# Research on Influencing Factors of Building Carbon Emissions in Extremely Cold Regions of China: A Case Study of Liaoning Province

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**Abstract.** Effective control of carbon emissions from the construction industry in China's extremely cold regions is of decisive significance for achieving the goal of "carbon peak". This study uses STIRPAT and regression models to analyze carbon emissions in the construction industry in Liaoning Province from 2006 to 2021. Results suggest the added value of the tertiary industry, construction area, resident population, and urbanization level are the main factors affecting carbon emissions.

**Keywords:** construction carbon emissions · the extremely cold areas · STIRPAT model

## 1 Introduction

To curb global warming, China proposed at the UN General Assembly to peak by 2030 and strive for carbon neutrality by 2060. In 2020, the total carbon emission of the construction industry in China was 5.08 billion tCO2, accounting for 50.9% of the national carbon emission [1], indicating that the construction industry is the key field of emission reduction. The extremely cold region refers to the region where the temperature is less than 10 degrees in January and the average temperature is less than 25 degrees in July [2], roughly 1/3 of the country's land area, including Liaoning, Jilin, Heilongjiang, Inner Mongolia, northern Xinjiang, northern Tibet and other regions. Liaoning Province, as one of the first pilot provinces of low carbon, the author chooses this province as representative of data measurement in severe cold regions. It has the important practical significance and value for realizing our "carbon neutralization" goal by studying the influencing factors of building carbon emission in severe cold regions and putting forward corresponding emission reduction countermeasures.

## 2 STIRPAT Model Construction

### 2.1 Carbon Emissions Measurement in the Construction Industry

The construction industry lacks a standardized method for carbon emissions accounting. The measured method is restricted to micro-level calculations, while the material balance method is unsuitable due to the complexity of construction processes. The whole life cycle method is therefore adopted in the study to calculate carbon emissions.


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Based on the whole life cycle theory and the imperative of sustainable development, this paper categorizes the construction industry's life cycle into four phases: construction preparation, construction, use, and demolition and garbage disposal. The sum of these four stages constitutes the total carbon emissions, as shown in (1).

$$\mathrm{E} = E_1 + E_2 + E_3 + E_4 \tag{1}$$

where $E_1$, $E_2$, $E_3$, $E_4$ are carbon emissions for construction preparation, construction, use and demolition and waste disposal, respectively. Carbon emissions at each stage are calculated according to the IPCC inventory method [3], as shown in (2).

$$\text{Emission} = \text{AD} \times \text{EF} \tag{2}$$

where *AD* is energy consumption and *EF* represents carbon emissions factors.

The recycling situation of metal building materials should be considered to avoid repeated calculations. Therefore, the calculation formula for the building materials preparation stage is as follows (3).

$$E_1 = \sum \left[ q_i \times u_i \times (1 - \xi_i) \right] + \sum \left( q_i \times d_i \times a_y \right) \tag{3}$$

where $q_i$, $u_i$, $\xi_i$, $d_i$, $a_y$ represent consumption of building materials, the carbon emissions coefficient, the recycling coefficient of building materials *i,* the transport distance of the *i-th* materials, the carbon emission factor of transportation of y mode of transportation, respectively. The calculation formula of the construction stage is the same as formula (2). The use stage accounting formula, as shown in (4):

$$E_3 = E_{GG} + E_{JM} + E_{GN} = \sum\nolimits_{i=GG}^{JM,GN} \left( AD_{ji} \times \alpha_j \times EF_j \times \rho_j \right) \tag{4}$$

$E_{GG}$ represents public buildings, $E_{JM}$ represents residential buildings, $E_{GN}$ represents heating, and $AD_{ji}$ represents the consumption of j energy in phase *i*. The calculation formula for the demolition and waste treatment stage is as follows (5):

$$\begin{aligned} E_4 = E_{CC} + E_{CL} = \sum AD_j \times \alpha_j \times EF_j \times \rho_j \\ + (S_{SG} \times R_{SG} + S_{CC} \times R_{CC}) \times d_i \times a_y \end{aligned} \tag{5}$$

*Ecc* and $E_{CL}$ represent the carbon emissions in the demolition stage and the waste disposal stage, respectively; $R_{SG}$ and $R_{CC}$ represents the amount of garbage generated by the construction areas and demolition; $S_{SG}$ represents the construction areas; $S_{CC}$ represents the demolition areas.

