Land Use Policy 140 (2024) 107117

Contents lists available at ScienceDirect

Land Use Policy

journal homepage: www.elsevier.com/locate/landusepol

The nonlinear influence of land conveyance on urban carbon emissions: An interpretable ensemble learning-based approach

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ARTICLE INFO

Keywords:
Land conveyance
Carbon emissions
Industrial structure
Urban analytics
Machine learning
Planning support systems
Urban dynamics

ABSTRACT

Land allocation and pricing substantially impact carbon emissions, yet their nonlinear effects remain understudied. This research employs ensemble machine learning models to examine the complex relationships between land conveyance and per capita carbon emissions across 104 major Chinese cities from 2009 to 2017. The results reveal that keeping industrial land allocations below 35% helps reduce emissions, whereas higher ratios increase emissions. Allocating over 8% and 33% to business and public land respectively also lowers emissions. Land prices demonstrate heterogeneity – a higher residential land price promotes efficiency only when its relative price level to the comprehensive land price is below 1.1. The findings highlight customised policies balancing development and emissions reduction, based on local conditions and development stages, can forge sustainable pathways. Overall, the nonlinear modelling quantifies nuanced emissions responses to land allocation thresholds and strategic pricing incentives. By considering these complex mechanisms, urban planners can devise tailored strategies that simultaneously nurture growth and curb emissions. The novel method and evidence-based insights contribute to planning support systems and sustainable policy-making.

1. Introduction

Cities are responsible for over 67% of global greenhouse gas emissions from fossil fuel usage (Fu et al., 2017), a figure projected to rise to 73% by 2030 (Grimm et al., 2008a). Land use patterns in cities, which determine the distribution of buildings, transportation systems and other infrastructure, in turn affect a city's energy use and emissions (Wang et al., 2017, 2015). Land conveyance, referring to the transfer of land use rights or land ownership for specific purposes such as residential, industrial, commercial or public service use, plays a crucial role in shaping these patterns. In countries where land is publicly owned, the government exerts considerable influence over land conveyance by determining land use allocations based on urban planning and development objectives. Even where land markets are privately owned, regulations on land transfers and usage play an important role in shaping development to align with city-level aspirations. Therefore, urban planners and policymakers need to make informed decisions to help reduce emissions and promote sustainable development by studying and understanding the impact of land conveyance on carbon emissions.

The relationship between land resources and carbon emissions is substantial. Research demonstrated that a properly allocated land use structure would reduce energy-related CO_2 emissions by approximately 12% (Li et al., 2022; Wu et al., 2015a). Activities like deforestation and other land use changes can cause carbon stored in trees and soils to be released into the atmosphere, leading to increased carbon emissions (Jaiarree et al., 2011; Wu et al., 2015b). Furthermore, a study indicated that more compact land use patterns could enable the transport sector to

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https://doi.org/10.1016/j.landusepol.2024.107117
Received 30 August 2023; Received in revised form 29 January 2024; Accepted 23 February 2024
Available online 28 February 2024

significantly contribute to the IPCC's greenhouse gas reduction targets (Tayarani et al., 2018).

Land conveyance can influence the location and concentration of industries in a region. Different types of land supply can also affect the development of emerging industries (Stern et al., 1996; Dong et al., 2020). Allocating land for industrial development can draw manufacturers to an area. Simultaneously, the concentration of certain industries in a region can foster the development of a strong industrial cluster, thereby enhancing competitiveness and economic growth (Fragkias et al., 2013). Conversely, allocating land for residential and commercial development can affect the availability of industrial land, potentially leading to an increase in land prices that hinders industry establishment in the area (Wu et al., 2022a; Long, 2015).

The decisions regarding land allocation and the resulting market prices play a significant role in shaping a region's industrial structure. Therefore, it is essential to consider the impact of these decisions on the local carbon emissions level. Understanding this relationship can help formulate policies that strike a balance between economic growth and environmental sustainability.

Despite its importance, research on the relationship between land conveyance and carbon emissions usually stays limited to a single-sector scenario like industrial land and typically assumes a basic linear relationship. A more in-depth analysis is required to assess the heterogeneous impact of different sites on carbon emissions. The rise of artificial intelligence (AI) technology offers a range of advantages in quantitative research, including improved accuracy, enhanced predictive power and reduced model assumptions (Wu et al., 2022a).

Against this backdrop, this paper employs machine learning algorithms to explore the nonlinear driving mechanism of land conveyance, including both land allocation and land prices, on carbon emissions using urban panel data. This approach aims to help cities promote sustainable development that balances economic growth with environmental protection and provides flexible and effective policy recommendations for different urban phases.

This paper contextualises its discussions within China, where land use and conveyance are primarily government-managed. According to China's Ministry of Finance, fiscal revenue from land concessions reached RMB 3.37 trillion in 2015, which constituted more than 40% of China's total local government revenue (Xie et al., 2018a). This high fiscal share led the Chinese government to favour a short-sighted land allocation policy (Xie et al., 2018b). The emphasis on maximising government revenues from land transfers and leases in the face of rapid urbanisation and industrialisation tends to overlook the long-term environmental impact and carbon emissions (Xu et al., 2013; Arvin et al., 2015).

China's land tenure system is unique because the state or collectives own all land, leading to government-driven decisions in land use rather than market-driven ones. This unique system in China offers an exceptional opportunity to study precisely how government-directed land allocation affects carbon dioxide emissions, delineating an impact pathway that is not easily observable in other countries. Furthermore, China's rapid urban growth in recent years has caused significant changes in land use and increased environmental challenges, particularly in carbon emissions. This urbanisation is not merely about an increase in the urban population but also the transformation of land, which often results in higher energy use and more emissions. Understanding the relationship between land conveyance and carbon emissions can help outline strategies for achieving carbon neutrality amid China's rapid development (Xie et al., 2018b; Peng et al., 2017). For example, determining the proportions and price thresholds for different types of land use development could aid in managing the increase in carbon emissions (Artmann et al., 2019a), mitigating pollution levels (Artmann et al., 2019b) and ensuring adequate public services and infrastructure to support carbon mitigation efforts (Song et al., 2018). Thus, understanding how China's unique land ownership and fast urbanisation affect land use and carbon emissions can provide essential insights into sustainable land use and urban development globally, especially for countries undergoing rapid urban growth and facing similar environmental issues.

The rest of this paper is laid out as follows. Section 2 delves into a comprehensive review of relevant literature, highlighting the extant research and identifying gaps that this study seeks to address. Section3 offers an overview of the study's geographical focus and elucidate the specifics of the data employed. Section 4 describes the research workflows and methodologies employed for result analysis. Sections 5 and 6 present the empirical findings of our research and proffer actionable insights for practitioners in the field. Finally, Section 7 encapsulates the conclusions drawn from the study.

2. Literature review

2.1. Related work

The impact of land use on carbon emissions is a critical research area in urban ecology and sustainability, with numerous studies highlighting the complex interactions between urban development, land allocation and carbon cycles. Seto et al. provided global forecasts on urban expansion and its direct impacts on biodiversity and carbon pools, emphasising the significant role of urban areas in global carbon emissions (Seto et al., 2012). Churkina et al. estimated the carbon stored in residential and commercial land uses in the United States, contributing to the understanding of carbon sequestration in different land types (Churkina et al., 2010). Pataki et al. explored the role of urban ecosystems in the North American carbon cycle, with a focus on emissions from land use (Pataki et al., 2006). Comprehensive reviews of urban ecology research have been provided by Wu and Grimm et al (Grimm et al., 2008b; Wu, 2014)., discussing how land use change and urbanisation contribute to carbon emissions. Bai et al. advocated for a systems approach to sustainable cities, highlighting the need for integrated strategies that consider land use patterns in efforts to reduce urban carbon emissions (Bai et al., 2016). Together, these studies underscore the significance of land conveyance and land use planning in mitigating carbon emissions and advancing towards sustainable urban development.

The impact of urban land allocation on carbon emissions has been extensively researched in recent years, with many studies indicating that urban land use patterns and changes significantly affect carbon emissions. Quantitative analysis techniques have been developed, and several researchers have created empirical models using land use conveyance and carbon emissions data to uncover the mechanisms driving carbon emissions from different land use patterns (Zhu et al., 2019; Ali and Nitivattananon, 2012; Chen et al., 2018). Alexander et al. pointed out that the impact of land use change on carbon stock loss is second only to fossil fuel combustion (Popp et al., 2012). Major land use conversion types, such as urban land expansion, have been a particular focus (Lai et al., 2016).

Dong et al. discovered that all Chinese provinces are within the rising phase of the Environmental Kuznets Curve for land urbanisation and carbon emission intensity, according to the Instrumental Variable-Fixed Effects Model (Dong et al., 2020). Other studies have demonstrated that controlling construction land expansion is necessary to curtail carbon emissions growth, using the Kaya identity and the logarithmic mean Divisia index method (Li et al., 2019). In addition to examining the effect of land allocation on carbon emissions, many researchers have included other control variables, such as population and innovation, into their models to enhance result accuracy (Allard et al., 2018; Ziaei, 2015).

In contrast to land allocation, fewer studies have examined the impact of land price on carbon emissions. Zhang and Xu observed that local governments' eagerness to lease land to earn revenue exacerbates carbon emissions, based on the STIRPAT statistical model and city data from 2004 to 2013 (Zhang and Xu, 2017). Another related report indicated that the higher the price distortion of industrial land, the more harmful it is to the development of a green and low-carbon economy (Gao et al., 2023). Zeng et al. discovered that land transaction prices significantly curb carbon emissions using a fixed-effect model. The higher the transfer proportion of industrial land, the higher the carbon emissions, while the transfer proportion of residential land is significantly negatively correlated with carbon emissions (Zeng et al., 2022).

The exploration of carbon emission patterns is based on decomposition methods and regression methods. The decomposition method is commonly used to analyse and understand the potential driver of carbon emission changes in socioeconomic indicators, urbanisation, etc. This method is mainly divided into structural decomposition analysis (SDA) and index decomposition analysis (IDA), the latter of which is an effective way to analyse the drivers of energy consumption and greenhouse gas emissions (Huang et al., 2018). A two-level logarithmic mean Divisia index (LMDI) model was used to assess the impact of its drivers from different sectors on provincial carbon emissions interactively and collectively (Ye et al., 2017). However, these methods have stronger model assumptions that are relatively disconnected from reality and are primarily constrained to linear regression.

