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Forecasting Carbon Emissions by Considering the Joint Influences of Urban Form and Socioeconomic Development—An Empirical Study in Guangdong, China

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Abstract

Carbon emission forecasting is a critical step in addressing climate change and effective environmental management. However, previous studies have concentrated mainly on socioeconomic factors, with less attention directed toward the significant impact of urban form. To address the shortcomings of previous studies, this study introduced three types of landscape indices that can characterize urban form and combined them with conventional socioeconomic factors to create a new carbon emission forecasting method. The enhanced STIRPAT and PLUS models were employed to forecast future changes in various socioeconomic factors and urban form, with the aim of forecasting carbon emissions in 21 cities of Guangdong during 2025–2060. The results confirm that urban form has an obvious influence on carbon emissions. In comparison to the baseline model, which considered only socioeconomic factors, the incorporation of urban form into the carbon emission forecast resulted in a reduction in the mean absolute percentage error from 7.16% to 6.18%. Moreover, carbon emissions were found to be positively correlated with GDP per capita, energy intensity, permanent population, share of secondary sector, LSI, and PLADJ but negatively correlated with PD. Furthermore, Guangdong will not be able to accomplish its "carbon peaking" objective around 2030, except in a low-carbon situation. Our proposed method could enhance the rationality of carbon emission forecasting, thereby providing a reasonable decision-making basis for low-carbon management.

Keywords: CO_2 emissions; carbon management; urban form; forecasting; STIRPAT model; climate change mitigation; Guangdong Province

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1. Introduction

The alarming rise in carbon emissions has been identified as a key contributing factor to the intensification of global climate change, leading to serious ecological and environmental concerns [1,2]. This phenomenon poses a substantial threat to the sustainable development of human society, and therefore the global consensus is to reduce carbon emissions [3,4]. As a crucial tool for addressing climate change, carbon emission forecasting could serve as a foundation for developing effective low-carbon management strategies and achieving sustainable development goals [5,6].

Notably, land is an indispensable resource for the maintenance of socioeconomic development. Effective land management can facilitate the sustainable development of cities [7,8]. The acceleration in global urbanization has triggered a profound transformation

in land use [9,10]. This transformation has caused an alarming rise in carbon emissions while facilitating economic growth [3,11]. Studies have shown that land resource development is the second greatest contributor to the rise in greenhouse emissions following fossil fuel consumption [12,13]. The evolution of urban form provides a comprehensive reflection of land development at the urban scale. Optimizing urban form can effectively enhance land-use efficiency, promote more efficient transportation patterns, and reduce carbon emissions, which is particularly important for accomplishing the "carbon peaking" objective [14,15]. Furthermore, socioeconomic factors can directly impact energy consumption and carbon emissions by influencing industrial structure and consumption patterns [6,16].

Consequently, the forecast of carbon emissions, considering the evolution of both urban form and socioeconomic factors, could serve as a basis for developing effective low-carbon management strategies and urban planning. However, there is a notable knowledge gap in existing carbon emission forecasting research. Specifically, few studies have attempted to forecast future carbon emissions by integrating the future evolution of urban form. Therefore, it remains unclear whether incorporating urban form into carbon emission forecasting improves its predictive accuracy and how future carbon emissions will change in response to urban form and socioeconomic conditions. The objective of this study is to address the aforementioned knowledge gap, thereby enhancing the rationality of carbon emission forecasting.

For this purpose, it is essential to simulate and forecast future land-use development, which can be achieved by using land-use change models, including cellular automaton, the future land-use simulation (FLUS) method, and the patch-generating land-use simulation (PLUS) method [17–20]. Recently, the PLUS model has gained increasing popularity due to its accuracy and stability [21,22]. Compared with earlier studies, the incorporation of a land-use change model into carbon emission forecasting allows for the effective consideration of dynamic land use and urban form changes. Therefore, the principal goal of this research is to determine how to incorporate the simultaneous effect of urban form and socioeconomic environment in the forecasting of carbon emissions. To achieve this objective, we combined the improved STIRPAT (Stochastic influences by regression on population, affluence, technology) and PLUS models with scenario analysis to develop a new carbon emission forecasting method. This method not only extends the existing framework for carbon emission forecasting but also facilitates the management of low-carbon cities. The Guangdong Province in China was selected as a case study due to its status as one of the most urbanized provinces in China and its ongoing struggle with serious carbon emission challenges.

The rest of this paper is organized as follows: The second part provides an overview of the existing literature on urban form and carbon emissions. The third part introduces the methodology, including the landscape pattern index, PLUS model, STIRPAT model, scenario analysis method, and a description of the data and case study. The fourth part presents the results, discussion, and policy recommendations. The fifth part puts forward the conclusions. The abbreviations are listed at the end of this paper.

2. Literature Review

2.1. Methods for Carbon Emission Forecasting

Previous studies have proposed a number of carbon emission forecasting methods from a socioeconomic perspective, which can be generally categorized as "top-down" and "bottom-up". The latter forecasts carbon emissions by analyzing the use of diverse energy sources. For example, Cai et al. [23] constructed a LEAP method for forecasting Bengbu's carbon emissions and stated that the "carbon neutrality" goal hinges on the upgrading of tertiary industries and the advancement of energy technology. Nevertheless,

the long-term and fine-scale energy data required for this methodology are challenging to obtain and are not applicable in areas with limited data availability. In contrast, the "top-down" approaches forecast future carbon emissions by analyzing the change trend of the leading factors for carbon emissions (e.g., gross domestic product (GDP), population, and energy intensity). For example, using the enhanced STIRPAT equation, Ren et al. [24] examined the effect of socioeconomic environment (e.g., permanent population, economic level, and urbanization level) on carbon emissions and forecasted Guangdong's carbon emissions during 2020–2060 under various scenarios. Their results indicated that this province is challenging to accomplish "carbon peaking" around 2030. While the "top-down" approaches may not fully account for the impact of energy use on carbon emissions, they can assist in identifying the general trajectory of carbon emissions in a more efficient manner.

Among the "top-down" approaches, the STIRPAT model has gained considerable traction in the research community due to its advantageous extensibility and flexibility. This feature enables researchers to extend the model in accordance with their specific research objectives, thereby facilitating the incorporation of diverse dimensions in carbon emission forecasting [1,25,26]. However, few studies have included urban form factors in their methodological framework. As the connection between carbon emissions and socioeconomic environment becomes increasingly decoupled, it is challenging to fully capture the change in carbon emissions by considering only socioeconomic factors [27,28]. Since the primary objective of this study is to explore whether the incorporation of urban form factors can enhance the performance of carbon emission forecasting, the structurally simple STIRPAT model was selected to facilitate the joint consideration of urban form and socioeconomic factors.

2.2. Impact of Urban Form on Carbon Emissions

To date, a unified definition of the term "urban form" has yet to be established. Previous studies have typically defined urban form as the spatial configuration of urban land, the scale of the urban fabric, and the distribution of population within an area [29–31]. The measurement methods and indicators of urban form vary depending on the specific application scenario but are generally related to the scale and geometric characteristics of urban land [32–34]. Previous studies have mainly employed landscape indices to assess the form of land-use patches so that the geometric characteristics of urban form, such as compactness and regularity, can be quantified [35,36]. The complexity reflects the irregularity of the edges of the city's buildings, while the compactness reflects the closeness and connectivity of the city's building layout. In fact, it is important to consider the effect of urban form on carbon emission forecasting. Urbanized areas consume approximately 75% of global energy and produce approximately 70% of carbon emissions [30,37,38]. In particular, urban form exerts an obvious effect on carbon emissions by indirectly affecting travel patterns and heat island intensity [31,39,40]. Several studies indicated that up to 50% of carbon emissions were closely correlated with urban form [24,41].

The connection between urban form and energy consumption is currently the subject of a growing number of studies. For instance, Li, Wang, Kang, Wang, Chen, Miao, Zhang, Ye and Zhang [32] reported substantial heterogeneity in the effect of built-up compactness on city-level carbon emissions in 275 counties. Falahatkar et al. [35] quantified the connection between urban form and energy consumption using a regression model in fifteen cities of Iran between 2001 and 2015. Their results indicated an increasingly positive connection between built-up complexity and energy consumption, while the inverse was observed for urban compactness and energy consumption. Sha et al. [42] examined the effect of urban form on greenhouse emissions in the Yangtze River region and reported that the complexity of built-up areas generally intensifies carbon emissions. Carpio et al. [43] investigated

the joint effects of urban form and land use on energy consumption in Mexico. Shu and Xiong [44] demonstrated that the fragmentation of built-up areas in the Yangtze River area was associated with a considerable rise in greenhouse emissions. Wiedenhofer et al. [45] reviewed a considerable amount of research related to urban form and greenhouse emissions. They reported that urban form and population play an influential part in decreasing direct energy consumption and carbon emissions related to daily mobility and housing. All these findings indicated that the role of urban form in greenhouse emissions cannot be ignored. Therefore, the integration of socioeconomic and urban form variables into carbon emission forecasting is expected to enhance the rationality of the forecasting results. Unfortunately, despite the well-recognized importance of urban form on carbon emissions, previous research has yet to fully consider the impact of dynamic changes in urban form on carbon emission forecasting.

Indeed, it has been demonstrated that both the socioeconomic environment and urban form have a significant influence on carbon emissions [46–48]. Given the complexity and dynamism of urban systems, it is necessary to consider the joint influence of socioeconomic development and urban form in carbon emission forecasting. This consideration has a sufficient theoretical basis, as socioeconomic development is frequently accompanied by urban sprawl and changes in urban form [4,7,44], which in turn can indirectly affect carbon emissions by changing the socioeconomic configuration and human behavior [30,33,43,49]. In light of these findings, recent research has endeavored to explore the mechanisms by which urban form and socioeconomic development jointly contribute to carbon emissions. For example, Li, Wang, Kang, Wang, Chen, Miao, Zhang, Ye, and Zhang [32] found that although socioeconomic variables (e.g., GDP) have a greater effect on carbon emissions than urban form (e.g., patch density), the contribution of urban form shows a rapidly increasing trend. Wang, Liu, Zhou, Hu, and Ou [47] indicated that the impact of urban form on carbon emissions is spatially heterogeneous and interacts with socioeconomic variables to jointly affect carbon emissions. Li, Wu, and Wu [48] demonstrated that increasing the compactness of built-up land helps mitigate carbon emissions, while economic growth and population growth result in increased carbon emissions. Therefore, the integration of socioeconomic and urban form variables into carbon emission forecasting is expected to enhance the rationality and accuracy of forecasting results.

