Carbon Emission Accounting of Typical Megacities Based on Electricity Statistics

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Abstract. With the continuous improvement of the urbanization rate, the pressure on my country's cities to reduce emissions is increasing. In the context of emission peak and carboon neutrality, the quantification of urban carbon emissions is of great significance. Considering producer responsibility and consumer responsibility comprehensively, starting from the shared responsibility sharing accounting method, and taking electricity equivalent value and electricity equivalent value as important indicators, a power carbon emission accounting model based on the principle of shared responsibility is constructed. Select urban characteristic factors closely related to urban carbon emissions to construct an extended STIRPAT equation; use XGBoost to score the importance of multiple features to complete important feature selection; take carbon emissions as the dependent variable, night lights, electricity carbon emissions data, other Significant influencing factors are independent variables, and urban carbon emissions are calculated with the help of the spatial Durbin model.

Keywords: Shared Responsibility · Electricity Carbon Emissions · Urban Carbon Emissions · Carbon Emissions Accounting

1 Introduction

At present, domestic and foreign scholars use the input-output model to calculate carbon emission data more. Ref. [1] used the input-output model to calculate the carbon emissions of 13 cities in China from the perspective of consumption, and found that there were significant differences in the levels of carbon emissions obtained from the perspectives of consumption and production. Ref. [2] builds an estimation model for China's urban carbon emissions data based on the energy balance sheet, which includes 47 socio-economic sectors, 17 fossil fuels and 9 basic production sectors. Some scholars have used night light data to study the related issues of regional carbon emissions. Ref. [3] built a model to explore the relationship between the carbon emissions of provincial residents and night lights, and found that the goodness of fit between the two was as high

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as 0.94. Ref. [4] uses a variety of socioeconomic factors to correct nighttime lights. The study found that after the nighttime light data is corrected, it can effectively alleviate the carbon emission estimation problem caused by the lack of statistical data in county-level areas. Ref. [5] found that there is a one-way causal relationship between urbanization, economic growth and carbon emission intensity by testing the causal relationship, and the study showed that economic growth is the main determinant of carbon emission intensity. Ref. [6] uses the symbolic regression method and the data from 1995 to 2014 to the influencing factors of carbon emission intensity in 34 OECD member countries, and finds that there are differences in the influencing factors of carbon emission intensity in each country. In 17 of these countries, the most common and important factor in carbon intensity is GDP; in 4 of these countries, the most prominent factor is industrialization and technological innovation; in 3 of these countries, urbanization, population and foreign direct investment play a positive role effect.

Through the above related literature, it can be obtained that the factors affecting urban carbon emissions in the current related research include: population, urbanization, industrialization, economic level, GDP, affluence, industrial structure, technological progress and innovation, climate difference, foreign investment, etc. Among them, factors such as population, GDP, economic level and affluence are closely related to urbanization.

In order to avoid the drawbacks of carbon emission accounting from the perspective of production and consumption, and considering that most of the carbon emissions in municipal areas come from energy consumption, this paper will adopt the principle of carbon emission accounting shared by producers and consumers, comprehensively consider night lights, Influencing factors such as electricity carbon emissions are independent variables, and urban carbon emissions are calculated with the help of the spatial Durbin model.

2 Shared Responsibility Principle

The principle of shared responsibility, that is, the responsibility for carbon emissions is shared by producers and consumers. This accounting principle can incorporate all links and consumers in the industrial chain into the emission accounting system, so that all parties involved bear the corresponding emission responsibilities. The core issue of the shared responsibility principle accounting method is to determine the share of emissions between producers and consumers. The share ratio proposed in this subject is the urban power generation efficiency, which is determined according to the equivalent value and equivalent value of urban power. Taking the power generation efficiency of each city as the shared proportion, on the one hand, it can reflect the differences in the power generation efficiency of cities, and effectively encourage cities to adopt more efficient and low-carbon power generation methods and power generation technologies to reduce their emission responsibilities; Consumers take more measures to reduce electricity consumption, thereby reducing their emission responsibilities.

$$EEV_y = \frac{\sum\limits_i FC_{i,y}R_i}{TP_y} + \frac{\sum\limits_j FQ_{j,y}S_j}{TQ_y} \tag{1}$$

$$K_y = \frac{ECV}{EEV_y} \tag{2}$$

$$\theta_y = 1 - K_y \tag{3}$$

where: EEV_y denotes the equivalent value of urban electricity in year y; $FC_{i,y}$ denotes the consumption of fossil fuel i in urban thermal power generation in year y; R_i denotes the converted standard coal coefficient of fossil fuel i; TP_y denotes urban thermal power in year y Power generation; $FQ_{j,y}$ denotes the consumption of clean energy j in urban clean energy power generation in year y (mainly refers to the carbon emissions generated by the full life cycle of clean energy power generation equipment, including manufacturing, installation, operation and maintenance, scrapping, etc.); S_j represents the standard coal coefficient converted by clean energy j; TQ_y refers to the urban clean energy power generation in year y; i denotes the type of fossil fuel consumed in thermal power generation; K_y denotes the thermal power generation efficiency in the yth year; ECV denotes the equivalent value of electricity; θ_y denotes the emission commitment of the power production side in the yth year. Since the ratio of commitment is inversely related to the thermal power generation efficiency, it is conducive to promoting the provinces to take effective measures to improve the thermal power generation efficiency and reduce the carbon emission responsibility of their electricity.

