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Industrialization, urbanization, and innovation: Nonlinear drivers of carbon emissions in Chinese cities

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HIGHLIGHTS

- The carbon emission of the secondary sector is decoupled as output rises.
- High tertiary sector output per capita will reduce carbon emissions.
- Technological application limits the carbon-reducing effect of innovation output.
- Traditional industries mask the low-emission from technological innovation.
- Constructing accurate nonlinear driving patterns by ensemble learning algorithms.

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ABSTRACT

As the world's largest developing nation, China has emerged as the predominant carbon emitter due to its swift industrialization and urbanization. Achieving low-carbon development in China necessitates a tailored approach that accounts for each city's unique industrial phase, technological advancements, urbanization level, and resources. This research endeavors to elucidate the nonlinear mechanism influencing carbon emissions in Chinese cities using a machine-learning framework, drawing on panel data from 290 cities from 2000 to 2017. The result indicates that China is experiencing a transition in the primary drivers of carbon emissions from the agriculture sector to the industrial and service sectors. A city transitions to the carbon decoupling phase when the outputs of primary, secondary, and tertiary industries surpass 1500, 125,000, and 100,000 CNY per capita, respectively. Additionally, we observed that expanding the urban built-up area beyond 10% can significantly mitigate carbon emission intensity. However, the study also highlights a critical challenge: the initial emission-reducing effects of innovation in burgeoning high-tech industries are negated by the higher emissions from traditional industries. Moreover, our analysis indicates that R&D investments exceeding RMB 8000 per capita may paradoxically lead to an increase in emissions. With these conclusions of nonlinearity, we emphasize designing policies tailored to the specificities of each city, stressing the importance of adaptability in policy creation.

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1. Introduction

The phenomenon of global warming and the resulting increase in extreme weather events have been widely recognized and are causing significant negative impacts on both the human and ecological environments [1,2]. Thus, the issue of greenhouse gas (GHG) emissions from human activities has received great international attention. To address this concern, the 26th Conference of the Parties of the United Nations Framework Convention on Climate Change (UNFCCC) reached an agreement that calls for a 45% reduction in global GHG emissions by 2030 based on 2010 average. Over the past few decades, China has experienced remarkable economic growth, propelling it to the position of the world's foremost developing country [3]. In parallel, it has emerged as the largest emitter of carbon emissions, responsible for more than a third of the global total. To address the concern, the Chinese government has proactively embarked on substantial measures, like setting the goal of a 60% reduction in carbon emissions per unit of GDP by 2030 [4]. These initiatives underscore China's unwavering dedication to confronting the task of managing carbon emissions.

To realize this objective, the study employs a sophisticated machine-learning framework to dissect the complex dynamics of carbon emissions across Chinese cities. This approach enables us to intricately analyze the nonlinear interplay between urbanization, industrialization, and technological innovation and how they collectively shape carbon emissions patterns, identifying critical thresholds in industrial outputs and urban development. In addition, the research generates valuable insights that can guide the development of bespoke policy interventions for managing carbon emissions in Chinese cities. This involves taking into account the distinct characteristics and developmental stages of each city to ensure that policies are not only effective but also contextually relevant. By doing so, the study contributes to a deeper understanding of the multifaceted challenges and solutions in the realm of urban carbon management in China, offering a roadmap for policymakers and urban planners in their efforts to forge a sustainable future.

1.1. Literature review and aim

The increase in carbon emissions has corresponded with rapid growth in the world's population. In the past century, urbanization has become a dominant trend, with 55% of the global population residing in cities in 2018 [5]. Despite occupying less than 3% of the earth's surface, cities consume 75% of the world's energy and are responsible for 80% of global GHG emissions [6].

In China, cities play a crucial role in implementing policies related to carbon emission reduction because cities are centers of economic activity, energy consumption, and infrastructure development [7–10]. Many industries that contribute to high carbon emissions are also concatenated in urban areas [11]. Urbanization has been identified as a potentially significant driver for China's carbon intensity, leading to its increased consideration in studies examining the issue [6,12]. Some scholars have suggested the existence of an Environmental Kuznets Curve (EKC) relationship between urbanization and carbon emissions [13], while others have found no evidence to support this [14]. Therefore, examining city-level measures and operational mechanisms can provide valuable insight into meeting China's carbon emission reduction targets [15,16].

Industry development drives the growth and transformation of cities, and cities provide the necessary resources and environment for industry. Currently, industrialization is the primary driver of China's economic expansion and escalating energy consumption [17]. The industrial sector shares around 70.3% of the country's energy consumption, marking a persistent upward trajectory in recent years. However, China's energy composition is dominated by fossil fuels, with coal alone accounting for approximately 70% of the fossil energy mix, resulting in a significant environmental toll [18]. From an industrial perspective, a 4.9% upswing in industrial final energy consumption corresponds with a concurrent 5.4% rise in carbon emissions [19], underscoring the close connection between industrial energy usage and its environmental ramifications. The effects of energy intensity, energy mix, and industrial structure on carbon intensity have been studied using regression analysis and decomposition methods [19–23]. Liu et al. used the logarithmic mean division index (LMDI) to decompose changes in Chinese industrial carbon emissions and found that industrial activity and energy intensity were the main contributors to changes in emissions [24]. Wang et al. employed the stochastic impacts by regression on population, affluence, and technology (STIRPAT) model and determined that the proportion of the industrial sector is generally conducive to a reduction in carbon intensity [25].

Technological advancements offer substantial potential in reducing carbon emissions intensity by optimizing the energy mix and enhancing industrial efficiency. For example, the transformation of the economic structure from energy-intensive heavy industries to high-tech industries can lead to a reduction in carbon emissions [26]. Lan et al. have studied the impact of foreign direct investment (FDI) on pollution emissions in China and found that FDI has a negative association with pollution emissions in provinces with higher levels of human capital but a positive association with pollution emissions in provinces with lower levels of human capital [27]. Huang et al. have investigated the effects of FDI, local research and development (R&D), and technology spillover on carbon intensity and found that local R&D and technology spillover can significantly reduce carbon intensity in China [28].

Previous studies have examined the influence of multiple economic, demographic, technological, and NTL factors on carbon emissions by employing regression modeling or decomposition methods, including STIRPAT, LMDI, and Environmental Kuznets Curve (EKC) [14,25,29,30]. However, these methods may be biased in analyzing the driving forces of carbon emissions since simple regression methods cannot accurately quantify the underlying mechanisms. Nevertheless, nonlinear driver pattern on carbon emissions still requires more comprehensive investigation and the refinement of previous research. Machine learning (ML) approaches can fit nonlinear data relationships and explore the marginal effects of emission drivers in different value domains [5].

In addition, the existing research are conducted on a national level, provincial level, or only a limited number of cities. This is because the Chinese government typically only releases carbon emissions data at the provincial level, and data at the city level is scarce [31]. In response to the data constraints, an NTL-based top-down approach has been proposed to estimate urban carbon emissions, like Lu et al. and Shi et al. [32,33]. One method involves utilizing nighttime lighting (NTL) based on satellite remote sensing images, which has the potential to estimate human activities such as population, economy, and urban construction [29,34]. Given the robust correlation between human activities and carbon emissions, the NTL method has been validated in prior studies [35,36]. These studies about city-level carbon emission estimations established a foundation for our investigation of the emission mechanism.

In this research, we employed an ensemble learning algorithm to establish the carbon emission empirical model and utilized the Shapley additive explanations (SHAP) algorithm to provide an intricate understanding of the underlying coupling mechanisms influencing carbon emissions. Our investigation pursued a tripartite aim: (1) to elucidate the synergistic impacts of economic development, industrial structure, urbanization, and population dynamics on carbon emissions; (2) to probe the nonlinear driving mechanisms of individual factors on emissions, discerning distinct thresholds via sophisticated ML techniques; and (3) to chart a municipal-level pattern of carbon emissions in China, drawing upon panel data from 290 Chinese municipalities.

2. Study area and data

2.1. Study area

As the largest carbon emitter in the world, research on China's carbon emissions has far-reaching implications for global ecological trends. China's administrative divisions include provincial, municipal, county, and township-level units, and national policies are implemented at all levels of government. In this study, we focus on prefectural administrative units as they are the basic units for developing and implementing emission reduction policies in China. Due to data limitations, our study. Focused on a targeted sample of 290 prefecture-level cities. These cities account for 87.09% of all prefectural administrative units within China. The spatial distribution of these cities is illustrated in Fig. 1.

2.2. City-level carbon emissions

Numerous researchers have made significant contributions to the estimation of city-level carbon emissions and established a robust research foundation and database. In prior research, methods for estimating carbon emissions can be broadly classified into two categories: top-down and bottom-up approaches [31,32,35,37–41]. The bottom-up approach requires extensive data collection efforts, and data completeness can significantly affect the accuracy of the final carbon emission estimates. The top-down approach estimates carbon emissions by interpolation or empirical models and can accurately evaluate larger-scale regional carbon emissions. However, this method falls short of providing a precise evaluation of individual point sources of carbon emissions.

