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Multiple Heterogeneity Impacts of Territorial Space Development and Protection on Carbon Emissions in Resource-Based Cities in China

Li Ji[A], Huadong Gao[B*], Longgao Chen[C] and Jihong Dong[D]
[A]College of Economics and Management, Wenzhou University of Technology, Wenzhou 325027, China.
[B]College of Architecture and Energy Engineering, Wenzhou University of Technology, Wenzhou 325027, China.
[C]School of Public Policy and Management, China University of Mining and Technology, Xuzhou 221116, China.
[D]School of Environment and Spatial Informatics, China University of Mining and Technology, Xuzhou 221116, China
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*to whom all correspondence should be addressed: e-mail: gaohuadong1314@163.com
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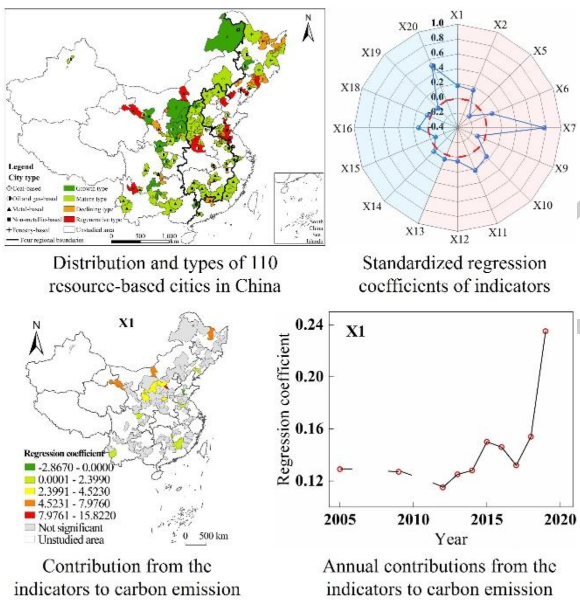
Graphical abstract



Abstract

Resource-based cities are an important source area of carbon emissions in China. Urban carbon emissions are significantly affected by territorial space development and protection (TSDP). Based on the panel data of 110 resource-based cities in China from 2005 to 2020, an empirical model is constructed. The heterogeneous impacts of TSDP on carbon emissions are explored at multiple levels and angles, key influencing factors are identified, and carbon emission reduction strategies and differentiated low-carbon development paths are proposed. The results of the study: (1) On the global scale, the degree of explanation of TSDP on the carbon emissions of the overall cities reaches 76.2%, in which the GDP, energy consumption per unit of GDP and the proportion of tertiary industry make the greatest positive contribution. (2) At the local scale, the impact of TSDP is heterogeneous by type. GDP has no significant influence on economically backward cities, and the total population has the strongest positive contribution to less populated cities. (3) At the urban scale, the impact of TSDP has spatial heterogeneity. Economic development has the greatest influence on carbon emissions, while population aggregation has the opposite effect. GDP and energy consumption per unit of GDP are no longer the dominant factors in all cities. (4) The impact of TSDP is time-differentiated. During the study period, GDP and energy consumption per unit of GDP significantly and positively affect carbon emissions, and their contributions show "W"-shaped and "U"-shaped fluctuation changes respectively. The proportion of construction land area significantly and positively affects carbon emissions in 10 years, and the effect increases with time. The research results can provide theoretical support and decision-making reference for resource-based cities to realize low-carbon sustainable development.

Keywords: Resource-based cities; territorial space development and protection; carbon emissions; impact of heterogeneity; multi-perspective empirical modeling

1. Introduction

China is the world's largest fossil energy consumer and carbon emitter, with carbon emissions reaching 11.47 billion t in 2021, accounting for 31% of the world's total carbon emissions (Energy 2022). The Chinese government has actively undertaken the task of carbon emission reduction and formulated a series of related policies. In September 2021, strengthening the role of territorial space planning and use control in the ecosystem's carbon sequestration and sink enhancement was explicitly proposed. In October 2021, constructing a TSDP pattern conducive to carbon peaking and carbon neutrality, and promoting the green and low-carbon transformation of urban and rural construction was proposed. As the core content of territorial space planning, TSDP influences the urban carbon balance through the land use structure and intensity and its changes, as well as the way of human activities carried (Bao *et al*. 2022; Ding *et al*. 2022), which is an important factor affecting carbon emissions. Therefore, the study of the impact of TSDP on carbon emission has important academic value and urgent practical significance.

Resource-based cities are cities with mining and processing of natural resources as their leading industries, accounting for 40% of the total number of cities in China (Yu *et al*. 2018), and they are an important region for the source of carbon emissions(Liao *et al*. 2022; Xu *et al*. 2023). In 2020, China's prefectural-level resource-based cities carried about 30% of population and contributed 22% of the GDP, but they accounted for one-third of carbon emissions. Their per capita carbon emissions, and 10,000 yuan of GDP carbon emissions are 7.56 t/person and 1.68 t/million yuan, which are 1.16 and 1.60 times higher than those of non-resource-based cities, respectively(Liao *et al*. 2022; Wu *et al*. 2023). In 2013, China promulgated the National Sustainable Development Plan for Resource-Based Cities (2013-2020) (hereinafter referred to as “the Plan”), which restricts the resource development activities of resource-based cities and guides them to explore low-carbon development models (State 2013). At the end of 2021, China called for categorization of policies, tailoring to local conditions, accelerating the low-carbon transformation of resource-based areas, and promoting high-quality development of resource-based cities. In the context of carbon peaking and carbon neutrality, it is necessary to reduce anthropogenic carbon emissions from the perspective of territorial space development. On the other hand, it is necessary to enhance the carbon sequestration capacity of different ecosystems from the perspective of territorial space protection (Huang *et al*. 2022). As resource-based cities are important contributors to China's “dual-carbon” goal, exploring the impacts of TSDP on carbon emissions is a prerequisite for proposing low-carbon transition paths.

Scholars have paid great attention to the study of carbon emission influencing factors, and explored the influence of economic level, population size, technological progress, energy intensity and industrial structure on carbon emissions. Li *et al*. (2021) analyzed the impact of structural changes on carbon emissions from the four aspects of the economy, energy, society and trade, found that the economic growth and the economic structure are the most significant positive and negative factors respectively. Koilakou *et al.* (2023) analyzed the link between energy-related carbon emissions and economic growth, and found that economic growth and energy intensity were the main factors. Ren and Long (2022) found that economic growth, population size and industrial structure would positively promote carbon emissions, while technological progress, foreign trade volume, and energy structure are the opposite. Wang *et al*. (2021) concluded that the structural adjustment of socio-economic development is an important way to reduce carbon emissions. Xu and Lin (2016) and Meirun *et al*. (2020) demonstrated that the green technological innovation can effectively reduce carbon emissions. Luo *et al*. (2022) found that in the context of rapid urbanization, upgrading the consumption structure can significantly increase carbon emissions. Qi *et al*. (2023) found that the proportion of secondary industry is significantly negatively correlated with carbon emissions. Wang *et al*. (2018) found that the scale effect (income and population) is the main influencing factor, whereas the technological effect (energy intensity and emission coefficients) is the slowing down of the emission key drivers. According to the study by Wu *et al*. (2025), digital trade can effectively reduce carbon emission intensity. Liu and Liu (2025) indicated that digital finance and green finance enhance carbon emission efficiency through technological innovation and the reduction of carbon emission intensity. Other studies have found that factors such as direct investment (Dong *et al*. 2023; Zhao and Zhu 2022), the digital economy (Qin *et al*. 2023; Wu *et al*. 2021), urbanization (Wang *et al*. 2021; Xu *et al*. 2018), population age structure (Zhao and Sun 2023), and institutions (Jiang and Lu 2022; Ma *et al*. 2023) also have an impact on carbon emissions.

In addition, a few scholars have studied the relationship between TSDP and carbon emissions. Xiong *et al*. (2021) and Cui and Zhu (2022) explored the inherent logical relationship between the “dual-carbon” goal and territorial space planning. Xiao *et al*. (2015) elaborated the low-carbon oriented spatial planning theories and technologies. Glaeser and Kahn (2010) found that the more restrictive the constraints and limitations on land development and utilization are, the greater carbon emissions reduction from residents' lives. Zhang *et al*. (2025)indicated that the urban expansion of China's Yangtze River Delta Urban Agglomeration promoted an increase in carbon emissions, but decoupling also occurred. Wang *et al*. (2018) found that compact urban transportation system planning helped to reduce per capita carbon emissions. Zhang et al. (2016) found that the intensity of construction land development and its carbon emission efficiency were dynamically changing. Ren *et al.* (2022) established a carbon emission calculation model for the coal development process, and proposed to promote the application of coal development energy saving and efficiency technology to reduce carbon emissions. Huang *et al*. (2021) pointed out that carbon emission reduction and carbon sink enhancement are the ways to realize low-carbon territorial space development.

To summarize, the current research has the following shortcomings: first, the relationship between carbon emissions and their influencing factors is not fixed but has spatial and temporal heterogeneity. However, most of the existing studies are based on the overall analysis of time series, ignoring the spatial heterogeneity. Second, empirical studies on the impact of TSDP on carbon emissions are still insufficient, and most of the existing literature is centered on the theory of low-carbon territorial spatial planning. Thirdly, the main contradictions and problems faced by different types of cities are not the same, and thus the carbon emission levels, influencing factors and low-carbon development paths of different types of cities are also significantly different. However, focusing on different development stages, dominant resource types and geographic locations of cities, there is still a lack of research on the impact of TSDP of resource-based cities on carbon emissions.

To reveal the impact of TSDP on carbon emissions in resource-based cities and its heterogeneity patterns, thereby formulating more scientific and targeted low-carbon development strategies for such cities, this paper takes the panel data of 110 resource-based cities in China from 2005 to 2020 as research samples, analyzes the connotation and constructs the index system of TSDP in resource-based cities, and analyzes the mechanism of TSDP on carbon emission. The study explores the heterogeneous effects of TSDP on carbon emissions from the perspectives of time and space, as well as from the perspectives of the overall and different types of cities, and identifies the key factors. As a result, carbon emission reduction strategies and differentiated low-carbon development paths are proposed to provide scientific theoretical basis and policy suggestions for resource-based cities to realize low-carbon sustainable and high-quality development.

