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Impact of land resource misallocation on carbon emission efficiency: empirical evidence from 274 cities in China

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Introduction: With the acceleration of urbanization and the implementation of the "dual carbon" goals, the impact of Land Resource Misallocation (LRM) on Urban Carbon Emission Efficiency (UCEE) has attracted increasing attention.

Methods: Based on panel data from 274 Chinese cities during the period 2010–2022, we constructed a LRM index and employed a two-way fixed-effects model to empirically analyze the relationship between LRM and UCEE.

Results: The results revealed that LRM significantly hindered the improvement of carbon emissions efficiency in cities. The mechanism analysis indicates that this negative effect is primarily transmitted through the obstruction of Industrial Structure Upgrading (ISU) and Green Technological Innovation (GTI). Further, regional heterogeneity tests showed that the suppressive effect was more pronounced in the central and western regions, small- and medium-sized cities, and non-resource-based cities.

Discussion: In terms of policy implications, deepening market-oriented reforms of the land system, optimizing land use structures, reducing administrative intervention in land allocation, and simultaneously promoting industrial upgrading and GTI to enhance UCEE are recommended.

KEYWORDS

land resource misallocation, urban carbon emission efficiency, industrial structure upgrading, green technological innovation, panel data analysis

1 Introduction

Global warming poses an unprecedented challenge to sustainable development, and the urgency to reduce greenhouse gas (GHG) emissions never increased. Rapid urbanization and industrialization, especially in developing economies, significantly intensified energy consumption and carbon emissions (Abbasi et al., 2020). Although cities occupy only a small proportion of the Earth's surface, their energy use contributes approximately 70% of global CO_2 emissions (Luqman et al., 2023). Therefore, improving Urban Carbon Emission Efficiency (UCEE) (i.e., achieving greater economic and social output while reducing carbon emissions) has become a key strategy for addressing climate change and maintaining economic growth. Enhancing urban carbon emission efficiency is crucial not only for achieving global climate goals such as those outlined in the Paris Agreement but also for promoting sustainable urban development (Fan and Xu, 2025). This is particularly relevant for China, which, despite significant progress in deploying renewable energy in recent years, has also become one of the largest carbon emitters globally (Raihan and Bari, 2024; Wang et al., 2024). China pledged to reach peak carbon emissions by 2030 and achieve carbon neutrality by 2060 (Zhang et al., 2023; Zhang H. et al., 2024). Achieving this transformation requires a fundamental decoupling of economic growth from carbon emissions, which, in turn, requires significant improvements in carbon efficiency across all sectors of the urban economy. Carbon emission efficiency generally reflects the effectiveness with which an economy or city generates output or achieves development goals per unit of carbon emissions (Chen et al., 2025). Quantitatively, carbon emission efficiency is often expressed as the ratio of economic output (or other benefit indicators) to carbon emissions or inversely as the carbon intensity of economic activities (Li et al., 2024). A higher UCEE implies that a city produces more GDP, services, or social welfare per ton of CO_2 emitted, indicating a higher degree of sustainable, low-carbon development. Therefore, enhancing the urban carbon emission efficiency is critical for achieving emission reductions while sustaining socioeconomic progress (Zhang Y. et al., 2024).

Numerous studies explored the determinants of UCEE. Technological innovation and energy structure are frequently identified as key drivers. For instance, clean energy and advanced technologies can significantly enhance efficiency by reducing carbon emissions per unit of energy use or output (Miao et al., 2024). Similarly, industrial structure plays an important role: cities dominated by high-tech industries and services typically exhibit better carbon efficiency than those centered on heavy industry because of the lower emissions of the tertiary sector (Zhang H. et al., 2024). Robust environmental policies and regulations can also improve the UCEE by promoting energy conservation and emission control. Recent analyses of Chinese cities show that stricter environmental regulations and lower energy intensity (energy use per unit GDP) are significantly associated with higher carbon efficiency, emphasizing the importance of governance and green investment (Zhang H. et al., 2024). Summarily, existing literature suggests that technological, structural, and policy-related factors jointly contribute to improvements in UCEE.

However, one critical factor was overlooked in the discussion on urban carbon efficiency, namely, the role of urban land use and allocation. The spatial distribution of land across different uses and cities may also substantially affect carbon emissions (Wen et al., 2025). Urban form and land use patterns fundamentally shape energy demand and emissions. For example, unplanned urban sprawl often leads to increased vehicle use and higher *per capita* emissions, while compact, well-planned cities enable more efficient infrastructure and lower carbon footprints (Abbasi et al., 2020). Studies emphasize that optimizing urban spatial structures (e.g., promoting polycentric layouts and higher density) can enhance carbon efficiency by reducing travel distances and conserving land resources (Fan and Xu, 2025). These findings suggest that urban planning and land management are crucial for achieving emission reduction goals. Furthermore, in many emerging economies, land is not fully allocated through market forces, although it is heavily influenced by government policies and institutional arrangements (Wen et al., 2025). This often results in Land Resource Misallocation (LRM), in which the distribution of land across industrial, commercial, and residential uses deviates from economically efficient or environmentally optimal patterns. China is a typical case in which land ownership is shared between the state and collectives, giving governments the dominant authority over land allocation. Land use has become a critical policy instrument for stimulating economic growth. Under the "land-for-development" strategy, local governments tend to allocate large portions of urban land to industrial uses at artificially low prices to attract manufacturing investment and boost GDP (Han and Huang, 2022). While this approach has fueled rapid industrialization, it has also led to inefficient urban layouts such as oversized and underutilized industrial parks. This reflects an imbalance in land use and a misallocation of land resources away from potentially more efficient or higher-value applications (Han and Huang, 2022). For example, land misallocation results in higher emissions and lower efficiency. Using data from Chinese cities, Han and Huang (2022) found that land misallocation, especially overallocation to industrial land, significantly increases urban carbon emissions. Their analysis suggests that this effect operates through multiple channels: land misallocation hampers industrial upgrading, inhibits technological innovation, and undermines the benefits of economic agglomeration, thereby locking cities into inefficient, high-carbon development paths (Han and Huang, 2022). Similarly, Zhou et al. (2022) directly confirmed the adverse effects of land resource misallocation on urban carbon emission efficiency. They reported that cities with higher degrees of misallocation tend to have significantly lower carbon efficiency, implying that poor land allocation results in higher total emissions and lower economic output per unit of carbon (Zhou et al., 2022).