Where Chen et al. provided county-level carbon dioxide emission data spanning the period from 1997 to 2017 [35], we aggregated county-level data to city-level to match the spatial hierarchy adopted in our study:

Here, CE_{city} and CE_{county} refers to the carbon emissions on the city and county level, respectively. The n is the number of counties that fall under the jurisdiction of the city.

2.3. Built-up area

To gain insight into the spatio-temporal dynamics of urban form in our study area units, we utilized the ArcGIS Pro 2.5.0 (ERSI) software (https://www.esri.com/en-us/arcgis/products/arcgis-pro/overview) to extract the built-up area of each city from the ESA's dataset Climate Change Initiative Land Cover (CCI_LC) [30]. This dataset categorizes the land surface into 22 classes based on the United Nations Food and Agriculture Organization's (UNFAO) Land Cover Classification System (LCCS). The urban land category was chosen as the focus of our study.

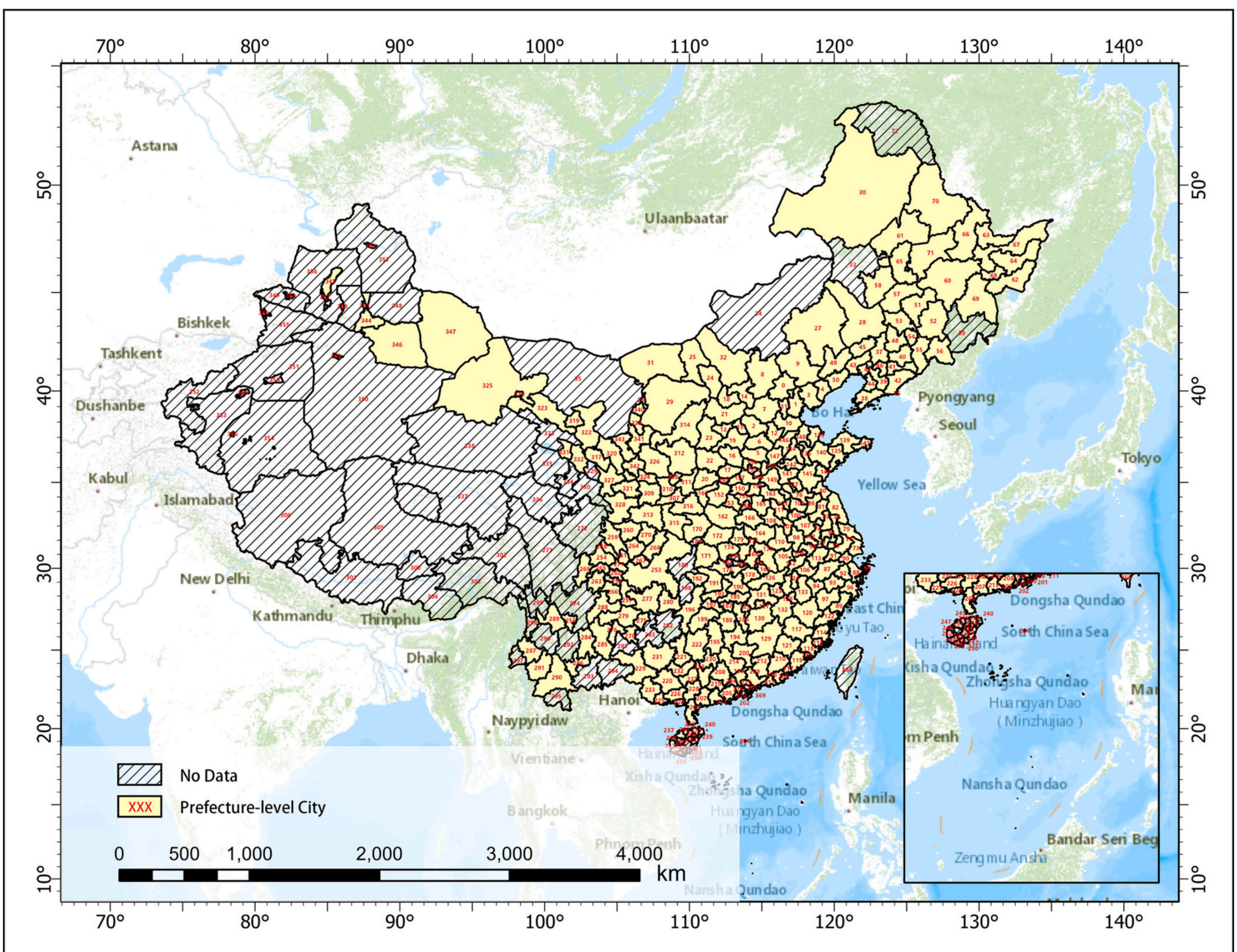

Fig. 1. Geographical areas in China covered in the study.

2.4. Urban social development

Urban development encompasses the growth of urban spatial morphology, economy, population, industrial patterns, and other social development aspects. Studies delving into the impacts of urban development on carbon intensity have found a noteworthy connection between variations in industrial structure across cities and their consequential influence on carbon emissions [42]. Industries in China can be grouped into three categorizations, including primary, secondary, and tertiary industry. This categorization was established in 1985 to facilitate the establishment of GNP statistics and has undergone several revisions, remaining in active use to the present day. According to the National Economic Classification of Industries (GB/T 4754-2017), the primary industry comprises agriculture, forestry, animal husbandry, and fishery; the secondary sector includes mining, manufacturing, electricity, heat, gas, and water production, and supply, as well as construction; and the tertiary sector refers to industries other than the primary and secondary industries, i.e., the service industry.

In this study, we use a panel dataset that covers 290 prefecture-level cities in China and spans from 2000 to 2017. The dataset includes each city's GDP, population, and industrial structure which were obtained from the China City Statistical Yearbook.

2.5. Urban innovation

Technological progress is widely recognized as a critical factor in influencing carbon emissions [26,43,44]. In an era of deepening globalization, transnational connections are drawing even closer, igniting a heightened flow of knowledge and technology spillovers across countries. While local protectionism has emerged in recent years, worldwide technology spillover effects have contributed to significant advances in technological innovation in China over the past several decades [45]. International knowledge spillovers primarily arise from investment and trade, whereby both imports and exports hold the capacity to augment technological advancements and energy efficiency in developing nations.

Numerous studies have highlighted the influence of innovation-related factors on carbon emissions [46–48], but they are provided on large-scale domains such as countries or provinces due to the lack of data on smaller scale. To investigate the driving effects of innovation on urban carbon emissions, this study employs research and development investment (R&D) as a measure of innovation input and the number of patents (PN) as a measure of innovation output. Panel data on R&D for 290 cities were obtained from the China City Statistical Yearbook, and PN data were collected from the QiZhiDao Patent Database.

2.6. Data variables

The study employed a dataset consisting of ten categories of variables to describe the development of municipal industries, technology innovation, social structure, and resource endowment. The model's resulting output data is the municipalities' per capita carbon emissions (see Table. 1).

3. Methodology

3.1. Carbon emission spatio-temporal characteristics

The first law of geography states that "everything is connected to everything else, but near things are more related than distant things" [49], which has been shown to apply to urban carbon emissions in previous studies. This suggests that the carbon emissions in different cities can be influenced synergistically by their surrounding areas. To measure the degree of spatial autocorrelation, the Global Moran's I and Local Moran's I are commonly used, and they can be expressed as:

Table. 1
The variables of the municipal carbon emission model.

	Variable	Description	Mean	SD
Independent Variables	Primary_PC	Agricultural product value per capita	2944.85	1933.95
	Secondary_PC	Industry product value per capita	16,462.84	21,105.03
	Tertiary_PC	Service product value per capita	13,206.42	20,455.70
	GDP_PC	Agricultural product value per capita	32,616.95	40,160.13
	RD_PC	R&D investment per capita	1239.81	5124.55
	Patant_PC	Number of patents granted per capita	0.47	1.39
	Built_PC	Urban built-up area per capita	7.19	6.31
	Built_PAA	Proportion of urban built-up areas to urban administrative districts	0.03	0.05
	City_X	Latitude of the city center point	113.80	7.36
	City_Y	Longitude of the city center point	32.93	6.74
Dependent Variables	Emission_PC	Carbon emissions per capita	6.17	5.93

$$I = \frac{n}{\sum_{i=1}^{n}\sum_{j=1}^{n}\omega_{ij}} \times \frac{\sum_{i=1}^{n}\sum_{j=1}^{n}\omega_{ij}(y_i - \bar{y})(y_j - \bar{y})}{\sum_{i=1}^{n}(y_i - \bar{y})^2} \tag{3-1}$$

$$I_i = \frac{n(y_i - \bar{y})}{\sum_{i=1}^{n}(y_i - \bar{y})^2} \times \sum_{i=1}^{n}\omega_{ij}y_i \tag{3-2}$$

Moran's I is calculated using the gross number of cities in the study area, represented by n, and the value of areas i and j,j represented by y_i and y_j. The average value of gross areas is represented by $\bar{y}$. The value of the spatial weight between areas i and j is represented by ω_{ij}. Moran's I ranges from -1 to 1, with the larger absolute value of Moran's I indicating a more significant spatial correlation, whether positive or negative. A value around 0 would suggest a random spatial pattern.