2.3. Extensions of the STIRPAT Model

This study proposes the extension of landscape indices as urban form factors into carbon emission forecasting. Previous studies have demonstrated that the STIRPAT model is a flexible tool that enables the extension of diverse factors, thereby facilitating the identification of anthropogenic drivers behind environmental change [1,25,26]. To date, a number of studies have extended the drivers of policy, land use, and investment into the STIRPAT model, which can effectively explore the factors that influence carbon emissions. The results of these studies have demonstrated the feasibility and effectiveness of such extensions. In recent years, there has also been a growing number of studies that have incorporated the effects of urban land use on carbon emissions into the STIRPAT model.

To characterize urban form, a number of indicators related to urban land use have been used in these studies, including the degree of urbanization, urban land density, and urban landscape pattern [1,50,51]. All these studies have demonstrated that landscape indices can be effectively extended into the STIRPAT model. In addition, the landscape indices can be utilized to evaluate the human–environment relationship, which is consistent with the objective of the STIRPAT model to identify the key influencing factors of the natural environment. Therefore, it can be concluded that the extension of landscape indices into the STIRPAT model is scientifically rigorous.

3. Materials and Methods

3.1. Case Study

Guangdong Province in China was selected as a case study due to the region's serious carbon emissions challenges. Guangdong is the leading province in China in terms of GDP and population. It is the most important economic entity in China and has made significant progress in this country's reform, opening-up, and modernization drive [24,52]. Nevertheless, the rapid expansion of built-up areas in Guangdong Province in recent years has resulted in significant changes in the urban form of each city and different development trends. Currently, carbon emissions in Guangdong Province are still on the rise. As outlined in the socioeconomic data, Guangdong's carbon emissions reached 493.35 million tons in 2020, placing the province fifth in the country in terms of emissions [53]. This process has been accelerated by rapid economic and population growth, as well as urban sprawl [54,55]. Therefore, reducing carbon emissions through reasonable urban design while maintaining high-quality socioeconomic development has become a key challenge for Guangdong Province.

3.2. Data Sources

Three types of data from 2000, 2005, 2010, 2015, and 2020 are required for this study: spatial data, carbon emission data, and socioeconomic statistics (see Table 1). The sources of the spatial data are described below. The land development information for Guangdong Province was produced from the Chinese Land-Cover Database, which exhibits an overall accuracy of 79.31% in classification [56]. The digital elevation model (DEM) information was obtained from the Copernicus Contributing Missions (https://dataspace.copernicus.eu, accessed on 30 November 2023), with a resolution of 30 m. The slope information was generated using the "Slope" tool in ArcMap 10.2 based on the DEM and is measured in degrees. The "Resample" tool in ArcMap 10.2 was employed to adjust the data to a spatial resolution of 300 m. The traffic network and river channel records were obtained from OpenStreetMap (www.openstreetmap.org), while the administration center records were obtained from the China Academy of Science. These data were initially organized in vector format. The "Euclidean distance" tool in ArcMap 10.2 was employed to generate distance grids for roads of each level, administrative centers of each level, and rivers. The output pixel size was set to 300 m × 300 m. The spatial distributions of the annual average temperature and rainfall records were produced by the China Academy of Science, with a resolution of 1000 m. The resolution of the average annual temperature was rescaled using the "Resample" tool in ArcMap 10.2, with the resampling method set to "Bilinear". The precipitation was firstly resampled by employing the "Nearest" method, and subsequently, the raster calculator was utilized to calculate the value of each precipitation raster according to the area scaling relationship. The aforementioned spatial information was rescaled to a resolution of 300 m. We employed these spatial data to operate the PLUS model, thereby simulating future land-use in Guangdong Province.

Furthermore, city-level carbon emission data for Guangdong were obtained from the Chinese Carbon Emission Accounting Dataset [53]. This dataset was calculated using nighttime light data, and the coefficient of determination (R-squared) was found to be 0.9895, indicating a high degree of the model goodness of fit. The dataset has been extensively utilized in studies related to carbon emission forecasting. Energy intensity data were calculated from energy consumption data [57]. The socioeconomic statistics, including GDP per capita, permanent population, and share of secondary sector, were summarized from the socioeconomic data of Guangdong (http://stats.gd.gov.cn/gdtjnj/, accessed on 30 November 2023). These two types of data are tabulated and do not participate in the

PLUS model run. Instead, they were employed directly as variables in the construction of the carbon emission forecasting models.

Table 1. Summary of the datasets.

Data	Detailed Information	Source
Land use	30 m cell size	Yang and Huang, 2021 [56]
Traffic network	Expressway Railway Road	OpenStreetMap (www.openstreetmap.org)
River channel		
DEM	Elevation, slope, 30 m cell size	Copernicus Contributing Missions (https://dataspace.copernicus.eu/, accessed on 30 November 2023)
Temperature	1000 m cell size	China Academy of Science (https://www.resdc.cn/)
Precipitation	1000 m cell size	
Administration centers	City centers and district centers	
Carbon emission	2000, 2005, 2010, 2015, 2020	Chen et al., 2020 [53]
Socioeconomic data	GDP, population, the proportion of secondary industry, 2000, 2005, 2010, 2015, 2020	http://stats.gd.gov.cn/gdtjnj/, accessed on 30 November 2023
	Energy intensity, 2000, 2005, 2010, 2015, 2020	Chen et al., 2022 [57]

Due to limited data availability, it is challenging to obtain comprehensive data for the period prior to 2000 and for 2025. However, the period from 2000 to 2020 encompasses the pivotal stages of Guangdong Province's accelerated urbanization and industrial upgrading. The carbon emission driving mechanisms (e.g., industrial transformation, energy structure, and changes in urban form) are also highly representative in this stage. Furthermore, recent studies exploring the correlation between urban form and carbon emissions in China have focused on this same period [30,48,58]. Therefore, it is reasonable to designate the study period as 2000–2020.

3.3. Methods

First, landscape indices were employed to quantify the characteristics of urban form. Then, we constructed the STIRPAT model by combining these factors with conventional socioeconomic variables and using ordinary least squares for linear regression. Next, we utilized the PLUS method for forecasting future land use and the associated urban form. Finally, we used a scenario analysis approach for forecasting future carbon emissions by simultaneously considering the effects of urban form and socioeconomic environment (Figure 1).

3.3.1. Urban Form

Landscape indices are effective tools for reflecting the shape, composition, and spatial heterogeneity of land development [59–62]. According to previous studies, we utilized the Fragstats 4 package to measure three types of landscape indices: percentage of like adjacencies (PLADJs), patch density (PD), and landscape shape index (LSI) [31–33,35,49,63] (Table 2). The above indices can be utilized to effectively examine the level of compactness, fragmentation, and shape complexity of land development in Guangdong.

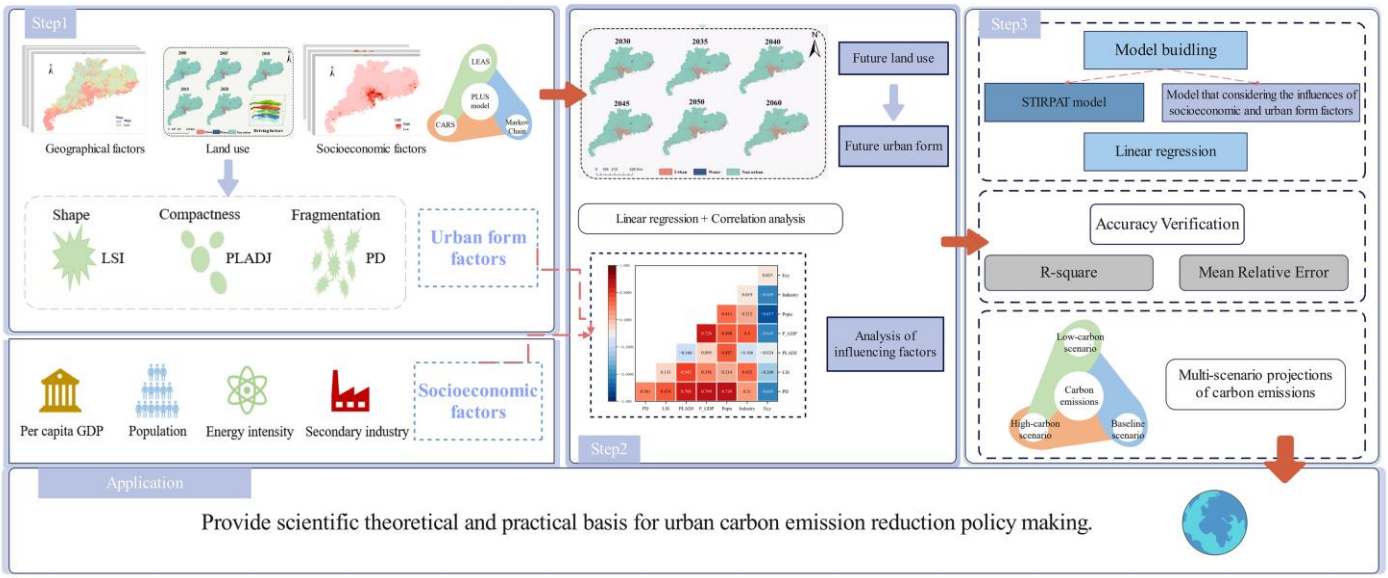


Figure 1. Framework of carbon emission forecasting.

Table 2. Landscape indices adopted in this research.

Category	Index	Calculation	Meaning
Compactness	PLADJ	$\frac{g_{ll}}{\sum_{j=1}^{m} g_{lj}}$	Measures the degree of patch aggregation, with a higher value indicating more compact patches.
Shape complexity	LSI	$\frac{E}{4\sqrt{A}}$	Measures the complexity of patches, a value close to 1 indicates a more regular shape, and a greater value suggests a more complex shape.
Fragmentation	PD	$\frac{N}{A}$	Measures the degree of patch fragmentation, and a greater value suggests a higher degree of fragmentation.

Note: A means the size of urban land, E means the perimeter of urban land patches, N means the number of urban land patches, g_{ll} means the size of similar adjacencies between grids of patch category l, and g_{lj} means the size of similar adjacencies between grids of patch categories l and j.

3.3.2. Forecast of Urban Form

The PLUS model is an enhanced land-use development modeling approach built upon the FLUS method and has been demonstrated to effectively capture and forecast land-use development at the patch scale [21]. Historical drivers are typically employed to obtain the probability of land-use development when employing the PLUS model to simulate future land use. This approach is characterized by simplicity and efficiency. However, it is deficient in its inability to adequately account for external shocks to land use resulting from future policy changes or natural disasters. One possible solution to this issue is to consider future drivers when evaluating land-use demands and development probabilities. For instance, shared socioeconomic pathways (SSPS) could be incorporated into land-use change simulation models to generate high-quality future land cover products [64,65]. Considering the cost of time and labor, as well as the research objective of this study, which differs from the latter, the former approach was adopted. This model has been extensively utilized in land-related research [66–69]. Consequently, we employed the PLUS method

to forecast land-use development in the study area. Specifically, a Markov chain was employed to predict the amount of land use for each category from 2025 to 2060.

