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Review

A Review of Research on the Estimation Methods and Influencing Factors of Urban Carbon Emission

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Abstract
Urban carbon emissions have a significant impact on global climate and environmental changes. Therefore, research on carbon emission has attracted worldwide attention. Based on studies of urban carbon emissions in recent years and aimed at the influence of different elements of urban carbon emissions, this paper attempts to summarize and compare the accounting methods for carbon emissions of energy consumption. To achieve this purpose, this paper reviews 5 methods of estimating carbon emissions (analysis of influencing factors, the eddy-covariance, inventory approaches, estimation of building energy models, remote sensing technologies). Focusing on these different methods, their advantages, disadvantages and applicability in countries, provinces, cities, buildings and other spatial scales, this paper can provide a reference for the scientific and reasonable estimation of carbon emissions in China.

Keywords: energy consumption, carbon emission, estimation methods

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1 INTRODUCTION

The carbon cycle is one of the basic driving forces of global climate. It has a significant impact on environment changes and global warming[1]. Studies have shown that global warming has been on the rise since the mid-19th century[2], and that greenhouse gases from human activities are the main cause of global warming[2,3]. Some studies suggest that China's greenhouse gas emissions in

2006 exceeded those of the United States, making China the world's largest carbon emitter[4]. The United Nations Framework Convention on Climate Change[5] was adopted in May of 1992, and the Kyoto Protocol[6] was adopted in December of 1997 in Kyoto, Japan. In 2015, China made the commitment to reduce its carbon emissions by 60-65% of the 2005 levels at the Paris Climate Change Conference. This put immense pressure on China's efforts to reduce its carbon emissions.

Major cities account for 75-80% of global greenhouse gas emissions[7] from buildings, transport facilities, large number of people, energy and waste[8]. A reasonable estimate of major cities' carbon emissions would therefore be cardinal to the development of a low carbon economy and energy saving strategies, and in the setting of targets carbon emission reduction.

This paper uses Meta analysis to review the literature on carbon emission research. The specific method used is that of searching the Web of Science database and sorting out the relevant literatures using such keywords as "carbon emission", "CO_2 emission" and "carbon dioxide emission". The paper only focusses on literature published since 2010. The paper attempts to systematically introduce and compare existing urban energy consumption emissions from the perspective of urban factors and estimation methods. It also attempts to summarize the characteristics of various methods and analyze their advantages, disadvantages, adaptability and limitations in different spatial scales, with a view to providing reference for further research of urban carbon emission reduction in China.

2 IMPACTS OF URBAN FACTORS ON CARBON EMISSION

Studies of the global carbon cycle have identified 3 main sources of anthropogenic greenhouse gas emissions namely fossil fuels, cement production, and changes in usage of land[9]. As a complex ecosystem of energy, industry and agriculture, consumption, production and transportation of urban fuel and changes in usage of land, waste emissions and other data are all related to the research of any country's carbon emissions[10]. The industrial layout, mode of transportation mode and construction of infrastructure all have important implications on energy demand and the carbon footprint[11]. Based on previous studies, this paper classifies the factors that have an important impact on carbon emissions in the urban ecological environment. These include such factors as land, population, the economy and energy. Please see Table 1 for details.

3 METHODS FOR ESTIMATING URBAN CARBON EMISSIONS

Many studies have been carried out on anthropogenic heat emissions on different scales both at home and abroad. These mainly include analysis of influencing factors, the eddy-covariance (EC), inventory approaches, estimation of building energy models and remote sensing technologies. Each of these methods has its own set of advantages and disadvantages, and should be carefully selected according to different scales and accuracy requirements. Table 2 illustrates the various methods of estimating carbon emissions.

3.1 Analysis of Influencing Factors

3.1.1 Decomposition Analysis

3.1.1.1 Index Decomposition Analysis (IDA)

The most widely used method was the logarithmic mean decomposition method (LMDI). This method does not produce residuals[23]. In addition, it was proved that LMDI was also more easily used by factor reversal and residual test[24].

