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Dynamic Evolution and Trend Prediction in Coupling Coordination between Energy Consumption and Green Development in China

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Abstract: In light of the pressing concerns about worldwide warming and environmental degradation, understanding the nexus between energy consumption and green development has become vital to fostering a low-carbon transition in energy consumption, and promoting environmentally friendly development. After exploring the connotations of energy consumption and green development, this paper constructed evaluation systems for energy consumption and green development. By leveraging quantitative methods; such as the entropy method, coupling coordination model, spatial Markov model, and gray model GM (1, 1); we conducted an empirical study into the dynamism and evolutionary trends in the coupling coordination degree between energy consumption and green development in China, spanning from 2006 to 2020. Our findings delineate several key trends: (1) overall, the levels of each system have witnessed a marked increase, with the average energy consumption slightly exceeding that of green development; (2) the coupling coordination degree has displayed a consistent rise over time, with spatial distribution patterns exhibiting a "higher in the south, lower in the north" and a "center-edge" characteristic; (3) the dynamic evolution of coupling coordination types manifests a stability, continuity, and heterogeneity, eliciting distinct effects across different neighbourhood types; (4) within the forecast period, the coupling coordination degree among Chinese provinces is projected to undergo further enhancement, with the majority of provinces transitioning from a barely coordinated stage to a coordinated development stage. Above all, to stimulate a more qualitative coupling coordination between energy consumption and green development, this paper provides relevant policy implications.

Keywords: energy consumption; green development; coupling coordination; dynamic evolution; trend prediction

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1. Introduction

Energy serves as the cornerstone for all socio-economic activities, with its consumption playing a pivotal role in the sphere of green development. According to the 2022 BP Statistical Review of World Energy, there was a significant surge of 5.8% in the global demand for primary energy in 2021, which is the largest increase ever recorded [1]. This spike led to a corresponding rise in carbon emissions, by 5.7% yearly. The escalating concentrations of greenhouse gases pose a significant threat to the world's ecosystems. Given these drastic alterations in climate and the international energy framework, the priority in international green development is primarily pivoting towards strategies concerning carbon offsetting and carbon governance [2,3]. Furthermore, efforts are being channeled towards limiting global warming to a 1.5 °C increase, a notable reduction from the previous 2 °C target [4]. Certain countries have embraced proactive energy policies aimed at fostering energy technology innovation and encouraging upgrades in industrial structures to boost green development [5–7]. These initiatives primarily encompass an augmentation in the share of non-fossil-fuel energy sources on the provision end, and an enhancement of the energy utilization efficiency on the requisition end [8,9].

As the preeminent energy consumer and carbon emitter globally, China has indeed carved out noteworthy achievements in its economic progression. However, these advancements have been coupled with significant challenges concerning extensive energy consumption and environmental pollution [10]. In China, the primary focus of energy consumption is centred on the consumption of fossil fuels [11,12]. To share an eye-opening statistic, it has been found that a staggering 85% of China's carbon emissions are indeed attributable to production activities powered by these non-renewable resources. The environmental issues caused by such activities have become a considerable barrier in China's pursuit of green development. Consequently, the fostering of efficient and low-carbon energy consumption has emerged as a paramount objective in China's endeavor towards implementing a green transformation in its development approach [13–15].

In contemporary research, there have been a multitude of studies conducted on the subject of energy consumption efficiency and its correlation with economic growth. These studies have yielded valuable insights. However, there are comparatively few studies on the coupling coordination mechanism linking energy consumption and sustainable development. In recognition of the current literature gap, this study aims to conduct a thorough examination of the coupling coordination mechanisms that link energy consumption and green development across various provinces in China, leveraging a multifaceted analysis approach. This exploration carries significant implications for guiding energy consumption decarbonization processes and strengthening green development initiatives.

The remaining sections of this paper are structured as follows. Section 2 delivers a succinct summary of the pertinent research. Section 3 emphasizes the research methodologies and sources of data. Section 4 presents a four-pronged analysis of the empirical outcomes. Lastly, Section 5 recapitulates the paper's conclusions, offering policy implications that foster the coupling coordination between energy consumption and sustainable development.

2. Literature Review

2.1. Research on Energy Consumption

2.1.1. Research on the Connotations of Energy Consumption

To effectively mitigate the conflict between eco-degradation and economic growth [16,17], a continuous advancement towards a low-carbon energy transition should strategically incorporate four principal drivers: the market, policy, innovation, and behavior [18]. Market-driven mechanisms are at the core of this low-carbon energy transition [19–21]. A flexible market design coupled with mature market mechanisms can act as a stimulation for a transition and subsequent upgrade in the energy industry. Policy-driven mechanisms, on the other hand, provide a vital thrust to the transition towards low-carbon energy [22–25]. Intervention by governments, through the setting of energy consumption targets and policy guidelines, is vital to steering enterprises towards a reduction in fossil energy consumption, and to the successive incorporation of novel energy technologies. Innovation-driven mechanisms serve as the key to a low-carbon transition in energy consumption [26–28]. Energy technology innovation plays a paramount role in curbing carbon emissions and enhancing the efficiency of energy usage. Lastly, behavior-driven mechanisms complement and complete the strategies for a low-carbon energy transition [29–31]. A concerted effort to boost the public awareness of green living principles, and to foster a healthy perspective towards green development, is an essential component of these mechanisms.

2.1.2. Research on the Measurement of Energy Consumption Levels

Typically, energy consumption levels are evaluated using either a singular index or a multi-index. The singular index measurement primarily encompasses aspects such as the efficiency of energy consumption, the allocation of energy consumption, energy-related CO_2 emissions, etc., as well as other micro-perspectives [32–34]. Considering that energy consumption is subject to influences from urbanization, industrial, and household structures, technological advancements, and several other aspects [35–37], the multi-index measurement approach selects a diverse array of indicators from economic, social, and environmental dimensions, to evaluate the energy consumption level in a holistic manner [38,39]. Much of the research in this field primarily uses methods such as the entropy method, principal component analysis, slack-based measure (SBM), and data envelopment analysis (DEA) to quantify and construct a comprehensive ranking for the energy consumption system and its subsystems [40–42].

2.2. Research on Green Development

2.2.1. Research on the Connotations of Green Development

The connotations of green development embrace a range of interpretations, principally defined as follows: (1) sustainable development [43–45], a grounding notion that aims to harmonize relationships between population, resources, and energy with the objective of facilitating enduring economic development; (2) a green economy [46–48], an economic development paradigm that endeavors to improve human wellbeing, enhance social equality, mitigate environmental risks, and alleviate ecological scarcity; (3) a circular economy [49–51], a model that emphasizes the integrative functioning of the economic system and the ecosystem, collectively constituting a large eco-economic system to strike a balance between the internal and external elements; and (4) low-carbon economy [52,53], a novel economic paradigm that incorporates low-carbon technology and industry, with an emphasis on raising the quality of human life via an increased resource-utilization efficiency.

2.2.2. Research on the Influence Factors and Policy Effects of Green Development

Research findings indicate that the industrial sector serves as a facilitator, while transportation acts as a constraining factor, in the quest for green development [54–57]. Urban regions adopting policies focused on energy conservation and emission reduction have witnessed significant declines in energy consumption and carbon emissions, accompanied by substantial improvements in air quality [58,59]. However, due to the one-way causal relationship among energy consumption, income, and CO_2 emissions, an exclusive emphasis on the merits of urban energy saving and emission mitigation could potentially undermine urban green development efforts [60]. To mitigate this causal relationship, cities might consider implementing a range of complementary policies [61]. Studying these influencing factors and policy effects is essential to facilitating the design and implementation of strategies for green development.

