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Real-Time Carbon Emissions Monitoring of High-Energy-Consumption Enterprises in Guangxi Based on Electricity Big Data

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Abstract: Real-time carbon emissions monitoring at the enterprise level is a crucial tool in shifting macrolevel carbon peak and carbon neutrality plans toward micro-level implementations. This study extends the existing CO_2 emissions accounting framework to enterprise emissions monitoring. We analyze the correlation mechanism between electricity consumption and CO_2 emissions by industries, calculate the electricity–CO_2 coefficients, and finally model an enterprise-level real-time carbon emissions monitoring method based on electricity big data. Taking Guangxi region as a sample, the results show that (1) the proportion of electricity-related emissions is on the rising stage in Guangxi, with 441 g CO_2/KWh emitted from electricity consumption in 2020, (2) the carbon emissions from the energy-intensive industries account for over 70% of the whole society, and they all have high electricity–CO_2 coefficients, far exceeding the industry average of 1129 g/kWh, and (3) the monitoring method is applied to 1338 enterprises from over 40 industries. The emission characteristics reflect the regional and industrial heterogeneity. This enterprise-level monitoring method aims to optimize the carbon emissions calculation method toward higher temporal and spatial resolutions, so as to provide an important numerical basis for promoting carbon emission reduction and sustainable development.

Keywords: carbon emissions monitoring; electricity big data; enterprise emissions

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1. Introduction

Realizing carbon peak and carbon neutrality has become an important strategic path for international efforts to address climate change, achieve temperature control targets, and transform economic development mode. As the world's largest energy consumer and carbon emitter, China accounts for over 30% of global carbon emissions [1]. Its energy conservation and emission reduction actions are not only related to domestic environmental protection and ecological civilization construction but also crucial for global efforts to address climate change. In September 2020, China announced at the United Nations General Assembly that it aims to achieve carbon peak before 2030 and carbon neutrality before 2060 (i.e., dual carbon goals) and will promote the achievement of carbon peaking and carbon neutrality as one of the important goals for developing a circular economy during the 14th Five-Year Plan period.

Monitoring carbon emissions is the preliminary foundation for assisting the implementation of policies related to dual carbon goals, and building a multi-level carbon accounting and monitoring system of nation–region–industry–enterprise is a key support for planning, managing, and reducing carbon emissions. The power grid in the southwestern region represented by Guangxi Zhuang Autonomous Region has been carrying out a top-level design for optimizing the power structure and reducing emissions during the 13th and 14th Five-Year Plans, but the total carbon emissions of the whole society are still in the upward phase of the carbon peak path. From 2015 to 2019, the total carbon emissions from all industries in Guangxi increased from 203 Mt to 247 Mt, with an average growth rate of 5%. In 2019, it accounted for 2.52% of the national total, and the share of energy production emissions in the total carbon emissions of all sectors increased from 32.08% in 2015 to 42.19% in 2019, reaching 104 Mt in 2019 [2,3]. Therefore, various regions will face the arduous task of achieving carbon peak and carbon neutrality in the future. As a macro policy target, dual carbon goals have a long-time span, multiple responsible entities, and numerous uncertainties, the key point is to scientifically decompose the target into various micro-entities and use the long-term target to guide, calibrate, and regulate their short-term emission behavior. Enterprises are important responsible entities in the construction, route, and schedule of the goals. In 2022, high-energy-consumption enterprises such as metal smelting and nonmetal mineral manufacturing accounted for 43.2% of the electricity-consumption enterprises monitored in real time by the power grid in Guangxi. To enhance the effectiveness of the policy for achieving the dual carbon goals, it is urgent to map out the carbon emissions of enterprises, track their carbon emission trends in real time, precisely regulate their emission behavior, and dynamically calibrate their carbon emissions with the national dual carbon path.

1.1. The Challenge and Importance of Improving CO_2 Monitoring Resolution

To effectively track and control enterprise carbon emissions, it is essential to have high-frequency, detailed, and reliable carbon emission data. On the one hand, due to the limitations of China's statistical system and technical means, the current data mostly focus on regional or industry levels, resulting in a scarcity of micro-level data for enterprises [4,5]. Moreover, the use of annual energy consumption statistics for carbon emission accounting introduces significant time lags [6]. Additionally, the colorless and odorless nature of carbon dioxide makes direct observation challenging, leading to difficulties in public monitoring and government oversight. This situation has raised concerns about the authenticity of carbon emission data, with reports of potential concealment and omission [7]. The lack of quality data on corporate carbon emissions poses challenges for the government in formulating precise policies to guide enterprise emission behaviors. The Metrology Development Plan (2021–2035), released by the State Council on 31 December 2021, highlights the importance of developing and enhancing a monitoring and measurement system for carbon emissions in enterprises to help achieve the dual carbon goals. On the other hand, to achieve high coverage of enterprise carbon emissions monitoring, traditional monitoring methods require large investment in monitoring equipment and devices, which is costly [8]. In addition, some carbon emissions monitoring techniques rely on enterprise emission inventory information, which is not timely and cannot reflect the carbon emission impact of political and economic events in real time, nor can it support the timely adjustment of emission reduction policies. Therefore, it is crucial to establish an enterprise carbon emissions monitoring technology with high coverage and high frequency in order to comprehensively grasp the situations and patterns of enterprise carbon emission.

Based on the real-time data of electricity consumption of enterprises to monitor the carbon emissions, this study proposes a carbon verification, carbon accounting, and carbon monitoring scheme for enterprises. Specifically, by establishing a carbon accounting method, this study analyzes the direct and indirect carbon emissions in Guangxi, discover the correlation mechanism between electricity consumption and carbon emissions in each industry, and thus, provide enterprise-level emissions monitoring data as support for Guangxi's dual carbon goal. Realizing more refined carbon emissions monitoring and management of different enterprises in different industries in Guangxi based on electricity big data plays an important role in promoting the low-carbon transformation of enterprises, as well as the sustainable development of Guangxi's economy and society. Second, the study of carbon emissions of different industries/enterprises based on electricity consumption data is of great value in guiding the adjustment of electricity supply and demand of different industries/enterprises. Third, other cities and provinces can also use electricity consumption data and build a "region–industry–enterprise" multi-level carbon system in a similar approach. Finally, this study can provide a basis for guiding the carbon quota trading of electricity in each province and help establish a more perfect national carbon trading market, thus contributing to the realization of China's dual carbon goals.

1.2. Literature Review on CO_2 Monitoring Methods

Carbon emissions data are the key indicators for assessing climate change issues, and since 2007, the United Nations Framework Convention on Climate Change (UNFCCC) has required member countries to submit carbon emissions data inventories on an annual basis. High-quality carbon emissions data are the key basis for setting emission reduction targets and measuring action to reduce emissions. However, the current global carbon emissions measurement system still suffers from large spatial and temporal granularity and lagging data. Therefore, scholars are starting to work on improving and optimizing the carbon emission measurement system in terms of emission measurement scope, measurement spatial and temporal accuracy, and measurement methods. The following literature review will focus on three aspects of the existing carbon emission measurement system: the measurement scope, the measurement spatial and temporal scales, and the measurement methods.

From the scope of carbon emissions measurement, the existing emission accounting system includes three accounting scopes: direct carbon emissions (Scope 1) and indirect carbon emissions (Scope 2 and Scope 3) [9,10]. Common GHG emission inventories [3,11,12] typically use Scope 1 to aggregate fossil energy combustion carbon emissions from production processes and cement production-dominated carbon emissions from industrial processes [13,14], reflecting the production-based principle in carbon accounting. Meanwhile, existing studies further quantified carbon emissions from land use in Scope 1 [15]. Scope 2 separates the indirect carbon emissions associated with electricity from the energy production sector and reallocates them to consumers, reflecting the consumption-based principle in carbon accounting. Network analysis [16–18] is commonly used to trace and allocate indirect carbon emissions from electricity. Scope 3 further considers carbon emission flows from cross-regional and cross-sectoral product trade, with bilateral trade models or input–output methods being the main methods to account for such emissions [19–21].

