

Retraction

Retracted: Analysis on the Pattern of County Carbon Emission Intensity and the Evolution of Influencing Factors in China Based on LMDI Model

Wireless Communications and Mobile Computing

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This article has been retracted by Hindawi following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of one or more of the following indicators of systematic manipulation of the publication process:

- (1) Discrepancies in scope
- (2) Discrepancies in the description of the research reported
- (3) Discrepancies between the availability of data and the research described
- (4) Inappropriate citations
- (5) Incoherent, meaningless and/or irrelevant content included in the article
- (6) Peer-review manipulation

The presence of these indicators undermines our confidence in the integrity of the article's content and we cannot, therefore, vouch for its reliability. Please note that this notice is intended solely to alert readers that the content of this article is unreliable. We have not investigated whether authors were aware of or involved in the systematic manipulation of the publication process.

Wiley and Hindawi regrets that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our own Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

References

- [1] Y. Chen, "Analysis on the Pattern of County Carbon Emission Intensity and the Evolution of Influencing Factors in China Based on LMDI Model," *Wireless Communications and Mobile Computing*, vol. 2022, Article ID 3658679, 9 pages, 2022.

Research Article

Analysis on the Pattern of County Carbon Emission Intensity and the Evolution of Influencing Factors in China Based on LMDI Model

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The global economy is deteriorating, and the problem of climate anomalies is becoming more prominent. Countries around the world are actively developing. The progress by leaps and bounds of China's economy has brought huge environment, resources, and other problems, and the problem of carbon emissions is more prominent. Based on this, this paper studies the evolution analysis of county carbon emission intensity pattern. Based on the simple analysis of carbon emission research and the research progress of influencing factors, according to the economic development status, the counties in China are divided into four parts, the county carbon emission intensity analysis model is constructed, and the influencing factors are studied by using LMDI model. The results of empirical analysis show that the intensity of county carbon emissions in China has been growing, and there are many influencing factors. The increase of population and economy will lead to a certain level of carbon emissions.

1. Introduction

The global economy has been developing rapidly. Fossil energy is the material basis to promote economic development [1, 2]. With the extensive use and overexploitation of fossil energy, environmental problems have become increasingly prominent, and the global air pollution, greenhouse effect, and other problems have become very common [3]. How to control further deterioration of the environment has become a hot topic in various countries. At present, carbon emissions have been discussed at home and abroad, and various emission reduction measures have been formulated [4]. Before the implementation of emission reduction measures, the causes of excessive carbon dioxide emissions have been analyzed. In addition to qualitative research, various quantitative analysis models have been added to the current research methods [5]. However, most of the studies focus on some regions and do not investigate the differences of carbon emissions in different regions.

Section 1 first gives a brief introduction to the research on carbon emissions and the chapter arrangement of this

study. Section 2 introduces environmental pollution at home and abroad, introduces the research status of LMDI model, and summarizes the shortcomings of the current research. In Section 3, the analysis model of county is established. The Theil index method is used to analyze the county carbon emission degree as a whole. By establishing the data of carbon emissions under different economic circles, this paper analyzes and references the different influencing factors in the model. Section 4 makes an empirical analysis on the county carbon emission intensity model and influencing factor analysis method constructed in this paper. The data research continues to grow, and there are great differences among different county carbon emission intensities. The Northeast county has the highest carbon emission intensity. The analysis of influencing factors shows that population growth and economic development emissions and the change of industrial structure have a great difference on its impact.

The innovation of this paper lies in the use of research methods. In the research of relevant achievements on energy issues, the Theil entropy standard index method is used to

divide the county according to the economic circle and analyze the differences of county carbon emissions in the national region. The Theil entropy measure or the Theil index is often used as an indicator to measure the income gap (or inequality) between individuals or regions. Theil entropy standard is named after Theil (1967) who uses the concept of entropy in information theory to calculate income inequality. In the analysis of influencing factors of carbon emission intensity, the LMDI model is used for decomposition to improve the sensitivity of the model to data changes, focusing on the impact of economic development and demographic factors.

2. State of the Art

The low-carbon economy was put forward in 2003 to promote the sound development of society. At present, it has been recognized by the public. Countries are also gradually aware of the harm brought by the energy problem. They are constantly transforming towards the development of low-carbon economy, and emissions are also emerging. On the basis of 2015, Zhang and Hao focus on carbon dioxide, combine the subjective and objective, discuss the impact of different industries, and establish a ZSG-DEA model to test the results [6]. In their research, Shahzad et al. used the ARDL boundary cointegration test method to test the cointegration relationship between Pakistan's carbon emissions, through the establishment of the model of the relationship between carbon emissions and energy consumption; this paper analyzes the energy, trade, and financial development in different states. The threshold levels in different stages of trade opening are analyzed [7]. Han et al. improved the model, established an evaluation model method based on information entropy, and made an empirical analysis with Chinese industry as the research object. It is found that the improved model is more accurate in discrimination than the DEA model [8]. Jiang and Li discussed construction industry, calculated the whole life cycle, and analyzed the influencing factors. At the same time, the different growth rates of carbon emissions in China are analyzed. The annual average growth rate of total carbon emissions from buildings in China is pointed out, so as to analyze the carbon emission effect in the market. [9]. Jiang et al. combined LMDI decomposition with Q-type hierarchical clustering and systematically evaluated the contribution of relevant driving factors of 30 provinces to China's national carbon emission growth, and based on the actual development data of each province, the main mechanism of the impact on the growth of CO₂ emissions is clarified. It is considered that there are great differences among each province, and they are discussed separately in combination with economy, energy, and structure [10]. The model allocation factors under different extensions are studied and analyzed, and the model discussion and analysis of carbon dioxide are mainly driven and matched. At the same time, different factors are discussed by using the model of extended analysis [11].

