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Original Paper

Identifying Major Influencing Factors of CO2 Emissions in Chengdu: Date Analysis Based on Extended STIRPAT Model from 2005 to 2022

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Abstract

With the global economy's continuous development, the issue of carbon emissions has become the focus of international attention. As one of the most important cities in western China, it is of positive significance to study the factors influencing carbon emission in Chengdu to realize the construction of a low-carbon city. Most studies believe that population size, urbanization level, energy structure, industrial structure, and other factors impact carbon emissions. But in reality, more factors affect carbon emissions. Taking Chengdu as an example, based on traditional factors such as population and economy, this paper puts forward new influencing factors such as building construction area, number of buses, length of subway lines, green area of parks, and green coverage rate of built-up areas, and verifies their correlation with carbon emission intensity in Chengdu. It is found that these factors also have a certain correlation with carbon emissions in Chengdu. Then, the paper constructs the STIRPAT model of carbon emission. Through the multicollinearity test and ridge regression analysis, the contribution of each influencing factor to the carbon emission intensity in Chengdu was obtained. Finally, this paper puts forward the strategy of low-carbon construction in Chengdu. Hope to provide a reference for relevant departments.

Keywords

carbon emission, influencing factors, STIRPAT model, regression analysis

1. Introduction

With the global economy's continuous development and population growth, the issue of carbon emission has become the hot spot and focus of international attention. Carbon emissions mainly refer to greenhouse gases in the atmosphere, especially carbon dioxide emissions. Carbon emission is the main factor leading to global warming, frequent extreme weather events, sea level rise, and other environmental problems, it poses a great threat to human society and the natural environment. Therefore, in-depth research on the influencing factors, trends, and emission reduction strategies of carbon emissions is of great significance for promoting global sustainable development and protecting the ecological environment of the earth.

Domestic and foreign scholars have carried out a large number of studies on the spatial distribution of carbon emissions and its influencing factors. From the perspective of the research scope, it can be mainly divided into national-level, regional-level, and urban-level research. For example, Sicong Zhang et al. divided 30 provinces in China into three regions, namely advantageous regions, potential regions, and backward regions, according to different levels of social development such as urbanization, economy, energy utilization, industry, and technology, and evaluated the impact of carbon dioxide emissions in China at the national and different regional levels, and concluded that economic growth had the greatest positive impact on the three regions. Based on the specific situation of the three regions, corresponding solutions are proposed (Zhang & Zhao, 2019). Ji Zhang et al. used the energy consumption data of Sichuan Province and Chongqing Municipality from 2000 to 2019 to analyze the carbon emission of the Chengdu-Chongqing urban agglomeration and its influencing factors. It is concluded that the overall carbon emission of Chengdu-Chongqing urban agglomeration increases first and then decreases, and presents obvious spatial agglomeration characteristics. Factors such as GDP, population, urbanization rate, and industrialization structure have significant impacts on carbon emissions (Zhang et al., 2025). Wu Yao et al. took the Inner Mongolia Autonomous Region as an example to study the contribution rates of industrial structure, energy intensity, and energy structure to the reduction of carbon emission intensity in resource-based areas. The results show that industrial structure and energy intensity have a positive driving effect on carbon emission intensity, while energy structure has a negative inhibiting effect on carbon emission intensity (Yao et al., 2024).

Domestic and foreign scholars have also carried out corresponding research from different fields and perspectives of carbon emission research. Min Zhao et al. used the LMDI method to study the influencing factors of industrial carbon emission in Shanghai. According to the study, China's energy intensity is much higher than the world average level, and it is more important to adjust the industrial structure by developing low-carbon emission industries than the energy structure (Zhao et al., 2010). Kuokuo Zhao et al. studied the influencing factors of carbon emission from the perspective of population development and put forward corresponding strategies (Zhao et al., 2021). Jianfeng Lu studied the relationship between travel behavior characteristics and carbon emissions of residents in different types of residential areas from the perspective of architecture and the environment. The results show that, compared with individual socioeconomic factors, the built environment has a more significant impact on travel carbon emissions. Travel distance and travel mode are factors that directly affect residents' travel carbon emissions (Lu, 2023). Xinyu Zhang et al. analyzed the spatial distribution characteristics and influencing factors of carbon emissions in the industrial sector. The study shows that China's urban industrial carbon emissions generally show a trend of first growth and then a slow decline. Urban industrial structure, industrial agglomeration level, industrial enterprise scale, and urban economic development level are positively correlated to industrial carbon emissions, while industrial structure and industrial ownership structure are negatively correlated to urban industrial carbon emissions (Zhang et al., 2022). Peng Zhao et al. studied the influencing factors of carbon emissions in China's transportation sector. The research results show that GDP per capita, population, urban road area, and private cars per capita are important factors causing the increase in urban transport carbon emissions, while the improvement of urban density, the improvement of public transportation efficiency, and the government's environmental protection can mitigate emissions and promote low-carbon development in urban transportation (Zhao et al., 2024). Shi-Chun Xu et al. analyzed the influencing factors of carbon emission from the field of energy consumption and proposed such influencing factors as energy structure, energy intensity, industrial structure, economic output, and population size effect (Xu et al., 2014).

