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How does the concentration of spatial allocation of urban construction land across cities affect carbon emission intensity in China?☆

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ABSTRACT

Optimizing the spatial allocation of urban construction land (UCL) from the national perspective and promoting its moderate concentration are imperative prerequisites for synergistically accomplishing economic growth and carbon emission reduction goals. However, how the concentration of spatial allocation of urban construction land (CSA) across cities influences carbon emission intensity (CEI) remains unclear. To bridge this knowledge gap, we investigated the impact of CSA on CEI in 282 cities in China by using multi-source panel data (e.g., urban carbon emissions data, construction land area data, and socio-economic data) from 2005 to 2020 and applying econometric models: fixed effect model, mediating effect model, and spatial Durbin model. The results revealed that CSA exhibited a significant and robust U-shaped effect on CEI. During the study period, the proportion of cities crossing the inflection point slightly decreased from 57.80 % in 2005 to 55.67 % in 2020, and their spatial distribution pattern remained relatively stable. It is predicted that this proportion will drop to 53.90 % in 2030, and the average CEI of these cities will decrease by 67.93 % from 2005 to 2030. In this scenario, China's carbon emission reduction target for 2030 can be attained in the sampled cities. The heterogeneity analysis showed that the impact of CSA on CEI followed a U-shaped pattern in both the developed and developing regions, as well as in the eastern, central and western regions. Additionally, the analysis revealed a similar pattern in both the resource- and non-resource-based cities. Conversely, this impact was significantly positive in the northeastern region. The mediating effect analysis suggested that CSA indirectly influenced CEI through economic agglomeration (EA), technological innovation (TI), and industrial structure upgrading (ISU). The spatial spillover effect analysis demonstrated that CSA exerted a U-shaped effect on CEI in neighboring regions through the spatial spillover effect. The geographical extent of this effect depends on the geographical distance between cities and their gross domestic product per capita. These findings provide reference values for the spatial allocation and scale control of UCL, and carbon reduction in countries whose UCL allocation and land planning are primarily controlled by the government.

1. Introduction

Comprising less than 1 % of the world's land area but generating nearly 76 % of global carbon emissions, urban areas have become the primary focus of global carbon reduction efforts (Hutyra et al., 2011; Sullivan, 2010). Land-use change generates carbon emissions directly through land-use change processes and indirectly by influencing human activities (Peng et al., 2022; Xiao et al., 2024). After fossil fuel burning,

Abbreviations: UCL, Urban construction land; CSA, Concentration of spatial allocation of urban construction land; CEI, Carbon emission intensity; EA, Economic agglomeration; TI, Technological innovation; ISU, Industrial structure upgrading; OP, Opening-up level; ECS, Energy consumption structure; TS, Technology support; FDI, Foreign direct investment.

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land-use change has constituted the second largest source of carbon discharge (Houghton et al., 1983; Stuiver, 1978), accounting for approximately 26.1 % of global carbon emissions from 1870 to 2015 (Le Quéré et al., 2018). Among the various land use types, construction land has become the most important source of carbon emissions owing to its accumulation of large amounts of material and high energy consumption (Zeng et al., 2016). As the world's largest CO_2 emitter, China contributed 30.7 % of global carbon emissions in 2020 (Wang et al., 2022a), resulting in its carbon emission reduction becoming a global concern (Gregg et al., 2008; Liu et al., 2022). In 2020, the Chinese government proposed its carbon reduction goals, which aim to reach peak carbon emissions by 2030 and achieve carbon neutrality by 2060. However, it is challenging for China to achieve these targets during its current development stages of industrialization and urbanization (Li et al., 2021).

Urban construction land (UCL) is a fundamental factor resource for industrialization and urbanization and a spatial carrier of human social and economic activities (Avagyan, 2018; Li et al., 2023a). Since the utilization and spatial layout of UCL can reflect the spatial configuration of various production and living activities (Li et al., 2023b; Wang et al., 2021), the allocation of UCL exerts a profound impact on carbon emissions (Lu and Guldmann, 2012; Wang et al., 2021). Reasonable UCL allocation through scientific land use planning plays a vital role in global low-carbon economic transformation and green development during urbanization (Anguelovski et al., 2016; Gao et al., 2023; Hu et al., 2023a; Liu et al., 2018a). In China, the spatial allocation of new UCL has been a main task of land use planning, which involves a top-down, administrative indicator decomposition (Liu et al., 2018b; Wang et al., 2020). The spatial allocation of UCL is generally guided by two fundamental strategies: concentration and dispersion. These strategies substantially influence urban economic development and carbon emissions by influencing UCL expansion and the spatial agglomeration of resources and production factors (Yang et al., 2020a). In view of this, determining the allocation strategy most conducive to addressing the dilemma between economic growth and carbon reduction has become an urgent requirement for China to realize its carbon reduction goals.

Numerous scholars have investigated the impact of UCL allocation on carbon emissions (Liu et al., 2023; Zhou et al., 2022). Existing literature primarily focuses on three aspects. (1) Existing research has extensively explored how UCL scale influences carbon emissions. However, a consistent conclusion has not been reached. Some studies have confirmed that UCL growth significantly contributes to carbon emission reduction (Zhang and Xu, 2017). Conversely, other scholars argue that the UCL area is the main catalyst of increased carbon emissions (Li et al., 2022; Peng et al., 2022). Moreover, the UCL scale has exhibited a U-shaped effect on carbon emissions in some studies (Li et al., 2018). (2) Research has explored the impact of land misallocation, which refers to the supply distortion of urban industrial and commercial land, on carbon emissions and efficiency. These studies suggest that land misallocation significantly increases carbon emissions (Bai et al., 2020; Han and Huang, 2022; Zhang and Xu, 2017) and decreases efficiency (Zhou et al., 2022). (3) Several scholars have used the proportion of the first city to measure the concentration of spatial allocation of UCL (CSA) in 23 provincial-level regions of China, and explored its impact on carbon emission intensity (CEI) (Zhong et al., 2023). They discovered a significant U-shaped effect of UCL concentration on CEI. However, there is little evidence of the relationship between CSA and CEI at the urban level and the underlying mechanisms.

In this study, we define the CSA at the urban level as the phenomenon where, after the government's spatial allocation of UCL across cities, UCL is relatively concentrated in certain cities. Useful explorations have been conducted in the existing literature for the spatial allocation of UCL and carbon emissions; however, several research gaps can be identified. First, although the existing literature has explored the relationship between CSA and CEI in China's provincial-level regions, the CSA was measured by the concentration of UCL in the largest city within the specific province. Therefore, the findings of this literature are not applicable to the urban level and could not provide effective policy implications for the central and local government to decompose new UCL indicator among cities when compiling land planning. Second, prior research has defined CEI as carbon emissions per unit of UCL area, whereas CEI, expressed as carbon emissions per unit of gross domestic product (GDP), is a crucial metric for guiding carbon reduction efforts in China (e.g., the Paris Agreement and the 14th Five-Year Plan of China). Thus, testing the impact of CSA on carbon emissions per unit of GDP is vital in offering a stronger practical guidance for carbon reduction in China. Third, there are various intricate underlying mechanisms by which CSA affects carbon emissions that have not been systematically revealed. In this context, it is difficult for governments to deliver comprehensive, reasonable, and targeted carbon reduction policies based on the spatial allocation of UCL. Fourth, although there is evidence of significant spatial spillover effects on carbon emissions (Yu et al., 2020), profound analyses of the spatial spillover effect of CSA on the CEI have not received attention in previous studies, potentially leading to biased regression coefficient estimations.

Considering these research deficiencies, this study aims to address three research questions to satisfy the urgent requirement for carbon emission reduction. (1) Does CSA affect CEI at the urban level? (2) What are the transmission mechanisms underlying the relationship between CSA and CEI? (3) How CSA influences the CEI in neighboring regions through the spatial spillover effect? This study's possible innovations and main contributions are as follows.

First, it explores the effect of CSA on CEI and its heterogeneity at the urban level. Unlike the existing literature that use the proportion of the first city to measure CSA in provincial-level regions and explore its influence on carbon emission per unit of UCL, this study innovatively defines CSA from the perspective of spatial allocation of land resource across cities and investigates its impact on carbon emission per unit of GDP in prefecture-level cities. Such research ideas can enrich the relevant theory on the carbon reduction effects of resource allocation and resource agglomeration, and provide strong practical guidance for the central and local government to optimize the spatial allocation of UCL to reduce CEI.

Second, the intrinsic mechanisms through which CSA affects CEI are investigated. The mediating effect model is employed to analyze the transmission mechanism underlying the relationship between CSA and CEI. A scientific analysis of such intrinsic mechanisms can fill the knowledge gap on the effect of CSA on CEI. Moreover, by providing a more systematic understanding of their relationship, this study can help policymakers to incorporate the spatial allocation of UCL and mediating factors into a unified system when developing and implementing the relevant policies to more effectively promote carbon reduction.

