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Analysis of Carbon Emission and Its Temporal and Spatial Distribution in County-Level: A Case Study of Henan Province, China

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ABSTRACT

Estimating carbon emissions and assessing their contribution are critical steps toward China's objective of reaching a "carbon peak" in 2030 and "carbon neutrality" in 2060. This paper selects relevant statistical data on carbon emissions from 2000 to 2018, combines the emission coefficient method and the Logarithmic Mean Divisia Index model (LMDI) to calculate carbon emissions, and analyses the driving force of carbon emission growth using Henan Province as a case study. Based on the partial least squares regression analysis model (PLS), the contributions of inter-provincial factors of carbon emission are analyzed. Finally, a county-level downscaling estimation model of carbon emission is further formulated to analyze the temporal and spatial distribution of carbon emissions and their evolution. The research results show that: 1) The effect of energy intensity is responsible for 82 percent of the increase in carbon emissions, whereas the effect of industrial structure is responsible for -8 percent of the increase in carbon emissions. 2) The proportion of secondary industry and energy intensity, which are 1.64 and 0.82, respectively, have the most evident explanatory effect on total carbon emissions; 3). Carbon emissions vary widely among counties, with high emissions in the central and northern regions and low emissions in the southern. However, their carbon emissions have constantly decreased over time. 4) The number of high-emission counties, their carbon emissions, and the degree of their discrepancies are gradually reduced. The findings serve as a foundation for relevant agencies to gain a macro-level understanding of the industrial landscape and to investigate the feasibility of carbon emission reduction programs.

INTRODUCTION

The issue of climate change is one of the most severe challenges in the world today, which has attracted much attention from the international community. With the development of China's industry, greenhouse gas emissions, mainly CO_2, are gradually increasing, it is urgent to realize a low-carbon economy as soon as possible (Shu et al. 2018). According to the Intergovernmental Panel on Climate Change (IPCC fifth)'s study report, only severe emission controls can reduce the global warming trend (Stocker et al. 2013). The Chinese government, as the world's largest energy consumer and CO_2 emitter, places a high priority on climate change, publicly declaring in 2015 that China's carbon emissions will peak by 2030 and that "carbon neutrality" will be achieved by 2060 (Song et al. 2020). As China's largest carbon-consuming province, Henan, the CO_2 emission reduction and peaking plan directly affect the national peaking progress. To further respond to climate change, promote sustainable economic and social development in China, how to reduce carbon emissions in the field of final consumption has gradually become an urgent question that should be answered. Effectively assessing the contribution of carbon emissions according to the emission inventory and predicting the carbon emissions are crucial.

Henan is in the center of China, with a wide area of jurisdiction, a large population, a complex industrial structure, strong dependence on fossil energy, large differences between economic and industrial, and a typical carbon emission situation. Currently, there are 18 cities and 158 counties under the jurisdiction of Henan Province. As China's administrative regions are divided into three government levels, which are provincial administrative districts, city administrative districts, and county administrative districts, the different scale analysis and evaluation of carbon emissions, along with spatial and temporal distribution of carbon emissions and their drivers can provide a data basis for emission reduction, which has a great significance.

Past Studies

As an important strategy for economic and social development, the field of the low-carbon economy has become a topic in recent years.

The emission coefficient approach (Abdul-Wahab 2015), life cycle assessment method (Dascalaki et al. 2020), economic input-output analysis (Qi & Zhang 2013), and other methods are currently used to estimate carbon emissions. It has now been established that there is a link between carbon emissions and economic growth. Grossman & Krueger (1992) investigated the link between pollution and economic growth. They discovered an inverted U-shaped association between these two factors.

In terms of the calculation scope, Zhu et al. (2018) analyzed China's carbon emissions, predicted that China's emissions could rise by more than 50 % in the next 15 years. Guo et al. (2011) adopted the data envelopment analysis method (DEA) to evaluate the carbon emission performance of 29 Chinese provincial administrative regions by computing the potential of carbon emission reductions and the energy structural adjustment (ESA) with the energy conservation technology (ECT). Their study shows that ECT promotion and reductions in inter-regional technological disparity would be effective in reducing carbon emissions in technically inefficient regions. Martinez-Botas (2013) described a model that analyzed the cost and impact of alternating current CO_2 emission transmission types from 2010 to 2050. In the semi-prefabricated construction process, Mao et al. (2013) constructed a quantitative model by defining a calculation boundary with five emission sources. Nässen et al. (2007) evaluated overall energy usage using the input-output approach, comparing the performance of top-down and bottom-up methods of a particular energy. Frankignoulle (1998), Mao et al. (2013), and Mi et al. (2017) are among the studies that address this topic.

