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China's Largest City-Wide Lockdown: How Extensively Did Shanghai COVID-19 Affect Intensity of Human Activities in the Yangtze River Delta?

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Abstract: COVID-19 has been the most widespread and far-reaching public health emergency since the beginning of the 21st century. The Chinese COVID-19 lockdown has been the most comprehensive and strict in the world. Based on the Shanghai COVID-19 outbreak in 2022, we analyzed the heterogeneous impact of the COVID-19 lockdown on human activities and urban economy using monthly nighttime light data. We found that the impact of lockdown on human activities in the Yangtze River Delta is very obvious. The number of counties in Shanghai, Jiangsu, Zhejiang and Anhui showing a downward trend of MNLR (Mean of Nighttime Light Radiation) is 100%, 97%, 99% and 85%, respectively. Before the outbreak of COVID-19, the proportion of counties with a downward trend of MNLR was 19%, 67%, 22% and 33%, respectively. Although the MNLR of some counties also decreased in 2019, the scope and intensity was far less than 2022. Under regular containment (2020 and 2021), MNLR in the Yangtze River Delta also showed a significant increase (MNLR change > 0). According to NLRI (Nighttime Light Radiation Influence), the Shanghai lockdown has significantly affected the surrounding provinces (Average NLRI < 0). Jiangsu is the most affected province other than Shanghai. At the same time, Chengdu-Chongqing, Guangdong–Hong Kong–Macao and the Triangle of Central China have no obvious linkage effect.

Keywords: COVID-19 lockdown; NPP-VIIRS; Yangtze River Delta; spatio-temporal change; human activity intensity

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1. Introduction

The Corona Virus Disease 2019 (COVID-19), as a major health and safety emergency with the widest spread and the most far-reaching impact since the beginning of the 21st century, has continued to spread throughout the world until now [1,2]. COVID-19 has plunged the world economy into a deep recession, seriously affecting people's production and life, and has aroused widespread concern in society [3,4]. Since the outbreak of COVID-19, China's prevention measures have been the most comprehensive, strict and thorough in the world [5,6]. In particular, China has taken decisive control measures in several events with a large range, such as Wuhan, Beijing, Shanghai, Zhengzhou and Urumqi [7]. How to assess the extent of human activities and urban economy affected by COVID-19 control is an important direction of research on public emergency monitoring. Effective monitoring and evaluation of the impact of epidemic control is of great significance to economic recovery and development and can provide valuable experience for handling similar public security emergencies in the future.

Multi-dimensional assessment of the impact of COVID-19 control using statistical data is a common method [8–10]. Many scholars use statistical data and geographical analysis methods to carry out related research [11–13]. Most scholars' research focuses on the use of statistical data to establish evaluation indicators to define the different stages of COVID-19 development [14], analyze the differences in space–time transmission of COVID-19 [15], reveal the differences in results caused by different control policies [16], explore the spatio-temporal evolution process of COVID-19 [17], and use the point of interest data to reflect the spatio-temporal differences of epidemic impact [18]. However, due to the limitation of the statistical system, the data have a temporal lag, which cannot be obtained in time. At the same time, although the impact of COVID-19 has been assessed at different levels, the data are not representative or open enough. There is a lack of a spatio-temporal difference assessment method to quickly estimate the impact of COVID-19 on the socio-economic activities at a macro scale. Nighttime light remote sensing data provide a new means for the impact assessment of COVID-19.

Nighttime Light (NTL) data can quickly, accurately and objectively obtain information about the surface and human activities [19], and are widely used in economic development, urbanization process, natural disasters and accidents (such as war, large-scale power outage) [20–22]. At present, some studies have used nighttime light data to assess the impact of epidemic disasters. NPP/VIIRS data are used to analyze the impact of the implementation of the closure policy after the epidemic [23,24], spatio-temporal evolution of confirmed cases of COVID-19 in different countries [25], the monthly changes in the total amount of nighttime light after COVID-19 in different countries [26], the impact on human life and natural environment in different urban areas [27], the impact on economic activities in different big cities [28], the mobility of people in different countries or cities during the closure period [29], power consumption [30], daily confirmed cases, etc. [31–33].

In fact, the geospatial extent of the strict lockdown conditions covered all 16 Districts in Shanghai. Then, as the center of the Yangtze River Delta, Shanghai has very close economic ties with other cities. The Shanghai COVID-19 lockdown inevitably affects surrounding cities. We speculate that Shanghai will be the most affected city, and the Yangtze River Delta will also be affected by the lockdown of Shanghai. Based on remote sensing image of nighttime light, the research on the COVID-19 situation has achieved certain results. However, previous studies have ignored the spatial difference and temporal growth of the absolute value of nighttime light brightness, which makes it difficult to accurately reflect the spatial difference and baseline growth of the impact of COVID-19 on the urban economy. At the same time, there are some limitations in monitoring the impact of large-scale epidemic control such as temporal lag of statistical data and low temporal and spatial resolution of other remote sensing data.

The Shanghai COVID-19 lockdown restricted residents' activities and the operation of public places such as factories, malls, and shops. Nighttime light is often closely related to human activities and public places, which can directly reflect the changes of human activity and economic intensity. The lockdown for the epidemic, human and economic activities and nighttime light are simultaneous variations. Based on the COVID-19 control in Shanghai from April to May 2022, we try to use NPP-VIIRS monthly data to extract the information of epidemic changes, study the potential of nighttime light remote sensing in large-scale epidemic control and monitoring, and provide an auxiliary reference for domestic and international public security event processing. Our research contents and objectives are as follows: (1). Analyze spatio-temporal changes of nighttime light radiation in April 2022, and explore the impact of COVID-19 control in Shanghai on the economic activities in the Yangtze River Delta; (2). Analyze spatio-temporal changes of nighttime light radiation in the Yangtze River Delta before the COVID-19 outbreak, and explore the benchmark changes of economic development in the Yangtze River Delta; (3). By comparing spatio-temporal changes of nighttime light radiation in the Yangtze River Delta before and after the COVID-19 outbreak, we can explore how extensive COVID-19 control in Shanghai has affected economic activities; (4). Analyze the spatio-temporal changes of the nighttime light radiation of four major agglomerations in China and reveal whether there is a significant linkage effect between agglomerations.