Third, the spatial spillover effect of CSA on CEI is examined. By using the spatial Durbin model, this study can effectively address the spatial spillover problem, reveal the effect of CSA on the CEI in neighboring cities, and provide reliable conclusions and important decision-making references for promoting collaborative regional carbon reduction. In summary, through the aforementioned efforts, this paper bridges the gap in existing studies and provides an important and accurate decision-making basis for the relevant authorities.

2. Theoretical analysis and research hypotheses

Fig. 1 reveals the mechanism of how CSA affects CEI, which involves direct, mediating, and spatial spillover effects. We first uncovered the fundamental mechanism of CSA influencing CEI through direct effect analysis. Then, based on the classic theoretical analysis framework for the relationship between environment and economy proposed by Grossman and Krueger (1995), we investigated the transmission mechanism underlying the relationship between CSA and CEI by selecting three mediating variables—economic agglomeration (EA), technological innovation (TI), and industrial structure upgrading (ISU)—from

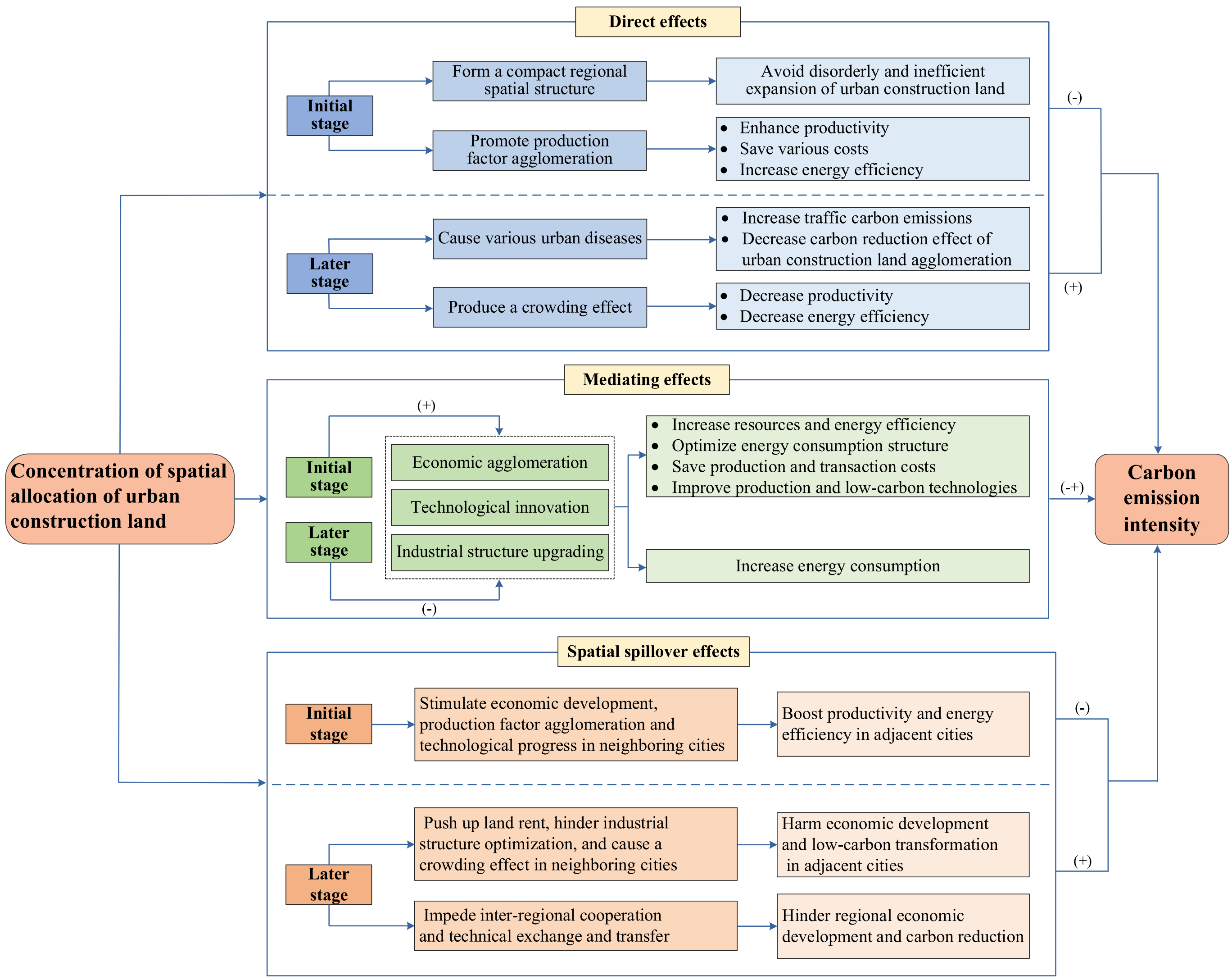

Fig. 1. Theoretical mechanism analysis.

three dimensions: scale effect, technological effect, and structural effect. Last, we explored how CSA affects the CEI of neighboring cities through spatial spillover effect analysis.

2.1. Direct effects of CSA on CEI

In classical economics, labor, capital, and land are recognized as the three traditional production factors that are important sources of wealth creation (Smith, 2003). In cities, UCL serves as the primary spatial carrier of other production factors. Given a constant UCL area nationwide, an increase in CAS in specific cities implies that more UCL is concentrated in these cities, resulting in UCL agglomeration. This will further attract the inflow of talent and investment, and facilitate the agglomeration of production factors and economic activities in these cities (Zheng, 2023). CSA facilitates the formation of a compact regional spatial structure, thereby reducing carbon emissions resulting from disorderly and inefficient UCL expansion (Poumanyvong and Kaneko, 2010). The agglomeration economics theory states that the spatial agglomeration of economic activities and various production factors, can promote urban productivity promotion and economic growth through scale economy, technology spillover, and competition effects (Giuliano et al., 2019; Rosenthal and Strange, 2004). Consequently, CSA and subsequent production factor agglomeration may help to boost productivity and decrease CEI. Specifically, by forming economies of scale, CSA and accompanying production factor agglomeration could help to reduce the inputs of various resources and energy, thereby improving resource utilization efficiency and energy efficiency, and reducing costs, ultimately decreasing CEI (Yan and Huang, 2022; Feng et al., 2022). The technology spillover and competition effects are manifested in that CSA and accompanying production factor agglomeration can generate the spillover of production technology and low-carbon technology, and intensify competition among enterprises by promoting the spatial agglomeration of enterprises, which may help to enhance productivity, decrease energy consumption, and thus reduce CEI (Fujita et al., 1999; Liu and Zhang, 2021; Zhong et al., 2023). Moreover, according to the externality theory, carbon emission represents a typical case of external diseconomy (Zhou et al., 2019a). With the enhancement of CSA and subsequent enterprises agglomeration, the connection among enterprises is becoming closer. This makes it easier for governments to regulate the implementation of environmental regulations and internalize the externalities of carbon emissions through market mechanisms and policy measures, thereby encouraging enterprises to reduce their carbon emissions (Coase, 1960; Keohane, 2009; Ren et al., 2020).

However, excessive CSA and the resultant excessive population agglomeration may cause a series of urban diseases and even urban public crisis events, such as traffic congestion and soaring land and housing prices, that may directly increase traffic carbon emissions, hinder economic growth, and indirectly increase CEI (Fan et al., 2024; Li et al., 2018; Li et al., 2020). This dynamic occurs through diminishing the carbon reduction efficacy of CSA owing to reductions in the profit margins of enterprises and, subsequently, a city's attractiveness for talent and new investments. Additionally, the optimal scale theory of industrial agglomeration states that excessive agglomeration can diminish returns to scale and even produce a crowding effect (Hoover, 1948). In this context, excessive CSA and production factor agglomeration may lead to rapid population growth and expanded production scale; this increases material input and energy consumption and causes scale diseconomies, thereby decreasing productivity and energy efficiency and ultimately increasing CEI (Liu et al., 2022; Martin Andersson, 2009). When the negative externalities of CSA offset and even surpass its positive externalities, a further increase in CSA subsequently increases the CEI. Therefore, H1 was formulated as follows:

H1. CSA exerts a "U"-shaped effect on CEI.

2.2. Effects of mediating factors of CSA on CEI

2.2.1. Mediating effects of EA

According to the agglomeration economics theory, a moderate CSA and accompanying UCL expansion can promote the spatial concentration of capital, population, enterprises, and public services by providing more space for social and economic activities, thus fostering EA (Porter, 2000). The increase in EA can help to generate economies of scale and improve economic efficiency by sharing resources (e.g., infrastructure, labor markets, and information) and increasing returns to scale (Giuliano et al., 2019; Yu et al., 2022; Zeng and Zhao, 2009). This, in turn, will further promote the spatial concentration of production factors and economic activities, thereby reinforcing EA (Glaeser and Kahn, 2010). However, excessive CSA and subsequent UCL expansion may produce various urban diseases and a crowding effect, such as traffic congestion, environmental pollution, and inadequate infrastructure, which may restrain economic growth and productivity enhancement, force existing talent and enterprises to leave, and obstruct the inflow of external population and capital; this thereby restrains EA and may even cause economic activities to spatially disperse (Zheng, 2023). EA has both positive and negative CEI externalities. Theoretically, EA generates positive externalities through producing scale (Fujita et al., 1999; Krugman, 1992), knowledge spillover (Fujita, 1989), and competition effects (Dixit and Stiglitz, 1997), which can increase the efficiency of resources and energy (Zhang et al., 2012a), save production and transaction costs (Wang et al., 2022b), and improve production and low-carbon technologies. Thus, EA contributes to a reduction in carbon emissions and CEI. However, the rising EA involves a rapid expansion in production scale and infrastructure investment, leading to a substantial increase in energy consumption and carbon emission, thereby enhancing CEI (Wang et al., 2022b; Yan et al., 2022a). Accordingly, this study proposes hypothesis H2a as follows:

H2a. CSA affects CEI through EA.

