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Land urbanization and urban CO_2 emissions: Empirical evidence from Chinese prefecture-level cities

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ABSTRACT

Changes in land use and the resulting human practices in the land urbanization process would lead to variations in the function, intensity, and efficiency of CO_2 emissions and greatly influence urban CO_2 emissions. Therefore, using Chinese prefecture-level data for a time period ranging from 2003 to 2017, we systematically examine the mechanism of how land urbanization influences CO_2 emissions based on land-use intensity regulation, land-use structure optimization, and land-use efficiency improvements. First, the benchmark results show that land urbanization's influence on urban CO_2 emissions is significantly positive. This indicates that the consumption effect caused by land urbanization exceeds the agglomeration effect. Furthermore, the results of the nonlinear analysis using the spatial adaptive semi-parametric and semi-parametric spatial dynamic panel models show that the association between land urbanization and carbon emissions demonstrates an inverted U-shaped curve. Simultaneously, land urbanization represents a dynamic cumulative and spatial spillover effect on urban CO_2 emissions. Second, a mechanism analysis reveals that effective land urbanization can promote CO_2 emission reductions through efficiency improvement, structure optimization and proper control of the land-use intensity. Additionally, we analyze heterogeneity in regional differences. In the line with study findings, the central government in China should promote the optimization of territorial spatial governance, optimize energy consumption structures, make comprehensive use of its funds, tax policies, industrial development support, and market-oriented mechanisms, and further optimize the layout of urban space.

1. Introduction

Since 1978's implementation of the Open and Reform Policy, China has significantly promoted economic development through rational allocation and effective utilization of land resources augmented the urbanization process and affected the urban CO_2 emissions [1–3]. The change in land use has also accelerated, with the acceleration in urbanization. As a result, substantial areas of unused and agricultural land are transformed into construction of urban land. The proposed process is referred to as land urbanization. This process also drives changes in the patterns of land-use, promoting variations in the efficiency, structure, and land-use efficiency [4–6].

Abbreviations: 2SLS, two-stage least squares; R&D, research and development; SASP, spatial adaptive semi-parametric model; SPSD, semi-parametric spatial dynamic model.

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It further affects the carbon emission process, carbon cycle, and climate, which consequently forces changes in carbon's emission levels [7,8]. Simultaneously, human activities such as population growth, industrial development, energy consumption, and technological change using land resources further affect the level of urban CO_2 emissions by influencing energy consumption structures, energy utilization intensity, and efficiency [9–11]. Besides this, land-use changes and the resulting human activities have led to changes in the function, intensity, and efficiency of CO_2 emissions, which are important driving forces of changes in CO_2 emissions level in urban areas [10,12,13].

The land-use changes' effect on the urban CO_2 emission levels related to the land urbanization's process, is majorly presented in four aspects. First, the enhanced level of urban land construction significantly increases carbon's emissions and sharply declines absorption capacity of carbon [14]. The China's urban construction land enhanced to 55,155.5 square kilometers in 2017, from 20,877 square kilometers in 1999; thereby, displaying an upsurge of 164% [15]. In addition to this, the urban construction land's expansion is followed by a sharp increase in CO_2 emissions because this type of use represents CO_2 emissions' net source. Second, the energy consumption's structure and carbon emission process are profoundly affected by the variations in the land-use structure. In China, the proportion of industrial to construction land is maintained at approximately 20%. However, in urban areas with more developed production industries including the Pearl and Yangtze River Deltas, the share of industrial land commonly exceeds 40pc, compared to the average proportion of 5%–8% globally. Meanwhile, the process of carbon discharge and energy consumption's structure change due to the changes in the structure of land-uses; thus, leading to changes in urban CO_2 emissions levels. Third, extreme intensity of land development disturbs the biosphere's carbon balance, thereby affecting CO_2 emission levels. China's unit construction land output, that is, land output intensity, almost tripled from 530 million Yuan per square kilometer in 2004 to 1.5 billion Yuan per square kilometer in 2017. This intensified land use and excessive intensity of land development destroy the biosphere's original carbon balance; resultantly, affecting and enhancing the process of carbon emissions [15,16]. Fourth, energy-use efficiency is influenced by the land-use's efficiency, which consequently affects CO_2 emission levels. In conclusion, land urbanization can stimulate the urban carbon emissions in four aspects: the urban land's construction level, the land-use structure, land development intensity, and land-use efficiency. Therefore, there is a need to determine the land urbanization mechanism that influences the level of urban CO_2 emissions.

As the urbanization levels improved, many farmers migrated to the cities, where they were exposed to high levels of carbon. Besides this, there is a rise in the infrastructure demand and energy consumption; hence, increasing carbon emissions [17,18] and this finding is the scholar's dominant perspective. The second perspective is that there is an indirect association between urbanization and emissions of CO_2 [19,20]. This indicates that CO_2's emissions are significantly reduced due to urbanization, owing to the higher efficiency of energy utilization, and enhanced technical and management levels [19,20]. The third consensus is that there exists an inverse U-shaped association between urbanization and CO_2's emissions [21,22]. This means that during the early stage of urbanization, there is an increase in CO_2 emissions whereas the carbon emissions reduce in the later stages of urbanization [17–20]. The fourth outlook puts forward that there exists an insignificant association between urbanization and emissions of carbon [23].

Although many research studies performed on the association between land urbanization and CO_2's emissions, few extant studies integrate the impact of land urbanization on the land-use's efficiency, structure, and intensity into a unified analysis framework, which is the main innovation of this study.

Several factors such as economic, social, and natural environment affect land urbanization. Among them, the natural environment is the basic factor that catalyzes changes in land use, such as climate, soil, and hydrology. Other human factors including technology, society, and economy determine the efficiency of land resource allocations through land ownership systems, price, and operating mechanisms [24,25], and thus change factors such as regional land-use structure, spatial distribution, efficiency, and efficiency. Meanwhile, changes in land-use structure, utilization efficiency, and intensity either in direct or indirect manner impact the process and level of carbon emission [26–29]. Therefore, it is necessary to integrate factors such as the appropriate intensity control, structure optimization, and effective improvement of land-use's efficiency into a complete theoretical framework, in order to investigate the internal mechanism of how to land urbanization affects CO_2 emissions. The most imperative significance of this research article lies in the aforementioned fact. Furthermore, the influence effect and mechanism of land urbanization on CO_2 emissions should also be linked to the scale, agglomeration, consumption, and spatial spillover effects of land use, which is another innovation point of this study.

The major contribution of this research paper is associated with the following two dimensions: Firstly, this article systematically explores the land urbanization's mechanism that affects CO_2 emissions, combined with the agglomeration, consumption, and spatial spillover effects of land use. Secondly, this paper as a part of the empirical model comprehensively uses the spatial adaptive semi-parametric (SASP) model and semi-parametric spatial dynamic (SPSD) model, to confirm the non-linear association between land urbanization and CO_2's emissions.

The remainder of this article is structured as follows. Section 2 reviews the literature and presents the theoretical foundation. Section 3 discusses the research data and methodology adopted in this study. Section 4 presents the empirical, benchmark, and nonlinear analysis results, and delineates the endogeneity and robustness analysis. Section 5 section expounds on the findings of the mechanism analysis, while section 6 presents the results of the heterogeneity analysis. Finally, section 7 summarizes the study's implications and policy recommendations.

2. Literature review and theoretical foundation

2.1. Theoretical research on the land urbanization's effect on the CO_2 emissions level

As land urbanization's level improved, abundant quantities of agricultural land were transformed into urban construction land which changed the land-use structure, efficiency, and intensity, thus affecting the carbon emissions' level. In this process, land urbanization's impact on CO_2 emissions was mainly reflected in the scale, consumption, agglomeration, structure optimization, technological improvement's spillover effect, and reasonable control effect of government policy.

First, many farmers migrated to cities, where they were exposed to high levels of carbon during the land urbanization process, thus resulting in a substantial increase in residential energy demand. Simultaneously, land urbanization promoted secondary industrial development, and the migration of farmers to cities promoted the development of tertiary industries, which further supported a significant rise in energy consumption. Furthermore, the increase in demand for energy caused by the household, secondary, and tertiary industrial sectors resulted in an uplift in the levels of CO_2 emissions. This effect can be seen as the scale or consumption effect of land urbanization that tends to increase CO_2 emission levels.