Although the academic community has gradually begun to explore the relationship between LRM and UCEE, this field is still in its infancy, with several important knowledge gaps yet to be addressed. For example, whether land misallocation is a significant determinant of urban carbon emission efficiency has not been fully examined or empirically validated in the existing literature (Gao and He, 2024). Furthermore, the underlying mechanisms through which land misallocation affects carbon efficiency are poorly understood. Much of the empirical literature focuses on either the direct impact of the industrial structure on emissions or treats the industrial structure as a mediating variable for other factors (Gao and He, 2024; Cheng Y. et al., 2025; Xue et al., 2025), neglecting its potential role as a transmission mechanism linking land misallocation and urban carbon efficiency. While some studies explored the relationship between land misallocation and green technological innovation (Xu et al., 2025), a lack of research still exists on the mediating pathway of "Land Resource Misallocation–Green Technological Innovation–Urban Carbon Emission Efficiency," which overlooks the crucial role that green innovation may play in this linkage (Nan et al., 2022).

Therefore, we examined the impact of LRM on UCEE, identified whether misallocation is a key determinant, and uncovered its transmission mechanism. Using panel data from 274 prefecture-level cities in China between 2010 and 2022, we constructed a two-way fixed-effects model to empirically assess the relationship between LRM and carbon emission efficiency. The results show that land misallocation significantly inhibits improvements in carbon emissions efficiency, and robustness checks confirm the validity of the baseline findings. These empirical results

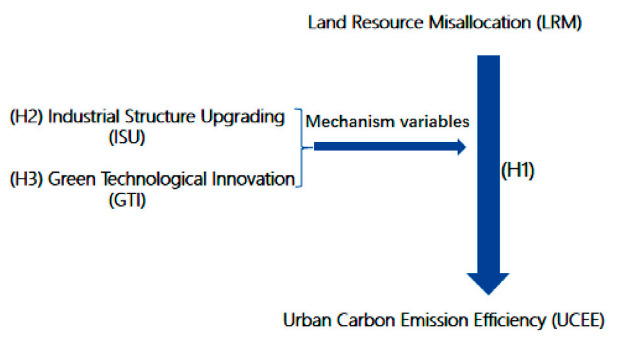

FIGURE 1
Conceptual framework.

contribute to the literature by addressing a previously overlooked dimension in environmental economics—highlighting LRM as a significant factor influencing UCEE. The mechanism analysis reveals that LRM impedes carbon efficiency, primarily by suppressing Green Technological Innovation (GTI) and hindering Industrial Structure Upgrading (ISU). The identification of these two mediating variables confirms that ISU and GTI play pivotal roles in the transmission mechanism through which land misallocation affects UCEE. This finding not only enriches the theoretical framework of the mechanism but also addresses a significant gap in the existing literature. Heterogeneity analysis further showed that this inhibitory effect was more pronounced in the central and western regions, small- and medium-sized cities, and non-resource-based cities. We verified the robustness of our findings by replacing the core explanatory variable with the ratio of land transfer revenue to urban construction land area. Additionally, we address endogeneity concerns using the interaction term between the average urban terrain slope and the annual economic growth target of the city as an instrumental variable, and the conclusions remain robust. The use of this instrumental variable strengthens the validity of causal identification in assessing the effect of LRM on UCEE, thus contributing to the methodological literature by addressing endogeneity concerns that have been largely overlooked in prior studies. These findings confirm the rigorous identification of LRM as an important determinant of urban carbon emissions efficiency.

The remainder of this paper is organized as follows. Section 2 develops the theoretical framework and research hypotheses; Section 3 describes the data, variables, and empirical model; Section 4 presents and discusses the empirical results; Section 5 concludes with key findings, policy implications, and future research directions; and Section 6 provides a brief summary.

2 Theoretical framework and hypotheses

To illustrate the hypothesized relationships between LRM and UCEE, this study constructs a conceptual framework, as shown in Figure 1. Specifically, H1 tests the direct effect of LRM on UCEE, while H2 and H3 explore the mediating roles of ISU and GTI, respectively.

2.1 Direct impact of land resource misallocation on urban carbon emission efficiency

LRM refers to the inefficient allocation of land across industrial sectors and functional uses, often stemming from government intervention deviating from market-oriented mechanisms (Zhou et al., 2023). In China, such distortions are reflected not only in the quantity or spatial distribution of land supply but also deeply embedded in land pricing structures and property rights systems (Huang et al., 2025). A prominent manifestation of this phenomenon is that local governments, driven by short-term fiscal revenue and economic growth targets, allocate land at artificially low prices to high-energy-consuming industries (An, 2024; Chen and Yuan, 2025), effectively reducing land use costs for carbon-intensive sectors (Gao et al., 2022). This practice distorts urban spatial development patterns, constrains the emergence of low-carbon industries, and undermines the competitiveness of green and innovative enterprises in the land market, thereby limiting their expansion and contribution to carbon reduction (Jiang et al., 2022; Wu et al., 2023). Such an institutional bias exacerbates the feedback loop between resource misallocation, industrial path dependence, and carbon lock-in, locking cities into a high-emission growth trajectory (Cheng Y. et al., 2025). Furthermore, existing literature suggests that the concentration of land allocation in low-productivity sectors also leads to structural inefficiencies, reflected in declines in total factor productivity (TFP). This misallocation reinforces traditional high-pollution industrial structures, further entrenching rigid emission patterns and reducing the overall carbon emission efficiency (Gao and He, 2024). For instance, Zhou et al. (2022), based on panel data from Chinese cities, found that higher degrees of land misallocation were associated with poorer urban carbon performance. Summarily, we argue that LRM has become a significant structural barrier to improving the efficiency of urban carbon emissions. Hence, we propose the following hypotheses:

H1. LRM hinders improvements in UCEE.

2.2 Mechanism of industrial structure upgrading

In the context of carbon neutrality, the optimization and upgrading of industrial structures are widely recognized as key pathways for improving the efficiency of urban carbon emissions. The core lies in transforming urban economies from traditional high-carbon, resource-intensive industries toward green, low-carbon, and high-value-added emerging sectors (Zhou et al., 2022), ultimately targeting the development of industries characterized by elevated value capture, advanced technological embeddedness, and eco-efficient production paradigms (Ran et al., 2023). This transformation not only helps reduce carbon intensity and improve energy structure but also enhances green productivity at the urban level through technological advancement (Chen and Yuan, 2025). However, as a typical institutional distortion, land–resource misallocation may serve as a suppressive mechanism during this transition. The misallocation compresses the accessibility of land for high-tech industries and modern services, hampers spatial agglomeration and capital-deepening of green industries, and thus weakens the advancement of industrial upgrading (Xie et al., 2022; Cheng G. et al., 2025). Furthermore, resource dependence impedes the advancement and upgrading of industrial structure (Wang et al., 2019). The suboptimal allocation of land factors may reinforce existing high-carbon industrial structures through "path dependence," resulting in a "lock-in effect" preventing the transition to more advanced industrial forms and undermines carbon efficiency (Cheng G. et al., 2025). Therefore, we argue that LRM may suppress improvements in UCEE by obstructing ISU. Accordingly, we propose the following hypothesis:

H2. LRM inhibits the improvement of UCEE by impeding ISU.

