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Spatial Network Structures and Nonlinear Association Characteristics of Synergistic Pollution Reduction and Carbon Mitigation in China: Evidence from the CatBoost–SHAP Model

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Abstract

Synergistic pollution reduction and carbon mitigation (SPRCM) is a critical pathway for advancing global climate governance and promoting green and low-carbon transitions. It also represents an important practice for strengthening ecological civilization and achieving regional sustainable development in China. Based on panel data from 31 Chinese provinces during 2010–2024, this study employs an improved entropy-weighted TOPSIS method to measure SPRCM levels and integrates a modified gravity model, social network analysis, and the CatBoost-SHAP explainable machine learning approach to examine its spatiotemporal evolution, spatial network structure, and nonlinear association characteristics. The main findings are as follows. First, China's overall SPRCM level shows a gradual upward trend, while significant regional disparities remain. Second, the interprovincial spatial association network has gradually evolved toward a polycentric structure and exhibits clear hierarchical characteristics. Although network connectivity has continuously improved, linkages between core and peripheral provinces remain relatively weak. Third, individual network characteristics display distinct regional differentiation. Eastern coastal provinces consistently occupy core network positions, whereas northeastern and some western provinces remain relatively peripheral. Fourth, the block model analysis identifies four functional groups within the network: net beneficiaries, net spillovers, brokers, and two-way spillovers. These blocks play differentiated roles in spatial association and network interactions. Fifth, the CatBoost-SHAP analysis indicates that road density, freight volume, and human capital are the most important variables in explaining model predictions, with their combined mean absolute SHAP importance accounting for 54.59%. Moreover, these factors exhibit significant nonlinear association patterns with predicted SPRCM levels.



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Keywords: pollution reduction; carbon mitigation; social network analysis; explainable machine learning; human capital

1. Introduction

Global climate change, intensified atmospheric compound pollution, and the increasing frequency of extreme climate events have highlighted the limitations of traditional governance approaches that separate environmental management from climate mitigation [1]. Since pollutant emissions and greenhouse gas emissions share highly similar sources in energy consumption, industrial production, and transportation, isolated pollution control or carbon reduction policies are increasingly insufficient to achieve the dual

objectives of environmental improvement and low-carbon development [2]. Therefore, promoting synergistic pollution reduction and carbon mitigation (SPRCM) has become an important pathway for global green and low-carbon transformation. Its core lies in coordinating pollution control, carbon emission management, and resource utilization optimization to achieve synergies among environmental quality improvement, carbon reduction performance, and green transformation goals. Meanwhile, with the deepening of regional economic linkages and industrial specialization, pollution control and carbon mitigation processes have increasingly transcended administrative boundaries and exhibited significant spatial interdependence [3]. Identifying regional synergies and understanding their underlying formation mechanisms have therefore become critical issues in green governance research.

As the world's largest developing economy and a major carbon emitter, China is at a critical stage of pursuing high-quality economic development while advancing green and low-carbon transformation [4]. In recent years, China has proposed the "dual-carbon" goals and incorporated SPRCM into its ecological civilization strategy and green development framework [5]. The Implementation Plan for SPRCM emphasizes the need to significantly improve synergistic governance capacity by 2030. The Third Plenary Session of the 20th Central Committee of the Communist Party of China further highlighted the coordinated promotion of carbon reduction, pollution mitigation, ecological expansion, and economic growth, indicating a shift from traditional single-objective environmental governance toward multi-objective collaborative governance. However, substantial regional disparities exist in China due to differences in economic development levels, industrial structures, and environmental governance capacity [6]. These disparities contribute to significant spatial heterogeneity in SPRCM performance. In particular, with increasingly interconnected regional economies, pollution control capacity, green technology diffusion, and factor flows in one region may influence other regions through interregional networks, causing SPRCM to exhibit spatial dependence beyond administrative boundaries [1,7]. Moreover, the effects of different factors on collaborative governance may vary across development stages and exhibit nonlinear patterns, which are difficult to fully capture using conventional linear approaches [8]. Therefore, identifying the spatial network structure and nonlinear association characteristics of SPRCM is essential for understanding regional disparities in China's green transformation and designing more effective pathways for collaborative governance.

Existing studies have provided important foundations for understanding SPRCM by examining coordination level measurement, spatial spillover effects, and driving factors. However, three major limitations remain. First, previous studies have mainly focused on single dimensions, such as pollutant emissions, carbon emissions, or governance efficiency, while paying insufficient attention to the systematic interactions among environmental pressure, governance capacity, ecological conditions, and resource utilization, making it difficult to comprehensively characterize SPRCM [7,9]. Second, existing spatial studies have primarily examined the spatial spillover effects of pollution emissions or carbon emissions, whereas limited attention has been paid to how interregional linkages are formed within the integrated governance system of SPRCM and how different network positions reflect variations in regional governance capacity [3,10]. Third, conventional econometric models mainly identify the average effects of variables, which makes it difficult to capture nonlinear association patterns and potential threshold characteristics in the impacts of different driving factors [11,12]. To address these gaps, this study focuses on the following core question: How are the spatial disparities in SPRCM formed under the background of increasingly interconnected regional economies and continuous green and low-carbon transformation? Specifically, this study aims to answer three questions: (1) How can a comprehensive evaluation framework be constructed to accurately measure regional SPRCM

levels and their spatiotemporal evolution characteristics? (2) Does interprovincial SPRCM form a spatial association network, and what structural positions and functional roles do different regions exhibit within this network? (3) Which factors contribute most to SPRCM prediction, and do these factors exhibit nonlinear association patterns with SPRCM?

To address these questions, this study uses panel data from 31 Chinese provinces during 2010–2024. The improved entropy-weighted TOPSIS method is applied to measure SPRCM levels. The modified gravity model and social network analysis are further employed to characterize the interprovincial spatial association network. In addition, the CatBoost-SHAP model is adopted to identify key predictive variables and their nonlinear association patterns. The marginal contributions of this study are threefold. First, this study conceptualizes SPRCM as a comprehensive governance process jointly shaped by environmental pressure, governance capacity, ecological conditions, and resource utilization. This perspective extends the analytical framework for evaluating regional green and low-carbon development performance. Second, this study reveals the structure of the interprovincial SPRCM network and regional functional differences from a spatial governance perspective. It further examines the asymmetric governance capacity underlying the core–periphery structure, providing spatial evidence for understanding the uneven diffusion of green governance capacity and development factors across regions. Third, this study introduces an interpretable machine learning approach to identify the relative contributions of different factors to SPRCM predictions and their nonlinear association characteristics, providing empirical insights into complex multi-factor interactions.

2. Literature Review

2.1. Measurement of SPRCM

Early studies mainly used single indicators to measure the synergy between pollution reduction and carbon mitigation. For example, CO₂ emissions were used to represent carbon mitigation, while PM_{2.5} or SO₂ emissions were used to characterize pollution control [13–15]. The relationship between the two was then evaluated through correlation analysis. However, this approach cannot adequately capture the systemic synergistic characteristics of pollution reduction and carbon mitigation. With the advancement of research, scholars have gradually developed comprehensive evaluation frameworks, which can be broadly classified into two approaches. The first approach follows a “dual-system” framework, where pollution control and carbon reduction are measured separately, and their synergistic level is evaluated using coupling coordination models [16]. The second approach further expands the evaluation scope by incorporating source reduction, end-of-pipe treatment, ecological protection, and economic development into an integrated framework [2,17,18]. In addition, some studies have examined the effects of specific factors, such as green finance, on the synergistic efficiency of pollution and carbon reduction [19,20]. Regarding measurement methods, the coupling coordination degree (CCD) model is currently one of the most widely applied approaches. However, conventional CCD models may suffer from the problem of overestimating coupling levels. To improve measurement accuracy, Meng proposed an improved CCD model, while Zhang further applied the super-efficiency SBM model to evaluate SPRCM efficiency from an input–output perspective [2,21]. Meanwhile, composite system synergy models and remote sensing-based approaches have also been introduced. For instance, Xu employed a composite system synergy model to assess the coordination between pollution and carbon mitigation, while Jiang constructed a remote sensing-based synergistic reduction index for CO₂ and PM_{2.5} using multi-source remote sensing data [22,23].

Overall, existing studies have advanced the measurement of SPRCM from single indicators toward comprehensive evaluation frameworks. However, several limitations

remain. On the one hand, previous research has mainly focused on the coordination between pollution control and carbon mitigation, while paying insufficient attention to the integrated roles of ecological conditions, resource consumption, and green growth. On the other hand, current indicator systems still require further improvement in capturing the systemic interactions among environmental pressure, governance capacity, ecological support, and resource constraints.

2.2. Spatial Spillover and Network Governance

Due to the strong spatial interdependence between pollutant emissions and carbon emissions, the spatial evolution of SPRCM has gradually become a key research focus. Existing studies have mainly examined this issue from two perspectives: spatial econometric models and social network analysis. Regarding spatial spillover effects, spatial econometric models have been widely applied to identify spatial dependence in pollution control and carbon mitigation processes [3,6]. Studies based on the Spatial Durbin Model have found significant spatial autocorrelation in pollution reduction and carbon mitigation coordination levels, while carbon emissions and pollution control also exhibit notable regional spillover effects [3,24]. Furthermore, studies using spatial difference-in-differences models indicate that policies such as low-carbon city pilots may generate spatial effects through technological diffusion and regional linkages [25]. These findings suggest that SPRCM does not evolve independently but is influenced by regional economic connections and spatial interactions. With the development of network analysis methods, social network analysis has been increasingly applied to reveal interregional linkage structures. Based on modified gravity models and SNA approaches, existing studies have found that pollution reduction and carbon mitigation networks exhibit significant “small-world” and “core-periphery” structures [4,26]. Different regions also demonstrate substantial disparities in network connectivity and structural positions [27,28]. In addition, QAP analysis shows that spatial adjacency, economic disparities, technological capabilities, and green innovation influence the formation of regional network linkages [26,29].

Overall, existing studies provide important insights into the spatial relationships between pollution control and carbon mitigation. However, several limitations remain. On the one hand, previous research has mainly focused on the spatial spillover effects of pollutant emissions or carbon emissions, while network-based analyses of SPRCM as an integrated system remain relatively limited. On the other hand, existing SNA studies have primarily emphasized overall network characteristics, whereas the structural positions, functional differences, and their potential relationships with synergistic governance performance across regions require further investigation.

2.3. Nonlinear Driving Factors and Explainable Machine Learning

Existing studies on the driving factors of SPRCM have mainly relied on econometric approaches, including panel regression models, spatial econometric models, and quasi-experimental methods. These studies have shown that factors such as green technological innovation, green finance, and policy instruments can influence pollution reduction and carbon mitigation synergies by promoting technological progress, industrial upgrading, and governance capacity improvement [3,30,31]. These findings provide important insights into the conditions underlying SPRCM development. However, traditional econometric models generally rely on linearity assumptions and focus primarily on average marginal effects [22,32]. As a result, they may fail to adequately capture nonlinear variations, threshold patterns, and complex interactions among multiple factors across different development stages. Although previous studies have identified spatial heterogeneity and stage-dependent effects of factors such as green innovation, industrial structure, and policy

instruments using approaches including GTWR and spatial quantile regression [2,23,33], the dynamic changes in SPRCM predictions under the joint influence of multiple factors, as well as the relative contribution of different factors, remain insufficiently explored.