In summary, research methods on influencing factors of carbon emissions can be roughly divided into structural decomposition analysis (SDA) and Index decomposition analysis (IDA) (Yunke & Jianguo, 2024). Among them, structural decomposition analysis is based on the input-output table to study the relationship between economy and energy consumption, mainly including environmental Kuznets curve (EKC), Kaya identity (Jianyu and Tao, 2021) (Wang et al., 2023) (Junting, 2023), IPAT model (Yu et al., 2013) and STIRPAT mode (York et al., 2003) (Li et al., 2015) (Wang et al., 2017) and other methods, reflecting the degree of influence of independent variables on dependent variables (Yunke & Jianguo, 2024). The exponential decomposition analysis method decomposed the target variable into multiple influencing factors and studied the contribution rate of each influencing factor to the target variable (Yunke & Jianguo, 2024). The commonly used methods are arithmetic mean Dix index decomposition (AMDI) and logarithmic mean Dix index decomposition (LMDI) (Xuefei et al., 2024) (Yao et al., 2024) (Siwei et al., 2023) (Moutinho et al., 2018).

STIRPAT model is one of the commonly used methods to study the influencing factors of carbon emission. The STIRPAT model is derived from the IPAT model, and its model expression is:

$$I = PAT \tag{1}$$

Where I is defined as the environmental impact, P is defined as the number of population, A is defined as the per capita wealth or economic level, and T is defined as the environmental impact of technology level or unit wealth (Nosheen et al., 2020). It is a widely recognized formula for analyzing the impact of human activities on the environment.

However, the main limitation of the IPAT model is that it does not allow for hypothesis testing and assumes a priori that the functional relationships between the factors are proportionate. To overcome these limitations, the STIRPAT model was developed. The advantage of the STIRPAT model is that by introducing exponential and random terms, it enables the model to test hypotheses, and allows the analysis of non-proportional and non-monotonic relationships between various factors. At the same time, it allows researchers to introduce other variables or interaction terms according to the specific research problem, to enhance the explanatory and predictive power of the model(Jingfu and Guohua, 2024). The model expression is:

$$I = \alpha P^{b} A^{c} T^{d} e \tag{2}$$

Where, α is the coefficient of the model, b, c, and d are the exponents of the independent variables, and e is the error term(Mao, 2023). To perform regression analysis, it is common to take the natural logarithm of both sides of the formula. The formula becomes:

$$\ln I = \ln\alpha + b(\ln P) + c(\ln A) + d(\ln T) + \ln e \tag{3}$$

2. Research on Influencing Factors of Carbon Emission

2.1 Research Scope and Data Source

This paper selects Chengdu as the research object for the following reasons: Firstly, as the economic center of southwestern China and one of the core cities of the Chengdu-Chongqing economic circle, Chengdu has experienced rapid economic growth and accelerated urbanization in recent years. The rapid economic growth often leads to an increase in energy consumption and carbon emissions, making Chengdu a typical city for studying carbon emissions issues. At the same time, on the policy level, Chengdu has been designated as a national low-carbon pilot city and has made innovative explorations in implementing the "Carbon Benefits of Chengdu" plan and exploring the carbon emissions peak tracking system. The policy of building the Chengdu-Chongqing dual-city economic circle proposed in 2020 also regards ecological environmental protection planning as an important part of building the Chengdu-Chongqing dual-city economic circle. Therefore, selecting Chengdu as the object of carbon emission research is important.

The research methods of this paper are as follows: First, through the review of the literature, the influence factors that may affect the carbon emission in Chengdu are initially proposed. Secondly, the correlation analysis of the proposed carbon emission factors is carried out based on the data over the years, and the factors affecting carbon emissions in Chengdu are finally determined. Finally, the collinearity of these factors is tested by a multiple regression model. If there are collinearity problems, the ridge regression model is used to further analyze them. Finally, the factors affecting carbon emission in Chengdu are analyzed based on the STIRPAT model.