Many academics are interested in determining the elements that influence carbon emissions. Ehrlich and Holdren (1971 & 1972) used the IPAT model (I=Human Impact, P=Population, A=Affluence, T=Technology) to examine the effects of population size, affluence, and technology on the environment, dubbed the environmental pressure control model. The carbon emission intensity of several African countries was decomposed by Ebohon & Ikeme (2006) using the structural decomposition method. They discovered that the primary elements impacting carbon emission intensity are energy intensity, energy type, and economic structure.

Lin (2016) studied the influencing elements of carbon dioxide emissions in China's food industry from 1999 to 2012 using an input-output technique. Emission factors, energy structure, energy intensity, and overall output are the key driving forces. From the perspectives of population, carbon emissions per capita, energy intensity, and carbon emissions per unit of energy, Tavakoli (2017) employed the Kaya model to examine the carbon emission driving forces and their evolving features of the European Union. Between 1970 and 2000, Lantz & Feng (2006) used an econometric model to do regression analysis of Canada's per capita GDP, population, technology, and carbon emissions. In recent years, the Logarithmic Mean Divisia Index Model (LMDI) in Di's index decomposition method has been frequently employed in assessing the components that influence CO2 emissions. The LMDI model was developed by Lin & Ahmad (2017) for the period 1990-2014. In 2009, Pakistan carried out a comprehensive factor analysis based on carbon emissions from energy usage. (Market Allocation Model) MARKAL (Chi et al. 2021), Long-range Energy Alternatives Planning System Model (Leap) (Jaskolski 2016), and Environmental Kuznets Curve) EKC (Chi et al. 2021), among others, are similar methodologies for this topic.

Although lots of work have been done on carbon emission and its driving factors, previous studies always adopted a unitary method. What's more, most of the works away considered few types of energy, which lacked detailed investigations of carbon emissions. Furthermore, the research mostly focuses on large-scale carbon emissions, leaving small-scale carbon emissions, particularly in counties, largely unexplored. As a result, this paper integrates the carbon emission factor technique with the LMDI decomposition model, taking into account 17 different energy sources, including power for the consumer terminal (McPherson & Karne 2014, Mishra & Smyth 2017). The terminal consumer industry in Henan Province was studied in terms of energy consumption intensity, GDP growth, population growth, and industrial structure from 2000 to 2018. Then carbon emission driving forces in the five aspects of the energy structure are analyzed; Then the partial least square regression analysis method is also adopted to analyze the contribution of inter-provincial carbon emission factors, which complements the analysis results of carbon emission driving factors. Furthermore, by analyzing the carbon emission relationship between provinces and counties, a county-level downscaling carbon emission estimation model is formulated, and the temporal-spatial distribution and evolution of carbon emissions in county-level are analyzed. Finally, carbon emission driving forces and carbon emission estimates are integrated to systematically examine Henan Province's future carbon reduction potential and make some plausible recommendations.

MATERIALS AND METHODS

LMDI-Based Driving Factors Decomposition

It should be mentioned that "carbon emission" and "carbon dioxide emission" are two different concepts, and carbon dioxide emissions are a part of carbon emissions. In this paper, we use the definition of carbon emissions to replace the "carbon dioxide emissions".

According to the method provided by IPCC, the emission of CO_2 of the final consumption can be calculated as follows:

$$C = \frac{44}{12} \times \sum_i B_i P_i E_i \quad \ldots(1)$$

In which, C *(100 mt)* represents the total carbon emissions, *I* identifies the type of energy, B_i is the standard coal conversion coefficient of the *i-th* energy, P_i is the carbon emission coefficient of the *i-th* energy, and E_i indicates the total consumption of the *i-th* energy. The factors of energy conversion for standard coal and carbon emission coefficients are shown in Table1.

By formula 1, we can get the total carbon emissions of the final consumption. Table 1 list the factor of energy conversion for standard coal and carbon emission coefficients.

This paper adopts the Kaya inequality model and analyzes the affecting factors of carbon emissions in Henan Province into six aspects: population scale, economic scale, industrial structure, energy structure, energy intensity, and carbon emission factors. The formula can be expressed as:

$$C = \sum_i^7 \sum_j^{17} \frac{C_{i,j}}{E_{i,j}} \times \frac{E_{i,j}}{E_i} \times \frac{E_i}{GDP_i} \times \frac{GDP_i}{GDP} \times \frac{GDP}{POP} \times POP = \sum_i^7 \sum_j^{17} B_{i,j} * e_{i,j} * q_i * g_i * pa * P \quad \ldots(2)$$

In formula (2), $C_{i,j}$ is the amount of carbon dioxide emitted by *j-th* energy in the *i-th* industry; $E_{i,j}$ is the total amount of energy consumed by the *j-th* energy in the *i-th* industry; E_i is the total energy consumption in the *i-th* industry; GDP_i is the gross national product of the *i-th* industry; *GDP* is the gross national product of all industries in the certain year; *POP* is the total population; $B_{i,j}$ is the emission factor of the *j-th* energy in the *i-th* industry; $e_{i,j}$ is the energy structure of the *i-th* industry; q_i is the energy intensity of the *i-th* industry; g_i is the industrial structure of the *i-th* industry; *pa* is the GDP per capita and *p* is the total population.

