Monitoring urban carbon emissions from energy consumption over China with DMSP/OLS nighttime light observations

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Abstract
This paper constructs a model to accurately estimate the urban CO2 emissions in 2000, 2005, and 2013 in China, using the combined data of DMSP/OLS nighttime light data and the provincial energy statistical yearbook data. We calculate and analyze the growth of urban built-up areas and carbon emissions in different time periods both all over the country and the four economic zones in China. It was shown a good fitting relationship between urban growth and carbon emissions, with the $R^2$ at 0.6188 in 2000, 0.7132 in 2005, and 0.7195 in 2013. The growth rate of developed land area was 13.4% from 2000 to 2005 and 15.9% from 2005 to 2013. During the same period, CO2 emissions had been increasing as well, at an average annual growth rate of 12.2% from 2000 to 2005 and 6.5% from 2005 to 2013. From a spatial point of view, carbon emissions are far greater in the eastern region of China than in western China. The carbon emissions are the highest in major metropolitan cities such as Beijing, Shanghai, and Guangzhou. Per capita carbon emissions are also higher in eastern China, which is consistent with the people’s higher living standards. In some cities with large energy and heavy industry concentrations, especially in the northeastern and western regions, the growth rate of carbon emissions has risen faster than in other cities.

1 Introduction
Global climate change has become a critical global issue with severe threats to the environment, economic development, and public health (Zhou et al. 2013). Because of its massive volume, carbon dioxide (CO2), a greenhouse gas (GHG) produced by human activities, has received a lot of attention. Carbon emissions from energy consumption are caused by the burning of fossil fuels, mainly coal, oil, and natural gas, which are the main sources of GHG emissions generated by human activities. Many scholars have conducted in-depth research on carbon energy emission calculations, emission reduction strategies, and influencing factors (Zhang et al. 2011; Dong and Zhang 2010). Chen et al. 2007; Wang and Watson 2010). During the past decades, China has experienced rapid economic growth. It is of great implications to investigate the environmental effects of the dramatic changes in land use and energy consumption for policy making towards sustainable development. Therefore, it is necessary to develop reliable approaches to estimate and analyze carbon emissions in different economic regions and implement strategic plans for carbon emission reduction.

The administrative regimes of China are divided into three levels: provincial level, municipal level, and county
level. The statistics on energy carbon emissions in China are usually collected at the national or provincial level by the National Bureau of Statistics and its affiliated agencies. Since detailed city-level data is comparatively rare, it is difficult to analyze the temporal trends and spatial patterns of carbon emissions at a micro-scale. Therefore, more advanced techniques are needed to assess carbon emissions in China. Due to the limited sources of energy data in China, the related research (Zhao et al. 2010; Wang and Zhu 2008; Su 2015) mainly used energy statistics to calculate the energy consumption of CO$_2$ emissions according to the IPCC standard. Up to now, the most used approaches for calculating carbon emissions in the world are the material balance algorithm, the life cycle method, emission coefficient method, model method, and the method of decision tree of real objects (IPCC 1990, 2001, 2006, 2007; Jarvis, et al. 1997; Lee 1998; Malhi et al. 1998; Wang and Gu 2006; Che 2010). Based on detailed fuel classification, Schimel (1995) estimated the amount of global anthropogenic CO$_2$. Their results show that the consumption of fossil fuels and cement production in the 1980s accounted for 78% of the world’s total anthropogenic CO$_2$ emissions. Park and Hong (2013) adopted the fuel CO$_2$ estimation method provided by IPCC and estimated the seasonal emission of Korean energy CO$_2$ using the energy consumption data provided by Korea’s energy statistics system and conducted correlation analysis with economic and energy data. Iihan and Ali (2010) analyzed the long-term causality between Turkey’s carbon emissions and economic growth, energy consumption, and employment, using CO$_2$ data provided by the World Development Institute with an auto-regressive co-integration method. Biogeochemical models are usually used to simulate the processes of the ecological carbon cycle to obtain the flux of GHG, such as the MS-MRT model used in the Kyoto Protocol and the SDA model used in the USA for carbon emissions.

On the account of the research background and knowledge gap, this paper constructed a model to estimate and calculate the municipal carbon emissions of China using nighttime lighting data and provincial-level carbon emissions data.

2 Methods and data

2.1 Study area and data sources

The study area covers mainland China, excluding Hong Kong, Macao, and Taiwan. The spatial distribution of CO$_2$ emissions in mainland China was analyzed respectively at the provincial and municipal levels.

