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Research Article

Research on Carbon Emission Allocation in Urban Public Buildings in Guangxi

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ABSTRACT

Currently, the allocation of carbon emissions in public buildings in China is mainly concentrated at the provincial level. This paper uses a hybrid research method of entropy method and data envelopment analysis under zero-sum games to study the allocation of carbon emissions in public buildings among different cities in Guangxi province. This method is flexible and comprehensive, taking into account various factors. Finally, through calculations, the feasibility of this method is verified, and the allocation of carbon emissions in urban public buildings in Guangxi province, under the condition of fixed total carbon emission, is determined. Among them, Nanning and Liuzhou can increase their carbon emission quotas by 96.8% and 91.6%, respectively, to improve economic efficiency and achieve the highest efficiency in carbon emission investment. On the other hand, baise needs to significantly reduce its carbon emission quota by 82.9% due to its lower efficiency. Guigang city, because of the balance between carbon emission investment and the current economic scale, requires a smaller adjustment, within 10%. This approach will help the government's efforts to reduce carbon emissions.

Keywords: Carbon Allocation, Urban Public Buildings, Entropy Method, Data Envelopment Analysis, Zero-Sum Games.

INTRODUCTION

With the continuous progress of urbanization, the issue of carbon emissions in urban public buildings has gradually become a hot topic in the field of global sustainable development. This issue involves multiple dimensions such as resource allocation, environmental protection, and social responsibility, and is crucial for improving the sustainability of urban construction. Especially in China, a country with a large urban population and a complex energy structure, the issue of carbon emissions in public buildings is of great concern.

In 2019, China's total energy consumption reached 4.86 billion tons of standard coal, an increase of 3.3% compared to 2018 (Ministry of Ecology and Environment of the People's Republic of China, 2020). The energy consumption of the building sector accounts for about 20% of the total energy consumption in society and is one of the largest sectors of energy consumption. Among them, urban public buildings are the focus of energy conservation and emission reduction efforts in the building sector, and promoting energy conservation and emission reduction in urban public buildings is of great importance and urgency.

Carbon Emission Allocation Methods

Research on carbon emission allocation methods is mainly focused on the national, regional, or industry-specific levels, with limited studies on urban public buildings. From a practical perspective, the primary methods for allocation in the building sector are historical emissions and baseline methods. From a research perspective, primary allocation methods can be further divided into indicator-based methods, optimization methods, game theory-based methods, and hybrid methods, among others (Zhou & Wang, 2016; Sun, 2021).

Historical Emissions Method

Japan's TMG ETS system uses the historical emissions method for carbon emission quota allocation in the building sector. In the "Shanghai 2016 Carbon Emission Quota Allocation Plan" (Hufagaihuanzi [2016] No. 138), the historical emissions method is also applied to buildings such as shopping malls, hotels, business offices, and airports. The annual basic quota for enterprises is equal to the historical emission base, which is generally the average emission from 2013 to 2015. The historical emissions method is simple but has dual disadvantages for energy-efficient buildings. First, energy-efficient buildings have low historical emissions, resulting in lower emission quotas, which is unfair to early emission reduction efforts. Secondly, the low potential for emission reduction and high cost hinder the deepening of emission reduction (Liu, Wu, & Chen, 2013).

Baseline Method

In the field of construction, Li, You, Zhang, and Xie (2012) determined the emission path of construction land under baseline conditions as the baseline, which varies with multiple factors such as time, output, and intensity. Pan (2015) believes that in the process of reducing emissions, countries should adjust their carbon emission standards according to their different stages. The establishment of benchmarks often requires a large amount of data support, especially if the buildings of an urban public building have significant differences. Setting benchmarks based on regions and categories is a challenging task and a high administrative cost for decision-makers (H. Jiang, 2019). Due to the lack of industry-level data on building energy consumption and greenhouse gas emissions (Science and Technology Development Promotion Center of the Ministry of Housing and Urban-Rural Development, 2013), More research is needed on the allocation of indicators using benchmark indicators and how to better utilize them.

Multi-Indicator Methods

Han, Yu, Tang, Liao, and Wei (2017) and Yi, Zou, Guo, Wang, and Wei (2011) established a complete set of evaluation indicators to overcome the problem of a single objective not taking into account multiple configuration principles. They weighted three standards, namely emission responsibility, capacity, and quantified various models in China and various provinces accordingly.

Optimization Methods

On this basis, linear and nonlinear optimization methods were used to optimize the allocation of carbon reduction emissions for enterprises. The most commonly used method is Data Envelopment Analysis (DEA) for performance evaluation and reconfiguration. For example, Wang, Zhang, Wei, and Yu (2013), Chiu, Lin, Hsu, and Lee (2013) and Chiu, Lin, Su, and Liu (2015), as well as Pang, Deng, and Chiu (2015) have focused their efforts on the national or provincial level.