2. Materials and Methods

2.1. Study Area

Yangtze River Delta is located in the lower reaches of Yangtze River in China, bordering the Yellow Sea and East China Sea. It is an alluvial plain formed before the Yangtze River enters the sea. The Yangtze River Delta includes 41 cities including Shanghai, Jiangsu Province, Zhejiang Province and Anhui Province. The Yangtze River Delta is one of the most active regions in China's economic development, and has a pivotal strategic position [34]. By the end of 2019, the Yangtze River Delta had a population of 227 million and a regional area of 358,000 km^2 (Figure 1) [35]. In 2022, the GDP of Yangtze River Delta reached 29,028.9 billion yuan, and the urbanization rate of the permanent population exceeded 60%. With less than 4% of the land area, it will create nearly 1/4 of China's total economic output and 1/3 of China's total import and export [36]. Shanghai is located at the core of the Yangtze River Delta. Shanghai is China's international economic, financial, trade, shipping, scientific and technological innovation center, with a total area of 6340.5 km^2. By the end of 2021, the permanent resident population of Shanghai was 24.89 million [37]. In 2022, Shanghai's GDP reached 4,465,280 billion yuan.

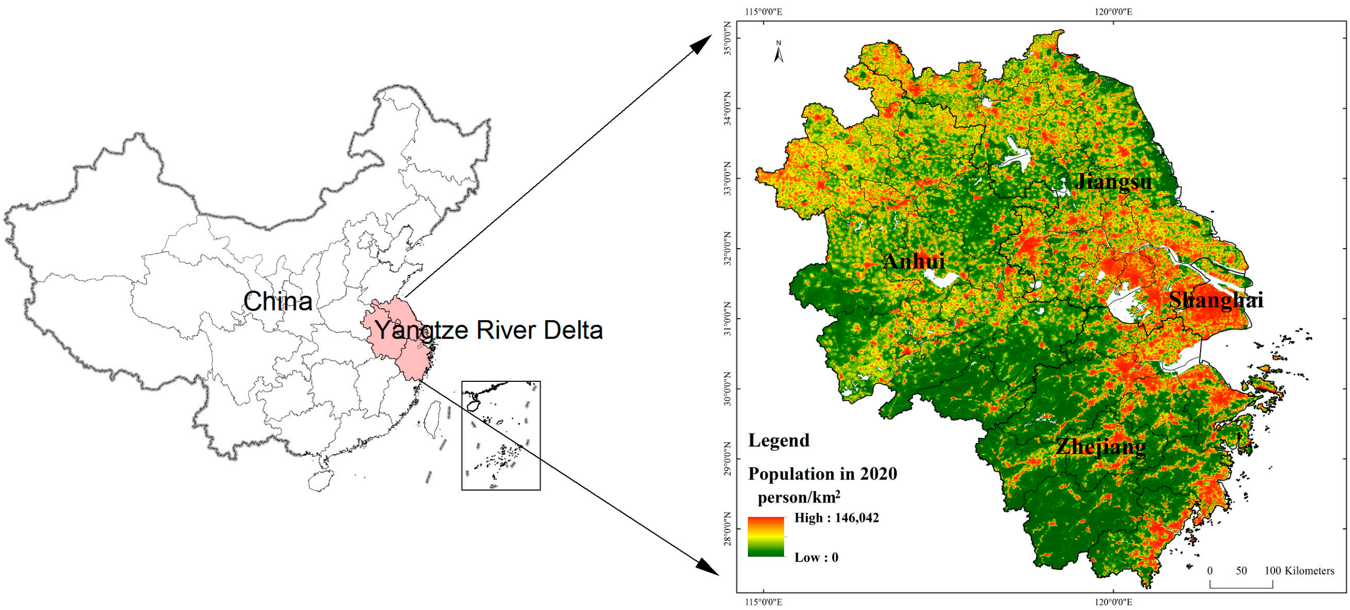

Figure 1. Geographic location and population distribution of the Yangtze River Delta.

The importance of Yangtze River Delta and Shanghai to the contribution of China's economy is self-evident, which can create nearly $\frac{1}{4}$ of China's total economic output and 1/3 of China's total import and export [36]. The Shanghai COVID-19 outbreak in 2022 began on 6 March 2022. After 10 March, the number of newly confirmed cases and asymptomatic infections in Shanghai increased rapidly [38]. From 28 March 2022 to 1 April 2022, Shanghai Pudong New Area implemented closed management; On 1 April 2022, the closed management of Puxi began until the closed management of the whole Shanghai; only on 1 June 2022 did Shanghai realize the nationwide release [39]. From the beginning to the end of the whole epidemic control, Shanghai has implemented the most stringent epidemic control policy since 28 March 2022 [40]. April 2022 is the most obvious time for Shanghai and the whole Yangtze River Delta to be affected by epidemic control.

2.2. Materials

We use NPP/VIIRS data to measure and evaluate the intensity of human and urban activities before and after epidemic control. The National Oceanic and Atmospheric Administration of the United States began to release NPP/VIIRS data in April 2012. These data effectively make up for the problem of oversaturation of pixel DN (Digital Number, the measurement unit is nW/cm^2/sr) value in the urban core area. The monthly NPP/VIIRS products we use come from the official website of the EOG Group of Colorado School of Mines (https://eogdata.mines.edu/products/vnl/, accessed on 5 March 2023). Considering that the data quality has a decisive impact on the results, we choose VIIRS Cloud Mask (VCM) version data from which stray light has been removed [41–43]. We use the boundary of the Yangtze River Delta to cut the corresponding monthly data of nighttime lighting. In order to avoid the influence of image mesh deformation and facilitate the calculation of bright pixel area in the image, we convert the data projection coordinate system into Asia North Alberts Equal Area Conic. Among them, the resampling method adopts the proximity method suitable for discrete data processing, and the spatial resolution is 500 m. Inevitably, the overpass time (1:30 a.m.) may affect the intensity of the nighttime light, which is determined by the data itself. Although the above impacts may exist, our research is a comparison of data before and after the Shanghai COVID-19 lockdown, which is a relative value at the same point of time. As the most economically developed region in China, Shanghai is also active and has strong nighttime lights at night. Therefore, the overpass time (1:30 a.m.) will not have a significant impact on the results.

