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Spatial Patterns Exploration and Impacts Modelling of Carbon Emissions: Evidence from Three Stages of Metropolitan Areas in the YREB, China

Yichen Ding ^{1,2,3,†}, Yaping Huang ^{1,2,3,†}, Lairong Xie ⁴, Shiwei Lu ^{1,2,3,5,*}, Leizhou Zhu ^{1,2,3}, Chunguang Hu ^{1,2,3} and Yidan Chen ^{1,2,3}

¹ School of Architecture and Urban Planning, Huazhong University of Science and Technology, Wuhan 430074, China

² Hubei Engineering and Technology Research Center of Urbanization, Wuhan 430074, China

³ The Key Laboratory of Urban Simulation for Ministry of Natural Resources, Wuhan 430074, China

⁴ Wuhan Huazhong University of Science and Technology Architectural Planning and Design Institute Co., Ltd., Wuhan 430074, China

⁵ Key Laboratory of Urban Land Resources Monitoring and Simulation, Ministry of Natural Resources, Shenzhen 518034, China

* Correspondence: lusw@hust.edu.cn; Tel.: +86-27-87543156

† These authors contributed equally to this work.



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Abstract: Metropolitan areas in China are not only the core spatial carriers of urbanization development but also the main generators of land use carbon emission (LUCE). However, existing research lacks comparative studies on the differential patterns and impact factors of LUCE in different stages of metropolitan areas. Therefore, this paper deeply analyzes the spatial characteristics of LUCE and the coupling coordination degree (CCD) of the economy contributive coefficient (ECC) and ecological support coefficient (ESC) in three different stages of metropolitan areas in the Yangtze River Economic Belt (YREB), China. Moreover, quantitative modelling of the impact factors of LUCE in these different stages of metropolitan areas is furtherly revealed. Results show that: (1) The more mature stage of the metropolitan area, the higher the amount of LUCE, and the more districts or counties with high carbon emissions levels are clustered. (2) At the metropolitan area scale, the more mature the metropolitan area is and the lower the CCD between ECC and ESC is, while at the finer scale, more developed counties have lower CCD. (3) Resident population, per capita GDP, and urbanization rate have good explanatory effects on carbon emissions in these three metropolitan areas; however, except for the urbanization rate, which has a negative effect on LUCE in Nanchang metropolitan area (NMA), the other two factors have positive effects on LUCE in these three metropolitan areas. This study has important implications for different stages of metropolitan areas to formulate targeted LUCE reduction policies.

Keywords: land use carbon emissions; metropolitan areas; coupling coordination degree; STIRPAT model; driving factors

1. Introduction

Climate change brings enormous challenges to the natural environment and human society. Studies have reported that carbon dioxide is one of the dominant contributors to climate change [1], which has become the main area of concern at home and overseas. Since the industrial revolution, land use carbon emissions (LUCE) have contributed around 30% of human carbon emissions (CE) [2,3]. At present, research on LUCE is relatively rich in mainly two parts. Firstly, in terms of research content, the spatio-temporal characteristics of LUCE and the influencing factors [4,5], the relationships of LUCE [6], the network relationship and spillover effects [7], the efficiency [8], the economy contributive coefficient (ECC) and ecological support coefficient (ESC) of LUCE [9,10] are the research concerns

of most studies. However, these studies do not focus as much on the CCD (coupling coordination degree) between ECC and ESC of LUCE and are unable to offer specific improvements to this relationship. Secondly, in terms of spatial scales, studies have been carried out on the urban agglomeration [11], provincial or state [12], municipal [13], and watershed scales [14], while few studies have been conducted in metropolitan area scale. However, as the main form of urbanization [15], the land use of metropolitan areas is not only the spatial projection of the main economic activities of human society but also the main generator of carbon emissions [16,17]. Therefore, it is of great urgency to scientifically identify the CCD between ECC and ESC and the impact factors of carbon emissions in metropolitan areas, which is helpful for formulating targeted low-carbon development measures in this kind of important area.

Studies have reported that different regions and areas had different network synergistic capabilities and driving power [18]. Similarly, the LUCE characteristics of metropolitan areas at different development stages may also differ significantly. When Fujii et al. studied the relationship between economic development and CO₂ emissions in 276 global metropolitan areas, they assumed that the urban CO₂ emissions per capita in the same sector would show differences in different urban economic development stages [19]. However, verifications of the above assumptions have not been conducted. In addition, the current studies on CO₂ emissions in urban areas of China are usually focused on a single evolution type of study area [20,21]. The same problem also exists for the Yangtze River Economic Belt (YREB), which is leading China's high-quality economic development. For instance, much attention has been paid to the environmental and economic development of the YREB, which is crucial to both regional ecological security and sustainable development in China [22]. The existing studies mainly concern the patterns [23], the influencing factors [24,25], and the efficiency of LUCE [26] in the YREB. For example, spatial autocorrelation [27], social network analysis (SNA) [7], and information entropy model [28] are often introduced to analyze the spatio-temporal patterns of LUCE in the YREB. The grey relational analysis model [29], regression models regarding spatial lag model, spatial error model [30], or LMDI [31] are used to model the impact factors; DEA, SBM-DEA [32], and SBM-UN model [33] are often used to measure efficiency under the constraint of LUCE. In addition, over 95% population lives in the 34 metropolitan areas in China, but few studies have compared the LUCE characteristics of metropolitan areas in different development stages. Therefore, a systematic study on the spatial differentiation of LUCE in metropolitan areas at different development stages is needed.

In summary, existing studies have made some achievements in regional LUCE in the YREB. However, there is still a lack of comparative investigations in metropolitan areas with different development stages. Simultaneously, the CCD between ECC and ESC of LUCE and impact factors are rarely analyzed. Therefore, the purpose of this study is to conduct a comparative study on the spatial patterns of LUCE in metropolitan areas at various development stages in the YREB and to explore the CCD between ECC and ESC, and the impact factors of LUCE in each metropolitan area. Contributions of this paper are two-fold: Firstly, the spatial differentiation characteristics and the spatial patterns of LUCE in cultivating, developmental and mature metropolitan areas are identified, which is conducive to the determination of sub-regional and differentiated low-carbon sustainable development goals for each metropolitan area. Secondly, differential analysis of the impact factors of LUCE from metropolitan areas is conducive to the targeted formulation of carbon reduction measures for each metropolitan area. The findings of this study can serve implications for the low-carbon development of metropolitan areas at different development stages.