Game Theory Methods

This project is based on the game theory of Zhou and Wang (2016) that attribute the initial allocation problem of carbon reduction to a cooperative game problem involving multiple participants, including dynamic game, cooperative game, and imperfect information game. Liao (2016) analyzed the electricity industry and found that the results of using the Shapley value method for allocation were very close to the results of using the baseline method, theoretically demonstrating that the baseline method is a more suitable initial allocation method (Tan, Lai, Gu, Zeng, & Li, 2018).

Regional Studies on Carbon Emissions in Chinese Public Buildings

Previous studies on the allocation of carbon emissions in Chinese public buildings have mainly focused on assessing and allocating emissions among different provinces. This provincial perspective is partly due to the incomplete statistics of panel data at the city level, which limits in-depth research on urban-level carbon emissions. However, in recent years, with the continuous advancement of data collection and analysis technologies, there have been more opportunities to delve into urban-level carbon emission issues.

This study aims to address the shortcomings of previous research by using a hybrid research method that includes a literature review, entropy method, and data envelopment analysis under the conditions of zero-sum games. It aims to investigate the issue of carbon emissions in urban public buildings at the city level, with a focus on cities in Guangxi province. This research not only focuses on carbon emission assessment but goes further to address a practical and complex problem: how to allocate carbon emission rights to achieve maximum efficiency under a fixed carbon emission cap.

To achieve this goal, the analysis and calculation data come from a combination of available panel data and calculated data. By using this model, we can quantitatively evaluate carbon emissions in multiple regions and spatiotemporal scales, thereby achieving an accurate understanding of carbon emissions at the urban scale.

This paper will unfold according to the following structure: before continuing with the detailed methods and data analysis of this research, we will first review relevant literature, including classical literature and recent studies, to identify the factors influencing carbon emissions in public buildings. On this basis, using panel data of different factors, identify factors with important weights, and conduct in-depth research on them using the entropy weight method. Secondly, the ZSG-DEA method was applied to optimize public buildings in different regions of Guangxi, obtaining their carbon reduction quotas at the highest effective level. On this basis, this article provides a brief summary of the research results and points out their role in future sustainable development.

LITERATURE REVIEW

Application of the Entropy Method in the Field of Carbon Emissions

On this basis, a new evaluation index system called entropy method was proposed. This method obtains the weights of each indicator by calculating the entropy of each indicator, achieving a comprehensive evaluation of multi indicator and multi indicator decision-making problems.

When studying carbon emissions, different information entropy methods were used. Han, Yu, Tang, Liao, and Wei (2017) used the revised Environmental DEA dataset (Information Coefficient DEA) method to evaluate the carbon emissions of various industries in China. The results indicate that the algorithm is more effective than conventional algorithms. Suh (2018) analyzed CO2 emissions in the United States using the entropy method. The research results indicate that the differences in carbon emissions between different regions will gradually increase, while the differences within the region will gradually decrease. The research approach is to take into account the differences between industries in order to minimize transaction costs. They believe that doing so is a reward for efficient companies and a punishment for inefficient companies.

Anex, Lund, and Grant (1999) used the maximum entropy method to estimate the volatile organic compound emissions in the wooden furniture industry. Their probabilistic approach provided information support for air quality modeling, policy assessment, and risk analysis. Remuzgo, Trueba, and Sarabia (2016) used a multidimensional general entropy measurement method to study the evolution of global greenhouse gas emission inequality from 1990 to 2011. They found that the greatest reduction in inequality occurred when emissions transfers between major polluters were weighted and the substitutability of pollutants was low.

Li, X. Li, Sun, and Xie (2022) proposed a balanced analysis model to predict carbon emissions in China and analyze influencing factors. They used grey relational analysis and logarithmic mean divisia index decomposition to identify key factors and predict future emissions using ridge regression. Their scenario analysis demonstrated the accuracy and practicality of the model in regional forecasting. Sabolová, Sečkárová, Dušek, and Stehlík (2015) analyzed methane emission data in Czech wetlands using entropy and Kullback-Leibler divergence. They developed a graphical tool to assess entropy in the system and applied it to wetland data. Qu et al. (2020) reviewed the theoretical basis, methods, and assessments of carbon emission decomposition analysis. The framework analyzed the characteristics and mechanisms of emission changes. Various studies indicate the wide applicability of entropy methods in understanding carbon emissions.