2.2.2. Mediating effects of TI

According to the agglomeration economics theory, in the initial stage, an increase in CSA and the geographic concentration of population and economic activities can stimulate TI by promoting human capital accumulation, knowledge diffusion, technology spillover, cooperation, and competition among enterprises (Lai et al., 2014). Furthermore, according to the knowledge spillover theory, the spatial agglomeration of enterprises can accelerate the diffusion speed of TI, and promote the collaborative innovation among enterprises (Acs et al., 2009). However, after CSA exceeds a certain level, it may increase land rent, housing prices, and production factor costs, decrease profit margins, and increase enterprise supply chain risk; this generates centrifugal forces that produce a crowding effect, thereby decreasing urban innovation vitality (Combes et al., 2019; Yao et al., 2023; Zheng, 2023). Furthermore, according to the free rider theory, excessive knowledge spillover may lead to the "free-rider" phenomenon, suppressing the enthusiasm for enterprise-level innovation and subsequently decreasing urban innovation capacity (Ma and Li, 2014). TI plays a vital role in improving energy efficiency (Dubey et al., 2019), optimizing energy consumption structure (ECS) (Gerlagh and Van Der Zwaan, 2004) and decreasing fossil fuel consumption (Zhang et al., 2012b), thereby significantly reducing CEI (Huang et al., 2018). However, technological advancements may produce an energy rebound effect, wherein an increase in energy efficiency and expansion in economic scale are facilitated by technological improvements that may, in turn, increase energy consumption and carbon emissions (Chen et al., 2020; Jevons, 1865). Consequently, we propose hypothesis H2b:

H2b. CSA influences CEI through TI.

2.2.3. Mediating effects of ISU

Theoretically, a reasonable CSA can promote the flow and reconfiguration of production factors, such as capital, labor, and technology, among regions. In new regional economics, the interregional flow of production factors can bring more employment opportunities and a new economic growth point to the region, promoting ISU in this region (Hoover and Giarratani, 1975). Hence, CSA could promote ISU. Furthermore, CSA, along with the subsequent growth and agglomeration of population, increases the demand for tertiary industry and provides it with essential talent support, which will boost the development of tertiary industry, thereby optimizing the industrial structure (Yan and Huang, 2022). Nevertheless, according to the path dependence theory, excessive CSA and production factor agglomeration may lead to industrial homogenization due to excessive competition between enterprises and an industry's "lock-in effect". Under these circumstances, an increase in CSA may squeeze out original advantageous industries in the locality and obstruct the entry of new industries, thereby restraining ISU and creating an increasingly singular industrial structure (Ma and Li, 2014). Tertiary industries are generally more efficient, energy-saving, and environmentally friendly (Hu et al., 2023b). Industrial structure advancement, represented by an increase in the share of tertiary industry in GDP, significantly increases energy efficiency (Chuai and Feng, 2019), and has been recognized as a critical pathway for reducing carbon emissions and CEI (Yu et al., 2018). Based on this analysis, we propose hypothesis H2c:

H2c. CSA affects CEI through ISU.

2.3. Spatial spillover effects of CSA on CEI

The first law of geography states that due to information exchange and resource sharing among regions, various spatial factors in socioeconomic activities generally have significant spatial spillover effects (Sui, 2004; Zhang et al., 2020). As regional integration has continued to improve in recent years, interregional economies have become more closely linked, and interregional interactions have become increasingly prominent in China (Zhang et al., 2022). Under the special land management and UCL administrative allocation system in China, UCL supply has been closely related to urban economic growth and carbon emissions (Deng et al., 2008; Hu et al., 2023c; Jin et al., 2020), and the spatial allocation of UCL across cities strongly influences adjustments in resource allocation and guides the flow of production factors among regions (Yang et al., 2020a). Therefore, CSA may have a prominent impact on economic growth, production factor agglomeration, and carbon emissions within an individual city as well as in neighboring cities.

According to spatial economics, both CSA and CEI may exhibit strong spatial correlation due to the radiation effect and competition effect in regional development (Song et al., 2020; Zhang et al., 2020). Specifically, a moderate CSA and subsequent production factor agglomeration can stimulate economic development, production factor agglomeration and technological progress in neighboring cities through industrial division, mutual imitation, knowledge dissemination, and technology spillover across regions (Liu and Zhang, 2021). In this context, CSA can boost productivity and energy efficiency in adjacent cities, thereby decreasing CEI in these cities. However, after CSA exceeds a certain level, the soaring land rent and increasing environmental protection pressure will stimulate labor emigration and industry, particularly high-consumption and high-emission industry transfer to cities nearby (Zheng, 2023). These may push up the land rent, hinder the industrial structure optimization, and cause a crowding effect in neighboring cities, which will harm economic development and low-carbon transformation in this region (He and Zheng, 2011). Furthermore, the intensified competition between cites may impede inter-regional cooperation and technical exchange and transfer, thereby hindering regional economic development and carbon reduction. Therefore, excessive CSA may enhance the CEI in neighboring regions. Consequently, hypothesis H3 is proposed:

H3. CSA influences the CEI in neighboring regions through a spatial spillover effect.

3. Methods and data

3.1. Model specification

3.1.1. Benchmark regression model

Based on theoretical analysis, we established the following benchmark regression models to explore the nonlinear relationships between CSA and CEI:

$$lnCEI_{it} = \beta_0 + \beta_1 lnCSA_{it} + \beta_2 ln^2CSA_{it} + \phi_0 lnX_{it} + \mu_i + \omega_t + \varepsilon_{it} \tag{1}$$

$$U = \frac{-\beta_1}{2 * \beta_2} \tag{2}$$

where $lnCEI_{it}$ is the natural logarithm of CEI of city i in year t; $lnCSA_{it}$ and ln^2CSA_{it} represent the natural logarithms of CSA of city i in year t and its quadratic term, respectively; β_0 is a constant term; X_{it} refers to the control variables; β_1, β_2, and ϕ_0 denote the correlation coefficients; μ_i and ω_t stand for the city and time fixed effects, respectively; ε_{it} indicates a random disturbance; and U is the inflection point of the quadratic curve.

3.1.2. Nonlinear mediating effect model

Following our theoretical analysis and referring to Yang et al. (2020b), we established the following two-step nonlinear mediating effect model:

$$lnM_{it} = \lambda_0 + \lambda_1 \mathrm{ln}CSA_{it} + \lambda_2 ln^2CSA_{it} + \phi_1 lnX_{it} + \mu_i + \omega_t + \varepsilon_{it} \tag{3}$$

$$lnCEI_{it} = \alpha_0 + \alpha_1 lnCSA_{it} + \alpha_2 ln^2CSA_{it} + \alpha_3 lnM_{it} + \phi_1 lnX_{it} + \mu_i + \omega_t + \varepsilon_{it} \tag{4}$$

where M_{it} represents a set of mediating variables; X_{it} stands for the control variables; λ_0 and α_0 refer to the constant term; and λ_1, λ_2, ϕ_1, and α_1–α_3 are the correlation coefficients.

3.1.3. Spatial econometric model

According to the first law of geography, CEI may exhibit spatial correlation. Thus, the spatial effect model was employed to explore the spatial spillover effect of CSA on CEI. The spatial error model (SEM), spatial autoregressive model (SAR), and spatial Durbin model (SDM) are the three most commonly used spatial panel models. When applying the spatial lag terms of both explanatory and explained variables, the SDM is more general than the other two models (Elhorst, 2014). The general spatial econometric model is as follows:

$$\begin{aligned} lnCEI_{it} = {} & \alpha + \rho \boldsymbol{W} lnCEI_{it} + \beta_3 lnCSA_{it} + \beta_4 ln^2CSA_{it} + \phi_1 X_{it} + \beta_5 \boldsymbol{W} lnCSA_{it} \\ & + \beta_6 \boldsymbol{W} ln^2CSA_{it} + \phi_2 \boldsymbol{W} lnX_{it} + \mu_i + \omega_t + \varepsilon_{it} \end{aligned} \tag{5}$$

where α is a constant term; W_{ij} represents the spatial weight matrix of asymmetric economic geographical distance; p and ϕ_2 denote the spatial lag coefficients of the explained and control variables, respectively; β_3 and β_4 refer to the coefficients of the independent variable and its quadratic term, respectively; β_5 and β_6 are the spatial lag coefficients of the explanatory variable and its quadratic term, respectively; and X_{it} and ϕ_1 represent the control variables and their coefficients, respectively.