Administrative division data are mainly divided into China's provincial, municipal and county, sourced from the Resource and Environmental Science and Data Center, Chinese Academy of Sciences (https://www.resdc.cn/Datalist1.aspx?FieldTyepID=20,0, accessed on 5 March 2023). Each grid of population spatial data represents the number of people within 1 km^2, unit: person/km^2 (https://www.resdc.cn/DOI/DOI.aspx?DOIID=32, accessed on 5 March 2023).

2.3. Methods

(1) Total Nighttime Light Radiation (TNLR) and Mean of Nighttime Light Radiation (MNLR) are visual descriptions of the impact of nighttime light radiation:

$$\mathrm{TNLR} = \sum_{i}^{n} DN_i \quad (1)$$

$$\mathrm{MNLR} = \frac{TNLR}{n} \quad (2)$$

where: DN_i is the DN value of the ith pixel; n is the sum of pixel count in the study area.

(2) Nighttime Light Radiation Change (NLRC) and Nighttime Light Radiation Influence (NLRI) are indicators to measure the extent of the impact of COVID-19:

$$\mathrm{NLRC} = MNLR_r - MNLR_j \quad (3)$$

$$\mathrm{NLRI} = \frac{NLRC_{2022}}{NLRC_{2019}} \quad (4)$$

where: NLRC represents the value of April minus March; NLRI represents the ratio between $NLRC_{2022}$ and $NLRC_{2019}$ in this paper; r represents April; j represents March; if NLRI < 0, it means that the change of nighttime light in the Yangtze River Delta before and after COVID-19 is not consistent. The lower the NLRI, the greater the impact of the region during the epidemic control period; if 0 < NLRI < 1, it means that the change of nighttime light in the Yangtze River Delta before and after COVID-19 is consistent, but the epidemic has a small impact on the region; if NLRI > 1, it means that the change of nighttime light in the Yangtze River Delta before and after COVID-19 is consistent, and the epidemic has no impact on the region.

On the one hand, we study the change of nighttime light through Formula (3); on the other hand, we use nighttime light data to build evaluation indicators to evaluate the impact of epidemic control on urban activities, spatial differences and evolution. Based on normal changes of urban nighttime lights before the COVID-19 outbreak in China, in order to more accurately reflect the substantial impact of epidemic control on urban economy, we build NLRI to assess the impact before and after COVID-19 control.

Corresponding to the lockdown time in Shanghai in April 2022, there was no large-scale outbreak of COVID-19 in April 2019. Therefore, nighttime light at this time point is regarded as the reference light under normal conditions, so as to evaluate the change of nighttime light during the COVID-19 control period. In addition to analyzing the changes before and after the epidemic, it is also instructive to compare the changes at the same time point (2020 and 2021) after COVID-19, which can objectively reflect the impact of the epidemic control compared with normalized management. Compared with the previous direct subtraction calculation method, NLRI can reduce the impact caused by the large difference in the nighttime light base, and limit the nighttime light change to epidemic control.

3. Results

3.1. Spatio-Temporal Changes of MNLR in the Yangtze River Delta under Largest Lockdown

On 6 March 2022, the outbreak in Shanghai continued to grow, and a comprehensive and strict epidemic control policy was implemented on 28 March. April was the most affected period for Shanghai's economy. Therefore, the impact of epidemic control can be most directly reflected after difference calculation of MNLR in March and April. As shown in Figure 2, when Shanghai began to implement strict control, the intensity of MNLR decreased significantly ($p < 0.01$), and the scope also decreased significantly ($p < 0.01$). At the same time, the impact on the intensity of human activities in the Yangtze River Delta is very obvious, which represents that MNLR change is a large reduction.

First of all, Shanghai is the most directly affected city. The MNLR of Shanghai weakens and that of the whole Yangtze River Delta also decreased. The MNLR of all 16 districts in Shanghai showed a downward trend. Huangpu District and Jing'an District showed the largest decline (MNLR decreased by more than 10), and the other districts declined from high to low in the following order: Yangpu District, Xuhui District, Hongkou District, Changning District, Putuo District, Minhang District, Pudong New Area, Baoshan District, Jiading District, Songjiang District, Qingpu District, Fengxian District, Jinshan District, Chongming District (MNLR variation range is -9.3–-0.55). Only three of the 96 counties in Jiangsu Province have an increasing trend of MNLR (the MNLR of Zhonglou District, Changzhou City, increased by 0.1, the MNLR of Dongtai City, Yancheng City, increased by 0.11, and the MNLR of Sihong County, Suqian City, increased by 0.03), while the MNLR of the remaining 93 counties has all decreased (the MNLR variation range is -4.94–-0.07), accounting for 97% of total number of counties in Jiangsu Province. The decline in Nanjing was relatively the largest (MNLR dropped by more than 3). Compared with Shanghai, the decline of MNLR in Jiangsu Province is only about half of that in Shanghai. Only one of 90 counties in Zhejiang Province has an increasing trend of MNLR (MNLR of Shengsi County, Zhoushan City has increased by 0.51), while MNLR of the remaining 89 counties and districts has all decreased (MNLR variation range is -3.86–-0.01), accounting for 99% of the total number of counties in Zhejiang Province. The decline in downtown Hangzhou was the largest (MNLR dropped by more than 3). Compared with Shanghai, the decline of MNLR in Zhejiang Province is only about 40% of that in Shanghai. Of 105 counties in Anhui Province, only 16 counties have an increasing trend of MNLR (MNLR of Anqing has increased by 0.46), while the MNLR of the remaining 89 counties has all decreased (MNLR variation range is -1.92–-0.01), accounting for 85% of the total number of counties in Anhui Province. Compared with Shanghai, the decline of MNLR in Zhejiang Province is only about 20% of that in Shanghai.

