The Spatiotemporal Coupling Coordination Model Between Socioeconomic Activity and Eco-environment and Climate Factors: Case Study of Guangdong-Hong Kong-Macao Greater Bay Area, China

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Abstract. Urbanization demands high-quality coordinated development of human-earth relationship. Although a large number of studies have explored the long-term and large-scale coupling effects of urbanization and eco-environment, there is a lack of fine-scale research. Therefore, this paper constructs a coupling coordination model in urban agglomeration based on multi-source remote sensing images, aiming to explore the relationship between climate factors, human activity and vegetation changes of Guangdong-Hong Kong-Macao Greater Bay Area during the period of 2001 to 2018. The results show that the coupling coordination degree in the urban core area showed a slight downward trend, while the high-intensity human activity areas around the urban core area showed an upward trend. The climate factors, human activity and vegetation changes of the urban agglomerations have not reached a highly coordinated coupling stage and high quality coordination. The annual analysis and assessment realize monitoring and comparative analysis of the coordinated development degree of human-earth relationship in urban agglomerations, and provide theoretical support for urban agglomeration development planning.

Keywords: Urbanization development; Coupling coordination degree; Eco-environment; Climate change

1 Introduction

Urbanization has become the most significant human activity process since the 21st century. China's urbanization level reached 63.89% in 2021 (http://www.stats.gov.cn/), the proportion of urban population increased from 36.22% in 2000 to 60.6% in 2019 (China Statistics Press, 2020). According to "the14th Five-Year Plan", China's urbanization rate will increase to 65% in 2025. Urbanization has resulted in the transfer of large-scale agricultural labor, which has significantly promoted economic growth. At the same time, urbanization has also had a significant impact on landscape patterns [1], causing a series of ecological problems, including urban waterlogging [2], urban heat island effect [3], air pollution [4], water pollution [5], biodiversity reduction [6] etc. In addition, the huge urban population poses major challenges to construction land, infrastructure, energy, etc. Urbanization has brought negative impacts to natural resources and ecological environment.

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As a comprehensive geographical process of the earth's surface, urbanization is not only a socioeconomic development activity, but also a complex process of interactive coupling of human activities, social culture, and natural elements. The long-term, large-scale coupling effects of urbanization and ecological environment have been explored in a large number of studies, but there is a lack of more refined spatiotemporal methods and assessments [7].

Remote sensing technology is widely used in earth resources surveys and man-land relations researches, land use monitoring and planning, environmental pollution monitoring. Night light intensity is closely related to human activities and is an intuitive indicator of human activities that can characterize the spatial heterogeneity of human activities [8]. Vegetation is an important part of the terrestrial ecosystem, and the net primary productivity (NPP) is used to monitor vegetation conditions widely. Land surface temperature (LST) is an important indicator for monitoring regional climate change. This paper objectively evaluates the change characteristics of human activity intensity, vegetation and climate factors based on night light intensity, vegetation net primary productivity and land surface temperature. Fine-scale coupling models of climate factors, human activity and vegetation changes can help support sustainable development decisions and spatial planning management of urban agglomerations, and provide scientific solutions to regional ecological and environmental problems.

2 Study area and data processing

2.1 Study area

As a megacity agglomeration, the Guangdong-Hong Kong-Macao Greater Bay Area is one of the main areas of new urbanization in China. It consists of 9 cities in the Pearl River Delta urban agglomeration, two special administrative regions of Hong Kong and Macao. It covers an area about 56,000 km^2 and is geographically located at 111°12′E-115°35′E and 21°25′N-24°30 ′N.

2.2 Materials and pre-processing

2.2.1 remote sensing data

The annual nighttime light (NTL) remote sensing image selected in this paper is global NPP-VIIRS-like nighttime light data (https://doi.org/10.7910/DVN/YGIVCD). The spatial resolution is 500 m and the spatial coordinate is WGS84. It can be observed that the rise in radiance is more pronounced in urban areas. The logarithmic transformation function can normalize data with skew and bias. The MOD13A3 NDVI, MOD11A2 LST images, and land use type data MCD12Q1 images from 2001 to 2018 were reprojected into the WGS84 coordinate system, and the spatial resolution was resampled to 0.00833° × 0.00833° to match the spatial resolution of $\log\_VIIRS$.