This paper analyzes Chengdu's data from 2005 to 2022 and draws corresponding conclusions. The data mainly come from major public websites and statistical platforms. The carbon emission data came from the Global Atmospheric Research Emissions Database (EDGAR), and the population and economic data came from the Chengdu Statistical Yearbook over the years.

2.2 Proposal of Impact Factors

2.2.1 Selection of Impact Factors

Domestic and foreign literature studies show that the population size, population structure, affluence, urbanization rate, energy structure, technology level, and other factors of a country or region jointly affect the carbon emissions of the area. Still, these factors have different contribution rates to carbon emissions (Wang, 2017). Taking Beijing as an example, Zhu Yuancheng et al. concluded through data analysis that factors such as population size, urbanization process, per capita GDP, energy intensity, and proportion of secondary industry have important impacts on urban carbon emissions (Changchang & Shijie, 2012). Xiaodong Zhang et al propose that the main factors affecting the spatial distribution and emission of CO2 emissions are urbanization, economy, industry, investment, and residential energy consumption (Zhang et al., 2023). In addition, most literature studies also mentioned that population, economy, energy structure, industrial structure, GDP, and other factors have a certain impact on regional carbon emissions (Li et al., 2011) (Fan et al., 2006) (Zhang & Zhao, 2019) (Wu et al., 2019). In addition, some studies suggest some new perspectives and influencing factors. For example, Wang Zonghao pointed out in his research that the aging rate of the population also has a certain impact on carbon emissions (Zonghao, 2024). Zhang Wang believes that vehicle ownership reflects the level of people's living affluence, and indirectly affects the carbon emissions of cities (Wang, 2017).

Chengdu, as an important city in western China, has undergone great changes in economy, population, technology, and living standards in the past 20 years. With the opening of the metro line in 2010, residents have a new choice of ways to travel. The secondary industry has gradually withdrawn from the city center, and more and more tertiary industries have occupied an important position. With the proposal of Park City and other policies, the area of parks and green spaces in Chengdu is also increasing continuously. These green resources not only improve people's living environment but also indirectly affect the carbon emission of the city.

In summary, combined with domestic and foreign literature research and the development and construction of Chengdu itself, The paper initially put forward 13 factors as influencing factors, such as population size, urbanization rate, proportion of labor population, total number of households, proportion of secondary industry, energy intensity, per capita GDP, resident car ownership, building construction area, number of buses, length of subway operating lines, green area of parks, and green coverage rate of built-up areas. Analyze their impact and contribution to carbon emissions. Among them, the population, urbanization rate, labor population proportion, and total number of households explain the population factors in the IPAT model. The proportion of secondary industry and energy intensity correspond to the technical factors in the IPAT model. Per capita GDP and car ownership correspond to the affluence factor in the IPAT model. In addition, the paper puts forward five new influencing factors, such as construction area, number of buses, length of subway lines, green area of parks, and green coverage rate of built-up areas. The description of each impact factor is shown in Table 1.