All data is from Liaoning Province Statistical Yearbook and Standards for building carbon emission calculation. The calculation result of the whole life cycle carbon emissions of buildings in Liaoning Province from 2006 to 2021 are shown in Fig. 1.

During the observation period, the carbon emissions of the construction industry in Liaoning Province showed a "several-shaped" pattern, with an initial increase followed by a decrease. Specifically, carbon emissions from 2006 to 2013 steadily rose by 465.35%, then began to decline, with only a slight increase in 2019. Regarding the carbon emission composition of buildings, the production and use stages of building materials account for 98% of total emissions. In contrast, the construction, demolition, and garbage disposal stages only account for 2%.

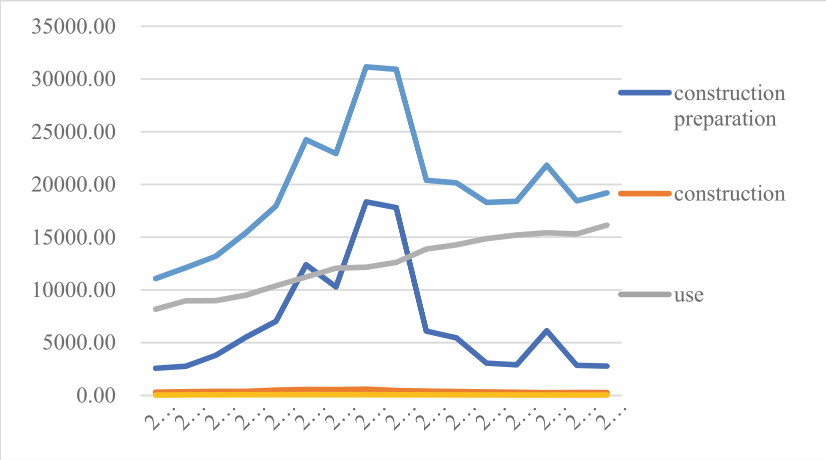


**Fig. 1.** Carbon emissions of construction industry in Liaoning Province from 2006 to 2021

### 2.2 Determination of Influencing Factors

Since a variety of factors impact carbon emissions in every stage of the whole life cycle of buildings, this paper chooses the largest consumption in each stage based on the results of the calculations. At the same time, based on the sorting of relevant references [4–9], the author selects cement, electric power, permanent resident population, the added value of the tertiary industry, the level of urbanization, the construction area, the labor productivity of construction enterprises, the total output value of the construction industry and energy intensity as the influencing factors.

## 3 Model

Dietz et al. carried out an extended, modified stochastic regression model in the IPAT model [10]. The expression as shown in (6)

$$\mathrm{I} = \mathrm{a}p^{b}A^{c}T^{d}e \tag{6}$$

The model includes a proportionality constant term denoted by A, the population factor represented by *P*, the degree of affluence denoted by *A*, the technical factor represented by *T,* and the elastic coefficients of the three variables *P*, A, and *T*, represented by *b*, *c*, and *d,* respectively. Additionally, the model includes a random error represented by e. Logarithm processing is typically employed to construct the STIRPAT model for the nonlinear index factor model. In this study, the dependent variable is the carbon emissions of the construction industry in Liaoning Province, while the nine selected factors are the independent variables. The resulting influencing factor model of building carbon emissions in Liaoning Province is an exponential function, as shown in (7).