Table 1: The factors of energy conversion for standard coal and carbon emission coefficient.

Energy type	Converted coefficient	Emission factor
raw coal	0.7143	0.7559
Washed coal	0.9	0.7559
Other coal washing	0.2857	0.7559
Briquette	0.6	0.7559
Coke	0.9714	0.855
Coke oven gas	0.5714	0.3548
Blast furnace gas	0.6	0.3548
Other gas	1.1	0.6449
Other coking products	0.7143	0.7559
Crude	1.4286	0.5857
Gasoline	1.4714	0.5538
Kerosene	1.4714	0.5714
Diesel oil	1.4571	0.5912
Fuel oil	1.4286	0.6185
Other petroleum products	1	0.5857
Liquefied petroleum gas	1.7143	0.5042
Natural gas	1.33	0.4483
Hydropower, nuclear power	0.1229	0

In this part, we take 2000 as base year 0, set the carbon emissions in 2000 as the base amount of carbon emission, and let *t* denote the target year. The total carbon emissions of Henan Province will be decomposed into population-scale effect, economic scale effect, industrial structure effect, energy structure effect, and energy intensity effect, which can be expressed as:

$$\delta C = \delta C_e^{0,t} + \delta C_q^{0,t} + \delta C_g^{0,t} + \delta C_{pa}^{0,t} + \delta C_p^{0,t} \quad \ldots(3)$$

In which, $\delta C_e^{0,t}, \delta C_q^{0,t}, \delta C_g^{0,t}, \delta C_{pa}^{0,t}, \delta C_p^{0,t}$ represent the effects, in other words, the increment in CO_2 emissions caused by changes in energy structure, energy intensity, industrial structure, economic scale, and population-scale respectively.

According to the LMDI additive decomposition method, the influence of each factor on the carbon emissions of *0 - t* years can be further obtained. Which can be expressed as:

$$\begin{cases} \delta C_e^{0t} = \dfrac{C_e^t - C_e^0}{\ln C_e^t - \ln C_e^0} \times \ln\left(\dfrac{e_{i,j}^t}{e_{i,j}^0}\right) \\ \delta C_q^{0t} = \dfrac{C_q^t - C_e^0}{\ln C_q^t - \ln C_q^0} \times \ln\left(\dfrac{q_{i,j}^t}{q_{i,j}^0}\right) \\ \delta C_g^{0t} = \dfrac{C_g^t - C_g^0}{\ln C_g^t - \ln C_g^0} \times \ln\left(\dfrac{g_{i,j}^t}{g_{i,j}^0}\right) \\ \delta C_P^{0t} = \dfrac{C_P^t - C_P^0}{\ln C_P^t - \ln C_P^0} \times \ln\left(\dfrac{P_i^t}{P_i^0}\right) \\ \delta C_e^{0t} = \dfrac{C_{pa}^t - C_e^0}{\ln C_{pa}^t - \ln C_{pa}^0} \times \ln\left(\dfrac{pa_i^t}{pa_i^0}\right) \end{cases} \quad \ldots(4)$$

The above formula can be used to obtain the driving effects of the five factors on the increment of emissions from the base year 0 to the target year *t*.

PLS Modeling and Analysis

In this section, the PLS model is adopted to evaluate the impact of the factors on carbon emissions.

Partial least squares regression can simultaneously integrate multiple linear regression, principal component analysis, and canonical correlation analysis between variables. It can organically combine the modeling and forecasting data analysis approach with the non-model data cognitive analysis method, in which the information is successfully recombined to reduce the interference caused by information overlap and redundant data. There are two types of PLS: single dependent variable PLS and multiple dependent variables PLS. Because carbon emission is the only dependent variable considered in this paper, so single dependent variable PLS regression is involved in analysis.

Consider a PLS regression progress with P independent variables and one dependent variable, and further assume that each variable has N observation samples for regression analysis. Therefore, the set of the independent variables and the dependent variables are expressed as $X = [x_1, x_2, ..., x_N]_{P?N}$ and $Y = [y]$, respectively. According to the PLS model, it is necessary to extract m principal component variables from the independent variables. The purpose of the PLS model is to explain the independent variables as much as possible while ensuring the greatest correlation between the dependent variables, which is a linear combination of all independent variables. The detailed process of modeling is as follows.