2.3. The Research on the Relationship between Energy Consumption and Green Development

The existing literature extensively explores the correlation between energy consumption and a key facet of green development: economic growth. Several studies employ decoupling models, highlighting that the decoupling index remains stable and tends towards absolute decoupling in developed countries. In contrast, the decoupling index in developing countries demonstrates a relative decoupling with marked fluctuations [62,63]. The majority of the research asserts that increasing renewable energy usage and escalating oil prices can stimulate the decoupling of energy consumption from economic growth [64]. Building on these findings, subsequent studies have elucidated three potential relationships between energy consumption and economic growth: unidirectional causality, bidirectional causality, or no discernable correlation [65–67].

In the evolving landscape of socio-economics, the interlinkages between energy consumption and ecological environment are intensifying. Consequently, scholars are progressively pivoting their research focus towards exploring the relationship between energy consumption and green development [68,69]. In its current state, China's energy supply framework largely depends on fossil fuels, supplemented by non-fossil energy sources. The accelerated expansion of energy-dependent industries in China has exacerbated the issue of energy-related pollution, thereby impeding green development [70]. Under this context, the formulation of strategies to harmonize energy consumption with green development, and to curtail carbon and pollutant emissions, has emerged as a pressing subject of discourse within Chinese society [71].

To summarize, academics have carried out a multitude of studies focused on energy consumption and green development, yielding invaluable insights that underpin the present study. However, there are still areas that can be further explored. Firstly, the existing literature primarily examines the characteristics of the evolution of the coupling coordination between energy consumption and green development from either a temporal or spatial perspective, and lacks a holistic analysis integrating these two dimensions. Secondly, the existing literature typically concentrates on independent discussions of the transition in coupling coordination types within a region, neglecting the influence exerted by the spatially adjacent regions. Thirdly, much of the existing literature was confined to analyzing the coupling coordination as it is, without extending into the predictive analysis of its future trajectory. In response to the above deficiencies, this paper conducted a comprehensive analysis of the spatial and temporal evolutionary features of the coupling coordination between energy consumption and green development. This paper also contrasted the transition matrix under scenarios considering and not considering neighbouring influences, and ultimately predicted and analyzed its future trends. Figure 1 provides a concise representation of this study's research framework.

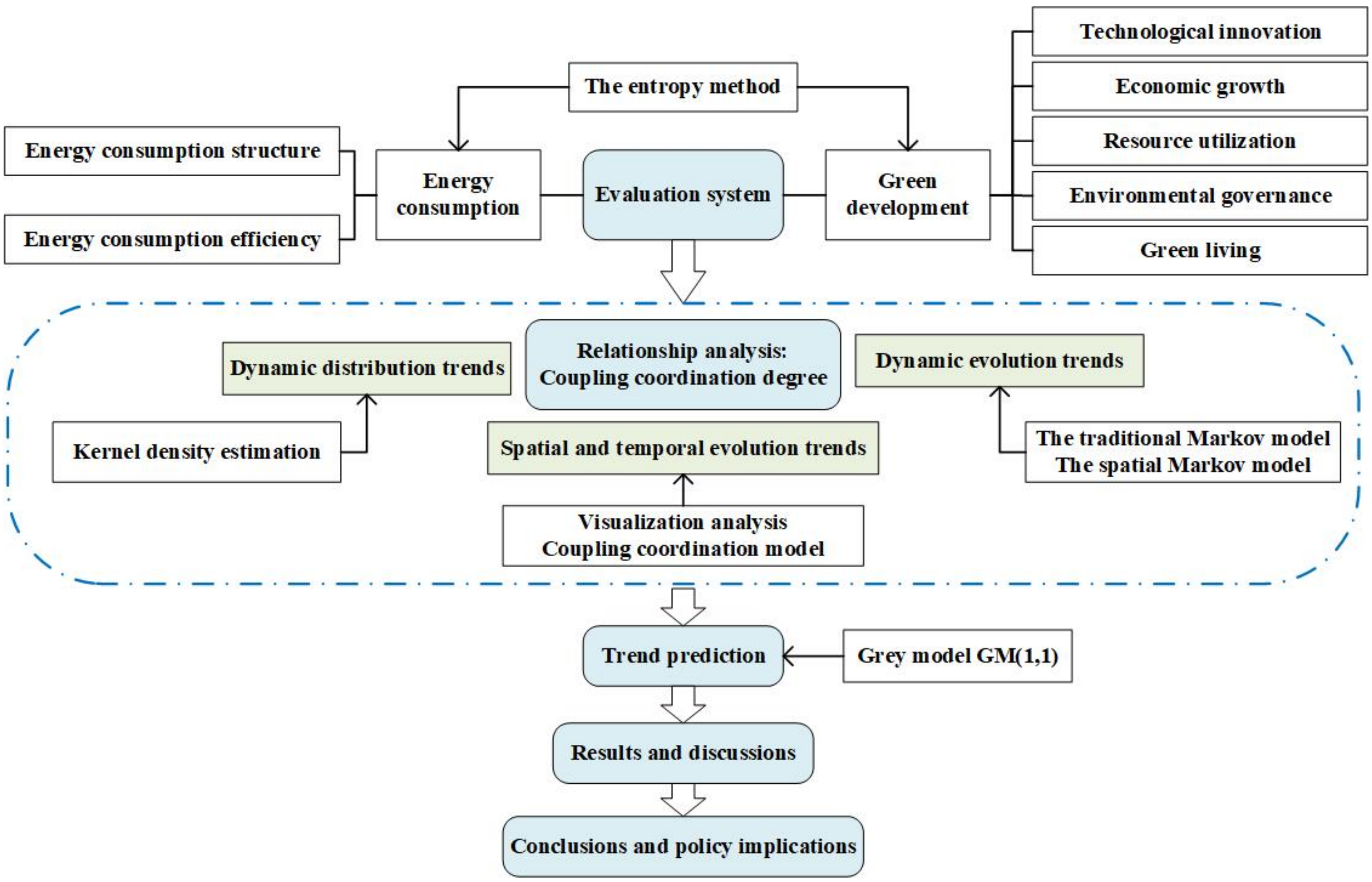

Figure 1. Overview of the research framework.

3. Methods and Data

3.1. Methods

3.1.1. Construction of Evaluation System

In the current epoch, the evolution of China's energy consumption system strategically leans towards a low-carbon framework, with an emphasis on enhancing the utilization efficiency of fossil fuels, and vigorously promoting non-fossil-fuel energy sources. In the contemporary era, the evolution of energy consumption systems in China has been characterized as a distinct shift towards low-carbon initiatives, featuring an enhanced focus on optimizing fossil fuel use and promoting non-fossil energy. Consequently, this study adopted a sustainability-orientated perspective in the selection of indicators for the energy consumption system. In total, 11 indicators have been chosen, encompassing two domains: the energy consumption structure and energy consumption efficiency. This selection, to a certain extent, objectively encapsulates China's energy consumption status, as detailed in Table 1. The numerical values enclosed within brackets denote the quantity of indicators incorporated within the respective systems or sub-systems. The weighting coefficients assigned to these indicators are computed through a sequence of equations, ranging from Equations (1)–(5), as explained in the subsequent sections.

Green development system measurement entails a comprehensive appraisal of social, economic, and environmental dimensions. Drawing from the "Green Development Indicator System" put forth by China's National Development and Reform Commission (NDRC), and considering the data availability, this study constructed a green development system through five lenses: technological innovation, economic growth, resource utilization, environmental governance, and green living. A compilation of 28 indicators represents the green development system, broadly encapsulating the green development objectives and tasks delineated in China's national plan.

Table 1. The evaluation system of energy consumption and green development.

