

## Article

# Towards a Sustainable Yangtze River Economic Belt: Deciphering the Spatiotemporal Dynamics and Multivariate Influencing Mechanisms Based on Spatial Spillover Effects for Urban Carbon Productivity

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## Abstract

Enhancing urban carbon productivity (UCP) is crucial for achieving the dual carbon goals in China. This study investigates the spatiotemporal patterns and underlying drivers of UCP in the Yangtze River Economic Belt (YREB) from 2010 and 2020. Utilizing a comprehensive dataset of 110 cities, we employ kernel density estimation, spatial autocorrelation analysis, and the Spatial Durbin Model (SDM). The results reveal a significant overall improvement in UCP alongside intensified internal disparities and a fundamental spatial restructuring—from a monocentric eastern-led pattern to a multipolar network driven by the Yangtze River Delta, middle Yangtze, and Chengdu-Chongqing agglomerations. The SDM decomposition reveals a shift in core drivers towards green technological innovation and advanced industrial structure, while energy consumption remains the primary constraint. Crucially, complex spatial spillover effects are identified: factors like advanced industrial structure and digital governance are associated with positive synergistic spillovers, whereas government intervention (government public budget expenditure) and urban sprawl exhibit negative competitive spillovers, collectively corresponding to the polarized regional pattern. Furthermore, urban form shows strong spatial externalities: urban compactness is linked to a “local-neighborhood” double dividend, while urban sprawl is associated with a “local-neighborhood” double curse. The influence of digital factors appears to evolve from early widespread spillovers to later localized deepening. The findings suggest the necessity of implementing spatially differentiated policies, strengthening regional collaborative governance to manage spatial externalities, and promoting compact regional spatial planning to foster synergistic and equitable low-carbon transitions across the YREB.

**Keywords:** urban carbon productivity; spatiotemporal dynamics; digitalization; green technological innovation; urban form; Spatial Durbin Model

Academic Editor: Isidoro Fasolino

Received: 28 May 2026

Revised: 25 June 2026

Accepted: 26 June 2026

Published: 28 June 2026

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## 1. Introduction

Global climate governance is advancing at a slow pace, and disagreements regarding emissions reductions and funding continue to be the central issues in international climate negotiations. The 2025 Emissions Gap Report, which is released by the United Nations Environment Programme, indicates that even when all countries comprehensively execute their present nationally determined contributions, global warming within this century is anticipated to reach 2.3 to 2.5 degrees Celsius, surpassing the 2-degree target established by the Paris Agreement [1]. Against this backdrop, identifying a high-quality development path that strikes a balance between economic growth and carbon emission mitigation has emerged as a key agenda item. Carbon productivity, which is defined as the economic value generated per unit of carbon emissions, serves as a crucial indicator for evaluating the efficiency of factor input and output in an economy under carbon emission constraints [2,3]. Therefore, enhancing carbon productivity, that is, increasing the economic value produced per unit of carbon dioxide emitted, has emerged as a vital approach to decouple economic development from carbon emissions [2–6].

As the world's largest carbon emitter, China is confronted with unprecedented pressure to reduce emissions and challenges in the transition of its development model [7,8]. Cities, serving as the primary consumers of energy and sources of carbon emissions, contribute to over 85% of China's total carbon emissions [9]. Nevertheless, existing research mainly concentrates on the national, provincial, or industry levels, leaving substantial gaps in systematic, multi-scale studies of carbon productivity at the city level. Meanwhile, achieving China's "dual carbon" goals requires accounting for the country's vast territory and uneven regional development [10–13]. The disparities in development levels, industrial structures, technological endowments, and policy environments among cities are considerable, leading to a highly complex and nonlinear spatiotemporal evolution of carbon productivity [14–17]. Therefore, selecting representative regions for in-depth analysis of urban carbon productivity (UCP) evolution patterns and improvement pathways holds significant value for designing differentiated low-carbon transition strategies.

The Yangtze River Economic Belt (YREB) encompasses China's eastern, central, and western regions, encompassing 11 provinces and municipalities. It constitutes approximately 21% of the country's land area yet accounts for over 40% of its population and economic output, rendering it one of China's most influential and strategically important regions. Simultaneously, the YREB is a hotspot for energy consumption and carbon emissions, bearing substantial ecological significance and environmental pressure. Three characteristics make the YREB particularly representative for UCP research. Firstly, the YREB is a typical area where high-intensity carbon emissions coincide with ecological constraints, necessitating an urgent reduction in emissions and an improvement in carbon productivity. Previous studies have documented strong coupling between urban expansion and carbon emissions in the Yangtze River Delta [18], carbon injustice within this region [19], complex decoupling relationships between emissions and economic growth across different basin segments [20], and substantial pressure on certain cities to achieve carbon neutrality even under optimistic technological scenarios [21]. Secondly, the YREB is confronted with the dual challenges of industrial spatial restructuring and the reshaping of carbon emission patterns. The spatial heterogeneity and spillover effects of carbon productivity demand more in-depth investigation. As the development strategy for the YREB progresses, the processes of regional industrial division and transfer have accelerated significantly, producing both "pollution haven" effects and technological spillovers that reshape carbon productivity patterns [22]. This intricate process of industrial spatial restructuring renders the spatial pattern of UCP in the YREB more deserving of in-depth study. Meanwhile, the continuous evolution of the internal spatial structure within the YREB [23], the spatiotemporal variations in factor agglomeration capacity [24], and the

differentiated patterns of urban land-use efficiency [25] are significantly reshaping the spatial pattern of regional carbon emissions. She et al. discovered a substantial correlation between satellite remote-sensing indicators of urban morphology and air quality in the Yangtze River Delta; the findings demonstrated that morphological features, including the compactness and fragmentation of the urban spatial structure, directly affect transportation carbon emissions and energy utilization efficiency [26]. Luo et al. carried out a multi-scale characterization and prediction of carbon emissions in the Yangtze River Delta by leveraging land use and interpretable machine learning models; their study confirmed the crucial regulatory role of land use change in determining regional carbon source-sink patterns [27]. Song et al. further disclosed, through a spatiotemporal analysis of green economic efficiency in the Yangtze River Delta, that the convergence of green efficiency within the region is still inadequate, and there is a significant spatial imbalance [28]. Moreover, both the spatial spillover effects of industrial ecological efficiency in the Yangtze River Delta region [29] and the spatiotemporal differentiation of industrial ecologization [30,31] suggest a high degree of spatial interdependence among cities within the region in terms of environmental performance. Thirdly, as a national pilot for synergistic development and carbon neutrality, the YREB's internal gradients in economic development, industrial structure, and energy consumption create a typical study area for examining the complex, nonlinear evolution of UCP and its driving mechanisms.

Although the existing literature has yielded substantial outcomes in the calculation methods, spatial patterns, and driving mechanisms of carbon productivity, notable deficiencies persist. Firstly, the majority of studies are confined to the national, provincial, or sectoral levels. Meanwhile, systematic research on carbon productivity at the prefectural level and above in China remains fragmented, lacking a unified data foundation and a comparable framework. Secondly, numerous studies rely on static or short-term panel analyses, and there is an insufficient comparative analysis of the long-term trends in urban carbon productivity. Thirdly, the driving mechanisms of carbon productivity have given inadequate consideration to new factors such as technological innovation, the digital economy, and urban morphology. Moreover, the spatial spillover effects of influencing factors still demand further exploration. Therefore, this study selects 110 prefecture-level and above cities in the YREB from 2010 and 2020 as its research objects, computes urban carbon productivity using a single-factor indicator, and systematically uncovers the spatiotemporal evolution patterns of carbon productivity and their multidimensional mechanisms driven by spatial spillover effects through the integrated utilization of kernel density analysis, spatial autocorrelation, and the SDM. The marginal contributions of this study are mainly manifested in three aspects: Firstly, it extends the spatial economics literature by integrating urban form and digitalization into the carbon productivity framework, moving beyond conventional socioeconomic and technological factors. Secondly, using the SDM, this research quantifies both direct and spatial spillover effects of these multidimensional drivers—a dimension largely overlooked in prior work. Thirdly, this study offers actionable insights for policymakers in the YREB and beyond. The identification of positive spillovers and negative spillovers enables the design of differentiated, spatially synergistic low-carbon policies. These insights offer actionable guidance for achieving the “dual carbon” goals in a highly interconnected region.

## 2. Literature Review

Research on carbon productivity predominantly centers on its measurement, evolutionary patterns, and driving mechanisms. Kaya et al. systematically put forward a sustainability framework that integrates energy, environment, and economy, which lays the theoretical foundation for carbon productivity analysis [4]. Bakker et al. explicitly state in their report titled “Breaking the climate deadlock: a global deal for our low-carbon future”

that the core of the climate issue resides in economic efficiency and development models, rather than simply emission restrictions [2]. Successful climate action must concurrently attain two seemingly conflicting objectives: “stabilizing atmospheric greenhouse gas concentrations” and “maintaining global economic growth,” highlighting a substantial increase in “carbon productivity,” which refers to the GDP generated per unit of carbon emissions. Beinhocker et al., in their report “The carbon productivity challenge: Curbing climate change and sustaining economic growth,” emphasize the necessity and feasibility of decoupling global economic growth from carbon emissions while comprehensively addressing concerns about the high cost of emission reductions from both economic and technological perspectives, thereby transforming carbon productivity from a theoretical metric into a quantifiable and operational strategic framework [3].

### *2.1. Urban Carbon Productivity Accounting*

The computation of carbon productivity acts as a vital basis for analyzing spatiotemporal patterns and comprehending the underlying drivers. In the early studies, single-factor carbon productivity, which is defined as economic output per unit of carbon emissions ( $GDP/CO_2$ ), was mainly adopted. This concept is intuitive and straightforward to calculate, and it has been extensively utilized in international comparisons and trend analysis [2,3,6,32–36]. Subsequently, relevant scholars developed a total-factor carbon productivity that integrates both desirable output (GDP) and undesirable output ( $CO_2$ ). This development was mainly based on data envelopment analysis (DEA) and its derivatives, such as the Malmquist-Luenberger index and directional distance functions, with the aim of more comprehensively measuring the overall economic efficiency under environmental constraints [37–44]. Although total-factor carbon productivity has achieved theoretical advancements, its large-scale implementation at the urban level still encounters challenges related to data availability and computational stability. Most measurement results based on the DEA are highly sensitive to the selection of input-output indicators and model specifications [45,46], and they find it difficult to clearly disclose the direct technological relationship between carbon emissions and economic output as intuitively as single-factor indicators.

### *2.2. The Spatial Patterns of Urban Carbon Productivity*

The investigation of the spatial patterns of carbon productivity uncovers the uneven geographical distribution and spillover effects between carbon emissions and economic output. As spatial econometrics has advanced, research on carbon productivity has shifted from conducting isolated analyses of individual regions to concentrating on spatial interdependencies and heterogeneity among regions. A considerable amount of empirical evidence demonstrates significant spatial disparities in carbon productivity across diverse regions of China. Pan et al. previously concentrated on the regional disparities in China’s carbon productivity, demonstrating that carbon productivity is higher in eastern China compared to central and western regions [33]. Subsequent studies further verified the existence of this disparity through methods such as the Theil index and the coefficient of variation, and discovered that it demonstrates fluctuating characteristics [47]. Studies conducted by [36,48] have identified a significant positive spatial autocorrelation in China’s inter-provincial carbon productivity. This finding suggests that the local carbon productivity levels are positively affected by those of neighboring regions. Refs. [49] and [48] respectively verified the spatial dependence and club convergence characteristics of carbon productivity from the perspectives of spatial agglomeration and spatial convergence. Bai et al. identified a convergence trend in total-factor carbon productivity through a global-perspective analysis; meanwhile, their studies concentrating on China indicated the presence of different regional convergence clubs [39].