2. Mechanism analysis of the impact of TSDP on carbon emissions in resource-based cities

2.1. Connotation of TSDP in resource-based cities

"Territorial space development and protection" encompasses both territorial space development and territorial space protection, emphasizing that the two go hand in hand. Compared with other cities, the economic development of resource-based cities is dominated by the secondary industry. Large-scale resource development can easily lead to environmental damage (Liao *et al*. 2022; Zhao *et al*. 2022), and ecological governance and pollution prevention will become the focus and difficulty of spatial construction (Huang *et al*. 2021; Zhao *et al*. 2012). The connotation of TSDP in resource-based cities is as follows:

Table 1. Measurement index system of TSDP in resource-based cities

First-level indicators	Second-level indicators	Third-level indicators (unit)	Interpretation of indicators	Notation
territorial space development	land resource development	Proportion of construction land area (%)	Proportion of construction land area in total city area	X1
		Proportion of cultivated land area (%)	Proportion of cultivated land area in total city area	X2
		Density of road network (km^2/km^2)	Proportion of total road area in total city area at the end of the year	X3
	population aggregation	Total population (ten thousand)	Total resident population of the city at the end of the year	X4
		Population density (person /km^2)	Ratio of total resident population to total city area	X5
		Urbanization rate (%)	Proportion of urban population in total permanent resident population	X6
	economic development	GDP (100 million yuan)	The gross national product of the city	X7
		Annual income per capita (Yuan)	Average annual salary of on-the-job workers in the city	X8
		Annual consumption per capita (Yuan)	Ratio of the total value of social consumer goods to the total resident population of the city	X9
		Proportion of secondary industry (%)	Proportion of the output value of the secondary industry in the city's gross national product	X10
		Proportion of tertiary industry (%)	Proportion of the output value of the tertiary industry in the city's gross national product	X11
	resource exploitation	Proportion of employment personnel in the mining industry (%)	Proportion of employment in mining in total employment	X12
		Proportion of investment in fixed assets in the mining industry (%)	Proportion of fixed asset investment in mining in total fixed asset investment	X13
territorial space protection	ecosystem protection	Proportion of forest area (%)	Proportion of forest area in total city area	X14
		Proportion of water and wetland area (%)	Proportion of water and wetland area in total city area	X15
		Green coverage rate of built-up area (%)	Proportion of the green coverage area in the built-up area to the total area of the built-up area	X16
	pollution control	Harmless treatment rate of	Proportion of harmless disposal volume	X17

		household garbage (%)	of household garbage in total household garbage	
		Sewage treatment rate (%)	Proportion of sewage treatment volume in total sewage discharge	X18
		Comprehensive utilization rate of industrial solid waste (%)	Proportion of total amount of industrial solid waste utilized in total amount of industrial solid waste	X19
	resource conservation	Energy consumption per unit of GDP (ton of standard coal/ten thousand yuan)	Ratio of total energy consumption to the city's gross national product	X20
		Water consumption per unit of GDP (m^3/ ten thousand yuan)	Ratio of total water use to the city's gross national product	X21
		Output per unit of land (ten thousand yuan /km^2)	Ratio of gross national product to total city area	X22

(1) Territorial space development involves not only land resource development, economic development and population aggregation, but also resource exploitation. The most typical manifestation of territorial space development is the expansion of construction land and the reduction of cultivated land, forest land, grassland and so on. Compared with construction land, cultivated land has ecological protection functions. However, the transformation of land use type from ecological land to productive land belongs to the territorial space development, such as the development of ecological land such as unutilized land, forest land, and grassland into cultivated land (Yang *et al*. 2021). Therefore, this study includes the expansion of construction land and cultivated land into territorial space development.

(2) Territorial space protection includes ecosystem protection, pollution control and resource conservation. Ecosystem protection refers to the protection of various types of natural ecological land, with the aim of enhancing the carbon storage and absorption capacity of forests, grasslands and so on. Pollution control mainly refers to the management of pollutants in the atmosphere, water and soil environment. Resource conservation mainly including the conservation and utilization of water, land and energy.

2.2. Index system for measuring TSDP in resource-based cities

The index system covering seven elements, including land resource development (Chen and Wang 2023; Yang *et al*. 2021), population aggregation (Chen and Wang 2023; Liu *et al*. 2013), economic development (Chen and Wang 2023; Li and Li 2023), resource exploitation, ecosystem protection (Cheng *et al*. 2013), pollution control (Xu 2023) and resource conservation(Cheng *et al*. 2013; Deng *et al*. 2019) is constructed, as shown in **Table 1**.

2.3. Mechanism analysis of the impact of TSDP on carbon emissions

Land resource development will lead to the expansion of construction land, which not only leads to the generation of new carbon sources, but also destroys the carbon sequestration and sink enhancement of the original carbon sink land (Zhang *et al*. 2012). Cultivated land is both a carbon source and sink, and the growth of crops will directly affect carbon emission and absorption (Chuai *et al*. 2015). The better the transportation location conditions, the higher the degree of land use and economic output level is usually higher, and it is also easier to meet the demand for the expansion of construction land (Gao *et al*. 2018). The direct motivation for TSDP is population growth and economic development (Kong *et al*. 2020). A larger population means more carbon emissions (Zhang and Wu 2020), and changes in the structure of population will bring about changes in the type of land use and production and living styles, which in turn will affect carbon emissions. Economic development will increase the demand for construction land and challenge the protection of cultivated land (Feng *et al*. 2023). The improvement of residents' living standards due to economic development will change the demand for energy consumption, and the economic restructuring makes changes in the way of territorial space utilization, thus affecting carbon emissions. Resource exploitation has the characteristics of high input, high energy consumption and high pollution, which contribute to carbon emissions. The idea that protecting ecosystems is an effective measure to reduce carbon emissions has been widely recognized (Dong *et al*. 2022). Pollution control can effectively curb carbon emissions, but some scholars believe that pollution control reduces the unit production cost through technological advances, and enterprises expand the production scale to obtain greater profits, but exacerbates carbon emissions (Zeng *et al*. 2022). Resource conservation means directly reducing fossil energy use, which is the main way to reduce carbon emissions from the source.

3. Overview of the study area, research methods and data sources

3.1. Study area

According to "the Plan", there are 126 prefecture-level resource-based cities in China. Considering the removal and merger of administrative regions and the lack of statistical data in some cities, 110 cities are finally selected as the research objects, and the national prefecture-level administrative region division in 2020 is taken as the standard. According to the development stage of cities, "the Plan" divides resource-based cities into growth, mature, declining and regenerative types. According to the dominant resources of cities, resource-based cities can be divided into metal-based, non-metallic-based, forestry-based, coal-based and oil and gas-based (Liu 2006). According to the geographical location of cities, resource-based cities are distributed in the eastern, central, western and northeastern regions. The spatial distribution and type classification of 110 cities are shown on **Figure 1**.

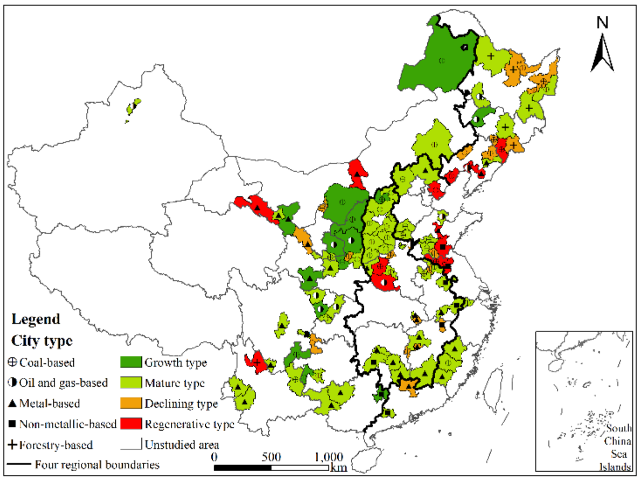


Figure 1. Distribution and types of 110 resource-based cities in China

3.2. Multi-perspective empirical modeling of carbon emission impacts

This study involves a total of 1,760 city-annual observations, with the dependent variable set as carbon emissions and the independent variables set as indicators of TSDP. The multiple linear regression model is used to explore the multiple heterogeneity of the impact of TSDP on carbon emissions. Linear regression analysis can effectively establish quantitative relationships between variables and has been widely used in various studies (Xu *et al*. 2019). Stepwise regression can eliminate model multicollinearity, which is one of the important methods to establish the optimal linear regression model (Whittingham *et al*. 2006; You and Yan 2017).

Given n independent variables, the model can be expressed as (Chen *et al*. 2022):

$$y=\beta_0+\sum_{i=1}^{n}\beta_i x_i+\varepsilon \quad (1)$$

where *y* is the dependent variable, x_i is the independent variable, β_0 is the intercept, *n* is the number of potential independent variables, and ε is the residual term. β_i is the regression coefficient of the *i*-th independent variable, which indicates the contribution of x_i to *y*. Standardized regression coefficients eliminates the effect of different independent variables' units and can be used to compare the relative magnitude of the effect of different independent variables on the dependent variables(Chen *et al*. 2022).

The model is developed using SPSS 26.0 software, and the modeling procedure is as follows:

(1) Correlation analysis. Pearson correlation analysis is conducted between each indicator and carbon emissions to initially determine whether there is a correlation between each independent variable and the dependent variable.

(2) A collinearity diagnostic was performed on the 22 indicators using the Variance Inflation Factor (VIF). The results indicated that all VIF values of the explanatory variables were below the empirical threshold of 10, demonstrating the absence of significant multicollinearity. This confirms the reliability of individual indicator contributions and supports the feasibility of constructing a regression model.

(3) Multi-perspective carbon emission impact empirical model construction.

1) In the global scale, based on the regression model and the indicator data of each city from 2005 to 2020, the overall impact of the indicators of TSDP on carbon emissions is explored.

2) In the local scale, the contribution of each indicator to carbon emissions in different types of resource-based cities are calculated.

3) In the city scale, the contribution of each indicator to carbon emissions is calculated separately for 110 cities to reveal the spatial variability of the impact of TSDP on carbon emissions.

4) In the time series, the overall contribution of all cities each year are calculated to reveal the annual variability of the impact of TSDP on carbon emissions.

3.3. Data sources

The socio-economic data of each city mainly come from China City Statistical Yearbook (2006-2021), China Urban Construction Statistical Yearbook (2005-2020), Statistical Yearbooks of provinces (autonomous regions) and prefecture-level cities (2006-2021), and Statistical Bulletin of National Economic and Social Development (2005-2020), and linear interpolation method is used to supplement some missing data (Jasmine *et al*. 2025). The city's land use data from Annual China Land Cover Dataset (Yang and Huang 2021), which has good accuracy and continuity, has been widely used in academic research (Feng *et al*. 2023; Yan *et al*. 2025). 110 resource-based cities carbon emissions data from the municipal carbon listing (https://www.ceads.net.cn/data/city/) provided by China Emission Accounts and Datasets (CEADs). This data is obtained from DMSP/OLS and NPP/VIIRS night light satellite images, and the goodness of fit R^2 reaches 0.998 (Shan *et al*. 2022; Shan *et al*. 2019), which is considered as the authoritative and scientific carbon emission accounting database in China, and widely used in academia (Feng *et al*. 2023; Li *et al*. 2022; Wang *et al*. 2021).

