Accuracy analysis of inverting provincial-level carbon emissions from night-time light data in China: comparison based on international carbon emission data

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Abstract. It is an indisputable fact that carbon emissions lead to global warming. Finding a rapid and accurate method for estimating carbon emissions is the prerequisite for making real-time emission reduction measures. In this paper, an estimation method for quick inversion of provincial-level carbon emissions in China is proposed by using night-time light data. This method was based on the corrected night-time light image and combined with the statistical data of the built-up area to extract the total night light value (TDN) in the built-up areas of 30 provinces (Municipalities directly under the Central Government and autonomous regions were collectively referred to as provinces; Tibet, Hong Kong, Macao and Taiwan were not involved here) in Chinese mainland from 1997 to 2017. The regression equation was established by using the TDN of the built-up areas in each province from 1997 to 2014 and the provincial-level carbon emission data released by CEADs (China emission accounts and datasets) in the same period, and then the TDN values from 2015 to 2017 were used as the independent variable to estimate the carbon emission of each province according to the established regression equation. Finally, we used the entropy method and carbon emission allocation model to distribute China's national-level carbon emission data released by the international authoritative databases to each province and compared them with the provincial-level carbon emissions estimated by the above regression equations from 2015 to 2017. The results show that: (1) There was a significant linear relationship between the established carbon emission estimation models in all provinces, with R² values greater than 0.8 except Beijing, Hainan and Shanxi. (2) Comparing the difference between the estimated carbon emissions and the carbon emissions allocated to provinces by the database, except for Shandong, Shanxi, Inner Mongolia and Shaanxi provinces, the errors of the other provinces were relatively small, RMSE and MAE were less than 260mt, and the MAPE of most provinces were less than 50%, indicating that the estimation models have high goodness-of-fit and accuracy. (3)The provincial-level carbon emissions allocated by the four international databases from 2015 to 2017 and the carbon emissions estimated by the model were plotted separately, and it is found that the corresponding scatter points of most provinces were distributed near the 1:1 line, which once again showed that the carbon emissions inverted based on night-time light data were close to the carbon emissions allocated to the provinces by each database, especially the provincial-level carbon emissions from CEADs database. The above results demonstrate that this method can provide a faster and more accurate estimation of provincial-level carbon emissions for China.
1. Introduction
The biggest environmental challenge facing mankind in the 21st century is global climate change characterized by climate warming, and CO₂ emission caused by human activities is the main cause of global climate change[1]. At the World Climate Conference, the Chinese government pledged its commitment to reducing the carbon emissions per unit GDP by 60%-65% by 2030 compared with 2005. The achievement of this target depends on the effective development of carbon emission reduction measures in the various provinces, and the rapid and accurate acquisition of carbon emissions in each province is the premise for laying down scientific carbon emission reduction measures in real time. At present, the estimation of China's provincial-level carbon emissions is mostly based on direct energy consumption data. The methods used include the input-output model method, energy balance table method and carbon emission coefficient method[2-3]. However, due to the lag of energy statistics, carbon emissions estimated by energy consumption data can not reflect the changes of China's provincial-level carbon emissions in real time. Besides, due to the different caliber of energy statistics in different provinces, the various industrial departments set among provinces, and the different emission factor parameters used in the estimation methods, there are obvious uncertainties and inconsistencies in carbon emission estimation of different provinces in China[4-5], which affects the accurate formulation and implementation of carbon emission reduction policies in China to a certain extent. Therefore, finding a quick and accurate method to estimate carbon emissions has become an urgent problem to be solved at present, and the features of the night-time light data such as wide monitoring range, strong timeliness, quick acquisition and low-cost make it possible for real-time and rapid estimation of carbon emissions.

2. Literature review
Night-time light data is a good data source for monitoring the intensity of human activity because it is unaffected by light shadows at night and can detect low-intensity light emitted by city light or even small-scale residential areas and traffic[6]. Currently, night-time light data has been widely used in several fields such as the reconstruction of urban spatial processes[7-9], monitoring of urbanization levels[10-13], estimation of population density[14-16] and GDP[17-19], and energy consumption[15]. Since the production activities, mainly human activities, are the main driving force of carbon emissions, night-time light data can be used to invert carbon emissions at different spatial scales, the conclusion that has been gradually proved by many scholars at home and abroad. For example, Elvidge et al. [18] studied 21 countries using 1994-1995 DMSP/OLS night-time light data and found a strong linear relationship between lighting area and GDP, energy consumption, and carbon emissions. Similarly, Doll et al.[20] concluded that the total lighting area of a country had a significant positive correlation with GDP and carbon emissions and that lighting data can be used to model the spatial and temporal characteristics of carbon emissions. Meng et al. [21] used night-time light images and energy statistical data to estimate city-scale carbon emissions with a top-down method. Guo et al.[22] constructed a spatially lagged regression model of carbon emissions by integrating DMSP/OLS night-time light images, NDVI data and statistical data, and used it to simulate the spatial distribution of carbon emissions in Jiangsu Province. Su et al.[23] conducted regression analysis on the carbon emission data of built-up areas in cities extracted from night-time light image, and obtained the remote sensing estimation method of carbon emission from urban energy consumption in China, which to some extent solved the problem of missing energy consumption statistics and inconsistent statistical calibers at different spatial scales in China. A review of the existing literature reveals that, despite the extensive research on carbon emission estimation conducted by domestic and foreign scholars, the following deficiencies remain. First, at present, studies at home and abroad are mostly based on global, national or region-specific, and less work has been done to establish carbon emission estimation models for each province in China based on night-time light data. Although Su[23] has selected more than 300 cities in China to establish the overall regression relationship between light value and carbon emission, considering the spatial heterogeneity of different regions, it is biased to establish the regression relationship from the overall perspective; Second, different scholars have differences in
obtaining energy consumption data, selecting carbon emission source categories and emission factors[24], making China's carbon emission estimation have great uncertainty, while the energy consumption data used to estimate carbon emissions is lagging, thus preventing the rapid and real-time measurement of carbon emissions. Third, there are few studies comparing the provincial-level carbon emissions inverted from night-time light data with those distributed to provinces by international authoritative databases.

Compared with the existing literature, the contribution of this paper mainly includes three aspects: (1) With the real-time and convenient night-time light data, we can quickly and accurately estimate carbon emissions, effectively reducing the uncertainty of carbon emission estimates due to different energy consumption data and emission factors. (2) Considering the spatial heterogeneity of different provinces, the regression models of China's provincial-level carbon emission estimation were established by using the extracted light values of built-up areas in provinces and the carbon emissions from each province released by CEADs. (3) The model estimation results were compared with the carbon emissions distributed to each province from four international authoritative databases, and the accuracy of estimating China's provincial-level carbon emissions based on night-time light data was analyzed. The research results can provide basic data for China to formulate reasonable and feasible carbon emission reduction policies in real time. Based on this, the technical route of this paper is shown in Figure 1.