3.2. Carbon emissions driving model

Urban carbon emissions are influenced by a highly complex set of factors, such as industry structure, technology level, and energy endowment. The impact of these factors on carbon emissions is often difficult to disentangle due to the data limitation. Carbon emission data usually consists of only a few thousand observations, exacerbating the problem of the curse of dimensionality. This phenomenon occurs when models lose accuracy as the number of variables increases [50]. We used an ensemble learning algorithm to obtain a driver model that can overcome the aforementioned limitation. The ensemble learning algorithm combines the predictions of multiple individual learners to improve the model's accuracy and robustness. This approach results in better learning performance than a single learner, and the model has excellent generalization performance and is less prone to overfitting. Additionally, the model is insensitive to outliers and has good noise immunity, making it suitable for analyzing complex datasets with high variability.

We used an ensemble learning algorithm through the Light Gradient Boosting Machine (LightGBM) framework to address the challenges of modeling municipal carbon emissions. This algorithm is an optimized version of the Gradient Boosting Decision Tree (GBDT) framework, which uses two additional algorithms - Exclusive Feature Bundling (EFB) and Gradient-Based One-Sided Sampling (GOSS) - to improve performance [51]. The GOSS algorithm assigns weights to each sample point based on its gradient value, with points having higher gradients contributing more to the model. To maintain accuracy while reducing computation time, the algorithm keeps the high-gradient points and randomly selects a subset of low-gradient points. In addition, the algorithm uses a histogram approach to merge mutually exclusive features and reduce the dataset's dimensionality.

By combining these algorithms (EFB, GOSS, and histogram) under the LightGBM framework, the model can better handle the complex and interdependent relationships among the various influencing factors of municipal carbon emissions. The ensemble learning approach enables the model to learn from multiple individual learners and integrate their results, leading to better generalization performance and reducing the risk of overfitting. The model is also robust to outliers and noise in the data, making it a reliable tool for studying municipal carbon emissions.

3.3. Optimization of driving model

When developing the driving model for municipal carbon emissions, setting appropriate model hyperparameters is essential. While the LightGBM framework allows for spontaneous iteration over model weights, manual parameter adjustment or global search optimization can result in artificially biased outcomes and significant computing power expenditure. This can be attributed to the multidimensional data structure of the emission dataset and the complexity of the driving model's framework. This study employed Bayesian Optimization (BysO) to tune the model's hyperparameters. The process relied on two critical indicators, Prior Function (PF) and Acquisition Function (AF), respectively [52]. The Gaussian process was utilized to establish the PF to calculate the mean and variance of each hyperparameter per observation point. Points with higher mean values were exploited, while points with higher variance values were explored during optimization. Conversely, the AF aimed to measure and evaluate the balance between exploitation and exploration. The AF was computed using the following formula:

$$AF = \begin{cases} (\mu(x) - f(x^{+}))\Phi(Z) + \sigma(x)\phi(Z), & \sigma < 0 \\ 0, & \sigma \geq 0 \end{cases} \tag{3-3}$$

$$Z = \frac{\mu_x - f(x^{+})}{\sigma} \tag{3-4}$$

In the aforementioned formula, the variable x denotes an observation point, whereas $\mu(x)$ and $\sigma(x)$ represents the average and variance values of the observation points, respectively. Moreover, $f(x^{+})$ denotes the current maximum value of the objective function. $\Phi(Z)$represents the cumulative distribution function (CDF) of the standard normal distribution, whereas the probability density function (PDF) of the standard normal distribution is denoted by $\phi(Z)$.

3.4. Nonlinear driving pattern of municipal carbon emissions

In the realm of modeling nonlinear relationships, ML algorithms demonstrate superior fitting accuracy compared to classical statistical regression models. This can be attributed to the advanced structure and flexible activation functions that ML algorithms employ. However, as a trade-off for this increased accuracy, ML models tend to be less interpretable than statistical models. Although tree-based models such as GBDT, CatBoost, and Random Forest have been developed to interpret the contribution of features by tracking the number of times a feature is used and the degree of loss function decrease, these methods only provide a global interpretation. As a result, they fail to capture the full nonlinear advantage of the ML model.

To obtain a more comprehensive interpretation of the municipal carbon emission driving model, we utilized the Shapley Additive Explanation (SHAP) algorithm, which is a post hoc interpretation method for machine learning models. The algorithm is designed to calculate the marginal contribution of each feature to the model output, allowing for both local and global interpretation of the model's nonlinearity.

The SHAP algorithm calculates the impact of each feature by measuring the change in the expected model output when the feature value is included in the model prediction. It considers all possible combinations of feature values and calculates the Shapley value, representing each feature's expected marginal contribution to the model output. By aggregating the Shapley values of all features, the SHAP algorithm provides a global interpretation of the model's nonlinearity.

In addition to the global interpretation, the SHAP algorithm also provides a local interpretation of the model's nonlinearity. It calculates the Shapley values for a specific instance, revealing the contribution of each feature to the model output for that particular instance [53,54]. The calculation is as follows:

$$SHAP_j = \sum_{S \subseteq [V_1 + V_2 + \cdots + V_p]/[V_j]} \frac{|S|!(p - |S| - 1)!}{p!} \left(f_x\left(S \cup [V_j]\right) - f_x(S)\right) \tag{3-5}$$

$$y_i = y_{base} + \sum_{j=1}^{p} SHAP\left(x_{i\_j}\right) \tag{3-6}$$

In the SHAP algorithm, the SHAP value of feature j is denoted by $SHAP_j$, and S represents the feature subset. V_p represents the model's feature, and p represents the number of features. The model's prediction of the feature subset is denoted by $f_x(S)$. Moreover, y_i represents the model's predictive value at the sample i, while y_{base} represents the mean value of the predictive value at other samples. The SHAP value of feature j at the sample i is denoted by $SHAP\left(x_{i\_j}\right)$. By calculating the SHAP value of each feature for each sample point, the algorithm characterizes the positive and negative influence of different municipal features and carbon emissions on per-sample points in the study area, providing both global and local interpretability of the ML model.

4. Results and discussion

Our municipal carbon emission driving model was developed using Python 3.8 programming language. The experiments were conducted on a platform equipped with high-performance computing resources, including an NVIDIA GeForce RTX 3080 Ti Graphics Processing Unit (GPU), an Intel Core i9-11900K Central Processing Unit (CPU), and Radeon Graphics.

4.1. Spatio-temporal aggregation trend of carbon emissions

Chinese cities' energy resource and development policies often exhibit regional characteristics, leading to spatio-temporal aggregation trends in carbon emissions at the city level. To establish an accurate driving model, this study utilized Moran's I test to explore the distribution characteristics of carbon emissions. Given the different sizes of urban administrative districts, a spatial weight matrix based on the Queen's Case approach was constructed to calculate the global Moran's I index.

The result of Moran's I test indicates that the development of global spatial aggregation in China can be divided into two stages and was significant at the 99% confidence level. The first stage was before 2008, during which the global Moran's I index rapidly increased from 0.39 in 2000 to 0.47 in 2008. This sharp increase suggests a growing spatial aggregation of carbon emissions among Chinese cities, potentially driven by rapid industrialization and urbanization during this period. The expansion of industrial activities and energy consumption patterns during these years likely led to more pronounced spatial correlations in carbon emissions, as cities with similar industrial structures or developmental stages exhibited similar emission patterns. From 2008 to 2017, the second stage saw a small but volatile upward trend in the index, reaching 0.48 in 2017. The slight increase in the index could be attributed to several factors, including the maturation of industrialization, the slowed-down urbanization processes, and the implementation of regional environmental policies. In fact, China's 11th Five-Year Plan, which was implemented in 2006, made energy conservation and emission reduction an essential goal of national development for the first time. Although this plan was adopted in 2006, its impact was gradually felt in the following years.

In general, the carbon emissions of Chinese cities are closely related to their geographical locations. As a result, to improve the accuracy of the carbon emission-driven model, this study incorporated urban spatial variables in the subsequent modeling to capture the spatial relationships among cities.