4. Results and analysis

4.1. Impacts of TSDP on carbon emissions at the global scale

4.1.1. Overall regression results

The results of Pearson correlation analysis show that there is a significant correlation between carbon emissions and the 22 indicators of TSDP (p-value is less than 0.01), and all 22 indicators can be used for modeling. **Table 2** shows the fitting results of the multivariate linear stepwise regression model, and the goodness-of-fit R^2 is 0.762. It indicates that the degree of explanation of TSDP on carbon emissions is 76.2%. The F value of the model is 4.444, which is significant at 5% level, indicating that the constructed model is effective. According to the regression coefficients, a total of 16 variables enter the model and significantly affect the carbon emissions of overall cities.

Table 2. Results of multiple linear regression based on overall resource-based cities

Independent variable	Regression coefficient	Standardized regression coefficient
Constant term	-17.757	
Dependent variable		
X1	0.114**	0.169**
X2	0.216**	0.148**
X5	-0.189**	-0.174**
X6	0.253**	0.102**
X7	0.905**	0.771**
X9	-0.148**	-0.111**
X10	0.545**	0.151**
X11	0.888**	0.225**
X12	0.037**	0.051**
X13	0.041**	0.060**
X14	0.021**	0.055**
X15	-0.060**	-0.078**
X16	0.347**	0.126**
X18	0.098**	0.043**
X19	-0.055*	-0.028*
X20	0.948**	0.509**
N	1760	
R^2	0.762	
Adjusted R^2	0.760	
F	4.444*	

*Note: ** and * indicate that the variables are significant at the 1% and 5% levels, respectively.*

4.1.2. Analysis of the impact of TSDP on carbon emissions

The regression coefficients of the land resource development indicators X1 and X2 are 0.114 and 0.216, respectively, indicating that the expansion of construction land and cultivated land will contribute to carbon emissions. In the population aggregation, the regression coefficient of X5 is -0.189, indicating that the increase in population density suppresses carbon emissions. Relevant studies have shown that the increase of population density will bring about the innovation of production technology, thus indirectly reducing carbon emissions (Guo *et al*. 2023). The regression coefficient of X6 is 0.253, indicating that for every 1% increase in the urbanization rate, the carbon emissions will increase by 0.253%. The increase in urban population is often accompanied by the increasing demand for urban construction, transportation, housing, etc., which increases energy consumption and generates more carbon emissions (Wang and Qin 2015). Among the economic development, X7, X9, X10, and X11, the other three indicators are positively correlated with carbon emissions, except for X9. X7 has the largest positive impact, which is the most important factor, which is in line with the conclusions of the studies by Li (2024) and Guo (2011). X9 has a negative effect on carbon emissions, contrary to the theoretical analysis. This may be since high consumption is often accompanied by a strong sense of environmental protection, and people's green and low-carbon consumption will reduce carbon emissions. In industrial structure, the proportion of secondary and tertiary industries all have a significant positive contribution to carbon emissions, which means that the expansion of the scale of almost all industries will promote carbon emissions. The regression coefficients of resource exploitation indicators X12 and X13 are 0.037 and 0.041, respectively, which indicates that large-scale resource extraction will exacerbate urban carbon emissions, in line with theoretical expectations.

X15 significantly negatively influencing carbon emissions and X14 and X16 the opposite. The higher area proportion of watersheds and wetlands means that more other land is converted into ecological land, which in turn reduces carbon emissions. The regression coefficients of X14 and X16 are 0.055 and 0.126, respectively, which may be attributed to the following reasons: the proportion of forested land area and the greening coverage rate of the built-up area reflect the greening level of the city, and the higher the level in general, the higher the level of urban development is also relatively high, which usually brings more carbon emissions. Pollution control has a relatively small impact on carbon emissions, especially the comprehensive utilization rate of industrial solid waste has the smallest effect on carbon emissions. The regression coefficient of X20, a indicator of resource conservation, is 0.948. For every 1% increase in energy intensity, carbon emissions will increase by 0.948%. In the 11th Five-Year Plan, the Chinese government takes reducing energy intensity and improving energy efficiency as an important way to reduce carbon emissions, and energy intensity is an important factor in carbon emissions (Wang and Fan 2022).

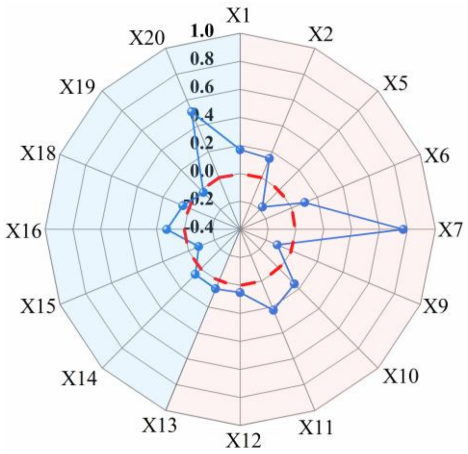


Figure 2. Radar chart showing standardized regression coefficients of indicators in overall resource-based cities

4.1.3. Identification of core influencing factors

Among the 16 indicators of TSDP in the model, X5, X9, X15 and X19 have a significant negative impact on carbon emissions, while the remaining 12 indicators are on the contrary. The standardized regression coefficients show that different indicators have different degrees of influence on carbon emissions (**Figure 2**), from strong to weak: X7, X20, X11, X5, X1, X10, X2, X16, X9, X6, X15, X13, X14, X12, X18, and X19. GDP, energy consumption per unit of GDP, and proportion of tertiary industry are the top three indicators, while the related indicators characterizing pollution control have a smaller degree of influence on carbon emission.

4.2. Differences in the impact of different types of cities on carbon emissions at the local scale

4.2.1. Resource-based cities at four development stages

Table 3 shows that land resource development does not have a significant effect on regenerative type cities, and X1 has a gradually decreasing role in promoting carbon emissions in mature, declining and growth type cities. Cultivated land expansion has the strongest inhibitory effect in growth type cities, which may be since this type of city is in the rising stage of resource exploitation, with a high potential for resource security, and the phenomenon of cultivated land non-agriculturalization is less manifested as a carbon sequestration effect. Population aggregation has a significant effect on all four types of cities, but the direction and size of the effect varies. Especially X6, which has the largest positive effect on growth type cities, with a regression coefficient of 1.249. However, it has a negative effect on regenerative type cities with higher urbanization rates, reflecting that moderate population agglomeration can promote low-carbon development of cities. The total population has a significant positive effect on the least populated declining type cities and the most populated regenerative type cities, and the effect on the former is larger than that on the latter. X5 only has a significant negative effect on mature type cities. Economic development has a smaller effect on declining type cities, and only one indicator, X8, enters its regression model. This may be since the declining type cities tend to deplete their resources and lag in economic development. X7 has the greatest impact on mature type cities, while X10 has the greatest impact on regenerative type cities. Resource exploitation has a significant contributing effect on regenerative type cities, which may be since the impact of resource exploitation on carbon emissions has a certain lagging effect, and even if the resource extraction activities are stopped, the carbon emissions will continue for a period.

Table 3. Results of multiple linear regression of resource-based cities at different development stages

Types	**Constant term**	**X1**	**X2**	**X4**	**X5**	**X6**	**X7**	**X8**
growth type	-13.194	0.100*	-0.435**			1.249**	0.636**	
mature type	-14.840	0.184**	0.114**		-0.064*	0.307**	0.883**	
declining type	-12.992	0.139**	0.145**	0.404**				0.772**
regenerative type	-16.800			0.321**		-0.279**	0.628**	
Types	X9	X10	X11	X12	X13	X14	X15	X16
growth type		0.324*						
mature type	-0.189**	0.463**	0.649**		0.041**	0.057**	-0.024*	
declining type					0.068*	0.041**	-0.105**	0.822**
regenerative type	0.405**	0.738**	1.134**	0.184**	0.046**			
Types	X17	X19	X20	X21	X22	N	R^2	F
growth type			1.082**		0.293**	224	0.888	4.658*
mature type	0.148**	-0.208**	0.915**			960	0.796	4.040*
declining type			0.909**	0.232**	0.157**	352	0.612	5.473*
regenerative type		-0.446**	0.854**			224	0.949	10.511**

*Note: ** and * indicate that the variables are significant at the 1% and 5% levels, respectively. The values of the indicators in the table are regression coefficients; a null regression coefficient indicates that the corresponding indicator did not enter the regression model.*

Ecosystem protection has a significant effect on the carbon emissions of mature and declining type cities. X14 and X16 are significantly positive, which means that greening construction cannot directly reduce the carbon emissions. X15 can significantly inhibit the carbon emissions of mature and declining type cities. Pollution control has a significant effect on mature and regenerative type cities, of which X17 only has a significant role in promoting carbon emissions of mature type cities, X18 has no significant effect on the four types of cities, X19 is significantly negatively correlated with carbon emissions of mature and regenerative type cities, and has the strongest inhibiting effect on regenerative type cities. Resource conservation can significantly contribute to carbon emissions in declining type cities. X20 has a significant positive effect on carbon emissions in all four types of cities, and has the greatest effect on growth type cities. X21 only positively affects carbon emissions in declining type cities, and X22 only significantly positively affects carbon emissions in growth and declining type cities.

4.2.2. Cities with five dominant resource types

Table 4 shows that land resource development has no significant effect on carbon emissions in forestry-based cities and has a significant effect on other types of cities. X3 only enters the regression model of coal-based cities. The effect of population aggregation on non-metallic-based cities is not significant. X4 only has a positive effect on forestry-based cities with the smallest population size. X5 has a braking and driving effect on coal-based and oil and gas-based cities, respectively, which may be since oil and gas-based cities have a higher population density, and the average annual population density is nearly 227 people/km^2, which is about 1.24 times higher than that of coal-based cities. Research has shown that, within a certain threshold, higher population densities are more likely to produce agglomeration effects, which are conducive to improving the efficiency of infrastructure and resource utilization, thereby reducing carbon emissions. However, when the population density is high, cities face increased pressure on resources and the environment, which will promote infrastructure development and construction, bringing the expansion of energy-intensive and labor-intensive industries, resulting in inefficient energy use and further increasing carbon emissions (Yang and Zhao 2023). X6 has a contributing effect on metal-based and coal-based cities. Economic development mainly plays a facilitating role on urban carbon emissions. However, the effect of X7 on economically backward forestry-based cities is not significant. Income and consumption only significantly and negatively affect non-metallic-based cities. The industrial structure has the greatest influence on metal-based cities. Resource exploitation has no significant effect on non-metallic-based cities, and has a significant promotion effect on coal-based, oil and gas-based and metal-based cities, and a significant inhibition effect on forestry-based cities.