2. Materials and Methods

2.1. Study Area

The Yangtze River Economic Belt (YREB) is an important strategic area for China's economic development [34,35]. YREB is divided into three parts (namely, the upper,

middle, and lower reaches). Chongqing, Sichuan, Guizhou, and Yunnan provinces are in the upper reach. Hubei, Jiangxi, and Hunan provinces are in the middle of reach. Anhui, Zhejiang, Jiangsu, and Shanghai provinces are in the lower reach. The lower reach is the most developed, which has the famous Yangtze River Delta (YRD), while the economic levels of the other two reaches are relatively low [36]. The Chengdu, Nanchang, and Hangzhou metropolitan areas are located in the upper, middle, and lower reaches of the YREB, respectively. According to the China Metropolitan Area Development Report 2021 [37] announced by the China Institute of New Urbanization of Tsinghua University, the Chengdu, Nanchang, and Hangzhou metropolitan areas belong to the developmental type, cultivating type, and mature type respectively. Thus, these three different stages of metropolitan areas are the study cases of this research (as shown in Figure 1).

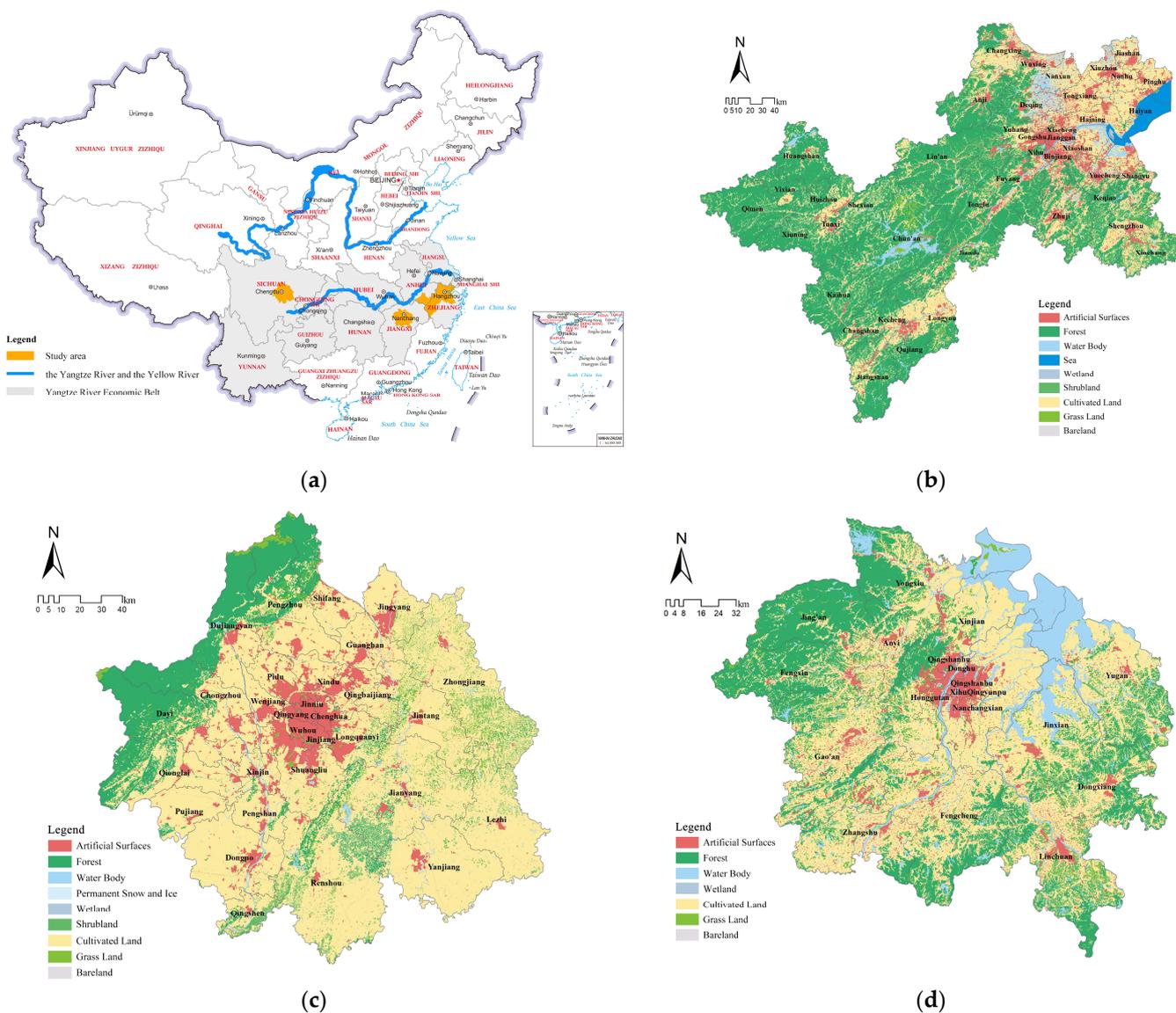


Figure 1. Study areas. (a) Locations of the study areas in China. (b–d) land use of the Hangzhou, Chengdu, and Nanchang metropolitan areas, respectively.

Chengdu Metropolitan Area (CMA) is in the upper reach of the YREB and the economic centers of southwestern China. According to the CMA Development Plan, the CMA is centered in Chengdu City and consists of 30 districts or counties with an area of 2.70×10^4 km²; the resident population of the CMA in 2020 is 27.61 million, and the economic output accounts for 2.11% of China’s Gross Domestic Product (GDP).

Nanchang Metropolitan Area (NMA) is in the middle reach of YREB. According to NMA Plan (2015–2030), the NMA consists of 18 districts or counties with a total area of $2.45 \times 10^4 \text{ km}^2$; the resident population of NMA reaches 11.58 million in 2020, and its total GDP accounts for 0.71% of China.

Hangzhou Metropolitan Area (HMA) is located downstream of the YREB. According to the HMA Development Plan (2020–2035), the HMA includes 6 cities, including Hangzhou, Jiaxing, Huzhou, Shaoxing, Quzhou, and Huangshan, with a total of 44 districts or counties and a total area of about $5.48 \times 10^4 \text{ km}^2$; by 2020, the population of HMA was 27.46 million, and its GDP accounted for 3.11% of the country.

2.2. Data Sources and Pre-Processing

Land use classification results are 30-meter spatial resolution GlobeLand30 images of year 2020 (<http://www.globallandcover.com/>) (accessed on 10 May 2022), which has become quite popular for many scholars to conduct related research [38,39]. Social and economic data are respectively derived from the 2020 Statistical Yearbooks of each province and China City Statistical Yearbook involved in the study areas. The resident population data are mainly from the 7th National Census bulletin and the statistical yearbooks and bulletins of the corresponding districts or counties. The energy consumption per unit of GDP was calculated from the total energy consumption and total GDP in the statistical yearbooks of each region.

