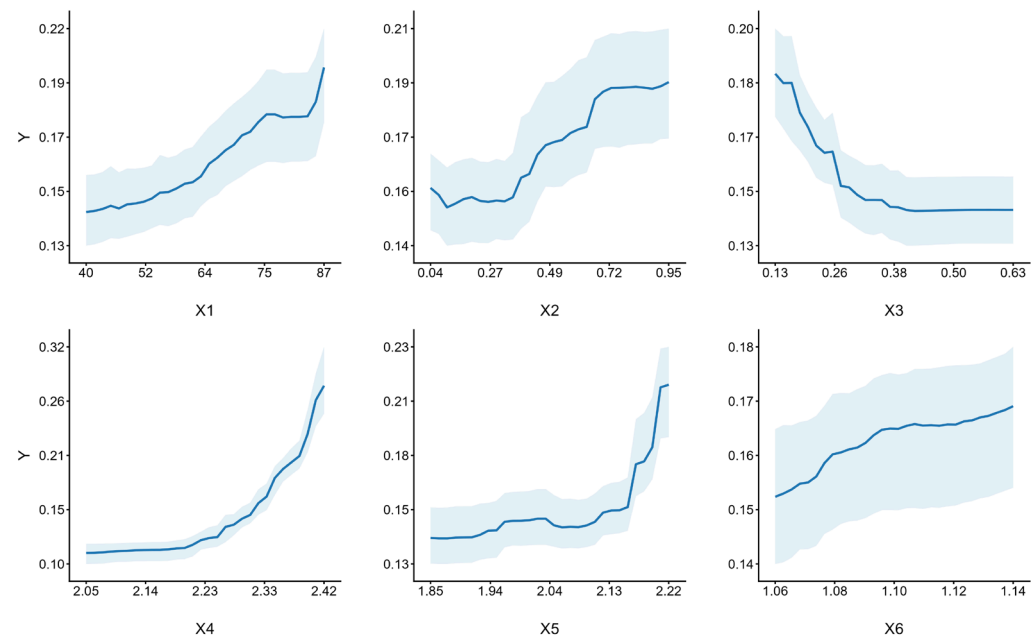


Figure 7. Partial dependence plots of influencing factors on new-quality productive forces.

Total economic output (X4): A clear staged and nonlinear relationship was observed between total economic output and the predicted value of new-quality productive forces (NQPFs). Bootstrap PDP analysis identified a median nonlinear transition point of 2.2946 for total economic output, with a 95% bootstrap interval of 2.2566–2.3185. Below this transition range, the predicted NQPF index remained relatively low and changed only gradually. Beyond this range, the partial dependence response became markedly steeper. This pattern suggests that economic scale may constitute a basic condition for the development of NQPFs. Regions with larger economic output generally have stronger fiscal capacity, larger market demand, and better infrastructure provision, which can support R&D investment, information infrastructure construction, transport network improvement, and industrial upgrading. By contrast, regions with weaker economic foundations may face constraints in market demand, innovation investment, and industrial carrying capacity, thereby limiting the improvement in NQPFs [59].

Population size (X5): The importance of population size was second only to that of total economic output, indicating a strong association between population scale and interprovincial differences in NQPFs. Bootstrap PDP analysis identified a median nonlinear transition point of 2.1540 for population size, with a narrow 95% bootstrap interval of 2.1446–2.1635. Below this range, the predicted NQPF index remained relatively low, whereas the partial dependence response increased substantially beyond the transition range. This nonlinear response suggests that population agglomeration may exhibit stronger scale-related predictive contributions at higher population levels. Regions with larger populations usually have a more abundant labor supply, larger consumer markets, and denser knowledge exchange networks. These conditions help form multi-level talent reserves, specialized divisions of labor, and market-demand support. Population agglomeration and market scale may further influence technology absorption and industrial innovation through knowledge spillovers, factor mobility, and demand-driven mechanisms [60,61].

Degree of government intervention (X3): The degree of government intervention showed a nonlinear negative association with the predicted value of NQPFs. Bootstrap PDP analysis identified a median nonlinear transition point of 0.2967 for government intervention, with a 95% bootstrap interval of 0.2584–0.3222. Below this transition range, the predicted NQPF index declined relatively rapidly as government intervention increased.

Beyond this range, the negative partial dependence response weakened and gradually approached a plateau. This result does not imply that government intervention necessarily suppresses NQPFs. Rather, it indicates that the relationship between government intervention and NQPFs may be stage-dependent and conditional. On the one hand, government intervention can compensate for market failures through infrastructure construction, public R&D investment, green governance, and industrial policies, thereby providing institutional support for the development of NQPFs. On the other hand, excessive administrative intervention or inefficient policy implementation may be associated with lower resource allocation efficiency, weaker market vitality, and reduced incentives for enterprise innovation. Therefore, the key role of government lies not in simply increasing the intensity of intervention, but in improving policy implementation quality, optimizing resource allocation mechanisms, and strengthening the synergy between an effective market and a well-functioning government.

Urbanization rate (X1): The urbanization rate exhibited a staged nonlinear association with the predicted NQPF index. Bootstrap piecewise-linear analysis identified a median transition point of approximately 64.22%, with a relatively broad 95% bootstrap interval of 51.74–78.69%. Below this transition range, the partial dependence response increased only gradually, suggesting that urbanization at an early stage may still be dominated by conventional factor agglomeration and infrastructure expansion, with limited capacity to support the concentration of innovation resources and the development of emerging industries. Across the intermediate urbanization range, the response became steeper, which may reflect the increasing agglomeration of population, capital, information, and industrial activities in urban areas. Such agglomeration can strengthen knowledge spillovers, industrial linkages, infrastructure sharing, and innovation diffusion. At higher levels of urbanization, the curve showed a temporary flattening followed by a further increase at the upper end. This pattern may be associated with the transition from scale-oriented urban expansion to quality-oriented urban development, metropolitan coordination, and enhanced digital and spatial connectivity. The relatively broad bootstrap interval indicates that the relationship does not involve a sharply defined universal threshold and may vary across provinces and stages of development.

