International Journal of Geo-Information

Article

Exploring Inequality: A Multi-Scale Analysis of China's Consumption Carbon Footprint

Feng Xu [1], Xinqi Zheng [1,2,3,4,*], Minrui Zheng [5,6], Dongya Liu [1,2], Yin Ma [7], Jizong Peng [8], Ye Shen [1], Xu Han [9] and Mengdi Zhang [10]

[1] School of Information Engineering, China University of Geosciences, Beijing 100083, China; 3004210010@email.cugb.edu.cn (F.X.); dyliu@cugb.edu.cn (D.L.); 2004220038@email.cugb.edu.cn (Y.S.)
[2] Frontiers Science Center for Deep-Time Digital Earth, China University of Geosciences, Beijing 100083, China
[3] Observation and Research Station of Beijing Fangshan Comprehensive Exploration, Ministry of Natural Resources of the People's Republic of China, Beijing 100083, China
[4] Technology Innovation Center for Territory Spatial Big-Data, Ministry of Natural Resources of the People's Republic of China, Beijing 100036, China
[5] Technology Innovation Center for Territory Spatial Big-Data, Renmin University of China, Beijing 100036, China; minruizheng@ruc.edu.cn
[6] Digital Government and National Governance Lab, Renmin University of China, Beijing 100872, China
[7] China Aero Geophysical Survey and Remote Sensing Center for Natural Resources, China Geological Survey, Beijing 100083, China; mayin@mail.cgs.gov.cn
[8] School of Statistics and Data Science, Jiangxi University of Finance and Economics, Nanchang 330013, China; pengjizong@jxufe.edu.cn
[9] School of Economics and Finance, Huaqiao University, Quanzhou 362000, China; 22011020003@stu.hqu.edu.cn
[10] Natural Resources Comprehensive Survey Command Center, China Geological Survey, Beijing 100037, China; zmengdi@mail.cgs.gov.cn
* Correspondence: zxqsd@126.com or zhengxq@cugb.edu.cn

Abstract: Carbon emission inequality has become a critical factor constraining the coordinated development of socio-economic systems and the natural environment. This inequality exacerbates the disparity in carbon emissions across regions, hindering efforts to achieve sustainable development and environmental justice. Previous research has primarily focused on the structure of carbon footprints and their influencing factors, but there has been limited quantitative research on carbon emission inequality, particularly from a multi-scale perspective. This study constructs a 250 m-high-resolution consumption-based carbon footprint grid for China and uses the Theil index to reveal significant spatial inequalities in carbon footprints. The results indicate that smaller-scale analyses better reveal the spatiotemporal heterogeneity of carbon footprints within regions. At the county level, carbon footprints exhibit significant inequalities, with hotspots concentrated in regions such as Beijing–Tianjin–Hebei, the Yangtze River Delta, and the Pearl River Delta. The top 5% of areas with the highest carbon footprints (139 cities) contributed 19.6% of the national total, indicating a concentration in a few large cities. The decomposition of the Theil index shows that county-level cities contributed 55% of the national carbon inequality. The study also reveals the complex relationship between carbon footprints and income, as well as urban-rural disparities. The underdeveloped central and western regions exhibit a pronounced spatial lag effect, with the growth rate of carbon footprints in rural areas surpassing that of urban areas. Carbon footprints in impoverished areas and inter-provincial marginal areas overlap significantly with low-emission zones, demonstrating characteristics of "low-carbon growth". To achieve carbon peak and carbon neutrality targets, China must adopt comprehensive measures to reduce carbon footprints and their inequalities, including strengthening multi-scale carbon inequality monitoring, implementing differentiated carbon reduction policies, and promoting coordinated emission reduction development at the county level.

check for updates

Academic Editors: Wolfgang Kainz and Godwin Yeboah

Received: 25 November 2024
Revised: 17 January 2025
Accepted: 23 January 2025
Published: 26 January 2025

Citation: Xu, F.; Zheng, X.; Zheng, M.; Liu, D.; Ma, Y.; Peng, J.; Shen, Y.; Han, X.; Zhang, M. Exploring Inequality: A Multi-Scale Analysis of China's Consumption Carbon Footprint. *ISPRS Int. J. Geo-Inf.* **2025**, *14*, 49. https://doi.org/10.3390/ijgi14020049

Keywords: carbon inequality; carbon footprint; multi-scale analysis; Theil index; carbon peaking and carbon neutrality

1. Introduction

As the global consensus on sustainable development and the green economy emerges, the United Nations has established 17 Sustainable Development Goals (SDGs), which call for the balanced development of economic, social, and environmental aspects [1]. Within this framework, mitigating climate change and reducing inequality have emerged as two urgent issues that need to be addressed. However, the Kyoto Protocol, in allocating responsibilities for mitigating climate change, failed to adequately consider differences in emissions and the capacities of individual countries to address climate change, resulting in its inability to fundamentally resolve the imbalance in global carbon emissions [2,3].

Carbon emissions from household consumption have gradually attracted international attention. The 2020 United Nations Environment Programme's "Emissions Gap Report" indicates that consumption-related carbon emissions account for 70% of global carbon emissions [4,5], 2020. According to the International Energy Agency's "CO_2 Emissions from Fuel Combustion 2020", China's household carbon emissions in 2019 represented 53% of the country's total carbon emissions and accounted for 19% of global household emissions, the highest share worldwide [6,7]. Given this trend, household carbon emissions are increasingly becoming a significant component of China's total carbon dioxide emissions. Furthermore, as China continues to implement policies to stimulate consumption and boost domestic demand, household consumption is surpassing industrial production as the primary driver of carbon emissions' growth in the country [8].

Carbon footprint inequality arises from differences among individuals and organizations in production and consumption patterns, energy usage, and technological capabilities. Compared to income inequality, carbon footprint inequality is more comprehensive, can be localized to specific areas of consumption, and exhibits greater spatial variation [9,10]. As the largest emitter of carbon and a nation with significant disparities in wealth, China displays distinct regional differences in resource distribution and economic development. Carbon footprint inequality often leads to disputes over the allocation of carbon neutrality responsibilities, with differences in regional carbon emission rights and resource flows potentially exacerbating economic inequality. For example, disparities in energy, infrastructure, and socioeconomic resources lead to variations in carbon emissions between developed and underdeveloped regions [11], urban and rural areas [12,13], and urban cores and suburban areas [14]. The significant wealth gap and pronounced spatial disparities in carbon emissions greatly impact both spatial carbon footprint inequality and the effectiveness of emission-reduction efforts [15,16]. A profound understanding of spatial carbon emission inequalities can help formulate more targeted and equitable mitigation policies, ensuring fair climate responsibility among all parties. Ignoring spatial carbon emission inequality could hinder the achievement of carbon peak and carbon neutrality goals.

Through a comparative analysis of existing research, numerous deficiencies were identified: (1) A lack of multi-scale spatial patterns of carbon emissions. Most studies analyze carbon inequality at the national, regional, provincial, or sectoral level, but there is limited integration of carbon emission data at meso and micro scales, making multi-scale policy formulation challenging. Additionally, there is a lack of research on finer geographic units, which hampers an in-depth investigation of intra-regional carbon footprint management and emission disparities [1,17,18]. (2) Deficiency in the spatial dimension. Current research on carbon emissions inequality primarily focuses on socio-economic groups and sectoral differences, with limited attention to spatial variation [10,19]. (3) Data and modeling limitations. The lack of high-resolution data constrains the accuracy of fine-scale modeling [3,20]. (4) Lack of inter-regional spatial linkages. The spatial spillover effects of carbon emissions between regions have not been fully revealed. This study aims to address the spatial dimension of carbon emission inequality, overcome data and modeling limitations, and deepen the understanding of spatial carbon emission inequalities [21,22].

This research focuses on the spatial analysis of consumption-based carbon footprint inequality. Therefore, by constructing a high-resolution consumption carbon footprint model for China, the study aims to create a micro-level carbon footprint grid data map. The Theil index and Lorenz curve are employed to quantify multi-scale carbon footprint inequality levels and to analyze the main driving factors of this inequality. This provides a novel perspective for a more equitable and reasonable allocation of carbon reduction targets among regions in China, supplementing existing macro-level studies. This is of significant importance for achieving China's overall carbon reduction goals.

2. Data and Methods

2.1. Data

The environmentally extended multi-regional input-output (EE-MRIO) model for China, along with provincial and county-level [23] carbon emission inventories, were sourced from the China Emission Accounts and Datasets [24] (CEADS, https://www.ceads.net/, accessed on 16 April 2024). Economic data for cities and counties, as well as urban and rural disposable income data, were gathered from statistical yearbooks of various districts and counties, government websites, and statistical bulletins. Population data were obtained from WorldPop (https://www.worldpop.org/, accessed on 16 April 2024). Data on urban built-up areas (GLB) were sourced from Tsinghua University (http://data.ess.tsinghua.edu.cn/, accessed on 16 April 2024).

2.2. Research Methods

2.2.1. Constructing the Consumption-Based Carbon Footprint Grid Model

To accurately estimate China's consumption-based carbon emissions, it is crucial to develop a rapid and precise quantitative estimation method applicable at the national, provincial, county, and grid scales. However, input-output data are only available at the national level, resulting in a one-dimensional research scale that limits the ability to conduct multidimensional spatial analysis. This study addresses this limitation by employing a four-level data model that encompasses national, provincial, county, and urban-rural scales. By utilizing population density as a key linkage, the model integrates diverse datasets and enables the construction of a fine-grained, multiscale grid model for estimating China's consumption-based carbon emissions. The structure of this model is depicted in Figure 1.

The construction of China's fine-grained consumption-based carbon emission grid model involved four main steps:

(1) Integrating China's energy consumption carbon emission data for 2015 and 2017 with the Environmentally Extended Multi-Regional Input-Output (EE-MRIO) model, disaggregating provincial consumption emissions based on sectoral and regional links.

Using the EE-MRIO model, China's total carbon emissions were calculated and subsequently allocated to each province. This study included eight consumption categories, as detailed in Table 1.

Table 1. The 42 sectors of the reclassified input-output table.