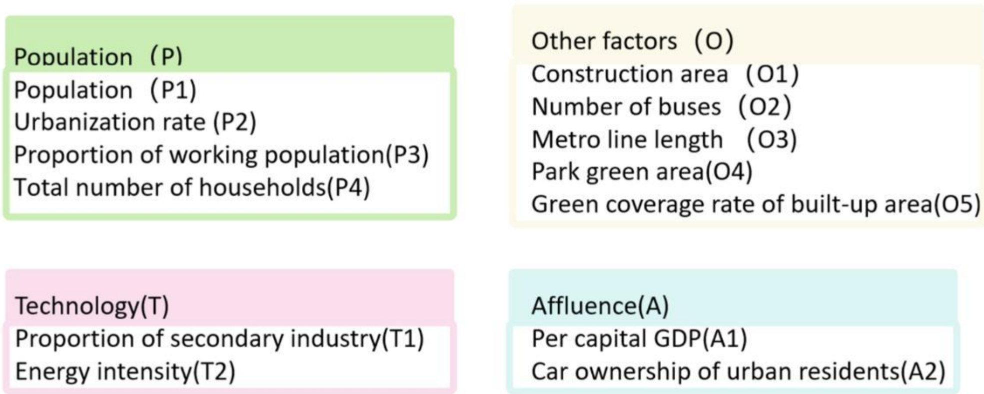

Figure 1. Influencing Factors of Carbon Emissions in Chengdu

2.2.2 Data Description

This paper makes a statistical analysis of the 13 impact factors initially proposed and the carbon emission data of Chengdu from 2005 to 2022, and the results are shown in Figure 2. As can be seen from the figure, during this period, indicators such as population, urban population, working population, and urbanization rate all showed an increasing trend. Per capita GDP and motor vehicle ownership have also increased significantly, which shows that people's living standards have been significantly improved. At the technical level, energy consumption and total output value of the secondary industry are growing, but the secondary industry and energy intensity are declining after reaching their peaks. The proportion of the secondary industry gradually fell after reaching a peak in 2011, which is related to a series of policies and industrial structure adjustments such as "two backward, three forward" in Chengdu. Energy intensity also showed a downward trend after 2008, and then gradually stabilized, which is closely related to technological progress and other factors. The construction area showed an inverted U-shaped curve and showed a downward trend after reaching a peak in 2015. In terms of residents' travel, the number of buses in operation shows a growing trend. Since 2010, Chengdu's first subway line has been put into operation, and the mileage of subway operation has been growing rapidly since then and will be stable by 2020. The construction of these public transportation has an important impact on the travel mode of citizens and indirectly affects the carbon emissions of Chengdu. The green areas of parks and the greening rate of built-up areas are also increasing steadily. This greening plays an important role in carbon sequestration and also affects the carbon emission of Chengdu. The total carbon emission of Chengdu showed a rapid growth trend in the early stage, reached a peak around 2010, and then showed a steady fluctuation state. In recent years, with the attention of the government and scholars on carbon emissions, as well as the development of relevant policies and technologies, the carbon emissions in Chengdu began to decline slowly.

Table 1. Description of Carbon Emission Impact Factors

	Influence factor	Description		Influence factor	Description
others	Construction area	Construction area of the year	population	Population	Current population
	Number of buses	Number of buses in the year		Urbanization rate	The proportion of urban population to regional population
	Metro line length	Length of subway line in operation in that year		Proportion of the working population	The proportion of the working population in the resident population
	Park green area	The green area of the park in that year		Total number of households	Total number of households in that year
	Green coverage rate of built-up area	The proportion of green cover area in total built-up area	affluence	Per capita GDP	Per capita GDP of the year
technology	Proportion of secondary industry	The output value of the secondary industry accounts for the proportion of the three major industries.		Car ownership of urban residents	The number of cars owned by residents that year
	Energy intensity	The amount of energy consumed per unit of GDP produced		Carbon emission intensity	Carbon emissions per unit of GDP

2.3 Determination of Impact Factors

This paper analyzes the correlation between the 13 factors that initially proposed to affect carbon emission and the carbon emission intensity of Chengdu over the years, and the analysis results are shown in Table 2. It can be seen from the analysis results that there is a strong correlation between the proposed influencing factors and carbon emission intensity.

Among them, population size, urbanization rate, the total number of households, per capita GDP, car ownership of urban residents, construction area, number of buses, length of subway lines, green area of parks, and green coverage rate of built-up areas all show a significant negative correlation with carbon emission intensity. This result is highly reliable. The reason is that with the continuous development of the economy and society, Chengdu has entered a relatively developed stage of social development. The higher the urbanization rate, the more concentrated the population, and the more the economy has scale effects, which is conducive to reducing carbon emissions. At the same time, the development of science and technology and the adjustment of industrial structure can achieve the growth of per capita GDP while maintaining the reduction of energy intensity, and carbon emission intensity will also be reduced. In addition, the development of public transportation can reduce people's energy consumption but is also conducive to the reduction of carbon emissions. Finally, the increase of green coverage in parks and built-up areas is conducive to carbon sequestration, thereby reducing carbon emissions.

The energy intensity and the proportion of the secondary industry are significantly positively correlated with the carbon emission intensity. This shows that the industry is energy-consuming, and the higher the industrialization rate, the higher the carbon emission intensity will increase. There is no significant correlation between the proportion of the working population and carbon emission intensity. This shows that Chengdu is dominated by the tertiary industry and its employment structure. The increase of the tertiary industry absorbs more workers, but it will also lead to the reduction of carbon emission intensity and energy intensity. However, considering the increasing aging trend of the population in recent years, the proportion of the working population is one of the important indicators reflecting the age structure of the population, so this influencing factor is retained in the subsequent analysis. To sum up, considering that all factors are significantly correlated with carbon emission intensity, the final influencing factors are the 13 factors originally proposed, which have not been eliminated.

