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Spatial–Temporal Characteristics and Influencing Factors of Land-Use Carbon Emissions: An Empirical Analysis Based on the GTWR Model

Jie He [1] and Jun Yang [2,*]

[1] College of Civil Engineering and Architecture, Zhejiang University, Hangzhou 310058, China; hjcy@zju.edu.cn
[2] School of Civil Engineering and Architecture, Wuhan Institute of Technology, Wuhan 430074, China
* Correspondence: hgyjyll@wit.edu.cn

Abstract: An in-depth comprehension of the spatial–temporal characteristics of land-use carbon emissions (LUCE), along with their potential influencing factors, is of high scientific significance for the realization of low-carbon land use and sustainable urban development. Academic investigations pertaining to LUCE predominantly encompass three key dimensions: assessment, optimization, and characterization research. This study aimed to investigate the spatial and temporal variations in LUCE within Zhejiang Province by analyzing data from 11 cities and identifying the key factors influencing these emissions. This research work employed the geographically and temporally weighted regression (GTWR) model to explore the patterns of variation in these factors across each city. The results reveal that (1) the temporal changes in LUCE display two predominant trends, while the spatial distribution exhibits a distinct "high in the northeast and low in the southwest" divergence; (2) the average intensity of each factor follows the order of economic level > government intervention > urban compactness > public facilities level > urban greening level > industrial structure > population density; (3) and the influencing factors exhibit significant spatial and temporal heterogeneity, with varying direction and intensity of effects for different cities at different stages of development. This study integrated the dimensions of time and space, systematically examining the evolutionary trends of influencing factors on LUCE within each region. Consequently, it contributes to the comprehension of the spatiotemporal effects associated with the driving mechanisms of LUCE. Moreover, it offers a foundation for formulating customized patterns and strategies to mitigate such emissions, taking into account specific local contexts.

Keywords: land-use carbon emissions; spatial–temporal characteristics; influencing factors; geographically and temporally weighted regression; Zhejiang Province

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1. Introduction

China's land financial model has yielded expeditious economic growth; however, it has concurrently fostered incautious land utilization and extensive urban sprawl, culminating in a discernible upsurge in carbon emissions. This, in turn, has instigated grave climate issues and the occurrence of extreme weather events, which substantively encroach upon the productivity and well-being of the population [1,2]. Global climate change poses new requirements and challenges for energy efficiency and low-carbon sustainable development in cities. Land-use changes and their associated land cover modifications represent the second most prominent factor contributing to the escalation of environmental issues, particularly the surge in carbon emissions, behind the combustion of fossil fuels [3]. Land-use changes exert influences not only on the urbanization process [4] and energy consumption [5,6] but also assume a crucial role within the complex interplay between carbon emissions and carbon sequestration. Furthermore, they directly or indirectly impact the mechanisms of carbon emission and sequestration at the interface of the terrestrial ecosystem and the atmosphere [7]. These influences are primarily manifested through modifications in land-use type, function, and structure [8–10]. Currently, due to inefficient land urbanization in China, leading to urban sprawl and generating large amount of carbon emissions [11,12], establishing how to coordinate the relationship between urban land and carbon emissions is a major issue to be solved [13]. Studying the spatial and temporal characteristics of land-use carbon emissions (LUCE), as well as the underlying influencing factors, holds paramount practical significance in achieving low-carbon land utilization and fostering a sustainable economy with a reduced carbon footprint.

The investigation of LUCE has garnered significant attention in recent academic research endeavors. In terms of the research scope, scholars have extensively investigated LUCE across various scales, encompassing national [10,14], regional [2,15], provincial [16], municipal [17], and county levels [18]. Furthermore, considering diverse research objectives, scholars commonly adopt a comprehensive approach by integrating spatial research scales and land-use types into a research matrix. For instance, some scholars focus on examining the spatial and temporal characteristics of carbon emissions within the same land type but across different regions, such as analyzing carbon emissions from industrial land in various cities [19]. Conversely, others concentrate on analyzing different land types within a specific region [20] or conducting detailed studies on a singular land type within the same region [21]. Additionally, comprehensive research and analysis encompassing various land types across different regions have been conducted to align with distinct emission reduction objectives aimed at fostering differentiation and coordination [22].

In terms of research content, the current scholarly investigations pertaining to LUCE can be broadly categorized into three primary aspects.

Firstly, there is a focus on assessing the effectiveness, efficiency, and carbon emission intensity of different land uses. LUCE should be considered in a comprehensive manner for economic and social benefits as well as ecological benefits [23]. Furthermore, certain scholars have developed an evaluation index system to assess the level of land-intensive use [24], focusing on land-use efficiency as a key perspective. This evolution is evident in the transition from single-index measurements to the adoption of multi-index measurement systems [25]. The research scope encompasses individual cities and urban agglomerations, enabling a more comprehensive analysis [26]. The evaluation methodologies employed have advanced from descriptive models to encompass regression models, data envelopment models, and panel data models [27].

The second aspect of current research on LUCE involves investigating the optimization of land-use structures and patterns. Human activities can significantly influence regional carbon emissions by altering land-use patterns [28], subsequently impacting energy consumption patterns and ultimately influencing the quantity of carbon emissions. Given that the configuration and distribution of land use profoundly shape the spatial arrangement of the built environment and associated human activities, particular emphasis is placed on the spatial layout of urban land use as a pivotal factor with a significant impact on carbon emissions [29]. It is essential to explore the relationship between land-use patterns and overall carbon emissions, analyze the carbon emission effects resulting from land-use changes, and propose viable and effective approaches for land managers and policymakers to consider for reducing carbon emissions [28]. Notably, optimization studies employ optimization models where varying constraints represent the values associated with adopting different optimization strategies. When optimizing the spatial distribution of land use with the constraint of minimizing carbon emissions, scholars incorporate additional factors such as population carrying capacity [30], economic development [31], and the ecological environment [32] to account for various considerations.

The third aspect encompasses the examination and analysis of LUCE mechanisms from the perspective of mixed land use and compact cities. Achieving effective mixed land use in urban areas necessitates moving beyond the traditional approach of functional zoning in urban planning [33]. Instead, it requires the rational integration of work, living, and recreational spaces at the community level. Mixed land use exerts both direct and indirect effects on carbon dioxide emissions. The direct effect involves the carbon source and carbon sink dynamics of the land, while the indirect effect primarily stems from enhanced production efficiency, increased public transport utilization, and reduced traffic congestion. Existing research indicates a positive U-shaped correlation between mixed land use and carbon dioxide emissions [34], suggesting that a certain degree of mixed land use can contribute to carbon dioxide reduction. The term "compact" embodies three key aspects: functional compactness, scale compactness, and morphological compactness [35]. The realization of spatially compact cities can substantially alleviate road traffic, particularly the reliance on private vehicles, thereby mitigating traffic congestion, reducing oil consumption, preserving resources, and curbing air pollution [33]. Emphasis is placed on optimizing the internal structure of urban areas, renewing inefficient land use within built-up areas, and fostering polycentric urban configurations within the framework of compact development.

The academic research on LUCE and their influencing factors has experienced continuous improvement and expansion and yielded fruitful outcomes. These studies have utilized various models selected at appropriate scales to investigate significant issues. For instance, researchers have employed the Future Land Use Simulation (FLUS) model to predict optimal spatial land-use configurations [32,36], utilized Cellular Automaton (CA) to simulate natural processes of land-use changes [37], and more recently, adopted machine learning methods like the Back Propagation Neural Network (BPNN) to forecast urban LUCE [18]. Nevertheless, these studies are not without limitations. Primarily, geographic models predominantly focus on investigating the spatial distribution characteristics of carbon sources and sinks, as well as the spatial correlation of LUCE from a spatial geography perspective. However, only a few studies have effectively integrated both time series and spatial geographic dimensions to analyze LUCE comprehensively. Furthermore, previous studies have often utilized factor decomposition methods such as the Logarithmic Mean Divisia Index (LMDI) model to rank influencing factors and generalize the factors contributing to LUCE [38,39], neglecting the diverse development stages of cities and failing to provide policy recommendations tailored to specific developmental phases. The geographically and temporally weighted regression (GTWR) model has been extensively employed in carbon emissions research [40–42] and is applicable to the realm of LUCE. Therefore, the primary aim of this study is to conduct a comprehensive analysis of the spatial and temporal differentiation characteristics of LUCE, utilizing an extended time series in conjunction with the GTWR model. Additionally, it seeks to investigate the patterns and trends of crucial influencing factors associated with LUCE across various stages of urban development.

2. Overview of the Study Area and Data Source

2.1. Study Area

Zhejiang Province is situated on the southeast coast of China and represents the southernmost part of the Yangtze River Delta (118°01′~123°10′ E, 27°02′~31°11′ N). It is bordered by the East China Sea to the east, Fujian Province to the south, Shanghai and Jiangsu Province to the north, and Anhui Province and Jiangxi Province to the west. The province spans approximately 450 km in both the north–south and east–west directions (Figure 1). Since the implementation of China's reform and opening-up policy, Zhejiang Province has strategically capitalized on its coastal location, yielding notable advancements in economic development. Concurrently, this progress has engendered substantial modifications in land-use patterns and carbon emissions [43]. Additionally, as the birthplace of the "Two Mountains Theory", an innovative framework for ecological civilization construction, Zhejiang Province demonstrates commendable ingenuity in the realm of low-carbon sustainable development practices. Analyzing the LUCE can provide a distinctive standpoint for comprehensively understanding the developmental trajectory of the province from diverse perspectives.

This study focused on the correlation between land-use change and carbon emissions at the city scale within Zhejiang Province. The research encompassed 11 prefecture-level cities that fall under the administrative division of the province, namely, Hangzhou, Ningbo, Wenzhou, Jiaxing, Huzhou, Shaoxing, Jinhua, Quzhou, Zhoushan, Taizhou, and Lishui. The inclusion of diverse cities within the same province as the research subjects served to mitigate the impact of macro policies on carbon emissions across different provinces. Moreover, it facilitated a comparative analysis across cities in distinct stages of urbanization and varying levels of development.