To sum up, we can see that there are many studies on carbon emissions, and the early studies mainly focused on the simple description of carbon emissions. With the deep-

ening of research, we began to use various models to conduct quantitative research, discuss the influencing factors of carbon emissions, and partially use intelligent algorithms to predict carbon emissions. To predict carbon emissions, we need to grasp the change trend of the above links. There are two methods to achieve this goal: the first method is to build a special prediction model, which requires many exogenous assumptions. The second kind of method is the method of empirical analogy, that is, with the help of the experience of other developed economies at similar stages of development and analogy of the evolution trend of relevant factors in China in the future. The latter method has the following characteristics: first, it is relatively simple; second, we do not need too many exogenous assumptions. In addition, from the perspective of prediction reliability, especially from the perspective of the reliability of basic trend prediction, the method of empirical analogy is not inferior to complex models.

The current industrial structure of China determines the current situation of carbon emission growth. China's energy consumption structure is the main cause of carbon dioxide emissions. Per capita GDP growth is the biggest driver of carbon emission growth. In addition, population changes, environmental policies, and the international environment will also have an important impact on China's carbon emissions. Most of them carry out regional or industrial carbon emission analysis from a macro perspective, but they rarely take county carbon emissions as the research object and lack of targeted research. On the other hand, in the analysis of influencing factors, most of the research factors are in the aspects of energy intensity and unit energy consumption emissions, which are rarely studied from the perspective of industrial structure, and most of them use static analysis methods without discussing the time factor.

3. Methodology

3.1. Design of County Carbon Emission Model. With the progress by leaps and bounds of economy, environmental problems have become increasingly prominent, and the problem of greenhouse effect has become more obvious. In order to avoid further deterioration of the environment, it is necessary to solve the problem of carbon dioxide emissions from the root causes. In addition to protecting the marine environment and protecting terrestrial vegetation to help the environment increase its ability to absorb carbon dioxide, what humans can do is mainly to reduce carbon emissions. At present, there are mainly the following technical directions and options for reducing carbon emissions: adopting clean energy, improve the utilization rate of energy, develop the basic theory of energy utilization, carbon capture and resource utilization, and condensation recovery carbon emissions. China proposes to achieve the carbon peak goal around 2020. However, China has vast territory and different industrial economies in different counties. In order to improve the universality of the research results, the typical counties in China are selected for research and analysis.

The coastal counties, northeast counties and Yangtze River counties in China are selected as examples for discussion. The coastal and Yangtze River counties enjoy rapid economic development and superior County conditions. They have concentrated a large number of manufacturing industries in China. The energy structure is complex, the population is dense, and the total economic output ranks high [12]. Northeast county is an old industrial county in China. In recent decades, its economic development lags behind, its energy structure is complex, and its population density is gradually decreasing. There is a great difference between Northeast county and other county environments, which is representative. Although the economic development in Northwest China is slow, the environment is good. For example, the carbon emission in Yunnan County is very low, so it is not included in the research and analysis. The study takes these counties as the research objects; sorts out the economic development status, population data, energy status, and carbon emission data for analysis; decomposes them with LMDI model; and summarizes the influencing factors of carbon emission. See Figure 1 for the specific analysis process.

3.2. Emission Intensity. It involves the population overview of each county concept, energy consumption, output of each department, etc. For the convenience of calculation, representative counties are selected for analysis. The statistical data analyzed the yearbook statistics of different years. Through the balance comparison of different energy consumption concepts, this paper expounds the different concepts in the statistical yearbook. At present, in the calculation of carbon emissions, the vast majority of countries have not formed a fixed detection standard or calculation formula. When analyzing the carbon emissions of counties, the carbon emissions of cities are mainly investigated. Therefore, it is necessary to make necessary estimates [13]. In the more authoritative calculation of carbon emissions, the 2006 who designated the national greenhouse gas inventory provided the method.