In terms of the spatial and temporal scales of carbon emissions measurement, the existing measurement accuracy usually falls at the country/city level, and research is expanding the annual resolution of emission inventories to near real-time resolution. Current carbon emission databases (China Emission Accounts and Datasets, CEADs; Multi-resolution Emission Inventory, MEIC) and studies [5] have completed annual country/provincial sectoral carbon accounting, which usually uses the "bottom-up" approach to aggregate carbon emissions by sector and energy type in the region. In the pursuit of spatial accuracy, some studies have been conducted at the municipal level [22] and point-source carbon emissions [12]. In addition, existing emission inventories usually have a time horizon of years and a lag of more than two years, so the temporal accuracy of carbon emission measurements has been further extended to monthly [23], daily [24,25], and real time [26].

As for the methods of carbon emissions measurement, there are currently four main types: IPCC inventory accounting, big data methods, proxy variable methods, and physical measurement methods. The IPCC inventory accounting method is based on the statistical results of fossil fuel consumption to infer carbon emissions, reflecting a bottom-up approach to accounting from the social sector to the regional level [27]. However, this method is limited by the coarse granularity and lag of available energy data, making it difficult to expand to high spatial and temporal resolution. The big data methods are based on the analysis of high-frequency economic data from different industry sectors, such as electricity, transportation [28], and shipping [29], to explore the correlation mechanism between the massive data and carbon emissions and, then, to establish carbon emissions monitoring methods for different industries and regions [4]. The proxy variable methods are to estimate carbon emissions at different spatial and temporal scales with the help of indicators that do not directly cause carbon emissions but have relevance to emission activities, such as population density [30,31], nighttime lighting [32], and urban morphology and GDP data [33]. This method can replace part of the unavailable emission data with observable variables, but the accuracy of emissions monitoring by this method is poor. The physical measurement methods include the chemical measurement method [34], spectral analysis measurement method, and satellite remote-sensing monitoring [35,36]. Such methods use specific devices to identify carbon emissions at the enterprise and regional levels in real time, but are difficult to apply widely because of deployment costs [37,38]. Furthermore, the monitoring accuracy of the physical measurement method is related to the monitoring environment and is susceptible to interference from external factors, thus having a large uncertainty [39,40].

Previous studies have basically established regional/industry-level and near real-time emissions monitoring systems but have not yet expanded to more micro-enterprise entities. Moreover, there is still a certain distance between the existing carbon emission accounting system and the carbon emissions monitoring system. The former focuses on the fairness and efficiency of carbon emission responsibility distribution and, therefore, has derived three types of accounting scope, Scope1–Scope3, while the later focuses more on the expansion of the accuracy of spatial and temporal resolution and usually only focuses on Scope 1 or only homogenizes the brief treatment of electricity carbon emissions in Scope 2, blurring the responsibility transfer contained in the carbon emission stream. In summary, this study further optimizes the carbon emissions monitoring model in terms of measurement accuracy and scope, and the main contributions are as follows:

1. Expanding the existing carbon accounting methods to real-time carbon emissions monitoring and extending the accuracy of emissions monitoring to the enterprise level. Existing methods such as network analysis and input–output method realize carbon emission accounting under the shared responsibility principle at the regional/industry level. Following similar ideas, by introducing carbon emission factors for electricity consumption reflecting regional heterogeneity, this study will expand from the emission accounting system considering regional purchasing electricity to the real-time carbon emissions monitoring at the industry/enterprise level, reflecting the shared responsibility principle for carbon emissions.
2. Based on the correlation mechanism between electricity consumption and carbon emission historical data of different industries, the electricity–CO_2 coefficient is measured. Specifically, we use the time-series method to establish the prediction method of the short-term electricity–CO_2 coefficient of different industries, combine the high-frequency electricity big data, and finally form an objective, fine, and real-time monitoring method of enterprise carbon emissions.
3. Achieving the multiple goals of carbon emissions monitoring in terms of promotion and application of low-cost, high-operability, low-time granularity, high industry coverage and precise positioning of carbon emissions to enterprises. Traditional point-source carbon emissions monitoring methods mainly include chemical detection, spectral analysis, and satellite carbon monitoring, which are not only costly but also impossible to promote on a large scale. This study fully exploits the existing power data resources of power grid enterprises and builds a carbon emissions monitoring method for enterprises with the distinctive features of objective, fine, and real-time electricity data, which downscales the traditional carbon emission data from the annual to hourly level.

2. Methods for Enterprise CO_2 Emissions Monitoring Using Electricity Big Data

2.1. The Electricity–CO_2 Coefficient Covering Direct and Indirect Emissions

The key to realizing real-time carbon emissions monitoring at the enterprise level in different industries using electricity big data is to construct an electricity–CO_2 coefficient that reflects the correlation mechanism between total carbon emissions and electricity consumption, as shown in Figure 1.

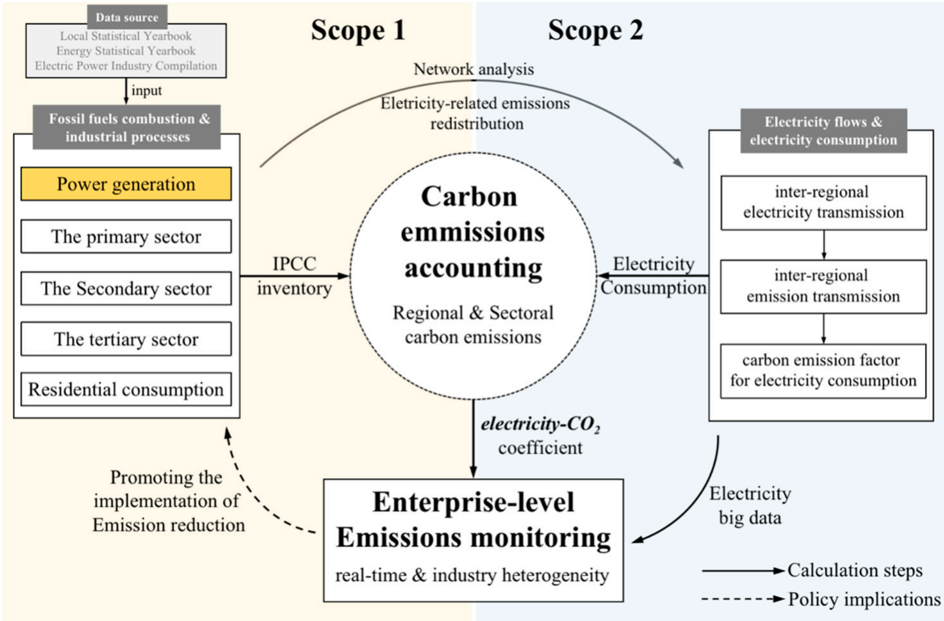

Figure 1. The technology road map for enterprise-level carbon emissions monitoring.

The electricity–CO_2 coefficient for sector s in region i is calculated as shown in Equation (1), where $em^1_{i,s}$ is the direct carbon emissions from fossil energy combustion and industrial processes in sector s (see Section 3.2); $em^2_{i,s}$ is the indirect carbon emissions from electricity use in sector s (see Section 3.3); $c_{i,s}$ is the electricity consumption in sector s. To avoid potential double counting of the electricity sector as both a producer and a consumer of electricity, direct carbon emissions from the electricity sector $em^1_{i,s}$ do not include carbon emissions from the combustion of fossil fuels in thermal power generation, and the carbon emission of electricity will be redistributed to all sectors of society under the consumption-based principle.

$$ecc_{i,s} = \frac{em^1_{i,s} + em^2_{i,s}}{c_{i,s}} \quad (1)$$

Further correlate the electricity–CO_2 coefficient of each sector in region i with the electricity consumption, $c_{i,s,m}$, of enterprise m in it, so that the carbon emissions, $em_{i,s,m}$, of the enterprise can be monitored (see Equation (2)). By using the power grid enterprise's big data, we can realize real-time carbon emissions monitoring at enterprise level in different industries.