Table 4. Results of multiple linear regression of resource-based cities with different dominant resource types

Types	Constant term	X1	X2	X3	X4	X5	X6	X7
coal-based	-14.406	0.117**	0.203**	-0.050*		-0.167**	0.229**	1.023**
oil and gas-based	-4.506	0.189**	-0.537**			0.279**		0.595**
metal-based	-14.700	0.191**					0.338**	0.608**
non-metallic-based	-10.215	0.341**	-0.419**					1.009**
forestry-based	-4.726				1.710**			
Types	X8	X10	X11	X12	X13	X14	X15	X16
coal-based				0.068**	0.045*		-0.053**	
oil and gas-based			0.418**	0.175**		0.067**	0.159**	-0.511**
metal-based		0.723**	0.821**		0.094**	-0.044**	-0.092**	0.273**
non-metallic-based	-0.432*	0.446*				0.161**	-0.200*	
forestry-based			-0.519*	-0.158**	-0.263**			0.453**
Types	X17	X18	X19	X20	X21	N	R^2	F
coal-based				0.874*		848	0.729	5.624*
oil and gas-based		-0.198*		0.715**	-0.401**	192	0.806	5.475*
metal-based	0.207**	-0.163**	-0.071*	0.714**		480	0.847	12.514**
non-metallic-based	-0.499**		0.592**	0.483**	-0.172*	144	0.890	4.720*
forestry-based			-0.286**			96	0.893	5.274*

*Note: ** and * indicate that the variables are significant at the 1% and 5% levels, respectively. The values of the indicators in the table are regression coefficients; a null regression coefficient indicates that the corresponding indicator did not enter the regression model.*

Ecosystem protection affects carbon emissions of different types of cities in different directions and degrees. Increasing the area of ecological land do not necessarily lead to a reduction in carbon emissions. Pollution control fails to significantly affect carbon emissions in coal-based cities, but it can inhibit carbon emissions in oil and gas-based and forestry-based cities. Increasing the rate of harmless treatment of domestic garbage can significantly promote the carbon emissions of metal-based cities. Increasing the comprehensive utilization rate of industrial solid waste can promote the carbon emissions of non-metallic-based cities. The reason may lie in the fact that the improved level of pollutant management reduces the demand for raw materials and production costs of enterprises while protecting the environment, which leads to the expansion of production and increase in energy consumption, which in turn generates more carbon emissions, i.e., the rebound effect of environmental management (Ma and Dong 2020). Except for forestry-based cities, resource conservation has a significant effect on the other four types of cities. Among them, X20 has a significant promotion effect on urban carbon emissions, especially the strongest effect on coal-based cities.

Table 5. Results of multiple linear regression of resource-based cities in different regions

Types	**Constant term**	**X1**	**X2**	**X3**	**X4**	**X6**	**X7**	**X8**	**X9**
eastern region	-9.631					-0.296	0.614		
central region	-15.590	0.158	0.515		0.588	0.553		0.277	
western region	-28.007		0.358	-0.063		0.688	1.166		-0.178
northeastern region	-19.485		0.434		0.922	0.969		0.397	
Types	X10	X11	X12	X13	X14	X15	X16	X17	X18
eastern region		1.128	0.255	0.053		-0.068			-0.213
central region	1.059	0.867		0.116	0.100		0.354		
western region	1.473	1.422	0.076				0.228		
northeastern region			-0.152	0.087		-0.216	0.926	0.309	0.239
Types	X19	X20	X21	X22	N	R^2	F		
eastern region	-0.434	0.773		0.366	304	0.885	6.015*		
central region		0.723	-0.263		544	0.743	1.280*		
western region		0.956		-0.283	604	0.837	3.882*		
northeastern region		1.173	0.136	0.318	304	0.793	5.908*		

*Note: ** and * indicate that the variables are significant at the 1% and 5% levels, respectively. The values of the indicators in the table are regression coefficients; a null regression coefficient indicates that the corresponding indicator did not enter the regression model.*

Table 6. Number of resource-based cities in which individual indicators significantly contributed to carbon emission

	Total number of cities	**X1**	**X2**	**X3**	**X4**	**X5**	**X6**	**X7**	**X8**	**X9**	**X10**	**X11**
Amount	110	16	15	11	4	11	10	9	7	8	16	12
	X12	X13	X14	X15	X16	X17	X18	X19	X20	X21	X22	
Amount	17	13	14	13	19	7	15	15	14	12	11	

Note: The values in the table are the number of cities for which the corresponding indicator entered the model.

4.2.3. Resource-based cities in the four distribution regions

Except for the cities in the eastern region, land resource development has a significant effect on the other three types of cities. X2 is significantly and positively related to carbon emissions in central, western and northeastern region cities, and has the strongest effect on central region cities. X1 and X3 only have positive and negative effects on central and western region cities, respectively. Population aggregation has a significant relationship with carbon emissions in all four types of cities, but the direction of correlation is different. For example, X6 has a positive effect on central, western and northeastern regions, but a negative effect on eastern region. As a developed coastal region in China, the eastern region has advanced technology, strong material base and financial support, so its higher urbanization rate is more conducive to low-carbon development. X4 has the greatest positive effect on the northeastern region, mainly because of its small and continuous population loss, resulting in a significant reduction in carbon emissions. Economic development basically has a significant positive contribution to all four types of cities. Specifically, X9 has a significant negative effect only on the western region, probably since the per capita consumption level is the lowest in the western region, and the negative environmental externality generated by consumption is relatively small, and the positive effect on carbon emissions is weaker. Consumption can effectively contribute to the economic growth, development stage leap and TSDP level in the western region, bring about a modernized production and life style, and promote urban green development and carbon emission reduction. Except for the northeastern region, industrial structure has a significant contribution to the other three types of cities, and the contribution is strongest in the western region. Among the resource exploitation indicators, X12 has the largest positive contribution to the economically developed eastern region and the largest negative contribution to the economically backward northeastern region. X13 promotes carbon emissions in the eastern, central and northeastern region cities, but has no significant effect on the western region.

Increasing the proportion of watershed and wetland areas can significantly reduce carbon emissions in the eastern and northeastern region cities, but increasing the area of forested land and the greening coverage of built-up areas can significantly increase carbon emissions in the central, western and northeastern region cities. The possible reason is that the direction of the influence of urban greening on carbon emissions is related to the level of urban development. When the city develops to a certain level, the city has the capacity to achieve greening construction under a low-carbon program. Otherwise, urban greening construction and maintenance will consume more human, material and financial resources, exacerbating carbon emissions. Pollution control has a significant inhibitory effect on the eastern region, while the opposite is true for the northeastern region. The reason is that the northeastern region is economically backward, and improving the level of pollutant control will promote enterprises to expand production and improve economic efficiency, while exacerbating carbon emissions. In terms of resource conservation, X20 is still an important factor in promoting urban carbon emissions and has the greatest impact on the northeastern region, followed by the western region. X21 is only significantly correlated with the central and western region. X22 significantly promotes urban carbon emissions in the eastern and northeastern regions but significantly suppresses urban carbon emissions in the western region. This indicates that the higher the land output efficiency, the higher the carbon emissions in the eastern and northeastern region cities, while the opposite is true in the western region. This may be due to a certain threshold effect of land output efficiency on carbon emissions.

4.3. Spatial differences of the impact on carbon emissions in individual prefecture level city

4.3.1. Regression results for prefecture level resource-based cities

The number of cities in a single indicator significantly affecting urban carbon emissions can measures the degree of influence of each indicator on carbon emissions (**Table 6**). X16, X12, X1 and X10 have a significant impact on carbon emissions in 19, 17, 16 and 16 cities, respectively. While X4 has a less significant impact and only has a significant impact on 4 cities.

4.3.2. Spatial differences in the impact of TSDP on carbon emissions

The contribution of each indicator to carbon emissions was interpolated in ArcGIS to characterize its spatial variability (**Figure 3**). X1 contributes much more positively to carbon emissions than negatively, and X1 contributes more to carbon emissions in the north than in the south. X2 emerges as a significant contributor to urban carbon emissions in central region, whereas its impact remains statistically insignificant in southern China. X3 significantly affects the carbon emissions of eleven cities, with a more pronounced effect on the western region cities. X4 did not significantly affect the carbon emissions of most cities. The Hu Huanyong line connecting Heihe City in Heilongjiang Province and Tengchong City in Yunnan Province is the demarcation line between dense and sparse population in China (Lu et al. 2016). X5 has no significant effect on the carbon emissions of cities west of the Hu Huanyong line, and contributes significantly to the carbon emissions of densely populated cities east of the line, albeit in a different direction. X6 has a significant effect on 10 cities, but does not show any obvious distributional characteristics. X7 only has a positive contribution to 9 cities. X8 and X9 mainly positively affecting only 7 and 8 cities, respectively, implying that increasing income and consumption increases urban carbon emissions. In industrial structure, X10 has a significant effect on 16 cities, but the spatial correlation is not obvious. X11 mainly contributes to carbon emissions in cities in Shaanxi, Shanxi, and Hebei Provinces. X12 significantly affects 17 cities, which are mainly located in Shanxi and Henan Province in the central region, and Shandong Province in the eastern region. X12 contributes most positively to Yangquan City, followed by Datong City. X13 significantly affects 13 cities, 9 of which are positive, but the spatial correlation is not obvious.

The contribution of X14 to urban carbon emissions is both positive and negative, and the spatial distribution is not characterized clearly. X15 significantly affects 13 cities, which are mainly located in the western and central regions. X16 significantly affects 19 cities, which is more than the other indicators, implying that ecological environmental protection has a broader impact on carbon emissions. X16 has a significant effect mainly on cities in the eastern and central regions. X17 influences 7 cities, scattered in the northeastern, eastern and western regions. X18 and X19 both influence 15 cities, and X18 mainly positively affects cities in northwest and south China, and negatively affects cities in the central region. The city most affected positively by X19 is Wuwei, Gansu, followed by Suqian, Jiangsu. X20 contributes significantly to the carbon emissions of 14 cities, and these cities are mainly located in the eastern and western regions. X21 significantly affects 12 cities, and the spatial distribution has no obvious characteristics. X22 positively contributes to the carbon emissions of 11 cities, and the cities are mainly located in the central region.