Figure 1. Technical flowchart.

Note: due to spatial limitations, HCE represents historical carbon emissions, CEI represents carbon emission intensity, and STI stands for the share of tertiary industry.
3. Data and methods

3.1. Data sources

Based on the availability of data, Chinese mainland's 30 provinces, autonomous regions and municipalities directly under the central government (collectively referred to as provinces) except Tibet province are selected for the study. Data used mainly includes night-time light data, statistical data and related auxiliary data.

3.1.1. Night-time light data. The night-time light image comes from the National Geophysical Data Center (NGDC) under the National Oceanic and Atmospheric Administration (NOAA). Combined with the public information of carbon emission data (CEADs is currently released from 1997 to 2017), we select the light images from 1997 to 2017 as the research data. The spatial resolution of DMSP/OLS night-time light data (1997-2013) is 30 arc second, about 1km at the equator. The grayscale values in the visible and near-infrared wavelengths range from 0 to 63. Images include cities, towns and other light source areas, and have been removed from accidental light noise such as gas flaring and firelight. NPP-VIIRS night-time light data (2014-2017) can detect faint visible radiation such as moonlight, star-light, city light and atmospheric glow at night, the sensor has 22 bands with a wavelength range of 0.4~12 μm and resolution of 500m. The wide-band radiation detector and in-orbit radiation correction techniques give it a higher micro-light detection capability and temporal-spatial resolution than DMSP/OLS, making it a good data source for modeling carbon emissions. However, due to the long time series of night-time light data, the discontinuity between images and the saturation of DN in a single image, it is necessary to make the regional correction before use. In this paper, the invariant target method proposed by Cao[25] is used for the mutual correction, saturation correction and inter-image continuity correction on the night-time light images extracted from each period in China in order to improve the continuity and stability of the long time series night-time light dataset. In addition, since the NPP-VIIRS data is not filtered for fire, gas flaring, volcanoes, or aurora, and background noise is not eliminated, the effective light of NPP-VIIRS needs to be extracted using DMSP/OLS before correcting it.

3.1.2. Statistical data. The statistics mainly include carbon emissions and socio-economic data. Currently, national-level and global-level carbon emissions are mainly estimated by international agencies based on energy statistics according to the methodology of the Intergovernmental Panel on Climate Change (IPCC). Due to the long-term lack of basic data in China, emission data are mainly released by research and government agencies in western developed countries, including the Carbon Dioxide Analysis Center of Oak Ridge National Laboratory (CDIAC), the World Bank, the U.S. Energy Information Administration (EIA), and the International Energy Agency (IEA), etc. In fact, these databases and current greenhouse gas (GHG) inventories generally overestimate China's carbon emissions. In order to present the latest research findings on China's multi-scale energy, carbon and socio-economic inventories, a group of scholars from the UK, US, Europe and China have been brought together with the support of the UK Research Councils, the Newton Foundation, the National Natural Science Foundation of China and the Chinese Academy of Sciences to compile an accurate and reliable China Emission Accounts and Datasets (CEADs). CEADs has compiled China's total energy volume, structure and emission sector pattern, increasing China's voice in global energy, economic and environmental decision-making and international climate change negotiations, providing solid basic data for China's further development of carbon emission reduction and carbon trading, as well as scientific and technological support to carry out emission reduction measures for China's specific sectors and technologies. Moreover, CEADs has been recognized as the most accurate estimation of China's carbon emissions so far. Therefore, we use the data released by CEADs and the light value extracted from the night-time light data to establish a carbon emission estimation model, which is reliable. The carbon emission data used to verify the accuracy come from some international authoritative databases (Table 1). For the convenience of application, the carbon emission units were
uniformly converted into millions of tons (104 ton, mt); Other socio-economic data (e.g. population, economy, industrial structure and built-up area) were taken from the China Statistical Yearbook and the China City Statistical Yearbook for the years from 1998 to 2018. To eliminate the effects of price fluctuations, the economic data used were converted to constant prices in 2000. Administrative boundary data are from the National Fundamental Geographic Information Centre.

### Table 1. Basic information about international authoritative carbon emission databases.

| Databases | Database sources | Start and end time | Scale | Website | Use of this article |
|-----------|------------------|--------------------|-------|---------|---------------------|
| IEA       | International Energy Agency | 1960—2017 | Country | https://webstore.iea.org | Accuracy Verification |
| EDGAR     | Emissions Database for Global Atmospheric Research | 1970—2018 | Country | https://data.jrc.ec.europa.eu/collection/EDGAR | Accuracy Verification |
| EIA       | U.S. Energy Information Administration | 1979—2017 | Country | https://www.eia.gov/international/data/world/other-statistics/emissions-by-fuel | Accuracy Verification |
| CEADs     | China Emission Accounts and Datasets | 1997—2017 | Country &Province | http://www.ceads.net/ | Construction of the estimation model & Accuracy Verification |