Five main types of data sets were used in this paper:

1. Nighttime lighting data from the DMSP/OLS in 2000, 2005, and 2013. This data was obtained from the NGDC (National Geophysical Data Center), a unit of NOAA (National Oceanic and Atmospheric Administration) of the USA. The data provides a spatial resolution of 30 arc seconds including stable light from cities and towns with human activities. The instantaneous light of transient events such as fire and abandoned combustion has been eliminated. Because there are a few differences and some noises, it is also necessary to adjust these night light data for de-noising, cutting, relative radiation calibration, and geographic coordinate conversion. The data is used to get light brightness values and extract urban and urban built-up areas.

2. Image data from Landsat TM. The Landsat TM5 image data for Beijing in 2005 is collected to validate the extraction accuracy of urban built-up areas.

3. Yearbooks of statistical data on provincial energy consumption in mainland China (excluding Hong Kong, Macao, and Taiwan) in 2000, 2005, and 2013. The energy data reports the consumption of raw coal, coke, crude, gasoline, kerosene, diesel, fuel oil, natural gas, electricity, and other fossil fuels.

4. City population data for the years 2000, 2005, and 2013.

5. China administrative maps, provincial and municipal.

2.2 Methods

Figure 1 presents the overall research ideas and the technical route of this paper. In this study, we use night lighting data to extract urban built-up areas in China and verify the accuracy of the extraction with TM data, to provide a basis for counting the lighting brightness values in Chinese provinces and municipalities.

The detailed analyzing process is as follows:

Firstly, nighttime lighting data is processed, including image projection conversion, re-sampling, and cropping. The original images without radiometrically calibrating are mutually corrected, and the series of images are subjected to steps of year-fusing and inter-annual correction. In the mutually corrected step, we recalculate the new DN values of each raster in China annually by processing its DN value from the raw data (in the same year) with a group of parameters obtained from the regressions between the DN values extracted from F16 in 2006 and values from other series of light data in the “benchmark city”. There are 33 groups of parameters since 34 series of raw data existed from 1992 to 2013. The benchmark city here is Hegang in Heilongjiang province, the reason for which has been elucidated by scholars in remote sensing fields (Cao et al. 2015). Secondly, the carbon emissions of each province are calculated using the statistical...
yearbook data. Thirdly, we construct an urban carbon emissions estimation model based on regression analysis of carbon emissions and lighting brightness in each province. Finally, the characteristics of urban carbon emissions, urban expansion, and provincial carbon emissions in spatial–temporal perspective are analyzed.

### 2.2.1 Urban area extraction

According to Wang et al. (2019), the urban area to be extracted can be divided into three parts: the demarcation zone, the urban area outside the demarcation zone, and the urban area within the demarcation zone. After obtaining the urban area and the area within the demarcation zone, we can then calculate the whole urban area of each city. The whole urban area of each city is composed of two parts: one is the urban area within the demarcation zone, and the other is the main urban area outside the demarcation zone. The whole urban area can be expressed as Eq (1):

\[
\text{whole urban area} = \text{main urban area} + \text{urban area(within the demarcation zone)}
\]

(1)

### 2.2.2 Construction of the municipal energy carbon emission model

Similar to the related literature (Elvidge et al. 1997; Doll et al. 2000; Raupach et al. 2010; Meng et al. 2014; Su et al. 2014), a city-level CO₂ emission estimation model can be constructed if the nighttime light correlates to the total yearly carbon emissions of all provinces. The inversion model is shown in Eq. (2):

\[
\text{City CO}_2 \text{ emissions} = \frac{\text{Provincial CO}_2 \text{ emissions}}{\text{Provincial nighttime light brightness}} \times \text{City nighttime light brightness}
\]

(2)

**Calculation of energy carbon emissions** The provincial carbon emission data used in this paper is collected from the statistical yearbooks of various provinces in 2000, 2005, and 2013, reporting the carbon emissions from the consumption of raw coal, coke, crude oil, gasoline, kerosene, diesel, fuel oil, natural gas, and electricity. The total yearly CO₂ values of all the provinces in 2000, 2005, and 2013 were calculated using the carbon emission factor formula (Su et al. 2015; Wang et al. 2019; Che 2010) shown in Eq. (3):

\[
\text{CO}_2 = \frac{44}{12} \times \sum_{i=1}^{g} K_i E_i
\]

(3)

where \(E_i\) is the consumption of energy \(i\), according to the standard coal unit, 10⁴ t; \(K_i\) is the coefficient of carbon emission of energy \(i\), (10⁴ t carbon)/(10⁴ t standard coal); \(i\) is the type of energy; and the value of \(K_i\) is calculated according to the default value of the IPCC Carbon Emissions Calculation Guidelines.