Degree of opening-up (X2): The openness level displayed a nonlinear pattern characterized by an initial decline, a subsequent increase, and eventual stabilization. Bootstrap piecewise-linear analysis identified a dominant transition point of 0.4129, with a 95% bootstrap interval of 0.3660–0.6240. This transition range broadly corresponded to the stage at which the partial dependence response shifted from a weak or negative association to a more pronounced positive association. At relatively low levels of openness, the potential benefits of external knowledge and technology inflows may be partly offset by intensified external competition, technological dependence, and the adjustment costs faced by local firms and regional innovation systems. As openness increases and regional absorptive capacity improves, institutional learning, knowledge spillovers, and market competition are more likely to be transformed into innovation momentum. At relatively high levels, the partial dependence response gradually approached a plateau, suggesting that the marginal predictive contribution of further opening-up may weaken. Under such conditions, additional improvements in NQPFs may depend more strongly on indigenous innovation capacity, industrial-chain coordination, knowledge absorption, and institutional quality. Because the PDP contains multiple changes in direction and the estimated bootstrap interval is relatively broad, the individual stages should be interpreted as descriptive response patterns rather than as fixed statistical or policy thresholds.

Industrial structure (X6): The industrial structure index exhibited a relatively weak nonlinear response compared with the other external factors. Bootstrap piecewise-linear

analysis identified a median transition point of 1.0873, with a 95% bootstrap interval of 1.0736–1.1051. Before this transition range, the predicted NQPF index increased moderately as the industrial structure index rose. This pattern may indicate that structural upgrading, the development of modern services, and their integration with manufacturing can stimulate innovation demand, facilitate cross-sectoral coordination, and support value-chain upgrading [62]. Beyond the transition range, however, the partial dependence response gradually flattened, suggesting that changes in the proportional composition of industries alone may generate diminishing marginal contributions to NQPFs. Further improvements may therefore depend more on the technological sophistication, digital transformation, green upgrading, and intersectoral integration of industries than on changes in industrial shares alone. Given that X6 did not pass the significance test in the permutation-importance analysis and showed the smallest mean absolute SHAP contribution, this nonlinear pattern should be interpreted cautiously as supplementary evidence rather than as a dominant explanatory relationship.

3.3.3. Robustness Checks and Supplementary Diagnostics

The annual Moran's I values of the leave-one-province-out cross-validation residuals ranged from -0.2741 to -0.1373 , with a mean of -0.2075 . Significant negative spatial autocorrelation occurred in 2013, 2014, 2020, and 2022, while the Moran's I of the province-level mean residuals was -0.2627 ($p = 0.010$). These results indicate some residual spatial dependence but no persistent positive clustering, motivating supplementary spatial panel analysis.

Under the same cross-validation framework, random forest, XGBoost, and support vector regression produced RMSE values of 0.0675, 0.0707, and 0.0689, and Nash–Sutcliffe efficiency coefficients of 0.7678, 0.7451, and 0.7579, respectively. Their predictive performance was therefore broadly comparable. The one-period-lag random forest also showed stable performance (RMSE = 0.0696; MAE = 0.0450; NSE = 0.7612), with variable importance ranked as $X4 > X5 > X1 > X2 > X3 > X6$. Economic scale and population size remained the leading predictors, suggesting possible lagged associations.

The two-way fixed-effect spatial lag and spatial error models identified a significant positive association between economic scale and NQPFs. Other coefficients varied across specifications. Neither the spatial lag parameter ($\rho = -0.0799$, $p = 0.250$) nor the spatial error parameter was significant at the 5% level, although the latter was marginally significant at the 10% level ($\lambda = -0.1428$, $p = 0.075$). Residual Moran's I values were also insignificant at the 5% level. Overall, the alternative algorithms, lagged model, and spatial panel estimates provide complementary support for the random forest results without reproducing all variable effects.

4. Discussion

This study reveals significant spatiotemporal heterogeneity in new-quality productive forces (NQPFs) across China. It also shows the coexistence of path dependence and dynamic adjustment in spatiotemporal associations, as well as a complex internal–external feedback mechanism characterized by nonlinear and threshold-dependent relationships. These findings address important gaps in the existing literature and provide a geographical basis for the theoretical interpretation and policy design of NQPFs.

4.1. Path Dependence and the Core–Periphery Structure of Spatial Differentiation in New Quality Productive Forces

This study finds that provincial NQPFs in China showed an overall upward trend from 2012 to 2022, but spatial differentiation remained pronounced. The eastern coastal region exhibited substantially higher levels than the central, western, and northeastern regions,

and the spatial centroid remained consistently southeast of the Hu Huanyong Line. This finding is broadly consistent with previous studies that have identified a pattern of “eastern leadership and western lagging” [14–20]. However, this study further shows that this spatial pattern is not driven solely by differences in economic scale. Rather, it is shaped by the combined effects of institutional quality, innovation ecosystems, policy implementation capacity, and regional absorptive capacity. The eastern region not only has a stronger economic foundation and larger market scale, but has also developed a more mature regional innovation system. Its transformation chain from R&D to industrial application is relatively complete, making it easier to convert innovation inputs into actual productive capacity. Through high-tech industries, technology markets, and digital infrastructure, the eastern region has therefore formed a sustained development advantage [36].

This spatial differentiation is consistent with Friedmann’s core–periphery theory. Core regions tend to reinforce their advantages by concentrating capital, technology, talent, and institutional resources [63]. Although the development of the digital economy and transport infrastructure has created new conditions for overcoming traditional spatial constraints [64], the results of this study show that the key factors supporting NQPFs remain highly concentrated in the eastern coastal region. This suggests that digitalization has not automatically eliminated traditional geographical patterns. Under differentiated institutional environments, innovation ecosystems, and absorptive capacities, digital technologies and innovation resources may instead further strengthen the advantages of core regions.