$$em_{i,s,m} = ec_{i,s} \times c_{i,s,m} \quad (2)$$

2.2. Methods for Measuring Direct Carbon Emissions

Direct carbon emissions, $em^1_{i,s}$, from industries/enterprises include carbon emissions from fossil energy combustion in production processes and from cement-based industrial processes [41]. Based on the consumption data of major energy species by sector and cement production in the Guangxi Statistical Yearbook and China Carbon Emissions Database (CEADs) in previous years, combined with the carbon emission coefficients of different energy products in the Guidelines for National Greenhouse Gas Inventories prepared by the Intergovernmental Panel on Climate Change (IPCC), the direct carbon emissions of sector s in region i can be calculated (see Equation (3)), where fossil fuel combustion carbon emissions are obtained by multiplying the kth fossil energy consumption, $cs_{i,s,k}$, in sector s of region i with the carbon emission factor ef_k, which is related to the low-level calorific value v_k of the kth fossil, the carbon content per unit calorific value f_k, the oxidation rate o_k, and the C-CO_2 conversion factor of 44/12. Industrial process carbon emissions are obtained by multiplying the cement consumption $cs_{i,s,c}$ and the carbon emission factor ef_c for electricity consumption.

$$\begin{aligned} em^1_{i,s} &= \sum_{k=1}^{n} cs_{i,s,k} \times ef_k + cs_{i,s,c} \times ef_c \\ &= \sum_{k=1}^{n} cs_{i,s,k} \times v_k \times f_k \times o_k \times \frac{44}{12} + cs_{i,s,c} \times ef_c \end{aligned} \quad (3)$$

2.3. Methods for Measuring Indirect Carbon Emissions

The indirect carbon emissions, $em^2_{i,s}$, from the industry/enterprise depend on both the total electricity consumption, $c_{i,s,m}$, of the industry and the carbon emission factor, ef^c_i, for electricity consumption in region i (see Equation (4)).

$$em^2_{i,s} = c_{i,s,m} \times ef^c_i \quad (4)$$

Due to the large differences in resource endowments and electricity production technologies among regions in China, the carbon emissions and intensity of electricity production vary from region to region. Moreover, the complex electricity network distorts the relationship between electricity production and electricity end-consumption in terms of quantity and source because of the spatial mismatch of electricity supply and demand. The carbon emissions implicit in the supply of electricity also flow through the transmission network, so the accounting of carbon emissions caused by electricity consumption in different regions is often inaccurate. In terms of electricity production and consumption, Guangxi, as a major clean energy province, sends electricity to Guangdong, Hunan, and Guizhou on a large scale and also receives electricity input from Guizhou, Hunan, Yunnan, etc. The impact of local power supply structure and electricity flows on its electricity consumption carbon emissions cannot be ignored, so it is crucial to accurately account for the electricity consumption carbon emissions in Guangxi and its different sectors and to complete the tracing of electricity carbon emissions.

This study combines the inventory accounting methods in the Guidelines for National Greenhouse Gas Inventories prepared by the IPCC with the fossil fuel consumption data for thermal power generation in each province from the China Energy Statistics Yearbook (2016–2021) to calculate the direct carbon emissions of electricity in each province. The results of direct carbon emissions from electricity in each province provide the data basis for calculating indirect carbon emissions caused by electricity inflow from different regions of Guangxi consumption. The total CO_2 emissions from the power sector in region i using m different types of fossil fuels for electricity generation are:

$$e^G_i = \sum_{k=1}^{m} fc_{i,k} \cdot ef_k \quad (5)$$

where $fc_{i,k}$ denotes the input of the kth fossil fuel used for electricity generation in region i, and ef_k denotes the CO_2 emission factor for the kth fossil fuel.

The network analysis method assumes that electricity bought in a region is first mixed with locally produced electricity and then used for local consumption or sold. Using the network analysis method makes full use of the data on electricity flows in the transmission network over a period of time to calculate the implicit carbon emissions in the purchased electricity. There are significant differences between the emission intensity obtained using the network analysis method and other methods. The network analysis method is beneficial in obtaining more accurate indirect carbon emissions from electricity consumption, as it takes into account the higher-order electricity flows through the transit region [42]. Therefore, this study adopts the network analysis to account for indirect carbon emissions from electricity consumption in Guangxi.

In the network analysis method, each grid can be considered as a node in the network, while the electricity flows between different grids in the transmission network can be considered as edges in the network. In this study, each province can be considered as a grid, and the total inflows and outflows of each node in the transmission network can be determined based on the electricity flow data between different provinces [21]. The sum of incoming and produced electricity in a region is equal to the sum of outgoing and consumed electricity in that region (see Equation (6)):

$$x_i = p_i + \sum_{j=1}^{n} T_{ji} = c_i + \sum_{j=1}^{n} T_{ij} \tag{6}$$

where x_i represents the total electricity flows in region I, p_i and c_i indicate the local electricity generation and consumption in region i, respectively, and T_{ji} denotes the electricity delivered in region i to region j.

Given the electricity flows between n regions, an $n \times n$ dimensional electricity flow matrix T can be obtained as Equation (7). Based on the total electricity outflow (or inflow) from each region, a direct electricity flow ratio matrix B can be defined as Equation (8).

$$T = \begin{bmatrix} 0 & T_{1,2} & \cdots & T_{1,n} \\ T_{2,1} & 0 & \cdots & T_{2,n} \\ \vdots & \vdots & \ddots & \vdots \\ T_{n,1} & T_{n,2} & \cdots & 0 \end{bmatrix} \tag{7}$$

$$B = \hat{x}^{-1}T = \begin{bmatrix} 0 & \frac{T_{1,2}}{x_1} & \cdots & \frac{T_{1,n}}{x_1} \\ \frac{T_{2,1}}{x_2} & 0 & \cdots & \frac{T_{2,n}}{x_2} \\ \vdots & \vdots & \ddots & \vdots \\ \frac{T_{n,1}}{x_n} & \frac{T_{n,2}}{x_n} & \cdots & 0 \end{bmatrix} \tag{8}$$

Thirty-one provinces (excluding Hong Kong, Macao, and Taiwan) in China were included in the calculation for this study (n = 31). Data on cross-region electricity exchanges are from the Compilation of Statistics on the Electricity Industry (2015–2020). The (i, j)th element of matrix B represents the proportion of total electricity of region i flowing to region j.

Equation (9) is obtained from Equation (6):

$$x = p + xB \tag{9}$$

The derivation leads to Equation (10):

$$x = p(I - B)^{-1} = pG \tag{10}$$

where I is the unit matrix, $G = (I - B)^{-1} = I + B + B^2 + B^3 + \cdots$ indicates direct and indirect electricity flows among regions, and the element g_{ij} represents the total amount of electricity flowing to region j for each unit of electricity produced in region i, including the total amount flowing through transit regions and without transit regions, as well as the amount of electricity produced locally. The unit matrix I indicates electricity flows within the region, B denotes electricity flows directly between two nodes without passing through a transit region, B^2 represents electricity flows through a transit region, B^3 shows electricity flows through two transit regions, and so on.