4.2. Collinearity testing of carbon emission features

Before constructing a model to predict urban carbon emissions, it is necessary to examine the variables for collinearity. Collinearity can lead to distorted model estimates due to high correlations between the explanatory variables in the regression model. As this study involves a nonlinear fit of municipal carbon emission patterns using an ML algorithm, the covariance matrix of the variables was calculated using Spearman correlation coefficients. The formula used to calculate the covariance matrix is as follows:

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

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 from -1 to $+1$, with higher values indicating greater correlation between the variables. A coefficient exceeding 0.8 suggests that two variables are highly correlated [55].

Fig. A1 illustrates that City_X, City_Y, and Primary_PC are weakly correlated with the other features. On the other hand, GDP_PC, Secondary_PC, Tertiary_PC, Built_PC, and Patent_PC exhibit more significant correlations with each other, albeit still below the 0.8 threshold. Therefore, there is no severe collinearity issue among the independent variables, and all the variables can be included in the carbon emissions model training. The absence of a high correlation between the variables indicates that they are not overly redundant in their contributions to the model. As such, including all of them can provide a more comprehensive and accurate prediction of carbon emissions in Chinese cities.

4.3. Accuracy assessment of municipal carbon emission models

The study utilized the LightGBM framework based on Bayesian optimization (BysO_LightGBM) to examine carbon emission patterns in Chinese municipalities. The spatial autocorrelation analysis demonstrated highly significant spatial aggregation of carbon emissions in China, thus highlighting the importance of incorporating spatial variables such as City_X and City_Y to capture the relative spatial relationship of cities. To assess the accuracy and generalizability of the model, a 5-fold cross-validation test was conducted, where 30% of the data were randomly selected to form the test set, and 70% were used as the training set. The coefficient of determination (R-square) was employed as the model evaluation index to measure the quality of the regression fit, with higher R-square values indicating better agreement between the predicted and actual results.

Table. A1 presents the average R-square values obtained from the 5-fold cross-validation process. The results showed a significant increase in R-square values in the test set when the model included spatial variables, indicating satisfactory generalization of the model. The incorporation of spatial variables in the BysO_LightGBM model resulted in a robust and reliable prediction of carbon emissions patterns, with a high capacity for extrapolation.

4.4. Global interpretation of municipal features

The study utilized BysO_LightGBM to build a decoupling model that establishes the connection between city-level development characteristics and municipal carbon emissions. To further understand this relationship, the global SHAP value of each variable was calculated. The global SHAP value represents the average absolute value of the SHAP of a feature, indicating the degree of influence of the feature on carbon emissions. The calculation formula for global SHAP is as follows:

$$SHAP_{global\_j} = \frac{\sum_{i=1}^{n}|SHAP(x_{i\_j})|}{k} \tag{4-2}$$

Where $SHAP_{global\_j}$ represent the global SHAP value of the feature j.

Fig. 2 demonstrates the impact degree of each municipal feature on carbon emissions, as measured by the global SHAP values calculated using BysO_LightGBM. Among all the features, Secondary_PC has the most dominant influence on carbon emissions, with its contribution accounting for over one-third of the total impact. Specifically, the change in secondary production per capita in the sample would result in an average effect of 2.27 tons of carbon emissions per capita. This finding indicates the substantial impacts of the secondary industry on carbon emissions, highlighting its pivotal role in the formulation of effective emission reduction policies.

A city's geographical location was also found to wield a significant influence on its carbon emissions. The longitude and latitude variables, with the contribution rate surpassing 36%, are the second and third most crucial variables following secondary production. This observation suggests that the spatial distribution of cities plays a crucial role in determining their carbon emissions patterns. The unique emission patterns in different cities may be attributed to the differences in resource endowments of urban geographic spaces. This finding aligns with prior research that emphasized the importance of location-specific factors in shaping carbon emissions patterns [56].

Furthermore, it is worth noting that the variables characterizing municipal technology innovation, RD_PC, and Patent_PC, have a meager contribution to carbon emissions. Their sample change affects only approximately 0.1 tons of carbon emissions per capita. Such a result can be attributed to the fact that municipal technology innovation does not always lead to direct emissions reduction. While technological innovation can play a crucial role in the transition to a low-carbon economy, it is not a sufficient condition for mitigating carbon emissions in the short term. Instead, it may require long-term investments and policy support to achieve sustainable technological breakthroughs that can contribute to emissions reduction.

4.5. Influence of industrial structure

To generate a nonlinear model interpretation, an additive feature attribution method based on the SHAP algorithm was employed. This method defines the output model as an impact addition of the input variables, providing a means of visualizing the impact of industrial structure on municipal carbon emissions. The results are presented in Fig. 3, where the X-axis displays the per capita output of the three industries, and the Y-axis displays their respective impact on per capita carbon emissions, represented by the SHAP values for each sample. The zero line on the y-axis represents the dataset's average carbon emissions per capita value.

By utilizing the SHAP algorithm, we present the impact of China's three industries on municipal carbon emissions (scatter plots in Figure 3). The results indicate that the per capita output of the secondary sector has the most significant influence on carbon emissions, with the ability to impact emissions of up to 19.15 tons as it changes. In contrast, the primary and tertiary industries have a relatively weak impact on per capita emissions, affecting emissions of 6.24 tons and 5.34 tons, respectively.

Fig. 3-a highlights the impact of the Primary_PC variable on per

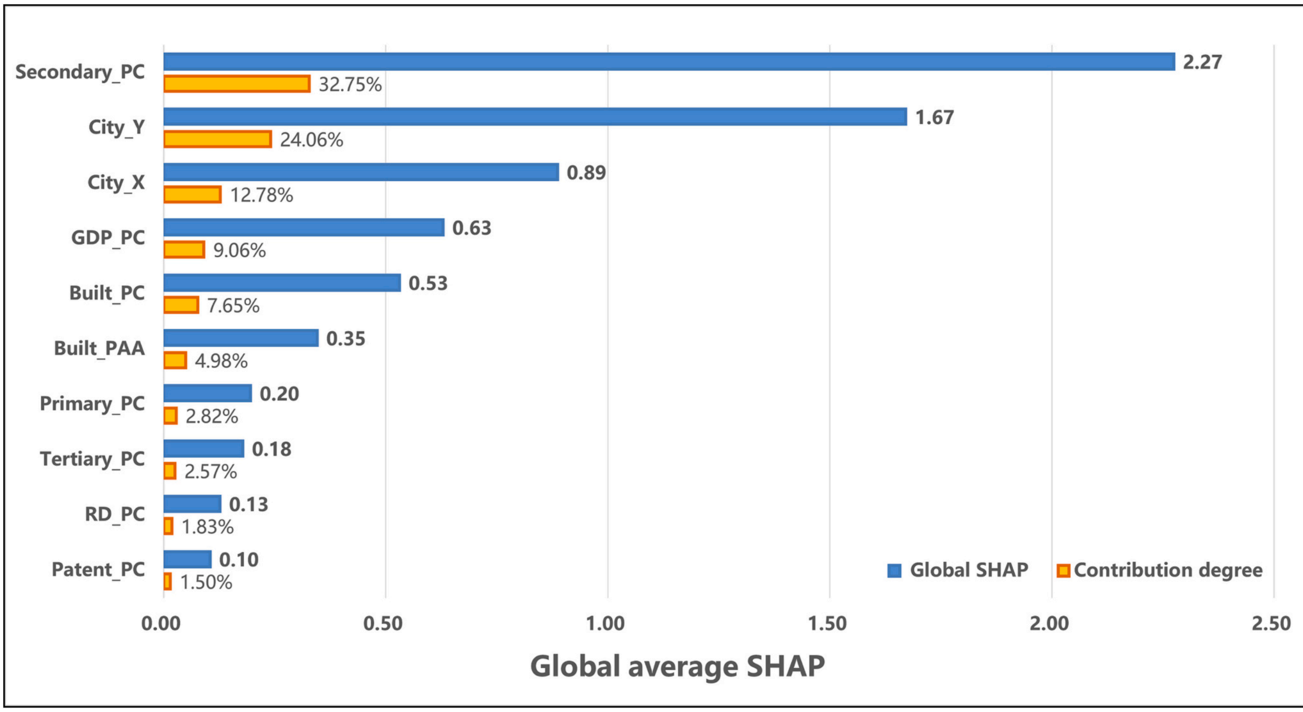

Fig. 2. The global SHAP and contribution degree of municipal variables.