2.2.2 meteorological data

The National Meteorological Science Data Center provides 2001-2018 national standard meteorological station data (http://data.cma.cn/). The monthly average temperature, monthly total solar radiation, monthly total precipitation of 85 meteorological stations in Guangdong Province were extracted. ArcGIS 10.3 software was used to perform inverse distance weight interpolation on the meteorological data based on the longitude and latitude information and DEM data of each meteorological station. The rasterized meteorological data spatial distribution map has the same spatial resolution and projection information as the nighttime light remote sensing image.

3 Model and Methods

The workflow of the coupling coordination model of socioeconomic activity and eco-environment and climate factors is shown in Figure 1.

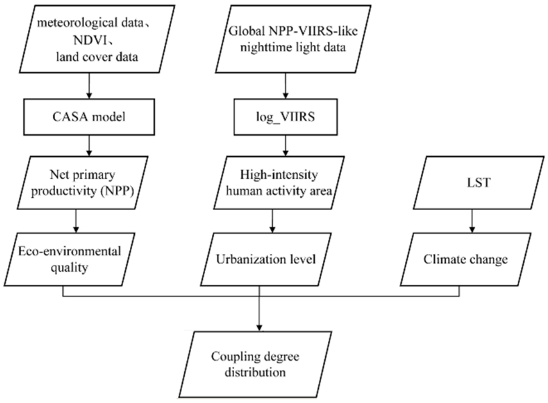

Figure 1. Evaluation framework for the coupling coordination model.

Coupling describes the effects of different systems through various interactions, it is often used in urbanization and ecosystem researches. The coupling coordination degree model (CCDM) is widely used in urbanization and ecological environment systems. CCDM is often used for coupling analysis of two subsystems. When CCDM is applied to multi-subsystem coupling, the calculation formula is as follows:

$$\begin{cases} C = \left\{ \dfrac{f(X)\times g(Y)\times h(Z)}{\left[\frac{f(X)+g(Y)+h(Z)}{3}\right]^3} \right\}^{\frac{1}{3}} \\ D = \sqrt{C \times T} \\ T = \alpha \times f(X) + \beta \times g(Y) + \gamma \times h(Z) \end{cases} \tag{1}$$

In the formula, C reflects the strength of the interaction between different systems, which represents the coupling degree (CD). It ranges from 0 to 1. C=1 indicates the highest degree of coupling, the different systems and its internal elements reach the status of benign resonance, and the integrated system structure is developing in a more orderly direction. C=0 indicates the lowest coupling degree, the different systems and its internal elements are independent, and the integrated system structure will develop into disorder. $f(X)$, $g(Y)$ and $h(Z)$ are the levels of each subsystem respectively, α, β and γ represent the contribution of different subsystem. This paper assumes that each subsystem is equally important, therefore, $\alpha = \beta = \gamma = \frac{1}{3}$. D stands for coupling coordination degree (CCD), which is an index that measures the coupling level in the development of integrated systems. T describes the overall development level of different subsystem [9].

4 Results

4.1 correlation analysis

According to gray correlation analysis, the statistical results of the gray distance correlation between NPP, LST and NTL in 2001, 2010 and 2018 showed good correlation in different years, and the correlation between different years was similar. NPP showed a high correlation with LST, NPP showed a moderate correlation with NTL, and LST showed a moderate correlation with NTL.

4.2 expansion of high-intensity human activity areas

The urban core area has high population density and high intensity of social and economic activities. The annual composite nightlight intensity value reach highest in the urban core area and expands outward. As the intensity of human activities weakens, the nightlight intensity gradually decreases. The spatial scope of this paper is limited to high-intensity human activity areas. This paper analyzes the distribution and expansion of high-intensity human activity areas in 2001, 2010, 2018 where ln $(VIIRS_i)$ is greater than 0.