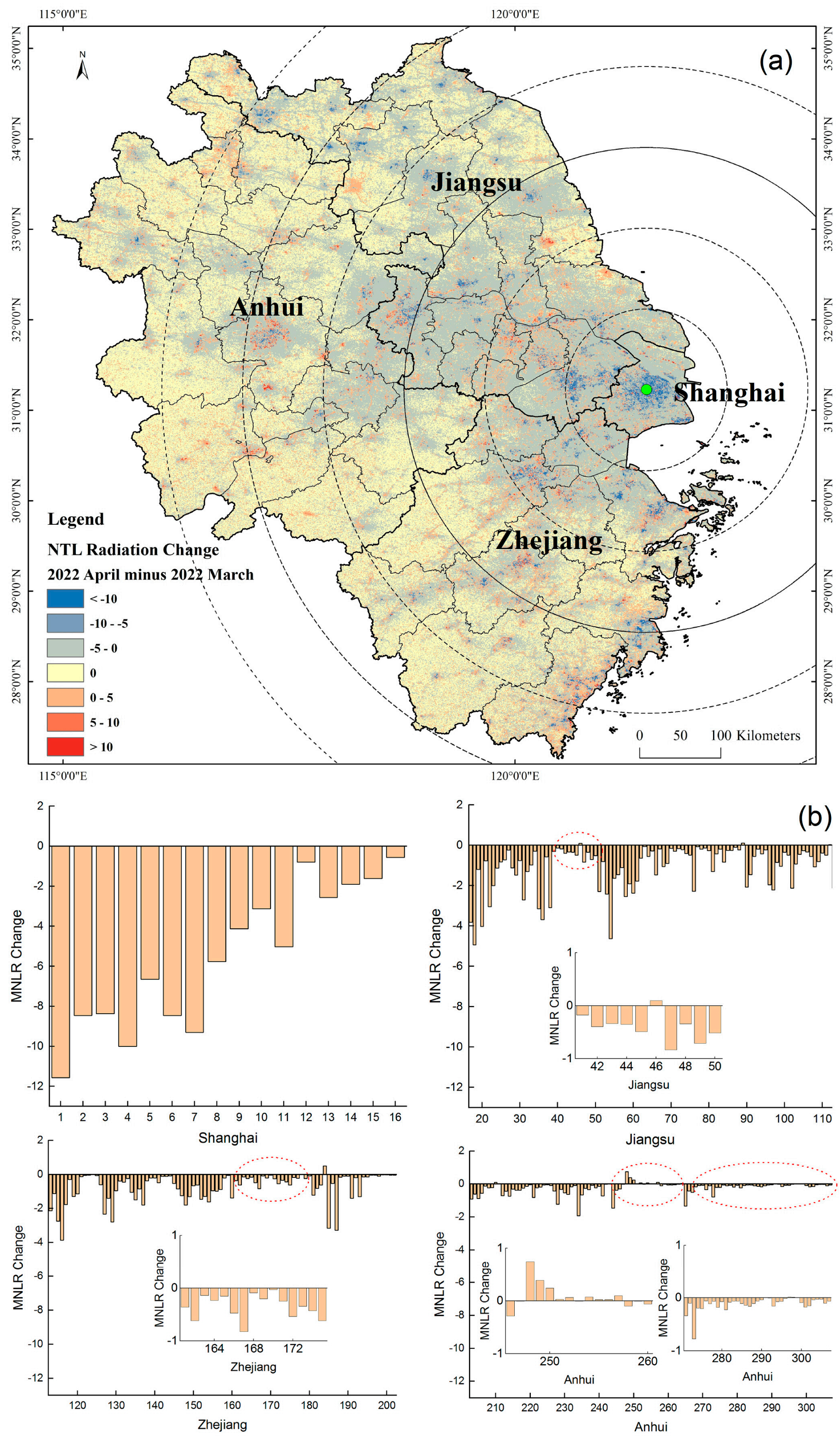

Figure 2. Spatio-temporal variation of MNLR from March to April 2022: (**a**) spatio-temporal variation of MNLR in the Yangtze River Delta; (**b**) MNLR changes of 307 counties in the Yangtze River Delta (Shanghai, Jiangsu, Zhejiang and Anhui). The serial number of the horizontal axis is arranged according to the county code. The red dashed box shows the portion with smaller values, which we have enlarged.

According to the statistics of the MNLR classification area, the area of MNLR decline in Shanghai is 7052 km^2, accounting for 87.51% of the area of Shanghai; the area of MNLR decline in Jiangsu Province is 81,214.25 km^2, accounting for 79.20% of the area of Jiangsu Province; the area of MNLR decline in Zhejiang Province is 70,209.5 km^2, accounting for 66.90% of the area of Zhejiang Province; the area of MNLR decline in Anhui Province is 94,821 km^2, accounting for 67.68% of the area of Anhui Province (Table 1).

Table 1. Statistics of MNLR change classification area in April 2022 of Yangtze River Delta (km^2).

		Yangtze River Delta			
		Shanghai	**Jiangsu**	**Zhejiang**	**Anhui**
MNLR change classification	<−10	557.75	796.50	917.25	167.00
	−10–−8	319.25	561.25	512.75	132.75
	−8–−6	472.50	1048.75	904.25	280.50
	−6–−4	654.00	2080.00	1710.00	646.00
	−4–−2	977.00	4720.25	3971.25	1562.50
	−2–0	4071.50	72,007.50	62,194.00	92,032.25
	>0	1006.25	21,326.00	34,740.00	45,275.75
	Total	8058.25	102,540.25	104,949.50	140,096.75

3.2. Spatio-Temporal Changes of MNLR before Outbreak of COVID-19

Corresponding to the COVID-19 control time in Shanghai, there was no large-scale outbreak of COVID-19 in April 2019. The analysis of nighttime light change at this time point can be regarded as the baseline change in normal condition before the outbreak of COVID-19. As shown in Figure 3, the MNLR in Shanghai increased significantly from March to April 2019, with a large range ($p < 0.01$). On the one hand, the MNLR in most areas of Shanghai has shown an increasing trend; on the other hand, the intensity of human activities in the whole Yangtze River Delta has also increased. Few urban regions have a decreasing trend. Although the MNLR in some urban areas of the Yangtze River Delta has also decreased under normal conditions, it is undeniable that the scope and intensity of the reduction are far greater than under this COVID-19 control.