1. Data standardization

The main function of data standardization is to eliminate the dimensional relationship between variables, to make the data comparable. The standardized process can be expressed as:

$$\begin{cases} x^*_{i,j} = \dfrac{x_{i,j} - \overline{x_{i,j}}}{s_j}, j \in [1, P] \\ y^*_j = \dfrac{y_j - \overline{y_j}}{s_j}, j \in [1, P] \end{cases} \quad \ldots(5)$$

The set of processed independent variables is expressed as $X^* = [x_{i,j}{}^*]_{N?P} = [x_1{}^*, x_2{}^*, ..., x_P{}^*]$. $\overline{x}_{i,j}$ and $\overline{y_j}$ represents the mean value of $x_{i,j}$ and y_j respectively.

2. Variable composition analysis

According to the model of PLS, the component $t_1 = x_i^* w_1$ is extracted first, in which w_1 is the first axis of x^*, and $||w_1|| = 1$. According to the idea of the principal component analysis method, the maximum covariance between t_1 and x^* should be satisfied, that is $\max_{||w_1||} J = Cov(t, y)$. The aforementioned problem can be solved using the Lagrangian algorithm. The procedure would finish if the set accuracy value was reached; otherwise, the regression residual would be utilized to supplement the regression process for the selection of the second component, and iteration would continue. Finally, the regression result would be determined.

3. Cross-validation analysis

Partial least squares regression equation can select some components to get a model with better prediction performance. The cross-validity coefficients for principal components t_h can be defined as:

$$Q_h^2 = \frac{\sum_{k=1}^{P} y_k - y^*_{k,h-1}}{\sum_{k=1}^{P} y_k - y^*_{-k,h}} \quad \ldots(6)$$

The formula $y^*_{k,h-1}$ represents the predicted value corresponding to the i-th sample point when the first $h - 1$ component regression is selected. Moreover, $y^*_{-k,h}$ is the predicted value obtained by the first h component regression after removing the i-th sample point.

Choosing the component t_g can significantly improve the prediction model when $Q^2_h \geq 0.0957$. Otherwise, the component would be discarded.

This paper combines the five factors mentioned above in the decomposition of LMDI. The provincial and municipal-level checkable items in the Henan provincial statistical yearbook are adopted. The total GDP, the total population, the urbanization rate, the proportion of secondary industries in Henan Province from 2000 to 2018 are selected and set as independent variables, and the carbon emissions are selected as the dependent variables.

The final regression model can be obtained through PLS regression, which is expressed as follows:

$$Y^{predict} = \sum_{i=1}^{6} a_i x_i + c + e \quad \ldots(7)$$

In which, e is the error value, a_i is the regression coefficient of x_i, and c is a constant value.

Construction of the Estimation Model at the County Level

The regression model generated using the partial least squares method is only suited for inter-provincial carbon emission prediction due to inadequate data, and it must be downscaled to be corrected at the county-level carbon emission forecast. Considering that the calculation of provincial carbon emissions is derived by summing the carbon emissions in all counties, the two carbon emission regression models in different levels correspond to the six independent variables that are consistent and should have the same slope. So, the corresponding regression coefficients in the carbon emission regression equations are the same, and only the constant term and the error term caused by carbon emissions downscaling need to be adjusted.

Let B denotes the set of the county in Henan Province, and let $X^t_j = [x_1^{\ t}, x_2^{\ t}, ..., x_6^{\ t}]_{|B|\times 6}$, $j \in B$ denotes the set of the independent variables in year t. The dependent variable in a year t is denoted by $y_j^{\ t}, j \in B$.

For the county data in each year, their carbon emissions can be represented by a linear combination of the six statistical elements of the county, which can be expressed as:

$$y_j^t = \sum_{i=1}^{i=6} a_i x_{j,i}^t + cl^t + \rho_j^t + \beta_j^t, \forall j \in B \quad \ldots(8)$$

Where a_i is the regression coefficient of the independent variable $x_{i,j}$, cl^t is the constant value in a year t, $b^t_{\ j}$ and $r_j^{\ t}$ are the downscaling error item and prediction error item respectively.

To obtain the value of the constant, we sum forecast formulas for all counties in the same certain year. Then the final forecast equations for all counties in that year can be obtained, which can be expressed as:

$$\begin{aligned} y^t &= a_i \sum_{j\in B} x_{j,i}^t + |B|(cl^t) + \sum_{j\in B}(\rho_j^t + \beta_j^t) \\ &= a_i x_i + |B|(cl^t) + \sum_{j\in B}(\rho_j^t + \beta_j^t) \end{aligned} \quad \ldots(9)$$

According to the proportional relationship of the constant term, we have:

$$|B|\ cl^t = C \quad \ldots(10)$$

The error term is the result of a correlation between the six key components and the constant term, which cannot be calculated directly. As a result, it can be allocated based on the fraction of expected carbon emissions without taking the error term into account. Let $y_i^{t*} = a_i x_{j,i}^{\ t} + cl^t$, the calculation progress is as follows:

$$\rho_j^t + \beta_j^t = (y^t - y^{t*}) \times \frac{y_j^{t*}}{y^t} \quad \ldots(11)$$

Finally, the value calculated can be brought into the formula (8) to get the annual carbon dioxide emissions of each county.