No.	Household Consumption Sector	Input-output Table Department
1	Food alcohol and tobacco	Food and alcohol and tobacco, Agriculture, forestry and fishing
2	Dress	Textile, garment, shoes, hats, leather, eiderdown and their products
3	Housing	Non-metallic ores and other mineral products, Manufacture of Non-metallic Mineral Products
4	Daily necessities and services	Wood products and furniture, Electrical machinery and equipment
5	Transportation and Communications	Transportation, warehousing and postal services, Information transmission, software and information technology services
6	Health care	Health and social work
7	Education, culture and entertainment	Paper printing and cultural and educational sporting goods, education, Culture, Sports and Entertainment
8	Other	Residential services, repairs and other services

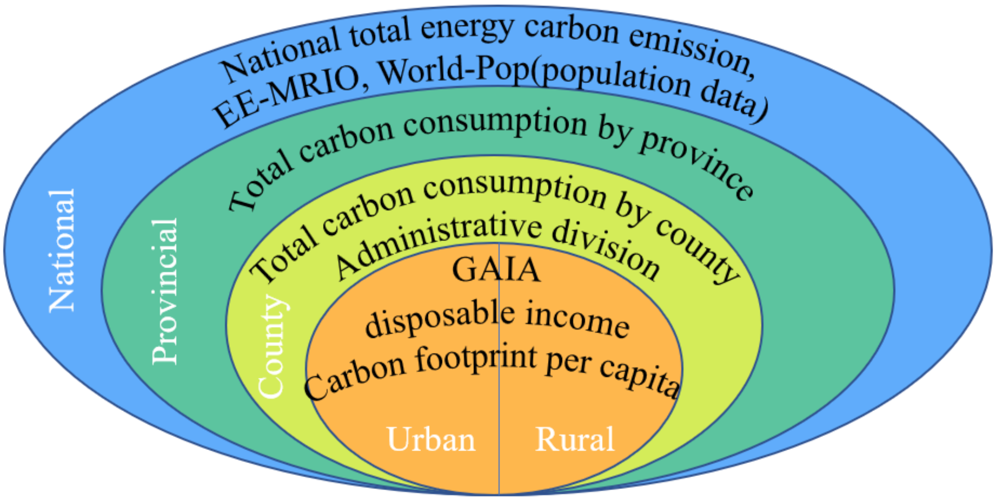

Figure 1. Grid model of China's fine-scale consumption-based carbon footprints.

The basic linear equation is expressed as follows:

$$X = (I - A)^{-1} Y \tag{1}$$

Using matrix representation, the technical coefficient matrix is as follows:

$$A = \begin{bmatrix} A^{11} & A^{12} & \cdots & A^{1m} \\ A^{21} & A^{22} & & A^{2m} \\ & \vdots & \ddots & \vdots \\ A^{n1} & A^{n2} & \cdots & A^{nm} \end{bmatrix} \tag{2}$$

I is the identity matrix, $(I - A)^{-1}$ is the Leontief inverse matrix, and the final demand is as follows:

$$F = \begin{bmatrix} F^{11} & F^{12} & \cdots & F^{1m} \\ F^{21} & F^{22} & & F^{2m} \\ & \vdots & \ddots & \vdots \\ F^{n1} & F^{n2} & \cdots & F^{nm} \end{bmatrix} \tag{3}$$

Here, $X = \begin{bmatrix} X^1 \\ X^2 \\ \vdots \\ X^m \end{bmatrix}$, $A^{nm} = \left[a_{ij}^{nm}\right]$, and $a_{ij}^{nm} = \frac{z_{ij}^{nm}}{x_j^m}$, where a_ij^{nm} represents the technical coefficient for sector i in region n to sector j in region m; z_{ij}^{nm} denotes the intermediate demand from sector i in region n to sector j in region m; x_j^m is the output of sector j in region m; and $F^{nm} = \left[F_i^{nm}\right]$ indicates the final consumption in region m of goods produced by sector i in region n. To account for environmental impacts, the emission coefficient EEE is introduced, defined as the CO_2 emissions generated per unit of output. The consumption-based CO_2 emissions can then be calculated as follows:

(2) Disaggregation of Provincial Consumption-Based Emissions to Municipalities and Counties

In this study, the decomposition of consumption-based carbon emissions was conducted based on population distribution, urban-rural differences, and residents' income levels. Due to data limitations, the consumption proportions for each province were calculated using the MRIO model. Municipal-level consumption economic data were further disaggregated to the county level. The proportion of county-level consumption economic data was determined, and county-level consumption-based carbon emissions were calculated using the county-level carbon emissions data from CEADs. This dataset was derived by leveraging the strong correlation between night-time light data and human activities. Two sets of night-time light data (DMSP/OLS and NPP/VIIRS) were used to estimate the CO_2 emissions of 2735 counties in China from 1997 to 2017.

$$C_d = \frac{M_{cons}}{M_{total}} \times \frac{G_{prec}}{G_{pro}} \times \frac{G_d}{G_{prec}} \times C_{d-total} \tag{4}$$

Here, C_d represents the consumption-based carbon emissions of county d, M_{total} refers to the overall input-output data for the province, M_{cons} denotes the provincial consumption data, G_{pro} indicates the provincial consumption economic data, G_prec represents the municipal consumption economic data within the province, G_d refers to the consumption economic data for county d within the municipality, and $C_{d-total}$ represents the total county-level carbon emissions from CEADs.

(3) Classification of Data Based on Urban and Rural Regions, Disposable Income, and Population Differences

County-level consumption-based carbon emissions were further disaggregated to grid units using population grid maps, urban built-up area vector data, and urban-rural disposable income data. Urban-rural boundaries were first determined using urban built-up area data, where populations inside built-up areas were classified as urban and those outside were classified as rural.

The urban and rural consumption footprints were allocated based on the total disposable income of urban and rural populations. The consumption-based carbon footprint of each grid unit was calculated by multiplying the population of the grid unit by the disposable income of that area. To ensure data accuracy and comparability, the WorldPop population data (100 m resolution) were resampled to 250 m resolution.

2.2.2. Multiscale Inequality Assessment Methods

To assess multiscale carbon inequality, this study employed an improved Theil index model and Lorenz curve to quantitatively evaluate the spatial distribution disparities of China's consumption-based carbon footprint. The Theil index [25] is one of the most common methods for estimating regional carbon emission inequality. It decomposes overall disparities into within-group and between-group differences, facilitating observation of the direction and magnitude of each variability and their contribution to overall disparities. This makes it widely used for quantifying spatial and social differences.

Accordingly, the total carbon footprint at provincial, municipal, and county scales is decomposed into between-group and within-group differences, calculated as follows:

$$Theil = \sum_{i=1}^{m} T_i \ln(mT_i) = T_{WR} + T_{BR} \tag{5}$$

$$T_{WR} = \sum_{i=1}^{m_n} T_i ln\left(m_n \frac{T_i}{T_n}\right) \tag{6}$$

$$T_{BR} = \sum_{i=1}^{m} T_n ln\left(T_n \frac{m}{m_n}\right) \tag{7}$$

Here, T_{WR} and T_{BR} represent within-region and between-region differences, respectively; m denotes the total number of units, m_n is the number of units at each scale, T_i is the ratio of carbon emissions of unit i to the total, and T_n is the ratio of emissions at each scale to the national level. A larger Theil index indicates greater regional disparities.

Additionally, the Lorenz asymmetry coefficient was used to visualize the inequality in consumption-based carbon footprints. The Lorenz curve and Gini coefficient [26] are widely used in economic and geographic research to measure inequality in carbon emissions and energy use. The traditional Lorenz curve graphically represents income distribution disparities. The Gini coefficient represents the area between the Lorenz curve and the horizontal axis as A, and the area between the Lorenz curve and the vertical axis as B. It is calculated simply as A/(A + B). In the context of carbon emissions, the variables in the Gini coefficient calculation were further modified: the horizontal axis was replaced by the cumulative proportion of cities, and the vertical axis was replaced by the cumulative proportion of carbon emissions in each region. The modified formula is given as follows:

$$G = \frac{A}{A + B} \tag{8}$$

Here, A represents the area between the Lorenz curve and the horizontal axis, B represents the area between the Lorenz curve and the vertical axis, and G denotes the Gini coefficient.

Additionally, spatial patterns and correlations of carbon footprint inequality are explored using methods such as Moran's Index, kernel density analysis, and spatial lag analysis. This study analyzed factors influencing carbon footprints by utilizing 22 indicators derived from China's Urban Statistical Yearbook, including carbon intensity, urbanization rate, municipal industrial structure, energy structure, and per capita GDP.

The structure of this study is as follows: Section 1 provides a comprehensive review of the relevant literature. Section 2 introduces the data and research methods, including the processes for calculating the carbon footprint and the Theil index. Section 3 focuses on the analysis of the consumption carbon footprint and is divided into three parts: first, a spatial analysis of multi-scale consumption carbon footprint patterns and their differences; second, a calculation of the Theil index to assess inequality at multiple scales; and third, an in-depth exploration of regional disparities in carbon footprints. Section 4 presents discussions and policy recommendations, while Section 5 summarizes the main conclusions. The process flow of the study is illustrated in Figure 2.

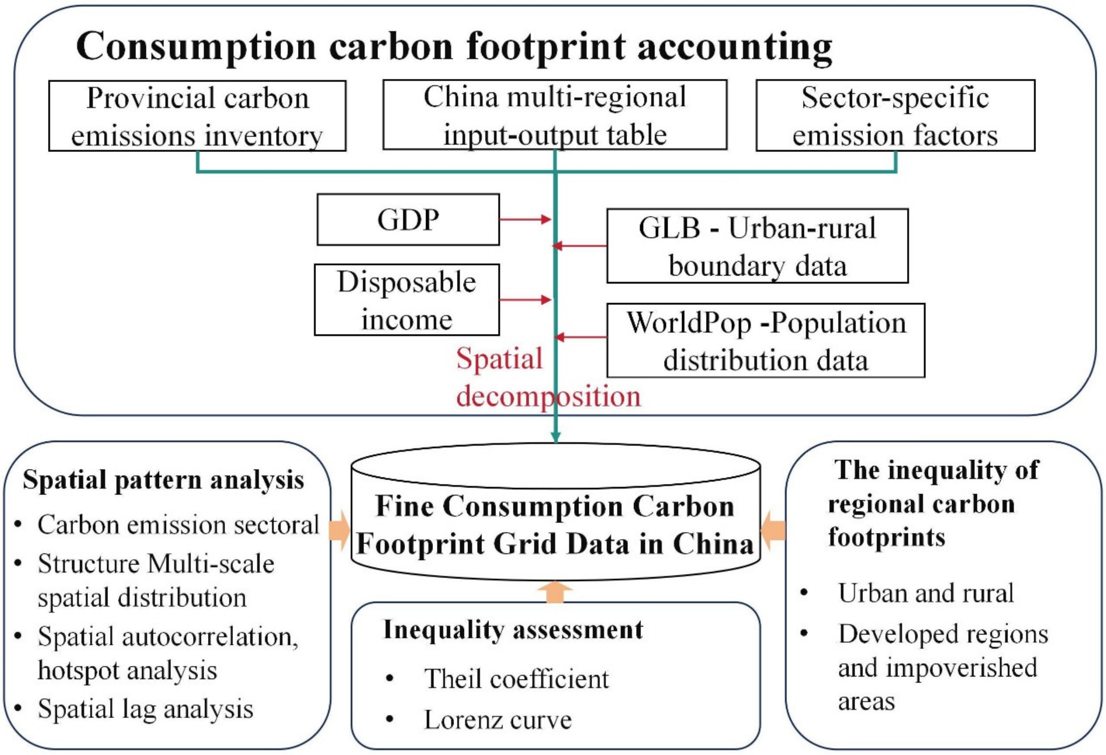

Figure 2. Technical process flowchart.