Of the 16 districts in Shanghai, only Huangpu District, Jing'an District and Putuo District showed a downward trend (MNLR reduction range was 0.90–3.44), accounting for 19% of all districts in Shanghai. The rest of districts show an upward trend, from high to low, Xuhui District, Hongkou District, Chongming District, Fengxian District, Songjiang District, Pudong New Area, Qingpu District, Changning District, Yangpu District, Baoshan District, Jinshan District, Jiading District, Minhang District (MNLR variation range 0.15–2.55). The MNLR of 31 of 96 counties in Jiangsu Province showed an increasing trend (MNLR variation range was 0.02–0.58), while the MNLR of 65 counties showed a decreasing trend (MNLR variation range was 0.01–6.48), accounting for 67% of the total number of counties in Jiangsu Province. The decline in Nanjing was relatively the largest (MNLR dropped by more than 3.42). Only 20 of the 90 counties in Zhejiang Province have a downward trend (the change range of MNLR is 0.01–5.25), accounting for 22% of all counties in Zhejiang Province. The MNLR of the remaining 70 counties shows an increasing trend (MNLR change range is 0.01–2.10). The decline in Hangzhou was the largest (MNLR dropped by more than 2.56). Only 35 of the 105 counties in Anhui Province have a downward trend (the change range of MNLR is 0.01–1.38), accounting for 33% of all counties in Anhui Province. The MNLR of the remaining 70 counties all increased (MNLR variation range is 0.01–0.79).

According to the statistics of the MNLR classification area, the area of MNLR decline in Shanghai is 1773.25 km^2, accounting for 22% of the area of Shanghai; the area of MNLR decline in Jiangsu Province is 35,000.25 km^2, accounting for 34.13% of the area of Jiangsu Province; the area of MNLR decline in Zhejiang Province is 36,801.75 km^2, accounting for 35.06% of the area of Zhejiang Province; the area of MNLR decline in Anhui Province is 42,979.75 km^2, accounting for 30.68% of the area of Anhui Province (Table 2).

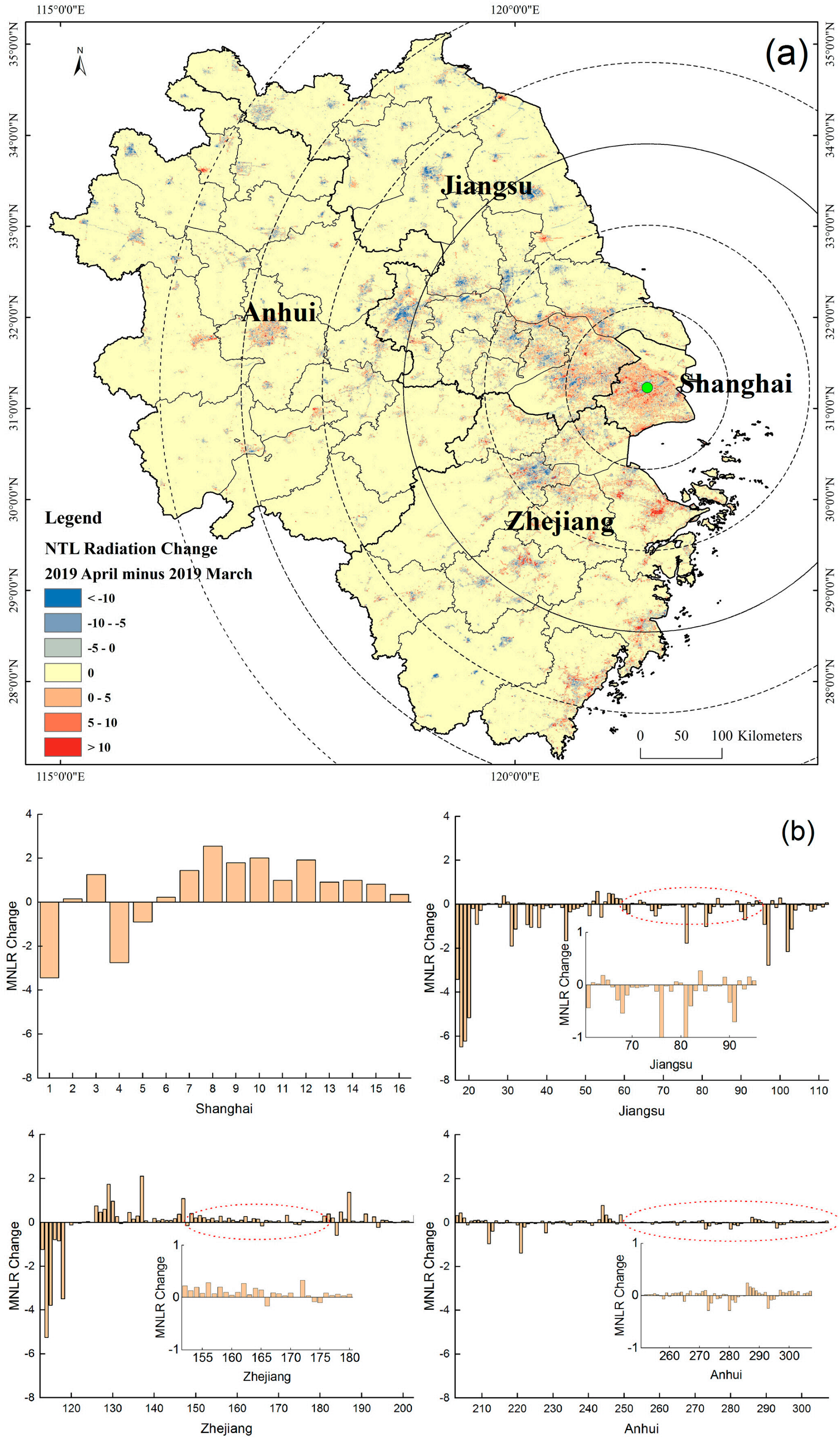

Figure 3. Spatio-temporal variation of MNLR from March to April 2019: (**a**) spatio-temporal variation of MNLR in the Yangtze River Delta; (**b**) MNLR changes of 307 counties in the Yangtze River Delta (Shanghai, Jiangsu, Zhejiang and Anhui). The serial number of the horizontal axis is arranged according to the county code. The red dashed box shows the portion with smaller values, which we have enlarged.