The carbon emission factors for energy (IPCC 2006, 2013; Song 2012; Zhou et al. 2013) are shown in Table 1:

| Energy type | Raw coal | Coke | Crude | Gasoline |
|-------------|----------|------|-------|-----------|
| Converted to standard coal (t standard coal/t) | 0.7143 | 0.9714 | 1.4286 | 1.4714 |
| Carbon emission coefficient (10⁴ t carbon/10⁴ t standard coal) | 0.7559 | 0.855 | 0.5857 | 0.5538 |
| Energy type | Kerosene | Diesel | Fuel oil | Natural gas | Electricity |
| Converted to standard coal (t standard coal/t) | 1.4714 | 1.4571 | 1.4286 | 1.33 | 0.345 |
| Carbon emission coefficient (10⁴ t carbon/10⁴ t standard coal) | 0.5714 | 0.5921 | 0.6185 | 0.4483 | 0.272 |
3 Results and analysis

3.1 Extraction of urban area

Figure 2 shows the final construction maps in the years 2000, 2005, and 2013. The urban area of China increased by 13.4% from 2000 to 2005, and 15.9% from 2005 to 2013 (Fig. 3).

3.2 Accuracy verification results

We further accurately calibrated the extracted urban area in this paper. Given the relatively high spatial resolution of Landsat TM images (30 m x 30 m), scholars generally believe that the construction of map spots based on TM image data extraction is a reliable verification data source (Cao et al. 2009; He et al. 2006). Su et al. (2015) used TM image data to calibrate the extract urban areas based on DMSP/OLS nighttime light data, and their results showed a significant correlation between the total number of pixels of the urban area extracted by the two datasets.

In this paper, the accuracy of the DMSP/OLS nighttime lighting data was calibrated by using the TM data image map of Beijing in 2005. The verification results presented in Fig. 4 suggest a highly consistent relationship between the urban areas extracted respectively by light data and TM data. The difference between the numbers of pixels is 528, and the accuracy reaches 90.3%. Therefore, it is scientifically feasible to use the nighttime lighting data neighborhood analysis method to extract China’s urban areas.

3.3 Provincial carbon emission calculation results

Using the above methods, China’s CO2 emissions in 2000, 2005, and 2013 were calculated. It can be seen from the calculation results that CO2 emissions in various provinces in China are expanding constantly, with the values in the eastern provinces far exceeding those in the western provinces. The line graphs of CO2 emissions in 2000, 2005, and 2013 are shown in Fig. 5. From 2000 to 2013, there was a rising trend in CO2 emissions in China. The emission volume grew from 4.30 billion tons in 2000 to 12.64 billion tons in 2013, with an average annual growth rate of 8.6%. From a global point of view, CO2 emissions in China have undergone two major changes: from 2000 to 2005, the increase has been relatively rapid, with an average annual growth rate of 12.1%; from 2005 to 2013, the growth rate has slowed down, with an average annual growth rate of 6.5%.

3.4 Correlation analysis of energy carbon emission and nighttime light brightness

A correlation analysis of provincial carbon emissions and provincial nighttime light brightness was conducted to explore whether there is a correlation between nighttime light brightness and carbon emissions. The fitted results shown in Fig. 6 suggest a clear linear relationship between the nighttime lighting data and the CO2 emission statistics, with $R^2$ moving between 0.62 and 0.72. These results are consistent with the conclusion that there is a linear relationship between night light data and CO2 at the global level, national level, provincial level, and some urban levels.

Fig. 2 Extracted China urban area
3.5 Municipal carbon emission results and analysis

3.5.1 Municipal carbon emission results

According to the above fitting analysis, the provincial nighttime light brightness linearly correlates with the CO₂ emissions. Through provincial and municipal administrative division maps of China, zone statistics were applied to the nighttime lighting data, so we can obtain statistics on the nighttime lighting data of more than 300 cities in China in 2000, 2005, and 2013. By using the municipal energy carbon emission model in
formula 2, China’s municipal CO$_2$ emission volume can be calculated.