The central and western regions have improved their NQPF levels in recent years, but they remain constrained by underdeveloped innovation ecosystems and insufficient absorptive capacity. According to absorptive capacity theory, whether external knowledge can be transformed into innovation performance depends on the ability of regional actors to identify, assimilate, and apply knowledge [4]. Therefore, undertaking industrial transfer, building digital infrastructure, and expanding openness do not necessarily lead to a leap in NQPFs. The key lies in whether regions possess sufficient high-tech talent, innovation service systems, and green governance capacity. By contrast, the northeastern region faces more evident industrial path dependence and institutional inertia. Its high proportion of traditional industries, continued population outflow, and insufficient innovation vitality impose structural constraints on the improvement in NQPFs.

4.2. Spatiotemporal Inertia, Path Lock-In, and Methodological Contributions

The spatial associations of provincial NQPFs in China exhibited strong spatiotemporal inertia and path lock-in, as most provinces did not experience substantial transitions in local spatial association types during the study period. This finding indicates that the spatial evolution of NQPFs is highly cumulative, and that short-term policy interventions or improvements in a single factor are unlikely to rapidly change regional positions. This is consistent with Williamson’s view that institutional change is generally gradual rather than instantaneous [65]. Institutional arrangements, local protectionism, sunk costs, and switching costs may jointly reinforce existing development trajectories, making regional development patterns persistent and difficult to reverse. In the context of NQPFs, innovation infrastructure, talent structures, industrial systems, and governance modes all show strong historical continuity. Therefore, interregional disparities cannot be quickly eliminated through a single policy measure or a single type of factor input.

Unlike previous studies that have mainly relied on static ESDA methods, this study introduces ESTDA to characterize the temporal trajectories, directional changes, and transition inertia of local spatial associations. This approach deepens the dynamic understanding of how NQPFs agglomerate, diffuse, and transform across space. In addition, existing studies on influencing factors have largely depended on traditional linear models and have

generally focused on the average effects of factors such as the institutional environment, digital economy, financial agglomeration, urban scale, and industrial structure [19–21]. By contrast, this study employs a random forest model to reveal that the associations between external factors and NQPFs are not simply linear, but are characterized by threshold effects, stage-dependent responses, and diminishing marginal associations. This finding helps address an important methodological limitation in the existing literature.

The identification of threshold effects among external determinants has practical implications for region-specific policy design. For regions lagging behind in NQPF development, policy efforts should first focus on crossing the critical thresholds of key enabling factors, such as economic scale, population agglomeration, innovation capacity, and infrastructure support, before shifting toward more refined innovation-oriented strategies. Similarly, the stage-dependent response to openness suggests that opening-up policies should be matched with regional absorptive capacity and the maturity of local innovation ecosystems. The nonlinear negative association between government intervention and NQPFs further highlights the need to calibrate policy intervention, improve policy implementation quality, and properly coordinate the relationship between an effective market and a well-functioning government.

4.3. Internal–External Coupling Mechanism in the Formation of New-Quality Productive Forces

Based on the internal obstacle-factor analysis and the external random forest model, this study provides an explanatory synthesis of the formation mechanism of new-quality productive forces (NQPFs) from the perspectives of endogenous growth theory, regional innovation system theory, and complex systems theory. It should be noted that the obstacle degree model and random forest model mainly reveal internal constraints, variable importance, and nonlinear explanatory associations, rather than strict causal effects. Accordingly, the formation of NQPFs can be interpreted as an internal closed-loop mechanism of talent–innovation–environment, an external nonlinear linkage mechanism of scale–structure–policy, and a synergistic feedback mechanism between internal capabilities and external enabling conditions (Figure 8).

In terms of the internal mechanism, human capital provides the knowledge and capability base for the formation of NQPFs. High-quality talent supports technological accumulation, knowledge absorption, achievement transformation, technological innovation, and industrial upgrading [56]. Innovation and entrepreneurship vitality further reflects the operational efficiency of regional innovation systems. A higher level of innovation and entrepreneurship activity may enhance market vitality and provide incubation support for the application of new technologies, new models, and new business forms [66]. Green development capacity also constitutes an important supporting condition. Stronger pollution-control capacity can help maintain ecological carrying capacity and improve regional attractiveness for green investment [67]. Therefore, talent supply, innovation vitality, and environmental governance jointly form an internal closed-loop system. If any of these elements remains weak, the overall development of NQPFs may be constrained.

In terms of the external mechanism, macroeconomic and market conditions provide the basic external environment for NQPF development. A larger population size usually implies a broader pool of potential innovation actors and stronger market demand, while a larger economic scale can provide financial and material support for technological innovation, industrial upgrading, and related activities [68]. Structural and spatial effects provide further support through industrial upgrading, urbanization, factor agglomeration, and knowledge spillovers, which may facilitate interregional collaborative innovation and total factor productivity improvement. The spatial dependence and spillover effects of innovation factors also help explain the uneven spatial distribution of NQPFs [69]. Policy

regulation and openness represent the institutional dimension of the external mechanism. Appropriate government intervention and external openness may improve market coordination, promote technology spillovers, and enhance innovation dynamics, but their effects are likely to be nonlinear and conditional on regional development foundations [70].