To determine the optimal parameter settings for the PLUS model, we first referred to previous research on the modeling of urban expansion in Guangdong Province, as well as the model's user manual [21,55,70,71]. This process allowed us to identify a preliminary range of parameters that could be considered for use. Among these, the parameters of the LEAS module were evaluated based on the root mean square error (RMSE) of the random forest regression model. Through a process of repeated tuning, the optimal number of regression trees was determined to be 100, with a sampling rate of 0.1 and a mtry of 8. In addition, the parameters of the CARS module were determined based on the accuracy of the simulation outcomes produced by the PLUS model. Considering the development characteristics of Guangdong Province and the findings of previous research, the model parameters were subjected to multiple rounds of tuning. As a result, the optimal neighborhood weights for urban land, water bodies, and nonurban land were determined to be 0.8, 0.2, and 0.6, respectively. In addition, the optimal patch generation was set to 0.2, the expansion coefficient to 0.5, the neighborhood size to 11, and the sampling rate to 0.1 based on the same methodology.

Furthermore, a variety of spatial variables were adopted for calibrating the PLUS model in light of previous related research, including proximity to city centers, proximity to district centers, proximity to expressways, proximity to railways, proximity to roads, and proximity to rivers, slope, annual average temperature, and precipitation [21,60,72–74].

The Kappa coefficient and the figure of merit (FoM) are commonly employed to measure the accuracy of the PLUS model. The Kappa coefficient quantifies the classification accuracy of land use based on a confusion matrix. It reflects the degree of similarity between observed and simulated results. In addition, the FoM score measures the accuracy of patch changes, providing a comprehensive evaluation of the model's performance in dynamic simulations. Specifically, a higher Kappa coefficient and FoM score indicate better simulation accuracy of the PLUS model.

3.3.3. STIRPAT

The STIRPAT equation was introduced by Dietz et al. [75]. This model addresses the weakness of the IPAT approach by allowing for the adjustment of its parameters according to different relevant factors and local situations of the case study. The original function of the STIRPAT equation is shown below:

$$I = \alpha P^d A^e T^f g \tag{1}$$

where I signifies ecological pressure, P signifies population, A signifies capital, T signifies technique, d, e, and f represent the exponents of P, A, and T, α is a coefficient, and g is error.

To ensure that the time series variables remain stationary and homoscedastic, the modified STIRPAT model was obtained by taking logarithms on every part of Formula (1), as follows:

$$\ln I = c + d \ln P + e \ln A + f \ln T + \ln g \tag{2}$$

In this study, city-level carbon emissions during 2000–2020 were employed as the dependent variable. These data are annual, and 105 observations were included in each regression run. Two distinct carbon emission forecasting models were established for comparison. Model I is a conventional STIRPAT model that considers only socioeconomic factors. Model II is an enhanced model based on Model I, which has been augmented with landscape indices that reflect the characteristics of urban form. These two models were

then subjected to a comparison with actual carbon emissions, with the fitting accuracy of both models verified by R^2 and mean absolute percentage error (MAPE).

Since the STIRPAT model was adopted in this study, the selected socioeconomic factors must align with the requirements of this model, which is a crucial criterion for determining the relevant factors. Furthermore, additional emphasis was placed on ensuring the accuracy of the carbon emission forecasting results. First, the most commonly used socioeconomic factors were selected in accordance with the relevant literature [24,25,32]. Subsequently, the most appropriate variables representing population, capital, and technique were identified based on the accuracy of the carbon emission forecasting results. These variables were found to be permanent population, GDP per capita, and energy intensity, respectively. In addition, the industrial structure of Guangdong Province has undergone continuous optimization throughout the study period, which has a significant influence on the carbon emissions from energy consumption [24]. Therefore, the proportion of the secondary sector was also included to reflect the industrial structure.

Model I: a conventional model considering only socioeconomic factors [26,52].

$$C_{at} = a_1 Pop_{at}^{h} PG_{at}^{i} IS_{at}^{j} E_{at}^{k} \varepsilon_{at} \tag{3}$$

where C_{at} denotes carbon emissions of city a in year t ($a = 1, \ldots, 21$; t = 2000, 2005, 2010, 2015, 2020), Pop denotes permanent population, PG denotes GDP per capita, IS denotes the share of secondary sector, E denotes energy intensity, a_1 is a coefficient, ε is error, and h, i, j, and k are variables to be estimated.

By taking logarithms on each side of the above formula, a new formula was derived, as follows:

$$\ln C_{at} = \ln a_1 + h \ln Pop_{at} + i \ln PG_{at} + j \ln IS_{at} + k \ln E_{at} + \ln \varepsilon_{at} \tag{4}$$

Model II: an enhanced model built upon Model I, with the inclusion of urban form variables.

$$\begin{aligned} \ln C_{at} = \ln a_2 + h \ln Pop_{at} + i \ln PG_{at} + j \ln IS_{at} + k \ln E_{at} + l \ln \mathrm{PLADJ_{at}} \\ + m \ln \mathrm{LSI_{at}} + n \ln \mathrm{PD_{at}} + \ln \varepsilon_{at} \end{aligned} \tag{5}$$

where PLADJ, LSI, and PD are landscape indices of urban land, a_2 is a coefficient,ε is the error, and h, i, j, k, l, m and n are the variables to be estimated (Table 3).

Table 3. Factors in the carbon emission forecasting models.

Factor	Meaning	Unit	Source
Permanent population (Pop)	Total permanent population at year end	-	http://stats.gd.gov.cn/gdtjnj/, accessed on 30 November 2023
GDP per capita (PG)	-	Yuan/person	
Industrial structure (IS)	Share of the secondary sector's GDP in total amount	%	
Energy intensity (E)	Share of total energy consumption in total amount	Ton of standard coal/CNY 10,000	Chen et al., 2022 [57]
PD	Urban fragmentation degree	Number per 100 hectares	Calculated from land-use data (Yang and Huang, 2021 [56])
LSI	Urban shape complexity	-	
PLADJ	Urban compactness degree	%	

3.3.4. Development Scenarios

The scenario analysis method depends on historical information and the current status of development to establish different future change trends for each influencing factor. When this method is applied to the forecasting of carbon emissions, it is reasonable and common practice to adopt three-level settings, namely low, medium, and high scenarios [24,52,76].

Given the government's active role in China's economic development and the effective implementation of various medium- and long-term policy documents, it is reasonable to set scenario parameters based on these policy documents [28,41,77]. Consequently, in this study, the period between 2020 and 2060 was divided into five-year increments. A baseline scenario, a low-carbon scenario, and a high-carbon scenario were established in accordance with the actual development status and relevant policies of Guangdong Province.

The baseline scenario represents the socioeconomic development and carbon emission status under the historical development trend. The change rate of each socioeconomic factor under the baseline scenario was set in relation to the document issued by the Guangdong Provincial Government entitled "Profile of the 14th Five-Year Strategy for Domestic Socioeconomic Information in Guangdong and Prospect 2035" (http://www.gd.gov.cn/zwgk/wjk/qbwj/yf/content/post_3268751.html, accessed on 30 November 2023) (hereinafter referred to as the "Strategy Profile").

In the low-carbon situation, all cities will intensify the execution of energy-saving and emission mitigation activities. Specifically, local governments will allocate a considerable amount of funds to develop new technologies for energy production and emission mitigation, with a focus on building an efficient, green, and circular economy. Consequently, the increasing rate of GDP per capita is lower than the number in the baseline situation, and the decline rates of energy intensity and the proportion of secondary sector are faster. Furthermore, the growth process of the permanent population is moderated to reconcile the contradiction between population growth and resource availability.

The high-carbon scenario pursues high economic growth and relaxes a range of carbon emission reduction policies. Specifically, local governments will relax restrictions on industrial and energy transformation, which may exacerbate Guangdong Province's carbon emission problem. In this scenario, the growth potential of GDP per capita is faster than that in the baseline scenario. Furthermore, the decline rates of energy intensity and the proportion of the secondary sector are lower, while the growth process of permanent population is faster. The following sections outline the characteristics of these three scenarios.

(1) Permanent population

According to the National Population Development Plan (2016–2030) (https://www.gov.cn/gongbao/content/2017/content_5171324.htm, accessed on 30 November 2023), China's total population will peak at approximately 2030. Given the promotion of the "three-children proposal" and the generally high-fertility intentions of Guangdong's residents, it is anticipated that this province will not enter a period of negative population growth until 2030. In accordance with the Population Growth Strategy in Guangdong (2017–2035) (http://www.gd.gov.cn/zwgk/gongbao/2018/7/content/post_3365816.html, accessed on 30 November 2023), the annual increasing rate of the permanent population of Guangdong is expected to decrease to less than 0.5% after 2027. Therefore, the annual increasing rate of the permanent population of Guangdong was set at 0.5% during the 2021–2025 baseline scenario. The population is projected to enter a negative growth phase after 2030 [25,54]. Under the high-carbon and low-carbon situations, the mean increasing rates of permanent population were adjusted upward and downward by 0.2%, respectively, compared with the baseline scenario. These settings were informed by scenario projections of the rate of population change in Guangdong Province, as presented in the works of Ren et al. [24] and Chen et al. [52].

(2) GDP per capita

Guangdong is the most important economic entity in China and has experienced an unprecedented period of high GDP growth, averaging more than 10% per year during 2000–2010. From 2010 to 2015, Guangdong's GDP continued to rise at a medium-to-

high average annual rate of 8.7%. During the 13th Five-Year Strategy, the coronavirus disease outbreak exerted a negative effect on economic growth in Guangdong, with a lower average GDP growth rate of approximately 5.6%. The "Strategy Profile" indicates that during 2021–2025, Guangdong's GDP will probably rise at a steady annual rate of 5%. Based on relevant policies and studies [23,51], the annual increasing rate of GDP per capita in Guangdong was set at 5% during the 2021–2025 baseline scenario. Over time, the increasing rate of GDP per capita gradually declined. In the low-carbon and high-carbon situations, the average increasing rate of GDP per capita was 0.5% lower and 1.0% greater, respectively, than the number in the baseline scenario. These settings were informed by scenario projections of future rates of change in per capita GDP in Guangdong Province from the State Information Center of China (https://www.cec.org.cn/upload/1/editor/1632290978966.pdf, accessed on 30 November 2023), according to Li et al. [25] and Chen et al. [52].