The measurement of carbon emissions adopts the material balance algorithm. The material balance method means that the algebraic sum of the volume changes of oil, natural gas, and water in the oil and gas reservoir is always zero under the condition of a certain volume of the oil and gas reservoir. That is to say, in oil and gas reservoirs, the remaining oil, gas, and water at any time + cumulative recovery = original geological reserves, and the PV/T relationship is always in balance. The estimation method is adopted, generated by the combustion of fossil fuels, covering three. In the statistical yearbook, many energy data have been converted into standard format data, so they need to be converted into physical objects [14]. The carbon emission calculation formula is expressed as

$$C = E_c \times \delta_c + E_s \times \delta_s + E_t \times \delta_t, \quad (1)$$

where C is carbon emission, BB is physical consumption, where CC is coal, DD is oil, EE is natural gas, and FF is conversion factor. In the process of calculating, this paper only

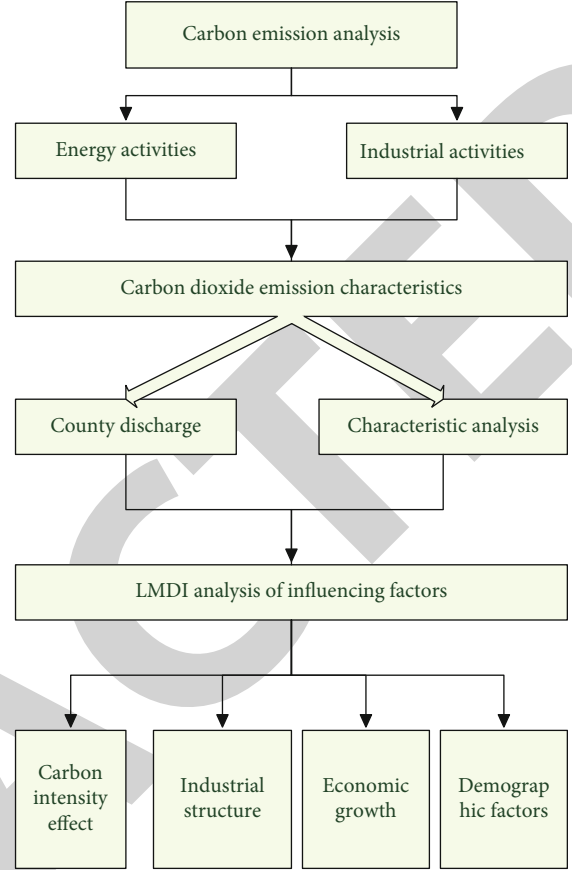


FIGURE 1: County carbon emission analysis process.

analyzes the carbon dioxide generated by primary energy consumption, and the energy consumption generated during processing and transportation is not included in the calculation of carbon emissions [15]. The carbon emission coefficient adopts the average value and is brought into the formula. The carbon emission calculation formula can be expressed as

$$C = E_c \times \delta_c + E_s \times \delta_s + E_t \times \delta_t = 0.733E_c + 0.557E_s + 0.423E_t. \quad (2)$$

Further calculation shows that

$$C = E(1.026a + 0.309b + 0.259r), \quad (3)$$

where a represents the proportion of coal in the resources calculated by the industrial foundation, b represents the proportion of oil, and r represents the proportion of natural gas. In the research of carbon emission decomposition, due to the late research time, the standards adopted by different regions are different, and the Theil index is widely used [16].

The Theil index was initially used to analyze the income differences among countries and later applied to income research at different levels. This method can decompose a whole into different groups, then analyze the differences within groups and the comparison between groups, observe

the differences between groups and within groups, and find out the causes and influencing factors of the changes [17]. The value range of Theil index is 0~1. [18]. Assuming the probability that the event will occur is p , the amount of information about the event must be a minus function of the probability. Based on this research, the difference is decomposed according to the that index, and the formula is expressed as follows:

$$T = T_w + T_b = \sum_j \frac{C_j}{C} T_{wi} + T_b, \quad (4)$$

where T represents the Theil coefficient of carbon emission, T_w represents the carbon emission index of each unit, and T_b represents the Theil coefficient within the county.

3.3. Analysis on Influencing Factors. The LMDI model is used to decompose the changes in the county. Considering that it is affected by many factors, it is difficult to describe all the causes. Therefore, before the analysis, the most important influencing factors are assumed in combination with the existing research results, and other factors can be explained by these factors [19], as shown in Figure 2.

Carbon emissions vary greatly in different counties, and the influencing factors are also different. The influencing factor changes are divided into four parts, namely, carbon emissions intensity, industrial institutions, population size, and economic changes. The five-year cycle is analyzed with the help of the differential decomposition formula [20, 21]. It is assumed that in space, the research object can be decomposed into the product of AA factors, which changes within a certain time range. According to the multiplication, it can be decomposed into

$$D_{\text{tot}} = D_{x1} \times D_{x2} \times \cdots \times D_{xn}. \quad (5)$$

It is decomposed into

$$\Delta V_{\text{tot}} = V^t - V^0 = \Delta V_{x1} + \Delta V_{x2} + \cdots + \Delta V_{xn}, \quad (6)$$

where tot represents the total change of carbon emission. In order to avoid the multiplicative and complementary problems in decomposition and the subjectivity of parameter estimation, the multiplication formula and addition formula are decomposed, and the formula is expressed as