IDA is a carbon emission relation established by the Kaya identity to decompose the CO_2 emission factors. The Kaya identity expressed the total carbon emission, F, as a product of 4 driving factors[25] according to Equation (1):

$$\mathrm{F} = \mathrm{P}\left(\frac{\mathrm{G}}{\mathrm{P}}\right)\left(\frac{\mathrm{E}}{\mathrm{G}}\right)\left(\frac{\mathrm{F}}{\mathrm{E}}\right) = \mathrm{Pgef}. \quad (1)$$

In the equation, P, G and E refer to the global population, global GDP and global energy consumption respectively. g=G/P is the per-capita global GDP, e=E/G is the energy intensity of global GDP, and f=F/E is the carbon intensity of energy. Obviously, carbon emissions were directly related to the per-capita GDP levels, energy intensity, the carbon intensity and population size.

Setting ΔX as the increment of variable X, and using LMDI, we can obtain the LMDI decomposition formula of carbon emission change (ΔF)[26] as shown in Equation (2):

$$\Delta \mathrm{F} = F_T - F_0 = \Delta F_p + \Delta F_g + \Delta F_e + \Delta F_f. \quad (2)$$

Population effect of scale:

$$\Delta F_P = \sum L(P_T, P_0) \ln\left(\frac{P_T}{P_0}\right)$$

Economies of scale:

$$\Delta F_g = \sum L(g_T, g_0) \ln\left(\frac{g_T}{g_0}\right)$$

Energy intensity effect:

$$\Delta F_e = \sum L(e_T, e_0) \ln\left(\frac{e_T}{e_0}\right)$$

Carbon emission intensity effect:

$$\Delta F_f = \sum L(f_T, f_0) \ln\left(\frac{f_T}{f_0}\right)$$

For a>0, b>0, the logarithmic mean L (a, b) was defined

Table 1. Influencing Factors

Influencing Factor	Characteristic	References
Land Use	There was a certain relationship between land use structure and carbon emissions. Urbanization and industrialization both accelerated the rate of increase of total carbon emissions.	Svirejeva-Hopkins et al.[12], Houghton[13], Sun[14]
Increased Population	There is a dynamic relationship between CO_2 and population growth. Population growth and urbanization, and miniaturization of the family increase carbon emissions by varying degrees.	Knapp et al.[15], Chen[16]
Economic Growth	There was a clear relationship between GDP and carbon emissions. Economic growth was one of the key factors contributing to carbon emissions.	Holtz-Eakin et al.[17], Guo[18], Tian et al.[19]
Energy Consumption	The intensity and type of energy, and industrial structure all had important implications on carbon emissions.	Bhattacharyya et al.[20], Gingrich et al.[21], Yang et al.[22]

as Equation (3):

$$L(a,b) = \begin{cases} \frac{a-b}{\ln a - \ln b} & a \neq b \\ A & a = b \end{cases}. \quad (3)$$

Based on LMDI and quantitative analysis, Fu et al.[27] analyzed the influencing factors of CO_2 emission in China. The results showed that the influence of economic output, energy structure, and population size on carbon emissions is positive, while that of energy intensity and industrial structure is negative. Li et al.[28] analyzed the influencing factors of China's carbon emissions from the national, regional and industrial scale from 2000 to 2012. He concluded that the continuous decline of energy intensity, especially industrial energy intensity, made an excellent contribution to the reduction of carbon emission. Using the LMDI factor decomposition model, Liu et al.[29] analyzed the impact of energy intensity, industrial structure and energy structure factors on carbon emission intensity in the 3 major industries. The results showed that our carbon emission intensity in general and in the 3 major industries moved downwards with the reduction of energy intensity and industrial structure adjustment.

3.1.1.2 Structural Decomposition Analysis (SDA)

The IDA method requires less data, and the annual change data is more easily obtained[30]. However, the IDA can only provide the effect of dynamic changes such as population size, economic scale, energy intensity and carbon intensity on carbon emission. It cannot comprehensively analyze the inter-industry correlation, neither can it examine the needs of indirect effects on carbon emissions in each department.

SDA is based on the input-output model. It was first proposed by Leontief and was studied in conjunction with SDA in 1971[31], including indirect demand effects[30]. Currently, SDA is applied in a wide range of different fields like energy, economy and trade.