Table 2. Statistics of MNLR change classification area in April 2019 of Yangtze River Delta (km^2).

		Yangtze River Delta			
		Shanghai	**Jiangsu**	**Zhejiang**	**Anhui**
MNLR change classification	<−10	42.75	500.00	183.75	128.00
	−10–−8	29.75	330.00	138.00	103.75
	−8–−6	66.50	633.25	277.75	213.75
	−6–−4	163.75	1185.75	669.00	439.75
	−4–−2	342.25	2712.00	1818.25	1114.25
	−2–0	1128.25	29,639.25	33,715.00	40,980.25
	>0	6285.00	67,540.00	68,147.75	97,117.00
	Total	8058.25	102,540.25	104,949.50	140,096.75

3.3. Comparison of MNLR Changes before and after Outbreak of COVID-19

Corresponding to April 2022, there was no large-scale outbreak of COVID-19 in April 2019. The strictest static control (normalization control) was not implemented in 2020 and 2021 after the outbreak of COVID-19. As shown in Figure 4, from March to April 2019, the MNLR in most areas of the Yangtze River Delta showed an increasing trend.

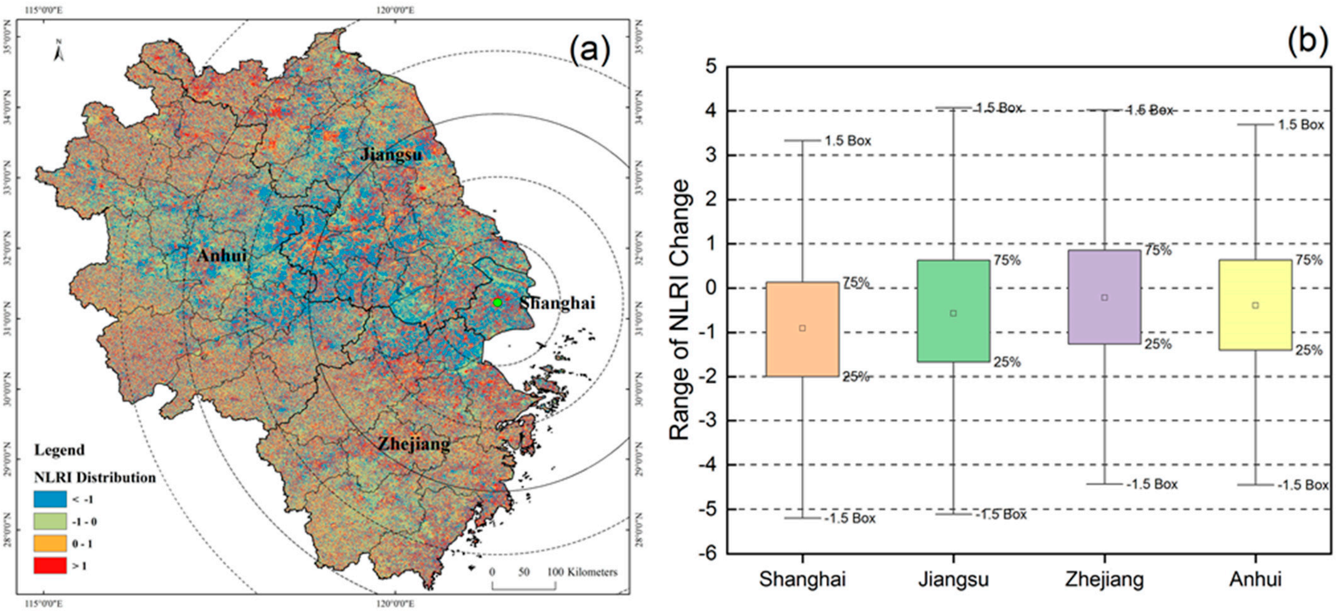

Figure 4. NLRI variation and spatial distribution in the Yangtze River Delta: (**a**) NLRI spatial distribution; (**b**) NLRI variation of Yangtze River Delta (Shanghai, Jiangsu, Zhejiang and Anhui).

Compared with the changes in April 2019, 2020, 2021 and 2022, although the MNLR in some urban areas of the Yangtze River Delta region also decreased under normalized control, it is undeniable that the scope and intensity of the reduction of MNLR is far less than that under this strict control. After the outbreak of COVID-19, the MNLR under the normalized control did not decrease, but showed a significant increase ($p < 0.01$, the average change of MNLR was greater than 0 in 2019, 2020 and 2021, and the MNLR change of at least 75% of the area was greater than 0). This change shows that the normalized COVID-19 control has not greatly inhibited the economic development or the intensity of human activities. The COVID-19 lockdown in Shanghai in 2022 will undoubtedly have a huge impact. The change of MNLR is mostly less than 0 (Box Chart shows at least 75%), and the minimum value of the MNLR change is also significantly reduced. This fully shows that the strength of epidemic control is closely related to the intensity of human activities and economic development.

Considering the continuous increase of nighttime light in China's rapid urbanization process, we have constructed NLRI to eliminate the impact of the normal increase of nighttime light on the change. As shown in Figure 5, the control of Shanghai COVID-19 has significantly affected nighttime light radiation of surrounding cities, with Shanghai and Nanjing as the center to radiate around. The cities in the south of Jiangsu Province, the cities in the middle and east of Anhui Province and the cities in the north of Zhejiang Province have the greatest impact (NLRI is less than −1). Northern cities in Anhui Province and Jiangsu Province and most cities in Zhejiang Province are slightly affected (NLRI is greater than 0). This can also be confirmed by the quantitative characteristics of NLRI. First, the average NLRI is all less than 0, reflecting that the four provinces are indeed affected by the epidemic control. Secondly, the average NLRI is Zhejiang, Anhui, Jiangsu and Shanghai from the largest to the smallest, which shows that Jiangsu is the most affected province and Zhejiang is the least affected.