(3) Proportion of secondary industry

The industrial sector is a fundamental component of the economy. With emphasis on pioneering manufacturing and tertiary industries, this province has established an industrial economy with newly emerging industries as the guiding principle. Therefore, the share of secondary industry displayed an overall decreasing tendency over time. According to the "Medium and Long-term Targets, Blueprints and Pathways for Socioeconomic Development" (https://www.cec.org.cn/upload/1/editor/1632290978966.pdf, accessed on 30 November 2023) released by the State Information Center, the share of the secondary sector in China will probably decline to 24.22% around 2050 under the baseline scenario. Based on relevant policies and studies [78,79], the mean increasing rate of the share of secondary sector was set at −2.5% during the 2021–2025 baseline scenario, with an average decline of 0.2% in every succeeding phase. In the high-carbon and low-carbon situations, the mean increasing rates of the share of the secondary sector increased and decreased by 0.5%, respectively, in comparison to those in the baseline situation. These settings were informed by scenario projections of China's future rates of change in the proportion of secondary industry by the State Information Center of China (https://www.cec.org.cn/upload/1/editor/1632290978966.pdf, accessed on 30 November 2023) and Li et al. [76]. We have adjusted it to account for the rate of change in the proportion of secondary industry in Guangdong Province over time.

(4) Energy intensity

The "Carbon Peaking Implementation Plan for Guangdong Province" (http://www.gd.gov.cn/zwgk/gongbao/2023/4/content/post_4091315.html, accessed on 30 November 2023) states that "by 2030, the control level of energy demand and carbon emission per unit of GDP will remain at the forefront in the country". According to the "Strategy Profile", the Guangdong government will make every effort to achieve the objective of decreasing energy demand per unit of GDP by 13.5% during 2021–2025. Based on relevant policies and studies [52,79], the average increasing rate of energy intensity was specified at −3.0% during the 2021–2025 baseline scenario. Owing to the continuous progress of energy use technology, the mean increasing rate of energy intensity will gradually decrease by 0.2%. With respect to the low-carbon and high-carbon situations, the mean increasing rate of energy intensity decreases by 0.2% and increases by 0.3%, respectively, compared with the baseline scenario. These settings were informed by scenario projections of future rates of change in China's energy intensity by Liu et al. [78] and Zhao et al. [79]. All specific settings are presented in Table S1.

4. Results

4.1. Construction of the Carbon Emission Forecasting Module

The regression results of Model I and Model II are presented in Tables 4 and 5, respectively. It is widely accepted that if the variance inflation factor for all variables is less than ten and the t-test is significant, this indicates the absence or only slight collinearity among the variables, and the regression model is robust and valid [80,81]. In our study, all the independent variables reached a significance level of 5%, demonstrating that these variables had a considerable impact on carbon emissions. Furthermore, the variance inflation factor for every variable was less than ten, which means that the regression models did not suffer from multicollinearity. The R^2 of Model I is 0.981, while that of Model II is 0.987. Therefore, the proposed model, which considers a set of urban form factors, is more effective at explaining carbon emissions.

Table 4. Regression outcomes for Model I.

Variable	Coefficient	Standard Error	Standardized Coefficient	t	*p*	VIF	R^2	F
Constant	−10.166	0.358	-	−28.420	0.000 ***	-		
lnPop	0.910	0.022	0.733	41.488	0.000 ***	1.677		
lnPG	0.807	0.020	1.070	40.401	0.000 ***	3.769	0.981	F = 1318.683
lnIS	0.168	0.048	0.052	3.478	0.001 ***	1.215		*p* = 0.000 ***
lnE	0.730	0.030	0.714	24.046	0.000 ***	4.739		

Note: *** signifies significance level of 1%.

Table 5. Regression outcomes for Model II.

Variable	Coefficient	Standard Error	Standardized Coefficient	t	*p*	VIF	R^2	F
Constant	−10.161	0.334	-	−33.304	0.000 ***	-		
lnPop	0.708	0.039	0.570	18.023	0.000 ***	7.248		
lnPG	0.691	0.027	0.916	25.775	0.000 ***	9.164		
lnIS	0.149	0.053	0.049	2.801	0.006 ***	1.982		F = 1021.709
lnE	0.597	0.034	0.584	17.328	0.000 ***	8.247	0.987	*p* = 0.000 ***
lnPLADJ	0.341	0.081	0.157	4.238	0.000 ***	9.913		
lnLSI	0.479	0.080	0.159	6.010	0.000 ***	5.059		
lnPD	−0.047	0.022	−0.037	−2.175	0.032 **	2.133		

Note: *** and ** signify significance levels of 1%, 5%, respectively.

Next, these two models were employed to simulate city-level carbon emissions during 2000–2020, and we compared the outcomes with the ground-truth carbon emissions (Figure 2). The mean absolute percentage error (MAPE) for Model I is 7.16%, while that for Model II is 6.18%. Furthermore, the MAPE for each city (except Zhuhai) in 2020 according to Model II are within 20%. In contrast, the MAPE for three cities (Zhuhai, Chaozhou, and Yangjiang) in the same year according to Model I are greater than 20%. In general, the number of cities in which the MAPE for carbon emissions is lower than 10% each year is seven in Model II, while there are only five cities in Model I. Therefore, the simulation results of Model II were more consistent with the real-world situation, and the incorporation of urban form variables enables a more comprehensive explanation of carbon emissions.

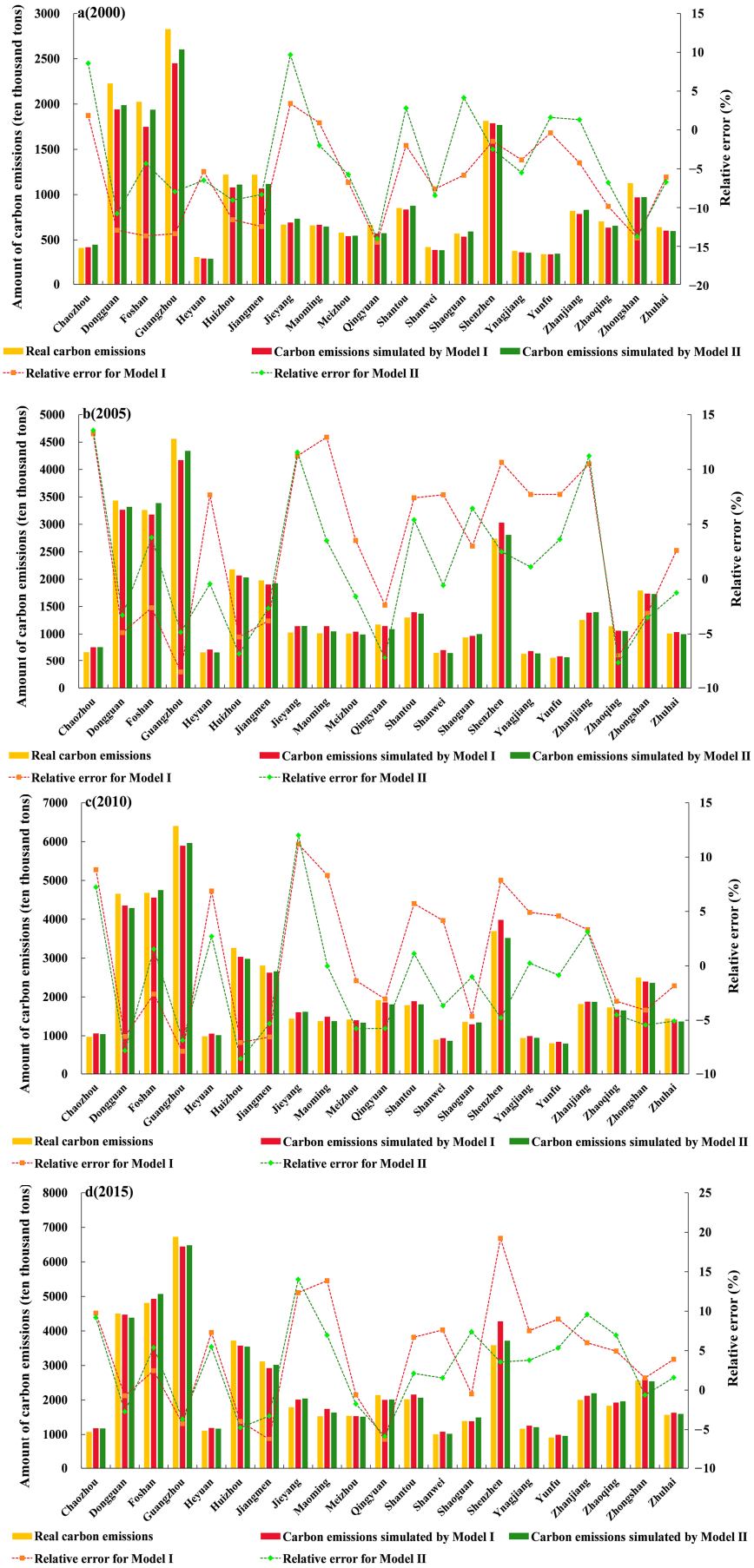


Figure 2. *Cont.*

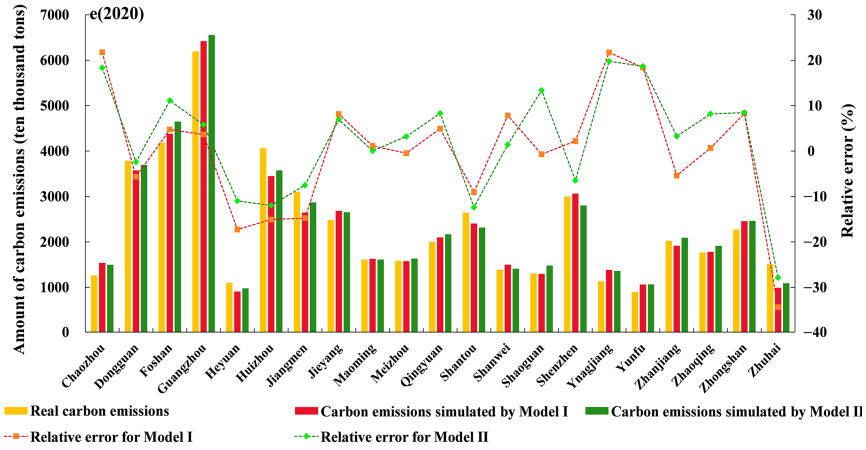


Figure 2. Comparison of actual and simulated carbon emissions during 2000–2020. (**a**) 2000; (**b**) 2005; (**c**) 2010; (**d**) 2015; (**e**) 2020.