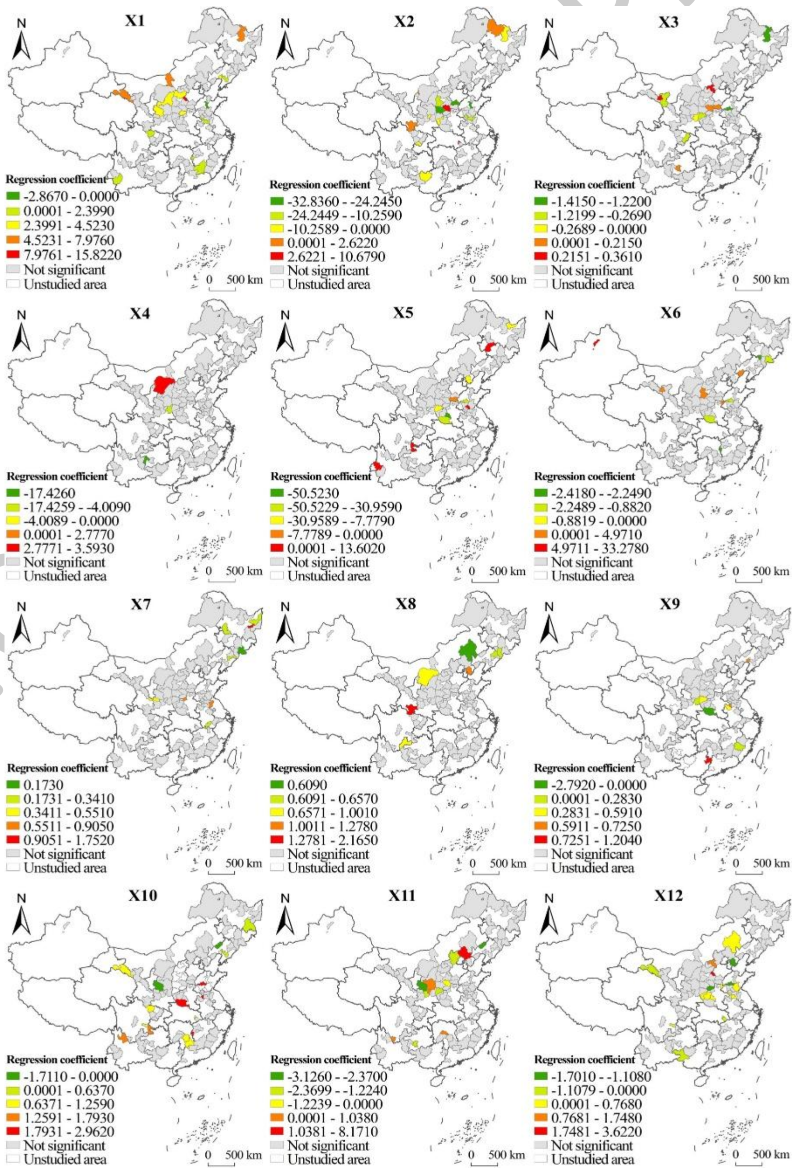
4.3.3. Summary of the characteristics of factors influencing carbon emissions in the whole region, local area, and individual prefecture-level cities

Whether or not the same indicator has an impact on carbon emissions varies according to the scale of the study. For example, total population has no significant impact on carbon emissions in a global study, while the opposite is true in localized and urban studies. The nature of the impact of the same indicator on carbon emissions also changes depending on the scale of the study. For example, the energy consumption per unit of GDP always has a positive contribution in the global and local studies, but both positive and negative contributions exist in the individual prefecture-level city studies. The degree of influence of the same indicator also varies with the rise and fall of the study scale. For example, population density is the most important factor in the global study, while population density does not have the greatest impact on carbon emissions in all cities in the local and urban studies. The extent to which the same indicator affects carbon emissions also varies by city type. The total economic volume, the proportion of construction land area, and the energy consumption per unit of GDP significantly affect the carbon emissions of coal-based, oil and gas-based, metal-based, and non-metallic-based cities, but none of them significantly affects forestry-based cities.

4.4. Annual contribution analysis of carbon emission impact factors from 2005 to 2020

4.4.1. Time series regression results

A stepwise regression model was used to regress the impact of different years of TSDP on urban carbon emissions in order to obtain the contribution coefficients of each indicator in different years (**Table 7**). X7, X20, X1, X13, and X11 had the most years of significant contribution to urban carbon emissions. X2, X5, X9, X15, and X18 all had significant impacts on urban carbon emissions in only 1 year. X3, X4, X8, X17, X19, X21, and X22 failed to enter the regression model, implying that these indicators did not contribute significantly to urban carbon emissions on an annual basis.



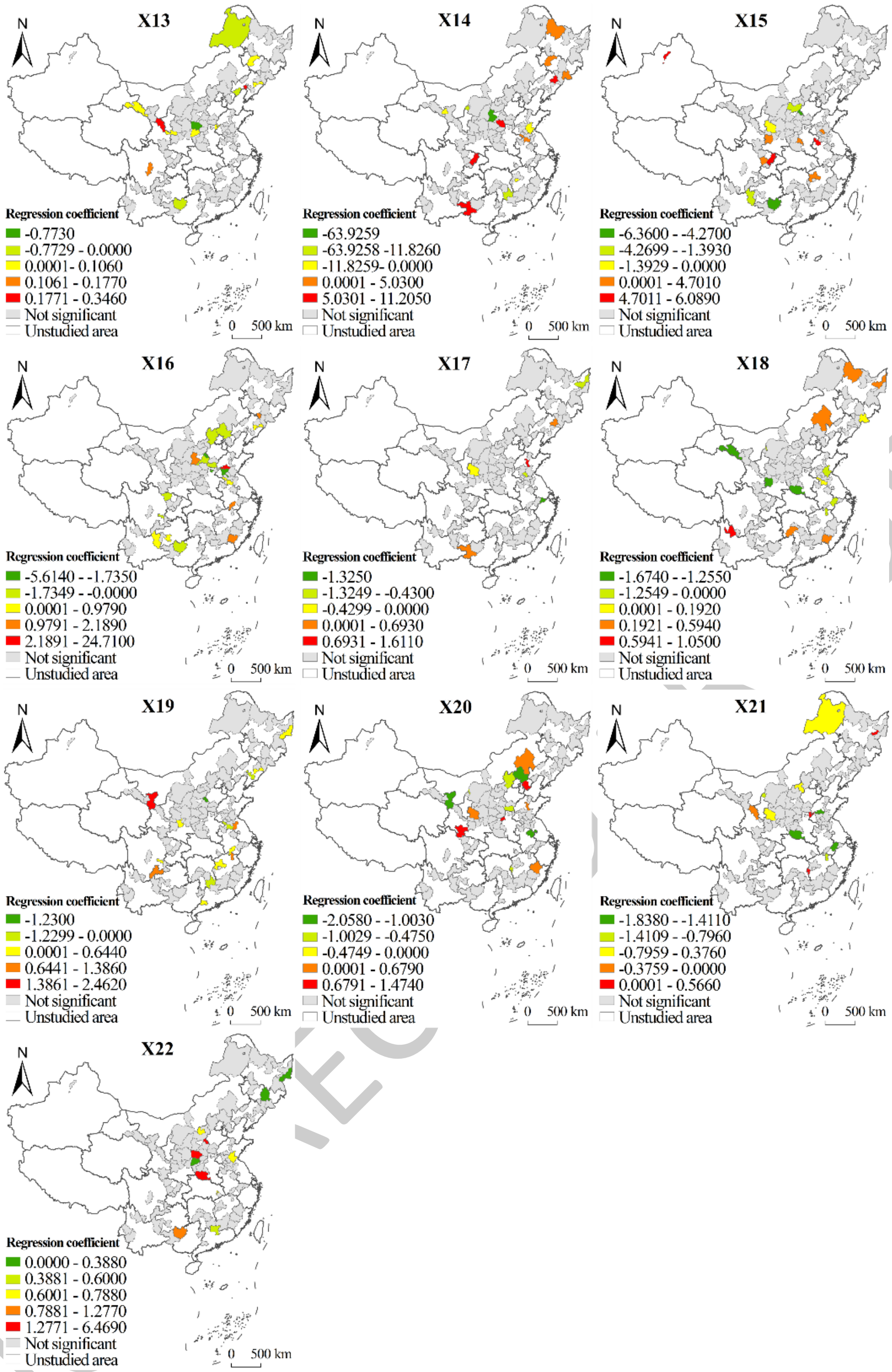


Figure 3. Contribution from the measurement indicators of TSDP to carbon emission revealed in the city-based assessment

4.4.2. Temporal differences in the impact of TSDP on carbon emissions

The trend of the contribution of each indicator to carbon emissions from 2005 to 2020 is plotted, as shown in **Figure 4**. The annual contribution of X2 and X3 in land resource development to carbon emissions is insignificant. X1 in most years significantly and positively affects carbon emissions and shows a clear upward trend. Among the population aggregation indicators, X4 and X5 do not have significant annual contributions, and X6 positively contributes to carbon emissions in 2010, 2012 and 2020 respectively. Among the economic development indicators, the contribution coefficient of X7 is always positive, indicating that economic growth is an important driver of carbon emissions growth. Among the industrial structure indicators, X10 has no significant effect on carbon emissions in the late stage of the study, and only enters the model in the early stage of the study in three years with a positive contribution. Compared with X10, X11 contributes to carbon emissions in more years, 8 years, and its positive contribution shows a decreasing trend overall. Among the resource exploitation indicators, X12 and X13 have significant positive contributions in 5 and 9 years, respectively. X12 had a significant positive impact on urban carbon emissions mainly at the beginning of the study, while X13 had a significant impact on carbon emissions for the first time in 2009, and its contribution coefficient showed an "inverted U-shape" change over time, and reached its maximum in 2014.

There are fewer years in which territorial space protection contributes to carbon emissions. Among the ecosystem protection indicators, X15 fails to enter the model, and the years in which X14 and X16 significantly and positively affect carbon emissions are only three and four years, respectively. The three indicators of pollution control have no significant annual contribution to carbon emissions. X20 is one of the resource conservation indicators with the highest number of entries into the time model. The impact of the X20 on carbon emissions fluctuates a lot before 2013, and the positive contribution of the X20 gradually increases after 2013. This is closely related to the fact that since the 18th CPC National Congress, China has paid more attention to technological innovation and energy utilization efficiency improvement, as well as the introduction of "the Plan".

Table 7. Results of multiple linear regression based on time series

Years	**Constant term**	**X1**	**X2**	**X5**	**X6**	**X7**	**X9**	**X10**	**X11**	**X12**
2005	-13.188	0.129				0.983				0.110
2006	-14.904					0.956				0.136
2007	-20.052					0.808		0.948	1.122	0.096
2008	-18.403					0.876		0.677	0.786	0.091
2009	-12.992	0.127				0.969				
2010	-20.326		0.254		0.287	0.948		0.572	1.089	
2011	-15.440					1.026			0.541	0.135
2012	-14.743	0.115			0.250	0.877			0.716	
2013	-14.049	0.125				0.890			0.730	
2014	-13.950	0.128				0.863			0.813	
2015	-13.419	0.150				0.862			0.667	
2016	-9.254	0.146				0.760				
2017	-11.509	0.132				0.775				
2018	-10.477	0.154				0.842				
2019	-9.962	0.235		-0.242		0.892				
2020	-13.690				0.791	1.115	-0.428			
Years	X13	X14	X15	X16	X18	X20	N	R^2	F	
2005		0.060				1.122	110	0.721	5.094*	
2006		0.051		0.626		1.219	110	0.781	7.825**	
2007				0.407	0.215	0.985	110	0.807	5.122*	
2008				0.509		0.991	110	0.808	5.984**	
2009	0.119	0.048				1.095	110	0.799	7.765**	
2010	0.107		-0.093			0.888	110	0.801	5.650*	
2011						1.092	110	0.738	6.663*	
2012	0.172					0.882	110	0.741	8.169**	
2013	0.178					0.866	110	0.724	8.810**	
2014	0.184					0.873	110	0.704	7.810**	
2015	0.178					0.942	110	0.720	4.523*	
2016	0.171					0.970	110	0.689	12.277**	
2017	0.143			0.578		1.034	110	0.738	10.786**	
2018	0.116					1.164	110	0.705	8.811**	
2019						1.194	110	0.678	7.349**	
2020						1.156	110	0.660	6.255*	

*Note: ** and * indicate that the variables are significant at the 1% and 5% levels, respectively. The values of the indicators in the table are regression coefficients; a null regression coefficient indicates that the corresponding indicator did not enter the regression model.*

4.5. Differentiated low-carbon development paths for different types of resource-based cities

4.5.1. Key influences on carbon emissions in different types of resource-based cities

According to the standardized regression coefficients, the relative influence sizes of different variables on carbon emissions are compared to get the top three core influencing factors in different types of resource-based cities, as shown in **Table 8**.