2.3. Uncertainty Analysis

The results of this study underwent multiple reliability validations, including uncertainty analyses conducted through data comparison, spatial consistency checks, and simulation analysis. First, carbon emission data from 21 reference regions for the same study year were sampled and compared. The error rates were all within 17%, with some regions showing errors as low as 0.16%. Second, the study data were compared with globally recognized ODIAC data, which have a spatial resolution of 1 km × 1 km. The validation results indicated a high degree of spatial trend consistency, with a coefficient of determination (R^2) of 0.7258, and high detail accuracy in hotspot areas with clear directional precision. Finally, considering the uncertainties arising from regional price consistency in MRIO data and the estimation of county-level carbon emissions, a Monte Carlo simulation was conducted. Assuming that both carbon emission and income data followed normal distributions, the results demonstrated that the uncertainty for all cities was below 10%, within a reasonable range. These findings suggest that the estimation results of this study are highly reliable and suitable for fine-grained spatial analyses of carbon emissions. Detailed reference data and comparative results are provided in the Supplementary Materials.

3. Results

3.1. Spatial Distribution and Multi-Scale Variability of Carbon Footprints

The spatial patterns of carbon footprints are often influenced by scale dependency, where analyses at larger scales may obscure subtle spatial variations while smaller-scale analyses can more effectively reveal spatiotemporal heterogeneity within regions. This study constructed a high-resolution 250 m-grid model of China's consumption carbon footprint, uncovering spatial patterns of inequality. Analyses at provincial and county scales were conducted to explore the spatiotemporal dynamics of carbon footprints.

3.1.1. Spatial Patterns of Multi-Scale Carbon Footprints

Figure 3 shows the distribution of consumption-based carbon footprints at a high spatial resolution of 250 m, revealing significant spatial imbalances. Carbon emissions in the eastern coastal areas were significantly higher than those in the central and western regions. In the central region, overall carbon emissions were relatively low, with footprints concentrated in provincial capitals and economic centers such as Chengdu, Chongqing, and Xi'an. The western region, particularly Inner Mongolia and the northwestern areas (e.g., Xinjiang and Gansu), exhibited low carbon emission intensity.

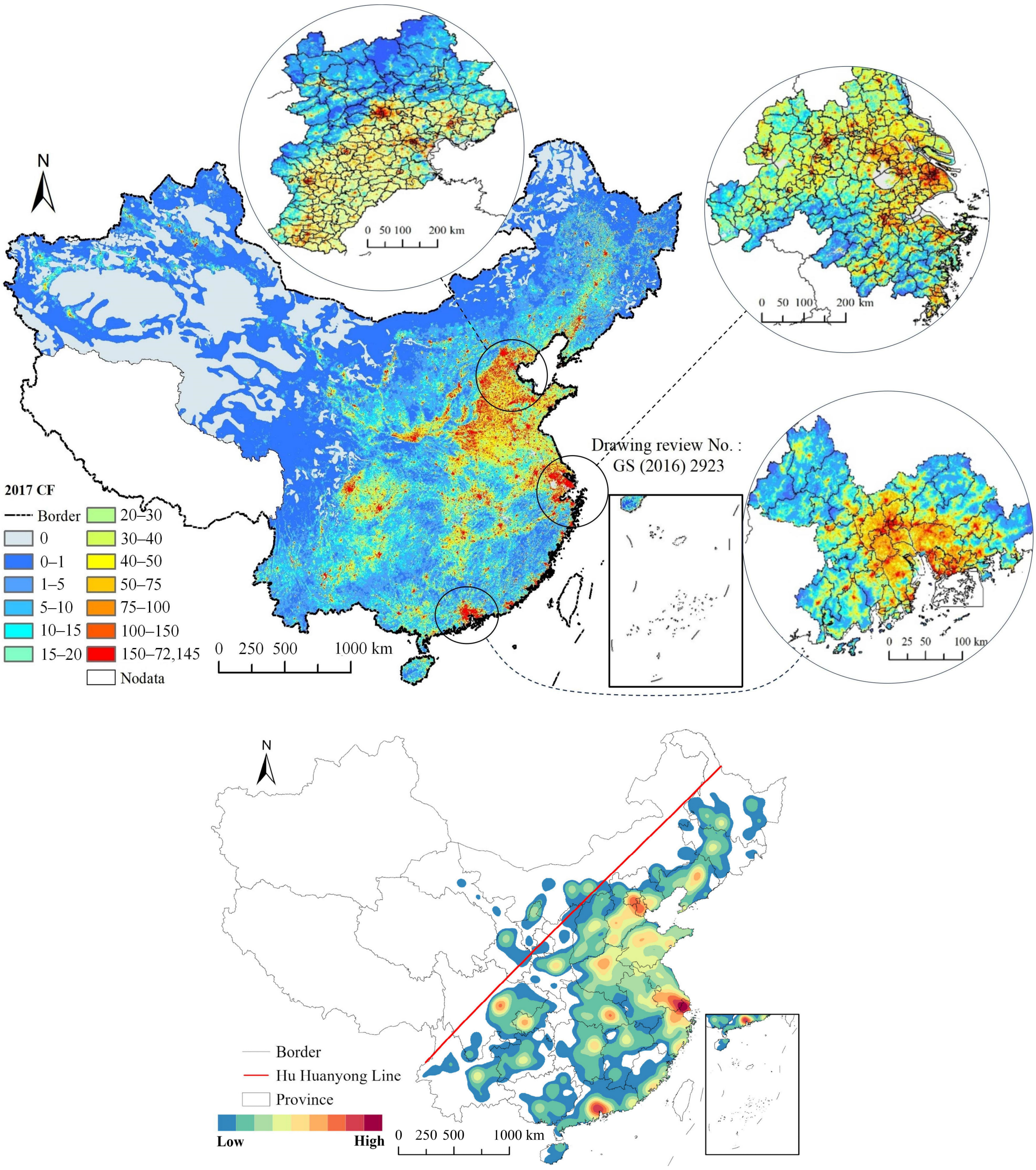

Figure 3. High-resolution (250 m) Grid Distribution of 2017 Consumption-Based Carbon Footprints and Kernel Density Analysis of Carbon Emissions.

Kernel density analysis based on fine-scale grid data (Figure 3) indicated that carbon emissions were predominantly concentrated in areas east and south of the Hu Line. The Beijing–Tianjin–Hebei region, the Yangtze River Delta, and the Pearl River Delta represent the most carbon-intensive regions in China. Among these, the Yangtze River Delta is the most prominent due to its position as one of China's most developed economic hubs, characterized by high urbanization and concentrated industrial activity. The Pearl River Delta follows, serving as a critical manufacturing base with high population density and economic vitality. The Beijing–Tianjin–Hebei region ranks third, functioning as the economic hub of northern China, driven by the presence of Beijing and Tianjin. Secondary hotspots of carbon emissions were primarily distributed around provincial capitals. These findings highlight the pronounced spatial inequality of carbon emissions in China, with economically developed regions exhibiting significantly higher footprints, reflecting a strong correlation between carbon emissions and economic development.

We analyzed the spatial concentration of carbon footprints by plotting county-level consumption-based carbon footprints and Lorenz curves (Figure 4). The results indicate that carbon footprint inequality increased from 2015 to 2017. The Lorenz curve shifted further toward the bottom-right corner in 2017, indicating a higher degree of inequality. Carbon footprints were highly concentrated in a small number of major cities: in 2015, 147 cities accounted for 20% of total emissions, while in 2017, this number decreased to 136 cities. Similarly, the number of cities contributing 50% of emissions dropped from 594 in 2015 to 578 in 2017. The distribution of 80% of carbon emissions also became more concentrated, suggesting widening inequality, as the carbon emission gap between large and small cities continued to grow annually.

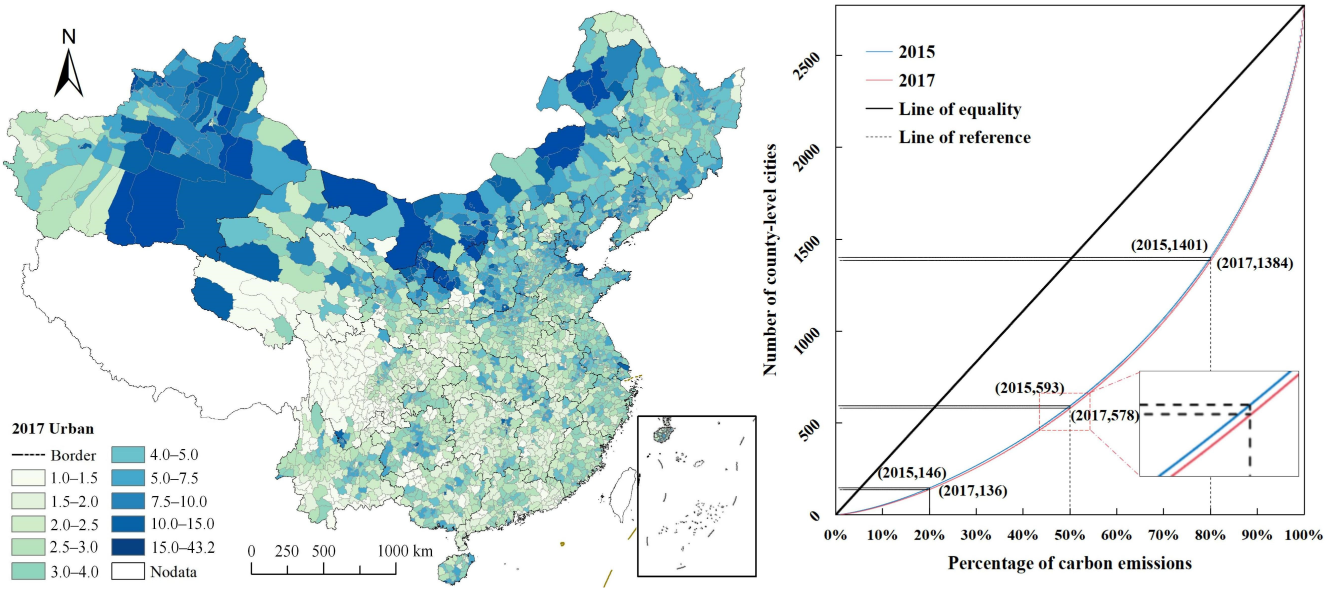

Figure 4. Spatial distribution of county-level consumption-based carbon footprints and—Lorenz curve in 2017.

