Spatiotemporal Characteristics and Factors Driving Exploration of Industrial Carbon-Emission Intensity: A Case Study of Guangdong Province, China

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Abstract: Research on spatiotemporal characteristics and influencing factors of industrial carbon emissions intensity is crucial to the efforts of reducing carbon emissions. This paper measures the industrial carbon emissions intensity (CI) by energy consumption in Guangdong from 2012 to 2020 and evaluates the regional differences of CI. In addition, we apply the extended STIRPAT (stochastic impacts by regression on population, affluence and technology) and GTWR (geographically and temporally weighted regression) models to reveal the influence of driving factors on CI from spatial–temporal perspectives, based on the economic panel data and night-time light (NTL) data of 21 cities in Guangdong. To show the robustness of the results, we introduce the ordinary least squares (OLS) model, geographically weighted regression (GWR) model and temporally weighted regression (TWR) model compared with the GTWR model and find that the GTWR model outperforms these models. The results are as follows: (1) CI shows an overall downward trend and presents a pattern of being low in the middle and being high on both sides in space. (2) The industrial carbon emission is mainly affected by six main factors: economic development level, population scale, energy intensity, urbanization level, industrial structure and energy consumption structure. Among them, energy intensity occupies a significant position and poses a positive impact on the CI of the industrial sector.

Keywords: industrial carbon emission intensity; NTL; driving factors; STIRPAT; GTWR; Guangdong

1. Introduction

The problem of global warming has become increasingly serious, and it is considered one of the most pressing threats to the existence of the human race [1,2]. The main cause of global warming is carbon emissions derived from large amounts of energy consumption, especially in the production processes of industrial enterprises [3]. In China, the industrial sector is the pillar of the national economy and is an important source of carbon emissions, accounting for about 70% of carbon emissions in 2021. Guangdong Province, located in the far south part of mainland China, has the highest GDP, largest population, and greatest energy consumption [4]. As with the case at the national level, the main cause of carbon emissions is derived from massive energy consumption in Guangdong [3,5]. Therefore, reducing industrial carbon emissions from energy consumption in Guangdong is of vital importance.

Given the urgent requirement for cutting industrial sector energy-related carbon emissions, a growing number of researchers have focused on the issue of carbon emissions [6–9]. Wang [10] evaluated the spatial and temporal changes of carbon emissions in high-carbon manufacturing industries of 30 provinces in China. Singpai [11] employed an extended Kaya identity-based LMDI decomposition analysis (Logarithmic Mean Divisia Index) with a two-stage data envelope analysis (DEA) to identify causes for changes in energy consumption and CO₂ emissions and to evaluate environmental and economic
efficiency. Chekouri [12] used the STIRPAT model to exam the driving factors of CO₂ emissions in Algeria. The results indicate that population has a positive and significant effect on CO₂ emissions.

However, existing research on carbon emissions needs to be further explored in the following aspects. First, most of these studies mainly focus on carbon emissions of scale from the national [13–15] to provincial [16–19], and few studies have researched the city level. Second, an extended version of the IPAT model and the “Kaya Identity” and LMDI have been widely applied to study the influencing factors of CO₂ emissions in the existing literature [13,20–22]. Cansino [23] employed the LMDI-I method to carry out a multisector analysis of the 35 productive sectors included in Spain and found that renewable energy sources (RES) acted in detriment to the drivers of CO₂ emissions. Tavakoli [24] evaluated four driving forces of greenhouse gas (GHG) emissions among the top ten emitters by using the method of Kaya Identity. However, these methods cannot reveal the driving factors of the discrepancy in carbon emissions from the spatial–temporal perspectives. Thus, this paper introduces the extended STIRPAT and GTWR model, to explore the spatial–temporal heterogeneity of driving factors on CI. Third, among all the potential influential factors of carbon emissions, urbanization has been taken into account, being a key driving factor in recent years [9,25]. In most of these studies, urbanization is represented by a single indicator [26,27], such as the urban population percentage is not comprehensive enough because it relates to population, spatial, economic and social systems [28]. Hence, we calculate the city-level NTL data as a proxy of urbanization, based on the satellite data [29]. It is proven that the NTL data are reliable and comprehensive for characterizing the urbanization level at different regional scales [30].