In recent years, machine learning methods have been increasingly applied in environmental economics, providing new approaches for analyzing complex nonlinear relationships. Compared with traditional models, ensemble learning algorithms such as CatBoost can effectively handle high-dimensional variables, nonlinear relationships, and interaction effects among predictors, while identifying important features from a data-driven perspective [34]. Meanwhile, the SHAP interpretation framework can further quantify the marginal contribution of individual variables to model predictions and improve the interpretability of machine learning models [35]. Therefore, this study introduces the CatBoost-SHAP approach as a predictive analytical framework to identify the relative contributions of different factors to SPRCM predictions and to explore their potential nonlinear association patterns.

2.4. Regional Network Positions and Collaborative Governance

Due to the significant spatial interdependence of pollutant emissions, carbon emissions, and green governance activities, SPRCM does not evolve independently within individual regions but may be shaped by interregional resource flows, technological diffusion, and the transmission of governance experience [4,7]. Existing studies have mainly explored these spatial linkages from two perspectives: spatial econometric models and social network analysis. Spatial econometric studies have demonstrated significant spatial dependence in pollution control and carbon mitigation processes, indicating that the governance performance of one region may affect neighboring regions through economic linkages, technological diffusion, and policy transmission [22,36]. Further social network analysis has revealed that regional emission reduction networks often exhibit core–periphery structures, with different regions playing distinct roles in network connectivity and resource transfer [4,26]. For example, core cities in the Yangtze River Delta carbon mitigation network demonstrate stronger capacities for knowledge diffusion and governance experience sharing, whereas some peripheral regions are less effectively integrated into regional cooperation networks due to limitations in resources and capabilities [26,27].

These studies suggest that spatial association networks not only reflect the strength of interregional connections but also indicate functional differences among regions in resource allocation, technological diffusion, and collaborative governance. However, existing research has mainly focused on network structural characteristics and their determinants, while systematic understanding remains limited regarding whether differences in network positions can explain regional disparities in SPRCM and how network linkages between core and peripheral regions shape collaborative governance processes. Moreover, previous network studies have primarily examined pollution control or carbon mitigation as separate objectives, whereas the spatial association structure and governance implications of SPRCM, as an integrated system involving environmental governance, ecological improvement, and economic development, remain insufficiently explored. Therefore, this study constructs the SPRCM spatial association network to examine interregional collaborative structures and network role differences. Furthermore, it combines explainable machine learning methods to identify the contributions of different factors to SPRCM predictions and their nonlinear association characteristics, thereby providing deeper insights into the spatial evolution of regional collaborative governance.

3. Research Design

3.1. Theoretical Foundation

The evolution of SPRCM is not determined by a single factor but is shaped by the combined effects of regional development foundations, socioeconomic structures, and factor endowments. Based on Ecological Modernization Theory, Porter's Hypothesis, Regional Innovation Systems Theory, Spatial Spillover Theory, and Network Theory, this study develops a theoretical framework covering three dimensions: economic foundations, social structure, and factor endowments. This framework is used to explain the potential associations between different factors and regional SPRCM levels and provides a theoretical basis for variable selection in the subsequent machine learning model.

First, the economic foundation perspective: green transition capacity and governance conditions. Ecological Modernization Theory suggests that economic growth and environmental improvement are not necessarily contradictory. As economies advance, capital accumulation, technological progress, and enhanced governance capacity can provide essential support for green transformation [37,38]. From this perspective, regional economic foundations may be closely associated with SPRCM performance. Higher levels of economic development generally indicate stronger resource allocation capacity, more developed public service systems, and greater capacity for green transition [39]. The development of green finance can improve the allocation of green resources and provide support for green technology adoption and low-carbon projects [19]. Environmental protection expenditure reflects regional investment in environmental governance, which may capture local governance capacity and environmental management foundations [20]. Social consumption levels represent changes in market demand structures, and increasing demand for green consumption may encourage production transformation and industrial upgrading toward lower-carbon development [22]. In addition, according to Porter's Hypothesis, appropriate environmental regulation and governance investment do not necessarily reduce economic efficiency. Instead, they may promote technological innovation, improve resource utilization efficiency, and facilitate green industrial transformation, thereby generating coordinated improvements in environmental and economic performance [20,40]. Therefore, factors such as environmental investment and green technological innovation may exhibit potential statistical associations with SPRCM performance.

Second, the social structure perspective: urbanization transformation and industrial restructuring. Social structure theory and industrial transformation theory suggest that population concentration, changes in industrial structure, and adjustments in the organization of economic activities can reshape regional resource utilization patterns and environmental governance demands, thereby influencing green and low-carbon development performance [2,41,42]. Urbanization rate, industrial structure upgrading, and industrialization level reflect regional socioeconomic structures, and their changes may be associated with pollution pressure, resource efficiency, and environmental governance capacity. Specifically, urbanization can improve infrastructure, promote public service concentration, and enhance resource utilization efficiency, thereby creating favorable conditions for green development [43,44]. However, rapid urbanization may also increase energy demand and environmental pressures. Industrial structure upgrading generally reflects the transition from traditional industries toward service-oriented and technology-intensive economic activities, which may influence the formation of greener production patterns [14]. Industrialization level represents the stage of regional industrial development, and regions at different industrialization stages may exhibit different patterns of resource consumption and pollutant emissions. Therefore, social structural factors may affect regional development patterns and resource allocation modes, thereby contributing to varying degrees of information contribution in SPRCM prediction.

Third, the factor endowment perspective: innovation capacity, human resources, and spatial connectivity. Regional Innovation Systems Theory emphasizes that knowledge accumulation, human capital, and innovation infrastructure are essential foundations for technological progress and green transformation [2,14]. Regional green development capacity depends not only on existing resource conditions but also on innovation accumulation and technological diffusion capabilities. Human capital and green technological innovation reflect regional knowledge resources and innovation capacity [2]. These factors may be associated with SPRCM performance by promoting green technology development, improving pollution control efficiency, and facilitating low-carbon technology adoption. Meanwhile, Spatial Spillover Theory highlights that regional development is not an isolated process. The development performance of one region may be influenced by resource flows, technological diffusion, and economic linkages with surrounding regions [3,7]. Transportation infrastructure and logistics connectivity serve as important channels for interregional factor mobility and can facilitate knowledge diffusion, industrial cooperation, and the exchange of governance experience [18]. Therefore, road density and freight volume reflect regional spatial connectivity and economic linkage intensity and may provide important information for predicting SPRCM. Furthermore, Network Theory suggests that regional development depends not only on the internal conditions of individual regions but also on interregional connections and network structures. In the context of collaborative pollution reduction and carbon mitigation, regions form complex networks through industrial linkages, technological exchanges, infrastructure connections, and environmental governance cooperation [4,45]. Core regions within these networks may possess stronger capacities for resource agglomeration and diffusion, whereas peripheral regions may face constraints due to limited network embeddedness [46,47]. Therefore, this study further applies social network analysis to characterize the spatial association structure of provincial SPRCM, aiming to reveal differences in network positions and functional roles among regions in collaborative governance networks.

3.2. Model Specification

3.2.1. Improved Entropy Weight–TOPSIS Method

Considering the differences in measurement scales among indicators, this study employs an improved entropy-weighted TOPSIS method to measure SPRCM development levels. This method offers two major advantages. First, it combines entropy weighting and the coefficient of variation method, using the average of the two weights as the final indicator weights, thereby considering both information content and regional heterogeneity [48]. Second, it adopts global panel min–max normalization based on fixed extreme values, avoiding the problem of intertemporal incomparability caused by year-by-year standardization and ensuring both cross-sectional and longitudinal comparability [49]. The TOPSIS method evaluates the relative distance between each observation and the positive and negative ideal solutions to achieve a comprehensive ranking of multidimensional indicators. Combined with the improved weighting approach, it enhances the robustness of the evaluation results. The main calculation steps are as follows:

First, the original data are normalized using global panel data standardization. For positive and negative indicators, the transformation formulas are as follows:

$$X'_{\theta ij} = \frac{X_{\theta ij} - \min(X_{\theta ij})}{\max(X_{\theta ij}) - \min(X_{\theta ij})} \quad (1)$$

$$X'_{\theta ij} = \frac{\max(X_{\theta ij}) - X_{\theta ij}}{\max(X_{\theta ij}) - \min(X_{\theta ij})} \quad (2)$$

Second, based on the standardized matrix, the entropy weighting procedure is applied to calculate the entropy weight of indicator j , denoted as W_{1j} . Meanwhile, the coefficient of variation method is used to calculate the variation coefficient of each indicator, generating the corresponding variation coefficient weight W_{2j} . Based on the calculated indicator weights, the weighted decision matrix R is constructed as follows:

$$W_j = \frac{W_{1j} + W_{2j}}{2} \quad (3)$$

$$R = (r_{\theta ij}), r_{\theta ij} = W_j \times X'_{\theta ij} \quad (4)$$

Finally, the relative closeness of each evaluation object to the ideal solution is calculated as $R_{\theta i}$:

$$R_{\theta i} = \frac{d_{\theta i}^-}{d_{\theta i}^+ + d_{\theta i}^-} \quad (5)$$

where $R_{\theta i}$ ranges from 0 to 1. A larger value of $R_{\theta i}$ indicates a higher level of SPRCM in province i during year θ , whereas a smaller value indicates a lower level of SPRCM.

3.2.2. Social Network Analysis

The traditional gravity model assumes that the intensity of regional interaction is mainly determined by the development scale and spatial distance between two regions. Specifically, regions with larger economic scales and shorter geographic distances tend to exhibit stronger linkages [46]. However, spatial associations of SPRCM are not solely determined by economic differences but are also closely related to regional governance capacity and green development performance. Therefore, following Fan and Wang, this study extends the traditional gravity model by incorporating population size, economic development level, and SPRCM level into the regional comprehensive influence index [46,47]. This extension aims to capture the potential role of regional green governance capacity in shaping spatial associations. Equation (6) is as follows.

$$F_{ij} = \frac{D_i}{D_i + D_j} * \frac{\sqrt[3]{P_i G_i D_i} \sqrt[3]{P_j G_j D_j}}{[d_{ij}]^2}, d_{ij} = \frac{ds_{ij}}{|agdp_i - agdp_j| + \theta} \quad (6)$$

where F_{ij} denotes the spatial association strength of SPRCM between provinces i and j ; P , G , D and $agdp$ represent provincial population, gross domestic product (GDP), the coordination degree of SPRCM, and GDP per capita, respectively. d_{ij} and ds_{ij} denote the geographic distance and economic distance between provinces, respectively. Population size reflects regional production activities and environmental governance demand, while GDP represents economic capacity and resource allocation capability. Together, these two factors characterize regional development scale and the foundation for green transition. Therefore, this study adopts a multiplicative form to construct the regional comprehensive scale indicator, capturing the combined effects of different scale-related factors rather than a simple linear additive relationship. This specification is also widely adopted in the existing literature. Although the per capita GDP values in this study are not equal to zero, a small positive constant θ is introduced following Wang's study to avoid potential computational issues caused by a zero denominator [47]. The value of θ is set to 0.01 to improve the numerical stability of the model.