2.3 Mediating mechanism of green technological innovation

Under the guidance of the "dual carbon" goals, GTI is widely regarded as a critical lever to enhance UCEE. Its essence lies in decoupling economic growth from carbon emissions by improving resource utilization efficiency and environmental performance through technological progress and institutional innovation (Deng et al., 2019; Nan et al., 2022). The Green Technological Innovation encompasses not only clean production, energy-saving technologies, and renewable energy, but also green transformation in institutions, management, and business models, forming the core of urban green development capacity that aligns with the long-term sustainability paradigm (Li and Liao, 2020). As land is an essential input for green innovation, its allocation directly influences the formation of the green technological capacity of a city. The existence of LRM may hinder the GTI, thereby weakening UCEE. An imbalanced allocation of industrial land increases the carbon intensity per unit of economic output and limits the potential for large-scale adoption of clean technologies (Chu et al., 2019). For example, when land is preferentially allocated to polluting and energy-intensive industries, green firms face higher land costs, weaker infrastructure support, and insufficient innovation network connections, ultimately suppressing investments in green R&D and the diffusion of sustainable technologies (Du and Li, 2021). Contrarily, green industries and service sectors depend on high-quality land and a supportive ecological environment; however, under a distorted land allocation regime, such sectors are often marginalized in urban space, weakening the capacity for sustainable development of the city (Cheng G. et al., 2025). Based on this logic, we propose the following hypothesis.

H3. LRM inhibits the improvement of UCEE by hindering the development of GTI.

3 Methodology

3.1 Sample selection and data sources

We used panel data from 274 prefecture-level cities in China over a 13-year period from 2010 to 2022, comprising 3,562 observations, to investigate the relationship between LRM and carbon emissions efficiency, as well as its underlying mechanisms. Observations with missing values (city-year pairs) were excluded to ensure consistency in the alignment of all variables, and 3,004 valid observations were ultimately retained for the benchmark regression. All data were analyzed using the Stata software. To address heteroscedasticity, robust standard errors were used in all regressions. To mitigate the influence of outliers, all continuous variables are winsorized at the top and bottom 1%.

The data for each indicator were sourced as follows: LRM data were obtained from the *China Urban Construction Statistical Yearbook* and carbon emission efficiency data were derived from the CEADS database. Data on ISU, population density, human capital, financial development level, foreign direct investment, and per-capita fiscal expenditure were collected from statistical yearbooks, bulletins, and statistical bureaus at various government levels in China. GTI data are obtained from the CNRDS database. The environmental regulation intensity was compiled from government work reports published on official government websites.

3.2 Variable measurement

3.2.1 Explanatory variable

LRM serves as the central explanatory variable within this empirical framework. Land resource allocation refers to the distribution of land across industries (Cheng G. et al., 2025). Under the vertically integrated governance system and current land policy framework of China, land is publicly owned and the government holds substantial discretion over its allocation. In pursuit of economic benefits, local governments tend to supply large quantities of industrial land, while restricting the provision of land for commercial and residential purposes, leading to the excessive expansion of industrial land. This phenomenon was defined here as the land resource misallocation (Zhang Y. et al., 2024). Accordingly, we measured LRM using the proportion of industrial land within the total urban construction land. This ratio reflects the extent to which land allocation is biased toward secondary industries, capturing the potential influence of government-led land resource distribution on carbon emission efficiency.

LRM was calculated using the following Equation 1:

$$LRM = \frac{Industrial\ Land\ Area}{Total\ Construction\ Land\ Area} \times 100 \tag{1}$$

3.2.2 Dependent variable

The dependent variable is UCEE. We adopt a super-efficiency Slack-Based Measure (SBM) model incorporating undesirable outputs (CO_2 emissions) to measure UCEE. This method was first proposed by Tone (2001), and we followed the approach of Zhou et al. (2022) by simultaneously considering both input and output indicators with indicator selection based on data availability. Compared with traditional models for measuring UCEE, the proposed model offers several advantages. First, it directly incorporates undesirable outputs (i.e., CO_2 emissions), thereby avoiding efficiency distortion caused by data transformation in conventional approaches. Second, it relaxes the upper bound of efficiency scores, allowing differentiation among highly efficient cities. Third, by adopting a non-radial optimization framework and a directional distance function, it accurately identifies the improvement potential of individual input and output factors. These features make the model a robust and suitable tool for assessing UCEE. The specific indicators used to calculate the UCEE were as follows:

(1) Input variables include the following factors.
   i) Capital input, represented by the annual stock of fixed assets in the city (unit: ten thousand yuan).
   ii) Labor input, measured by the number of employed persons in the city (unit: ten thousand persons)
   iii) Energy input, represented by the total energy consumption in the city (unit: ten thousand tons of standard coal).
(2) Desirable output variable: Real GDP of the city (unit: ten thousand yuan).
(3) Undesirable output variable: Urban CO_2 emissions (unit: 10,000 tons), which are estimated based on the consumption of major energy types and their corresponding emission factors, including coal, oil, natural gas, and electricity.

The corresponding model is as follows:

$$Min\,\varphi = \frac{1+\frac{1}{m}\sum_{k=1}^{m}\frac{\delta_k^-}{x_{ko}}}{1+\frac{1}{n+s}\left(h_1\sum_{r=1}^{n}\frac{\delta_r^+}{y_{ro}}+h_2\sum_{q=1}^{s}\frac{\delta_q^b}{b_{qo}}\right)} \tag{2}$$

In Equation 2 above, the variables δk^-, δr^+, and δqb are referred to as *slack variables*. δk^-, δr^+, and δqb represent the slack in the k-th type of capital input, the shortfall in the r-th desirable output, and the surplus in the q-th undesirable output, respectively. While φ denotes the carbon emission efficiency score of the decision-making unit (DMU o). Correspondingly, xko, yro, and bqo denote the inputs of the k-th capital, r-th desirable output, and q-th undesirable output for decision-making unit o (DMU o). The objective of the model is to minimize input redundancies and excessive undesirable outputs while maintaining the current level of desirable outputs, thereby improving the carbon emission efficiency.