### 2.3. *The Multivariate Influencing Mechanisms of Urban Carbon Productivity*

Uncovering the underlying mechanisms behind the changes in carbon productivity is crucial for formulating effective improvement strategies. Existing research has carried out comprehensive discussions from multiple perspectives, such as the economy, urbanization, trade, investment, and energy. Yao et al. utilized a spatial comparative path selection model to identify the determinants of regional disparities in carbon productivity, finding that industrial carbon intensity serves as a crucial factor influencing both regional variations and provincial-level enhancement of carbon productivity, while industrial structure also exerts a significant influence on these disparities [50]. Li and Wang reveal that GDP per capita, technology, trade openness, and foreign direct investment significantly enhance China's carbon productivity while energy structure, industrialization, and urbanization exert negative effects, with evident regional imbalances favoring eastern coastal provinces over central and western regions [51]. Mehmood et al. examine the top 18 CO<sub>2</sub>-emitting countries and find that GDP per capita, trade, and foreign direct investment significantly enhance carbon productivity while energy consumption and urbanization curtail it, with 83% of sample countries exhibiting a positive socio-economic development–carbon productivity nexus [6]. Murshed et al. show that energy efficiency gains directly enhance carbon productivity in E7 countries (Emerging Seven countries, i.e., Turkey, Russia, Mexico, India, Indonesia, China, and Brazil) while moderating the negative effects of financial inclusivity, trade globalization, and urbanization, and mediating alongside renewable energy to jointly improve carbon productivity, though economic growth persistently inhibits it [52]. Foreign trade [53], foreign direct investment [54], and outward foreign direct investment [55] have all been verified as significant transmission variables influencing the spatial spillover of carbon productivity.

In addition, novel factors, including technological innovation and digitalization, have been integrated into the carbon productivity analysis framework. Technological innovation is commonly recognized as the fundamental impetus for enhancing carbon productivity. Theoretically, green technological innovation not only directly boosts energy efficiency but also fosters an increase in carbon productivity through the optimization of the allocation structure of production factors [40]. Empirical research has verified the role of various types of technological progress, including the applications of artificial intelligence [35] and mediating effects of the quantity and quality of green innovation [56]. Departing from the conventional focus on the intensity or level of technological innovation, Wang et al. draw on the theory of directed technical change to distinguish between capital-labor technological progress bias and energy-augmenting technological progress bias, and examine their respective impacts on carbon productivity using China's provincial panel data from 2006 to 2020, furthermore, this research demonstrate that capital-labor technological progress bias significantly enhances carbon productivity whereas energy-augmenting technological progress bias persistently undermines it [57]. Zhao et al. reveal a U-shaped relationship between environmentally induced R&D and total factor carbon productivity, where government support including direct investment, subsidies, tax deductions, and talent introduction positively moderates this effect and serves as a threshold that transforms short-term inhibition into long-term enhancement with significant spatial spillovers to neighboring regions [58]. Hou et al. demonstrate a U-shaped relationship between environmental regulation and carbon productivity where green technology progress steepens this curve by amplifying both the short-term cost burden and the long-term innovation compensation effects of regulatory pressure on carbon productivity [59]. Zhou and Tang demonstrate that China's Action Plan of Air Pollution Prevention and Control significantly promoted carbon productivity in pollution-intensive industries through incentivizing R&D expenditure in instruments and equipment, thereby advancing technical efficiency and technological frontier [60]. Wang et al. demonstrate that

industrial intellectualization significantly enhances carbon productivity by promoting technological progress and industrial structure upgrading, though this positive effect is contingent upon sufficient information technology infrastructure and skilled labor availability while being undermined by regional resource dependence [61].

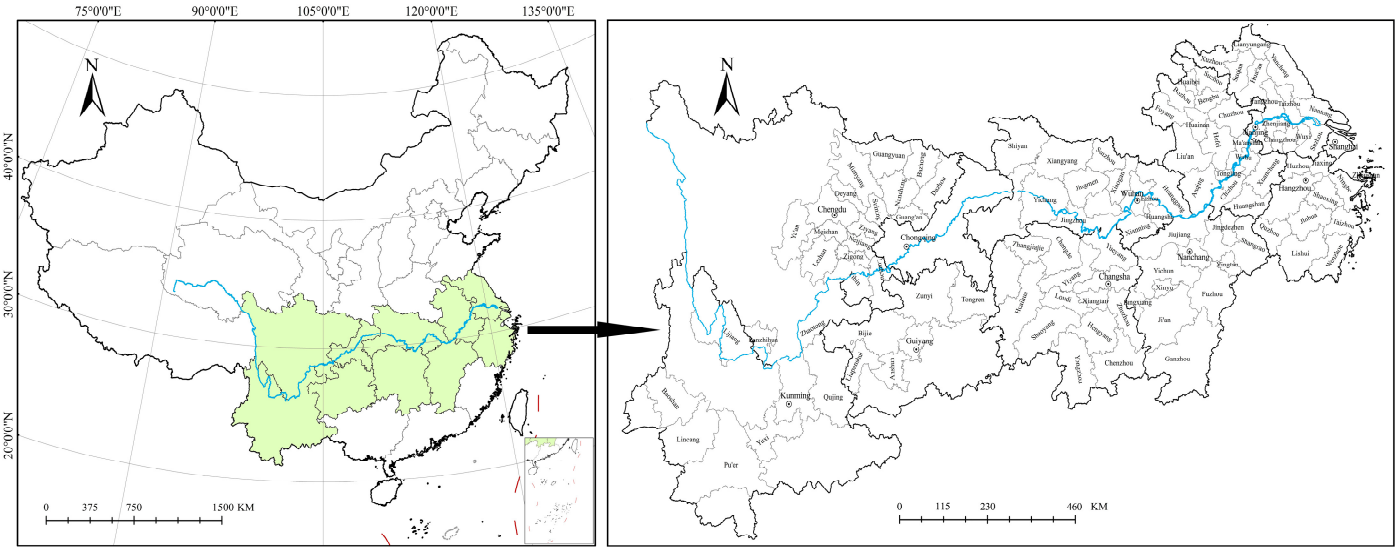
In recent years, the digital economy and financial development have attracted substantial attention as emerging driving forces. Research commonly posits that digital technologies improve carbon productivity by mitigating information asymmetry, optimizing resource allocation, and enabling traditional industries to make a transition towards green development [62]. Studies employing quasi-natural experiments, such as “Broadband China” [42,63], smart city [64], the Internet development [14], have consistently confirmed the positive impacts of digital infrastructure. Xu et al. exploit the Broadband China pilot and find that digital infrastructure significantly enhances carbon productivity by promoting green technological progress and facilitating industrial upgrading, with stronger effects in cities with lower electrification levels and more developed green finance systems [42]. Furthermore, Tao et al. show that the Broadband China pilot significantly boosts carbon productivity with pronounced effects in eastern, central and southern regions, while innovation, financial development and urbanization amplify this impact and positive spatial spillovers extend to neighboring areas [63]. Song et al. find that China’s smart city pilot policy significantly improves urban carbon productivity through technological progress, industrial structure upgrading and energy structure optimization [64]. Tian and Pang find that internet development significantly enhances green total-factor productivity in the Yangtze River Economic Belt through both direct effects and indirect channels of technology innovation and industrial structure upgrading [16]. Yu et al. demonstrate that internet development significantly enhances green total factor productivity in Chinese cities through promoting technological innovation, while generating substantial positive spatial spillovers that considerably outweigh its direct local effect [14]. Meanwhile, the development of digital finance can alleviate the financing constraints encountered by green innovation. However, its impact on carbon performance may demonstrate nonlinear threshold characteristics [65,66]. Sun et al. find that digital finance significantly enhances urban carbon productivity through human capital accumulation and marketization channels while generating positive spatial spillovers to neighboring cities, with fixed-asset investment exerting a positive nonlinear moderating effect [65]. Zhou et al. reveal that digital finance exerts a nonlinear “first-inhibit-then-promote” effect on carbon performance in China, operating through green technology innovation, industrial upgrading and energy structure optimization, with the effect being more pronounced in eastern regions and in provinces with higher marketization levels and narrower urban-rural income gaps [66]. He et al. illustrate that the coupling coordination degree among digital economy, green finance, and carbon productivity steadily improved from primary to intermediate coordination across Chinese provinces, with spatial patterns decreasing from east to west and openness, industrial agglomeration, and digital innovation as the main drivers [67]. Li et al. reveal a positive U-shaped relationship between green finance and carbon productivity across Chinese cities, where both the quantity and quality of green innovation mediate this effect, with the quality-driven pathway proving more pronounced in non-resource cities and across eastern, central and western regions [56].

### 3. Materials and Methods

#### 3.1. Materials

The Yangtze River Economic Belt (YREB) extends across China’s eastern, central, and western regions, encompassing 11 provincial-level administrative divisions, namely Shanghai, Jiangsu, Zhejiang, Anhui, Jiangxi, Hubei, Hunan, Chongqing, Sichuan, Guizhou, and Yunnan (Figure 1). Having a total area of approximately 2.057 million square

kilometers, it constitutes 21.27% of the country’s land area. This study designates the 110 prefecture-level cities and above (including the municipalities of Shanghai and Chongqing, excluding prefectures, leagues, and regions) as its basic analytical units. All the study units have permanent populations exceeding one million, consisting of seven megacities, 33 large cities, 36 Type I cities (with urban populations ranging from 3 to 5 million), and 34 Type II cities (with urban populations ranging from 1 to 3 million). The YREB serves as an ideal laboratory for investigating urban carbon productivity due to its pronounced internal gradients in economic development, industrial structure, and energy consumption patterns.



**Figure 1.** Location of the Yangtze River Economic Belt.

The dependent variable is urban carbon productivity (UCP), defined as the ratio of real gross domestic product to total CO<sub>2</sub> emissions. This single-factor metric offers computational simplicity and straightforward economic interpretation, making it particularly suitable for comparative analysis across heterogeneous urban units, while effectively capturing the core objective of decoupling economic growth from carbon emissions.

Drawing on the theoretical framework established in the literature review, this research has developed a comprehensive indicator system that encompasses four dimensions: socioeconomic development, energy and innovation, digital development, and urban forms (Table 1).

**Table 1.** Multi-factor indicator system for urban carbon productivity.

| Factors                   | Indicators                    | Abbreviation | Symbol | Unit                   |
|---------------------------|-------------------------------|--------------|--------|------------------------|
| Dependent variable        | Urban carbon productivity     | UCP          | Y      | Billion Yuan/Million t |
| Socioeconomic development | Urbanization                  | URBA         | X1     | %                      |
|                           | Advanced industrial structure | AIS          | X2     | %                      |
|                           | Fixed asset investment        | FAI          | X3     | %                      |
|                           | Foreign trade                 | FTR          | X4     | %                      |
|                           | Government intervention       | GPBE         | X5     | %                      |
| Energy and Innovation     | Energy consumption            | TEC          | X6     | Billion kWh            |
|                           | R&D expenditure               | RDE          | X7     | %                      |
|                           | Green innovation output       | GPG          | X8     | Piece                  |
|                           | Digital human capital         | DHC          | X9     | %                      |
| Digital development       | Digital finance               | DFIN         | X10    | /                      |
|                           | Digital governance            | DGOV         | X11    | /                      |

|            |                        |          |     |   |
|------------|------------------------|----------|-----|---|
| Urban form | Urban sprawl           | LPI      | X12 | / |
|            | Urban shape complexity | PARA_MN  | X13 | / |
|            | Urban compactness      | PLADJ    | X14 | / |
|            | Urban connectivity     | COHESION | X15 | / |

X1, X2, X3, X4, and X5 represent the macro-socioeconomic context of urban development and serve as fundamental factors that influence resource allocation and emission levels. Urbanization (URBA, X1), namely, the proportion of the permanent resident population in urban districts at the end of the year relative to the total population. URBA controls for the scale effects and environmental pressures induced by population agglomeration. Advanced industrial structure (AIS, X2), measured as the ratio of tertiary industry value-added to GDP, characterizes the transition from energy-intensive manufacturing toward a service-oriented economic structure, a process theoretically expected to improve carbon productivity. Fixed asset investment (FAI, X3), namely, the proportion of total annual urban investment in fixed assets in the urban GDP. FAI accounts for capital deepening and infrastructure-driven economic growth. Foreign trade (FTR, X4), namely, the proportion of total annual volume of the city's import and export trade in the urban GDP. FTR captures the dual influences of foreign openness—the pollution halo versus pollution haven effects. General public budget expenditure (GPBE, X5) represents government intervention capacity, namely, the proportion of general public budget expenditure in the urban GDP.