System	Sub-System	Indicator	Type	Weight	Sum
Energy consumption (11)	Energy consumption structure (7)	Total energy consumption (10,000 tce)	−	2.05%	86.83%
		Coal consumption/total energy consumption (%)	−	4.12%	
		Oil consumption/total energy consumption (%)	+	6.22%	
		Natural gas consumption/total energy consumption (%)	+	13.69%	
		Electricity consumption/total energy consumption (%)	+	5.49%	
		New energy (wind, water, nuclear) consumption/total energy consumption (%)	+	21.64%	
		Other energy consumption/total energy consumption (%)	+	33.62%	
	Energy consumption efficiency (4)	Decarbonization index of the energy consumption structure	+	7.56%	13.17%
		Energy carbon emissions (10,000 t)	−	1.98%	
		Carbon intensity of energy (tc/tce)	−	2.67%	
		Elasticity coefficient of energy consumption	−	0.96%	

Table 1. *Cont.*

System	Sub-System	Indicator	Type	Weight	Sum
Green development (28)	Technological innovation (5)	Number of R&D personnel in industrial enterprises above designated size (IEADS)/number of employed personnel in urban units (%)	+	3.56%	58.61%
		The proportion of R&D expenditure in the prime operating revenue of IEADS (%)	+	10.40%	
		The proportion of sales revenue of new products in the prime operating revenue of IEADS (%)	+	17.54%	
		Technology market turnover (CNY 10,000)	+	15.57%	
		Authorized number of domestic patent applications (pieces)	+	11.54%	
	Economic growth (7)	Per capita GDP (CNY)	+	2.88%	21.56%
		Per capita disposable income of urban residents (CNY)	+	3.27%	
		Per capita disposable income of rural residents (CNY)	+	3.28%	
		Per capita retail sales of consumer goods (CNY)	+	3.31%	
		Growth rate of total investment in fixed assets (%)	+	0.23%	
		Ratio of dependence on foreign trade (%)	+	6.37%	
		The proportion of tertiary industry in GDP (%)	+	2.22%	
	Resource utilization (5)	Per capita water resources (m^3/person)	+	7.32%	8.71%
		Energy consumption per unit of GDP (tce/CNY 10,000)	−	0.26%	
		Water consumption per unit of GDP (m^3/CNY 10,000)	−	0.13%	
		Agricultural acreage (1000 ha)	−	0.46%	
		Area of city construction land (1000 ha)	−	0.54%	
	Environmental governance (7)	Comprehensive utilization rate of industrial solid waste (%)	+	1.55%	7.39%
		Harmless disposal rate of urban household waste (%)	+	0.72%	
		Centralized treatment rate of urban sewage (%)	+	0.70%	
		The proportion of investment in environmental protection to GDP (%)	+	2.76%	
		Industrial wastewater discharge (10,000 t)	−	0.56%	
		Industrial sulphur dioxide emission (10,000 t)	−	0.73%	
		Industrial smoke (dust) emissions (10,000 t)	−	0.37%	
	Green living (4)	Urban population density (person/km^2)	−	0.40%	3.73%
		Per 10,000 people with public transport vehicles (unit)	+	1.72%	
		Greening coverage of built-up areas (%)	+	0.65%	
		Per capita park green areas (m^2/person)	+	0.96%	

3.1.2. The Entropy Method

The entropy method was employed as an objective way to quantify the levels of energy consumption and green development. Throughout the index evaluation procedure, weights are assigned, commensurate with the volume of information embodied in the variability of each index. Indices carrying a greater volume of information signify a lesser uncertainty and reduced entropy, hence warranting a higher weight. Conversely, the inverse relationship applies. To ensure meaningful data processing, it is crucial to eliminate the zero values that surface in the standardized data. Consequently, this research applies a shift of 0.0001 to the overall standardized data. The calculation steps are as follows:

Step1: Standardize the data:

$$\begin{cases} \text{Positive indicator}: X_{ijt}^{+} = \frac{x_{ijt} - minx_j}{maxx_j - minx_j} \\ \text{Negative Indicator}: \ X_{ijt}^{-} = \frac{maxx_j - x_{ijt}}{maxx_j - minx_j} \end{cases} \tag{1}$$

Step 2: Calculate the ratio:

$$P_{ijt} = \frac{X_{ijt}^{\pm}}{\sum_{t=1}^{k} \sum_{i=1}^{n} X_{ijt}^{\pm}} \tag{2}$$

Step 3: Calculate the information entropy of the indicator:

$$e_j = -\frac{1}{ln(kn)} \sum_{t=1}^{k} \sum_{i=1}^{n} \left(P_{ijt} \times lnP_{ijt} \right), \left(0 \leq e_j \leq 1 \right) \tag{3}$$

Step 4: Calculate the variation coefficients (g_j) and weights (w_j) of each indicator:

$$g_j = 1 - e_j \tag{4}$$

$$w_j = \frac{g_j}{\sum_{j=1}^{m} g_j} \tag{5}$$

Step 5: Calculate a composite score (D_{it}):

$$D_{it} = \sum_{j=1}^{m} X_{ijt} w_j \tag{6}$$

where i shows the province ($i = 1, 2, \ldots, n$), j shows the indicator ($j = 1, 2, \ldots, m$), t shows the year ($t = 1, 2, \ldots, k$), x_{ijt} is the original value of the j indicator of the province i in the t year, X_{ijt}^{+} and X_{ijt}^{-} are the standardized values, and $minx_j$ and $maxx_j$ show the minimum and maximum values of the j indicator.

3.1.3. Kernel Density Estimation

Kernel density estimation was employed to research the unbalanced distribution and estimate the unknown density function, and is a non-parametric estimation method. This approach perceives the distribution pattern of the study object as a probabilistic distribution, generates a continuous density curve through smoothing techniques, and subsequently employs this density curve to discern the trend characteristics of the study object over time. Kernel density functions can be categorized as quartic, triangular, or Gaussian according to their formal expression. For the purpose of this study, we elected to use the Gaussian kernel density function to estimate the dynamic distribution of the coupling coordination degree linking energy consumption and green development. The relevant equations are as follows:

$$f(x) = \frac{1}{Nh} \sum_{i=1}^{N} K\left(\frac{X_i - x}{h} \right) \qquad K(x) = \frac{1}{\sqrt{2\pi}} e^{\left(-\frac{x^2}{2}\right)}, \tag{7}$$

where X_i, x, N, h represent the observed value, mean value, number of observations, and bandwidth, respectively. $K(x)$ stands for the Gaussian kernel density function. Bandwidth h satisfies Equation (2):

$$\lim_{N\to\infty} h(N) = 0 \qquad \lim_{N\to\infty} Nh(N) = N \to \infty, \tag{8}$$

3.1.4. Coupling Coordination Model

A coupling coordination model can be utilized to analyze the relationship between energy consumption and green development. The formulas are as follows:

$$c = \left[\frac{U_1 U_2}{\left(\frac{U_1+U_2}{2}\right)^2} \right]^{\frac{1}{2}}, \tag{9}$$

$$t = \alpha U_1 + \beta U_2, \tag{10}$$

$$d = \sqrt{c \times t}, \tag{11}$$

where c, t, and d represent the coupling degree, comprehensive development level, and coupling coordination degree between the systems, respectively. U_1, U_2, and U_3 correspond to the comprehensive indices of each system, respectively. The parameters α and β are the weights of the two systems, satisfying the equation $\alpha + \beta = 1$. In this research, both systems are considered to be of equal significance; hence, α and β are both set to 0.5. Drawing on the pertinent research [72], this study categorized the degree of coupling coordination into 10 levels, with the detailed classification criteria displayed in Table 2.