The computational methods for these slack variables are expressed in Equations 3–5:

$$\delta_k{}^- = x_{ko} - \sum\nolimits_i \lambda_i x_{ki} \tag{3}$$

$$\delta_r{}^+ = \sum\nolimits_i \lambda_i y_{ri} - y_{ro} \tag{4}$$

$$\delta_q{}^b = b_{qo} - \sum\nolimits_i \lambda_i b_{qi} \tag{5}$$

The weighted linear combinations in Equations 3–5 are defined as follows: $\sum_i\lambda_i x_{ki}$ represents the minimum required input of factor k, based on a weighted combination of peer DMU. $\sum_i\lambda_i y_{ri}$ indicates the maximum achievable level of desirable output r, under current technology. $\sum_i\lambda_i b_{qi}$ denotes the lowest attainable level of undesirable output q, considering environmental constraints. Here, λ_i is the weight assigned to each DMU in constructing the reference (efficient) frontier.

Based on the super-efficiency SBM model, 3,562 observations of UCEE were calculated using Equation 2. The efficiency values range from 0.020 to 1.110, with a mean of 0.332, indicating an overall low level of carbon efficiency. This finding suggests that significant room for improvement exists in the synergy between carbon reduction and economic growth in Chinese cities. Although a few cities exhibited UCEE values approaching 1, indicating relatively balanced development, most cities fell into the low-efficiency range, reflecting their continued reliance on traditional high-emission, low-output development models.

3.2.3 Mechanism variables

We introduced two mechanism variables: ISU and GTI.

To measure the level of industrial structure upgrading, we follow the method by Murakami (2015), employing a structural indicator widely used in related research, namely, the level of service-oriented industrial transformation, referred to in this study as ISU. Specifically, this indicator is measured as the ratio of the added value of the tertiary sector to that of the secondary sector. This reflects the shift in economic activity from traditional manufacturing to high-value-added and low-carbon modern services (Zhou et al., 2023). A higher ratio indicates a greater share of the service sector in the national economy, representing a higher level of industrial structural upgrade.

The second variable is GTI. Following the method of Wu et al. (2022), we use the number of obtained green patents as a proxy. This metric is widely accepted in environmental economics. Prior to the regression analysis, we apply a log transformation to the count of green patents after adding one (Liu et al., 2021). This transformation helps smooth the skewness of distribution and enhances the comparability of green innovation levels across cities.

3.2.4 Control variables

UCEE is affected by several factors. Referring to existing literature (Zhou et al., 2023; An, 2024; Shao et al., 2024; Huang et al., 2025), we control for the following variables: (1) Population Density (PD), measured by the number of permanent residents per unit of land area (unit: persons/km^2); (2) Financial Development (FD), calculated as the ratio of the sum of year-end loan and deposit balances of financial institutions to the GDP of the city in the same year; (3) Human Capital (HC), measured by the share of permanent residents holding an associate degree or higher (unit: %); (4) Foreign Direct Investment (FDI), measured as the share of actual utilized foreign direct investment in the annual GDP of the city (unit: %); (5) Per Capita Fiscal Expenditure (PCFE), based on the general public budget expenditure *per capita*, where population is defined as the number of permanent residents (unit: yuan/person); (6) Environmental Regulation Intensity (ERI), represented by the proportion of environment-related terms in the annual work report of the local government.

3.3 Empirical model

Following the methodology of Ma et al. (2025), we constructed a two-way fixed effects model in a benchmark regression to capture the inhibitory effect of LRM on carbon emissions efficiency across cities and over time, thereby testing Hypothesis 1.

TABLE 1 Descriptive statistics.

Variables	N	Min	Max	Mean	SD	p25	p50	p75
UCEE	3,004	0.150	0.834	0.326	0.115	0.252	0.302	0.374
LRM	3,004	2.091	37.710	18.640	8.191	12.270	19.000	24.330
PD	3,004	23.220	2,614.000	471.700	427.900	191.400	358.200	620.500
FD	3,004	0.987	6.559	2.459	1.122	1.670	2.154	2.906
HC	3,004	0.113	9.607	1.863	1.993	0.642	1.169	2.093
FDI	3,004	0.007	7.677	1.769	1.730	0.395	1.277	2.528
PCFE	3,004	2,643.000	21,706.000	8,819.000	3,849.000	5,960.000	8,292.000	11,009.000
ERI	3,004	0.479	1.905	0.949	0.271	0.759	0.908	1.086

Note: UCEE, urban carbon emission efficiency; LRM, land resource misallocation; PD, population density; FD, financial development; HC, human capital; FDI, foreign direct investment; PCFE, per capita fiscal expenditure; ERI, environmental regulation intensity.

TABLE 2 Correlation test.

Variables	UCEE	LRM	PD	FD	HC	FDI	PCFE	ERI
UCEE	1							
LRM	−0.029	1						
PD	0.001	0.194***	1					
FD	−0.038**	−0.072***	0.201***	1				
HC	0.007	0.003	0.261***	0.589***	1			
FDI	0.030	0.141***	0.295***	0.043**	0.260***	1		
PCFE	0.002	−0.019	0.063***	0.395***	0.275***	0.017	1	
ERI	0.010	−0.071***	−0.115***	0.060***	0.044**	−0.097***	0.133***	1

Note: Pearson correlation coefficients are reported. ***p < 0.01, **p < 0.05, *p < 0.1.

Baseline regression model:

$$UCEE_{ct} = \alpha_c + \alpha_t + \alpha_0 + \beta_1 LRM_{ct} + \gamma X_{ct} + \varepsilon_{ct} \tag{6}$$

In the model, c, t, α_c and α_t, α_0, ε_{ct}, $UCEE_{ct}$, and γX_{ct} denote the city, year, capture city and year fixed effects, constant term, error term, carbon emission efficiency, and a vector of control variables, respectively.

4 Empirical results and analyses

4.1 Descriptive statistics

To better understand the characteristics of the research sample and obtain an overview of the panel data, we conducted a descriptive statistical analysis of the main variables. The analysis was performed using the Stata software, and the results are presented in Table 1.

The dependent variable, UCEE, has a mean value of 0.150, a median of 0.302, and a standard deviation of 0.115, indicating a certain degree of variation in carbon efficiency, which provides a sound foundation for further empirical investigation. The independent variable, LRM, shows a mean of 18.64 and a median of 19.00, suggesting that the overall level of the variable is concentrated around 19. Additionally, the descriptive statistics of the other variables indicated that all variables fell within a reasonable range, confirming the appropriateness of the sample selection in this study.