3 The Accounting Model of Urban Electricity-Related Carbon Emissions Based on the Principle of Shared Responsibility

3.1 Production-Side Carbon Emissions

$$EP_y = \theta_y EM_y \tag{4}$$

where EP_y denotes the emission borne by the urban power generation in year y; EM_y denotes the direct emission of urban electricity in year y.

$$EM = \sum_i AC_i \cdot EF_i \tag{5}$$

where AC_i denotes the consumption of fuel i in the electricity production process; EF_i denotes the emission factor of fuel i.

3.2 Consumer Carbon Emissions

The emissions borne by the power consumer are composed of two parts: the power consumption emissions in the regional power grid and the net transfer (transfer) power consumption emissions from other regional power grids [7, 8].

$$EC_{p,y} = (1 - \theta_y)EM_y + EFIC_y NEP_y \tag{6}$$

where $EC_{p,y}$ denotes the city's electricity consumption emissions in the power grid in the yth year; $EFIC_y NEP_y$ denotes the net transfer (transfer) to the city's electricity emissions.

3.3 Grid Carbon Emissions

The transmission loss emission of the power grid can be regarded as the emission of power consumption of the power grid. To calculate this part of the emission, the power consumption of the provincial power grid can be directly multiplied by the emission factor of the corresponding urban power consumption end. The carbon emission factor of electricity consumption can be estimated according to the carbon emission of electricity consumption and the total electricity consumption in the city.

$$EFC_y = \frac{EC_y}{CE_y} \tag{7}$$

where $EFC_{p,y}$ denotes the carbon emission factor of the city's electricity consumption in the yth year; CE_y denotes the total electricity consumption of the city in the yth year.

$$E_{grid,y} = EFC_y \cdot CE_{s,y} \tag{8}$$

where $E_{grid,y}$ denotes the carbon emission responsibility of the grid side in the yth year; $CE_{s,y}$ denotes the power transmission loss of the grid in the yth year.

4 Urban Carbon Emission Accounting Based on Electricity Statistics

Select urban characteristic factors closely related to urban carbon emissions, covering social, economic, physical geography, etc., including GDP, industry, transportation, total population, energy structure, industrial structure, technology level, foreign trade, energy consumption intensity, land Statistical data of each factor are obtained from statistical data such as China Urban Statistical Yearbook, China Statistical Yearbook and China Regional Statistical Yearbook over the years [9].

With the help of the extended STIRPAT equation, the influence of k factors on urban carbon emissions is analyzed, and m factors that have a significant impact on carbon emissions are obtained.

Using the extended STIRPAT equation to analyze the influence of k factors on urban carbon emissions, according to [10]:

$$\ln E = a + b_1 \ln B_1 + b_2 \ln B_2 + \ldots + b_k \ln B_k + \varepsilon_1 \tag{9}$$

where E denotes the urban carbon emission; a denotes a constant quantity; $B_1, B_2 \ldots B_k$ are the k factors that characterize the urban carbon emission characteristics; $b_1, b_2 \ldots b_k$ are the k factor coefficients respectively.

SPSS is used to process the data related to m factors that have a significant impact on urban carbon emissions over the years, and the method of ridge regression analysis is used to model the urban carbon emissions data and carry out a significance test. The constant number and k factors can be obtained. Factor coefficients. According to the obtained coefficients, the influence degrees of k independent variables on carbon emission changes are summarized, and m factors with significant influence on urban carbon emissions are obtained after sorting the influence degrees [11, 12].

Use XGBoost to calculate the feature importance of m factors, and select *n* factor sets for subsequent urban carbon emission accounting after scoring the importance of m features.

With the help of XGBoost, the feature importance of m factors is calculated, that is, the number of factors used in key decisions in the statistical decision tree. The more the number of times, the higher the relative importance. Then, the feature importance of m factors is scored to complete feature selection. The main steps are as follows:

1) Divide the data into training set and test set, and conduct model training on the entire training data set;
2) The feature importance calculated by using the training data set, that is, the number of factors used in the key decision-making in the statistical decision tree. The more the number of times, the higher the relative importance;
3) Wrap the training model in a Select From Model instance, repeat feature selection by setting different thresholds, and form feature subsets;
4) The model is then evaluated on the test set until the subset of the most important features is obtained.

Taking carbon emissions as the dependent variable, night lights and *n* significant influencing factors as independent variables, and calculating the urban carbon emissions with the help of the spatial Durbin model.

$$E_i = \omega Q_{ij} E_i + \lambda_1 C_i + \lambda_2 R_i + \gamma_1 Q_{ij} C_i + \gamma_2 Q_{ij} R_i + \varepsilon \tag{10}$$

where E_i denotes the carbon emission of city i; ω denotes the spatial regression coefficient of the carbon emission of city i; Q_{ij} denotes the spatial weight matrix, which is 1 when cities i and j are adjacent, and 0 otherwise; C_i is the night lights of carbon emission in city i; λ_1 and γ_1 are the accounting coefficients and spatial lag coefficients of night lights, respectively; R_i is the set of the aforementioned n factors in city i; λ_2 and γ_2 are the accounting coefficients and spatial lag coefficients of the set factors; ε denotes a random disturbance term that satisfies the normal independent and identical distribution.

5 Conclusion

Taking the typical megacities in my country as the research object, comprehensively considering the responsibility of producers and consumers, starting from the shared responsibility sharing accounting method, and using the equivalent value of electricity and the value of electricity as important indicators, the power carbon emission accounting model with shared responsibility for production and consumption is constructed. Select the urban characteristic factors that are strongly related to urban carbon emissions, based on the extended STIRPAT equation, and use XGBoost to score the importance of multiple features to complete the important feature selection. Taking carbon emissions as the dependent variable, night lights, electricity carbon emissions data, and other significant influencing factors as independent variables, the urban carbon emissions are calculated with the spatial Durbin model.

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