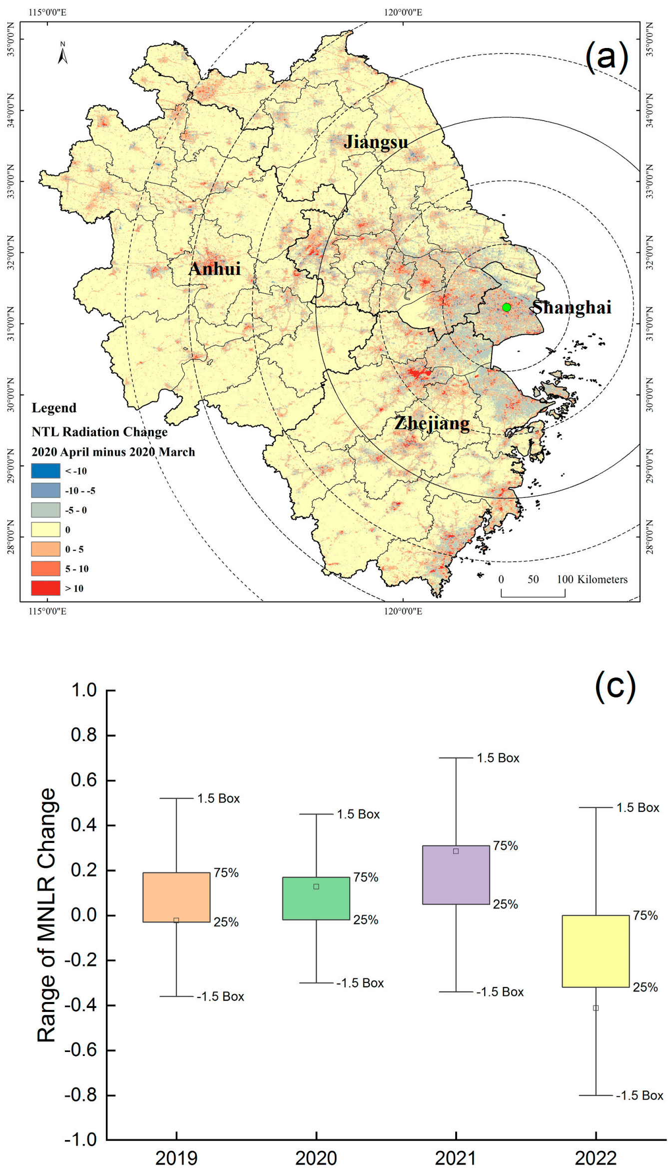

Figure 5. Comparison of spatio-temporal variation of MNLR from March to April before and after COVID-19: (**a**) from March to April 2019; (**b**) from March to April 2020; (**c**) from March to April 2021.

3.4. Comparison of MNLR Changes in Major Agglomerations in China

From the perspective of economic scale, the top five urban agglomerations in China are: Yangtze River Delta Urban Agglomeration (YRD), Beijing–Tianjin–Hebei Urban Agglomeration (BTH), Guangdong–Hong Kong–Macao Bay Area (YGA), Triangle of Central China (TCC) and Chengdu–Chongqing City Group (CCCG). We compare MNLR changes of other four major urban agglomerations except Yangtze River Delta to explore whether their MNLR has been affected during the period from March to April 2022. There are no strict COVID-19 lockdowns in the other four urban agglomerations during April 2022.

As shown in Figure 6, on the whole, MNLR changes in the Beijing–Tianjin–Hebei Urban Agglomeration are consistent with those in the Yangtze River Delta, while the MNLR changes in the Chengdu–Chongqing City Group, the Guangdong–Hong Kong–Macao Greater Bay Area, and Triangle of Central China are opposite to those in the Yangtze River Delta. The MNLR in the Beijing–Tianjin–Hebei Urban Agglomeration has decreased significantly (the average MNLR change is less than 0), which is consistent with the decline in the Yangtze River Delta. The MNLR in the core cities of Beijing and Tianjin decreased significantly, while the surrounding areas of the city center showed a slight increase. The MNLR growth in the Guangdong–Hong Kong-Macao Greater Bay Area is the most obvious (the average change of MNLR is greater than 0.4), and it is also the region with the most obvious MNLR growth in the five major urban agglomerations. The possible reason is that there were fewer cases of epidemic transmission in the Guangdong–Hong Kong–Macao Greater Bay Area during the same period of time, and that economic activity was rapidly increasing in April. The most strict control measures were not taken. On the whole, the MNLR of Chengdu–Chongqing City Group and Triangle of Central China showed a small increase. Of course, MNLR shows a downward trend in some cities.