### 3.2. Methods

#### 3.2.1. Built-up area extraction. As an important resource base for the socio-economic development of each province, the differences in quantity, structure and spatial pattern of built-up areas will have an impact on the amount of provincial-level carbon emissions and the level of the economic environment. In 1978, Croft[26] put forward the possibility of extracting urban built-up areas using DMSP/OLS night-time light data. Accordingly, Su[27] achieved the estimation of carbon emissions at the urban scale in China based on the extraction of urban built-up areas through night-time light data. However, accurate extraction of built-up areas in each province is a prerequisite for precise estimation of carbon emissions by using light images. It has been shown that the key to extracting built-up areas using night-time light data is to obtain optimal lighting thresholds. Currently, the main methods for extracting thresholds are empirical threshold methods[28, 29], mutation detection methods[7], statistical data comparison methods[30] and high-spatial-resolution image comparison methods[31]. In this paper, the statistical data comparison method provided by He[30] was adopted, with statistical data as reference data, a series of lighting thresholds were set, and the built-up areas extracted based on the lighting thresholds were compared with the built-up area published in the statistical yearbook. According to the principle of minimum error, the optimal thresholds of the built-up areas in various provinces in China from 1997 to 2017 were extracted, the night-time light data were segmented by using the thresholds, and the areas with TDN values greater than or equal to the thresholds were taken as the extracted areas. Table 2 shows that the relative error (RE) between the built-up area extracted based on night-time light data and the built-up area published in the Statistical Yearbook varies from 0% to 10% in the whole study period, and the RE in most provinces are less than 3%, indicating that the built-up areas extracted through night-time light data are very close to the statistical data, which means that it is feasible to further use the provincial built-up area lighting values to estimate carbon emissions.
| Provinces | 1997 | 2001 | 2005 | 2009 | 2013 | 2017 |
|-----------|------|------|------|------|------|------|
| BJ        | 502  | 488  | 2.87 | 788  | 780  | 1.03 |
| TJ        | 374  | 380  | -1.58| 422  | 424  | -0.47|
| HE        | 651  | 653  | -0.31| 692  | 700  | -1.14|
| SX        | 344  | 352  | -2.27| 493  | 489  | 0.82 |
| IM        | 323  | 321  | 0.62 | 446  | 444  | 0.45 |
| LN        | 1166 | 1152 | 1.22 | 1271 | 1269 | 0.16 |
| JL        | 482  | 477  | 1.05 | 490  | 493  | -0.61|
| HL        | 990  | 994  | -0.40| 1032 | 1048 | -1.53|
| SH        | 407  | 412  | -1.21| 547  | 550  | -0.55|
| JS        | 782  | 782  | 0.00 | 1051 | 1050 | 0.10 |
| ZJ        | 491  | 491  | 0.00 | 787  | 777  | 1.29 |
| AH        | 483  | 484  | -0.21| 787  | 782  | 0.64 |
| FJ        | 262  | 262  | 0.00 | 349  | 349  | 0.00 |
| JX        | 232  | 230  | 0.87 | 364  | 365  | -0.27|
| SD        | 889  | 904  | -1.66| 1182 | 1182 | -0.84|
| HA        | 628  | 623  | 0.80 | 856  | 859  | -0.35|
| HB        | 549  | 550  | -0.18| 689  | 688  | 0.15 |
| HN        | 490  | 501  | -2.20| 650  | 648  | 0.31 |
| GD        | 1070 | 1112 | -3.78| 1600 | 1549 | 3.29 |
| GX        | 420  | 419  | 0.24 | 494  | 491  | 0.61 |
| HI        | 59   | 60   | -1.67| 64   | 64   | 0.00 |
| CQ        | 188  | 190  | -1.05| 265  | 268  | -1.12|
| SC        | 501  | 502  | -0.20| 796  | 794  | 0.25 |
| GZ        | 181  | 183  | -1.09| 200  | 199  | 0.50 |
| VN        | 150  | 151  | -0.66| 209  | 208  | 0.48 |
| SN        | 331  | 334  | -0.90| 438  | 436  | 0.46 |
| GS        | 309  | 311  | -0.64| 305  | 304  | 0.33 |
| QH        | 60   | 60   | 0.00 | 62   | 61   | 1.64 |
| NX        | 89   | 89   | 0.00 | 113  | 114  | -0.88|
| XJ        | 148  | 146  | 1.37 | 205  | 210  | -2.38|

Note:

- "Ext" (Extraction) refers to the built-up area obtained based on the lighting data threshold.
- "Stats" (Statistics) refers to the built-up area obtained from the statistical yearbook, "Ext" and "Stats" both in km².
The formula for the RE is \( RE = \frac{y_i - \bar{y}_i}{y_i} \times 100\% \), where \( \bar{y}_i \) represents the "Ext" of province i and \( y_i \) represents the "Stats" of province i.

Due to space limitations, only results for typical years are presented. Provinces are represented by provincial abbreviations, similarly hereinafter.

3.2.2. Construction of carbon emission estimation model. With reference to the research results of Elvidge[17] and Su[27], regression equations for estimating carbon emission in each province were established by using the extracted TDN values of night-time light in the built-up areas of each province from 1997 to 2014 (Table 3) and the carbon emissions of each province in the same period of CEADs, and its general expression is as follows:

\[
CO_{2(t,i)} = a \times TDN_{(t,i)} + b
\]

(1)

In the formula, \( CO_{2(t,i)} \) is the carbon emissions in year t of province i released by CEADs, \( TDN_{(t,i)} \) is the total value of night-time light in the built-up area in year t of province i, and a, b are constants.

Table 3. Results of TDN extraction from built-up areas of provinces in China in typical years.

| Provinces | 1997  | 1999  | 2001  | 2003  | 2005  | 2007  | 2009  | 2011  | 2013  | 2015  | 2017  |
|-----------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|
| BJ        | 72748 | 72748 | 109060| 153397| 153397| 164833| 168991| 158207| 164833| 177781| 177840|
| TJ        | 49221 | 50681 | 56130 | 62758 | 67944 | 72745 | 80303 | 85903 | 89863 | 103494| 122508|
| HE        | 79332 | 83438 | 85770 | 104046| 111893| 121333| 127673| 135684| 139957| 159499| 166967|
| SX        | 43933 | 48399 | 60205 | 62580 | 68654 | 72925 | 78814 | 87701 | 92086 | 96099 | 99799 |
| IM        | 39448 | 42644 | 51307 | 55301 | 63768 | 74775 | 79899 | 81963 | 90648 | 102309| 101285|
| LN        | 140754| 147679| 152907| 161662| 168506| 178674| 186666| 206673| 209781| 213232| 234002|
| JL        | 54031 | 52684 | 57122 | 61653 | 67208 | 82616 | 80376 | 85715 | 88668 | 97537 | 95576 |
| HL        | 108519| 107806| 116456| 117191| 129139| 134999| 137687| 146815| 151681| 154064| 155245|
| SH        | 58143 | 76075 | 76075 | 76075 | 106474| 117121| 117121| 121769| 126927| 128199| 128199|
| LS        | 93886 | 102699| 122340| 158977| 178722| 199275| 223542| 253479| 286767| 314584| 313616|
| ZJ        | 52479 | 65782 | 82427 | 96977 | 112703| 122580| 133715| 144719| 168016| 177453| 190878|
| AH        | 52450 | 66241 | 76181 | 85425 | 103275| 105073| 116864| 129266| 133896| 140895| 147543|
| FJ        | 31194 | 35833 | 41071 | 53037 | 57896 | 67186 | 74564 | 92163 | 95513 | 104110| 113567|
| JX        | 19354 | 20800 | 28532 | 37480 | 41674 | 47287 | 54451 | 60439 | 66933 | 73573 | 77110 |
| SD        | 109654| 122926| 144029| 176031| 200688| 223811| 253996| 273482| 321071| 349388| 375378|
| HA        | 73874 | 81739 | 97284 | 111150| 128476| 142841| 151593| 166056| 178148| 183423| 200490|
| HB        | 59699 | 65887 | 72244 | 81078 | 83193 | 101826| 103800| 117568| 124101| 126438| 138498|
| DN        | 41084 | 48442 | 53417 | 62183 | 64187 | 71407 | 80716 | 89065 | 92154 | 96086 | 100017|
| GD        | 151524| 177684| 218782| 319463| 334297| 373721| 398141| 431491| 468180| 576740| 592066|
| GX        | 42630 | 45367 | 49521 | 59594 | 64366 | 70324 | 73814 | 186872| 88228 | 93679 | 100722|
| HI        | 7667  | 8234  | 8234  | 11595 | 2535  | 16073 | 13674 | 14403 | 17536 | 20169 | 20510 |
| CQ        | 17300 | 22422 | 24075 | 35147 | 39271 | 51406 | 52572 | 67381 | 72017 | 80787 | 83507 |
| SC        | 42201 | 52836 | 64529 | 82874 | 84903 | 91955 | 97341 | 108920| 121281| 134374| 150338|
| GZ        | 13951 | 14321 | 16002 | 18906 | 21278 | 24133 | 25868 | 27353 | 29335 | 32456 | 34596 |
| YN        | 18285 | 22269 | 25570 | 35118 | 44502 | 43958 | 49353 | 52627 | 61832 | 64935 | 69018 |
| SN        | 41665 | 46782 | 51554 | 56175 | 59857 | 66319 | 75045 | 81365 | 92580 | 97481 | 109244|
| GS        | 31444 | 31950 | 31823 | 39290 | 43500 | 47553 | 48714 | 50737 | 54455 | 57315 | 58420 |
| QH        | 5706  | 6122  | 6444  | 6411  | 6643  | 6711  | 4792  | 7668  | 10853 | 11045 | 10924 |
3.2.3. Methods for the allocation of national-level carbon emissions in authoritative databases. In order to verify the reliability of the carbon emission estimation method using night-time light images, this paper intends to compare the carbon emission data from 2015 to 2017 released by the four major authoritative databases (Table 1) of CEADs, IEA, EDGAR and EIA with the carbon emissions estimated by regression models in the same period. Considering that IEA, EDGAR and EIA only provide carbon emission data at the national level (CEADs provides two types of carbon emission data at the national and provincial scales), it is necessary to allocate the carbon emissions from these three databases to each province in advance, which requires us to establish scientific and reasonable carbon emission allocation indicators. Based on the principles of equity, efficiency and feasibility, we selected population, GDP, historical carbon emissions (the first three indicators represent the principle of equity), carbon emission intensity (the principle of efficiency) and the proportion of tertiary industry (the principle of feasibility) as the provincial allocation indicators of national carbon emissions[32].