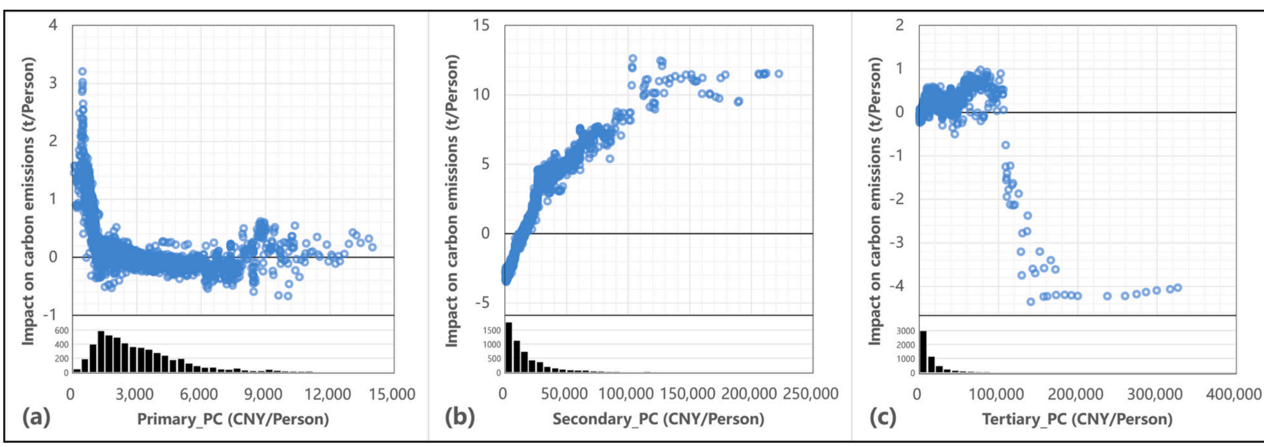

Fig. 3. The impact of industrial structure on carbon emissions and the data distribution. Blue scatters indicate the sample in the study. Black bars are the distribution of samples. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

capita carbon emissions, revealing a broadly divided trend into two phases. The impact exhibits a positive trend when the per capita output of the primary industry is below 1500 CNY, but as the output increases, its influence diminishes rapidly. This phenomenon arises from the nature of primary industries such as agriculture, forestry, and fisheries, which often entail resource-intensive activities and, therefore, possess a substantial carbon footprint. However, with technological advancements and increased efficiency within these industries, their impact on emissions gradually diminishes. After the per capita output value exceeds 1500 CNY, the primary industry's effect on emissions tends to stabilize. At a higher level of output, the primary sector may begin to give way to more advanced industries [57], and the finishing volume of the primary sector is limited to a certain extent, reducing the impact on carbon emissions [58]. 75% of the dataset shows stabilization of the effect of the primary sector on emissions, a fact that suggests that this pattern may be a common feature of carbon emissions in Chinese cities.

In Fig. 3-b, the Secondary_PC variable has a tremendous enhancement effect on per capita carbon emissions, with a trend that differs from that of the primary industry. Its impact trend can be divided into three phases. The significant enhancement effect of the variable on emissions for intervals of less than 25,000 CNY per person suggests that at low output levels, the production process and associated emissions are not optimized, resulting in a higher environmental cost. When the output exceeds 25,000 CNY per person but is below 125,000 CNY, the enhanced implications for carbon emissions gradually diminish. As output increases, the enhanced impact on carbon emissions gradually decreases, indicating a possible shift towards cleaner production technologies or improved energy efficiency measures [59]. Eventually, when it exceeds 125,000 CNY per person, the effect on carbon emissions flattens and slightly decreases. This can be explained by the fact that some industries within the secondary sector, such as high-end manufacturing, have a lower carbon footprint and a higher economic output compared to heavy industries like steel production. Thus, as the outcome of the secondary industry continues to increase, the share of low-carbon industries within the sector also increases, leading to a slight decrease in the overall impact on per capita carbon emissions [60,61].

Fig. 3-c illustrates the relationship between per capita carbon emissions and the per capita output of the tertiary industry in China. The passage notes that this impact trend is more complex than the trends observed for the primary and secondary sectors. Specifically, when the per capita output of the tertiary industry is below 100,000 CNY, the impact on per capita carbon emissions slowly increases as the output increases from approximately 0 to 1 ton, which suggests that the tertiary industry has a slightly positive effect on carbon emissions at inefficient output levels. This is because most of the services are labor-intensive in the early stage of the tertiary sector. It is a low-value-added production activity with minimal value-added capacity and is generally a resource-consuming industry. However, when the per capita output exceeds 100,000 CNY, the impact on carbon emissions quickly changes from positive to negative. At this point, the effect on emissions shifts from an increase of 0.98 tons to a decrease of 4.35 tons until the output reaches 200,000 CNY per person, demonstrating that at higher production levels, the tertiary industry has a more remarkable ability to reduce carbon emissions. This may be due to the gradual transition within the tertiary sector to high-end service industries, such as fintech and other knowledge-intensive industries, which enhances energy use efficiency and slows greenhouse gas emissions [62,63]

Overall, these findings highlight the need for industry-specific policies to effectively mitigate carbon emissions in China, considering the varying impacts of different industries at different output levels.

4.6. Influence of urbanization and innovation

The difference in impact between the ratio of built-up area and per capita built-up area on carbon emissions may be due to the fact that these variables measure different aspects of urbanization. The percentage of built-up area, which is the ratio of built-up land to total land, maybe more indicative of the overall level of urbanization in a region. In contrast, per capita built-up area measures the amount of built-up land per person, which may be more indicative of population density and urban sprawl.

Fig. 4-a illustrates the relationship between the Built_PAA variable and per capita municipal carbon emissions. The SHAP value of the variable is mainly positive when the ratio of the built-up area is less than 10%. However, the positive impact diminishes rapidly from 4.76 tons to 0 tons as the ratio increases. When the ratio exceeds 10%, there is an overall negative effect from 0 tons to a decrease of 1.25 tons (-1.25 in the Figure), with slight fluctuations between 20% and 40%. This may be due to increased energy consumption and emissions from transportation, buildings, and other urban activities resulting from the growing built-up areas. However, the economies of scale generated by urbanization will promote urban development and facilitate knowledge spillovers and technological advances, which in turn may promote the invention and application of clean technologies and new energy sources, thus providing mitigation effects for carbon emissions. This phenomenon was suggested in previous research findings [63].

We noted that the level of municipal innovation development (represented by the Built_PC variable) has significant impacts on per capita municipal carbon emissions. Fig. 4-b shows that as the built-up area per capita increases from 0 to 300 square meters, the impact of carbon

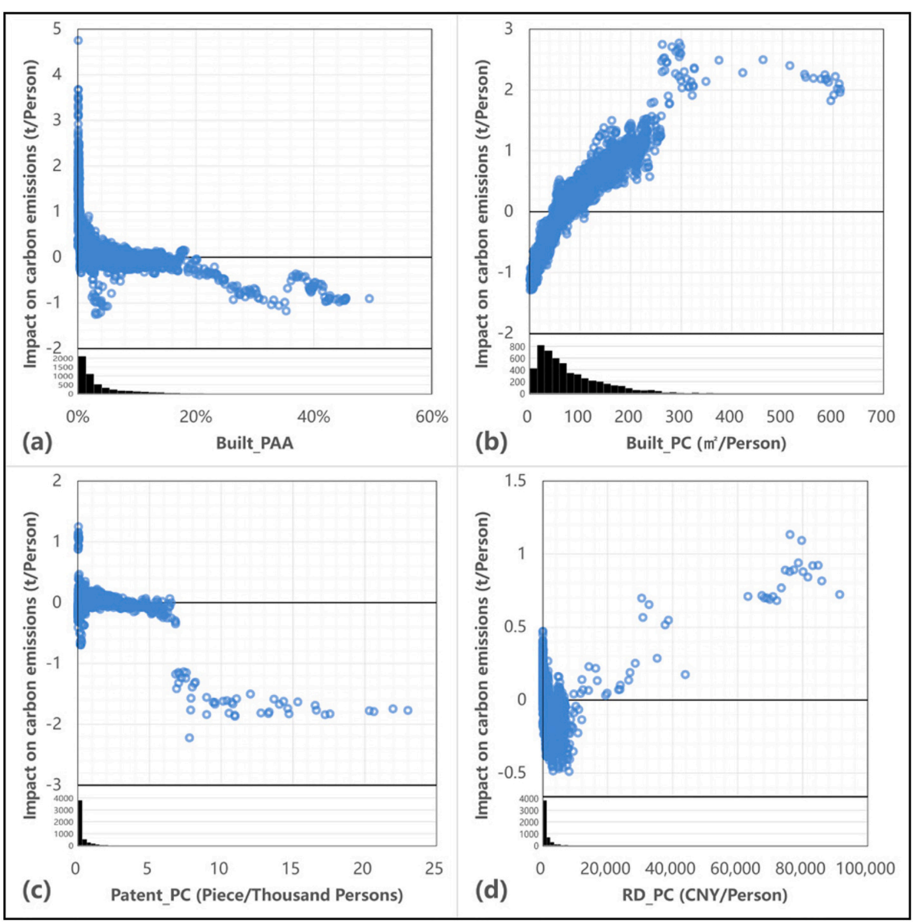

Fig. 4. The impact of urbanization and innovation on carbon emissions and the data distribution. Blue scatters indicate the sample in the study. Black bars are the distribution of samples. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

emissions experiences a swift escalation, reaching a peak of 2.77 tons per person. However, as the variable exceeds the threshold of 300 square meters, the positive effect on emissions starts to diminish slightly, and the boosting effect stays at around 2.25 tons.