Machine learning is extremely capable of nonlinear fitting relationships in complex environments. Due to the superior accuracy of machine learning models, researchers predominantly employ these techniques for applications such as carbon emission forecasting and downscaling studies (Chen et al., 2020; Wu et al., 2023). However, due to the inherent 'black-box' nature of machine learning models, there has been a paucity of studies delving into the mechanisms underpinning carbon emissions. A notable exception is a study that proposed an ensemble structure-based neural network model to analyse the nonlinear relationship between NTL data and provincial-level carbon emission statistics (Yang et al., 2020).

2.2. Challenges and contribution

In the existing body of literature, scholars have intensively explored the interplay between various economic, demographic and technological factors and their subsequent impact on carbon emissions (Fu et al., 2017; Dong et al., 2020; Chen et al., 2018; Liu et al., 2022). Nevertheless, the effect of land factors still requires more comprehensive investigation and the refinement of previous research. Consequently, this study aims to contribute to the existing literature and address these challenges.

Previous studies on China's carbon emissions have often focused on only one or two types of factors influencing emissions and have generally been limited to the provincial level (Ye et al., 2017; Zhang et al., 2021). Notably absent from this discourse is an in-depth exploration of the ramifications of land conveyance—a salient instrument in governmental planning and regulation—especially in the context of land prices (Yang et al., 2021). This lacuna has inadvertently obfuscated a holistic comprehension of the intricate interplay and coupling mechanisms that influence carbon emissions at the urban scale. In contrast, this study uses panel data from main Chinese cities to elucidate the confluence of factors such as land conveyance, economic trajectory, industrial composition, and more, on carbon emissions, aspiring to delineate a comprehensive landscape of carbon emissions in China's municipal echelon.

In addition, the carbon emission factors of cities have highly complex influence mechanisms and decoupling relationships. Traditional statistical regression models typically depend on a linear or a simple nonlinear regression relationship (Wu et al., 2023). In contrast, machine learning models, with their intricate architectures and numerous activation functions, excel at discerning nonlinear relationships, thereby enhancing modelling accuracy. The method has become a new research paradigm across various fields for deepening our understanding of nonlinear mechanisms and threshold effects (Chen et al., 2024; Lundberg et al., 2020; Delavaux et al., 2023). Furthermore, the impact of urban land attributes on carbon emissions may be revealed as marginal effects (Ling et al., 2024; Yang, 2020). Advanced AI algorithms are particularly suited to detect and quantify these nuanced variations with enhanced precision. Consequently, this study implemented an ensemble machine learning algorithm to establish the carbon emission pattern and applied the SHAP algorithm to examine the drivers.

3. Data

3.1. Study area

The study focuses on the impact of land allocation on carbon emissions in China, a topic of great significance due to China's massive carbon footprint and its crucial role in global ecological trends. The study is carried out at a municipal administrative level, which is critical in the development and implementation of emission reduction policies.

The study encompasses 104 cities in mainland China, which are key monitoring cities as per the *China Land and Resources Statistical Yearbook*. These cities, which contribute 66.37% to China's overall GDP, are the driving forces behind China's economy. Fig. 1 illustrates the geographical distribution of the urban provinces under study.

3.2. Land allocation and prices

Land allocation and price features serve as the central focus of this research. In China, both national and local governments hold the power to manage land allocations. This management is conducted by controlling the supply of land and the subsidies for specific industry sectors, which subsequently impacts the fluctuations in land prices. For this study, data were gathered from the *China Land and Resources Statistical Yearbook* to calculate the supply and land price of various types of land in a city, which are used as explanatory variables in the model. Specifically, the land allocation and price data were sourced from statistical sub-tables in the yearbook, namely the price of urban construction land and the supply of state-owned construction land. The data items can be divided into total land, business land, industrial land and residential land.

To more effectively incorporate the concept of elasticity into land variables, the ratio of each specific type of land supply to the total land supply is applied as the land supply variable. In a parallel fashion, the land price variable is determined by using the ratio of the price of each type of land to the comprehensive land price. This approach allows for a more nuanced and cross-city comparable understanding of the impact of land conveyance and prices on carbon emissions.

3.3. Carbon emissions per capita

Several researchers have dedicated their work to city-level carbon emission estimation, establishing a robust research foundation and database. Energy-related carbon emissions account for more than 85% of China's total carbon emissions (Yang et al., 2020). Using a top-down approach provided by the IPCC (https://www.ipcc.ch/), the carbon emissions from energy are estimated. Chen et al. (2020) further provided accurate county-level carbon dioxide emission data from 1997 to 2017. For the spatial hierarchy of our study, we aggregated municipal carbon emissions by the county data, which can be defined as follows:

$$CE_{city} = \sum_{i=1}^{n} CE_{county} \qquad (3\text{-}1)$$

where CE_{city} is the city's carbon emissions; CE_{county} is the county's carbon emissions; and n is the number of counties of a city.

3.4. City development characteristics

Urban development is reflected in social aspects such as economic development, population growth, urbanisation and technology level. Several scholars have studied the effects of population, energy intensity

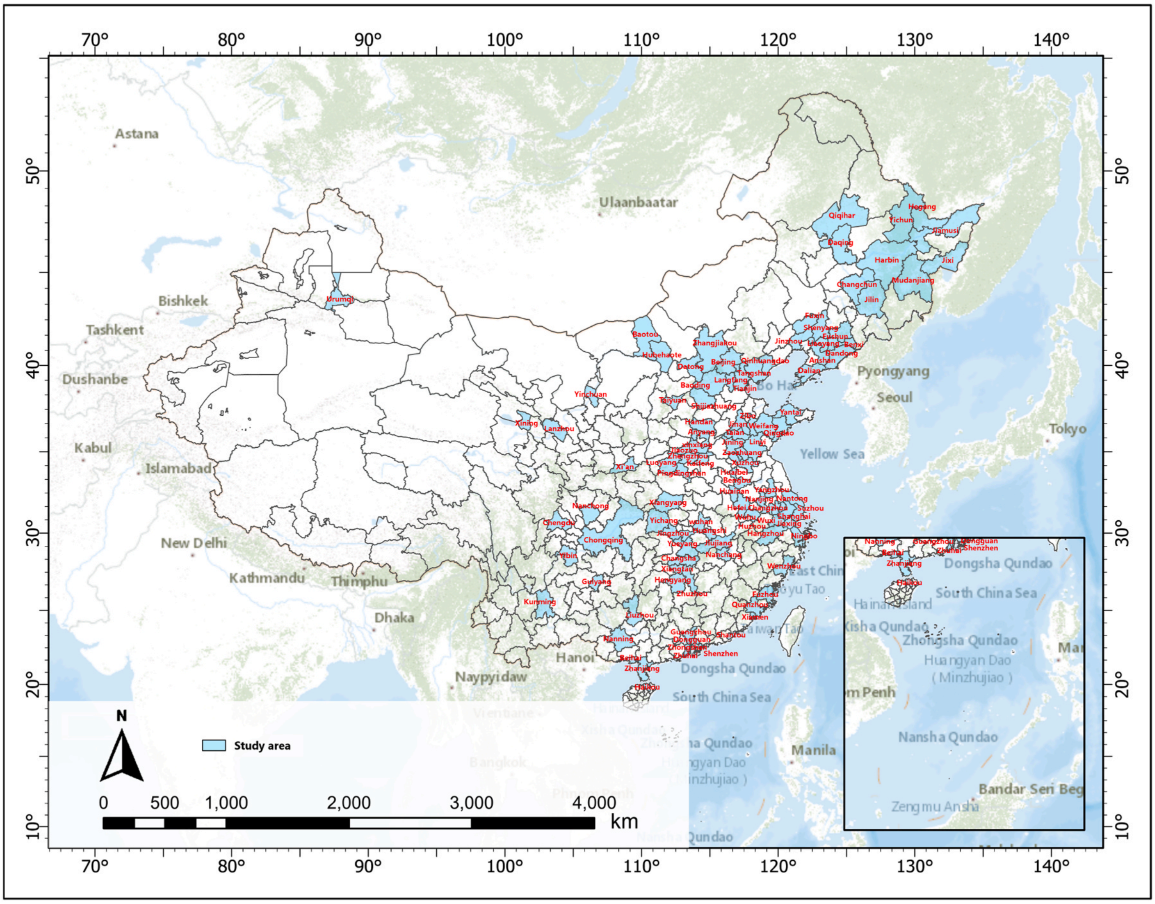

Fig. 1. Geographical location of the study area in China.

and industrial structure on carbon intensity using regression analysis and comparative analysis.

We chose the GDP per capita and the GDP of agriculture, industry and service sector per capita, average population of the administrative area, built-up area per capita, patent per capita and R&D of investment to represent the city's development characteristics. Data on each prefecture-level city's GDP, industrial structure, population, built-up area, patent and R&D investment are sourced from the *China City Statistical Yearbook* (http://www.stats.gov.cn/tjsj/) and the China National Intellectual Property Administration (https://english.cnipa.gov.cn/).

3.5. Data variables

In this investigation, a total of 18 variables serve as the foundational input datasets. Among these, eight are designated as primary explanatory variables, elucidating the allocation and pricing of urban land. The subsequent ten variables, informed by an extensive review of the literature, encapsulate aspects of the city's industrial revolution, technological advancements and societal composition (Dong et al., 2020; Chen et al., 2020; Wu et al., 2023; Zhang et al., 2021). The model's output data is the municipal carbon emissions per capita (see Table 1).

4. Methodology

The methodology section describes the analysis of spatial features of carbon emissions and the use of machine learning models to understand the impact of land conveyance features on carbon emissions. Fig. 2 shows the overall flow of the study.

Table 1
The variables of the land-conveyance model.