2.3. Methods

In this study, the total LUCE of each metropolitan area is obtained by measuring the number of sources and sinks of LUCE in the three stages of metropolitan areas. The relationship between the ECC and ESC of each district and county in the metropolitan areas is studied by the CCD model, and the STIRPAT model is introduced to investigate the dominant factors affecting LUCE in the three types of metropolitan areas. Figure 2 shows the analysis clue of this study.

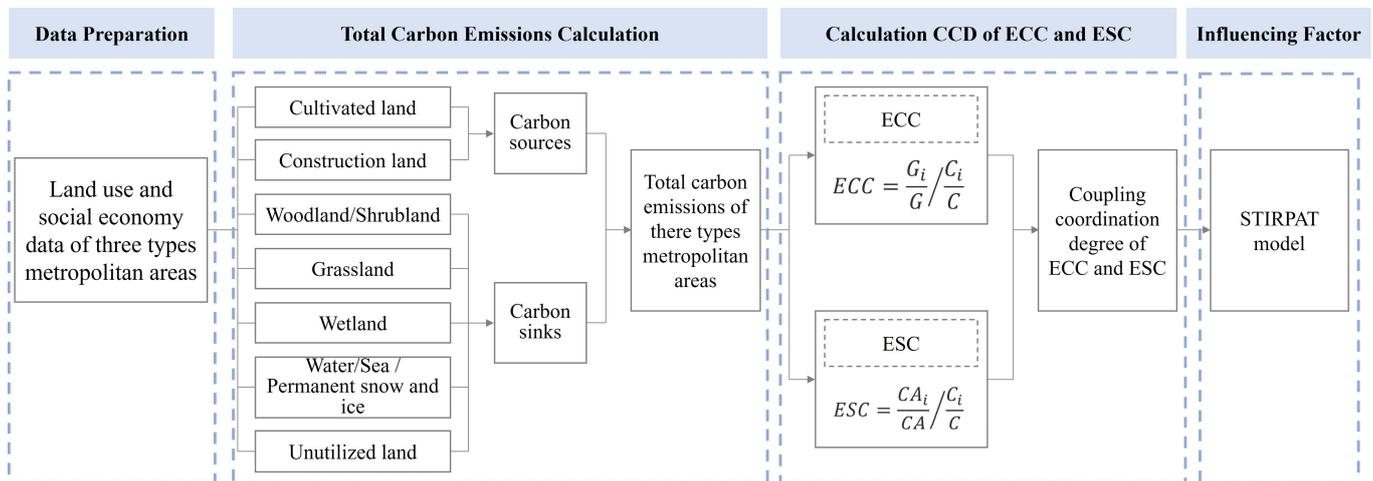


Figure 2. Research framework.

2.3.1. Measurement of LUCE

The total amount of LUCE is equal to the sum of carbon sources and sinks [40], as shown in Equation (1):

$$CE = CO_2_{sources} + CO_2_{sinks} \tag{1}$$

where CE is the total amount of LUCE; $CO_2_{sources}$ represents the number of carbon sources of LUCE; and CO_2_{sinks} represents the number of carbon sinks of LUCE.

(1) Calculation of the number of carbon sources

The number of land use carbon sources for each district and county in the metropolitan areas is calculated from the cultivated and construction land. The number of LUCE from cultivated land use is the area of this kind of land use multiplied by its carbon emission factor, which is taken as 0.0422 according to Sun [41] and Zhang [42]. The number of LUCE from construction land use is usually measured indirectly based on the energy consumption of the city (such as coal, oil, natural gas, electricity, etc.). However, energy consumption data for each district and county in the metropolitan areas is difficult to obtain. According to relevant studies [43,44], since the value of secondary and tertiary industries is mainly contributed by construction land, the number of carbon emissions from construction land in each district and county can be approximated from the total GDP of secondary and tertiary industries. The calculation formula of carbon sources amount is as follows:

$$CO_2 \text{ sources} = A_c \times \delta_c + P_i \times M_i \times \theta_i \quad (2)$$

where $CO_2 \text{ sources}$ is the total land use carbon sources; A_c represents the area of cultivated land use; δ_c represents the coefficient of cultivated land; P_i represents the energy consumption per unit of GDP; M_i represents the total GDP of secondary and tertiary industries in each district and county; and θ_i is the coefficient of standard coal.

(2) Calculation of the number of carbon sinks

Land with carbon sink function and its corresponding carbon sink coefficient [45] are involved in calculating the carbon sinks of each district and county in the metropolitan areas. The land with carbon sink function includes green lands (such as grassland, woodland, and shrubland), water (such as wetland, water, and sea), unutilized land, permanent snow and ice, and so on. According to relevant research, woodland and shrubland [42] and water and sea were combined [46]. Referring to existing studies, the corresponding carbon sink coefficients δ_i for different land use types are shown in Table 1. Since the percentage of permanent snow and ice in these study areas is only 0.0017%, this study uses the LUCE coefficient of water to replace its coefficient. The carbon sinks are calculated as follows:

$$CO_2 \text{ sinks} = \sum e_i = \sum A_i \times \delta_i \quad (3)$$

where $CO_2 \text{ sinks}$ is the total amount of carbon sink; e_i represents the amount of carbon sink generated by land use type i ; A_i and δ_i represent the spatial area; and sink coefficient of land use type, respectively.

Table 1. CE coefficient of different land use types ($\text{kg}\cdot\text{m}^{-2}\cdot\text{a}^{-1}$).

Land Use	Coefficient	References
Woodland/Shrubland	−0.0644	Zhang et al., [42]; Fang et al., [47]
Grassland	−0.0021	Sun et al., [41]; Zhang et al., [42]
Wetland	−0.0001	Zhang et al., [42]
Water/Sea	−0.0253	Yang et al., [48]
Unutilized	−0.0005	Yang et al., [48]

2.3.2. Global Moran's I

Global Moran's I is used to analyze the overall correlation degree of LUCE spatial distribution of each metropolitan area [49], and the calculation formula is as follows:

$$\text{Moran's } I = \frac{n \sum_{i=1}^n \sum_{j=1}^n W_{ij} (x_i - \bar{x})(x_j - \bar{x})}{\left(\sum_{i=1}^n \sum_{j=1}^n W_{ij} \right) \sum_{i=1}^n (x_i - \bar{x})^2} \quad (4)$$

where n is the number of districts and counties in the metropolitan area; x_i and x_j are the LUCE of district or county i and j , respectively; W_{ij} is the spatial weight matrix of district

or county i and j ; and \bar{x} is the average value. The values of Moran's I range from $[-1, 1]$; Moran's $I > 0$, Moran's $I < 0$, and Moran's $I = 0$ represent positive correlation, negative correlation, and no spatial correlation, respectively.