Application of Data Envelopment Analysis in the Field of Carbon Emission Allocation

Data Envelopment Analysis (DEA), proposed by Charnes et al. in 1978, is a mathematical programming method for evaluating the relative efficiency of different decision-making units (DMUs) with multiple inputs and outputs (Chiu et al., 2013). It is widely used in various comprehensive evaluation studies and has also been widely applied to the issue of carbon emission allocation.

Efficiency Evaluation for Allocation

When using DEA models for the efficiency evaluation of carbon emission quota allocation, CO2 emissions and carbon emission quotas are commonly used as two input or output indicators. CO2 emissions can be used as either input indicators (Pang et al., 2015; Miao, Geng, & Sheng, 2016; Chiu et al., 2015) or non-desirable output indicators (Cai & Ye, 2019; Fang et al., 2019; Chiu et al., 2013), with the latter construction of the production function being more realistic. Carbon emission quotas are typically used as input indicators (Ruan, 2017), and their corresponding output indicators usually include GDP and population, among others. Although treating carbon emission quotas as resource inputs is more realistic, using output indicators such as GDP and population also poses challenges in explaining the practical significance of the model. Some models simultaneously include both CO_2 emissions and carbon emission quotas, as Chiu et al. (2013) did, using carbon emission quotas as input indicators and CO_2 emissions as non-desirable outputs. They used the input-oriented super-efficiency SBM-ZSG-DEA model to study 24 European Union countries, considering more factors and being more suitable for cases where allocation has been completed in practice and efficiency needs to be evaluated (Banker, Charnes, & Cooper, 1984).

Efficiency Optimization for Allocation

Through efficiency evaluation, the efficiency status of each DMU can be determined, and the allocation of non-DEA efficient DMUs can be optimized. In the ZSG-DEA model, with a fixed total carbon emission, any gain (or loss) of carbon emission rights by one DMU inevitably leads to a loss (or gain) of carbon emission rights by other DMUs. Non-DEA efficient DMUs achieve maximum efficiency (reaching the production frontier) and must reduce inputs or increase outputs, thereby changing the production frontier. Through this process, all DMUs can become DEA efficient, achieving Pareto-efficient allocation of carbon emission rights. For example, Gomes and Lins (2008) conducted a carbon emission reallocation study of 64 countries worldwide. They used CO_2 emissions as input factors, and population, energy consumption, and GDP as invariant outputs. They initially used the traditional CCR DEA model to determine the efficiency of each DMU and then used the ZSG-DEA CCR input-oriented model to reallocate CO2 emissions, achieving 100% efficiency for all emission entities to achieve fairness (Wu, Du, Liang, & Zhou, 2013). Pang et al. (2015), building on the theory of Lins et al. (2003), developed a non-desirable output-oriented ZSG-DEA model to reallocate carbon emission quotas for 124 Kyoto Protocol participating countries (Cai & Ye, 2019).

Factors Influencing Carbon Emissions in Urban Public Buildings

This research focuses on the factors influencing carbon emissions in urban public buildings. To conduct this study, a literature analysis approach was employed. Searches were conducted in databases such as CNKI and Google Scholar using keywords like "urban public buildings," "carbon emissions," "influence factors," and "carbon emission influencing factors." After obtaining relevant literature, a screening process was carried out, followed by analysis. Six key aspects were identified as factors influencing carbon emissions in urban public buildings: urban population, urban development, economic development, industrial structure, per capita income level, and forest resources. These factors formed the basis for the allocation of carbon emission rights at the provincial and city levels.

Urban Population

Urban public buildings serve as places for providing public services, and population factors are considered one of the potentially significant factors in carbon emissions related to public buildings (Ying, 2015; X. Jiang, 2012). Carbon emissions result from indoor activities, and an increase in urban population and population density leads to an increase in the number of people served by public buildings, thereby increasing carbon emissions (Wu, 2012). In studies related to carbon emissions within urban areas, urban population size and population density have consistently been key factors of research (Wu, 2012). Some studies suggest that cities with higher population densities generally have higher levels of economic development, widespread use of energy-saving technologies, and a better awareness of energy conservation and emission reduction, which contributes to reducing carbon dioxide emissions (Cai, 2011). Therefore, this research adopts two indicators, namely, total urban population and population density, to assess population differences across regions.

Urban Development

With the acceleration of urbanization in China, the area of urban construction land continues to expand, and its greenhouse gas emissions have also increased (X. Zhang, 2018). The quantitative research on the degree of urban development generally adopts the methods of urban land use, fixed assets investment, etc. Urban land includes a portion of the city's public services. In addition, the increasing amount of urban construction land in China has led to CO2 emissions (Wu, 2012). Infrastructure investment includes infrastructure investment, renovation investment, and other investments related to municipal public facilities. Therefore, this article selects urban construction land and urban fixed asset investment index as the standard to measure the gap in urban development level among different regions.