RESULTS AND DISCUSSION

The carbon emission coefficient is used in this section to determine Henan Province's carbon emissions from 2000 to 2018. The LMDI decomposition model analyses five components that are regarded to be the key driving forces of carbon emissions: GDP, population, industrial structure, energy structure, and energy intensity. The PLS regression model is formulated to calculate the six indicators including

Table 2: Decomposition results of carbon emission drivers.

Year	ESE	EIE	ISE	EGE	PGE
2001	-68.3	-696.9	330.6	758.7	269.5
2002	-81.3	-882.3	186.9	805.2	378.9
2003	-86.6	-575.2	-124.6	1244.6	381.6
2004	169.4	4320.1	353.3	1481.4	538.9
2005	614.0	5653.7	400.2	1934.0	927.3
2006	210.1	10520.8	149.5	1840.1	870.2
2007	226.2	11419.5	205.2	2264.3	1149.9
2008	173.7	11738.5	-90.2	2310.1	575.3
2009	168.9	14972.3	-8.0	133.8	735.7
2010	1211.1	14996.9	-7.2	1950.2	448.4
2011	675.6	16721.3	-201.5	1617.1	494.0
2012	454.4	14581.7	-179.2	827.6	317.9
2013	820.2	12248.0	-98.1	402.1	473.0
2014	2037.1	14472.4	-132.6	1199.0	-338.3
2015	1966.5	14444.1	-151.7	409.7	198.5
2016	1699.9	13063.6	-69.6	750.6	-15.6
2017	782.4	11134.0	-454.5	1081.7	253.2
2018	914.7	6299.4	-450.4	973.2	-68.0

the population, the urbanization rate, the proportion of the secondary industry, the energy intensity, and household consumption level to evaluate the contribution of carbon emissions. Finally, the corresponding downscaling county carbon emissions model is given, and the temporal and spatial distribution of the carbon emissions is analyzed.

Driving Force Analysis in Henan Province

In Table 2, ESE, EIE, ISE, EGE, PGE denote the effect of energy structure, the effect of energy intensity, the effect of industrial structure, the effect of economic growth, and the effect of population growth.

Table 2 lists the results of the driving forces of the five major factors for the carbon emissions in Henan Province from 2000 to 2018. In Fig. 1, the corresponding cumulative contribution to carbon emissions is visually displayed. It can be seen from Table 2 and Fig. 1, from 2000 to 2018, energy intensity has accounted for 80% of the carbon dioxide increment in Henan Province, followed by economic growth effects and energy structure effects, which are 12% and 11%, respectively. The contribution of energy intensity first grew, then fell, contributing little to the increase in carbon emissions. The impact of the industrial structure was shown to be negatively connected with the increase in carbon emissions, which accounted for -8% of total emissions.

Fig. 2 shows the carbon emissions of the three major industries of terminal consumption in Henan Province. The secondary industry is responsible for the majority of the province's carbon emissions, with the tertiary industry coming in second. Both industries increased and then dropped, with the latter reaching its highest point in nearly two decades in 2011. The change in carbon emissions in the tertiary sector is not immediately apparent. We may deduce that the secondary industry is the biggest source of carbon dioxide emissions in Henan Province based on the pattern of carbon emissions of the three industries.

PLS-Based Carbon Emission Regression Analysis

In this section, the statistical data and the results of the carbon emissions are used to perform regression through the SIMCA-P software. The historical GDP, the population, the urbanization rate, the proportion of the secondary industry, the energy intensity, and the household consumption level are selected as independent variables, which denotes by X_1, X_2, ..., X_6, respectively. Moreover, the indicator of carbon dioxide emissions is considered as the dependent variable.

Through the SIMCA-P, we can get the calculation value of the cross-validity. In the regression process of the carbon emissions prediction of Henan Province between 2000 and 2018, the optimal number of principal components is 2, and the value of the cross-validity, $Q_2^2 = 0.79848 > 0.0975$, satisfies the corresponding principal component extraction criteria. The index $R2VY(cum)$ is 0.933055, which indicates that the two components can explain 93.3055% of the dependent variable variation information, which contains sufficient information of independent variables and have good applicability to the model.

Fig. 3 shows the comparison between the regressed value of the carbon emissions and the actual value of carbon emissions from 2000 to 2018. From Fig. 3 we can see that there is a small gap between the two curves. Through the calculation of relative error between the two values in the considered time domain, the average relative error between the predicted value and the actual value is -0.33185801 between 2000 and 2018, which has a good performance of prediction.