	Variable	Description
Explanatory Variables	ILR	The ratio of the industrial land to the total land supply
	BLR	The ratio of the business land to the total land supply
	RLR	The ratio of the residential land to the total land supply
	OLR	The ratio of public service land (public facilities, public buildings, transportation, water conservancy facilities, and special land) to the total land supply
	ILPR	The ratio of the industrial land price to the comprehensive land price
	BLPR	The ratio of the business land price to the comprehensive land price
	RLPR	The ratio of the residential land price to the comprehensive land price
	CLP	Comprehensive land price
Control Variables	Agricultural_PC	Agricultural product value per capita
	Industry_PC	Industry product value per capita
	Service_PC	Service product value per capita
	GDP_PC	Agricultural product value per capita
	RD_PC	R&D investment per capita
	Patent_PC	Number of patents granted per capita
	Built_PC	Urban built-up area per capita
	POP_PA	The average population of the administrative area
	City_X	Latitude of the city centre point
	City_Y	Longitude of the city centre point
Dependent Variables	Emission_PC	Carbon emissions per capita

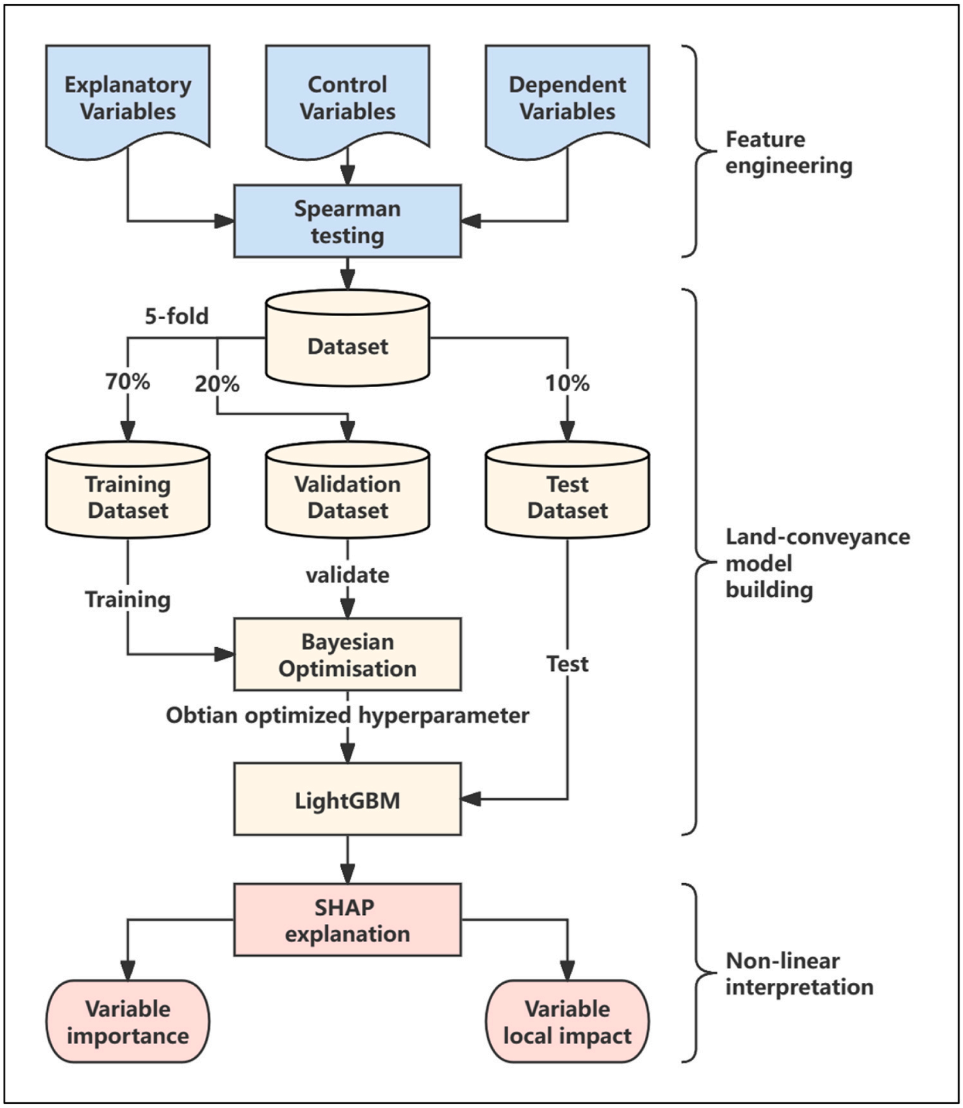

Fig. 2. Overall flow chart of the methodology.

4.1. Spatial features of carbon emissions

The analysis of spatial features of carbon emissions is based on the first law of geography, which states that everything is related, but things that are closer are more related. The degree of spatial correlation between carbon emissions and other factors can vary between adjacent cities.

Two measures, Moran's I and Getis–Ord G*, are used to quantify spatial correlation. Moran's I measures global spatial autocorrelation, while Getis–Ord G* identifies local spatial clusters. Moran's I can be expressed as:

$$I = \frac{n}{\sum_{i=1}^{n}\sum_{j=1}^{n}\omega_{ij}} \times \frac{\sum_{i=1}^{n}\sum_{j=1}^{n}\omega_{ij}(y_i - \overline{y})(y_j - \overline{y})}{\sum_{i=1}^{n}(y_i - \overline{y})^2} \tag{4 -1}$$

In the calculation, y_i and y_j is the value of the variable of interest (in this case, carbon emissions) in areas i and j; $\overline{y}$ represents the average value of the variable of interest across all s areas; ω_{ij} is the spatial weight between areas i and j. The value of Moran's I ranges from −1–1. is between plus and minus 1. A positive value indicates positive spatial autocorrelation (similar values cluster together), and a negative value indicates negative spatial autocorrelation (dissimilar values cluster together). A value close to 0 suggests a random spatial pattern.

Getis–Ord G* can be expressed as:

$$G_i = \frac{\sum_{j=1}^{n}\omega_{ij}y_j - \overline{X}\sum_{j=1}^{n}\omega_{ij}}{S\sqrt{\frac{\left[n\sum_{j=1}^{n}\omega_{ij}^2 - \left(\sum_{j=1}^{n}\omega_{ij}\right)^2\right]}{n-1}}} \tag{4 -2}$$

$$\overline{X} = \frac{\sum_{j=1}^{n}y_j}{n} \tag{4 -3}$$

$$S = \sqrt{\frac{\sum_{j=1}^{n}y_j^2}{n} - (\overline{X})^2} \tag{4 -4}$$

In the formulas, each variable has the same meaning as in Moran's I. The Getis–Ord G* statistic is a z-score; it measures how extreme a value is relative to the mean in standard deviation units. A high positive z-score for a particular area suggests a significant clustering of high values (hot spot), while a low negative z-score indicates significant clustering of low values (cold spot).

4.2. Land-conveyance decoupling model

The complexity of carbon emission mechanisms necessitates the use of advanced machine learning algorithms, such as ensemble learning

(Qiao et al., 2024). Ensemble learning integrates multiple basic learning algorithms to produce more accurate and reliable predictions.

Specifically, the Gradient Boosting Decision Tree (GBDT), an ensemble learning framework, is used. As data volume and dimensionality increase, the Light Gradient Boosting Machine (LGBM), a configuration based on GBDT, has been developed (Ke et al., 2017). LightGBM has three key improvements: (1) Gradient-based one-side sampling, which uses gradient information to sample data, focusing on high-gradient samples and reducing low-gradient ones; (2) Exclusive feature bundling, which addresses sparse high-dimensional features by bundling some features, reducing the feature dimension; and (3) the histogram technique that converts continuous data split into discrete data, improving model generalisation (Chen et al., 2019). Due to its advantages, LightGBM is chosen to build a decoupling model for this land-conveyance research.

4.3. Land-conveyance model optimisation

Machine learning models automatically adjust parameters, such as weights and split points, through iterative training. However, these models require pre-determined hyperparameters. For LightGBM, there are many hyperparameters available, which create a large search space for optimisation. Given the high data volume, each optimisation search consumes significant computing power.

To overcome this challenge, Bayesian Optimisation (BO) is used for efficient and global optimisation of the hyperparameter selection process (Shahriari et al., 2015). This study combines the BO algorithm and the LightGBM framework to develop the BO-LightGBM model for land-conveyance modelling. This combination offers an efficient and effective solution to model complex relationships between land conveyance features and carbon emissions.

4.4. Collinearity testing of features

The variable covariance, which is a linear combination of two or more independent variables, should be checked before building the carbon emission model. Covariance may affect the accuracy and stability of the model and potentially lead to incorrect statistical conclusions.

The Spearman correlation coefficient is used to calculate the covariance matrix of variables, estimating the covariance among features. The formula is as follows:

$$\rho_{Spearman} = \frac{\sum_{i=1}^{N}(R_i - \overline{R})(S_i - \overline{S})}{\sqrt{\sum_{i=1}^{N}(R_i - \overline{R})^2 \sum_{i=1}^{N}(S_i - \overline{S})^2}} \quad (4\ \text{-}5)$$

where R_i and S_i are the ranks of sample i at features x and y, respectively; $\overline{R}$ and $\overline{S}$ are the average ranks of features x and y, respectively. The Spearman correlation coefficient is a measure of the monotonic association between two variables, ranging from -1 to $+1$. A correlation coefficient greater than 0.7 between two features indicates a high correlation (Akoglu, 2018).

4.5. Land-conveyance driver interpretation

The SHAP algorithm is used to explain the prediction of the BO-LightGBM model. The algorithm assigns each feature an importance value by considering its marginal contribution to the prediction for a specific instance.

SHAP values reflect the combined effect of all features on the prediction, making it possible to identify both linear and nonlinear relationships between the features and the prediction outcome (Lundberg and S-IJAinips, 2017). They provide a more accurate nonlinear interpretation of the model's prediction compared to traditional feature importance metrics that only consider the global significance. The calculation is as follows:

$$SHAP_j = \sum_{S\subseteq[V_1+V_2+\cdots+V_p]/[V_j]} \frac{|S|!(p-|S|-1)!}{p!}\left(f_x\left(S\cup\{V_j\}\right) - f_x(S)\right) \quad (4\ \text{-}6)$$

$$y_i = y_{base} + \sum_{j=1}^{k} SHAP(x_{i\_j}) \quad (4\ \text{-}7)$$

In the calculation, $SHAP_j$ is the SHAP value of the feature j; S is the subset of features used in the model; V_p is the feature of the model; p is the number of features; $f_x(S)$ is the prediction of the model at the subset; y_i is the predictive value of the model at sample i; y_{base} is the mean value of the predictive value at other samples; $SHAP(x_{i\_j})$ is the SHAP value of the feature j at sample i; and k is the number of features.

To accurately represent the independent variable's influence, the study takes the necessary steps to exclude the interaction effects among the independent variables. This approach ensures that the results are unbiased, providing a more straightforward and precise evaluation of the individual variables' impact on city emissions (Lundberg and S-IJAinips, 2017). The calculation is as follows:

$$SHAP(X_{i\_jj}) = SHAP(X_{i\_j}) - \sum_{j\neq z}^{n} SHAP(X_{i\_jz}) \quad (4\ \text{-}8)$$

In this calculation, $SHAP(X_{i\_jj})$ is the eliminated-interactive-impact SHAP value of the feature j.