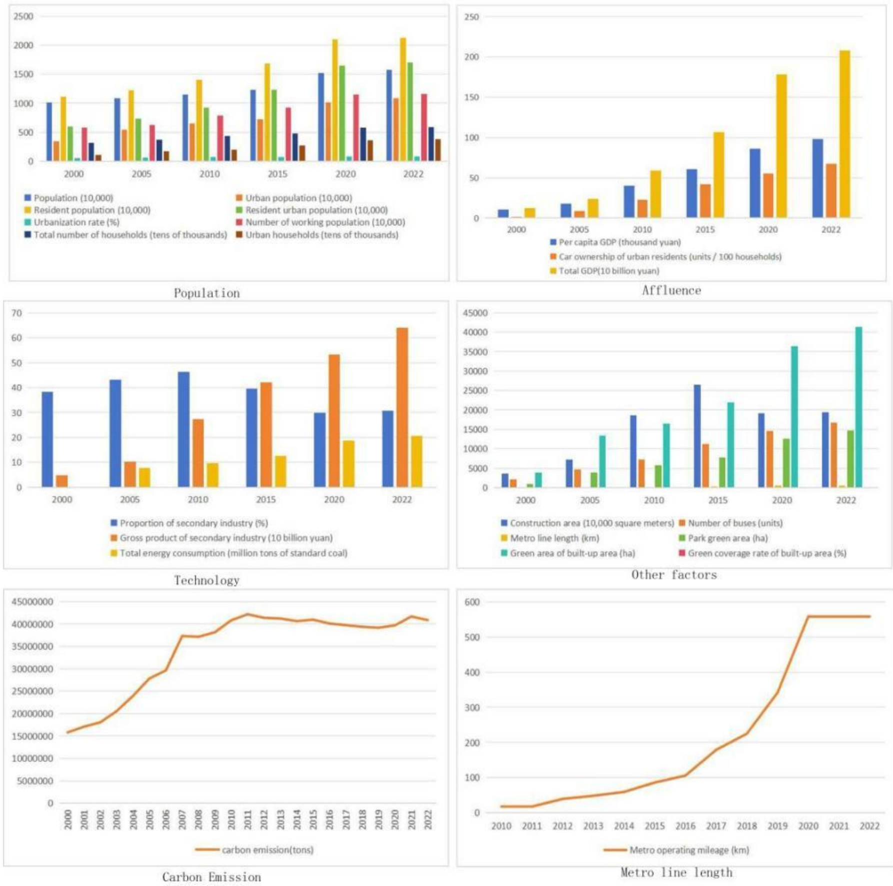

Figure 2. Data Statistics of Chengdu from 2005 to 2022

Table 2. Correlation Analysis between Influencing Factors and Carbon Emission Intensity

		Carbon emission intensity
Population	Pearson correlation	-.842**
Urbanization rate	Pearson correlation	-.954**
Proportion of the working population	Pearson correlation	-.350
Total number of households	Pearson correlation	-.923**
Per capita GDP	Pearson correlation	-.956**
Car ownership of urban residents	Pearson correlation	-.942**
Energy intensity	Pearson correlation	.955**
Proportion of secondary industry	Pearson correlation	.748**
Construction area	Pearson correlation	-.783**

Number of buses	Pearson correlation	-.921**
Metro line length	Pearson correlation	-.702**
Park green area	Pearson correlation	-.849**
Green coverage rate of built-up area	Pearson correlation	-.723**

3. Multicollinearity Testing

If carbon emission intensity is regarded as the dependent variable and each influencing factor as the independent variable, then in addition to the correlation between each independent variable and the dependent variable, there is also a certain correlation between each independent variable. Multicollinearity will affect the accuracy of the regression coefficient, and then have a certain impact on the model results (Huang et al., 2023). Therefore, before building the model, it is necessary to carry out a multicollinearity test for each influencing factor.

This paper uses SPSS to conduct multiple regression analyses for each influencing factor, and the regression results are shown in Table 3. It can be seen from the regression results that the total number of households is directly excluded because of the strong correlation with other variables, and the variance expansion factor (VIF) of the remaining variables is greater than 10 except for the construction area, which indicates that this regression equation has serious collinearity problems.