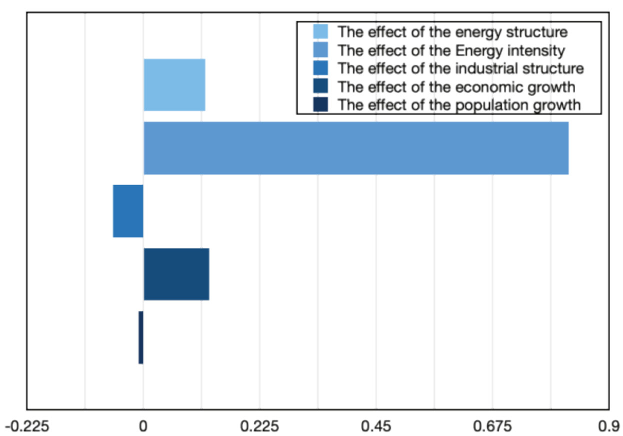

Fig. 1: The contribution of the factors to carbon emissions.

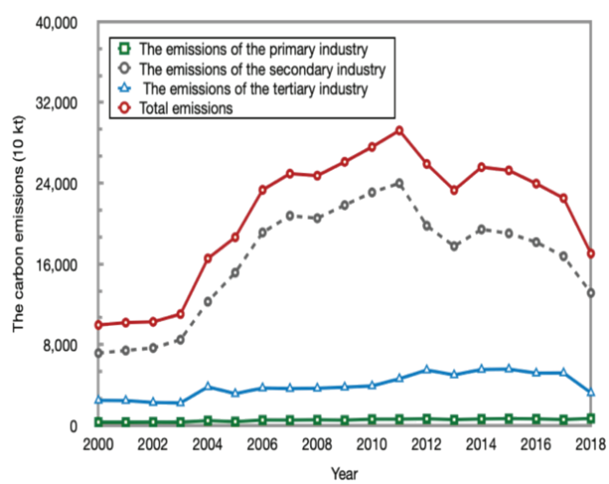

Fig. 2: The carbon emissions in the three industries.

As the fitting degree and accuracy of the model are easily affected by the specific points, in Fig. 4, a photo of T^2 an ellipse is constructed to test whether the specific points exist. As Fig. 4 shows, all the sample points are within the specified range and there are no specific points. We can conclude that the model has good adaptability to sampled data.

Fig. 5 shows the importance of selected six independent variables (Variable Importance in Projection, VIP), which are used to express the explanatory power of the independent variables on the dependent variable. The six factors sorted by importance are the proportion of the secondary industry, energy intensity, urbanization rate, population, GDP, and household consumption level. Among them, the VIP of the secondary industry is 1.64, which contributes most to carbon emissions, while the VIP of carbon emissions intensity is 0.82. So to decrease carbon emissions, the changing of industry structure is the primary policy that should be considered in addition to energy intensity.

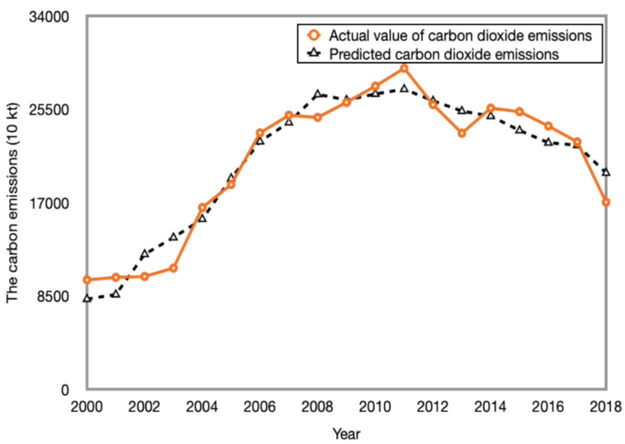

Fig. 3: The comparison of regressed carbon emissions and the actual carbon emissions.

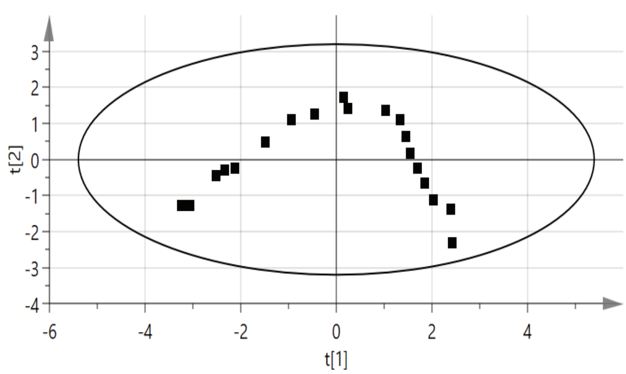

Fig. 4: The T^2 ellipse of sample points.