4.2 Correlation analysis

Table 2 presents the results of correlation analyses. At the preliminary level, LRM appeared to be negatively correlated with UCEE, although the relationship was not statistically significant, indicating the need for further investigation. Additionally, most *p*-values in the correlation test were <0.01, suggesting that the variables exhibited strong correlations at the 1% significance level.

4.3 Multicollinearity test

Multicollinearity refers to a strong correlation among the explanatory variables in a regression analysis, which may result in unstable coefficient estimates and reduced statistical significance. The Variance Inflation Factor (VIF) test is commonly used to detect multicollinearity. Here, we applied the VIF test to examine the multicollinearity among the explanatory variables. As shown in Table 3, all the VIF values were below the critical threshold of

TABLE 3 VIF test.

Variables	VIF	1/VIF
LRM	1.060	0.941
PD	1.200	0.831
FD	1.740	0.573
HC	1.700	0.588
FDI	1.190	0.844
PCFE	1.210	0.829
ERI	1.040	0.958

TABLE 4 Baseline regression.

Variables	(1)	(2)
	UCEE	UCEE
LRM	−0.001***	−0.001***
	(-3.11)	(-2.96)
PD		0.000
		(1.53)
FD		−0.005
		(-1.45)
HC		0.010***
		(2.77)
FDI		−0.001
		(-0.77)
PCFE		−0.000
		(-0.55)
ERI		0.002
		(0.30)
Constant	0.347***	0.322***
	(50.04)	(11.71)
Observations	3,004	3,004
R-squared	0.585	0.587
City FE	YES	YES
Year FE	YES	YES

Note: ***p < 0.01, **p < 0.05, *p < 0.1; robust t-statistics in parentheses.

10, indicating that multicollinearity was not a concern. Therefore, multicollinearity does not threaten the validity of the empirical results.

4.4 Baseline regression analysis

The baseline regression employed a two-way fixed effects model and adopted a stepwise regression approach. The results of Equation 6 are presented in Table 4. In the first step, the control variables were excluded. The estimation results show that the coefficient of the variable LRM (β_1) is negative and statistically significant at the 1% level. In the second step, after including the control variables, the coefficient of LRM (β_1) remains significantly negative at the 1% level (coefficient = -0.001, $p < 0.01$). Therefore, Hypothesis 1 is supported, confirming that LRM significantly reduces UCEE.

4.5 Robustness and endogeneity tests

4.5.1 Alternative measurement of independent variables

To ensure the robustness of the empirical findings, we replace the core independent variable with an alternative measure: the ratio of land concession revenue to urban construction land area. Land concession revenue data were compiled from the National Bureau of Statistics of China, the *China Land and Resources Yearbook*, and official disclosures from local governments. The results in Column (1) of Table 5 show that the coefficient remains significantly negative at the 1% level. This confirmed the reliability of the core conclusions.

4.5.2 Robustness test: excluding the impact of COVID-19

To further verify robustness, we excluded observations from 2020 to 2021, which were significantly affected by the COVID-19 pandemic. The regression results reported in column (2) of Table 5 indicate that the core findings remain stable and are not influenced by major external shocks, thereby reinforcing the robustness of the study.

4.5.3 Endogeneity test: Instrumental variable approach

To address potential endogeneity issues arising from omitted variables or measurement errors, we employed the two-stage least squares (2SLS) method with an instrumental variable (IV). We constructed IV as the interaction term between the average terrain slope of a city and its economic growth target for the corresponding year. The terrain slope data were sourced from the *Gridded Dataset of Terrain Relief Degree in China*, and the economic growth target was obtained from local government work reports. The theoretical rationale is as follows: terrain conditions affect the amount of developable land, while the economic growth target reflects the preference of the local government for land development intensity. Their interaction captures the pressure a city faces in achieving its economic goals under specific topographic constraints, which in turn affects its land allocation behavior. Therefore, this interaction term is theoretically correlated with land-resource misallocation. Simultaneously, it does not directly influence carbon emission efficiency but only affects it indirectly through the land allocation mechanism. Given that the main effects of both terrain slope and economic growth targets are controlled, the exogeneity assumption of the instrument is also satisfied. This variable was calculated by multiplying the average slope (in degrees) with the economic growth target of the by the city (in percentages) and scaling the product by a factor of 100.

Table 6 presents the estimation results. Column (1) reports the first-stage regression, in which the coefficient of the instrumental

TABLE 5 Robustness tests.

Variables	Alternative independent variable	Excluding the impact of COVID-19
	(1)	(2)
	UCEE	UCEE
LCR	−0.001***	
	(-3.64)	
LRM		−0.001***
		(-2.92)
PD	0.000*	0.000
	(1.67)	(1.17)
FD	−0.005	−0.005
	(-1.55)	(-1.40)
HC	0.011***	0.008*
	(2.86)	(1.83)
FDI	−0.001	−0.001
	(-0.55)	(-0.56)
PCFE	−0.000	−0.000
	(-0.50)	(-0.19)
ERI	0.002	0.002
	(0.28)	(0.29)
Constant	0.299***	0.324***
	(11.36)	(10.27)
Observations	3,000	2,597
R-squared	0.586	0.606
City FE	YES	YES
Year FE	YES	YES

Note: ***p < 0.01, **p < 0.05, *p < 0.1; robust t-statistics in parentheses. LCR, land concession revenue.

variable is 0.091 and is significantly positive at the 5% level ($p < 0.05$), confirming its relevance in explaining LRM. In Column (2), after incorporating the instrumental variable, the second-stage regression results show that the coefficient of LRM remains negative (−0.020) and significant at the 10% level ($p < 0.1$), indicating that the core conclusion remains robust after accounting for endogeneity.

4.6 Mechanism analysis

Given the potential over-identification issues associated with the traditional three-step approach to causal mechanism identification, we adopt a revised two-step empirical strategy inspired by Zhou et al. (2023) and Qing et al. (2024). This approach was designed to empirically test the mechanism by which LRM affects UCEE. The first step involved empirically testing the effect of LRM on the two mediating variables of ISU and GTI. In the second step, rather than conducting an additional regression analysis, we rely on existing authoritative literature and logical inferences to verify the established correlations between the mediating variables and carbon emissions efficiency. This allowed us to infer the mediating role of ISU and GTI in the relationship between LRM and UCEE.