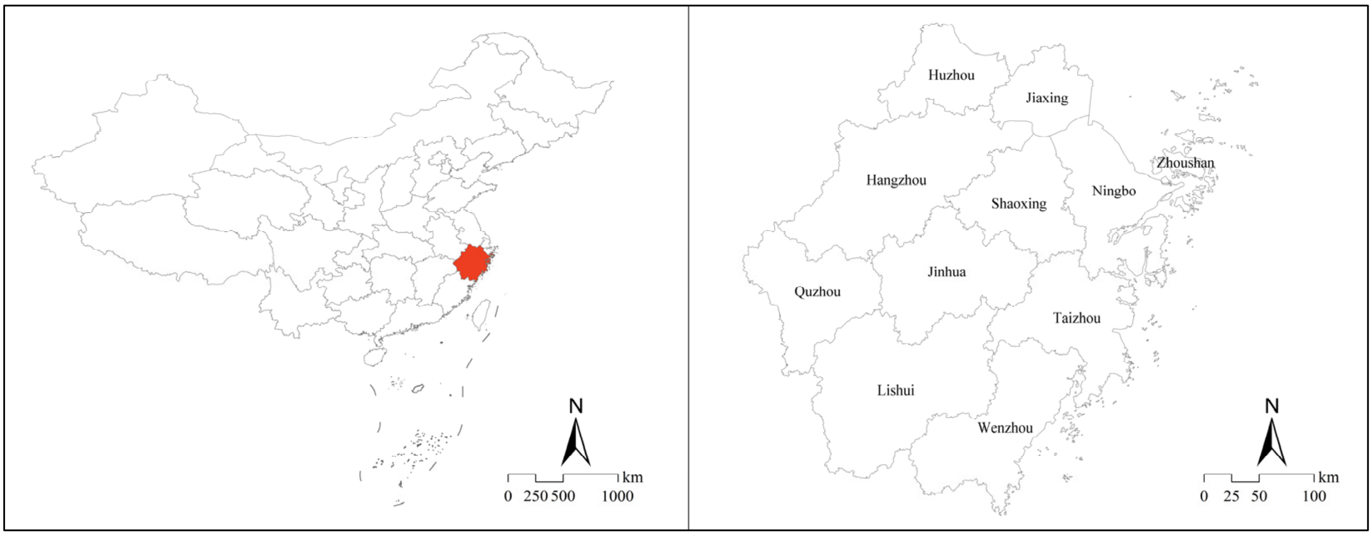


Figure 1. Location of the study area.

2.2. Data Sources

The present study utilized a comprehensive database to conduct a case study on preprocessing and further analysis. The database included the following components:

(1) Land-use data obtained for the interval of one year (10 years in total) from 2001 to 2019 were acquired. The relevant data were obtained from a widely utilized dataset [44] (https://zenodo.org/record/5816591, accessed on 10 May 2023), which has been widely used as the basic data for LUCE research [45,46]. The dataset was subjected to preprocessing, and ArcGIS 10.8 software was employed to extract information on construction land. Subsequently, the construction land patches within each city of Zhejiang Province were obtained through mask extraction operations. Patches with an area smaller than 0.01 km^2 and those exhibiting scattered distribution were excluded and manually corrected, resulting in the acquisition of construction land patches for the 11 cities in Zhejiang Province for each year;

(2) Socioeconomic data, including population, GDP, industrial structure, government revenue, general public budget expenditure, fixed asset investment, and livestock population, were retrieved from the *Zhejiang Statistical Yearbook*. Additionally, data on the completed area's green-covered area were obtained from the *China Urban Statistical Yearbook*. The accuracy and consistency of all of the aforementioned data were cross-referenced and verified against the statistical yearbooks of each city;

(3) Carbon emission data for the 11 cities in Zhejiang Province from 2001 to 2019 were obtained. These data represent estimated carbon emissions resulting from the primary energy consumption in each city. These data serve as a partial estimation of carbon emissions from construction land in the present article. The data were sourced from the Carbon Emission Accounts and Datasets (https://www.ceads.net.cn/, accessed on 10 May 2023), which comprise carbon emission inventories for 290 Chinese cities over the years under investigation. Previous studies have confirmed the comprehensiveness and effectiveness of these datasets [47,48].

It is worth noting that this study covered a substantial time period, and as a result, data for certain cities may have been missing for specific years. To address this issue, a limited number of missing data were supplemented using data from adjacent years or compensated for using the linear interpolation method. Moreover, all data were normalized before calculation.

3. Methodology

3.1. Calculation of LUCE

The present study classified land types into seven distinct categories, namely, cropland, forestland, shrubland, grassland, water bodies, construction land, and other lands. These land-use categories within Zhejiang Province can be further classified into two overarching types: "carbon sources" and "carbon sinks". In order to estimate carbon sinks and carbon emissions, calculations were performed based on established research findings and guidelines outlined by the Intergovernmental Panel on Climate Change (IPCC).

3.1.1. Accounting for Total Carbon Sinks

Carbon sinks primarily arise from the sequestration of carbon within terrestrial ecosystems, including forestland, shrubland, grasslands, water bodies, and other land categories. These specific land types can be directly quantified. Table 1 presents the carbon emission coefficients for different land-use types, which were derived from previous research findings. The total volume of carbon sinks (CS) in a natural ecosystem is calculated using the following formula:

$$CS = \sum CS_i = \sum (A_i \times \theta_i) \tag{1}$$

where CS_i is the carbon sink amount of each land type; A_i is the area of each carbon sink land type; and θ_i is the carbon sink coefficient per unit area of each carbon sink land type.

Table 1. Carbon emissions and sink coefficients.

Notation	Carbon Emission Component	Coefficient	Units	Source
θ_1	Forestland	−0.586	$t/(hm^2 \cdot yr)$	[15]
θ_2	Shrubland	−0.161	$t/(hm^2 \cdot yr)$	[49,50]
θ_3	Grassland	−0.021	$t/(hm^2 \cdot yr)$	[15,51]
θ_4	Water bodies	−0.253	$t/(hm^2 \cdot yr)$	[22,51]
θ_5	Other lands	−0.005	$t/(hm^2 \cdot yr)$	[15]
θ_c	Cropland	0.497	$t/(hm^2 \cdot yr)$	[15]
δ_1	Human respiration	0.079	$t\,C/(person \cdot yr)$	[50,52]
δ_2	Pig respiration	0.082	$t\,C/(head \cdot yr)$	[50,53]
δ_3	Cattle respiration	0.374	$t\,C/(head \cdot yr)$	[50,53]

3.1.2. Accounting for Total Carbon Emissions

Construction land and cropland function as significant sources of carbon emissions, with construction land facilitating various economic and social activities encompassing human habitation and production. Notably, the primary factors under consideration pertain to energy consumption and respiratory emissions originating from both human activities and livestock. Specifically, the main livestock species taken into account are pigs and cattle. The following formula is utilized:

$$CE = C_u + C_c = C_e + C_p + C_c = C_e + \sum (p_i \times \delta_i) + A_c \times \theta_c \tag{2}$$

where C_u and C_c represent the emissions from construction land and cropland, respectively; C_e represents the carbon emissions of apparent energy consumption; C_p represents the carbon emissions of human and livestock respiration; P_i is the number of humans and livestock in a city; δ_i indicates the annual carbon emissions per person (head); A_c is the area of cropland; and θ_c is the carbon emission coefficient of cropland.

3.2. Net Land-Use Carbon Emissions

Net land-use carbon emissions (NLUCE) are the sum of carbon sources and sinks in a region and are calculated as follows:

$$C = CS + CE \tag{3}$$

where C is the NLUCE; CS is the total volume of carbon sinks; and CE is the total carbon emissions.

3.3. Influencing Factors

Drawing on relevant studies, this study focuses on the following influencing factors based on three aspects—socioeconomic aspects, urban form aspects, and urban environment aspects:

- Socioeconomic aspects

(1) Population density, represented by the number of people per unit area;
(2) Economic level, represented by GDP per capita to measure economic level;
(3) Industrial structure, represented by the ratio of secondary industry to GDP;
(4) Government intervention, represented by the ratio of general budget expenditure to total financial revenue;
(5) Public facilities level, represented by the ratio of investment in fixed assets to GDP.

- Urban form aspects

(6) The compactness of the peripheral profile form in urban areas holds significant importance as an indicator of urban spatial structure. In general, during the phase of rapid urban expansion, the compactness tends to decrease, whereas it tends to increase when cities transition toward internal filling and transformative development stages. The cyclical expansion of cities is intricately linked to the cyclical nature of urban economic development, and investigating the changes in the compactness of urban form allows for the identification of such cyclic patterns in urban expansion.

Enhancing the urban compactness index contributes to reducing the distance between various parts within the city, thereby improving the efficiency of urban infrastructure and optimizing the utilization of developed land. The compactness index CI is calculated by means of the following formula [54]:

$$CI = \frac{2\sqrt{\pi A}}{P} \tag{4}$$

where A is the area of the built-up area, and P is the perimeter of the built-up area of the city. A higher value of the compactness index indicates a more compact shape of the city;

- Urban environment aspects

(7) Urban greening level, represented by the proportion of green covered area to the built-up area.

3.4. GTWR Models

Compared with previous research models, this study incorporates the GTWR model into the investigation of LUCE. It focuses on comprehensively examining the dynamic evolution of influential factors contributing to LUCE during various stages of development within each city. Consequently, this approach enhances the ability to elucidate the spatiotemporal effects of the driving mechanisms behind LUCE in a scientifically robust manner. The conventional geographically weighted regression (GWR) model is subject to certain limitations when applied in specific contexts, primarily due to the restricted sample size of cross-sectional data. One prominent drawback is that the explanatory stability is constrained by the sample size, thereby impeding the accurate estimation of model parameters. In an effort to address this issue, researchers [55] introduced the temporal dimension to the GWR model, thereby incorporating the combined influence of spatiotemporal factors.