$$lnI = m + a_1 lnF1 + a_2 lnF2 + a_3 lnF3 + a_4 lnF4$$

$$+ a_5 lnF5 + a_6 lnF6 + a_7 lnF7 + a_8 lnF8 + a_9 lnF9 \quad (7)$$

*I* represents the total carbon emissions of the construction industry, *F1* represents cement, *F2* represents electricity, *F3* represents the number of permanent residents, *F4* represents the added value of the tertiary industry, *F5* represents the level of urbanization, *F6* represents the labor productivity of construction enterprises, *F7* represents the total output value of construction, *F8* represents energy intensity, and *F9* represents the construction area. $A_2$, $a_3$, $a_4$, $a_5$, $a_6$, $a_7$, $a_8$, and $a_9$ represent the corresponding coefficients of each variable, and m is the constant term.

# 4 Model Analysis

## 4.1 Ridge Regression Analysis

The ridge regression model is one of the most effective solutions to multicollinearity, and multiple regression models are usually sorted into (8).

$$\mathrm{Y} = \mathrm{X}\beta + \zeta \quad (8)$$

where $Y$ is the dependent variable, X is the independent variable, $\beta$ is the coefficient, and $\zeta$ is the error. Using the ordinary least squares method to find $\hat{\beta} = \left(X^T X\right)^{-1} X^T Y$, If there is a collinearity relationship between the independent variables $X$, $\left|X^T X\right|$ is equal to or close to zero.

However, in ridge regression, a constant matrix KI will be added to the parentheses, so the expression of $\beta$ is $\hat{\beta}(\mathrm{k}) = \left(\mathrm{X^T X} + \mathrm{kI}\right)^{-1}\mathrm{X^T Y}$. In this case, $\hat{\beta}(\mathrm{k})$ is called the ridge estimate of the regression coefficient. When $\mathrm{k} = 0$, $\hat{\beta}(\mathrm{k})$ becomes the least square estimation. When $k > 0$, matrix *KI* has played a role and can get more stable and reliable coefficient values [11]. Too much *K* loses its effect, usually between 0 and 1. Observing the ridge trace map, the k value when the ridge trace curve of each variable tends to be stable is selected. Use Python for the Ridge regression model, and this paper gets the ridge trace Fig. 2.

According to Fig. 2, when $\mathrm{K} = 0.1$, the standardized regression coefficient of the independent variable tends to be stable and greater than zero, the curve's trend becomes flat. Therefore, this article chooses $\mathrm{K} = 0.1$ for ridge regression, and Table 1 shows the specific results.

Table 1 shows that the coefficient of determination R-Square is 0.9988, which means that the nine influencing factors can explain 99.88% of the carbon emissions of construction industry in Liaoning Province, with a high degree of fit. Moreover, in the hypothesis test of the Ridge regression model, the F value is 272.20, and the P value is Sig $\mathrm{F} < 0.01$, indicating that this model is practically significant. B is the non-standard regression coefficient, namely the value of model coefficients a and Beta. Std is the standard regression coefficient used to compare the absolute effect between the coefficients. According to the above analysis, the STIRAPT model is obtained as follows:

$$\begin{aligned} \mathrm{lnI} = 0.1677 + 0.1081F_1 + 0.1179F_2 + 0.122F_3 + 0.1324F_4 \\ + 0.1212F_5 + 0.1091F_6 + 0.1111F_7 + 0.0286F_8 + 0.132F_9 \end{aligned} \quad (9)$$