3.2. Variable descriptions

3.2.1. Dependent variable

In this study, CEI is the dependent variable represented by carbon emissions per unit of GDP (Eq. (6)). This measure aligns with China's carbon reduction goals and has been widely used in relevant studies (Zhou et al., 2019b). A decrease in CEI indicates progress in low-carbon development in a specific region (Chen et al., 2023). Total carbon emissions data were collected from the China City Greenhouse Gas Working Group (CCG). Equation (6) is as follows:

$$CEI_{it} = \frac{CE_{it}}{GDP_{it}} \tag{6}$$

where CEI_{it}, CE_{it}, and GDP_{it} represent CEI, total carbon emissions, and GDP in year t for city i, respectively.

3.2.2. Independent variable

Under China's land use planning and land management system, the government carries out the spatial allocation and scale control of UCL across cities. In this study, CSA essentially reveals the degree of inequality in status and imbalance in scale among cities in terms of UCL allocation. The higher CSA, the more UCL concentrated on a certain land area and the higher UCL dominance of a city. Location entropy is an effective measure of the relative concentration of resources and factors across different regions, which can reflect the dominance of these resources and factors in a specific region within a higher-level region (Zheng and Lin, 2018). It possesses the advantage of better eliminating the endogenous influence stemming from different regional scales, and more accurately outlining the distribution of the concentration of resources and factors (Yuan et al., 2020). The bigger this indicator, the more concentrated the spatial allocation of UCL in certain cities. It is calculated as follows:

$$CSA\_e_{it} = \frac{(C_{it}/C_t)}{(S_{it}/S_t)} \tag{7}$$

where CSA_e_{it} is the CSA in year t for city i, which is measured by the location entropy; C_{it}, and Sit represent the UCL area, and total land area in year t for city i, respectively; and C_t and S_t refer to the area of UCL and total land respectively, in year t for all the cities in China.

3.2.3. Control variables

Six control variables were introduced into the models to control for potential effects.

(1) Economic level (EL) is represented by GDP per capita (Wang et al., 2016). According to the environmental Kuznets curve theory, in the initial stage of industrialization, the increasing EL is usually accompanied by the rapid expansion of production scale, which leads to a surge in energy consumption, and thus enhances CEI (Wang et al., 2016; Zhu et al., 2014). However, with economic growth, cities with higher EL may have more advanced production and low-carbon technologies as well as stronger environmental awareness and environmental governance capacity, thereby enabling EL to decrease CEI (Li et al., 2017). Consequently, the effect of EL on CEI needs further examination.
(2) Urbanization level (UL) is characterized by the share of the urban population in the total population (Yan et al., 2022b). As more

highly educated people inflow into cities, UL may promote the increase in the consciousness of environmental governance, thereby promoting the reduction in CEI (Zhang et al., 2020). With the increase in UL, numerous rural residents are transferring to the urban area. According to the spatial agglomeration theory, this transfer may stimulate the improvement of urban infrastructure and public service, which promotes EA in cities, thus increasing energy and production efficiency through the scale effect and ultimately reducing CEI (Zhang et al., 2020). However, this transfer may spark a surge in urban sprawl and population growth, which will lead to a boost in the production and consumption of various products, thereby increasing energy consumption and ultimately enhancing CEI (Song et al., 2020). Therefore, the total effect of UL on CEI is uncertain.

(3) Opening-up level (OP) is calculated as the ratio of the total import and export volume to GDP (Wang et al., 2023). OP generally facilitates trade diffusion, which may stimulate the scale expansion of production and energy consumption, thereby increasing CEI (Xiao et al., 2019). However, according to the new trade theory, trade openness can stimulate local technical progress through technology transfer or technology spillover, thus reducing CEI (Melitz, 2003; Wang and Wang, 2021). Therefore, the effect of OP on CEI remains ambiguous.

(4) Energy consumption structure (ECS) is defined as the proportion of coal in total energy consumption (Xiao et al., 2019). ECS has a fundamental influence on CEI (Zhou et al., 2019b). Fossil fuels produce more carbon emissions than other energy sources, and the ratio of fossil fuels to the total energy consumption generally increases CEI (Xu et al., 2021). Therefore, ECS enhances CEI.

(5) Technology support (TS) is calculated by dividing the amount of science and technology expenditures by the total fiscal expenditures (Shao et al., 2019). According to the technical innovation theory, governmental TS can stimulate technological advancement, which may help to improve energy efficiency, thereby curbing CEI (Fan et al., 2022). However, this effect will be valid only when TS is devoted to promoting green development and carbon emission reduction instead of improving productivity (Yu et al., 2020). Therefore, the influence of TS on CEI is uncertain.

(6) Foreign direct investment (FDI) is measured by the ratio of foreign direct investment to GDP (Yang et al., 2020b). According to the pollution haven hypothesis, FDI may increase regional CEI by transferring energy-intensive and high-polluting industries to the host country (Shao et al., 2019; Yan and Huang, 2022). However, the pollution haven hypothesis states that the inflow of environmentally friendly technologies and productions can help to decrease the pollution in the host country (Albornoz et al., 2009; Shao et al., 2019). Therefore, FDI can also diminish CEI through technology and environmental spillovers (Shao, 2018). Consequently, the effect of FDI on CEI remains ambiguous.

3.2.4. Mediating variables

According to the theoretical analysis, prior literature and empirical detection, three derived variables, EA, TI, and ISU, were selected to test their mediating effects on the impact of CSA on CEI (Grossman and Krueger, 1995). We used the GDP generated per unit area of the UCL as a measure of EA (Yu et al., 2022). TI represents the number of technical patent applications (Liu and Zhang, 2021). Additionally, the proportion of the added value of tertiary industry in GDP was employed to indicate ISU (Liu et al., 2018c).

To minimize the effect of heteroscedasticity and sample dispersion, all variables used in this study were converted into a natural logarithmic form before performing the regression analysis. The value of CSA was increased 100 times before being logarithmized to avoid a biased evaluation caused by negative natural logarithms.

3.3. Data

Panel data from 282 Chinese cities from 2005 to 2020 were used for the empirical analysis in this study. The cities were divided into eastern, central, western, and northeastern regions, according to their geographic locations (Fig. 2). Urban carbon emissions data were derived from the CCG (https://wxccg.cityghg.com). Other statistical data for this study were collected from the China Urban Statistical Yearbook (2006–2021) and China Urban Construction Statistical Yearbook (2005–2020). All currency values were deflated to those at 2005 constant prices.

4. Empirical analysis results

4.1. Baseline regression results

Table 1 presents the regression results. The Hausman test, reported in columns (1) and (2), indicates the appropriateness of the fixed-effects model. Columns (1) and (2), with and without the control variables, respectively, investigate the nonlinear relationship between CSA and CEI. The regression results in columns (1) and (2) show that the coefficients of *lnCSA_e* and ln^2CSA_e were significantly negative and positive, respectively, demonstrating the U-shaped effect of CSA on CEI. Therefore, H1 was validated. Moreover, the inflection point of the U-shaped curve ranged between 5.246 and 5.291, which is within the sample range. Specifically, when CSA is below 1.898, an increase in CSA contributes to a reduction in CEI. Notably, in 2005, CSA in 57.80 % of the sample cities crossed the inflection point, whereas this proportion slightly decreased to 55.67 % in 2020. Moreover, based on the varying trend of CSA during the study period, we predicted the CSA of the sample cities for 2035. The prediction results show that the proportion of cities crossing the inflection point will drop to 54.26 % in 2035. As shown in Fig. 3, the cities crossing the turning point were mainly located in the eastern, central, and northeastern regions in 2005, 2020 and 2035, and the spatial distribution pattern of these cities remained relatively stable during this period.

For the control variables, the coefficients of *lnEL*, *lnUR* and *lnTS* were all negative at the 1 % level, demonstrating that the economic growth, urbanization advancement, and technological support from the government can significantly stimulate CEI reduction. By contrast, the coefficients of *lnOP*, *lnECS*, and *lnFDI* were all significantly positive, showing that the increases in the level of openness, the proportion of coal in total energy consumption, and the ratio of foreign direct investment to GDP increased CEI.

4.2. Robustness test results

4.2.1. Robustness tests for addressing the omitted variable issue and endogenous problem

In many literature, the instrumental variables approach was selected as an ideal approach to tackle the omitted variable issue and endogenous problem. However, it was difficult to find a suitable instrumental variable in our study. Therefore, referring to the existing literature (Bu et al., 2022; Cao et al., 2022), the sensitivity analysis for the omitted variable issue and robustness test for mitigating the endogenous problem were used as alternatives to the instrumental variable approach to address the omitted variable issue and endogenous problem, respectively.