5. Results

5.1. Spatial aggregation of carbon emission per capita

The spatial autocorrelation test was employed to quantify the spatial association of per capita carbon emission across different locations. Considering that the data were aggregated at the administrative unit level, the Queen's Case method was utilised. This method defines neighbours as those areas sharing a common boundary or vertex and is particularly suitable for accounting for the differing sizes of urban districts (Wu et al., 2023). Thus, the study can determine the degree of spatial clustering of carbon emissions within cities.

Fig. 3 shows a fluctuating upward trend in the global Moran's I index for nine years (significant at the 99% confidence level). Remarkably, the index increased from 0.398 in 2009–0.425 in 2017, suggesting that carbon emission characteristics among Chinese cities were becoming increasingly clustered. The phenomenon could be attributed to a combination of factors related to China's rapid urbanisation, economic growth and policy shifts during that period. The conclusion of the 11th Five-Year Plan in 2010 and the commencement of the 12th Five-Year Plan in 2011 marked a significant transition in China's developmental goals and environmental protection strategies. This transition could potentially result in alterations to the distribution of industries and land use development patterns.

5.2. Hot spot analysis of urban carbon emission per capita

The study adopted Gi*, which combines Moran's I and general G statistics to reveal the spatial clustered characteristics of urban carbon emission distribution, pinpointing the spatial distribution of high and low urban carbon emissions. The calculation results are shown in Fig. 4, where red patches represent areas of high carbon emission agglomeration and blue patches represent areas of low carbon emission agglomeration.

Fig. 4 shows the spatial distribution of high and low urban carbon emissions. High-carbon emission cities experienced a migration in their clustering pattern over the course of nine years. Cities in Inner Mongolia, Gansu and Xinjiang, such as Hohhot, Jiuquan and Hami, showed a more significant clustering of high-carbon emissions, while some cities in Liaoning had a reduced degree of high-carbon emission convergence.

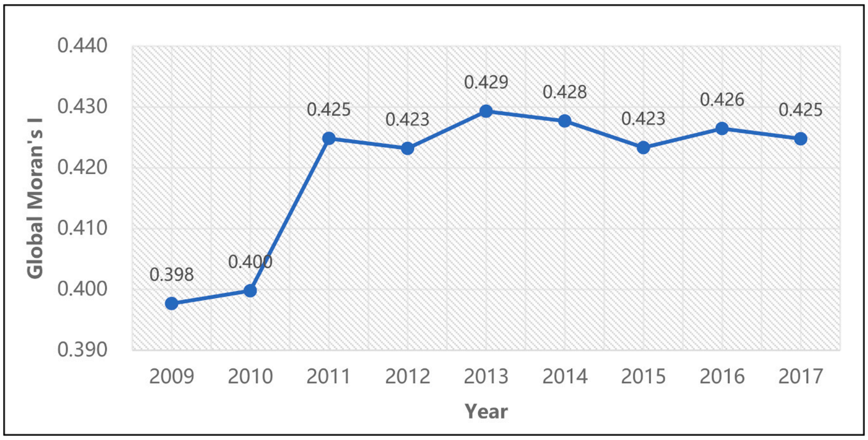

Fig. 3. Trend of global Moran's I from 2009 to 2017.

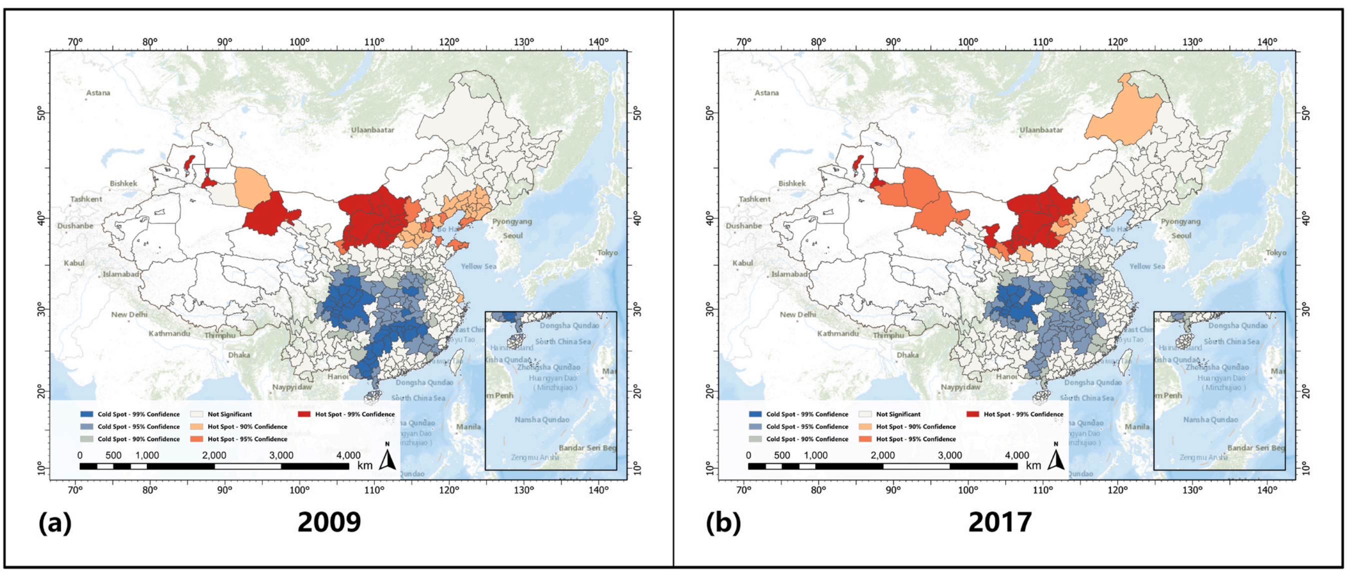

Fig. 4. Agglomeration degree of urban carbon emissions in 2009 and 2017.

Low-carbon emission cities generally showed stability in their overall distribution, but with some changes in the internal aggregation of cities. Sichuan, Guangxi, Hunan and Jiangxi had a significant low-carbon emission aggregation effect in 2007, but this characteristic diminished in subsequent years, except for Sichuan.

5.3. Correlation of independent variables

The land conveyance model consisted of 18 independent variables and one dependent variable. In order to avoid collinearity impacts on the model, the study calculated the Spearman correlations between these independent variables to ensure the validity of the model results.

Fig. 5 presents the correlations between different variables used in the land-conveyance decoupling model. Industry_PC and Service_PC have strong positive correlations with GDP_PC, with coefficients of 0.75 and 0.76, respectively. These strong correlations indicates that these two sectors (industry and services) play a significant role in the Chinese economy.

Despite these correlations, the results suggest that there is no severe collinearity problem among these variables, except for GDP_PC. Therefore, by excluding GDP_PC, the other independent variables could be used in the land-conveyance model training without causing substantial collinearity issues.

5.4. Land-conveyance decoupling model

Conventional methods of dividing the dataset into training and test sets in machine learning models can lead to inaccurate performance evaluations for a carbon emission estimation model for cities. To overcome this challenge, the study adopts a cross-validation approach by randomly dividing the municipal data into ten sub-sets. Two sub-sets were used as the validation set to evaluate the model's performance, seven sub-sets served as the training set, and the final sub-set served as the test set. This process was repeated five times to ensure that the results are not biased towards a single test and to provide sufficient training data. The hyperparameters for the model, determined through the BO algorithm, are specified as follows: 'num_iterations' is 974, 'colsample_bytree' is 0.5, 'subsample' is 0.5, 'learning_rate' is 0.02, 'max_depth' is 17, and 'num_leaves' is 234.

The results presented in Table 2 demonstrate the exceptional performance of the BO-LightGBM models in fitting the dataset through each round of cross-validation. The training sets consistently exhibited extraordinary R-square values, surpassing 0.998, and the test sets showed R-square values ranging from 0.981 to 0.996, indicating the outstanding robustness and stability of the models. The hight test set R-square of 0.991 underscores the BO-LightGBM model's strong generalisation performance and its ability to avoid over-fitting. These findings

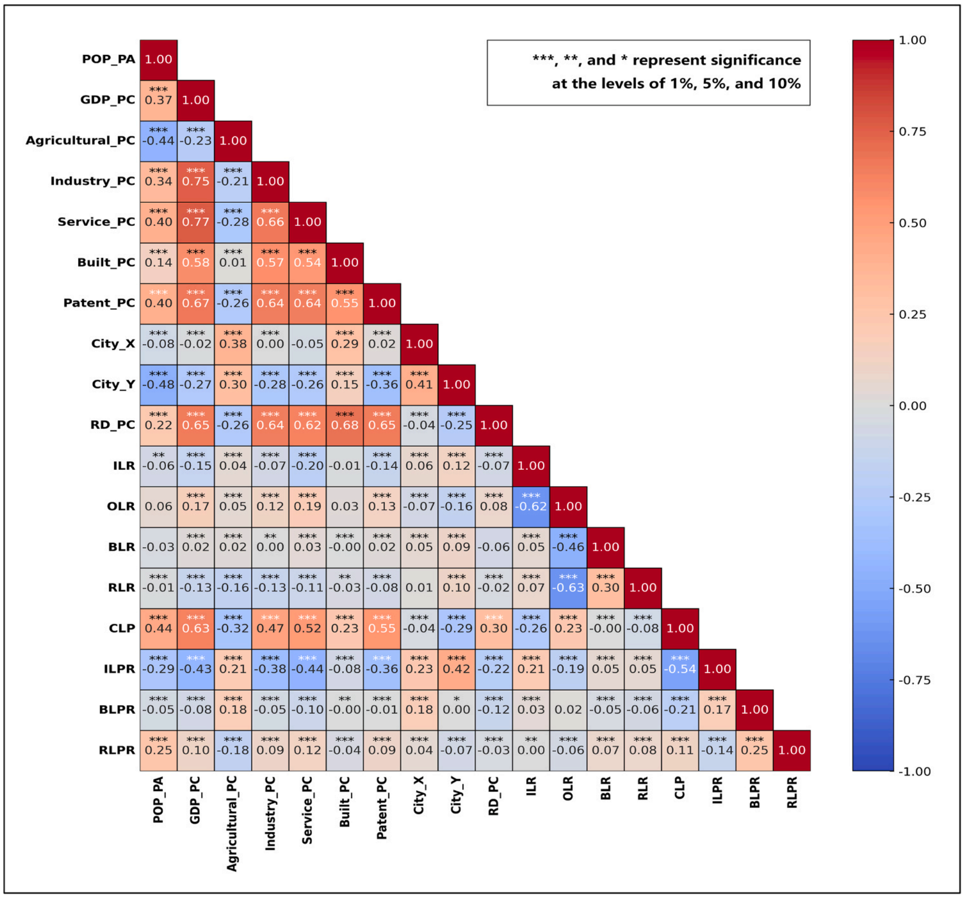

Fig. 5. Correlation of independent variables.