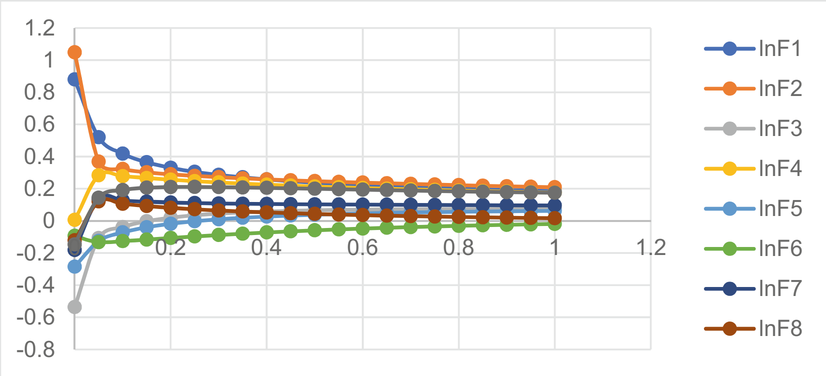


**Fig. 2.** The Ridge Trace

**Table 1.** k = 0.3 Ridge regression result

| | B | Beta.std | R-Square | Adj R-Square | F |
|---|---|---|---|---|---|
| $\ln F_1$ | 0.1081 | 0.008 | 0.9988 | 0.9951 | F = 272.20<br>Sig F = 0.0003 |
| $\ln F_2$ | 0.1179 | 0.136 | | | |
| $\ln F_3$ | 0.1220 | 0.139 | | | |
| $\ln F_4$ | 0.1324 | 0.121 | | | |
| $\ln F_5$ | 0.1212 | 0.153 | | | |
| $\ln F_6$ | 0.1091 | 0.107 | | | |
| $\ln F_7$ | 0.1111 | 0.009 | | | |
| $\ln F_8$ | 0.0286 | 0.189 | | | |
| $\ln F_9$ | 0.1320 | 0.008 | | | |
| Constant | 0.1677 | 0.105 | | | |

## 5 Analysis and Results

According to the STIRPAT equation, the impacts on the carbon emissions of the construction industry in Liaoning Province from large to small are as follows: added value of the tertiary industry (0.1324), construction areas (0.1320), permanent resident population (0.1220), urbanization level (0.1212), electricity (0.1179), the total output value of the construction industry (0.1111), labor productivity of construction enterprises (0.1091), cement (0.1091) and energy intensity (0.0286).

The tertiary industry has the greatest impact on carbon emissions, with the corresponding carbon emissions increasing by 0.1324% for every 1% increase. This is because most of the activities of the tertiary sector occur within buildings, leading to high energy consumption and increased carbon emissions. There is a need to address the imbalance between economic development, industrial structure, and building carbon emissions.

The government should support restructuring the industry to promote energy-efficient and green building industries, while fostering relevant market players and creating a market-based mechanism for long-term carbon emission reduction.

Construction area ranked second in the impact on carbon emissions, with carbon emissions increasing by 0.13% for every 1% increase. Construction area ranked second in the impact on carbon emissions, with carbon emissions increasing by 0.13% for every 1% increase. By 2021, only 21% of prefabricated buildings will be built in Liaoning Province. To reduce emissions, Liaoning needs to strengthen green building construction and cultivate the service industry related to building energy conservation and green building.

The permanent population ranks third. The increase in population leads to an increase in demand, energy consumption and carbon emissions. However, the increase in education level can reduce the impact, with an increase in the proportion of people receiving higher education and a gradual decrease in carbon emissions.

In fourth place is urbanization, which brings population, land and economic activity together and increases energy consumption. At the same time, urbanization changes people's lifestyle and increases their demand for energy, shopping and tourism. In Liaoning Province, urbanization is developing rapidly, but the public awareness of energy conservation is not high, which leads to the increase of energy consumption and carbon emissions in the construction industry. It is necessary to raise public awareness of energy conservation, increase the use of renewable energy in cities, and improve the energy consumption structure, such as solar lighting, heating systems, and ethanol and gasoline.

## 6 Conclusions

This paper examines the main factors affecting carbon emissions in extremely cold regions using Liaoning Province as a case study. The construction industry in Liaoning is divided into four stages, and carbon emissions are calculated for each stage using the whole life cycle theory. The study identifies 9 influencing factors, processes and models the data, and concludes that the added value of the third industry, construction area, resident population, and urbanization level are the key factors affecting carbon emissions. These findings can be used to inform policies aimed at reducing building carbon emissions in extremely cold regions.

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