First, the impact threshold of a confounding variable (ITCV) analysis was used as a sensitivity analysis to evaluate how high the correlation between the explanatory variable and dependent variable had to be to alter the benchmark regression results (Busenbark et al., 2022; Cao et al., 2022; Frank, 2000). The estimated results of the ITCV analysis are reported in Table 2. Considering the impact thresholds used in the existing literature (Cao et al., 2022; Hill et al., 2019), the results of *lnCSA_e* and its quadratic term and the six control variables were satisfactory and demonstrated that the effect of CSA on CEI was unlikely to

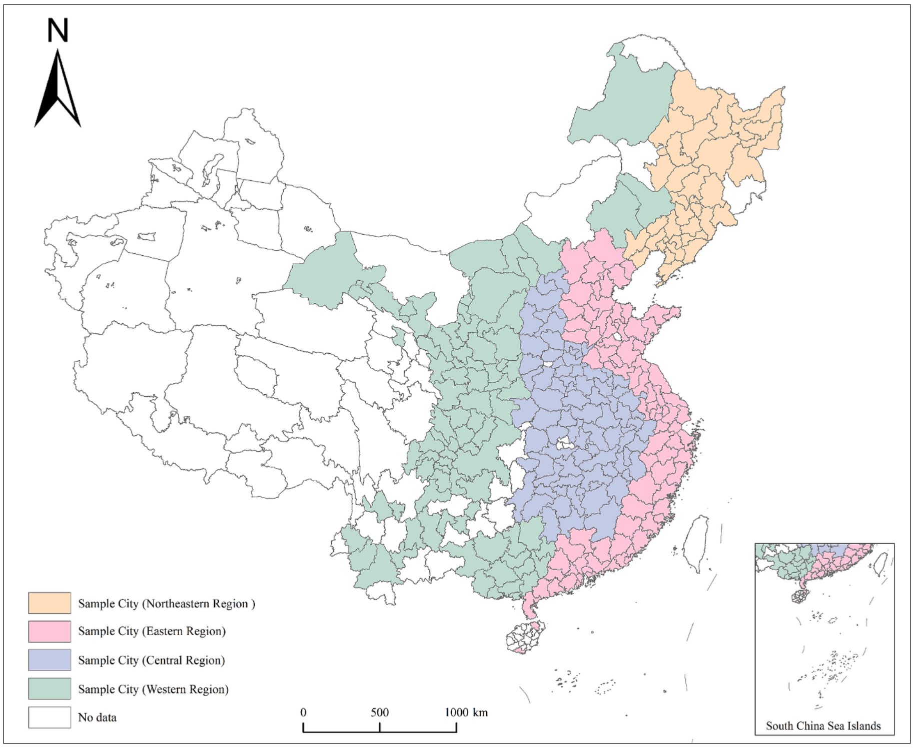

Fig. 2. Location and regional classification of the sample cities.

Table 1
Estimation results of the direct effects of CSA on CEI.

Variable	(1)	(2)
lnCSA_e	−1.217***	−0.640***
	(−9.57)	(−5.96)
ln^2CSA_e	0.115***	0.061***
	(10.72)	(6.68)
lnEL		−0.004***
		(−6.72)
lnUR		−0.383***
		(−12.55)
lnOP		0.103***
		(10.03)
lnECS		1.322***
		(22.02)
lnTS		−0.173***
		(−26.62)
lnFDI		0.012***
		(7.83)
Hausman test	33.60***	144.48***
N	4512	4512
R^2	0.036	0.329

Notes: The data in parentheses is the t-statistic value adjusted for robust standard error. ***, **, and * indicate significance at the 1 %, 5 %, and 10 % levels, respectively.

be driven by a correlated omitted variable. Consequently, the results in the baseline regression are robust.

Second, referring to Bu et al. (2022), Pu and Fei (2022), and Zheng et al. (2023), we treated the dependent variable and six control variables with a one-period lag to mitigate the endogenous problem caused by potential reverse causality. The regression results are shown in columns (1) and (2) in Table 3. We found that CSA maintained a U-shaped effect on CEI, which further verified that the basic regression findings are robust.

4.2.2. *Replacing the regression model for robustness testing*

To validate the robustness of the estimation results, this study explored the impact of CSA on CEI using the Tobit model (columns (3) and (4) in Table 3). The estimation coefficients and significance of *lnCSA_e* and its quadratic term were consistent with the baseline model, which demonstrated a U-shaped effect of CSA on CEI and verified that the benchmark regression findings are robust.

4.2.3. *Replacing the dependent variable for robustness testing*

Considering that the CEI varied significantly owing to the different data sources and accounting methods of urban carbon emissions, we replaced the carbon emissions data with the dependent variable to examine the robustness of the findings in the benchmark regression. Alternative data sources and methods for measuring carbon emissions are presented in Appendix A2. The coefficients of *lnCSA_e* and its quadratic term (columns (5) and (6) in Table 3) were significantly negative and positive, respectively, indicating that the basic regression results were robust.

4.2.4. *Replacing the independent variable for robustness testing*

Concentration ratio is an effective method to measure the absolute concentration of resources and factors across different regions. To verify the robustness of baseline regression results, we further employed the concentration ratio to measure CSA and replaced the independent variable in the baseline regression with it. This new variable was tagged CSA_r. Referring to Wang (2024), Zheng and Lin (2018) and Deng et al. (2020), this study used each city's share of the national total UCL to describe CSA_r. Columns (7) and (8) in Table 3 show that the coefficients of *CSA_r* and its quadratic term were significantly negative and positive, respectively. This demonstrates the robustness of the previous regression results.

4.2.5. *Robustness test for distinguishing between low-carbon and non-low-carbon pilot cities*

Considering that the effect of CSA on CEI may be influenced by low-carbon city pilot programs, a dummy variable (set to 1 if the city was incorporated into the pilot; otherwise 0) was added to the benchmark regression model (Jia et al., 2021; Yan and Huang, 2022). The list of

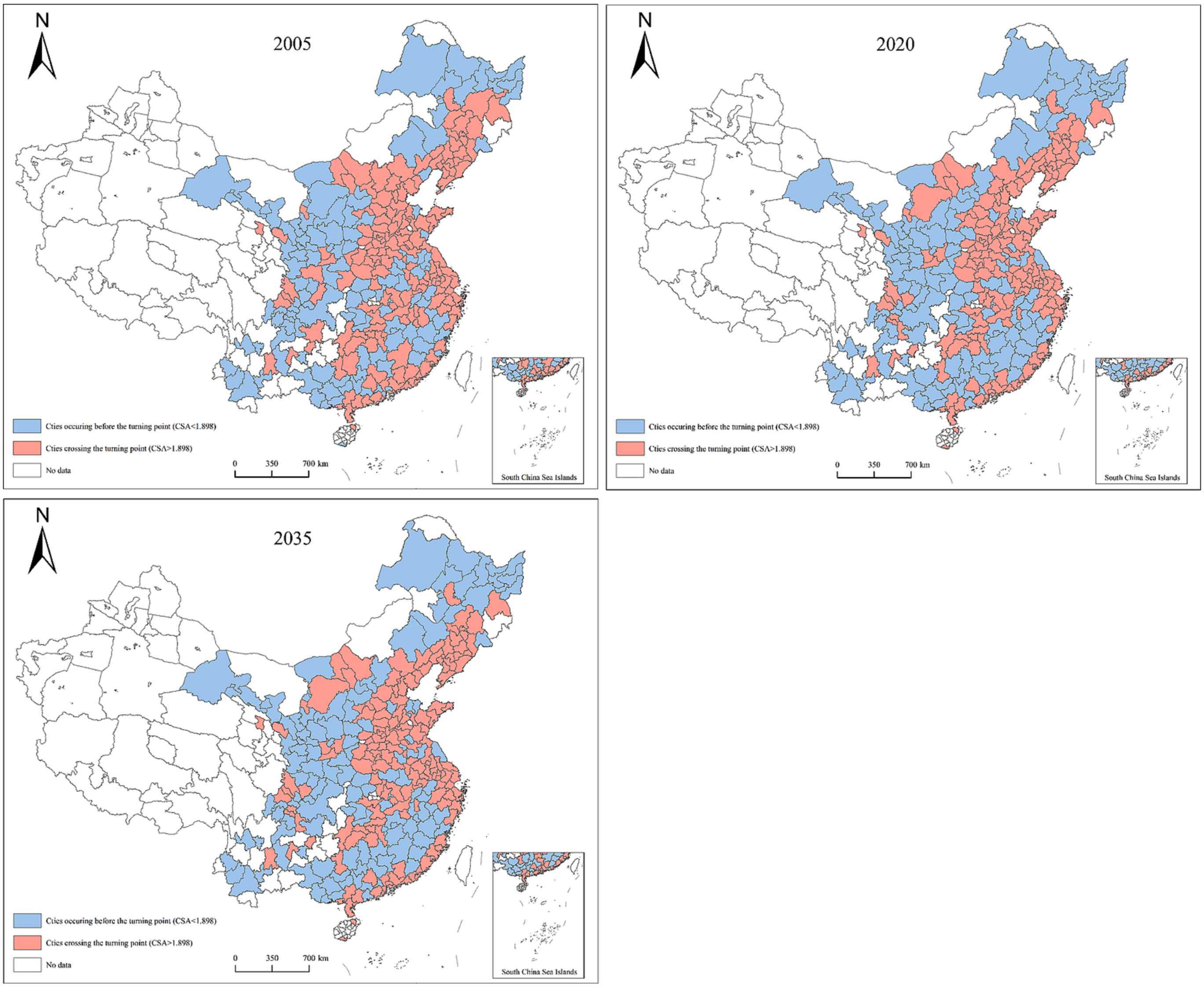

Fig. 3. Spatial distribution of cities crossing the turning point in 2005, 2020, and 2035.