In order to fill the gap, this paper has two main purposes based on previous studies. One is to estimate the CI of the Guangdong industrial sector from 2012 to 2020 and to analyze the spatiotemporal characteristics of CI in 21 cities of Guangdong. Another is to apply the extended STIRPAT and GTWR models, aiming to explore the spatial–temporal heterogeneity of driving factors on CI changes, based on the economic panel data and NTL data. To show the robustness of the results, we introduce the OLS model, GWR model and TWR model compared with the GTWR model, and we found that the GTWR model outperforms those models. Ultimately, we can have a clear understanding of the factors that affect the inequality of regional carbon emission intensity in Guangdong and offer a reference for the local government to formulate regional low-carbon industrial policy.

This paper is organized as follows: Section 2 describes the study area, Guangdong province. Section 3 introduces the material and methods, including data sources, carbon-emission estimation method, some empirical models on industrial carbon emissions and the method of using nighttime light data as a proxy for urbanization level. Section 4 presents the results of spatial–temporal distribution of carbon emissions and driving forces in 21 cities of Guangdong province. Analysis of carbon emission estimation methods, the application of the GTWR model on carbon emissions, and the impact of the COVID-19 pandemic on carbon emissions are discussed comprehensively in Section 5. Finally, the conclusions are presented in Section 6.

2. Study Area

The province of Guangdong has the highest GDP, largest population, and greatest energy consumption in China [4]. It borders Hong Kong and Macao in the far south part of mainland China (Figure 1) and is divided into four sub-regions: the Pearl River Delta, Eastern Guangdong, Western Guangdong, and Northern Guangdong. Guangdong comprises 21 prefecture-level cities (including two sub-provincial cities). At the end of 2021, the permanent population of the whole region was 126.84 million, of which the urban population was 94.66 million. The region’s per GDP reached 15,234 USDs with an increase of 7.1% over the previous year. In recent years, rapid industrialization and urbanization have led to a surge in energy consumption and carbon emissions. Therefore, it is urgent to achieve industrial carbon reduction in Guangdong.
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Figure 1. Study area.

3. Materials and Methods

3.1. Materials

The chosen period of this study is 2012–2020. This period encompasses the time of the 12th Five-Year Plan and 13th Five-Year Plan. The energy-consumption data include coal, coke, natural gas, gasoline, kerosene, diesel, fuel oil, and liquefied petroleum gas obtained from the statistical yearbooks of Guangdong and its 21 cities. The industrial value-added data were obtained from the Guangdong Statistical Yearbook (2012–2020) with 2012 as the constant price. This study used NPP-VIIRS data (Suomi National Polar-orbiting Partnership Visible Infrared Imaging Radiometer Suite), which were a type of NTL data to denote the urbanization level, which can be downloaded from (https://eogdata.mines.edu/products/vnl/) accessed on 1 September 2021. The remaining driving factors including economic development level, energy consumption structure, population-scale, energy intensity and industrial structure were obtained from the statistical yearbooks of Guangdong and its 21 cities, and the geographical coordinates of 21 cities of Guangdong were obtained from Baidu Map (https://map.baidu.com/) accessed on 1 October 2021. See Table 1 for details of the data.

Table 1. Research data and sources (2012–2020).

| Data Type                  | Contents                                                                 | Data Sources                                                                 |
|----------------------------|--------------------------------------------------------------------------|-------------------------------------------------------------------------------|
| Industrial energy consumption | coal, coke, natural gas, gasoline, kerosene, diesel, fuel oil, and liquefied petroleum gas. | the statistical yearbooks of Guangdong and its 21 cities.                     |
| Economic panel data        | industrial value-added data, driving factors (apart from urbanization)   | the statistical yearbooks of Guangdong and its 21 cities.                     |
| Night-time light data      | NPP-VIIRS data                                                           | (https://eogdata.mines.edu/products/vnl/) accessed on 1 September 2021.       |
| Geographical coordinates   | 21 cities of Guangdong                                                   | (https://map.baidu.com/) accessed on 1 October 2021.                          |

3.2. Methods

3.2.1. Carbon-Emission Estimation Method

Fossil fuels account for a large proportion of the industrial carbon emission. Thus, the industrial carbon emissions in this study can be calculated by fossil energy consump-
We calculate the carbon emissions of the industrial sector by using the energy consumption data. Table 2 shows the parameters of various energy fuels. The industrial emissions can be calculated by:

\[
C_h = \left( \sum_{i=1}^{8} (E_i \times NCV_i \times K_i \times COF_i \times \frac{1}{1000}) \right)
\]  
(1)

where \(C_h\) is the carbon emission (t) of industry; \(E_i\) is energy consumption of above-scale industry (t); \(NCV_i\) is the net calorific value of energy (TJ/Gg); \(K_i\) is the default carbon content coefficient of energy (kg/GJ); \(COF_i\) is the default carbon oxide factor; and \(1/1000\) is the unit-conversion coefficient.