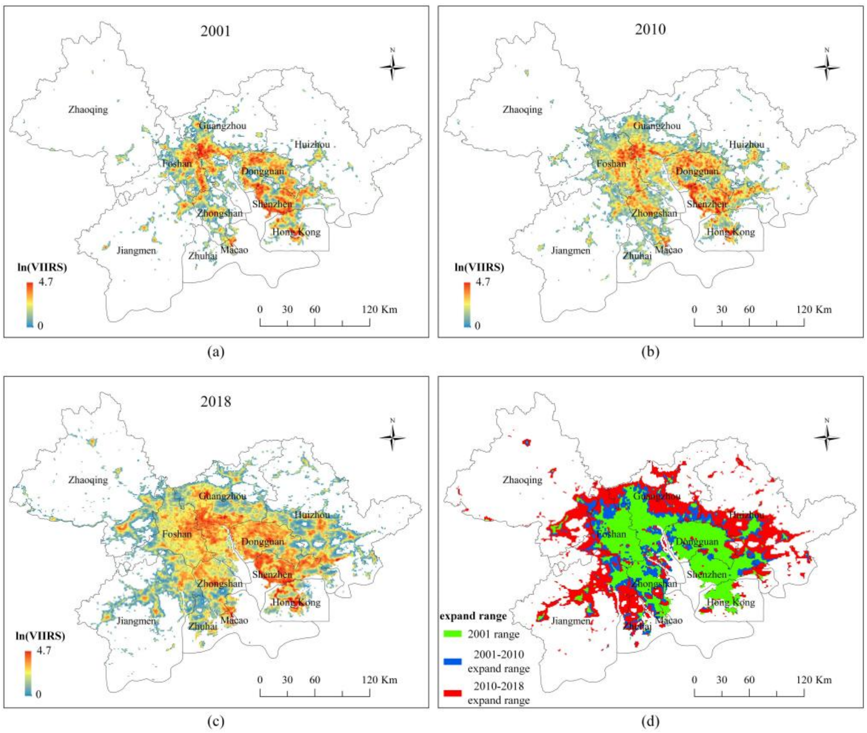

Figure 2. Night light intensity distribution and expansion in areas with high intensity of human activities: (a) 2001, (b) 2010, (c) 2018 and (d) expand range

As shown in Figure 2, in 2001, high-intensity human activity areas were mainly distributed in Guangzhou, Foshan, Zhongshan, Dongguan, Shenzhen and Hong Kong. Night light intensity was generally low in the eastern and western districts of the Greater Bay Area. The night light value of Zhaoqing is at a low level, the night light value of Jiangmen, Zhuhai and Huizhou is slightly higher than that of Zhaoqing. In 2010, multiple high-intensity human activity areas appeared in many cities. While high-intensity human activity areas expanded outward around the original high-intensity human activity areas, they also gathered and expanded in other areas of the city. High-intensity human activity areas continue to expand in Guangzhou, Foshan, Zhongshan, Dongguan and Shenzhen. Among them, Foshan's expansion scope is relatively large. As the three cities with the lowest per capita gross domestic product in the study area, Zhaoqing, Jiangmen and Huizhou had a slightly higher expansion scope than Zhaoqing from 2001 to 2010. The study area experienced limited expansion of high-intensity human activity areas between 2001 and 2010.

During China’s 12th and 13th Five-Year Plans, the Greater Bay Area accelerated urbanization process. The scope of high-intensity human activity areas expanded significantly from 2010 to 2018, the central region of Guangzhou and the northwest region of Zhuhai appeared a large number of high-intensity human activity areas. The extent of expansion in Zhaoqing, Jiangmen and Huizhou is more significant than that between 2001 and 2010, and new core area have emerged. The scope of expansion in Dongguan, Shenzhen and Hong Kong is not obvious.