2.3.3. Measurement of CCD

The CCD model is introduced to measure the relationship between the ECC and ESC of CE for each district and county in the metropolitan areas. The calculation formula of CCD [50] is as follows:

$$C = \frac{U_1 U_2}{\left(\frac{U_1 + U_2}{2}\right)^2} = \frac{2\sqrt{U_1 U_2}}{U_1 + U_2} \quad (5)$$

$$T = a_1 U_1 + a_2 U_2 \quad (6)$$

$$\text{CCD} = \sqrt{C \times T} \quad (7)$$

where CCD is between 0 and 1; C and T are the coupling degree and integrated coordination index between ECC and ESC, respectively; U_1 and U_2 are the values of ECC and ESC respectively; a_1 and a_2 are the weights of indicators ECC and ESC, in this study, ECC and ESC are considered equally important, so the weights of both indicators a_1 and a_2 are taken as 0.5, then $T = 0.5U_1 + 0.5U_2$.

According to the CCD grading method [51,52], the CCD was classified into five classes as shown in Table 2:

Table 2. Levels of CCD.

Development Category	Level	Balanced or Not	Degree
Coordinated Transformation	$0.8 < \text{CCD} \leq 1.0$	Balanced	Highly
	$0.6 < \text{CCD} \leq 0.8$	Balanced	Moderately
Uncoordinated	$0.4 < \text{CCD} \leq 0.6$	Balanced	Basically
	$0.2 < \text{CCD} \leq 0.4$	Unbalanced	Moderately
	$0 < \text{CCD} \leq 0.2$	Unbalanced	Seriously

(1) Calculating ECC

ECC is introduced to estimate the equity of economic contribution of CE among districts or counties within a metropolitan area [53] and can reflect the socio-economic benefits that accompany the process of generating carbon emissions. ECC is calculated as:

$$ECC = \frac{G_i}{G} / \frac{C_i}{C} \quad (8)$$

where G_i and G are the GDP of each district and county and the whole metropolitan area, respectively; and C_i and C are the carbon emissions of each district and county and the whole metropolitan area, respectively. When the economic contribution of a district or county is greater than its share of carbon emissions ($ECC > 1$), it indicates that the district or county has a high level of economic efficiency and green development. When ECC is less than 1, the economic contribution of the district is smaller than its carbon emissions contribution, and its economic efficiency of carbon emission is relatively low.

(2) Calculating ESC

ESC is introduced to estimate the equity of contribution of carbon ecological capacity among districts or counties in the metropolitan area [54], which could reflect the carbon sink capacity of each district and county [55] as a reflection of ecological benefits. ESC is calculated by the ratio of the carbon sink of each city to the carbon sink of all cities,

divided by the ratio of carbon emissions of each city to the carbon emissions of all cities. The calculation formula of *ESC* is:

$$ESC = \frac{CA_i}{CA} / \frac{C_i}{C} \quad (9)$$

where CA_i and CA are the carbon sinks of each district or county and the whole metropolitan area, respectively. Districts with carbon sinks contribution greater than their share of carbon emissions ($ESC > 1$), indicate positive impacts on the absorption of CE in the whole metropolitan area and generate positive externalities that help other districts or counties, while districts with *ESC* less than 1 indicate negative externality to other districts or counties.

(3) Data normalization

Since the distribution range of *ECC* and *ESC* values are different, the coupling coordination degree between the two cannot be calculated directly, so they must be normalized. According to existing research [56,57], the formulas of positive and negative standardization are:

$$Y_i = \frac{X_i - \min(X_i)}{\max(X_i) - \min(X_i)} \quad (10)$$

$$Y_i = \frac{\max(X_i) - X_i}{\max(X_i) - \min(X_i)} \quad (11)$$

where Y_i represents the standardized value of X_i ; X_i represents the actual value of indicator i ; $\max(X_i)$, $\min(X_i)$ are the maximum and minimum values of X_i , respectively.

2.3.4. Impact Factor Measurement Model

STIRPAT is a commonly used model to investigate the impact of population, affluence, and technology on the environment in the field of carbon emissions [58], which is expressed as follows:

$$I = aP^b A^c T^d e \quad (12)$$

where a is a constant variable; b , c , and d represent the coefficients of population, affluence, and technology, respectively; and e is an error variable.

Equation (11) transforms to Equation (12) by logarithms method:

$$\ln I = a + b \ln P + c \ln A + d \ln T + e \quad (13)$$

where I is the LUCE of each district and county in each metropolitan area; P , A , and T are the residential population, per capita GDP and urbanization rate of each district or county, respectively; a is a constant variable; b , c , and d represent the coefficients of P , A , and T , respectively; e is an error variable.

3. Results

3.1. Spatial Characteristics of LUCE

3.1.1. Structures of LUCE in Metropolitan Areas

Overall, the total amount of LUCE in the metropolitan area is consistent with its development stage. The total LUCE in HMA (the mature metropolitan area) of 7802.7285×10^4 t is the highest, which is much higher than the total carbon emissions in CMA (the developmental metropolitan area) of 4678.7527×10^4 t, and in NMA (the cultivating metropolitan area) of 1421.2675×10^4 t. Construction land use types are the main contributor of LUCE in these three metropolitan areas, accounting for 99.18%, 96.71%, and 98.34%, respectively, while the proportion of LUCE from cultivated land use types is much lower. Regarding the composition structure of carbon sequestration, the carbon sinks of the three metropolitan areas are also very similar, with woodland accounting for the largest proportion of carbon sequestration, 95.29%, 84.93%, and 95.84% of the carbon sinks in HMA, NMA, and CMA,

respectively, while wetland and unutilized land are both weaker due to their smaller carbon sink coefficients and weaker carbon sink capacities, as shown in Table 3.

Table 3. Land use carbon emissions/sinks of three metropolitan areas ($\times 10^4$ t/a).

	Cultivated Land	Construction Land	Woodland	Grassland	Wetland	Water	Unutilized Land	Total
Nanchang Metropolitan Area	48.4964	1424.5591	-43.9845	-0.2845	-0.0006	-7.5160	-0.0024	1421.2675
Chengdu Metropolitan Area	77.9751	4631.6161	-29.5562	-0.2083	-0.0003	-1.0737	0.0000	4678.7527
Hangzhou Metropolitan Area	65.6841	7936.4449	-190.0182	-0.2788	-0.0006	-9.1028	-0.0001	7802.7285

3.1.2. Spatial Differentiation of LUCE in Metropolitan Areas

The spatial distribution characteristics of LUCE in NMA, CMA, and HMA metropolitan areas are weak core cluster type, strong core cluster type, and flat extension respectively. Based on the natural breakpoint method, the sources and sinks of LUCE of the three metropolitan areas were reclassified, as shown in Figures 3 and 4. The areas with high carbon emissions (more than 74.62×10^4 tons) in NMA are mainly concentrated in the southwest, probably due to the higher development level of the economy in its southwest, such as the “Feng-Zhang-Gao” (Fengcheng-Zhangshu-Gaoan) industrial development area. The areas with high carbon sinks (more than 4.49×10^4 tons) were mainly concentrated in two parts (the northwestern and southeastern parts) of the region. However, the LUCE of districts or counties in the CMA shows an obvious “core-edge” spatial distribution pattern, with carbon emissions decreasing from the middle to the periphery of the metropolitan area. Areas with large carbon absorption are in the northwest of the CMA. The cause of this spatial distribution may be due to the concentration of construction land being mainly distributed in the central CMA, and the fact that the non-agricultural industries are also most developed in the central part of the area and the central city of the metropolitan area is more attractive. The spatial distribution of LUCE in the HMA shows a “flattened” extension. Areas with large carbon emissions (more than 74.62×10^4 tons) are distributed in the northeast of the metropolitan area. Areas with large carbon absorption (more than 4.49×10^4 tons) are concentrated in the southwest of this metropolitan area. From the west to the east, the carbon emissions of districts or counties gradually increased.