Table 2. Parameters of various energy fuels.

| Energy      | Raw Coal | Coke  | Gasoline | Kerosene | Diesel | Fuel Oil | Liquefied Petroleum Gas | Natural Gas |
|-------------|----------|-------|----------|----------|--------|---------|--------------------------|-------------|
| Default carbon content coefficient of energy (kg/GJ) | 25.8     | 29.2   | 18.9     | 19.6     | 20.2   | 21.1    | 17.2                     | 15.3        |
| Net calorific value (TJ/Gg) | 28.2     | 28.2   | 44.3     | 43.8     | 43.0   | 40.4    | 47.3                     | 48.0        |
| Oxidation rate of carbon | 1        | 1      | 1        | 1        | 1      | 1       | 1                         | 1           |

The industrial value added represents the industrial development level. Thus, the industrial carbon intensity is defined as the industrial carbon per industrial value added [32], and it is a key indicator to reflect the standard of low-carbon development of the areas [33]. The formula is as follow:

\[
CI = \frac{C_h}{VOI_i}
\]  
(2)

where \(CI\) denotes industrial carbon emission intensity; \(VOI_i\) is the industrial added value and \(C_h\) is the industrial carbon emissions.

3.2.2. Empirical Model

This paper conducts an empirical study on industrial carbon emissions in Guangdong province by the extended STIRPAT (Stochastic Impacts by Regression on Population, Affluence and Technology) model and the GTWR model. The STIRPAT model was constructed by Dietz and Rosa [34]:

\[
I_i = a \times P_i^b \times A_i^c \times T_i^d \times e_i
\]  
(3)

where \(a, b, c, d\) are model coefficients; \(I, P, A\) and \(T\) are environmental influences, population-scale, wealth and technological advancement, respectively; \(e_i\) is the error term.

According to the definition of the STIRPAT model [16], environmental indicator (I) is related to population-scale (P), the average level of affluence (A) and technology index (T). Thus, industrial carbon-emission intensity (CI), per capita industrial value added (PIVA), the industrial population as a proportion of total population (IPOP) and energy intensity (EI) denote environmental indicator (I), affluence effects (A), population scale (P) and technological development (T) in the industrial sector, respectively.

Furthermore, urbanization level (UL), industrial structure (IS) and energy consumption structure (ES) are factors that affect carbon emissions intensity [35–40]. We expand the STIRPAT model and incorporate these factors into the model, then take the natural logarithm of the variable on both sides, and eliminate the possible heteroscedasticity to obtain the following formula:

\[
\ln CI_{it} = \alpha_{it} + \sum_{k=1}^{P} \beta_{kit}(\ln X_{it}) + \epsilon_{it}
\]  
(4)
where CI denotes industrial carbon emission intensity; X represents a set of explanatory variables affecting industrial carbon emission intensity, including PIVA, IPOP, EI, UL, IS, and ES. See Table 3 for details of the variables.

Table 3. Variables and their definitions.

| Variable                            | Meaning                                                                 |
|-------------------------------------|-------------------------------------------------------------------------|
| Carbon emission intensity (CI)      | Ratio of carbon emissions from industrial sector to its industrial value added |
| Economic development level (PIVA)   | Ratio of industrial value added to industrial population                |
| Population scale (IPOP)             | Industrial population split by total urban population                     |
| Energy intensity (EI)               | Ratio of expenditure on research and development of industrial enterprises to its industrial value added |
| Urbanization level (UL)             | Total NTL of a city                                                     |
| Industrial structure (IS)           | Industrial added value of industrial sector accounts for the proportion of GDP |
| Energy consumption structure (ES)   | Ratio of coal consumption to total energy consumption in industrial sector |