Economic Development

There exists a regional imbalance in building carbon emissions, and factors such as economic development and consumption levels are essential contributors (Pan, 2015). Particularly in the case of public buildings, regional economic development can drive the construction of urban public buildings, leading to a substantial increase in the number and size of large urban public buildings, resulting in an increase in carbon emissions (Wu, 2012). Hence, the design of a carbon emissions trading mechanism for urban public buildings needs to consider the coordination of economic development and emission reduction goals in different regions. Flexible allocation rules need to be formulated based on the varying levels of economic development in different regions (Gao, 2018). To assess differences in regional economic development, the regional gross domestic product (GDP) is chosen as a research indicator.

Industrial Structure

Industrial structure has a significant impact on changes in carbon emissions from urban public buildings (Wu, 2012). Various regions have different industrial structures. Although increases in the output value of the primary, secondary, and tertiary industries all lead to increased carbon emissions in regions, for the third industry corresponding to urban public buildings, there are relatively fewer avenues for emissions reduction, lower emissions reduction potential, and higher emissions reduction costs. Regions with better economic development and higher levels of urbanization have a larger proportion of the tertiary industry, leading to increased carbon emissions demand (Xiang, 2013). Therefore, the proportion of added value of the tertiary industry corresponding to urban public buildings in GDP is selected as an indicator of industrial structure, used to measure differences in industrial structure between regions. The added value of an industry refers to the value added by production activities in that industry, reflecting the scale and pace of production. Different types of public buildings have different functions, and the production activities that occur within these buildings differ. However, energy consumption and carbon emissions are both used to maintain the normal operation of buildings and provide necessary support for production activities. The industries corresponding to urban public buildings include wholesale and retail trade, accommodation and catering services, transportation, warehousing, and postal services, among others (Wei, 2004).

Per Capita Income Level

The per capita income level of urban residents directly influences their consumption behavior. According to research by Xiang (2013), the largest sectors of expenditure for Chinese residents are education, medical care, and public services (accounting for 15.65%), followed by wholesale and retail trade, accommodation, and catering services (accounting for 12.39%) (Charnes, Cooper, & Rhodes, 1978). These two categories of consumer behavior indirectly promote increased energy consumption and carbon emissions in the operation of urban public buildings. Additionally, as per capita income levels rise, people tend to increase their demands for building comfort, leading to increased demand for indoor heating, cooling, appliances, lighting, and other energy-consuming services, resulting in increased energy consumption and carbon emissions (X. Jiang, 2012). Per capita income levels vary across regions, and people's expectations for the services provided by urban public buildings also differ, thereby affecting the allocation of carbon emission rights between regions. Therefore, the per capita disposable income of urban residents is chosen as an indicator to measure differences in per capita income levels.

Forest Resources

Protecting forests and reducing tree loss can absorb and offset the carbon dioxide emissions produced by people in their production and daily lives, mitigating greenhouse gas pollution to some extent. Different regions have different ecological environments, and the capacity of urban public buildings to absorb carbon dioxide emissions varies accordingly. For example, in regions with a lower forest coverage rate, where the percentage of forest area to total land area is smaller, the space available for carbon emissions from urban public buildings will be more constrained. Allocating fewer carbon emission rights can promote emission reduction and trading. Therefore, the forest coverage rate indicator is chosen to assess the differences in the urban ecological environment between regions.

The specific data for the influencing factors are obtained from the "Guangxi Statistical Yearbook" and calculations. The sources of the indicators for the influencing factors are presented in **Table 1**, and the specific data for each indicator are provided in **Table 2**.

Table 1. Indicators and Sources of Influencing Factors

Factor	Indicator	Unit	Source
Urban Population	Urban Population Count	Ten thousand people	Guangxi Statistical Bureau
Urban Development	Urban Construction Land Area	Square kilometers	Guangxi Statistical Bureau
	Urban Fixed Asset Investment	Hundred million yuan	Guangxi Statistical Bureau
Economic Level	Regional Gross Domestic Product (GDP)	Hundred million yuan	Guangxi Statistical Bureau
Industrial Structure	Proportion of Added Value of Tertiary Industry	%	Guangxi Statistical Bureau, calculations
Per Capita Income Level	Per Capita Disposable Income	Yuan	Guangxi Statistical Bureau
Forest Resources	Forest Coverage Rate	%	Guangxi Statistical Bureau

Table 2. Specific Data for Each Indicator (2021)

