Driving factors and emission reduction scenarios analysis of CO_2 emissions in Changsha based on LMDI and STIRPAT

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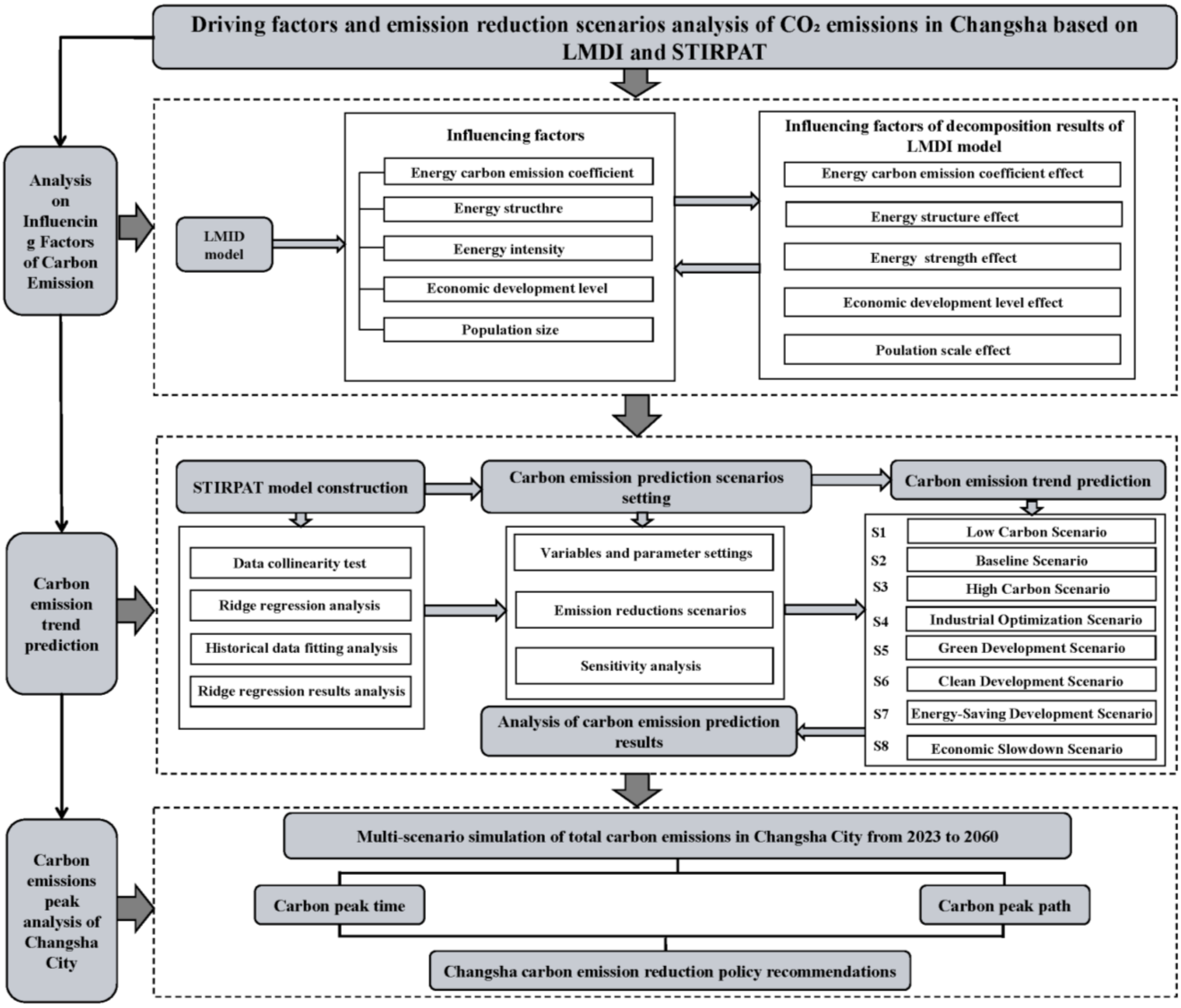
Graphical abstract



Abstract

As the central city of Hunan Province, Changsha is a key to grasping how carbon emission growth is playing out and getting the peak carbon emission event to happen faster than initially planned. In this study, it adopts the data from 2011 to 2022 to build the LMDI-STIRPAT model and forecast the carbon emission trend of Changsha. Through scenario simulations, the research identifies the primary factors influencing carbon emissions, projects future emission trajectories, and determines the optimal pathways for emission reduction. The main results: (1) The energy structure restrains the growth of carbon emission, while the population size is still a big pusher that helps increase the carbon emission. (2) Out of eight forecasting situations, only situation S1 arrives at the carbon peak goal by 2030, which achieves 20.37 Mt, whereas the others vary in their delay. (3) Changsha reaches its carbon peak according to the plan in the low-carbon situation S1, making it the most effective option for emission cuts. To achieve this, the paper gives recommendations such as modifying energy consumption structure, optimizing industrial layout, and reinforcing related the policy framework supporting cities low carbon transition and explained in conclusion.

Keywords: energy intensity; sensitivity analysis; carbon emission forecasting; scenario analysis

1. Introduction

With the rapid development of the global economy, carbon dioxide emissions have been rapidly increasing, and the degree of global warming has also been increasing. The occurrence frequency of natural disasters (Babu *et al.* 2025) all over the world has been rapidly rising, and the occurrence of extreme days is also becoming more and more frequent (Jasmine et al. 2025). The melting of sea ice, increase of sea level, floods and storm and other disasters have become more serious by the effects of rising sea level, it is a big danger for ecosystem, climate (Kumar *et al.* 2025)and sustainable development of humans. As per the IPCC, the temperature of the entire world has been increasing since the last 100 years due to the greenhouse gases produced from the burning of fossil fuel and the industries. So, reducing carbon emissions has become the main way to stop the earth getting too warm, and all the countries need to work together. During the Reform and Opening-up period, China's economic growth is based on the huge amount of energy consumption which leads to a large continuous emission of carbon dioxide. In response to the increasing climate risk, China has made the commitment at 75th session of UN General Assembly to achieve peak carbon before 2030 and carbon neutral before 2060.

Dual carbon goal, Carbon Peak and Carbon Neutrality, have turned into a central theme for policies and academic works in China. Now we are trying to find low-carbon development models. Government supported low carbon city pilot project is one of the earliest policy instruments to promote these goals. It attempts to reconcile ecological sustainability with economic growth. In 2010, 2012 and 2017, 81 cities became national low-carbon pilot cities, including Changsha in the third batch. The Changsha government wants to promote high quality development and encourage the use of energy saving and emission reduction technology, so they have made making the economy less polluting a key goal.

In terms of factors influencing carbon emissions, from the research literature we can see that most of the papers will use IDA to analyze which components affect carbon dioxide emissions, like urban population, economy scale, energy intensity, energy consumption. Also, it can be investigated well on the influence that every factor has over carbon emission (Liu *et al.* 2021; Fan *et al.* 2017). As for different IDA approaches, LMDI is most acknowledged as a good approach to adopt for resource and environment research because it has the advantage of being a zero-residual property, additivity, and ease of result interpretation (Dong *et al.* 2019; Long *et al.* 2019; Ding *et al.* 2020; Yang *et al.* 2020);

(Ang *et al.* 2001). Furthermore, it handles zeros in the data well (Ang 2005; Ang *et al.* 2007). Existing studies using the LMDI method decompose emissions by carbon emission coefficients, energy structure, energy intensity, industrial structure, economic development, and population size (Chong *et al.* 2019; Mohmmed *et al.* 2019; Zheng *et al.* 2019). Take Shanghai as an example, it is shown that an increase in per capita GDP and population size is the main cause of the increase in carbon emissions, and a decrease in energy intensity has greatly reduced the amount of emissions. (Gu *et al.* 2019; Li *et al.* 2023b) carried out an empirical decomposition of CO_2 emissions in Tianjin with the LMDI method, and found that improvement of energy efficiency and energy structure optimization are very important to reduce carbon emissions.

Forecasting carbon emissions generally uses the system dynamics models (Feng *et al.* 2013; Zhao *et al.* 2024; Li *et al.* 2024), neural network models (Sun *et al.* 2021), long-term energy alternatives planning system (LEAP) models (Nieves *et al.* 2019; Maduekwe *et al.* 2020), STIRPAT models (Rokhmawati *et al.* 2024; Xiao *et al.* 2023). (Luo *et al.* 2023) used system dynamic models to forecast the carbon emission peak and post-peak trends in the Guangdong - Hong Kong - Macao Greater Bay Area and its surrounding cities. (Ren *et al.* 2021) developed an improved fast learning network prediction algorithm to forecast the carbon emissions of Guangdong from 2020 to 2060. (Cai *et al.* 2023) applied the LEAP model to do 4 scenario analysis about the CO_2 emissions of Bengbu, Anhui Province in 2030, also simulating the influence of various emission reduction policies. (Fang *et al.* 2019) used STIRPAT model combined with scenario analysis to check if the carbon emissions in 30 Chinese provinces would peak in 2030. Among them, among all these methods dynamics system, has a strong advantage in a large number of variables, multiple variables situation, more feedback, nonlinear. However this heavily dependents on the modeler's skill, so it would be subjective. Neural network models have better fit on complex data patterns, more accurately, but needs a lot of data set. The LEAP model has the flexibility and transparency of scenario simulation and policy evaluation. But, it relies heavily on expert input, which may introduce bias. On the contrary, STIRPAT model is a kind of statistic model, which can take into account the factors that reflect the real situation and policy implementation. Moreover, we can do the scenario analysis for different emission trackways by changing these elements, which is also flexible.

In summary, this paper has the following major contributions: The first is that most of the studies on carbon emissions driving forces and forecasts at present are focused on the national and provincial levels, but the studies at the city level are still few. Second, this is a combined approach using LMDI method + extended STIRPAT model. This combined model allows us to conduct comprehensive and systematic analysis on the factors driving carbon emissions at city level. It also forecasts when Changsha will reach its carbon peak and looks at what changes might happen in reducing carbon. With Changsha in focus this research looks at, projects its main drivers of carbon emissions and offers advice to help the city develop.

