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Original Research

Impacts of the Urban Environment on Carbon Emissions from Residential Building Operations in Small Cities: An Empirical Study in China

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Abstract

Small cities warrant focused attention for robust low-carbon development strategies due to their significant numbers. In these cities, residential buildings emerge as notable contributors to carbon emissions, consuming substantial energy in their operations. This study employs an optimized IPAT equation, utilizing government statistical data, satellite remote sensing images, and panel data models to analyze the impact of the urban environment on carbon emissions from residential building operations (CERBOs) in 36 small Chinese cities. The findings reveal geographical variations in sensitivity to scale, economic, and spatial structure factors. Population size, municipal jurisdiction area, urbanization level, GDP, and per capita disposable income significantly contribute to CERBOs. Particularly, a 1% increase in municipal jurisdiction area leads to a 1.698% increase in total CERBOs, the highest influencing factor. Spatial structure only affects western cities, with compact development being more conducive to reducing CERBOs. Notably, carbon emissions from electricity are more influenced by environmental factors than those from heating and gas. The study proposes region-specific low-carbon planning strategies based on these findings. The theoretical optimization model proposed in the study, as well as the identified impact factors, will provide a theoretical basis and data support for understanding and reducing carbon emissions in small cities.

Keywords: urban environment impact, residential building, operational carbon emissions, small cities, panel data model

Introduction

Small cities are the basic units of national territory in the "city–town–village" system. Its low-carbon development plays an important role in achieving the "carbon peaking and neutrality" goal for the country. Although the carbon emissions of small cities are lower than those of large cities, their quantity is relatively large, and the contradiction between economic development needs and carbon emission reduction goals is more prominent [1-3]. In other words, the economic foundation of small cities is relatively backward, and low-carbon

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development faces significant financial challenges, requiring attention to more affordable and controllable factors [4, 5]. Under the promotion of urbanization, small cities will continue to prioritize economic development and increase construction in the future, which will continue to increase energy demand and carbon emissions in urban buildings [6]. Operational carbon emissions account for a considerable proportion of the entire life cycle of a building, up to 80% [7-9], including carbon emissions from electricity, gas, and heating [9, 10]. Residential buildings lead in both energy consumption and carbon emissions among all types of buildings [11, 12]. According to the Report on Carbon Emissions in China's Urban and Rural Construction Sector in 2022, the carbon emissions from residential building operations accounted for about 61% of the overall building operational carbon emissions in 2021, which is much higher than those of public buildings [13]. Reducing carbon emissions from residential building operations will have a significant impact on overall carbon reduction in small cities [14, 15].

Scholars widely agree that by comprehensively considering and optimizing urban environmental factors, effective strategies can be implemented in cities to reduce overall carbon emissions from residential buildings [16-22]. The universally recognized elements of urban environmental impact include two aspects: socio-economic and spatial structure.

- Regarding socio-economic factors, the IPAT equation has consistently been one of the most crucial theoretical models for studying the impact of socio-economics on carbon emissions, which considers environmental impacts (I) as a function of population (P), affluence (A), and technology (T) [23]. The impact of population factors is much higher in underdeveloped regions than in developed countries, meaning that population growth in small cities or rural areas contributes much more to environmental impacts than in large cities [24]. Affluence is another recognized aspect of influence, typically measured by per capita GDP and per capita disposable income [25]. The higher the level of affluence, the greater the pressure on the environment [26]. An increasing number of studies argue that solely evaluating affluence through GDP per capita overlooks the multifaceted sociological dimensions of this metric [27]. Additionally, a single linear relationship does not align with the environmental Kuznets curve, which illustrates an inverted U-shaped correlation between per capita income and environmental degradation [28, 29]. However, identifying a turning point in the curve, where environmental conditions notably improve without deliberate shifts toward carbon-reducing technologies, poses a significant challenge in countries where CO_2 emissions escalate alongside energy consumption and economic growth [30, 31]. The technology variable is generally treated as a residual term in the model and is not evaluated directly. It acts as a complementary variable in the equation to represent all factors involved, except population and affluence level [32, 33].
- In the realm of urban spatial structure, current research suggests that factors like land use patterns and urban density significantly impact the clustering of regional development, urban economic levels, and the scale and layout of infrastructure construction, thereby affecting cities' overall carbon emissions [34-36]. Moreover, studies confirm that maintaining an appropriate level of urban compactness can effectively manage urban sprawl and preserve green spaces to mitigate building carbon emissions [37]. Nevertheless, a certain threshold of urban compactness can lead to various socio-environmental challenges, including urban heat islands, a deterioration in air quality, and an increased release of greenhouse gases [38, 39]. Despite the consensus among scholars regarding the importance of rationalizing the spatial structure of cities and towns to achieve long-term carbon constraints [40-42], the research on low-carbon spatial planning for small cities is still in the exploratory stage due to the limitations of statistical data and research methods.