Temporal and Spatial Distribution of Carbon Dioxide Emissions in Counties of Henan Province

In this part, we give the CO_2 emissions, the numbers of countries with different emission levels, and associate with geographic information to analyze the temporal and spatial distribution of carbon dioxide emissions in counties of Henan Province.

Due to the changes in the statistical method of the Henan statistical yearbook in the year 2010, there exists a big difference between the dada 2000-2009 and 2010-2018. Considering the unity and adequacy of the data, we summarize the carbon dioxide emissions of counties in Henan Province in the years 2010, 2014, and 2018, which are listed in Table 2. In the table, AE, AEI, VE, VEI denote carbon emissions, carbon emission intensity, carbon emission variance, and carbon emission intensity variance respectively. It can be observed in the table that the average emission, emission intensity, emission variance, and emission intensity variance of counties have decreased year by year. The results indicate that the economy between counties is developing towards a green economy. Moreover, the difference in emissions and emissions levels is gradually shrinking.

Let *DED* and *DEI* denote the numbers of counties counted according to their carbon emissions and their intensity. We count the number of counties according to different intervals. For the carbon emissions, we set the split points as A:26.8, B:53.5, C:80.3, D:133.8, E:187.3, F:500 (10 kt).

Table 3: CO_2 emissions at county-level in Henan Province

Year	AE (10 kt)	VE	AEI	VEI
2010	176	1.48	9240	1.6
2014	163	0.725	6110	0.725
2018	108	0.482	2710	0.237

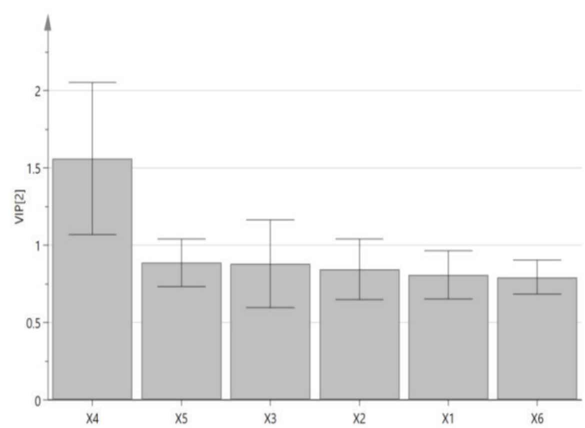

Fig. 5: The VIP indicators of the variables.

For the carbon emissions intensity, we set the split points as A:0.22, B:0.43, C:0.87, D:1.30, E:2.16, F:11.

Table 4 shows the distribution of carbon dioxide emissions of counties in Henan Province. We compared the number of counties in Henan Province by carbon emissions and carbon emission intensity in different intervals in 2010, 2014, and 2018. We used intervals to compare the number of counties in Henan Province by carbon emissions and carbon emission intensity in different intervals in 2010, 2014, and 2018. The right border of the interval is defined as the highest value of carbon emissions and carbon emissions intensity in counties in any given year between 2010 and 2018, while the left boundary is defined as zero. The emission volume in any year is divided into 6 intervals according to the 10%, 20%, 30%, 50%, 70% of the maximum value. Similarly, for the measurement of carbon emissions, set the split point according to 5%, 10%, 20%, 30%, and 50% of the maximum value. The fifth interval and the sixth interval are regarded as the ultra-high emission interval and the high emission interval respectively. The third and fourth intervals are regarded as the medium emission intervals. And the first interval and the second interval are regarded as low emission intervals. It can be seen from Table 3 that the number of counties with high carbon emission intensity and carbon emissions gradually decreases in the time domain, and the number of counties with low carbon emissions and carbon emission intensity gradually increases. It can be concluded that the status of carbon emissions of all counties in Henan Province is gradually improving.

Fig. 6 and Fig. 7 use ArcGIS tools to show the spatial distribution of carbon emissions and emission intensity in Henan Province. The results show that areas with high carbon emissions are mainly concentrated in most areas of northern Henan and a small part of central Henan, such as Zhengzhou, Luoyang, and their surrounding counties, while the carbon emissions in southern Henan are at a relatively low level. The higher carbon emission intensity is mostly concentrated in the central and a small number of northern regions, such as Pingdingshan, Sanmenxia, Jiaozuo, Anyang, etc. The obvious feature of such regions is that the coal-related industries in such regions are relatively thriving. According to the data in Table 3, the number of high carbon emission counties ac-