$$D_{xK} = \exp \left[\sum_{i=1}^m \frac{L(V_i^t, V_i^0)}{L(V^t, V^0)} \right] \ln \frac{x_{ki}^t}{x_{ki}^0}, \quad (7)$$

$$\Delta V_{xK} = \sum_{i=1}^m L(V_i^t, V_i^0) \ln \frac{x_{ki}^t}{x_{ki}^0}.$$

With the help of carbon emission index decomposition model, county carbon emissions can be expressed as

$$C = \sum_{i=1}^n I_i \times S_i \times P \times \text{GDP}. \quad (8)$$

n represents the industrial sector, the calculation formula is further decomposed by difference, and the calculation is expressed as follows:

$$\Delta C = \sum_{i=1}^n I_i^t \times s_i^t \times p^t \times \text{GDP}^t - \sum_{i=1}^n I_i^0 \times s_i^0 \times p^0 \times \text{GDP}^0. \quad (9)$$

By decomposing the above factors, we can get

$$\begin{aligned} \Delta I &= \sum_i \frac{C_i^t - C_i^0}{\ln C_i^t - \ln C_i^0} \times \ln \frac{I_i^t}{I_i^0}, \\ \Delta S &= \sum_i \frac{C_i^t - C_i^0}{\ln C_i^t - \ln C_i^0} \times \ln \frac{S_i^t}{S_i^0}, \\ \Delta P &= \sum_i \frac{C_i^t - C_i^0}{\ln C_i^t - \ln C_i^0} \times \ln \frac{P_i^t}{P_i^0}, \\ \Delta \text{GDP} &= \sum_i \frac{C_i^t - C_i^0}{\ln C_i^t - \ln C_i^0} \times \ln \frac{\text{GDP}_i^t}{\text{GDP}_i^0}. \end{aligned} \quad (10)$$

According to the above calculation results,

$$r_{\text{GDP}} = \frac{\Delta \text{GDP}}{\Delta C} \times 100\%, \quad (11)$$

where r represents the contribution rate of factors. If the contribution rate of carbon emission intensity, population size, and other factors is calculated, it can be directly brought into the data for calculation.

4. Result Analysis and Discussion

4.1. Carbon Emission Status. According to the research needs, the counties in the Yangtze River Basin, coastal counties, northeast counties, and central plain counties are selected for research and analysis. The numerical changes of counties after 1995 are calculated according to the carbon emission calculation formula. Taking the data in 1995 as the basic data, we first count the population data and then average carbon emissions to individuals. The primary energy is selected for analysis, and the physical object is calculated according to the energy conversion reference coefficient (see Figure 3).

From the data changes in Figure 3, different counties have common ground, and there are also great differences. From the perspective, it has been showing an increasing trend, increasing by more than 4 times. There is a great difference in the growth of differences within counties, and the difference in per capita this indicator has increased. Before 2000, the Northeast county had the highest per capita this indicator, which has increased by nearly 6 times. From the perspective of counties, in 1995, the counties with the highest this indicator were concentrated in the northeast. In the subsequent time, the this indicator of the Yangtze River and coastal counties also began to increase. Overall, the total this indicator and per capita are increasing, with obvious differences (Figure 4).

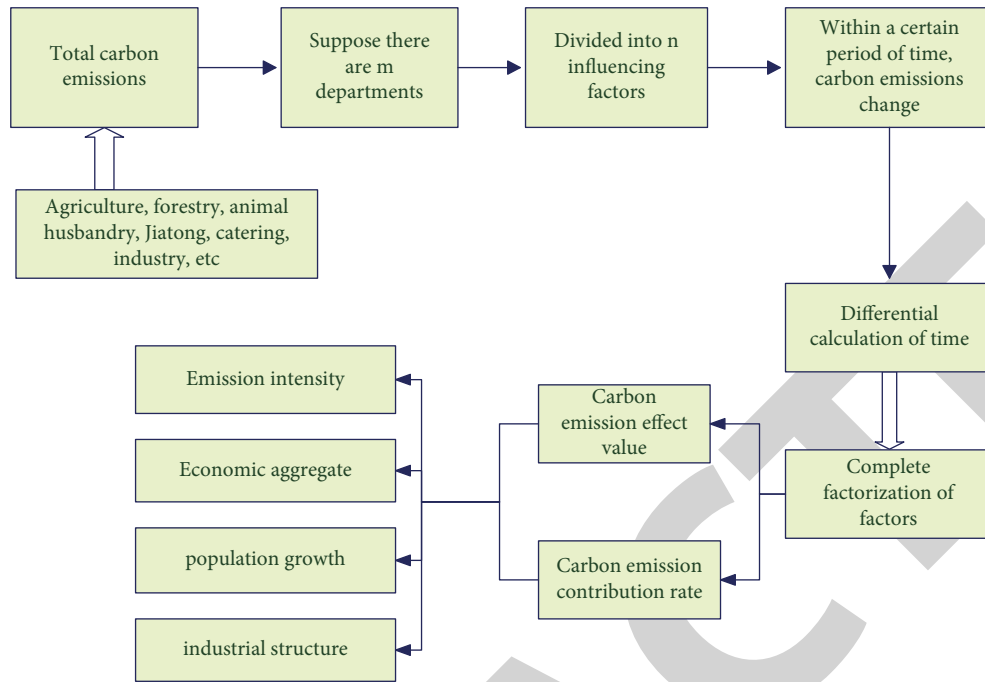


FIGURE 2: Analysis process of carbon emission.