China's 2783 county-level cities emitted 3681.19 MtC and 3895.45 MtC in 2015 and 2017, respectively, accounting for 40% and 43% of national carbon emissions. The top 5% of cities (139 out of 2783) accounted for 19.28% and 19.6% of the total emissions in 2015 and 2017, respectively. In contrast, 51% of cities, representing 38.4% of the population, contributed only 20% of the carbon footprint. This disproportionate distribution highlights carbon inequality in most small- and medium-sized cities; despite their large populations and significant land area, these cities contribute only a small share of national emissions. Globally, the wealthiest 10% of the population account for nearly 50% of global emissions, while the poorest population (those in the bottom 50% of income distribution) contribute only 10–13%. The carbon footprint of the wealthiest 1% is estimated to be 175 times that of the poorest 10%. In China, however, the proportion of national emissions contributed by the wealthiest 10% of cities was significantly lower than the global average, while the middle-income population's contribution was relatively larger.

From the analysis of county-level carbon footprint hotspots (Figure 5), it is evident that the distribution of carbon emissions in China is highly spatially uneven. Hotspot areas are primarily concentrated in economically developed eastern coastal regions and resource-intensive cities. For instance, the Yangtze River Delta and the Beijing–Tianjin–Hebei region exhibit high carbon footprint densities due to their extensive industrialization, dense populations, and the influence of high-income groups and consumption patterns, making them major carbon footprint hotspots. Meanwhile, resource-dependent cities such as Inner Mongolia and Ningxia rely heavily on high-carbon industries like mining and heavy manufacturing, resulting in elevated carbon intensities. In contrast, low-value areas form contiguous regions along provincial borders in Guangxi, Guizhou, Jiangxi, and Hunan, as well as in peripheral areas around the Sichuan Basin and parts of eastern Harbin and western Xinjiang.

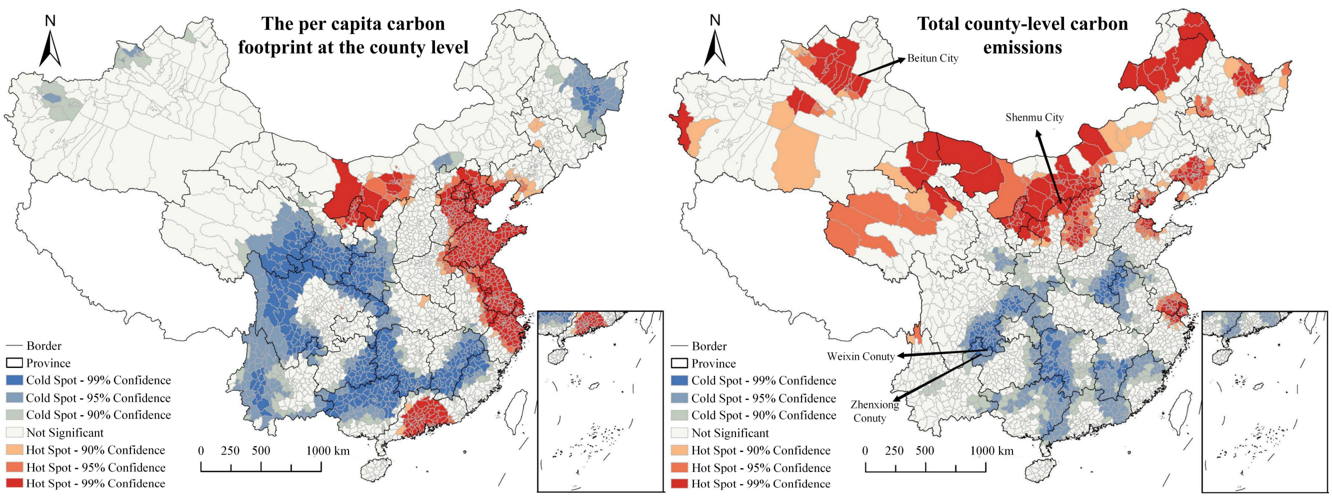

Figure 5. Hotspot analysis of county-level total carbon emissions and per capita carbon footprints i-n 2017.

The per capita carbon footprint hotspot map reveals a more dispersed pattern, with hotspots concentrated in resource-intensive areas such as Inner Mongolia, Shaanxi, Shanxi, Xinjiang, and parts of Northeast China. Additionally, hotspots around Shanghai highlight the role of high consumption levels in economically developed areas in driving carbon emissions. In contrast, cold spots are predominantly located in less developed border regions of central and western provinces, particularly at the Anhui–Henan border, where low levels of industrialization correspond to minimal carbon footprints. Notably, megacities such as Beijing and Shenzhen do not emerge as per capita carbon footprint hotspots, as their economies are dominated by low-carbon service industries, leading to lower carbon intensities.

From a temporal perspective (see Supplementary Materials), China's carbon footprint shows a modest upward trend, but its growth is relatively slower compared to economic and income growth. During the study period, total carbon footprints increased by 9.29%, while per capita carbon footprints grew by 8.33%. In comparison, per capita disposable income increased by 17.37%. Although total and per capita carbon emissions rise with higher income levels, the slower growth of carbon footprints indicates that China is gradually transitioning towards a low-carbon economy, with less reliance on carbon-intensive industries. Spatially, the overall distribution of total carbon footprint hotspots remains relatively stable, except for a notable reduction in hotspots in Liaoning. Conversely, cold spots show significant changes, with large areas in Sichuan, Yunnan, and Guangxi shifting from 99% cold spots to 95% cold spots, indicating increased carbon emissions in these regions. Similarly, the spatial changes in cold and hotspot distributions for per capita carbon footprints reveal consistent patterns. Traditional resource-dependent areas such as Northeast China and Inner Mongolia show shrinking hotspots, while the extent of cold spots in central and western provinces expands, though some regions exhibit downgraded significance.

The carbon emissions gap among provinces is substantial, with a predominance of carbon-intensive consumption structures (Figure 6). From the perspective of carbon emissions on the consumption end of provincial residents, the structural composition of consumption-based carbon emissions across China's provinces was calculated. The results, as shown in the figure, indicate that the emissions of the highest-emitting province are 20 times greater than those of the lowest. From the consumption-based carbon emissions per province, there was a slight increase in 2017 compared to 2015, with significant variation among provinces. The provinces with the highest emissions were Shandong, Guangdong, and Jiangsu, with consumption-based emissions of 302.83 Mt, 271.39 Mt, and 237.19 Mt, respectively, in 2015. The provinces with the lowest emissions were Hainan, Qinghai, and Tianjin, with emissions of 15.75 Mt, 20.36 Mt, and 46.4 Mt, respectively, in 2015. The largest emissions gap between provinces was 285.18 Mt in 2015 and 303.96 Mt in 2017, indicating a widening disparity in consumption-based carbon emissions among provinces.

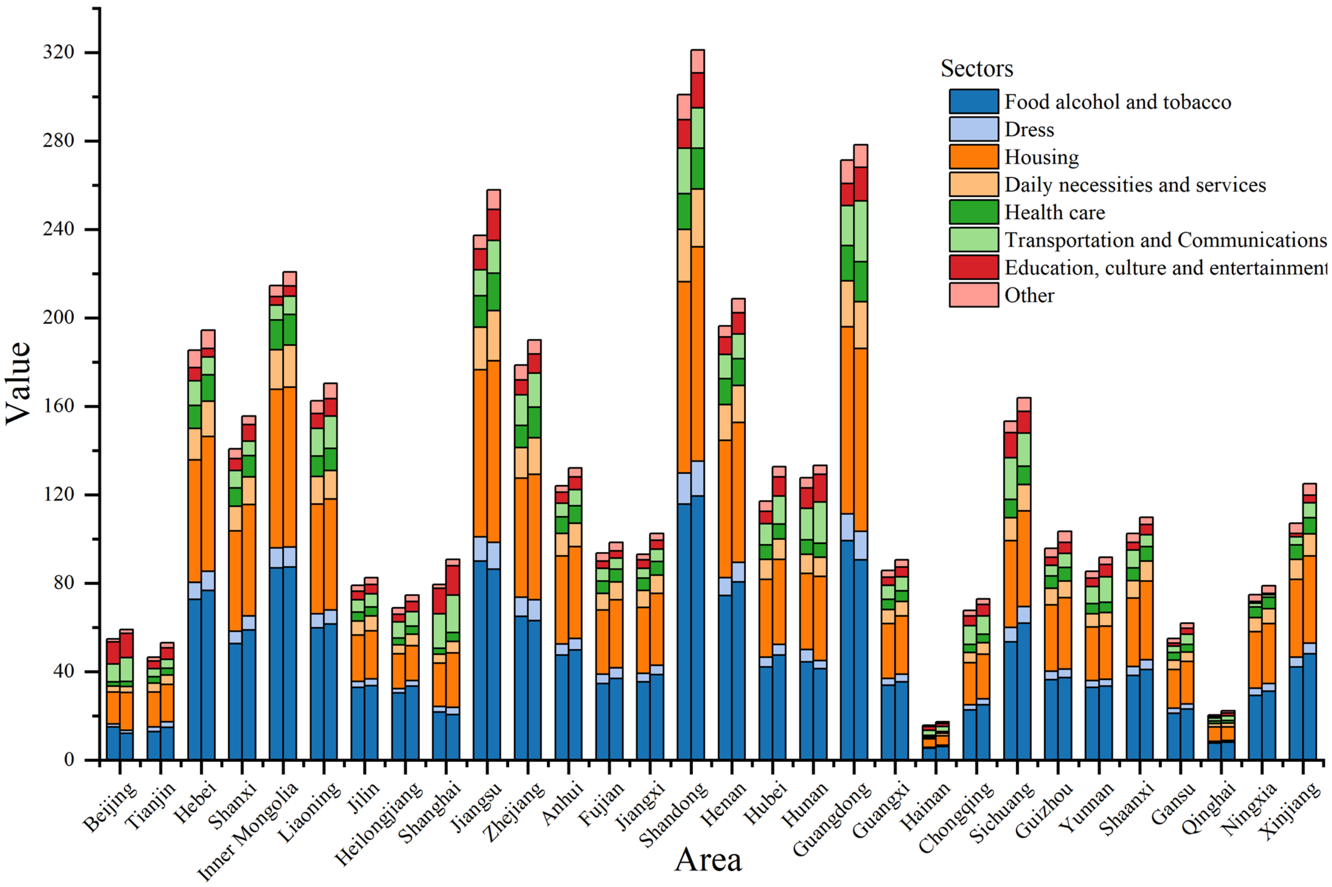

Figure 6. Provincial consumption-based carbon emissions and emission structures—in 2015 and 2017.

In terms of the structure of consumption-based carbon emissions, there was little change between 2015 and 2017. Food-related emissions accounted for the largest share, exceeding 30%, followed by housing-related emissions, which accounted for more than 25%. Economically developed provinces such as Beijing, Tianjin, and Shanghai had a food emissions share of approximately 27%, whereas remote provinces like Heilongjiang, Ningxia, and Inner Mongolia had shares as high as 40%. Additionally, transportation and education categories accounted for a significantly higher share in provinces like Beijing and Shanghai, exceeding 10% compared to other provinces. From 2015 to 2017, the proportion of food- and housing-related emissions gradually declined, with the largest reduction observed in Beijing, where the food share decreased by 7%, and in Shanghai and Jiangsu, where the transportation and education shares increased by 5% and 2%, respectively. Regions such as Beijing and Guangdong saw a 3% increase in the transportation share and a 2% increase in the education share. While food and housing—both carbon-intensive sectors—continued to dominate, their shares decreased, whereas sectors like scientific research and education saw an increasing share.