In conclusion, urban environmental factors play a significant role in the carbon emissions of residential buildings. However, existing studies predominantly concentrate on large or typical cities, leaving the applicability of these findings to small cities yet to be fully confirmed. In light of this, this study first builds a theoretical model of the environmental impacts of carbon emissions from residential building operations in small cities based on the classical IPAT equation. Then, 36 small cities in 11 provinces (including county-level cities) are selected as research objects to conduct an empirical study on the impact of urban environments on carbon emissions from residential building operations, including carbon emissions from electricity, gas, and heating. Primary databases are constructed from government statistical yearbooks. Urban spatial structures based on land use data are obtained from remote sensing images. Panel data models and stepwise regression models are established for quantitative calculation. Finally, based on the results of the analysis, we propose low-carbon-oriented planning recommendations for small cities in different regions. The results are expected to provide a theoretical basis for recognizing the mechanism of influence of urban environments on the carbon emissions of residential buildings and a practical basis for providing methodological and quantitative results to support decision-making in low-carbon-oriented planning for small cities.

Data and Methods

Overview of Sample Cities

The criteria for determining small cities refer to the classification issued by the State Council of China, which refers to cities with a permanent urban population of less than 500,000 [43]. At present, the statistical method of urban data in China is bottom-up, including socio-economic data and energy consumption data, which may lead to differences in the statistical method, data form, and data category of each city. Especially in small cities with relatively lagging economic development, urban data statistics are not standardized, and the lack of energy consumption data required for this study is quite common. In the data collection process of this study, we found that overall, the statistical work of urban data in small cities began to gradually improve after 2015, especially in terms of urban energy consumption. Therefore, considering the classification criteria for small cities and whether they have complete statistical basic data, the final observation period of the study was determined to be from 2015 to 2021, and 36 county-level cities in 11 provinces were chosen as the study areas. The preliminary data for 36 sample cities is shown in Table 1 (using 2021 data as an example). The sample cities are scattered across four economic zones in China, including the eastern, western, central, and northeastern regions. From Table 1, it can be seen that although the population of these cities is below 500000, they are not consistent in terms of area, urbanization level, and economic development, which also ensures that the selected samples cover the diversity of small city development as much as possible. Due to the wide variety and large amount of data involved in this study, the study considers that outliers may have an impact on subsequent analysis results. Therefore, in the process of data collection, boxplot statistics will be conducted for each type of data to find individual outliers, and they will be removed or replaced using interpolation methods according to specific situations.

Carbon Emissions from Residential Building Operations (CERBOs)

CERBOs encompass both direct and indirect carbon emissions [44, 45]. Direct emissions originate from fossil energy sources like cooking, hot water, and decentralized heating. Indirect emissions stem from electricity and heat usage. Considering energy sources, CERBOs comprise electricity (CE), gas (CG), and heating (CH) components [46, 47]. Data for these energy types were sourced from the 2015–2021 Statistical Yearbook of China's Urban Construction and city-specific statistical yearbooks. As all energy consumption data were standardized to coal equivalent, the IPCC 2006 National Greenhouse Gas Inventory Guidelines' emission factor method was employed to calculate CERBOs (Equation (1)). The descriptive statistics of CERBOs obtained from the sample cities through research calculations are shown in Table 2.

$$C_T = \sum_{i=1}^{n} e_i * f_i \tag{1}$$

where C_T represents CERBOs (tons), e_i is the terminal consumption of energy source i, f_i is the carbon emission factor for energy source i, and n is the number of energy sources.

Urban Environmental Impact Factors

This study made targeted optimizations based on the classical IPAT equation, which usually involves three categories: (1) population; (2) economy; and (3) technology [48, 49]. First, this study incorporated factors related to land size. In addition, the urban spatial structure replaced the classic T elements, considering that factors like energy consumption intensity and energy structure have a limited impact on CERBOs [50]. In summary, this study considers the following three types of factors:

Scale Factors

According to existing studies, the scale factors refer to the indicators of population size, land use size, and urbanization level [51-55]. The total population of urban and rural residents (POP_t) is used to characterize the elements of population size. The area of municipal jurisdiction (A_m) and the proportion of urban construction land (p_c) is used to represent the element of land size. The urbanization level (UL) and urban population proportion (p_{pop}) are used to

Table 1. Primary data of sample cities.

Region	Province	Number of cities	Area (km^2)	Population (10^4 people)	Urbanization rate (%)	GDP (100 million yuan)
Eastern	Jiangsu Zhejiang Fujian Shandong	18	500.00–2171.00	14.06–37.5	41.70–70.82	448.02–3151.08
Central	Shanxi, Anhui, Henan, Hubei	7	367.10–4093.70	23.68–43.00	48.65–68.17	762.23–3362.11
Western	Inner Mongolia, Shaanxi	5	393.80–3212.00	26.08–45.80	51.07–74.76	903.61–2087.21
Northeastern	Jilin	6	432.40–2568.80	22.75–46.17	32.26–73.67	463.49–817.71

Table 2. Descriptive statistics of total CERBOs in sample cities.

