

Article

Household Energy Consumption Patterns and Carbon Emissions for the Megacities—Evidence from Guangzhou, China

Lu Jiang ^{1,2,3,*} , Bowenpeng Ding ⁴, Xiaonan Shi ⁵, Chunhua Li ¹ and Yamei Chen ¹

¹ Academy of Plateau Science and Sustainability, People's Government of Qinghai Province and Beijing Normal University, Xining 810016, China; tzslnmj@163.com (C.L.); cym17792351968@163.com (Y.C.)

² Faculty of Geographical Science, Beijing Normal University, Beijing 100875, China

³ Guangzhou Institute of Geography, Guangdong Academy of Sciences, Guangzhou 510030, China

⁴ College of Earth and Environmental Sciences, Lanzhou University, Lanzhou 730000, China; dingbwp18@lzu.edu.cn

⁵ Northeast Institute of Geography and Agroecology, CAS, Jilin 130102, China; shixiaonan@iga.ac.cn

* Correspondence: jianglu@gdas.ac.cn

Abstract: Over the last 20 years, energy consumption in the residential sector in China has grown rapidly, and the growth is faster than that of any other energy form. To assess the limitations of the spatial characteristics of household energy consumption in urban areas, this paper selected Guangzhou as the research area. Specifically, the old town, core area, central area and peri-urban areas, which best reflect the evolutionary characteristics and spatial differentiation of households, were assessed. Based on the surveyed database of community-scale household energy consumption (N = 1097), the spatial heterogeneity of household energy consumption and carbon emissions at the community scale were assessed through exploratory spatial data analysis and the standard deviation ellipse method. The results report that (1) the main sources of energy consumption in Guangzhou households were water heating equipment, kitchen equipment and refrigeration equipment, which were related to the climatic conditions and cultural traditions of the city. (2) There was significant spatial heterogeneity in the carbon emissions from household domestic energy use in Guangzhou. (3) The economic level, the effects of the Lingnan culture and the characteristics of residents are the main drivers influencing the spatial characteristics of household energy consumption and carbon emissions in Guangzhou. We propose that policy development should actively promote energy-efficient equipment, such as water heating and cooling equipment, in urban households and take full account of the basic household energy needs of residents in old urban and suburban areas while promoting the development of low-carbon buildings.

Keywords: household energy consumption; spatial differentiation; community scale; mega cities; carbon emission



Citation: Jiang, L.; Ding, B.; Shi, X.; Li, C.; Chen, Y. Household Energy Consumption Patterns and Carbon Emissions for the Megacities—Evidence from Guangzhou, China. *Energies* **2022**, *15*, 2731. <https://doi.org/10.3390/en15082731>

Academic Editor: Krushna Mahapatra

Received: 22 February 2022

Accepted: 31 March 2022

Published: 8 April 2022

Publisher's Note: MDPI stays neutral with regard to jurisdictional claims in published maps and institutional affiliations.



Copyright: © 2022 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (<https://creativecommons.org/licenses/by/4.0/>).

1. Introduction

At present, the center of gravity of global energy consumption is gradually shifting from the production side to the consumer side. On the one hand, residential energy use has become the highest consumer of energy after the industrial sector and the transport sector. Global domestic energy use accounted for 22% of total end-use energy consumption in 2016, second only to the industrial sector in energy consumption, with the US accounting for 16% of the total domestic energy consumption; the UK, 30%; Germany, 25%; and China, 16% [1]. On the other hand, residential energy use is growing rapidly. The growth of energy consumption in the household sector has become one of the main sources of global energy consumption and carbon emissions [2]. In particular, although the total final energy consumption in the transport sector of China has continued to grow rapidly since 2000, it

has approached but never exceeded that of the residential sector up to 2018. Meanwhile, the 14th Five-Year Plan for National Economic and Social Development and the Long-Range Objectives Through the Year 2035 [3] clearly states that efforts should be made to improve energy consumption patterns, cultivate production and lifestyle patterns that conserve energy and use green energy, promote low-carbon and smart energy transformations and promote high-quality development of new energy sources. Mitigating the growth of household energy consumption to ensure environmental sustainability and managing carbon emissions from household consumption are particularly important in the context of promoting a green transformation of economies and societies and achieving “carbon neutrality” targets [4].

To the best of our knowledge, most research on household energy consumption is rich in macro–micro polarization studies at the regional and individual scales, with a focus on rural areas. There is a lack of refined research on the spatial characteristics of household energy consumption in the context of China’s economic transition and social change and the emergence of significant spatial differentiation in urban communities. Moreover, limited by the lack of microscale data, most studies treat the domestic sector ambiguously, i.e., they examine domestic energy use only as a whole and do not take into account the differences in indoor energy use. However, as urbanization and the postpandemic era overlap, changes in household structures and lifestyles have led to a new spatial differentiation and structuring of household energy consumption, particularly in large cities with high levels of urbanization and openness. Communities represent mesoscopic geospatial patterns within cities, and there is not only spatial differentiation in the characteristics of household energy consumption at the intraurban scale but also sociospatial differentiation at the community scale [5]. Most of the existing studies reflect a distinction between urban and rural policy concerns, but there are relatively few studies on carbon emissions at the level of urban social subdivisions. Therefore, the analysis of community spatial structure can better reveal the territorial and spatial processes of energy consumption in urban households. Furthermore, in the analysis of the factors influencing household energy consumption, attention to cultural factors (e.g., dietary traditions, bathing practices) is still lacking.