3.2.3. CatBoost-SHAP Model

To identify the nonlinear driving mechanisms of Synergistic SPRCM, this study employs the CatBoost model to evaluate the importance and influence patterns of different

driving factors. CatBoost is an ensemble learning algorithm based on the Gradient Boosting Decision Tree framework [50]. By incorporating ordered boosting and symmetric tree structures, it effectively reduces prediction bias and mitigates overfitting. Compared with conventional linear econometric models, CatBoost does not require predefined functional relationships among variables and can capture complex nonlinear relationships and interaction effects [12,34]. Therefore, it is well suited for identifying and analyzing the determinants of SPRCM. The iterative process of the model can be expressed as follows:

$$F_t(x) = F_{t-1}(x) + \alpha \cdot h_t(x) \quad (7)$$

where $F_t(x)$ denotes the ensemble model obtained after the first $t - 1$ iterations, α represents the learning rate, and $h_t(x)$ denotes the weak decision tree learner generated in the t -th iteration.

Considering that machine learning models are often criticized for their limited interpretability, this study further introduces the SHAP method to explain the prediction results of the CatBoost model. Based on Shapley value theory from cooperative game theory, SHAP quantifies the marginal contribution of each feature to the model output and identifies both the magnitude and direction of its influence [51,52]. Moreover, SHAP satisfies an additive explanation framework, under which the model prediction can be decomposed into the sum of feature contributions, thereby improving the interpretability of machine learning results [53,54]. The SHAP decomposition is expressed as follows:

$$f(x) = \phi_0 + \sum_{i=1}^n \phi_i \quad (8)$$

where $f(x)$ represents the predicted value of the model, ϕ_0 denotes the baseline value calculated from the average prediction of all samples, and ϕ_i represents the SHAP contribution of the i -th explanatory variable. These values are used to identify the direction, marginal effect, and heterogeneous threshold characteristics of different driving factors.

3.3. Data Sources and Variable Selection

The study examines 31 provincial-level administrative regions in China (excluding Hong Kong, Macao, and Taiwan) and constructs a provincial panel dataset covering the period from 2010 to 2024. The data are primarily collected from official statistical sources, including the China Statistical Yearbook, China Energy Statistical Yearbook, China Environmental Statistical Yearbook, as well as the statistical bulletins on national economic and social development and water resources bulletins issued by provincial governments. CO₂ emissions data are obtained from the Emissions Database for Global Atmospheric Research (<https://edgar.jrc.ec.europa.eu/>, accessed on 22 July 2026). Missing values are addressed using linear interpolation.

Based on the theoretical framework of SPRCM, as well as the common-source and co-governance characteristics of pollutant and carbon emissions, this study develops an evaluation index system for SPRCM from four dimensions: environmental pressure, environmental governance, ecological status, and resource consumption (Table 1). The framework is designed to comprehensively capture the overall level of regional SPRCM. Specifically, environmental pressure reflects the pollution burden imposed by socioeconomic activities on the ecological environment. Environmental governance measures the capacity and effectiveness of pollution control and environmental management [3]. Ecological status represents regional ecological endowments and ecosystem support capacity [52]. Resource consumption reflects the constraints imposed by energy and resource use on green and low-carbon development [20,55]. To examine the robustness of the evaluation results, this study further applies the entropy weight method and the entropy-weighted

TOPSIS method for validation. The results show that the Pearson correlation coefficients among the SPRCM levels obtained from different evaluation approaches all exceed 0.8, indicating a high degree of consistency and robustness in both the indicator system and the evaluation results.

Table 1. Evaluation Index System for SPRCM.

Criterion Layer	Indicator Layer	Attribute	Weight
Environmental Pressure	Total Nitrogen Oxides (NO _x) Emissions	—	0.01353
	Total Sulfur Dioxide (SO ₂) Emissions	—	0.16880
	Smoke (Dust) Emissions	—	0.14479
	Carbon Dioxide (CO ₂) Emissions	—	0.14060
	Annual Average Concentration of Inhalable Particulate Matter	—	0.21636
	General Industrial Solid Waste Generation	—	0.10004
	Ammonia Nitrogen Emissions	—	0.00861
	Chemical Oxygen Demand Emissions	—	0.02570
Environmental Governance	Harmless Treatment Rate of Municipal Solid Waste	+	0.01891
	Urban Wastewater Treatment Capacity	+	0.01091
	Comprehensive Utilization of Industrial Solid Waste	+	0.02762
	Investment in Environmental Pollution Control	+	0.01866
Ecological Status	Total Water Resources	+	0.01963
	Forest Coverage Rate	+	0.01531
	Green Coverage Rate in Built-up Areas	+	0.04009
Resource Consumption	Coal Consumption	—	0.00498
	Crude Oil Consumption	—	0.01103
	Total Water Supply	—	0.01443

4. Results

4.1. Measurement Results of SPRCM

Spatiotemporal Evolution of SPRCM

Using the natural breaks method, the SPRCM level is classified into five categories: low coordination (0.00, 0.18], relatively low coordination (0.18, 0.23], moderate coordination (0.23, 0.26], relatively high coordination (0.26, 0.37], and high coordination (0.37, 0.49]. Furthermore, this study selects the years 2010, 2015, 2020, and 2024 for visualization analysis, and the spatiotemporal evolution patterns are presented in Figure 1. In terms of coordination-level distribution, the hierarchical structure of provincial SPRCM has continuously improved. In 2010, four provinces were classified as having low coordination, eight as relatively low coordination, seven as moderate coordination, ten as relatively high coordination, and two as high coordination. By 2024, the number of provinces in the low coordination category decreased to three, while those in the relatively low, moderate, relatively high, and high coordination categories were five, two, fifteen, and six, respectively. Overall, SPRCM levels across China gradually shifted toward higher coordination categories.

From the perspective of spatial distribution, SPRCM exhibits significant regional disparities. Eastern coastal provinces generally maintained relatively high coordination levels, whereas the central and western regions showed more pronounced internal differentiation. Guangdong and Tibet remained consistently within the high coordination category during the study period, but their development pathways differed substantially. Tibet's industrial structure is dominated by agriculture, animal husbandry, and ecological tourism, with limited heavy industrial activities and relatively low pollution and carbon emission pressures. Meanwhile, as a key national ecological security barrier and an important ecological functional area, Tibet has implemented strict ecological protection policies and promoted

clean energy development, providing a favorable ecological foundation for coordinated governance [56]. In contrast, Guangdong has a large economic scale and intensive industrial activities, resulting in relatively high initial pollution and carbon emission pressures [6]. However, relying on a mature green innovation system, well-established environmental governance mechanisms, and continuous industrial transformation toward greener development, Guangdong has achieved simultaneous improvements in pollution control and carbon reduction under conditions of high development intensity [4].

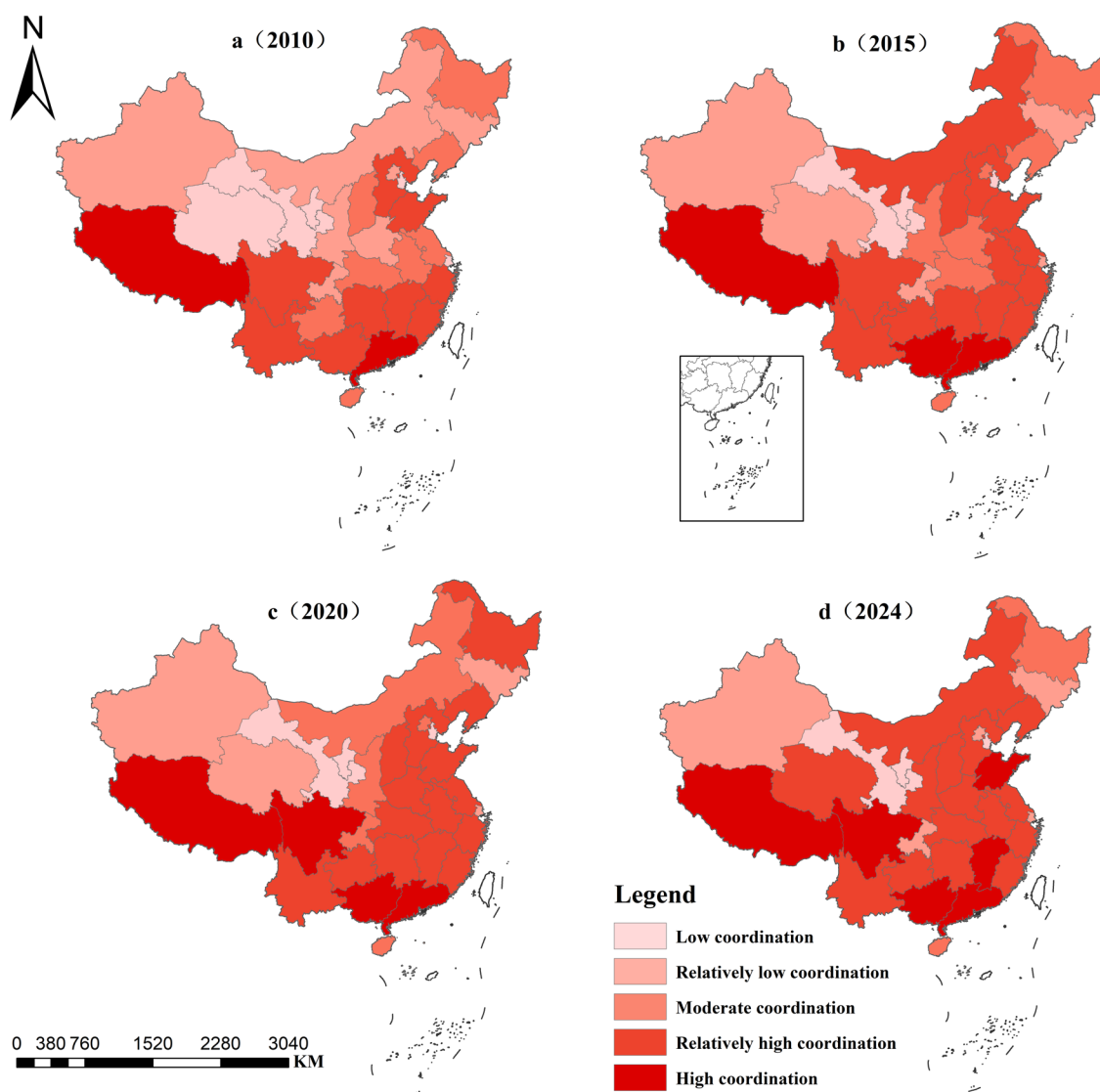


Figure 1. Spatiotemporal evolution of provincial SPRCM in China.