The corresponding models are presented in Equations 7, 8:

$$ISU_{ct} = \alpha_c + \alpha_t + \alpha_0 + \beta_1 LRM_{ct} + \gamma X_{ct} + \varepsilon_{ct} \tag{7}$$

$$GTI_{ct} = \alpha_c + \alpha_t + \alpha_0 + \beta_1 LRM_{ct} + \gamma X_{ct} + \varepsilon_{ct} \tag{8}$$

Table 7 presents the results. Column (1) shows that the coefficient of LRM on ISU is negative and statistically significant at the 5% level (coefficient = −0.002, $p < 0.05$), indicating that LRM inhibits ISU. Column (2) shows that the coefficient of LRM on GTI is also negative and significant at the 5% level (coefficient = −0.005, $p < 0.05$), suggesting that LRM impedes the development of GTI.

Regarding the correlation between ISU, GTI, and UCEE, experts and scholars provided substantial evidence. Studies showed that the advancement and upgrading of industrial structures can, to a certain extent, suppress carbon emissions in neighboring regions and significantly improve urban carbon emission efficiency (Deng et al., 2023; Cheng Y. et al., 2025). Miao et al. (2017) and Liao et al. (2024) empirically validated the relationship between Green Technological Innovation and urban carbon emission efficiency. Their findings indicate that green innovation plays a key role in promoting low-carbon transformation and has a significantly positive impact on improving UCEE, a view widely acknowledged in academic circles.

Summarily, LRM impedes ISU, thereby suppressing improvements in UCEE; similarly, it hinders the advancement of GTI, which in turn limits the enhancement of UCEE. These two causal pathways are well substantiated, thus confirming hypotheses 2, 3.

4.7 Heterogeneity analysis

4.7.1 Geographic heterogeneity of cities

To further examine the spatial differences in the impact of LRM on UCEE, we followed the approach of Zhou et al. (2022) and conducted regional regressions based on the eastern, central, and western regions of China. The regression results are presented in Table 8.

These findings indicate significant regional heterogeneity in the impact of LRM on carbon emission efficiency. Specifically, in the Central and Western regions, the coefficients of the land misallocation variables were negative and statistically significant at the 5% and 10% levels, respectively. This suggests that LRM significantly suppresses improvements in UCEE in these regions. Contrastingly, the coefficient in the eastern region is statistically insignificant, which may be attributed to the more developed institutional environment of the region and higher factor allocation efficiency, thus partially offsetting the negative effects of land misallocation.

This result aligns with that of the known regional differences in terms of administrative governance capacity, land market

TABLE 6 Endogeneity test: 2SLS.

Variables	First stage	Second stage
	(1)	(2)
	LRM	UCEE
IV	0.091**	
	(0.04)	
LRM		−0.020*
		(0.01)
PD	−0.003**	−0.000
	(0.00)	(0.00)
FD	0.413**	0.002
	(0.17)	(0.01)
HC	−0.187	0.006
	(0.17)	(0.01)
FDI	−0.206**	−0.005*
	(0.08)	(0.00)
PCFE	0.000	−0.000
	(0.00)	(0.00)
ERI	0.550	0.013
	(0.36)	(0.01)
Observations	2,987	2,987
R2		−0.83
F	5.03	1.54
CD Wald F	6.33	
SW S stat.	9.27	

Note: ***p < 0.01, **p < 0.05, *p < 0.1; robust t-statistics in parentheses. IV: the interaction term between the average terrain slope of a city and its economic growth target for the corresponding year.

development, and industrial maturity. Cities in the central and western regions are more reliant on administratively driven land allocation and industrial expansion for their economic development, making them more vulnerable to inefficient land use. Such distortions in land allocation hinder ISU and weaken the green innovation ecosystem, ultimately exerting a negative impact on carbon emission efficiency.

Therefore, policies aimed at improving UCEE should fully consider the regional disparities. Particularly, greater emphasis should be placed on strengthening land market institutions and optimizing land use structures in Central and Western China to mitigate the environmental externalities resulting from resource misallocation.

4.7.2 Heterogeneity by city size

To further investigate whether the impact of LRM on UCEE varies by city population size, we conducted group regressions based on city size, following the classification criteria proposed by An (2024). According to the *Notice of the State Council on Adjusting the Standards for City Size Classification* (Guo Fa (2014) No. 51), cities with a permanent urban population of one million or more are categorized as large cities, whereas those with fewer than one million residents are classified as small- and medium-sized cities. Table 9 presents the estimation results for the two groups.

The results revealed significant heterogeneity based on city size. Specifically, in small and medium-sized cities, the coefficient of the Mismatch variable was significantly negative at the 5% level, indicating that LRM significantly suppressed improvements in carbon emission efficiency. Contrastingly, the effect is statistically insignificant in large cities, suggesting that the impact is weaker or negligible in these contexts.

This difference may stem from the disparities in governance capacity, industrial maturity, and institutional flexibility between large and small cities. Large cities generally possess more efficient land markets, better regulatory frameworks, and stronger technological infrastructures, enabling them to absorb or offset the distortions caused by land misallocation. Comparatively, small- and medium-sized cities are more constrained by administrative land allocation mechanisms and are more susceptible to the inefficiencies of distorted land use patterns, which in turn limits their ability to pursue low-carbon transformation.

These findings highlighted the need for different policy interventions. Large cities should focus on optimizing existing mechanisms to enhance carbon efficiency, whereas small- and medium-sized cities urgently need to address structural distortions in land allocation to unlock their potential to improve carbon emission performance.

4.7.3 Heterogeneity by resource endowment type

To examine whether the impact of LRM on UCEE differs between resource-based and non-resource-based cities, we followed the classification method of Zhang Y. et al. (2024). Based on the *National Plan for the Sustainable Development of Resource-Based Cities (2003–2020)*, the sample cities were divided into two subgroups, resource-based and non-resource-based cities, and separate regressions were conducted. According to official documents, resource-based cities refer to those that have long relied on the extraction and primary processing of natural resources such as coal, petroleum, and non-ferrous metals as their primary economic foundation. Table 10 presents the regression results for both city types.

The regression results reveal that the resource endowment type leads to significant heterogeneity in the effect of LRM on UCEE. Specifically, in non-resource-based cities, the coefficient of LRM variable was significantly negative at the 5% level (−0.001, $t = -2.38$), indicating that LRM significantly hindered improvements in UCEE. Contrastingly, in resource-based cities, the coefficient is not statistically significant (−0.001, $t = -1.43$), suggesting that in cities with strong resource dependence, LRM may not be a primary constraint on UCEE enhancement.

This discrepancy may be attributed to entrenched industrial structures and relatively rigid land-use policies in resource-based cities. In these cities, economic operations are often heavily influenced by state-led investment priorities and legacy infrastructure. Even if land allocation becomes more efficient, its effect may be offset by the dominance of resource-intensive, high-

TABLE 7 Mechanism test.