2021	Urban Population Count (ten thousand people)	Urban Construction Land Area (ten thousand square meters)	Urban Fixed Asset Investment (hundred million yuan)	Regional Gross Domestic Product (GDP) (hundred million yuan)	Proportion of Added Value of Tertiary Industry (%)	Per Capita Disposable Income (yuan)	Forest Coverage Rate
Nanning City	616.4	327.1	5320.76	4140.94	69.48	41394	35.26
Liuzhou City	293.65	275.9	3090.19	2337.65	51.11	41442	44
Guilin City	264.2	132.8	2785.35	974.89	65.91	40739	40.81
Wuzhou City	157.09	68.86	2231.55	693.09	45.49	37185	43.02
Beihai City	110.25	84.96	1681.3	1153.01	43.03	40727	41.88
Fangchenggang City	66.09	50.38	618.25	648	34.08	39676	42.97
Qinzhou City	141.77	90.16	1935.65	726.21	52.25	40170	40.21
Guigang City	219.45	179.23	1411.32	788.5	43.58	36756	41.66
Yulin City	293.11	73.57	2441.04	685.04	60.56	40314	39.68
Baise City	159.17	65.01	1270.16	543.95	39.68	36375	39.51
Hezhou City	100.66	56.72	965.33	557.96	43.61	36665	41.44
Hechi City	157.03	43.12	874.01	385.35	57.05	33351	39.29
Laibin City	102.04	53.36	787.43	413.09	50.01	38705	38.9
Chongzuo City	93.64	31.79	1565.86	238.76	51.98	36947	40.09

METHODOLOGY

Entropy Method

The entropy method is an objective weight determination technique for multi-index decision-making, which is based on information entropy theory and utilized to assess the level of dispersion of an index. The greater the degree of dispersion, the more significant the impact this index has on comprehensive evaluation. In the entropy method, first, all carbon emission influencing factors were normalized to ensure they have similar measurement scales. Then, the entropy value of each factor was calculated to measure its uncertainty. The relative entropy value represents the importance of each factor. Finally, these relative entropy values were used to calculate the weights to determine each factor's contribution to carbon emissions. The calculation formulas are as follows. Normalized Data:

Positive Indicator

$$\frac{X-Min}{Max-Min} \tag{1}$$

Inverse Indicator

$$\frac{Max-X}{Max-Min} \tag{2}$$

Where X is the original data, Min, and Max are the minimum and maximum values of the indicator, respectively.

Entropy Value

$$E_j = -\sum_{i=1}^{n}\left(P_{ij}\cdot\log\left(P_{ij}\right)\right) \tag{3}$$

Ej: The entropy value of the jth factor; n: the number of decision units; Pij: the probability distribution of normalized data Xij.

Relative Entropy Value

$$RE_j = 1-\frac{E_j}{\log(n)} \tag{4}$$

REj: The relative entropy value of the jth factor.

Weights

$$W_j = \frac{RE_j}{\sum_{j=1}^{m} RE_j} \quad (5)$$

Wj: The weight of the jth factor; m: the number of factors.

ZSG-DEA Model Analysis

To evaluate the efficiency of carbon emission allocation, it is necessary to consider whether carbon emission rights can adapt to the development of urban public buildings. A DEA model, which includes input and output variables, is constructed for this purpose. By explicitly considering the utilization of multiple inputs and the generation of multiple outputs, it can be utilized to compare the efficiency of various service units providing similar services, employing a technique known as data envelopment analysis (DEA). This approach eliminates the need for calculating the standard cost of each service by converting multiple inputs and outputs into numerators and denominators of efficiency ratios without requiring conversion into a common monetary unit. Therefore, utilizing the efficiency of DEA measurement can provide a complete and reliable characterization of the input-output structure, which is more inclusive and reliable compared to a set of operating ratio or income measurement methods. Currently, when using DEA methods to evaluate carbon allocation efficiency, there are often four situations: one is using carbon dioxide emissions as the input index, and the other is Cucchiella, D'Adamo, Gastaldi, and Miliacca (2018); Using CO2 emission values as unsatisfactory output indicators, just like Pang et al. (2015) and Miao et al. (2016); Cai and Ye (2019) and Fang et al. (2019) used carbon emission rights as a measure of input. Chiu et al. (2013) used greenhouse gas emissions and CO2 emissions as indicators of input and suboptimal output, respectively.

On this basis, based on the carbon quota system, the carbon reduction of public buildings is taken as the research object to evaluate their allocation efficiency. High-weighted factors extracted using the entropy method are considered as output variables, constructing an input-oriented ZSG-DEA model (Zero Sum Game-Data Envelopment Analysis).