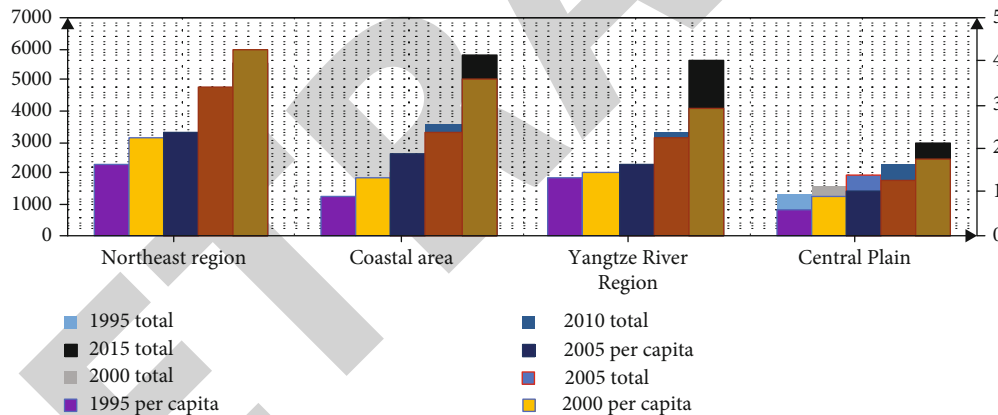


FIGURE 3: Total and per capita carbon emissions.

Calculate the Theil coefficient and per capita coefficient of carbon emission intensity at an interval of 5 years. The calculation results of Theil coefficient are all between 0 and 1, and the results are reliable. From the perspective of overall Theil coefficient, in recent times, the maximum value of Theil coefficient appeared in the eighth five-year plan, and the minimum value appeared in 1995. The per capita Theil coefficient was the largest in 2015, indicating that the matching degree between this indicator and GDP was less than the individual matching coefficient.

4.2. Factor Analysis. Before analyzing the influencing factors of county carbon emissions, first analyze the whole and four factors. In the decomposition process, the industrial departments analyze according to the industries. The calculation results are shown in Figure 5.

From the data change in Figure 5, it can be seen that among the decomposed influencing factors, it shows a negative effect, and the others are positive effects. Carbon emission intensity can restrain the continuous growth of this indicator. For population growth, it will promote the growth of this indicator, indicating that China’s industrial structure needs to be adjusted, especially in the industrial structure with high this indicator. In terms of economic effects, China’s economy is developing at a high speed. Although the economy shows a positive effect on carbon emission inhibition, this effect has decreased. The industrial structure contributed to the increase of this indicator, but this performance is not very obvious, which also shows that there is room for improvement. In terms of population size, because the base is too large and the demand is too large, it shows this indicator.

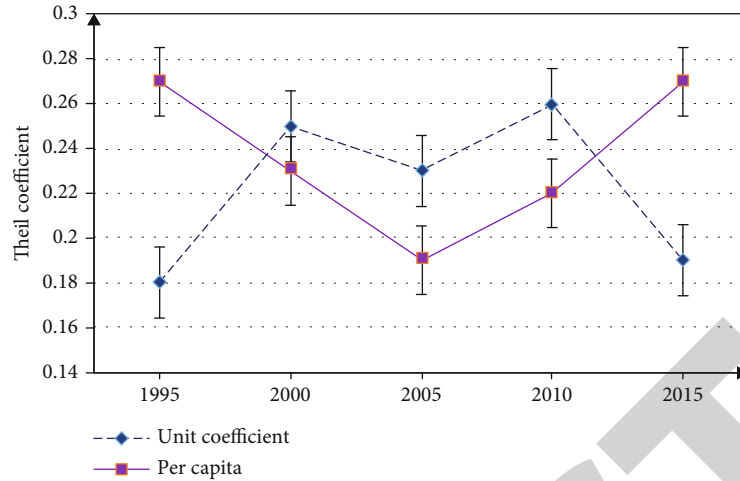
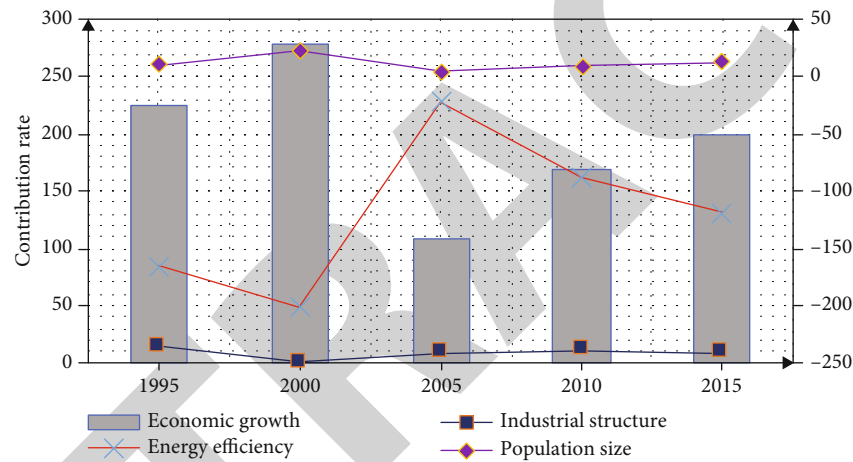