Table 2
Impact Threshold for a Confounding Variable (ITCV).

Variable	*lnCSA_e*	*ln²CSA_e*	*lnEL*	*lnUR*	*lnOP*	*lnECS*	*lnTS*	*lnFDI*
% Bias threshold	69.78 %	67.48 %	69.61 %	84.37 %	80.49 %	89.45 %	92.47 %	68.42 %
ITCV	0.074	0.067	0.073	0.170	0.131	0.261	0.363	0.069
Square root of ITCV	0.272	0.258	0.271	0.412	0.362	0.511	0.603	0.263

low-carbon pilot cities is shown in Appendix A3. Columns (9) and (10) in Table 3 show the estimation results. The results indicate that the relationship between CSA and CEI followed a U-shaped pattern after considering the influence of low-carbon city pilot programs, which verifies the robustness of the benchmark regression results.

4.3. Heterogeneity analysis results

4.3.1. Economic development heterogeneity analysis

Considering the differences in production factor agglomeration, human resources, technological development, and environmental awareness among cities with different levels of economic development (Li et al., 2017; Wang et al., 2016), CSA may have heterogeneous effects on CEI across cities. Therefore, based on the average GDP per capita during 2005–2020, cities were classified as developing regions if their GDP per capita was in the bottom 50 %; the remaining cities were categorized as developed regions. The regression results for the developed and developing regions are presented in Table 4. Column (2) illustrates that the coefficients for *lnCSA_e* and ln^2CSA_e in the developed region are −0.651 and 0.059, respectively ($p < 0.01$ for both). Column (4) shows that the coefficients for *lnCSA_e* and ln^2CSA_e in the developing region are −0.595 and 0.059, respectively ($p < 0.05$ for both). These findings reveal that the relationship between CSA and CEI follows a U-shaped pattern in both the developed and developing regions. The absolute values of the coefficients of *lnCSA_e* and ln^2CSA_e in the developed region are greater than those in the developing region, suggesting that CSA had a stronger effect on the CEI in the developed region, regardless of whether it exceeded the turning point. Additionally,

Table 3
Robustness test results.

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
lnCSA_e	0.069***	−0.599***	0.045***	−0.240**	−0.045**	−0.534***			0.046***	−0.458***
	(4.08)	(−5.39)	(3.11)	(−2.56)	(−2.55)	(−4.81)			(2.96)	(−4.50)
ln^2CSA_e		0.057***		0.025***		0.042***				0.043***
		(6.09)		(3.07)		(4.46)				(5.01)
CSA_r							−0.108***	−0.142***		
							(−7.11)	(−5.95)		
$(CSA\_r)^2$								0.002*		
								(1.86)		
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.320	0.327			0.326	0.330	0.210	0.211	0.397	0.401
N	4230	4230	4512	4512	4512	4512	4512	4512	4512	4512

Notes: The data in parentheses is the t-statistic value adjusted for robust standard error. ***, **, and * indicate significance at the 1 %, 5 %, and 10 % levels, respectively.

Table 4
Regression results of economic development heterogeneity analysis.

Variable	Developed region		Developing region	
	(1)	(2)	(3)	(4)
lnCSA_e	0.064**	−0.651***	0.003*	−0.595**
	(2.53)	(−2.89)	(1.55)	(−4.71)
ln^2CSA_e		0.059***		0.059**
		(3.19)		(5.44)
Controls	Yes	Yes	Yes	Yes
R^2	0.418	0.420	0.517	0.237
N	2256	2256	2256	2256

Notes: The data in parentheses is the t-statistic value adjusted for robust standard error. ***, **, and * indicate significance at the 1 %, 5 %, and 10 % levels, respectively.

the inflection points in the developed and developing regions were 5.517 and 5.042, respectively, indicating that the inflection point in the developed region occurred later than that in the developing region. This result reveals that the enhancement of economic development level could help to delay the turning point to a certain extent, thereby allowing for a fuller leveraging of CSA's carbon reduction effect.

4.3.2. Regional heterogeneity analysis

Considering the heterogeneity of the natural environment, socioeconomic development, and national policy support across regions, the relationship between CSA and CEI may also vary across regions. Therefore, the sample cities were classified into eastern, central, western, and northeastern regions based on their geographic location (Xie et al., 2022). As shown in columns (2), (4), and (6) of Table 5, the coefficients of *lnCSA_e* for the eastern, central, and western regions were all significantly negative, while those of *ln^2CSA_e* for these regions were significantly positive. This suggests a U-shaped relationship between CSA and CEI in these regions. Moreover, the regression results show that the inflection point of the U-shaped curve was the largest in the eastern region (5.904), followed by the central region (5.604) and the western region (4.994). However, in the northeastern region, CSA significantly increased CEI throughout the study period. The main reason for this may be that in this region, the industrial structure has long been dominated by the secondary industry, and the enterprises are mainly concentrated on resource-intensive industries. The enhancement of CSA may promote the spatial agglomeration of resource-intensive industries in this region, thereby increasing CEI.

4.3.3. Heterogeneity analysis of resource- and non-resource-based cities

The heterogeneity in industrial structure, development model, and development status between resource-dependent and non-resource-dependent cities may lead to a significant difference in the impact of CSA on the CEI in these two areas. To explore this heterogeneity, the 282 cities in the sample were grouped into resource- and non-resource-based cities according to the National Sustainable Development Plan for Resource-Based Cities (2013–2020). The results of the heterogeneity analysis between the two groups are presented in Table 6. As shown in column (2), the coefficients of *lnCSA_e* and *ln^2CSA_e* in resource-based cities are −0.292 ($p < 0.10$) and 0.036 ($p < 0.01$), respectively. These

Table 6
Regression results of heterogeneity analysis for resource- and non-resource-based cities.

Variable	Resource-based cities		Non-resource-based cities	
	(1)	(2)	(3)	(4)
lnCSA_e	0.117***	−0.292*	0.037**	−0.685***
	(4.12)	(−1.95)	(2.08)	(−4.78)
ln^2CSA_e		0.036***		0.060***
		(2.78)		(5.08)
Controls	Yes	Yes	Yes	Yes
R^2	0.331	0.335	0.463	0.469
N	1824	1824	2688	2688

Notes: The data in parentheses is the t-statistic value adjusted for robust standard error. ***, **, and * indicate significance at the 1 %, 5 %, and 10 % levels, respectively.

Table 5
Results of regional heterogeneity analysis.

Variable	Eastern region		Central region		Western region		Northeastern region	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
lnCSA_e	0.015	−0.307*	0.065**	−0.807***	−0.038	−0.889***	0.235***	−0.326
	(0.79)	(−1.69)	(2.44)	(−3.65)	(−0.77)	(−4.41)	(5.01)	(−0.92)
ln^2CSA_e		0.026*		0.072***		0.089***		0.048
		(1.78)		(3.97)		(4.35)		(1.60)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.487	0.488	0.596	0.601	0.270	0.281	0.385	0.388
N	1376	1376	1280	1280	1312	1312	544	544

Notes: The data in parentheses is the t-statistic value adjusted for robust standard error. ***, **, and * indicate significance at the 1 %, 5 %, and 10 % levels, respectively.

findings indicate that CSA exhibited a U-shaped effect on CEI in resource-based cities. The regression results in column (4) show that the coefficients of *lnCSA_e* and *ln²CSA_e* for non-resource-based cities are −0.685 and 0.060 respectively ($p < 0.01$ for both). This demonstrates a U-shaped relationship between CSA and CEI in non-resource-based cities. Moreover, the estimated results in columns (2) and (4) suggest that the effect size and turning point in non-resource-based cities were greater than those in resource-based cities. These results reveal that resource-dependent cities have smaller UCL carrying capacity due to their relatively single industrial structure and excessive reliance on resource extraction industries. Additionally, the reasonable control of CSA has a stronger effect on the CEI reduction in non-resource-dependent cities, as compared to resource-dependent cities.

4.4. Mediating effect analysis results

To understand the internal mechanism of how CSA affects CEI scientifically and comprehensively, a nonlinear mediating effect model was applied to examine the mediating effects of the three mediating variables (EA, TI, and ISU). The results are reported in Table 7. Specifically, columns (1) and (2) summarize the mechanism analysis of EA. The mediating effect analysis of TI is presented in columns (3) and (4). Columns (5) and (6) present the regression results for the mediating effect test for ISU.