X6, X7, X8, and X9 are directly associated with the sources of carbon emissions and the driving forces behind energy conservation and emission reduction (technological innovation and human capital), acting as the direct techno-economic factors that determine carbon productivity. Electricity consumption (TEC, X6) serves as a direct proxy for total energy consumption, the primary source of urban carbon emissions. R&D expenditure (RDE, X7) captures the intensity of innovation input, while green patent grants (GPG, X8) reflect direct green innovation output. RDE represents research and development expenditure of the city. GPG represents the total number of green patents granted in the city. These two variables jointly characterize a city's capacity and achievement in environmentally oriented technological advancement. Digital human capital (GHC, X9), namely, the proportion of employees in the software and information technology service industry among urban workers. GHC measures the concentration of information and communication technology talent, capturing the core labor force of the digital economy.

X10 and X11 represent the role of digital transformation in the allocation of financial resources and the efficiency of government governance, acting as an emerging driving force that influences the green operational efficiency of the economy. Digital finance (DFIN, X10) gauges the depth of digital technology integration with financial services, which may alleviate financing constraints for green projects. Digital governance (DGOV, X11) reflects the government's digital transformation capacity, potentially enhancing environmental regulatory efficiency and public participation in pollution monitoring.

X12, X13, X14, and X15 represent urban form indices. These indices quantify the urban sprawl, urban shape complexity, urban compactness, and urban connectivity from the perspective of spatial morphology and are employed to examine the potential impact of urban spatial structure on carbon productivity. Largest Patch Index (LPI, X12) quantifies the dominance of the largest contiguous urban patch, with higher values indicating a more monocentric and sprawling urban form. Perimeter-Area Ratio Mean (PARA\_MN, X13) captures the mean shape complexity of urban patches, where elevated values reflect irregular and fragmented urban boundaries. Percentage of Like Adjacencies (PLADJ, X14) measures the degree of aggregation among urban built-up pixels, distinguishing compact contiguous development from dispersed leapfrog patterns. Patch Cohesion Index

(COHESION, X15) assesses the physical connectivity of urban patches, quantifying the spatial linkages among urban sub-centers.

The cross-sectional dataset covers the period for 2010 and 2020, balancing data availability with temporal coverage that captures China's rapid urbanization and subsequent low-carbon policy transitions. City-level CO<sub>2</sub> emissions were sourced from the China High Resolution Emission Database (<http://www.cityghg.com/> (accessed on 6 November 2025)), which were estimated following the Intergovernmental Panel on Climate Change (IPCC) reference approach. Socioeconomic and energy data (X1, X2, X3, X4, X5, X6, X7, and X9) were primarily extracted from the China City Statistical Yearbook, the China Energy Statistical Yearbook, and provincial and municipal statistical yearbooks. Green patent grants (X8) were identified by matching patent data from the China National Intellectual Property Administration with the World Intellectual Property Organization's Green Inventory to extract patents classified under environmentally sound technologies. The Digital Financial Inclusion Index (X10) was sourced from the Institute of Digital Finance, Peking University (<https://idf.pku.edu.cn/zsbz/bjdxszphjrzs/index.htm> (accessed on 16 December 2025)). Digital governance (X11) was sourced from the Tsinghua University Report on Fiscal Transparency of Chinese Municipal Governments, <https://www.sppm.tsinghua.edu.cn/xycbw/yjbg.htm> (accessed on 16 December 2025). Land use and land cover data for computing urban morphology metrics (X12, X13, X14, and X15) were obtained from GlobeLand30, a 30 m resolution global land cover dataset (Resource and Environmental Science Data Platform, CAS, <https://www.resdc.cn/> (accessed on 6 July 2025)). These metrics were computed using Fragstats 4.2, providing a multidimensional characterization of urban morphological features that may influence commuting distances, energy consumption patterns, and ultimately urban carbon productivity.

### 3.2. Calculation of Urban Carbon Productivity

The calculation of urban carbon productivity serves as the foundation of this study. In order to clearly reflect the economic output efficiency per unit of carbon emissions, ensure the availability of data at the city level, and guarantee the comparability of results, this research employs the widely used single-factor carbon productivity for measurement [35,57,65,66,68]. The calculation formula is as follows:

$$UCP_{it} = \frac{GDP_{it}}{CE_{it}}$$

$UCP_{it}$  represents the carbon productivity of city  $i$  in year  $t$  (unit: Billion Yuan/Million  $t$ ); denotes the real regional gross domestic product calculated at 2010 constant prices (in billion yuan); and  $CE_{it}$  represents the total carbon emissions of city  $i$  in year  $t$  (in million  $t$ ). A higher value of  $UCP_{it}$  implies a stronger capacity of the city to generate economic value through carbon emissions.

### 3.3. Kernel Density Estimation

To unveil the dynamic evolution of the overall distribution pattern, location, and extensibility of urban carbon productivity in the Yangtze River Economic Belt, and to circumvent the limitations imposed by prior assumptions in parametric estimation, this study utilizes a non-parametric estimation method, namely Gaussian Kernel Density Estimation (KDE). This method can smoothly estimate the probability density function of random variables, clearly depicting the shape of the distribution, the number of peaks, and tail characteristics [69,70]. Its expression is:

$$f(x_{ucp}) = \frac{1}{Nh} \sum_{i=1}^N K\left(\frac{x_{ucp} - X_{ucpi}}{h}\right)$$

The function  $f(x_{ucp})$  represents the estimated probability density at a given UCP level  $x$ . A higher density value indicates a greater concentration of cities with UCP levels around.  $N$  is the total number of observations (i.e., cities, with  $N = 110$  in this study). The symbol  $K$  stands for the Gaussian kernel function, and  $h$  represents the bandwidth, which is selected in accordance with Silverman's rule of thumb to strike a balance between smoothness and fidelity.  $X_{ucpi}$  is the observed UCP value for the  $i$  city. By plotting the kernel density curves for the years 2010 and 2020, we are able to visually evaluate whether the UCP distribution is unimodal or multimodal, whether its center has shifted to the right, and to what extent it has broadened (dispersed). This enables us to characterize the overall improvement in regional efficiency and the evolution of internal disparities.

### 3.4. Spatial Autocorrelation Analysis

To investigate whether the urban carbon productivity along the Yangtze River Economic Belt demonstrates spatial agglomeration or differentiation patterns, this study utilizes spatial autocorrelation analysis at both global and local scales [71].

Global spatial autocorrelation is measured by means of the Global Moran's  $I$  index to evaluate the extent of spatial dependence of urban carbon productivity throughout the entire Yangtze River Economic Belt. The calculation formula is:

$$I = \frac{N}{\sum_{i=1}^N \sum_{j=1}^N w_{ij}} \cdot \frac{\sum_{i=1}^N \sum_{j=1}^N w_{ij} (X_{ucpi} - \bar{X})(X_{ucpj} - \bar{X})}{\sum_{i=1}^N (X_{ucpi} - \bar{X})^2}$$

$N$  represents the number of cities,  $X_{ucpi}$  and  $X_{ucpj}$  denote the UCP of cities  $i$  and  $j$  respectively,  $\bar{X}$  stands for the mean, and  $w_{ij}$  is an element of the spatial weight matrix. The value of Moran's  $I$  generally ranges from  $-1$  to  $1$ . A significantly positive value implies positive spatial autocorrelation (agglomeration), a significantly negative value implies negative spatial autocorrelation (dispersion), and a value close to zero indicates a random spatial distribution [71–73].

Local Spatial Autocorrelation: In order to identify specific locations and types of spatial clustering, the Anselin Local Moran's  $I$  and LISA (Local Indicators of Spatial Association) cluster maps were employed for analysis [74]. The formula is as follows:

$$I_i = \frac{(X_{ucpi} - \bar{X})}{S^2} \sum_{j=1, j \neq i}^N w_{ij} (X_{ucpj} - \bar{X})$$

$S^2$  denotes the sample variance. The outcomes are generally presented as four spatial association patterns: high-high clustering (HH), low-low clustering (LL), high-low outliers (HL), and low-high outliers (LH) [68]. This precisely uncovers the hotspots, cold-spots, and spatial heterogeneity patterns of urban carbon productivity within the study area.

### 3.5. Specification and Estimation of the Spatial Econometric Model

To identify the determinants of UCP and rigorously investigate the existence of spatial spillover effects, this study constructs a spatial econometric model. Disregarding such spatial dependence would lead to biased and inconsistent estimates when using traditional ordinary least squares (OLS) methods. First, this study conducts Lagrange Multiplier (LM) tests to ascertain whether spatial dependence mainly appears in the error term or in the lagged terms of the dependent variable. The test results support a more comprehensive form that encompasses both spatial lag and spatial error terms. Therefore, this

study employs the Spatial Durbin Model (SDM) as the baseline model, which concurrently incorporates spatial lags of both the dependent and independent variables, facilitating unbiased estimation of local effects and spatial spillover effects [75,76]. The SDM specification utilized in this study is as follows:

$$UCP_{it} = \rho \sum_{j=1}^N W_{ij} UCP_{jt} + \beta X_{it} + \theta \sum_{j=1}^N W_{ij} X_{jt} + \varepsilon_{it}$$

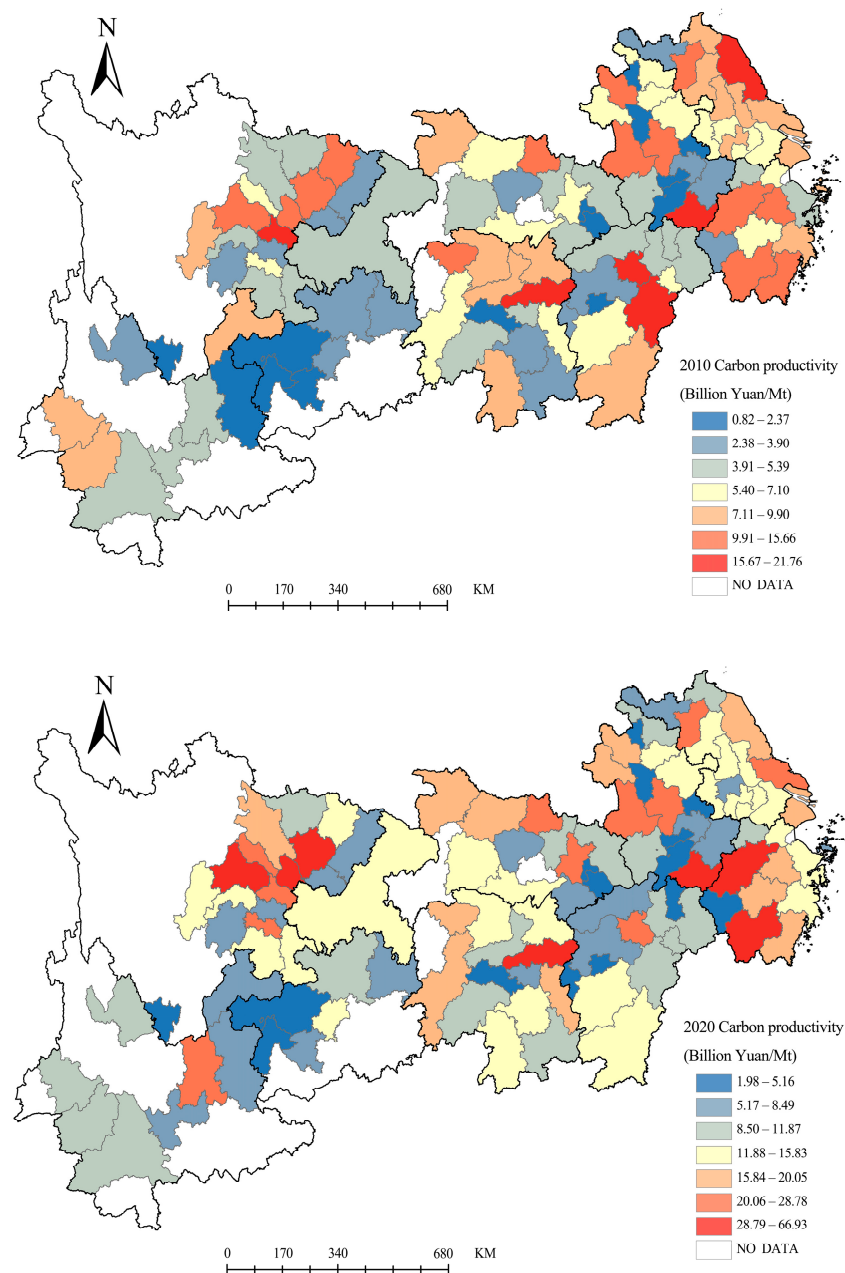
$UCP_{it}$  represents the carbon productivity for city  $i$  in year  $t$ .  $\rho$  denotes the spatial autoregressive coefficient, which measures the degree to which the carbon productivity of neighboring cities influences a given city and serves as the core parameter for spatial dependence.  $W_{ij}$  is an element of the spatial weight matrix  $W$ . The matrix has been row-standardized.  $X_{it}$  is a  $k \times 1$  vector that encompasses all the explanatory variables described above (see Table 1).  $\beta$  represents the vector of local effect coefficients for the explanatory variables.  $\theta$  is the vector of coefficients for the spatial lag of explanatory variables, which captures the spatial spillover effects of these variables on neighboring regions.  $\varepsilon_{it}$  is the composite error term.