FIGURE 4: Theil coefficient and per capita coefficient.

FIGURE 5: Contribution rate of *i* decomposition.

In the analysis of influencing factors, the LDMI model is also used to decompose and investigate the influencing factors. Figure 6 shows the different strategic impacts of industrial structure on carbon emissions. Overall, the intensity of this indicator has decreased.

In China's industrial structure, industry plays a leading role and has a great energy consumption which is also the largest. Figure 7 shows the impact of various industries' figure that the carbon emission of agriculture and forestry fluctuates, the carbon emission intensity of the construction industry decreases, and other industries have little change. China's economy has been constantly adjusted, the proportion of industry and agriculture has begun to decline, and the service industry has been increased, and this change is still being updated. The industrial adjustment is not stable enough, and there is still much room for improvement.

The influencing factors of carbon emissions are analyzed counties. According to the LMDI complete decomposition method, the causes are already very comprehensive and can cover other unanalyzed factors. The analysis results are shown in Figure 8. From the data change in Figure 8, it can be seen that among the influencing factors of county this

indicator, there are still negative effects of carbon intensity and positive effects of other factors, among which the most obvious factor causing this indicator is the economic factor. The changes of the four major influencing factors are time-dependent, and there are great differences in county this indicator across the country. In economically developed counties, such as coastal counties, the effect values of influencing factors are relatively high. And economic factors play a leading role. As a developing country, economic growth is a necessary condition to meet people's material life. As a basic input, energy consumption reflects the intensity of economic activities. As a direct product, this indicator is directly related to economic development.

Population factors also have a greater growth of population size which can also promote the increase intensity. With the development of society and the gradual improvement of medical conditions, population growth is an inevitable structure, and this trend is more obvious with the increase of migrant population. Before 2010, the population growth rate has been increasing, and the impact of population size on this indicator can reach more than 55%, which changes slowly in the subsequent time, which may be related to the

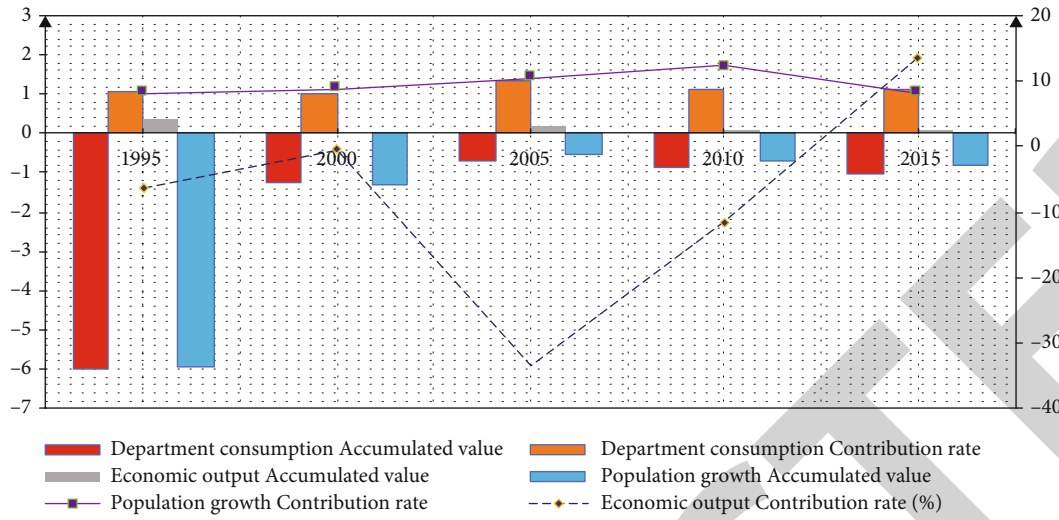


FIGURE 6: Contribution rate emission intensity decomposition.