2. Methods and Data

2.1 Calculation of carbon emissions

In terms of prior research, energy consumption is usually the largest part of a nations greenhouse gas inventory and accounts for more than 90% of CO_2 emissions (Wen *et al.* 2020). Therefore, many scholars concentrate their research on calculating the carbon emissions from energy use. For this paper, we're going to be using the emission factor to find the CO_2 emission for Changsha. Using relevant literature (Angin *et al.* 2022) and city-level data on the consumption of major energy, as well as using the 2006 IPCC guidelines for national greenhouse gas inventories, we quantify the CO_2 emissions from the major energy source of the city. Calculate it is:

$$I=\sum_{i=1}^{n} EC_i \times EE_i \times EF_i \quad (1)$$

Where, I is the total amount of carbon emission of Changsha; EC_i is the consumption of the i-th kind of energy; EE_i is the carbon emission factor for the i-th kind of energy; EF_i is the standard coal conversion factor for the i-th kind of energy.

2.2 LMDI model

This article uses the LMDI model to decompose and analyze the carbon emissions of Changsha, and to decompose the carbon emissions of Changsha associated with various factors. Considering the city's context, we take the following decomposition factors: the carbon emission coefficient of energy, the structure of energy, the intensity of energy, economic development, and the scale of the population, as expressed in Equation (2):

$$I=\sum_{i=1}^{n}\frac{I_i}{E_i}\times\frac{E_i}{E}\times\frac{E}{G}\times\frac{G}{P}\times P=\sum_{i=1}^{n} CI\times ES_i\times T\times A\times P \tag{2}$$

Where I denotes total carbon dioxide emissions; I_i denotes the carbon dioxide emissions from the i-th energy source; E_i denotes the consumption of the i-th energy source; E denotes the total energy consumption; G denotes the gross regional product; P denotes the population size; $CI = I_i/E_i$ denotes the carbon emission coefficient of energy; $ES_i = E_i/E$ denotes the energy structure; $T = E/G$ denotes energy intensity; $A = G/P$ denotes the level of economic development.

According to the LMDI model, the change in Changsha's CO_2 emissions from period 0 (base period) to period t (target period) is $\Delta I=I^t-I^0$. It is then possible to calculate the effect of 5 driving factors on Changsha's CO_2 emissions, as shown in Eqs (3)-(8).

$$\Delta I=I^t-I^0=\sum_{i=1}^{n} CI_i^t\times ES_{\mathrm{i}}^{\mathrm{t}}\times T_i^t\times A_i^t\times P_i^t-\sum_{i=1}^{n} CI_i^0\times ES_i^0\times T_i^0\times A_i^0\times P_i^0$$

$$=\Delta I_{CI}+\Delta I_{ES}+\Delta I_T+\Delta I_A+\Delta I_P \tag{3}$$

$$\Delta I_{CI}=\sum_{i=1}^{n}\frac{I_i^t-I_i^0}{\ln I_i^t-\ln I_i^0}\times\ln\frac{CI_i^t}{CI_i^0} \tag{4}$$

$$\Delta I_{ES}=\sum_{i=1}^{n}\frac{I_i^t-I_i^0}{\ln I_i^t-\ln I_i^0}\times\ln\frac{ES_i^t}{ES_i^0} \tag{5}$$

$$\Delta I_T=\sum_{i=1}^{n}\frac{I_i^t-I_i^0}{\ln I_i^t-\ln I_i^0}\times\ln\frac{T_i^t}{T_i^0} \tag{6}$$

$$\Delta I_A=\sum_{i=1}^{n}\frac{I_i^t-I_i^0}{\ln I_i^t-\ln I_i^0}\times\ln\frac{A_i^t}{A_i^0} \tag{7}$$

$$\Delta I_P=\sum_{i=1}^{n}\frac{I_i^t-I_i^0}{\ln I_i^t-\ln I_i^0}\times\ln\frac{P_i^t}{P_i^0} \tag{8}$$

Where t denotes the last year of the reporting period, and 0 represents the beginning year of the reporting period, ΔI denotes the change in CO_2 in Changsha City from period 0 (base period) to period t, ΔI_{CI} denotes energy carbon emission coefficient effect, ΔI_{ES} denotes energy structure effect, ΔI_T denotes energy intensity effect, ΔI_A denotes the effect of economic development level, and ΔI_P denotes the population size effect.

To quantify the contribution of each factor from the base period to period *t*, we extend the carbon emission effect formulation. The contribution rate of each factor to the total CO_2 emissions is defined as:

$$CR=\frac{\Delta I_C}{\Delta I}=\frac{\Delta I_{CI}}{\Delta I}+\frac{\Delta I_{ES}}{\Delta I}+\frac{\Delta I_T}{\Delta I}+\frac{\Delta I_A}{\Delta I}+\frac{\Delta I_P}{\Delta I}=CR_{CI}+CR_{ES}+CR_T+CR_A+CR_P \tag{9}$$

Where *CR* stands for the contribution rate of each factor, ΔI_C stands for the amount of CO_2 emission increased by factor *C*, ΔI stands for the total amount of increase in CO_2 emission, CR_{CI} represents the contribution rate of energy carbon emission coefficients, CR_{ES} represents the contribution rate of energy structure, and CR_T represents the contribution rate of energy intensity; CR_A represents the contribution rate of economic development, and CR_P represents the contribution rate of population size.

2.3 STIRPAT model

IPAT identity (Ehrlich *et al.* 1971) has been used extensively since the 1970s to analyze environmental impacts, which assumes that all drivers have equal proportional impacts. To solve the problems discussed before, (Dietz *et al.* 1997) introduced the STIRPAT model in which different effects of those factors could be provided. The basic form of the IPAT model is as follows:

$$I=aP^bA^cT^de \quad (10)$$

where I denotes environmental impact, P denotes population size, A denotes GDP per capita, T denotes technology level, a denotes model coefficient, b, c, and d denote elasticity exponents of the corresponding variables, and e denotes random error term.

On the foundation of IPAT identity, the STIRPAT model is chosen here as an adaptable stochastic framework to evaluate environmental impacts. Based on the specific circumstances of Changsha City and the findings of prior research (Kong *et al.* 2022; Zeng *et al.* 2022), we added up three traditional P, A, T variables to three influential drivers of CO_2 emissions, they were population, economic growth rate, energy intensity, the proportion of urbanization, the structure of industry, and carbon intensity. Model is set up like this:

$$\ln I=\ln a+b\ln P+c\ln A+d\ln T+f\ln U+g\ln N+h\ln M+\ln e \quad (11)$$

Where I is Changsha's CO_2 emissions, P is the total number of people, A is GDP per capita, T is energy intensity, U is urbanization rate, N is industrial structure, and M is carbon emission intensity. The parameter a is the model coefficient, while b, c, d, f, g, and h are the elasticity coefficients corresponding to each variable. The term e represents the random error. Detailed definitions of these variables and their changes over the study period are presented in **Error! Not a valid bookmark self-reference.** and illustrated in Figure 1.

Table 1 Explanation of the variables in the STIRPAT model

Symbol	Variables	Description	Units
I	CO_2 emissions	Total carbon dioxide emissions	metric tonnes (Mt)
P	Population size	Total Resident Population at Year-End	10^4 persons
A	GDP per capita	The ratio of regional GDP to the total population at the end of the year	CNY 10, 000 Yuan /Person
T	Energy intensity	Energy consumption per unit of GDP	Tons of standard coal / CNY 10, 000 Yuan
U	Urbanization rate	Ratio of urban residents to the total population at the end of the year	%

N	Industrial Structure	Ratio of Tertiary Industry Output Value to Regional Gross Domestic Product	%
M	Carbon emissions intensity	The ratio of total carbon emissions to regional gross domestic product	—