This advancement has led to the proposal of the geographically and temporally weighted regression model, known as GTWR. The GTWR model effectively extends the GWR framework by integrating temporal and spatial information, thus enhancing the weighting matrix and resolving the challenge of spatial and temporal nonsmoothness. Consequently, the estimation process is significantly improved. The specific equation for the GTWR model can be represented as follows:

$$Y_i = \beta_0(u_i, v_i, t_i) + \sum_{k=1}^{p} \beta_k(u_i, v_i, t_i)X_{ik} + \varepsilon_i \tag{5}$$

where Y and X represent the dependent and explanatory variables, respectively. The variable i represents the sample region, while u and v represent the geographical coordinates of the sample region. Additionally, the variable t represents time. The term $\beta_0(u_i, v_i, t_i)$ corresponds to the intercept term, and $\beta_k(u_i, v_i, t_i)$ signifies the estimated coefficient for the explanatory variables. A positive value of β indicates a positive correlation between the explanatory and dependent variables, while a negative value indicates a negative correlation. The term ε_i represents the random disturbance term.

4. Results and Discussion

4.1. Land-Use Changes

As urbanization progresses, cities in Zhejiang Province require the ongoing expansion of construction land to facilitate their developmental needs. Consequently, urban construction land areas have expanded outward, resulting in substantial alterations to land-use patterns. The observed increase in construction land area across each city between 2001 and 2019 was approximately twice the original area. Notably, Hangzhou and Ningbo exhibited the most significant increments in construction land expansion, measuring 831.92 km^2 and 879.01 km^2, respectively. Furthermore, Jiaxing experienced substantial growth in construction land from 248.03 km^2 to 778.33 km^2, exceeding three times its initial size. Table 2 reveals that the augmentation of construction land predominantly occurred through the conversion of three land-use types: cropland, forestland, and water bodies. Five distinct land-use transformation patterns can be identified: first, the primary conversion involved cropland transforming into construction land, exemplified by Jiaxing. Second, there were instances of forestland being converted into both construction land and cropland, as observed in Wenzhou, Quzhou, and Lishui. Third, the most prevalent land-use change pattern entailed the conversion of cropland and forestland into urban construction land, evident in Hangzhou, Huzhou, Shaoxing, Jinhua, and Taizhou. Fourth, the conversion of cropland and water bodies into construction land was evident in the island city of Zhoushan. Finally, the city of Ningbo demonstrated the conversion of cropland, forestland, and water bodies into construction land. Irrespective of the specific conversion mode, whether involving a single land type such as cropland or forestland, or the combined conversion of cropland, forestland, and water bodies to facilitate construction, all these processes result in diminished carbon sinks and increased carbon sources. Therefore, it is imperative to conduct further investigations to explore the spatial and temporal differentiation of LUCE and their underlying influencing factors.

Table 2. Major land-use changes in Zhejiang's cities from 2001 to 2019.

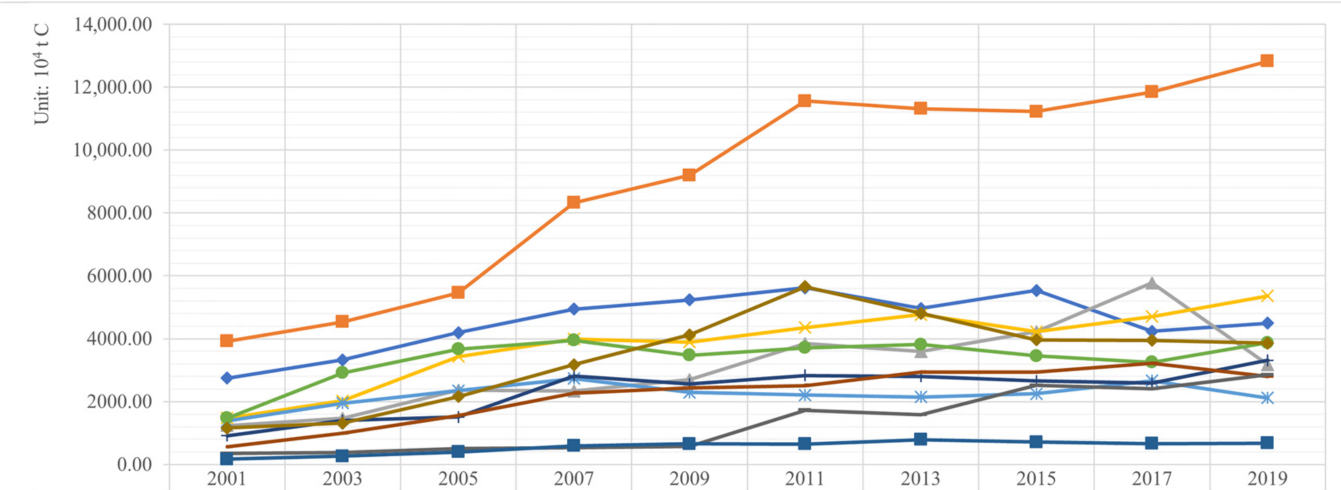
Cities	Land-Use Types	2001 (km^2)	2011 (km^2)	2019 (km^2)	2001–2019 (km^2)
Hangzhou	Cropland	3205.45	2553.36	2686.83	−518.63
	Construction land	636.69	1167.11	1468.61	831.92
	Forestland	12,201.59	12,280.22	11,930.67	−270.92
	Water bodies	836.67	879.03	794.27	−42.40
Ningbo	Cropland	3253.42	2901.97	2850.59	−402.84
	Construction land	698.29	1303.45	1577.30	879.01
	Forestland	4521.21	4348.68	4266.27	−254.94
	Water bodies	755.51	674.04	534.61	−221.10
Wenzhou	Cropland	2047.19	1801.55	2109.13	61.94
	Construction land	441.43	680.23	814.82	373.39
	Forestland	8698.51	8716.95	8313.80	−384.70
	Water bodies	242.19	232.49	194.81	−47.38
Jiaxing	Cropland	3591.53	3321.43	3117.16	−474.38
	Construction land	248.03	550.66	778.33	530.30
	Forestland	25.39	22.80	23.68	−1.71
	Water bodies	1049.84	1019.25	995.61	−54.23
Huzhou	Cropland	2849.06	2646.92	2589.38	−259.68
	Construction land	210.68	424.66	603.73	393.05
	Forestland	2523.62	2389.94	2284.23	−239.39
	Water bodies	240.64	361.76	346.64	106.00
Shaoxing	Cropland	2557.55	2265.12	2363.91	−193.64
	Construction land	423.85	710.55	867.12	443.27
	Forestland	4925.04	4911.33	4715.85	−209.19
	Water bodies	372.05	391.05	331.94	−40.11
Jinhua	Cropland	3118.94	2651.72	2817.73	−301.21
	Construction land	426.40	790.21	983.04	556.65
	Forestland	7276.66	7326.01	6993.81	−282.84
	Water bodies	138.41	191.90	166.06	27.65
Quzhou	Cropland	2046.61	1944.41	2079.32	32.72
	Construction land	218.11	322.73	409.76	191.64
	Forestland	6519.36	6479.76	6262.37	−256.99
	Water bodies	90.66	127.88	123.64	32.97
Zhoushan	Cropland	420.34	403.46	360.30	−60.04
	Construction land	95.48	168.92	214.31	118.83
	Forestland	568.12	531.55	559.48	−8.64
	Water bodies	95.01	74.96	44.89	−50.12
Taizhou	Cropland	2508.14	2280.38	2300.04	−208.10
	Construction land	416.91	714.22	860.08	443.18
	Forestland	6258.94	6182.98	6050.61	−208.33
	Water bodies	257.26	263.93	231.44	−25.82
Lishui	Cropland	870.00	731.62	1075.23	205.23
	Construction land	123.89	188.09	257.07	133.18
	Forestland	16,234.14	16,278.26	15,866.92	−367.82
	Water bodies	75.97	107.25	107.05	31.08

4.2. Spatial and Temporal Variation Characteristics of LUCE

4.2.1. Temporal Evolution Characteristics

Between 2001 and 2019, the total LUCE in Zhejiang Province exhibited a pattern of rapid growth followed by a period of stability. The emissions increased from 153.90 million tons in 2001 to 446.56 million tons in 2011, representing a substantial increase of 292.66 million tons. By 2019, LUCE reached 453.43 million tons, signifying an additional increase of 6.87 million tons compared to 2011. These data indicate a significant slowdown in the growth rate of carbon emissions, suggesting that Zhejiang Province is gradually exploring a sustainable development path characterized by a green economy, resulting in more effective carbon reduction outcomes.

Specifically, when examining LUCE at the city level, two distinct trends emerge (Figure 2). The first trend is exemplified by Ningbo, Wenzhou, Jiaxing, Quzhou, Zhoushan, and Lishui, where carbon emissions have consistently risen over the past two decades. Among these cities, Ningbo exhibits the highest annual average LUCE of 90.21 million tons, making it the city with the greatest annual emissions in Zhejiang Province. The second trend entails a phased rise and subsequent stabilization of LUCE. Hangzhou, Huzhou, Shaoxing, Jinhua, and Taizhou exemplify this pattern. Notably, Taizhou achieved the largest reduction in carbon emissions between 2011 and 2019, with a decrease of 17.92 million tons in LUCE compared to 2011. Overall, the cities in Zhejiang Province possess significant potential for carbon emission reduction. Whether following a trend of continuous growth or a phased rise followed by stabilization, the carbon emission increment index displays a general slowdown, indicating a shift away from the initial stage of crude carbon emission control and management. Instead, cities in Zhejiang Province are gradually embracing strategies and initiatives for green and low-carbon urban development.