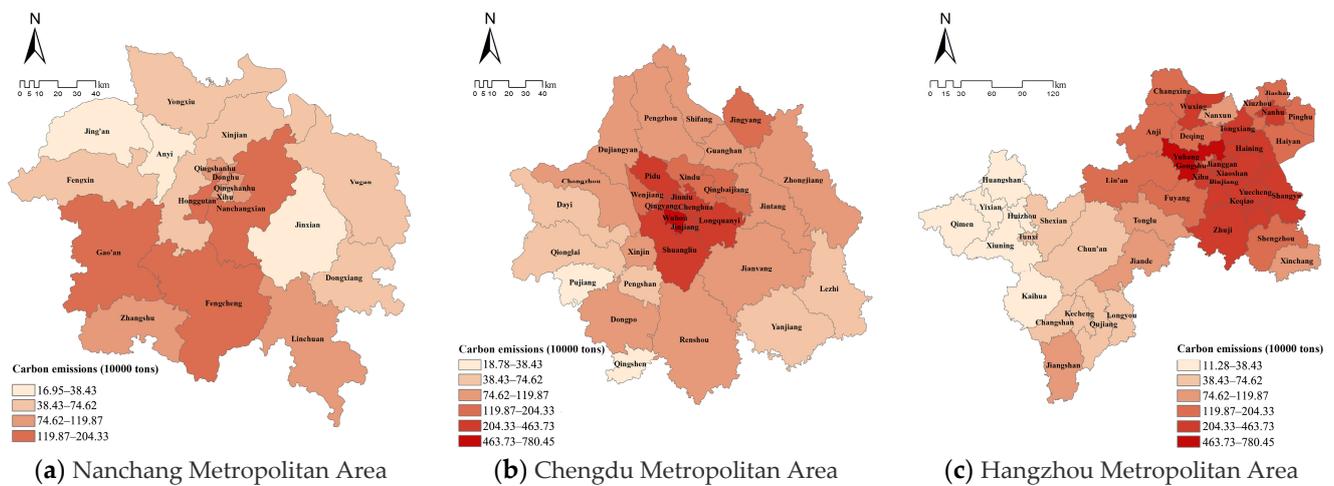


Figure 3. County-level distribution of LUCE in Nanchang, Chengdu, and Hangzhou metropolitan areas.

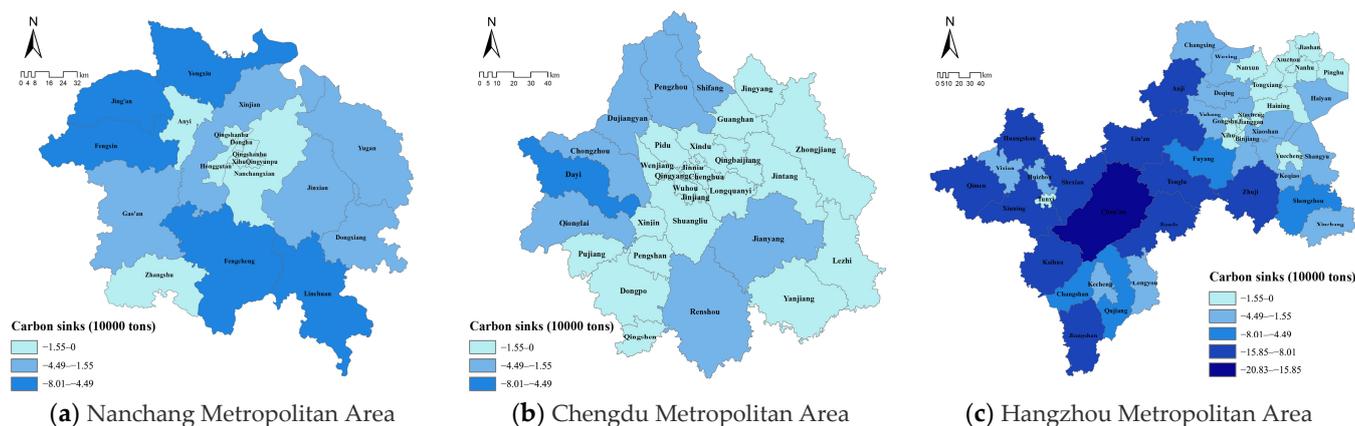


Figure 4. County-level distribution of LUCE sinks in Nanchang, Chengdu, and Hangzhou metropolitan areas.

3.1.3. Spatial Clustering Characteristics of LUCE in Metropolitan Areas

Except for NMA (the cultivating metropolitan area), which showed no significant positive spatial correlation, the carbon sources in CMA (the developmental metropolitan area) and HMA (the mature metropolitan area) showed significant positive correlation results. The Moran’s *I* value is 0.7957 in the Hangzhou metropolitan area, which is larger than that of 0.7425 in CMA (Table 4). In addition, the carbon sequestration of all three metropolitan areas shows a significant positive correlation result (Table 5). The specific Moran’s *I* value of NMA is 0.8501, which is much higher than 0.4795 of HMA, and 0.4561 of CMA, due to the contiguous distribution of carbon sink spaces, such as woodland and water, within the metropolitan area.

Table 4. Global Moran’s *I* of LUCE sources.

	Moran’s <i>I</i>	z-Score	<i>p</i> -Value
Nanchang Metropolitan Area	0.0266	0.5065	0.6125
Chengdu Metropolitan Area	0.7425	9.0600	0.0000
Hangzhou Metropolitan Area	0.7957	7.8238	0.0000

Table 5. Global Moran’s *I* of LUCE sinks.