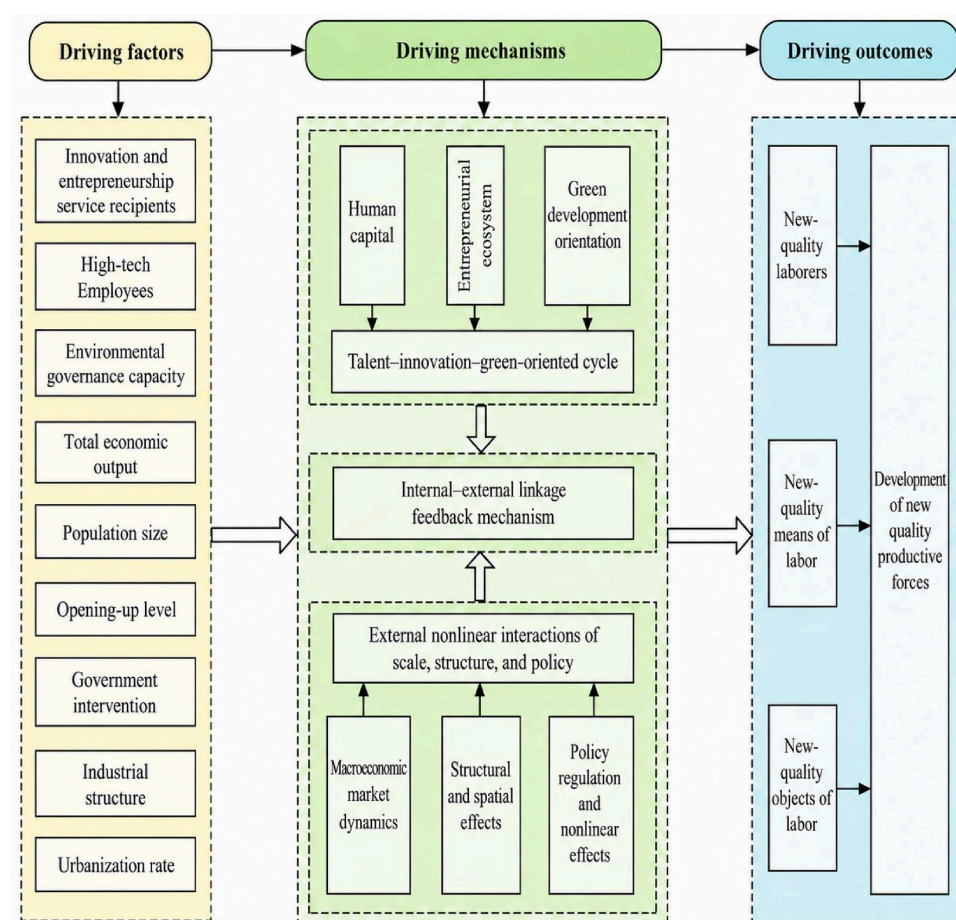


Figure 8. Explanatory framework of the internal–external coupling mechanism of NQPF formation.

The internal–external coupling mechanism emphasizes the interaction between endogenous capabilities and external enabling conditions. External factors provide resources, markets, spatial carriers, and institutional opportunities, whereas internal factors determine whether these external conditions can be effectively absorbed, transformed, and amplified. When internal capabilities and external conditions reach a relatively coordinated state, positive feedback between them may strengthen the accumulation and transformation of NQPFs. Conversely, when internal capabilities are insufficient, external resources may not be effectively converted into productivity upgrading. The nonlinear feedback identified in this study further suggests that policy regulation should be adjusted according to regional development stages so as to correct market failures, stimulate innovation vitality, and optimize factor allocation [71]. Overall, the formation of NQPFs is not driven by a single factor, but by the coordinated evolution of internal capabilities and external conditions.

The supplementary robustness analyses further show that economic scale is the most stable external factor across methods. It exhibits strong explanatory power in the random forest model, SHAP analysis, the one-period-lag model, and both spatial panel specifications. By contrast, the estimated directions of several variables are not fully consistent between the random forest and the two-way fixed-effect spatial panel models. This difference largely reflects the distinct information used by the two approaches. Random forest exploits both interprovincial differences and temporal variation to identify nonlinear

predictive contributions and interactions across the full sample. The two-way fixed-effect models, however, estimate average linear associations mainly from annual changes within the same province.

Population size and urbanization may therefore generate agglomeration advantages across regions, while their further expansion within a province may also create pressures on resource and environmental carrying capacity, public-service provision, infrastructure, and factor allocation [72]. The insignificant linear coefficients of openness and government intervention in the spatial panel models do not necessarily imply an absence of association. The effects of openness may depend on regional absorptive capacity and complementary institutional conditions [73]. Similarly, the effects of government intervention may vary with the stage of development, policy design, and implementation efficiency [74,75]. Taken together, the spatial panel estimates provide complementary rather than identical evidence to the machine learning results.

4.4. Policy Implications

Based on the findings of this study, the development of NQPFs should follow the principles of place-based adaptation and differentiated policy implementation. Policy design should focus on four interrelated priorities: region-specific development pathways, internal capacity building, macro-governance optimization, and cross-regional collaborative governance.

First, regionally differentiated development strategies should be implemented to address uneven spatial distribution and path lock-in. Each region should formulate policies according to its resource endowments, development stage, and dominant constraints. Developed eastern regions, such as Guangdong and Jiangsu, should shift from factor agglomeration and scale expansion toward quality leadership and innovation-driven development. Policy priorities should include original technological breakthroughs, frontier industry development, and the construction of globally competitive innovation hubs. At the same time, eastern regions should strengthen industrial coordination and technology spillovers to central and western regions through enclave economies, industrial cooperation parks, and cross-regional innovation platforms, thereby enhancing coordinated regional development. Central China should make fuller use of its locational advantages and capacity to undertake industrial transfer. Policy efforts should focus on improving technology markets, entrepreneurship service systems, and the efficiency of scientific and technological achievement transformation. Western China should prioritize the construction of transport, energy, and digital infrastructure corridors, improve factor mobility, strengthen green governance capacity, and cultivate new growth poles, particularly in Northwest China. It should also promote the high-end utilization of characteristic resources and help lagging regions cross the key thresholds required for NQPF development. Northeast China should focus on the digital transformation of traditional industries, the construction of green manufacturing systems, talent return, and the reconstruction of innovation ecosystems so as to weaken path lock-in and overcome structural transformation bottlenecks. Second, regions should build a virtuous “talent–innovation–green development” cycle by strengthening high-tech talent attraction and training, improving innovation service systems, enhancing green governance, and accelerating the commercialization of scientific and technological achievements. Policy priorities should be stage-specific: weaker regions should consolidate industrial systems, infrastructure, and public services, whereas advanced regions should emphasize original innovation, institutional optimization, and frontier industries. The government should provide strategic guidance, public goods, and institutional support, while allowing the market to play a decisive role in resource allocation. Third, dynamic monitoring and cross-regional governance should be strengthened. Given spatial dependence and