Although the traditional Geographical Weighted Regression (GWR) model adopted in the previous studies can deal with the relevant influencing factors [41], it only considers the spatial dimension, while it fails to take account of the temporal factors, which may be insufficient to provide practical references. In view of the above, this paper combines the extended STIRPAT model with the GTWR model to reveal the impact on spatial–temporal heterogeneity of various driving factors on CI [16]. The GTWR model was constructed by Huang et al. [42]:

\[
y_i = \beta_0(\mu_i, v_i, t_i) + \sum_{k=1}^{m} \beta_k(\mu_i, v_i, t_i)x_{ik} + \epsilon_i (i = 1, 2 \ldots n)
\]

where \( y_i \) is the explained variable for city \( i \); \( m \) is the number of cities; \( k \) is the number of explanatory variables for city \( i \); \( t_i \) is the temporal coordinate of city \( i \); \( \beta_0(\mu_i, v_i, t_i) \) is the spatiotemporal intercept term for city \( i \); \( x_{ik} \) is the \( k \)th explanatory variable for city \( i \); \( \beta_k(\mu_i, v_i, t_i) \) is the regression coefficient of the \( k \)th explanatory variable for city \( i \) and the spatiotemporal intercept function; \( \epsilon_i \) is the error term.

Through the spatiotemporal weight function and the spatiotemporal distance in the Gaussian function method, the proposed GTWR model combines spatial and temporal information:

\[
d_{ij}^{ST} = \sqrt{\lambda \left[ (\mu_i - \mu_j)^2 + (v_i - v_j)^2 \right] + \mu(t_i - t_j)^2}
\]

\[
w_{ij}^{ST} = \exp \left\{ \frac{-\lambda \left[ (\mu_i - \mu_j)^2 + (v_i - v_j)^2 \right] + \mu(t_i - t_j)^2}{b_{ST}^2} \right\}
\]

where \( (\mu_i, v_i) \) and \( (\mu_j, v_j) \) are the spatial coordinates of city \( i \) and city \( j \) respectively; \( t_i \) and \( t_j \) are the observation times of sample points \( i \) and \( j \); \( \lambda \) and \( \mu \) are the scaling factors measuring the different effects of spatial and temporal distances in the uncorrelated metric system; \( b_{ST} \) is the bandwidth of the spatiotemporal weight function.

3.2.3. Nighttime Light Data as a Proxy of Urbanization Level (UL)

The spatial resolution of the NPP-VIIRS NTL data is much higher (15 arc-s, about 500 m) than the Defense Meteorological Satellite Program—Operational Linescan System (DMSP-OLS) [43,44], which may cause fewer saturation problems. In this study, we employed the NPP-VIIRS annual NTL data for 2012–2020 (unit: nano-W cm\(^{-2}\) sr\(^{-1}\)), which are available from (https://eogdata.mines.edu/products/vnl/) accessed on 1 September.
In order to accurately measure the level of urbanization (UL) of 21 cities of Guangdong, the NPP-VIIRS nighttime data must be corrected [47]. Other outliers in the NTL intensity data are further removed by extracting the maximum intensity in Guangzhou for 2020 as the threshold. Satellite pixels that are still above the maximum intensity of Guangzhou are assumed to be unrealistic, and we eliminate them. The NTL data were projected into the Lambert Azimuthal Equal Area Projection. Then, the city-level urbanization indicator was generated by summing up all grid cells of NTL data within the administrative boundaries of each city in Guangdong. ArcGIS 10.8 software was used to extract Figure 2. The ArcGIS was developed by Environmental Systems Research Institute (the company is headquartered in Redlands, California, USA), and first released in 1999. Only the results of 2012 and 2020 are shown, due to the limited space.

Figure 2. Results of NTL data processing.

4. Results

Applying the established methodology, the spatial–temporal distribution of carbon emissions and driving forces in 21 cities of Guangdong province are calculated and analyzed.

4.1. Estimation of Industrial Carbon-Emission Intensity of Guangdong

4.1.1. Time Series

Figure 3 shows the industrial carbon emission intensity (CI) in 21 cities of Guangdong. Overall, CI in the 21 cities of Guangdong tend to decrease, indicating that the implementation of low-carbon policies has significantly curbed the growth of industrial carbon emissions [30].

The CI of cities in the Pearl River Delta (PRD) has a relatively tiny base and tends to decrease over the study period. Among them, Jiangmen’s carbon emission intensity is much larger than other cities in the PRD region, falling from 1.09 kg/USD in 2012 to 0.49 kg/USD in 2020, with the largest decrease; except for Jiangmen, the CI of the remaining cities in the PRD area is less than 0.71 kg/USD, among which industrial carbon intensity of Zhongshan and Shenzhen is at a lower level, and the value is basically stable at less than 0.14 kg/USD.