	2001	2003	2005	2007	2009	2011	2013	2015	2017	2019
Hangzhou	2747.68	3327.29	4191.84	4938.31	5230.94	5618.24	4962.24	5535.80	4232.32	4493.95
Ningbo	3919.27	4537.89	5454.71	8323.78	9199.99	11,562.77	11,317.07	11,223.59	11,847.97	12,823.24
Wenzhou	1239.68	1466.80	2362.79	2329.66	2698.58	3840.80	3592.34	4223.06	5769.78	3170.04
Jiaxing	1474.31	2024.01	3432.98	3990.75	3893.56	4353.82	4764.27	4219.82	4703.60	5361.25
Huzhou	1384.83	1950.58	2347.52	2728.52	2295.06	2208.81	2142.65	2252.84	2659.15	2118.70
Shaoxing	1472.68	2915.19	3668.79	3950.67	3469.93	3707.86	3816.43	3454.28	3247.50	3874.41
Jinhua	916.30	1398.53	1508.15	2816.95	2558.11	2827.07	2799.29	2656.03	2581.24	3315.15
Quzhou	556.44	992.47	1555.97	2271.05	2434.10	2510.89	2935.00	2937.98	3213.14	2795.66
Zhoushan	349.85	379.36	500.32	533.27	572.45	1728.36	1575.75	2513.80	2402.83	2853.53
Taizhou	1161.28	1310.52	2155.95	3171.17	4125.57	5650.37	4807.12	3964.21	3946.90	3858.22
Lishui	167.70	260.66	399.29	592.59	653.75	647.25	788.62	713.14	660.15	679.32

Figure 2. Trends in the evolution of LUCE of cities in Zhejiang Province.

4.2.2. Spatial Distribution Characteristics

The spatial distribution of carbon emissions resulting from land-use activities in Zhejiang Province exhibits a distinct “high in the northeast and low in the southwest” pattern (Figure 3). Examining regional agglomeration, in 2001, the areas with elevated LUCE were primarily concentrated in the northern part of Zhejiang Province, with Hangzhou and Ningbo, the two central cities of the metropolitan area, accounting for the highest emissions. Huzhou, Jiaxing, and Shaoxing followed closely in the second gradient. Between 2001 and 2007, the northern region of Zhejiang Province maintained consistently high carbon emissions, while Hangzhou and Huzhou gradually decelerated their emission rates. From 2007 to 2017, there was a shift in the spatial distribution of the dual-center cities, with Ningbo emerging as the sole city with the highest carbon emissions. This shift in spatial dynamics indicated a transition in the center of carbon emission aggregation from the northern part of Zhejiang Province to the eastern coastal region. Moreover, a trend of carbon emission concentration and a circular spatial distribution pattern emerged. In 2019, Ningbo remained the largest urban area in terms of carbon emissions, with most cities experiencing a reduction in emissions compared to the previous period. The center of carbon emissions shifted from the east to the northeast, and the spatial distribution transformed from a scattered pattern to a more concentrated circular configuration. At the city level, Ningbo in the northeast consistently ranked highest regarding carbon emissions, exerting significant influence on the overall spatial distribution of carbon emissions in Zhejiang Province. Conversely, Lishui and Wenzhou in the southern part of the province maintained a relatively steady state in terms of total carbon emissions.

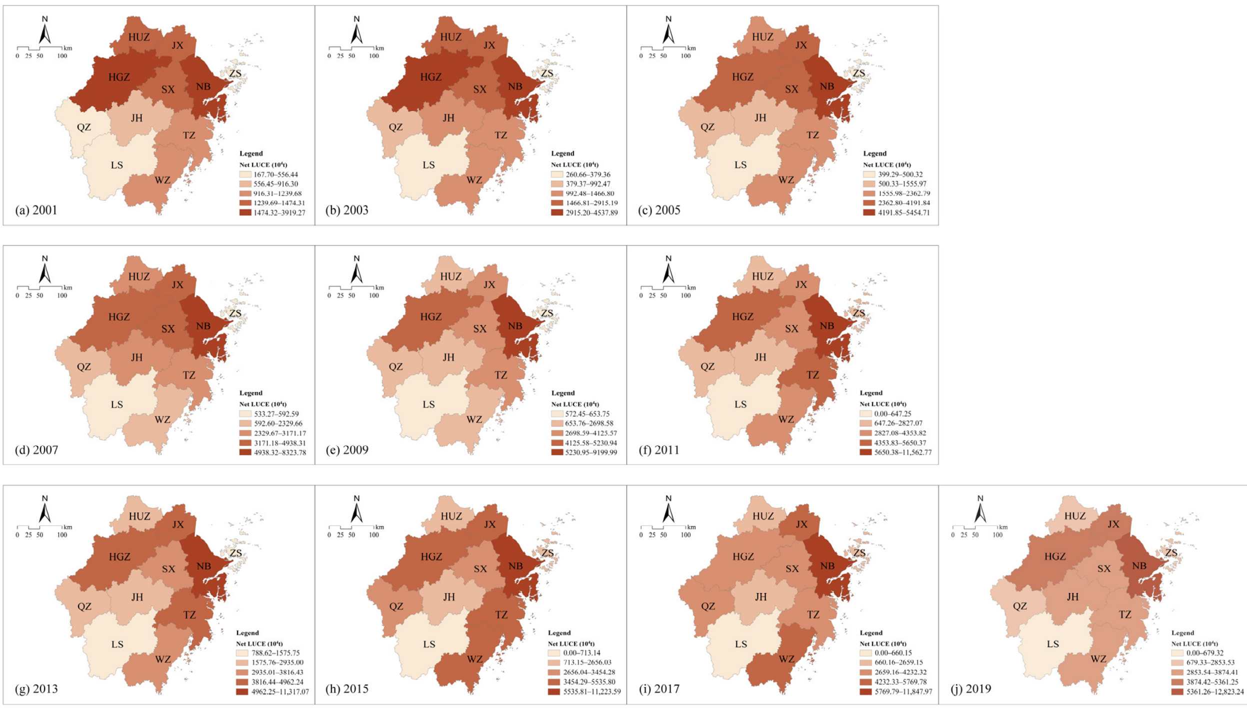


Figure 3. Spatial distribution of LUCE by cities in Zhejiang Province. Note: HGZ, Hangzhou City; NB, Ningbo City; WZ, Wenzhou City; JX, Jiaxing City; HUZ, Huzhou City; SX, Shaoxing City; JH, Jinhua City; QZ, Quzhou City; ZS, Zhoushan City; TZ, Taizhou City; LS, Lishui City. The same abbreviations are used for the following figures.

4.3. Spatial and Temporal Variation Characteristics of LUCE Influencing Factors

4.3.1. GTWR Empirical Results

Moran’s I was employed to examine the global autocorrelation of the seven influencing factors, and the corresponding results are presented in Table 3. It was observed that each influencing factor demonstrated a positive Moran's index, with all global spatial autocorrelation coefficients being significantly greater than 0 at the 1% significance level. These findings indicate the presence of positive spatial correlation among the factors, implying a spatial clustering characteristic.

To investigate the localized correlation between different factors and LUCE, the GTWR model was used to analyze the spatial heterogeneity considering the influence of the "First Law of Geography". The obtained results are presented in Table 4, where both the R^2 and the adjusted R^2 surpass the threshold of 0.95. This indicates a high level of model fit and suggests that the regression model possesses substantial explanatory power. Consequently, the model outcomes can effectively illuminate the spatial heterogeneity of the influence.

Table 3. Statistical tests of spatial autocorrelation using Moran's I.

Influencing Factors	Moran's Index	Z-Score	*p*-Value	Confidence Interval
Population density (PD)	0.3238	17.1222	<0.01	99%
Economic level (EL)	0.0863	4.8947	<0.01	99%
Industrial structure (IS)	0.2749	14.5810	<0.01	99%
Government intervention (GI)	0.3584	18.9851	<0.01	99%
Public facilities level (PF)	0.1717	9.4052	<0.01	99%
Urban compactness (UC)	0.6188	32.3278	<0.01	99%
Urban greening level (UG)	0.0732	4.2427	<0.01	99%

Note: The contents in parentheses represent the respective abbreviations of the influencing factors.

Table 4. Index of model evaluation.

Bandwidth	Sigma	Residual Squares	AICc	R^2	Adjusted R^2
0.1575	0.0342	0.1288	−208.1290	0.9697	0.9677

4.3.2. Spatial and Temporal Heterogeneity of LUCE Influencing Factors

Through statistical analysis of the regression coefficients (Table 5), it was determined that the average intensity ranking order of each influencing factor is as follows: economic level > government intervention > urban compactness > public facilities level > urban greening level > industrial structure > population density. Among the top three factors, the median regression coefficient of economic level is 0.3417, and the mean value is 0.4171; the median regression coefficient of government intervention is −0.3115, and the mean value is −0.3962; and the median regression coefficient of urban compactness is −0.2977, and the mean value is −0.2850. Their median and mean values exhibit consistent changes in the same direction and are relatively close to each other. Moreover, by examining the range between the minimum and maximum values, it becomes apparent that both positive and negative correlations exist between all seven factors and LUCE. For instance, when considering urban compactness, the minimum compactness value is −0.7052, while the maximum value is 0.4190. The positive and negative effects of urban compactness exhibit variations across different cities, indicating that the general understanding, which posits that higher compactness results in lower carbon emissions from land use and advocates for continuous improvement in compactness in urban development, fails to account for the divergent developmental stages among cities. Therefore, when pursuing low-carbon development, cities need to adopt an adaptive and stratified approach that takes into consideration the specific characteristics of each locality.

Figures 4–10 depict the spatial distribution of the regression coefficients for the seven influencing factors derived from the GTWR model. The figures visually demonstrate the spatial heterogeneity in the impact of various factors on carbon emissions across different time periods.

Table 5. Descriptive statistics of regression coefficients of influencing factors.

Influencing Factors	Mean	S.D.	Min.	Median	Max.
Population density (PD)	−0.0248	0.2895	−1.2100	0.0260	0.4001
Economic level (EL)	0.4171	0.3597	−1.0195	0.3417	1.1011
Industrial structure (IS)	−0.0733	0.2862	−0.7208	−0.0080	0.4078
Government intervention (GI)	−0.3962	0.4375	−1.7426	−0.3115	0.6037
Public facilities level (PF)	−0.1018	0.2595	−1.0618	−0.0122	0.3481
Urban compactness (UC)	−0.2850	0.2438	−0.7052	−0.2977	0.4190
Urban greening level (UG)	−0.0967	0.2556	−1.2192	−0.0201	0.1961

Note: The contents in parentheses represent the respective abbreviations of the influencing factors.

- Socioeconomic Aspects

(1) Spatial and temporal heterogeneity of the influence of the population density factor on LUCE (Figure 4).