Here, it is necessary to calculate the carbon dioxide emissions of urban public buildings. Calculating carbon emissions from the bottom up is more accurate but requires extensive, continuous, and actual data support. Using macroeconomic statistical data is more convenient and transparent and is more operationally feasible at the present stage. Therefore, this study employs a top-down calculation method, using data from the China Energy Balance Sheet in the China Statistical Yearbook to calculate carbon emissions from urban public buildings.

Calculating actual carbon emissions for each region:

$$\mathrm{CO}_{2\ total,\ year} = \Sigma E_i \times CEF_i \quad (6)$$

Where: CO2 total, year—Total carbon emissions from urban public buildings in a certain year (kgCO2)

Ei—Energy consumption of urban public buildings of type i (unit/a)

CEFi—CO2 emission coefficient of energy type i (kgCO2/unit)

i—Energy consumption types of urban public buildings, including electricity, gas, petroleum, municipal heating, etc.

Zero-Sum Game Data Envelopment Analysis (ZSG- DEA):

$$S_i = \frac{\sum_{j=1}^{m} \lambda_j \cdot x_{ij}}{\sum_{j=1}^{m} x_{ij}} \quad (7)$$

Si: Efficiency score of the ith decision unit; m: number of input factors; Xij: Value of the ith decision unit on the jth factor; λj: Weights in the zero-sum game model.

Research Model

Figure 1 represents the research model for this paper.

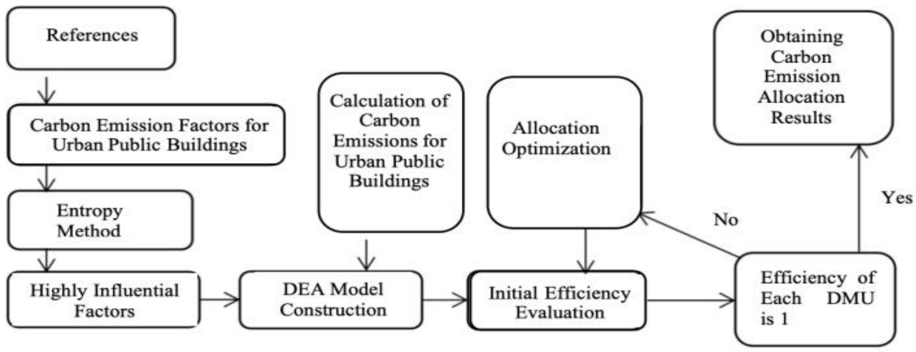

Figure 1. Research Model

RESULTS

Factors Affecting Carbon Emissions in Urban Public Buildings

Official figures are delayed, and according to the most recent data available, using the Guangxi Statistical Yearbook 2022 edition, relevant data for factors affecting carbon emissions in urban public buildings were queried and calculated, as shown in **Table 3**.

Table 3. Factors Affecting Carbon Emissions in Urban Public Buildings

2021	Urban Population Count (ten thousand people)	Urban Construction Land Area (ten thousand square meters)	Urban Fixed Asset Investment (hundred million yuan)	Regional Gross Domestic Product (GDP) (hundred million yuan)	Proportion of Added Value of Tertiary Industry (%)	Per Capita Disposable Income (yuan)	Forest CoverAge Rate
Nanning City	616.4	327.1	5320.76	4140.94	69.48	41394	35.26
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Chongzuo City	93.64	31.79	1565.86	238.76	51.98	36947	40.09

Entropy Method Solution

The results of the entropy method analysis on the normalized data for factors affecting carbon emissions in public buildings are shown in **Table 4**.

The weight distribution for each factor and descriptive statistics can be found in **Figure 2** and **Table 5**.

Table 4. Summary of Entropy Method Weight Calculation Results

Item	Entropy Value (e)	Information Utility Value (d)	Weight Coefficient (w)
Urban Population Count(ten thousand people)	0.8496	0.1504	18.46%
Urban construction land area (ten thousand square meters)	0.8173	0.1827	22.43%
Urban fixed asset investment (hundred million yuan)	0.8671	0.1329	16.31%
Regional gross domestic product (GDP) (hundred million yuan)	0.8073	0.1927	23.66%
Proportion of Added Value of Tertiary Industry (%)	0.9303	0.0697	8.56%
Per Capita Disposable Income (yuan)	0.9527	0.0473	5.81%
Forest Coverage Rate	0.9612	0.0388	4.77%