The production–consumption matrix, namely the electricity consumption structure matrix, is as follows:

$$H = G\hat{c}\hat{x}^{-1} \tag{11}$$

where $\hat{c}$ is a diagonal matrix consisting of the electricity consumption of each region. To maintain consistency across different sections and data in this study, the electricity consumption of each region in this study is equal to the electricity generated in that region plus the inflow electricity and minus the outflow electricity. The matrix H links electricity production and consumption in different regions, and the elements $H_{ij} = g_{ij} \cdot c_j / x_j$ of the matrix represent the total amount of electricity consumed by region j per unit of electricity generated in region i. Furthermore, Equation (12) translates electricity flows to electricity-related CO_2 emission flows.

$$\begin{aligned} E^C = \hat{E}^G H &= \begin{bmatrix} e_1^G & & & \\ & e_2^G & & \\ & & \ddots & \\ & & & e_n^G \end{bmatrix} \begin{bmatrix} g_{11} & g_{12} & \cdots & g_{1n} \\ g_{21} & g_{22} & \cdots & g_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ g_{n1} & g_{n2} & \cdots & g_{nn} \end{bmatrix} \begin{bmatrix} \frac{c_1}{x_1} & & & \\ & \frac{c_2}{x_2} & & \\ & & \ddots & \\ & & & \frac{c_n}{x_n} \end{bmatrix} \\ &= \begin{bmatrix} \frac{e_1^G g_{11} c_1}{x_1} & \frac{e_1^G g_{12} c_2}{x_2} & \cdots & \frac{e_1^G g_{1n} c_n}{x_n} \\ \frac{e_2^G g_{21} c_1}{x_1} & \frac{e_2^G g_{22} c_2}{x_2} & \cdots & \frac{e_2^G g_{2n} c_n}{x_n} \\ \vdots & \vdots & \ddots & \vdots \\ \frac{e_n^G g_{n1} c_1}{x_1} & \frac{e_n^G g_{n2} c_2}{x_2} & \cdots & \frac{e_n^G g_{nn} c_n}{x_n} \end{bmatrix} \end{aligned} \quad (12)$$

The vector E^G is composed of carbon emission e_i^G generated by electricity generation in each region. After diagonalizing it, the production–consumption matrix can connect it with electricity consumption as Equation (12). The (i, j)th element $\frac{e_i^G g_{ij} c_j}{x_j}$ of E^C in Equation (12) represents the carbon emissions implicit in the electricity from region i consumed by region j.

Once the above results are obtained, the carbon emissions implicit in the electricity consumption in each region and the corresponding carbon emission factors can be calculated. The e^C in Equation (13) is an n-dimensional row vector representing the implicit carbon emissions from electricity consumption in each region. The ef^C in Equation (14) is an n-dimensional row vector representing the CO_2 emission factor for electricity used in region j.

$$e^C = [1, \cdots, 1] E^C \quad (13)$$

$$ef^C = e^C \hat{c}^{-1} \quad (14)$$

3. Results and Discussion

3.1. Total Carbon Emissions of Different Industries in Guangxi

Based on the published data, we calculate the total CO_2 emissions of the whole society and different industries in Guangxi from 2014 to 2020, and the results are shown in Figure 2. The total CO_2 emissions in Guangxi show a trend of steady increase from 205.72 Mt in 2015 to 270.28 Mt in 2020, with an average growth rate of 5.65%. The CO_2 emission of the whole society is composed of fossil energy combustion emission, industrial process emission, and electricity emission, among which the carbon emission of electricity in the whole society accounts for 31.96% of the total emission in 2020, reaching 86.39 Mt. The carbon emission of the industrial sector in Guangxi dominates, and its emissions over the past years have reached more than 75% of the total carbon emission of the whole society. In addition, carbon emissions from the primary industry and rural residents' consumption show a slow downward trend.

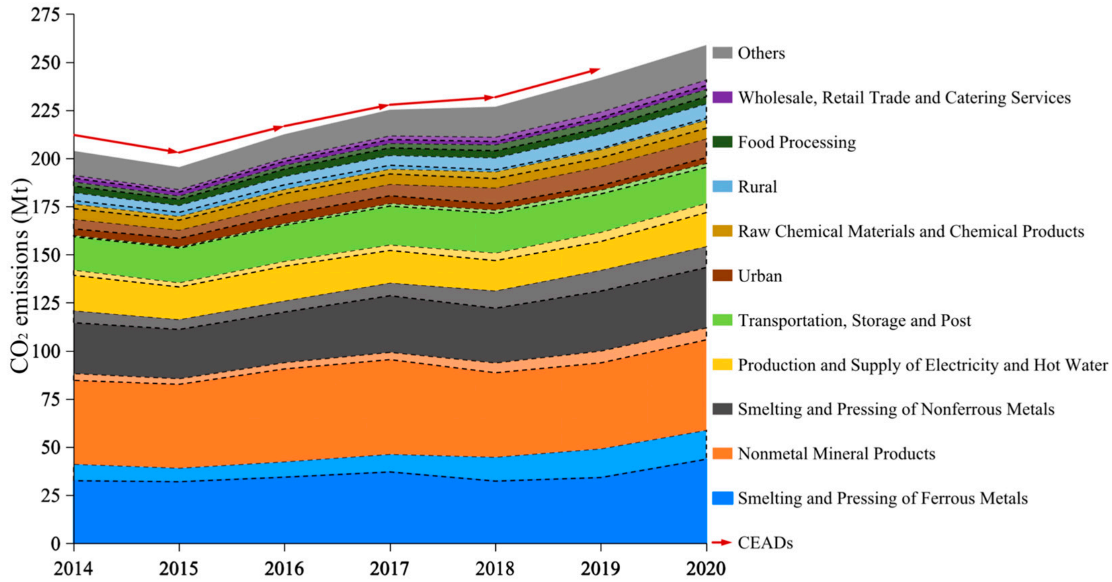

Figure 2. Carbon emissions of different sectors in Guangxi in 2020. Note: the areas with dotted lines represent emissions related to electricity consumption. To avoid double counting, emissions from power generation are separated from the related sector and distributed to other sectors through network analysis. The difference of the results with CEADs is within 3%, which is mainly caused by the flowing-out emissions contained in electricity flows.

In terms of direct carbon emissions by sector (fossil energy combustion and industrial processes), there are large differences between the emission characteristics of each sector from 2014 to 2020. The industries of nonmetal mineral products, smelting and pressing of ferrous metals, and smelting and pressing of nonferrous metals are the most important sources of carbon emissions in Guangxi, generating 49.13 Mt, 43.69 Mt, and 31.33 Mt of direct carbon emissions in 2020, accounting for 26.83%, 23.76%, and 17.04% of the total direct emissions in Guangxi, respectively. Transportation, storage, and post is another major emitting sector of direct carbon emissions in Guangxi, with its CO_2 emissions rising year by year from 17.27 Mt in 2014 to 20.58 Mt in 2018, with an average annual growth rate of 4.50%. Direct carbon emissions from the energy supply sector flow to other consumption sectors under the Scope 2 accounting principle, resulting in 17.54 Mt or 9.54% of the whole society. In addition, the emissions and shares of the primary industry, manufacturing, and rural residential consumption in Guangxi showed a downward trend during the study period, with direct carbon emissions from agriculture, forestry, animal husbandry, and the fishery declining from 3.43 Mt in 2016 to 2.35 Mt in 2019, with an average decline rate of 11.05%.

Indirect carbon emissions are influenced by the regional power structure, electricity consumption, and interprovincial electricity flows. This study measures interprovincial carbon flows and regional carbon emission factors for electricity consumption in 2020 based on the network analysis (see Figures 3 and 4). Guangxi maintains an electricity import and export relationship with Yunnan, Guizhou, Hunan, and Guangdong. In 2020, Guangxi receives a total of 16.478 TWh of electricity input from Yunnan and Hunan and 11.58 TWh of electricity transmission to Guangdong, Yunnan, and Hunan, showing a net electricity outflow. Therefore, in the network analysis, the actual electricity carbon emission in Guangxi is influenced by the implicit carbon impact of electricity, with a net implicit carbon outflow of about 2.17 Mt. The model calculation results show that the actual carbon dioxide emission per kWh consumed in Guangxi is 441 g, which is lower than the national average of 524.11 gCO_2/KWh. Furthermore, by correlating the regional carbon emission factor for electricity consumption with the electricity consumption of each sector, the sectoral electricity-related carbon emissions can be obtained (see Figure 2).