path inertia, a monitoring and early-warning system should track innovation resources, industrial upgrading, green governance, and regional coordination. Cross-regional innovation platforms, collaborative R&D institutions, and technology transfer networks should be promoted to enhance knowledge sharing, factor mobility, and innovation diffusion, while targeted support should prevent widening regional disparities.

4.5. Limitations and Future Research

By integrating a spatiotemporal coupling perspective with nonlinear modeling, this study responds to several limitations in the existing literature, particularly the insufficient attention paid to geographical perspectives, temporal dynamics, and nonlinear relationships in the study of new-quality productive forces (NQPFs). The proposed framework also provides an operational basis for place-based policy design. Nevertheless, several limitations should be acknowledged. First, although this study identified the internal constraints and external nonlinear associations of NQPFs using the obstacle degree model and the random forest model, the results are primarily explanatory and should not be interpreted as strict causal identification. In particular, economic scale, population size, industrial structure, and NQPFs may be characterized by bidirectional relationships. Moreover, the random forest model cannot fully address potential endogeneity problems. Although this study further incorporated one-period-lagged variables and two-way fixed-effect spatial panel models, the results remain observational and should not be interpreted as establishing strict causal effects. The lagged specification improves the temporal ordering between the predictors and NQPFs, while the spatial panel models account for spatial dependence and unobserved fixed effects. Nevertheless, neither approach can fully eliminate potential reverse causality or omitted-variable bias. Future research could combine spatial econometric models, instrumental variables, quasi-natural experiments, or causal machine learning methods to further examine the causal mechanisms underlying the formation of NQPFs. Second, this study used provincial-level data as the unit of analysis, which is suitable for revealing macro-regional patterns and interprovincial differences. However, this scale is less able to capture micro-level mechanisms at the city, enterprise, and industrial-chain levels. With the increasing availability of fine-grained data, future studies could conduct multi-scale analyses using enterprise innovation data, patent text data, industrial-chain data, and firm-level production network data. In addition, the indicator system for NQPFs could be further refined by incorporating frontier elements that better reflect its advanced characteristics, such as artificial intelligence, computing-power infrastructure, data-factor flows, green technological innovation, and future-oriented industries.

5. Conclusions

This study examined the spatiotemporal patterns, spatiotemporal associations, and influencing mechanisms of NQPFs in China from 2012 to 2022. By integrating the entropy weight method, standard deviational ellipse, exploratory spatiotemporal data analysis, the obstacle degree model, and the random forest model, this study reveals the spatial differentiation, dynamic evolution, and internal–external constraints of provincial NQPFs. The main conclusions are as follows:

China's NQPF development is characterized by significant spatiotemporal differentiation. From 2012 to 2022, NQPFs maintained a steady upward trajectory at the national, regional, and provincial levels. However, the overall national level remained relatively low, and disparities across regions and provinces continued to widen. Spatially, both the level of NQPFs and its interdimensional coordination showed a clear pattern of higher values in the east and lower values in the west. South China and East China consistently occupied leading positions, while Guangdong and Jiangsu formed a dual-core growth structure.

During the study period, the centroid of NQPFs remained near Xinyang City, southeast of the Hu Huanyong Line. Its expansion direction was broadly parallel to the Hu Huanyong Line, indicating a relatively stable but increasingly pronounced spatial orientation.

Spatiotemporal associations of NQPFs reflect the coexistence of path dependence and dynamic evolution. The local spatial association structure in eastern China displayed stronger dynamism, whereas that in western China remained comparatively stable. In most provinces, local spatial structures exhibited strong temporal inertia, limited transition probability, and clear path-dependent characteristics. The LISA time-path and space–time transition results further indicate that the evolution of NQPFs was not a simple linear diffusion process, but a dynamic spatial adjustment process shaped by both regional interaction and path lock-in.

NQPF development is jointly shaped by internal bottlenecks and nonlinear external associations. Internally, the supply of high-skilled talent, innovation and entrepreneurship vitality, and ecological governance capacity remain the principal constraints. Externally, economic scale and population size emerge as the most stable core predictors across the random forest, SHAP, and one-period-lag models. Economic scale also retains a significant positive association in the spatial panel models. By contrast, government intervention, openness, urbanization, and industrial structure exhibit varying degrees of nonlinearity, stage dependence, and heterogeneity across model specifications. Overall, the alternative machine learning algorithms, lagged models, and spatial panel models provide robustness evidence that is partly consistent and mutually complementary.

Supplementary Materials: The following supporting information can be downloaded at: <https://www.mdpi.com/article/10.3390/su18157521/s1>, Table S1: Robustness checks of NQPF index construction under alternative measurement schemes; Figure S1: Agreement among alternative NQPF measurement schemes; Figure S2: Consistency between the baseline and No-A1 NQPF indices; Figure S3: Within-dimension Pearson’s correlation matrices; Figure S4: VIF within hierarchical dimensions; Figure S5: Leave-one-indicator-out sensitivity analysis; Table S2: Spatial autocorrelation tests of leave-one-province-out prediction residuals; Table S3: Alternative algorithms under identical LOPO-CV folds; Table S4: One-year-lagged random forest performance; Table S5: Permutation importance in the one-year-lagged random forest; Table S6: Global importance results.