4.2. Spatial Association Network Analysis of SPRCM

4.2.1. Spatiotemporal Evolution of the Spatial Association Network of SPRCM

To further characterize the spatial association relationships of SPRCM among provinces, this study first applies the modified gravity model to calculate the spatial association intensity between each pair of provinces and constructs a 31×31 spatial association matrix, denoted as $F = (F_{ij})$ [7,46]. However, the association values derived from the gravity model are continuous measures that capture the strength of interprovincial linkages but cannot be directly applied to social network analysis. Therefore, following the treatment commonly adopted in social network studies, this study further transforms the continuous association matrix into a directed binary relational matrix [47]. Specifically, the

mean threshold method is employed to determine the existence of network ties [4,57]. If the spatial association intensity between province i and province j exceeds the average value of all association intensities during the study period, the two provinces are considered to have a spatial association relationship; otherwise, no direct linkage is identified:

$$A_{ij} = \begin{cases} 1, & F_{ij} > \bar{F} \\ 0, & F_{ij} \leq \bar{F} \end{cases} \quad (9)$$

where A_{ij} indicates whether a spatial association exists between province i and province j , and $\bar{F}$ represents the average value of all interprovincial association intensities.

Subsequently, the natural breaks method was applied to classify the gravity values into five levels: level 1 network (0, 800], level 2 network (800, 3000], level 3 network (3000, 5200], level 4 network (5200, 7400], and level 5 network (7400, 73,602]. ArcMap10.7 was then used to visualize the spatial association network topology (Figure 2). Overall, the spatial association network of SPRCM exhibited an expanding trend during the study period. The network structure gradually evolved from an early stage characterized by weak connections and low-intensity linkages into a multi-level and multi-node spatial network system. In 2010, the provincial SPRCM network was mainly composed of low- and medium-low-intensity associations, with only a limited number of high-intensity linkage channels, indicating relatively weak overall connectivity. By 2024, a multi-core and hierarchical spatial association pattern had gradually emerged, with a substantial increase in high-intensity linkage channels and stronger interprovincial connections. From a spatial perspective, the core areas of the network were primarily concentrated in eastern coastal regions. Provinces such as Beijing, Tianjin, Hebei, Shandong, Jiangsu, Shanghai, and Zhejiang gradually became important nodes in China's SPRCM network, demonstrating stronger connectivity and higher central positions. Meanwhile, spatial associations between central provinces and eastern core regions continued to strengthen, and their participation in the network gradually increased, allowing them to serve as important transitional areas connecting different regions. In contrast, western provinces exhibited significant internal disparities. Provinces such as Sichuan, Chongqing, and Shaanxi maintained relatively strong modeled associations with other regions, whereas Xinjiang, Qinghai, and Gansu were still characterized by low-intensity associations and remained relatively peripheral within the network.

4.2.2. Overall Network Characteristics of SPRCM

The overall structural characteristics of the spatial association network of SPRCM across Chinese provinces from 2010 to 2024 were measured using Ucinet6.212 software (Figure 3). In terms of the number of network ties, the value increased from 194 in 2010 to 218 in 2014, then declined to 187 during 2014–2021, before rebounding to 206 in 2024. This pattern reflects a stage-specific evolution characterized by “expansion–contraction–recovery.” The results indicate that interprovincial collaborative linkages in SPRCM generally strengthened over the study period. However, influenced by regional development disparities and network restructuring, the scale of interprovincial associations contracted during the middle stage. With the continued advancement of regional collaborative governance, network connections subsequently recovered and expanded. In terms of network density, the value remained within a narrow range of 0.201–0.229 throughout the study period, exhibiting only minor fluctuations and indicating strong structural stability of the network. Regarding network hierarchy, the index remained around 0.54 during 2010–2018, increased to above 0.57 during 2019–2021, and then declined to 0.539 in 2024. This finding suggests that network resources and connections became increasingly concentrated in a

small number of core provinces during the middle stage, resulting in stronger hierarchical differentiation. In the later stage, however, a growing number of provinces became involved in cross-regional collaborative governance. The radiation effects of core nodes gradually expanded, leading to a reduction in hierarchical disparities and a partial mitigation of network polarization. In terms of network efficiency, the index exhibited an inverted U-shaped trend, rising from 0.664 in 2010 to 0.717 in 2021 and then falling to 0.691 in 2024. The improvement in network efficiency indicates that redundant linkages decreased during the early stage, while the transmission pathways of information and resources became more efficient. The subsequent decline in efficiency reflects the continuous emergence of new association ties, increasing network complexity and reintroducing a certain degree of redundancy into the network structure.

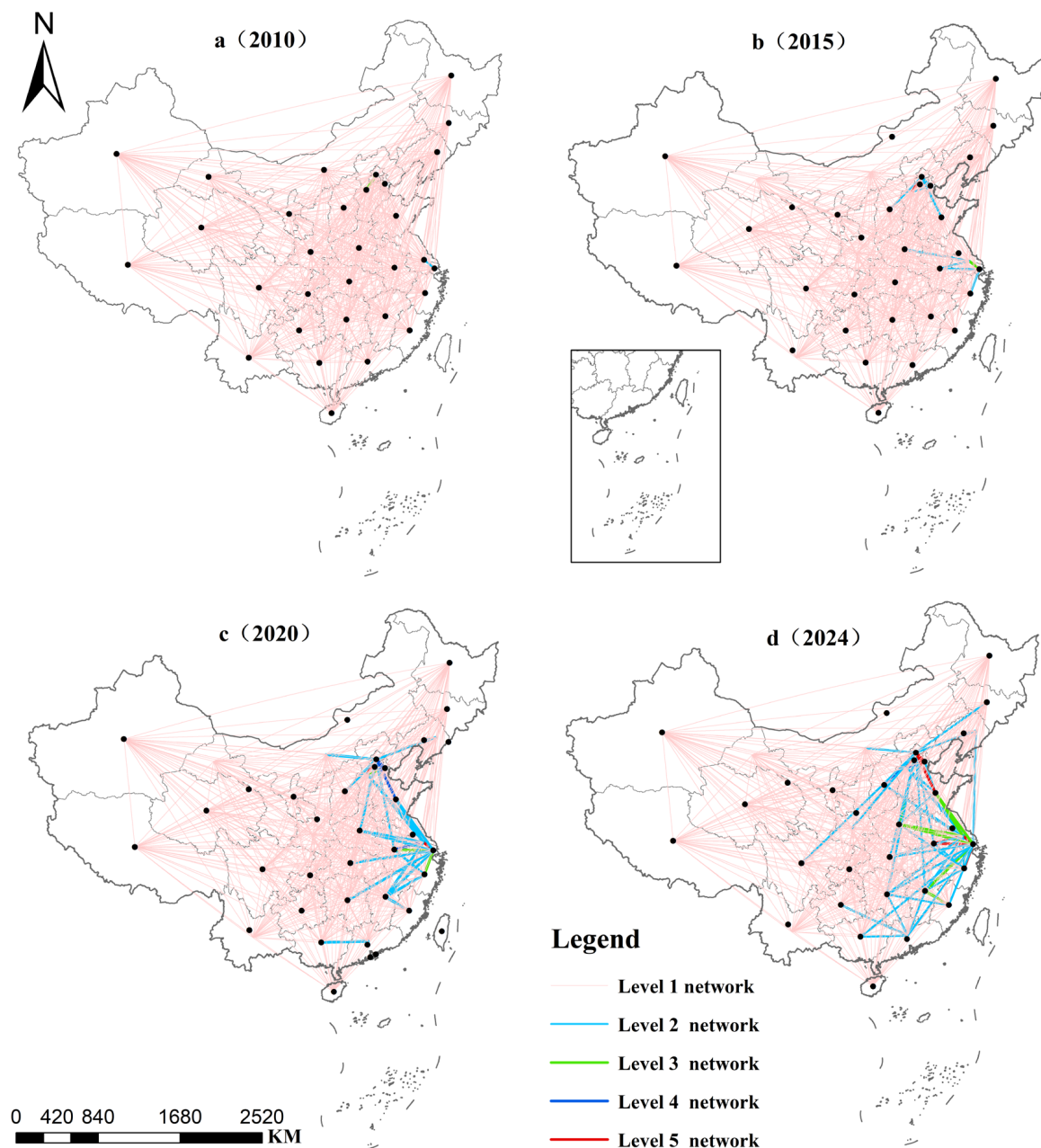


Figure 2. The Spatial Association Network of SPRCM.

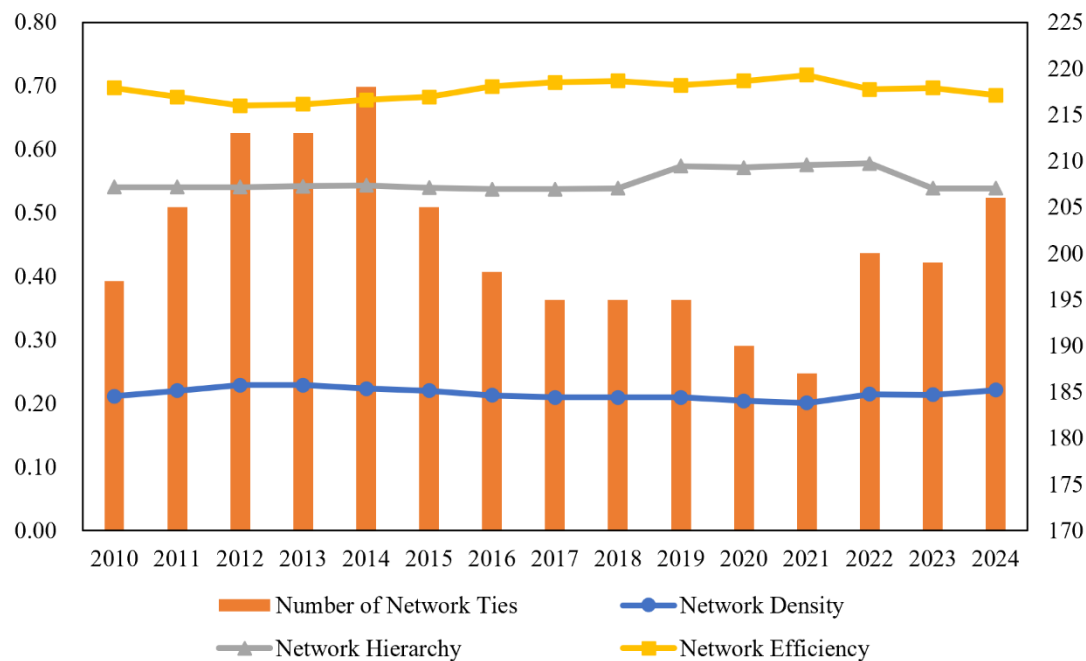


Figure 3. Temporal Evolution of Overall Network Characteristic Indicators.

4.2.3. Individual Network Characteristics of SPRCM

Individual network characteristics of the provincial SPRCM spatial association network in 2010 and 2024 are reported in Table 2. The two values under each indicator represent the measurement results for 2010 and 2024, respectively, allowing a comparison of changes in provincial structural positions within the network. First, out-degree and in-degree capture a province's external connectivity and its capacity to receive associations from other provinces, respectively. From 2010 to 2024, most provinces experienced increases in network connectivity, indicating that interprovincial SPRCM associations have become increasingly strengthened. In 2024, eastern coastal provinces generally exhibited higher levels of both out-degree and in-degree. Guangdong, Hubei, Guizhou, and Gansu recorded an out-degree of 9, suggesting that these provinces established extensive spatial linkages with other regions. Meanwhile, Shanghai, Beijing, Jiangsu, and Zhejiang ranked among the highest in in-degree, indicating strong network attractiveness and their important positions as key nodes in the national SPRCM association network. In contrast, some northwestern provinces exhibited in-degrees close to zero, implying relatively limited linkages with other provinces.