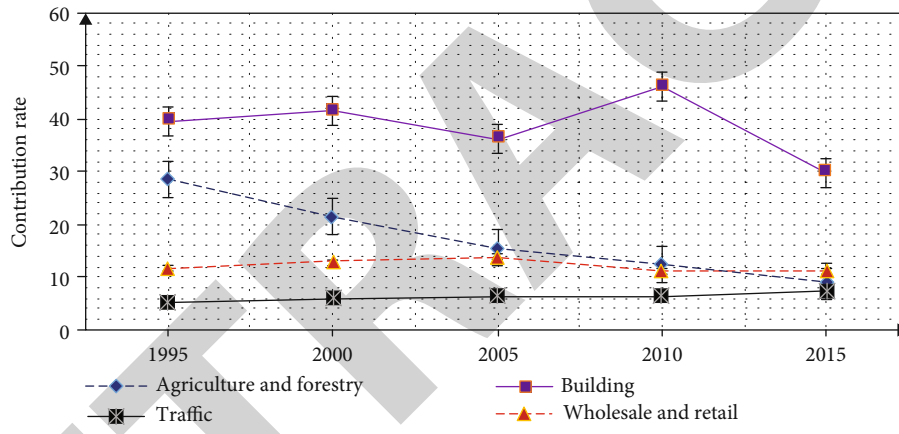


FIGURE 7: Impact of various industries on carbon emission intensity.

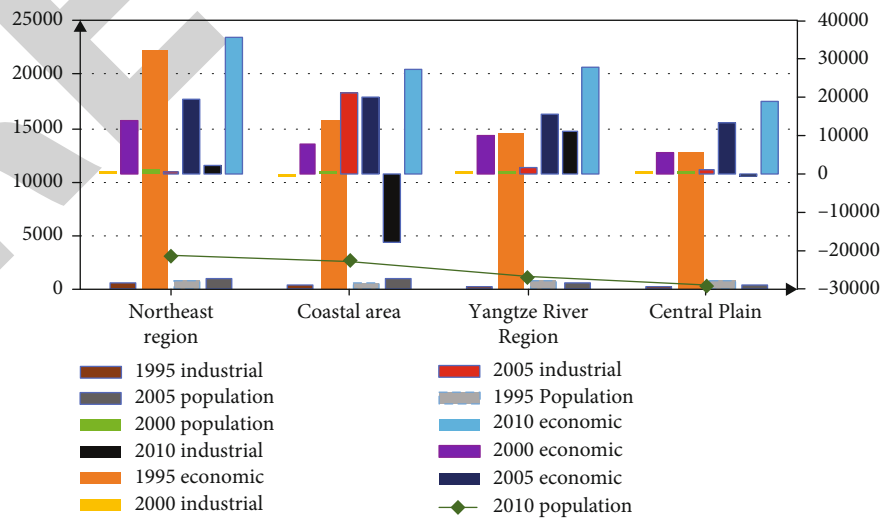


FIGURE 8: Different emission influencing factors.

slower population growth. Energy intensity can reflect the change of domestic GDP and energy efficiency index to a certain extent. In the factor decomposition results, it can be seen that for counties with rapid economic development, such as coastal counties, the energy intensity fluctuates greatly, but on the whole, it presents a negative effect, which can inhibit the intensity of this indicator. However, this result is not stable, and some years show a positive effect, which may be related to economic development. Coal is the highest. When the proportion of low-carbon energy is increased, the intensity of carbon emission can be reduced to a certain extent. It can be seen from the data changes that although the carbon emission intensity fluctuates to some extent, the average coefficient is declining, indicating that the energy structure has been improved to some extent.

5. Conclusion

The greenhouse effect is caused by the large-scale emission of greenhouse gases, of which carbon dioxide is the main greenhouse gas causing the greenhouse effect. Effective control is of great value to improve the environment. Based on the simple analysis of carbon emission research and the research progress of influencing factors, according to the economic development status, the counties in China are divided into four parts, the county carbon emission intensity analysis model is constructed, and the influencing factors are studied by using the LMDI model. The results of empirical analysis show that the intensity of county carbon emissions in China has been growing, and there are many influencing factors. The increase of population and economy will lead to a certain level of carbon emissions. The results show that the county this indicator is increasing, and the intensity of this indicator has a negative effect. Among the influencing factors, the impact of economic growth on carbon emission intensity has always occupied a dominant position, the driving effect of population factors has slowed down, and the carbon emission intensity of counties shows great imbalance, showing a multilevel pattern. It should be pointed out that there are many estimation methods. The analysis is carried out from the overall perspective without detailed analysis. In the analysis of influencing factors, there are many research models. This paper only uses the LMDI model in the discussion and does not compare with the analysis results of other models. In addition, in order to calculate, only the main factors are analyzed, and other factors are not discussed. These need to be further studied.

Data Availability

The figures used to support the findings of this study are included in the article.

Conflicts of Interest

The author declares that there are no conflicts of interest.