Region	statistics	2021	2020	2019	2018	2017	2016	2015
Eastern	Min	271.43	258.31	247.63	236.94	209.19	202.98	175.80
	Max	2173.68	2041.15	1886.84	1743.38	1603.24	1521.27	1436.42
	Std Dev	450.32	421.38	386.37	352.09	322.40	305.41	293.62
	Mean	700.45	658.47	613.57	580.91	530.80	485.99	434.24
Central	Min	381.92	363.31	343.76	343.69	320.21	205.66	163.86
	Max	2413.23	2403.35	2219.30	2035.08	1648.79	1523.83	1395.02
	Std Dev	749.62	726.46	659.16	592.50	488.91	506.49	461.64
	Mean	1196.39	1141.64	1046.68	982.28	844.56	714.59	636.06
Western	Min	453.76	474.19	445.35	427.86	392.35	174.52	121.71
	Max	2248.92	2311.27	2254.97	2219.29	1986.82	1702.09	1366.88
	Std Dev	668.75	701.84	702.77	688.56	608.79	591.52	471.74
	Mean	924.35	914.63	856.26	846.57	778.25	526.33	427.88
Northeastern	Min	341.20	333.70	309.96	298.59	281.64	269.09	254.20
	Max	857.40	812.73	979.35	970.14	871.37	950.91	891.17
	Std Dev	177.30	164.76	229.75	228.05	202.93	226.47	214.95
	Mean	626.60	603.61	632.83	615.14	580.24	580.31	554.15

*unit of the CERBOs : 10^3 ton

characterize the element of the urbanization level. The key indicators are explained below:

- The proportion of urban construction land (p_c): the proportion of urban construction land in the total land area.
- Urbanization level (UL): the proportion of the urban population to the total population.
- Urban population proportion (p_{pop}): the proportion of the resident population in the main metropolitan area to the total population.

Economic Factors

The economic influence on CERBOs mainly manifests in the economic level of cities and the living consumption level of residents [56-58]. The gross domestic product (GDP) is used to characterize the element of regional economic scale. The proportion of tertiary industry to secondary industry (p_{t-s}) and per capita GDP (GDP_{pc}) are used to describe the urbanization level of the regional economy. Per capita disposable income (DI_{pc}) is used to characterize the consumption level of the residents.

Spatial Structure Factors

The urban spatial structure discussed in this study is based on the perspective of land use at the urban macro-level. The landscape pattern index is a widely recognized indicator for characterizing urban macro-scale spatial structure [59, 60]. The following five indicators are selected to calculate the urban spatial structure based on the previous studies.

The cohesion index (COHESION) and artificiality index (AI) are key metrics for characterizing urban compactness, with COHESION measuring physical connectivity (0-100 range) [61, 62] and AI representing urban concentration (0-100 range) [63]. Urban complexity is quantified using the mean patch shape index (SHAPE_MN), with higher values indicating more irregular shapes. Circumscribing circle distribution (CIRCLE_MN) is employed to assess urban shape by measuring the circularity and elongation of patches [64]. The largest patch index (LPI) gauges the extent of a singular center [65], indicating the proportion of the main center area relative to the total built-up area, with higher values indicating a larger city center. Remote sensing data from 2015 was chosen for analyzing urban spatial structure due to the cyclical nature of data acquisition and stable land use characteristics in small cities over short periods. Data was sourced from the Institute of Geographic Sciences and Resources of the Chinese Academy of Sciences, and interpreted through Landsat TM/ETM imagery (30*30m resolution). City boundary shapefiles were obtained from the National Mapping Center of China. Computational analyses were conducted using Fragstats software.

Panel Data Modeling

In this study, panel data analysis was employed to develop regression models for estimating carbon emissions. This methodology helps control potential biases arising from unobservable individual and temporal effects, enhancing data accuracy. Additionally, it captures the dynamic adjustment process, improving understanding of variable interrelations [66]. The model equation is detailed in Equation (2). To address heteroscedasticity and non-stationarity in the time series data, a natural logarithm transformation was applied to all variables. This adjustment was conducted using Stata statistical software.

$$y_{it} = \sum_{i=1}^{n} \beta_{it} x_{it} + u_{it} \quad (2)$$

where y_{it} denotes the value of the dependent variable corresponding to individual i at time t, specifically representing CERBOs within the scope of this study; x_{it} signifies the value of the independent variable for individual i at time t, encompassing scale and economic factors.

Stepwise Regression Modeling

We opted for a step-by-step regression model to assess the impact of spatial structure factors on CERBOs, as temporal changes in relationships weren't a concern. Initially, we conducted Spearman correlation analysis to identify significant factors affecting CERBOs, considering correlations with significance levels of 0.01 or 0.05 (two-tailed). Since the spatial structure factors are scattered and do not show a normal distribution, Spearman correlation analysis was chosen. Addressing multicollinearity is crucial, as it can lead to unstable coefficient estimates [67]. To evaluate multicollinearity, we utilized the variance inflation factor (VIF) as a test indicator (Equation (3)). If VIF exceeds 5, removing the variable from the model should be considered [68].

$$VIF = \frac{1}{1 - R_i^2} \quad (3)$$

where R_i^2 is the coefficient of determination obtained by regressing the i-th independent variable on all other independent variables.