Table 2
The quality of BO-LightGBM models in validation and test sets.

	Time	MAE	RMSE	R-square
Validation set	1	0.416	0.672	0.981
	2	0.406	0.655	0.996
	3	0.411	0.664	0.994
	4	0.408	0.659	0.995
	5	0.416	0.672	0.982
Test set		0.410	0.668	0.991

highlight the effectiveness and reliability of the BO-LightGBM models in fitting complex and diverse carbon emission datasets.

5.5. Global interpretation of the relationships between land-conveyance features and carbon emissions in urban areas

This study employed the BO-LightGBM approach to precisely discern the complex nonlinear associations between land conveyance attributes and per capita carbon emissions. Subsequent SHAP analysis was conducted to elucidate the relationship revealed by the BO-LightGBM model, quantifying the significant drivers. This application of interpretable machine learning fosters transparency, similar to conventional statistical models, while also recognising nonlinear effects.

Table 3 presents the SHAP summary plots, which describe the global influence and significance of land allocation and price variables on per capita carbon emissions. The importance ranking of various land use categories differs between allocation and price aspects. In terms of land allocation, industrial land emerges as the most crucial variable, contributing 4.53% to the impact on carbon emissions per capita, followed by public service, residential and business land.

Table 3
Global SHAP of explanatory variables.

	Variable	Global SHAP	Percentage
Land allocation	ILR	2.37	4.53%
	BLR	1.21	2.32%
	RLR	1.28	2.46%
	OLR	1.30	2.50%
Land price	ILPR	19.13	36.67%
	BLPR	17.21	32.99%
	RLPR	9.67	18.53%
	CLP	21.78	41.76%

In contrast, land price variables play a significant role in determining a city's per capita carbon emissions of a city. Comprehensive land price has the most critical impact, accounting for 41.76% of the influence, while industrial land price level follows at 36.67%.

Therefore, the influence of land conveyance features on per capita carbon emissions is heterogeneous across allocation and price aspects, emphasising the necessity of considering both land allocation and price when devising efficient low-carbon sustainable development strategies.

5.6. Nonlinear effects of land-conveyance variables

The SHAP algorithms were employed to differentiate the influences of different land-related variables on per capita carbon emissions at the city level. The model results highlight the non-linearity in the relationship between land-conveyance features and urban emissions.

5.6.1. Land-allocation variables

Fig. 6 provides a graphical representation of the impacts (measured

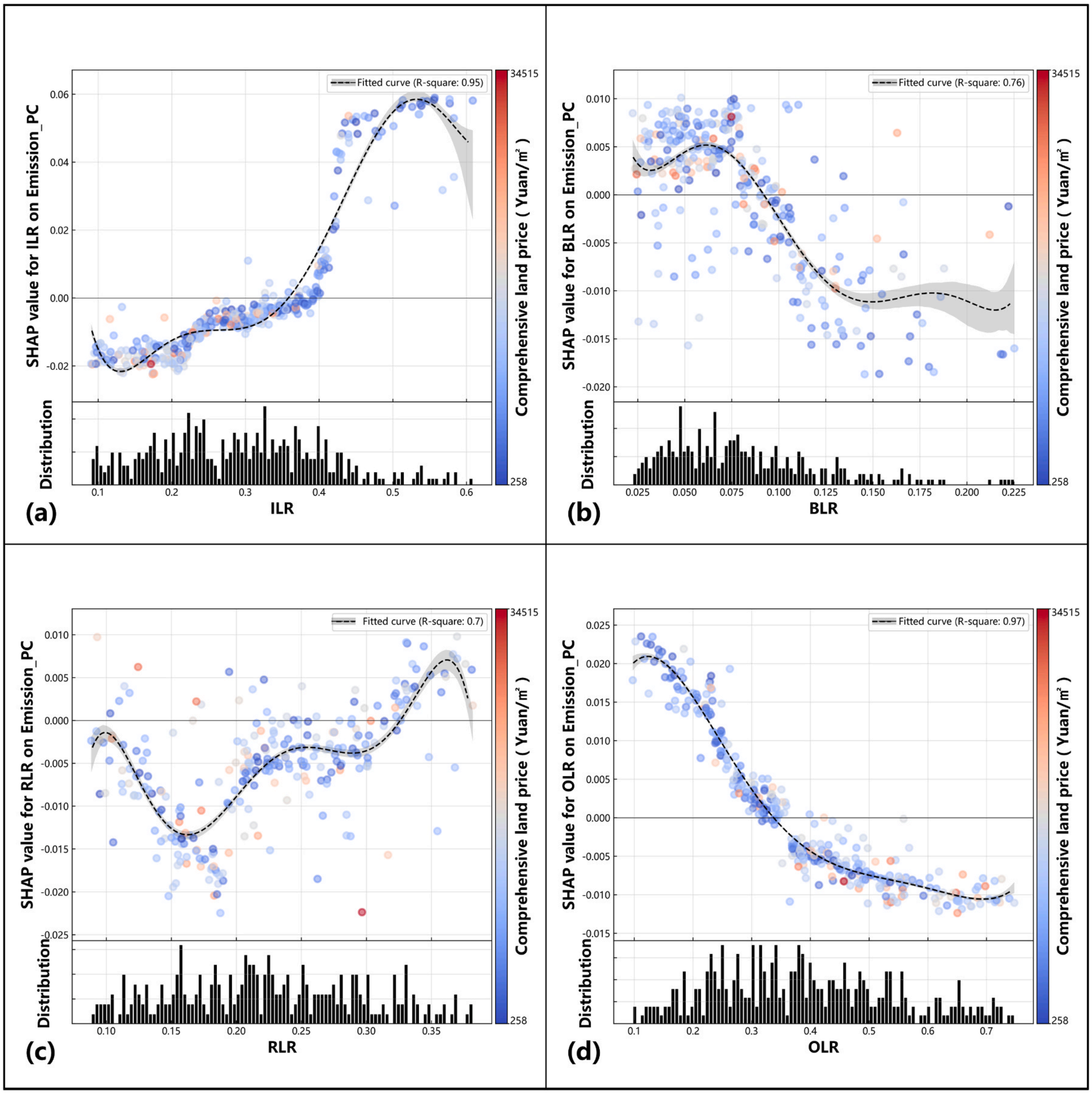

Fig. 6. SHAP dependence plots of land-allocation variables.

by SHAP values) of various land-allocation factors (i.e. ILR, BLR, RLR and OLR) on carbon emission per capita at the city level. The colour of each sample point (i.e. a city) is determined by its comprehensive land price, representing the overall economic development level of a city.

The impact of land allocation by land-use category on per capita carbon emissions at the city level exhibits a nonlinear relationship. Specifically, for industrial land, there is a positive correlation between a higher proportion of land supply and increased carbon emissions per capita when ILR is below 52%. At an ILR of 35%, the influence of land allocation on carbon emissions approaches zero. Therefore, allocating a smaller proportion of industrial land (below 35%) can contribute to lowering per capita carbon emissions, while a larger ratio (35–52%) is associated with increased emissions. These findings align with the general relationship between industrial land allocation and carbon emission levels observed in prior research (Zhou et al., 2022; Wang et al., 2019). It is noteworthy that a substantial number of cities, exhibiting varying comprehensive land prices, possess ILR values within the 20–40% range. Monitoring their industrial land allocation plans is crucial to ensure positive contributions towards reducing per capita carbon emissions levels.

The effect of business land allocation on per capita carbon emissions presents an inverse relationship compared to that of industrial land allocation. As the allocation ratio of business land increases, its impact on emission reduction shifts from negative to positive. Notably, cities possessing a low BLR value (BLR < 8%) are associated with elevated carbon emissions per capita. In contrast, cities with BLR values exceeding 8% generally observe diminished emissions. This phenomenon can be attributed to the ongoing industrial transformation in cities with a higher BLR ratio, transitioning from conventional industries to service-oriented, technology-driven sectors, consequently reducing per capita carbon emissions. The data reveal that the mean BLR in China stands at 7%, signifying a marginal fraction of the total land provision in comparison to developed nations such as the United States and Japan, where the average BLR surpasses 20% (Pandey et al., 2021). The gap also indicates that China possesses considerable potential for carbon emission reduction.

The land allocation ratio of residential developments has fluctuating impacts on per capita carbon emissions, where the RLR range between 0% and 32% is associated with positive impacts on carbon emissions reduction. Upon surpassing this threshold, an augmented residential land supply inadvertently promotes a slight increase in carbon emissions. This may be attributable to real estate development encroaching upon substantial natural vegetation, engendering severe urban heat island effects (Wu et al., 2022b). Such phenomena could exacerbate energy consumption related to heating and cooling in residences, leading to heightened carbon dioxide released into the atmosphere (Li et al., 2020a). Moreover, excessive living spaces elevate citizens' transportation requirements, which further contribute to carbon emissions. This is particularly relevant in the context of most Chinese cities, where public transportation infrastructure remains underdeveloped, and residents predominantly rely on private vehicles for commuting (Qiao et al., 2022).

In terms of the influence of public service land allocation on urban carbon emissions, the effect exhibits a similar pattern to that of BLR. Cities with OLR values less than 33% correspond to negative impacts on carbon emissions reduction. As many less-developed cities (as measured by lower comprehensive land prices) have an OLR value less than 33%, opportunities exist to enhance their carbon emission performance through increase public investment in services.

5.6.2. *Land-price variables*

Similar to the land-allocation variables, the land-price variables present varying impact patterns on per capita carbon emissions (Fig. 7).

For industrial land, cities with higher levels of economic development generally have a lower ILPR due to their high comprehensive land prices (used as a denominator for calculating ILPR). When ILPR is below 0.15, a lower ILPR is typically associated with a decreased contribution to per capita carbon emissions. However, for cities with middle and low development levels, a higher ILPR often results in lower per capita emissions. This may be because high industrial land prices incentivise industries to adopt more efficient and environmentally friendly production processes to maintain high yields and minimise costs (Wu et al., 2020).