Table 2. The classification criteria of the coupling coordination degree.

k	**Coordination Stage**	**Sub-Stage**	**Coupling Coordination**
1	Dysfunctional decline stage	Extreme disorder	(0.0~0.1]
		Severe disorder	(0.1~0.2]
		Moderate disorder	(0.2~0.3]
		Mild disorder	(0.3~0.4]
2	Nearly dysfunctional stage	Near disorder	(0.4~0.5]
3	Barely coordinated stage	Barely coordinated	(0.5~0.6]
4	Coordinated development stage	Primary coordination	(0.6~0.7]
		Middle coordination	(0.7~0.8]
		Good coordination	(0.8~0.9]
		Quality coordination	(0.9~1.0]

3.1.5. The Markov Model

The Markov model characterizes a process with discrete states and time. In a traditional Markov model, the subject under study is first categorized into k types. Subsequently, the probability distribution of each type is calculated, ultimately leading to the derivation of a $k \times k$ transfer probability matrix M. Herein, m_{ij} represents the probability that a region of type i at time t transitions to type j at time $t+1$. The variables n_{ij} and n_j denote the number of regions transitioning from type i to type j at time t to $t+1$ and the total count of regions of type j, respectively.

$$m_{ij} = n_{ij}/n_j, \tag{12}$$

The spatial Markov model further considers the interactions between neighbours on space. This model introduces spatial lags into the traditional Markov model, categorizing these lags into k types as conditions, and similarly decomposes the $k \times k$ transfer probability matrix into 'k' $k \times k$ transfer probability matrices. In this study, we employed an adjacency matrix to determine the spatial relationship among regions, designating a value of 1 to neighbouring provinces and 0 to non-neighbouring ones. A hypothesis test is required to verify the significance of the spatial lag effect. Assuming spatial independence for the type transfer concerning the coupling coordination among provinces, the test equation is presented as below:

$$Q = -2log\left\{\prod_{l=1}^{k}\prod_{i=1}^{k}\prod_{j=1}^{k}\left[\frac{m_{ij}}{m_{ij}(l)}\right]^{n_{ij}(l)}\right\}, \tag{13}$$

where $m_{ij}(l)$ represents the transfer probability under the spatial lag type l, while $n_{ij}(l)(l = 1, 2, \ldots, k)$ represents the number of provinces being analyzed. Q adheres to the χ^2 distribution of $k(k-1)^2$.

3.1.6. Grey Model GM (1, 1)

The principle underpinning the gray model GM (1, 1) is based on the analysis of developmental trends informed by historical data, which subsequently facilitates the construction of a mathematical model. The resultant model is used to make scientifically substantiated forecasts about future trends. Such predictions aid decision-makers in shaping future development strategies and policies. We employed this model to forecast the coupling coordination degree between energy consumption and green development for the period from 2021 to 2025. The computation steps are performed as follows.

Firstly, we set the time series $X_0 = \{x_0(1), x_0(2), \ldots, x_0(n)\}$, consisting of n observations. This series gets accrued to form a new series $X_1 = \{x_1(1), x_1(2), \ldots, x_1(n)\}$. Subsequently, the corresponding differential equation for the gray model GM (1, 1) is formulated as follows:

$$\frac{dX_1}{dt} + \theta X_1 = \mu, \tag{14}$$

where θ represents the developmental gray number, while μ represents the endogenous control gray number.

Secondly, we set $\hat{\theta} = (\theta/\mu)$, which is solved through least squares to obtain $\hat{\theta} = \left(B^T B - 1\right) B^T Y_n$. The prediction model is then derived via solving the differential equation, which is expressed as:

$$x_1^T \hat{X}_1(k+1) = \left[x_0(1) - \frac{\mu}{\theta}\right] e^{-\theta k} + \frac{\mu}{\theta}\ ,\ (k = 1, 2, \ldots, n), \tag{15}$$

Following the establishment of the prediction model, an accuracy assessment is indispensable. The criteria to evaluate the test result level are shown in Table 3. If the *p*-values and C-values fall within the pass range, then trend prediction may be performed. Otherwise, an in-depth analysis of the residual series is needed, along with a subsequent correction of the formula.

Table 3. Gray model GM (1, 1) accuracy grade criteria.

Model Accuracy Grade	C-Value	*p*-Value
Excellent	$C \leq 0.35$	$p > 0.95$
Good	$0.35 < C \leq 0.5$	$0.8 < p \leq 0.95$
Pass	$0.5 < C \leq 0.65$	$0.7 < p \leq 0.8$
Fail	$C > 0.65$	$p \leq 0.7$

3.2. Data

In this study, we selected 30 provinces within China (excluding Tibet, Hong Kong, Macao, and Taiwan) as empirical samples, encompassing the time period from 2006 to 2020. We compiled empirical data from several comprehensive resources, included but not limited to the China Statistical Yearbook (2007–2021), China Energy Statistical Yearbook (2007–2021), China Environmental Statistical Yearbook (2007–2021), and the China Urban Statistical Yearbook (2007–2021). We also integrated data from provincial statistical yearbooks and statistical bulletins to enrich our data. Furthermore, the base map data for China were procured from the National Geomatics Center of China, and are accessible via their official website (http://bzdt.ch.mnr.gov.cn/, accessed on 12 January 2023). Individual missing values were supplemented via interpolation and moving average methods.

4. Results and Discussion

4.1. The Level of Energy Consumption and Green Development in Each Province

Based on the evaluation system established in preceding sections, we assessed the level of energy consumption and green development in each province from 2006 to 2020, using the entropy value method. The results of this comprehensive analysis are shown in Table 4. However, due to spatial constraints, we have opted to showcase only the results corresponding to the years 2006, 2011, 2016, and 2020, and the same below. The main characteristics of the temporal evolution are as follows.

Firstly, the overall trend in the energy consumption level reveals a consistent growth, registering an increase of 44.32% in 2020, compared to 2006. The five provinces with the highest average energy consumption index are Sichuan, Chongqing, Hainan, Qinghai, and Hunan. Located in Southwestern China, Sichuan and Chongqing boast abundant river resources and serve as focal areas for large-scale hydroelectric construction in the basin. Notably, in Sichuan, hydroelectric power generation constitutes over 80% of the total power generation, leading to elevated levels of energy consumption in both Sichuan and Chongqing. Furthermore, Qinghai and Hainan rank highly due to their copious wind and solar resources, making them suitable for the development of photovoltaic and windmill power generation. The global lockdown induced by COVID-19 significantly curtailed the demand for foreign oil and natural gas imports, while the demand for coal was marginally affected. Consequently, a decline in the energy consumption system has been observed among specific provinces.

Secondly, the overall trend in the green development level has exhibited a significant increase, with a marked growth of 138.30% in 2020 compared to 2006. This substantiates the extraordinary strides that China has made in the realm of green development under the guidance of the Communist Party of China. The top five provinces in terms of the average green development level are Beijing, Guangdong, Shanghai, Jiangsu, and Zhejiang, all of which are classified as first-tier cities. This ranking primarily stems from the robust technological innovation and accelerated economic growth that these first-tier cities have demonstrated, which has, consequently, propelled them to higher echelons in terms of green development.

Finally, from a comparative standpoint, the average level of the energy consumption system marginally surpasses that of the green development system. However, the growth rate of the green development system is conspicuously superior to that of the energy consumption system. Furthermore, the provinces that rank highest in terms of averages differ between these two systems. Provinces demonstrating robust green development levels tend to exhibit comparatively lower levels of energy consumption, suggesting that the process of green development may lead to increased energy usage. For instance, Shanghai and Jiangsu, which are ranked 3rd and 4th, respectively, in terms of average green development levels, instead place 14th and 23rd within the average energy consumption levels.

Table 4. The level of each system and the coupling coordination degree.