The impact of innovation variables, Patent_PC and RD_PC, on carbon emissions is relatively small compared to other municipal feature variables, but their impact characteristics are diverse and complex (Fig. 4-c and Fig. 4-d). The impact of Patent_PC variable (Fig. 4-c), representing the level of patent innovation in the municipality, has two stages. The first stage shows a downward impact as Patent_PC increases from 0 to 1.5 Piece/Thousand Persons and then levels off. The downward impact on per capita carbon emissions may be because a low number of patents indicate a lack of technological development, which may lead to higher carbon emissions. When the Patent_PC exceeds 7.3 Piece/Thousand Persons, its impact enters the second stage, with a relatively flat negative contribution. However, as the number of patents increases, it may also indicate an increase in technological development, which can lead to the development of cleaner and more efficient technologies, resulting in lower carbon emissions. The flattening out of the impact of the variable at higher levels may be due to the diminishing returns of innovation, where further increases in innovation may have a limited effect on reducing carbon emissions.

Fig. 4-d demonstrates the impact of the RD_PC variable on per capita municipal carbon emissions. The RD_PC variable represents the municipality's research and development investment level. Similar to Patent_PC, the impact of RD_PC on per capita carbon emissions shows an initial period of decline, from an increase of 0.47 tons to a decrease of 0.49 tons. However, after the RD_PC crosses 8000 CNY per person, the effect quickly transforms into a positive impact and reaches a peak at 1.13 tons. The development of innovation variables on carbon emissions is complex and nonlinear, suggesting that a comprehensive approach is necessary to promote innovation and reduce carbon emissions.

4.7. Influence of industrial heterogeneity

The dynamics underlying carbon emissions are complex and multifaceted, particularly in the context of China, where the industrial sector emerges as the predominant source of carbon emissions [64]. This complexity is further amplified by the sector's internal diversity, characterized by significant variations in emission intensities across different industrial sub-sectors [65]. However, a notable challenge in analyzing this heterogeneity stems from the limited availability of subdivided industrial data in China, i.e., the government only releases the output value of 35 subdivided industries aggregated at the provincial level in the China Industry Statistical Yearbook. In response to this challenge, we categorize Chinese cities into three distinct clusters based on the government standard: the 'light industry' cluster, dominated by the production of consumer goods; the 'heavy industry' cluster, dominated by manufacturing production means; and the 'high-tech industry' cluster, dominated by the production of high-technology products.

In the analysis of industrial heterogeneity, the results indicate that the three sectors—primary, secondary, and tertiary—exhibit a similar range of influence on carbon emissions. Among these, the secondary sector is identified as the principal contributor to emissions. In contrast, the primary and tertiary sectors demonstrate a comparable and lesser impact on carbon emissions.

In the nonlinear analysis presented in Fig. 5, the impact of the Secondary_PC variable on per capita carbon emissions presents a significantly decreasing marginal utility. However, the thresholds for this effect vary across the three industrial clusters. Notably, the secondary sector within the heavy-industry cluster exhibits the lowest threshold at 40,000 CNY, yet it is associated with the highest emission intensity. This

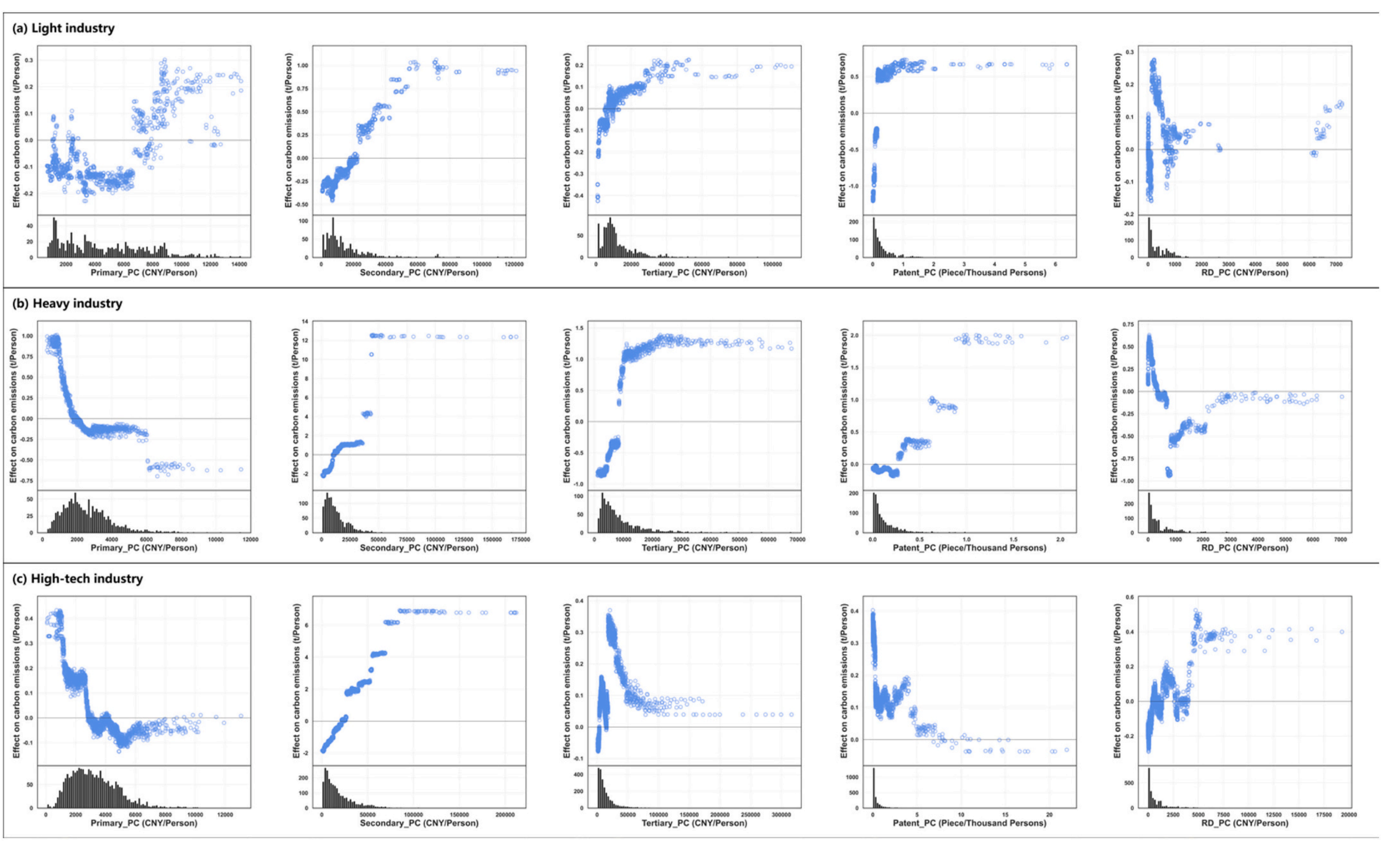

Fig. 5. The impact of industrial structure and innovation on carbon emissions and the data distribution among three industrial clusters. Blue scatters indicate the sample in the study. Black bars are the distribution of samples. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

sector demonstrates a capacity to influence emissions of up to 15.72 tons as its output changes. In stark contrast, the secondary sector in the high-tech-industry cluster shows a relatively gradual increase in carbon emissions, while simultaneously generating more economic output. The average per capita output value of secondary products in the light-industry, heavy-industry, and high-tech-industry clusters are 14,397 CNY, 13,220 CNY, and 19,231 CNY, respectively, demonstrating the high output characteristics of the high-tech-industry cluster.

Diverging from the secondary sector, the tertiary sector exhibits contrasting effects across the clusters. Initially, there is a notable increase in carbon emissions. However, upon surpassing a certain threshold, a decline in emissions is observed in the tertiary sector of the high-tech-industry cluster, differing from the marginal utility trends in the other two clusters. Specifically, in the high-tech-industry cluster, the Tertiary_PC (per capita tertiary sector output) contributes to a reduction in emissions from 0.37 tons to 0.04 tons as the output exceeds 20,000 CNY per person. This evidence underscores the potential effectiveness of promoting urban industrial transformation in China as a strategy for sustainable development [66].