3.1.2. Quantifying the Inequality of the Carbon Footprint of Consumption

Through the decomposition analysis of the Theil index (Figure 7), this study reveals the significant contributions of various administrative levels to carbon inequality. In 2015 and 2017, the Theil indices of carbon inequality at provincial, municipal, county, and urban-rural levels showed an upward trend from the provincial to the urban-rural scale, reflecting increasingly pronounced carbon emission disparities with finer administrative granularity. Specifically, the national interprovincial inequality indices were 0.0838 and 0.0918 in 2015 and 2017, respectively; intermunicipal indices were 0.1774 and 0.1891; intercounty indices were 0.3304 and 0.3476; and urban-rural inequality indices were 0.3076 and 0.3514. This trend indicates that carbon footprint inequality intensifies as the scale becomes more granular, with county-level disparities being particularly pronounced. (The detailed results of the Theil index calculations are provided in the Supplementary Materials).

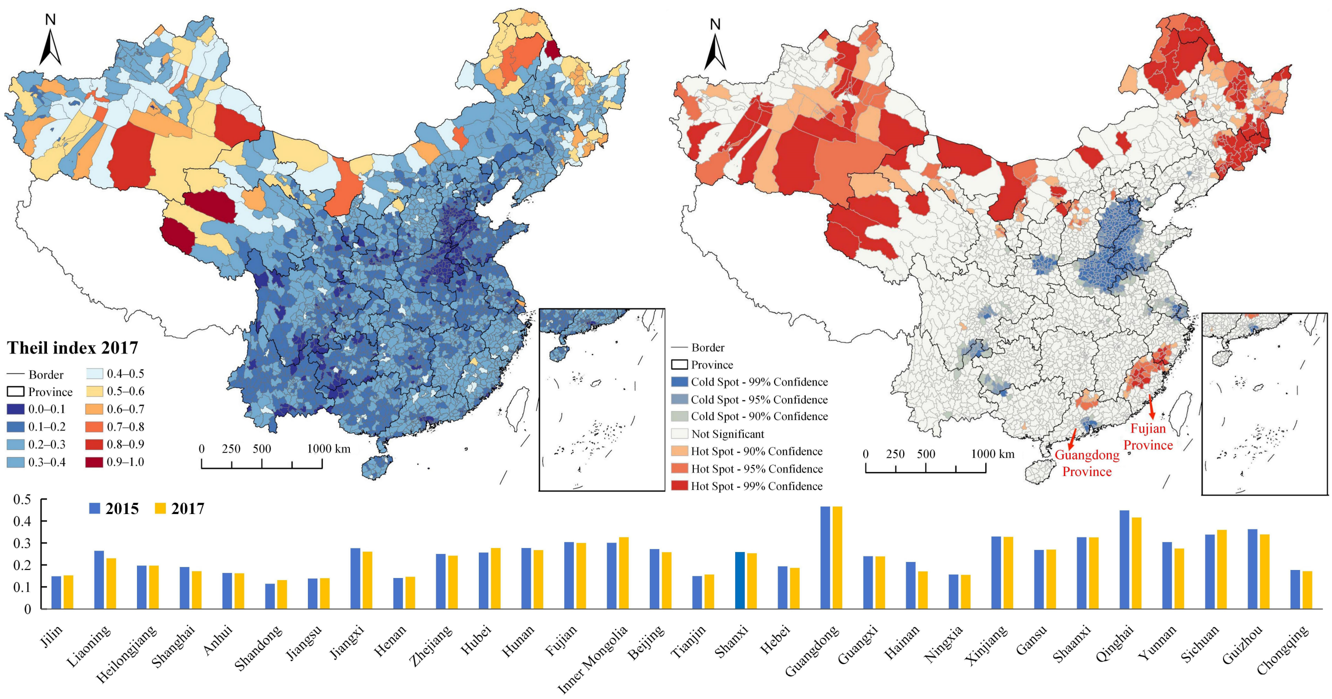

Figure 7. The Theil Index and Hotspot Analysis of County-level Carbon Footprints in 2017.

This study highlights that intercounty inequality contributes most to national carbon inequality, accounting for 55.42% and 54.39% of the total inequality in 2015 and 2017, respectively—far surpassing the contributions of provincial and municipal levels. This finding underscores that disparities in carbon footprints among county-level cities are the primary driver of national carbon inequality. Developed counties are highly dependent on energy-intensive industries such as steel and chemicals, while less-developed counties are dominated by agriculture or services, resulting in lower carbon intensities. The pronounced inequality at the county level not only exacerbates nationwide carbon inequality but also poses challenges for achieving carbon reduction targets. Therefore, carbon reduction policies must consider the differentiated needs and capacities of county-level cities.

Temporally, the Theil indices of most provinces exhibited a downward trend from 2015 to 2017. For example, the indices for Hainan and Qinghai decreased by 4.29% and 3.32%, respectively. However, some provinces saw an increase in their Theil indices, such as Inner Mongolia and Sichuan, which rose by 2.53% and 2.18%, respectively. Spatially, carbon footprint inequality measured by the Theil index was particularly pronounced in the northwest and northeast regions. Western provinces such as Sichuan, Xinjiang, Guizhou, and Shaanxi had intercounty inequality indices exceeding 0.32, while economically developed provinces such as Jiangsu and Shandong had lower inequality indices below 0.14. By contrast, despite Guangdong's overall economic development, significant inequality persists in its northern regions, driven by the stark contrast between the rapid development of the Pearl River Delta and the economic underdevelopment of its peripheral areas. Additionally, in 2017, inequality in western Fujian's mountainous regions decreased, while inequality in northern Guangdong intensified.

Socioeconomic factors influence consumption patterns, thereby affecting consumption-based carbon footprints. This study analyzed 22 driving factors, including carbon intensity, GDP, built-up area, industrial structure, urbanization rate, per capita GDP, energy structure, and social electricity consumption. To quantify the contribution of socioeconomic factors to carbon footprint inequality, spatial regression methods such as the Geodetector, random forest, and geographically weighted regression (GWR) were employed to conduct a city-level quantitative analysis of these factors' relative contributions. Among the key variables, carbon intensity emerged as the most influential factor, accounting for 31% of total carbon inequality, followed by actual GDP (22%) and per capita GDP (21%). These results indicate a strong correlation between carbon footprint growth and economic development. Mitigating carbon footprint inequality can be achieved primarily through adjusting industrial structures, promoting a green economy, and reducing carbon intensity. At the same time, increasing consumer purchasing power to facilitate a shift from carbon-intensive to low-carbon consumption patterns is essential for promoting sustainable economic growth.

3.2. Analysis of Regional Carbon Footprint Inequality

In the in-depth analysis of regional carbon footprint inequality, several intriguing characteristics were identified when examining localized details. These include spatial lag effects between income and carbon footprints, differences in carbon footprints between rural and urban areas, and disparities between PSC and developed regions. These relationships reveal the complex interplay between income levels, urban-rural differences, regional development disparities, and carbon emissions.

3.2.1. Compared to Income, the Spatial Lag of Carbon Footprint Is More Significant

Spatial lag analysis of carbon emissions and disposable income in county-level cities reveals significant spatial lag effects in economic development and carbon footprints (Figure 8). Most regions exhibit a lagging development pattern. However, areas such as the eastern coastal regions, southern Inner Mongolia, and some provincial capitals and their surrounding areas demonstrate a significant positive development trend. These regions have shown a noticeable decoupling effect between economic growth and carbon footprints.

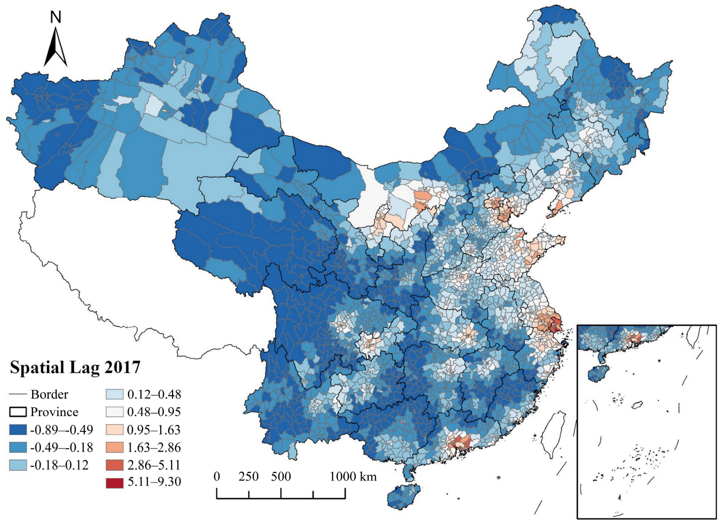

Figure 8. Spatial lag analysis of carbon emissions and disposable income in county-level cities.

In contrast, less developed areas in central and western regions, particularly in the southwest and northwest, display significant spatial lag effects, indicating that carbon-intensive economic structures and consumption patterns have yet to undergo effective transformation. The spatial lag indices for 2015 and 2017 were 0.0723 and 0.062, respectively. Although spatial lag effects have slightly eased over this period, the overall change remains limited, and the lag phenomenon is still pronounced. In 2015, 1504 county-level cities exhibited spatial lag effects, and by 2017, this number decreased to 1436, reflecting the gradual emergence of decoupling effects between carbon emissions and income growth in certain areas.

The persistence of high spatial lag effects is primarily attributed to existing carbon-intensive consumption patterns. While economic development has progressed rapidly, consumption levels have not kept pace. Therefore, the formulation and implementation of low-carbon management strategies for county-level regions should not be confined to individual counties but should account for spatial spillover effects, fostering the further decoupling of economic growth from carbon emissions.

3.2.2. The Growth Rate of Carbon Footprints in Rural Areas Outpaces That of Urban Areas

Addressing rural carbon inequality is crucial for achieving carbon neutrality. Rural areas are more susceptible to carbon inequality due to economic disparities, unequal land use, and spatial dispersion. Figure 9 illustrates the urban-rural per capita carbon footprints across counties within provinces. Urban residents consistently exhibit higher per capita carbon footprints than rural residents. However, the gap is more pronounced in poorer western provinces, such as Ningxia, Shaanxi, and Gansu, where urban per capita carbon footprints are typically 2–3 times higher than that of rural areas. In contrast, wealthier regions like Beijing, Shanghai, and Jiangsu exhibit smaller gaps, with urban per capita carbon footprints only 1.05–1.3 times that of rural residents. This variation stems largely from economic integration between urban and rural areas and the geographic location of the cities within each province. Further analysis reveals that carbon footprint inequality is more pronounced among rural households compared to urban households. For example, in 2015, the highest urban carbon footprint was found in Jungar Banner (41.23 tons of carbon, TC), and the lowest was in Yanjin County (1.02 TC), a 40-fold difference. For rural areas, the highest carbon footprint was in Ejin Banner (20.31 TC), and the lowest was in Weixin County (0.204 TC), a 98-fold difference. By 2017, the lowest urban carbon footprint was observed in Zhenxiong County (1.03 TC), while the highest was in Beitun City (43.23 TC).