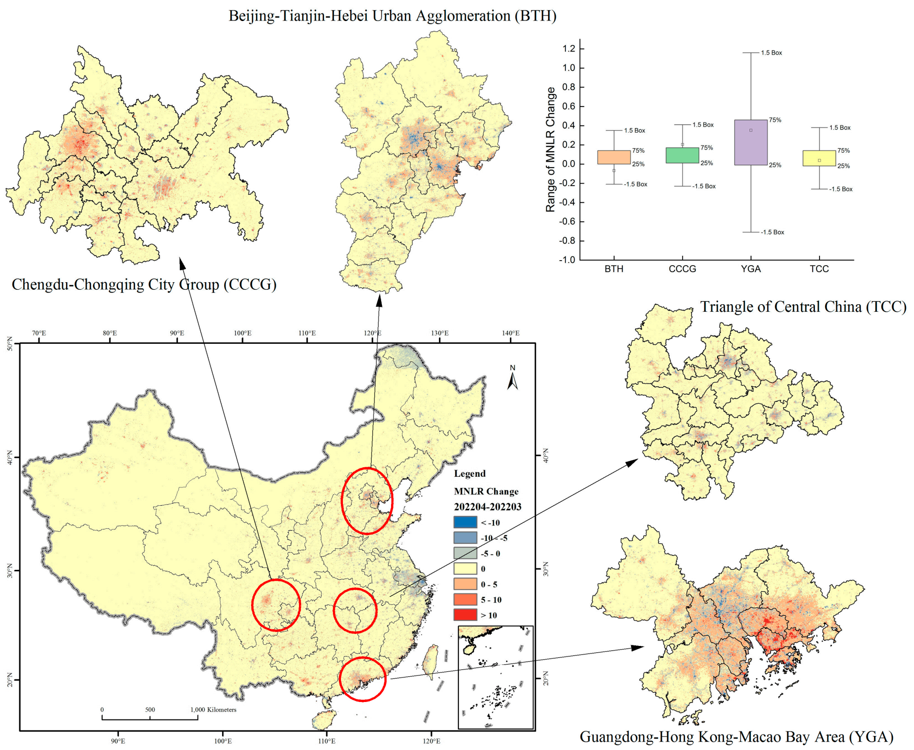

Figure 6. Spatio-temporal variation of MNLR of major agglomerations from March to April 2022. The urban agglomeration name abbreviations are: Yangtze River Delta Urban Agglomeration (YRD), Beijing–Tianjin–Hebei Urban Agglomeration (BTH), Guangdong–Hong Kong–Macao Bay Area (YGA), Triangle of Central China (TCC) and Chengdu–Chongqing City Group (CCCG).

4. Discussion

With the continuous improvement of the spatial, temporal and spectral resolution of nighttime light satellites, the research on urban issues surrounding nighttime light remote sensing data has entered a rapid development stage [44]. Nighttime light data have been applied to urban public security fields such as natural disasters, war, environmental health and epidemic [45,46]. The results of many studies show that nighttime light remote sensing can play an important role in urban public security [47–49]. In order to prevent and control COVID-19, the policies such as city closure and stay-at-home order have significantly affected the production and life of urban residents [50], and nighttime light remote sensing can effectively capture changes in urban socio-economic activities [51]. Our research shows that nighttime light remote sensing can effectively monitor the changes in urban socio-economic activities caused by public health prevention and control measures, and provides a new perspective for assessing the socio-economic impact of COVID-19. At the same time, our research provides a reference for China and other countries to evaluate the impact of epidemic prevention and control measures.

The research results show that the epidemic control policy implemented in Shanghai from March to April 2022 has significantly weakened the intensity of human and economic activities. At the same time, due to the close relationship between the Yangtze River Delta and Shanghai, the impact on the intensity of human activities in the Yangtze River Delta is also very obvious, which is consistent with the research results of many scholars [52–54]. Before the outbreak of COVID-19, the nighttime light intensity in most areas of the Yangtze River Delta showed an increasing trend. Although nighttime light intensity in some urban areas also decreased, the NLRI showed that the scope and intensity of the reduction was far less than under the control of the epidemic. Moreover, the nighttime light under the control of the normalized control showed a significant increase, which did not significantly inhibit the economic development or the intensity of human activities. During the Shanghai COVID-19 lockdown, government restricted residents' walking and driving. Public facilities such as factories, malls, and shops have also been closed, except for necessary living facilities. The decrease in nighttime lighting in Shanghai includes traffic lighting, mall lighting, and factory lighting. The efforts in this lockdown are significantly stronger than those in other regions of China. This fully shows that the intensity of epidemic control has a very close impact on the intensity of human activities and economic development. At the same time, there is no obvious linkage effect in the Guangdong–Hong Kong–Macao Bay Area, the Triangle of Central China and the Chengdu–Chongqing City Group.

5. Conclusions

Based on the COVID-19 lockdown in Shanghai in 2022, we tried to use NPP-VIIRS monthly data to analyze the spatio-temporal changes of nighttime light radiation in the Yangtze River Delta, and compared the differences before and after COVID-19 outbreak to explore how the extensive Shanghai COVID-19 lockdown has affected economic activities. The results showed that the impact of the epidemic control on the intensity of human activities in the Yangtze River Delta was very obvious. The MNLR of all 16 districts in Shanghai showed a downward trend (MNLR variation range was -10–-0.55). The MNLR of 93 of the 96 counties and districts in Jiangsu Province has all decreased (the range of MNLR is -4.94–-0.07). The MNLR of 89 of the 90 counties in Zhejiang Province has all decreased (the range of MNLR is -3.86–-0.01). The MNLR of 89 of the 105 counties and districts in Anhui Province has all decreased (the MNLR variation range is -1.92–-0.01). In 2019, the number of counties with a downward trend in Shanghai, Jiangsu, Zhejiang and Anhui Province was 3 (MNLR decreased from 0.90 to 3.44), 65 (MNLR changed from 0.01 to 6.48), 20 (MNLR changed from 0.01 to 5.25), and 35 (MNLR changed from 0.01 to 1.38). Although the MNLR in some regions of Yangtze River Delta has also decreased, the scope and intensity of the reduction is far less than that of this control. Under normalized control (2020 and 2021), the MNLR in the Yangtze River Delta did not decrease, but showed a significant increase (the MNLR change in 2019, 2020 and 2021 was greater than 0, and the MNLR change in at least 75% of the area was greater than 0).

From the perspective of NLRI, Shanghai COVID-19 lockdown has significantly affected the nighttime light radiation of surrounding cities. The four provinces are indeed affected by this epidemic control (the average NLRI is all less than 0). The average NLRI from the largest to the smallest is Zhejiang, Anhui, Jiangsu and Shanghai. It shows that Jiangsu is the most affected province except Shanghai and Zhejiang is the least affected.

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Data Availability Statement: The monthly NPP/VIIRS products we used come from the official website of the EOG Group of Colorado University of Mines (https://eogdata.mines.edu/products/vnl/, accessed on 5 March 2023). Administrative division data is mainly divided into China's provincial, municipal and county, which is sourced from Resource and Environmental Science and Data Center, Chinese Academy of Sciences (https://www.resdc.cn/Datalist1.aspx?FieldTyepID=20,0, accessed on 5 March 2023). Each grid of population spatial data represents the number of people within 1 km^2, unit: person/km^2 (https://www.resdc.cn/DOI/DOI.aspx?DOIID=32, accessed on 5 March 2023).

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