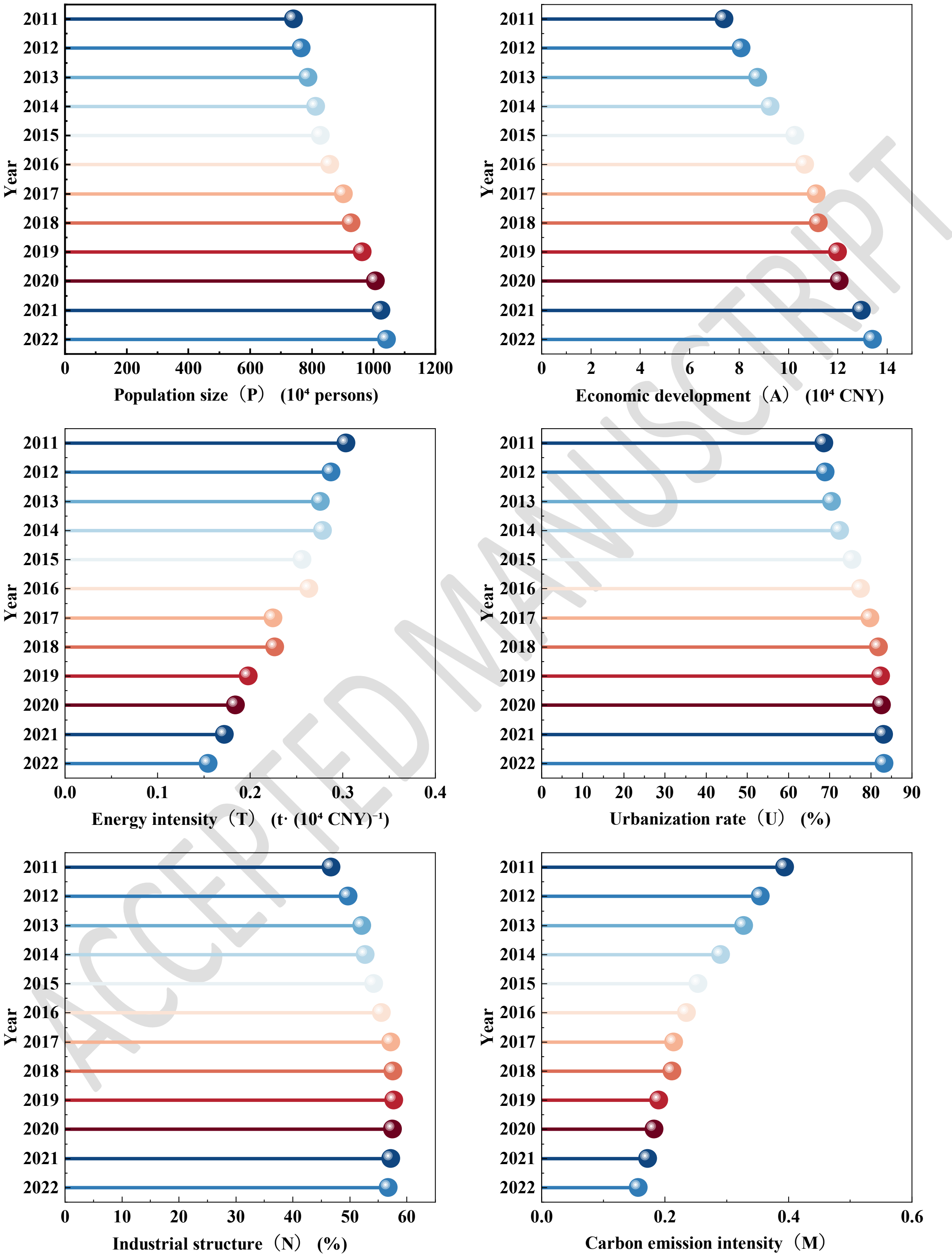


Figure 1 Changes in the indicators during the study period

2.4 Scenario analysis

Using scenario analysis, we project Changsha's future CO_2 emissions. To examine whether and when the city will reach its peak emissions, scenarios and forecasts were developed for the period of 2023−2060. The growth rates of population size, economic development, energy intensity, industrial structure, urbanization, and carbon emissions intensity were determined based on historical trajectories, policy plans, and related studies. Accordingly, each variable was assigned high, medium, and low growth paths. The parameter settings are listed in Table 2.

2.4.1 Population size

According to the Changsha Statistical Yearbook, the resident population at the end of 2022 was 10.4206 million, and the natural population growth rate is 0.59 percent higher than in the previous year. Based on the 2012-2022 data, the average natural population growth rate is 4.79 percent. In recent years, this rate has slowed noticeably. From 2018 to 2022, Changsha's average natural population growth rate declined to 2.7 percent and exhibits a slowing, stable pattern. Accordingly, under the baseline scenario (S2), the population growth rate for 2023 to 2025 is set at 2.7 percent. The detailed parameters are listed in Table 2.

2.4.2 Per capita GDP

The growth rate of per capita GDP aligns with the overall economic growth rate. According to Changsha's Fourteenth Five-Year Plan and the 2035 long-term objectives (the Plan), the city targets an average annual GDP growth rate of 7.8 percent during 2021-2025. Based on the plan and recent GRP data, the computed five-year average GDP growth rate for Changsha is 6.8 percent. Accordingly, we set the growth path for 2023-2060 as follows: Under the baseline scenario (S2), per capita GDP grows at 6.8 percent during 2023-2025. As the economy transitions to a new normal, the growth rate is expected to decline gradually. The detailed parameters are listed in Table 2.

2.4.3 Energy intensity

Drawing on the GDP growth plan set out in the Thirteenth Five-Year Plan for National Economic and Social Development, the Implementation Plan for Carbon Peaking in Changsha, and the Outline of the Vision Goals for 2035, from 2015 to 2020, energy intensity falls by 20 percent in Changsha, averaging about 4 percent per year. By 2025, it will be 15% less than the 2020 level which would amount to around a 3% average annual decrease. So for our baseline scenario (S2) we go 3% annually off from 2023-2025. In parallel, broader development trends and local conditions are considered. The detailed parameters are listed in Table 2.

2.4.4 Urbanization rate

The urbanization rate (U) is a key indicator of social development. In recent years, Changsha has advanced integrated urban and rural development, and the rate of urbanization has risen steadily. Given the high starting level, its growth converges to a stable pace. This rate reached 83.27 percent in 2022. To limit the impact of interannual variation, we used the Five-Year average growth rate of 0.5 percent for 2018-2022 as the representative value. Accordingly, under the baseline scenario (S2), the urbanization rate is set at 0.5 percent per year for 2023-2025. The detailed parameters are listed in Table 2.

2.4.5 Industrial structure

Changsha's industrial structure (N) shifts from the secondary to the tertiary sector, with the share of services exceeding 50 percent in 2013. In line with the moderation of economic growth, the pace of structural upgrading has stabilized in recent years. Drawing on statistics for 2013 to 2022, the tertiary sector recorded an average annual growth rate of 0.71 percent. Accordingly, under the baseline scenario (S2), the annual pace of industrial structure (N) is set at 0.7 percent for 2023 to 2025. The detailed parameters are listed in Table 2.

2.4.6 Carbon emission intensity

Drawing on the Thirteenth Five-Year Plan for National Economic and Social Development, CO_2 emissions per unit of gross regional product declined by 17 percent from 2015 to 2020, corresponding to an average annual decrease of 3.4 percent. On January 13th, 2023, the Changsha municipal government issued the Plan for Implementing Changsha's Efforts Towards carbon peaking which states that it aims to reach an 18% drop in CO_2 emission per unit of GDP by 2025 in line with China's target. Therefore, under the baseline scenario, carbon emission intensity will drop by 3.6 percent annually from 2023 to 2025. The detailed parameters are listed in Table 2.

Table 2 Parameter settings in low (L), medium (M), and high (H) speed development conditions

		2023-2025	2026-2030	2031-2040	2041-2050	2051-2060
	L	2.2	1.7	1.2	0.7	0.2
Population Size（P）	M	2.7	2.2	1.7	1.2	0.7
	H	3.2	2.7	2.2	1.7	1.2
	L	6.8	5.8	4.8	3.8	2.8
Per Capita GDP（A）	M	7.8	6.8	5.8	4.8	3.8
	H	8.8	7.8	6.8	5.8	4.8
	L	-2.5	-2	-1.5	-1	-0.5
Energy Intensity（T）	M	-3	-2.5	-2	-1.5	-1
	H	-3.5	-3	-2.5	-2	-1.5
	L	0.45	0.4	0.35	0.3	0.25
Urbanization Rate（U）	M	0.5	0.45	0.4	0.35	0.3
	H	0.55	0.5	0.45	0.4	0.45
Industrial Structure（N）	L	0.6	0.5	0.4	0.3	0.2

	M	0.7	0.6	0.5	0.4	0.3
	H	0.8	0.7	0.6	0.5	0.4
Carbon Emission Intensity（M）	L	-3.3	-3.6	-3.9	-4.2	-4.5
	M	-3.6	-3.9	-4.2	-4.5	-4.8
	H	-3.9	-4.2	-4.5	-4.8	-5.1

1) Note: “L”, “M,” and “H” represent low, medium, and high parameter levels.

2.4.7 Sensitivity analysis

A sensitivity analysis is used to assess the stability and robustness of the model. It quantifies how each factor affects CO_2 emission outcomes. For the sensitivity analysis, the rates of change are set within their observed ranges as follows: population size (P) at 0.2 percent, 1.7 percent, and 3.2 percent; per capita GDP (A) at 2.8 percent, 4.8 percent, and 7.8 percent; energy intensity (T) at −0.5 percent, −2.0 percent, and −3.5 percent; urbanization rate (U) at 0.25 percent, 0.4 percent, and 0.55 percent; industrial structure (N) at 0.2 percent, 0.5 percent, and 0.8 percent; and carbon emissions intensity (M) at −4.5 percent, −4.2 percent, and −3.9 percent. The sensitivity results are shown in Figure 2. The sensitivity analysis showed that population size (P) is one of the strongest determinants of emissions; increasing its rate to 3.2 percent raises CO_2 emissions by 0.71 percent. By contrast, the impact of industrial structure (N) is modest; a 0.8 percent increase in industrial structure (N) raises emissions by 0.09 percent. Accordingly, scenario design must pay attention to population changes, and industrial structure should be improved at the same time.