4.5.2. Resource-based cities at different stages of development

Carbon emissions from growth type cities are most prominently affected by energy use efficiency, economic volume and population urbanization. Growth type cities should develop in an orderly manner, implement green development strategies, develop resources rationally, pay attention to emission reduction in the growth rate stage of resource development, and emphasize the green and efficient mode of resource conservation and intensive use. Improve the level of deep processing and green processing of resources, control the intensity of resource development, and form a development model that synchronizes development and governance. Vigorously develop clean energy, guide the transformation and upgrading of traditional industries, and promote the optimization of energy structure. In addition, in the process of transferring a large number of people to cities and towns, it has promoted the use of clean energy and vigorously publicized the concept of low-carbon living.

Total economic output, energy use efficiency and the proportion of construction land area are the top three core factors in mature type cities. Mature type cities should focus on the intensification and efficiency of space utilization and avoid blind expansion of construction land. They should vigorously improve the level of science and technology, accelerate the development of leading enterprises and industrial clusters focusing on deep processing of resources, promote the upgrading and adjustment of industrial structure, and establish diversified pillar-type successor industries as soon as possible. Attention should be paid to the problem of over-exploitation of resources, to the intensive and efficient utilization of resources, to innovative production technologies for better carbon unlocking, and to driving the development of low-carbon clean energy and green industries.

Table 8. The first three core factors affecting carbon emissions in different types of resource-based cities

Types		**Top three core influences on carbon emissions**
Different stages of development	growth type	Energy consumption per unit of GDP, GDP, Urbanization rate
	mature type	GDP, Energy consumption per unit of GDP, Proportion of construction land area
	declining type	Energy consumption per unit of GDP, Annual income per capita, Green coverage rate of built-up area
	regenerative type	GDP, Energy consumption per unit of GDP, Annual consumption per capita
Different dominant resource types	coal-based	GDP, Energy consumption per unit of GDP, Population density
	oil and gas-based	GDP, Proportion of cultivated land area, Energy consumption per unit of GDP
	metal-based	GDP, Energy consumption per unit of GDP, Proportion of construction land area
	non-metallic-based	GDP, Proportion of forest area, Proportion of construction land area
	forestry-based	Total population, Proportion of investment in fixed assets in the mining industry, Green coverage rate of built-up area
Different distribution regions	eastern region	GDP, Output per unit of land, Energy consumption per unit of GDP
	central region	Energy consumption per unit of GDP, Total population, Proportion of forest area
	western region	GDP, Energy consumption per unit of GDP, Proportion of secondary industry
	northeastern region	Energy consumption per unit of GDP, Total population, Output per unit of land

Energy efficiency, income level and green coverage of built-up areas are the top three important factors in declining type cities. Declining type cities should actively carry out transformation and development, learn from regenerative type cities and make efforts to transform and upgrade traditional industries and promote industrial transformation and upgrading. Fully explore emerging industries, cultivate new economic growth poles, break the dependence on the original development path, and promote the development of low-carbon economy. Focus on solving the remaining problems of past development and supervise the implementation of comprehensive management of abandoned land, subsidence areas and environmental pollution.

Economic aggregate, energy utilization efficiency and consumption level are the top three key factors in regenerative type cities. This type of city should focus on innovative development, improve the level of scientific and technological innovation, accelerate the upgrading of low-carbon technologies, convert the original mode of production and promote clean energy. While developing the economy, they should pay attention to urban greening, improve urban greening coverage and enhance urban carbon absorption capacity. Focus on alleviating the contradiction between economic development and environmental protection, and enhance the carrying capacity of urban resources and environment. Enhance residents' awareness of environmental protection, publicize green and low-carbon consumption, and advocate low-carbon living.

4.5.3. Resource-based cities with different dominant resource types

The top three core factors in coal-based cities are total economic volume, energy utilization efficiency and population density, respectively. This type of cities should actively adjust the coal industry structure, guarantee the supply of funds for the development of low-carbon economy by coal enterprises, and accelerate the low-carbon development. Extend the coal-based industrial chain, increase the production of coal accessories, improve the utilization value of coal, and form a value multiplier effect. Strengthen the transformation of coal resources, such as coal-to-oil, coal-to-hydrogen, coal-to-dimethyl ether and other clean energy with lower carbon content. Vigorously urging green mining of coal resources, actively upgrading technology and reforming equipment to improve the resource recovery rate, raw coal processing rate and coal combustion efficiency. The mining of coal resources is accompanied by corresponding ecological restoration work, such as the treatment of coal mining subsidence land and the treatment of heavy metals in soil.

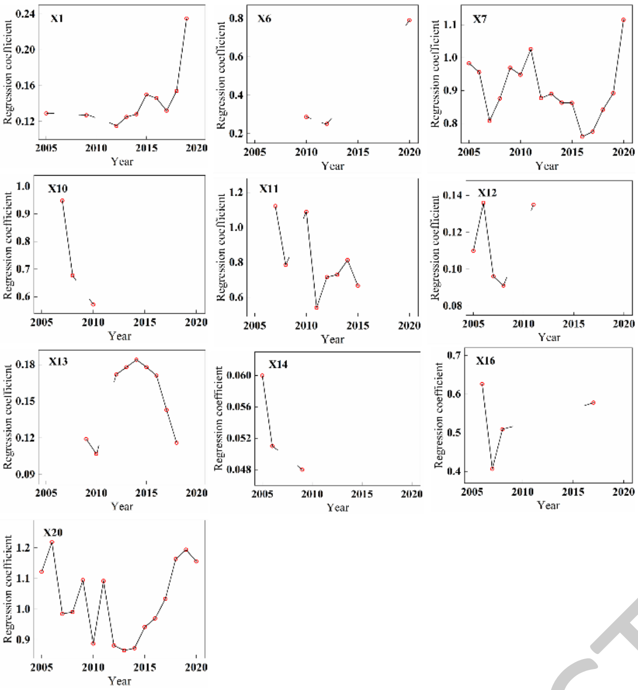


Figure 4. Annual contributions from individual indicators to carbon emission of resource-based cities from 2000 to 2020

The total economic volume, the proportion of cultivated land area and energy utilization efficiency are the top three key factors in oil and gas-based cities. Oil and gas-based cities should pay attention to the optimization of industrial structure and promote the development of “one main and multiple” modern industries. Optimize the well deployment plan, rationally plan the land for oilfield construction, timely dispose of mud ponds and sand pits at the operation sites, and protect the cultivated land from pollution and encroachment. Increase the oil and gas adoption rate, support the growth of oil and gas supply with the development of new energy sources, and extend the life of oilfields. Develop wind power and photovoltaic power generation in oil and gas mining areas and surrounding areas, implement clean power and heat substitution for energy used in oil and gas exploration and development, and build a low-carbon oil and gas production system. Organized foreign technology and labor export, strengthen international strategic cooperation, and jointly seek new opportunities for oil and gas cooperation.

The top three core factors in metal-based cities are total economic volume, energy utilization efficiency and the proportion of construction land area. Metal-based cities should actively promote industrial transformation and upgrading, enhance the added value of their products and create a metal industry chain. They should strengthen the environmental management of mines, promote green mining techniques and technologies, reduce the damage to land resources and the ecological environment, and strictly prohibit the disorderly expansion of industrial and mining land. Increase investment in research, development and application of green technologies, develop low-carbon metallurgical technologies, electric furnace smelting technologies, etc., and reduce resource consumption and carbon emissions. It is necessary to introduce high-end intelligent equipment, promote intelligent metal smelting, and strive to build a harmless-productized-high-value whole industry chain.

The top three core factors in non-metallic-based cities are the total economy, the proportion of forest land area and the proportion of construction land area. Non-metallic-based cities should strictly control emissions from industrial enterprises, promote soil remediation and water pollution prevention, and protect green vegetation from being poisoned. Formulate scientific and reasonable urban planning, focus on the protection of forest land and cultivated land, strictly control the total amount of new construction land, and strictly prohibit the occupation of forest land and cultivated land by the disorderly expansion of construction land. Focus on the recycling of resources and the minimization of waste, and promote the development of a circular economy.

The total population, the proportion of fixed-asset investment in the mining industry and the green coverage rate of built-up areas are the top three core influences in forestry-based cities. The government should increase its assistance to forestry-based cities, provide long-term financial support for urban economic development, and support and encourage forestry-based cities to establish successive alternative industries to prevent forest exhaustion and city decline. Attracting talents and enterprises by introducing foreign investment, supporting entrepreneurship and innovation, and improving the social security and welfare system. Encourage the development and utilization of forest tourism resources, develop new industries such as ecotourism and green leisure, and provide tourism activities and services related to forest ecology. Strengthen the application of new energy sources, energy conservation and emission reduction, intelligentization and other technologies to reduce energy consumption and pollution in the forest industry.

4.5.4. Resource-based cities in different distribution regions

The top three core factors in resource-based cities in the eastern region are economic aggregate, land use efficiency and energy use efficiency. Cities in the eastern region should continue to maintain and play the role of transformation model, focusing on the development of high-tech industries and innovative industries. Utilizing their economic advantages, they should vigorously promote the research and development of key technologies in the fields of energy conservation, emission reduction and new energy, and improve the efficiency of resource utilization. Reasonable use of location advantages and knowledge innovation to play a radiation-driven role in cities in central and western regions, and strengthen cooperation and exchanges with central and western regions to help them reduce carbon emissions.