Similarly, for rural areas, the lowest CF was in Weixin County (0.23 TC), and the highest was in Shenmu County (21.06 TC). The urban-rural divide has exacerbated household carbon footprint inequality.

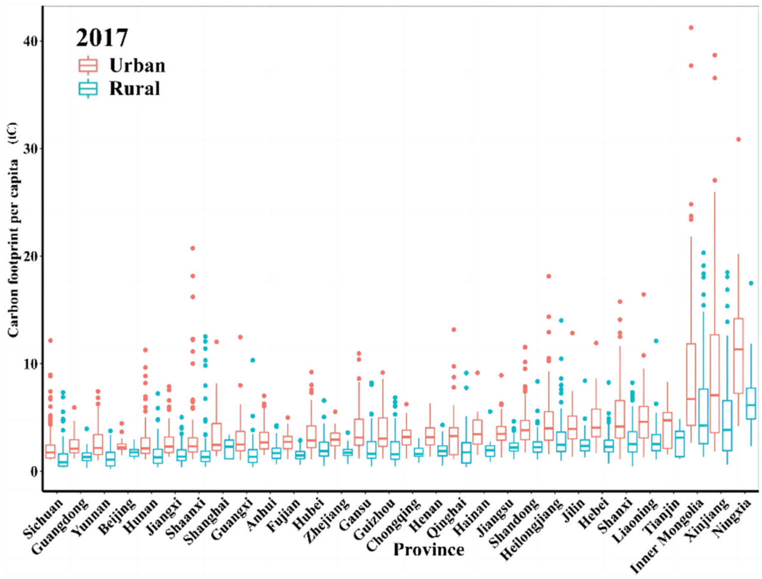

Figure 9. Boxplot of urban and rural per capita carbon footprints by province in China.

Notably, affluent regions tend to have smaller urban-rural carbon footprint differences, while less-developed regions exhibit larger disparities. This suggests that in wealthier regions, household carbon footprints are converging, whereas in poorer regions, efforts to bridge urban-rural gaps are increasing carbon emissions. For instance, in underdeveloped central and western provinces such as Xinjiang, Ningxia, and Guangxi, rural carbon footprints grew by over 18%, compared to 7.7% for urban areas nationwide and 9.4% for rural areas nationwide. The growth in rural carbon footprints is primarily driven by economic lags, inadequate infrastructure, and reliance on carbon-intensive energy sources such as coal and firewood. While modern energy sources like electricity are becoming more common, their coverage and usage frequency remain limited. Additionally, rising incomes and changing consumption patterns in rural areas have led to an increased demand for energy-intensive goods, further driving carbon footprint growth.

Since the reform and opening-up period, consumption levels of both urban and rural residents have risen steadily. However, due to urbanization and declining rural populations, the total rural carbon footprint has shown a downward trend. In contrast, urban carbon footprints have grown significantly, with their share of total carbon emissions rising from 56.55% to 58.27%, further widening the urban-rural gap. While carbon footprint inequality between urban and rural areas remains evident, supportive rural policies such as the rural revitalization strategy and poverty alleviation programs have promoted rural economic development and improved living conditions, helping to mitigate urban-rural inequality trends.

3.2.3. Low-Carbon-Footprint Areas and Poor Counties Have a Large Overlap

Income inequality is one of the primary drivers of the urban-rural carbon footprint gap. China has identified 832 poverty-stricken counties (PSCs) based on the poverty line standard of USD 15.4 per person per day, as shown in Figure 10. The analysis reveals a significant overlap between PSC and low-carbon emission areas. In the county-level carbon footprint hotspot analysis, 72.6% of PSCs were identified as cold spots. In the spatial lag analysis, all PSCs exhibited spatial lag effects, with 63% categorized as highly lagging and 28% as moderately lagging. This indicates that these regions not only have low economic development levels but also relatively low carbon emissions. However, with the implementation of poverty alleviation policies and infrastructure improvements, carbon emissions in these areas are likely to increase rapidly [27]. Without timely intervention, this growth could negatively impact overall carbon reduction goals. Therefore, for low-carbon development in PSC, it is crucial to adopt strategies that integrate economic growth with carbon reduction, ensuring a balanced and sustainable approach.

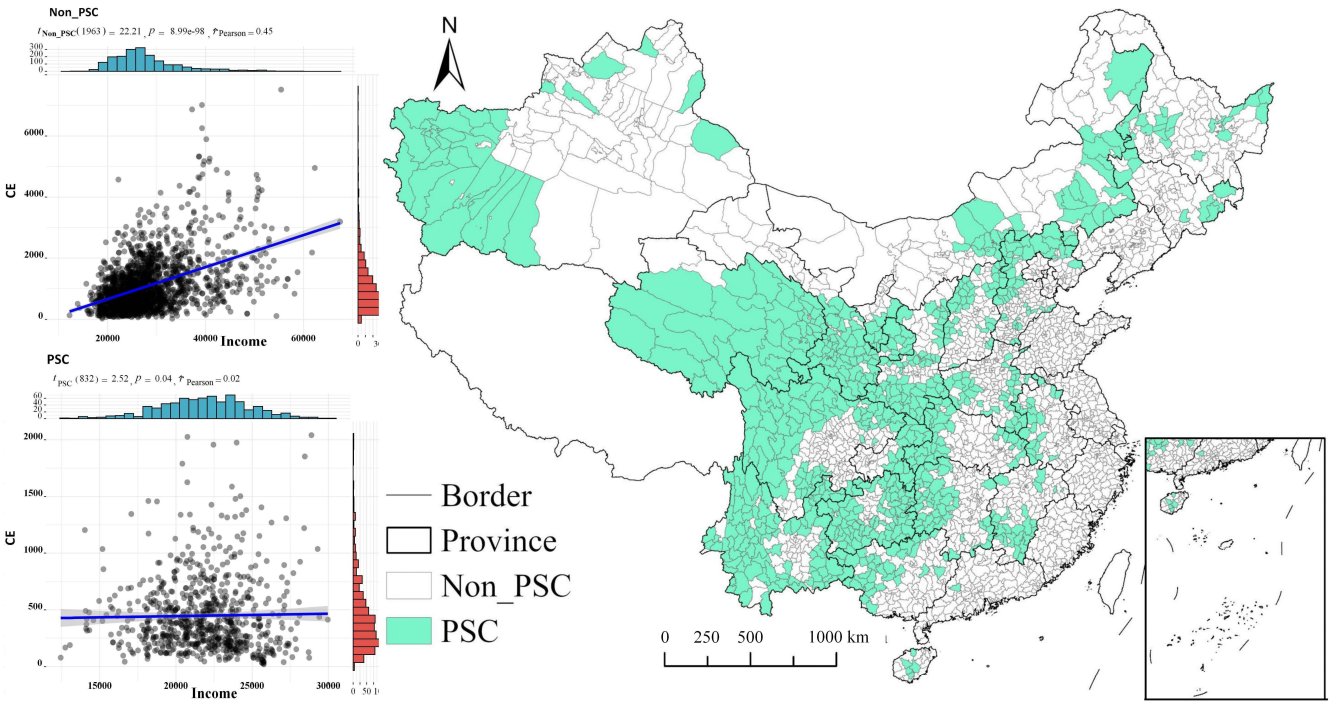

Figure 10. Distribution of national PSCs in China and scatter plot of linear regression between carbon emissions and income for PSCs and non-PSCs. (The blue line represents the trend of the correlation between carbon emissions and disposable income, the black dots indicate the disposable income and carbon emissions of individual county-level cities, the green bar chart shows the distribution of income data, and the orange bar chart illustrates the distribution of carbon emissions data).

Significant differences in carbon footprints exist between PSCs and non-PSCs. A comparative analysis of economic indicators, disposable income, and carbon footprints reveals that PSCs, due to lower levels of economic development and limited consumer capacity, exhibit relatively low carbon emission intensities. On average, the carbon emissions of non-PSCs are 1.2 times higher than those of PSCs. Specifically, the average carbon emissions in non-PSCs are 1149.53 tons, compared to 566.5 tons in PSCs.

Income disparities between the two groups significantly influence carbon emission levels. The average annual income in non-PSCs is CNY 34,463, whereas in PSCs, it is only CNY 24,467. Correlation analysis shows a strong association between income and carbon emissions in non-PSCs. In contrast, income and carbon emissions in PSCs follow an approximately parallel trend line, indicating that income growth does not lead to a substantial increase in carbon emissions. This finding aligns with the earlier conclusion that the economic growth patterns of PSCs are not strongly linked to carbon footprint increases.

3.2.4. Regional Marginality in Economy and Carbon Emissions: Characteristics of Carbon Emissions in Interprovincial Border Areas

The study highlights the unique characteristics of interprovincial border regions. Carbon hotspots and cold spots for total emissions and per capita carbon emissions (Figure 6), as well as areas with high spatial lag effects, are often located near provincial boundaries. Typical regions include the border areas between Qinghai, Shaanxi, and Sichuan; the junctions of Guangxi, Guizhou, and Hunan; and the boundary regions of Jiangxi, Guangdong, and Fujian. The findings indicate that interprovincial border areas are intersections of provincial economic policies, often facing policy isolation and coordination challenges. These areas are also closely associated with impoverished counties, making them critical regions for coordinated development and poverty alleviation. Interprovincial border regions are frequently situated in ecologically fragile areas, where geographic constraints hinder large-scale industrialization and infrastructure development. For example, the border regions of Qinghai, Sichuan, and Shaanxi are characterized by high altitudes; the Guangxi, Guizhou, and Hunan border areas suffer from severe rocky desertification; and the Jiangxi, Guangdong, and Fujian borders are located in hilly and mountainous terrain. Economic activities in these regions are concentrated in agriculture, animal husbandry, and light industries, leading to lower carbon emission demands and a pattern of "low-carbon growth". However, this relative decoupling of economic activity and carbon emissions presents unique challenges for achieving coordinated low-carbon and economic development. Policy efforts should prioritize these regions' ecological and economic capacities by formulating targeted low-carbon development strategies. Such policies can simultaneously promote economic growth and carbon reduction, addressing the dual objectives of development and sustainability.

4. Discussion

4.1. Variations in Carbon Footprint Inequality

In this study, we developed a multi-scale consumption-based carbon footprint model, quantifying carbon footprint inequality at the urban-rural scale for the first time. Compared to previous research [28,29], the multi-scale analysis enables a more precise identification of the spatial distribution of carbon footprint inequality, deepening our understanding of the mechanisms underlying its formation.