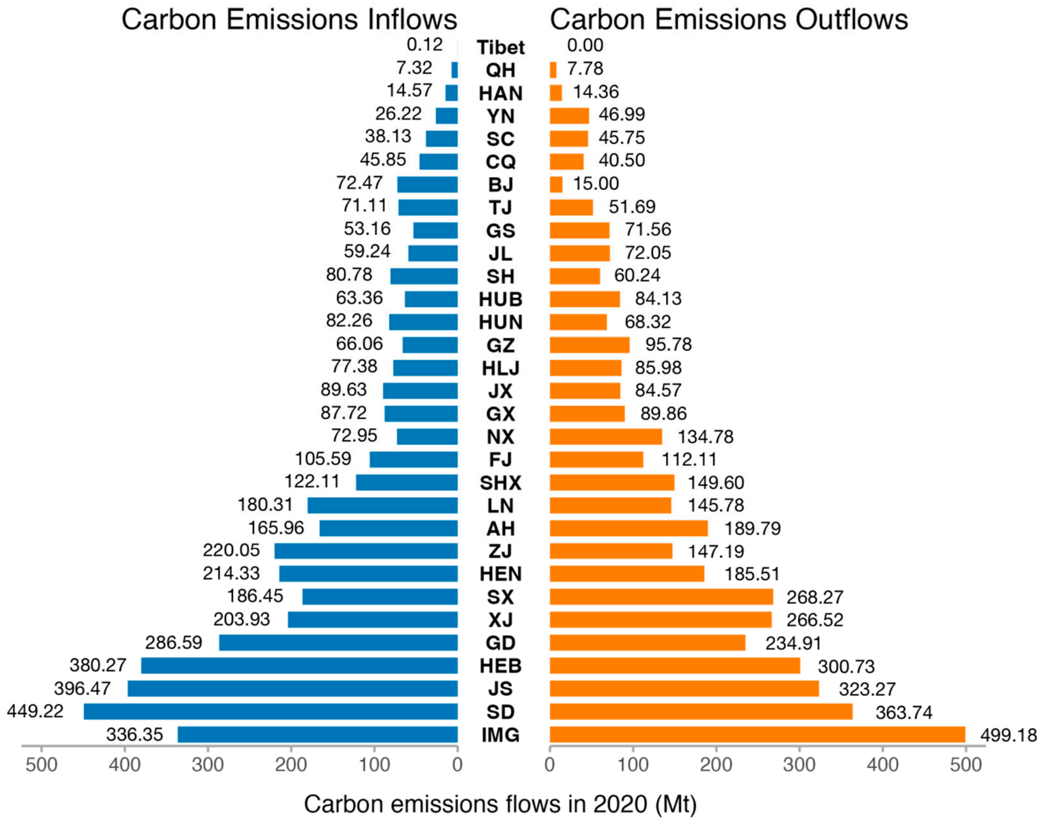

Figure 3. CO_2 emission flows in 2020.

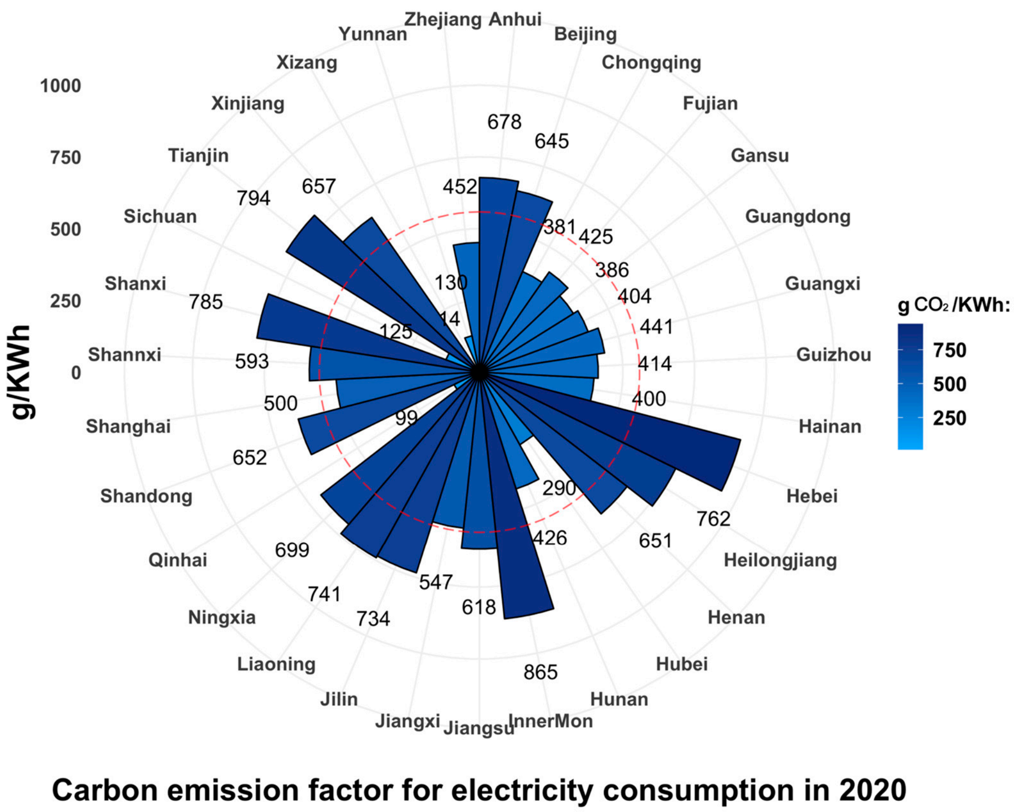

Figure 4. Regional emission factors of Guangxi in 2020.

3.2. Electricity–CO_2 Coefficient by Sector in Guangxi

Correlating the total carbon emissions of the Guangxi by industry with its total electricity consumption, the electricity–CO_2 coefficient of each industry is calculated (see Table A1 (Appendix A)). According to carbon emissions and the electricity consumption by industries in Guangxi, the average carbon emission of the whole society is 1129 g/KWh, with significant differences between industries (see Figure 5).

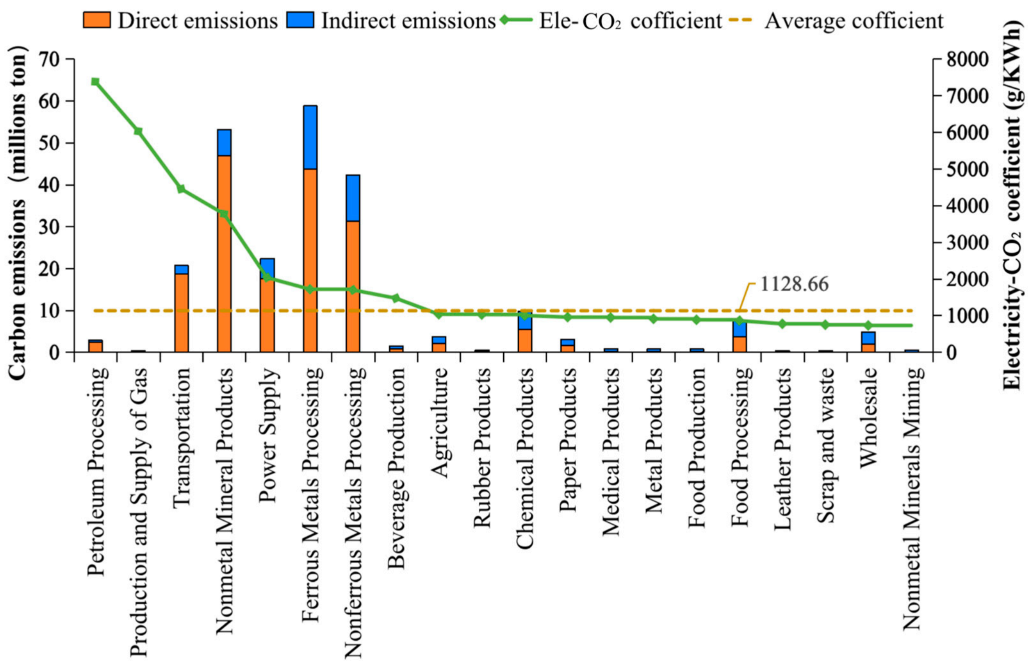

Figure 5. Electricity–CO_2 coefficient of different industries in Guangxi (2020). Note: this figure shows only the 20 industries with the largest coefficients. Petroleum processing (petroleum processing and coking), transportation (transportation, storage, and post), power supply (production and supply of electric power and hot water), agriculture (agriculture, forestry, animal products, and fishing), and wholesale (wholesale, retail trade, and catering services).