Regarding the impact of innovation on carbon emissions, there is a significant divergence among the three industrial clusters, particularly in the direction of influence when considering patent activities. This variation is most pronounced between the high-tech-industry cluster and the other two clusters (light-industry and heavy-industry). In the high-tech-industry cluster, an increase in the number of patents per capita is associated with a rapid decrease in carbon emissions. This inverse relationship continues until a certain point; when the number of patents exceeds 10 Piece/Thousand Persons, the impact on reducing carbon emissions begins to stabilize. Conversely, in the light-industry and heavy-industry clusters, the scenario is markedly different. Here, an increase in the number of patents correlates with an increase in carbon emissions. Even though the average number of patents in these clusters is relatively low, at only 0.36 and 0.14 patents per thousand, respectively. This could imply that in these traditional clusters, the nature of innovation might be more focused on enhancing production efficiency or output rather than environmental sustainability [67].

4.8. Influence of urbanization heterogeneity

The urbanization stages of different cities exhibit considerable heterogeneity, with some cities experiencing an acceleration phase of urbanization while others have progressed to the later stages. This disparity manifests in significant variations in urban expansion and construction sector investments. To effectively address and analyze these variations, this study adopts a categorization approach based on the Northam curve. Accordingly, Chinese cities are classified into three distinct clusters: the 'low-urbanization' cluster with an urbanization rate of less than 30%; the 'medium-urbanization' cluster with an urbanization rate of between 30% and 70%; and the 'high-urbanization' cluster with an urbanization rate of more than 70% [68]. The urbanization rate is calculated based on yearbook data through the ratio of the population within the built-up area to the total population.

Within the three urbanization-stage clusters, the influence trends of the Built_PAA and Built_PC variables on carbon emissions exhibit similar patterns, albeit with varying degrees of intensity and distinct marginal thresholds (see Fig. 6). In a comprehensive analysis, it is observed that

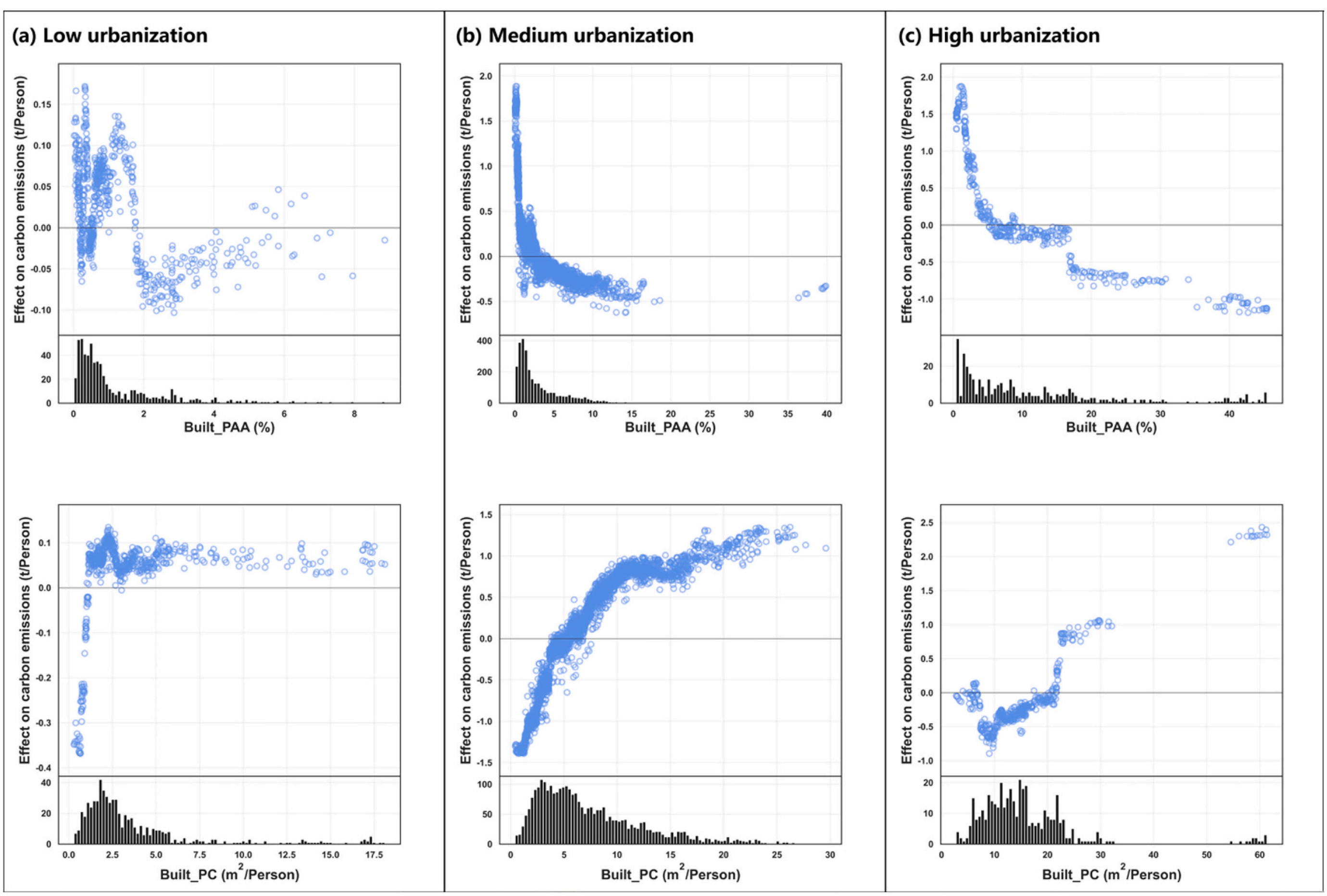

Fig. 6. The impact of construction demosions on carbon emissions and the data distribution among three urbanization-stage clusters. Blue scatters indicate the sample in the study. Black bars are the distribution of samples. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

the impact of the construction dimensions, represented by Built_PAA and Built_PC, on carbon emissions is comparatively subdued in cities at the nascent stage of urbanization, amounting to only 0.27 and 0.52 tons, respectively. This level of impact is considerably lower than what is witnessed in cities that are in the middle and late stages of urban development, which means that as cities progress through stages of urbanization, the influence of construction-related variables on carbon emissions appears to intensify.

In the context of medium urbanization, there is a clear pattern of diminishing marginal utility in the relationship between construction dimensions and carbon emissions. This trend starkly contrasts with the scenario in highly urbanized areas, where growth in influence on carbon emissions persists even amidst a slowdown in the impact of construction activities in regions with high development intensity. Notably, this study finds that when Built_PC reaches 60 square meters per capita, it correlates with a substantial increase in per capita carbon emissions by 2.49 tons.

5. Discussion

5.1. Industry development and transformation

The driving force behind regional carbon emissions in China is undergoing a shift from primary to secondary or tertiary industries [69]. As China continues to adjust its economic growth, the general trend of its industrial structure is moving towards upgrading traditional industries to high-tech ones. The development of primary production, such as agriculture, shows a decoupling effect on carbon emissions, as seen in Fig. 3-a. Additionally, data published by the FAO of the United Nations indicates that the carbon emission intensity of agriculture in China has been decreasing from 1978 to 2018, suggesting that efforts to reduce chemical inputs, comprehensively utilize agricultural waste, and improve energy conservation through mechanization have yielded significant results. Notably, the per capita output of China's urban primary production has exceeded 1500 CNY, indicating that primary production has entered a benign phase, and its further development is not expected to generate more significant emissions. As such, continuing efforts to improve the efficiency of the primary sector and further reduce its carbon footprint is a viable development strategy.

The impact of the per capita output of the secondary industry on carbon emissions fits with the three stages of industrial development in China (see Fig. 3-b). During the early stages of industrialization, the majority of China's secondary production was dominated by energy-dependent heavy industries, such as energy extraction, processing manufacturing, and energy extraction and processing [70]. As a result of China's coal energy resource endowment, fossil fuels were the primary energy source in this early stage [71]. Consequently, economic growth was closely tied to carbon emissions in the initial phase of secondary industry development. However, with the advancement of technology and a subsequent increase in resource utilization efficiency, the output value of China's secondary production has increased significantly. During China's 12th Five-Year Plan, the per capita output value of secondary production exceeded 25,000 CNY, marking the beginning of a phase of relative decoupling between economic growth and carbon emissions. As the development of some heavily industrialized cities, such as Suzhou, Dongguan, and Foshan, have progressed, they have entered the stage of full carbon emission decoupling with their per capita output value of secondary industries exceeding 100,000 CNY. This has led to a decrease in per capita carbon emissions in these cities in recent years.