Table 2. Individual Network Metrics of SPRCM for 2010 and 2024.

Province	Out-Degree (2010, 2024)	In-Degree (2010, 2024)	Betweenness Centrality (2010, 2024)	In-Closeness Centrality (2010, 2024)	Out-Closeness Centrality (2010, 2024)
Shanghai	6, 6	27, 27	35.025, 31.678	88.235, 88.235	7.895, 7.813
Beijing	4, 5	25, 26	59.231, 110.146	85.714, 88.235	7.653, 7.792
Jiangsu	5, 6	25, 26	30.161, 39.999	83.333, 85.714	7.833, 7.813
Zhejiang	6, 6	24, 21	66.185, 35.404	81.081, 73.171	7.874, 7.833
Guangdong	8, 9	19, 12	155.929, 50.725	63.830, 51.724	8.021, 8.065
Shandong	8, 5	13, 9	49.292, 17.434	63.830, 58.824	7.937, 7.813
Tianjin	4, 3	14, 6	18.892, 2.632	62.500, 52.632	7.653, 7.557
Anhui	5, 5	6, 4	25.555, 6.085	54.545, 50.000	7.979, 7.853
Henan	7, 7	4, 11	26.464, 71.328	52.632, 61.224	8.021, 7.979

Table 2. Cont.

Province	Out-Degree (2010, 2024)	In-Degree (2010, 2024)	Betweenness Centrality (2010, 2024)	In-Closeness Centrality (2010, 2024)	Out-Closeness Centrality (2010, 2024)
Hebei	2, 2	4, 5	0.000, 2.967	50.847, 53.571	7.335, 7.463
Jiangxi	6, 6	5, 6	26.059, 20.231	50.847, 51.724	8.021, 7.937
Shanxi	6, 7	3, 2	12.200, 30.264	48.387, 48.387	7.772, 7.792
Hunan	6, 8	4, 7	9.188, 15.710	48.387, 49.18	8.021, 8.000
Hubei	5, 9	2, 8	2.245, 45.767	46.875, 48.387	7.979, 8.065
Fujian	7, 7	9, 17	11.015, 46.724	42.254, 62.5	7.895, 7.895
Guangxi	6, 8	2, 6	3.841, 5.057	40.541, 45.455	8.021, 8.000
Guizhou	9, 9	2, 3	33.147, 55.850	40.000, 38.961	8.108, 8.086
Sichuan	7, 8	2, 1	3.275, 0.817	40.000, 22.901	8.043, 8.065
Yunnan	6, 8	1, 0	1.813, 0.000	39.474, 3.226	8.021, 8.746
Chongqing	7, 8	1, 3	0.500, 31.142	28.846, 29.412	8.065, 8.065
Liaoning	6, 5	2, 1	1.000, 0.000	3.448, 3.333	9.317, 8.357
Jilin	8, 7	1, 0	6.200, 0.000	3.444, 3.226	9.524, 9.146
Inner Mongolia	6, 6	1, 4	0.583, 3.790	3.444, 35.714	8.357, 7.853
Gansu	8, 9	1, 1	1.200, 2.250	3.333, 3.333	9.524, 8.721
Qinghai	8, 8	0, 0	0.000, 0.000	3.226, 3.226	8.746, 8.696
Heilongjiang	8, 7	0, 0	0.000, 0.000	3.226, 3.226	10.49, 8.547
Tibet	7, 6	0, 0	0.000, 0.000	3.226, 3.226	8.721, 8.596
Ningxia	7, 6	0, 0	0.000, 0.000	3.226, 3.226	8.696, 8.547
Hainan	6, 7	0, 0	0.000, 0.000	3.226, 3.226	8.696, 8.646
Shaanxi	6, 6	0, 0	0.000, 0.000	3.226, 3.226	8.671, 8.547
Xinjiang	7, 7	0, 0	0.000, 0.000	3.226, 3.226	10.453, 9.464

Note: This study adopts the default Freeman normalization method in Ucinet6.212 to calculate individual network characteristic indicators. The two columns of values in the table represent the model outputs for 2010 and 2024, respectively.

Second, betweenness centrality measures the bridging role and information connectivity capacity of a node within the network. The results show that Beijing's betweenness centrality increased from 59.231 in 2010 to 110.146 in 2024, indicating that it plays an important intermediary and connecting role and serves as a key hub for cross-regional collaborative linkages. In contrast, most provinces in the northwestern region exhibit betweenness centrality values close to zero, suggesting their limited intermediary roles within the SPRCM spatial association network. Third, in-closeness centrality reflects a province's ability to receive external associations. Shanghai, Beijing, Jiangsu, and Zhejiang consistently maintained high levels of in-closeness centrality, indicating strong network agglomeration advantages. By comparison, provinces such as Qinghai, Heilongjiang, Tibet, Ningxia, Hainan, Shaanxi, and Xinjiang showed relatively lower in-closeness centrality, suggesting that their degree of network embeddedness still requires improvement. Finally, out-closeness centrality captures the breadth of a province's external connections. Xinjiang and Jilin exhibited relatively high out-closeness centrality, indicating strong external connectivity. However, compared with eastern core provinces, their network influence and capacity to attract collaborative resources remain relatively limited.

It should be noted that this study employs the built-in Freeman normalization method in Ucinet6.212 to calculate various centrality indicators. Unlike some previous studies that apply 0–1 normalization, Freeman-standardized closeness centrality is not restricted to the interval of [0, 1]. Its value range depends on the total number of network nodes and the shortest path structure. Therefore, values of out-closeness centrality exceeding 10 and in-closeness centrality values of approximately 3.226 for peripheral provinces are reasonable outcomes under this normalization approach. In addition, some provinces exhibit an in-degree of zero. In-degree represents the number of direct incoming connections

received by a node, whereas closeness centrality measures a node's accessibility within the entire network, namely its ability to establish connections with other nodes through both direct and indirect paths. Therefore, in a directed network, closeness centrality reflects network-based accessibility rather than simply the number of direct incoming links. Consequently, even if a node has no direct incoming connections, its closeness centrality can still be calculated when it maintains effective paths to other nodes through intermediate provinces.

4.3. Block Model Analysis of SPRCM

For network block identification, this study applies the Convergence of Iterated Correlations (CONCOR) method to classify regions with similar structural positions within the network. CONCOR performs iterative correlation calculations on the network relationship matrix and groups regions based on structural similarity. In this study, the maximum partition depth was set to 2, the convergence criterion was set to 0.200, and the maximum number of iterations was set to 25. Accordingly, the 31 provinces were classified into four functional blocks (Table 3). In 2010, based on the block model classification criteria, the four blocks were categorized as follows. For Block I, the actual internal relationship ratio (7.14%) was lower than the expected internal relationship ratio (33.33%). The number of outgoing spillover ties (65) and incoming ties (20) was relatively balanced. Therefore, it was classified as a broker block. For Block II, the actual internal relationship ratio (8.86%) was lower than the expected ratio (36.67%). Its outgoing spillover ties (72) substantially exceeded its incoming ties (9), indicating a net spillover block. For Block III, the actual internal relationship ratio (37.50%) exceeded the expected ratio (6.67%). The difference between outgoing spillover ties (10) and incoming ties (46) was relatively small. Thus, it was identified as a bidirectional spillover block. For Block IV, the actual internal relationship ratio (25.00%) was higher than the expected ratio (13.33%). Its incoming ties (96) far exceeded its outgoing spillover ties (24), and it was therefore classified as a net beneficiary block.

Table 3. Spillover Effects of Different Blocks in the SPRCM Spatial Association Network.

Year	Block	I	II	III	IV	Number of Provinces in the Block	Number of Outgoing Inter-Block Ties	Number of Incoming Inter-Block Ties	Expected Internal Relationship Ratio	Actual Internal Relationship Ratio
2010	I	5	0	13	52	11	65	20	33.33%	7.14%
	II	0	7	31	41	12	72	9	36.67%	8.86%
	III	1	6	6	3	3	10	46	6.67%	37.50%
	IV	19	3	2	8	5	24	96	13.33%	25.00%
2024	I	14	0	97	5	16	102	28	50.00%	12.07%
	II	0	1	18	9	5	27	7	13.33%	3.57%
	III	26	3	15	4	7	33	122	20.00%	31.25%
	IV	2	4	7	1	3	13	18	6.67%	7.14%

Note: Blocks I–IV represent the four network blocks identified through the CONCOR analysis, reflecting the different positions of provinces within the SPRCM spatial association network.

By 2024, the composition of the four blocks had changed substantially. In Block I, the actual internal relationship ratio (12.07%) remained below the expected ratio (50.00%), while outgoing spillover ties (102) greatly exceeded incoming ties (28), leading to its reclassification as a net spillover block. In Block II, the actual internal relationship ratio (3.57%) was lower than the expected ratio (13.33%), and the difference between outgoing spillover ties (27) and incoming ties (7) was relatively small. Thus, it was categorized as a broker block. In Block III, the actual internal relationship ratio (31.25%) exceeded the expected ratio (20.00%), while incoming ties (122) far outnumbered outgoing spillover ties

(33), indicating a net beneficiary block. In Block IV, the actual internal relationship ratio (7.14%) was slightly higher than the expected ratio (6.67%), and the difference between outgoing spillover ties (13) and incoming ties (18) was relatively limited. Therefore, it was identified as a bidirectional spillover block.

To further reveal the provincial composition of each block and its evolution within the SPRCM spatial association network, the spatial distribution patterns of the four blocks in 2010 and 2024 were mapped (Figure 4). A comparison of the two periods shows substantial adjustments in the functional roles of provinces within the network. Specifically, Hebei, Shanxi, Liaoning, Heilongjiang, and Jilin, which belonged to the net spillover block in 2010, shifted to the broker block by 2024. This transition indicates that their network functions evolved from simple association output toward facilitating interregional connections and resource transmission. Meanwhile, Anhui, Jiangxi, Sichuan, Guizhou, Guangxi, Hainan, Chongqing, Hunan, Yunnan, and Tibet, which were originally classified as broker blocks, shifted to the net spillover block. Their external connectivity and spillover functions were further strengthened, making them important output nodes within the spatial association network. In addition, Hubei transitioned from the broker block to the net beneficiary block, while Beijing moved from the bidirectional spillover block to the net beneficiary block, indicating a continuous enhancement of their capacity to attract network connections within the SPRCM spatial association network.