Second, owing to industry- and population's concentration in larger, denser cities, the agglomeration effect results in reduced energy consumption and CO_2 emission levels. Compact city theory proposes that high-density urban developments can exert agglomeration and economies of scale, leading to a significant lowing of the CO_2 emission's intensity.[1] Besides, the industry and population's agglomeration can reduce transaction costs and transportation distances, and improve production efficiency by sharing factors, hence, enhancing the energy resource allocations' efficiency and reducing CO_2 emissions.

Third, the agglomeration of population and industry improves the resource allocation's efficiency and generates the spillover effect of innovative technology and knowledge. Meanwhile, skillful labor adopts formal and informal learning exchanges to transmit ideas and information in the agglomeration area. This contributes to production efficiency, organizational competitiveness, and technological innovation. Complementary enterprises' collective learning could obtain differentiation and complementary knowledge creation, diffusion, and accumulation; as a result, improving enterprise innovation. Technological progress plays a substantial role in CO_2 emission reductions and consists of various types, such as price-, R&D-, and learning-induced technological progress.[2]

Fourth, the change in the structure- and intensity of land-use also affects CO_2's emission levels. Variations in the landscape patterns demonstrate a significant association with changes in different land uses. Consequently, the expansion in urbanization constitutes the pattern of an urban landscape which reduces aggregation and increases fragmentation [4]. The land-use structure's optimization is accompanied by transformation of energy- and industrial consumption structure, which results in the low-carbon technologies' development, improvements in energy-efficiency, and reduction in discharge of CO_2 [30,31]. There are various effects of land urbanization's expansion on CO_2 emissions, owing to variations in spatial industrial and energy consumption structures [19,23,32]. Land-use, infrastructure, population, economic, and public service intensities exhibit a positive effect on carbon emissions [2].

The rapid increases in urban sprawl and land-use intensity have increased energy demand and consumption. Additionally, owing to the uplift in the built-up land, natural land may go through a proportionate reduction. This not only increases carbon emissions but also reduces carbon sinks. Many studies insist that growth of land-use intensity uplifts the carbon's emissions. Wang et al. (2015) [2] find out that, owing to commuting, changes in urban structures significantly increase CO_2's emissions. Furthermore, Liu et al. (2014) [33] report that urban compactness is directly associated with carbons' economic efficiency in urban areas.

However, urban planning and spatial optimization strategies, particularly those highlighting the urban development's intensity, are starting to display a progressively significant role in the CO_2 emissions mitigation [2]. The state authorities can appropriately regulate the intensity of land development through territorial spatial planning policies, which benefits reducing the possible effect of land-use intensity on CO_2 emissions. In this regard, some scholars believe that the effective control of land-use intensity can reduce CO_2's emission levels. Subsequently, Ou et al. (2013) [31] analyzed the association between land use and carbon's discharge and concludes that a compact pattern of development related to urban land facilitates reducing CO_2 emissions. Similarly, Lee and Lee (2014) [34] quantified the urban structures' effect on the individual households' CO_2 emissions. The study findings suggest that there is an important role of smart growth policies in developing transit-friendly and compact cities; thus, thereby lowing emissions of greenhouse gases. Parallel to this, Wang et al. (2021) [35] demonstrated that the surge in carbon emissions can be effectively mitigated by implementing the transfer policy and land development rights throughout the region. The proposed initiative will also ensure the associated spatial transfer of carbon emission rights.

Fifth, the land urbanization's effect on CO_2 emissions is spatially dependent [36]. Based on the geography's 1st law, geographical characteristics are associated with each other in their spatial distributions, and the closer the distances, the closer these attributes are connected [37]. Consistent with this, the geographic law is also applicable to carbon emissions. When a city externally lowers carbon emissions, the air's carbon density in the city decreases in the short-term; thereby, reducing the carbon density in the neighboring regions with higher carbon densities. Contrary to this, a surge in the city's carbon emission increases the carbon level in the adjacent cities. As a result, the geography's first law confirms that CO_2's emissions demonstrate significant spatial spillover effects in various regions [38].

2.2. The effect of government's land-use decisions on the association between land urbanization and CO_2 emissions

China's two-tier land system, consisting of collectively owned and state-owned land, emphasizes urban land [39]. Following the tax-sharing reform of 1994, the central government garnered a significant share of the fiscal revenue, and created an imbalance between the administrative and financial powers of local governments. Accordingly, the financial pressures on local governments force them to obtain huge land transfer fees by monopolizing the primary market of land, which is termed as land finance [39]. The

[1] Agglomeration resulting in carbon emission reductions can be divided into two major categories namely: diversification and specialization. Detailed analysis on this point is available upon request from the author.

[2] Detailed analysis on the impact of different types of technological progress on carbon emissions is available upon request from the author.

investment decisions of local authorities are largely influenced by the assessment and promotion mechanism of the central government authorities [40]. In the same vein, when the main evaluation indicators for official promotion are economic growth, tax revenue, employment, and others, local governments have a strong incentive to compete for investment from enterprises, including those with high pollution and high energy consumption [41]. Fortunately, in the past decade, the central government's assessment indicators such as environmental quality and carbon emission targets have become increasingly important [42], and accordingly, local governments face a trade-off between economic growth and carbon emission reductions. Currently, the scale, structure, and distribution of land are the most effective policy tools in China for balancing economic growth and reducing CO_2's emission.

Local governments in different regions of China compete to attract investments in political performance evaluations, land finance, and other aspects [43]. They must strive for more land development rights and allocation of resources within the framework of central government responsibilities and participate in horizontal competition among regions. Therefore, local government applies their powers of land disposal strategically to establish land transfer prices and scales in the monopolized land market [40]. On the one hand, industrial land is sold by the agreement at a low price as a means of attracting investment which is also known as attracting investment by land. On the other hand, commercial- and residential lands can be sold at high prices to earn high land transfer fees, which is also known as generating wealth from the land. The competitive behaviors and strategies around land use impact enterprises' investments, which makes land urbanization's effect on carbon emissions spatially dependent and correlated. Previous studies on the spatial spillover effect of land urbanization on carbon's emissions, from the perspective of local government's land-use strategies, mostly report two results. First, they find that the land urbanization's spatial spillover effect on CO_2's emissions is positive, which is majorly caused by the local governments' behaviors in response to carbon emission targets. The second is that the spatial spillover effect of land urbanization on carbon emissions is negative, which can be explained by Tiebout's voting with one's feet theory.

Several studies have been conducted on the scale, spatial spillover effect, consumption, agglomeration of land use, and government's strategy of land-use. However, these studies did not integrate the structural optimization, intensity control, and efficiency improvements of land use with the related scale, consumption, agglomeration, and spatial spillover effects to explore the mechanism of land urbanization's influence on carbon emissions. Therefore, this study comprehensively integrates these dimensions to comprehensively examine the mechanisms underpinning land urbanization's impact on urbanization. This integration serves as the main contribution of this study.

3. Data and methodologies

3.1. Data

This study uses panel data on 280 prefecture-level cities from 2003 to 2017 in mainland China. It excludes prefecture-level cities that have undergone division changes, adjustments, or have missing data. The research data is retrieved from the Statistical Yearbook of Chinese cities (2004–2018). This study uses carbon emissions as the explained- and land urbanization rate as the explanatory variables. In addition to this, a series of macroeconomic and characteristic variables that affect CO_2 emissions are selected as control variables. Based on these variables, we empirically analyze land urbanization's effect on carbon emissions. Besides this, the intermediate variables are efficiency-, intensity-, and structure of land-use. Consistently, each variable's measurement methods and data sources are indicated in Table 1.