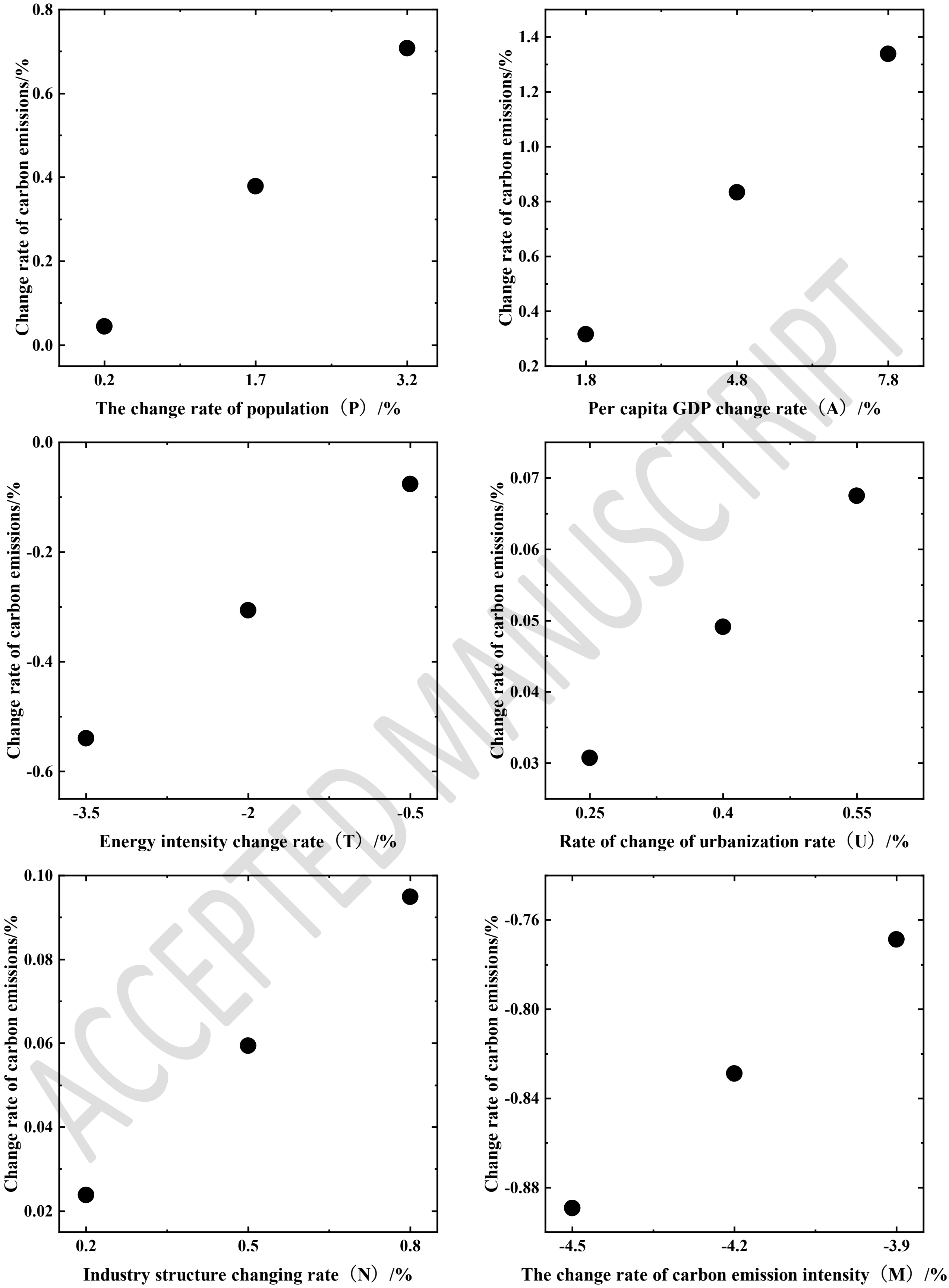


Figure 2 Sensitivity of carbon emission changes to the rate of various factors

2.4.8 Scenario settings

Scenario analysis is a vital tool for forecasting carbon emission pathways across multiple scales. It gives likely future trends by judging key drivers under various assumptions. By relying on the expanded STIRPAT model, we did scenario analysis to predict the CO_2 emission trends from 2023 to 2060 of Changsha under different situations. There were 8 scenarios based on sample data and relevant studies (Li, Chen, and You 2023b; Li *et al.* 2023a; Dong *et al.* 2022): low carbon (S1), baseline (S2), high carbon (S3), industrial optimization (S4), green development (S5), clean development (S6), energy saving (S7), and economic slowdown (S8). The specific parameter of all scenarios is Table 3.

(1) Low carbon scenario (S1)

Low carbon scenario (S1): all variables have low rates of change and strong control. Scenario evaluates the natural trend of emissions taking aggressive policies to limit growth.

(2) Baseline scenario (S2)

In baseline scenario (S2) all the rates of change for all variables are set to medium. This situation is in line with how Changsha is currently developing, following what has already happened, accounting for the continued impact of existing policies as is, without making further changes.

(3) High carbon scenario (S3)

Set all variables to their highest growth rates to simulate carbon emissions under the fastest urbanization in Changsha, assuming that each index grows at its maximum.

(4) Industrial optimization scenario (S4)

Industrial structure (N) is set to be a high growth rate, but all others are middle. Guided by Changsha's 14th Five-year plan and related policy, it expands the third industry, especially modern service industry, education and social security, and improves traditional industry. These efforts can hold back high energy consuming and emitting industries.

(5) Green development scenario (S5)

Building upon the baseline scenario, this case sets high rates for energy intensity (T), industrial structure (N), and carbon emission intensity (M), whereas the other variables remain unchanged. According to the Implementation Plan for Changsha's carbon peaking work, it emphasizes the regulation of the energy mix and the promotion of the application of new energy to change industrial structure in order to achieve environmental goals.

(6) Clean development scenario (S6)

Building on the baseline case, this one assigns a high rate of reduction to carbon emission intensity (M), and holds all else constant. It is prioritizing eco and environment safety and is enforcing strict dual constraints on total energy consumption and intensity of consumption, providing an all-around and systematic incentive for the improvement, usage of the high-efficient energy-saving facilities and tools and strengthening control on the emissions from industrial production as well as household activities.

(7) Energy-saving development scenario (S7)

The rate of change for energy intensity (T) is a high value but the rest are medium. Environmental protection has been strengthened in Changsha in recent years, its energy intensity is also showing an improvement trend in the past five years, and there is still great room for energy reduction. In this case, we make things even stricter about following energy rules, we step up our talks with other places about new tech, and we push ourselves to get better at using new tech, which makes it go down faster for us to use less energy, and that causes our emissions to go down too.

(8) Economic slowdown scenario (S8)

The rates of change for GDP per capita (A) and the urbanization rate (U) are set to high values, while the other variables are set to medium values. This scenario represents Changsha's emission trend under a binding national carbon peaking constraint, where low carbon development is prioritized over economic growth. The city moderates economic growth by implementing energy-saving and carbon-reduction policies, which lower CO_2 emissions and bring the emissions peak forward.

Table 3 Scenario settings.

Scenario	Population Size（P）	Per Capita GDP（A）	Energy Intensity（T）	Urbanization Rate（U）	Industrial Structure（N）	Carbon Emission Intensity（M）
Low Carbon Scenario (S1)	L	L	L	L	L	L
Baseline Scenario (S2)	M	M	M	M	M	M
High Carbon Scenario (S3)	H	H	H	H	H	H
Industrial Optimization Scenario (S4)	M	M	M	M	H	M
Green Development Scenario (S5)	M	M	H	M	M	H
Clean Development Scenario (S6)	M	M	M	M	M	H
Energy-Saving Development Scenario (S7)	M	M	H	M	M	M

Economic Slowdown Scenario (S8)	M	H	M	H	M	M

2.5 Data source

Data for other indicators, including year-end resident population and gross domestic product, are drawn from the Changsha Statistical Yearbook, the Hunan Statistical Yearbook, and the China Energy Statistical Yearbook for the period 2011 to 2022. Carbon emission factors by fuel and standard coal conversion coefficients are obtained from data released by national authorities and the China Statistical Yearbook.

3. Results and Discussion

3.1 Analysis of Changsha carbon emission influencing factors

Using equations (2) to (8), we calculate the effects of the carbon emissions coefficient, energy structure, energy intensity, economic development, and population size on Changsha's CO_2 emissions for 2012-2022. The decomposition results and contribution rates for 2012-2022 are presented in Figure 3 and Figure 4.