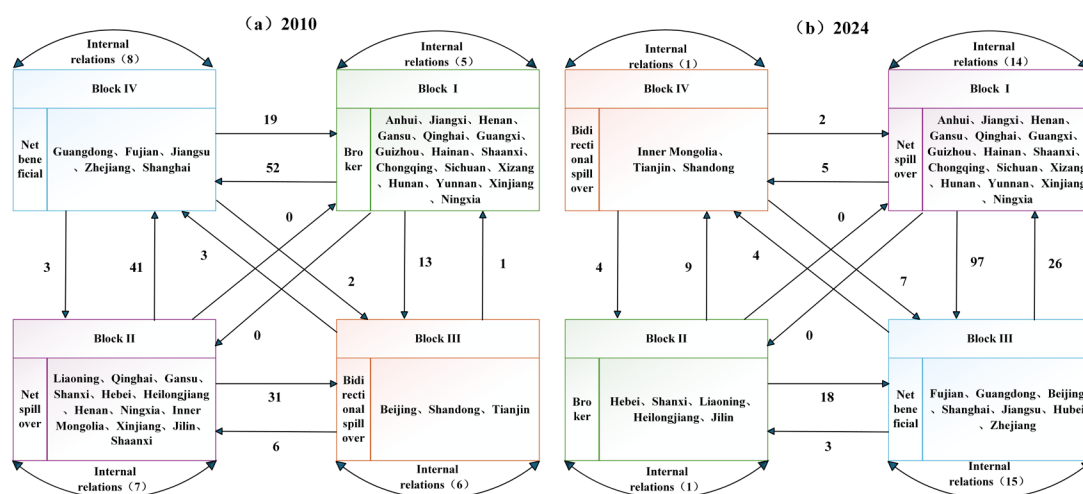


Figure 4. Association Relationships among the Four Blocks in the SPRCM Network.

From the perspective of block stability, Henan, Gansu, Qinghai, Shaanxi, Ningxia, and Xinjiang consistently remained in the net spillover block throughout the study period and continued to perform association output functions. Tianjin and Shandong persistently belonged to the bidirectional spillover block, serving both as resource recipients and spillover sources. Guangdong, Fujian, Jiangsu, Zhejiang, and Shanghai consistently remained within the net beneficiary block and functioned as major aggregation centers in the national SPRCM network, maintaining relatively stable network positions. Overall, the block structure of China's SPRCM spatial association network underwent substantial reconfiguration between 2010 and 2024. On the one hand, several traditional industrial provinces in northern China gradually evolved from simple spillover providers into organizers and coordinators of network linkages [6]. On the other hand, provinces in central and western China strengthened their spillover functions and became increasingly integrated into the network [42,56]. At the same time, the developed eastern coastal regions maintained their core positions by virtue of stronger green innovation capacity, superior resource allocation capability, and institutional advantages [1,39]. These changes indicate that the national

SPRCM network is gradually evolving from a relatively simple core–periphery structure toward a more collaborative and multi-level network system characterized by multiple participating centers and stronger interregional linkages.

To further reveal the inter-block linkage structure within the SPRCM spatial association network constructed based on the gravity model, this study employs density matrix and image matrix analyses to examine the relational characteristics and potential interaction directions among different blocks. The results are presented in Table 4. From the perspective of intra-block association characteristics, in 2010 only Blocks III and IV exhibited internal densities exceeding the average network density threshold (0.2118), with corresponding diagonal entries in the image matrix equal to 1. This indicates strong internal linkages among provinces within these blocks and the presence of pronounced club convergence effects. In particular, the internal density of Block III reached 1.000, demonstrating extremely strong internal cohesion. By contrast, the internal densities of Blocks I and II were substantially below the threshold, suggesting relatively weak collaborative linkages among member provinces and the absence of stable intra-block interaction networks. Regarding inter-block spillover relationships, both Block I and Block II generated significant spillover effects toward Blocks III and IV in 2010, while Block IV also exerted a reverse spillover effect on Block I, forming several prominent cross-block transmission channels. In contrast, although Block III displayed strong internal cohesion, it lacked significant outward spillover capacity and primarily functioned as a recipient of external linkages. Overall, the network structure in 2010 exhibited a pattern characterized by the dominance of the net spillover block, the concentration of the net beneficiary block, and the linkage of the two-way spillover block. Inter-block connections were mainly established through a limited number of core association channels.

Table 4. Density Matrix and Image Matrix of the Blocks.

Year	Block	Density Matrix				Image Matrix			
		I	II	III	IV	I	II	III	IV
2010	I	0.045	0.000	0.394	0.945	0	0	1	1
	II	0.000	0.053	0.861	0.683	0	0	1	1
	III	0.030	0.167	1.000	0.200	0	0	1	0
	IV	0.345	0.050	0.133	0.400	1	0	0	1
2024	I	0.058	0.000	0.866	0.104	0	0	1	0
	II	0.000	0.050	0.514	0.600	0	0	1	1
	III	0.232	0.086	0.357	0.190	1	0	1	0
	IV	0.042	0.267	0.333	0.167	0	1	1	0

Compared with 2010, the inter-block association structure changed substantially by 2024. In terms of intra-block relationships, only Block III maintained an internal density above the average network density threshold of that year (0.2215), indicating that it continued to exhibit strong internal clustering characteristics. The internal densities of all other blocks remained below the threshold, suggesting weaker intra-block collaborative linkages and a noticeable decline in club convergence effects. Regarding cross-block spillover relationships, multiple transmission pathways emerged in 2024, including “Block I → Block III,” “Block II → Blocks III and IV,” “Block III → Block I,” and “Block IV → Blocks II and III.” These patterns indicate a more complex inter-block association structure than that observed in 2010. Notably, Block III gradually evolved from a passive recipient into a key node with both receiving and feedback functions, and the direction of network transmission became increasingly bidirectional. Meanwhile, the number of outward transmission channels from Block I declined markedly, and its network role gradually shifted from cross-block

transmission toward the reception of external linkages. Overall, between 2010 and 2024, the block structure of the SPRCM spatial association network evolved from a relatively unidirectional hierarchical transmission pattern into a multi-directional and multi-actor interactive network. Although the number of inter-block transmission channels increased and cross-regional collaborative linkages became stronger, internal interactions remained relatively weak in most blocks except Block III. This finding suggests that improvements in cross-regional collaboration have not been accompanied by equivalent strengthening of intra-regional coordination, resulting in a persistent imbalance between external and internal collaborative development.

4.4. Association Factors of SPRCM

4.4.1. Selection of Association Factor Indicators

SPRCM is a comprehensive outcome shaped by the joint effects of economic development, social structural transformation, and resource allocation [2,58,59]. Based on relevant theoretical foundations, existing studies, and data availability, this study selects 11 explanatory variables from three dimensions: economic foundation, social structure, and factor endowment, to identify the relative contributions and association patterns of different factors in predicting SPRCM [7,21,60]. Specifically, the economic foundation dimension includes the economic development level, green finance development level, the proportion of environmental protection expenditure, and social consumption level [20,61]. These variables mainly reflect regional economic conditions, financial resource allocation capacity, and consumption structure characteristics. The social structure dimension includes the urbanization rate, industrial structure upgrading, and industrialization level, which capture population agglomeration, industrial transformation, and industrial development characteristics [20,61]. The factor endowment dimension includes human capital level, green technology innovation level, road density, and freight transport volume, representing regional innovation resources, infrastructure conditions, and economic connectivity [40,62,63]. The definitions of all variables are provided in Table 5.

Table 5. Definition of Associated Indicators.

Dimension	Variables	Measurement	Unit
Economic Foundation	Economic development level (X1)	Logarithm of GDP per capita	CNY/person
	Green finance development level (X2)	Entropy method	—
	Proportion of environmental protection expenditure (X3)	Environmental protection expenditure/Local general public budget expenditure	%
	Social consumption level (X4)	Total retail sales of consumer goods/GDP	%
Social Structure	Urbanization rate (X5)	Urban population/Total population	%
	Industrial structure upgrading (X6)	Value added of tertiary industry/Value added of secondary industry	%
	Industrialization level (X7)	Industrial value added/Regional GDP	%

Table 5. Cont.

Dimension	Variables	Measurement	Unit
Factor Endowment	Human capital level (X8)	Number of students enrolled in higher education institutions/Total population	%
	Green technology innovation level (X9)	Number of green patents per 10 ⁴ people	patents/10 ⁴ persons
	Road density (X10)	Road mileage/Administrative area	km/km ²
	Freight transport volume (X11)	Freight transport volume/GDP	tons/10 ⁴ CNY

4.4.2. Model Selection

Considering that the explanatory variables differ in measurement scales and value ranges, this study first divides the sample into a training set and a test set. Specifically, 80% of the samples are used for model training, while the remaining 20% are reserved as an independent test set to evaluate the model's generalization ability [64]. To ensure reproducibility, a fixed random seed (random_state = 42) is set during the sample partitioning process. Subsequently, continuous explanatory variables are standardized using Z-score normalization based on the mean and standard deviation of the training set, and the same transformation rules are applied to the test set [64]. This procedure improves the comparability among variables and avoids potential information leakage during data processing. In addition, to reduce estimation bias caused by a single sample split, this study applies 5-fold cross-validation during model training and hyperparameter optimization. The training set is further divided into five subsets, and model training and validation are performed iteratively to evaluate the stability of model prediction performance [52]. Furthermore, the Grid Search method is employed for hyperparameter optimization. By comparing cross-validation results under different parameter combinations, the optimal model parameters are determined. The final optimal parameter combination is obtained as follows: learning_rate = 0.05, max_depth = 5, and n_estimators = 400 [52].

To evaluate the predictive performance of different machine learning models, this study compares five evaluation metrics, including mean absolute error (MAE), mean absolute percentage error (MAPE), mean squared error (MSE), root mean squared error (RMSE), and coefficient of determination (R^2) [65]. The results are presented in Table 6. Smaller error values and a higher R^2 indicate better model performance. The results show that the CatBoost model achieves the best overall performance across the evaluation metrics. Specifically, the RMSE of CatBoost is 0.0385, which is lower than that of LightGBM (0.0398) and XGBoost (0.0405), indicating smaller prediction errors and stronger fitting capability. Meanwhile, the R^2 of CatBoost reaches 0.7141, suggesting that the model explains 71.41% of the variation in SPRCM levels, which is higher than LightGBM (0.6942) and XGBoost (0.6835) [65]. Overall, CatBoost demonstrates advantages in both predictive accuracy and interpretability. Therefore, this study selects CatBoost as the baseline model for subsequent analysis of the driving factors of SPRCM.

Table 6. Model Evaluation Results.

Model	MAE	MAPE	MSE	RMSE	R^2
LightGBM	0.0271	0.0915	0.0016	0.0398	0.6942
XGBoost	0.0257	0.0899	0.0016	0.0405	0.6835
CatBoost	0.0254	0.0910	0.0015	0.0385	0.7141
SVR	0.0499	0.1945	0.0036	0.0596	0.3147
RF	0.0274	0.0947	0.0017	0.0417	0.6657

Table 6. Cont.