The dependent variable for carbon's emission (*cemiss*) is estimated by using the amount of nighttime light data as a proxy in accordance with Chen et al. (2021) [44] and Chen et al. (2020) [26] (Table 1). First, the Chinese provincial CO_2 emissions are calculated as per the Intergovernmental Panel on Climate Change and Chinese provincial energy consumption data. Then, we match DMSP/OLS and NPP/VIIRS nighttime light data and predict the CO_2's emissions for 280 Chinese prefecture-level cities for a time period from 2003 to 2017 [44]. The main explanatory variable is land urbanization (*urbanrate*) which is estimated through the

Table 1
Variables and data descriptions.

Variables	Definition	Variable Notation	Unit	Description or Calculation Method
Explained variable	Carbon emission	cemiss	Million ton	Use of nighttime light data as a proxy to estimate CO2 emissions
Explanatory variable	Land Urbanization Rate	urbanrate	%	It is measured by the proportion of construction land to total land in urban districts.
Control variables	Population	population	Ten thousand	The data is obtained from Statistical Yearbook of Chinese cities.
	Economic growth level	pergdp	yuan	It is measured in terms of gross regional product per capita in urban districts.
	Greening level	bupgrate	%	It is measured by the green coverage of urban built-up areas.
	Water Pollution emissions	pwater	Ten thousand ton	It is measured by the amount of industrial wastewater discharged by each prefecture-level city.
	Air Pollution emissions	semiss	ton	It is measured by the industrial emissions of sulfur dioxide in each prefecture-level city.
	Advanced industrial structure	hindustr	n/a	It is measured by the ratio of the output value of the tertiary and the secondary industries of each prefecture-level city.
	R&D expenditure	rd	million yuan	It is measured by the provincial R&D expenditure data of each prefecture-level city.

proportion of construction land to the total land in urban districts. The control variables include population, economic growth level, greening level, water pollution emissions, air pollution emissions, advanced industrial structure, and R&D expenditure. The economic growth level (*pergdp*) is measured as gross regional product per capita in urban districts. The greening level (*bupgrate*) is estimated with the help of urban built-up regions' green coverage. The water pollution emissions (*pwater*) are measured by the amount of industrial wastewater discharged by each prefecture-level city. Air pollution emissions (*semiss*) are measured by the industrial emissions of sulfur dioxide in each prefecture-level city. The advanced industrial structure (*hindustr*) is scaled using the ratio of the output value of the tertiary and secondary industries of each prefecture-level city. R&D expenditure (*rd*) is measured by the provincial R&D expenditure data of each prefecture-level city.

Table 2 populates the descriptive statistics of the explained (*cemiss*), explanatory (*urbanrate*), and control variables and indicates the approximate distribution of each variable.

3.2. Methodologies

3.2.1. Benchmark empirical model

This study's benchmark empirical model that uses panel data model with fixed effects is provided below:

$$Y_{it} = c + \alpha Z_{it} + \beta X_{it} + \mu_i + \lambda_t + \varepsilon_{it} \tag{1}$$

where, Y_{it} stands for the CO_2 emissions of the prefecture-level city *i* in period *t*. Z_{it} is the land urbanization rate of prefecture-level city *i* in period *t*. X_{it} represents a series of control variables, including a series of macroeconomic and characteristic variables affecting CO_2 emissions (e.g., *population, pergdp, bupgrate, pwater, semiss, hindustr, rd*). $\mu_i, \lambda_t, \varepsilon_{it}$ represent urban and time-fixed effects, and standard error terms, respectively. The time-fixed effects adjust for shocks to preferences and technology common to all cities. The city-fixed effects capture differences in unobservable factors across cities.

The changes in the efficiency, intensity, and structure of land use in an area impact industrial development, CO_2 emissions, and efficiency. In turn, CO_2 emissions and efficiency will influence the land-use efficiency and decisions of local governments. Because all the variables that affect urban CO_2 emissions cannot be included, there may be some missing variables, and therefore endogeneity, in the benchmark model. Therefore, there is a need to devise instrumental variables to resolve the possible endogeneity.

A robustness analysis of the benchmark model is conducted using the instrumental variables. The specific robustness analysis is divided as follows: First, we replace the dependent variable with urban energy consumption and ascertain the land urbanization's effect on energy consumption. Second, we replace land urbanization with population urbanization to investigate and analyze the population urbanization's effect on carbon emissions. Third, this paper further explores land urbanization's effect on CO_2's emissions with a one-year lag, to prevent the possible lag effect in the analysis.

In addition, this paper conducts the following heterogeneity analysis to determine the benchmark model's robustness: First, prefecture-level Chinese cities are categorized into the southern and northern regions. Second, Chinese prefecture-level cities are classified into the western, eastern, and central areas to conduct a heterogeneity analysis and perform the benchmark model's robustness test. Third, this study divides all the city samples into key and non-key cities for environmental protection to conduct group regressions to further investigate the regional differences related to the land urbanization's role in the CO_2's emissions. Fourth, we perform group regressions based on whether a city is a resource- or non-resource based to examine the effect of regional differences in land urbanization on CO_2 emissions.

3.2.2. Semi-parametric spatial panel data analysis

There is an uneven distribution of urban CO_2 emissions in space and time. In terms of spatial distribution, there exist variations in terms of the intensity, scale, and efficiency of CO_2 emissions in various regions; thus, leading to an uneven distribution of CO_2 emissions in geographical space. Additionally, CO_2 emissions are related to economic development in terms of variables, such as industrial development, technological levels, natural ecological environment, climate conditions, residents' lifestyles, and human carbon emission reduction behaviors and investments. Furthermore, the land use's effect on urban carbon emissions depends on the economic development's stage and is nonlinear. Therefore, both the spatial effect and the nonlinear characteristics of the impact should be considered while studying the land use's effect on urban CO_2 emissions. The SPSD panel model can simultaneously capture the nonlinear relationship, spatial correlation, and dynamic effect between dependent and independent variables [45]. Moreover, it

Table 2
Descriptive statistics of the main variables.

Variables	Mean	SD	Min	Max	N
cemiss	24.797	22.904	1.530	230.710	4,200
urbanrate	8.353	9.334	0.000	93.810	4,188
population	139.540	179.227	14.080	2451.000	4,196
pergdp	45,100.000	35,100.000	1847.000	468,000.000	4,162
bupgrate	36.957	14.025	0.360	386.640	4,187
pwater	7253.293	9464.162	7.000	91,300.000	4,129
semiss	56,100.000	58,100.000	2.000	683,000.000	4,127
hindustr	0.985	0.585	0.090	5.340	4,199
rd	32,600.000	43,700.000	121.260	234,000.000	4,200

can consider and improve the estimation accuracy and fitting efficiency of the model [46]. Simultaneously, the land urbanization's spatial and dynamic effects and nonlinear characteristics on the urban carbon emissions is analyzed in depth.

Taking urban carbon emission as the explained variable and land urbanization rate as the explanatory variable while selecting the previously mentioned control variables, we established an SPSD panel model of the land urbanization's impact on CO_2's emissions. We employ the proposed model to empirically forecast the role of land urbanization on urban CO_2's emissions [45,46]:

$$Y_{it} = \alpha Y_{i,t-1} + \rho WY_{it} + f(Z_{it}) + \delta X_{it} + \mu_i + \lambda_t + \varepsilon_{it} \tag{2}$$

W denotes the spatial weight matrix, $Y_{i,t-1}$ stands for the urban CO_2 emissions with one year lag and α reflects the dynamic effect of urban CO_2's emissions. ρ is the spatial autocorrelation coefficient, which indicates the spatial impact of CO_2's emissions of geographically adjacent regions or regions with similar levels of economic development on CO_2 emissions in this region. Lastly, δ stands for the control variables' estimated coefficient and $f(Z_{it})$ indicates the non-parametric term.