Variables	(1)	(2)
	ISU	GTI
LRM	−0.002**	−0.005**
	(-2.58)	(-2.32)
PD	0.000	0.000***
	(0.29)	(4.16)
FD	0.157***	−0.090***
	(9.29)	(-5.23)
HC	0.036***	0.021
	(3.01)	(1.34)
FDI	0.001	0.026***
	(0.11)	(3.62)
PCFE	−0.000	0.000*
	(-0.40)	(1.65)
ERI	0.003	−0.086***
	(0.19)	(-2.75)
Constant	0.597***	4.603***
	(8.24)	(41.77)
Observations	3,004	3,004
R-squared	0.885	0.960
City FE	YES	YES
Year FE	YES	YES

Note: ***p < 0.01, **p < 0.05, *p < 0.1; robust t-statistics in parentheses. ISU, industrial structure upgrading; GTI, green technological innovation.

emissions industries. Comparatively, non-resource-based cities typically possess more diversified industrial structures and greater institutional flexibility, making them more responsive to land allocation distortions.

These findings emphasize the importance of designing differentiated policy frameworks. For non-resource-based cities, correcting LRM is the key to improving UCEE. However, for resource-based cities, more fundamental structural reforms, such as industrial transformation or the implementation of environmental compensation mechanisms, may be required to achieve sustainable low-carbon transition goals.

5 Discussion

5.1 Key findings

Based on panel data from Chinese cities, we constructed a two-way fixed effects model to systematically assess the impact of LRM on UCEE. Furthermore, it empirically examines two mediating mechanisms, ISU and GTI, through which misallocation exerts indirect effects. The main findings were as follows:

First, LRM significantly hinders the improvement of UCEE, confirming that such institutional distortions lead to higher carbon emissions per unit output. This finding is consistent with that of Zhou et al. (2022), who showed that a higher degree of misallocation between industrial and commercial land is correlated with lower carbon efficiency. Similarly, Cheng Y. et al. (2025) quantitatively estimated that a 1% increase in the land misallocation index results in an average increase of 0.502% in urban carbon emissions. This implies that the oversupply of low-cost industrial land by the local governments aimed at rapid development promotes the expansion of energy-intensive industries, reduces energy efficiency, and substantially suppresses carbon emission efficiency (Han and Huang, 2022). Generally, the recent studies overwhelmingly confirms the significant negative effect of LRM on carbon efficiency. However, not all studies reached consistent conclusions. For instance, Chen and Yuan (2025) argued that the negative effect of land misallocation on carbon efficiency is significantly weakened in regions where land marketization reforms progressed. This finding suggests that in economically advanced regions with sound market mechanisms, the inhibitory effect of land misallocation is relatively weak. Therefore, differences in regional development stages and policy environments explain the variations in empirical results across studies.

Second, the mechanism analysis indicates that LRM reduces carbon emission efficiency by obstructing the transition of the industrial structure from high-carbon to low-carbon sectors, thereby inhibiting industrial upgrading. Numerous studies support the notion that barriers to industrial transformation are a critical transmission channel through which land misallocation affects carbon efficiency (Zhou et al., 2022; Cheng Y. et al., 2025). Zhou et al. (2022) explicitly stated that land misallocation delays industrial upgrading, increases the proportion of highly polluting and energy-intensive industries, and suppresses carbon efficiency improvements. Cheng Y. et al. (2025) further demonstrated through a mediation analysis that approximately 16.3% of the total effect of land misallocation is transmitted via changes in industrial structure. This provides additional evidence that land misallocation indirectly hinders the shift from high-carbon to low-carbon industries, thus lowering the CEs. However, Cheng Y. et al. (2025) also highlighted that industrial upgrading accounts for only a small part of the total effect, suggesting the existence of other influential mechanisms beyond the scope of structural transformation.

Third, our study shows that LRM suppresses GTI, further weakening UCEE. Several scholars argue that the distorted allocation of land factors restricts the concentration and input of green innovation, thereby indirectly reducing carbon efficiency (Han and Huang, 2022). Han and Huang (2022) provided empirical evidence that land misallocation significantly inhibits green innovation activities and weakens economic agglomeration, leading to increased emissions. Xu et al. (2025) find that land misallocation has a direct and significant negative impact on urban green innovation capacity, operating through structural, scale, and spatial agglomeration. Similarly, Chen and Yuan (2025) showed that misallocated land leads to insufficient investment in green R&D and delays in technological advancement, thus reducing the driving force for emission reduction. However, other studies offer different perspectives. Zhou et al. (2023), through mechanism analysis, empirically

TABLE 8 Heterogeneity by geographic location.

Variables	(1)	(2)	(3)
	Eastern	Central	Western
LRM	0.000	−0.002**	−0.001*
	(0.04)	(-2.58)	(-1.95)
PD	0.000***	−0.000	0.000
	(2.64)	(-0.21)	(0.51)
FD	0.004	−0.007	−0.021**
	(0.84)	(-1.06)	(-2.02)
HC	−0.003	0.009	0.024***
	(-0.50)	(1.61)	(2.96)
FDI	0.002	−0.007**	0.000
	(0.88)	(-1.98)	(0.10)
PCFE	−0.000	0.000	−0.000
	(-0.74)	(0.61)	(-0.97)
ERI	0.024**	−0.011	0.000
	(2.02)	(-1.05)	(0.02)
Constant	0.241***	0.388***	0.350***
	(5.29)	(8.79)	(7.36)
Observations	1,116	1,163	725
R-squared	0.637	0.537	0.619
City FE	YES	YES	YES
Year FE	YES	YES	YES

Note: ***p < 0.01, **p < 0.05, *p < 0.1; robust t-statistics in parentheses.

TABLE 9 Heterogeneity by city size.

Variables	(1)	(2)
	Large cities	Small and medium cities
LRM	−0.001	−0.001**
	(-0.98)	(-2.47)
PD	0.000	0.000**
	(0.94)	(2.36)
FD	0.009	−0.010**
	(1.45)	(-2.41)
HC	−0.003	0.021***
	(-0.53)	(4.10)
FDI	0.003	−0.004*
	(0.98)	(-1.80)
PCFE	0.000	−0.000
	(0.05)	(-0.92)
ERI	−0.005	0.006
	(-0.37)	(0.76)
Constant	0.285***	0.314***
	(4.24)	(11.43)
Observations	846	2,158
R-squared	0.504	0.616
City FE	YES	YES
Year FE	YES	YES

Note: ***p < 0.01, **p < 0.05, *p < 0.1; robust t-statistics in parentheses.

identify economic agglomeration, industrial structure, and urbanization as joint mediators of the impact of land misallocation on energy efficiency, without highlighting green innovation as a channel. This may be due to the differences in the measurements of energy efficiency versus carbon efficiency. Overall, the majority of the literature supports the pathway of "land misallocation → inhibited green innovation → reduced carbon efficiency," though a few studies show divergent conclusions due to differences in research focus or the selection of control variables. This highlights the importance of considering multiple research perspectives and carefully selecting appropriate covariates.