The results indicate that carbon footprint inequality increased significantly in 2017 compared to 2015. This trend aligns with existing studies [30,31] and is primarily driven by the rapid expansion of consumption demand, which has caused the growth rate of consumption-based carbon footprints to outpace that of total carbon emissions. In developed regions, consumption capacity has increased rapidly, while in less-developed regions, industrial transfers from developed areas have led to higher carbon intensity. Although carbon footprint inequality in China is widening, its level remains significantly lower than the global average. For instance, the wealthiest 10% of the global population contributes nearly 50% of global carbon emissions, whereas in China, the top 593 cities (representing 34.6% of the population) account for only 50% of the national total [32]. Similarly, the lowest 51% of Chinese cities contribute just 20% of the national carbon footprint.

The exacerbation of inequality is evident across multiple dimensions. The Theil indices at the provincial, municipal, and county levels have all increased, with county-level cities contributing 55.42% of the national carbon footprint inequality, making them the largest contributors. This finding is consistent with previous studies [33]. When formulating carbon reduction policies, it is essential to pay greater attention to disparities at the county level and implement more targeted measures to address them.

4.2. Urban-Rural Disparities in Carbon Footprint

The results reveal that the proportion of urban carbon footprints continues to grow, further supporting existing research conclusions that urban areas remain the primary focus of carbon reduction efforts [21]. However, the growth rate of per capita carbon footprints in rural areas has surpassed that of urban areas, and carbon footprint inequality within rural regions is significantly higher than in urban areas. This disparity is especially pronounced in rural areas of economically underdeveloped regions such as Xinjiang, Ningxia, and Guangxi, where carbon footprints are increasing at a faster rate than in other areas. These rural regions face greater challenges and pressures in carbon reduction due to lagging living conditions, underdeveloped infrastructure, and slower economic progress. He's research highlights that in low-income countries such as those in Africa, urban carbon emissions are 2–9 times higher than rural emissions, with poorer nations experiencing greater urban-rural disparities. In contrast, China's urban-to-rural carbon footprint ratio is 5.6:4.4, significantly lower than the global average. Against this backdrop, the Chinese government's initiatives—including rural revitalization, agricultural support policies, and targeted poverty alleviation—are gradually promoting rural economic development and improving living conditions for rural residents. These efforts also provide critical support for achieving more effective carbon reduction in rural areas.

4.3. Reducing Carbon Footprint Inequality While Eliminating Poverty

This study reveals a significant overlap between low-carbon-footprint regions, lagging areas, impoverished counties, and interprovincial border regions, underscoring the close relationship between carbon footprints and regional economic development levels. This finding provides a critical foundation for formulating regional carbon reduction policies. In economically underdeveloped areas, industrial structures are often dominated by traditional high-carbon industries, energy efficiency is low, and carbon emission intensity is high. Consequently, these regions experience slow carbon footprint growth, forming lagging areas. Additionally, impoverished counties are often located in mountainous, arid, or semi-arid regions and border areas with harsh geographical conditions, further constraining socioeconomic development and exacerbating inequalities in these regions [34].

Existing research shows that poverty alleviation has a minimal impact on total carbon emissions [35]. Even if 1 billion people globally escape poverty (reaching a daily income of USD 1.9 per capita), global carbon emissions would increase by only 1.6% to 2.1%. China has made remarkable progress in poverty alleviation, with extreme rural poverty largely eradicated by 2020. However, poverty alleviation efforts must be aligned with addressing regional inequalities, particularly the imbalance between the eastern coastal regions and inland areas such as the southwest and northwest. By improving living conditions in impoverished areas, developed regions should take greater responsibility for promoting economic development in these regions, ensuring that carbon reduction efforts proceed in tandem. This approach offers valuable insights not only for China but also for other developing countries facing similar challenges of poverty and ecological constraints [36]. Addressing the dual goals of poverty reduction and carbon mitigation is essential for achieving sustainable development globally.

4.4. Recommended Measures

Based on the findings, addressing multi-scale carbon inequality and spatial imbalances in carbon footprints requires efforts in monitoring and evaluation, differentiated policy design, and regional coordinated development. The following recommendations are proposed.

4.4.1. Strengthening Monitoring and Evaluation

To address regional carbon inequality, a standardized multi-level monitoring system should be established to enhance a quantitative analysis of carbon emissions at all administrative levels. At the national level, a unified carbon emission assessment framework should be developed, integrating indicators such as carbon intensity, economic level, and population distribution. Regular national reports on carbon emission inequality should be published. Regional- and county-level governments should establish dedicated monitoring agencies to investigate local carbon emission characteristics comprehensively and build carbon inequality databases to provide accurate evidence for policymaking. Additionally, real-time monitoring mechanisms leveraging big data and artificial intelligence should be introduced to track carbon emission trends and enable timely interventions in high-emission areas.

4.4.2. Designing Differentiated Regional Policies

To mitigate spatial imbalances in carbon footprints, regional reduction policies should reflect differentiation, particularly in the consumption sector. Developed cities should promote low-carbon consumption by incentivizing green products through subsidies, carbon credit rewards, and encouraging the use of energy-efficient appliances, green building materials, and low-carbon transportation options such as shared bicycles and electric vehicles. Urban planning should be optimized to foster shared economy models, reducing high-carbon footprint consumption. In less-developed regions, the focus should be on accelerating the transition to clean energy and promoting awareness of green consumption. Strategies could include increasing the supply of green products, advocating low-carbon lifestyles, and reducing dependence on high-carbon energy sources. Differentiated measures should also address regional consumption patterns, such as housing and food, by promoting energy-efficient housing and low-carbon technologies to gradually reduce carbon footprint disparities.

4.4.3. Addressing County-Level Carbon Inequality

As the primary contributors to national carbon footprint inequality, county-level cities should adopt integrated measures, including regional coordination, industrial upgrading, and consumption transformation, to narrow the carbon footprint gap. Strengthening regional coordination mechanisms is essential, focusing on optimizing the integration of transportation, energy, and ecological resources, and advancing shared infrastructure to enhance resource utilization efficiency. Clean energy adoption and green transportation systems should be prioritized to achieve synergistic effects.

Additionally, promoting low-carbon lifestyles through policy incentives and market mechanisms is critical. Expanding the adoption of energy-efficient appliances, green buildings, and clean energy—particularly in housing and food consumption—can guide residents toward low-carbon consumption patterns, supporting both county-level carbon reduction and sustainable development.

4.4.4. Challenges on the Path to Success

The journey toward these goals is fraught with challenges. First, inconsistencies and gaps in regional and county-level carbon emission data could undermine the reliability of monitoring and evaluation results. Second, underdeveloped regions may face technical and financial constraints that hinder the implementation of policies, particularly in developing low-carbon infrastructure and promoting clean energy. Third, conflicts of interest among regions and groups may complicate cross-regional cooperation, especially in redistributing resources and allocating carbon reduction responsibilities. Finally, promoting green consumption and low-carbon lifestyles may encounter resistance due to cultural habits and economic burdens, requiring sustained public awareness campaigns and incentives to enhance public acceptance.

4.5. Limitations of the Study

This study has several limitations that we hope future research can address. First, due to data availability, we only had access to MRIO tables for two specific years. Incorporating more recent and comprehensive MRIO data would enable a more robust and detailed analysis. Second, the lack of compatibility between data sources prevented the use of higher-resolution datasets, such as those from social surveys. While the current data may lack granularity, they still allow for an effective analysis of national carbon inequality patterns.

5. Conclusions

The improvement of carbon footprint inequality in China has significant practical implications for future sustainable development strategies. This study constructed a 250 m-high-resolution dataset of consumption-based carbon footprints, revealing the spatial characteristics and patterns of carbon footprint inequality in China from 2015 to 2017. Using Theil indices and Lorenz curves, the study analyzed multi-scale carbon footprint inequality and conducted an in-depth exploration of disparities between urban and rural areas as well as between developed and PSCs. The findings underscore the existence of significant carbon inequality in China, highlighting the need for a more equitable and reasonable allocation of carbon reduction responsibilities.

5.1. Carbon Footprint Growth and Intensifying Inequality

From 2015 to 2017, China's total carbon footprint increased by 214.26 Mt, accompanied by a notable intensification of carbon inequality. The share of total emissions contributed by the top 20% of emitters decreased from 147 cities in 2015 to 136 cities in 2017. In 2015, the top 5% of cities (139 out of 2783) accounted for 19.28% of the national total, which increased slightly to 19.6% in 2017. In contrast, 51% of cities, representing 48% of the population, contributed only 20% of the total carbon footprint. Consumption patterns remain predominantly carbon-intensive, with high carbon intensity and steadily rising consumption capacity.

5.2. Spatial Trends in Carbon Footprint Inequality

Spatial analysis revealed varying trends of carbon footprint inequality across different scales. At the provincial scale, Shandong emerged as the largest emitter. At the county scale, carbon footprints were concentrated in affluent urban regions such as the Yangtze River Delta, Pearl River Delta, and Beijing–Tianjin–Hebei areas, while many western regions exhibited faster growth in consumption-based carbon footprints. At the grid scale, kernel density analysis highlighted the Yangtze River Delta as the largest carbon footprint region nationwide.

5.3. Scale-Dependent Theil Indices and Regional Disparities

The Theil indices of carbon footprint inequality increased with finer spatial scales, with county-level disparities contributing over 55% to overall inequality. Significant spatial imbalances were observed in the northwest and northeast regions, as well as within Guangdong Province and western Fujian. These imbalances are driven by uneven resource allocation and lagging industrial structures. Driver analysis identified carbon intensity as the most influential factor contributing to these disparities.

5.4. Spatial Lag and Urban-Rural Differences

Multi-scale analysis revealed pronounced spatial lag effects in county-level carbon footprints, with significant positive development trends only in the eastern coastal regions. Urban carbon footprints grew by 7.7%, while rural footprints increased by 9.4%. Despite the faster growth in rural areas, urban carbon footprints continued to dominate, emphasizing the importance of urban carbon reduction efforts. Poverty-stricken areas showed a 72.6% overlap with low-carbon emission zones and a full overlap with spatial lag regions, highlighting poverty as a critical driver of inequality.

Supplementary Materials: The following supporting information can be downloaded at: https://www.mdpi.com/article/10.3390/ijgi14020049/s1.

Author Contributions: Feng Xu: Formal analysis; Writing—original draft; Writing—review and editing; Minrui Zheng: Conceptualization; Methodology; Project administration; Dongya Liu: Investigation; Resources; Data; Xinqi Zheng: Methodology; Software; Funding acquisition; Yin Ma: Conceptualization; Methodology; Formal analysis; Jizong Peng: Software; Formal analysis; Ye Shen: Investigation; Writing—review and editing; Xu Han: Data; Writing—original draft. Mengdi Zhang: Methodology. All authors have read and agreed to the published version of the manuscript.