The input-output model is calculated using Equation (4):

$$x = (I-A)^{-1}y. \quad (4)$$

Where y refers to the total input, $(I\text{-}A)^{-1}$ is the Lyndon mat matrix, and x is the total output. Multiplying the two ends of the formula by the carbon emission factor E, we obtain the total amount of carbon emissions[32,33] as shown in Equation (5):

$$F = E(I-A)^{-1}y. \quad (5)$$

If $y_v y_s y_t$ is divided by y, then the SDA model of energy consumption carbon emissions can be obtained as shown in Equation (6):

$$F = E(I-A)^{-1}y_v y_s y_t. \quad (6)$$

Where y_v is the scale effect, y_s is the structural effect, and y_t is the technical effect. The increment in energy consumption can be expressed as shown in Equation (7):

$$\begin{aligned} \Delta F = F_T - F_0 = \Delta F + \Delta F_g y_v y_s y_t \\ + F\Delta y_v y_s y_t + F y_v \Delta y_s y_t + F y_v y_s \Delta y_t. \end{aligned} \quad (7)$$

Li et al.[34] adopted the input-output method and established the SDA model. This divided the influencing factors into direct carbon emission intensity effect, intermediate production technology effect, export total effect and export structure effect to account for the implied carbon emissions from China's trade in 1997-2007. Guan et al.[35] used SDA to study the driving factors of rapid CO_2 growth in China from 2002 to 2005, and concluded that carbon emissions related to construction, machinery and equipment, and electronic products were important contributors to total carbon emissions. Yin et al.[36] analyzed the impact of population aging and upgrading of industrial structures on regional carbon emissions by using spatial econometric methods. The study found that the upgrading of industrial structures has a significant positive impact on the reduction of regional carbon emission. The current population aging and industrial structure upgrade have a significant positive correlation with regional carbon emission reduction.

3.1.2 Regression Analysis

Regression analysis was based on statistical data. It set all the principal components as a variable and used ordinary least square in the variable screening method to carry out regression modeling[37]. The research was mainly focused on two aspects: one was the environmental kuznets curve (EKC) between environmental quality and economic growth, and the other was on influencing factors of carbon emission based on the STIRPAT model. The EKC curve was proposed by Grossman et al. in 1991[38]. The resource demand generated by economic growth will have a negative effect on the environment. At the same time, the economic development promoted by technological progress and structural optimization will ultimately reduce pollution and improve the environment. Stern[39], Dina[40] and others conducted a further examination of the relationship between the environment and income. On the other hand, Zhu et al.[41] used the STIRPAT model to test carbon emissions in China from 1980 to 2007, and proved that population and consumption had a significant impact on changes of carbon emission in China. Using STIRPAT, Zhao et al.[42] found that 5 factors namely the population, level of economic development, energy intensity, urbanization and energy consumption structure were all positively correlated with carbon emissions.

The STIRPAT model is a random form of the environmental pressure equation IPAT. In order to study the environmental impact of human development, Ehrlich et al.[43] proposed the IPAT equation in 1971. This is shown in Equation (8):

$$\mathrm{I} = \mathrm{P} \cdot \mathrm{A} \cdot \mathrm{T}. \quad (8)$$

Where I is the environmental impact, P is the population size, A is the per-capita GDP, and T is the technology.

However, IPAT has some defects. It can only analyze one factor while keeping other factors constant. In order to overcome this limitation, Dietz et al.[44] proposed the STIRPAT model that can be used to analyze the effects of population on the nonlinearity of the environment. This is shown in Equation (9):

$$I_i = a \cdot P_i^b \cdot A_i^c \cdot T_i^d \cdot e_i. \quad (9)$$

Where a is a constant, b, c, d is the index to be estimated, and e is a random error. Taking its natural logarithm, we can obtain Equation (10) as shown below:

$$\ln I = \ln a + b \ln P + c \ln A + d \ln T + \ln e. \quad (10)$$

3.2 EC Approaches

The EC can be used to directly observe the urban carbon flux by determining the material and energy flux between the ecosystem and the atmosphere[45]. It is most commonly used for measuring surface fluxes[46]. The EC method requires flat terrain and homogenous wind conditions[45]. Therefore, studies using the EC method generally divided the research area into the central area, green area and suburbs[47]. While locating the instrument, it is important to consider the purpose of observation and to clearly define the land use information around the site[48]. However, since the urban system is complex and the EC method is still a small-scale observation approach, accuracy should be considered when the EC method is used in urban areas.