	Energy Consumption					Green Development					Coupling Coordination Degree				
Province	**2006**	**2011**	**2016**	**2020**	**Average**	**2006**	**2011**	**2016**	**2020**	**Average**	**2006**	**2011**	**2016**	**2020**	**Average**
Beijing	0.170	0.230	0.302	0.374	0.265	0.185	0.236	0.338	0.421	0.287	0.558	0.662	0.800	0.904	0.725
Tianjin	0.150	0.171	0.246	0.271	0.205	0.152	0.180	0.219	0.242	0.195	0.499	0.553	0.659	0.700	0.597
Hebei	0.071	0.052	0.072	0.113	0.067	0.064	0.101	0.130	0.181	0.115	0.221	0.267	0.357	0.484	0.309
Shanxi	0.058	0.072	0.090	0.125	0.086	0.061	0.092	0.129	0.139	0.104	0.185	0.302	0.391	0.453	0.339
Inner Mongolia	0.105	0.107	0.126	0.140	0.135	0.072	0.108	0.141	0.157	0.119	0.295	0.385	0.459	0.494	0.424
Liaoning	0.121	0.115	0.153	0.177	0.133	0.088	0.117	0.146	0.180	0.131	0.359	0.410	0.494	0.560	0.446
Jilin	0.097	0.113	0.321	0.284	0.220	0.072	0.099	0.130	0.431	0.131	0.286	0.375	0.587	0.843	0.492
Heilongjiang	0.216	0.171	0.123	0.253	0.177	0.073	0.101	0.131	0.151	0.114	0.378	0.434	0.441	0.583	0.452
Shanghai	0.187	0.198	0.225	0.253	0.212	0.183	0.221	0.258	0.318	0.239	0.572	0.620	0.677	0.747	0.647
Jiangsu	0.120	0.141	0.170	0.206	0.158	0.131	0.209	0.245	0.361	0.223	0.437	0.549	0.613	0.730	0.575
Zhejiang	0.200	0.225	0.277	0.293	0.246	0.135	0.189	0.255	0.341	0.222	0.521	0.612	0.717	0.795	0.655
Anhui	0.096	0.102	0.138	0.176	0.123	0.074	0.114	0.162	0.216	0.135	0.294	0.388	0.497	0.594	0.435
Fujian	0.183	0.203	0.287	0.286	0.241	0.123	0.144	0.193	0.222	0.166	0.488	0.537	0.660	0.691	0.591
Jiangxi	0.123	0.123	0.181	0.204	0.162	0.074	0.110	0.146	0.188	0.124	0.321	0.409	0.521	0.593	0.461
Shandong	0.091	0.090	0.147	0.175	0.120	0.097	0.142	0.182	0.276	0.163	0.344	0.407	0.529	0.641	0.466
Henan	0.078	0.129	0.228	0.208	0.160	0.056	0.089	0.128	0.184	0.109	0.174	0.370	0.530	0.591	0.419
Hubei	0.230	0.127	0.208	0.280	0.211	0.078	0.114	0.173	0.228	0.142	0.406	0.420	0.579	0.693	0.523
Hunan	0.155	0.455	0.293	0.302	0.322	0.078	0.103	0.152	0.206	0.129	0.359	0.579	0.609	0.685	0.566
Guangdong	0.218	0.277	0.196	0.278	0.248	0.161	0.207	0.257	0.409	0.242	0.572	0.669	0.649	0.826	0.674
Guangxi	0.158	0.321	0.306	0.341	0.306	0.075	0.103	0.132	0.181	0.119	0.351	0.528	0.583	0.677	0.546
Hainan	0.459	0.324	0.353	0.345	0.338	0.094	0.131	0.147	0.157	0.134	0.555	0.590	0.633	0.646	0.599
Chongqing	0.413	0.298	0.477	0.252	0.347	0.087	0.130	0.161	0.198	0.141	0.513	0.575	0.712	0.642	0.607
Sichuan	0.210	0.521	0.447	0.425	0.347	0.073	0.103	0.143	0.203	0.127	0.376	0.601	0.669	0.749	0.577
Guizhou	0.085	0.109	0.164	0.221	0.146	0.059	0.089	0.119	0.162	0.104	0.205	0.348	0.464	0.575	0.406
Yunnan	0.191	0.213	0.329	0.385	0.279	0.077	0.099	0.127	0.152	0.112	0.380	0.458	0.586	0.657	0.522
Shaanxi	0.146	0.149	0.177	0.181	0.168	0.066	0.111	0.155	0.201	0.128	0.300	0.436	0.530	0.585	0.467
Gansu	0.249	0.190	0.213	0.274	0.229	0.059	0.080	0.109	0.136	0.094	0.301	0.389	0.482	0.572	0.440
Qinghai	0.323	0.341	0.296	0.404	0.332	0.113	0.145	0.154	0.197	0.148	0.552	0.623	0.614	0.731	0.621
Ningxia	0.203	0.164	0.163	0.154	0.177	0.076	0.103	0.129	0.148	0.114	0.385	0.434	0.480	0.499	0.454
Xinjiang	0.179	0.169	0.218	0.243	0.200	0.089	0.112	0.141	0.147	0.123	0.412	0.456	0.543	0.570	0.496
Average	0.176	0.197	0.231	0.254		0.094	0.129	0.168	0.224		0.387	0.480	0.569	0.650	

4.2. Coupling Coordination Degree of Each Province

Building on the assessment of energy consumption and green development systems in China, this study extended its exploration into the trends in temporal evolution, spatial transitions, and dynamic distribution associated with the coupling coordination between energy consumption and green development.

4.2.1. Temporal Evolution Trends

Upon examination of Table 4, it becomes evident that the degree of coupling coordination between energy consumption and green development has steadily risen in China. Specifically, a 67.96% increase is observed in 2020 relative to the levels in 2006, with a notable annual growth rate of 5.66%. This suggests that China has collectively undergone a transition from the dysfunctional decline stage to the coordinated development stage. However, despite this progress, the absolute level of this coupling coordination remains an issue with considerable room for improvement. For 2006, the degree of coupling coordination paints an unpromising picture. Only five provinces—Beijing, Shanghai, Zhejiang, and Qinghai—are at the barely coordinated stage, whereas the majority of provinces are stuck in a stage of dysfunctional decline or a stage of near dysfunction. This observation is attributable to China's rapid phase of industrial economic expansion in 2006, a period characterized by an elevated energy consumption and significant environmental degradation. Consequently, fewer provinces exhibited optimal levels of coordination during this time. In contrast, as we move to the conclusion of 2020, the trajectory of the coupling coordination degree has undergone a significant transformation, with the absolute level across all provinces witnessing marked improvements. Approximately 13 provinces, including Hebei, Shanxi, and Inner Mongolia, have managed to jump out of the dysfunctional decline stage. Furthermore, over half of the provinces have now reached the coordinated development stage, with Beijing boasting the highest level of coupling coordination, and thereby being the leading province in the realm of coordination development. Over the course of the past decade, China has resolutely committed to an agenda of ecological prioritization, integrating principles of green development into the overarching framework of its socio-economic advancement. This strategic focus has yielded significant synergistic outcomes, particularly in the fields of pollution mitigation and carbon reduction.