In terms of the temporal evolution of influence, population density has the greatest influence on LUCE in Quzhou and Shaoxing. In Quzhou, population density exhibits a negative correlation with LUCE, with the strength of this influence diminishing over time. Conversely, population density in Shaoxing shows a positive correlation with LUCE, and its impact remains relatively stable. In a broader context, the effect of population density on LUCE in each city undergoes a transition from initially negative to ultimately positive. The clustering of the population facilitates the spatial concentration of economic activities and production factors, as well as the sharing of social infrastructure [6,56]. This can result in reduced fixed investment costs, management costs, and improved energy and resource utilization efficiency, thereby lowering carbon emissions. However, excessive population density can lead to heightened energy consumption, hence displaying a positive correlation. The impact of population density on LUCE, while generally modest, should not be disregarded. It is imperative to judiciously manage the influx of migrants, endeavor to enhance demographic conditions, and encourage reasonable growth of the resident population [38].

Concerning the spatial distribution of influence, the impact of population density on LUCE is more significant in inland cities located in western Zhejiang Province compared to their counterparts in the eastern coastal areas.

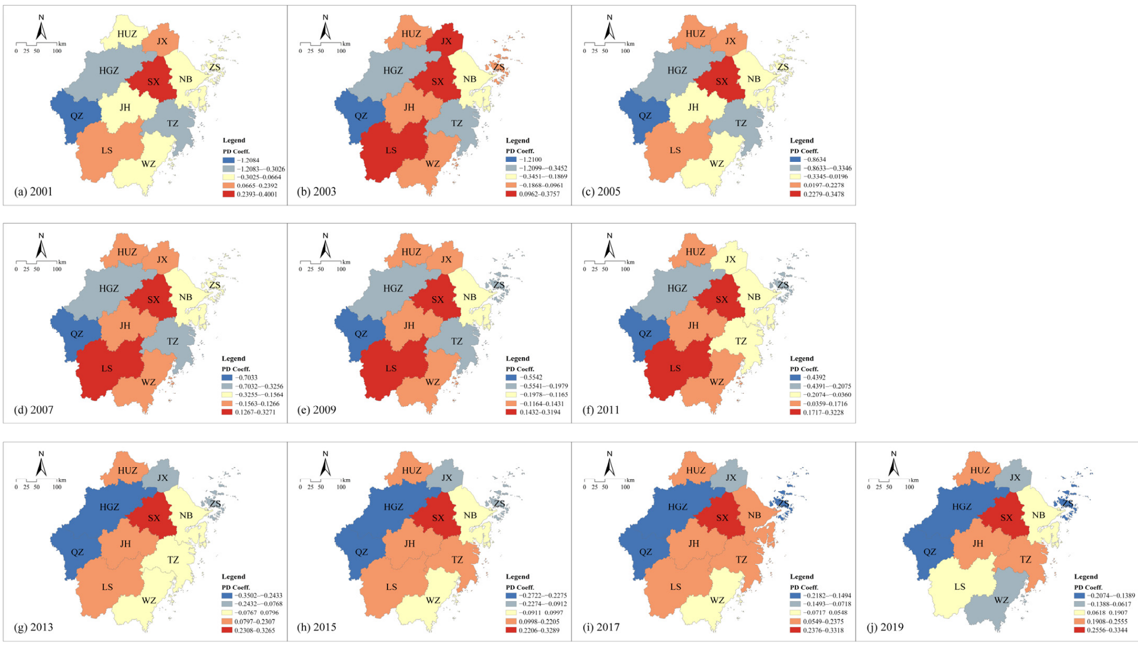


Figure 4. Spatial distribution of population density regression coefficients in Zhejiang's cities from 2001 to 2019.

(2) Spatial and temporal heterogeneity of the influence of the economic level factor on LUCE (Figure 5).

In terms of the temporal evolution of the degree of influence, a positive correlation is observed between the economic level and LUCE in the cities of Zhejiang. Moreover, this influence maintains a consistent stability. These findings align with prior research outcomes [2,39], underscoring the imperative of exploring strategies that foster an optimal equilibrium between economic advancement and LUCE. The economic level exhibits the strongest degree of influence on LUCE in two cities, namely, Ningbo and Taizhou, consistently maintaining a high level of influence. Notably, a negative correlation emerges between the economic level and LUCE in Wenzhou and Lishui after 2015, with the degree of influence steadily increasing. The negative effect of economic development on LUCE is similarly verified within the examination of the Chang–Zhu–Tan urban agglomeration [57]. This trend aligns with the advancement of economic development, optimization of the economic development model, and the implementation of low-carbon economic strategies, including the establishment of carbon emission reduction targets. These measures effectively regulate LUCE resulting from economic development, thereby fostering the emergence of a low-carbon economic development model as a potential catalyst for coordinated economic, social, and environmental development [58].

Regarding the spatial distribution of the degree of influence, the impact of the economic level on LUCE is more pronounced in the eastern coastal cities of Zhejiang Province compared to the western cities. This spatial pattern exhibits a trend characterized by higher influence in the eastern cities and lower influence in the western cities, commonly referred to as a "high in the east and low in the west" distribution. Specifically, Ningbo, Taizhou, Zhoushan, and Jiaxing, situated in the eastern region of Zhejiang Province, consistently experience the significant influence of a high economic level on LUCE. Conversely, Quzhou and Jinhua, located in the western region, demonstrate a lower level of economic influence on their LUCE.

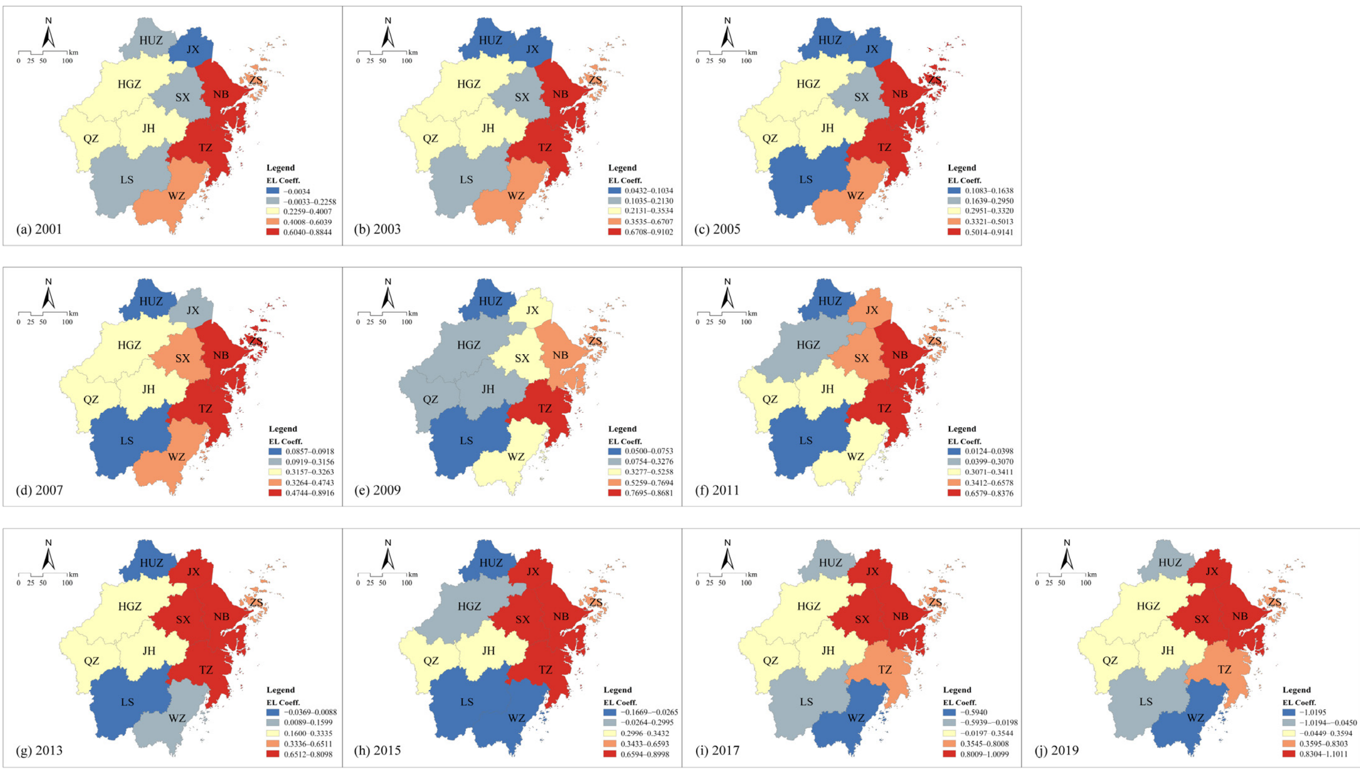


Figure 5. Spatial distribution of economic level regression coefficients in Zhejiang's cities from 2001 to 2019.

(3) Spatial and temporal heterogeneity of the influence of the industrial structure factor on LUCE (Figure 6).

From a temporal perspective, the relationship between industrial structure and LUCE in Hangzhou and Quzhou consistently exhibits a positive association, with a stable degree of influence. This implies that higher proportions of secondary industry in these cities lead to elevated levels of LUCE. To effectively mitigate total LUCE, cities can appropriately reduce the proportion of secondary industry and prioritize the development of tertiary industry by modifying their industrial structure [2,17]. The impact of the industrial structure on LUCE in most cities shifted from a negative to a positive effect after 2009. A possible explanation is the inadequate transformation and upgrading of industrial structures during the initial stages of urban development. The mismatch between the industrial pattern and the high demand for industries like steel and cement in urban construction results in reduced carbon emissions from the reduced share of secondary industry, which is outweighed by the increased energy consumption associated with urbanization, thereby establishing a negative correlation between the two variables.

The influence of industrial structure on LUCE exhibits significant spatial heterogeneity in Zhejiang Province. Analyzing the dynamic evolution of the influence degree reveals a decreasing influence on cities in northeastern Zhejiang, represented by Ningbo, while cities in southwestern Zhejiang, such as Quzhou and Lishui, experience an increasing influence from the industrial structure.