The increase in carbon emissions in 2005 over 2000 and the increase in 2013 over 2005 are shown in Fig. 7. At the city level, the total amount of CO$_2$ emissions had been continuously increasing from 2000 to 2013 as the urban area gradually expanded. China’s CO$_2$ emissions grew from 11.91 million tons in cities in 2000 to 34.85 million tons in 2013, with an average annual growth rate of 8.6%. From 2000 to 2005, the total volume of CO$_2$ emissions increased rapidly with an average annual growth rate of 12.2%, followed by a steady growth with an average annual growth rate of 6.5%. When comparing the urban carbon emissions of different urban areas, the carbon emissions of different cities were not balanced. For example, the carbon emissions in the metropolitan areas of Beijing, Shanghai, and Guangzhou were far beyond those of other cities. Shanghai emitted the most carbon among all the cities. Shanghai’s CO$_2$ emissions amounted to 204.73 million tons in 2000, and by 2013, this number had reached 275.07 million tons, with an average annual increase of 5.41 million tons. Shanghai, as a global metropolis and China’s economic center, emitted far more CO$_2$ than other cities because of its rapid industrial and economic development for policy superiority.

From the perspective of regional heterogeneity, most of the CO$_2$ emissions were concentrated in the eastern regions of China. After 2000, China’s economic development began to switch towards harmonious development in each region, and therefore, carbon emissions began to grow steadily in the eastern and western regions. The eastern region optimized its economic structure and devoted itself to improving the quality of development. At the same time, the economic growth rate and public policies in the central region were relatively stable, and its carbon emissions had stabilized. For the western region, carbon emissions were relatively low. Since the beginning of the western development policy,
regional carbon emissions began to rise slowly over the period. Though the western economy did not grow rapidly due to insufficient funds and imperfect infrastructure, carbon emissions in western China also increased in 2005 and 2013 compared to 2000. As for northeastern China, since the 1990s, due to the gradual decline of the old industrial bases, the gap between the northeastern region’s economy and the developed eastern coastal regions continuously expanded. Since 2003, after the country officially began to make important strategic decisions for the rejuvenation of the industries in that region, the CO₂ emissions in northeastern China began to rise rapidly. Regional GDP was one of the factors influencing the total amount of carbon emissions in different regions.

To further analyze the temporal and spatial changes of CO₂ emissions in cities, the annual average growth of each city from 2000 to 2013 was calculated and classified. There were five types of energy sources of city CO₂ emissions all over China. The criteria for its classification were shown in Table 2, including the slower growth type, the slow growth type, medium-speed growth type, the fast growth type, and the faster growth type. The results showed that 9 faster growth cities, and 17 fast growth cities, which were mainly concentrated in the eastern areas with comparatively well-developed economy (Fig. 8). In addition, 89 cities were classified as slow growth types, and 211 cities as slower growth types, which were mainly concentrated in the less developed regions such as the western region and the northeastern and central regions (Fig. 8). It can be concluded that the growth rate of total CO₂ emissions in different regions of China is closely related to its economic development speed and degree of development.

3.5.2 Analysis of per capita carbon emissions

From the above analysis of the total amount of carbon emissions, due to differences in the status, policies, and industrial development structures of economic development during different time periods, the total amount of CO₂ emissions in the four major economic zones, the eastern, central, western, and northeastern regions of China, present different characteristics. The eastern region, the most densely populated and best economically developed region, has released the most CO₂ emissions.

Further examination of the four major economic regions’ per capita carbon emissions reveals that between 2000 and 2013, per capita carbon emissions increased. Due to better economic development and higher living standard in the eastern region, which has a greater total amount of energy consumption, the per capita carbon emissions are slightly higher. Because the northeastern region is dominated by heavy industries, the per capita carbon emission level is relatively higher due to its low energy efficiency and huge

| Type of growth | Slower growth type | Slow growth type | Medium speed growth type | Fast growth type | Faster growth type |
|----------------|-------------------|------------------|-------------------------|-----------------|-------------------|
| Annual growth (10 thousand tons) | 0–150 | 150–250 | 250–350 | 350–500 | > 500 |

Fig. 8 Types of total CO₂ emissions growth over the period 2000–2013
amount of consumption. Due to the much smaller population and higher energy consumption, the per capita carbon emissions in some central regions are even higher than in the eastern region. Per capita carbon emissions from 2000 to 2013 are shown in Fig. 9. The per capita carbon emission growth rate was 11.8% from 2000 to 2005, and 5.2% from 2005 to 2013. The calculation is shown in Eq. (4).