4.3 NPP changes

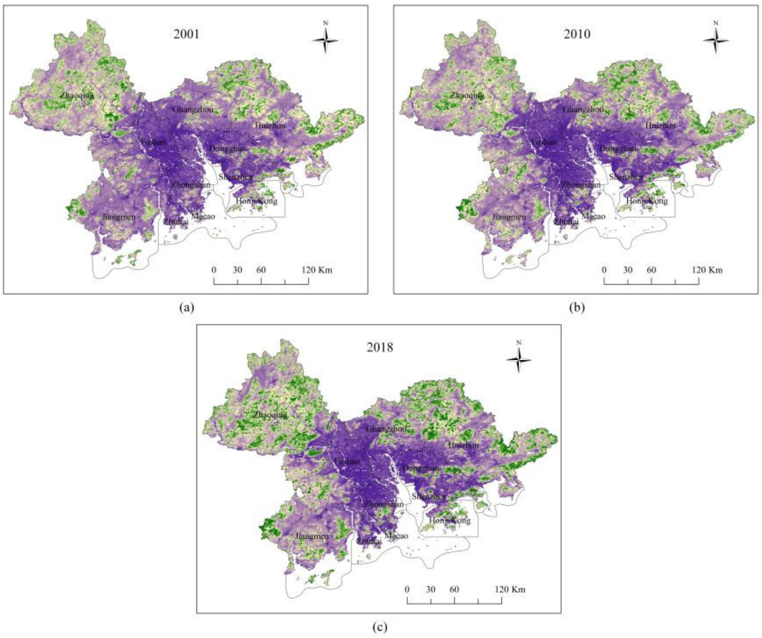

Figure 3. The distribution of NPP: (a) 2001, (b) 2010, (c) 2018

Monthly NPP is calculated through CASA (Carnegie-Ames-Stanford approach) model, and annual NPP is calculated through the sum of monthly NPP. The distribution of NPP values in the Greater Bay Area in 2001, 2010, and 2018 is shown in Figure 3. The NPP in the Greater Bay Area shows a decreasing distribution from the northwest and northeast to central part. Zhaoqing, Jiangmen and Huizhou have relatively high NPP values. Zhaoqing is significantly higher, the NPP value of most areas in Zhaoqing is above $800g\cdot m^{-2}a^{-1}$, followed by Huizhou. The main reason is the hydrothermal conditions in these cities are relatively good, with a large proportion of forest vegetation and high vegetation coverage. In contrast to these three cities, the NPP values in most areas are below $500g\cdot m^{-2}a^{-1}$ in Foshan, Zhongshan, Shenzhen and Dongguan.

The Global Moran's I index of the NPP value in 2001, 2010 and 2018 was calculated to analyze the spatial agglomeration characteristics. The Moran's I values are all over 0, indicating that NPP has strong aggregation and obvious regular regional distribution, the moran's I values in 2001, 2010, and 2018 are 0.513, 0.502, and 0.492, with small fluctuations, indicating that spatial agglomeration remains stable.

4.4 LST change trend

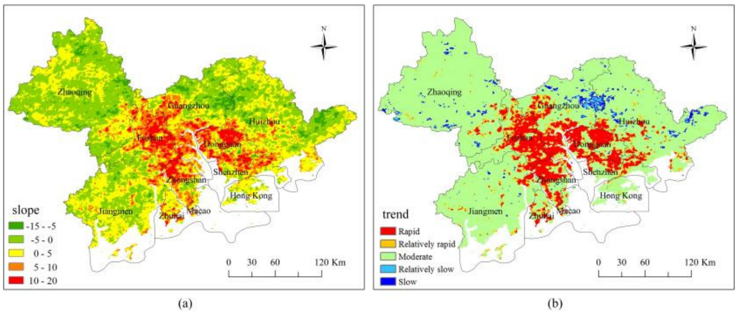

Figure 4. LST change trend and significance test from 2001 to 2018

According to linear regression method, the LST change trend and significance test characteristics from 2001 to 2018 are obvious, as shown in Figure 4. The areas with elevated LST is significantly higher than that of decreasing area, and the overall spatial pattern shows the characteristics of increasing in the middle areas and decreasing in the around areas. The areas with extremely significant increases in LST are mainly concentrated in southern Guangzhou, Foshan, northern Zhongshan, southern Zhuhai, northwest Shenzhen, and Dongguan, and they are scattered in Zhaoqing, Jiangmen, and Huizhou. The areas with extremely significant increases accounts for 13.2%. The significantly increased areas are evenly distributed in the study area, accounting for 6.06%. The areas with no significant change in LST are mainly distributed in northern Guangzhou, northern Zhuhai, Zhaoqing, Jiangmen, Huizhou and Hong Kong, accounting for 78.05%. The LST of the Hong Kong showed no significant change during 2001-2018, which is significantly different from other cities. The areas with extremely significant reduction and significant reduction accounted for 0.56% and 2.13%.