For business land, the BLPR generally exhibits a negative correlation with per capita carbon emissions. Cities with a BLPR less than 2.3 tend to have larger negative impacts on decreasing per capita carbon emissions. Conversely, the impacts turn positive for cities with a BLPR greater than 2.3. The increase in costs due to rising local prices significantly impacts the development of low-end services, placing them under strain to maintain their operations. High-end technology companies, on the other hand, can sustain high output through efficient and environmentally friendly production processes, making a transition necessary. The median number of patents per capita in cities with a BLPR exceeding 2.3 is 0.83, surpassing the median for all cities by 42.97%. Thus, as high-end

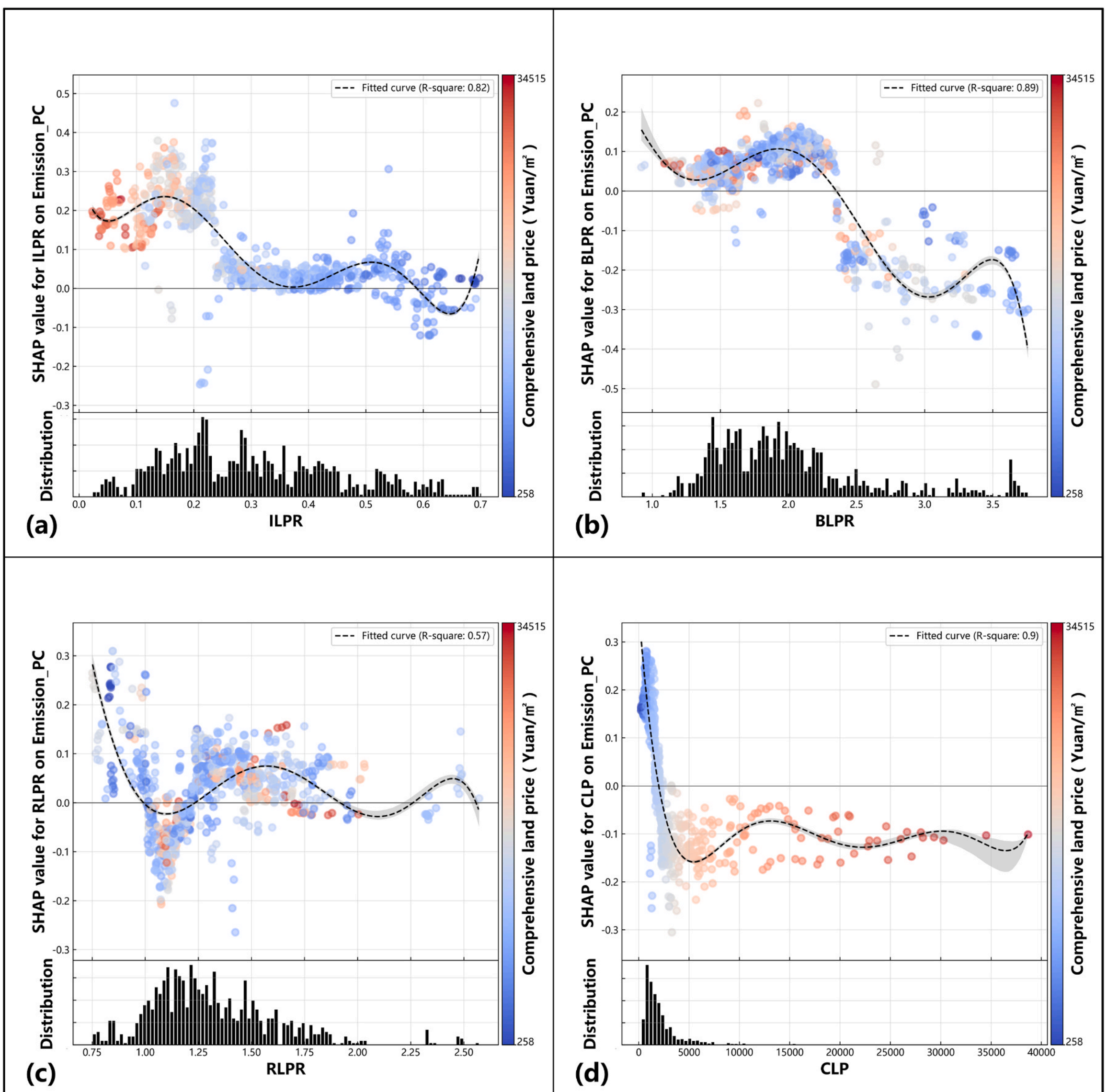

Fig. 7. SHAP dependence plots of land-price variables.

companies move in, they introduce advanced technology and environmental awareness, which in turn helps control and reduce per capita carbon emissions.

The relative price of residential land exhibits a significant nonlinear relationship with per capita carbon emissions. For cities with an RLPR less than 1.1, an increase in RLPR contributes to improved performance in reducing carbon emissions. However, the relationship reverses for RLPR values ranging between 1.1 and 1.6. RLPR values ranging from 1.0 to 1.25 are associated with the most optimal performance in carbon emission reduction, as indicated by SHAP values below 0. This suggests that balanced residential land prices within this range can stimulate efficient land use and sustainable urban development practices, thereby reducing per capita carbon emissions. For cities with an RLPR greater than 1.9, the effects become mixed, likely due to the relatively small sample size that falls into this category.

For the average land price, an increase is generally associated with reduced per capita carbon emissions when the price is below ¥5000/m^2. However, the impacts tend to become stable and remain almost unchanged for CLP values over ¥5000/m^2. Low land prices are often associated with higher carbon emissions, as CLP values exceeding ¥2000/m^2 tend to negatively impact per capita carbon emissions at the city level. This observation can potentially be explained by the escalating costs associated with local land price increases. These higher costs significantly affect the development of low-end services and industries, which might be compelled to enhance their efficiency of land use to maintain profitability. This increased efficiency could in turn lead to reduced emissions. However, for extremely high land prices, the high prices may start to encourage more luxurious and less efficient developments. These types of developments often have larger carbon footprints, which could gradually offset the additional benefits that come with increased land use efficiency.

6. Discussions

The findings highlight the importance of carefully considering land conveyance and pricing strategies in urban planning and policy-making, as they can significantly influence a city's carbon footprint in a nonlinear manner (Ahmed et al., 2019). The study is based on a comprehensive dataset covering 104 major Chinese cities over a period of nine years (2009–2017). This data-driven strategy enhances the robustness and credibility of our findings, as it is based on actual data patterns rather than assumptions. The model shows high accuracy (test R-square: 0.991), suggesting the thresholds it identifies are valid and not a result of overfitting. SHAP plots with 95% confidence intervals were also employed, providing a clear visual interpretation and confirming the reliability of the identified thresholds. Unlike previous studies that primarily focused on linear associations, our approach provides a more nuanced understanding of how changes in land use types impact carbon emissions. This is particularly important for policy-making, as it highlights the thresholds beyond which changes in land conveyance may have diminishing or even adverse effects on emission reduction efforts.

Due to rapid industrial expansion and urban development, certain regions of China have witnessed carbon emissions growing at an annual rate of over 10% (Xie et al., 2018a). This development underscores the necessity to ensure that government-led land allocation and price guidance do not adversely impact the environment, or lead to inefficiencies and pollution. A delicate balance must be struck between nurturing economic growth and safeguarding low-carbon development. The findings of this study contribute significantly to this discourse by providing evidence-based insights into the role of land allocation and pricing in shaping a city's carbon emissions. These insights can be used to guide decisions regarding land allocation and pricing towards achieving both economic and environmental sustainability.

6.1. Land allocation

The impact of urban land allocation on carbon emissions and its associated pathways have important implications for global low-carbon development (Li et al., 2023). Specific thresholds in the ratio of land use development across various categories are instrumental in this context (Dong et al., 2020; Xia et al., 2022). Notably, these thresholds closely align with the average values observed for each land type, with industrial, business, residential and public service lands constituting 30%, 7%, 22% and 39%, respectively. This correlation suggests that the trajectory towards reducing emissions in urban settings is intricately linked with the broader developmental stage of the country, underscoring the need for tailored strategies that consider both local and national contexts in the pursuit of sustainable urban development (Lu et al., 2022; Qu et al., 2023).

To optimise urban land use with the aim of reducing carbon emissions, specific thresholds for various land types are proposed. Keeping the ratio of industrial land supply below 35% can help alleviate emissions by promoting quality-oriented development, which encourages cleaner and more efficient industrial practices (Li et al., 2020b). A residential land ratio below 32% promotes compact urban living, thereby reducing the risk of overcrowded transportation systems and their associated emissions (Zuo et al., 2020). A business land allocation ratio of over 8% is recommended to bolster the growth of service-oriented industries. These industries generally have a smaller carbon footprint compared to manufacturing industries (Su et al., 2020). Lastly, maintaining a public service land ratio above 33% enhances urban life quality and encourages sustainable practices, such as the use of public transportation and the development of green spaces, contributing to further reduction in emissions (Wegener, 1996).

In addition, there is considerable potential for carbon emission reduction in the local context. For instance, with the anticipated decrease in the industrial land allocation ratio and an increase in the business land allocation ratio, better performance in terms of carbon emissions can be projected.

Land mismatches in China have a significant negative impact on carbon emission efficiency, especially the mismatch between industrial and commercial land use is particularly serious (Zhou et al., 2022). Efforts should be made to compile and oversee city-level land allocation plans, ensuring a reasonable allocation ratio of different land use types. This approach would involve a thorough understanding of the local context, as well as careful planning and coordination among different sectors. By keeping the allocation ratios within these specific thresholds, cities can make significant strides towards reducing their carbon footprints.

6.2. Land prices

In terms of land prices, a strong positive correlation has been identified between comprehensive land prices and the number of green patent grants, which is particularly pronounced in cities with higher land prices (see Fig. A1). In this vein, economic factors such as land prices are regarded as significant drivers of environmental innovation and the consequent reduction in carbon emissions. These findings are consistent with those of Zeng et al., who posits that land transaction prices can significantly curb carbon emissions (Zeng et al., 2022; Leibowicz, 2017). However, these observations may also reflect governmental constraints on high-emission industries in more developed cities. Although an exhaustive exploration of the factors driving carbon emission reductions falls outside the remit of this study and requires further city-specific investigation, the present study adds a new dimension to this understanding by highlighting that the relationship between land prices and carbon emissions is not linear. As land prices continue to escalate, the initial positive effects on carbon emissions may begin to diminish or even reverse. The delineated non-linearity and identified thresholds provide a basis for fostering more comprehensive debates on the specific factors driving carbon emission reductions.

In the initial stages, elevated land prices serve as a catalyst for more judicious land use, exemplified by the construction of high-density residential and commercial structures. Such developments epitomise efficient land utilisation, culminating in a tangible reduction in carbon emissions. Nevertheless, this relationship is not linear and reaches a tipping point when relative land prices fall within a specific bracket (e.g., 1.1–1.6 for residential land). Beyond this threshold, the rising land prices may inadvertently foster the development of more lavish, yet less efficient, developments (Carpio et al., 2021; Bjelle et al., 2021). This shift in development patterns can lead to an increase in carbon emissions, as these luxurious developments typically have larger carbon footprints.