After completing the above two tests, the study constructs a forward stepwise regression model, which gradually adjusts the model by adding or removing variables according to specific criteria at each step to find the best fit. The entry and exit probabilities for the F-test were set to 0.05 and 0.10, respectively.

Results

The study approaches the identification and quantification of influencing factors through two main aspects. Firstly, the study unifies the factors of scale and economy into one model for discussion, mainly considering the certain correlation between urban scale and socio-economic factors, which usually change together with urban development. This integrated analysis facilitates the comparison of impact strengths, assisting in the prioritization of factor adjustments during planning decisions. Second, the spatial structure is addressed separately due to its slower rate of change and indirect influence on carbon emissions compared to scale and economic factors.

Impact of Scale and Economics on CERBOs

We first constructed four panel data models, which respectively describe the relationship between impact factors and total carbon emissions, electricity-related carbon emissions, gas-related carbon emissions, and heat-related carbon emissions.

First, the HT test (hypothesis testing) for the smoothness test was conducted since the data in this study are short panel data ($t < n$). The p-value of all HT tests was below 0.1, indicating that a panel data model can be directly established. Then, both F-tests and Hausman tests were executed to ascertain a suitable structure for the panel data models (Table 3). The outcomes of the four models consistently indicated the adoption of variable intercepts in these models, based on the F-statistic. The obtained p-values of Hausman tests imply that a fixed effects estimator is more suitable for both Models 1, 2, and 3, and a random effects model is more fitting for Model 4.

In this study, the logarithmic treatment of CERBOs and dependent variables was used to enhance the comparability of the same indicators. The results of the panel data model (Table 4) show that the environmental impact factors of C_T and C_E are the same: POP_t, UL, A_m, GDP_{pc}, $p_{t\text{-}s}$, and DI_{pc}. The coefficients of determination of the regression models for these two types of carbon emissions are also the highest among the four models, which are 0.44 and 0.399, indicating that the influence of environmental factors on the CERBOs is mainly reflected in C_E. In contrast, C_G has a weaker relationship with environmental factors and is positively correlated only with POP_t in the scale factors and DI_{pc} in the economic factors. Carbon emissions from heating do not show a significant correlation with environmental factors. Taking C_T as an example, UL, pt-s, and DI_{pc} are more closely related to the elasticity of carbon emission growth. The regression coefficients show that for every 1% increase

Table 3. F-test results and Hausman test results of Model 1 to Model 4.

Model	F-test	Hausman test (p-value)
Model 1 (C_T)	$F(12.938293)>F_{0.05}(1.4482692)$	0.0039
Model 2 (C_E)	$F(11.110746)>F_{0.05}(1.4482692)$	0.0093
Model 3 (C_G)	$F(33.425717)>F_{0.05}(1.4482692)$	0.0097
Model 4 (C_H)	$F(3.9786499)>F_{0.05}(1.7268983)$	0.6444

in POP_t, UL, A_m, GDP_{pc}, $p_{t\text{-}s}$, and DI_{pc}, C_T increases by 0.428%, 0.664%, 1.698%, 0.306%, 0.239%, and 0.42%, respectively. It is easy to see that the element of land use size has a robust elasticity mechanism in C_T, and other indicators have a similar contribution to the elasticity of C_T growth.

The development level of small cities in different regions and the living habits of residents vary greatly. Therefore, panel data models are constructed separately for the samples of the eastern, central, western, and northeastern regions. The test results indicate that the random effects model is more suitable for the eastern city, and the fixed effects model is selected for panel data regression for the other three models (Table 5).

Overall, environmental factors significantly impact C_T in the eastern and western regions, with significant differences in the indicators and a minor impact on CERBOs in the northeastern and central regions (Table 6). The results for small cities in the east show that DI_{pc} is more strongly correlated with C_T, and the indicators of land use size contribute more to the elasticity of C_T. Neither the population nor the economic urbanization level significantly affects CERBOs in eastern cities. On the contrary, the results for small cities in the west show that both the population and economic urbanization levels affect C_T, and the elasticity coefficients are significantly higher than the national level of all samples. For every 1% increase in UL and every 1% increase in pt-s, C_T rises by 3.256% and 0.927%, respectively. In addition, the effects of Am and DI_{pc} on C_T are similarly higher than those at the national level. The impact of the urban environment on CERBOs in small northeastern cities is relatively homogeneous, mainly in terms of UL, and the trend is opposite to the national average. For every 1% decrease in UL and 1% decrease in ppop, C_T will increase by 0.386% and 0.66%, respectively. The environmental impact of economic factors on CERBOs in small cities in central China is dominant. With a 1% increase in DI_{pc}, C_T will rise by 1.235%.