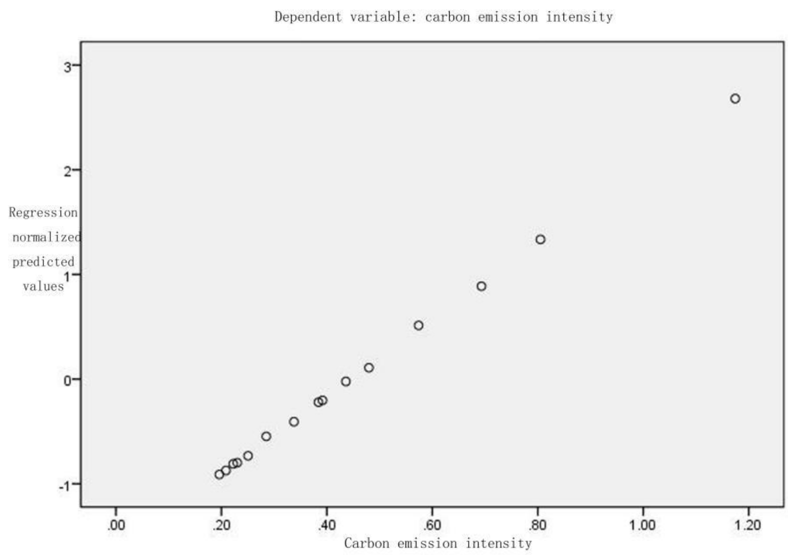

Figure 3. Collinearity Analysis

Table 3. Results of Multiple Linear Regression

model		Nonnormalized coefficient		Standardization coefficient			Collinear statistics	
		B	Standard error	Beta	T	significance	tolerance	VIF
1	(constant)	1.273	2.242		.568	.627		
	Population	.001	.001	.384	.619	.599	.000	2119.117
	Urbanization rate	-.029	.026	-.645	-1.117	.380	.001	1839.865
	Proportion of the working population	-.004	.030	-.016	-.118	.917	.010	102.178
	Per capital GDP	-9.161E-6	.000	-.776	-.655	.580	.000	7772.794
	Car ownership of urban residents	.005	.003	.295	1.718	.228	.006	162.984
	Energy intensity	2.021	1.310	.459	1.542	.263	.002	489.725
	Proportion of secondary industry	.011	.026	.282	.430	.709	.000	2375.863
	Construction area	3.103E-6	.000	.061	1.670	.237	.135	7.420
	Number of buses	2.317E-5	.000	.340	.912	.458	.001	769.197
	Metro line length	.000	.000	.219	.838	.490	.003	379.197
	Park green area	-9.628E-6	.000	-.121	-.204	.857	.001	1947.192
	Green coverage rate of built-up area	.002	.011	.015	.144	.899	.017	58.783

Dependent variable: carbon emission intensity

4. STIRPAT Model Construction

To solve the multicollinearity problem of the regression equation without eliminating the independent variables, the ridge regression method is used to re-fit the original data. The ridge regression method is an improved least squares estimation method. By giving up the unbias of the least square method, at the cost of losing part of the information and reducing the accuracy, the regression coefficient obtained is more realistic and reliable (Huiyan et al., 2024). Although Ridge regression is a biased estimation method, it does not need to eliminate independent variables (Changchang & Shijie, 2012) and can obtain more significant results of parameter coefficients.

Based on the impact factors identified in Section 2.3, this paper constructs a STIRPAT model for carbon emissions. After logarithmic the model, the model becomes:

$$\ln I = \ln\alpha + b_1(\ln P_1) + b_2(\ln P_2) + b_3(\ln P_3) + b_4(\ln P_4) + t_1(\ln T_1) + t_2(\ln T_2)$$
$$+ a_1(\ln A_1) + a_2(\ln A_2) + o_1(\ln O_1) + o_2(\ln O_2) + o_3(\ln O_3) + o_4(\ln O_4) + o_5(\ln O_5) + \ln e \quad (4)$$

Where: I is the carbon emission intensity, P1 is the population, P2 is the urbanization rate, P3 is the proportion of the working population, and P4 is the total number of households. T1 is the proportion of the secondary industry, T2 is energy intensity, A1 is per capita GDP, A2 is the number of residents' car ownership, O1 is the construction area, O2 is the number of buses, O3 is the length of the subway line operation, O4 is the green area of the park, and O5 is the green coverage rate of the built-up area.

In this paper, the ridge regression method was used to re-fit the original data. The range of ridge regression coefficient K was set as (0,1), and the step size was 0.05. The ridge trace map was obtained, as shown in Figure 4. As can be seen from the figure, when K=0.4, the regression coefficient tends to be stable. The specific fitting results are shown in Table 4. After substituting the coefficients in Table4, the final model becomes:

$$\begin{aligned} \ln I = {} & 1.964975 - 0.00006(\ln P_1) - 0.005486(\ln P_2) - 0.011393(\ln P_3) \\ & - 0.000329(\ln P_4) + 0.000993(\ln T_1) + 0.998152(\ln T_2) - 0.000001(\ln A_1) \\ & - 0.001698(\ln A_2) - 0.000008(\ln O_1) - 0.000006(\ln O_2) - 0.00002(\ln O_3) \\ & - 0.000004(\ln O_4) + 0.000046(\ln O_5) \end{aligned} \quad (5)$$

The above results show that the population, urbanization rate, proportion of working population, total number of households, proportion of secondary industry, energy intensity, per capita GDP, resident car ownership, construction area, number of buses, length of subway operating lines, green area of parks and green coverage rate of built-up areas change by 1% for each influencing factor. Will cause carbon emission intensity of -0.00006%, -0.005486%, -0.011393%, -0.000329%, 0.000993%, 0.998152%, -0.000001%, -0.001698%, -0.000008%, -0.00006%, -0.0 Changes of 0002%, -0.000004%, and 0.000046%.