Model	MAE	MAPE	MSE	RMSE	R ²
DT	0.0340	0.1191	0.0033	0.0572	0.3687
GBR	0.0307	0.1109	0.0018	0.0429	0.6446

4.4.3. Feature Importance Ranking

Building on the optimal CatBoost model, this study further calculates the SHAP values and contribution shares of each explanatory variable (Figure 5). It identifies the relative contributions of different factors to the predicted SPRCM outcomes from both dimensional and variable perspectives. It also examines the potential nonlinear association patterns between key variables and SPRCM levels. From the dimensional perspective, the factor endowment dimension has the highest average SHAP contribution share, accounting for 56.29%, and represents the most influential category in the model prediction. The economic foundation and social structure dimensions contribute 22.02% and 21.70%, respectively. These results indicate that, within the CatBoost prediction framework, factor endowment-related variables contain more information for explaining differences in SPRCM levels. This may be because the factor endowment dimension includes variables such as human capital, green technology innovation, and transportation infrastructure [7]. These indicators not only reflect regional development capacity and innovation resource accumulation but also capture conditions related to interregional factor flows and spatial connectivity [66]. Therefore, they provide greater information contributions during the prediction process. From the perspectives of spatial spillover theory and network theory, transportation infrastructure and innovation resources are closely associated with knowledge diffusion, technological exchange, and the transfer of governance experience across regions [24]. Thus, they provide important information for explaining spatial disparities in SPRCM. In contrast, although the economic foundation and social structure dimensions also contribute to model prediction, their relatively lower contributions suggest that variables such as economic development level, financial development, fiscal support, urbanization, and industrial structure contain comparatively limited predictive information within the current sample and modeling framework.

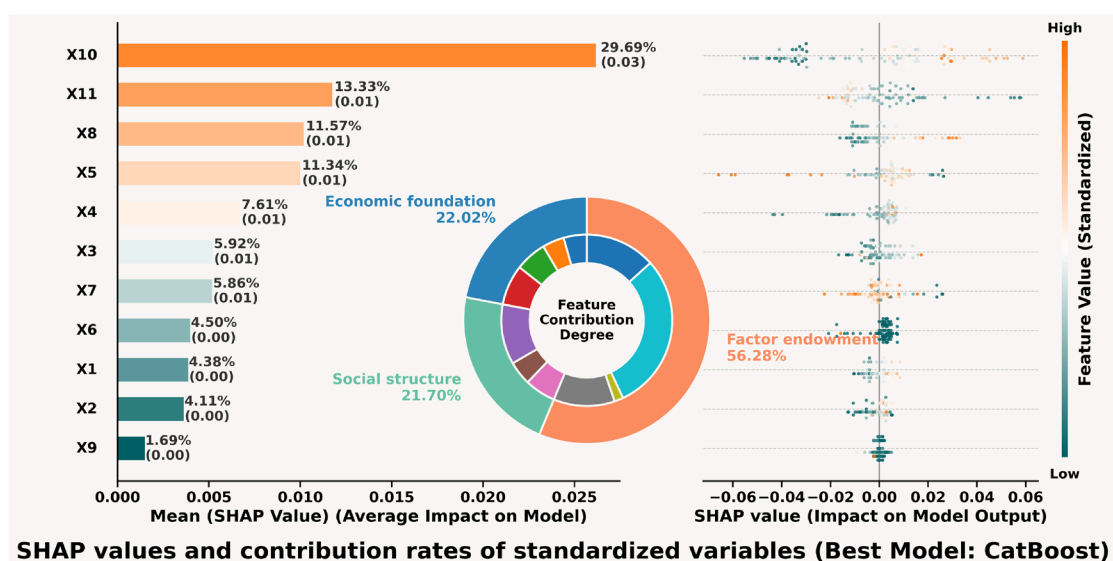


Figure 5. SHAP-Based Feature Importance Interpretation in the CatBoost Prediction Model.

At the individual variable level, road density (X10) exhibits the highest average SHAP contribution, accounting for 29.69% of the total contribution, making it the most

influential variable in predicting SPRCM levels. This finding indicates that transportation infrastructure-related information provides substantial explanatory value in the model prediction process. Its high importance may be associated with regional connectivity, factor mobility, and resource allocation efficiency [11,18,63]. Specifically, well-developed transportation networks may reflect stronger economic linkages and spatial interactions among regions, and they may also be related to the diffusion of green technologies, industrial cooperation, and environmental governance information exchange [6,14]. Therefore, transportation infrastructure can provide important information for explaining differences in SPRCM levels across regions. Freight volume (X11) contributes 13.33% of the total SHAP importance and ranks second, suggesting that the intensity of regional economic activities and industrial connectivity contain important predictive information. Its contribution may be related to factor mobility, industrial linkages, and interregional economic interactions [19,20]. Human capital (X8) ranks third, with a contribution of 11.57%, indicating that talent resources provide valuable information for model prediction. This may reflect regional innovation capacity, the potential for green technology application, and the foundation of environmental governance capacity. Urbanization rate (X5) also contributes 11.57%, suggesting that information related to population concentration and urban development has considerable explanatory value for SPRCM prediction. Its importance may be associated with infrastructure improvement, public service provision, and changes in resource allocation patterns [7,67]. In addition, social consumption level (X4), environmental protection expenditure ratio (X3), industrialization level (X7), and industrial structure upgrading (X6) also show certain predictive contributions, although their individual contributions are all below 10%. Overall, the SHAP results indicate that regional connectivity, innovation resource accumulation, and development conditions are important sources of information for predicting differences in SPRCM levels. However, these findings should be interpreted as reflecting complex association patterns between variables and SPRCM rather than strict causal effects.

To further examine the robustness of the CatBoost-based findings, this study conducts a sensitivity analysis using LightGBM as an alternative machine learning model. Since different ensemble learning algorithms employ distinct mechanisms for capturing nonlinear relationships and variable interactions, consistent rankings of key variables across models would indicate that the findings are not driven by a specific algorithmic specification. The results show that both CatBoost and LightGBM identify X10 (road density), X11 (freight volume), X8 (human capital), and X5 (urbanization rate) as the most important variables. Among them, X10 ranks first in both models, with contribution proportions of 29.69% and 29.88%, respectively. In addition, both models indicate that the factor endowment dimension provides the highest information contribution, accounting for 56.29% and 58.33%, respectively. These results suggest that the identification of key contributing factors and the underlying contribution structure of SPRCM is robust across different machine learning models.

4.4.4. Nonlinear Association Patterns Between Key Factors and SPRCM

Figure 6 further presents the SHAP dependence plots of the six most important variables to identify potential nonlinear association patterns between different factors and the predicted SPRCM outcomes. As shown in Figure 6, all variables exhibit varying degrees of nonlinear relationships with the predicted SPRCM values. Specifically, the SHAP values of road density (X10) show an inverted U-shaped pattern, increasing initially and then declining gradually. At relatively low levels, the SHAP values of X10 are mainly negative. As road density increases, its contribution gradually becomes positive, accompanied by a noticeable turning point [68]. This finding suggests that, within the sample range, transportation

infrastructure and SPRCM predictions exhibit a nonlinear association, which may be related to regional factor mobility, resource allocation efficiency, and technological diffusion capacity. Freight volume (X11) demonstrates a gradual declining trend followed by stabilization. At lower levels, X11 presents relatively higher SHAP values, while its contribution gradually decreases and becomes stable as the indicator increases. This pattern indicates that freight activity and SPRCM may have a complex nonlinear association, which is likely influenced by economic activity intensity, industrial structure, and energy utilization patterns [69]. Human capital (X8) exhibits a relatively clear increasing nonlinear pattern. As X8 increases, its SHAP values gradually shift from negative to positive, indicating that higher levels of human capital provide greater information contribution to the model prediction. This pattern may reflect the potential association between human capital accumulation, regional innovation capacity, and the adoption of green technologies [53,68]. Urbanization rate (X5) shows a pattern of initial stability followed by decline. At low to moderate levels, the SHAP values of X5 remain close to zero or slightly positive. However, with further increases in urbanization, its contribution gradually decreases and shifts into the negative range. This suggests that, within the current sample scope, high urbanization levels may exhibit a nonlinear association with predicted SPRCM outcomes, potentially due to changes in population concentration, energy demand, and urban resource–environmental pressures.

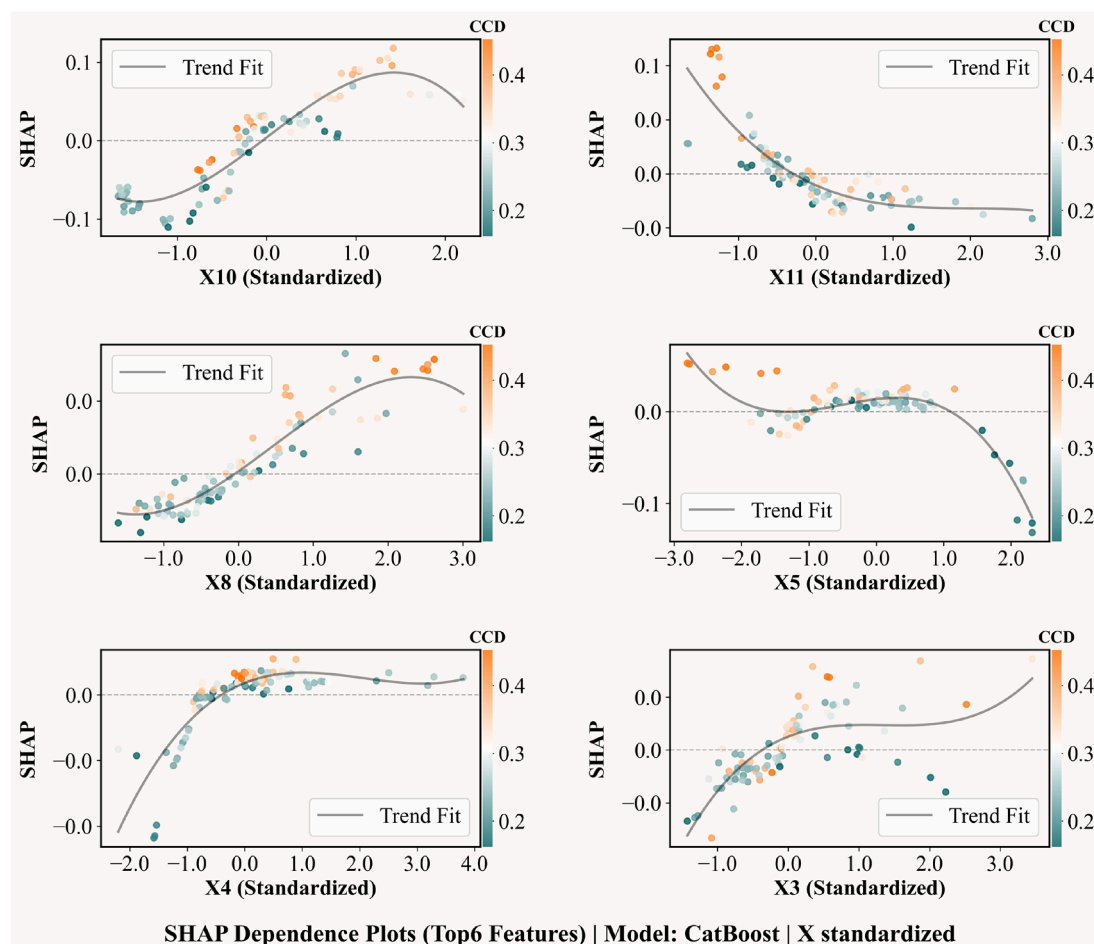


Figure 6. SHAP dependence analysis of key variables in the CatBoost model.