Impact of Spatial Structure on CERBOs

Fig. 1 shows the urban land use map identified in this study based on remote sensing image data. Land types are divided into six categories: cropland, forestland, grassland, rivers, construction land, and unused land.

The stepwise regression results show that COHESION is the only influential indicator (Table 7), negatively related to CT, which means the more compact the spatial structure of a small city, the lower the total CERBOs. However, the coefficient of determination of the regression equation is low, which indicates that the overall sample model has low explanatory power. Due to the fact that gas is mainly used for cooking and heating among the three types of CERBOs, its relationship with urban spatial

Table 4. Results of the panel data model estimation of Model 1 to Model 4.

Variable	Model 1 (All samples)	Model 2 (Electricity)	Model 3 (Gas)	Model 4 (Heating)
	$\ln(C_T)$	$Ln(C_E)$	$Ln(C_G)$	$Ln(C_H)$
$\ln(POP_t)$	0.428**	0.448*	0.417**	0.025
$\ln(A_m)$	1.698**	1.761**	0.194	0.440
$\ln(p_c)$	0.155	0.173	0.088	0.194
ln(UL)	0.664***	0.702**	0.096	0.526
$\ln(p_{pop})$	0.115	0.144	0.070	-0.434
ln (GDP)	-0.031	-0.030	-0.004	0.085
$Ln(GDP_{pc})$	0.306**	0.343**	0.053	0.173
$Ln(p_{t\text{-}s})$	0.239***	0.254***	0.074	0.100
$Ln(DI_{pc})$	0.420***	0.407***	0.743***	0.584
_cons	20.136***	19.932***	6.737***	2.763
N	252.000	252.000	252.000	98.000
r2	0.440	0.399	0.228	0.171

*, ** and *** indicate significance at 10%, 5% and 1%, respectively.

Table 5. F-test results and Hausman test results of Model 5 to Model 8.

Model	F-test	Hausman test (p-value)
Model 5 (C_T of eastern)	$F(10.199691)>F_{0.05}(1.6578673)$	0.8201
Model 6 (C_T of central)	$F(3.0490751)>F_{0.05}(1.9805283)$	0.0016
Model 7 (C_T of western)	$F(11.258395)>F_{0.05}(2.3209534)$	0.0003
Model 8 (C_T of northeastern)	$F(8.5990365)>F_{0.05}(2.1655403)$	0.0001

Table 6. The panel data model estimation results of Model 5 to Model 8.

Variable	Model 1 (All samples)	Model 5 (Eastern Region)	Model 6 (Central Region)	Model 7 (Western Region)	Model 8 (Northeastern Region)
	$\ln(C_T)$	$\ln(C_T)$	$\ln(C_T)$	$\ln(C_T)$	$\ln(C_T)$
$\ln(POP_t)$	0.428^{**}	0.383^{**}	0.736	1.632	0.064
$\ln(A_m)$	1.698^{**}	0.776^{**}	16.470	6.342^{**}	0.335
$\ln(p_c)$	-0.155	0.152^{**}	-0.365	-0.330	0.161
$\ln(UL)$	0.664^{***}	0.035	-0.263	3.256^{***}	-0.386^{*}
$\ln(p_{pop})$	0.115	0.097	-0.015	-1.920	-0.660^{***}
ln (GDP)	-0.031	0.277^{**}	-0.053	-1.438	-0.021
$\mathrm{Ln}(GDP_{pc})$	0.306^{**}	0.089	0.444	1.287	-0.019
$\mathrm{Ln}(p_{t\text{-}s})$	0.239^{***}	0.085	-0.215	0.927^{***}	0.023
$\mathrm{Ln}(DI_{pc})$	0.420^{***}	0.454^{***}	1.235^{**}	1.502^{**}	0.228
_cons	20.136^{***}	2.792	129.296	64.403^{***}	22.122^{***}
N	252.000	119.000	56.000	35.000	42.000
r2	0.440	0.882	0.621	0.849	0.700

*, ** and *** indicate significance at 10%, 5% and 1%, respectively.