Funding: This work was supported by the National Natural Science Foundation of China (72033005); "Deep-time Digital Earth" Science and Technology Leading Talents Team Funds for the Central Universities for the Frontiers Science Center for Deep-time Digital Earth, China University of Geosciences (Beijing) Fundamental Research Funds for the Central Universities (2652023001); The Third Xinjiang Scientific Expedition of the Key Research and Development Program by Ministry of Science and Technology of the People's Republic of China (2022xjkk1104); The National Natural Science Foundation of China (42201471); Beijing Social Science Foundation (2022YJC264); National Defense Science and Technology Key Laboratory Fund Project (6142A01210406).

Data Availability Statement: The raw data supporting the conclusions of this article will be made available by the authors on request.

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

References

1. Liu, H.; Wang, X.; Wang, Z.; Cheng, Y. Does Digitalization Mitigate Regional Inequalities? Evidence from China. *Geogr. Sustain.* **2024**, *5*, 52–63. [CrossRef]
2. Semieniuk, G.; Yakovenko, V.M. Historical Evolution of Global Inequality in Carbon Emissions and Footprints versus Redistributive Scenarios. *J. Clean. Prod.* **2020**, *264*, 121420. [CrossRef]
3. Wu, S.; Hu, S.; Frazier, A.E.; Hu, Z. China's Urban and Rural Residential Carbon Emissions: Past and Future Scenarios. *Resour. Conserv. Recycl.* **2023**, *190*, 106802. [CrossRef]
4. Oswald, Y.; Owen, A.; Steinberger, J.K. Large Inequality in International and Intranational Energy Footprints between Income Groups and across Consumption Categories. *Nat. Energy* **2020**, *5*, 231–239. [CrossRef]
5. Zhang, R.; Zhou, T.; Jing, R. Granular Insights into Occupant Behaviours and CO2 Emissions in the UK. *J. Clean. Prod.* **2024**, *478*, 143923. [CrossRef]
6. Nahar, D.; Unni, H.; Verma, P. Enabling Sustainable Consumer Choices with CarbonShunya: India's First Solution to Measure and Mitigate Carbon Impact of Consumer Transactions in Real-Time. *Environ. Res. Lett.* **2024**, *19*, 114011. [CrossRef]
7. Zheng, H.; Zhang, Z.; Dietzenbacher, E.; Zhou, Y.; Többen, J.; Feng, K.; Moran, D.; Jiang, M.; Shan, Y.; Wang, D.; et al. Leveraging Opportunity of Low Carbon Transition by Super-Emitter Cities in China. *Sci. Bull.* **2023**, *68*, 2456–2466. [CrossRef]
8. Lian, Y.; Lin, X.; Luo, H.; Niu, Y.; Zhang, J. Empirical Research on Household Consumption Carbon Emissions and Key Impact Factors in Urban and Rural China. *Environ. Sci. Pollut. Res.* **2023**, *30*, 62423–62439. [CrossRef]
9. Liang, L.; Chen, M.; Zhang, X. Measuring Inequality of Household Carbon Footprints between Income Groups and across Consumption Categories in China. *J. Clean. Prod.* **2023**, *418*, 138075. [CrossRef]
10. Xu, C. Economic Inequality and Carbon Inequality: Multi-Evidence from China's Cities and Counties. *J. Environ. Manag.* **2023**, *327*, 116871. [CrossRef] [PubMed]
11. Yu, B.; Xu, Z.; Du, C.; Xu, J.; Pan, Y.; Zhou, J.; Shan, Y. Spatiotemporal Evolution and Drivers of Carbon Inequalities in Urban Agglomeration: An MLD-IDA Inequality Indicator Decomposition. *Ecol. Indic.* **2024**, *162*, 112004. [CrossRef]
12. Guo, C.; Zhou, W.; Jing, C.; Zhaxi, D. Mapping and Measuring Urban-Rural Inequalities in Accessibility to Social Infrastructures. *Geogr. Sustain.* **2024**, *5*, 41–51. [CrossRef]
13. Luo, G.; Baležentis, T.; Zeng, S. Per Capita CO_2 Emission Inequality of China's Urban and Rural Residential Energy Consumption: A Kaya-Theil Decomposition. *J. Environ. Manag.* **2023**, *331*, 117265. [CrossRef]

14. Kilian, L.; Owen, A.; Newing, A.; Ivanova, D. Microdata Selection for Estimating Household Consumption-Based Emissions. *Econ. Syst. Res.* **2023**, *35*, 325–353. [CrossRef]
15. Liao, M.; Jia, J.; Han, G.; Wang, G.; Zhang, Z.; Wu, G. Reduced Carbon Footprint Inequality in China: Evidence from Latest Household Survey Data. *J. Clean. Prod.* **2023**, *384*, 135342. [CrossRef]
16. Zhou, X.-Y.; Gu, A.-L. Impacts of Household Living Consumption on Energy Use and Carbon Emissions in China Based on the Input-Output Model. *Adv. Clim. Chang. Res.* **2020**, *11*, 118–130. [CrossRef]
17. Xiao, D.; Guo, W.; Liu, X.; Zheng, Y.; Gong, H.; Wang, C. Tracing Embodied CO_2 Emissions and Drivers in China's Financial Industry under Inter-Provincial Trade. *Sci. Rep.* **2024**, *14*, 28668. [CrossRef] [PubMed]
18. Zhao, X.; Li, X.; Xi, Y. Evolution and Driving Factors of Inequality in CO2 Emissions from Agricultural Energy Consumption in China. *Sci. Rep.* **2024**, *14*, 12991. [CrossRef]
19. Li, Q.; Chen, C. A Characteristics Analysis of Carbon Emission Based on Multi-Dimensional Carbon Emission Accounting Methods and Structural Decomposition Analysis: A Case Study of Beijing, China. *Front. Earth Sci.* **2023**, *10*, 1073167. [CrossRef]
20. Ding, Y.; Xu, L.; Sun, Y.; Wu, Y.; Liu, X.; Geng, X. Large but Overlooked Carbon Differentiations inside China's Provinces Matters to Mitigation Strategies Design: Evidence from County-Level Analysis. *Sci. Total Environ.* **2023**, *898*, 165551. [CrossRef]
21. Sun, B.; Fang, C.; Liao, X.; Liu, M.; Liu, Z.; Guo, X. Revealing the Heterogeneous Effects of New Urbanization on Urban-Rural Inequality Using Geographically Weighted Quantile Regression. *Appl. Geogr.* **2023**, *159*, 103082. [CrossRef]
22. Zhou, K.; Yang, J.; Yang, T.; Ding, T. Spatial and Temporal Evolution Characteristics and Spillover Effects of China's Regional Carbon Emissions. *J. Environ. Manag.* **2023**, *325*, 116423. [CrossRef]
23. Chen, J.; Gao, M.; Cheng, S.; Hou, W.; Song, M.; Liu, X.; Liu, Y.; Shan, Y. County-Level CO_2 Emissions and Sequestration in China during 1997–2017. *Sci. Data* **2020**, *7*, 391. [CrossRef] [PubMed]
24. Zheng, H.; Bai, Y.; Wei, W.; Meng, J.; Zhang, Z.; Song, M.; Guan, D. Chinese Provincial Multi-Regional Input-Output Database for 2012, 2015, and 2017. *Sci. Data* **2021**, *8*, 244. [CrossRef]
25. Cui, Y.; Khan, S.U.; Deng, Y.; Zhao, M. Spatiotemporal Heterogeneity, Convergence and Its Impact Factors: Perspective of Carbon Emission Intensity and Carbon Emission per Capita Considering Carbon Sink Effect. *Environ. Impact Assess. Rev.* **2022**, *92*, 106699. [CrossRef]
26. Hu, S.; Zhao, R.; Cui, Y.; Zhang, D.; Ge, Y. Identifying the Uneven Distribution of Health and Education Services in China Using Open Geospatial Data. *Geogr. Sustain.* **2023**, *4*, 91–99. [CrossRef]
27. Wang, L.; Zhang, M. Exploring the Impact of Narrowing Urban-Rural Income Gap on Carbon Emission Reduction and Pollution Control. *PLoS ONE* **2021**, *16*, e0259390. [CrossRef]
28. Mi, Z.; Zhang, Y.; Guan, D.; Shan, Y.; Liu, Z.; Cong, R.; Yuan, X.-C.; Wei, Y.-M. Consumption-Based Emission Accounting for Chinese Cities. *Appl. Energy* **2016**, *184*, 1073–1081. [CrossRef]
29. Mi, Z.; Sun, X. Provinces with Transitions in Industrial Structure and Energy Mix Performed Best in Climate Change Mitigation in China. *Commun. Earth Environ.* **2021**, *2*, 182. [CrossRef]
30. He, K.; Mi, Z.; Zhang, J.; Li, J.; Coffman, D. The Polarizing Trend of Regional CO_2 Emissions in China and Its Implications. *Environ. Sci. Technol.* **2023**, *57*, 4406–4414. [CrossRef] [PubMed]
31. Peng, S.; Wang, X.; Du, Q.; Wu, K.; Lv, T.; Tang, Z.; Wei, L.; Xue, J.; Wang, Z. Evolution of Household Carbon Emissions and Their Drivers from Both Income and Consumption Perspectives in China during 2010-2017. *J. Environ. Manag.* **2023**, *326*, 116624. [CrossRef] [PubMed]
32. Wiedenhofer, D.; Guan, D.; Liu, Z.; Meng, J.; Zhang, N.; Wei, Y.-M. Unequal Household Carbon Footprints in China. *Nat. Clim Change* **2017**, *7*, 75–80. [CrossRef]
33. Long, Y.; Yoshida, Y.; Jiang, Y.; Huang, L.; Wang, W.; Mi, Z.; Shigetomi, Y.; Kanemoto, K. Japanese Urban Household Carbon Footprints during Early-Stage COVID-19 Pandemic Were Consistent with Those over the Past Decade. *npj Urban Sustain.* **2023**, *3*, 19. [CrossRef]
34. Xiong, S.; Yang, F.; Li, J.; Xu, Z.; Ou, J. Temporal-Spatial Variation and Regulatory Mechanism of Carbon Budgets in Territorial Space through the Lens of Carbon Balance: A Case of the Middle Reaches of the Yangtze River Urban Agglomerations, China. *Ecol. Indic.* **2023**, *154*, 110885. [CrossRef]
35. Sun, X.; Mi, Z.; Du, H.; Coffman, D. Impacts of Poverty Eradication on Carbon Neutrality in China. *Sci. Bull.* **2023**, *69*, 648–660. [CrossRef] [PubMed]
36. Zhang, Y.; Pan, J.; Zhang, Y.; Xu, J. Spatial-Temporal Characteristics and Decoupling Effects of China's Carbon Footprint Based on Multi-Source Data. *J. Geogr. Sci.* **2021**, *31*, 327–349. [CrossRef]