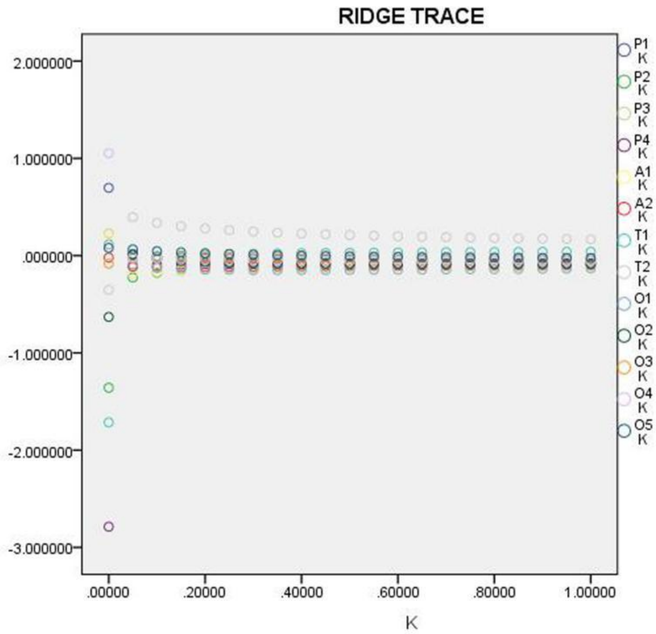

Figure 4. Ridge Trace Map

Table 4. Table 4: Ridge Regression Results when K=0.4

	B	SE(B)	Beta	B/SE(B)
P1	-.000060256	.000075949	-.039161053	-.793378781
P2	-.005486420	.001913354	-.123067043	-2.867435800
P3	-.011393469	.025410597	-.052133693	-.448374712
P4	-.000329449	-.000329449	-.086872958	-1.825864265
A1	-.000001477	.000000581	-.125156615	-.125156615
A2	-.001697863	.000914052	-.108447930	-1.857511894
T1	.000993462	.002940017	.025121453	.337910254
T2	.998152166	.396585498	.226731242	2.516865018
O1	-.000007546	.000005605	-.148853663	-1.346226239
O2	-.000005508	.000005470	-.080910069	-1.006934496
O3	-.000019784	.000122281	-.015548738	-.161787254
O4	-.000003965	.000003562	-.049763051	-1.113092005
O5	.000046024	.012603838	.000428924	.003651550
Constant	1.964974996	1.477025937	.000000000	1.330359168

5. Analysis of Research Results

The standardized coefficient of the standardized ridge regression equation is the Beta value in Table 4. As can be seen from the ridge regression results, The effects of each independent variable on carbon emission intensity were, in order of magnitude, energy intensity (0.2267), the proportion of secondary industry (0.0251), green coverage rate of built-up area (0.0004), length of subway operating line (-0.0155), population size (-0.0392), green area of park (-0.0498), and labor population ratio Weight (-0.0521), number of buses (-0.0809), total number of households (-0.0869), resident car ownership (-0.1084), urbanization rate (-0.1231), per capita GDP (-0.1252), construction area (-0.1489).

From the non-standardized regression equation coefficients of each index, energy intensity has the greatest impact on carbon dioxide emission intensity, and the elastic coefficient is 0.9982. That is, for every percentage point increase in energy intensity, carbon emission intensity will increase by 0.9982 tons per 10,000 yuan. This is consistent with the fact that the more energy consumed per unit of GDP, the more carbon emissions. The second is the influence of the proportion of secondary industry, the elasticity coefficient is 0.001. It can be seen that the traditional secondary industry has a large use and consumption of energy, which will lead to a large amount of carbon dioxide emissions. In recent years, the proportion of the secondary industry in Chengdu has shown a downward trend, and the situation of high energy consumption and high carbon emissions in the secondary industry has been improved, but it still shows a positive correlation change, which needs to be further optimized.