Energy utilization efficiency, total population and the proportion of forest land area are the dominant factors in central region. Cities in central region should actively undertake the transfer of industries from the eastern region. Actively adjust the industrial structure, vigorously develop low-carbon industries and optimize the energy consumption structure. Increase investment in scientific research, improve energy utilization, innovate clean technologies, and reduce carbon emissions while developing the economy. Guide the intensive development of cities, effectively control the uncontrolled expansion of construction land, and strictly prohibit the blind conversion of cultivated land and forest land into construction land.

The top three factors in western region are economic aggregate, energy utilization efficiency and the proportion of secondary industry. Cities in the western region should vigorously develop their economies in the context of national policy favoritism. Increase investment in science and technology at the same time as economic development, improve the welfare of scientific research personnel, attract and cultivate scientific research talents, strengthen the strength of low-carbon technological innovation, and improve the efficiency of resource utilization. Continuously strengthen environmental control and pollution management, and gradually increase the intensity of environmental regulations. Gradually improve the industrial structure, reduce the proportion of secondary industry, and focus on the development of low-carbon industries.

Energy use efficiency, total population and land use efficiency are the top three core factors in the northeastern region. The most important thing for resource-based cities in the northeastern region now is to actively reform and innovate, fully implement the Northeast Revitalization Strategy, improve their own development capacity, retain and attract human resources, and fill the talent gap. The government should establish a long-term and effective assistance mechanism to provide long-term financial support for the high-quality development of the northeastern region and promote regional economic development. Based on the rich land resources in the northeastern region, vigorously develop specialty agriculture, enhance the added value and technological content of agricultural products, improve the utilization efficiency of land resources, and make specialty agriculture a new economic growth pole for cities. Increase investment in the development of new industries and vigorously develop tourism and modern service industries so that they can become successor industries.

5. Conclusion

The study adopts the panel data of 110 Chinese prefecture-level resource-based cities from 2005 to 2020 to construct an empirical model from multiple perspectives, to explore the impact of TSDP on carbon emissions from the whole city, different types of cities and individual city, to identify the key indicators of the impact of TSDP on carbon emissions in different types of resource-based cities, and to clarify the time change trends of the contribution of different indicators to carbon emissions. The main conclusions are as follows:

(1) TSDP is an important factor affecting carbon emissions in resource-based cities. The degree of explanation of it on carbon emissions reaches 76.2%, in which the total GDP has the largest positive contribution, followed by energy consumption per unit of GDP and the proportion of tertiary industry, while the comprehensive utilization rate of industrial solid waste has the largest negative impact.

(2) The influence of TSDP on carbon emissions is obviously heterogeneous. The total GDP has no significant influence on the carbon emissions of cities with backward economic development, and the total population has the strongest positive contribution to the carbon emissions of cities with small population sizes. Energy consumption per unit of GDP and total economic volume are always the top two key indicators contributing to carbon emissions in growth, mature and regenerative type cities. Economic aggregate is the indicator that contributes the most to carbon emissions in coal-based, oil and gas-based, metal-based and non-metallic-based cities. Energy consumption per unit of GDP is the core factor contributing to carbon emissions of cities in different distribution regions.

(3) The influence of TSDP on carbon emissions is characterized by spatial differentiation. Economic development has the greatest impact on carbon emissions, and the affected cities are mainly concentrated in Gansu and Shaanxi provinces in the western region and Hebei province in the eastern region. Population concentration has the smallest impact on carbon emissions, and the spatial distribution is more in northern China than in southern China.

(4) The influence of TSDP on carbon emissions is characterized by temporal differentiation. The total economic volume and energy consumption per unit of GDP significantly and positively affect urban carbon emissions in the whole study period. With the evolution of time, the positive contribution of the proportion of construction land area to carbon emissions shows an upward trend, and the positive contribution of the total economic volume to carbon emissions shows a “W-shape” fluctuation change. The proportion of fixed asset investment in the mining industry did not have a significant contribution to urban carbon emissions at the beginning of the study, and showed an “inverted U-shaped” change after 2009. Energy consumption per unit of GDP positively affects urban carbon emissions in all years, and shows a “U-shaped” trend with 2013 as the “inflection point”.

The innovations of this study lie in: constructing an indicator system for TSDP in resource-based cities; elucidating the mechanism through which TSDP impacts carbon emissions in such cities; and revealing multi-type, multi-level, and multi-perspective heterogeneity characteristics of this impact. This study explores the impacts of TSDP on carbon emissions in resource-based cities from multiple perspectives of type differentiation and spatial and temporal differences, which is an important basis for the rational use of territorial space and the formulation of differentiated carbon emission reduction policies, and will help resource-based cities achieve precise carbon reduction.

Limitations of this study: ① Owing to constraints in data accessibility, continuity, and completeness, the research timeframe selected in this paper spans from 2005 to 2020. Future studies could consider employing datasets with broader temporal coverage and higher continuity to enhance the accuracy and timeliness of research findings. ② This study focuses on prefecture-level resource-based cities as the research subject. Future work may extend the research scope to include county-level cities, municipal districts, and counties. ③ The integration of multi-scale data and the improvement of socioeconomic data rasterization precision require further investigation.

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Data availability statement

The datasets generated and/or analysed during the current study are not publicly available due to confidentiality requirements but are available from the corresponding author on reasonable request.

Conflicts of Interest

The authors declare no conflict of interest.

References

Bao, H., Zhang, Y. and Wu, S. (2022). Low-carbon territorial space planning: Mechanism, approach and path. *China Land Science*, **36**, 1-10.

Chen, L., Yang, X., Li, L., Chen, L. and Zhang, Y. (2022). The natural and socioeconomic influences on land-use intensity: Evidence from China. *Land*, **10**, 1254.

Chen, Q. and Wang, Z. (2023). Spatio-temporal coupling and interactive effects of land development intensity and economic resilience in the Wuling Mountains Area. *Economic Geography*, **43**, 41-50.

Cheng, J., Chen, J. and Li, Y. (2013). Research on the measurement of China's ecological civilization development level. *Journal of Quantitative and Technological Economics*, **30**, 36-50.

Chuai, X., Huang, X., Wang, W., Zhao, R., Zhang, M. and Wu, C. (2015). Land use, total carbon emission's change and low carbon land management in Coastal Jiangsu, China. *Journal of Cleaner Production*, **103**, 77-86.

Cui, J. and Zhu, D. (2022). Territorial spatial policies under carbon emission peak and carbon neutrality visions: Key logic and realization path. *Planners*, **38**, 5-11.

Deng, Z., Zong, S., Su, C. and Chen, Z. (2019). Research on coupling coordination development between ecological civilization construction and new urbanization and its driving forces in the Yangtze River Economic Zone. *Economic Geography*, **39**, 78-86.

Ding, M., Yang, X., Zhao, R., Zhang, Z., Xiao, L. and Xie, Z. (2022). Optimization of territorial space pattern under the goal of carbon neutrality: Theoretical framework and practical strategy. *Journal of Natural Resources*, **37**, 1137-1147.

Dong, K., Zhao, J. and Dong, X. (2023). Research on the carbon effect of China's outward foreign direct investment (OFDI) on host countries–A spatial spillover perspective. *Journal of Industrial Technology and Economy*, **42**, 133-142.

Dong, Z., Bi, F. and Ji, Y. (2022). Current status, problems and suggestions of terrestrial ecosystems carbon sink in China. *Science and Technology Review*, **40**, 15-24.

Energy, I. (2022). BP Statistical review of world energy 2022, Energy Institute.

Feng, W., Zhao, R., Xie, Z., Ding, M., Xiao, L., Sun, J., Yang, Q., Liu, T. and You, Z. (2023). Land use carbon emission efficiency and its spatial-temporal pattern under carbon neutral target: A case Study of 72 cities in the Yellow River Basin. *China Land Science*, **37**, 102-113.

Feng, X., Li, Y., Yu, E., Yang, J., Wang, S. and Ma, J. (2023). Spatiotemporal pattern and coordinating development characteristics of carbon emission performance and land use intensity in the Yangtze River Delta Urban Agglomeration. *Transactions of the Chinese Society of Agricultural Engineering*, **39**, 208-218.

Gao, J., Bao, J., Liu, Y. and Chen, J. (2018). Regional disparity and the influencing factors of land urbanization in China at the county level, 2000-2015. *Acta Geographica Sinica*, **73**, 2329-2344.

Glaeser, E. L. and Kahn, M. E. (2010). The greenness of cities: Carbon dioxide emissions and urban development. *Journal of Urban Economics*, **67**, 404-418.

Guo, A., Niu, L., Liu, P. and Yufeng, L. (2023). Carbon emission from land use in urban agglomeration of the Yellow River Basin. *Economic Geography*, **43**, 172-178.

Guo, C. (2011). The factor decomposition on carbon emission of China—Based on LMDI decomposition technology. *Chinese Journal of Population, Resources and Environment*, **9**, 42-47.

Huang, X., Chen, Y., Zhao, Y., Shi, M. and Li, T. (2021). Optimization on land spatial development pattern in the Yellow River Basin: From the perspective of land development intensity. *Geographical Research*, **40**, 1554-1564.

Huang, X., Zhang, A., Zhao, R., Gao, F. and Zhang, H. (2022). Carbon emission peak, carbon neutrality and territorial spatial planning implementation mechanism. *Modern Urban Research*, 1-5.

Huang, X., Zhang, X., Lu, X., Wang, P., Qin, J., Jiang, Y., Liu, Z., Wang, Z. and Zhu, A. (2021). Land development and utilization for carbon neutralization. *Journal of Natural Resources*, **36**, 2995-3006.

Jasmine, J., Rayen, S. J., Ramesh, T. and Rajendran, S. (2025). Advanced weather prediction based on hybrid deep gated tobler's hiking neural network and robust feature selection for tackling environmental challenges. *Global NEST Journal*, **27**, 06757.

Jiang, S. and Lu, C. (2022). Environmental regulation affect the externality and heterogeneity of carbon emission efficiency: Based on the analysis of agglomeration and synergy of producer services. *East China Economic Management*, **36**, 56-69.

Koilakou, E., Hatzigeorgiou, E. and Bithas, K. (2023). Carbon and energy intensity of the USA and Germany. A LMDI decomposition approach and decoupling analysis. *Environmental Science and Pollution Research*, **30**, 12412-12427.

Kong, X., Jiang, X., Liu, Y. and Jin, Z. (2020). Spatiotemporal coupling between territorial space development intensity and resource environmental carrying capacity and its planning implications: A case study of Jiangsu Province. *China Land Science*, **34**, 10-17.

Li, J. and Li, J. (2023). Difference and formation mechanism of people's livelihood and well-being development in Guangdong Province. *Scientia Geographica Sinica*, **43**, 500-508.

Li, K., Zhou, Y., Huang, X., Xiao, H. and Shan, Y. (2024). Low-carbon development pathways for resource-based cities in China under the carbon peaking and carbon neutrality goals. *Environmental Science and Pollution Research*, **31**, 10213–10233.