Figure 3 presents the residual distribution of Model II. The results indicate that the frequency distribution of the residuals generally follows a normal distribution, with residuals randomly distributed around the zero line. Among these, 104 observations fall within two standard deviations of the mean, and only one mild outlier was detected (3.97 standard deviations). This outlier was identified as the carbon emissions data for Zhuhai City in 2020. In summary, the residual distribution of Model II complies with the fundamental assumptions of linear regression, thereby demonstrating its stability and applicability.

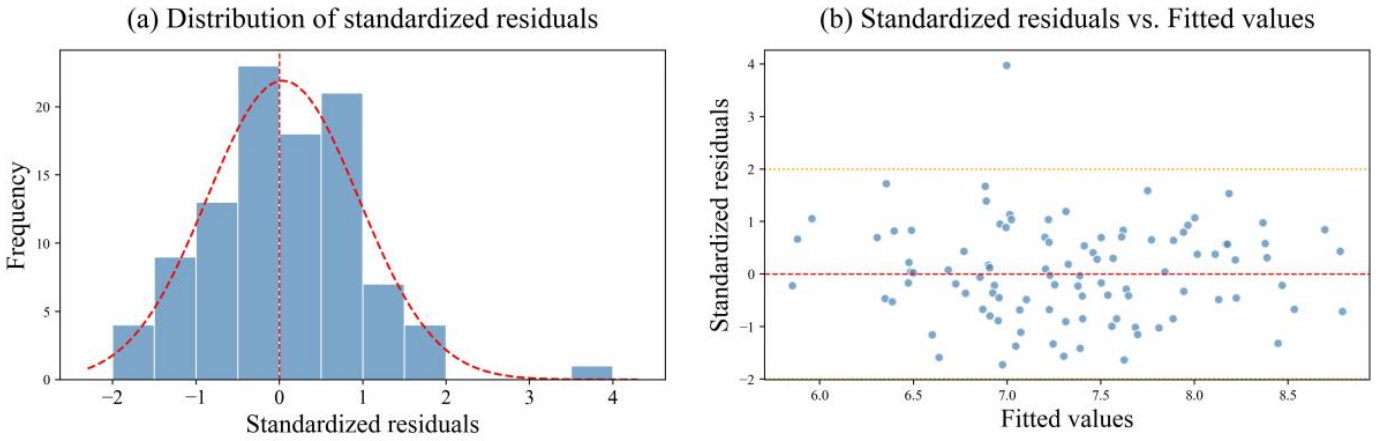


Figure 3. Residual diagnostics of Model II. (**a**) Distribution of standardized residuals; (**b**) Standardized residuals vs. Fitted values. The red dashed line and yellow dashed line indicate where the standardized residuals are equal to 0 and 2, respectively.

Finally, in order to further verify the importance of the urban form, Model III was constructed (Table 6), which considered only the urban form factors. The results indicated that Model III exhibited an R^2 of up to 0.889, with all variables being statistically significant and the absence of collinearity among them. This further justified the rationality of incorporating the urban form factors into the carbon emission forecasting model.

Table 6. Regression outcomes for Model III.

Variable	Coefficient	Standard Error	Standardized Coefficient	t	*p*	VIF	R^2	F
Constant	−7.653	0.358	-	−28.420	0.000 ***	-	0.889	F = 268.336 p = 0.000 ***
lnPLADJ	2.025	0.090	0.930	22.551	0.000 ***	1.541		
lnLSI	1.977	0.105	0.656	18.745	0.000 ***	1.108		
lnPD	−0.265	0.052	−0.210	−5.121	0.001 ***	1.526		

Note: *** signifies significance level of 1%.

Next, this study employed the standardized coefficients presented in Table 5 to quantify the role of each variable on carbon emissions. With respect to socioeconomic factors, there was a positive correlation between the permanent population, GDP per capita, energy intensity, the proportion of the secondary industry, and carbon emissions. An increase in permanent population and GDP per capita is linked with a rise in carbon emissions, whereas a decline in energy intensity and the proportion of secondary industry can act as limiting factors on carbon emissions. With respect to urban form factors, an important positive association was identified between carbon emissions and PLADJ, indicating that a more compact city is less conducive to mitigating carbon emissions. The LSI is another significant variable influencing carbon emissions. An increase in land-use shape complexity will cause a rise in carbon emissions. Furthermore, a negative correlation was observed between carbon emissions and PD, indicating that a higher urban fragmentation degree is associated with lower carbon emissions.

4.2. Future Carbon Emission Forecasting

4.2.1. Land-Use Development Forecasting

In our research, the PLUS method was employed to simulate land-use development during 2015–2020 (Figure 4). The modeling outcomes were then compared with real-world land information to quantify the effectiveness of the approach. The comparison revealed that the FoM score is 0.21, the kappa value is 0.93, and the overall accuracy is 0.99. The aforementioned indicators demonstrate that the modeling outcomes of the PLUS method exhibit an excellent degree of performance and can be employed to forecast future land-use changes [66,73]. Consequently, we employed the well-calibrated model to forecast urban land-use changes in this province between 2025 and 2060, after which each landscape index was calculated.

We further employed the control variable method to assess the impact of different parameter settings on the simulation accuracy of the PLUS model (Figure 5), thereby enhancing its robustness. The findings indicated that the calibrated PLUS model demonstrated notable stability, with the FoM score from multiple simulations generally exceeding 0.2. Among the various parameters, the patch generation threshold exhibited the most notable impact on the FoM score. Specifically, an increase in the patch generation threshold resulted in a decrease in the FoM score when the threshold exceeded 0.2. A potential explanation for this phenomenon is that an excessively elevated patch generation threshold hinders the interconversion of different land-use types, thereby distorting the simulation.

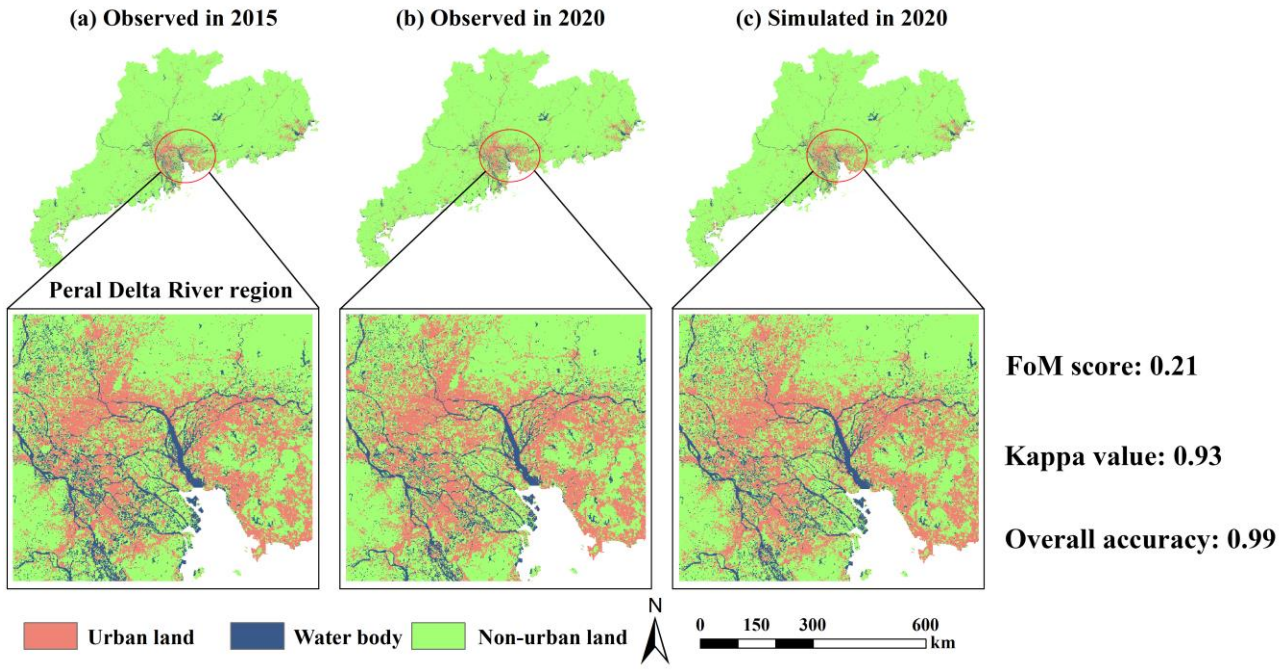


Figure 4. Simulation of urban land-use changes during 2015–2020.

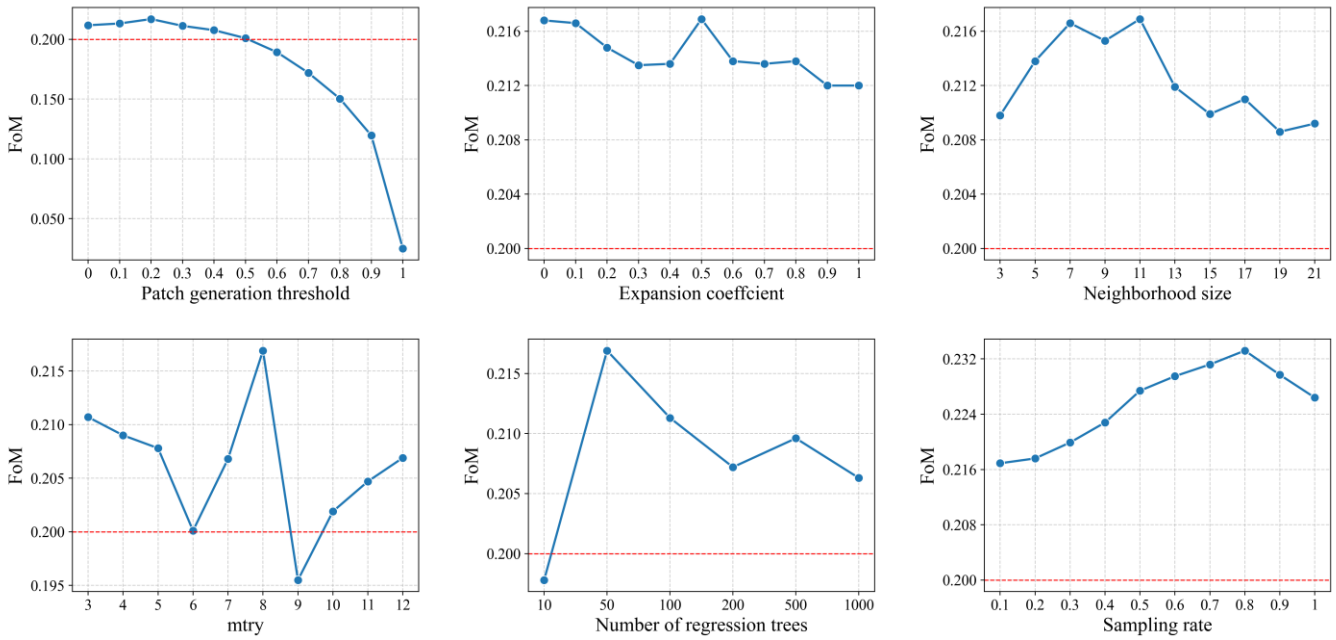


Figure 5. Sensitivity analysis of the PLUS model. The red dash indicates where the FoM score equals 0.2.