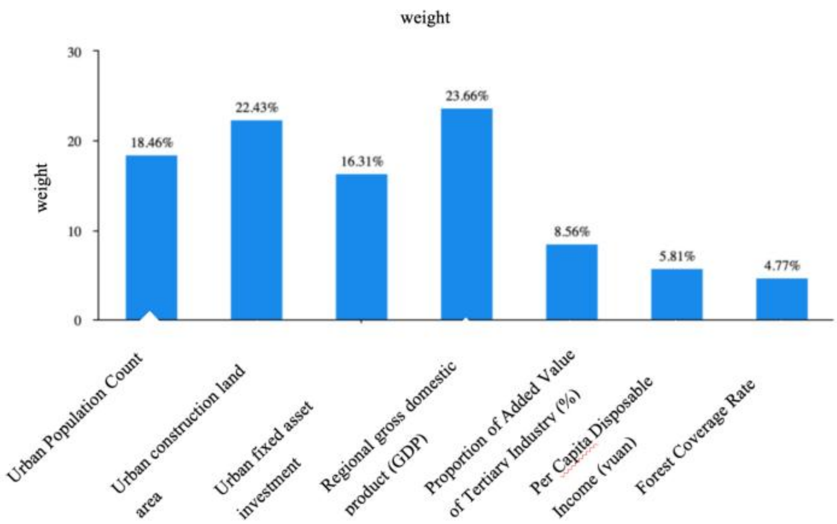

Figure 2. The Weight of Each Indicator

Table 5. Descriptive Statistics

Item	Sample Size	Mean	Standard Deviation
MMS_Urban Population Count(ten thousand people)	14	0.240	0.257
MMS_Urban construction land area (ten thousand square meters)	14	0.263	0.306
MMS_Urban fixed asset investment (hundred million yuan)	14	0.278	0.263

Item	Sample Size	Mean	Standard Deviation
MMS_Regional gross domestic product (GDP) (hundred million yuan)	14	0.200	0.264
MMS_Proportion of Added Value of Tertiary Industry (%)	14	0.465	0.284
MMS_Per Capita Disposable Income (yuan)	14	0.649	0.299
MMS_Forest Coverage Rate	14	0.614	0.250

From **Figure 2** and **Table 5**, it can be observed that the three factors, the proportion of the third industry output, per capita disposable income of urban residents, and forest coverage rate, have relatively weak influence and high data dispersion. These factors are not conducive to further analysis and calculation. Therefore, using the urban population, urban construction land area, urban fixed asset investment, and regional GDP as the four factors, the DEA analysis is carried out in the next step to determine the optimal carbon emission allocation for each city.

ZSG-DEA Model Solution

Based on the ZSG-DEA model, carbon emission rights allocation for urban public buildings is carried out. Urban public building carbon emissions are used as input indicators, and urban population, urban construction land area, urban fixed asset investment, and regional GDP are used as output indicators. The application process is shown in Figure 1. There are four main steps: constructing the input-oriented DEA model, conducting an efficiency evaluation, optimizing the allocation, and checking the efficiency of the optimized allocation. The optimization continues until the allocation efficiency for all decision-making units reaches 100%. The final results of carbon emission rights allocation for various cities in Guangxi Province are shown in **Table 6**, and the allocation efficiency and carbon emission quota for different cities under initial and final allocation conditions are shown in **Figure 3**.

Table 6. Allocation Efficiency Evaluation Data Based on DEA Model for Historical Emission Method

DMU	Initial Allocation (10,000 tons)	DEA CCR Initial Efficiency	Final Allocation (10,000 tons)	ZSG-DEA Final Efficiency	Allocation Difference (10,000 tons)	Change Rate
Nanning City	637.14	1	1253.651154	1	616.5111543	96.8%
Liuzhou City	441.56	1	845.8375854	1	404.2775854	91.6%
Guilin City	353.95	0.895	295.1436215	1	-58.80637851	-16.6%
Wuzhou City	238.55	1	209.8299203	1	-28.72007973	-12.0%
Beihai City	218.66	0.901	430.2403225	1	211.5803225	96.8%
Fangchenggang City	236.98	0.421	466.2868079	1	229.3068079	96.8%
Qinzhou City	262.99	0.833	219.8568541	1	-43.13314591	-16.4%
Guigang City	264.82	1	238.7148758	1	-26.10512416	-9.9%
Yulin City	258.83	1	207.3928185	1	-51.43718153	-19.9%
Baise City	962.13	0.16	164.6784463	1	-797.4515537	-82.9%
Hezhou City	217.22	0.527	168.9199117	1	-48.30008835	-22.2%
Hechi City	210.97	0.667	116.6629994	1	-94.3070006	-44.7%
Laibin City	299.7	0.351	125.0611558	1	-174.6388442	-58.3%
Chongzuo City	211.06	0.787	72.28352659	1	-138.7764734	-65.8%