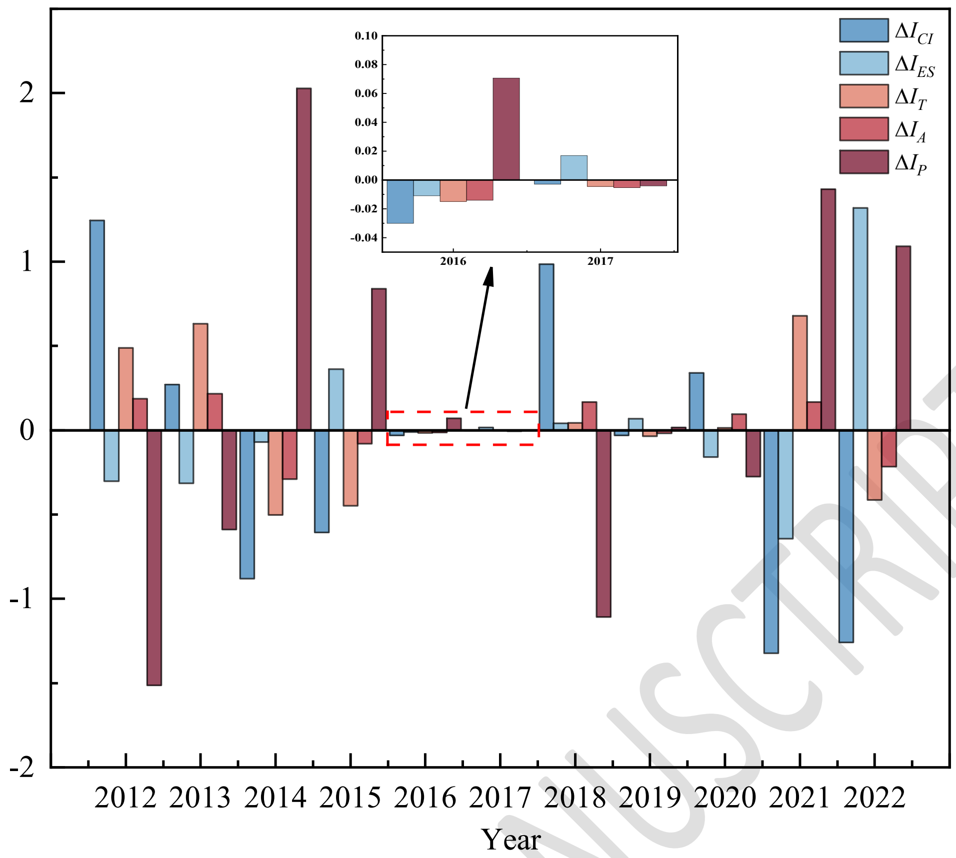


Figure 3 Decomposition of the Drivers of CO_2 Emissions in Changsha

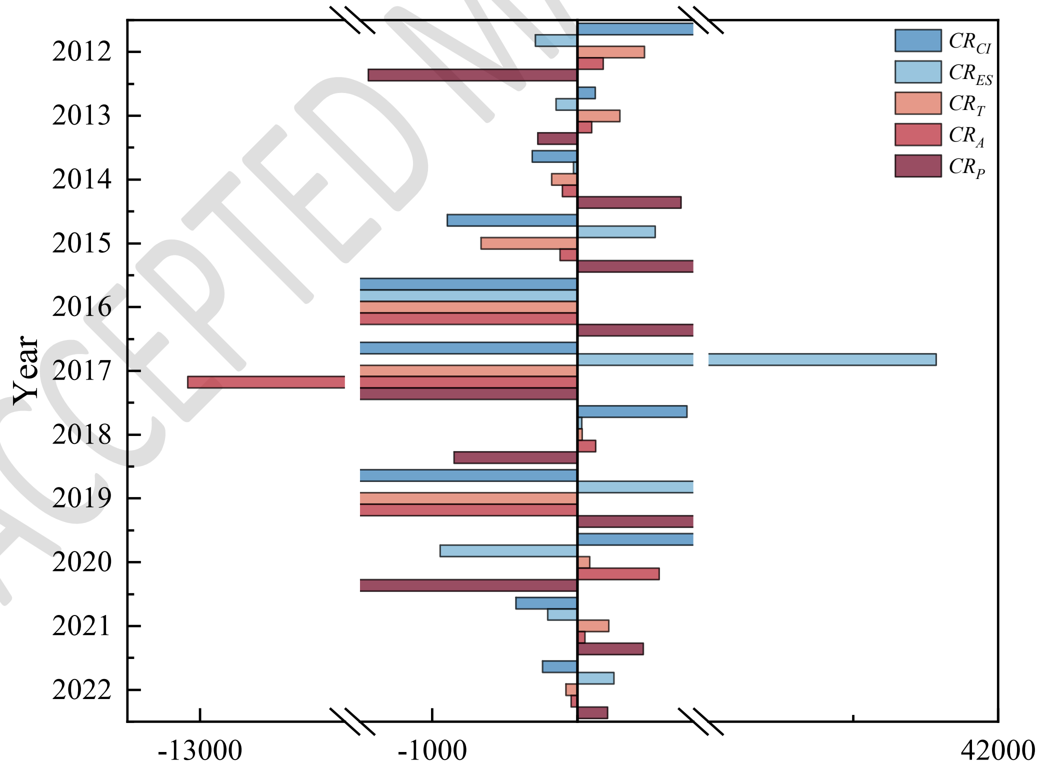


Figure 4 Contribution Rates of Drivers to Changsha's CO_2 Emissions

The LMDI decomposition indicates that changes in Changsha's CO_2 emissions are shaped by several drivers. Among the factors that reduce emissions, optimization of the energy structure and declines in the energy carbon-emission coefficient make the most consistent negative contributions. Their reducing effect is especially clear in 2015–2017 and again after 2021, matching coal-to-gas switching, the rollout of distributed photovoltaics, and industrial energy-saving upgrades. By contrast, the energy-intensity effect has generally acted as a positive driver of emissions; however, in recent years it turned negative, suggesting that industrial restructuring, technological progress, and upgrades in traditional heavy industry have started to cut energy use per unit of output and thus restrain emissions. Overall, the population-scale effect remains a promoter of emissions: with continued economic expansion and rising urbanization, population growth has exerted upward pressure on CO_2. Finally, the economic-development effect is the core driver of emissions growth. The economic-development effect is the core driver of emissions growth. It is directly tied to Changsha's expansion model, with average GDP growth above 8 percent. This pace has accelerated social development and encouraged industrial clustering, which in turn raises energy use and carbon emissions.

3.2 STIRPAT model

3.2.1 Multicollinearity test

In multiple regression analysis, multicollinearity among independent variables can distort the estimated coefficients (Yang *et al.* 2023). To address this issue, we used SPSS to test for multicollinearity among the regressors. Several pairs exhibit correlation coefficients as high as 0.9. The detailed results are shown in Figure 5. On this basis, assessed multicollinearity using the variance inflation factor (VIF); all variables had VIF values greater than 10 (

Table 4), indicating a serious multicollinearity problem. Therefore, multicollinearity among the explanatory variables should be eliminated to obtain valid results.

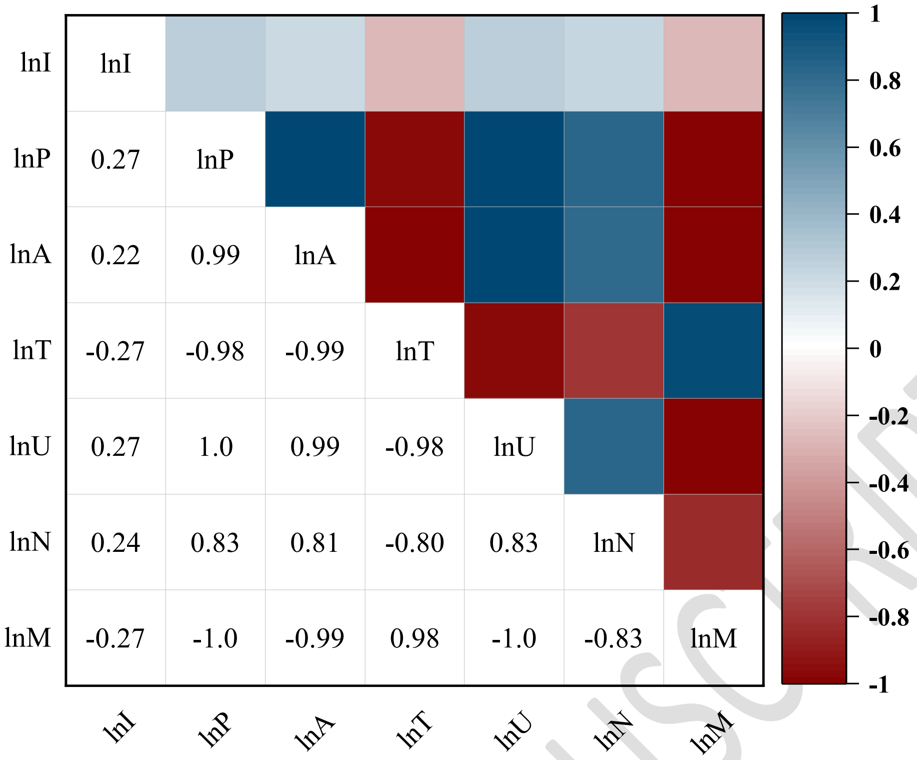


Figure 5 Test results of Spearman correlation coefficient for variables

Table 4 The results of the multicollinearity test.

Variable	t Value	Standard Error	Sig Value	VIF
c	-10.939	0.483	0.000	
lnP	13.668	0.074	0.000	44.162
lnA	10.067	1.131	0.000	347.811
lnT	-1.713	0.030	0.147	60.211
lnU	-0.289	0.124	0.784	52.861
lnN	-1.379	0.084	0.226	19.202
lnM	11.698	0.104	0.000	562.013

3.2.2 Analyses of model fitting

To prevent distorted model evaluation, the constructed model is estimated with ridge regression to mitigate multicollinearity in the independent variables. As shown in Figure 6 and Figure 7, when K = 0.03, the regression coefficients for the influencing factors become stable. The detailed results of the ridge regression analysis are presented in

Table 5.