3.2.3. Mechanism analysis

3.2.3.1. Land-use structure optimization. The theoretical analysis suggests that the relationship between land urbanization and urban CO_2 emissions may be influenced by the land-use structure. Land use structure optimization could reduce the impact of land urbanization on urban CO_2 emissions. The interaction effect model allows us to examine how the relationship between an independent and dependent variable varies depending on the value of a third variable. Therefore, we employ an interaction effect model to effectively capture the mechanism of land-use structure optimization. The land urbanization's mechanism model that influences urban CO_2 emissions by adjusting the land-use structure is as follows:

$$Y_{it} = \alpha Z_{it} + \beta M_{it} + \gamma Z_{it} * M_{it} + \delta X_{it} + \mu_i + \lambda_t + \varepsilon_{it} \tag{3}$$

where, M_{it} indicates the land-use structure, α represents the land urbanization's effect on urban emissions of carbon, and β represents the effect of land-use structure on urban CO_2's emissions. Meanwhile, the interaction term's coefficient γ between land urbanization and land-use structure reflects the mechanism by which land-use structure further influences urban CO_2 emissions in the land urbanization's process. The land-use structure in each prefecture-level city can be assessed by determining the proportion of wetland area to the total area. Wetlands are known to offer numerous valuable ecosystem services, such as carbon sequestration. They act as significant carbon sinks and play a crucial role in regulating the climate [47]. Therefore, we use the proportion of wetland area to the total area of each prefecture-level city to measure the mechanism variable of land-use structure in our study.

3.2.3.2. Land-use efficiency improvement. Similarly, the relationship between land urbanization and urban CO_2 emissions may be influenced by land-use efficiency, as suggested by theoretical analysis. Therefore, we also employ an interaction effect model to better capture the influencing mechanism of land-use efficiency improvement. The land urbanization's mechanism model on urban carbon emission by affecting land-use efficiency is as follows:

$$Y_{it} = \alpha Z_{it} + \beta P_{it} + \gamma Z_{it} * P_{it} + \delta X_{it} + \mu_i + \lambda_t + \varepsilon_{it} \tag{4}$$

where, P_{it} denotes the land-use efficiency, α shows the impact of land urbanization, and β indicates the impact of land-use efficiency on urban CO_2 emissions. Consistent with this, the interaction term's coefficient γ between land urbanization and land-use efficiency reflects the mechanism by which land-use efficiency further influences urban CO_2 emissions in the land urbanization process. Land-use efficiency is measured using the slack-based model with undesired output, which incorporates a range of indicators. These indicators include input indicators, expected output variables, and undesired output variables (refer to Table 3 for details) [48,49].

3.2.3.3. Land-use intensity control. Land use intensity encompasses both output intensity and input intensity per unit of land. It serves as an indicator of the extent to which human activities disrupt the natural ecosystem. The increase in land use intensity can be observed through changes in the structure of land use and improvements in the efficiency of land utilization. Consequently, it is crucial to examine the impact of land urbanization on land use intensity and the subsequent effect of land use intensity on carbon emissions. Accordingly, the land urbanization's influencing mechanism on urban carbon emissions by affecting land-use intensity is as follows:

$$N_{it} = \alpha Z_{it} + \delta X_{it} + \mu_i + \lambda_t + \varepsilon_{it} \tag{5}$$

$$Y_{it} = \gamma Z_{it} + \beta N_{it} + \delta X_{it} + \mu_i + \lambda_t + \varepsilon_{it} \tag{6}$$

Table 3
Input, expected output, and undesired output variables for measuring land-use efficiency.

Types of variables	Variables
Input variables	Capital input, labor input, built-up area, water consumption, electricity consumption
Expected output variables	Gross domestic product, fiscal revenue, urban green area
Undesired output variables	Wastewater discharge, exhaust gas

where, N_{it} stands for land-use intensity. It is measured by using the regional GDP of various prefecture-level cities divided by their administrative area.

If both the coefficients α and β are significant, the mediating effect of land-use intensity control is significant. Accordingly, if the coefficient γ is significant (insignificant), land urbanization's total effect on urban CO_2 emissions is realized only partially (completely) through land-use intensity.

4. Empirical results

4.1. Benchmark model's regression results

The empirical model's regression result, Eq. (1), which controls different fixed effects with or without control variables, is presented in Table 4. The findings show that the influence of land urbanization on urban CO_2's emissions is significantly positive regardless of whether the controlled variables are included, and whether the city, time-fixed effects or both, are controlled. The significantly positive coefficients of the land urbanization rate indicate that land urbanization indeed promotes carbon emissions in urban regions. This supports the finding that the consumption effect of land urbanization exceeds the agglomeration effect [32]. In addition to this, it further indicates that the rise in energy consumption, owing to the increment in consumption level, service demand, and economic output, exceeds the scale effect of land urbanization. Accordingly, our findings support the suggestion that the Chinese authorities must strengthen the integrated utilization of energy and support information's spillover and technology advancement supported by land urbanization [50–52]. Besides this, our results support the suggestion that local government should strengthen land-use management, optimize the structure, reasonably control the intensity, and strive to incline the land-use efficiency [15,32,53].

4.2. Regression results of the nonlinear analysis

At various stages of economic development, economic variables including population scale, industrial structure, technological levels, and consumption patterns are different [54]. Similarly, energy consumption represents several forms, processes, structures, and efficiencies at various stages of economic development [17,21]. Resultantly, all these factors cause nonlinear influence of land urbanization on urban carbon emissions [55–57]. Parallelly, we introduce the land urbanization rate's square term to the benchmark model, Eq. (1) to empirically estimate the nonlinear association between land urbanization and urban CO_2 emissions. Table 5 presents the non-linear model's regression results and indicates that the association between land urbanization and urban CO_2's emissions projects an inverted U-shaped curve. In the early stage of economic development, the economic growth level is relatively low, the land-use pattern is relatively extensive, and residents' consumption is not dominated by green and energy-saving products. As a result, these factors cause the consumption effect of land urbanization to exceed the agglomeration effect, which leads to a direct association between land urbanization and discharge of carbon.

In contrary to this, when the economy develops to an advanced phase, the land-use pattern shifts to high-quality use, the

Table 4
Results of the benchmark model.

Variables	(1) cemiss	(2) cemiss	(3) cemiss	(4) cemiss
urbanrate	0.210***	0.186***	0.161***	0.115***
	(0.027)	(0.021)	(0.018)	(0.018)
population		0.046***	0.053***	0.037***
		(0.003)	(0.002)	(0.002)
pergdp		0.000***	0.000***	0.000***
		(0.000)	(0.000)	(0.000)
bupgrate		0.082***	0.010	0.006
		(0.009)	(0.008)	(0.008)
pwater		−0.000	0.000	−0.000***
		(0.000)	(0.000)	(0.000)
semiss		0.000	0.000	−0.000***
		(0.000)	(0.000)	(0.000)
hindustr		1.358***	1.921***	1.864***
		(0.312)	(0.286)	(0.284)
rd		0.000***(0.000)	−0.000	−0.000
			(0.000)	(0.000)
_cons	22.907***	4.133***	2.116**	5.797***
	(0.257)	(0.726)	(0.926)	(0.664)
City fixed effect	Yes	Yes	No	Yes
Year fixed effect	No	No	Yes	Yes
R^2	0.015	0.511	0.525	0.636
N	4188	4059	4059	4059

Note: Standard errors are in parentheses, ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 5
Results of the nonlinear model.

Variables	(1) cemiss	(2) cemiss
urbanrate	0.449***	0.349***
	(0.062)	(0.047)
$urbanrate^2$	−0.004***	−0.003***
	(0.001)	(0.001)
population		0.048***
		(0.003)
pergdp		0.000***
		(0.000)
bupgrate		0.082***
		(0.009)
pwater		−0.000
		(0.000)
semiss		0.000
		(0.000)
hindustr		1.338***
		(0.312)
rd		0.000***
		(0.000)
_cons	21.574***	3.077***
	(0.401)	(0.774)
City fixed effect	Yes	Yes
Year fixed effect	No	No
R^2	0.020	0.513
N	4188	4059

Note: Standard errors are in parentheses, ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

technological levels, and energy efficiency are improved, and residents' consumption includes mostly green and energy-saving products. These factors cause the agglomeration effect of land urbanization to exceed the consumption effect, which leads to a direct relation between land urbanization and CO_2 emissions. Owing to this, the nonlinear association between land urbanization and urban carbon emissions is in accordance with the theories of urban environmental transition and ecological modernization. These theories indicate that more CO_2 emissions will be generated when the expansion of urbanization is dominated by economic growth. However, CO_2 emissions may be inhibited via technological innovation, environmental regulations, sustainable development, or variations in the composition of the economic sector when societies evolve to higher development stages [58,59]. Simultaneously, the nonlinear result is supported by Shahbaz et al. (2016), Martinez-Zarzoso and Maruotti (2011), Zhang et al. (2017), Shafiei and Salim (2014), Tiba (2019) [21,56,60–62], who reported inverted U-shaped curve between urbanization and CO_2's emissions.