In the SDM, the coefficients  $\beta$  and  $\theta$  of the explanatory variables cannot be directly construed as marginal effects. A variation in an explanatory variable within a specific city not only directly impacts the local dependent variable (direct effect) but also exerts an influence on other cities via spatial feedback loops, which subsequently feed back to the original city. Consequently, it is imperative to decompose the total effect into partial derivatives. The direct effect gauges the average impact on a city's own carbon productivity stemming from a one-unit change in its explanatory variable. The indirect effect (spatial spillover effect) assesses the average impact on the carbon productivity of all other cities as a result of a one-unit change in a given city's explanatory variable. The sum of the direct and indirect effects represents the overall average impact of a change in an explanatory variable in one city on the carbon productivity across all cities within the region.

## 4. Results

### 4.1. Spatial and Temporal Evolution of Urban Carbon Productivity Within the Yangtze River Economic Belt

Comparing the two cross-sections, the UCP along the YREB exhibited a substantial absolute increase on the whole. Nevertheless, the spatial imbalance and polarization among regions remained highly prominent. The pattern gradually transitioned from a single-gradient decline from coastal to inland areas to a new “multi-polar coordination and collective advancement” framework, with the Yangtze River Delta and the mid-Yangtze urban agglomeration acting as dual cores, propelling joint development together with inland hubs like Chengdu-Chongqing agglomerations (Figure 2). In 2010, the cities boasting the highest UCP were Huangshan, Fuzhou, Changsha, Nanchang, Ziyang, Yancheng, Hefei, Nanchong, Lu'an, and Zhangjiajie. By 2020, the ranking had changed to Huangshan, Changsha, Chengdu, Suining, Hangzhou, Nanchong, Lishui, Nanchang, Suizhou, and Suqian. Cities primarily focused on tourism exhibited the highest UCP, succeeded by provincial capital cities. This spatiotemporal evolution significantly reflects the spatial disparities in regional economic foundations, the extent of industrial structure transformation, and the capacity for green technological innovation.

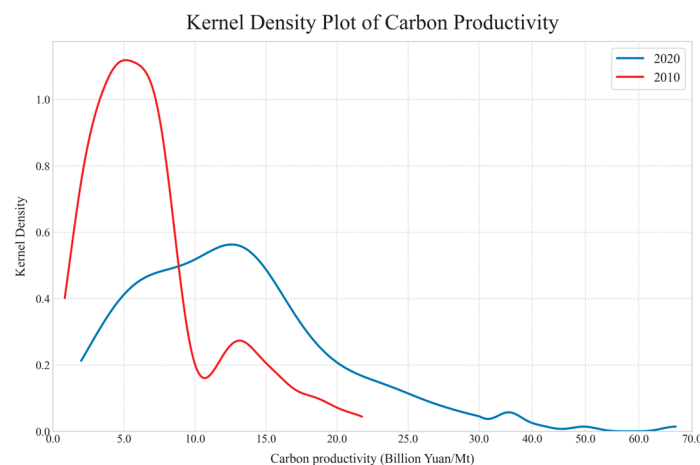


**Figure 2.** The spatial distribution of urban carbon productivity in the YREB.

#### 4.2. Kernel Density Estimation of Urban Carbon Productivity Within the Yangtze River Economic Belt

The primary peak of the kernel density estimation curve persists in shifting upward and to the right, clearly illustrating significant progress in decoupling economic growth from carbon emissions within the YREB, which indicates favorable results in the region's green and low-carbon transformation (Figure 3). The kernel density curve displays a clearly distinguishable multi-modal pattern, which significantly reveals the considerable heterogeneity in the low-carbon transition performance among cities within the region. In 2010, there was a notably high and steep main peak within the range of 5.0–10.0 billion yuan/million t on the horizontal axis. This peak represented the prevalent inefficient carbon utilization, which was typical among numerous traditional industrial and under-developed cities in the region at that time. By 2020, the height of this low-value peak had decreased significantly, and its distribution range had narrowed considerably. This

indicates that the elimination of outdated production capacity and the improvement of baseline energy efficiency have successfully elevated the carbon productivity of a large number of cities from extremely low levels. In 2020, the curve did not experience a rapid decline to zero in the high-value region above 20.0 billion yuan/million t. Instead, it displayed a gradual long-tail phenomenon and even presented minor secondary peaks in the range of 40.0–60.0 billion yuan/million t and above. This stands in stark contrast to the steep decline of the 2010 curve, which plummeted to its lowest point after reaching 10.0 billion yuan/million t. This suggests that as strategic initiatives such as the Yangtze River Delta integration are deepened, core cities within the region have not only attained high levels of UCP on their own but have also propelled surrounding cities towards higher value ranges, thus forming a distinct “high-value club” cluster.



**Figure 3.** The KDE of UCP in the YREB.

#### 4.3. Spatial Autocorrelation Analysis of Urban Carbon Productivity Within the Yangtze River Economic Belt

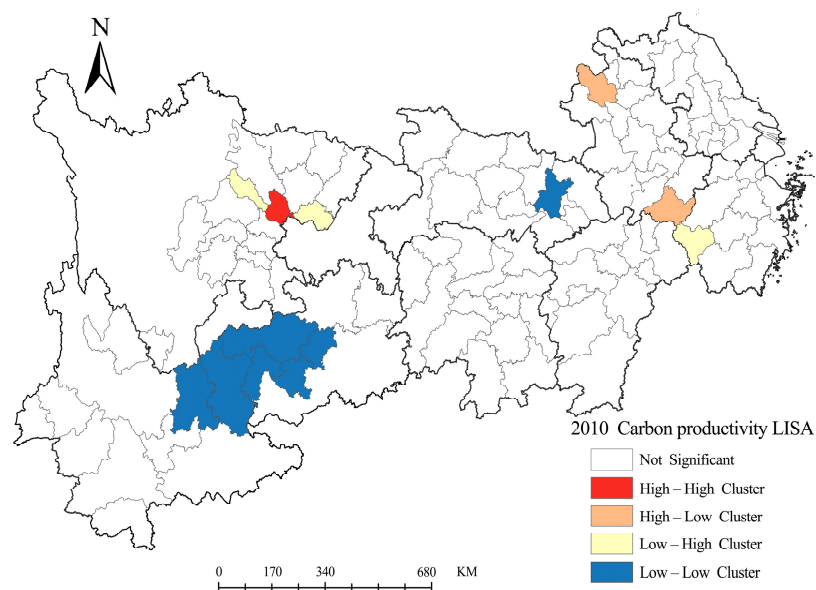
Spatial autocorrelation analysis reveals the spatial interdependence among geographical elements. This study quantifies the spatial agglomeration characteristics and heterogeneous patterns of UCP within the YREB through the calculation of the Global Moran’s I index and the analysis of local spatial association patterns (Tables A1 and A2, and Figure 4).

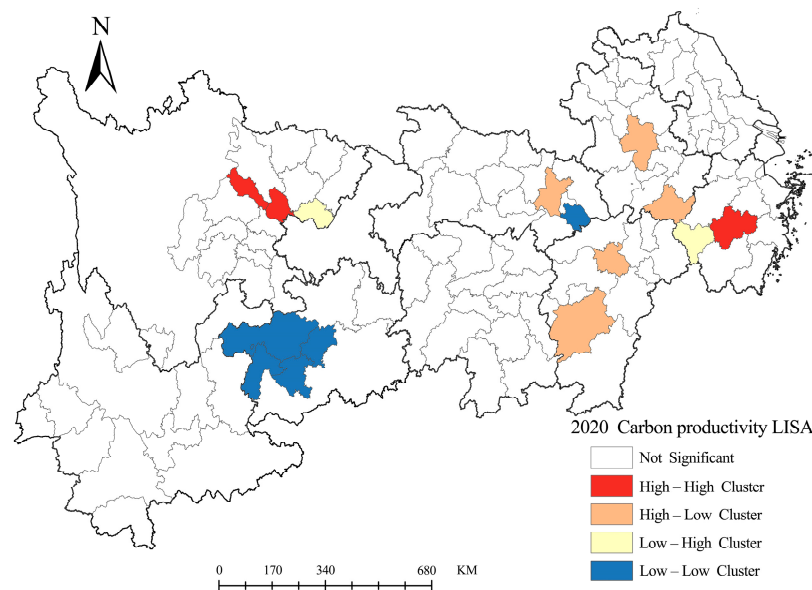
The Global Moran’s index is employed to quantify the extent of spatial association in UCP throughout the entire study area. In 2010, the Global Moran’s index for UCP in the YREB stood at 0.3014, which implies that at the onset of the study period, UCP already demonstrated significant positive spatial autocorrelation. This was characterized by the initial emergence of club clustering, where high-value areas were adjacent to high-value areas and low-value areas to low-value areas. From 2010 to 2020, the Global Moran’s index increased to 0.3597. Despite a substantial increase in the overall UCP levels over the past decade, the spatial Matthew Effect did not diminish but instead intensified. This indicates that the radiating and driving capacity of core high-productivity areas has widened the gap with the surrounding regions, or that the catch-up effect within the mid- and upper reaches has yet to overcome the existing spatial inertia, leading to increasingly close similarities in carbon productivity among geographically neighboring cities. Consequently, the entire economic belt exhibits a progressively more prominent pattern of spatial polarization.

The Local Indicators of Spatial Association (LISA) disclose heterogeneous clustering patterns of UCP at the local scale. In 2010, extensive contiguous areas characterized by significant low-low clusters were distributed across ecologically fragile or economically

underdeveloped regions, such as the Yunnan-Guizhou Plateau in the upstream region. This “low-value club” constituted the UCP depression zones within the YREB at that time, indicating that these areas were restricted by geographical conditions, infrastructure, and industrial structures, leading to overall inefficient carbon utilization. Owing to the absence of effective regional collaboration, they were caught in a pronounced negative spatial autocorrelation inertia. By 2020, significant high-high clusters were mainly concentrated in the downstream Yangtze River Delta urban agglomeration and the core areas of the upstream Chengdu-Chongqing agglomerations. Capitalizing on strong economic density, advanced technological innovation, and a comprehensive industrial chain, the Yangtze River Delta not only attained high carbon productivity on its own but also potentially promoted coordinated development among neighboring cities through spatial spillover effects, establishing a stable “high carbon productivity club.” Meanwhile, the Chengdu-Chongqing agglomerations, acting as a core driving force for Western China’s development strategy, achieved a significant improvement in regional carbon productivity by promoting internal industrial synergy and resource integration while accepting industrial relocation from eastern regions.

In the analysis of local spatial association, high-low outliers are defined as “spatial enclaves” in which a city possesses a relatively high UCP while being surrounded by neighboring cities with low UCP. The Wuhan metropolitan area demonstrates a distinct high-low outlier pattern. The central urban area of Wuhan is highly concentrated with high-value-added and low-energy-consuming industries, including optoelectronics, information technology, automotive manufacturing, and components. Conversely, the surrounding cities mainly accommodate heavy and chemical industries such as steel, petrochemicals, and building materials, or are located at the lower end of the industrial value chains. This asymmetric vertical industrial division leads to consistently high carbon emission intensities in the surrounding cities. Even with economic growth, it remains challenging to improve their carbon productivity, thus creating a remarkable “high-low” contrast with Wuhan in the spatial aspect.