Policymakers should be aware of the potential for high land prices to spur luxury developments, which can inadvertently escalate carbon emissions. Although land price is largely determined by the market's response, land-use regulations can be strategically enhanced in well-developed cities to counter the threat of carbon emissions. A key part of this strategy could involve designing and implementing incentives to promote low-carbon-related developments. These could include tax breaks or subsidies for developments that meet certain energy efficiency or sustainability criteria. In cities with the relative land price entering certain thresholds, stricter building codes and standards can be introduced to ensure that new constructions are energy-efficient and have minimal environmental impact.

6.3. Limitations and prospects

While this research sheds light on the complex nonlinear effects of land allocation and pricing determinants on carbon emissions, it is important to acknowledge several limitations that call for further exploration.

The analytical basis of this study relies on land data sourced from the statistical yearbooks. While we have endeavoured to incorporate a comprehensive dataset spanning multiple cities and years, the quantity of data may still be insufficient to capture the full complexity and variability inherent in urban land use and carbon emissions. In addition, the yearbooks do not break down urban and rural statistics. However, we acknowledge that the differentiation between urban and rural land prices is a complex issue, especially in the context of China's rapid urbanisation and land use changes. This limitation underscores the need to broaden and update the existing databases to capture the national dynamics of land carbon regulation fully.

Although this research highlights land price as a potential economic stimulus for environmental innovation, it should be recognised that this factor is part of a broader and intricate system. There are numerous pivotal factors that could also influence these dynamics. For instance, governmental policies play a significant role in driving industries toward sustainable practices, and their impact may sometimes overshadow the effects of market-driven economic factors such as land prices. Moreover, the affordability and accessibility of green technologies are crucial determinants of their uptake, which this study has not directly explored.

Future research can benefit from incorporating more detailed classifications of industrial land types. Carbon emissions vary significantly across different industry sectors, and this heterogeneity is not fully captured in the present study. Furthermore, the introduction of the land entropy concept can provide a novel lens to examine the repercussions of land mismatches on carbon emissions. Including this level of detail will enable more nuanced investigations into the landscape of carbon emissions and facilitate the development of tailored carbon mitigation strategies for different types of cities.

7. Conclusion

In this research, we have delved into the intricate mechanisms through which urban land allocation and pricing impact carbon emissions, employing an explainable artificial intelligence framework. The empirical findings underscore a distinct nonlinear relationship between land conveyance and carbon emissions, marked by diverse marginal effects and inversion thresholds. Linear methodologies, traditionally used in this field, have proven insufficient in addressing these nuanced variations.

For instance, our results suggest that while escalating land prices can initially drive more efficient land use and decrease emissions, there seems to be a threshold beyond which the benefits plateau and may even start to decline. Although market forces play a crucial role in determining land prices, a strategic and well-structured regulatory framework can help align economic incentives with environmental sustainability objectives.

The insights gleaned from the study indicate the necessity for bespoke land use policies that strike a balance between development and emissions reduction, catering to local conditions and varying stages of development. Such policies are pivotal for steering cities towards reduced carbon emission pathways. These insights hold significant implications for urban planners and policymakers who are involved in strategic planning for future urban development and the creation of custom regulatory policies tailored to the unique conditions of individual cities. By taking into account the complex, nonlinear relationships uncovered in this research, they can devise more effective strategies that promote sustainable development while minimising carbon emissions.

CRediT authorship contribution statement

Tianren Yang: Writing – original draft, Supervision, Project administration, Methodology, Conceptualization. **Xia Li:** Writing – review & editing, Data curation. **Shuo Gao:** Methodology, Formal analysis, Conceptualization. **Xiaochang Liu:** Writing – original draft, Formal analysis, Conceptualization. **Qingrui Jiang:** Visualization, Data curation. **Zhiqiang Wu:** Writing – review & editing, Supervision, Funding acquisition. **Renlu Qiao:** Writing – original draft, Visualization, Methodology, Formal analysis, Data curation, Conceptualization.

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.

Data Availability

Data will be made available on request.

Acknowledgements

This research was supported by the National Key R&D Program of China [2022YFC3800202] and the Young Elite Scientists Sponsorship Program by China Association for Science and Technology [2022ONRC001].

Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at doi:10.1016/j.landusepol.2024.107117.

References

Ahmed, Z., Wang, Z., Ali, S., 2019. Investigating the nonlinear relationship between urbanization and CO2 emissions: An empirical analysis. Air Qual., Atmosphere Health 12, 945–953.

Akoglu, H., 2018. User's guide to correlation coefficients. Turk. J. Emerg. Med. 18 (3), 91.