4.2.2. Scenario Forecasting of Carbon Emissions

Building upon the carbon emission forecasting method introduced in Section 4.1 (Model II), which simultaneously considers the influence of the socioeconomic environment and urban form, we forecasted the carbon emissions under each situation during 2025–2060 (Figure 6 and Table S2).

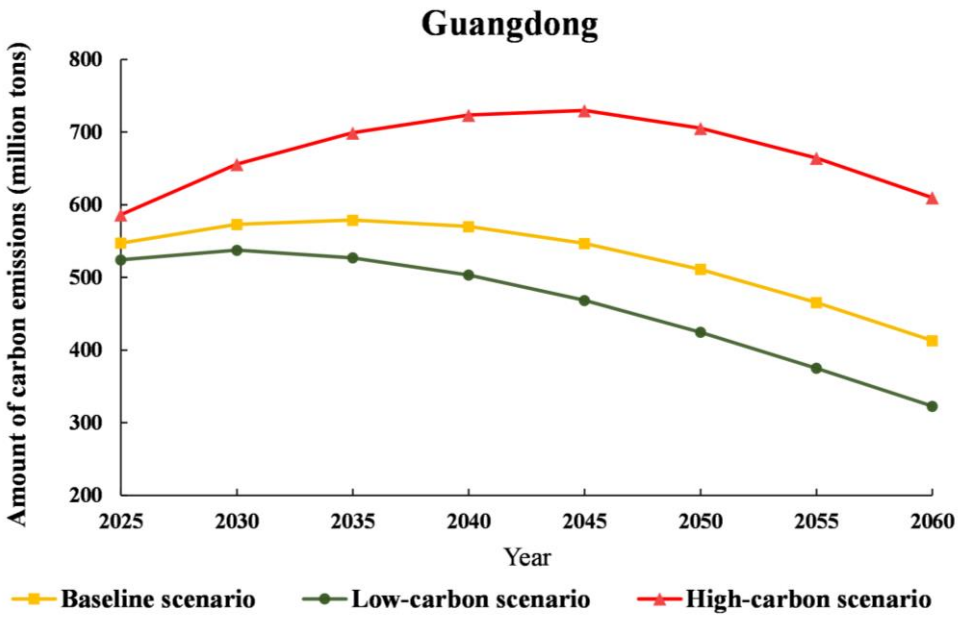


Figure 6. Carbon emission forecasting during 2025–2060 under each scenario.

Under the baseline situation, the historical development pattern during 2016–2020 of Guangdong is expected to continue. It is estimated that this province can fulfill its "carbon peak" by 2035, with a peak volume of 578.90 million tons. During 2020–2035, the mean annual increasing rate of carbon emissions is projected to reach 1.07%, after which there will be a continuous downward trend. By 2060, Guangdong's carbon emissions will decrease to 412.97 million tons, a decrease of 16.29% compared with 2020.

Under the low-carbon situation, socioeconomic development and population growth in Guangdong Province will decelerate, whereas the pace of industrial structure transformation and energy intensity improvement will accelerate. Guangdong Province is estimated to fulfill its "carbon peak" by 2030, with a peak value of 537.53 million tons. During 2020–2030, the mean annual increasing rate of carbon emissions in Guangdong is estimated to be only 0.86%. By 2060, Guangdong's carbon emissions are projected to decline to 322.67 million tons, a reduction of 34.59% compared with 2020.

Under the high-carbon scenario, it is estimated that Guangdong Province cannot fulfill its "carbon peak" until 2045, with a peak value of 729.62 million tons. During 2020–2045, the mean annual increasing rate of carbon emissions in this province is expected to reach 1.57%, which indicates a continued rapid upward trend. By 2060, Guangdong's carbon emissions are estimated to exceed 609.66 million tons, representing an increase of 23.57% from 2020.

Given the uncertainty associated with the regression coefficients of the ordinary least squares linear regression model, a total of 10,000 rounds of random sampling were conducted using the non-parametric bootstrap method, and the linear regression model was then refitted for each subsample. Finally, these models were used to estimate 90% confidence intervals (5th percentile to 95th percentile) for future carbon emissions in Guangdong Province under different scenarios (Figure 7), which helps to enhance the robustness of the forecasting results.

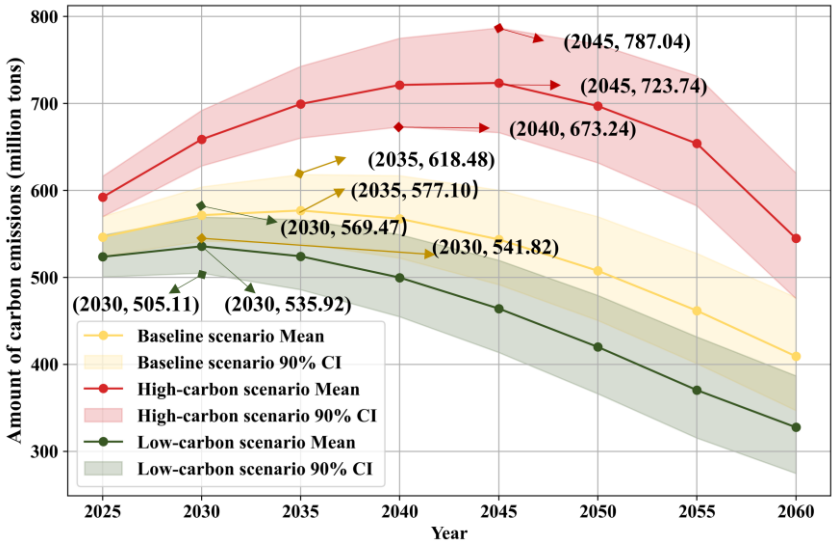


Figure 7. Uncertainty analysis of carbon emission forecasting in Guangdong Province.

The probability of Guangdong Province achieving "carbon peak" in each year (Figure 8) was further estimated based on the frequency of peak years. The most probable years in which the "carbon peak" will be achieved under the baseline, low-carbon, and high-carbon scenarios are 2035, 2030, and 2045, respectively, which is consistent with our previous analysis. Although the Guangdong Province is still expected to achieve its "carbon peak" in 2040 under the high-carbon scenario, this is far from being in line with its own stated expectation of reaching its peak in 2030.

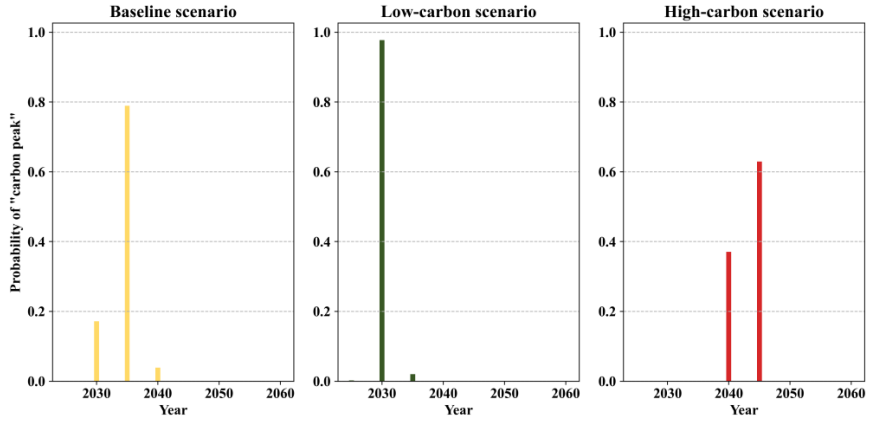


Figure 8. Uncertainty analysis of "carbon peak" in Guangdong Province.

In summary, Guangdong's carbon emissions could peak under all three scenarios, but the timelines and peak values differ substantially. It is unlikely that Guangdong will reach its "carbon peak" by 2030 if the current socioeconomic development pattern continues. The high-carbon scenario will further delay this goal. In contrast, the implementation of a low-carbon pattern would allow Guangdong to fulfill its "carbon peak" in 2030, as planned. It suggests that accelerating industrial restructuring, developing energy technology, and implementing rigorous energy-saving policies will effectively limit the growth in carbon emissions.

4.2.3. Scenario Analysis of City-Level Carbon Emissions

Figure 9 presents the forecast outcomes of city-level carbon emissions during 2025–2060 under the three situations. Under the baseline situation, Meizhou is projected to

fulfill the "carbon peak" by 2040, while the other cities will likely reach their "carbon peak" by 2035. As a mountainous city, Meizhou's economy is heavily reliant on energy-intensive industries such as thermal power, mining, and the cement industry. Consequently, its share of coal consumption is significantly higher than the provincial average, resulting in high energy intensity. The topographical constraints imposed by the mountainous terrain have resulted in the development of the older urban areas of Meizhou City along the Meijiang River, forming a belt-like configuration. In contrast, the newly developed urban areas, such as the Meixian District and Jiangnan New Town, exhibit a clear discontinuity in their urban layout. This phenomenon can be primarily attributed to the strategic avoidance of both farmland and ecological protection zones. The results of the land-use development simulation demonstrated that the shape complexity of Meizhou city will increase significantly in the future. The high carbon industrial structure and irregular urban layout may be the key reasons for the delayed realization of the "carbon peak" in Meizhou. Owing to its superior geographic location and substantial economic output, Guangzhou became the entity with the greatest emissions at the time of its "carbon peak" (a peak value of 7.52×10^7 tons). In addition, the excessively compact urban form is not conducive to reducing carbon emissions in Guangzhou. This has resulted in significant traffic congestion, which has led to increased energy consumption [27,36]. Furthermore, the high density of reflective glass façades absorbs and retains a substantial amount of solar radiation, thereby exacerbating the heat island effect and necessitating a considerable increase in the building's cooling energy consumption [82]. Foshan exhibited the fastest reduction in carbon emissions after its "carbon peak", with a mean annual change rate of −1.50% from 2035 to 2060.