\[
\text{Per capita carbon emissions} = \frac{\text{Total carbon emissions}}{\text{Total population}}
\]

4 Discussions

By using DMSP/OLS night light remote sensing data to estimate city-level energy carbon emissions, the research and methodology in this paper not only overcome the shortage of energy carbon emission statistics in prefecture-level cities but also unify the methods of carbon emission assessment at provincial and municipal levels, which can help in making more reasonable carbon emission reduction policies. There are a few studies on energy carbon emissions using DMSP/OLS night lighting data, most of which are at the global or national level, and very few is at the provincial or municipal level. The methods for estimating carbon emissions for municipal energy are still in their infancy. An important research extension would be to validate the estimated results with actual carbon emissions data on urban energy consumption. Equation (2) is established based on the high correlation between lighting brightness values and carbon emissions. Equation (2) has an implicit assumption that the ratio of CO₂ emission to light intensity is spatially homogeneous within a province. Using the ratio, this study realizes the estimation of municipal carbon emissions from the provincial units. The limitation of this model is the assumption that all cities within a province follow the proportion, but the cities in the province of carbon ratio may be a spatial heterogeneity. That is to say, in different cities of carbon proportion, light brightness may be different. If there is a municipal level of carbon emissions statistics, we can do further research.

5 Conclusions

In this paper, we constructed an estimation model for city carbon emissions to overcome the difficulty of collecting statistical data at the municipal level in China. The main conclusions can be summarized as follows:

(1) The results show that the developed land in China continued to expand from 2000 to 2013, with an annual growth rate of 13.4% from 2000 to 2005 and 15.9% from 2005 to 2013.

(2) It is found that there was a clearly linear correlation between nighttime lighting of Chinese cities and CO₂ emissions, with the \( R^2 \) at 0.62 in 2000, 0.71 in 2005 and 0.72 in 2013.

Fig. 9 Per capita carbon emission growth
(3) By constructing a city-level carbon emission inversion model, city-level CO₂ emissions were obtained. In general, during 2000 to 2013, the CO₂ emissions were on the rise in China. It grew from 4.30 billion tons in 2000 to 12.64 billion tons in 2013, with an average annual growth rate of 8.6%. From 2000 to 2005, the growth rate was rapid with an average annual growth rate of 12.2%. From 2005 to 2013, the growth rate slowed down and became less volatile to 6.5%. The growth rate of carbon emissions varied in different regions of China. Faster growth types and fast growth types of cities were mainly concentrated in the more economically developed regions in eastern China. In conclusion, the regional distribution of carbon emissions is characterized by “high concentration in the east and low concentration in the west.” In addition, carbon emissions per capita were also increasing year by year. The eastern region was far higher than the western region.

(4) The annual average growth rate of cities from 2000 to 2013 can be divided into 5 types. The results show that there are 9 faster-growing cities and 17 fast-growing cities, mainly concentrated in some eastern developed areas. In addition, 89 slow-growing cities and 211 slower-growing cities are found mainly in the less developed regions such as the western region, the northeastern and central regions. The growth rate of total CO₂ emissions in different regions of China is closely related to the economic development speed and degree of development of those regions.

The results have important implications for the emission reduction policy in China. The focus of emission reduction should be on the improvement of energy efficiency and capacity utilization in the heavy industrial cities, such as those in the western and northeastern provinces. For cities in the eastern and central regions that are dominated by light industry, the focus of their emission reduction should be on the adjustment of industry structure.

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Author contribution The corresponding author is responsible for ensuring that the descriptions are accurate and agreed by all authors. Li Wang designed the study, developed the methodology, and wrote the manuscript. Huanguang Deng was responsible for the revision and retrouche of the manuscript. Niyu Zhang performed the experiment and performed the data analysis. Peifa Wang and Fei Yang offered part of data and provided guidance. John J. Qu provided some guidance and revise opinion of the paper. Xiaoxue Zhou provided direction and formulated the original problem.

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Declarations

Ethics declarations Our research do not have any animal experiment and do not do harm to human beings and society.

Consent for publication All the authors confirm:
• that this paper has not been published before;
• that it is not under consideration for publication elsewhere;
• that its publication has been approved by all co-authors;
• that its publication has been approved (tacitly or explicitly) by the responsible authorities at the institution where the work is carried out.

Conflict of interest The authors declare no competing interests.

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