3.3 Inventory Approaches

Inventory approaches relied on energy consumption data to estimate the anthropogenic emission, assuming that all energy consumption was turned into anthropogenic heat. These approaches used various anthropogenic sources of energy from human metabolism, industry, transportation and building to get the corresponding anthropogenic heat emissions. The energy consumption data was then assigned to smaller scales in accordance with distribution law[49]. Based on the inventory algorithm, Li et al.[50] compiled the carbon emission inventory of Sichuan Province from 2010 to 2018 from 4 aspects: energy activities, industrial production, forestry activities and waste disposal. He then analyzed its change characteristics and judged the main emission sources. The results showed that energy activities were the main source of carbon emissions in Sichuan Province, and that developed areas produced a high level of carbon. Huang et al.[51] calculated the carbon emission inventory and future carbon emission reduction potential of Hubei Province by using the inventory and scenario methods. The results showed that the reduction of fossil energy consumption in high-energy consuming industries and the low-carbon treatment of garbage are the key points of carbon emission reduction in the future.

However, inventory approaches were done on the assumption that energy consumption was equivalent to anthropogenic sensible heat emissions without considering time lag, and they generally resolve energy consumption at coarse temporal scales[52].

3.4 Estimation of Building Energy Models

The building energy models used the energy consumption to derive the artificial heat of different types of buildings, and then derived upward to the research area[53]. Using meteorological data, building structure, heating and air conditioning system and system layout, indoor personnel case activities[54] and adopting the dynamic heat transfer process, these models can be used to calculate energy consumption at room temperature. Building energy models have made a few achievements. The Canadian CREEM model[55] divided residential areas into 6 types, and simulated the residential unit energy consumption by constructing model to estimate the energy consumption characteristics of Canadian buildings. The US HB model[56] simulated the spatial load of residential and commercial building blocks to estimate the energy consumption.

Wang et al.[57] used the SBM model to calculate the energy efficiency of the construction industry in different provinces of China from 2008 to 2017. The results showed that the development level of the construction industry, industrial concentration and energy structure have a significant positive impact on energy efficiency.

The building energy models provide new methods for studying carbon emission. However, it was difficult to obtain detailed parameters such as real-time meteorological data and people's living habits, which may have affected the accuracy of results to a certain extent.

3.5 Remote Sensing Technologies

3.5.1 Night Light Index Approaches

The Operational Linescan System (OLS) sensor, powered by the US Army Defense Meteorological Satellite Program (DMSP), can be used to detect low-intensity light data emitted by cities, residential areas, fires, etc. It was one of the ideal data used to monitor human activities. Elvidge et al.[58] demonstrated that DMSP/OLS nighttime light data can be used to estimate carbon emissions. Based on the DMSP/OLS night light image, Su et al.[59] estimated carbon emissions of the national prefecture-level city. Wu et al.[60] used DMSP/OLS nighttime light data to simulate the spatial and temporal dynamics of energy consumption throughout the country. However, the current use of DSMP/OLS night light images was generally used to estimate carbon levels at the global or national level.

Adopting night light images, the key to simulating carbon emissions is the establishment of the relationship between DMSP/OLS lighting data and carbon emissions statistics. Using the "2006 Greenhouse Gas Emissions Inventory" published by Intergovernmental Panel on Climate Change, CO_2 emissions from energy consumption can be calculated using Equation (11):

$$CO_2 = \frac{44}{12} \times \sum_{i=1}^{10} K_i E_i \,. \quad (11)$$

Where Ei is energy consumption (unit:10^4t), and Ki is carbon emission coefficient of i (unit: 10^4t carbon/10^4t coal).

The nighttime light data in the study area was obtained, a fitting analysis with the corresponding CO_2 emission statistics was conducted and the simulated values were compared to the statistics to verify the accuracy. The research conducted by Su et al.[59] and Wu et al.[60] showed that the accuracy of night light data is relatively high and reliable. However, factors such as the diffusion of light, special geographical location of cities and weak information on light in urban fringes and rural areas are likely to increase the uncertainty of night light data.

3.5.2 Heat Balance Model

The surface energy balance equation method measured or estimated the net radiation, horizontal conduction and underground heat storage, and used the energy conservation principle to indirectly calculate anthropogenic heat. In the study of anthropogenic heat emissions by energy balance, it was necessary to obtain meteorological data, surface cover data, ground albedo and impervious surface information for the inversion of artificial heat sources[61]. The surface energy balance was determined by the surface properties and the near surface artificial heat source, and an equation was proposed by Oke[62], as shown in Equation (12):

$$Q_f = H + LE + \Delta Q_S + \Delta Q_A - R_n. \quad (12)$$

Where R_n is the net radiation, H is the sensible heat, Q_f is the anthropogenic heat discharge, LE is the latent heat, ΔQ_S is the net heat reserve, and ΔQ_A is the horizontal advection heat.