In the context of the first law of geography, CO_2 emissions demonstrate spatial spillover effects [63,64] and are spatially dependent on different cities [36]. Thus, spatial factors should be considered when depicting the association between land urbanization and carbon emissions. Some Chinese studies consider the spatial effect of energy-based CO_2 emissions by using a spatial econometric model [36]. Nevertheless, these spatial econometric models cannot explain the spatial heterogeneity among different regions. Consequently, a SASP model is adopted to report the land urbanization's influential mechanism on CO_2 emissions, in order to accommodate spatial heterogeneity among various cities, and avoid model setting misspecification which is the dimensionality's drawback in the nonparametric model. The proposed SASP model is in accordance with Tang and Hu (2021) [15] and Ruppert et al. (2003) [65] and is

Table 6
Results of the spatial adaptive semi-parametric (SASP) model.

Variable	SASP Model
Population	0.0527*** (0.0000)
Pergdp	1.680E-04*** (0.0000)
Bupgrate	−1.244E-03 (0.9343)
Pwater	2.553E-04*** (0.0000)
Semis	9.986E-05*** (0.0000)
Hindustr	4.113*** (0.0000)
Rd	2.140E-05*** (0.0001)
N	2910
Degree of freedom	13.54
Spar Statistics	10.19
Number of knots	34

Note: p-values are in parentheses, ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

as follows:

$$cemiss_{it} = \beta_0 + \beta_1 population_{it} + \beta_2 pergdp_{it} + \beta_3 bupgrate_{it} + \beta_4 pwater_{it} + \beta_5 semiss_{it} + \beta_6 hindustr_{it} + \beta_7 rd_{it} + f(urbanrate) + \sum_{k=1}^{K_m} b_k \left(urbanrate - \kappa_k^m\right)_+^p \tag{7}$$

where β_0 is a constant, $\beta_i (i = 1, 2, \cdots, 7)$ represent the coefficients for each linear control variable, $f(urbanrate)$ connotes the non-parametric term, $\kappa_k^m (k = 1, 2, \cdots, K_m)$ show knots, K_m indicates the knots' dimension, $(urbanrate - \kappa_k^m)_+^p$ is equal to $(\text{urbanrate} - \kappa_k^m)^p$ if $(\text{urban}rate - \kappa_k^m) > 0$ and $b_k b_k$ is its coefficient, p stands for the exponential power of the kth knot, and m stands for the type of knot.

The SASP model's parametric estimation results, Eq. (7), of land urbanization and carbon emissions are presented in Table 6, whereas the fitting graph of land urbanization and CO_2 emissions is demonstrated in Fig. 1. Accordingly, Fig. 1 shows that the relation between land urbanization rate and total CO_2 emissions projects an inverted U-shaped curve [32,56,66]. Although most of the data still reflect that land urbanization promotes the increase of CO_2 emissions, carbon emission reductions may indeed be promoted with the optimization of the land urbanization's rate. Therefore, the Chinese government can promote the land urbanization's agglomeration effect to exceed its consumption effect by implementing systematic policies promoting the land-use structure's optimization, effectively regulating intensity, while striving to uplift the land-use efficiency. Accordingly, this may transform and upgrade the industrial structures, low carbonization of energy consumption structures, and enterprises' technological innovation levels, thereby improving the spatial spillover effects of the entire country. As a result, land urbanization and carbon emission reductions will accelerate sustainable development in China.

The SASP model uses only spatial adaptive characteristics in the process of fitting sample data. In addition, the impact of land urbanization policies and measures in other adjacent areas or areas with similar economic development on regional CO_2 emissions are not analyzed in the SASP model, nor does it consider the temporal dynamic effect of urban CO_2 emissions. Therefore, the temporal dynamic and spatial spillover effects of land urbanization on carbon emissions is further estimated with the help of SPSD model. This model accommodates the influences of certain covariates related to urban CO_2 emissions by extending the ordinary spatial autoregressive models [45,46,67]. The weight matrix W used in the model is the inverse distance weight matrix. The SPSD model's results according to the empirical model shown in Eq. (2) are shown in Table 7. Meanwhile, the linear prediction curve between land urbanization and CO_2's emissions for the SPSD model is shown in Fig. 2 and indicates that the SPSD model fits the data well. Moreover, the plot of partial derivatives of fitted values in the context of non-parametric term is shown in Fig. 3 which demonstrates that the marginal carbon emission effect of land urbanization shows an N-shaped relationship, which first increases, then decreases, and then increases again. This signifies that the marginal carbon emission effect of land urbanization decreases when the land urbanization rate is in the approximate range of 8%–22%. Consistently, Table 7 illustrates that the influence of urban CO_2's emissions with a one-year lag on current CO_2 emissions is significantly positive, as is the spatial autocorrelation coefficient. This indicates that the carbon emissions' influence represents a dynamic cumulative effect. Simultaneously, it demonstrates that the land urbanization level in neighboring areas exerts a significantly positive influence on carbon emissions in a particular region, which points out that land urbanization displays a spatial spillover effect on the urban CO_2's emissions.

4.3. Endogeneity analysis

Omitted variables and reverse causality may cause an endogeneity between land urbanization and CO_2 emissions [32,61]. As a result, this study selects the land urbanization's instrumental variables and performed a 2-stage least squares (2SLS) with instrumental variables, to resolve the possible endogeneity and undertake a further robustness check of the benchmark results (Table 4: [68–70]). In accordance with Tang and Hu (2021) [15] we chose the number of plots as leased land (M1), the area of leased land (M2), and nighttime light data (M3) as the land urbanization's instrumental variables. The VIIRS sensor on the Suomi NPP satellite is used to derive nighttime light data. This helps to provide spatially explicit observations at night of artificial lighting sources across the human settlements, without moonlight [5]. Afterward, the data on the number of land plots being leased, and the area of land that was leased are acquired from the Chinese Land and Resources Yearbook (2004–2018) and Chinese Land and Resources Statistical Yearbook (2004–2018).

The nighttime light data serves as economic development's appropriate instrumental variable, including land urbanization [69,71]. Additionally, the area and scale of land being leased also represent sound instrumental variables for land urbanization since these variables are not only directly associated with land urbanization but also serve as exogenous variables controlled by the federal government in China. Subsequently, the association between land urbanization and urban carbon emissions, based on 2SLS model with the instrumental variables, is shown in Table 8 and indicates that the previous results concerning land urbanization's influence on urban CO_2's emissions are robust. Besides, land urbanization displays a significantly positive influence on urban carbon emissions regardless of the combination of M1, M2, or M3 that are used as instrumental variables. In addition, the results support the benchmark model's results (Table 4).

4.4. Robustness analysis

This study performs a series of robustness tests, to further cross-check the baseline results' reliability. Firstly, we replace the dependent variable with urban energy consumption and assess the land urbanization's influence on energy consumption. The results

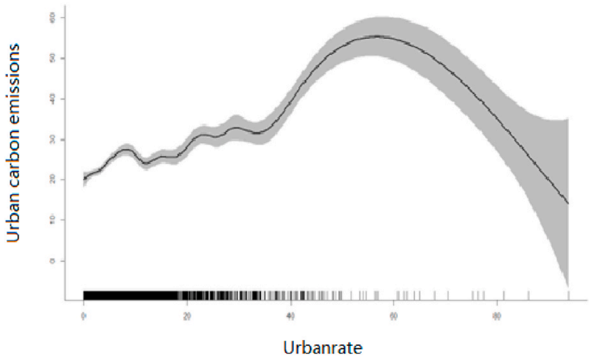

Fig. 1. The fitting curve between land urbanization and CO_2 emissions based on the spatial adaptive semi-parametric model for Chinese prefecture-level cities of year 2003–2017.