	Moran’s <i>I</i>	z-Score	<i>p</i> -Value
Nanchang Metropolitan Area	0.8501	5.3412	0.0000
Chengdu Metropolitan Area	0.4561	5.4008	0.0000
Hangzhou Metropolitan Area	0.4795	4.6800	0.0000

Overall, the more mature the development stage of the metropolitan area, the more clustered districts or counties with high LUCE levels. The districts or counties with high LUCE levels are more distributed in the core circles of the CMA compared to the NMA, while the districts or counties with high carbon emission levels in the HMA are more widely clustered in contiguous areas. This is related to the high concentration of construction land, industry, population, and other elements in and around the core area of the metropolitan area.

3.2. Coupling Coordination Degree Analysis of LUCE

3.2.1. ECC of LUCE in Metropolitan Areas

Districts or counties with high economic contribution coefficient (ECC) of LUCE are generally concentrated in the central part or the periphery and edge part of the metropolitan

area (Figure 5). The average values of ECC of carbon emissions of districts or counties in NMA, CMA, and HMA are 1.07, 1.04, and 1.13, respectively. The districts or counties with high ECC in Nanchang metropolitan area (cultivating metropolitan area), i.e., districts or counties with ECC higher than 1.23, are mainly located in the periphery of its central city. Nanchang, as the central city, accounts for 22.22% of the number of districts or counties in NMA, indicating that the economic efficiency of LUCE in the periphery of the central city is higher. The counties with higher ECC, i.e., those with ECC higher than 1.11, are mainly located in the periphery of the CMA, accounting for 20.00% of the total number of counties in the CMA, indicating that the contribution of the counties in the periphery to the economy of the entire metropolitan area is greater than the contribution of their LUCE to the LUCE of the entire metropolitan area. The ECC of HMA (mature metropolitan area) gradually decreases from west to east. The districts or counties with high ECC, i.e., districts or counties with ECC higher than 1.23, are concentrated in the western edge of the HMA, accounting for 15.91% of the total number of districts or counties in the HMA. The districts or counties in this area have higher economic efficiency than LUCE.

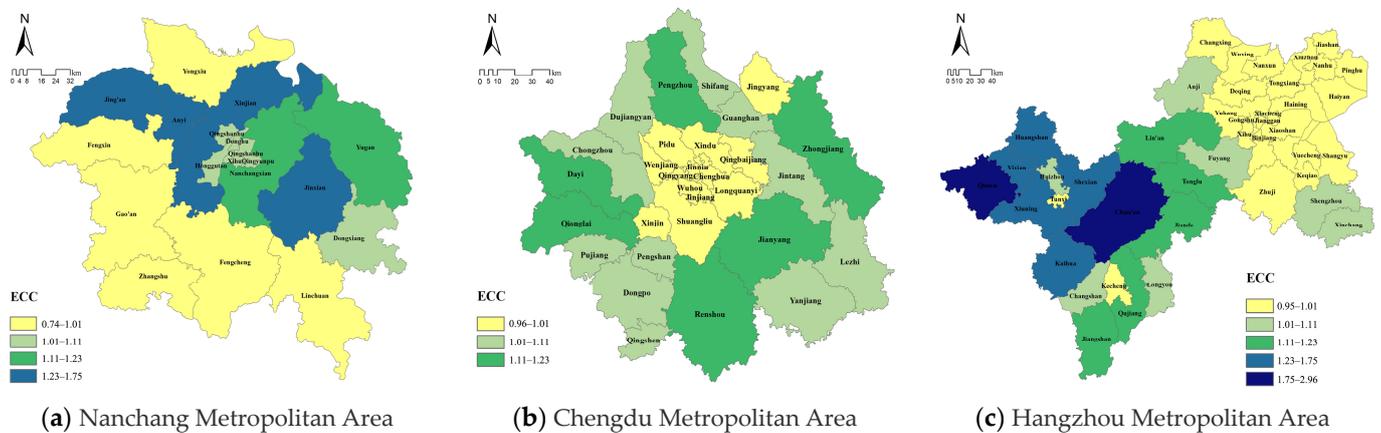


Figure 5. Economic contribution coefficients of three metropolitan areas.

3.2.2. ESC of Carbon Emission in Metropolitan Areas

The districts or counties with high ecological support coefficients (ESC) in the three metropolitan areas are all located in the peripheral regions of each metropolitan area (as shown in Figure 6), indicating that the carbon sinks capacity in the peripheral regions contributes more than their carbon emissions contribute to the carbon emissions of each metropolitan area. The mean values of ESC of NMA, CMA, and HMA are 2.31, 2.18, and 5.61, respectively. In addition, the number of districts or counties with higher ESC value in HMA and CMA, i.e., ESC higher than 3.58 is 29.55% and 26.67% respectively, which are much higher than the corresponding number of districts or counties in NMA, which is 11.11%. The results show that HMA and CMA are not only ahead of NMA in terms of the economic development stage, but also, the proportion of districts or counties with high contribution of carbon sink capacity is higher than the proportion of districts or counties at the corresponding level in NMA.

3.2.3. CCD of LUCE in Metropolitan Areas

The CCD (coupling coordination degree) between the ECC and ESC of each metropolitan area is closely bound up to the development stage of the metropolitan area. On the one hand, the more developed the metropolitan area, the lower the CCD. On the other hand, the more developed the economic districts or counties within the metropolitan area, the lower the CCD. The average CCD of NMA, CMA, and HMA is 0.27, 0.34, and 0.18 respectively. The more mature the development stage of the metropolitan area, the more unbalanced the economy contributive coefficient of LUCE and the ESC. Regarding the spatial distribution, there is an extreme imbalance between the ECC and ESC of carbon emissions

of districts or counties in the core circles of CMA and NMA. The number of districts or counties with extreme imbalance accounts for 40.00% and 44.44% in each metropolitan area, respectively. The spatial distribution characteristics of the CCD of ECC and ESC of the developmental metropolitan area (CMA) and cultivating metropolitan area (NMA) show similarity, except that the number of seriously unbalanced districts or counties in the developmental metropolitan area accounts for a larger proportion. The eastern part of HMA is seriously unbalanced and the western part is more balanced overall. The amount of seriously unbalanced districts or counties account for 65.91% of the total amount of districts or counties in HMA (as shown in Figure 7).