Taking the 2020 results as an example, the electricity–CO_2 coefficient of industries with high direct carbon emissions from energy consumption are generally at high values, such as transportation, storage, and post and nonmetal mineral products, amounting to 4449 g/KWh and 3768 g/KWh, respectively. In addition, some industries with small total carbon emissions but with a large difference between their emissions and electricity consumption also have high values of electricity–CO_2 coefficient, such as the petroleum processing and coking and the production and supply of gas, which reach 7376 g/KWh and 6024 g/KWh, respectively.

In order to obtain a real-time available electricity–CO_2 coefficient, we adopt the time trend analysis method and predict the electricity–CO_2 coefficient based on the ARMA (1,0) model for each industry in Guangxi based on electricity big data, thus solving the problem of lagging emission data. Furthermore, considering the short series of existing carbon emission factors, this study also uses the trend extrapolation method to forecast the related factors. The top 10 sectors with the highest emissions are shown in Figures 6 and 7. The results of the electricity and carbon factors for all sectors from 2014 to 2023 are shown in Table S1 (Supplementary Materials), where the values for 2014–2020 are the real measured values based on the electricity–CO_2 coefficient model, and the values for 2021–2023 are the projections. Based on the temporal trend of the electricity–CO_2 coefficients, it can be seen that some sectors with high emission characteristics, such as nonmetal mineral products, transportation, storage, and post, and production and supply of electric power and hot water, show small increase in their emission factors in 2021–2023 based on the previous trend. The share of manufacturing output in the primary and secondary sectors is declining, with agriculture, forestry, animal products and fishing, plastic products, and equipment and machinery manufacturing all showing declining trends in 2021–2023. In addition, the electricity–CO_2 coefficients for urban and residential consumption show a clear downward trend in all years from 2021 to 2023.

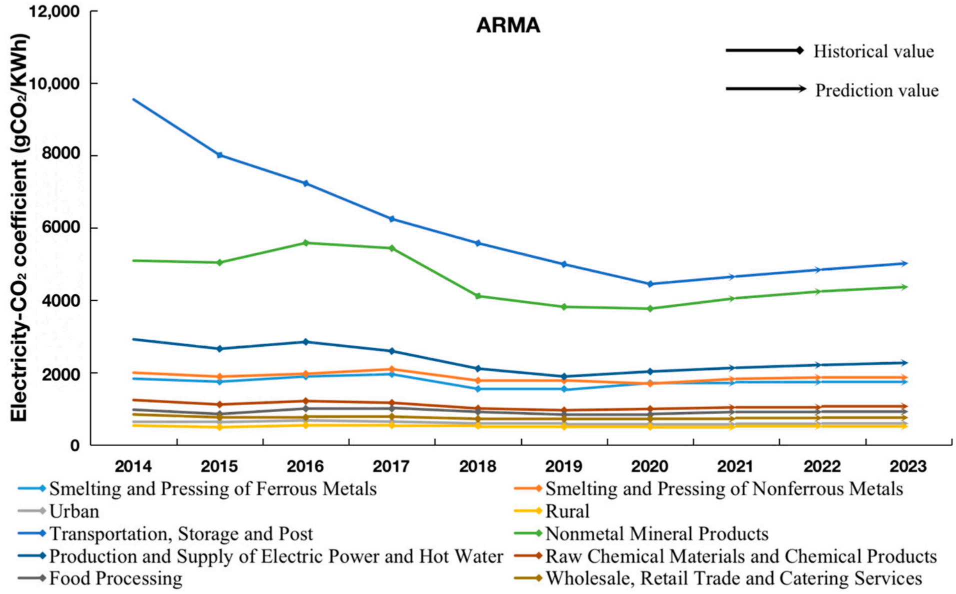

Figure 6. Prediction of electricity–CO_2 coefficient based on ARMA.

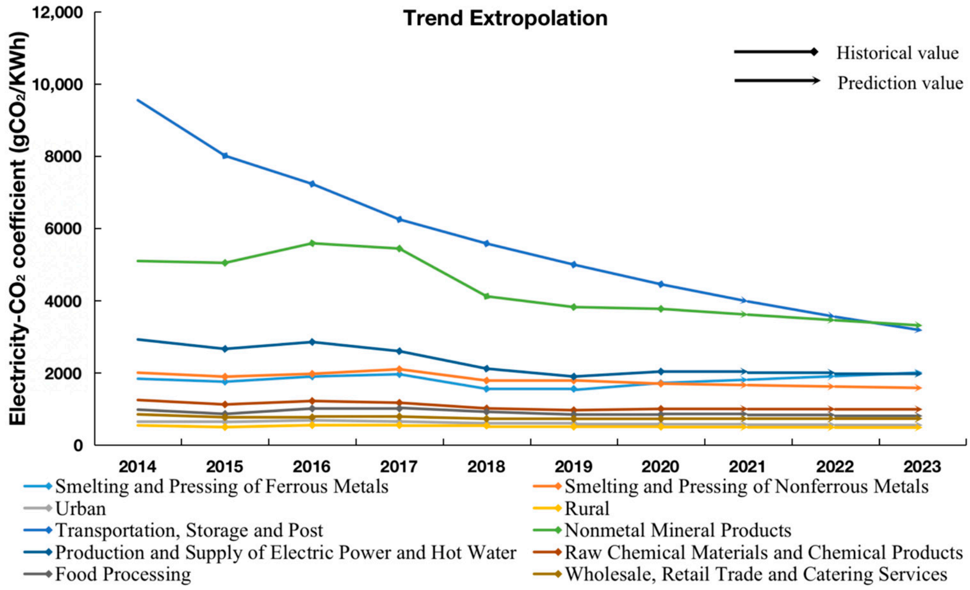

Figure 7. Prediction of electricity–CO_2 coefficient based on trend extrapolation. Note: the two figures above show only the 10 industries with the largest CO_2 emissions.

In order to ensure the accuracy of both the ARMA model and the trend extrapolation method in predicting the electricity–CO_2 coefficient, this study adopts data from 2018 and earlier to simulate the electricity–CO_2 coefficient for 2019 and 2020, so that the simulated values can be compared with the real values and the prediction accuracy of the model used can be analyzed. After the simulation of the forecast by sector, the 47 existing sectors in Guangxi were classified into 10 common sector categories, and the forecast accuracy of different sector categories was obtained (see Figures 8 and 9).

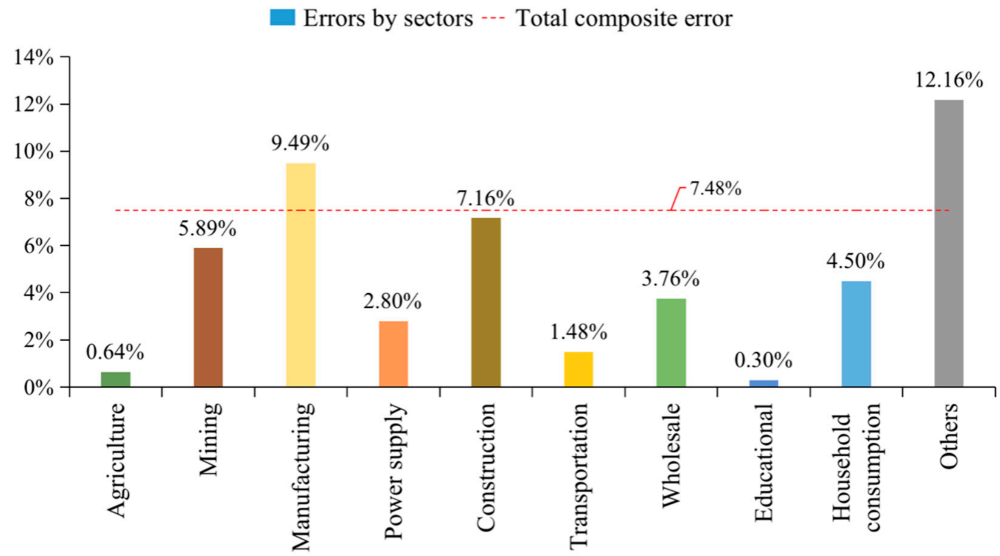

Figure 8. Prediction errors of electricity–CO_2 coefficient (ARMA).