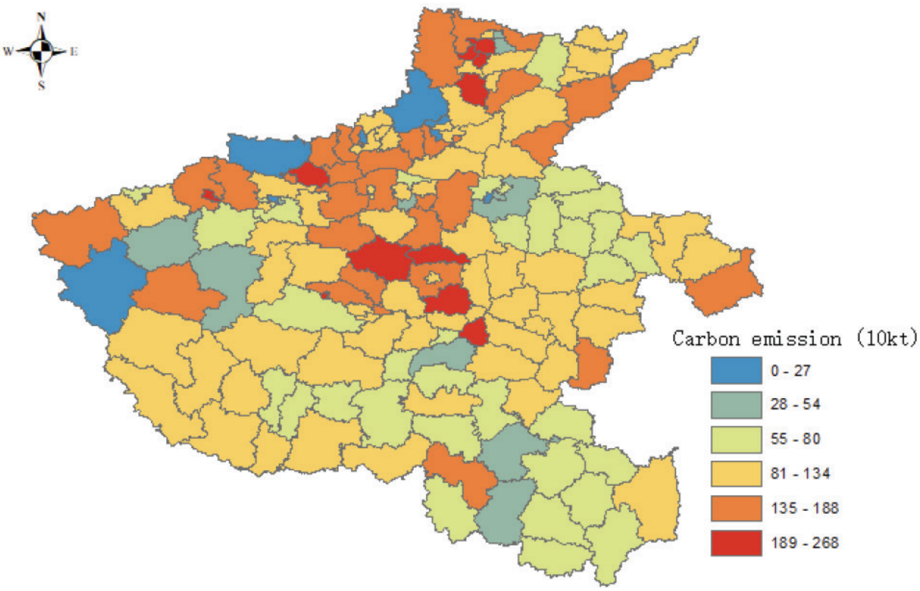

Fig. 6: The distribution of county emissions in Henan Province in 2018.

Table 4: Distribution of CO_2 emissions in counties of Henan Province.

YEAR	DEA (10kt)						DEI					
	0-A	A-B	B-C	C-D	D-E	E-F	0-A	A-B	B-C	C-D	D-E	E-F
2000	4	2	18	42	28	63	11	40	74	12	12	8
2014	6	3	9	36	53	50	11	40	74	18	8	6
2018	7	11	34	62	32	11	29	73	41	6	5	3

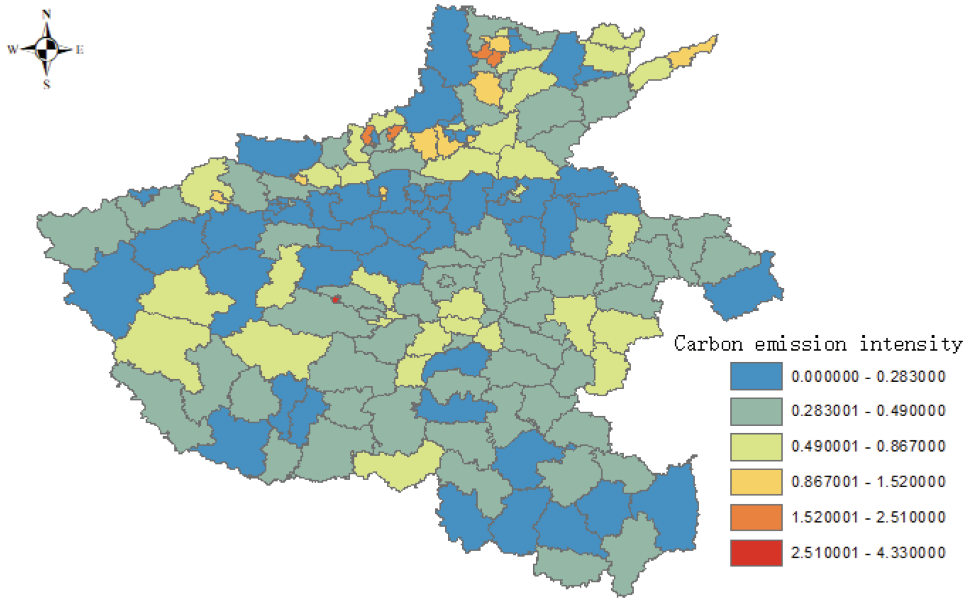

Fig. 7: The distribution of county-level carbon emission Intensity in 2018.

counted for 32.4% in 2010, and the number of high emission intensity counties accounted for 3.8%, which dropped to 7% and 1.9% n 2018. The proportion of counties with ultra-low carbon emissions and emission intensity increased from 2.5% and decreased to 7% in 2010 to 4.6% and 18.5% in 2018, indicating the large reduction efforts of carbon emissions have been done in Henan Province.

CONCLUSION

This article examines the driving forces of carbon growth using Henan Province's terminal consumption, pertinent statistical data on carbon emissions from 2000 to 2018, and a combination of the carbon emission factor method and the LMDI factor decomposition method to calculate carbon emissions. The contribution of provincial carbon emission factors is analyzed using partial least squares regression analysis, which complements the analysis of driving forces, and a county downscaling carbon emission estimation model is built to analyze the temporal and spatial distribution of carbon emissions in the province. The research presented in this article can serve as a foundation for relevant departments to develop policies for reaching carbon emission peaks.

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