Fourth, regarding heterogeneity, existing studies generally agree that land resource misallocation affects urban carbon emission efficiency, and also emphasize its heterogeneous effects based on city location (An, 2024), population size (Gao et al., 2023), and resource endowment (Zhou et al., 2022), which are consistent with those of the heterogeneity dimensions examined here. Our findings show that the inhibitory effect of land misallocation on carbon efficiency is significant only in the central and western regions (An, 2024), small and medium-sized cities (Gao et al., 2023), and non-resource-based cities (Zhou et al., 2022), aligning with that of most scholarly conclusions. However, Zhou et al. (2022) report that the effect is also significant in resource-based cities, which they attribute to the lagged effects of land policies—i.e., the land misallocation in the earlier period may affect current carbon efficiency. This does not contradict our findings as the lag effect may explain short-term inconsistencies in resource-based cities, whereas our analysis focused on the average effect over time.

5.2 Research contributions

This study contributes to the literature in both theoretical and methodological dimensions.

From a theoretical perspective, first, it supplements the institutional explanation of land-resource allocation from an environmental economics perspective. It explicitly highlights that land misallocation is not merely an issue of allocation efficiency but also one with far-reaching environmental consequences. Second, it constructs a dual-mechanism mediation framework of "Land Resource Misallocation–Industrial Structure Upgrading/Green Technological Innovation–Urban Carbon Emission Efficiency," addressing the limitations of earlier studies regarding the identification of transmission pathways (Gao and He, 2024; Cheng Y. et al., 2025).

TABLE 10 Heterogeneity by resource endowment type.

Variables	(1)	(2)
	Resource-based cities	Non-resource-based cities
LRM	−0.001	−0.001**
	(-1.43)	(-2.38)
PD	0.000	0.000*
	(0.09)	(1.86)
FD	−0.001	−0.007*
	(-0.14)	(-1.68)
HC	0.003	0.013***
	(0.60)	(2.66)
FDI	−0.003	−0.001
	(-0.89)	(-0.41)
PCFE	0.000	−0.000
	(1.45)	(-1.39)
ERI	−0.009	0.009
	(-0.97)	(0.99)
Constant	0.336***	0.305***
	(9.41)	(7.57)
Observations	1,207	1,797
R-squared	0.655	0.532
City FE	YES	YES
Year FE	YES	YES

Note: ***p < 0.01, **p < 0.05, *p < 0.1; robust t-statistics in parentheses.

From a methodological perspective, by introducing the interaction between the average terrain slope and the annual economic growth target of a city as an instrumental variable, we enhance the credibility of causal inferences regarding LRM and enrich methodological applications in environmental economics to tackle endogeneity problems.

5.3 Policy recommendations

From a policy perspective, our findings offer the following recommendations for promoting green development and optimizing land systems in China.

(1) Accelerate market-oriented reforms in land resource allocation, and break away from the administratively driven logic of land supply—especially by avoiding the preferential allocation of low-cost land to high-emission industries, to curb misallocation at its source.
(2) Strengthen land policy support for green enterprises, high-tech industries, and modern service sectors. The structure of land supply should be optimized to guide the upgrading of urban industrial layouts and facilitate low-carbon transformation.
(3) Use land allocation reform as a strategic entry point to promote a coordinated system of "green technology–institutional innovation–carbon governance". Leverage the synergy between industrial and technological policies to enhance innovation chains and strengthen emission reduction pathways.
(4) Implement differentiated land and industrial policies across various types of cities, with particular attention paid to non-resource-based and small-to medium-sized cities where land misallocation has constrained green development. The adaptability and inclusiveness of land allocation systems should be improved to support low-carbon governance.

5.4 Research limitations and future research directions

This study has some limitations.

First, although a comprehensive panel dataset was constructed and a two-way fixed-effects model was employed to explore the linear impact of LRM on UCEE, the spatial dependence and regional spillover effects of land misallocation were not fully addressed. Future research could incorporate spatial econometric models or multiscale geographically weighted regression (MGWR) models and update the dataset with post-2023 observations to further investigate the spatial transmission mechanisms and nonlinear characteristics of the influence of land misallocation on carbon efficiency across cities.

Second, in terms of mechanism analysis, future studies may consider introducing structural equation modeling (SEM) to enhance causal inference in mediating effect analysis. Furthermore, as current measurement indicators rely largely on static city-level data, future work could integrate remote sensing imagery, enterprise-level carbon emission records, and natural language processing (NLP) techniques to depict land-use behavior, green innovation activity, and policy enforcement intensity more dynamically and precisely at the micro level.

Third, given the diverse development stages and functional roles of Chinese cities, subsequent research could incorporate heterogeneity in urbanization levels and examine the distinct characteristics of tourism-oriented cities. Such efforts would provide more scientific and theoretical support and empirical evidence for achieving coordinated regional emission reduction and the modernization of land resource governance capacity.

6 Conclusion

Conclusively, we utilized panel data from 274 Chinese cities spanning the period from 2010 to 2022. A super-efficiency SBM model incorporating undesirable outputs was employed to measure UCEE, and empirical tests were conducted using panel regression models with both city and time fixed effects. The results confirmed that LRM significantly undermines the efficiency of urban carbon emissions. Distorted land-use patterns and entrenchment of carbon-intensive industrial structures hinder cities from decoupling carbon emissions from economic growth. These findings emphasize the critical urgency of advancing land market reforms and implementing integrated spatial planning to enhance UCEE and steer cities toward a green and low-carbon transformation. Furthermore, it is essential to further refine land governance strategies tailored to different types of cities and evaluate their long-term impacts on carbon emissions efficiency.

Data availability statement

The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding author.

Author contributions

ZW: Conceptualization, Data curation, Formal Analysis, Methodology, Software, Writing – original draft, Writing – review and editing. W-SL: Project administration, Resources, Supervision, Writing – original draft, Writing – review and editing. SW: Investigation, Validation, Visualization, Writing – review and editing.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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