Table 7
Results of the semi-parametric spatial dynamic (SPSD) model.

Variables	SASP Model
L.cemiss	0.383*** (0.014)
Wcemiss	2.07E-06*** (7.61E-08)
Population	0.003** (0.001)
Pergdp	−6.33E-06*** (1.83E-06)
Bupgrate	7.292E-04 (0.003)
Pwater	−1.3E-05 (1.03E-05)
Semis	1.44E-06 (1.59E-06)
Hindustr	0.179 (0.166)
Rd	6.75E-06*** (4.64E-06)
N	2910
Number of observations	3640
R^2	0.435

Note: Standard errors are in parentheses, ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

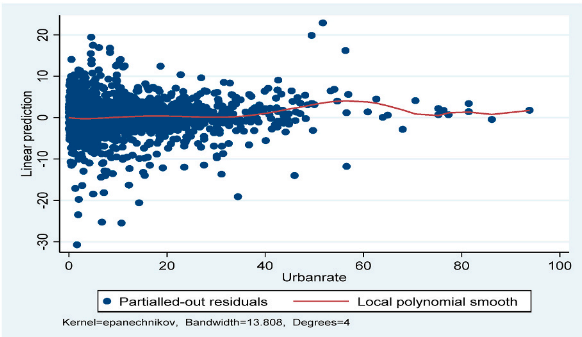

Fig. 2. The linear prediction curve between land urbanization and CO_2 emissions based on the semi-parametric spatial dynamic model for Chinese prefecture-level cities of year 2003–2017.

are populated in column (1) of Table 9 and demonstrate that the land urbanization's effect on urban energy consumption is significantly positive. This shows that the benchmark results are robust. Second, we replace land urbanization with population urbanization to estimate the population urbanization's effect on CO_2 emissions (column 2; Table 9). This result reveals that population urbanization exerts a significantly positive influence on carbons' discharge, thus suggesting that the estimated conclusions are still robust. Finally, to prevent the lag effect of land urbanization on CO_2's discharge, we further examine the land urbanization's effect on CO_2's emissions with one year lag. As demonstrated in Table 9's 3rd column, the land urbanization coefficient is also significant; thereby, reflecting that land urbanization exerts a significant lagged effect on promoting CO_2' emissions.

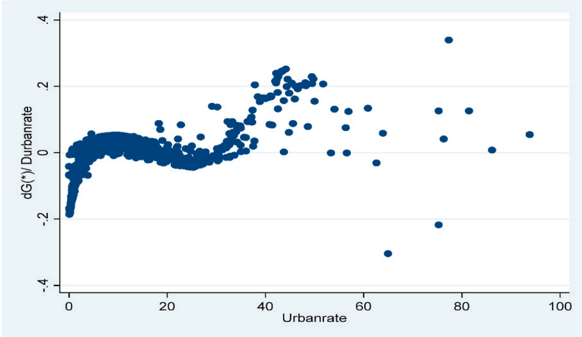

Fig. 3. Plot of partial derivatives of fitted values with respect to non-parametric terms based on the semi-parametric spatial dynamic model for Chinese prefecture-level cities of year 2003–2017.

Table 8
Results of two-stage least squares estimation with instrumental variables.

Variables	(1)	(2)	(3)	(4)
	cemiss	cemiss	cemiss	cemiss
urbanrate	0.689***	0.656***	0.670***	0.648***
	(0.109)	(0.112)	(0.109)	(0.111)
population	0.051***	0.052***	0.051***	0.052***
	(0.003)	(0.003)	(0.003)	(0.003)
pergdp	0.000***	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
bupgrate	−0.007	−0.007	−0.005	−0.007
	(0.015)	(0.015)	(0.015)	(0.015)
pwater	0.000***	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
semiss	0.000***	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
hindustr	3.937***	3.869***	3.885***	3.866***
	(0.438)	(0.450)	(0.438)	(0.450)
rd	0.000***	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
_cons	−6.764***	−6.975***	−6.697***	−6.942***
	(0.936)	(0.940)	(0.932)	(0.939)
M1	No	Yes	No	Yes
M2	No	No	Yes	Yes
M3	Yes	Yes	Yes	Yes
City fixed effect	Yes	Yes	Yes	Yes
Year fixed effect	No	No	No	No
R^2	0.650	0.651	0.650	0.652
N	4059	3722	4000	3722

Note: Standard errors are in parentheses, ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

5. Mechanism analysis

5.1. Land-use efficiency improvement

Our theoretical analysis explores the notion that land urbanization could potentially facilitate carbon emission reductions through enhanced land-use efficiency. Therefore, the interaction effect model is employed to test this theory as per the empirical model (Eq. (4)). Table 10 points out that the land-use efficiency's effect on CO_2's emissions is negative overall, whereas the land urbanization's effect is positive. However, the interaction coefficient of land-use efficiency and land urbanization is lower than the land urbanization coefficient. This result reveals that the improved land-use efficiency reduces the positive effect of land urbanization on carbon's emissions. As a result, land-use efficiency can be improved by land urbanization through scale, agglomeration, and spillover effects caused by technological innovation and efficiency improvements, thus promoting carbon emission reductions. Hence, the government

Table 9
Robustness check results.

Variables	(1)	(2)	(3)
	energy	cemiss	L.cemiss
urbanrate	7.841***		0.090***
	(1.228)		(0.018)
popurbanrate		0.115***	
		(0.021)	
population	3.347***	0.024***	0.033***
	(0.166)	(0.002)	(0.002)
pergdp	0.007***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)
bupgrate	0.864	−0.001	0.003
	(0.538)	(0.007)	(0.008)
pwater	−0.005***	−0.000***	−0.000***
	(0.001)	(0.000)	(0.000)
semiss	−0.001***	−0.000	−0.000***
	(0.000)	(0.000)	(0.000)
hindustr	12.331	0.002	1.825***
	(19.609)	(0.261)	(0.296)
rd	−0.000	−0.000***	−0.000
	(0.000)	(0.000)	(0.000)
_cons	137.239***	−1.610	7.441***
	(46.458)	(1.178)	(0.703)
City fixed effect	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes
R^2	0.514	0.623	0.635
N	4200	3420	3920

Note: Standard errors are in parentheses, ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 10
The regression results of the interaction effect between land urbanization and land-use efficiency.

Variables	(1)	(2)	(3)
	cemiss	cemiss	cemiss
urbanrate	0.148***	0.155***	0.076***
	(0.033)	(0.025)	(0.022)
urbanrate*eco	0.192***	0.093**	0.120***
	(0.059)	(0.043)	(0.037)
eco	1.894**	−2.193***	−2.477***
	(0.845)	(0.621)	(0.537)
population		0.046***	0.037***
		(0.003)	(0.002)
pergdp		0.000***	0.000***
		(0.000)	(0.000)
bupgrate		0.085***	0.009
		(0.009)	(0.008)
pwater		−0.000	−0.000***
		(0.000)	(0.000)
semiss		0.000	−0.000***
		(0.000)	(0.000)
hindustr		1.347***	1.854***
		(0.312)	(0.283)
rd		0.000***	−0.000
		(0.000)	(0.000)
_cons	22.229***	4.748***	6.492***
	(0.374)	(0.746)	(0.679)
City fixed effect	Yes	Yes	Yes
Year fixed effect	No	No	Yes
R^2	0.024	0.513	0.638
N	4188	4059	4059

Note: Standard errors are in parentheses, ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

authorities support industries with high energy efficiency to replace industries with low energy efficiency by adjusting land-use policies, in the land urbanization process. Simultaneously, the state authorities introduce tax incentives, fiscal subsidies, and other policies to support enterprises, in order to increase investment in technological innovation and improve land-use efficiency, thus reducing CO_2 emission levels. The results are parallel to Dong et al. (2020) [72], Talaei et al. (2020) [73], and Yu et al. (2020) [74], and prove that land-use efficiency exerts an indirect impact on carbon emission's intensity, and the agglomeration and spillover effects of urbanization is able to effectively improve the carbon emission's efficiency; thereby, lowering CO_2 emissions.