In order to objectively and scientifically determine the weight of each indicator in the distribution, this paper adopted the entropy method multi-index comprehensive confirmation to determine the weight of each index according to the amount of information transmitted by each indicator[33]. The basic steps are as follows: First, standardize the raw data of each index to eliminate the influence of different dimensions. For the positive and negative indicators, formula \( \frac{x_{ij} \times P_j \times G_j \times T_j \times \alpha}{Q_g} \) is used to calculate the probability of the \( j \)-th indicator, \( \frac{r_{ij} \times P_j \times G_j \times T_j \times \alpha}{Q_g} \) is the raw value of the \( j \)-th distributed indicator, \( x_{ij} \) is the raw value of the \( j \)-th distributed indicator, \( max\{x_j\} \) and \( min\{x_j\} \) are respectively represent the maximum and minimum raw value of the \( j \)-th distributed indicator. Second, the formula \( p_{ij} = \frac{r_{ij}}{\sum r_{ij}} \) is used to calculate the probability of the indicator and formula \( e_{ij} = \frac{\sum_{i=1}^{n} \ln p_{ij}}{-\ln n} \) is used to calculate the information entropy of the \( j \)-th indicator, resulting in the information utility value of the \( j \)-th indicator, calculated using formula \( g_j = 1 - e_j \).

Finally, the weight of each indicator is calculated using the formula \( w_j = \frac{g_j}{\sum_{j=1}^{m} g_j} \).

The results of the final weighting of the indicators showed that historical carbon emissions had the highest weighting of 30.76%, while GDP and population size accounted for 28.82% and 14.27% respectively, which means that the level of economic development, population and energy consumption structure can explain 73.85% of the variation in provincial-level carbon emissions. Moreover, the high cumulative share of historical carbon emissions, GDP and population as the three indicators of equity reflects that the principle of equity is the primary principle to be observed in the allocation of provincial carbon rights. Besides, the carbon emission intensity representing the principle of efficiency accounted for 17.79%, while the proportion of the tertiary industry representing feasibility was the lowest, only 8.36%.

Based on the above five indicators, a new carbon emission allocation model was constructed in eq(2) by combining the mixed carbon rights allocation mechanism model constructed by Chen et al. [34] and the total carbon emission measurement model proposed by Ma et al. [35] Using eq(2) to calculate the carbon emission quotas of each province, the national-level carbon emissions from 2015 to 2017 of IEA, EDGAR and EIA were allocated to each province accordingly.

\[
Q_j = \frac{Q_g}{\sum_{j=1}^{10} P_j} \times a + \frac{Q_g}{\sum_{j=1}^{10} G_j} \times b + \frac{Q_g}{\sum_{j=1}^{10} C_j} \times c + \frac{Q_g}{\sum_{j=1}^{10} T_j} \times d + \frac{Q_g}{\sum_{j=1}^{10} I_j} \times e
\]

In equation (2), \( Q_j \) is the carbon emission quota allocated by province \( j \); \( Q_g \) is the total carbon emissions of China; \( P_j \) is the population of province \( j \); \( G_j \) is the total GDP of province \( j \); \( C_j \) is the historical carbon emissions of province \( j \); \( I_j \) is the carbon emission intensity of province \( j \); \( T_j \) is the
proportion of tertiary industry of province $j$; $a$, $b$, $c$, $d$ and $e$ are the weights of the five indicators for carbon allocation, and $a + b + c + d + e = 1$ is satisfied.

4. Results and analysis

4.1. Results of provincial regression models and allocation of carbon emissions from databases

After removing the extracted abnormal light values, the carbon emission regression models, fitting degree and significance test results based on the TDN and carbon emissions released by CEADs in the same period from 1997 to 2014 are listed in Table 4. It can be seen from Table 4 that there was a very significant linear correlation between the carbon emissions released by CEADs and the TDN of built-up areas in each province. Except for Beijing, Hainan and Shanxi, the $R^2$ values of other provinces were almost greater than the $R^2$ value (0.818) of the model obtained by Su[27], and all provinces have passed the significance test at the level of 0.001. This implies that the regression models can explain at least 82% of the variation in the dependent variable, indicating that regression models work well. Developed regression equations were then used to estimate the carbon emissions of each province from 2015 to 2017 as independent variables (Table 5). Also, the national-level carbon emissions from 2015 to 2017 released by the IEA, EDGAR and EIA (the CEADs provide provincial-level data and do not need to be distributed here) were distributed to the provinces according to the methodology described in Section 3.2.3 (Table 5) for comparison with the carbon emissions of the provinces estimated by the regression models.