**Figure 4.** The Local Indicators of Spatial Association (LISA) of UCP in the YREB.

#### 4.4. Factors Influencing Urban Carbon Productivity in the Yangtze River Economic Belt and Their Spatial Spillover Effects

The spatial economic model employed in this study encompasses 15 explanatory variables across four dimensions: socioeconomic development, energy and innovation, digital development, and urban form. The results of descriptive statistics and spatial autocorrelation tests (Tables A1 and A2) indicate that the means of most explanatory variables witnessed a significant increase from 2010 to 2020, which reflects the rapid regional development in urbanization, industrial structure upgrading, technological innovation, and digitalization. The Moran's index for key variables exhibited a significantly positive value in most years, which indicates that there are strong spatial clustering characteristics among these socioeconomic and spatial factors (Tables A1 and A2). This statistically validates the necessity of employing spatial econometric models to capture complex spatial spillover effects. To conduct an in-depth investigation into the driving mechanisms underlying the spatio-temporal evolution of UCP in the YREB, through a comparison of log-likelihood, adjusted  $R^2$  and Akaike's Information Criterion (AIC), it becomes apparent that among the three models, the SDM offers the best fit (Tables A3 and A4). Consequently, this study employs the SDM for empirical analysis (Tables A5 and A6). An inverse distance matrix is adopted in the SDM. In addition, the K-nearest neighbor matrix is added to re-estimate the model (Tables A7 and A8). Additionally, we further exclude economically developed cities, including Shanghai, Chongqing, Wuhan, Chengdu, Hangzhou, and Nanjing, as well as less developed cities such as Zhangjiajie, Lijiang, Ya'an, Lincang, Bazhong, and Ziyang, and re-estimate the SDM. After excluding several cities, the main results remain qualitatively unchanged, suggesting that our findings are not driven by a few influential observations (Tables A7 and A8). The mechanisms through which diverse factors impact UCP, along with their evolutionary characteristics from 2010 to 2020, are elucidated below based on the effect decomposition results from SDM (direct effects, indirect/spatial spillover effects) (Tables 2 and 3).

**Table 2.** Estimation results of SDM.

| Factors                 | 2010        | 2020        |
|-------------------------|-------------|-------------|
| X1                      | −0.3429 *   | −0.1504     |
| X2                      | 0.1812 *    | 0.3374 ***  |
| X3                      | 0.0730      | −0.1232     |
| X4                      | −0.3262     | −0.2720 **  |
| X5                      | 1.5134 **   | 0.8857 *    |
| X6                      | −2.0897 *** | −1.3684 *** |
| X7                      | 1.1838 *    | 0.7555 *    |
| X8                      | 1.0748      | 0.8243 ***  |
| X9                      | 0.2521      | −0.6336 *** |
| X10                     | 0.1170      | 0.3674 **   |
| X11                     | 0.0535      | −0.0054     |
| X12                     | 0.2364      | −0.4054 *   |
| X13                     | 0.4556 **   | 0.1778 *    |
| X14                     | 0.4855 *    | 0.1898 *    |
| X15                     | −0.2330 *   | 0.1686      |
| W × X1                  | −0.2866     | −0.1380     |
| W × X2                  | 0.5546      | 0.5563 *    |
| W × X3                  | −0.4994     | 0.5759      |
| W × X4                  | 0.7241      | −0.3820     |
| W × X5                  | 2.4050      | −2.5570     |
| W × X6                  | −3.8601 **  | −1.7602 *   |
| W × X7                  | 1.7753 *    | 3.2650 ***  |
| W × X8                  | 2.0762      | 0.3501      |
| W × X9                  | 0.2966      | −1.3479 *** |
| W × X10                 | 0.8464 *    | 0.2954      |
| W × X11                 | 0.2796      | 0.3982 *    |
| W × X12                 | 0.5769      | −1.9883 *** |
| W × X13                 | 0.4719      | 0.0028      |
| W × X14                 | 1.6760 *    | 0.5393 *    |
| W × X15                 | −1.7971 *** | −0.0719     |
| R <sup>2</sup>          | 0.6559      | 0.8095      |
| Adjusted R <sup>2</sup> | 0.6517      | 0.7789      |
| Loglikelihood           | 47.5476     | 83.2462     |
| AIC                     | −31.0952    | −108.2159   |

Note: \*\*\*, \*\*, and \* denote statistical significance at the 1%, 5%, and 10% levels, respectively.

**Table 3.** The direct effect and indirect effect of SDM.

| Factors | Direct Effect | Z-Value | Indirect Effect | Z-Value |
|---------|---------------|---------|-----------------|---------|
| 2010    |               |         |                 |         |
| X1      | −0.501 **     | −2.24   | −0.0251         | −0.21   |
| X2      | 0.353 **      | 2.31    | 0.260 *         | 1.79    |
| X3      | −0.0285       | −0.32   | 0.135           | 0.87    |
| X4      | −0.327        | −1.54   | 0.573           | 1.58    |
| X5      | 0.82 *        | 1.59    | 0.349           | 0.92    |
| X6      | −3.45 ***     | −3.62   | −1.26           | −1.47   |
| X7      | 1.46 ***      | 3.48    | 2.37 **         | 2.42    |
| X8      | 0.643         | 1.81    | 0.47            | 1.43    |
| X9      | 0.473         | 1.45    | −0.0936         | −0.51   |
| X10     | 0.149         | 0.98    | 0.673 **        | 2.27    |
| X11     | 0.11          | 0.76    | 0.02            | 0.18    |

|      |            |       |           |       |
|------|------------|-------|-----------|-------|
| X12  | 0.184      | 1.23  | 0.519     | 1.76  |
| X13  | 0.503 **   | 2.35  | −0.181    | −1.12 |
| X14  | 0.747 ***  | 3.21  | 0.182     | 1.15  |
| X15  | −0.376     | −1.51 | −0.581 *  | −1.74 |
| 2020 |            |       |           |       |
| X1   | −0.123     | −0.87 | −0.154    | −0.72 |
| X2   | 0.280 ***  | 3.12  | 0.475 *** | 3.47  |
| X3   | −0.203     | −1.24 | 0.478 **  | 2.23  |
| X4   | −0.262 **  | −2.17 | −0.07     | −0.39 |
| X5   | 0.657 *    | 1.78  | −1.40 *   | −1.72 |
| X6   | −1.19 **   | −2.31 | −1.80 *** | −3.25 |
| X7   | 0.875 *    | 1.51  | 3.19 ***  | 3.68  |
| X8   | 0.702 **   | 2.28  | −0.280    | −0.95 |
| X9   | −0.548 *** | −3.56 | −1.10 *** | −3.02 |
| X10  | 0.357 *    | 1.75  | −0.124 *  | 0.61  |
| X11  | −0.038     | −0.29 | 0.072 *   | 0.43  |
| X12  | −0.410 *   | −1.83 | −0.606 ** | −2.21 |
| X13  | 0.237 *    | 1.7   | −0.149    | −0.81 |
| X14  | 0.245 *    | 1.42  | 0.402 *** | 2.89  |
| X15  | 0.143      | 0.94  | −0.00376  | −0.03 |

Note: \*\*\*, \*\*, and \* denote statistical significance at the 1%, 5%, and 10% levels, respectively.

(1) Socioeconomic Development: Coexistence of Structural Optimization and Competitive Effects.

Advanced industrial structure (AIS) stands as the most robust socioeconomic factor propelling the improvement of UCP. Its direct effect was notably positive in both 2010 and 2020, and its spatial spillover effect also turned significantly positive in 2020 (0.475 \*\*\*). This implies that the expansion of a city's service sector not only directly boosts local UCP but also subsequently generates positive synergistic impacts on neighboring regions through industrial linkages and knowledge spillovers. Conversely, foreign trade (FTR) exhibited a significant negative direct effect in 2020, along with a non-significant yet negative spatial spillover effect. This suggests that in the new context of globalization, excessive dependence on foreign trade may trap cities in low-to mid-end positions within global value chains, thus restricting local green transformation and exerting competitive pressures on surrounding areas. The spatial spillover effect of government intervention (GPBE) is significantly negative in 2020 (−1.40), a pattern consistent with inter-jurisdictional competition for green investments, whereby local governments' fiscal behaviors may impose negative externalities on neighboring regions. The direct effect remains positive, suggesting that local green investments are effective within the city itself.

(2) Energy and Innovation: Core Constraints and Fundamental Drivers.

Total electricity consumption (TEC) stands as the most stable restraining factor for UCP among all variables. Over the two-year period, both its direct and indirect effects are significantly negative. This clearly demonstrates that reducing energy intensity is the fundamental prerequisite for enhancing UCP. The impact mechanism of R&D expenditure (RDE) has experienced a profound transformation. In 2010, both its direct effect (1.46) and spatial spillover effect (2.37) were significantly positive, which reflects the extensive technological spillover benefits associated with early-stage R&D expenditure. By 2020, although the direct effect remained positive, its significance had diminished. Meanwhile, the spatial spillover effect increased substantially (3.19). This implies that generalized R&D expenditure contributes less marginally to local innovation, but the knowledge generated currently plays an unprecedentedly important role in regional flow and reintegration. In

contrast, green technological innovation (GPG) exhibited a significant and robust direct effect in 2020 (0.702), although its spatial spillover effect was not significant. This reveals a key mechanism: the driving force behind UCP improvement has shifted from “generalized R&D expenditure” to “targeted green innovation.” However, the diffusion of green knowledge faces higher barriers, showing strong localization and lacking an effective regional spillover network.

### (3) Digital Development: Novel Drivers and Governance Spillovers.

Digitalization has emerged as a novel driving force that shapes urban development models. This study investigates the dynamic and intricate mechanisms by which digital finance and digital governance impact urban UCP. In 2010, the direct effect of digital finance (DFIN) was negligible (0.149), yet its spatial spillover effect was significantly positive (0.673 \*\*). This suggests that in the initial stages of digital financial development, its primary function was to break down geographical barriers, enabling the inclusive flow and reallocation of capital across regions. The expansion of digital financial services in one region could readily benefit residents and businesses in neighboring areas by alleviating financing constraints and supporting the green transitions of small enterprises, thus generating significant positive regional spillovers, although the direct local impact remained restricted. By 2020, the direct effect of digital finance had become significantly positive (0.357 \*), indicating that it had been deeply integrated into the local economy by improving access to green credit and supporting green consumption choices, directly promoting local low-carbon economic activities. Nevertheless, its spatial spillover effect became negligible (−0.124). This implies that as the digital financial market reached maturity, the network effects of its services may have increasingly led to within-platform competition, weakening cross-regional synergies and even resulting in mild competitive tensions among cities regarding digital financial resources and users, ultimately causing the positive spillovers to disappear.

The impact of digital governance (DGOV), as represented by fiscal transparency, reflects the evolution from local management tools to regional collaborative infrastructure. In 2010, neither the local effect nor the spatial effect of digital governance was significant. In its initial stages, digital governance probably concentrated more on enhancing internal government efficiency or ensuring public access to information, without yet effectively transforming into a crucial governance capability that influences economic carbon efficiency or establishing cross-regional governance coordination. By 2020, the spatial spillover effect of digital governance is significantly positive (0.072 \*), while the direct effect is not. This is consistent with the notion that digital governance improvements in one city may facilitate regional coordination—possibly through reduced information asymmetries and improved policy predictability—rather than directly boosting local carbon productivity. However, alternative interpretations cannot be ruled out. For instance, transparent fiscal information reduces policy uncertainty for enterprises investing in neighboring cities, while standardized digital government platforms facilitate cross-city business operations. These factors have a positive influence on the decision-making of out-of-town enterprises and promote regional industrial chain collaboration, thereby indirectly enhancing carbon productivity in surrounding cities through improved regional governance effectiveness, thus creating a positive cross-regional externality associated with good governance.