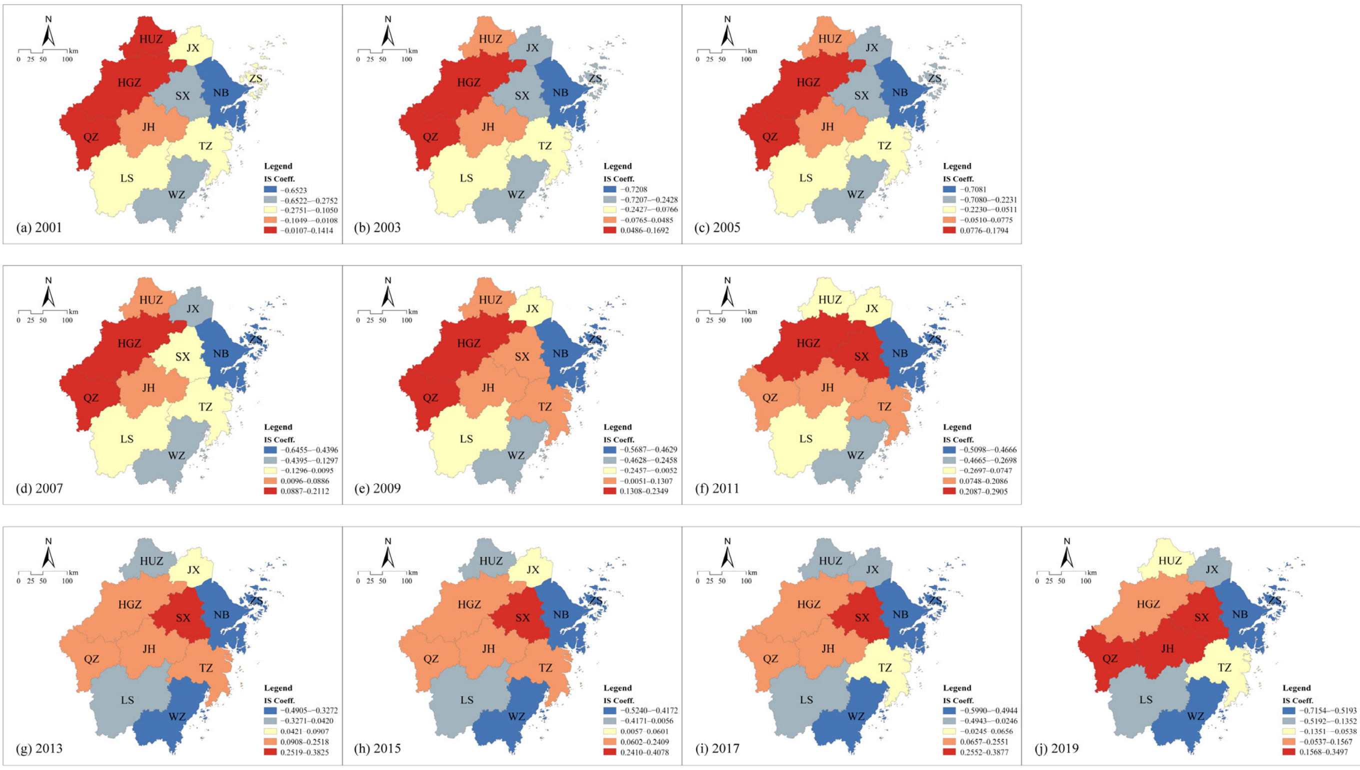


Figure 6. Spatial distribution of industrial structure regression coefficients in Zhejiang's cities from 2001 to 2019.

(4) Spatial and temporal heterogeneity of the influence of the government intervention factor on LUCE (Figure 7).

From a temporal perspective, the relationship between government intervention and LUCE in Zhejiang's cities exhibits a predominantly negative association. Notably, the city of Ningbo experiences the greatest influence; however, the strength of this influence has been gradually diminishing over time. Conversely, the impact of government intervention on LUCE in Jiaxing displays a consistent year-on-year increase. Furthermore, in Shaoxing, there exists a positive correlation between government intervention and LUCE, with the degree of influence showing a progressive rise after 2011. Among the extant studies, the identification of a robust positive relationship between the government intervention factor and LUCE represents an innovative contribution.

In terms of spatial distribution, the influence of government intervention on LUCE in Zhejiang Province shows a spatial heterogeneity of "high in the northeast and low in the southwest". The northeastern region, encompassing cities like Ningbo and Taizhou, experiences the most profound impact of government intervention on LUCE. In particular, the relationship between government intervention and LUCE in Shaoxing shifts from negative to positive, with the degree of influence continuing to grow. Conversely, in the southwestern region of Zhejiang Province, represented by cities such as Quzhou, Jinhua, and Lishui, the influence of government intervention on LUCE is comparatively weaker.

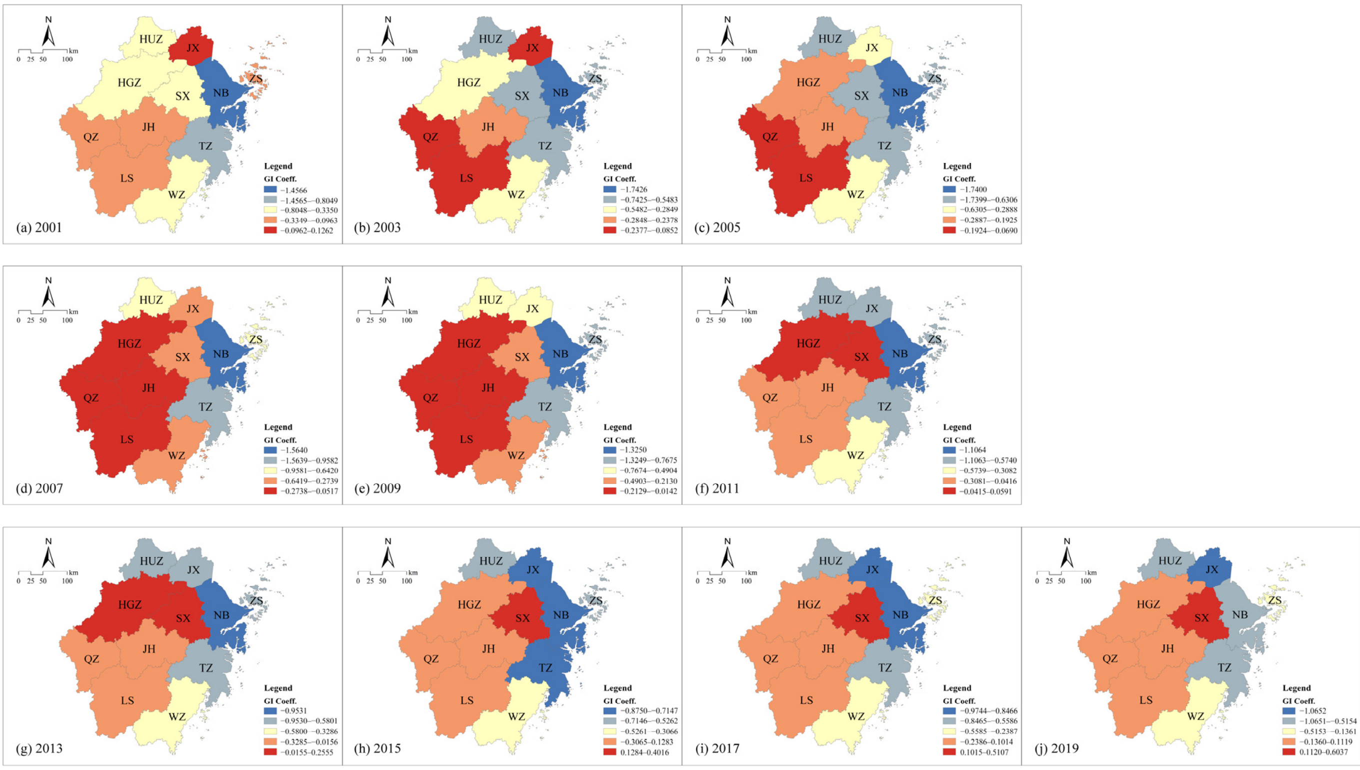


Figure 7. Spatial distribution of government intervention regression coefficients in Zhejiang's cities from 2001 to 2019.

(5) Spatial and temporal heterogeneity of the influence of the public facilities level factor on LUCE (Figure 8).

In terms of the temporal evolution of the influence degree, a positive correlation is observed between the level of public facilities and LUCE in Quzhou and Lishui, with a consistently stable degree of influence. Conversely, a negative relationship persists, albeit with a diminishing degree of influence, on LUCE in Zhoushan. Furthermore, the impact of the public facilities level on LUCE in Ningbo and Shaoxing has transitioned from a negative effect in the initial stages to a positive effect, and the magnitude of this influence has been progressively increasing over the years. Shaoxing, in particular, has consistently exhibited the highest influence degree since 2009. Local governments ought to enhance the criteria for approving high-emission and high-consumption projects, while expediting the implementation of a "carbon assessment" and regulatory framework for fixed-asset investments [56].

Regarding the spatial distribution of the influence degree, the relationship between the public facilities level and carbon emissions in cities across Zhejiang Province displays a three-tiered pattern. The northeast region exhibits the highest level of influence, followed by the southwest region, while the middle belt demonstrates the lowest level. Specifically, the cities in the northeast, such as Ningbo and Shaoxing, experience a significant influence from the public facilities level indicator, which has undergone a dynamic evolution of continuous enhancement. On the other hand, the cities in the southwest, represented by Quzhou and Lishui, as well as the cities in the middle belt, including Huzhou, Hangzhou, and Wenzhou, exhibit a weaker influence degree from the public facilities level indicator.