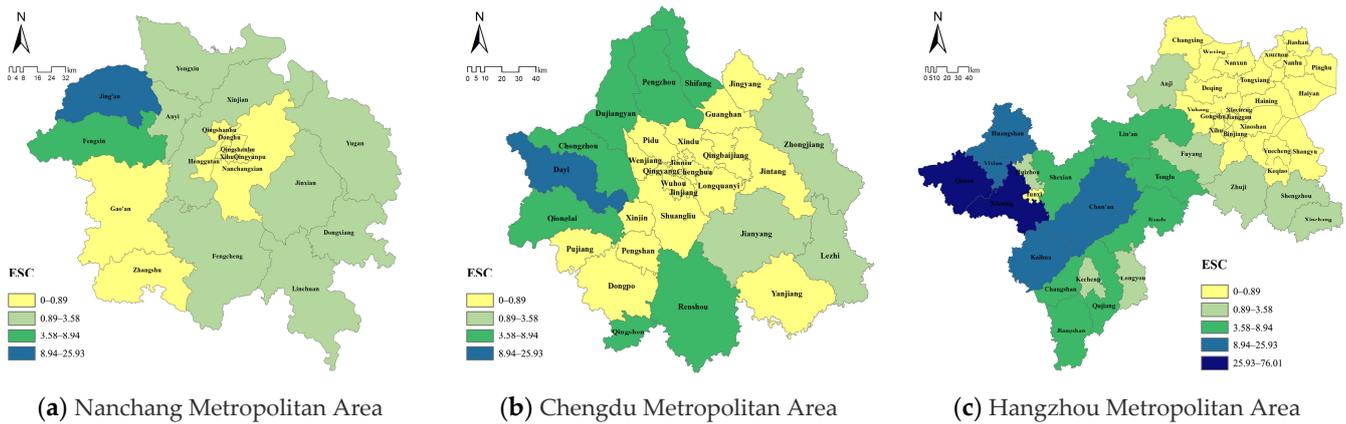


Figure 6. Ecological support coefficients of three metropolitan areas.

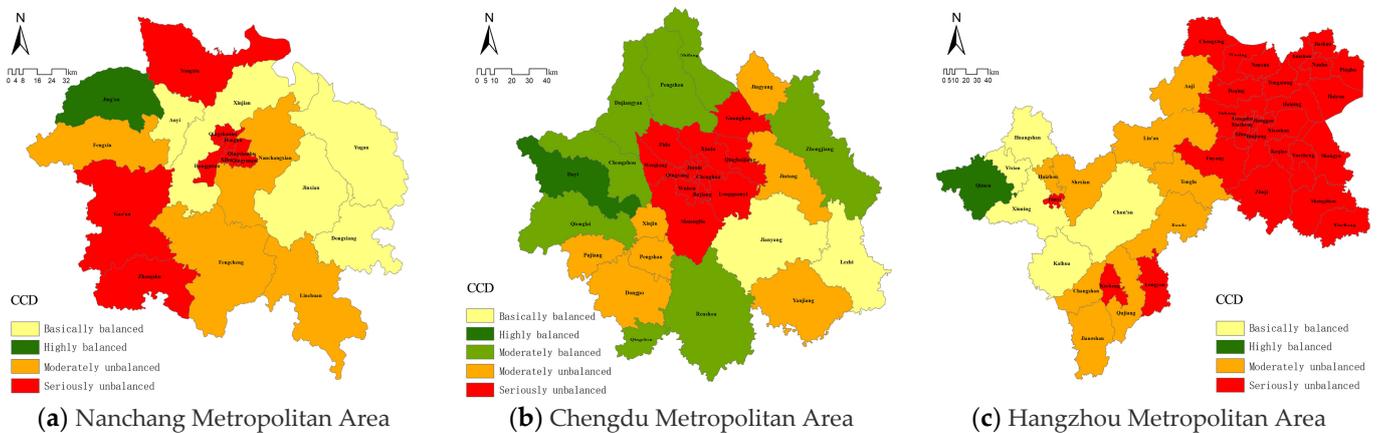


Figure 7. CCD between ECC and ESC in three metropolitan areas.

3.3. Driving Factors of LUCE in Different Stages of Metropolitan Areas

The LUCE of each district and county in the metropolitan areas are taken as the dependent variables, while the resident population, per capita GDP, and urbanization rate are the independent variables, and the carbon emissions of the three metropolitan areas are analyzed by the STIRPAT model. Regression results are shown in Table 6. The R-Square of all three models is close to 1, and the influencing factors of the model have good explanatory power. The lowest value of R-Square is 0.926 in NMA, indicating that the influencing factors in the model can explain carbon emissions to a degree of 92.60%, and the remaining 7.40% is not explained by the influencing factors selected by the model. The highest value of R-square is 0.998 in the CMA, and the influencing factors of its model can explain the carbon emissions of its districts or counties to 99.80%.

Table 6. Models Summary Table of Three Metropolitan Areas.

Model	R	R-Square	Adjusted R-Square	Standard Error in Estimation	Durbin-Watson
Nanchang Metropolitan Area (NMA)	0.962	0.926	0.910	0.230	1.604
Chengdu Metropolitan Area (CMA)	0.999	0.998	0.998	0.034	1.865
Hangzhou Metropolitan Area (HMA)	0.991	0.982	0.981	0.155	2.619

The results of NMA are shown in Table 7. The order of influence of carbon emission influencing factors is per capita GDP (A) > resident population (P) > urbanization rate (T). Meanwhile, the influence of resident population and per capita GDP on the LUCE of the NMA is positive, and the significance test value is $0.000 < 0.050$, which both pass the significance test. However, the influence of the urbanization rate on the LUCE of districts or counties is negative, and the significance test value is $0.183 > 0.050$, which does not pass the significance test. Therefore, for the NMA (the cultivating metropolitan area), increasing the urbanization rate of its districts or counties will be a good strategy to reduce LUCE in the region.

Table 7. Model test results of Nanchang metropolitan area.

Variables	Non-Standardized Coefficient		Standardized Coefficient			Colinearity Statistics	
	B	Std. Error	Beta	t	Significance	Tolerance	VIF
CONSTANT	−2.847	0.655		−4.343	0.001		
Resident population	1.084	0.092	0.916	11.795	0.000	0.876	1.141
Per capita GDP	1.376	0.186	0.758	7.393	0.000	0.503	1.988
Urbanization rate	−0.390	0.279	−0.138	−1.401	0.183	0.541	1.847

The regression results for CMA are shown in Table 8. The order of influence of carbon emission factors is resident population (P) > per capita GDP (A) > urbanization rate (T). The influence of all three factors on carbon emission in the CMA is positive. The significance test values of influencing factors are all 0.000, and all pass the significance test. Therefore, there exists a significant positive correlation between resident population, per capita GDP, urbanization rate, and carbon emissions for the CMA. In the process of continuous concentration of population, industry, and other factors, the carbon emissions of this area should be reduced by other strategies such as improving the carbon emission efficiency and optimizing the energy structure of districts or counties.

Table 8. Model test results of Chengdu metropolitan area.

