remote sensing

MDPI

Supplementary Material

The composition CO_2 emissions estimation

We used the open gridded CO_2 emissions maps in the paper of Dai, et al. [1-3]. The specific composition of these CO_2 emissions is shown in Table S1. From this table, it can be seen that the industrial sector was the largest source of CO_2 emissions.

Table S1. CO_2 emissions in Jinjiang city from different sectors in 2013.

Sectors	Emissions/10^3 t	Percentage of total
Residential	2600	15.62
Industrial	13,700	82.59
Transport	298	1.79
Total	16,598	100.00

Spatial patterns of the gridded CO_2 emissions maps

Spatial autocorrelation and spatial strata testing are important components for understanding the spatial distribution of CO_2 emissions. Moran's I is a global spatial autocorrelation indicator based on the first law of geography[4]. The neighborhood rule used in this study is the Moore neighborhood rule, which means that the eight cells surrounding each cell are deemed as adjacent grids.

$$\mathrm{I} = \frac{n \sum_{i=1}^{n} \sum_{j=1}^{n} w_{i,j} z_i z_j}{\sum_{i=1}^{n} \sum_{j=1}^{n} w_{i,j} \sum_{i=1}^{n} z_i^2} \qquad \text{(S1)}$$

where z_i, and z_j are the deviations of the attribute values of the ith and jth grids from their average values. $w_{i,j}$ is the spatial weights (1 represents the jth grid in the neighborhood of ith grid, while 0 represents otherwise). n is the total number of grids.

The Geographical Detector was originally used to study the risk of endemic diseases and related geo-environmental factors[5]. Later, Wang et al. proposed its use as a tool to measure spatial heterogeneity[6]. The model is:

$$q = 1 - \frac{\sum_{h=1}^{L} N_h \sigma_h^2}{N\sigma^2} \qquad \text{(S2)}$$

where equation (S6), q is a statistic ranging from 0 to 1. The larger the value of q, the stronger the spatial heterogeneity. H $(1,\ldots, L)$ is the stratification of direct emissions, with K-means and analysis of variance being used to determine the most significant differences in stratification (L ranging from 3 to 9). N_h and N are the grid numbers for layer h and the whole study region, respectively. $\sigma^2{}_h$ and σ^2 are the variance of direct emissions in layer h and whole region, respectively. Through K-means and ANOVA analysis, the classification of residential, industrial, transport, and the total emissions are 5, 3, 3, and 5 on the 30 m resolution map and 4, 3, 4, and 3 on the 500 resolution map, respectively.

The semi-variogram presents the function to distance of grid pairs, and represents spatial autocorrelation and spatial variability[7].

$$\gamma(x,h) = \frac{1}{2}Var[Z(x) - Z(x+h)] = \frac{1}{2}E[Z(x) - Z(x+h)]^2 \qquad (S3)$$

where $\gamma(x, h)$ is the semi-variogram, in which the larger the value of $\gamma(x, h)$, the stronger the spatial autocorrelation and spatial variability. $Z(x)$ and $Z(x+h)$ are the values of direct CO_2 emission of the xth grid and the grid for which the distance to xth grid is h. h is the distance on different grids.

Moran's I was calculated from the various maps and sectors (Table S2). The pattern of emissions was more aggregated in the 30 m resolution map, in which Moran's I was always more than 0.6. Industrial emissions were most aggregated (0.904). Moran's I was always more than 0.3 in the 500 m resolution maps, demonstrating that the pattern was aggregated. In contrast to the result of the 30 m resolution map, residential emissions were most aggregated in the 500 m resolution map (I = 0.781).Based on the corresponding results, the spatial differentiation characterization q value (Table S3) indicated strong spatial heterogeneity in the emission pattern on both the 30 m and 500 m resolution maps. The distribution of CO_2 emissions from different sources also showed strong spatial stratification, with all q values exceeding 0.8.

Table S2. Moran's I for the different CO_2 emissions sectors at different scales

Resolution	Total emission	Residential emission	Industrial emission	Transport emission
30 m	0.905***	0.793***	0.904***	0.693***
500 m	0.463***	0.781***	0.426***	0.304***

Note: ***represent P-Value is less than 0.001.

Table S3. Factor detector q value of different CO_2 emissions at different scales

Resolution	Total emission	Residential emission	Industrial emission	Transport emission
30 m	0.915***	0.826***	0.920***	0.940***
500 m	0.894***	0.891***	0.902 ***	0.903***

Note: ***represent P-Value is less than 0.001.

Reference:

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