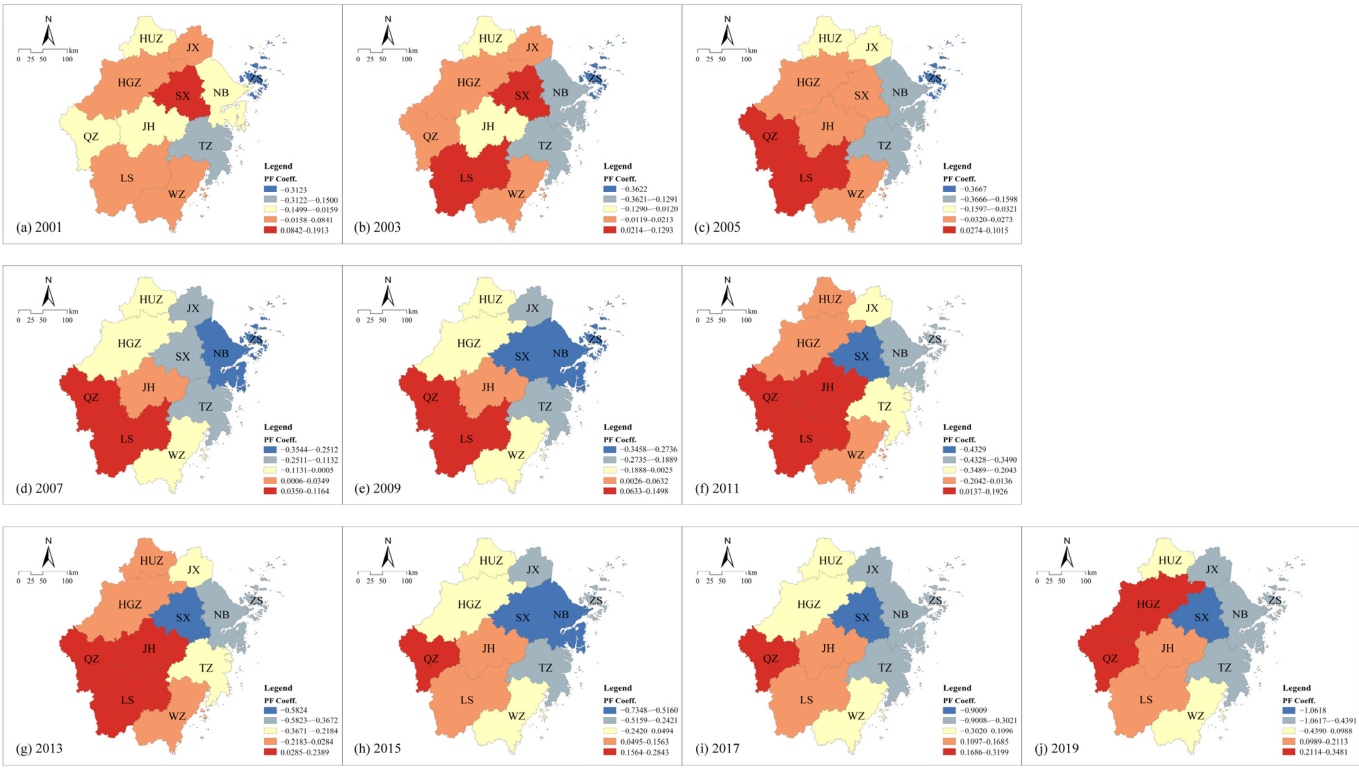


Figure 8. Spatial distribution of public facilities level regression coefficients in Zhejiang's cities from 2001 to 2019.

- Urban Form Aspects

(6) Spatial and temporal heterogeneity of the influence of the urban compactness factor on LUCE (Figure 9).

There exists a predominantly negative correlation between urban compactness and LUCE in cities across Zhejiang Province. This implies that compact urban construction land contributes to the reduction in urban carbon emissions, underscoring the importance for these cities, at their stage of development, to continually optimize and enhance their land-use layout. They should pursue a path of compact and intelligent development while continuously harnessing the effectiveness of urban land use. The impact of urban compactness on LUCE in Quzhou is substantial; however, its influence has been diminishing since 2013. Conversely, in Hangzhou and Huzhou cities, the impact has been deepening over time. Taizhou, on the other hand, consistently maintains a low level of influence. The relationship between urban compactness and LUCE in Jiaxing is particularly unique. Prior to 2013, a negative correlation was observed, with the degree of influence decreasing. Subsequently, a positive correlation emerged, and the degree of influence increased. This suggests that landscape pattern characteristics such as connectivity, complexity, and agglomeration of urban patches need to be taken into account in compact and low-carbon urban development [59]. To achieve this, urban management should exercise control over the peripheral areas of urban growth and redirect development efforts toward optimizing the internal structure of the city and revitalizing underutilized land within built-up areas [60].

Regarding the spatial distribution of the influence degree, the impact of urban compactness on LUCE in cities across Zhejiang Province exhibits a distinct pattern characterized by divergence, with higher levels of influence observed at both ends and lower levels in the middle. The cities that experience a high degree of influence are primarily concentrated in the northern and southern regions of Zhejiang Province, exemplified by Hangzhou, Huzhou, and Wenzhou. Conversely, the cities located in the middle belt, namely, Jinhua and Taizhou, demonstrate a relatively weaker driving force of urban compactness on their LUCE;

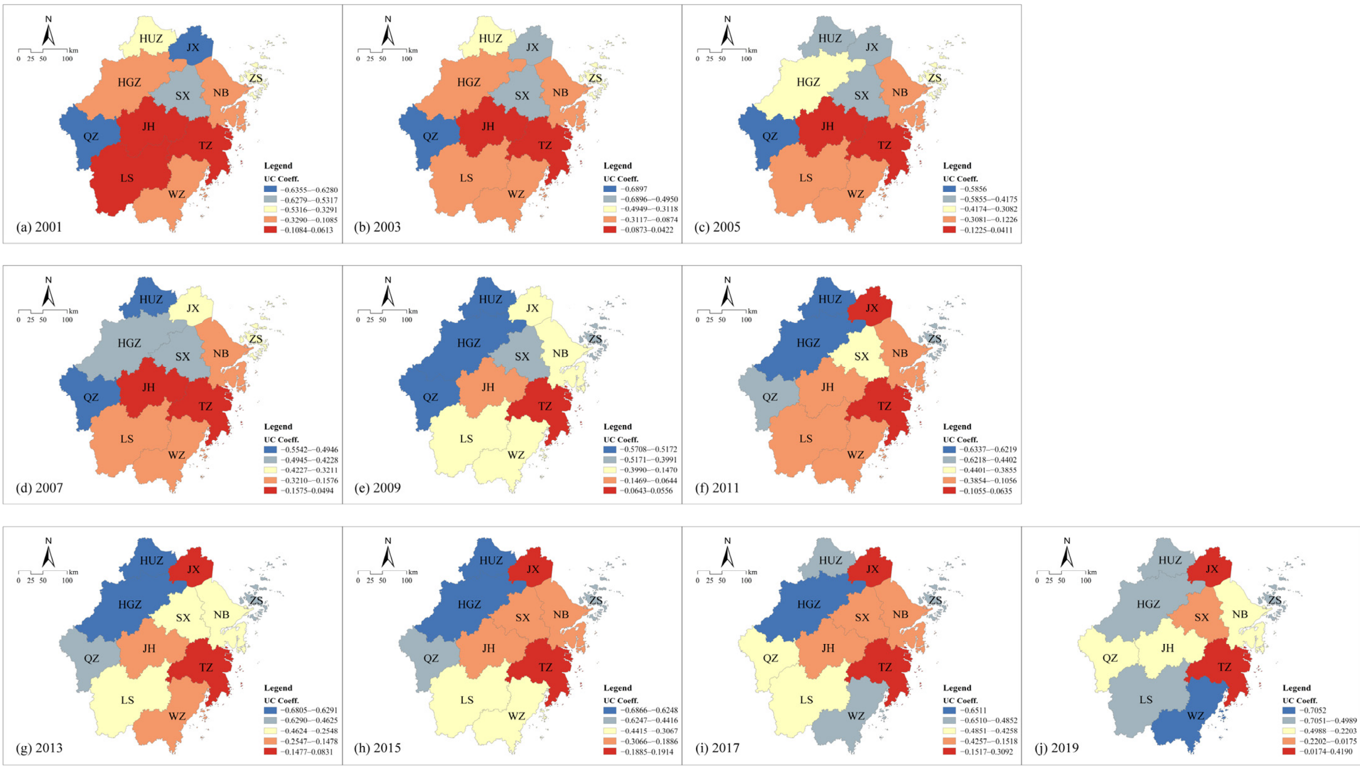


Figure 9. Spatial distribution of urban compactness regression coefficients in Zhejiang's cities from 2001 to 2019.

- Urban Environment Aspects

(7) Spatial and temporal heterogeneity of the influence of the urban greening level factor on LUCE (Figure 10).

From a temporal perspective, the degree of influence of the urban greening level on LUCE in Zhejiang's cities can be classified into three distinct types. Firstly, a consistent positive correlation is observed between urban greening level and the cities of Wenzhou and Lishui. Wenzhou experiences an increasing degree of influence over time, while Lishui demonstrates a fluctuating pattern with an initial decrease followed by an increase in its degree of influence. Secondly, there is a persistent negative correlation between urban greening level and Zhoushan, with the degree of influence continuously increasing. Thirdly, starting in 2007, a notable trend emerged whereby the influence of the urban greening level on LUCE in most cities undergoes a transition from a weakening positive effect in the early stages to a growing negative effect. This effect is most pronounced in Ningbo and Shaoxing, with Ningbo witnessing an increasing degree of influence, while Shaoxing tends to stabilize. This evolutionary trend indicates that promoting the enhancement of green cover facilitates carbon storage and contributes to the reduction in carbon emissions in urban land uses. Furthermore, the implementation of green space construction in built-up areas, coupled with dedicated endeavors to establish robust green infrastructure systems [61], can offer individuals a range of ecological service functions, thereby contributing to the enhancement of the residential living environment [62].

In terms of the spatial distribution of the influence degree, the impact of urban greening level on LUCE in each city of Zhejiang Province exhibits a spatial divergence characteristic, with higher levels of influence observed in the northern regions and lower levels in the southern regions. The northern cities of Ningbo, Shaoxing, and Zhoushan display a consistent increase and stability in the influence of this indicator on LUCE. Conversely, the southern cities of Lishui and Wenzhou exhibit a relatively lower level of influence in this regard.