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References

1. Schot, J.; Steinmueller, W.E. Three Frames for Innovation Policy: R&D, Systems of Innovation and Transformative Change. *Res. Policy* **2018**, *47*, 1554–1567. [[CrossRef](#)]
2. Romer, P.M. Endogenous Technological Change. *J. Polit. Econ.* **1990**, *98*, S71–S102. [[CrossRef](#)] [[PubMed](#)]

3. Cooke, P. Regional Innovation Systems, Clusters, and the Knowledge Economy. *Ind. Corp. Change* **2001**, *10*, 945–974. [\[CrossRef\]](#)
4. Cohen, W.M.; Levinthal, D.A. Absorptive Capacity: A New Perspective on Learning and Innovation. *Adm. Sci. Q.* **1990**, *35*, 128–152. [\[CrossRef\]](#)
5. Chung, Y.H.; Färe, R.; Grosskopf, S. Productivity and undesirable outputs: A directional distance function approach. *J. Environ. Manag.* **1997**, *51*, 229–240. [\[CrossRef\]](#)
6. Hidalgo, C.A.; Hausmann, R. The building blocks of economic complexity. *Proc. Natl. Acad. Sci. USA* **2009**, *106*, 10570–10575. [\[CrossRef\]](#) [\[PubMed\]](#)
7. Liu, Y.; Wang, J.; Ma, D.; Ding, J.; Peng, T. New quality productivity, labor quality and corporate high-quality green development. *J. Environ. Manag.* **2025**, *395*, 128018. [\[CrossRef\]](#)
8. Pu, Q.; Xiang, W. Connotation characteristics, internal logic, and realization paths of new quality productive forces: A new driving force for advancing Chinese-style modernization. *J. Xinjiang Norm. Univ. (Philos. Soc. Sci. Ed.)* **2024**, *45*, 77–85. [\[CrossRef\]](#)
9. Pu, Q.; Huang, Y. Generation Logic, Theoretical innovation and time value of general secretary Xi Jinping's important exposition on new quality productivity. *J. Southwest Univ. (Soc. Sci. Ed.)* **2023**, *49*, 1–11.
10. Ling, X.; Xie, H.; Tuo, L.; Jin, Z. The three dimensions of new quality productivity: Temporal-spatial, structural and technological dimensions. *J. Xinjiang Norm. Univ. (Philos. Soc. Sci.)* **2024**, *45*, 67–76.
11. Han, J.; Sha, D.; Li, C. Evolution of new quality productivity: Dimension, structure and path. *J. Tech. Econ. Manag.* **2024**, *1*, 8–16.
12. Zhang, J.; Xu, Z. Theoretical Review, Logical analysis and practical path of new quality productive forces from the perspective of Chinese-style modernization. *Soc. Sci. Xinjiang* **2024**, *2024*, 34–45.
13. Li, Z.; Cui, H. On new quality productivity from the perspective of historical materialism: Connotation, formation conditions and effective paths. *J. Chongqing Univ. (Soc. Sci. Ed.)* **2024**, *30*, 129–144.
14. Han, W.; Zhang, R.; Zhao, F. The measurement of new quality productivity and new driving force of the Chinese economy. *J. Quant. Technol. Econ.* **2024**, *41*, 5–25.
15. Wang, J.; Wang, R. New quality productivity: Index construction and spatiotemporal evolution. *J. Xi'an Univ. Financ. Econ.* **2024**, *37*, 31–47.
16. Ren, Y.; Wu, Y.; Wu, Z. Financial agglomeration, industry-university research cooperation, and new quality productivity. *Theory Pract. Financ. Econ.* **2024**, *43*, 27–34.
17. Liu, M.; Li, Q. How fiscal and tax policies drive the development of new qualitative productivity. *Shanghai J. Econ.* **2024**, *3*, 31–41.
18. Wu, W.; Rong, Y.; Wu, H. The digital economy empowers the development of new quality productivity—A research based on the urban agglomeration of the Yangtze River delta. *Financ. Econ.* **2024**, *4*, 15–27. [\[CrossRef\]](#)
19. Li, S.; Wu, F. Research on the development potential and driving factors of China's new quality productivity. *J. Tech. Econ. Manag.* **2024**, *45*, 7–12.
20. Gai, K.; Yan, C.; Liu, L. Developing new quality productive forces in line with local conditions: Regional disparities, dynamic evolution, and influencing factors—From the perspective of production relations. *Mod. Econ. Sci.* **2025**, *47*, 1–18.
21. Cheng, G.; Sun, X.; Liu, C.X. Dynamic evolution, regional differences and spatial convergence characteristics of new quality productivity. *Stat. Decis.* **2025**, *41*, 5–11.
22. Wang, Q.; Yang, J. Research on digital new quality productivity and high-quality development of Chinese agriculture. *J. Shaanxi Norm. Univ. (Philos. Soc. Sci. Ed.)* **2023**, *52*, 61–72.
23. Yu, C.; Li, Q.; Liu, Y. New quality productivity, consumption structure and high-quality development of tourism. *J. Henan Norm. Univ. (Nat. Sci. Ed.)* **2024**, *52*, 19–29.
24. Lu, L.; Yang, S. Research on the Influence Mechanism of the New Quality Productive Forces on the Structural Upgrading of China's Sports Industry—Analysis Based on the Mediating Effect and Threshold Effect. *China Sport Sci. Technol.* **2024**, *60*, 81–90.
25. Zhang, Y.; Lu, M. New quality productive forces and coordinated regional economic development: Synergy mechanism and progressive pathway—A case study of the Yangtze River delta region. *Huxiang Forum* **2024**, *37*, 36–49.
26. Zhang, Z. Empowering urban-rural integration with new quality productivity: Theoretical logic and path exploration. *J. Chongqing Univ. Technol. (Soc. Sci.)* **2024**, *38*, 11–21.
27. Li, Y. Research on the construction of industry-education integration community from the perspective of new quality productivity. *Nanjing J. Soc. Sci.* **2023**, *12*, 122–129.
28. Ren, B. Empowering Chinese path to modernization with new quality productivity: Priorities and tasks. *Econ. Probl.* **2024**, *5*, 1–6.
29. Fang, C.; Sun, B. The connotation of new quality productive forces and research priorities for driving urban-rural integrated development from the geographical perspective. *Acta Geogr. Sin.* **2024**, *79*, 1357–1370.
30. An, J.; Yuan, X.; Su, Q. Spatiotemporal Pattern, Regional Differences and Evolutionary Trend of Development Level of New Quality Productivity in China. *J. Earth Sci. Environ.* **2025**, *47*, 106–127.
31. Zhu, X.; Li, R.; Xu, X.; Sun, J. Construction and Spatiotemporal Evolution of New Productivity Indicators of China. *J. Ind. Technol. Econ.* **2024**, *43*, 44–53.