Table 4. Regression models of China's provincial-level carbon emissions from 1997 to 2014.

| Provinces | Regression Equation | $R^2$ | F value | P value | Provinces | Regression Equation | $R^2$ | F value | P value |
|-----------|---------------------|-------|---------|---------|-----------|---------------------|-------|---------|---------|
| BJ        | $y=0.0003x+35.982$  | 0.678 | 33.685  | 0.000   | HA        | $y=0.0048x-275.57$  | 0.894 | 134.361 | 0.000   |
| TJ        | $y=0.0022x-55.202$  | 0.887 | 125.569 | 0.000   | HB        | $y=0.0029x-74.856$  | 0.849 | 90.228  | 0.000   |
| HE        | $y=0.0065x-310.17$  | 0.954 | 330.158 | 0.000   | GN        | $y=0.0041x-115.36$  | 0.918 | 178.425 | 0.000   |
| SX        | $y=0.0231x-1125$    | 0.691 | 35.737  | 0.000   | GD        | $y=0.001x-34.374$   | 0.865 | 102.419 | 0.000   |
| IM        | $y=0.0133x-524.47$  | 0.895 | 136.715 | 0.000   | GX        | $y=0.0032x-115.2$   | 0.870 | 100.077 | 0.000   |
| LN        | $y=0.0043x-367.07$  | 0.964 | 423.639 | 0.000   | HI        | $y=0.004x-24.034$   | 0.742 | 45.897  | 0.000   |
| JL        | $y=0.0037x-103.69$  | 0.841 | 84.377  | 0.000   | SC        | $y=0.0027x-41.843$  | 0.846 | 87.939  | 0.000   |
| SH        | $y=0.0012x-11.307$  | 0.810 | 68.181  | 0.000   | GZ        | $y=0.0122x-104.98$  | 0.863 | 94.485  | 0.000   |
| JS        | $y=0.004x-55.868$   | 0.959 | 371.727 | 0.000   | YN        | $y=0.0039x-38.952$  | 0.879 | 116.568 | 0.000   |
| ZJ        | $y=0.003x-76.637$   | 0.943 | 266.595 | 0.000   | SN        | $y=0.0083x-327.95$  | 0.929 | 210.541 | 0.000   |
| AH        | $y=0.0035x-128.42$  | 0.880 | 117.306 | 0.000   | GS        | $y=0.0046x-85.228$  | 0.891 | 122.846 | 0.000   |
| FJ        | $y=0.0028x-58.485$  | 0.986 | 1086.701| 0.000   | QH        | $y=0.0135x-64.942$  | 0.850 | 84.840  | 0.000   |
| JX        | $y=0.0024x-7.7501$  | 0.951 | 307.824 | 0.000   | NX        | $y=0.0083x-85.15$   | 0.897 | 139.952 | 0.000   |
| SD        | $y=0.004x-206.05$   | 0.936 | 233.759 | 0.000   | XJ        | $y=0.0086x-125.77$  | 0.924 | 193.880 | 0.000   |
Table 5. Predicted carbon emissions of each province in 2015-2017 and carbon emissions allocated by four databases.

| Provinces | 2015 | 2016 | 2017 |
|-----------|------|------|------|
| BJ        | 89.32 | 243.60 | 289.65 |
| TJ        | 172.48 | 169.67 | 201.73 |
| HE        | 726.57 | 498.05 | 592.14 |
| SX        | 1094.89 | 382.90 | 455.23 |
| IM        | 836.24 | 362.78 | 429.46 |
| LN        | 549.83 | 362.78 | 429.46 |
| JL        | 257.20 | 244.57 | 290.77 |
| HL        | 379.63 | 258.38 | 307.19 |
| SH        | 163.62 | 255.28 | 303.51 |
| JS        | 699.13 | 542.14 | 664.56 |
| ZJ        | 455.72 | 376.79 | 449.97 |
| AH        | 364.71 | 302.81 | 360.31 |
| FJ        | 233.02 | 258.05 | 306.80 |
| JX        | 168.83 | 203.94 | 242.47 |
| SD        | 1603.60 | 629.58 | 748.52 |
| HA        | 604.86 | 451.53 | 536.83 |
| HB        | 286.59 | 334.47 | 397.66 |
|HN        | 281.54 | 308.34 | 366.59 |
| GD        | 542.37 | 585.78 | 696.45 |
| GX        | 184.57 | 205.80 | 244.74 |
| HI        | 56.64 | 90.94 | 108.13 |
| CQ        | 164.02 | 209.77 | 249.40 |
| SC        | 320.97 | 447.95 | 532.58 |
| GZ        | 333.81 | 262.86 | 312.52 |
|YN        | 214.29 | 219.65 | 261.15 |
|SN        | 481.14 | 239.57 | 284.83 |
|GS        | 178.42 | 192.50 | 228.88 |
|QH        | 84.17 | 146.59 | 174.29 |
|NX        | 211.22 | 188.50 | 224.12 |
|XJ        | 345.88 | 262.33 | 311.89 |

Note: A indicates carbon emissions estimated based on TDN according to the regression equation for each province, B-D respectively represent the carbon emissions allocated to provinces by IEA, EDGAR and EIA, and E indicates carbon emissions for each province by CEADs; The unit of carbon emission is millions of tons (mt).
4.2. Accuracy analysis in estimating carbon emissions

In this paper, three indicators (Table 6), namely mean absolute error (MAE), root mean square error (RMSE) and mean absolute percentage error (MAPE), were selected to analyze the accuracy of carbon emissions estimated in 2015-2017 about the carbon emissions allocated to each province from the databases.

| Evaluation Indicators | MAE | RMSE | MAPE |
|------------------------|-----|------|------|
| Formula                | $MAE = \frac{1}{N} \times \sum_{i=1}^{N} |y_i - \tilde{y}_i|$, $RMSE = \sqrt{\frac{1}{N} \times \sum_{i=1}^{N} (y_i - \tilde{y}_i)^2}$, $MAPE = \frac{1}{N} \times \sum_{i=1}^{N} \left| \frac{y_i - \tilde{y}_i}{y_i} \right| \times 100\%$ | |
| Significance           | Avoid offsetting errors and accurately reflect the magnitude of actual forecast errors. | Characterization of sample dispersion | Normalize the error at each point to reduce the effect of absolute error due to individual outliers, greater than 100% being an inferior model. |

Note: $\tilde{y}_i$ indicates the carbon emissions estimated in the i-th province, $y_i$ indicates the carbon emissions in the i-th province distributed based on the international database, and $N$ is the number of provinces. In the above evaluation indicators, the smaller the absolute value of the error, the higher the accuracy of the model.