The analysis of heterogeneity within the industrial sector provides essential insights into how the secondary sector's impact on carbon emissions varies across different industrial clusters. A key finding is the notable presence of diminishing marginal utility in carbon emissions within this sector. However, the thresholds at which this diminishing utility occurs vary significantly between clusters. This variation indicates that adopting a uniform environmental policy across all industrial sectors may not yield the most effective results. In particular, the heavy-industry cluster is characterized by a high emission intensity, which contrasts sharply with the lower emission profile of the high-tech-industry cluster. Despite the high-tech industry's higher economic output, it demonstrates a more gradual increase in carbon emissions. This suggests that technological advancement and efficient production methods in high-tech industries could be vital in achieving economic growth while minimizing environmental impact.

According to the impact degree of the tertiary industry, it is evident that low carbon emissions characterize the industries within the sector. Moreover, the tertiary industry's increased per capita output positively reduces the overall growth rate of carbon emissions. During the early stages of the transformation of the tertiary industry, low-end service industries such as restaurants and retail logistics experienced significant development, which resulted in a slight increase in carbon emission intensity. However, in recent years, the rapid integration and development of new-generation information technology and financial industries have increased per capita output value, particularly in cities such as Shenzhen, Shanghai, and Guangzhou, which have exceeded 100,000 CNY. As a result, the intensity of carbon emissions has significantly decreased. It is worth noting that the tertiary industry's low carbon emissions can be attributed to several factors, including a reduced reliance on energy-intensive production methods, more efficient use of resources, and a more excellent investment in renewable energy. The growth of the tertiary industry and the development of new technologies have led to a shift from manufacturing-based production to more service-based, less carbon-intensive activities. This shift has contributed to a significant reduction in the overall growth rate of carbon emissions.

5.2. Urbanization process

China is experiencing rapid growth in urbanization rates. This lifestyle shift has led to increased consumption of commodity energy, including coal, oil, and gas, as well as higher demands on consumer resources, such as shopping and travel. Currently, the central conflict in Chinese society is the imbalance between the people's growing pursuit of a better life and sustainable development. The accelerated urbanization process has led to the concept and awareness of energy saving not penetrating consumers' hearts. As a result, the general public is not sufficiently aware of the importance of energy conservation and emission reduction, especially in the highly energy-consuming and carbon-emitting urban construction industry [13]. The analysis reveals that while the Built_PAA and Built_PC variables consistently influence carbon emissions across different urbanization stages, their impact varies in intensity and exhibits distinct marginal thresholds.

In cities at the nascent stage of urbanization, the impact of construction dimensions on carbon emissions is relatively subdued. This lower level of influence might be attributed to the lower scale of construction activities or more efficient construction establishment in these emerging urban areas [63]. It also suggests that there is a window of opportunity in the early stages of urbanization to implement sustainable construction practices that can have long-term benefits in terms of carbon footprint. As cities progress from nascent to middle and late stages of urban development, the influence of construction on carbon emissions intensifies. High-density areas can be more energy-efficient due to reduced transportation emissions. Therefore, the government should plan for optimal urban density to minimize sprawl.

5.3. Science and technology innovation

Technological innovation has been identified as a crucial factor in promoting low-carbon development in China, which is consistent with previous research findings [28,43]. The impact of technological innovation and R&D investment on reducing carbon emissions per capita is significant. An increase in patents per capita leads to decreased carbon emissions per capita. However, as the number of patents increases, their ability to reduce emissions may become less effective and reach a saturation point. The study observes that cities with ultra-high R&D investments may experience an increase in carbon emissions per capita, which raises questions about the efficiency of R&D investments. This observation can be attributed to the low adoption rate of research results and the low output efficiency of R&D, which calls for improved management and evaluation of R&D investments. While technological innovation and R&D investments are essential for low-carbon development, there is a time lag between invention and implementation. Therefore, improving the technical absorptive capacity of cities is necessary for effectively implementing innovative technologies to reduce carbon emissions.

Combining overall and heterogeneity analysis, we uncover that the initial impact of emissions reductions driven by innovation in the early stages of high-tech industries tends to be overshadowed by the prevailing traditional industries in China. This phenomenon suggests that the substantial carbon emissions from traditional sectors (light and heavy industries) can dilute or mask the positive environmental impacts achieved through innovation in the high-tech industry. In the high-tech industry, increased patent activities correlate with a notable decrease in carbon emissions, illustrating an inverse relationship. This trend highlights innovation in the high-tech sector as being inherently aligned with environmental sustainability. Conversely, in the light and heavy industries, an increase in patents is associated with rising carbon emissions. This suggests that innovation in these traditional sectors is more focused on enhancing production efficiency rather than environmental sustainability. The relatively low average number of patents in these clusters further indicates a less aggressive pursuit of innovation, particularly in the context of environmental impact. The evidence supports the potential effectiveness of promoting urban industrial transformation as a strategy for sustainable development.

6. Limitations and prospects

This research illuminates the intricate nonlinear interplay between industrialization, urbanization, and innovation and their cumulative impact on carbon emissions. However, it's crucial to recognize certain constraints within this study, which present avenues for further research.

Firstly, our analytical approach is primarily grounded in industry data derived from statistical yearbooks. In our effort to understand the influence of industrial development on carbon emissions, we categorized Chinese cities into three primary industrial clusters based on provincial industrial breakdown data. Nevertheless, the absence of city-specific, disaggregated data may lead to an incomplete representation of the complex mechanisms linking urban dynamics to carbon emissions.

Furthermore, The absence of accurate bilateral data on urban energy or electricity to effectively identify the link between the supply side and demand side of energy consumption has led to a lack of in-depth research on the transfer effects of emissions. However, we recognize that emissions displacement is a complex issue, especially in the context of resource inequality in Chinese cities. This limitation underscores the need to broaden and update the existing databases to capture the city dynamics of resource carbon regulation fully.

7. Conclusions

Cities are a vital component of China's policy framework aimed at promoting energy conservation and emission reduction. To gain insights into the accurate patterns driving carbon emissions in Chinese cities, this study employs a carbon emission decoupling model based on panel data from 290 Chinese cities between 2000 and 2017. The model is developed using the BysO_LightGBM machine learning algorithm, which is further interpreted using the Shap interpretation algorithm to assess the nonlinear effects of economic development, industrial structure, urbanization, and science and technology innovation on carbon emissions.

The study reveals that the impact of China's municipal development characteristics on carbon emissions per capita is nonlinear and exhibits significant marginal utility. Traditional linear methods, such as decomposition or statistical regression models, fail to capture the many essential pattern changes, such as Wang et al. and Liu et al. [24,25]. To promote low-carbon development, it is vital to adopt a flexible approach that accounts for each city's unique characteristics, such as industrial development stage, technology level, urbanization level, and resource endowment, to meet their specific development needs.

The production output of industries is a crucial determinant of carbon emissions, with secondary production being the primary contributor. The relationship between per capita output of secondary production and per capita carbon emissions exhibits three stages of linkage - linkage, gradual decoupling, and decoupling. Therefore, the development of industrial clusters, focusing on high-end manufacturing to increase secondary production's per capita output value to over 125,000 CNY, is a promising path toward achieving the carbon peak. In addition, the development of the third sector, including financial, information service, and high-tech industries, can significantly mitigate the increase in carbon emissions. When the per capita output value of the third sector reaches 100,000 CNY, there will be a significant reduction in per capita carbon emissions.

The relationship between technological innovation and carbon emissions per capita is complex. As the number of innovations increases, the carbon emission intensity shows a stepwise decrease. Notably, in the early stages, high emissions from traditional industries can mask the emission reduction benefits of high-tech industries through technological innovation. However, the effect of innovation investment follows a V-shaped pattern, wherein the carbon emission intensity decreases up to a certain point, after which it increases again when the R&D investment per capita exceeds 8,000 CNY. Therefore, to promote synergistic development of China's economy and low carbon, it is imperative to enhance cities' technological absorption and application capacity.

In conclusion, to achieve low-carbon development in China, it is necessary to consider each city's unique characteristics, including its current stage of industrial development, level of technological advancement, degree of urbanization, and resource endowment. There is no one-size-fits-all solution to reducing carbon emissions in Chinese cities, and policies and strategies must be tailored to the specific context of each city.

CRediT authorship contribution statement

Renlu Qiao: Writing – original draft, Supervision, Conceptualization. **Xiaochang Liu:** Writing – review & editing, Resources. **Shuo Gao:** Writing – review & editing, Visualization. **Diling Liang:** Visualization, Conceptualization. **Gesang GesangYangji:** Writing – review & editing. **Li Xia:** Conceptualization. **Shiqi Zhou:** Conceptualization. **Xiang Ao:** Data curation. **Qingrui Jiang:** Writing – review & editing, Investigation. **Zhiqiang Wu:** Supervision, Conceptualization.

Declaration of competing interest

The authors declare that they have no conflict of interest.

Data availability

The authors do not have permission to share data.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.apenergy.2023.122598.

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