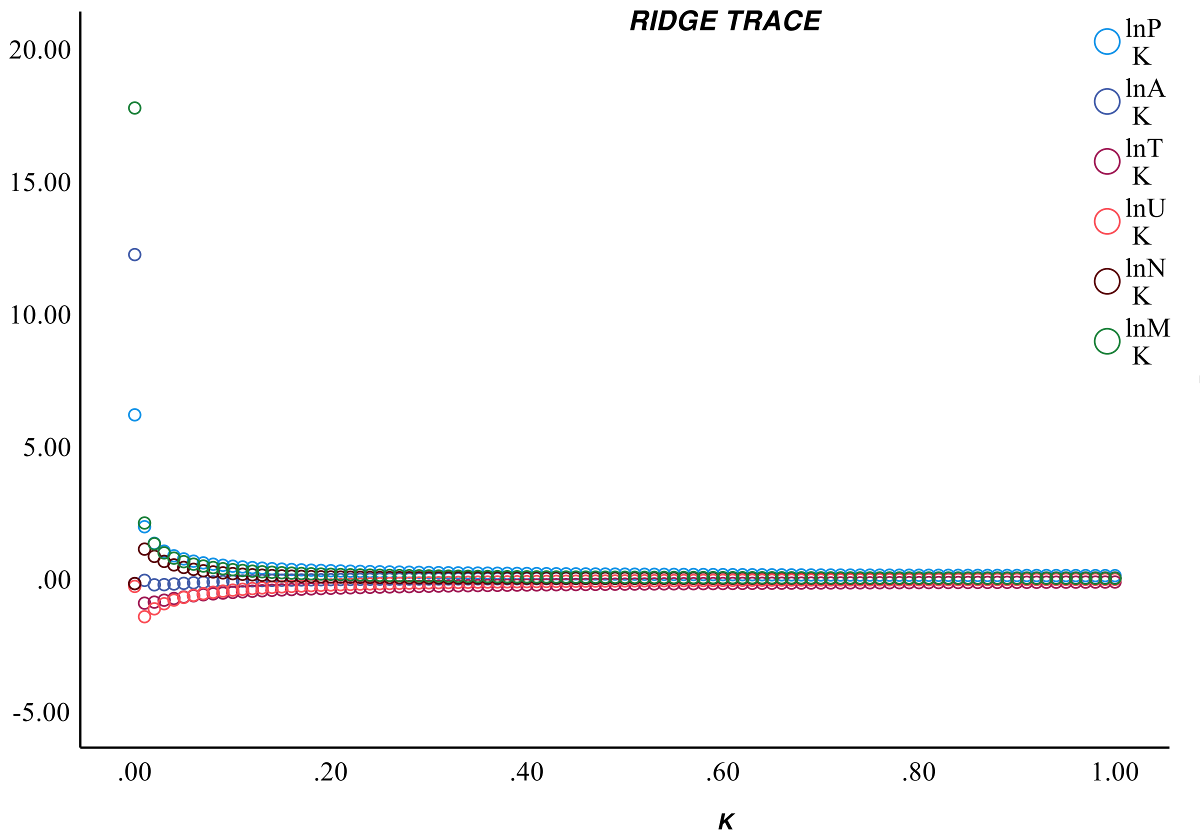


Figure 6 Ridge trace of various influencing variables

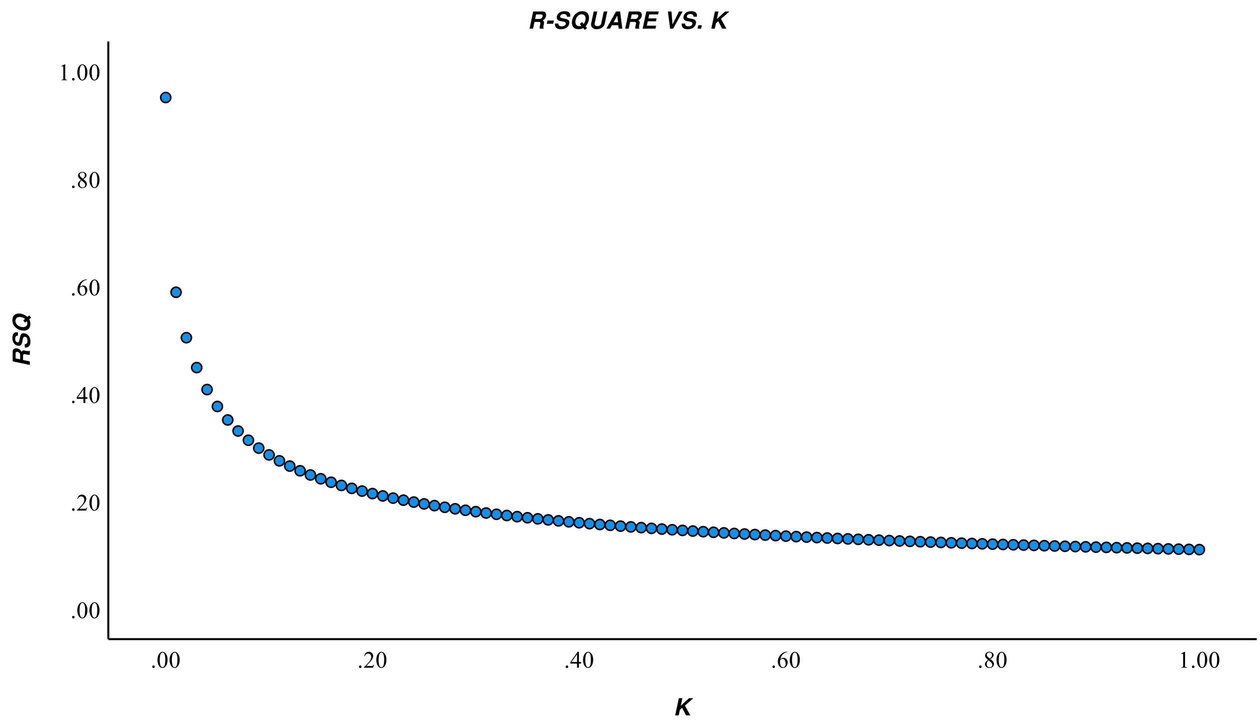


Figure 7 The ridge trace map of the R^2 value and k value

Based on the ridge regression diagnostics (Table 5), R^2 and the adjusted R^2 are above 0.99, the F value was 67.01, and the F statistic also passed the significance level test of 0.1%, indicating that the regression equation is significant and the fit is satisfactory. The STIRPAT model relating Changsha's CO_2 emissions to the explanatory variables is:

$$\ln I=0.07+0.224\ln P+0.177\ln A+0.152\ln T+0.123\ln U+0.119\ln N+0.194\ln M \tag{12}$$

Equation (12) indicates that a 1 percent change in population size, per capita GDP, energy intensity, urbanization rate, industrial structure, and carbon intensity corresponds to changes in CO_2 emissions of 0.224 percent, 0.177 percent, 0.152 percent, 0.123 percent, 0.119 percent, and 0.194 percent, respectively. Accordingly, the relative contribution ranking is: population size (P) > carbon intensity (M) > per capita GDP (A) > energy intensity (T) > urbanization rate (U) > industrial structure (N).

Table 5 Results of ridge regression analysis for each variable

	B	SE(B)	Beta	R^2	Adj R^2	F
Constant	0.07	0.207	0.000			
lnP	0.224	0.277	0.243			
lnA	0.177	0.366	0.230			
lnT	0.152	0.536	0.161	0.996	0.993	F=67.01,P=0.003, Sig F=0.00007
lnU	0.123	0.122	0.123			
lnN	0.119	0.118	0.119			
lnM	0.194	0.194	0.206			

To further validate the extended STIRPAT model after ridge regression, we compare the CO_2 emission simulated values with the actual values. As shown in Figure 8, the average annual error between the simulated values and the actual values for Changsha is 6 percent, indicating a satisfactory goodness of fit. The model is therefore suitable for projecting future CO_2 emissions in Changsha.

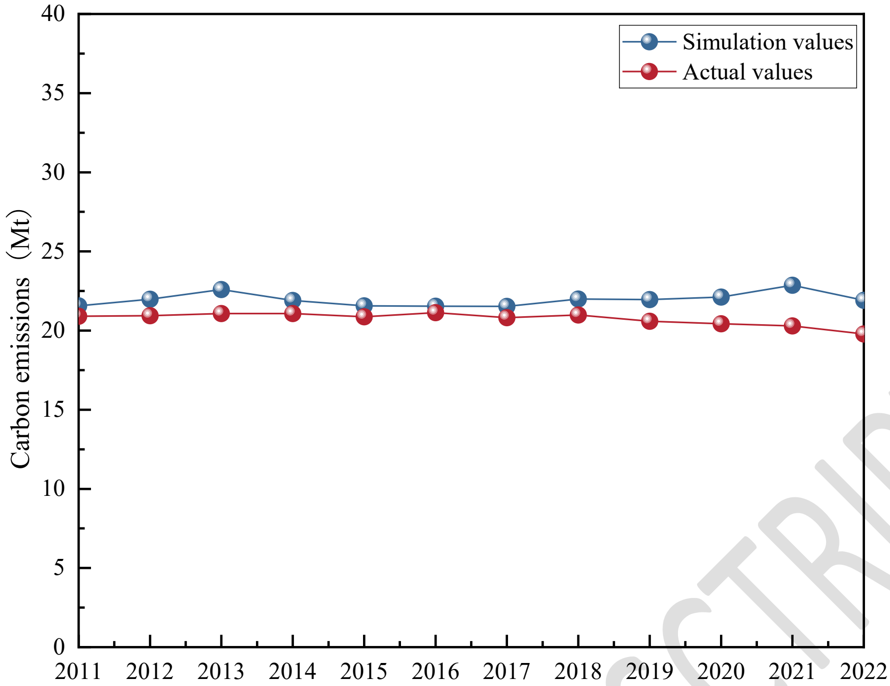


Figure 8 Comparison of CO_2 emission simulation values and actual values

3.2.3 Carbon emission prediction analysis

Based on the extended STIRPAT model, this study forecasts Changsha's CO_2 emission trends for 2023-2060. The results are shown in Figure 9 and Figure 10.