Apart from Zhanjiang, Maoming and Jieyang, the CI of the non-PRD region is on a downward trend, with Yunfu in Northern Guangdong experiencing the sharpest decline, from 2.17 kg/USD in 2012 to 0.83 kg/USD in 2020. As for Eastern and Western Guangdong, they show an insignificant decrease in CI. Although the base of industrial carbon-emission intensity in northern Guangdong is larger than other regions of Guangdong, the decrease in carbon emission intensity is stronger, which indicates that the industrial carbon emissions situation has improved significantly.
CI exists in regional differences in 21 cities of Guangdong, showing a pattern of low in the central zone and high in the distal zones (Figure 4). Figure 4 [32] was obtained by kriging interpolation, based on CI and geographical coordinates of 21 cities in Guangdong. The spatial distribution of CI has remained relatively stable, although varying significantly between regions. The cities with higher CI are Shaoguan, Shanwei and Meizhou, and the cities with lower CI are Shenzhen and Zhongshan.

In summary, the carbon emission intensity of the PRD region is significantly lower than other regions in Guangdong. That is mainly because the region is closely related to the continuous optimization of the energy structure and industrial structure, which vigorously develop high-tech industries and strategic emerging industries. On the contrary, the non-PRD regions have relatively high carbon emission intensity, as these regions are dominated by

Figure 3. Industrial carbon emission intensities in different cities in Guangdong, China.

4.1.2. Spatial Series

CI exists in regional differences in 21 cities of Guangdong, showing a pattern of low in the central zone and high in the distal zones (Figure 4). Figure 4 [32] was obtained by kriging interpolation, based on CI and geographical coordinates of 21 cities in Guangdong. The spatial distribution of CI has remained relatively stable, although varying significantly between regions. The cities with higher CI are Shaoguan, Shanwei and Meizhou, and the cities with lower CI are Shenzhen and Zhongshan.

Figure 4. Spatial distribution of industrial carbon-emission intensity in Guangdong, China.
energy-intensive industries that are, especially since the 13th Five-Year Plan, the start-up or resumption of high energy-consuming projects in some cities of non-PRD region [38].

4.2. Results of the GTWR Model

Before applying the GTWR model, the correlation test was conducted between carbon emission intensity (CI) and the six independent variables (Figure 5). The results show that all the six explanatory variables are significant at least at the 10% significance level. Then, we tested the multicollinearity of variables. The variance inflation factor (VIF) of all variables was less than 10 (Table 4), which indicates that there is no multicollinearity in the model and the setting is reasonable. Therefore, we applied the GTWR method to explore the spatiotemporal heterogeneity of the influencing factors of industrial carbon emissions of Guangdong. A summary of estimated coefficients is given in Table 5, which shows that the values of the bandwidth and AICc are 0.115 and −188.899, respectively. R^2 is equal to 0.9919, and adjusted R^2 is equal to 0.9916; thus, the fitting effect is good.

![Figure 5. Correlation analysis results.](image)

Table 4. Results of multicollinearity tests.

| Independent Variable | PIVA | IPOP | EI   | UL   | IS   | ES   |
|----------------------|------|------|------|------|------|------|
| VIF                  | 2.613| 4.222| 2.951| 2.062| 1.738| 2.098|
| Tolerance            | 0.383| 0.237| 0.339| 0.485| 0.575| 0.477|

Table 5. Regression coefficient of the GTWR results of variables.