4.2.2. Spatial Evolution Trends

To more accurately reflect the characteristics of the spatial evolution of the coupling coordination degree, we employed ArcGIS 10.5 software to create spatial visualization maps of the coupling coordination degree for the years 2006, 2011, 2016, and 2020. Each color represents a distinct type of coupling coordination, and the results are shown in Figure 2. The spatial distribution pattern in Figure 2 reveals that the coupling coordination degree in China has demonstrated a marked improvement overall, indicating that the disparities in regional development are being progressively mitigated. The salient characteristics of this spatial distribution can be summarized as follows: firstly, the spatial distribution exhibits a pattern of being "higher in the south, lower in the north"; secondly, the "center-edge" distribution characteristics are distinctly noticeable, accompanied by a certain spatial spillover effect. These two spatial characteristics demonstrate that there are significant spatial differences in the coupling coordination degree between different provinces, resulting in significant differences, mainly due to the following aspects: (1) disparities in energy resource endowments—the Southwestern region is overwhelmingly dominant in non-fossil energy production, accounting for about half of the total non-fossil energy production; (2) disparities in economic levels—provinces such as Beijing, Guangdong, and Zhejiang, which have a higher economic level, will generate a positive promotion effect on their surrounding provinces, and this effect will steer them towards a more coordinated path of development; and (3) disparities in industrial distribution—China's industrial layout is characterized as "light in the south and heavy in the north", which stems from the greater consumption of fossil energy and increasing ecological pollution in the northern provinces.

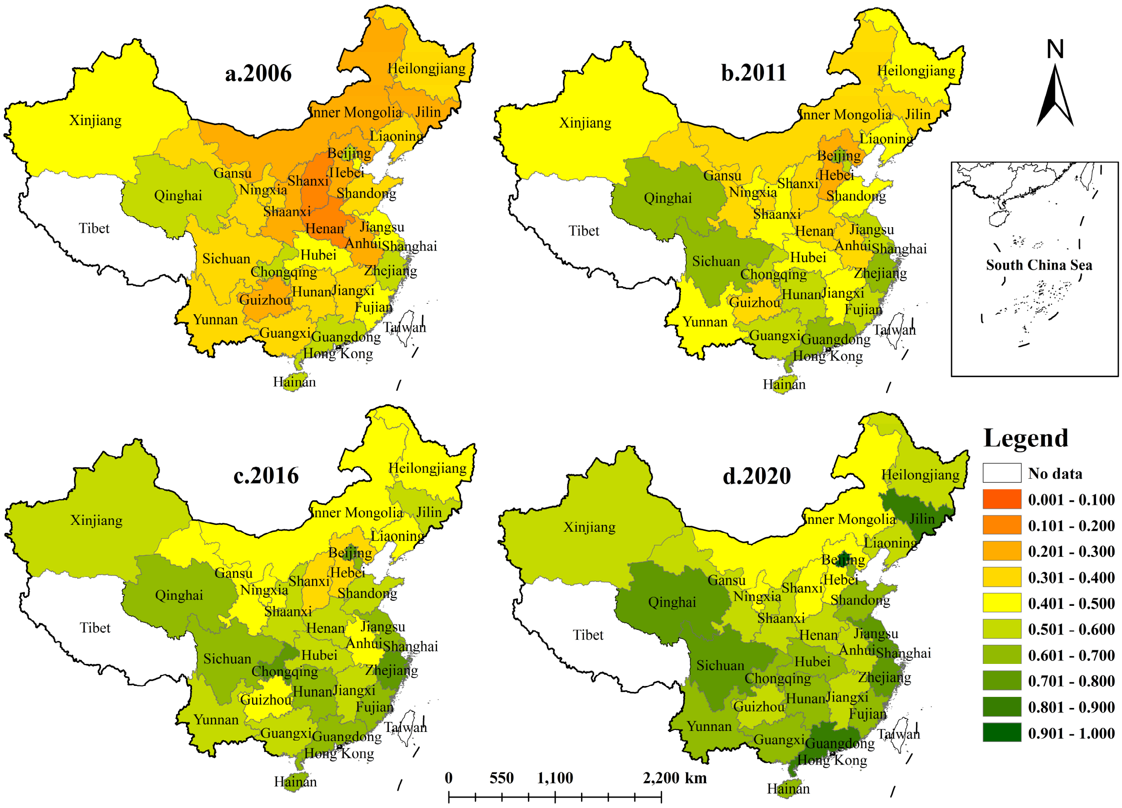

Figure 2. The spatial evolution of the coupling coordination. Subfigures (**a**–**d**) shows the spatial distribution in 2006, 2011, 2016, and 2020, respectively. The map is based on the standard map with the review number GS (2020) 4632 which is downloaded from the standard map service website of the National Geomatics Center of China, and the base map is not modified.

4.2.3. Dynamic Distribution Trends

To explore the dynamic distribution trends in the coupling coordination degree across 30 Chinese provinces, we employed the MATLAB 2016b software to estimate the kernel density and make a three-dimensional kernel density graph. The results are shown in Figure 3. Figure 3 highlights the key characteristics of the dynamic distribution of this coupling coordination, revealing three distinctive trends. Firstly, as can be discerned from the positional distribution of the kernel density curve, the curve's overall orientation veers to the right, indicating a progressive, albeit fluctuating, rise in the level of coupling coordination within China. Secondly, observations gleaned from the primary peak of the kernel density curve suggest that, despite its fluctuations, the main peak persists in a steady ascent. Simultaneously, the tails of the curve, both left and right, show a tendency to converge towards the centre, with a gradual decrease in the wave width. This reflects a shift towards a more homogeneous coupling coordination level among the provinces, signaling an incremental mitigation of the previously unbalanced development state. Thirdly, a character was observed in the shape of the kernel density curve in 2006; a prominent "bulge" on the curve's right side signaled a transition from a "single peak" towards a "double peak" schema. This implied an escalation in the polarization of the coupling coordination level among the provinces within this period. However, over subsequent years, this "bulge" gradually diminished, reverting to a singular peak structure, thus implying an effective attenuation of the polarization trend in provincial coupling coordination levels, effectively forestalling the manifestation of a "Matthew effect". As China diligently advances its strategy aimed at universal common prosperity, a discernible convergence has been observed among the provinces in key domains such as the labor quality, total factor productivity, and technological innovation capacity. This convergence has subsequently ameliorated the imbalances in the levels of coupling coordination.

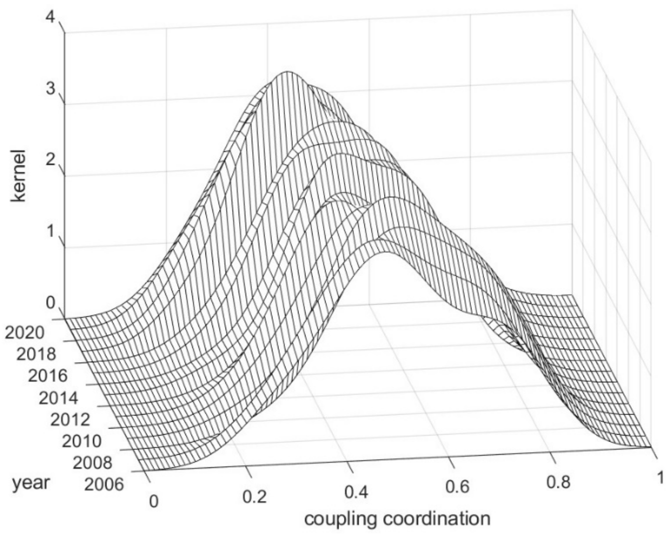

Figure 3. The dynamic distribution of the coupling coordination.

4.3. Dynamic Evolution Trends in Coupling Coordination Types

To delve into the characteristics of dynamic evolution in coupling coordination types within China, we constructed both the traditional and the spatial Markov models, the outcomes of which are presented in Tables 5–7. The coupling coordination degree is discretized into four categories: "dysfunctional decline, nearly dysfunctional, barely coordinated, and coordinated development", designated by $k = 1,\ 2,\ 3$, and 4, respectively. A higher k value signifies an elevated coupling coordination degree. The symbol $m_{ij/k}$ signifies the probability of a region transitioning from type i at a given moment t to type j at the subsequent moment $t + 1$, contingent upon the spatial lag type or neighbourhood type being k.