Ali, G., Nitivattananon, V., 2012. Exercising multidisciplinary approach to assess interrelationship between energy use, carbon emission and land use change in a metropolitan city of Pakistan. Renew. Sustain. Energy Rev. 16, 775–786.
Allard, A., Takman, J., Uddin, G.S., Ahmed, A.J.E.S., Research, P., 2018. T. he N. -shaped Environ. Kuznets curve: Empir. Eval. Using a Panel quantile Regres. Approach 25, 5848–5861.
Artmann, M., Inostroza, L., Fan, P., 2019a. Urban sprawl, compact urban development and green cities. how much do we know, how much do we agree? Ecol. Indic. 96, 3–9.
Artmann, M., Kohler, M., Meinel, G., Gan, J., Ioja, I.-C., 2019b. How smart growth and green infrastructure can mutually support each other — A conceptual framework for compact and green cities. Ecol. Indic. 96, 10–22.
Arvin, M.B., Pradhan, R.P., Norman, N.R.J.U.P., 2015. Transportation intensity, urbanization, economic growth, and CO2 emissions in the G-20 countries.Utilities Policy. 35, 50–66.
Bai, X., Surveyer, A., Elmqvist, T., Gatzweiler, F.W., Güneralp, B., Parnell, S., et al., 2016. Defining and advancing a systems approach for sustainable cities. Curr. Opin. Environ. Sustain. 23, 69–78.
Bjelle, E.L., Wiebe, K.S., Többen, J., Tisserant, A., Ivanova, D., Vita, G., Wood, R., 2021. Future changes in consumption: The income effect on greenhouse gas emissions. Energy Econ. 95, 105114.
Carpio, A., Ponce-Lopez, R., Lozano-García, D.F., 2021. Urban form, land use, and cover change and their impact on carbon emissions in the Monterrey Metropolitan area, Mexico. Urban Clim. 39, 100947.
Chen, B., Hu, J., Wang, Y., 2024. Synergistic observation of FY-4A&4B to estimate CO concentration in China: combining interpretable machine learning to reveal the influencing mechanisms of CO variations. npj Clim. Atmos. Sci. 7, 9.
Chen, C., Zhang, Q., Ma, Q., Yu, B., 2019. LightGBM-PPI: Predicting protein-protein interactions through LightGBM with multi-information fusion. Chemom. Intell. Lab. Syst. 191, 54–64.
Chen, J., Guo, F., Wang, H., Wang, Z., Wu, Y., 2018. Urban. Land Revenue Sustain. Urban. China.: Issues Chall. 10, 2111.
Chen, J., Gao, M., Cheng, S., Hou, W., Song, M., Liu, X., et al., 2020. County-level CO2 emissions and sequestration in China during 1997–2017. Sci. Data 7, 391.
Churkina, G., Brown, D.G., Keoleian, G., 2010. Carbon stored in human settlements: the conterminous United States. Glob. Change Biol. 16, 135–143.
Delavaux, C.S., Crowther, T.W., Zohner, C.M., Robmann, N.M., Lauber, T., van den Hoogen, J., et al., 2023. Native diversity buffers against severity of non-native tree invasions. Nature 621, 773–781.
Dong, Y., Jin, G., Deng, X., 2020. Dynamic interactive effects of urban land-use efficiency, industrial transformation, and carbon emissions. J. Clean. Prod. 270, 122547.
Fragkias, M., Lobo, J., Strumsky, D., Seto, K.C.J.P.O., 2013. Does size matter? Scaling of CO2 emissions and U.S. urban areas. PLOS 8, e64727.
Fu, B., Wu, M., Che, Y., Yang, K., 2017. Effects of land-use changes on city-level net carbon emissions based on a coupled model. Carbon Manag. 8, 245–262.
Gao, B.-y, Huang, Z.-j, Zhang, T.-t, Sun, X.-y, Song, M.-y, 2023. Explor. Impact Ind. Land Price Distortion Carbon Emiss. Intensity: Evid. China 12, 92.
Grimm, N.B., Faeth, S.H., Golubiewski, N.E., Redman, C.L., Wu, J., Bai, X., Briggs, J.M.Js, 2008a. Glob. Change Ecol. Cities 319, 756–760.
Grimm, N.B., Faeth, S.H., Golubiewski, N.E., Redman, C.L., Wu, J., Bai, X., Briggs, J.M., 2008b. Global Change and the Ecology of Cities. Science 319, 756–760.
Huang, J., Liu, Q., Cai, X., Hao, Y., Lei, H., 2018. The effect of technological factors on China's carbon intensity: New evidence from a panel threshold model. Energy Policy 115, 32–42.
Jaiarree, S., Chidthaisong, A., Tangtham, N., Polprasert, C., Sarobol, E., Tyler, S.J.P., 2011. Soil organic carbon loss and turnover resulting from forest conversion to maize fields in Eastern Thailand, 21, 581–590.
Ke, G., Meng, Q., Finley, T., Wang, T., Chen, W., Ma, W., et al., 2017. Light.: A highly Effic. gradient Boost. Decis. tree 30.
Lai, L., Huang, X., Yang, H., Chuai, X., Zhang, M., Zhong, T., et al., 2016. Carbon Emiss. Land-Use Change Manag. China 1990 2010 2, e1601063.
Leibowicz, B.D., 2017. Effects of urban land-use regulations on greenhouse gas emissions. Cities 70, 135–152.
Li, B., Han, S., Wang, Y., Wang, Y., Li, J., Wang, Y., 2020a. Feasibility assessment of the carbon emissions peak in China's construction industry: Factor decomposition and peak forecast. Sci. Total Environ. 706, 135716.
Li, J., Kagawa, S., Lin, C., 2020b. China's CO2 emission structure for 1957–2017 through transitions in economic and environmental policies. J. Clean. Prod. 255, 120288.
Li, J., Jiao, L., Li, R., Zhu, J., Zhang, P., Guo, Y., Lu, X., 2023. How does market-oriented allocation of industrial land affect carbon emissions? Evidence from China. J. Environ. Manag. 342, 118288.
Li, Q., Chen, X., Jiao, S., Song, W., Zong, W., Niu, Y., 2022. Can mixed land use reduce CO2 emissions? A case study of 268 Chinese Cities. Sustainability 14, 15117.
Li, Y.-N., Cai, M., Wu, K., Wei, J., 2019. Decoupling analysis of carbon emission from construction land in Shanghai. J. Clean. Prod. 210, 25–34.
Ling, C., Niu, X., Yang, J., Zhou, J., Yang, T., 2024. Unravelling heterogeneity and dynamics of commuting efficiency: Industry-level insights into evolving efficiency gaps based on a disaggregated excess-commuting framework. J. Transp. Geogr. 115, 103820.
Liu, X., Zhang, X., Sun, W., 2022. Does the agglomeration of urban producer services promote carbon efficiency of manufacturing industry? Land Use Policy 120, 106264.
Long, H.J.G.R., 2015. Land Use Transit. Land Manag. 34, 1607–1618.
Lu, X., Zhang, Y., Li, J., Duan, K., 2022. Measuring the urban land use efficiency of three urban agglomerations in China under carbon emissions. Environ. Sci. Pollut. Res. 29, 36443–36474.
Lundberg, S.M., S-IJAinips, Lee, 2017. A Unifi-.-. Approach Interpret. Model Predict. 30.
Lundberg, S.M., Erion, G., Chen, H., DeGrave, A., Prutkin, J.M., Nair, B., et al., 2020. From local explanations to global understanding with explainable AI for trees. Nat. Mach. Intell. 2, 56–67.
Pandey, P.C., Koutsias, N., Petropoulos, G.P., Srivastava, P.K., Ben Dor, E., 2021. Land use/land cover in view of earth observation: data sources, input dimensions, and classifiers—a review of the state of the art. Geocarto Int. 36, 957–988.
Pataki, D.E., Alig, R.J., Fung, A.S., Golubiewski, N.E., Kennedy, C.A., McPherson, E.G., et al., 2006. Urban ecosystems and the North American carbon cycle. Glob. Change Biol. 12, 2092–2102.
Peng, S., Ciais, P., Maignan, F., Li, W., Chang, J., Wang, T., Yue, C., 2017. Sensitivity of land use change emission estimates to historical land use and land cover mapping. Glob. Biogeochem. Cycles 31, 626–643.
Popp, A., Krause, M., Dietrich, J.P., Lotze-Campen, H., Leimbach, M., Beringer, T., Bauer, N.J.E.E., 2012. Addit. CO2 Emiss. Land Use Change—For. Conserv. a Preco Sustain. Prod. Second Gener. bioenergy 74, 64–70.
Qiao, R., Li, X., Gao, S., Ma, X., 2022. Improvement of thermal comfort for underground space: Data enhancement using variational autoencoder. Build. Environ. 207.
Qiao, R., Liu, X., Gao, S., Liang, D., GesangYangji, G., Xia, L., Zhou, S., Ao, X., Jiang, Q., Wu, Z., 2024. Industrialization, urbanization, and innovation: Nonlinear drivers of carbon emissions in Chinese cities. Appl 358, 122598.
Qu, Y., Zhan, L., Zhang, Q., Si, H., Jiang, G., 2023. Towards sustainability: The impact of the multidimensional morphological evolution of urban land on carbon emissions. J. Clean. Prod. 424, 138888.
Seto, K.C., Güneralp, B., Hutyra, L.R., 2012. Global forecasts of urban expansion to 2030 and direct impacts on biodiversity and carbon pools. Proc. Natl. Acad. Sci. 109, 16083–16088.
Shahriari, B., Swersky, K., Wang, Z., Adams, R.P., De Freitas, N.J.PotI., 2015. Tak. Hum. loop: A Rev. Bayesian Optim. 104, 148–175.
Song, Q., Zhou, N., Liu, T., Siehr, S.A., Qi, Y., 2018. Investigation of a "coupling model" of coordination between low-carbon development and urbanization in China. Energy Policy 121, 346–354.
Stern, D.I., Common, M.S., Barbier, E.B., 1996. Economic growth and environmental degradation: The environmental Kuznets curve and sustainable development. World Dev. 24, 1151–1160.
Su, K., Wei, D.-z, Lin, W.-x, 2020. Influencing factors and spatial patterns of energy-related carbon emissions at the city-scale in Fujian province, Southeastern China. J. Clean. Prod. 244, 118840.
Tayarani, M., Poorfakhraei, A., Nadafianshahamabadi, R., Rowangould, G., 2018. Can regional transportation and land-use planning achieve deep reductions in GHG emissions from vehicles? Transp. Res. Part D: Transp. Environ. 63, 222–235.
Wang, S., Fang, C., Wang, Y., Huang, Y., Ma, H.J.E.I., 2015. Quantifying the relationship between urban development intensity and carbon dioxide emissions using a panel data analysis. Ecol. Indicat. 49, 121–131.
Wang, S., Liu, X., Zhou, C., Hu, J., Ou, J., 2017. Examining the impacts of socioeconomic factors, urban form, and transportation networks on CO2 emissions in China's megacities. Appl. Energy 185, 189–200.
Wang, Y., Feng, Y., Zuo, J., Rameezdeen, R., 2019. From "Traditional" to "Low carbon" urban land use: Evaluation and obstacle analysis. Sustain. Cities Soc. 51, 101722.
Wegener, M., 1996. Reduction of CO2 Emissions of Transport by Reorganisation of Urban Activitie. Transport, Land-Use and the Environment,Boston. Springer US, MA, pp. 103–124.
Wu, C., Li, G., Yue, W., Lu, R., Lu, Z., You, H., 2015a. Effects of endogenous factors on regional land-use carbon emissions based on the grossman decomposition model: a case study of Zhejiang Province, China. Environ. Manag. 55, 467–478.
Wu, C., Li, G., Yue, W., Lu, R., Lu, Z., You, H.J.Em, 2015b. Eff. Endog. Factors Reg. Land-Use Carbon Emiss. Based Gross Decompos. Model.: A case Study Zhejiang Prov., China 55, 467–478.
Wu, H., Li, Y., Hao, Y., Ren, S., Zhang, P., 2020. Environmental decentralization, local government competition, and regional green development: Evidence from China. Sci. Total Environ. 708, 135085.
Wu, J., 2014. Urban ecology and sustainability: The state-of-the-science and future directions. Landsc. Urban Plan. 125, 209–221.
Wu, Z., Qiao, R., Zhao, S., Liu, X., Gao, S., Liu, Z., et al., 2022a. Nonlinear forces in urban thermal environment using Bayesian optimization-based ensemble learning. Sci. Total Environ. 838, 156348.
Wu, Z., Qiao, R., Zhao, S., Liu, X., Gao, S., Liu, Z., et al., 2022b. Nonlinear forces in urban thermal environment using Bayesian optimization-based ensemble learning. Sci. Total Environ. 838.
Wu, Z., Qiao, R., Liu, X., Gao, S., Ao, X., He, Z., Xia, L., 2023. CEDUP: Using incremental learning modeling to explore Spatio-temporal carbon emission distribution and unearthed patterns at the municipal level. Resour., Conserv. Recycl. 193, 106980.
Xia, C., Dong, Z., Wu, P., Dong, F., Fang, K., Li, Q., et al., 2022. How urban land-use intensity affected CO2 emissions at the county level: Influence and prediction. Ecol. Indic. 145, 109601.
Xie, H., Chen, Q., Lu, F., Wu, Q., Wang, W.J.Lup, 2018b. Spat. -Tempo disparities, Sav. Potential Influ. Factors Ind. Land Use Effic.: A case Study Urban Agglom. Middle Reach. Yangtze River 75, 518–529.
Xie, H., Zhai, Q., Wang, W., Yu, J., Lu, F., Chen, Q., 2018a. Does intensive land use promote a reduction in carbon emissions? Evidence from the Chinese industrial sector. Resour., Conserv. Recycl. 137, 167–176.
Xu, H., Guo, Y., Chen, Z., 2013. The relationship between land market development, urban land intensive use and carbon emission: An empirical study based on provincial panel data in China. China Land Science 27 (9), 26–29.

Yang, D., Luan, W., Qiao, L., Pratama, M., 2020. Modeling and spatio-temporal analysis of city-level carbon emissions based on nighttime light satellite imagery. Appl. Energy 268, 114696.

Yang, T., 2020. Understanding commuting patterns and changes: counterfactual analysis in a planning support framework. Environ. Plan. B-Urban Anal. City Sci. 47 (8), 1440–1455.

Yang, T., Pan, H., Zhang, X., Greenlee, A., Deal, B., 2021. How neighborhood conditions and policy incentives affect relocation outcomes of households from low-income neighborhoods—Evidence from intra-city movement trajectories. Cities 119, 103415.

Ye, B., Jiang, J., Li, C., Miao, L., Tang, J., 2017. Quantification and driving force analysis of provincial-level carbon emissions in China. Appl. Energy 198, 223–238.

Zeng, L., Wang, Y., Deng, Y., 2022. How Land Trans. Affect Carbon Emiss.: Evid. China 11, 751.

Zhang, H., Zhang, X., Yuan, J., 2021. Driving forces of carbon emissions in China: a provincial analysis. Environ. Sci. Pollut. Res. 28, 21455–21470.

Zhang, W., Xu, H., 2017. Effects of land urbanization and land finance on carbon emissions: A panel data analysis for Chinese provinces. Land Use Policy 63, 493–500.

Zhou, D., Huang, Q., Chong, Z., 2022. Analysis on the effect and mechanism of land misallocation on carbon emissions efficiency: Evidence from China. Land Use Policy 121, 106336.

Zhu, E., Deng, J., Zhou, M., Gan, M., Jiang, R., Wang, K., Shahtahmassebi, A., 2019. Carbon emissions induced by land-use and land-cover change from 1970 to 2010 in Zhejiang, China. Sci. Total Environ. 646, 930–939.

Ziaei, S., 2015. Effects of financial development indicators on energy consumption and CO2 emission of European, East Asian and Oceania countries. Renewable and Sustainable Energy Reviews 42, 752–759.

Zuo, S., Dai, S., Ren, Y., 2020. More fragmentized urban form more CO2 emissions? A comprehensive relationship from the combination analysis across different scales. J. Clean. Prod. 244, 118659.