| Variable     | Min      | Lower Quartile | Median  | Higher Quartile | Max      | Mean      |
|--------------|----------|----------------|---------|-----------------|----------|-----------|
| PIVA         | −0.3837  | −1.3345        | −0.0160 | −0.0574         | 0.6794   | −0.4332   |
| IPOP         | −0.5978  | −1.4989        | −0.0129 | −0.1783         | 0.4061   | −0.5627   |
| EI           | 0.5234   | 0.1110         | 0.9904  | 0.6644          | 1.1230   | 0.9242    |
| UL           | −0.3289  | −0.8350        | 0.0111  | −0.0925         | 0.6051   | −0.0279   |
| IS           | −0.8936  | −0.3623        | −0.2000 | 1.3348          | 2.6832   | −0.2420   |
| ES           | −0.2378  | 0.1482         | 0.0617  | 1.1176          | 6.3089   | 0.0699    |
| Intercept    | −1.9457  | 3.3702         | 0.1917  | 13.9788         | 23.7568  | 0.6986    |
| R^2          | 0.9819   |                |         |                 |          |           |
| Adjusted R^2 | 0.9916   |                |         |                 |          |           |
| Residual Squares | 1.4732 |                |         |                 |          |           |
| AICc         | −188.899 |                |         |                 |          |           |
| Sigma       | 0.0882   |                |         |                 |          |           |
| Bandwidth   | 0.1150   |                |         |                 |          |           |
4.2.1. Comparisons with Other Conventional and Spatiotemporal Models

To further understand the effects of spatial and temporal information on model performance improvement, conventional OLS, GWR and TWR models were fitted using the same variables as those used in the GTWR models. The results of these models are listed in Table 6. The $R^2$ of the GTWR model is larger than the other; thus, it is obvious that the GTWR model outperforms the other models.

Table 6. The performance of the OLS, GWR, TWR, and GTWR models.

| Indicators | OLS     | GWR     | TWR     | GTWR    |
|------------|---------|---------|---------|---------|
| AICc       | −104.005| −110.395| −153.922| −188.899|
| $R^2$      | 0.9671  | 0.9710  | 0.9816  | 0.9916  |

4.2.2. Time Evaluation of Carbon Intensity Influencing Factors

In this paper, we estimate the contribution coefficient of each driving factor to the carbon emission intensity and plot and observe the box diagram of each coefficient and its evolution trend over time (Figure 6).

During the study period, the impact of economic development level (PIVA) on carbon emissions is mostly negatively correlated. That is, the CI decreases as the level of economic development improves. The average of the regression coefficient rises over time, reaching a maximum in 2017 and then leveling off, which shows that the negative influence of PIVA on carbon emission is gradually weakening. With the improvement of the level of economic development and implementation of a series of low-carbon policies and energy policies, the carbon emissions caused by economic development can be curbed, and the fluctuation of the impact degree will be reduced.

The impact of population scale (IPOP) on CI is basically negative, indicating that industrial population agglomeration is conducive to energy saving and emission reduction. Similar to the change in the coefficient of economic development level, the average of the regression coefficient rises over time, reaching a maximum in 2017 and then leveling off. The industrial population agglomeration guides economic activities and production factors to agglomerate in space by exerting cost optimization effects, thereby improving the comprehensive utilization efficiency of energy and resources. At the same time, it also saves the cost of emission reduction to the greatest extent and facilitates the centralized supervision of government departments, which provides the possibility for centralized control of carbon emission problems.

The contribution rate of energy intensity (EI) to CI is positive, showing that EI has a positive impact on CI in the industrial sector. The average regression coefficient is 0.9242, which presents an upward trend during the research period. On the one hand, the government has been insisting on increasing energy conservation and enhancing energy efficiency in the first place through low-carbon production technologies. On the other hand, with the rapid development of the industry, urban infrastructure construction generates a large demand for heavy products such as steel and cement, and energy consumption has further increased, resulting in a tremendous amount of carbon emissions. Therefore, the overall energy intensity regression coefficient shows an upward trend. In conclusion, EI has a strong impact on CI. In general, improving energy efficiency and insisting on energy conservation and emission reduction are important ways to achieve carbon emission reduction.
and industrialization is still the main factor that aggravates carbon emissions. It indicates that the influence of industrial structure on carbon emissions is slowly diminishing, and the correlation is stronger with the decrease in the added value of the industrial sector. During the study period, the demand for heavy products such as steel and cement led to the carbon emissions increased.

When the PIVA indicator began to change from negative to positive. This may be because with the resumption of economic activities, the industrial population agglomeration has become a driving factor to the carbon emission problem. On the one hand, the improvement of energy conservation and enhancing energy efficiency in the first place through low-carbon production technologies. On the other hand, the deployment and implementation of urbanization development strategy, the improvement of urbanization level curbed carbon emissions to a certain extent, and the regression coefficient of urbanization level (UL) increased over time, reaching a maximum in 2017 and then leveled off. The average regression coefficient of UL is $-0.0279$, which indicates that UL has a negative correlation with CI. In the early stage of the study, due to the deployment and implementation of urbanization development strategy, the improvement of urbanization level curbed carbon emissions to a certain extent, and the regression coefficient of UL began to change from negative to positive. This may be because with the resumption of industrial production in some areas, the agglomeration of population, industry and various economic activities led to the carbon emissions increased.