32. Melitz, M.J. The Impact of Trade on Intra-Industry Reallocations and Aggregate Industry Productivity. *Econometrica* **2003**, *71*, 1695–1725. [\[CrossRef\]](#)
33. Zhang, J.; Liu, Y. How Does Digital Innovation Empower the Development of New Quality Productive Forces? An Empirical Study Based on Double Machine Learning. *Sustainability* **2025**, *17*, 2652. [\[CrossRef\]](#)
34. Zhang, W.; Zhu, B.; Li, Y.; Yan, D. Revisiting the Porter Hypothesis: A Multi-Country Meta-Analysis of the Relationship between Environmental Regulation and Green Innovation. *Humanit. Soc. Sci. Commun.* **2024**, *11*, 232. [\[CrossRef\]](#)
35. Acs, Z.J.; Audretsch, D.B. Innovation in Large and Small Firms: An Empirical Analysis. *Am. Econ. Rev.* **1988**, *78*, 678–690.
36. Cooke, P. Regional Innovation Systems: Competitive Regulation in the New Europe. *Geoforum* **1992**, *23*, 365–382. [\[CrossRef\]](#)
37. Jaffe, A.B.; Trajtenberg, M.; Henderson, R. Geographic Localization of Knowledge Spillovers as Evidenced by Patent Citations. *Q. J. Econ.* **1993**, *108*, 577–598. [\[CrossRef\]](#)
38. Wang, Q.; Li, G.; Du, M.; Zhou, X.; Liang, J. The Impact of New Digital Infrastructure on Green Total Factor Productivity. *Front. Energy Res.* **2024**, *12*, 1396872. [\[CrossRef\]](#)
39. Wang, S.; Zheng, Y.; Yang, H. Digital Economy and Green Total Factor Productivity in China. *PLoS ONE* **2024**, *19*, e0299716. [\[CrossRef\]](#) [\[PubMed\]](#)
40. Li, C.; Wen, M.; Jiang, S.; Wang, H. Assessing the Effect of Urban Digital Infrastructure on Green Innovation: Mechanism Identification and Spatial-Temporal Characteristics. *Humanit. Soc. Sci. Commun.* **2024**, *11*, 1–14. [\[CrossRef\]](#)
41. Yue, W.; Wu, T.; Liu, X.; Zhang, L.; Wu, C. Developing an urban sprawl index for China's mega-cities. *Acta Geogr. Sin.* **2020**, *75*, 2730–2743.
42. Guan, X.; Zang, Y.; Meng, Y.; Liu, Y.; Lv, H.; Yan, D. Study on spatiotemporal distribution characteristics of flood and drought disaster impacts on agriculture in China. *Int. J. Disaster Risk Reduct.* **2021**, *64*, 102504. [\[CrossRef\]](#)
43. Gong, J. Clarifying the standard deviational ellipse. *Geogr. Anal.* **2002**, *34*, 155–167. [\[CrossRef\]](#)
44. Wong, W.S. Several fundamentals in implementing spatial statistics in Gis: Using Centro graphic measures as examples. *Geogr. Inf. Sci.* **1999**, *5*, 163–174. [\[CrossRef\]](#)
45. Bi, D.; Wang, K.; Wang, S.; Fang, Y. Research on industrial eco-efficiency and spatiotemporal transition characteristics of the Yangtze River delta. *Econ. Geogr.* **2018**, *38*, 166–173. [\[CrossRef\]](#)
46. Rey, S.J. Spatial empirics for economic growth and convergence. *Geogr. Anal.* **2010**, *33*, 195–214.
47. Ma, D.; Zhang, J.; An, B.; Guo, Z.; Zhang, F.; Yan, Y.; Peng, G. Research on urban land green use efficiency and influencing factors based on DEA and ESTDA models: Taking 284 cities in China as an example. *Ecol. Indic.* **2024**, *160*, 111824. [\[CrossRef\]](#)
48. Rey, S.J.; Janikas, M.V. STARS: Space-time analysis of regional systems. *Geogr. Anal.* **2006**, *38*, 67–86.
49. Sun, X.; Zhou, Z.; Wang, Y. Water resource carrying capacity and obstacle factors in the Yellow River basin based on the RBF neural network model. *Environ. Sci. Pollut. Res.* **2023**, *30*, 22743–22759.
50. Pang, B.; Li, X.; Fu, Y. Coupling coordination analysis and obstacle factors of water-energy-environment-economy in the Yellow River Basin. *J. Clean. Prod.* **2024**, *468*, 143108. [\[CrossRef\]](#)
51. Vinuesa, R.; Azizpour, H.; Leite, I.; Balaam, M.; Dignum, V.; Domisch, S.; Felländer, A.; Langhans, S.D.; Tegmark, M.; Fuso Nerini, F. The role of artificial intelligence in achieving the Sustainable Development Goals. *Nat. Commun.* **2020**, *11*, 233. [\[CrossRef\]](#) [\[PubMed\]](#)
52. Breiman, L. Random forests. *Mach. Learn.* **2001**, *45*, 5–32. [\[CrossRef\]](#)
53. Álvarez-Díez, S.; Baixauli-Soler, J.S.; Lozano-Reina, G.; Rey, D.R.L. Subsidies for investing in energy efficiency measures: Applying a random forest model for unbalanced samples. *Appl. Energy* **2024**, *359*, 122725. [\[CrossRef\]](#)
54. Xie, J.; Wang, Z. Spatial mismatch and its formation mechanisms between tourism eco-efficiency and ecotourism attention in China. *J. Nat. Resour.* **2025**, *40*, 1012–1031. [\[CrossRef\]](#)
55. Pang, J. Five Major Issues Should Be Grasped for the Formation of New-Type Production Relations. *Frontiers* **2024**, *9*, 5–12.
56. Xu, Z.; Zheng, Z.; Chen, M. New Quality Productivity for High-quality Development: Advantageous Conditions, Key issues and Path Selection. *J. Southwest Univ. (Soc. Sci. Ed.)* **2023**, *49*, 12–22.
57. Zeng, S.; Fu, Q.; Jin, M. Research on the Theoretical Connotation, Realistic Basis, Challenges and Countermeasures of New Qualitative Productivity Forces from the Perspective of Innovation. *J. Shanghai Univ. Int. Bus. Econ.* **2024**, *31*, 49–63.
58. Huang, X.; Hu, A. The Understanding Dimension of Green Productivity, China's Innovation and Practice Prospect—Also on the New Quality Productivity Itself is Green Productivity. *J. Beijing Univ. Technol. (Soc. Sci. Ed.)* **2025**, *25*, 56–67. [\[CrossRef\]](#)
59. Wang, J. The Three-Stage Evolution Route of Chinese Modernization. *China Econ. Stud.* **2024**, *5*, 31–46.
60. Shi, Z.; Peng, R.; Wang, Z. High-quality Population Development to Cultivate New Quality Productivity: Internal Logic and Practical Path. *J. Shandong Univ. (Philos. Soc. Sci.)* **2024**, *5*, 83–96.
61. Yu, M. Understanding the High-Quality Development of the Chinese Economy. *J. Sun Yat-Sen Univ. (Soc. Sci. Ed.)* **2024**, *64*, 1–12.
62. Liao, W. On the Generation of New Productive Forces: Advanced Knowledge Production, Integration of Technological Elements and Industrial Technology Breakthroughs. *Chongqing High. Educ. Res.* **2024**, *12*, 75–86.
63. Karst, K.L. Regional Development Policy: A Case Study of Venezuela. *Hisp. Am. Hist. Rev.* **1969**, *49*, 368–369. [\[CrossRef\]](#)