In columns (1), (3), and (5), all the regression coefficients of *lnCSA_e* are significantly positive, and those of *ln²CSA_e* are significantly negative. These results indicate that CSA had an inverted U-shaped effect on EA, TI, and ISU. The results in columns (2), (4), and (6) reveal that EA, TI, and ISU can generally restrain CEI, and the relationship between CSA and CEI remained valid after considering the influence of these mediating variables on CEI. Accordingly, EA, TI, and ISU are partial mediating variables between CSA and CEI. Thus, H2a, H2b, and H2c were confirmed.

4.5. Results of spatial spillover effect analysis

The SDM was adopted to examine the spatial spillover effect of CSA on the CEI (the model selection process is displayed in Appendix A4). As the coefficients of the SDM regression results cannot reflect the marginal impact of CSA, this influence is divided into direct effects and indirect effects (LeSage, 2009). The spatial spillover regression results for the linear and nonlinear relationships between CSA and CEI before and after adding the control variables are presented in Table 8. The spatial models' results were consistent with those of the non-spatial models. In column (4), the regression results indicate that *lnCSA_e* has a negative direct effect on *lnCEI*, with a coefficient of −0.249 at the 1 % significance level, while *ln²CSA_e* exhibits a positive direct effect with a coefficient of 0.019 at the same significance level. The indirect effects of *lnCSA_e* and *ln²CSA_e* are also negative and positive respectively with estimated coefficients of −2.414 and 0.191 at the significance level of 1 %. These suggest that CSA had a U-shaped effect on both the local CEI as well as that of surrounding cities through the spatial spillover effect. Furthermore, the indirect effects of CSA and its quadratic term were stronger than their direct effects, respectively. These results were validated through a series of robustness tests (Appendix A5). Therefore, H3 was verified.

Table 8
Regression results of the spatial spillover effect analysis.

Variables	(1)	(2)	(3)	(4)
lnCSA_e	0.025*	0.020*	−0.249***	−0.151*
	(1.86)	(1.67)	(−2.85)	(−1.78)
ln²CSA_e			0.024***	0.012*
			(3.22)	(1.65)
*W*lnCSA_e*	0.052*	0.030	−1.760***	−1.320***
	(1.65)	(0.97)	(−7.35)	(−5.51)
*W*ln²CSA_e*			0.154***	0.105***
			(7.64)	(5.14)
p	0.775***	0.758***	0.736***	0.447***
	(68.97)	(64.86)	(58.85)	(23.01)
Direct effect				
lnCSA_e	0.038**	0.029*	−0.556***	−0.249***
	(2.48)	(1.86)	(−5.67)	(−2.80)
ln²CSA_e			0.051***	0.019***
			(6.12)	(2.59)
Indirect effect				
lnCSA_e	0.299**	0.191*	−6.960***	−2.414***
	(2.41)	(1.65)	(−8.96)	(−6.16)
ln²CSA_e			0.616***	0.191***
			(9.63)	(5.73)
Total effect				
lnCSA_e	0.337**	0.219*	−7.515***	−2.663***
	(2.56)	(1.78)	(−9.16)	(−6.39)
ln²CSA_e			0.666***	0.211***
			(9.84)	(5.90)
Controls	No	Yes	No	Yes
R^2	0.187	0.168	0.316	0.535
N	4512	4512	4512	4512

Notes: The data in parentheses is the t-statistic value adjusted for robust standard error. ***, **, and * indicate significance at the 1 %, 5 %, and 10 % levels, respectively.

Table 7
Estimation results of the mediating effect analysis.

Variable	(1)	(2)	(3)	(4)	(5)	(6)
	lnEA	*lnCEI*	*lnTI*	*lnCEI*	*lnISU*	*lnCEI*
lnCSA_e	0.200*	−0.574***	3.910***	−0.304**	0.303***	−0.510***
	(1.79)	(−6.38)	(8.77)	(−3.00)	(5.73)	(−4.84)
ln²CSA_e	−0.053***	0.035***	−0.355***	0.030***	−0.027***	0.049***
	(−5.64)	(4.64)	(−9.43)	(3.52)	(−6.15)	(5.48)
lnEA		−0.588**				
		(−51.64)				
lnTI				−0.086***		
				(−24.79)		
lnISU						−0.429***
						(−14.05)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.276	0.530	0.268	0.414	0.136	0.359
N	4512	4512	4512	4512	4512	4512

Notes: The data in parentheses is the t-statistic value adjusted for robust standard error. ***, **, and * indicate significance at the 1 %, 5 %, and 10 % levels, respectively.

5. Discussion

5.1. Boundary of carbon reduction effect of CSA on CEI

Under the "new normal" conditions of economic development and the goal of "double carbon" in China, it is critical to optimize the spatial allocation of UCL across cites to keep CSA within a reasonable range. In recent years, the central government has assigned new UCL to underdeveloped cities to support their development and narrow the economic disparity between underdeveloped and developed cities. Some scholars have noted that this allocation strategy will lead to a spatial dispersion and efficiency loss in UCL, and that more new UCL should be assigned to developed cities with high CSA levels to increase the overall utilization efficiency and allocation efficiency of UCL (Li and Wang, 2015). Nevertheless, this study revealed that CSA across cites has a significant U-shaped effect on CEI, suggesting that CSA cannot increase without constraints and that it also has an optimal scale. These findings are similar to the conclusions of Zhong et al. (2023), who found that the spatial concentration of UCL has a U-shaped effect on carbon emissions per unit of construction land area in China's provincial-level regions. Moreover, we found that 57.80 % and 55.67 % of the sample cities crossed the turning point in 2005 and 2020, respectively. According to the Action Plan for Carbon Dioxide Peaking Before 2030, China aims to reduce its CEI by 65.00 % from 2005 to 2030. Based on the varying trend of CSA and CEI during the study period of 2005 to 2020, we predicted the CSA and CEI of the sample cities in 2030. The prediction results indicate that the proportion of cities crossing the inflection point will decrease to 53.90 % in 2030, and the average CEI of the study area will decrease by 67.93 % in 2030 compared to 2005. Therefore, as long as the government ensures that CSA maintains its current trend of change and the proportion of cities crossing the inflection point does not exceed 53.90 % in 2030, China's urban carbon emission reduction target for 2030 can be achieved.

5.2. CSA has heterogeneous effect on CEI

The heterogeneity analysis results reveal that CSA had heterogeneous effects on CEI across regions. Specifically, in terms of economic development heterogeneity, we observed a U-shaped relationship between CSA and CEI in both the developed and developing regions. However, the effect size and inflection point in the developed region were both greater than those in the developing region. Therefore, improving the economic development level is an effective way to fully leverage the carbon reduction effect of CSA and delay the inflection point. Regional heterogeneity analysis shows that CSA had a U-shaped effect on CEI in the eastern, central, and western regions. However, in the northeastern region, CSA significantly enhanced CEI over the study period, mainly because this region is overly dependent on the secondary industry, particularly heavy and resource-intensive industries. Therefore, it is imperative for this region to optimize and upgrade its industrial structure and eliminate outdated production capacity. Moreover, both resource- and non-resource-based cities demonstrated a U-shaped relationship between CSA and CEI. However, the magnitude and inflection point of this U-shaped effect were much greater in non-resource-dependent cities compared to resource-based cities. Therefore, reducing reliance on resource-intensive industries and promoting industrial transformation and advancement are beneficial for releasing CSA's carbon reduction effect.

5.3. EA, TI, and ISU strongly mediate between CSA and CEI

The results of the mediating effect analysis showed that CSA affects CEI through EA, TI, and ISU. Specifically, EA significantly promoted the CEI reduction, which is consistent with the results of Chen et al. (2023). We found that CSA had an inverted U-shaped effect on EA, indicating that the positive effect of CSA on EA had a certain boundary. Excessive CSA blocked EA and even led to the spatial dispersion of economic activities resulting from agglomeration diseconomies. In terms of TI, our study demonstrated its positive contribution to decreasing the CEI, which is in accordance with the conclusions drawn by Huang et al. (2018). The U-shaped relationship between CSA and TI indicates that a moderately centralized allocation of UCL can stimulate TI, whereas excessive CSA may impede the urban innovation environment and innovation vitality, thus hindering technological advancement. ISU significantly promoted a CEI reduction over the study period, similar to the findings of Wang et al. (2019). This study indicates that a moderate CSA can effectively upgrade industrial structure. This is mainly because CSA improvements will increase the demand for tertiary industry by stimulating the growth and agglomeration of population and promoting industrial structure optimization through knowledge sharing and technology spillover. However, excessive CSA significantly restrains ISU owing to competition for industry homogenization.

5.4. Local CSA influences the CEI in neighboring regions through the spatial spillover effect

The results of the spatial spillover effect analysis confirm the existence of a spatial spillover effect through which CSA exerts a U-shaped effect on the CEI of adjacent cities. The main reason for this phenomenon may be that a moderate spatial concentration of UCL can indirectly promote human capital accumulation and the agglomeration of economic activities in nearby cities through industrial specialization and diffusion, infrastructure sharing, and knowledge and technology spillover; this may therefore promote economic growth and CEI reduction in these areas (Garrone and Grilli, 2010; Yan et al., 2022b). However, when CSA exceeds a certain level, the local congestion effect caused by the over-concentration of UCL may generate a crowding effect in neighboring regions due to disordered competition and the shift of population and enterprises with high energy consumption and carbon emissions among neighboring cities, thereby increasing their CEI (Yuan et al., 2020).