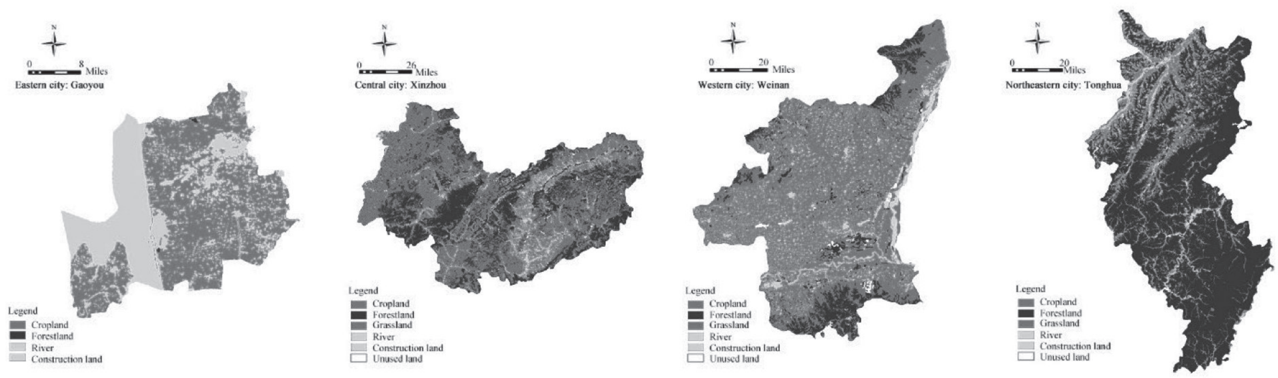

Fig. 1. Example of the remote sensing images of sample cities used to calculate the urban spatial structure indicators.

Table 7. Stepwise regression results of all samples.

Dependent Variable	Independent Variable	Non-Standardized Coefficient		Standardized Coefficient	Sig.	R^2
		B	Standard Error			
C_T	Constant	0.486	0.093	--	0.000	0.154
	COHESION	-0.376	0.151	-0.392	0.018	--
C_E	Constant	0.438	0.090	--	0.000	0.121
	COHESION	-0.317	0.147	-.348	0.038	--

structure is usually weak. The preliminary hypothesis is whether the type of CERBOs affects the explanatory power of the model. Therefore, we separately regressed the spatial structure factors with the three types of carbon emissions to further explore whether the effect acts only on a specific type of carbon emission. The results show that carbon emissions from electricity show a similar pattern to that of overall carbon emissions. However, the coefficient of determination is still low (0.121).

Furthermore, the study considers that spatial structure, to some extent, characterizes the development stage and urbanization level of a city, which also affects the electricity consumption of residents. Furthermore, this study hypothesizes whether the explanatory power of the model is influenced by the socio-economic differences within small cities themselves. Therefore, a separate stepwise regression analysis was conducted on small cities in different economic geographical zones (Table 8).

Table 8. Stepwise regression results of cities in the western region.

Dependent Variable	Independent Variable	Non-Standardized Coefficient		Standardized Coefficient	Sig.	R^2
		B	Standard Error			
C_T	Constant	0.815	0.188	--	0.023	0.807
	COHESION	-0.916	0.259	-0.898	0.038	--
C_E	Constant	0.760	0.174	--	0.022	--
	COHESION	-0.836	0.239	-0.896	0.040	0.803
C_G	Constant	0.240	0.045	--	0.013	--
	COHESION	-0.244	0.062	-0.916	0.029	0.840

As expected, the effect of the spatial structure on CERBOs in small cities varies considerably across regions. Specifically, under the current stage of development, the spatial structure only affects CERBOs in small cities in the western region. It is noteworthy that the coefficients of determination of the models for small cities in the western region are all higher than 0.8, indicating that the regression models have more substantial explanatory power. The regression results show that COHESION is still the only spatial structure indicator impacting CERBOs in small cities in the western region. The more compact the spatial structure, the lower the CERBOs. This conclusion applies not only to the total CERBOs but also to the carbon emissions from electricity and gas.

Discussion

Characteristics of the Impact of the Urban Environment on CERBOs in Small Cities

The research will discuss the study results from two perspectives: significant impact factors and affected types of carbon emissions. Analyzing impact factors aims to understand the reasons and pathways through which these factors affect CERBOs. This analysis of influencing mechanisms serves as a necessary foundation for forming low-carbon-oriented planning decisions. On the other hand, analyzing affected types of carbon emissions extends the previous analysis, aiming to clarify which types of carbon emissions are influenced by the indicators regulated in planning decisions, thereby making planning decisions more targeted.

Impact Factors

The total resident population and urban construction land proportion, reflecting population size and land use, along with GDP and per capita GDP indicating economic development, have a limited impact on CERBOs in small cities, unlike findings in large city research. While spatial structure influence trends align with large city research and impact factors, and indicators are more uniform.

Regarding scale factors, the municipal jurisdiction's area primarily influences CERBOs and is influential in national, eastern, and western models with high coefficients. However, urban construction land proportion only correlates with eastern cities, likely due to faster development and significant expansion with economic growth. In contrast, central, western, and northeastern regions' small cities experience slower economic growth, resulting in less significant changes in built-up areas over the study period. This may also explain why the resident population indicator is only adopted in the models for the national level and the eastern region. The impact of urbanization level on CERBOs is particularly noticeable in small cities within western and northeastern regions. The main reason is that the economic conditions in these regions are slower than those in other regions, and the living standards and energy use patterns in cities and villages are significantly different from those in other areas. The difference, however, is that an increase in the urbanization level of the population leads to a rise in CERBOs in the western region, while on the contrary, there is a decrease in the northeastern region. In our study, we attribute the contrasting outcomes of carbon emissions to heating practices. The northeast, being notably cold, sees substantial energy consumption for heating in the winter, especially in residential buildings. Centralized heating systems, commonly used in northeastern cities, prove more efficient in reducing carbon emissions compared to rural areas' reliance on firewood or coal for independent heating. Hence, the rise in urbanization levels in small northeastern towns, including urban population proportions, will lead to decreased CERBOs.