64. Zhong, Y.; Wu, S. Infrastructure, the dilemma, mechanism and countermeasures of new quality productive forces promoting regional coordinated development. *J. Chongqing Univ. (Soc. Sci. Ed.)* **2024**, *30*, 41–55.
65. Williamson, O.E. The New Institutional Economics: Taking Stock, Looking Ahead. *J. Econ. Lit.* **2000**, *38*, 595–613. [[CrossRef](#)]
66. Yang, Y.; Guo, J.; Wang, S. New Quality Productive Forces, Entrepreneurial Activity and High-Quality Urban Development. *Sci. Technol. Prog. Policy* **2024**, *12*, 75–86.
67. Han, J.; Lan, Q. Green Development in the New Development Stage: Theoretical Logic and Practical Path. *J. Beijing Norm. Univ. (Soc. Sci.)* **2022**, *2*, 5–16. [[CrossRef](#)]
68. Zhou, S.; Hu, H. A Political Economy Study on How New Quality Productivity Promotes Innovative Development. *J. Xinjiang Norm. Univ.* **2024**, *45*, 26–35. [[CrossRef](#)]
69. Zhang, Z.; Li, F. Infrastructure, Spatial Spillover and the Upgrading of Industrial Structure: Based on the Empirical Analysis of Prefecture-level Cities in the Yangtze Economic Belt. *J. Yunnan Univ. Financ. Econ.* **2019**, *35*, 55–63.
70. Liu, L.; Ren, R.; Cui, K.; Song, L. A Dynamic Panel Threshold Model Analysis on Heterogeneous Environmental Regulation, R&D Investment, and Enterprise Green Total Factor Productivity. *Sci. Rep.* **2024**, *14*, 5208. [[CrossRef](#)] [[PubMed](#)]
71. Sun, M.; Zhao, L. Impact of Environmental Regulatory Types and Green Technological Innovation on Green Total Factor Productivity in Polluted Areas of China. *Sustainability* **2024**, *16*, 3871. [[CrossRef](#)]
72. Pradhan, R.P.; Arvin, M.B.; Nair, M. Urbanization, transportation infrastructure, ICT, and economic growth: A temporal causal analysis. *Cities* **2021**, *115*, 103213. [[CrossRef](#)]
73. Chang, R.; Kaltani, L.; Loayza, N.V. Openness can be good for growth: The role of policy complementarities. *J. Dev. Econ.* **2009**, *90*, 33–49. [[CrossRef](#)]
74. Acemoglu, D.; Aghion, P.; Zilibotti, F. Distance to frontier, selection, and economic growth. *J. Eur. Econ. Assoc.* **2006**, *4*, 37–74. [[CrossRef](#)]
75. Aghion, P.; Cai, J.; Dewatripont, M.; Du, L.; Harrison, A.; Legros, P. Industrial policy and competition. *Am. Econ. J. Macroecon.* **2015**, *7*, 1–32. [[CrossRef](#)]

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