It is found that Shandong, Shanxi, Inner Mongolia and Shaanxi have high RMSE and MAE values in the four major databases, the errors between estimates and allocations in these four provinces are large, especially in Shandong Province, where the RMSE and MAE between estimates and allocations in the rest of the databases, except for CEADs, reach more than 900 mt. Except for the four provinces mentioned above, the errors between the carbon emission estimates and the database allocations are small, with RMSE and MAE less than 260 mt, indicating that the provincial-level carbon emissions based on the inversion of night-time light data have high accuracy. The MAPE results also show the same conclusion, that is, the MAPE between the carbon emission estimates of Shandong and Shanxi and the other three databases allocations are greater than 100%, except for the smaller difference with the carbon emissions of the CEADs, and the MAPE between the carbon emission estimates of Inner Mongolia and Shaanxi and the carbon emissions allocated by the IEA are also greater than 100%, which indicates that the accuracy of the carbon emission estimates based on night-time light data is relatively low in the above four provinces. Most of the MAPE between the estimates of the remaining provinces and the allocations of the four authoritative databases are less than 50%, showing that it is feasible to use night-time light data to estimate provincial-level carbon emissions and that the estimation models have certain accuracy and reasonableness.

|Errors| IEA| EDGAR| EIA| CEADs|
|------|----|------|----|------|
|BJ    | 155.37| 155.38| 63.49| 204.00| 204.03| 69.54| 196.86| 196.89| 68.78| 13.20| 14.30| 17.94|
|TJ    | 23.62| 28.53| 13.80| 15.34| 18.23| 7.55| 12.97| 16.05| 6.51| 86.12| 88.22| 97.89|
|HE    | 258.70| 259.62| 51.71| 159.27| 160.26| 26.54| 173.88| 175.09| 29.72| 160.32| 171.05| 27.60|
|SX    | 766.34| 767.30| 199.26| 689.90| 690.81| 149.60| 701.13| 702.12| 155.87| 325.43| 329.53| 22.00|
|IM    | 452.65| 453.07| 124.76| 380.54| 381.20| 87.53| 391.14| 391.63| 92.19| 57.62| 61.07| 7.61|
|LN    | 225.87| 228.44| 61.92| 153.45| 156.90| 35.06| 164.09| 167.21| 38.43| 81.25| 87.18| 15.90|
|JL    | 6.38| 7.94| 2.61| 42.45| 42.92| 14.40| 35.27| 35.78| 12.26| 36.17| 36.20| 16.75|
|HL    | 123.02| 123.02| 47.41| 71.43| 71.44| 22.97| 79.01| 79.03| 26.04| 26.36| 27.21| 7.44|
In addition, to further reveal the validity of estimating carbon emissions based on night-time light data, the intersection of carbon emissions distributed to provinces from the four major authoritative databases in 2015-2017 and estimated carbon emissions (referred to as the scatter) was visually plotted on a 1:1 wireframe plot. As can be seen in Figure 2, in the four major databases, if the six outliers (data of Shandong and Shanxi in 2015-2017) are removed, the scatters corresponding to most of the provinces during 2015-2017 are basically distributed around the 1:1 line, showing an obvious linear relationship, which indicates that the provincial-level carbon emissions estimated based on night-time light data can reflect the carbon emissions allocated to provinces by authoritative databases. Especially, it is very close to the carbon emissions allocated to provinces by CEADs database, the $R^2$ value of their regression equation reaches 0.95 and the equation passes the significance test at the 0.001 level, which once again shows that it is reasonable and feasible to estimate the provincial-level carbon emissions in China based on night-time light data.

| Province | SH   | JS   | ZJ   | AH   | FJ   | JX   | SD   | HA   | HB   | HN   | GD   | GX   | HI   | CQ   | SC   | GZ   | YN   | SN   | GS   | QH   | NX   | XJ   |
|----------|------|------|------|------|------|------|------|------|------|------|------|------|------|------|------|------|------|------|------|------|------|------|------|
|          | 91.96 | 175.48 | 96.96 | 76.03 | 12.66 | 31.77 | 1030.12 | 186.11 | 32.00 | 22.07 | 40.79 | 9.33 | 35.26 | 44.67 | 100.48 | 110.05 | 5.17 | 280.85 | 11.54 | 62.73 | 15.66 | 106.92 |
|          | 91.98 | 176.00 | 97.95 | 76.72 | 15.65 | 31.86 | 1030.91 | 188.66 | 35.01 | 22.33 | 40.85 | 12.62 | 35.28 | 44.68 | 102.28 | 115.41 | 5.36 | 283.63 | 11.80 | 62.81 | 16.52 | 109.85 |
|          | 35.86 | 32.22 | 25.60 | 25.00 | 4.90  | 15.52  | 162.89 | 40.99 | 9.56  | 7.13  | 6.94  | 4.53  | 38.61  | 21.21 | 189.91 | 41.59 | 2.34  | 233.02 | 5.96  | 42.59 | 8.29  | 40.50  |
|          | 142.92 | 67.25 | 21.74 | 15.58 | 64.17 | 72.48 | 904.44 | 95.97 | 98.78 | 83.63 | 157.73 | 50.43 | 53.41 | 86.55  | 190.54 | 66.74 | 42.25 | 233.02 | 49.97 | 42.90 | 21.97 | 54.55  |
|          | 142.94 | 68.03 | 24.82 | 17.44 | 64.64 | 72.49 | 905.16 | 100.40 | 99.64 | 83.65 | 157.78 | 50.92 | 53.45 | 86.56  | 190.54 | 66.74 | 42.43 | 236.25 | 49.98 | 42.43 | 22.91 | 59.86  |
|          | 46.50  | 10.29 | 4.77  | 4.26  | 20.68 | 29.53  | 119.28 | 17.61 | 24.56 | 22.53 | 22.37 | 44.39 | 48.78 | 34.27  | 35.24  | 18.09 | 15.99 | 240.05 | 44.33 | 21.56 | 9.65  | 17.20  |
|          | 135.44 | 83.16 | 32.79 | 24.46 | 56.61 | 66.50 | 922.91 | 109.22 | 88.97 | 74.58 | 140.55 | 45.05 | 50.75 | 80.40  | 176.77 | 73.30 | 13.99 | 240.05 | 44.41 | 44.41 | 16.44 | 66.63  |
|          | 135.47 | 83.89 | 34.93 | 26.29 | 57.17 | 66.53 | 923.67 | 112.85 | 89.82 | 74.62 | 140.56 | 45.05 | 50.76 | 80.40  | 177.67 | 21.03 | 36.05 | 243.08 | 44.41 | 44.41 | 17.56 | 66.63  |
|          | 45.16  | 13.05 | 7.39  | 6.87  | 18.70 | 27.76 | 124.77 | 19.30 | 46.00 | 20.60 | 20.43 | 44.39 | 47.51 | 32.63  | 33.61  | 21.06 | 15.99 | 64.28  | 19.60 | 19.60 | 7.40  | 20.11  |
|          | 5.62   | 75.89 | 88.03 | 14.93 | 19.70 | 2.30  | 578.89 | 95.77 | 47.24 | 23.62 | 34.89 | 14.24 | 6.70   | 29.63  | 104.94 | 30.79 | 9.56  | 64.28  | 6.70  | 6.70  | 8.80  | 43.67  |
|          | 6.25   | 77.09 | 88.57 | 17.62 | 23.10 | 2.48  | 579.32 | 99.07 | 47.24 | 24.21 | 35.83 | 14.52 | 7.27   | 30.79  | 108.60 | 15.53 | 9.56  | 66.16  | 9.73  | 9.73  | 8.80  | 44.51  |
|          | 3.56   | 11.78 | 22.71 | 3.81  | 8.60  | 1.31   | 53.41  | 17.54 | 17.75 | 9.04  | 6.86  | 7.77   | 10.58  | 22.06  | 43.42  | 10.36 | 18.82 | 66.16  | 4.88  | 4.88  | 8.80  | 10.53  |