The impact of industrial structure (IS) on CI is basically negative. That is, CI will increase with the decrease in the added value of the industrial sector. During the study period, the fluctuation of the regression coefficient of the industrial structure decreases, indicating that the influence of industrial structure on carbon emissions is slowly diminishing, and industrialization is still the main factor that aggravates carbon emissions.

The contribution rate of energy intensity (EI) to CI is mostly positive, indicating that the energy structure in most areas of Guangdong is optimized and reason-
able, which effectively promotes industrial carbon emission reduction. The overall trend of the energy consumption structure coefficient drops and then rises. Since the “Twelfth Five-Year Plan” period, China has implemented a series of policies to optimize the energy structure so that non-fossil energy sources, such as hydropower, solar power, nuclear power, wind power, etc., occupy a certain proportion of energy consumption. Therefore, there is a mostly positive correlation between ES and CI. However, in the later stage of the study, the energy consumption has further increased due to the start-up or resumption of high-energy-consuming projects in some cities of Guangdong [48], which leads to the coefficient rising briefly.

4.2.3. Spatial Heterogeneity of Carbon Intensity Influencing Factors

In order to visualize the discrepancy in the spatial distribution of each influence factor more intuitively, the average fitting results of each influencing factor in each region are selected for visualization in this paper (Figure 7).

![Figure 7. Spatial distribution of the driving factor coefficient in industrial carbon emission intensity of Guangdong.](image)

The impact of economic development level (PIVA) on regional industrial carbon emissions is negative, which indicates that PIVA is effective in curbing carbon emissions
reduction. In terms of spatial distribution, PIVA has great influence on reducing carbon emissions in Shanwei, Heyuan and Jieyang, mainly because the improvement of industrial development level will lead to technological progress, and then technological progress will enhance energy utilization rate, optimize energy structure and reduce industrial carbon emissions.

The regions with positive impact of population scale (IPOP) on CI are Shaoguan and Meizhou. The rest are negatively affected. In general, the impact of IPOP on regional carbon emissions is negative. The reason is that the industrial population agglomeration effect leads to the spatial agglomeration of economic activities and production factors, thus enhancing the comprehensive utilization efficiency of energy and resources and curbing carbon emission.

Energy intensity (EI) has great influence on carbon emissions in Shantou, Chaozhou, Jieyang, and Meizhou, mainly concentrated in Eastern Guangdong. This indicates that those areas have higher energy intensity, which has somewhat inhibited progress in reducing carbon emissions. The regression coefficient of energy intensity ranges from 0.8584 to 0.9703, showing a consistent positive correlation, and the span is small. This means that the impact of EI on carbon emissions in different regions of Guangdong are not much different. Overall, the impact of EI on regional carbon emissions is greatly positive. In terms of spatial distribution, the spatial distribution of the average regression coefficient of EI presents a gradient trend, which is low in the middle and high on both sides.

The impact of urbanization level (UL) on regional carbon emission is mostly negative, which shows that the urbanization level can curb carbon emissions. However, the UL has a significant positive impact on carbon emissions in Shantou, Chaozhou, Jieyang, and Meizhou, of which are mainly concentrated in Eastern Guangdong. This indicates that the urbanization process will aggravate carbon emissions, mainly due to massive concentrations of population, industry and various economic activities in those regions.

The industrial structure (IS) has both positive and negative effects on CI, which shows that the industrial structure has a different correlation with the CI. In terms of spatial distribution, IS has great influence on carbon emissions in Shaoguan and Zhanjiang, whose absolute value is relatively large. This is mainly because those regions are dominated by high energy-consuming industries, which accounts for a relatively high proportion in those regions, and the demand for energy is relatively high.

The energy consumption structure (ES) has great impact on industrial carbon emissions in Zhanjiang and Maoming, mainly due to the fact that heavy industries are mainly concentrated in Western Guangdong, where the consumption of coal resources is relatively high, leading to relatively high carbon emissions in this region. In terms of spatial distribution, the regression coefficient of ES gradually increases from northeast to southwest.