5.5. Limitations and future research

This study has some limitations that should be addressed in future research. First, owing to the lack of sufficient and official statistics for some prefecture-level cities in China (e.g., Wenchang and Linzhi), our sample was limited to 282 prefecture-level cities. However, the sample cities in this study covered most prefecture-level cities in China (nearly 95 %), which can comprehensively reflect the socio-economic development and the relationship between CSA and CEI in Chinese cities (Hu et al., 2023c; Xie et al., 2022). If relevant data becomes available, more cities can be included in future research. Second, although there are complex and multiple relevant factors influencing CSA and CEI, we captured only the primary relevant factors. Additional influencing factors may be captured in future studies. Third, the mechanism analysis revealed that EA, TI, and ISU have partial mediating effects on the impact of CSA on CEI, indicating that the transmission channels of CSA that affect CEI are very complex. Therefore, several mediating variables were not covered in this study. Future research may consider additional intermediary variables to further explore the transmission mechanisms underlying the relationship between CSA and CEI. Furthermore, due to the lack of effective methods to measure the mediating effects of the mediating variables and their proportion of the total effect in the two-step nonlinear mediating effect model, this study did not calculate them. If a feasible method becomes available in the future, we will further evaluate the size of the mediating effects of EA, TI, and ISU on CEI to provide a clearer understanding of their contribution to the overall mechanism.

Fourth, this study did not investigate the marginal effects of CSA on CEI. The effect of CSA on CEI may vary with the levels of CSA, CEI, and economic development. Overlooking this heterogeneous characteristic of the relationship between CSA and the CEI may lead to deviations in the estimation results and policy formation. Future studies could employ a quartile regression to analyze the marginal effects of CSA on the CEI at different points along the distribution. Fifth, this study only explored the overall heterogeneity among regions during the study period. The temporal variation in this heterogeneity and its policy implications need to be further explored in future research. Sixth, based on the data from Chinese cities, this study provided Chinese evidence for the relevant theoretical exploration and empirical study. Although the applicability of the findings for other countries requires further examination, this study could provide empirical support for the spatial allocation and scale control of UCL in countries such as Japan and Vietnam, where land planning is mainly controlled by the government. Additionally, this research has reference value for urban scale control and carbon reduction in other countries or regions.

6. Conclusions and policy implications

6.1. Conclusions

We systematically investigated the effect of CSA across cities on CEI and its intrinsic mechanism from the national perspective by using fixed and mediating effects and SDM models, based on panel data for 282 Chinese cities from 2005 to 2020. This study ultimately drew four key conclusions.

(1) CSA exerts a significant U-shaped effect on CEI, as confirmed by robustness tests. During the study period, the proportion of cities that crossed the inflection point presented a slight downward trend, from 57.80 % in 2005 to 55.67 % in 2020. Moreover, the spatial distribution pattern of these cities remained relatively stable. It is predicted that this proportion will decrease to 53.90 % in 2030, and the average CEI of these cities will decrease by 67.93 % in 2030 compared to 2005. Under such circumstance, China's target to reduce CEI by 65.00 % from 2005 to 2030 can be achieved in the sample cities. Therefore, the strategic adjustment of the spatial allocation strategy for UCL across cities to maintain CSA within a reasonable range is very important for China's carbon emission reduction efforts.

(2) The relationship between CSA and CEI has a notable heterogeneity that varies based on the economic development level, geographical region, and dependence on resource-based industries. In the northeastern region, CSA had a significant positive effect on CEI, whereas it followed a U-shaped pattern in other regions. This effect was stronger in the developed and central regions and non-resource-based cities than in the developing and eastern and western regions as well as resource-based cities. Moreover, the turning point occurred later in the developed and eastern regions and non-resource-based cities than in the others. Consequently, overlooking the spatiotemporal heterogeneity of this effect may make it difficult to establish and implement targeted policies to optimize UCL allocation and reduce CEI.

(3) EA, TI, and ISU were important partial mediating variables between CSA and CEI. In summary, CSA affects CEI indirectly through these mediating variables. This suggests that the transmission mechanisms of CSA on CEI are relatively complicated, and a comprehensive understanding of these mechanisms is conducive to formulating more comprehensive policies.

(4) The spatial spillover effect analysis revealed that CSA has a U-shaped effect on CEI in both local and adjacent cities. Therefore, when allocating UCL and developing policies to reduce the CEI, it is important to consider spatial spillover effects. These findings provide further evidence of cross-city cooperation in CEI reduction.

6.2. Policy implications

(1) Given the U-shaped relationship between CSA and CEI in China, cities must grasp the "turning point" in the process of reducing CEI. Therefore, land management departments should scientifically evaluate and accurately predict the UCL demand of each city, and then optimize the spatial allocation strategies of UCL across cities to promote its moderate concentration and avoid the crowding effect produced by excessive CSA. As CSA and CEI continue to change, great attention needs to be paid to the dynamic adjustment of UCL allocation policy. As for cities whose CSA occurs before the turning point, they could improve infrastructure and public service construction to attract the inflow of various production factors to maximize the carbon reduction effect of CSA and production factor agglomeration. As for cities whose CSA has already crossed the turning point, on the one hand, they should strictly control UCL expansion to avoid the further enhancement of CSA and take multiple measures to promote the development and application of low-carbon technologies; on the other hand, they should eliminate backward production capacity and transfer out low-end industries to make room for new industries to optimize industrial structure and accelerate low-carbon transformation.

(2) Since the effect of CSA on CEI is clearly heterogeneous, the government should tailor UCL allocation strategies and CSA management strategies for each city based on its development stage, economic development level, resource and environment carrying capacity. Considering that the turning point in the developing region occurred earlier than in the developed region, the developing region should both strictly control UCL expansion to keep CSA within a reasonable range, and accelerate sustainable and stable economic growth to delay the turning point in this region. As CSA significantly enhanced CEI in the northeastern region during the study period, the region should further promote the Northeast revitalization strategy, upgrade traditional industries, eliminate backward production capacity, strengthen the research and application of production technology and low-carbon technology, thereby improving the quality and efficiency of economic growth. Since the magnitude and inflection point of the U-shaped effect were smaller in resource-based cities than those in non-resource-based cities, it is therefore imperative for resource-based cities to reduce their dependence on natural resource and resource extraction industries, achieve industrial transformation and upgrading, and advance low-carbon technology innovation.

(3) The mediating effect analysis showed that the potential mechanisms by which CSA affects CEI are complex and diverse. Therefore, policymakers should integrate the spatial allocation of UCL across cities and its underlying mechanisms into a unified system and establish a comprehensive policy system. Moreover, our results demonstrated that EA, TI, and ISU can effectively reduce CEI, and CSA exerts an inverted U-shaped effect on these variables. Therefore, excessive CSA should be avoided to prevent its negative impact on mediating variables and CEI. Simultaneously, it is recommended to implement systematic and comprehensive measures to promote the moderate agglomeration of economic activities, advancement of production and low-carbon technologies, and green upgrading of industries and products, thus accelerating the fulfillment of carbon reduction targets. Specifically, the department concerned should improve public infrastructure and public service capacity, and provide more preferential policies to attract the inflow of advanced and high-quality production factors as well as innovative and environmentally friendly enterprises. It is suggested that more support and incentives be provided in areas such as funding, taxation, and land rent to encourage innovative enterprises to

accelerate green low-carbon innovations. Furthermore, it is necessary for the government to efficiently control land and housing prices to avoid the crowding-out effect of excessively high prices on innovative enterprises and talents.

(4) Considering the spatial spillover effect of CSA on CEI, it is crucial to establish a cross-regional collaboration mechanism for carbon emission reduction and ensure the coordinated implementation of cross-regional carbon reduction programs. Based on the contradiction between UCL supply and demand in various cities, the central government should expedite the market-based allocation of UCL and explore the establishment of a nationwide interregional trading mechanism for a UCL quota. This would optimize the spatial allocation of UCL, guide the rational flow of production factors, and fully leverage the carbon reduction potential of CSA, thereby contributing to the achievement of national carbon reduction targets. Moreover, an orderly industrial transfer, population migration, and the establishment of cross-city industrial parks are also effective in mitigating the negative effects of excessive CSA on carbon emission reduction.

CRediT authorship contribution statement

Hui Yang: Writing – original draft, Project administration, Methodology, Investigation. **Cheng Chen:** Writing – review & editing, Conceptualization. **Jingye Li:** Writing – review & editing, Visualization, Funding acquisition. **Min Li:** Writing – review & editing, Methodology. **Stefan Sieber:** Writing – review & editing, Software. **Kaisheng Long:** Writing – review & editing, Supervision, Project administration.

Declaration of competing interest

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

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Appendix A. Supplementary data

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Data availability

Data will be made available on request.

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