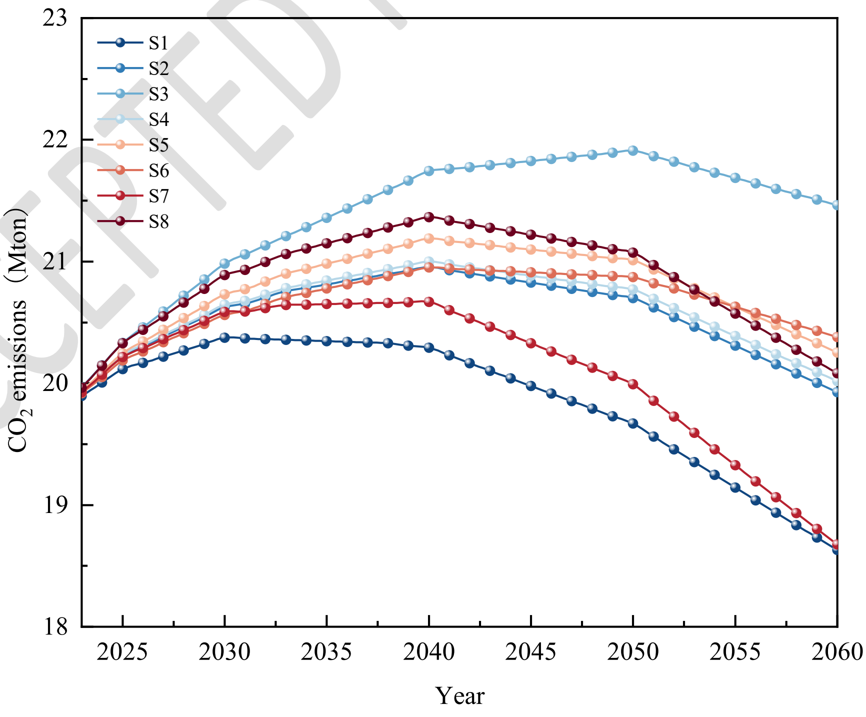


Figure 9 Eight scenarios of CO_2 Emission trends in Changsha from 2023 to 2060

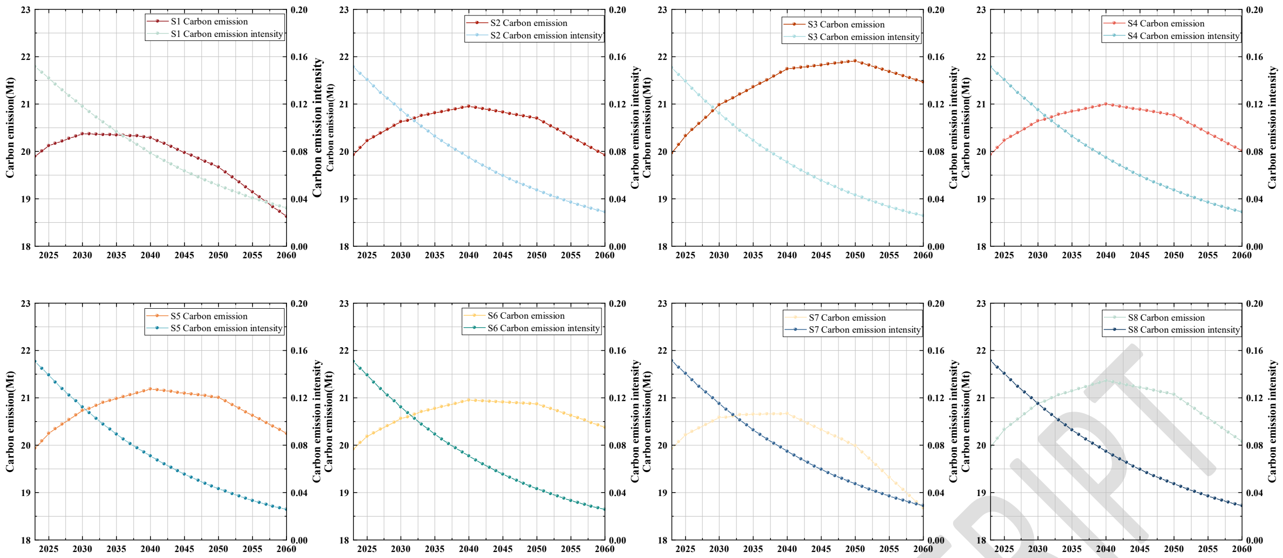


Figure 10 Predictions of carbon emissions and carbon emissions intensity in Changsha from 2023 to 2060 under 8 scenarios

Table 6 Peak year and peak CO_2 emissions in Changsha under different scenario Combinations

	S1	S2	S3	S4	S5	S6	S7	S8
Timing of peak CO_2 emissions	2030	2040	2050	2040	2040	2040	2040	2040
Peak CO_2 （Mt）	20.37	20.95	21.91	20.99	21.19	20.95	20.67	21.37

Based on various scenarios of the change of Changsha city's CO_2 emission from 2023 to 2060, and the actual situation and policy orientation of the development of the city, the main conclusions are as follows. The timing of Changsha's carbon peak varies significantly across different development paths, ranging from as early as 2030 (S1) to as late as 2050 (S3), as summarized in Table 6. The maximum value of CO_2 emissions is 20.37-21.91 Mt, as can be seen from Table 6, which further demonstrates that the regulatory impact can be seen in policy, a large amount of the use of new technology is the result of emission. Implementation point of view, among all, S1 (low-carbon) becomes the key approach to achieving carbon peak in 2030. And it also stresses on optimizing the energy mix and the more that we can have renewables, which is very aligned to what Changsha is doing in terms of green industrial transition, their goal is to grow more off photovoltaics, grow more energy storage. On the contrary, the delayed peaks shown in the high carbon and economic slowdown scenarios are due to the bad impacts of still depending on traditional energy intensive industries, slow economic speed, and slow adoption of green technology, all of which cause the peaking process to be postponed. In short, the above forecast can provide a certain amount of evidence for the differentiated policies of Changsha. In terms of keeping economic growth and clean energy substitution and improving energy efficiency to achieve an earlier and lower peak of CO_2 emissions.

4. Conclusions and Policy Implications

4.1 Conclusions

(1) Employ the LMDI method to discover what determines the CO_2 emissions of Changsha. Use an extended STIRPAT model, link emissions to some driving factors, and then calculate what the projected emission levels and their peak years will be in different situations.

(2) And the LMDI decomposition indicates that the energy structure (*ES*) is the main restriction for the CO_2 emission growth, and economic development (A) is the main reason for the emission increase in Changsha.

(3) Among the 8 scenarios, the time when the carbon peak occurs differs, and the carbon peaks in 2040 in the baseline (S2), industrial optimization (S4), green development (S5), energy-saving development (S7), and clean development (S6) scenarios; the high-carbon scenario (S3) peaks in 2050. Only the low carbon scenario S1 achieves its peak by 2030, satisfying the 2030 peaking goal.

(4) Comparison of S1 shows that the low-carbon scenario represents the optimal low-carbon path for Changsha. It can ensure that the city's economy can continue to develop, and at the same time achieve a relatively low peak in CO_2 emissions.

(5) When we built this carbon emission model, there is a sort of subjectivity that will prevent us from taking all of the factors that affect the emissions. Future studies will try more scientific and thorough

way and add more driving factors to improve the accuracy and authenticity of the model.

4.2 Policy implications

(1) A low-growth path centered on structural optimization and efficiency gains

Projection results indicate that low-carbon deployment is the main lever for realizing an earlier and lower peak in the low-carbon scenario. Well if we had an easier mix of energies, if we could just use the energy that we have, better if you will, then it would be like kind of a big deal. So, the policy of Changsha is to go from expanding the amount of increase to improving the carbon efficiency of each dollar of GDP. In real life, energy-intensive industries must go through technical renovations to transition from crude production with high value to refined production with high value, and should not increase in quantity. Given the deceleration of urbanization, effort should focus on making the best out of the existing urban space and upgrading the efficiency of the energy system. That is to say, directing a limited amount of public resources toward structural upgrades and technological innovation, so as to steer the economy and society towards higher quality, lower consumption endogenous growth even within a slower growth context.

(2) Deepen industrial structure optimization and develop green industries

Changsha gets an important chance to make things ready for deep decarbonization during the slower-growth part of the low-carbon situation. The city has to make up these deficiencies in infrastructure and management during this period. Important priorities are optimizing industrial structure for high-quality, sustainable progress, releasing more energy-saving possibilities, and making energy efficiency better. As for carbon-intensive projects, advanced efficiency techniques must be adopted to make thorough modernization for traditional manufacturing. At the same time, improve fiscal incentives and support green industry policies to promote the use of low carbon and clean production technologies. Development of green industrial parks, cultivation of clustering effects, it would be conducive to form robust low-carbon clusters.

(3) Improve basics and do long-term planning during low-growth period

According to the scenario projection, Changsha's carbon peak time and quantity differ greatly among different development paths. Low-carbon scenario (S1) emissions hit a peak sooner and lower. In contrast to this is the high carbon scenario S3, and the other pathways all delay the peak and have more emissions. In this way, Changsha should apply different emission reduction stage to each scenario. In a low carbon world, we would want to push energy transition. During times of economic slowdown, policies should focus more on promoting green technologies and innovations so that there would be lesser effect on CO_2 emissions due to lesser growth.

(4) To create a changing adjustment mechanism to make the reaching-peak process safe and controlling

Changsha must build a regulatory system if it wants to make the carbon peak work, we cannot ignore energy structure or number of people. Specific measure is to implement frequent monitoring of the rate of reduction of the structure of energy-saving in key areas and the rate of increase in carbon emissions due to population; establish specific warning threshold values for these indicators according to the results of the model's sensitivity analysis; and immediately trigger the corresponding tiered response measures whenever the threshold values are reached. It forms a loop of management: "watching-worrying-handling-updating". It points the limited policy resources to the most important risk factors with precision, so as to protect the peak emission path in a systematic way.

5. Discussion

This research will be using the LMDI method and the STIRPAT model to do a projection of Changsha's future CO_2 emissions under several different scenarios and it would give out the peak year and the amount of emission that year is at. Prediction will become the reference points of regulating Changsha's future carbon emissions in the future. Among the 8 scenarios, only the low-carbon scenario (S1) can allow Changsha to achieve carbon peaking in 2030. The way we go, requires regulation on how much we burn for energy, structural modifications on the structures that use energy, very slow rate of GDP (growing economy). This goes hand-in-hand with what the city has going on presently with their sustainable efforts in greener industries such as photovoltaics and storage. It seems as if the 2030 carbon peaking is likely to be achievable if the current policy can be preserved and strengthened. The high carbon scenario (S3) is quite different as there is a notable delay in reaching its peak because continuous consumption of traditional energy consumes results in more emission and postpones the decarbonization process.

Second, the use of many scenarios here has very good methodological worth and practical policy references. Compared with the low-carbon scenario (S1) and the high-carbon scenario (S3),as well as the economic slowdown scenario (S8),the analysis finds the best way out as well as imagining the risks caused by policy failure or unexpected disaster. It will promote some caution from policymakers, making them more sensitive to risk in that sense. For example, the delayed carbon peak in economic slowdown scenario (S8), which shows that we cannot sacrifice sustainable economic growth for the low carbon transition. A solid economy gives the important base for progress in energy tech and infra renewal.

There are some restrictions to this study because of data accessibility, the picked drivers might not include all the complex and different causes affecting CO_2 emissions. With more comprehensive and correct data, it is expected that the research in the future will be more extensive and rigorous. And Changsha is treated as an isolated system in this study, which does not take the interaction with other areas into account. Future work can improve the focus of a single city to the level of the urban agglomeration in order to more accurately reflect the regional CO_2 emissions. Although with limitations, the key findings and policy suggestions of this study are still reference materials. And it recognizes those limitations form the basis for where I should put my energy for research in the future.