Under the high-carbon scenario, no city can fulfill the goal of "carbon peaking" on schedule. It is anticipated that all cities in Guangdong Province will probably fulfill their "carbon peak" by 2045. The three cities with the highest emissions at the time of their "carbon peak" are Guangzhou, Foshan, and Huizhou. In contrast, it is anticipated that all cities in Guangdong Province will fulfill their "carbon peak" around 2030, as planned, under the low-carbon situation. The city with the lowest emissions at the "carbon peak" is Heyuan, with 1.08×10^7 tons.

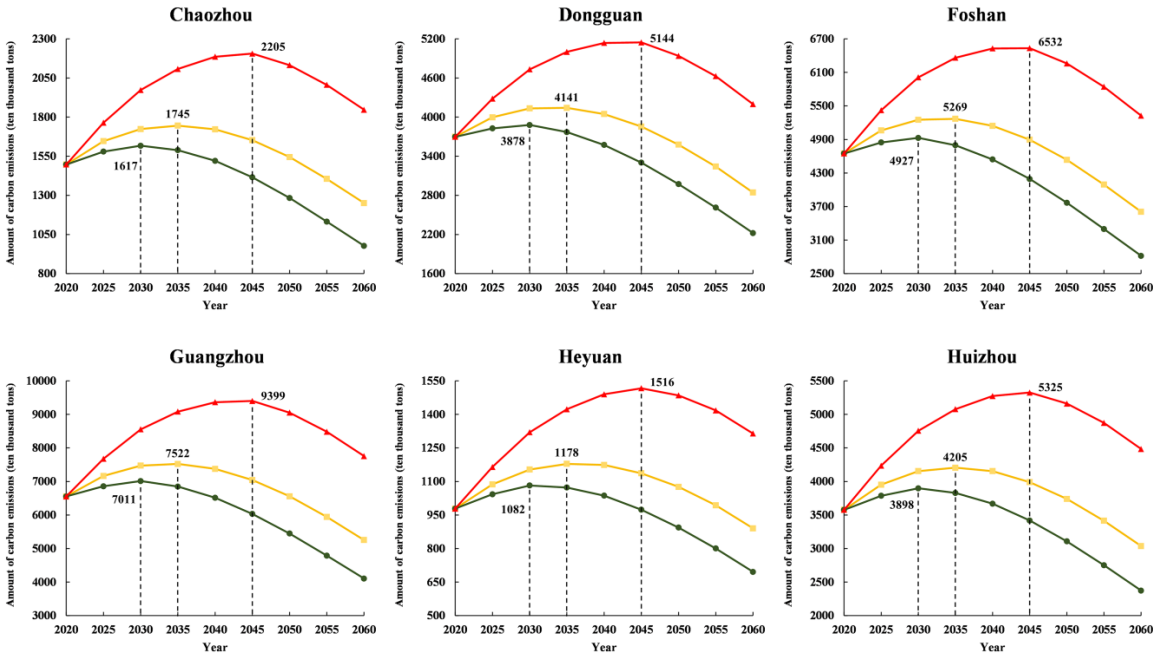


Figure 9. *Cont.*

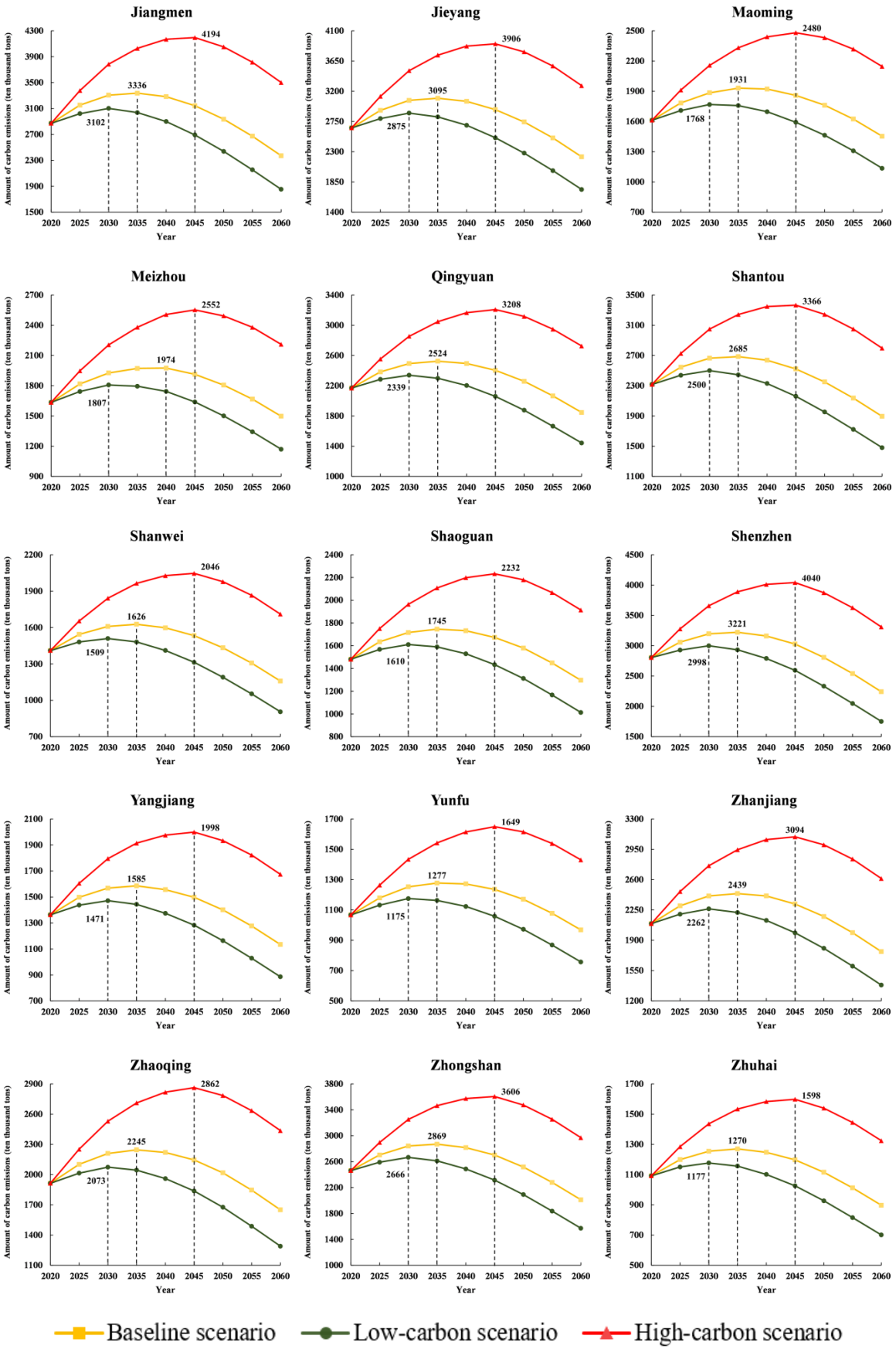


Figure 9. Carbon emission forecasting for each city during 2025–2060 under the three scenarios.

4.3. Discussions

4.3.1. Comparison with Prior Studies

The overreliance on socioeconomic regulation measures (e.g., improving energy sustainability and optimizing industrial technology), while ignoring the optimization of urban form, could significantly hinder the achievement of the "carbon peaking" target [2,4,58]. Although a number of studies have investigated the internal mechanisms of urban form on greenhouse gas emissions, few have incorporated these findings into carbon emission forecasting. To address this deficiency, we proposed a new carbon emission forecasting model that simultaneously considers the influences of socioeconomic environment and urban form. The outcomes suggested that urban form has profound effects on carbon emissions. Compared with the baseline model, which considers only conventional socioeconomic factors, the incorporation of urban form factors can enhance the rationality of carbon emission forecasting.

A number of studies have focused on improving the accuracy of carbon emission forecasting, primarily through the optimization of algorithms. For example, Ren et al. [24] proposed CSO-FLN, while Chen et al. [52] put forward TPE-BP, and Wan et al. [83] presented DIGM (1, N). While these studies have made notable contributions to improving accuracy, the models they constructed generally consider only socioeconomic variables. These studies have suggested the optimization of industrial and energy consumption structures as a significant strategy for mitigating carbon emissions. In contrast to previous studies, this study proposed a novel carbon emission forecasting framework that considers the joint influence of urban form and socioeconomic development. This could enhance the rationality of carbon emission forecasting. In addition to a more comprehensive consideration of the independent variables, another advantage of this study is the capacity to forecast carbon emissions at the municipal level while maintaining a high goodness-of-fit level. Despite the finding that Model II demonstrated an excellent fit for most cities, it is important to acknowledge that individual cases with large errors, particularly in Zhuhai, where the MAPE exceeded 20%, indicate that Model II falls short in adequately capturing the unique driving mechanisms of carbon emissions in Zhuhai City. In future research, we can attempt to apply more complex and advanced carbon emission forecasting models to explore whether we can further improve the accuracy of carbon emission forecasting results that take urban form into account.

The outcomes of the scenario forecasting indicated that Guangdong Province cannot fulfill its "carbon peak" in 2030 if the status quo or an extensive socioeconomic development pattern is adopted. This finding is in line with the conclusion of Ren and Long [24]. A low-carbon development pattern is a crucial pathway for Guangdong Province to fulfill the planned "carbon peak". In summary, it is recommended to control the pace of economic and population growth and optimize industrial technology and energy sustainability to limit the increase in carbon emissions. This finding was also in agreement with the outcome of previous studies [77,84,85].

Despite the importance of carbon emission reduction measures from a socioeconomic perspective, steady economic growth remains a fundamental goal for many developing countries and regions [36,86]. Consequently, the implementation of carbon emission mitigation measures will be more challenging when economic growth is a priority. Furthermore, the significant reliance on fossil fuels in these regions poses a challenge to the implementation of energy efficiency measures intended to reduce greenhouse gas emissions through the restructuring of the energy sector [5,87]. In this regard, rational urban design represents a promising approach to reducing carbon emissions [4,38,43]. The findings of this study indicate that carbon emissions will most likely increase if the urban form is not optimized.