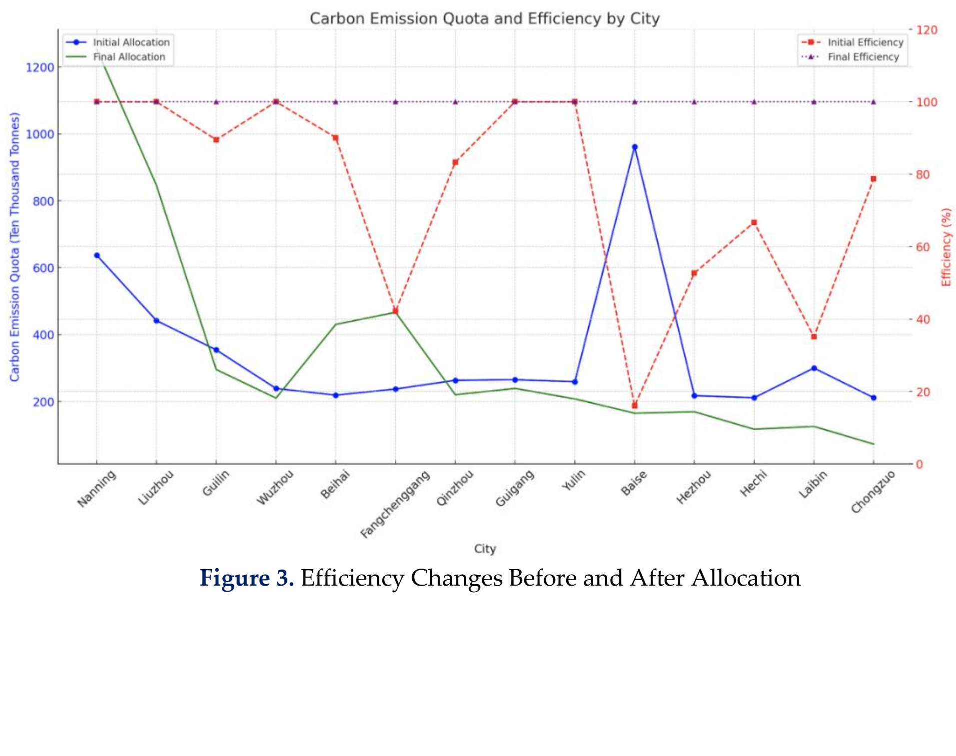

Figure 3. Efficiency Changes Before and After Allocation

From **Table 6**, it can be seen that the initial efficiency of carbon quotas for public buildings in Guangxi Province only reached 1 for five cities: Nanning, Liuzhou, Wuzhou, Guigang, and Yulin, which achieved efficiency at the frontier. Subsequently, under the premise of a constant total carbon emission allocation, the Zero-Sum Game-Data Envelopment Analysis (ZSG-DEA) was employed to optimize the allocation of urban public buildings in different regions, ultimately maximizing the allocation efficiency in all regions. Both the province and individual regions achieved 100% allocation efficiency. This approach not only achieved total control of carbon emissions in the province but also ensured that the allocated carbon emission rights in various regions were in line with their development foundation and structure, achieving the dual goals of fairness and efficiency.

Figure 3 shows the initial and final carbon emissions, as well as their corresponding comparisons of initial and final efficiency across cities. This graph adopts a bidirectional approach, where the main y-axis (left) is the carbon emissions calculated in tons, and the second y-axis is the efficiency calculated in percentage. From the initial distribution to the final distribution, most cities will see a significant decrease in carbon dioxide emissions, perhaps because carbon dioxide emissions will become more severe, or corresponding adjustments will be made based on actual emissions. Especially in the Baise region of Guangxi, the carbon reduction emissions have significantly decreased, indicating that the carbon reduction strategy in the region has changed. The tendency towards efficacy manifests in different forms; From beginning to end, some cities maintain a 100% energy efficiency level, demonstrating consistency in their performance compared to the assigned indicators. In sharp contrast, some other cities have encountered some problems in energy conservation, which can be understood as their performance being relatively low compared to carbon emissions. There are many factors that contribute to this change, including changes in industrial activities, the implementation of new technologies, and changes in management.

CONCLUSION

The project comprehensively applies various methods such as literature review, information entropy, and ZSG-DEA to study the allocation of carbon emission quotas in public buildings in China. This project theoretically demonstrates the rationality of the ZSG-DEA based carbon emission optimization configuration model for public buildings in China, reflecting its adaptability and universality to various elements. This project will further improve the role of the ZSG-DEA method in carbon emission trading for public buildings in China, and provide corresponding policy recommendations for the Chinese government. The empirical analysis of carbon emission rights allocation for 2018-2021 provided reference points for both the initial allocation and compensated allocation of carbon trading for urban public buildings.

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CONFLICT OF INTEREST

We declare that we do not have any commercial or associative interest that represents a conflict of interest in connection with the work submitted.

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