### (4) Urban Form: Local Optimization and Complex Spillover Effects.

Urban form acts as the physical medium for socioeconomic activities. It significantly impacts UCP via its structural features, which have an influence on energy consumption, transportation patterns, industrial distribution, and ecological functions. This research employs a series of landscape pattern indices to quantitatively analyze the local impacts

and spatial spillovers of spatial form on UCP, concentrating on four aspects: urban sprawl, shape complexity, compactness, and connectivity.

Urban sprawl (LPI) exhibits a pattern consistent with a “double curse”—negative direct and indirect effects—suggesting that dispersed land development may generate adverse spillover effects on both the city itself and its neighbors. In 2020, the negative spatial spillover ( $-0.606^{**}$ ) is indicative of potential cross-boundary cost shifting or regional resource competition, though causal confirmation requires further investigation. On one hand, the unregulated expansion of urban land directly impairs local intensive development efficiency, possibly because of increased commuting distances, decreased infrastructure utilization efficiency, and encroachment on ecological spaces. On the other hand, the sprawling expansion of a city generates substantial negative spatial externalities for neighboring areas. The transmission mechanisms may include cross-border cost shifting, which involves transferring energy-intensive industries or transportation burdens to administrative boundaries; regional resource competition, which intensifies disputes over land, water, and other resources, thus disrupting regional ecological security patterns; and development model lock-in, which creates a negative example of extensive growth for surrounding cities. This finding partially explains, from a mechanistic perspective, why in LISA analysis we observe prominent “high-low outliers,” such as those in the Wuhan metropolitan area, where a city maintains relatively high efficiency but is surrounded by inefficient neighbors, forming an isolated island. The sprawl of one or more core cities may continuously impede green transformation in their surrounding hinterlands. This also emphasizes the urgency of implementing cross-administrative, coordinated management of spatial form and land development intensity in highly interconnected regions such as the YREB.

Urban compactness (PLADJ) is associated with a “dual dividend” pattern—positive direct and indirect effects—consistent with the hypothesis that compact urban form generates positive spatial externalities, potentially through shared infrastructure and efficient land use. PLADJ exhibited a stable “dual promotion” effect in both 2010 and 2020. In 2020, both its direct effect ( $0.245^{*}$ ) and spatial spillover effect ( $0.402^{***}$ ) were significantly positive. On one hand, compact and contiguous urban spatial structures effectively reduce commuting distances, enhance infrastructure sharing rates, and facilitate knowledge spillovers, thereby directly enhancing local carbon productivity. On the other hand, compact development within a city can generate positive spatial spillovers to neighboring cities by establishing efficient and complementary functional layouts, sharing regional infrastructure, and minimizing encroachment on regional ecological spaces, thus achieving coordinated efficiency across the region. This validates the positive network effects of the “compact city” concept at the regional scale.

Urban shape complexity (PARA\_MN) demonstrated a significant positive direct effect in both 2010 and 2020, yet its spatial spillover effect remained persistently insignificant. The shape complexity represented by PARA\_MN is not a straightforward indicator of being either good or bad. In the development context of the YREB, its continuous positive direct effect uncovers a more profound logic: during the transition from rapid expansion to quality enhancement, a certain level of spatial form complexity and diversity might be more beneficial for improving carbon productivity than highly uniform and monotonous land-use patterns. This complexity could result from adaptation to natural topography, preservation of historic neighborhoods, or deliberate ecological buffer designs. Nevertheless, the relatively diminished effect in 2020, as reflected by reduced coefficients and lower significance levels, implies that as urban development enters a new stage centered on stock renewal and high-quality growth, the efficiency gains solely derived from spatial form complexity may have reached their limit.

The transformation in urban connectivity (COHESION), from a notably negative spatial spillover effect to an insignificant one, profoundly reflects the underlying logic of spatial structural reorganization within the YREB. In 2010, COHESION demonstrated a significant negative spatial spillover ( $-0.581^*$ ), indicating that during the initial phase of the analysis, an improvement in a city's landscape connectivity did not substantially enhance local UCP. Instead, it exerted a remarkable inhibitory effect on the UCP of neighboring cities. This implies that early improvements in internal spatial connectivity within individual cities mainly served to strengthen local agglomeration economies, manifesting their effects primarily as siphoning or screening of resources and factors from surrounding areas, thereby generating negative spatial externalities. As the infrastructure networks within the YREB (especially high-speed rail and intercity railways) have gradually improved, and the coordinated development strategies for urban clusters have advanced, the internal landscape connectivity (COHESION) within individual cities has gradually become a standard characteristic, with its disparities decreasing (its standard deviation dropping from 1.3043 in 2010 to 1.0234 in 2020). At this juncture, regional efficiency is no longer determined by the connectivity level of any single city but rather by the overall network connectivity among all cities and the rational functional layout within this network. Consequently, the marginal influence of the COHESION indicator at the individual city level has declined, being replaced or overshadowed by larger-scale, inter-city functional connectivity. This suggests that as regional integration deepens, the marginal impact of internal city connectivity lessens, while the overall network connectivity of the region becomes increasingly crucial.

## 5. Discussion

Enhancing carbon productivity is not only an essential requirement for tackling global climate change but also an inherent impetus for transitioning the economic development model from one driven by factors and investments to one driven by innovation and green initiatives.

The findings of this study regarding innovation-driven mode indicate a fundamental disparity in the mechanisms by which R&D expenditure (RDE) and green technological innovation (GPG) influence UCP. As early as 2010, general R&D expenditure exhibited strong local and spatial spillover effects. Nevertheless, by 2020, its direct local effect had diminished, while its spatial spillover effect had significantly strengthened. In stark contrast, GPG only manifested a robust direct local effect in 2020, with its spatial spillover effect remaining consistently negligible. This pattern of “one declining while the other grows” and “local lock-in” forms a knowledge diffusion paradox [77,78]. Traditional theories of technological innovation propose that knowledge is non-excludable and demonstrates positive externalities, rendering it susceptible to spatial spillovers through trade, investment, and talent mobility. The strong spatial spillover effect of R&D expenditure (RDE) is consistent with the emergence of an active knowledge exchange network within the YREB, which may reflect the maturation of regional innovation systems. However, this interpretation should be tempered by the possibility that unobserved common shocks or policy diffusion drive the observed pattern [79,80]. However, the diffusion of targeted green technological innovation (GPG) encounters higher barriers. This phenomenon may be attributed to three factors [81–83]. Firstly, green technologies frequently entail intricate cross-sector integration (e.g., new energy, new materials, and smart grids), which necessitates a higher absorptive capacity from the recipients. Secondly, the effectiveness of green technologies is generally closely associated with local industrial foundations, resource endowments, and policy environments, rendering their core know-how challenging to codify and transfer over long distances. Thirdly, as a crucial source of competitive advantage, the spillover effects of green technologies may be strategically restricted by

enterprises. Consequently, this places higher requirements on the policy design of the YREB for “innovation-driven low-carbon transformation”. It demands not only an increase in RDE but also the establishment of specialized channels and institutional arrangements that can effectively promote the cross-regional flow, matching, and transformation of green knowledge.

The findings of this study regarding urban form, specifically the “double dividend” associated with urban compactness (PLADJ) and the “double curse” related to urban sprawl (LPI), elevate the discourse on the compact city concept from a sole emphasis on local environmental performance to a more comprehensive consideration of the coordinated governance of regional spatial externalities. Traditional research has predominantly concentrated on how urban form influences local commuting patterns and energy consumption.

The SDM results provide evidence consistent with the presence of strong spatial externalities associated with urban form. Specifically, the positive direct and indirect effects of PLADJ align with the compact city hypothesis, while the negative effects of LPI suggest potential negative externalities from sprawl. A city’s compact and contiguous development (high PLADJ) not only improves its own efficiency but also generates positive externalities for neighboring cities by promoting efficient regional functional organization and shared infrastructure, representing a collaborative development model based on mutual benefit [84–86]. Conversely, a city’s unregulated sprawl (high LPI) imposes negative externalities on surrounding areas through cross-border industrial pollution, the degradation of regional ecological foundations, and intensified competition for land resources, reflecting a competitive model that is detrimental to neighbors [29,87,88]. Therefore, the optimization of urban form should no longer be merely an internal matter of individual cities, but should be regarded as a collective action with distinct characteristics of regional public goods. The high-low outliers pattern observed in the Wuhan metropolitan area is essentially the outcome of ineffective coordination between the core city and the surrounding cities in terms of spatial externalities. This necessitates a transformation of traditional urban planning paradigms from “urban autonomy” to “regional co-governance.” Future spatial governance must internalize the costs associated with the spread of negative externalities and share the benefits of the positive externalities of compact development, thus maximizing the overall regional welfare.

This study’s findings regarding digital factors—specifically, the shift in digital finance (DFIN) from regional inclusiveness to local deepening, and the evolution of digital governance (DGOV) from limited impact to regional coordination—indicate that the influence of the digital economy on the low-carbon transition has transcended a simple “efficiency-enhancement” tool framework and entered a new phase characterized by profound functional differentiation and governance restructuring. The positive spatial spillover effects observed in the early 2010 of DFIN were in line with the ideal vision of digital inclusion, where digital technologies reduce transaction costs and generate regional synergies in emissions reduction. However, by 2020, its effects had transformed into significant local direct impacts and insignificant spillovers, which marks a critical turning point: the emission-reduction benefits of digital finance are transitioning from broad coverage to deep integration within local economic cycles. It seems that the green utility of digital finance is increasingly manifested through empowering green consumption choices and digitizing services at the local level, while its role as a pipeline for cross-regional allocation of green capital and support for industrial transformation in neighboring regions has relatively declined. Although the digital economy enhances local efficiency, it may inadvertently strengthen the core cities’ ability to absorb resources, rather than promoting regional balance. In contrast to DFIN, DGOV demonstrates a significant positive spatial spillover effect in the later stages. This discovery has substantial policy implications, suggesting

that when digitalization is implemented in government governance, its core value lies not only in enhancing the internal efficiency of individual governments but also in establishing a regional institutional infrastructure. Consequently, DGOV generates positive externalities of good governance and positions digital technology as a key instrument for improving overall regional governance coordination. The dual pathways of digital factors imply that digitalization should not be regarded as a uniform entity. Its green transformation effects are highly dependent on how digital technologies are integrated with different social systems—market-financial systems and government governance systems—and the resulting distinct spatial political-economic logics. Digitalization is not a pre-determined, straightforward route towards regional synergy. It may either deepen local lock-in through market logic (e.g., platform finance) or act as a bridge for regional collaboration via governance logic (e.g., digital government). Recognizing and leveraging this functional differentiation is essential for the YREB to achieve high-quality coordinated transformation through digital technologies.

This study still exhibits certain limitations, which indicate directions for future research. Firstly, owing to constraints in data availability, the study employed a relatively long-term (ten-year) yet non-high-frequency observation period. Future research could utilize higher-frequency big data sources, such as nighttime light remote sensing and electricity consumption, to accomplish more refined dynamic monitoring and causal inference of UCP and its driving factors. Secondly, although this study identified the spatial spillover effects of various factors, it has not yet carried out intermediate mechanism tests on the specific micro-level channels through which these spillovers occur, such as firm relocations, talent mobility, technological collaboration networks, or cross-regional capital investment. Future studies could integrate firm-level investment data, patent collaboration networks, and large-scale transportation flow data to further uncover the agents and transmission pathways underlying spatial spillovers. Thirdly, and most importantly, the SDM identifies statistical associations that are consistent with hypothesized causal mechanisms, but it does not establish causation unequivocally. The observed patterns—such as the negative spatial spillover of GPBE, the “double curse” of LPI, and the positive spillover of DGOV—could also arise from omitted variables, spatial correlation in unobservables, or reverse causality. Therefore, the labels “competition effect” and “double curse” should be interpreted as heuristic descriptors of robust empirical regularities rather than confirmed causal mechanisms.