4.5 Pixel-based interaction of climate factors, human activity and vegetation changes

The distribution of CCD in high-intensity human activity areas in 2001, 2010, and 2018 is shown in Figure 5. In 2001, the CCD of Hong Kong was significantly higher than that of other cities, and CCD of Dongguan and Shenzhen was relatively high and widely distributed. The distribution characteristics of CCD in Guangzhou, Foshan and Zhongshan are similar, with high values showing a point-like cluster distribution, while the CCD in Zhaoqing, Jiangmen, Zhuhai and Huizhou are relatively low. As the Greater Bay Area promotes urbanization process, high-intensity human activity areas extend to the suburbs. In 2010, Hong Kong maintained an advantageous position in coupling coordination compared with other cities. Other cities showed upward trend to varying degrees. Among them, the CCD in Dongguan and Shenzhen changes weakly in spatial extent, but the value increases significantly. The CCD of new high-intensity human activity areas between 2001 and 2010 in each city is at a low value, indicating that the development of coupling effect is harmonious and orderly, but the coordination degree is low.

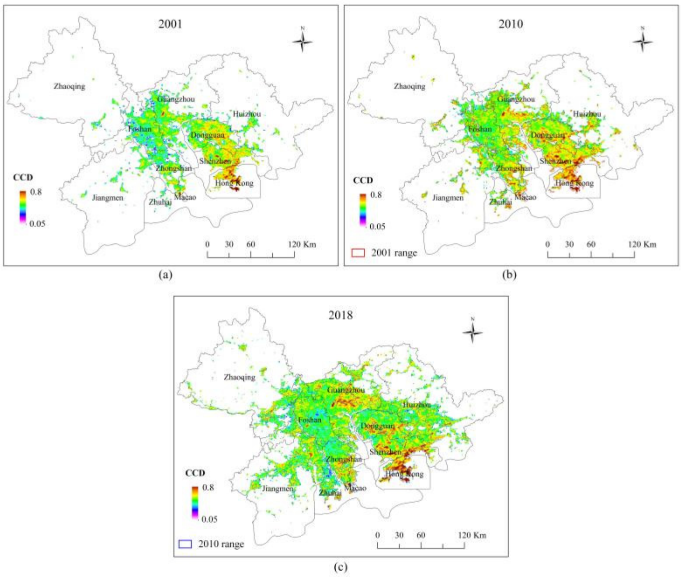

Figure 5. Spatial distribution of coupling coordination degree

From 2010 to 2018, the urbanization process accelerated, human activities intensified, and the expansion scope of high-intensity human activity areas was significantly higher than that in the previous decade. In 2018, Hong Kong's CCD remained basically unchanged, occupying a dominant position in the Greater Bay Area. Guangzhou's CCD has changed significantly. Compared with 2010, the CCD of the new high-intensity human activity areas is higher, and the coupling coordination between different subsystems is optimized. The CCD of Zhaoqing, Jiangmen and Huizhou is on the rise. The coupling relationship between socioeconomic activity and eco-environment and climate factors in most new high-intensity human activity areas has a low coordination degree, and each subsystem still cannot promote the development of each other.

5 Conclusion

In view of the current urbanization process, relevant research on the coupling relationship between socioeconomic activity and eco-environment and climate factors relies on statistical yearbook data, and the scale is mainly at the provincial, municipal, and administrative district levels. the data source and research scale are limited. This paper established a multi-subsystem coupling model of long-term series of socioeconomic activity and eco-environment and climate factors based on multi-source remote sensing image data. The paper analyzed the spatial variation and temporal variation characteristics of human activity areas, ecological environment and climatic factors in 2001, 2010 and 2018. The gray correlation analysis of the correlation between NPP, LST and NTL in 2001, 2010 and 2018 showed good correlation, indicating that there is mutual influence among the three systems. The CCDM is used to calculate the multi-subsystem coupling relationship between socioeconomic activity and eco-environment and climate factors. The results show that the CCD of Hong Kong, Shenzhen and Dongguan is relatively high compared to other cities, followed by Guangzhou and Foshan, and the CCD of Zhaoqing, Jiangmen and Huizhou is relatively low. As the Greater Bay Area accelerates urbanization, the CCD of socioeconomic activity and eco-environment and climate factors has increased, showing good coordination. Compared with the traditional coupling model based on statistical data, the method can broaden the research scale of the coupling model and is suitable for multi-scenario applications. The data source used in this paper is easy to obtain, reducing the dependence on statistical data. It is suitable for research on multi-subsystem coupling models of multi-scale and long-term series.

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