In terms of economic factors, most models indicate a positive correlation between per capita disposable income and CERBOs, with no observed inflection point. This result is consistent with the development stage of small cities in China. Currently, the overall awareness of emission reductions among residents of small cities is still insufficient. The priority of increasing affluence is to improve living environments and convenience, which, in turn, leads to more CERBOs. Although residents' affluence correlates with total GDP or economic intensity, recent population shrinkage or declining growth rates in small cities can disrupt the relationship between CERBOs and affluence/economic levels. This also manifests as the impact of GDP and per capita GDP on CERBOs being lower than per capita disposable income.

Compact urban structures, found to be conducive to reducing CERBOs, show similar benefits in both small and established large cities. However, this effect is particularly noticeable in small western cities, possibly due to differing approaches to urban development across China's geographic subregions. There has been a problem with the blind expansion of small cities in the western region. Although academics have recognized the drawbacks of such development forms, the decentralized urban structure formed in the past few decades and the low density and inefficient use of space caused by population loss in recent years have become typical characteristics of the western region. In addition, the SHAPE_MN and LPI indicators, which have received more attention in studies of large cities, are not included in the regression model of small cities. This result also reflects the particular characteristics of the development stage of small cities. Although the model has not shown an inflection point for the time being, it can be hypothesized that the higher the level of urban development, the more complex the mechanism of influence of spatial structural factors on CERBOs.

Types of Operational Carbon Emissions

Carbon emissions from residential buildings' electricity consumption in small cities are highly sensitive to urban environmental factors, particularly the economic urbanization level and residents' living consumption levels. The area of municipal jurisdiction, which characterizes the size of the city, has the most significant impact on elasticity coefficients. The results of this characterization align with the expectation that economic factors are more closely correlated with carbon emissions from electricity, but scale factors have a more significant impact on carbon emissions from electricity.

For carbon emissions from gas, the impact of economic factors is higher than that of scale factors. In many small cities in China, gas is used not only for cooking but also for domestic hot water. An increase in population size will inevitably lead to an increase in total gas demand, and an increase in the standard of living will also introduce the need for greater comfort.

Carbon emissions from heating do not exhibit any correlation with urban environmental factors in this study. However, speculative analysis suggests a negative correlation between urbanization levels and overall CERBOs, supported by existing research indicating the urban environment's notable influence on heating-related emissions. Therefore, we believe that the following are possible reasons for these results: 1) only 11 out of 36 sample cities require winter heating, which may not represent the overall situation of heating in small cities across the region; and 2) the development of small cities is relatively slow, and during the research period, the heating capacity of winter urban centralized heating systems did not show significant changes. Although urbanization levels may affect overall carbon emissions, their degree of impact may not be significant enough to be presented in a multi-factor model.

Suggestions for Low-Carbon-Oriented Small City Planning in Different Geographical Regions

The influence of environmental factors in small cities on CERBOs shows differences among regions. As the development stage, construction characteristics, and residents' living habits in small cities vary considerably across different regions, the low-carbon-oriented planning suggestions cannot be generalized.

The development speed of small cities in the eastern region surpasses the national average. Population size and land size have a more significant impact on CERBOs. Therefore, it is imperative to judiciously manage the growth rate and increment of scale factors in the development of small cities in the east. For instance, stringent control over land use planning and constraining land supply for construction are recommended measures. Urban development can be promoted by increasing the urbanization rate rather than the scale. This can be achieved through initiatives such as enhancing urban infrastructure, providing more employment opportunities, and attracting talent. At the same time, cities should persist in promoting low-carbon lifestyles, allowing residents to improve their living standards while improving energy efficiency, reducing energy waste, and ultimately achieving the goal of reducing CERBOs in their daily lives. Encouraging walking, cycling, and the use of public transportation to mitigate carbon emissions is advisable. Furthermore, incentives or subsidies can be offered to incentivize residents to purchase energy-efficient appliances and participate in energy-saving activities. Education and advocacy efforts should also be prioritized. Cities can organize campaigns for energy conservation and environmental protection, such as energy-saving promotion weeks or months, to disseminate energy-saving knowledge and environmental awareness among residents, thereby fostering the widespread adoption of low-carbon, green lifestyles [69].

Small cities in the western region are relatively underdeveloped regions in China, and the historical legacy of sprawl is common due to the process of urban development. Therefore, at this stage, small cities in western regions should prioritize the intensive and compact development of urbanization patterns. This entails taking measures in urban planning and land use. For instance, optimizing urban layouts by planning and designing them to ensure the rational distribution of infrastructure and public service facilities, thereby reducing resource waste and energy consumption, additionally, increasing building density and encouraging the construction of high-density residential and commercial areas within cities will minimize land usage and promote transportation convenience and resource utilization efficiency. Furthermore, these cities should exercise greater caution in land use and population urbanization to balance the delicate relationship between economic growth and CERBOs. It is necessary to control the speed and scale of land development by implementing stringent land use planning and control measures to restrict excessive land development and ensure the sustainable utilization of land resources. Regular assessments of population growth trends and the supply-demand status of urban resources should also be conducted to adjust urban planning and policy measures accordingly in order to adapt to population changes and urban development needs, thus avoiding excessive resource consumption and the exacerbation of environmental burdens. At the same time, they should also focus on advocating for and popularizing low-carbon lifestyles among residents.