In addition, Kato et al. also proposed near-surface energy balance equations[63,64], as shown in Equation (13):

$$Q_f = H + LE + G - R_n. \quad (13)$$

Where G is the ground heat flux. When the equation is used, the net radiation flux, sensible heat flux, latent heat flux and ground heat flux can be obtained by information of weather data, surface reflectivity and air-related parameters.

Based on this equation, Kato used AScTER and ETM + remote sensing and meteorological data to estimate the anthropogenic heat and latent heat in different seasons of Nagoya, Japan. The results were consistent with the energy consumption in this area, which proved that this method can be applied to a heat island study. However, the accuracy of the energy balance method was dependent on the resolution and algorithm of the underlying data, and appropriate spatial resolution should be identified in studies.

4 CONCLUSIONS AND DISCUSSION

The estimation methods and influencing factors of carbon emissions have made many explorations in theory and in practice. Urban carbon emission research has been transformed into a comprehensive model including a variety of elements such as population, economy, energy and technology. By combing through the existing research, this paper puts forward suggestions for further improving and perfecting the research of urban carbon emissions in the following aspects:

1) Currently, the methods on influencing factors of carbon emissions are relatively mature, and practical research has been carried out on different scales and in different fields. In order to better analyze carbon emissions in different regions of the world, we can focus on large-scale, long-term studies of carbon emission.
2) The most commonly used methods for studying urban carbon emissions were the EC and the inventory

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Table 2. Comparison of the 5 Carbon Emission Estimation Methods

Method			Features and Advantages	Limitations	Application Status
Influencing Factors	Decomposition Analysis	IDA	Easy access to data, less data required.	Unable to comprehensively analyze the relationship between industries.	LMDI is the most widely used method.
		SDA	Able to analyze direct and indirect impacts.	Requires a lot of data and complex calculations.	Widely used in energy, economy, trade and other fields.
	Regression Analysis		Based on statistics, all major influencing factors can be analyzed.	Unable to analyze indirect effects.	Widely used.
EC			Direct observation of urban carbon emission flux, and the results are more accurate.	Many conditions for on-site measurement, and its expensive.	Applicable to a certain range of small-scale observations.
Inventory App-roaches			Easy access to data.	The time-space lag is not considered, and the results are not very accurate.	Suitable for studies with low spatial and temporal resolutions.
Estimation of Building Ener-gy Models			Able to obtain unit energy consumption of different types of buildings by combining building models.	It is difficult to obtain data, which affects the accuracy of results.	Suitable for small-scale research in a given region.
Remote Sensing Technologies	Night light index approaches		Data is timely and easy to obtain.	Most discussions are about total carbon emissions.	Suitable for large-scale studies such as cities and countries.
	Heat balance model		Easy access to Remote sensing and meteorological data.	Accuracy depends on the resolution and algorithm of the underlying data.	Suitable for large-scale studies such as cities and regions.

approaches. However, these were limited by the observation condition. The EC approach is suitable for small scale studies, while the inventory approach is more suitable for large scale studies. The research of building monolithic on micro-scale has not made remarkable achievements in China. The database of building energy consumption is still not complete. This application could be combined with the survey data and the inventory approach.

3) The research of remote sensing technology methods in the field of carbon emissions mainly focuses on traditional remote sensing data such as night light data, surface cover data and ground albedo. There is a lack of research on new remote sensing data types such as unmanned aerial vehicle remote sensing data and multi-spectral remote sensing data. We can innovate and develop the application of multivariate remote sensing data in the field of urban carbon emission research.
4) With the introduction of various estimation methods, the research of urban carbon emissions will not be limited to the national and urban scales, but will be extended to cover microscopic scales such as different types of buildings and regions. For research on specific carbon emissions, the appropriate estimation methods should be selected according to the different temporal-spatial scale and accuracy requirements. In order to achieve carbon emission reduction targets, the development of low-carbon cities based on accurate estimation of carbon emissions will be the final direction of urban carbon emission management.

Conflicts of Interest

The authors declared no conflict of interest.

Author Contribution

All authors contributed to the manuscript and approved the final version.

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Abbreviation List

DMSP, Defense Meteorological Satellite Program
EC, Eddy-covariance
EKC, Environmental kuznets curve
IDA, Index decomposition analysis
LMDI, Logarithmic mean decomposition method
OLS, Operational Linescan System
SDA, Structural decomposition analysis

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