Table 5. Traditional Markov transfer probability matrix for coupling coordination.

$t \backslash t+1$	n	1	2	3	4
1	87	0.759	0.218	0.023	0.000
2	116	0.017	0.819	0.155	0.009
3	118	0.008	0.009	0.788	0.195
4	99	0.000	0.000	0.071	0.929

Table 6. Spatial Markov transfer probability matrix for coupling coordination.

Neighbourhood Types	$t \backslash t+1$	n	1	2	3	4
1	1	49	0.735	0.245	0.020	0.000
	2	16	0.125	0.813	0.062	0.000
	3	10	0.012	0.088	0.800	0.100
	4	2	0.000	0.000	0.111	0.899
2	1	31	0.721	0.247	0.032	0.000
	2	58	0.000	0.881	0.102	0.017
	3	36	0.000	0.000	0.833	0.167
	4	9	0.000	0.000	0.045	0.955
3	1	7	0.715	0.285	0.000	0.000
	2	36	0.000	0.750	0.250	0.000
	3	55	0.000	0.018	0.750	0.232
	4	45	0.000	0.000	0.040	0.960
4	1	2	0.505	0.495	0.000	0.000
	2	5	0.000	0.600	0.400	0.000
	3	16	0.000	0.000	0.813	0.187
	4	43	0.000	0.000	0.023	0.977

Table 7. Steady-state distribution of coupling coordination types.

State Type			1	2	3	4
Disregarding spatial lag	Initial state		0.600	0.167	0.233	0.000
	Ultimate state		0.011	0.025	0.256	0.708
Considering spatial lag	Ultimate state	1	0.001	0.120	0.387	0.492
		2	0.000	0.000	0.400	0.600
		3	0.000	0.023	0.316	0.661
		4	0.000	0.000	0.110	0.890

4.3.1. Traditional Markov Transfer Probability Matrix

Table 5 reveals certain distinctive characteristics of the dynamic evolution of coupling coordination types within China:

1. The evolution process of coupling coordination types displays stability, which is demonstrated as the values on the diagonal exceeding those off-diagonal, with a minimum value of 0.759 and a maximum value of 0.929;
2. The evolutionary trajectory of coupling coordination types demonstrates continuity; that is, the probability of transitioning to different types is concentrated adjacent to the diagonal; this suggests that transitions in coupling coordination types are typically to neighbouring types, with leap transitions (e.g., from a nearly dysfunctional stage directly to a coordinated development stage) proving challenging to accomplish within a brief period;
3. The dynamic evolution of coupling coordination types is heterogeneous, specifically: (1) provinces in the coordinated development stage exhibit a "club convergence" phenomenon, with a probability of maintaining the current stage as high as 0.929 and a mere 0.071 chance of transitioning downwards; (2) provinces that are at the nearly dysfunctional stage and barely coordinated stage display positive transitions; i.e., their likelihood of progressing to the subsequent stage is higher than that of regressing to the

preceding stage; (3) provinces in the dysfunctional decline stage demonstrate a strong intrinsic drive to overcome their limitations, with their probability of transitioning to a superior stage reaching 0.218; this implication suggests that directing support towards provinces currently mired in the dysfunctional decline stage, to enhance their coupling coordination levels, may serve as a particularly efficacious strategy for fostering coordinated development on a national scale.

4.3.2. Spatial Markov Transfer Probability Matrix

The evolution of coupling coordination types within each province is not entirely spatially independent, and may be influenced by the conditions of neighbouring regions. As $k = 4$, $Q_b = 83.358 > \chi^2(36)$ at a 1% significance level, the original hypothesis that the type transfer of coupling coordination is spatially independent can be rejected. Thus, spatial lag conditions should be integrated into our considerations. Upon the incorporation of these spatial lag conditions into the traditional Markov transition probability matrix, the results of this estimation are shown in Table 6. The comparison between Tables 5 and 6 yields the following conclusions:

1. The transition of coupling coordination types within a province is affected by the neighbourhood, with different neighbourhood types exerting varying influences on the transition probability; for instance, $m_{21/2} = 0.000 < m_{21/1} = 0.125$; $m_{34/2} = 0.167 < m_{34/3} = 0.232$;
2. Generally, neighbourhoods with higher type ranks exhibit stronger positive spatial spillover effects, such as $m_{12/1} = 0.245 < m_{12/2} = 0.247 < m_{12/3} = 0.285 < m_{12/4} = 0.495$; conversely, neighbourhoods with lower type ranks manifest stronger negative spatial spillover effects, such as $m_{43/4} = 0.023 < m_{43/3} = 0.040 < m_{43/2} = 0.045 < m_{43/1} = 0.111$.

4.3.3. Steady-State Distribution

The steady-state distribution of Markovian transition probabilities describes the distribution of various types as they reach an equilibrium state. Table 7 presents this steady-state distribution. When comparing the initial and final states without considering spatial lag, we observe a decline in the proportion of types 1 and 2, a minor increase for type 3, and a considerable increase for type 4. This trend implies a gradual shift among Chinese provinces from lower-level to higher-level coupling coordination types over time. Incorporating spatial lags into our considerations significantly alters the state of coupling coordination in China. Among varying neighbourhood types, the majority of provinces fall under types 3 and 4. The count of provinces classified as type 4 gradually increases as the neighbourhood type escalates, peaking at 0.890. Regardless of whether spatial lags are considered, the prospects for coordinated development between energy consumption and green development in China are quite optimistic. There is a clear trend towards a concentration of higher-level coupling coordination.

4.4. Trend Prediction of Coupling Coordination Degree

The coupling coordination degrees of 30 Chinese provinces from 2006 to 2020 as simulated values were brought into the gray model GM (1, 1), and the measured results show that the maximum C-value is 0.482 and the minimum p-value is 0.867, which are within the qualified range. The prediction period of this study extends from 2021 to 2025, and the corresponding projections are provided in Table 8. During this prediction period, the coupling coordination degree across Chinese provinces is expected to increase. Excluding Hebei, Shanxi, and Inner Mongolia, alongside two other provinces which remain in the barely coordinated stage, the remaining provinces are expected to transition from the barely coordinated stage to the coordinated development stage. Notably, Beijing is predicted to reach a superior level of quality coordination. Both Zhejiang and Sichuan are set to further progress to the quality coordination stage, building upon their current good coordination stage. Moreover, five provinces, including Tianjin, Jilin, and Shanghai, are forecasted to leap from the middle coordination stage to the good coordination stage. In conclusion, each province has a responsibility to maintain their current level of coupling coordination while breaking their limitations, so as to achieve a higher-quality coupling coordination level.

Table 8. Trend prediction of the coupling coordination degree.