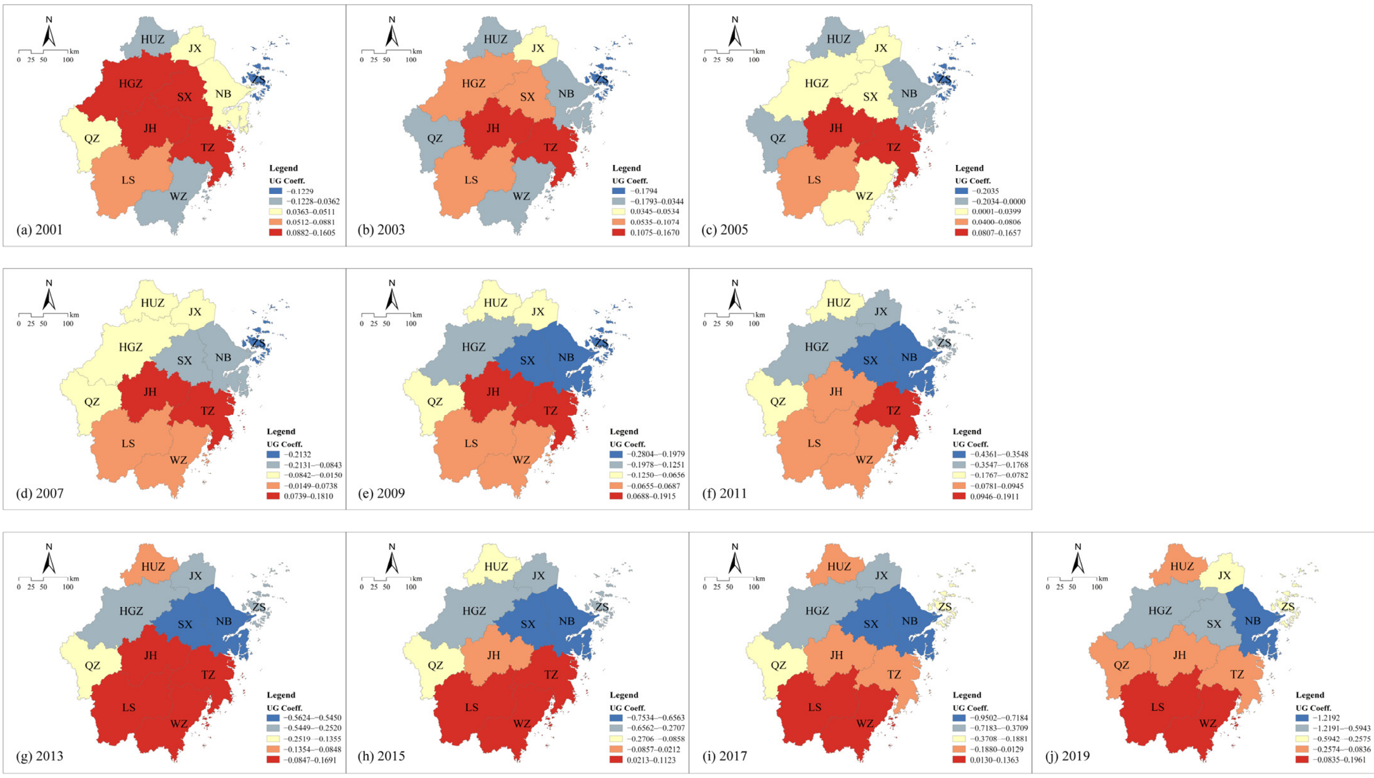


Figure 10. Spatial distribution of urban greening level regression coefficients in Zhejiang's cities from 2001 to 2019.

Based on the spatial and temporal distribution of regression coefficients concerning the influencing factors on LUCE within each city in Zhejiang Province, it is possible to delineate the principal determinants of such emissions in each city. The dominant drivers primarily hinge on the varying degrees of impact exhibited by individual influencing factors on LUCE across different cities (evident through the comparison of the absolute values of regression coefficients during different developmental stages within the same city). Certain cities are predominantly influenced by a single factor, whereas others are subject to the combined effects of multiple factors.

In Hangzhou, LUCE are mainly influenced by both urban compactness and urban greening level. The effect of urban compactness initially increases and then decreases, while urban greening level has exhibited a negative effect since 2007 and continues to increase. In Ningbo, LUCE are influenced by the economic level, government investment interventions, and urban greening level. The influence of the economic level remains stable, that of government investment shows an increasing and then decreasing trend, and the influence of urban greening level continues to increase. Wenzhou is influenced by the economic level, industrial structure, and urban greening level, with the economic level displaying a negative effect since 2013, while the influence of the latter two factors has been increasing since the same year. Jiaxing is primarily influenced by the economic level and government investment interventions, and the driving force of both factors has been increasing year by year. In Huzhou, LUCE are influenced by government investment interventions and urban compactness, with both drivers initially increasing and then stabilizing. In Shaoxing, LUCE are primarily influenced by a combination of the economic level, social infrastructure investment, and urban greening level, with all three drivers showing a continuous increase in influence. In Jinhua, LUCE are mainly influenced by the consistently stable economic level. In Quzhou, population density and urban greening level are the main drivers, with the influence of population density gradually weakening and the influence of urban greening level remaining stable. In Zhoushan, LUCE are influenced by the economic level and government investment interventions, with the former having a consistent and steady impact, while the influence of the latter initially increases and then gradually decreases. Taizhou's LUCE are mainly influenced by the economic level and government intervention, displaying a continuous and steady effect. In Lishui, LUCE are mainly influenced by the economic level and urban compactness, with the former transitioning to a negative effect since 2011, accompanied by an increasing degree of influence, while the influence of urban compactness continues to rise year by year. This analysis and trend assessment of the main driving forces in each city, based on the regression coefficients of the influencing factors, can provide a scientific basis for cities to explore low-carbon economic transition models and achieve differentiated and coordinated emission reduction.

5. Conclusions

This study employed GIS and RS technologies to extract seven types of land-use patches from 11 prefecture-level cities in Zhejiang Province. These patches were used to quantitatively assess the LUCE of each city and examine their spatial and temporal variations. Additionally, a GTWR model was employed to investigate the spatiotemporal characteristics of factors influencing LUCE in each city of Zhejiang Province. The main findings of this study are as follows:

(1) Over a period of nearly 20 years, from 2001 to 2019, the total LUCE in Zhejiang Province exhibited a pattern of rapid growth followed by stability. The change in LUCE in each city demonstrated two primary trends: a continuous increase over time, as observed in Ningbo, and a pattern of stabilization, exemplified by Hangzhou, where emissions initially increased and then decreased in phases. Furthermore, there was a noticeable spatial variation in LUCE among Zhejiang's cities, with higher emissions observed in the northeast region and lower emissions in the southwest;

(2) The influence of the seven indicators on LUCE exhibited significant heterogeneity in both the temporal and spatial dimensions. The statistical analysis of the regression coefficients for the influencing factors revealed that their average intensities were ranked as follows: economic level > government intervention > urban compactness > public facilities level > urban greening level > industrial structure > population density;

(3) The impact of population density on LUCE varied across cities, transitioning from a negative effect in the early stages to a positive effect. Inland cities in western Zhejiang Province exhibited a greater influence on LUCE compared to eastern coastal cities. The relationship between economic level and LUCE in Zhejiang's cities was generally positive and stable, with a spatial distribution characterized by higher levels in the east and lower levels in the west. The association between industrial structure and LUCE remained positive and stable in Hangzhou and Quzhou, while it decreased in northeastern Zhejiang's cities represented by Ningbo and increased in southwestern Zhejiang's cities represented by Quzhou and Lishui. Government intervention exhibited a negative correlation with LUCE in Zhejiang's cities, with a spatial distribution indicating higher levels in the northeast and lower levels in the southwest. The spatial distribution of the influence of public facilities level on carbon emissions in Zhejiang's cities demonstrated a three-tiered hierarchical pattern, with higher levels in the northeast, intermediate levels in the southwest, and lower levels

in the middle. Urban compactness exhibited a negative correlation with LUCE in each city of Zhejiang Province, and its impact displayed a spatial distribution characterized by higher levels at both ends and lower levels in the middle. The influence of urban greening level on LUCE varied among cities and exhibited a spatial divergence, with higher levels in the north and lower levels in the south;

(4) The LUCE in different cities are influenced to varying degrees by cities' respective stages of development. For instance, cities such as Ningbo, Wenzhou, Jiaxing, Shaoxing, Jinhua, Zhoushan, Taizhou, and Lishui are all influenced by their economic levels, albeit with variations in the extent and dynamic evolution of these influences. Therefore, when formulating differentiated low-carbon economic development strategies for different cities, careful consideration should be given to their specific developmental stages and the processes of dynamic evolution they are undergoing.

This study employs the GTWR model to examine the evolving patterns of factors influencing LUCE. This approach offers valuable insights into scientifically characterizing the spatiotemporal effects of the mechanisms driving LUCE. Consequently, it facilitates a more rigorous assessment of the developmental trajectories associated with LUCE. Moreover, the findings serve as a fundamental basis for establishing differentiated models and strategies for land-use carbon reduction, tailored to specific local contexts.

Disparities in urban development stages are not only evident within the 11 cities in Zhejiang Province but also extend to other regions worldwide. This study demonstrates a thorough recognition of the multifaceted nature, systematicity, dynamics, and variability inherent in the driving mechanisms of LUCE. Accordingly, leveraging an extensive time series, this research systematically identified seven pivotal influencing factors derived from the socioeconomic, urban form, and urban environment aspects. These factors were then utilized to investigate the dynamic evolution of the driving mechanism governing LUCE during distinct stages of urban development. The research methodology employed and the resulting findings hold significant potential for generalization and application in studies conducted in diverse regions worldwide.

The current study has certain limitations that need to be acknowledged. Firstly, the classification of land-use types in this study into seven categories may have overlooked the carbon emission variations that could be observed with a more detailed classification. Secondly, this study primarily focused on the city scale due to the availability of basic data. However, counties, being the fundamental administrative units in China, play a crucial role in implementing and enforcing low-carbon policies. Future studies should consider conducting more granular investigations at the county level to analyze the spatial and temporal characteristics of LUCE and their influencing factors.

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