In addition, to further reveal the validity of estimating carbon emissions based on night-time light data, the intersection of carbon emissions distributed to provinces from the four major authoritative databases in 2015-2017 and estimated carbon emissions (referred to as the scatter) was visually plotted on a 1:1 wireframe plot. As can be seen in Figure 2, in the four major databases, if the six outliers (data of Shandong and Shanxi in 2015-2017) are removed, the scatters corresponding to most of the provinces during 2015-2017 are basically distributed around the 1:1 line, showing an obvious linear relationship, which indicates that the provincial-level carbon emissions estimated based on night-time light data can reflect the carbon emissions allocated to provinces by authoritative databases. Especially, it is very close to the carbon emissions allocated to provinces by CEADs database, the $R^2$ value of their regression equation reaches 0.95 and the equation passes the significance test at the 0.001 level, which once again shows that it is reasonable and feasible to estimate the provincial-level carbon emissions in China based on night-time light data.
5. Conclusion and discussion

Generally, carbon emissions are accounted for based on energy statistics, due to the lag of statistical data, it is impossible to achieve the purpose of rapid measurement. Therefore, this study proposed a method to quickly estimate carbon emissions by using night-time light data, which can make up for the lag of traditional measurement methods and achieve rapid and accurate estimation of carbon emissions. In addition, considering the spatial heterogeneity, this paper built carbon emission estimation models according to the characteristics of each province, so as to form a complete and reliable carbon emission estimation method for 30 provinces in the Chinese mainland. The scientific nature of the research content of this paper is mainly manifested in the following aspects: First, from the data point of view, the night-time light data is more suitable for application research after being corrected by the constant target method, and the carbon emission statistics used to obtain the regression relationship were taken from CEADs, which greatly reduces the uncertainty from energy consumption data and emission factors; Secondly, from the method point of view, the linear correlation between the light value and carbon emission data in the built-up area of night-time light data has been proved by scholars at home and abroad, which is feasible; Finally, from the precision...
verification, the regression equations obtained by each province have high $R^2$ value and high model goodness-of-fit, and all of them have passed the 0.001 significance test. Comparing the 2015-2017 estimation results with the carbon emission data allocated to provinces from the international authoritative databases, it is found that, except for a small number of provinces such as Shandong, the errors between the estimation and allocation of carbon emissions were small. The scatter plot, which corresponded the carbon emissions distributed to provinces from the four major authoritative databases in 30 provinces in 2015-2017 to the estimated carbon emissions, showed that most of the points were distributed on both sides of the 1:1 line, and the estimated results were closest to the carbon emissions distributed to provinces from the CEADs database, indicating that carbon emissions estimation models are reliable and highly accurate. Based on the above, this paper finds that the path of accurate and rapid provincial-level carbon emissions measurement is effective and reasonable, and can provide necessary supports for the formulation of scientific and reasonable provincial emission reduction policies. However, there is still some room for improvement: for example, each province is treated as an independent and homogeneous unit and analyzed as a study area, but in fact, the carbon emissions of one province are not only influenced by the internal influence of the province but also have a potential correlation with the carbon emissions of the surrounding areas[36]. In addition, there are provinces with large errors in the model fit, which requires further partial correction of the model.

Acknowledgments
This work was supported by the National Social Science Foundation of China (No. 17BGL138) and Hunan philosophy and Social Science Fund (No. 18YBA151). We are also grateful to the NOAA/NGDC for providing night-time light products.

References
[1] Zhao, R., Huang, X., Zhong, T. (2010) Research on carbon emission intensity and carbon footprint of different industrial spaces in China. Acta Geographica Sinica, 65: 1048-1057.
[2] Wang, X.M., Wu, J., Wang, Z., Jia, X.T., Bai, B. (2020) An Accounting of CO₂ Emission in Chinese Cities and Spatial Pattern Analysis. Urban and Environmental Studies, (01): 67-80.(In Chinese)
[3] Bao, S., Tian, L.X., Wang, J.S. (2010) Trend Forecast of Energy Production and Consumption in China and Research of Carbon Emissions. Journal of natural resources, 25: 1248-1254. (In Chinese)
[4] Guan, D., Liu, Z., Geng, Y., Lindner, S., Hubacek, K. (2012) The gigatonne gap in China’s carbon dioxide inventories. Nature Climate Change, 2: 672-675.
[5] Liu, Z., Guan, D., Wei, W., Davis, S. J., Ciais, P., Bai, J., Peng, S., Zhang, Q., Hubacek, K., Marland, G. (2015) Reduced carbon emission estimates from fossil fuel combustion and cement production in China. Nature, 524: 335-338.
[6] Elvidge, C. D., Cinzano, P., Petit, D., Arvesen, J., Sutton, P., Small, C., Nemani, R., Longcore, T., Rich, C., Safran, J. (2007) The Nightsat mission concept. International Journal of Remote Sensing, 28: 2645-2670.
[7] Lawrence, W. (1997) A technique for using composite DMSP/OLS'city lights' satellite data to accurately map urban areas. Remote Sensing of Environment, 61: 361-370.
[8] Chen, J., Zhuo, L., Shi, P.J. (2003) The Study on Urbanization Process in China Based on DMSP/OLS Data: Development of a Light Index for Urbanization Level Estimation. Journal of Remote Sensing, 7: 168-175. (In Chinese)
[9] Zhuo, L., Li, Q., Shi, P.J., Chen, J., Zheng, J., Li, X. (2006) Identification and Characteristics Analysis of Urban Land Expansion Types inl China in the 1990s Using DMSP/OLS Data. Acta Geographica Sinica, 61: 169-178. (In Chinese)
[10] Yang, Y., Huang, Q.X., Zhang, L.L. (2015) The Spatial-Temporal Measurement on the Land Urbanization Level Using DMSP/OLS Nighttime Light Data-A Case Study of Bohai Rim. Economic Geography, 35: 141-148. (In Chinese)
[11] Elvidge, C. D., Baugh, K. E., Kihn, E. A., Kroehl, H. W., Davis, E. R. (1997) Mapping city lights with nighttime data from the DMSP Operational Linescan System. Photogrammetric Engineering and Remote Sensing, **63**: 727-734.