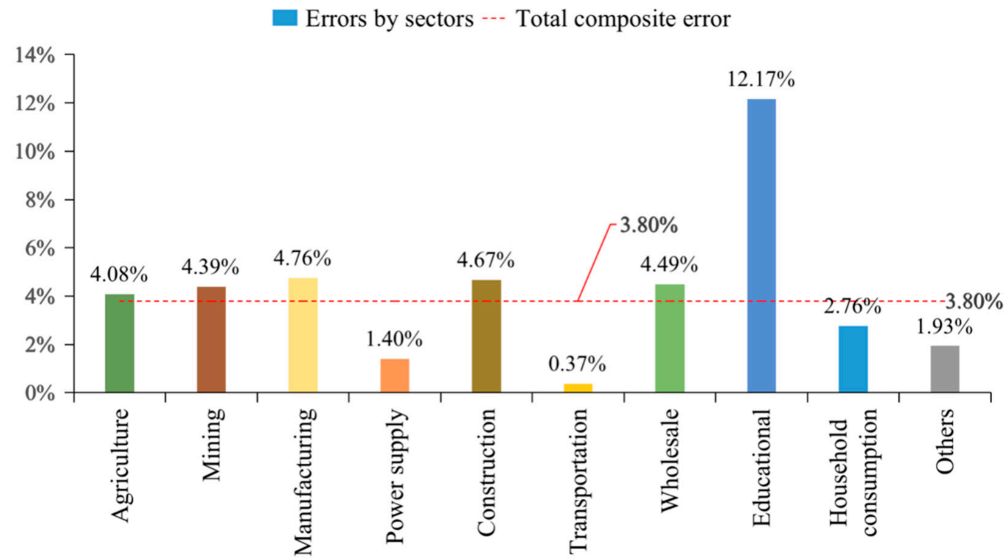

Figure 9. Prediction errors of electricity–CO_2 coefficient (trend extrapolation). Note: the total composite error is the emissions-weighted average of the sectoral forecast error. Agriculture (agriculture, forestry, animal products, and fishing), power supply (production and supply of electricity, gas, and water), transportation (transportation, storage, and post), education (cultural, educational, and sports articles).

The total composite error of the ARMA model forecast results was 7.48%, compared to 5.35% for the trend extrapolation method. Using the ARMA model as an example, the forecast errors for the four sectors of agriculture, forestry, animal products, and fishing, production and supply of electricity, gas, and water, transportation, storage, and post, and cultural, educational, and sports articles were all at a relatively small level, at 0.64%, 2.80%, 1.48%, and 0.30%, respectively. The others include the remaining industries that are not clearly classified, so their forecast error is at a higher level of 12.16%. As for the trend extrapolation method, only the cultural, educational, and sports articles have higher forecast errors for emissions. In summary, the ARMA model is more suitable for modeling series with a high degree of randomness, while the trend extrapolation method is more suitable for series with a trend. Therefore, when modeling short-term series related to the Guangxi economy, the trend extrapolation method shows higher accuracy than ARMA.

3.3. Carbon Emissions Monitoring of Guangxi Enterprises Based on Electricity Big Data

Using the forecasted values of the electricity–CO_2 coefficients for each industry in 2022 and combined with the hourly enterprise electricity consumption data, this study realizes real-time carbon emissions monitoring at the enterprise level (see Figure 10). The emissions monitoring covered a total of 1338 enterprises in different industries in Guangxi, of which 43.2% belonged to high-energy-consuming industries such as petroleum processing and coking, raw chemical materials and chemical products, nonmetal mineral products, smelting and processing of ferrous metals, smelting and processing of nonferrous metals, and sectors related to energy supply.

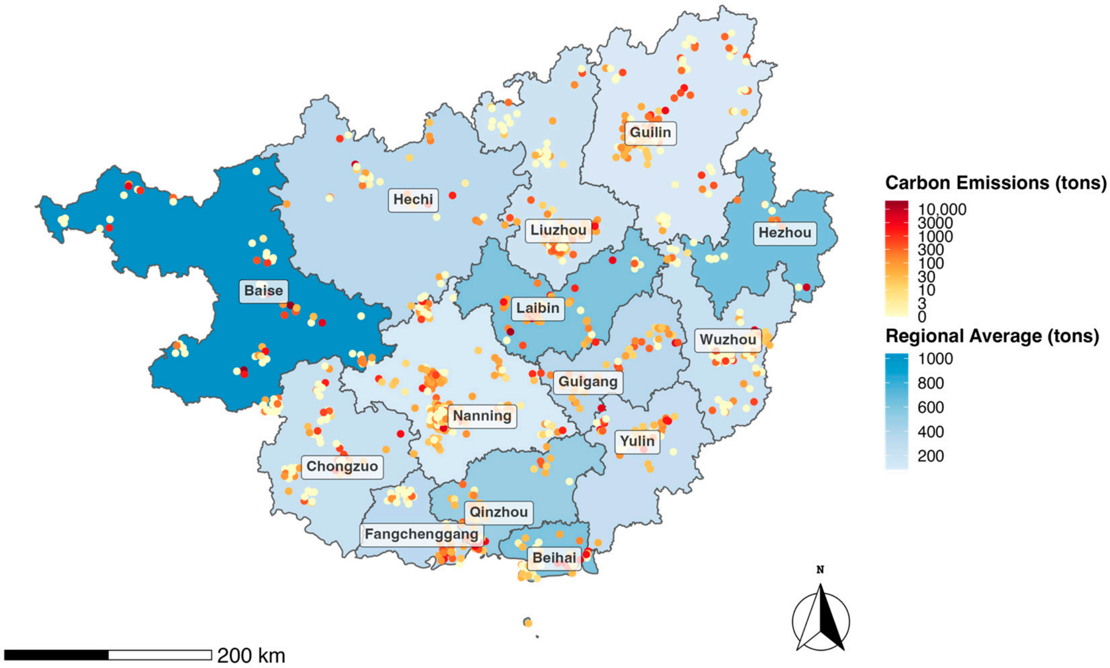

Figure 10. Real-time carbon emissions monitoring map of Guangxi in 2022. Note: the figure shows the carbon emissions monitoring values of some representative enterprises in Guangxi on a sample day.

The distribution of emissions is nonuniform among industries and regions, reflecting the heterogeneity of industry emission characteristics and the different industrial layout in Guangxi's various regions. The average daily emissions of monitored enterprises in Guangxi are 277.06 tons. Emissions from the nonmetal mineral products sector and smelting and pressing of metals enterprises are generally higher than the average, with some aluminum smelting enterprises emitting as much as 20,398.95 tons of CO_2 per day.

In terms of spatial emission distribution, the average daily carbon emissions of enterprises in Baise and Laibin reach 1039.32 tons and 602.03 tons, respectively, because of the concentration of aluminum and metallurgical industries, while the average daily carbon emissions of enterprises in Guilin and Nanning, where most of the monitored enterprises belong to the tertiary industry, are only 87.03 tons and 96.03 tons, respectively. Therefore, the different industrial layout plans make the carbon emission levels of enterprises in each region very different.