5. Discussion and Conclusions

5.1. Discussion

First, regarding the spatial association network. This study finds that the SPRCM spatial association network has gradually evolved into a “core–periphery” structure centered on the eastern coastal region. Provinces such as Guangdong, Jiangsu, and Shanghai have consistently acted as net beneficiaries, whereas many central, western, and northeastern provinces have mainly functioned as net spillover nodes. This finding is consistent with Chen, who reported the concentration of core nodes in urban agglomeration-based SPRCM networks [17]. However, unlike previous studies that mainly regard core regions as dominant nodes controlling network resources, this study further reveals the asymmetric governance capacity underlying the “net beneficiary” structure [20,27]. Specifically, being a net beneficiary does not simply imply that core regions passively absorb governance resources from other regions. Instead, it reflects their stronger capacity for resource integration and capability transformation. Benefiting from long-term accumulation of economic foundations, innovation resources, and institutional advantages, eastern regions may be better able to transform external inputs, such as green technologies, governance experience, and policy resources, into synergistic governance capacity. They can further influence peripheral regions through industrial cooperation, technological diffusion, and regional coordination. Therefore, the network advantages of core regions essentially derive from the combined effects of “absorptive capacity–transformation capacity–diffusion capacity,” rather than from geographical advantages alone. This interpretation extends the conventional understanding of “core-driven periphery” in spatial network studies [21,27]. The findings further suggest that if core regions mainly attract resources without effectively transforming them into governance capacity, spatial association networks may reinforce regional disparities rather than promote coordinated development. This study finds that some peripheral regions remain net spillover nodes over the long term. Although these regions participate in regional linkages, limited technological absorptive capacity, human capital accumulation, and industrial support constrain their ability to convert external connections into internal governance performance. This phenomenon of “high connectivity but limited benefits” indicates that the key to regional coordinated governance is not simply increasing the number of network connections, but improving the quality of network embeddedness in peripheral regions. Therefore, this study extends the theoretical interpretation of spatial network analysis by demonstrating that spatial association networks not only reflect the intensity of regional linkages but also reveal differences in governance capacity during green transformation. Future regional coordination policies should not focus solely on the diffusion of experiences from core regions but should also emphasize enhancing the technological absorptive capacity and institutional capacity of peripheral regions.

Second, regarding the identification of associated factors. Based on the CatBoost-SHAP model, this study finds that the relationship between urbanization level and SPRCM exhibits significant stage-dependent nonlinear characteristics rather than a simple positive or negative pattern. At relatively low levels of urbanization, further urbanization contributes positively to SPRCM. However, as urbanization continues to increase, its marginal contribution gradually declines and becomes negative at higher levels. This finding indicates that the effect of urbanization on SPRCM depends on the stage of urban development and regional carrying capacity. This result provides a meaningful dialogue with previous studies that report mixed conclusions regarding the environmental effects of urbanization. Some studies argue that urbanization can improve environmental governance performance by promoting industrial agglomeration, enhancing resource allocation efficiency, and facilitating green technology diffusion [52]. In contrast, other studies suggest

that rapid urbanization may increase energy consumption and environmental governance pressures [14,70]. This study argues that these findings are not contradictory but instead reflect differences in regional urbanization stages. From the perspective of agglomeration economics, population and industrial concentration during the early stage of urbanization can generate agglomeration economies. Shared infrastructure reduces governance costs, while knowledge spillovers facilitate the diffusion of green technologies, thereby improving SPRCM. However, when urban expansion exceeds a certain carrying capacity, congestion effects gradually become dominant. Problems such as traffic congestion, rising energy demand, excessive land expansion, and the reduction of ecological space may weaken agglomeration benefits and negatively affect synergistic governance. Therefore, this study does not reject the positive role of urbanization in green transformation. Instead, it reveals the stage transition mechanism underlying this relationship. Urbanization promotes SPRCM during the stage dominated by agglomeration benefits, whereas it may reduce synergistic efficiency at the stage of high-density development when congestion effects become more pronounced. This finding extends previous research that mainly focuses on whether urbanization promotes green development by emphasizing the importance of urbanization quality and development stages. Policy interventions should not simply pursue higher urbanization rates. Instead, they should optimize urban spatial structures, improve infrastructure efficiency, and enhance ecological carrying capacity according to different stages of urban development.

Finally, regarding the identification of nonlinear factors. This study further finds that road density, human capital, and freight volume are key predictive factors identified by the CatBoost model. However, their relationships with SPRCM are not characterized by stable linear patterns but instead exhibit clear stage-dependent features. This finding does not contradict previous econometric studies that emphasize the roles of economic development, industrial structure, and innovation capacity. Rather, it further explains why the effects of different factors may vary across development stages. For example, Zha used spatial econometric models and found that industrial structure, economic development, and innovation capacity are important determinants of SPRCM efficiency [14]. In comparison, this study further reveals the nonlinear and conditional characteristics of factor contributions by applying the CatBoost-SHAP approach. Specifically, road density exhibits a transition from a negative to a positive association with SPRCM. At the stage of insufficient infrastructure development, limited regional connectivity constrains the mobility of green technologies, governance experience, and innovation resources. As transportation networks improve, their contribution to spatially coordinated governance gradually increases. However, after reaching a relatively high level, the marginal contribution of road density begins to decline. This finding extends Wang, who highlighted the role of transportation conditions in promoting the formation of SPRCM networks [52]. It further suggests that transportation infrastructure not only affects network formation but also influences the ability of regions to obtain governance benefits from spatial connections. Freight volume demonstrates a nonlinear pattern, shifting from a positive to a negative contribution. This indicates that moderate logistics connectivity can facilitate industrial cooperation and technological diffusion, whereas excessive transportation activities may weaken synergistic effects due to increasing energy consumption and emission pressures. Meanwhile, human capital exhibits a clear accumulation effect. Only when regional talent resources reach a certain level can knowledge diffusion, technological absorption, and innovation transformation effectively contribute to SPRCM improvement. Therefore, this study further demonstrates that SPRCM does not follow a simple “input–output” relationship. Instead, it is jointly shaped by regional connectivity, factor accumulation, and technological absorptive capacity. Compared with previous studies that mainly focus on identifying influencing factors, this

study further reveals the stage-specific conditions under which different factors contribute to SPRCM. These findings provide a new mechanism-based perspective for understanding regional disparities in China's green transformation.

This study still has several limitations. First, the CatBoost-SHAP model is primarily used to identify the contribution of variables to model predictions and nonlinear association patterns, rather than replacing rigorous causal identification methods. Some explanatory variables may suffer from endogeneity issues. Therefore, future studies could further investigate causal mechanisms by incorporating instrumental variable approaches, quasi-natural experiments, or dynamic panel models. Second, this study evaluates model performance based on random sample splitting, with a primary focus on identifying variable contributions rather than forecasting future outcomes. It does not yet employ time-series validation or spatial block validation to examine the model's generalization ability across different periods and regions. Future research could introduce more rigorous spatiotemporal validation frameworks. Third, this study identifies nonlinear association patterns between variables and SPRCM based on SHAP dependence plots; however, the identified turning points should not be regarded as formal thresholds validated through statistical tests. Future studies could further examine these nonlinear mechanisms by combining panel threshold models, generalized additive models, and bootstrap methods. Finally, some indicators used to measure SPRCM may still contain information related to regional scale. Future research could further improve the SPRCM measurement system by incorporating per capita, intensity-based, and efficiency-based indicators, and conduct robustness tests using alternative weighting schemes and network construction methods.

5.2. Conclusions

First, the overall level of SPRCM in China increased steadily during the study period, although regional development imbalances remain evident. The national average coordination level improved from relatively low coordination to moderate coordination. The number of provinces reaching high coordination increased continuously, while the number of provinces classified as low coordination declined substantially. These trends indicate a gradual improvement in the overall level of coordination. Nevertheless, several provinces in western and northeastern China remained at relatively low coordination levels, suggesting that regional development disparities have not yet been fundamentally reversed. Second, the spatial association network of provincial SPRCM became increasingly integrated, although the overall level of network connectivity still has considerable room for improvement. During the study period, the network gradually evolved into a multi-core structure centered on eastern coastal provinces. Both network size and association intensity increased over time. Eastern provinces demonstrated strong capacities for both spillover and resource absorption. In contrast, several provinces in northeastern and northwestern China remained at the network periphery, with relatively weak cross-regional interactions and intermediary linkage functions. As a result, hierarchical differentiation within the network persisted. Third, the block structure of the SPRCM network underwent substantial evolution. The coverage of net spillover blocks expanded continuously. Several traditional resource-based and industrial provinces gradually shifted from net spillover roles to intermediary roles within the network, indicating an ongoing adjustment of network functions. Inter-block linkage channels increased, and the capacity for cross-regional factor transmission was strengthened. However, internal connectivity within some inland blocks remained relatively weak, suggesting that the foundation for regional collaboration still requires further consolidation. Fourth, factor endowments exhibit high information contributions in predicting SPRCM and show evident nonlinear association patterns. Among these factors, road density, freight volume, and human capital are identified as key predictive variables

with relatively high contributions. Their relationships with the predicted SPRCM levels demonstrate significant nonlinear variations.

Policy implications can be derived from the above findings. First, differentiated governance strategies should be adopted based on regional conditions. Future regional governance should fully consider differences in development foundations and resource endowments across regions [32]. For regions with relatively low SPRCM levels, policy priorities should focus on addressing deficiencies in transportation infrastructure, human capital accumulation, and environmental governance capacity, thereby improving their ability to participate in regional green transformation [20,63]. For regions with relatively high SPRCM levels, greater attention should be given to green technological innovation, industrial restructuring, and governance innovation to promote a transition from quantitative improvement to qualitative enhancement in synergistic development [62]. Second, regional coordination and network-based governance should be strengthened. It is necessary to further improve cross-regional cooperation platforms and promote green technology exchange, knowledge sharing, and information connectivity among regions [18]. Meanwhile, regional strategies, such as urban agglomeration development, coordinated regional development initiatives, and integrated watershed governance, can be leveraged to enhance interregional linkages and improve the overall coordination capacity of green governance networks [3]. Third, the allocation of key factors should be optimized to enhance support for green transformation. The CatBoost-SHAP results indicate that transportation infrastructure, human capital, and freight connectivity provide substantial information contributions in predicting SPRCM, suggesting that these factors contain important information for explaining regional differences in SPRCM. Therefore, policy implementation should place greater emphasis on infrastructure improvement, talent development, and the optimization of regional factor mobility [8]. However, it should be noted that the results of this study do not directly demonstrate that increasing specific inputs will necessarily improve SPRCM. Therefore, policymakers should avoid simply expanding investment scale and instead focus on improving resource allocation efficiency, development quality, and the alignment between policy measures and regional needs [20,56]. Finally, green transformation of urbanization patterns should be promoted. The findings reveal nonlinear associations between urbanization levels and SPRCM, indicating that urbanization at different development stages may generate different environmental governance demands. Therefore, future urbanization policies should emphasize coordination among population concentration, industrial distribution, and environmental carrying capacity [19,20]. In urban development, greater efforts should be made to improve green transportation systems, energy-efficient buildings, and environmental governance infrastructure, thereby shifting urban development from scale-oriented expansion toward a greener and low-carbon pathway.

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