## 6. Conclusions

This study systematically uncovers the spatiotemporal evolution patterns, driving mechanisms, and intricate spatial spillover effects of UCP in the YREB from 2010 to 2020 through the integration of kernel density estimation, spatial autocorrelation analysis, and the SDM. Four principal findings emerge. First, the spatial pattern of UCP has evolved from a single-gradient pattern of “high in the east, low in the west” in 2010 to a “multi-pole interconnection” network in 2020, led by three growth poles: the Yangtze River Delta, the mid-Yangtze region (Wuhan metropolitan area), and the Chengdu-Chongqing agglomerations. Despite overall improvement, absolute disparities persist, reflecting coexisting club convergence and regional divergence. Second, the driving mechanisms have shifted decisively from factor-driven to innovation- and structure-driven. Green technological innovation (GPG) and advanced industrial structure (AIS) now serve as the primary engines of UCP growth, while energy consumption (TEC) remains the most persistent constraint. Third, spatial spillover effects are both intricate and consequential. Positive spillovers from advanced industrial structure (AIS), digital governance (DGOV), and R&D expenditure (RDE) are associated with reinforced multicentric coordination, whereas negative spillovers from local government public budget expenditure (GPBE)

and urban sprawl (LPI) correspond to exacerbated regional fragmentation. These patterns, however, should be interpreted as empirical regularities rather than proven causal effects. This dual-edged spillover network explains the simultaneous emergence of high-value clusters and peripheral laggards. Fourth, urban form and digitalization exert profound structural influences with distinct spatial externalities. Urban compactness (PLADJ) yields a “local-neighborhood” double dividend, while urban sprawl (LPI) creates a “local-neighborhood” double curse. Digital finance (DFIN) has transitioned from an initial stage of inclusive spillover to a subsequent phase of local deepening, thereby weakening its regional synergistic effects. In contrast, digital governance (DGOV) has evolved from having a limited impact to becoming a crucial tool for regional collaborative governance.

To effectively promote the national strategy of ecological priority and green development for the YREB and achieve the carbon peak ahead of schedule, this study puts forward the following policy recommendations. (1) Considering the co-existence of “local lock-in” in green technological innovation (GPG) and the strong spill-over effects of R&D expenditure (RDE), policies should be precisely targeted to eliminate bottlenecks from knowledge creation to regional application, and establish a full-chain collaborative green innovation ecosystem covering “origin, transformation, and diffusion.” (2) In order to maximize the regional synergies of digital governance (DGOV), it is necessary to overcome city-level “data silos” by constructing regionally unified digital governance infrastructure and creating an integrated regional “carbon-data-intelligence” collaborative management platform. (3) To tackle the core constraint of total energy consumption (TEC), regional coordination is required to optimize the energy structure, enhance the capacity for clean power integration, and improve the green energy system through coordinated regional cooperation across generation, grid, load, and storage. (4) To counter the “double curse” of urban sprawl (LPI) and achieve the “dual benefits” of urban compactness (PLADJ), the strictest spatial use controls should be implemented at the regional scale, promoting a compact, green, and integrated development model from the source of land resources.

**Author Contributions:** C.W.: conceptualization, methodology, formal analysis, validation, visualization, writing—original draft. W.L.: formal analysis, data curation. X.W., X.Z., Q.Z. and F.W.: data curation, visualization. S.C. and C.S.: Founding, Supervision. All authors have read and agreed to the published version of the manuscript.

**Funding:** This research was supported by the Major Project of Wenzhou Science & Technology Bureau (ZG2024042), the Science and Technology Projects of Zhejiang Province (2022C03168), the University-level Research Projects of Wenzhou University of Technology (2024) (ky202402), the National Natural Science Foundation of China (42371317, 42401205, 41501144), the 2024 University-level Natural Science Research Project of Guangzhou Xinhua University (2024KYZDZK01, 2024J039-2), the Young Talent Project of GDAS (2025GDASQNR-0108), and the GDAS Special Project of Science and Technology Development (2024GDASZH-2024010102).

**Data Availability Statement:** The authors have not obtained permission to publish the data. Therefore, the data can be obtained from the corresponding author upon reasonable request.

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

## Appendix A

**Table A1.** Descriptive Analysis of Variables in 2010.

| Factors  | Symbol | Moran's <i>I</i> | Minimum Value | Maximum Value | Mean     | Standard Deviation | PCC        |
|----------|--------|------------------|---------------|---------------|----------|--------------------|------------|
| URBA     | X1     | 0.3409 ***       | 3.0567        | 89.2749       | 46.8243  | 14.8218            | 0.0701     |
| AIS      | X2     | 0.1446 ***       | 23.97         | 62.35         | 35.8943  | 7.5925             | 0.2432 **  |
| FAI      | X3     | 0.3157 ***       | 30.9779       | 149.1771      | 75.5256  | 25.4031            | 0.0535     |
| FTR      | X4     | 0.5593 ***       | 0.3094        | 197.489       | 19.949   | 31.7121            | 0.0218     |
| GPBE     | X5     | 0.2978 ***       | 7.9403        | 68.7608       | 17.4539  | 8.2889             | -0.0558    |
| TEC      | X6     | 0.3478 ***       | 0.3469        | 129.587       | 7.7112   | 15.3654            | 0.0064     |
| RDE      | X7     | 0.1822 ***       | 0.2432        | 14.1206       | 3.2158   | 2.2107             | 0.1200     |
| GPG      | X8     | 0.0390           | 1             | 400           | 19.3191  | 54.4881            | 0.1104     |
| DHC      | X9     | 0.1175 *         | 0.3158        | 7.8571        | 1.1591   | 0.8486             | 0.1160     |
| DFIN     | X10    | 0.5090 ***       | 13.28         | 93.61         | 64.4268  | 14.1189            | 0.2718 *** |
| DGOV     | X11    | 0.0761           | 10.0524       | 85.7937       | 43.2601  | 16.3885            | 0.0272     |
| LPI      | X12    | 0.0962 *         | 1.7107        | 45.5043       | 12.6209  | 8.0224             | -0.0308    |
| PARA_MN  | X13    | 0.6176 ***       | 145.4746      | 296.2508      | 214.8497 | 30.6262            | 0.0443     |
| PLADJ    | X14    | 0.4558 ***       | 86.8548       | 95.8732       | 90.9977  | 1.949              | 0.0964     |
| COHESION | X15    | 0.2664 ***       | 93.4964       | 99.3162       | 96.7055  | 1.3043             | 0.0457     |
| UCP      | Y      | 0.3014 ***       | 0.0828        | 2.1761        | 0.703    | 0.4758             | 1.0000 *** |

Note: \*\*\*, \*\*, and \* denote statistical significance at the 1%, 5%, and 10% levels, respectively. PCC represents Pearson correlation coefficient.

**Table A2.** Descriptive Analysis of Variables in 2020.

| Factors  | Symbol | Moran's <i>I</i> | Minimum Value | Maximum Value | Mean     | Standard Deviation | PCC         |
|----------|--------|------------------|---------------|---------------|----------|--------------------|-------------|
| URBA     | X1     | 0.3884 ***       | 37.81         | 89.5          | 63.2901  | 11.5741            | 0.1904 *    |
| AIS      | X2     | 0.3042 ***       | 39.02         | 72.73         | 49.167   | 6.7979             | 0.3532 ***  |
| FAI      | X3     | 0.2126 ***       | 17.4457       | 154.5304      | 66.7652  | 20.2377            | -0.2806 *** |
| FTR      | X4     | 0.5820 ***       | 0.0842        | 110.6665      | 17.3038  | 22.8075            | 0.0532      |
| GPBE     | X5     | 0.2160 ***       | 9.3057        | 48.5584       | 19.5896  | 7.1423             | -0.0833     |
| TEC      | X6     | 0.3840 ***       | 2.7916        | 156.8578      | 23.0897  | 26.0318            | 0.1628      |
| RDE      | X7     | 0.3002 ***       | 0.0221        | 6.188         | 1.6746   | 1.0598             | 0.1139 *    |
| GPG      | X8     | 0.2261 ***       | 26            | 7891          | 767.3776 | 1319.1585          | 0.2578 **   |
| DHC      | X9     | 0.3212 ***       | 0.3925        | 8.567         | 1.335    | 1.2103             | 0.2726 ***  |
| DFIN     | X10    | 0.6715 ***       | 200.4475      | 349.7485      | 260.7367 | 28.8224            | 0.2475 **   |
| DGOV     | X11    | 0.2259 ***       | 20.51         | 91.88         | 67.3189  | 14.4344            | 0.2017 **   |
| LPI      | X12    | 0.3354 ***       | 0.05          | 17.2996       | 1.5312   | 2.4867             | 0.1150      |
| PARA_MN  | X13    | 0.6939 ***       | 140.7393      | 273.3855      | 213.2232 | 31.9255            | 0.0929      |
| PLADJ    | X14    | 0.5487 ***       | 87.9761       | 97.7098       | 92.348   | 2.0213             | 0.2214 **   |
| COHESION | X15    | 0.2975 ***       | 94.8889       | 99.5945       | 97.7564  | 1.0234             | 0.2504 **   |
| UCP      | Y      | 0.3597 ***       | 0.1988        | 6.6929        | 1.4652   | 1.0449             | 1.0000 ***  |

Note: \*\*\*, \*\*, and \* denote statistical significance at the 1%, 5%, and 10% levels, respectively. PCC represents Pearson correlation coefficient.

**Table A3.** Estimation results of OLS, SLM, SEM and SDM in 2010.

| Factors | OLS        | SLM        | SEM         | SDM       |
|---------|------------|------------|-------------|-----------|
| X1      | -0.1047    | -0.1002    | -0.1499     | -0.3429 * |
| X2      | 0.3195 **  | 0.2712 **  | 0.1635      | 0.1812 *  |
| X3      | 0.0794     | 0.0662     | 0.0241      | 0.0730    |
| X4      | -0.4928 ** | -0.5104 ** | -0.4962 *** | -0.3262   |
| X5      | 0.6312     | 0.7078     | 1.0294      | 1.5134 ** |

|                         |             |             |             |             |
|-------------------------|-------------|-------------|-------------|-------------|
| X6                      | −2.8854 *** | −2.9005 *** | −3.4159 *** | −2.0897 *** |
| X7                      | 1.6064 **   | 1.6162 **   | 1.5676 ***  | 1.1838 *    |
| X8                      | 0.5803      | 0.5000      | 0.5818      | 1.0748      |
| X9                      | 0.0152      | 0.0719      | 0.1425      | 0.2521      |
| X10                     | 0.2337      | 0.2821 *    | 0.3526 **   | 0.1170      |
| X11                     | 0.0311      | 0.0337      | 0.0906      | 0.0535      |
| X12                     | 0.0610      | 0.0659      | 0.1360      | 0.2364      |
| X13                     | 0.4728 **   | 0.5138 ***  | 0.5781 ***  | 0.4556 **   |
| X14                     | 0.7711 **   | 0.8394 ***  | 1.0085 ***  | 0.4855 *    |
| X15                     | −0.1047     | −0.4986 **  | −0.6910 *** | −0.2330 *   |
| W × X1                  |             |             |             | −0.2866     |
| W × X2                  |             |             |             | 0.5546      |
| W × X3                  |             |             |             | −0.4994     |
| W × X4                  |             |             |             | 0.7241      |
| W × X5                  |             |             |             | 2.4050      |
| W × X6                  |             |             |             | −3.8601 **  |
| W × X7                  |             |             |             | 1.7753 *    |
| W × X8                  |             |             |             | 2.0762      |
| W × X9                  |             |             |             | 0.2966      |
| W × X10                 |             |             |             | 0.8464 *    |
| W × X11                 |             |             |             | 0.2796      |
| W × X12                 |             |             |             | 0.5769      |
| W × X13                 |             |             |             | 0.4719      |
| W × X14                 |             |             |             | 1.6760 *    |
| W × X15                 |             |             |             | −1.7971 *** |
| R <sup>2</sup>          | 0.5306      | 0.5429      | 0.498       | 0.6559      |
| Adjusted R <sup>2</sup> | 0.5294      | 0.5364      | 0.4842      | 0.6517      |
| Loglikelihood           | 25.2367     | 25.8428     | 27.5048     | 47.5476     |
| AIC                     | −18.4734    | −17.6856    | −26.0095    | −31.0952    |

Note: \*\*\*, \*\*, and \* denote statistical significance at the 1%, 5%, and 10% levels, respectively.