5.2. Land-use structure optimization

Reasonable and effective land urbanization can promote carbon emission reductions by optimizing land-use structures, adjusting industrial structures, and promoting industrial structure transformations. Therefore, the interaction effect model is applied to assess the mechanism of how to land urbanization promotes carbon emission reductions through land-use structure optimization as per the empirical model expressed in Eq. (3). Table 11 reflects that the interaction coefficient of land-use structure and land urbanization is lower than the land urbanization's coefficient, although the land-use structure's coefficients are insignificant in column (3). Furthermore, this result reveals that optimizing the structure of land-use can decrease the positive impact of land urbanization on carbon's emissions. By promoting land-use in low-carbon industries, land urbanization can effectively optimize the land-use structure, support the industrial structure transformation, and improve carbon emission efficiency, thus promoting carbon emission reductions. Hence, the regulatory bodies may encourage enterprises with high-energy efficiency to replace enterprises with low-energy efficiency by adjusting land-use policies in the land urbanization process [75–79]. The aforementioned literature found that land-use structure optimization could promote industrial structure adjusting, and thus negatively affect CO_2 emissions.

5.3. Land-use intensity control

The theoretical analysis shows that it is possible to promote carbon emission reductions, or at least reduce the rate at which they increase, by reasonably controlling land-use intensity in the land urbanization process; thus, reducing the disturbance of land-use activities to ecological and environmental systems. Therefore, we should investigate this mechanism using economic performance data. We use the mediation effect model to identify whether land urbanization can achieve carbon emission reductions by promoting land-use intensity control according to the empirical models shown in Eqs. (5) and (6). Table 12 (regression results) posits that land urbanization's influence on land-use intensity is significantly positive. In case both land-use intensity and land urbanization are included in the same empirical model, the land urbanization and land-use intensity's effect on CO_2's emissions are also significantly positive. This result indicates that land-use intensity performs a partially positive mediating role in the land urbanization's process affecting CO_2's emissions. Furthermore, it indicates that land-use intensity has not been properly controlled in China, and its impact on carbon emissions is still positive. In the future, the Chinese government should further rationally control and optimize land development intensity, strengthen territorial space planning, and cause the land-use intensity's effect on CO_2's emissions to change from positive to negative.

6. Heterogeneity analysis

The southern and northern regions of mainland China are classified based on the Qinling-Huaihe line (the Huai River line and the Qin Mountains). In addition, the prominent factors that separate the two stated regions are climate factors namely: precipitation and temperature. On the one end, the northern areas consist of Beijing, Gansu, Tianjin, Xinjiang, Hebei, Henan, Shanxi, Inner Mongolia, Jilin, Liaoning, Heilongjiang, Shandong, Shaanxi, Qinghai, and Ningxia. While, on the other end, the southern regions comprise Fujian, Shanghai, Hubei, Zhejiang, Anhui, Hainan, Jiangsu, Jiangxi, Hunan, Chongqing, Guangdong, Guangxi, Yunnan, Guizhou, and Sichuan. The heterogeneity analysis based on the southern and northern cities (Table 13) shows that land urbanization plays an affirmative role in terms of carbon's emission in both northern and southern cities, and the impact in the southern cities is higher than that in the northern cities since the land resources' scarcity in the southern regions forces the intensive use of land. However, land and mineral resources including natural gas, oil, and coal are relatively abundant, which makes the land use of northern cities relatively extensive. Simultaneously, southern cities have improved industrial development and have higher technological and human capital levels. This results in most of the mineral resources in the north being shipped to southern cities for consumption. As a result, land urbanization in southern cities demonstrates a higher impact on CO_2's emission than it does in northern cities.

Chinese provinces are divided into three regions namely: western, central, and eastern, from the perspective of economic zones. The northeastern, central, and western regions are combined and named mid-western regions. Primarily, the eastern zone consists of Tianjin, Beijing, Zhejiang, Hebei, Guangdong, Jiangsu, Fujian, Hainan, Shandong, and Shanghai. Moreover, the mid-western zone consists of the remaining other provinces. The heterogeneity analysis for the mid-western and eastern cities (Table 14) reflects that land urbanization exerts a positive effect on CO_2 emissions in both eastern and mid-western cities, and the impact in eastern cities is greater than it is in midwestern cities. The land-use intensification's degree is higher in the eastern zone than the mid-western zones. While, the eastern region's technological levels and economic development are comparatively high than the mid-western zones [30]. Because of greater economic development, better industrial development, and higher technological levels, residents, and enterprises in eastern cities have higher energy consumption demands, resulting in higher carbon emission levels. As a result, land urbanization, in eastern cities, demonstrates a higher effect on CO_2 emissions than it does in midwestern cities.

To further investigate the regional differences in terms of land urbanization's effect on CO_2 emissions, we divide all the city samples

Table 11
The regression results of the interaction effect between land urbanization and land use structure.

Variables	(1)	(2)	(3)
	cemiss	cemiss	cemiss
urbanrate	0.163***	0.106***	0.053**
	(0.032)	(0.026)	(0.022)
urbanrate*lstruc	0.006**	0.012***	0.010***
	(0.003)	(0.002)	(0.002)
lstruc	1.383***	−0.342***	0.029
	(0.089)	(0.078)	(0.070)
population		0.047***	0.037***
		(0.003)	(0.002)
pergdp		0.000***	0.000***
		(0.000)	(0.000)
bupgrate		0.083***	0.007
		(0.009)	(0.008)
pwater		−0.000	−0.000***
		(0.000)	(0.000)
semiss		0.000	−0.000**
		(0.000)	(0.000)
hindustr		1.315***	1.811***
		(0.311)	(0.283)
rd		0.000***	−0.000
		(0.000)	(0.000)
_cons	14.002***	5.969***	5.499***
	(0.608)	(0.849)	(0.772)
City fixed effect	Yes	Yes	Yes
Year fixed effect	No	No	Yes
R^2	0.096	0.515	0.639
N	4188	4059	4059

Note: Standard errors are in parentheses, ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 12
The regression results of the interaction effect between land urbanization and land use intensity.

	(1)	(2)
	linten	cemiss
urbanrate	377.149***	0.082***
	(9.988)	(0.024)
population	5.744***	0.045***
	(1.361)	(0.003)
pergdp	0.061***	0.000***
	(0.002)	(0.000)
bupgrate	11.206***	0.079***
	(4.138)	(0.009)
pwater	−0.015	−0.000
	(0.011)	(0.000)
semiss	−0.009***	0.000**
	(0.002)	(0.000)
hindustr	213.749	1.299***
	(149.306)	(0.309)
rd	0.020***	0.000***
	(0.002)	(0.000)
linten		0.000***
		(0.000)
_cons	−2.3e+03***	4.766***
	(347.366)	(0.724)
City fixed effect	Yes	Yes
Year fixed effect	No	No
R^2	0.535	0.519
N	4059	4059

Note: Standard errors are in parentheses, ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 13
Heterogeneity analysis of northern and southern cities.

	(1)	(2)
	Northern cities	Southern cities
	cemiss	cemiss
urbanrate	0.157***	0.255***
	(0.058)	(0.081)
population	0.077***	0.039***
	(0.023)	(0.007)
pergdp	0.000***	0.000***
	(0.000)	(0.000)
bupgrate	0.221***	0.051***
	(0.058)	(0.012)
pwater	−0.000	−0.000
	(0.000)	(0.000)
semiss	0.000	0.000
	(0.000)	(0.000)
hindustr	0.991	0.119
	(0.986)	(0.680)
rd	0.000*	0.000***
	(0.000)	(0.000)
_cons	−1.174	5.588**
	(4.437)	(2.456)
City fixed effect	Yes	Yes
Year fixed effect	No	No
R2	0.526	0.571
N	1884	2175

Note: Standard errors are in parentheses, ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 14
Heterogeneity analysis of eastern and midwestern cities.