Li, R., Wang, Q., Liu, Y. and Jiang, R. (2021). Per-capita carbon emissions in 147 countries: The effect of economic, energy, social, and trade structural changes. *Sustainable Production and Consumption*, **27**, 1149-1164.

Li, X., He, G., Luo, Y., Huang, F., Niu, Y., Lei, X., Liu, J. and Sun, W. (2022). Spatial characteristics of carbon emissions and carbon neutralization strategies for Guangdong-Hong Kong-Macao Greater Bay Area. *Urban Planning Forum*, 27-34.

Liao, Q., Li, P., Bin Roosli, R., Liu, S., Zhang, X., Zhang, C., Wang, Y., Wu, L. and Yao, H. (2022). Carbon emission characteristics of resource-based cities in China. *Iranian Journal of Science and Technology-transactions of Civil Engineering*, **46**, 4579-4591.

Liu, M. and Liu, C. (2025). How does the synergistic effect of green finance and digital finance affect carbon emission efficiency? An example from the Yangtze River Economic Belt. *Global NEST Journal*, **27**, 07690.

Liu, Y. (2006). The reconsideration of the method of defining Chinese resource-based cities. *Economic Geography*, **26**, 940-944.

Liu, Y., Liu, J., He, C. and Feng, Y. (2013). Evolution of the coupling relationship between regional development strength and resource environment level in China. *Geographical Research*, **32**, 507-517.

Lu, D., Wang, Z., Feng, Z., Zeng, G., Fang, C., Dong, X., Liu, S., Jia, S., Fang, Y., Meng, G., Deng, X., Ye, C., Cao, G., Du, H., Zhang, H., Ma, H. and Chen, M. (2016). Academic debates on Hu Huanyong population line. *Geographical Research*, **35**, 805-824.

Luo, D., Shen, W. and Hu, L. (2022). Impacts of urbanization and consumption structure upgrading on carbon emissions: An analysis based on provincial panel data. *Statistics and Decision*, **38**, 89-93.

Ma, G., Qin, J. and Zhang, Y. (2023). Does the carbon emissions trading system reduce carbon emissions by promoting two-way FDI in developing countries? Evidence from Chinese listed companies and cities. *Energy Economics*, **120**, 106581.

Ma, H. and Dong, S. (2020). Effects of different types of environmental regulations on carbon emission efficiency. *Journal of Beijing Institute of Technology (Social Sciences Edition)*, **22**, 1-10.

Meirun, T., Mihardjo, L. W. W., Haseeb, M., Khan, S. A. R. and Jermsittiparsert, K. (2020). The dynamics effect of green technology innovation on economic growth and CO_2 emission in Singapore: New evidence from bootstrap ARDL approach. *Environmental Science and Pollution Research*, **28**, 4184-4194.

Qi, H., Shen, X., Long, F., Liu, M. and Gao, X. (2023). Study on spatial-temporal pattern and influencing factors of county carbon emissions in Zhejiang Province. *Resources and Environment in the Yangtze Basin*, **32**, 821-831.

Qin, B., Yu, Y., Ge, L. and Guo, Y. (2023). Smart carbon reduction: The effect and mechanism of digital economy development on urban carbon emissions. *Journal of Guangdong University of Finance and Economics*, **38**, 4-23.

Ren, F. and Long, D. (2022). Measurement of carbon emissions, analysis of influencing factors and election of forecasting models in Guangdong Province. *Ecological Economy*, **38**, 21-37.

Ren, S., Xie, Y., Jiao, X. and Xie, H. (2022). Characteristics of carbon emissions during coal development and technical approaches for carbon neutral development. *Advanced Engineering Sciences*, **54**, 60-68.

Shan, Y., Guan, Y., Hang, Y., Zheng, H., Li, Y., Guan, D., Li, J., Zhou, Y., Li, L. and Hubacek, K. (2022). City-level emission peak and drivers in China. *Science Bulletin*, **67**, 1910-1920.

Shan, Y., Liu, J., Liu, Z., Shao, S. and Guan, D. (2019). An emissions-socioeconomic inventory of Chinese cities. *Scientific Data*, **6**, 190027.

State, C. (2013). National sustainable development plan for resource based cities (2013-2020).

Wang, Q., Zhao, M., Li, R. and Su, M. (2018). Decomposition and decoupling analysis of carbon emissions from economic growth: A comparative study of China and the United States. *Journal of Cleaner Production*, **197**, 178-184.

Wang, S., Huang, S. and Huang, P. (2018). Can spatial planning really mitigate carbon dioxide emissions in urban areas? A case study in Taipei, Taiwan. *Landscape and Urban Planning*, **169**, 22-36.

Wang, S., Xie, Z. and Wang, Z. (2021). The spatiotemporal pattern evolution and influencing factors of CO_2 emissions at the county level of China. *Acta Geographica Sinica*, **76**, 3103-3118.

Wang, W., Liu, L., Liao, H. and Wei, Y. (2021). Impacts of urbanization on carbon emissions: An empirical analysis from OECD countries. *Energy Policy*, **151**, 112171.

Wang, X. and Qin, M. (2015). An empirical study of different urbanization qualities affecting carbon emissions. *Journal of Lanzhou University (Social Sciences)*, **43**, 60-66.

Wang, Z. and Fan, J. (2022). The characteristics and prospect of influencing factors of energy-related carbon emissions: Based on literature review. *Geographical Research*, **41**, 2587-2599.

Whittingham, M. J., Stephens, P. A., Bradbury, R. B. and Freckleton, R. P. (2006). Why do we still use stepwise modelling in ecology and behaviour? *Journal of Animal Ecology*, **75**, 1182-1189.

Wu, H., Xue, Y., Hao, Y. and Ren, S. (2021). How does internet development affect energy-saving and emission reduction? Evidence from China. *Energy Economics*, **103**, 105577.

Wu, K., Zhang, W., Zhang, P., Xue, B., An, S., Shao, S., Long, Y., Liu, Y., Tao, A. and Hong, H. (2023). High-quality development of resource-based cities in China: Dilemmas and breakthroughs. *Journal of Natural Resources*, **38**, 1-21.

Wu, Y., Wang, X., Xie, H. and Ma, S. (2025). How digital trade can reshape the trajectory of green and low-carbon development under the leadership of "dual-control" objectives. *Global NEST Journal*, **27**, 07580.

Xiao, H., Sheng, S. and Liu, J. (2015). The review and prospect on the research of spatial planning of low carbon eco-city. *Urban Development Studies*, **22**, 8-12.

Xiong, J., Lu, K., Jiang, Z., Zhang, C., Fu, Q. and Jin, Y. (2021). Study and thoughts on territorial spatial planning under the goal of "carbon emissions peak and carbon neutrality. *Urban Planning Forum*, **4**, 74-80.

Xu, B. and Lin, B. (2016). A quantile regression analysis of China's provincial CO2 emissions: Where does the difference lie? *Energy Policy*, **98**, 328-342.

Xu, J. (2023). Research on coordinated development of high-quality economic development and ecological environmental protection under the "dual carbon" goal—A case study of Beijing-Tianjing-Heibei region. *Reform of Economic System*, 61-69.

Xu, Q., Dong, Y. and Yang, R. (2018). Urbanization impact on carbon emissions in the Pearl River Delta region: Kuznets curve relationships. *Journal of Cleaner Production*, **180**, 514-523.

Xu, W., Zheng, J., Zhou, J., Chen, X. and Liu, C. (2023). Transformation performance characteristics of resource-based cities and their carbon emission reduction effects. *Journal of Natural Resources*, **38**, 39-57.

Xu, Y., Wu, Y., Wu, J. and Chi, M. (2019). Multiwavelength regression algorithm for eliminating chamber surface effects of microfluidic chips. *Applied Spectroscopy*, **73**, 40-46.

Yan, H., Li, Y., Xing, Y., Chen, X., Guo, X., Yin, Y., Yu, W., Huang, M. and Zhuang, J. (2025). Increasing human-perceived temperature exacerbated by urbanization in China's major cities: Spatiotemporal trends and associated driving factors. *Sustainable Cities and Society*, **18**, 106034.

Yang, C. and Zhao, S. (2023). Scaling of Chinese urban CO_2 emissions and multiple dimensions of city size. *Science of the Total Environment*, **857**, 159502.

Yang, J. and Huang, X. (2021). The 30 m annual land cover dataset and its dynamics in China from 1990 to 2019. *Earth System Science Data*, **13**, 3907-3925.

Yang, Z., Wang, S., Guo, M., Tian, J. and Zhang, Y. (2021). Spatiotemporal differentiation of territorial space development intensity and its habitat quality response in Northeast China. *Land*, **10**, 573.

You, S. and Yan, Y. (2017). Stepwise regression analysis and its application. *Statistics and Decision*, **14**, 31-35.

Yu, J., Li, J. and Zhang, W. (2018). Identification and classification of resource-based cities in China. *Acta Geographica Sinica*, **73**, 677-687.

Zeng, S., Wang, C. and Dong, Z. (2022). Research on the synergistic effect of carbon emission reduction from environmental protection investment. *Jiang-huai Tribune*, **4**, 30-37.

Zhang, H., Li, J., Cui, Y., Zhang, Z., Wang, Y. and Hao, S. (2025). Spatial and temporal evolution of carbon emissions and urbanization in the Yangtze River Delta urban agglomeration of China. *Global NEST Journal*, **27**, 06925.

Zhang, M. and Wu, M. (2020). Analysis on the mechanism and transmission path of the impact of land use on carbon emissions: Empirical test based on structural equation model. *China Land Science*, **36**, 96-103.

Zhang, M., Gan, C., Chen, Y. and Chen, L. (2016). Carbon emission efficiency and optimization of low carbonfor construction land development intensity in China according to provincial panel data. *Resources Science*, **38**, 265-275.

Zhang, R., Pu, L., Wen, J. and Xu, Y. (2012). Hypothesis and validation on the Kuznets Curve of construction land expansion and carbon emission effect. *Journal of Natural Resources*, **27**, 723-733.

Zhao, R., Huang, X., Yun, W., Wu, K., Chen, Y., Wang, S., Lu, H., Fang, K. and Li, Y. (2022). Key issues in natural resource management under carbon emission peak and carbon neutrality targets. *Journal of Natural Resources*, **37**, 1123-1136.

Zhao, X. and Sun, B. (2023). Impact of population age structure on carbon emissions in China: Effect estimation and trend projection. *The World of Survey and Research*, **6**, 3-13.

Zhao, X. and Zhu, J. (2022). Impacts of two-way foreign direct investment on carbon emissions: From the perspective of environmental regulation. *Environmental Science and Pollution Research*, **29**, 52705-52723.

Zhao, Y., Liu, Y. and Long, K. (2012). Features and influencing factors of urban land development intensity of urban land resources in the Yangtze River Delta. *Resources and Environment in the Yangtze Basin*, **21**, 1480-1485.