**Table A4.** Estimation results of OLS, SLM, SEM and SDM in 2020.

| Factors | OLS         | SLM         | SEM         | SDM         |
|---------|-------------|-------------|-------------|-------------|
| X1      | −0.1376     | −0.1793     | −0.2151 **  | −0.1504     |
| X2      | 0.2391 **   | 0.2315 ***  | 0.2694 ***  | 0.3374 ***  |
| X3      | −0.1329     | −0.1030     | −0.0105     | −0.1232     |
| X4      | −0.1809     | −0.1766     | −0.1760 *   | −0.2720 **  |
| X5      | 1.4541 **   | 1.2281 **   | 0.5652      | 0.8857 *    |
| X6      | −1.2846 *** | −1.2837 *** | −1.3894 *** | −1.3684 *** |
| X7      | −0.1735     | 0.1217      | 1.1940 **   | 0.7555 *    |
| X8      | 0.9788 ***  | 0.9303 ***  | 0.8148 ***  | 0.8243 ***  |
| X9      | −0.5181 **  | −0.5392 *** | −0.6200 *** | −0.6336 *** |
| X10     | 0.3084 **   | 0.3419 ***  | 0.3499 ***  | 0.3674 **   |
| X11     | 0.0517      | 0.0535      | 0.0903      | −0.0054     |
| X12     | −0.2258     | −0.2960     | −0.4934 *** | −0.4054 *   |
| X13     | 0.1193      | 0.1539 **   | 0.1255 **   | 0.1778 *    |
| X14     | 0.1882      | 0.2513 **   | 0.2791 ***  | 0.1898 *    |
| X15     | 0.1482      | 0.1329      | 0.1158      | 0.1686      |
| W × X1  |             |             |             | −0.1380     |
| W × X2  |             |             |             | 0.5563 *    |
| W × X3  |             |             |             | 0.5759      |
| W × X4  |             |             |             | −0.3820     |

|                         |          |          |           |             |
|-------------------------|----------|----------|-----------|-------------|
| W × X5                  |          |          |           | −2.5570     |
| W × X6                  |          |          |           | −1.7602 *   |
| W × X7                  |          |          |           | 3.2650 ***  |
| W × X8                  |          |          |           | 0.3501      |
| W × X9                  |          |          |           | −1.3479 *** |
| W × X10                 |          |          |           | 0.2954      |
| W × X11                 |          |          |           | 0.3982 *    |
| W × X12                 |          |          |           | −1.9883 *** |
| W × X13                 |          |          |           | 0.0028      |
| W × X14                 |          |          |           | 0.5393 *    |
| W × X15                 |          |          |           | −0.0719     |
| R <sup>2</sup>          | 0.5742   | 0.6273   | 0.5631    | 0.8095      |
| Adjusted R <sup>2</sup> | 0.5671   | 0.6213   | 0.5584    | 0.7789      |
| Loglikelihood           | 64.5865  | 66.2558  | 70.4723   | 83.2462     |
| AIC                     | −97.1731 | −98.5116 | −103.9447 | −108.2159   |

Note: \*\*\*, \*\*, and \* denote statistical significance at the 1%, 5%, and 10% levels, respectively.

**Table A5.** Estimation results of LM-lag, LM-error, Wald tests and LR tests in 2010.

| Test Method             | Test Purpose                                       | Statistical | p-Value |
|-------------------------|----------------------------------------------------|-------------|---------|
| LM (lag) test           | Existence of spatial lag effect                    | 3.72 *      | 0.0538  |
| Robust LM (lag) test    | Spatial lag effect after controlling spatial error | 1.14        | 0.2857  |
| LM (error) test         | Existence of spatial error effect                  | 2.83 *      | 0.0762  |
| Robust LM (error) test  | Spatial error effect after controlling spatial lag | 3.79 *      | 0.0515  |
| Wald test spatial lag   | Whether SDM degenerates to SAR model               | 48.05 ***   | 0.0000  |
| Wald test spatial error | Whether SDM degenerates to SEM model               | 32.36 ***   | 0.0063  |
| LR test spatial lag     | Whether SDM degenerates to SAR model               | 34.85 ***   | 0.0026  |
| LR test spatial error   | Whether SDM degenerates to SEM model               | 27.59 **    | 0.0223  |

Note: \*\*\*, \*\*, and \* denote statistical significance at the 1%, 5%, and 10% levels, respectively.

**Table A6.** Estimation results of LM-lag, LM-error, Wald tests and LR tests in 2020.

| Test Method             | Test Purpose                                       | Statistical | p-Value |
|-------------------------|----------------------------------------------------|-------------|---------|
| LM (lag) test           | Existence of spatial lag effect                    | 3.15 *      | 0.0759  |
| Robust LM (lag) test    | Spatial lag effect after controlling spatial error | 3.29 *      | 0.0697  |
| LM (error) test         | Existence of spatial error effect                  | 4.43 **     | 0.0353  |
| Robust LM (error) test  | Spatial error effect after controlling spatial lag | 3.52 *      | 0.0651  |
| Wald test spatial lag   | Whether SDM degenerates to SAR model               | 51.55 ***   | 0.0000  |
| Wald test spatial error | Whether SDM degenerates to SEM model               | 36.45 ***   | 0.0015  |
| LR test spatial lag     | Whether SDM degenerates to SAR model               | 39.70 ***   | 0.0005  |
| LR test spatial error   | Whether SDM degenerates to SEM model               | 31.27 ***   | 0.0085  |

Note: \*\*\*, \*\*, and \* denote statistical significance at the 1%, 5%, and 10% levels, respectively.

**Table A7.** Additional robustness and endogeneity tests for 2010.

| Factors | SDM Based on Inverse Distance Matrix | SDM Based on K-Nearest Neighbor Matrix | SDM Based on the Exclusion of Some Samples |
|---------|--------------------------------------|----------------------------------------|--------------------------------------------|
| X1      | −0.3429 *                            | −0.4046 **                             | −0.3823 *                                  |
| X2      | 0.1812 *                             | 0.2935 **                              | 0.2093 **                                  |
| X3      | 0.0730                               | −0.0381                                | 0.0318                                     |
| X4      | −0.3262                              | −0.2288                                | −0.3161                                    |
| X5      | 1.5134 **                            | 1.5097 *                               | 1.3948 *                                   |
| X6      | −2.0897 ***                          | −2.4890 ***                            | −1.1799 ***                                |
| X7      | 1.1838 *                             | 1.1249 *                               | 1.2594 **                                  |
| X8      | 1.0748                               | 1.5177 ***                             | 0.5721                                     |
| X9      | 0.2521                               | −0.1042                                | 0.3214                                     |

|                         |             |             |             |
|-------------------------|-------------|-------------|-------------|
| X10                     | 0.1170      | 0.0889      | 0.2136      |
| X11                     | 0.0535      | −0.0405     | 0.0428      |
| X12                     | 0.2364      | 0.1651      | 0.2905      |
| X13                     | 0.4556 **   | 0.1709 **   | 0.5442 ***  |
| X14                     | 0.4855 *    | 0.3283 ***  | 0.7788 **   |
| X15                     | −0.2330 *   | −0.0696     | −0.4642 **  |
| W × X1                  | −0.2866     | −0.2994     | −0.2560     |
| W × X2                  | 0.5546      | 1.1975 *    | 0.3388      |
| W × X3                  | −0.4994     | −0.4552     | 0.6231      |
| W × X4                  | 0.7241      | 0.7536      | 0.3084      |
| W × X5                  | 2.4050      | 1.4400 *    | 1.0862      |
| W × X6                  | −3.8601 **  | −1.8008 *** | −3.7806 *** |
| W × X7                  | 1.7753 *    | 2.0938 *    | 1.2908 *    |
| W × X8                  | 2.0762      | 0.9992      | 1.1903      |
| W × X9                  | 0.2966      | 0.2920      | 0.2505      |
| W × X10                 | 0.8464 *    | 1.1180 *    | 1.4488 **   |
| W × X11                 | 0.2796      | 0.2297      | 0.2015      |
| W × X12                 | 0.5769      | 1.1497      | 0.4102      |
| W × X13                 | 0.4719      | −0.5266     | −0.2354     |
| W × X14                 | 1.6760 *    | 1.3102 **   | 0.8320 **   |
| W × X15                 | −1.7971 *** | −1.2171 *   | −1.6626 **  |
| R <sup>2</sup>          | 0.6559      | 0.6445      | 0.6805      |
| Adjusted R <sup>2</sup> | 0.6517      | 0.6398      | 0.6612      |
| Loglikelihood           | 47.5476     | 40.3348     | 43.2538     |
| AIC                     | −31.0952    | −16.6695    | −22.5076    |

Note: \*\*\*, \*\*, and \* denote statistical significance at the 1%, 5%, and 10% levels, respectively.

**Table A8.** Additional robustness and endogeneity tests for 2020.

| Factors | SDM Based on Inverse Distance Matrix | SDM Based on K-Nearest Neighbor Matrix | SDM Based on the Exclusion of Some Samples |
|---------|--------------------------------------|----------------------------------------|--------------------------------------------|
| X1      | −0.1504                              | −0.1499                                | −0.1668                                    |
| X2      | 0.3374 ***                           | 0.3344 *                               | 0.2391 **                                  |
| X3      | −0.1232                              | 0.0170                                 | 0.0217                                     |
| X4      | −0.2720 **                           | −0.3332 **                             | −0.1992 *                                  |
| X5      | 0.8857 *                             | 0.4324 *                               | 0.4589 **                                  |
| X6      | −1.3684 ***                          | −1.0607 **                             | −1.4066 ***                                |
| X7      | 0.7555 *                             | 0.6297 *                               | 0.8654 *                                   |
| X8      | 0.8243 ***                           | 0.3542 *                               | 0.7789 **                                  |
| X9      | −0.6336 ***                          | −0.6081 **                             | −0.6118 ***                                |
| X10     | 0.3674 **                            | 0.3134 *                               | 0.3181 **                                  |
| X11     | −0.0054                              | 0.0440                                 | 0.0068                                     |
| X12     | −0.4054 *                            | −0.2393 *                              | −0.2615 **                                 |
| X13     | 0.1778 *                             | 0.2015 *                               | 0.1576 *                                   |
| X14     | 0.1898 *                             | 0.2610 *                               | 0.1960 *                                   |
| X15     | 0.1686                               | 0.0337                                 | 0.0896                                     |
| W × X1  | −0.138                               | −0.4665 *                              | −0.1379                                    |
| W × X2  | 0.5563 *                             | 0.3251 *                               | 0.3253 **                                  |
| W × X3  | 0.5759                               | 1.1436 *                               | 1.1436 *                                   |
| W × X4  | −0.382                               | −1.1064                                | −0.1336                                    |
| W × X5  | −2.557                               | −0.1336                                | −1.1064                                    |
| W × X6  | −1.7602 *                            | 0.3979                                 | −1.5940 *                                  |
| W × X7  | 3.2650 ***                           | 4.0745 **                              | 3.4299 ***                                 |

|                         |             |            |             |
|-------------------------|-------------|------------|-------------|
| W × X8                  | 0.3501      | −0.7651    | 0.4495      |
| W × X9                  | −1.3479 *** | −0.5857 *  | −1.0635 *** |
| W × X10                 | 0.2954      | 1.2205 **  | 0.2801      |
| W × X11                 | 0.3982 *    | 0.3137 *   | 0.2965 **   |
| W × X12                 | −1.9883 *** | −1.9656 ** | −1.3655 **  |
| W × X13                 | 0.0028      | 0.0062     | −0.0355     |
| W × X14                 | 0.5393 *    | 0.8031 *   | 0.5291 *    |
| W × X15                 | −0.0719     | 0.3029     | 0.1602      |
| R <sup>2</sup>          | 0.8095      | 0.7649     | 0.7956      |
| Adjusted R <sup>2</sup> | 0.7789      | 0.7534     | 0.7724      |
| Loglikelihood           | 83.2462     | 71.3632    | 73.9388     |
| AIC                     | −108.2159   | −78.7265   | −83.8776    |

Note: \*\*\*, \*\*, and \* denote statistical significance at the 1%, 5%, and 10% levels, respectively.

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