In consideration of the typical and representative urbanization development pattern of Guangdong Province, the framework proposed in this study for forecasting carbon emissions by considering the joint influence of urban form and socioeconomic development can be extended to other regions. Specifically, the following three types of typical regions are applicable to this framework. Firstly, the developed coastal city clusters represented by the Yangtze River Delta exhibit similarities with Guangdong Province in that they are facing environmental pressures brought about by high-density urbanization; secondly, the major urban belts in the newly industrialized regions of Southeast Asia are exhibiting characteristics of urban expansion and industrial agglomeration that bear a strong resemblance to those of Guangdong Province's development at the beginning of the twenty-first century. These regions have experienced significant foreign investment in the manufacturing sector and rapid expansion of built-up areas. This framework is also applicable to the core economic zones of emerging economies (e.g., Brazil, India), which also need to rationalize urban sprawl and develop low-carbon economic development plans to control carbon growth. The adaptability of the framework's parameters and the ease with which data can be acquired contribute to its application advantage.

In order to further validate the universality of the model constructed in this study, the existing framework was followed to model carbon emissions in Jiangsu Province, China, which has an urbanization level comparable to that of Guangdong Province. Specifically, two groups of carbon emissions forecasting models were constructed: the baseline group and the improved group (Table 7). These were achieved by selecting indicators of the same type and year. The findings indicated that the carbon emissions forecasting model, which considered the joint influence of urban form and socioeconomic development, exhibited an enhanced fit. Furthermore, the model's fitting accuracy is comparable to that of Model II. These outcomes confirmed the validity and replicability of the framework proposed in this study.

Table 7. Comparison between baseline model and improved model for Jiangsu Province.

	MAPE	**R^2**
Baseline model	6.78%	0.982
Improved model	5.60%	0.988

4.3.2. Policy Recommendations for Carbon Emission Reduction

The results of this study suggest that the regulation of socioeconomic development can serve as an important strategy for the mitigation of carbon emissions. Therefore, it is suggested that the focus of socioeconomic development be on the quality of the process rather than its speed. It is essential to optimize the industrial structure, promote the development of industries with low energy consumption, and accelerate the development of high-tech industries and modern service industries. These policies can assist in reducing reliance on high-carbon industries. For example, Shenzhen has been a leader in the transition away from traditional energy-consuming industries, such as iron and steel and chemicals, which have been phased out much earlier in comparison to other cities of a similar population and economic scale, such as Guangzhou. Consequently, Shenzhen has achieved lower carbon emissions. Furthermore, the promotion of energy-saving technologies and equipment is essential for improving energy efficiency, while the accelerated development of clean energy sources (such as wind and solar power) is crucial for reducing reliance on fossil fuels. Specifically, the cities located in the eastern and western parts of Guangdong Province (Zhanjiang, Yangjiang, Shantou, Shanwei, etc.) are characterized by a long continental coastline and abundant wind resources. These regions have the potential to reduce their reliance on traditional energy sources by developing offshore wind farms. Cities in the

northern part of Guangdong Province (e.g., Shaoguan, Qingyuan) are characterized by abundant solar radiation and land resources, consequently rendering them highly conducive to the implementation of photovoltaic (PV) projects. In economically less developed regions of Guangdong Province, high energy-consuming industries such as iron and steel, cement, and minerals are significant contributors to the local economy, and their complete elimination in the short term is challenging. Therefore, in order to achieve a balance between economic development and carbon emissions, it is recommended that these regions proactively introduce advanced energy technologies to improve energy efficiency. In addition, the government should formulate stringent emission standards to encourage energy-consuming industries to increase their investment in emission reduction.

As the primary economic development region within Guangdong Province, the Pearl River Delta (PRD) is a typical example for the implementation of carbon reduction initiatives, given its generally high carbon emissions. It is recommended that the cities in the PRD region strengthen exchange and collaboration on low-carbon technologies and management experiences and implement joint emission reduction strategies. For example, it is recommended that a regional low-carbon technology sharing platform be established to facilitate the sharing of the outcomes of low-carbon technological innovations and practices among cities. Furthermore, it is recommended that regional emission reduction targets be formulated jointly in order to improve the efficiency of emission reduction. In addition, the substantial population influx is an important factor contributing to the high carbon emissions observed in the PRD region. In particular, those cities with high population density, such as Guangzhou and Foshan, may exacerbate the carbon emission situation if population growth is not adequately managed.

In addition to the traditional socioeconomic measures for carbon emission reduction, rational urban design can substantially contribute to low-carbon urban development. First, the PLADJ reflects the compactness of land use. Excessive agglomeration of urban land can intensify the heat island problem. This may cause a rise in the use of cooling equipment, which in turn generates higher energy demand and carbon emissions [58,88]. Second, the LSI characterizes the shape complexity of urban land. An irregular urban shape may result in the dispersion of urban functional areas. This can further reduce the accessibility of public transport and increase people's propensity to use private vehicles for transportation [31,89]. Consequently, the tendency of urban shape to be more complex increases the energy consumption of people traveling by transport [23,25]. Third, the PD reflects the fragmentation of urban land. Our results indicate a negative correlation between PD and carbon emissions. Several studies have suggested that increased urban fragmentation will result in longer commuting distances, thereby increasing carbon emissions [39,59]. Nevertheless, other studies have indicated that urban fragmentation may act as a deterrent to the increase in carbon emissions within mixed-use and industrial areas [32,90]. For instance, in the cases of Dongguan and Shenzhen, increased urban fragmentation curbs carbon emissions [54].

Based on the results of this study, a number of recommendations are presented for consideration in future urban planning initiatives. These recommendations are centered on three primary aspects, including urban compactness, urban shape complexity, and urban fragmentation. First, it is necessary to simplify the shape complexity of urban land. By rationally delineating urban functional zones (such as residential, commercial, and industrial), the overlap and mixing of urban functions will be reduced, and the urban structure will become more clearly defined. In addition, it is essential to establish an efficient transportation network and direct the development of urban land towards a more regular configuration. As a result, the accessibility and efficiency of the transportation system will be improved. Furthermore, while the results of this study indicate a positive correlation

between urban compactness and carbon emissions, it would be beneficial to increase urban compactness in regions where urban land is more dispersed. This is because a compact urban form typically implies a more efficient use of infrastructure [1,33]. Nevertheless, in regions where urban land is excessively compact, a polycentric urban form should be developed. For example, the construction of satellite cities by Guangzhou and Foshan could serve to disperse the population and industries from the primary urban areas. This strategy is expected to reduce inter-regional commuting and increase green space, thereby mitigating traffic congestion and the heat island effect [27,36]. In the case of cities such as Dongguan and Shenzhen, where mixed-use and industrial areas are concentrated, it is recommended to moderately increase the fragmentation of urban land to reduce carbon emissions. Specifically, feasible measures include the establishment of a decentralized green space system and a network of ventilation corridors. These measures are expected to enhance carbon sink capacity and mitigate the urban heat island effect.

The aforementioned policy implications and recommendations are considered credible prior to 2035, as the scenario parameters were strictly established in accordance with the stipulations of the "Strategy Profile". The scenario parameters for the period after 2040 were determined through trend extrapolation. In this case, the applicability of these recommendations depends on the alignment between future and current development trends, including policy continuity, socioeconomic stability, and technological development. If inconsistencies are identified, updated data will be required for further analysis. It is recommended that policymakers consider the forecasting results after 2040 as risk warnings rather than precise references for planning. This is especially important given that the forecasting horizon exceeds the time span of the sample.

In summary, the marginal contribution of this study lies in the development of a novel framework for carbon emission forecasting, which integrates urban form factors with socioeconomic factors. This framework addresses a specific knowledge gap in the field of carbon emission forecasting by incorporating the impact of urban form. Through an empirical case study in Guangdong Province, we have validated the effectiveness of the framework and also identified significant advantages in terms of forecasting accuracy. The carbon emission forecasting method proposed by this study is highly applicable, especially in regions experiencing rapid socioeconomic growth and urban expansion. These regions will encounter considerable carbon emission challenges if rational planning for urban forms is not implemented. In this regard, the new findings of our study could inform the promotion of low-carbon management policies and urban design.

4.3.3. Limitations

This research has the following deficiencies that should be enhanced in future investigations. First, while the carbon emission forecasting model considered a set of key socioeconomic factors, it is possible to enhance the model in the future by incorporating additional indicators. Second, in constructing the PLUS model, only the business-as-usual scenario was employed to forecast future land-use changes. It would be beneficial to consider additional urban expansion scenarios. Third, this study used a scenario analysis method to set a uniform change rate of socioeconomic factors across all prefecture-level cities. This process may have overlooked the variations in the socioeconomic development of different cities. Fourth, it would be advantageous to employ more complex and advanced regression models for the forecasting of carbon emissions. Finally, due to limitations in the data available, independent forecasts of emissions from sources such as industry, population, etc., remain to be conducted. It would be beneficial to consider emissions from different sources in forecasts. By addressing the aforementioned shortcomings, it will be

possible to gain a deeper insight into the variables affecting carbon emissions, thereby allowing for a more robust estimation of future carbon emissions.

5. Conclusions

Urban form exerts a considerable influence on carbon emissions. Nevertheless, most previous research on carbon emission forecasting has concentrated on socioeconomic factors, with less focus on the role of urban form. To address this limitation, we proposed a new carbon emission forecasting model that considers the joint influences of socioeconomic environment and urban form in Guangdong, China. Specifically, we employed the enhanced STIRPAT model to integrate urban form with socioeconomic factors and combined the PLUS model with a scenario analysis approach to forecast future carbon emissions. This method can be implemented in other regions, not only in Guangdong Province.

Our findings indicate that all the socioeconomic and urban form variables in the improved model had a significant impact on carbon emissions. Specifically, GDP per capita, energy intensity, permanent population, the proportion of secondary industry, LSI, and PLADJ (i.e., shape complexity, compactness) showed a positive correlation, while PD (i.e., fragmentation) was negatively correlated with carbon emissions. In addition, a Kappa coefficient of 0.93 confirmed the accuracy of the PLUS model.

Compared with the baseline model, the R-squared exhibited a slight increase from 0.981 to 0.987 after incorporating the above urban form factors into the carbon emission forecasting model. Moreover, the MAPE between the simulated and actual emissions for all cities decreased from 7.16% to 6.18%. In conclusion, the main contribution of this study is the development of a novel framework for carbon emission forecasting, which integrates urban form factors with socioeconomic factors. The proposed methodology is expected to offer a practical foundation for developing effective carbon emission mitigation policies.

Supplementary Materials: The following supporting information can be downloaded at https://www.mdpi.com/article/10.3390/ijgi14070270/s1, Table S1: Specific settings for carbon emission scenario forecasting; Table S2: Carbon emission forecasting during 2025–2060 under each scenario.

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Abbreviations

STIRPAT	Stochastic influences by regression on population, affluence, technology
PLUS	Patch-generating land-use simulation
GDP	Gross domestic product
LSI	Landscape shape index

PLADJ	Percentage of like adjacencies
PD	Patch density
DEM	Digital elevation model

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