References

- [1] C. T. Lee, H. Hashim, C. S. Ho, Y. V. Fan, and J. J. Klemeš, "Sustaining the low-carbon emission development in Asia and beyond: sustainable energy, water, transportation and low-carbon emission technology," *Journal of Cleaner Production*, vol. 146, no. 10, pp. 1–13, 2017.
- [2] M. Olguin, C. Wayson, M. Fellows et al., "Applying a systems approach to assess carbon emission reductions from climate change mitigation in Mexico's forest sector," *Environmental Research Letters*, vol. 13, no. 3, article 035003, 2018.
- [3] L. Yang, Y. Cai, X. Zhong, Y. Shi, and Z. Zhang, "A carbon emission evaluation for an integrated logistics system—a case study of the port of Shenzhen," *Sustainability*, vol. 9, no. 3, p. 462, 2017.
- [4] X. Chen, C. Shuai, Y. Wu, and Y. Zhang, "Analysis on the carbon emission peaks of China's industrial, building, transport, and agricultural sectors," *Science of the Total Environment*, vol. 709, 2020.
- [5] J. Jia, H. Jian, D. Xie, Z. Gu, and C. Chen, "Multi-scale decomposition of energy-related industrial carbon emission by an extended logarithmic mean Divisia index: a case study of Jiangxi, China," *Energy Efficiency*, vol. 12, no. 8, pp. 2161–2186, 2019.
- [6] Y. J. Zhang and J. F. Hao, "Carbon emission quota allocation among China's industrial sectors based on the equity and efficiency principles," *Annals of Operations Research*, vol. 255, no. 1–2, pp. 117–140, 2017.
- [7] S. J. H. Shahzad, R. R. Kumar, M. Zakaria, and M. Hurr, "Carbon emission, energy consumption, trade openness and financial development in Pakistan: a revisit," *Renewable and Sustainable Energy Reviews*, vol. 70, no. 70, pp. 185–192, 2017.
- [8] Y. Han, C. Long, Z. Geng, and K. Zhang, "Carbon emission analysis and evaluation of industrial departments in China: an improved environmental DEA cross model based on information entropy," *Journal of Environmental Management*, vol. 205, no. 1, pp. 298–307, 2017.
- [9] R. Jiang and R. Li, "Decomposition and decoupling analysis of life-cycle carbon emission in China's building sector," *Sustainability*, vol. 9, no. 5, p. 793, 2017.
- [10] J. Jiang, B. Ye, D. Xie, and J. Tang, "Provincial-level carbon emission drivers and emission reduction strategies in China: combining multi-layer LMDI decomposition with hierarchical clustering," *Journal of Cleaner Production*, vol. 169, no. 15, pp. 178–190, 2017.
- [11] S. Gu, B. Fu, T. Thriveni, T. Fujita, and J. W. Ahn, "Coupled LMDI and system dynamics model for estimating urban CO₂ emission mitigation potential in Shanghai, China," *Journal of Cleaner Production*, vol. 240, article 118034, 2019.
- [12] Y. Qi, "Environmental analysis of carbon emission decoupling and decomposition in regional economic growth in China," *Ekoloji*, vol. 27, no. 106, pp. 1443–1453, 2018.
- [13] R. G. Alajmi, "Factors that impact greenhouse gas emissions in Saudi Arabia: decomposition analysis using LMDI," *Energy Policy*, vol. 156, article 112454, 2021.
- [14] M. Guo and J. Meng, "Exploring the driving factors of carbon dioxide emission from transport sector in Beijing-Tianjin-Hebei region," *Journal of Cleaner Production*, vol. 226, no. 20, pp. 692–705, 2019.
- [15] M. Ma and W. Cai, "What drives the carbon mitigation in Chinese commercial building sector? Evidence from decomposing an extended Kaya identity," *Science of the Total Environment*, vol. 634, no. 1, pp. 884–899, 2018.

- [16] B. Zhou, C. Zhang, H. Song, and Q. Wang, "How does emission trading reduce China's carbon intensity? An exploration using a decomposition and difference-in-differences approach," *Science of the Total Environment*, vol. 676, no. 1, pp. 514–523, 2019.
- [17] P. M. de Oliveira-De Jesus, "Effect of generation capacity factors on carbon emission intensity of electricity of Latin America & the Caribbean, a temporal IDA-LMDI analysis," *Renewable and Sustainable Energy Reviews*, vol. 101, pp. 516–526, 2019.
- [18] G. Cui, Y. Yu, L. Zhou, and H. Zhang, "Driving forces for carbon emissions changes in Beijing and the role of green power," *Science of the Total Environment*, vol. 728, no. 9, article 138688, 2020.
- [19] L. Wen and Z. Li, "Provincial-level industrial CO₂ emission drivers and emission reduction strategies in China: combining two-layer LMDI method with spectral clustering," *The Science of the Total Environment*, vol. 700, p. 134374, 2020.
- [20] G. Chen, F. Hou, K. Chang, Y. Zhai, and Y. du, "Driving factors of electric carbon productivity change based on regional and sectoral dimensions in China," *Journal of Cleaner Production*, vol. 205, no. 1, pp. 477–487, 2018.
- [21] J. Han, H. Cheng, Y. Shi, L. Wang, Y. Song, and W. Zhnag, "Connectivity analysis and application of fracture cave carbonate reservoir in Tazhong," *Science Technology and Engineering*, vol. 16, no. 5, pp. 147–152, 2016.