[12] Zhang, Q., Seto, K. C. (2011) Mapping urbanization dynamics at regional and global scales using multi-temporal DMSP/OLS nighttime light data. Remote Sensing of Environment, **115**: 2320-2329.

[13] Zhuo, L., Shi, P.J., Chen, J. (2003) Application of Compound Night Light Index Derived from DMSP/OLS Data to Urbanization Analysis in China in the 1990s. Acta Geographica Sinica, **58**: 893-902. (In Chinese)

[14] Doll, C. N., Pachauri, S. (2010) Estimating rural populations without access to electricity in developing countries through night-time light satellite imagery. Energy policy, **38**: 5661-5670.

[15] Amaral, S., Câmara, G., Monteiro, A. M. V., Quintanilha, J. A., Elvidge, C. D. (2005) Estimating population and energy consumption in Brazilian Amazonia using DMSP nighttime satellite data. Computers, Environment and Urban Systems, **29**: 179-195.

[16] Zhuo, L., Chen, J., Shi, P.J., Gu, Z.H., Fan, Y.D. (2005) Modeling Population Density of China in 1998 Based on DMSP/OLS Nighttime Light Image. Acta Geographica Sinica, **60**: 266-276. (In Chinese)

[17] Elvidge, C. D., Baugh, K. E., Kihn, E. A., Kroehl, H. W., Davis, E. R., Davis, C. W. (1997) Relation between satellite observed visible-near infrared emissions, population, economic activity and electric power consumption. International Journal of Remote Sensing, **18**: 1373-1379.

[18] Elvidge, C. D., Imhoff, M. L., Baugh, K. E., Hobson, V. R., Nelson, I., Safran, J., Dietz, J. B., Tuttle, B. T. (2001) Night-time lights of the world: 1994-1995. ISPRS Journal of Photogrammetry and Remote Sensing, **56**: 81-99.

[19] Wang, Q., Yuan, T., Zheng, X.Q. (2013) GDP Gross Analysis at Province-Level in China Based on Night-Time Lights satellite Imagery. Urban Stud, **20**: 44-48. (In Chinese)

[20] Doll, C. H., Muller, J.-P., Elvidge, C. D. (2000) Night-time imagery as a tool for global mapping of socioeconomic parameters and greenhouse gas emissions. AMBIO: a Journal of the Human Environment, **29**: 157-162.

[21] Meng, L., Graus, W., Worrell, E., Huang, B. (2014) Estimating CO₂ (carbon dioxide) emissions at urban scales by DMSP/OLS (Defense Meteorological Satellite Program's Operational Linescan System) nighttime light imagery: Methodological challenges and a case study for China. Energy, **71**: 468-478.

[22] Guo, X.Y. (2016) Spatial distribution of carbon emissions based on DMSP/OLS nighttime light data and NDVI in Jiangsu province. World Regional Studies, **25**: 102-110. (In Chinese)

[23] Su, Y.X. (2015) Study on the carbon emissions from energy consumption in China using DMSP/OLS night light imageries. Doctor, Chinese Academy of Sciences (Guangzhou Institute of Geochemistry). (In Chinese)

[24] Zhang, Y.N., Pan, J.H. (2019) Spatio-temporal simulation and differentiation pattern of carbon emissions in China based on DMSP/OLS nighttime light data. China Environmental Science, **39**: 1436-1446. (In Chinese)

[25] Cao, Z.Y., Wu, Z.F., Kuang, Y.Q., Huang, N.S. (2015) Correction of DMSP/OLS Night-time Light images and Its Application in China. Journal of Geo-Information Science, **17**: 1092-1102. (In Chinese)

[26] Croft, T. A. (1978) Nighttime images of the earth from space. Scientific American, **239**: 86-101.

[27] Su, Y.X., Chen, X.Z., Ye, Y.Y., Wu, Q.T., Zhang, H.O., Huang, N.S., Kuang, Y.Q. (2014) The characteristics and mechanisms of carbon emissions from energy consumption in China using DMSP/OLS night light imageries. Acta Geographica Sinica, **68**:1513-1526. (In Chinese)
[28] Sutton, P., Roberts, D., Elvidge, C., Baugh, K. (2001) Census from Heaven: An estimate of the global human population using night-time satellite imagery. International Journal of Remote Sensing, 22:3061-3076.

[29] Milesi, C., Elvidge, C. D., Nemani, R. R., Running, S. W. (2003) Assessing the impact of urban land development on net primary productivity in the southeastern United States. Remote Sensing of Environment, 86:401-410.

[30] He, C.Y., Shi, P.J., Li, J.G., Chen, J., Pan, Y.Z., Li, J., Zhuo, L., Ichinose, T. (2006) Reconstruction of Chinese mainland city spatial process in 1990s based on DMSP/OLS night lighting data and statistics. Chinese Science Bulletin, 51:856-861. (In Chinese)

[31] Henderson, M., Yeh, E. T., Gong, P., Elvidge, C., Baugh, K. (2003) Validation of urban boundaries derived from global night-time satellite imagery. International Journal of Remote Sensing, 24:595-609.

[32] Wang, Y., Cheng, Y., Yang, G.C., Dong, Y. (2018) Provincial decomposition of China's carbon emission rights under the constraint of 2020 and 2030 carbon intensity targets. China Environmental Science, 38:3180-3188. (In Chinese)

[33] Li, S. (2019) Accounting for the Overall Carbon Emission Allowance and Its Cross-administrative Regional Allocation: A Case of Zhejiang Province. Master, Zhejiang University. (In Chinese)

[34] Chen, W.Y., Wu, Z.X. (1998) Carbon emission permit allocation and trading. Journal of Tsinghua University (Sci&Tech), 38:15-18. (In Chinese)

[35] Ma, H.L., Zhang, H.Y., Wu, F.P. (2016) Research on the Prediction of Carbon Emissions Distribution Based on Simulation Analysis. Soft Science, 30:75-78. (In Chinese)

[36] Liu, X.Z., Guo, R.X., Zhang, Y., Zhang, D.S., Wang, Z.Q., Gao, C.C., Xie, J.N. (2019) Nonparametric estimation and empirical analysis of spatial dependence structure of provincial carbon emissions in China. China Population, Resources and Environment, 29:40-51. (In Chinese)