Province	2021	2022	2023	2024	2025
Beijing	0.949	0.953	0.966	0.969	0.978
Tianjin	0.739	0.760	0.781	0.803	0.826
Hebei	0.492	0.518	0.545	0.571	0.599
Shanxi	0.479	0.497	0.515	0.534	0.553
Inner Mongolia	0.518	0.530	0.542	0.554	0.566
Liaoning	0.582	0.603	0.625	0.647	0.670
Jilin	0.750	0.785	0.820	0.855	0.891
Heilongjiang	0.531	0.542	0.552	0.563	0.573
Shanghai	0.748	0.762	0.776	0.791	0.805
Jiangsu	0.736	0.760	0.785	0.810	0.837
Zhejiang	0.828	0.854	0.880	0.907	0.935
Anhui	0.640	0.674	0.709	0.746	0.786
Fujian	0.727	0.747	0.768	0.789	0.810
Jiangxi	0.603	0.622	0.641	0.660	0.679
Shandong	0.653	0.682	0.714	0.746	0.781
Henan	0.657	0.689	0.723	0.757	0.791
Hubei	0.686	0.708	0.730	0.753	0.776
Hunan	0.707	0.725	0.743	0.761	0.780
Guangdong	0.809	0.828	0.848	0.868	0.888
Guangxi	0.691	0.709	0.728	0.747	0.766
Hainan	0.667	0.676	0.686	0.695	0.705
Chongqing	0.678	0.687	0.696	0.705	0.714
Sichuan	0.808	0.839	0.872	0.904	0.937
Guizhou	0.586	0.610	0.634	0.659	0.684
Yunnan	0.690	0.715	0.742	0.769	0.797
Shaanxi	0.616	0.635	0.655	0.675	0.695
Gansu	0.584	0.603	0.623	0.642	0.662
Qinghai	0.699	0.709	0.719	0.729	0.739
Ningxia	0.502	0.507	0.513	0.519	0.525
Xinjiang	0.606	0.622	0.639	0.656	0.673

5. Conclusions and Policy Implications

5.1. Conclusions

Based on the constructed evaluation system for energy consumption and green development, this study scientifically measured, analyzed, and predicted the degree of coupling coordination between energy consumption and green development across 30 Chinese provinces. The major conclusions of this study are as follows:

1. Evaluations conducted via the entropy method, applied to both energy consumption and green development systems, disclose a predominantly ascending trajectory for the period from 2006 to 2020. These findings substantiate that China has effectively executed strategies related to energy consumption transformation and ecological development. Nonetheless, both systems present significant potential for further enhancement at their absolute levels. Although the averages for the energy consumption system marginally surpass those for the green development system, the growth rate of the latter significantly outpaces that of the former. The speed of the low-carbon transition in energy consumption needs to be further accelerated in future economic development work.
2. The coupling coordination model's measurements reveal three key findings. Firstly, based on the temporal evolution, the overall coupling coordination degree across China from 2006 to 2020 demonstrates a consistent upward trend. This alteration

indicates that China has embarked upon a 'new normal' in its economic trajectory, transitioning from the dysfunctional decline stage to the coordinated development stage. Secondly, concerning spatial evolution, the distribution of the coupling coordination degree presents discernible "higher in the south, lower in the north" and "center-edge" patterns. Nevertheless, as China rigorously progresses in the implementation of its common prosperity strategy, these spatial disparities across its provinces are exhibiting a trend of convergence. Lastly, from the perspective of dynamic distribution trends, the level of coupling coordination among provinces increasingly concentrates.

3. The dynamic evolution of coupling coordination types is marked by four distinctive characteristics. Firstly, this dynamic evolution presents the traits of stability, continuity, and heterogeneity. Secondly, a province's transfer from one stage of coupling coordination to another may be influenced by neighbouring provinces, with the degree of influence varying depending on the neighbourhood type. Thirdly, the higher the neighbourhood stage's grade, the stronger the positive spatial spillover effect becomes, while the opposite is true for lower neighbourhood grades. For instance, regions such as Beijing and Shanghai demonstrate more pronounced positive spatial spillover effects, in contrast to Hebei and Shanxi, where these effects are comparatively subdued. Finally, in the long term, regardless of whether spatial lag is considered, there is a tendency for the coupling coordination in all provinces to concentrate towards the higher stages.
4. The predicted results from the grey model GM (1, 1) suggest the following: throughout the forecast period, the coupling coordination degree across Chinese provinces is set to further improve. With the exception of a handful of provinces—Hebei, Shanxi, and Inner Mongolia—which remain in the barely coordinated stage, the rest have effectively transitioned from the barely coordinated stage to the coordinated development stage. The study revealed that there is still space for improvement in the current development trajectory of several provinces, such as Hebei, Shanxi, and Inner Mongolia.

5.2. Policy Implications

Based on the above conclusions, this paper argues that, to effectively improve the degree of coupling coordination in China, the following policy implications could be considered. While these conclusions are primarily grounded in the context of China, the policy implications are equally applicable to other countries, including developed ones, because international energy and environmental concerns are gaining escalating prominence.

1. The ongoing advancement of technological innovation reform coupled with the persistent enhancement of green endogenous growth remains imperative. The research results obtained using the entropy method and coupling coordination model show that China's energy consumption level, green development level, and the coupling coordination degree are all on the rise, but there is still great room for growth in their absolute levels. At the current stage, it is necessary to continuously promote the reform of technological innovation to boost the potential green endogenous growth. Two specific aspects can be developed. Firstly, provinces are encouraged to incrementally incorporate new energy sources to augment the utilization of renewable energy and refine the structure of energy consumption; specifically, the main focus is on increasing the use of photovoltaic, wind, and nuclear power, as well as facilitating the accelerated development of distributed energy resources, smart grids, and energy-saving technologies to enhance energy efficiency. Secondly, it is recommended that each province continuously promotes the reform of the circulation of green innovation factors, such as high-technology personnel and R&D funds, thereby leading to a more equitable distribution of these factors and, ultimately, enhancing the overall level of green innovation.
2. Adjusting the economic development strategy in northern China is a crucial step towards further reducing the disparity in coupling coordination between the north

and south. The current analysis and trend prediction of coupling coordination indicate that the difference in the coupling coordination between southern and northern China is progressively narrowing, but the coupling coordination of the northern provinces still remains lower than that of the southern provinces. The northern provinces currently face problems such as heavy energy consumption and lagging environmental management, leading to their relatively low level of coupling coordination. In the future, the northern provinces need to accelerate the adjustment of economic growth patterns, improve energy use efficiency, reduce energy carbon emissions, and enhance eco-friendly awareness. Specifically, the northern region can address this issue through two primary approaches. The first is to concentrate on the low-carbon transformation of existing industries, especially the iron and steel industry, which ought to evolve consistently in a more technologically intensive and knowledge-intensive direction. The second is to assiduously foster new drivers for economic development by vigorously developing cleaner methods, such as wind power and photovoltaic power generation, with these fresh impetuses ultimately propelling the economic strategy towards green transformation.

3. Emphasizing the spatial linkage effect and leveraging the radiative influence of regions with a high level of coupling coordination is essential. The empirical findings elucidate that the degree of coupling coordination within China manifests a spatial distribution characterized by a "center-edge" pattern, and exhibits pronounced spatial linkage effects. Specifically, elevated neighbourhood levels correlate with enhanced positive spillover impacts. In light of these observations, fostering regional coordinated development in a holistic manner requires the leveraging of regional advantages. To this end, it is advisable to put in place coordinated development frameworks between contiguous regions. Examples include the integrated development mechanisms already in place for the Yangtze River Delta and the Beijing–Tianjin–Hebei conurbation. Such regional integrative approaches serve to enhance inter-regional communication, thereby catalyzing technological innovation, systemic improvements, and industrial upgradation, particularly in regions characterized by lower degrees of coupling coordination.
4. Drawing upon data pertaining to energy consumption and green development across 30 Chinese provinces from 2006 to 2020, we conducted a comprehensive measurement and analysis of the energy consumption index, the green development index, and their coupling coordination. This analysis holds considerable pragmatic significance for expediting the low-carbon transformation in energy consumption and fostering green development within China. Nonetheless, certain limitations persist. While we endeavored to construct evaluative frameworks for both energy consumption and green development, the data constraints specific to energy consumption rendered the resulting evaluation system suboptimal. Additionally, given that green development encompasses a broad array of economic and societal dimensions, its evaluative framework incorporates a more extensive set of indicators compared to its energy consumption counterpart. Consequently, future research avenues should focus on the development of a more scientifically robust and comprehensive evaluation system for energy consumption, as well as the streamlining of indicators within the green development framework, to enhance the rigor and credibility of the outcomes.

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