Variables	Non-Standardized Coefficient		Standardized Coefficient			Colinearity Statistics	
	B	Std. Error	Beta	t	Significance	Tolerance	VIF
CONSTANT	−1.308	0.134		−9.760	0.000		
Resident population	0.984	0.015	0.748	66.841	0.000	0.501	1.996
Per capita GDP	0.966	0.033	0.455	28.921	0.000	0.254	3.936
Urbanization rate	0.242	0.050	0.088	4.812	0.000	0.187	5.345

The results for the HMA are shown in Table 9. Similar to CMA, the order of influence of the factors affecting carbon emissions in the districts or counties of the HMA is resident population (P) > per capita GDP (A) > urbanization rate (T); besides, the impact of all three

factors on LUCE in HMA is positive, except for the significance test value of urbanization rate on carbon emissions which is $0.054 > 0.050$, which does not pass the significance test. The significance of resident population and per capita GDP all passed the test. Therefore, for the HMA (the mature metropolitan area), the influence degree of the resident population on LUCE of districts or counties is the strongest among the three metropolitan areas, and its urbanization rate has already reached a relatively high level. While in the process of continuous concentration of population and industries, the LUCE efficiency of districts or counties should be improved by other ways to reduce carbon emissions in the region.

Table 9. Model test results of Hangzhou metropolitan area.

Variables	Non-Standardized Coefficient		Standardized Coefficient			Colinearity Statistics	
	B	Std. Error	Beta	t	Significance	Tolerance	VIF
CONSTANT	−2.117	0.256		−8.266	0.000		
Resident population	1.142	0.041	0.700	28.129	0.000	0.717	1.394
Per capita GDP	1.078	0.066	0.438	16.314	0.000	0.614	1.627
Urbanization rate	0.265	0.134	0.059	1.984	0.054	0.509	1.966

4. Discussion

4.1. Factors Influencing the LUCE of Different Stages Metropolitan Area

Previous studies on the spatial patterns and impact modeling of LUCE have mainly concentrated on a single aspect of the research object [59–61], such as analyzing the spatial evolution characteristics [62] or the influencing factors of carbon emissions [63–65]. Few studies have focused on research objects at different development stages at the same time, thus failing to identify the spatial differentiation patterns and influencing factors of LUCE among different types of research objects. Different from previous studies, this study quantifies the LUCE of three different development stages of metropolitan areas in the lower, middle, and upper reaches of the YREB and measures the CCD and influencing factors of LUCE in each metropolitan area. The findings of this study show that the urbanization rate only had a negative impact on the LUCE of the cultivating metropolitan area (such as NMA), while the resident population and per capita GDP had a positive impact on the LUCE of the three stages of metropolitan areas. Similarly, Chel et al. found that population and per capita GDP are also positively related to LUCE after studying 103 metropolitan statistical areas (MSAs) in the United States [66]. The possible reason is that the level of social and economic development and urbanization of the cultivating metropolitan area (such as NMA) are lower than those of developmental and mature metropolitan areas (such as CMA and HMA respectively). Besides, the distribution of urban and rural populations, industry, land use, and other factors are not intensive and efficient enough. Therefore, it is necessary to formulate corresponding strategies to reduce LUCE for different types of metropolitan areas.

4.2. Policy Implications

For cultivating metropolitan areas, large numbers of the rural population will be continuously promoted to gather into central cities in the future to increase the urbanization rate. Meanwhile, changing spatial planning from incremental to stock will be accompanied by the development trend of more intensive urban and rural land use and more concentrated industries, etc. The above changes may make the carbon emissions from construction land in cultivating metropolitan area decrease to a certain extent.

For mature and developmental metropolitan areas, it may be possible to learn from the research of Yang et al. on metropolitan areas in the United States, that is, to increase the number of high-density areas (urban centers) in the metropolitan area to reduce commuting time and distance [67], thereby reducing traffic carbon emissions in the metropolitan area.

4.3. Limitations

However, there are some limitations and potential uncertainties in this study:

- (1) Due to the tiny percentage of permanent snow and ice in the research area, we substituted the permanent snow and ice emission coefficient with the water emission coefficient. However, if it occurs in other research regions where there is a sizable amount of permanent snow and ice or sea, it might lead to unreasonable results. Therefore, future studies should further explore the coefficient of permanent snow and ice and sea.
- (2) This study is only based on the STIRPAT model, which examines the effects on LUCE in metropolitan areas at each development stage regarding population (P), affluence (A), and technology (T), without selecting control variables, which may result in an incomplete analysis of the influencing factors.
- (3) Related studies show that regional climate and carbon cycle changes affect CO₂ emission pathways [68]. In addition, some studies have reported that the CO₂ emission level of metropolitan areas with a high level of sprawl is generally high [69]. However, climate change, urban form, and other aspects of the metropolitan area are not considered in this research. Therefore, further relevant studies are needed in the future.

5. Conclusions

Based on the GlobeLand30 land use type data of 2020 with 30-meter spatial resolution, this study calculated the total LUCE, analyzed the spatial characteristics, and revealed the relationship between the ECC and ESC of LUCE in each district and county of three metropolitan areas at different development stages, namely NMA, CMA and HMA in YREB. The STIRPAT model was further introduced to explore the impacts of various socio-economic factors on land use carbon emissions in these three metropolitan areas. The main conclusions of this work are drawn as follows.

- (1) The more mature the stage of the metropolitan area, the higher the amount of LUCE is. Meanwhile, the spatial distribution patterns of LUCE of Nanchang, Chengdu, and Hangzhou metropolitan areas show weak core grouping, strong core clustering, and flattening extension patterns respectively. In general, the more mature the development stage of the metropolitan area, the more concentrated the districts or counties with high carbon emission levels.
- (2) The districts or counties with a higher economy contributive coefficient (ECC) are generally concentrated in the central cities or on the periphery or edge of the metropolitan areas. The districts or counties with higher ecological support coefficient (ESC) in the three metropolitan areas are in the peripheral areas of each metropolitan area. Meanwhile, the more developed the metropolitan area, the lower the CCD between ECC and ESC. The more economically developed districts or counties are within the metropolitan area, the lower CCD is.
- (3) Based on the STIRPAT model, the resident population, per capita GDP, and urbanization rate have good explanatory effects on the carbon emissions of the three metropolitan areas. All these three factors have positive effects on carbon emissions, except for the urbanization rate, which contributes to a negative effect on the LUCE of NMA.

Our empirical study revealed the spatial patterns and CCD between the ECC and ESC of LUCE, and verified the effects of the resident population, per capita GDP, and urbanization rate on LUCE in each metropolitan area by applying the STIRPAT model. Both the characteristics of LUCE in metropolitan areas and the influencing factors show specific correlations with the development stage of metropolitan areas. Findings can help to identify sustainable development strategies [70] and formulate corresponding carbon reduction measures for metropolitan areas at different stages of development and different regions within the metropolitan areas. In future studies, we will conduct further

comparative analysis on the spatio-temporal evolution patterns of LUCE and other drivers in metropolitan areas at different development stages.

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