4. Conclusions and Implications

4.1. Conclusions

Through analyzing the carbon emissions caused by regional electricity consumption, this study explores the correlation mechanism between industrial carbon emissions and their electricity consumption and constructs the electricity–CO_2 coefficients for each industry. Finally, based on the real-time electricity consumption data of enterprises in Guangxi, this study realizes carbon emissions monitoring at the industry/enterprise level. The multi-level carbon emissions monitoring system of "region–industry–enterprise" established in this study aims to provide evidence-based support for local carbon emissions monitoring and the achievement of dual carbon goals. Taking Guangxi as an example, this study has drawn the following conclusions:

1. The current Guangxi society-wide carbon emissions are still in the rising stage of the carbon peak path, and the proportion of indirect carbon emissions from electricity consumption and the carbon emission factor of electricity consumption are both showing an increasing trend. In 2020, the direct carbon emissions of the whole industry in Guangxi are 183.89 Mt, and the direct carbon emissions from local electricity production is 86.39 Mt. From 2014 to 2020, the proportion of indirect carbon emissions in total carbon emissions in Guangxi increases from 22.17% to 31.96%. In 2020, each unit of electricity consumed in the region causes indirect CO_2 emissions of 441 g, but it is still lower than the national average value of 524.11 g CO_2/KWh.
2. Carbon emissions from the industrial sector occupy a dominant position, and the proportion of carbon emissions from the primary industry is slowly decreasing. Among them, the nonmetal mineral products sector, smelting and processing of ferrous metals sector, and smelting and processing of nonferrous metals sector are the largest sources of carbon emissions in Guangxi, and their actual CO_2 emissions and emission share are large. In addition, the total direct carbon emissions of the three sectors in 2020 are 154.33 Mt, accounting for 57.10%. Carbon emissions from the electricity production sector under the shared responsibility principle are 22.41 Mt, accounting for 8.29%. The transportation sector is another major source of emissions, with 20.75 Mt of CO_2 emissions in 2020, accounting for 7.68%. In addition, total carbon emissions from the primary sector have shown a fluctuating downward trend since 2014, standing at 3.75 Mt in 2020, a decrease of 8.67% compared to 2014.
3. There are significant differences in the electricity–CO_2 coefficients of different sectors. In the process of carbon emissions monitoring and accounting, attention should be paid to the differences in emissions between different industries, and customized carbon emissions monitoring and accounting should be carried out. Through real-time monitoring of the carbon emissions of enterprises in Guangxi, we find that the daily carbon emissions of enterprises in the primary, light, and tertiary industries are generally lower than the monitoring average of 275.02 tons per day, while enterprises in the nonmetal mineral products, metal smelting, and chemical products are characterized by both high energy consumption and high emissions, with the highest carbon emissions reaching 20,398.95 tons per day. In 2020, under the shared responsibility principle, the average value of the electricity–CO_2 coefficient for all sectors in Guangxi is 1129 gCO_2/KWh; the maximum value is for petroleum processing and coking with an average electricity–CO_2 coefficient of 7376 gCO_2/KWh; the minimum value is for petroleum and natural gas extraction, production and supply of tap water, and cultural, educational, and sports articles with an average electricity–CO_2 coefficient of 446 gCO_2/KWh.

4.2. Implications

The implementation of multi-level carbon emissions monitoring from region–industry–enterprise is an important part of the implementation of the dual carbon goals. The multi-level analysis from region to industry to enterprise can provide a comprehensive picture of carbon emissions in different regions, industries, and enterprises and provide a more scientific basis for the government and enterprises to formulate carbon emission reduction strategies. Moreover, multi-level carbon emissions monitoring can also help different regions and industries to detect and improve their carbon emission behaviors in advance, promoting the refinement and scientific and sustainable development of carbon emission reduction work. Based on the above findings, we put forward the following policy implications:

1. The government should seize the key industries when conducting dual carbon planning and objectively develop a dual carbon pathway by industry based on historical emission data. Taking Guangxi as an example, carbon emissions from the nonmetal mineral products, smelting and processing of ferrous metal, smelting and processing of nonferrous metal, power production, and transportation sectors often account for more than 70% of total social emissions under the shared responsibility principle (Scope 2) and have continued to grow in recent years. Policy makers should consider the pressure to achieve the dual carbon goals for each sector and further optimize the sectoral emission reduction constraints.
2. Use real-time carbon emissions monitoring at the enterprise level to promote carbon emission policy optimization, enterprise independent emission reduction innovation, and carbon market construction. First, enterprise carbon emissions monitoring based on electricity big data enables point-source tracing of high-frequency carbon emission streams, which supports the government in grasping the emission details in real time and carrying out timely emission accountability or support for relevant subjects. Second, the promotion of enterprise-level carbon emissions monitoring helps to promote enterprises to independently optimize their energy consumption in production processes, spontaneously promote their transformation from high energy consumption and pollution to low energy consumption and clean production, and acquire the economic benefits of energy saving and emission reduction innovation. Finally, enterprise emission data can be used as the basis for phased emission reduction compliance in a complete carbon market in the future, providing data support and endorsement for the market's operation and helping institutional and regulatory bodies to better carry out operations such as trading and auditing, thus further improving the effectiveness of the market and promoting the construction of a fully informed market.

Supplementary Materials: The following supporting information can be downloaded at https://www.mdpi.com/article/10.3390/en16135124/s1, Table S1: The Prediction of Electricity-CO_2 Coefficient.

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Data Availability Statement: The data presented in this study are available upon request from the corresponding author. The related open-source databases are CEADs (https://www.ceads.net/, accessed on 8 September 2022), the Guangxi Statistical Yearbook (http://tjj.gxzf.gov.cn/tjsj/tjnj/, accessed on 10 January 2023), and the IPCC inventory (https://www.ipcc-nggip.iges.or.jp/public/2019rf/, accessed on 10 January 2023).

Conflicts of Interest: The authors declare no conflict of interest.

Appendix A. The Calculation of Electricity–CO_2 Coefficients

Table A1. Electricity–CO_2 coefficient of different sectors in Guangxi (2020).

	Electricity Consumption (10^4 KWh)	Direct Emissions (Mt)	Indirect Emissions (Mt)	Total Emissions (Mt)	Ele-CO_2 Coefficient (g/KWh)
Agriculture, Forestry, Animal Products, and Fishing	363,939	215	161	375	1032
Coal Mining and Dressing	74,393	9	33	42	561
Petroleum and Natural Gas Extraction	2343	0	1	1	441
Ferrous Metals Mining and Dressing	155,473	25	69	93	601
Nonferrous Metals Mining and Dressing	174,121	14	77	90	519
Nonmetal Minerals Mining and Dressing	33,699	9	15	24	713
Other Minerals Mining and Dressing	64	0	0	0	481
Logging and Transport of Wood and Bamboo	0	0	0	0	0
Food Processing	886,047	368	391	759	857
Food Production	51,521	23	23	45	882
Beverage Production	79,002	81	35	116	1469
Tobacco Processing	12,040	3	5	8	674
Textile Industry	92,174	17	41	58	625
Garments and Other Fiber Products	8046	0	4	4	464
Leather, Furs, Down, and Related Products	11,393	4	5	9	771
Timber Processing, Bamboo, Cane, Palm Fiber, and Straw Products	272,619	14	120	135	493
Furniture Manufacturing	4047	0	2	2	517
Papermaking and Paper Products	332,183	170	147	317	953
Printing and Record Medium Reproduction	12,418	0	5	6	471
Cultural, Educational, and Sports Articles	2910	0	1	1	450
Petroleum Processing and Coking	34,320	238	15	253	7376
Raw Chemical Materials and Chemical Products	979,651	544	432	977	997
Medical and Pharmaceutical Products	55,724	28	25	53	943
Chemical Fiber	660	0	0	0	643
Rubber Products	26,070	15	12	27	1024
Plastic Products	73,551	8	32	40	547
Nonmetal Mineral Products	1,410,437	4692	622	5314	3768
Smelting and Pressing of Ferrous Metals	3,432,098	4369	1515	5884	1714
Smelting and Pressing of Nonferrous Metals	2,497,504	3133	1102	4235	1696
Metal Products	50,029	23	22	45	907
Ordinary Machinery	98,708	18	44	62	624
Equipment for Special Purposes	63,043	7	28	35	552
Transportation Equipment	188,998	45	83	129	680
Electric Equipment and Machinery	94,394	3	42	45	478
Electronic and Telecommunications Equipment	18,944	1	8	9	468
Instruments, Meters, and Cultural and Office Machinery	4534	0	2	2	455
Other Manufacturing Industry	11,990	1	5	7	552
Scrap and waste	3220	1	1	2	746
Production and Supply of Electric Power and Hot Water	1,103,267	1754	487	2241	2031
Production and Supply of Gas	1612	9	1	10	6024
Production and Supply of Tap Water	81,180	0	36	36	446
Construction	273,405	70	121	190	696
Transportation, Storage, and Post	466,254	1869	206	2075	4449
Wholesale, Retail Trade, and Catering Services	670,247	191	296	487	726
Others	1,439,624	36	635	671	466
Urban	2,237,446	292	987	1279	572
Rural	1,692,757	88	747	835	493

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