5. Discussion

5.1. Analysis of Carbon Emission Estimation Methods

Carbon emission is frequently estimated based on the Intergovernmental Panel on Climate Change (IPCC) methodology [49,50], which is applied in this paper. However, due to the lack of city-level energy consumption statistics, the analysis of China’s city-level CO₂ emissions issues is limited [51]. Therefore, future study aims to employ a new approach for accurately assessing China’s city-level CO₂ emissions from energy consumption, such as using nighttime light imagery.

5.2. Analysis of the Application of the GTWR Model on Carbon Emissions

This paper analyzes the driving factors of industrial carbon emissions of Guangdong. We employ the GTWR model to visualize the coefficients of each driving factor and reveal the contribution of each driving factor to CI from the spatial–temporal perspective. In addition, we find that the GTWR model outperforms several conventional models, such as the OLS, TWR, and GWR model. However, it does not reveal any insights regarding
policymaking, which can be explored in future research. Meanwhile, more driving factors can be chosen to explore the industrial carbon emissions.

Based on this paper, EI is the major driving force of CI in the industrial sector. Therefore, it is essential to strengthen the research and development (R&D) and innovation of energy technology to reduce the CI. In addition, the ES and IS need to be adjusted to reduce the consumption expenditure of high industrial energy consumption. In the process of urbanization, it is necessary to properly control the scale of the population and to take full advantage of the population clustering effect to reduce carbon emissions.

5.3. Analysis of the Impact of the COVID-19 Pandemic on Carbon Emissions

Existing studies have shown that the COVID-19 pandemic caused a sharp drop in carbon emissions in 2020 [52,53]. Affected by COVID-19, a large number of economic activities in China slowed down or even stopped in the first quarter of 2020. However, the impact of the COVID-19 pandemic was not significant for the CI of Guangdong in 2020. There are two main reasons. On the one hand, when dealing with economic development after the COVID-19 pandemic, the Guangdong government promoted resumption of industrial production in an accurate and steady way, which contributed to economic recovery quickly. On the other hand, since carbon emissions are falling at the same time as the economy in the COVID-19 pandemic, the industrial carbon intensity did not change significantly in 2020. The EI effect prominently reduced carbon emissions; thus, improving EI may also help to reduce carbon emissions after the COVID-19 pandemic by promoting energy-saving technologies and strengthening research and development in related technologies. In future research, more attention should be focused on estimating the impact of COVID-19 on carbon emissions reduction.

6. Conclusions

Based on the data of 21 cities of Guangdong from 2012 to 2020, this paper evaluated the regional spatial and temporal distribution and its driving factors of CI in the industrial sector. To explore the driving factors of CI, six factors were identified based on the extended STIRPAT model: PIVA, ES, IPOP, UL, EI and IS. In order to accurately measure the levels of urbanization (UL) of the cities of Guangdong, NTL data were adopted and used as a proxy for urbanization at the city level. On this basis, the GTWR model was employed to reveal the contribution of each driving factor to CI from the spatial–temporal perspective. Compared with other models such as the OLS model, GWR model and TWR model, the GTWR model presented more reliable results. The results led to the following conclusions:

Firstly, CI of all cities in Guangdong Province showed an overall decreasing trend, except for Zhanjiang, Maoming and Jieyang from 2012 to 2020. Yunfu in Northern Guangdong province had the largest decrease, with 1.34 kg/USD, which indicated that a series of low-carbon policies introduced by the region in recent years had achieved certain results. Compared to the industrial carbon emission intensity in 2020 vertically, Shaoguan had the highest emission intensity of more than 1.28 kg/USD, while Shenzhen and Zhongshan had the lowest emission intensity of less than 0.05 kg/USD.

Secondly, regarding the spatial distribution of CI in 21 cities of Guangdong, the regions with higher CI were mostly distributed in the non-PRD, while the regions with lower CI were mainly concentrated in the PRD. The regional difference of CI in Guangdong showed a pattern of being low in the middle and being high on both sides in space.

Thirdly, using the STIRPAT–GTWR method, this paper calculated the main driving factors for the CI of 21 cities of Guangdong from 2012 to 2020. The results show that EI was the major driving factor of CI in the industrial sector, which posed a positive influence on CI in 21 cities of Guangdong and contributed the most. Furthermore, ES had a positive effect on CI in most cities of Guangdong, while UL, IPOP, PIVA and IS factors had a negative effect on CI in most cities of Guangdong.
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