Compared with the two regions mentioned above, the problems faced by small cities in the central and northeastern parts of the country are relatively simple and homogeneous. In the central region, the impact of the population's affluence on CERBOs is much higher than the national average. Therefore, this region should emphasize and continue strengthening the guidance of low-carbon lifestyles for the population. Urban management should be encouraged to implement more incentive policies and economic compensations for low-carbon lifestyles. However, the urbanization level of the people in northeastern China should continue to improve. For example, enhancing urban infrastructure construction, including transportation, water supply, power supply, and communication, will improve urbanization levels and residents' quality of life. Improving the level of urban public services, such as education, healthcare, and social security, can attract more people to urban areas and promote the improvement of urbanization levels.

In addition, although the degree of compactness of spatial structure is relevant only in the western region, we still suggest that small cities should be oriented toward compact development, taking into account the existing studies and experiences of urban development. Although some studies have also pointed out that compact development may also lead to increased CERBOs (Jin, 2011), this inflection point is less likely to occur in the near-term development of China's small cities, considering the gap between small and large cities. At the same time, considering the current problem of population shrinkage in small cities in general, intensification and compactness will be necessary trends in developing their spatial structure.

Research Limitations

This study has two limitations that may affect the results: (1) The spatial structure factors cannot be collected for consecutive years. Remote sensing image maps are captured once every five years. Thus, the analysis of spatial structure factors in this study only matches the year 2015. In future research, we will expand access to spatial structure data by cooperating with government departments to obtain land use data or by searching through map libraries. (2) The sample cities did not achieve full national coverage. Due to the completeness of the statistical data for China's small cities, we excluded many small cities from the sample selection. However, we tried to ensure that a certain number of sample cities within each geographic sub-region were included. In the future, we will consider further expanding the primary database through cooperation with the government or relying on scientific research organizations.

In addition, the results of this study may only be able to characterize the unique situation in China, given the rapid socio-economic development of Chinese cities. Therefore, we believe that research in this area can be expanded in two ways: (1) comparing the differences in the impacts of urban environments on CERBOs in developed countries and low-carbon development regions around the world, either historically or at the current stage of development, and (2) continuously tracking the changes in the impact of the urban environment on CERBOs in small cities in the near future (peak carbon levels in 2030) and the far future (carbon neutral in 2060) under the influence of various related policies following China's "dual-carbon" goal proposal.

Conclusions

In this study, the urban environmental impact on CERBOs in 36 small cities in eastern, central, western, and northeastern China is empirically studied. Panel data models and stepwise regression models are adopted to identify the impact factors and the quantitative calculation of the degree of influence. Finally, low-carbon-oriented planning recommendations are proposed for small cities in different regions based on the analysis results. The main conclusions of the study are as follows:

First, the indicators and impact of the urban environment on CERBOs in small cities are not the same as those in large cities. Although the spatial structural elements are consistent with the influential trends observed in large cities, the types of indicators are relatively limited. It is worth noting that there are regional differences in the impact on CERBOs. CERBOs in the eastern small cities are more sensitive to scale factors. The indicator of the economic factor has a higher impact in the central and western regions. CERBOs in the western small cities are more sensitive to urbanization levels and the area of municipal jurisdiction. The west is the only region closely related to the spatial structure factor, where the spatial compactness shows a significant negative correlation with CERBOs. In the small cities in the northeast, CERBOs are more affected by urbanization levels, and the trend is opposite to that of other regions.

Second, carbon emissions from electricity are most influenced by environmental factors. The economic urbanization rate and the consumption level of residents are most closely related to carbon emissions from electricity. The area of municipal jurisdiction has the maximum elastic influence coefficient among all indicators. In small cities in the western region, the compactness of the urban spatial structure significantly affects carbon emissions from electricity, but to a lesser extent than carbon emissions from gas.

Finally, based on this study, we recommend low-carbon-oriented planning for small cities in different regions. The development of small cities in the eastern region should carefully control the increment in and growth rate of scale factors. Urban development can be promoted by increasing the level of urbanization rather than the scale. At this stage, small cities in the western region should focus more on the intensive and compact development of their urbanization patterns. In the northeastern region, the urbanization level of the population should be continuously increased.

The underlying data mainly cause the limitations of this study. In the future, we will explore acquiring and mining multivariate data and conducting comparative studies spanning both time dimensions and geographical latitudes.

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Conflict of Interest

The authors declare no conflict of interest.

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