Declaration of competing interest:

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix

Table 1 Changes in the indicators during the study period

Year	Population size（P）(10^4 person)	Economic development（A）(10^4 CNY)	Energy intensity（T）(t*(10^4 CNY)$^{-1}$)	Urbanization rate（U）(%)	Industrial structure（N）(%)	Carbon emission intensity（M）
2011	740.36	7.39697	0.30385	68.62	46.7	0.39381
2012	766.18	8.08941	0.28744	68.99	49.7	0.35473
2013	787.46	8.76523	0.27619	70.55	52.1	0.32735
2014	813.11	9.26649	0.27834	72.45	52.7	0.29064
2015	828.27	10.26549	0.25622	75.44	54.2	0.25361
2016	859.03	10.67064	0.26361	77.56	55.6	0.23492
2017	902.94	11.13053	0.22499	79.86	57.2	0.21418
2018	928	11.21297	0.22653	81.93	57.6	0.21135
2019	963.56	11.98963	0.19818	82.46	57.7	0.19002
2020	1006.08	12.06914	0.18436	82.6	57.5	0.18218
2021	1023.93	12.96056	0.17235	83.16	57.2	0.17225
2022	1042.06	13.40241	0.15488	83.27	56.8	0.15687

Table 2 Sensitivity of carbon emission changes to the rate of various factors

The change rate of population（P）/%	Rate of change in carbon emissions/%	Per capita GDP change rate（A）/%	Rate of change in carbon emissions/%	Energy intensity change rate（T）/%	Rate of change in carbon emissions /%	Rate of change of urbanization rate（U）/%	Rate of change in carbon emissions/%	Industry structure changing rate（N）/%	Rate of change in carbon emissions/ %	The change rate of carbon emission intensity（M）/%	Rate of change in carbon emissions/%
0.2	0.04477	1.8	0.31627	-0.5	-0.07616	0.25	0.03072	0.2	0.02378	-4.5	-0.88927
1.7	0.37831	4.8	0.83329	-2	-0.30661	0.4	0.04911	0.5	0.05937	-4.2	-0.82895
3.2	0.70807	7.8	1.33828	-3.5	-0.54007	0.55	0.06749	0.8	0.09487	-3.9	-0.76878

Table 3 Decomposition of the Drivers of CO_2 Emissions in Changsha

Year	ΔI_{CI}	ΔI_{ES}	ΔI_{T}	ΔI_{A}	ΔI_{P}
2012	1.24568	-0.30266	0.48789	0.18691	-1.51281
2013	0.27089	-0.31474	0.63286	0.21608	-0.58964
2014	-0.88117	-0.0701	-0.50342	-0.29016	2.02806
2015	-0.60527	0.36198	-0.44744	-0.08073	0.83889
2016	-0.03011	-0.01099	-0.01494	-0.01408	0.07064
2017	-0.00292	0.01694	-0.00451	-0.00533	-0.00414
2018	0.98595	0.04121	0.04476	0.16606	-1.10789
2019	-0.02947	0.06872	-0.03443	-0.01933	0.01544
2020	0.34078	-0.15811	0.01445	0.09444	-0.27485
2021	-1.32174	-0.64249	0.67973	0.16776	1.42955
2022	-1.25781	1.31972	-0.41395	-0.21672	1.09254

Table 4 Contribution Rates of Drivers to Changsha's CO_2 Emissions

Year	CR_{CI}	CR_{ES}	CR_{T}	CR_{A}	CR_{P}
2012	1186.26742	-288.229	464.62373	177.99108	-1440.65324
2013	125.72613	-146.07515	293.72374	100.28682	-273.66154
2014	-311.13817	-24.75216	-177.75512	-102.45497	716.10042
2015	-897.57067	536.78936	-663.51974	-119.7176	1244.01864
2016	-5674.73439	-2070.52581	-2816.58006	-2653.31278	13315.15304
2017	-7156.02484	41571.99577	-11073.93977	-13083.51117	-10158.51999
2018	757.88549	31.67584	34.40833	127.64935	-851.61902
2019	-3185.04794	7427.94807	-3721.60531	-2089.59506	1668.30024
2020	2039.62261	-946.32124	86.50834	565.22183	-1645.03154
2021	-422.53119	-205.38849	217.29451	53.6278	456.99737
2022	-240.13759	251.95761	-79.0294	-41.37573	208.5851

Table 5 Spearman examines the original data

Year	lnI	lnP	lnA	lnT	lnU	lnN	lnM
2011	3.07114	6.60714	11.23622	-1.19123	-0.37659	-0.76096	-0.9319
2012	3.0904	6.64142	11.3179	-1.24674	-0.37121	-0.69877	-1.0364
2013	3.11772	6.66881	11.39474	-1.28665	-0.34885	-0.65128	-1.11672
2014	3.08643	6.70087	11.45263	-1.2789	-0.32227	-0.64026	-1.23567
2015	3.071	6.71934	11.54832	-1.36173	-0.28183	-0.61337	-1.37196
2016	3.06963	6.7558	11.59591	-1.33328	-0.25412	-0.5873	-1.4485
2017	3.06924	6.80566	11.64464	-1.49168	-0.2249	-0.55893	-1.54093
2018	3.09069	6.83303	11.641	-1.48489	-0.1993	-0.55112	-1.55424
2019	3.08889	6.87063	11.71301	-1.61856	-0.19286	-0.55037	-1.66062
2020	3.09653	6.91382	11.72235	-1.69085	-0.19116	-0.55369	-1.70277
2021	3.12932	6.9314	11.781	-1.75821	-0.1844	-0.55822	-1.75882
2022	3.08691	6.94895	11.81451	-1.86509	-0.18308	-0.56658	-1.85231

Table 6 Comparison of CO_2 emission simulation values and actual values

Year	Simulation value	Actual value
2011	21.56646	20.90692
2012	21.98585	20.93799
2013	22.59471	21.07437
2014	21.89876	21.07665
2015	21.56345	20.87151
2016	21.53384	21.13568
2017	21.52564	20.81589
2018	21.99226	20.98343
2019	21.95272	20.59049
2020	22.12108	20.42587
2021	22.85854	20.29356
2022	21.90917	19.78551

Table 7 Eight scenarios of CO_2 Emission trends in Changsha from 2023 to 2060

Year	S1	S2	S3	S4	S5	S6	S7	S8
2023	19.89544	19.93074	19.96552	19.93309	19.93826	19.91869	19.92761	19.96486
2024	20.00597	20.07703	20.14716	20.08177	20.09219	20.05276	20.07073	20.14584
2025	20.11712	20.22439	20.33046	20.23156	20.24731	20.18774	20.21488	20.32846
2026	20.16817	20.30398	20.45935	20.31358	20.34327	20.26187	20.28874	20.43923
2027	20.21935	20.38388	20.58906	20.39592	20.43969	20.33627	20.36286	20.55061
2028	20.27066	20.46409	20.7196	20.4786	20.53656	20.41094	20.43726	20.66259
2029	20.32209	20.54462	20.85096	20.56162	20.63389	20.48588	20.51193	20.77519
2030	20.37366	20.62546	20.98315	20.64497	20.73168	20.5611	20.58687	20.8884
2031	20.36796	20.65354	21.05791	20.67553	20.77229	20.59516	20.59047	20.93105
2032	20.36227	20.7044	21.13293	20.72889	20.83589	20.65198	20.61674	20.99687
2033	20.35657	20.75538	21.20821	20.78239	20.89967	20.70895	20.64304	21.06289
2034	20.35088	20.78363	21.28377	20.81314	20.94061	20.74325	20.64666	21.10591
2035	20.34519	20.81193	21.3596	20.84395	20.98163	20.77761	20.65028	21.149
2036	20.3395	20.84027	21.43569	20.8748	21.02273	20.81203	20.65389	21.19219

2037	20.33381	20.86864	21.51206	20.9057	21.06392	20.8465	20.65751	21.23547
2038	20.32812	20.89706	21.5887	20.93664	21.10518	20.88104	20.66113	21.27883
2039	20.31011	20.92551	21.66561	20.96762	21.14652	20.91562	20.66475	21.32228
2040	20.29212	20.954	21.74279	20.99866	21.18795	20.95027	20.66838	21.36582
2041	20.22887	20.9285	21.75944	20.97559	21.17012	20.94251	20.59987	21.3364
2042	20.16582	20.90303	21.7761	20.95254	21.15232	20.93476	20.53158	21.30702
2043	20.10297	20.87759	21.79277	20.92952	21.13452	20.927	20.46353	21.27768
2044	20.04031	20.85218	21.80946	20.90653	21.11675	20.91925	20.39569	21.24838
2045	19.97785	20.8268	21.82616	20.88356	21.09898	20.9115	20.32809	21.21912
2046	19.91558	20.80146	21.84287	20.86061	21.08124	20.90376	20.26071	21.18991
2047	19.85351	20.77614	21.85959	20.83769	21.0635	20.89602	20.19355	21.16073
2048	19.79163	20.75086	21.87633	20.8148	21.04579	20.88828	20.12661	21.13159
2049	19.72994	20.7256	21.89308	20.79193	21.02808	20.88054	20.0599	21.10249
2050	19.66844	20.70038	21.90984	20.76909	21.0104	20.87281	19.9934	21.07343
2051	19.56235	20.6217	21.8649	20.69261	20.93348	20.82253	19.85712	20.97211
2052	19.45684	20.54333	21.82006	20.61641	20.85684	20.77748	19.7266	20.87128
2053	19.35189	20.46525	21.77531	20.54049	20.78049	20.72743	19.59213	20.77093
2054	19.24751	20.38747	21.73065	20.46485	20.70441	20.67751	19.45858	20.67106
2055	19.14369	20.30999	21.68608	20.38949	20.62861	20.6277	19.32594	20.57167
2056	19.03937	20.2328	21.6416	20.3144	20.55309	20.57802	19.1942	20.47276
2057	18.93668	20.1559	21.59721	20.2396	20.47785	20.52845	19.06337	20.37433
2058	18.83454	20.0793	21.55292	20.16507	20.40288	20.479	18.93342	20.27637
2059	18.73294	20.00298	21.50871	20.09081	20.32819	20.42968	18.80436	20.17888
2060	18.6319	19.92696	21.4646	20.01682	20.25377	20.38047	18.67618	20.08186

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