Variables	(1)	(2)
	Eastern cities	Midwestern cities
	cemiss	cemiss
urbanrate	0.185*	0.173***
	(0.100)	(0.053)
population	0.041**	0.048***
	(0.020)	(0.010)
pergdp	0.000***	0.000***
	(0.000)	(0.000)
bupgrate	0.049***	0.136***
	(0.014)	(0.037)
pwater	−0.000	0.000
	(0.000)	(0.000)
semiss	−0.000	0.000
	(0.000)	(0.000)
hindustr	1.393	1.431**
	(2.093)	(0.697)
rd	0.000*	0.000**
	(0.000)	(0.000)
_cons	12.066*	−0.648
	(6.227)	(2.059)
City fixed effect	Yes	Yes
Year fixed effect	No	No
R2	0.466	0.567
N	1234	2825

Note: Standard errors are in parentheses, ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

into key- and non-key cities for environmental protection to conduct group regressions. The 11th Five-Year Plan for National

Environmental Protection has listed 113 key cities for the control and comprehensive prevention of air pollution.[3] As a result of this, these cities represent the focus of emission reduction and energy conservation [69]. In this context, the local governments in these cities should concentrate on the adverse impacts of land development activities on environmental pollution and CO_2 emissions and impose stricter restrictions on them. Table 15 shows the heterogeneity analysis results for the key and non-key cities for environmental protection. The findings reflect that land urbanization's effect on CO_2 emissions is significantly positive in both key and non-key cities for environmental protection, and the impact in key cities is greater than in non-key cities. Consistently, to reduce the enhancing effect of land urbanization on CO_2's emission, governments in key cities for environmental protection should further optimize the structure, rationally control the efficiency, and improve the efficiency of land-use. Governments in non-key cities should also endeavor to optimize land urbanization, to ensure environmental protection and minimize CO_2 emissions.

The Sustainable Development Plan for Resource-based Cities of China (2013–2020) states that resource-based cities serve as the imperative strategic bases for resources and energy in China.[4] Generally, such cities are dominated by resource-based firms with high energy consumption and pollution, and their energy and resource utilization efficiency is relatively low [80]. In particular, these cities are also faced with substantial pressure to transform, and the Chinese government is committed to develop and transform these cities. Contrary to this, non-resource-based cities are substantial carbon emitters and energy consumers [69]. We perform group regressions based on whether the region includes non-resource- and resource-based cities to further highlight the regional differences in terms of the land urbanization's effect on carbon emissions. Table 16 shows the heterogeneity analysis results of resource-and non--resource-based cities, which confirm that the land urbanization's influence on CO_2's emissions is significantly positive for both of them. Furthermore, the impact in non-resource-based cities is higher than it is in resource-based cities. This reveals that local authorities of both type cities should further optimize the structure, rationally control the intensity, and improve the efficiency of land-use, to vigorously decline the adverse effect of land urbanization on increased CO_2 emissions.

7. Conclusion and policy commendations

Using Chinese prefecture-level data from 2003 to 2017, we systematically investigated land urbanization's effect on urban carbon emissions and explored the mechanism of how land urbanization influences CO_2's emissions based on the land-use structure optimization, efficiency improvement, and intensity regulation. The main results of our study are: First, in general, the land urbanization's effect on urban CO_2 emissions is significantly positive, which indicates that the land urbanization's consumption effect exceeds the agglomeration effect. Second, the nonlinear analysis confirms that the association between land urbanization and CO_2 emissions exhibits an inverted U-shaped curve. Third, a mechanism analysis reveals that effective land urbanization can promote CO_2 emission reductions through adequate control of the land-use intensity, land-use structure optimization, and efficiency improvements. Fourth, the heterogeneity analysis demonstrates that there exist regional differences in terms of land urbanization's impact on CO_2 emissions for northern, southern, eastern, mid-western, key- and non-key cities for environmental protection, as well as resource- and non-resource-based cities.

The aforementioned study conclusions are helpful for policy makers and local authorities to devise sound policies to preserve local land, reduce energy consumption, and minimize the carbon emissions. Therefore, this study proposes the following policy recommendations: Firstly, the Chinese government must transform the land-use policy and promote the optimization of territorial spatial governance and high-quality land use. Furthermore, the Chinese state should vigorously optimize the land use, effectively control the intensity, and strive to improve the efficiency of land-use, to ensure that the agglomeration effect of land use exceeds the consumption effect and to effectively promote carbon emission reductions. In particular, the state authorities should strengthen controlling the land use of industries with high energy consumption and emissions and allocate more land indicators to low-carbon and efficient industries by applying differentiated land supply policies. Simultaneously, the government should strengthen the connection between territorial spatial and industrial development planning, industrial energy consumption, and carbon emission control targets, and jointly control the total energy consumption of high-carbon industries. These initiatives will help to not only ensure an appropriate use of local land but also reduce the emission of greenhouse gases. Second, there is a need to optimize the energy-consumption's structure, reduce traditional fossil energy's consumption, and enhance renewable and green- and energy consumption. Particularly, the Chinese authorities need to control the connection between territorial space use and the reduction control plan for fossil energy. Meanwhile, controlling the use of territorial space is termed as a crucial channel to control the scale of fossil energy consumption and still ensure the green and renewable energy supply. Third, the Chinese government can make comprehensive use of its fiscal funds, tax policies, industrial development support, market-oriented mechanisms, and other policies and measures to rapidly promote land urbanization and carbon emission reductions. Finally, it should further optimize the layout of urban space, and develop compact cities, especially high-density, mixed-function, and multi-center cities, in order to promote reducing carbon emissions. A set of several policy recommendations put forward in this study are expected to not only benefit Chinese economy but also the surrounding developing economies who represent socio-economic conditions similar to China, and are either directly or indirectly adversely influenced by the carbon emissions of China.

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Table 15
Heterogeneity analysis of key and non-key cities for environmental protection.

Variables	(1)	(2)
	Key cities for environmental protection	Non-key cities for environmental protection
	cemiss	cemiss
urbanrate	0.331***	0.090***
	(0.044)	(0.019)
population	0.042***	0.030***
	(0.004)	(0.005)
pergdp	0.000***	0.000***
	(0.000)	(0.000)
bupgrate	0.191***	0.068***
	(0.033)	(0.007)
pwater	−0.000***	0.000***
	(0.000)	(0.000)
semiss	0.000**	−0.000
	(0.000)	(0.000)
hindustr	1.508**	0.996***
	(0.710)	(0.283)
rd	0.000***	0.000***
	(0.000)	(0.000)
_cons	3.772**	4.408***
	(1.874)	(0.652)
City fixed effect	Yes	Yes
Year fixed effect	No	No
R^2	0.565	0.260
N	1650	2550

Note: Standard errors are in parentheses, ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 16
Heterogeneity analysis of resource- and non-resource-based cities.

Variables	(1)	(2)
	Resource-based cities	Non-resource-based cities
	cemiss	cemiss
urbanrate	0.115***	0.208***
	(0.035)	(0.024)
population	0.079***	0.043***
	(0.009)	(0.003)
pergdp	0.000***	0.000***
	(0.000)	(0.000)
bupgrate	0.138***	0.071***
	(0.020)	(0.009)
pwater	0.000**	−0.000**
	(0.000)	(0.000)
semiss	−0.000	0.000***
	(0.000)	(0.000)
hindustr	2.304***	0.698*
	(0.450)	(0.404)
rd	0.000	0.000***
	(0.000)	(0.000)
_cons	−1.963	6.232***
	(1.234)	(0.982)
City fixed effect	Yes	Yes
Year fixed effect	No	No
R^2	0.306	0.662
N	1695	2505

Note: Standard errors are in parentheses, ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

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Author contribution statement

Maogang Tang: Conceived and designed the experiments; Analyzed and interpreted the data; Contributed reagents, materials, analysis tools or data; Wrote the paper. Fengxia Hu: Performed the experiments; Analyzed and interpreted the data; Contributed reagents, materials, analysis tools or data.

Data availability statement

Data will be made available on request.

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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