The green area of parks, the number of buses, the length of subway lines, and other factors also have an impact on the carbon emission of Chengdu. Each percentage point reduction in the carbon emission intensity will also decrease, but the impact degree is relatively low. In recent years, Chengdu has vigorously promoted the construction of Park City and the subway. Urban park green space plays a role in carbon sequestration and beautifying the urban environment, so it has a certain impact on the reduction of carbon emissions. The construction of subways and public transportation provides more choices for residents to travel, and public transportation also plays an important role in reducing carbon emissions and energy consumption.

Factors such as urbanization rate, per capita GDP, and construction area have a great impact on carbon emissions in Chengdu, showing a negative correlation. In theory, the higher the urbanization rate, the greater the energy consumption, and the greater the carbon intensity should be. However, the continuous development of the city, the progress of technology, the optimization of industrial structure, the construction of urban infrastructure, and the scale effect of population will improve the efficiency of energy use, and thus reduce carbon dioxide emissions. Therefore, the negative correlation between the urbanization rate and carbon emission intensity in Chengdu is also consistent with the situation in Chengdu, indicating that the urbanization rate of Chengdu has reached a relatively high level. Per capita GDP reflects the improvement of residents' living standards. In principle, the growth of per capita GDP will increase per capita income, which will lead to the improvement of consumption level and produce more living carbon emissions. However, with the improvement of people's living standards and the enhancement of environmental protection awareness, consumers are increasingly inclined to choose low-carbon and environmentally friendly products and services, which makes per capita GDP and carbon emission intensity show a negative correlation. There is usually a positive correlation between building construction area and carbon emissions because the building construction process involves a lot of energy consumption and material use, which will directly lead to an increase in carbon emissions. However, in some specific cases, a negative correlation can also occur. With the continuous progress of building technology and the improvement of environmental protection awareness, more and more energy-saving and emission-reduction technologies are applied in building construction. When these technologies are widely used in building construction, even if the building construction area increases, the overall carbon emissions will show a downward trend due to the reduction of carbon emissions per unit area.

6. Conclusions

From the above research results, it can be seen that many factors work together to affect the carbon emission of Chengdu. Due to the uncontrollability of population and other factors, to achieve the goal of carbon neutrality in Chengdu in the future, we can start from the following aspects:

6.1 Optimize the Industrial Structure and iImprove Energy Efficiency

It can be seen from the above research results that industrial structure has a significant impact on carbon emission intensity in Chengdu. The proportion of secondary industry is positively correlated with carbon emission intensity. It is well known that high-carbon industries, such as heavy industry and energy production, generally contribute more to carbon emissions. These industries require a large amount of energy consumption in the production process, resulting in a large amount of carbon emissions. Services, for example, contribute less to carbon emissions. From the data of Chengdu in the past 20 years, the proportion of secondary industry has been reduced from 43% in 2005 to about 30%, but it still occupies an important position. Therefore, to reduce the positive impact of industrial structure on carbon emissions in Chengdu in the future, Chengdu still needs to strengthen the optimization and adjustment of industrial structure, strengthen the use of low-carbon clean energy and green technology, and improve energy utilization efficiency while developing low-carbon industries such as service industry.

6.2 Strengthen the Construction of Public Transport

In recent years, Chengdu has stepped up the construction of public transportation. The number of buses in operation increased from 4,643 in 2005 to 16,657 in 2022. The construction of subway lines will increase from 17.6 kilometers in 2010 to 558 kilometers in 2022. It can be seen from the research results that these measures have a certain positive effect on reducing the carbon emission intensity of Chengdu, but the impact degree is relatively low, and there is a large potential for improvement. Most research results show that transportation is a high-carbon emission industry and contributes a lot to carbon emissions (Zhao et al., 2024) (Li et al., 2021). Therefore, in the future construction of public facilities in Chengdu, we should continue to increase the construction of public transportation, to achieve the goal of low-carbon transportation.

6.3 Continue to Promote the Construction of Park Cities

In recent years, Chengdu has put forward the policy and goal of park city construction, which is also of great significance for reducing carbon emissions. On the one hand, by increasing the green area and vegetation coverage, Park City improves the carbon sink capacity of the city, reduces the concentration of carbon dioxide in the atmosphere, improves the urban microclimate, and thus reduces energy consumption and carbon emissions. At the same time, the construction of Park City also promotes the popularization of a low-carbon lifestyle. Parks and green spaces provide a wealth of leisure and entertainment venues, encouraging residents to engage in outdoor activities and reducing reliance on indoor entertainment and transportation (Wang et al., 2023). From the current situation, the construction of Park City has a positive effect on reducing the carbon emission intensity of Chengdu city and has great potential. Therefore, in the future, Chengdu should continue to promote the construction of Park City, providing residents with more outdoor activity space while achieving the goal of energy saving and carbon reduction.

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