As the representative of megacities, Guangzhou is representative of mega cities, in that it has developed from a postindustrial city to a global megacity since the economic reform and opening up (1978). As urbanization steadily progresses, the share of industrial energy in the total energy use will steadily decline, while the shares of residential and commercial energy will continue to rise; furthermore, there has been a change in the relationship between people and land due to rapid urbanization and the resulting extensive energy consumption [6,7]. The conflict between energy supply and demand has become a major constraint on the sustainable development of the urban–land relationship. Guangzhou’s urban transformation has resulted in diverse community spaces, such as upscale communities, urban villages and community units [8]. Therefore, a spatial study of household energy consumption aimed at alleviating the conflict between energy supply and demand at the community scale in Guangzhou is representative of broad-scale patterns. In addition, the multiple geographical and climatic environments in Guangzhou, which has a low latitude and high solar radiation, and the influence of warm and humid ocean currents have contributed to the continuous development of food culture in the Lingnan region, which has become one of the most representative and internationally influential food cultures in China. However, the influence of cultural factors on household energy consumption has yet to be clarified.

This article is based on a panoramic household energy consumption survey [9] and was used to establish a large database of micro urban household energy consumption; the database summarizes household energy consumption characteristics in terms of the energy consumption activity process and time use. Using communities as an entry point, exploratory spatial data analysis (ESDA) and standard deviation ellipse (SDE) methods are used to visualize and analyze energy consumption and carbon emissions. Through

the transformation and integration of spatial scales, the patterns of spatial variation in household energy consumption are explored, and thus, the deep relationship between socio-spatial stratification and energy consumption is investigated. The application of the results to the management of energy decisions in Chinese cities can, on the one hand, help to slow the growth of residential energy consumption and optimize the structure of domestic energy use. On the other hand, the results can serve as an example of energy efficiency and low-carbon production through the choice of residents as consumers and provide a Chinese solution for many other developing countries around the world that are in the process of urbanization.

Based on this, in this paper we want to answer the following questions: 1. What is the volume of household energy consumption and carbon emissions in Guangzhou? 2. What are the characteristics of its regional distribution? and 3. What are the influencing factors that underlie these distribution facts?

2. Literature Review

For a long time, scholars have focused on two main aspects of household energy consumption. First, scholars have studied the characteristics of household energy consumption at different spatial scales. For example, Zheng, Wei, Qin, Guo, Yu, Song and Chen [10] conducted a comprehensive survey of 1450 households in 26 provinces in China, and the results reveal that district heating, natural gas and electricity were the three main sources of residential energy, while space heating, cooking and water heating were the three main energy-consuming activities. In addition, the findings show a large urban–rural gap in terms of energy sources and the reasons for energy use. Wang, Li, Li, Bai and Liu [11] investigated the energy consumption of 1440 households in eight typical counties of China's eight economic zones and found that traditional biomass energy was still the main energy source for rural households in China despite high-income families preferring commercial energies. Gao, Yuan, Geng and Tang [12] investigated rural household energy consumption from 5130 households covering 171 counties in Hebei Province and found that the most commonly used fuel for heating is coal products, representing 70% or more of all heating. Jiang, Yu, Xue, Chen and Mi [13] studied household energy consumption in agricultural, pastoral and mixed farming areas in Qinghai and found typical spatial differences between the three regions, with straw and fuelwood dominating energy consumption in agricultural areas, animal manure dominating in pastoral areas and mixed farming and pastoral areas having both agricultural and pastoral characteristics. Sun, Chen, Xu, Zhang, Hubacek and Wang [14] explored the carbon footprint and inequalities in household energy consumption in rural areas of five provinces in China using the 2018 micro-household survey data combined with environmentally extended input–output analysis. Another study used a city-scale input–output model and urban residential consumption inventories to investigate the relationship between city-level household consumption and energy demand. They found household emissions are substantially different among the various household age groups. In addition to the research from the perspective of provinces and cities, there were also studies on household energy consumption from the perspective of urban communities. Mashhoodi [15] found in a study of urban communities in Amsterdam, the Netherlands, that large businesses and traditional communities exhibited both household energy waste and conservation, with the transportation sector generating the most energy waste; the study also found that residents could improve their energy efficiency by purchasing insulation, energy-efficient equipment, etc. Jones, Taylor, Jennison Kipp and Knowles [16] found that high-class urban communities see energy as a medium for maintaining social relations and generate more conspicuous energy consumption. The wide variation in the physical geography and socioeconomic characteristics of China's regions makes household energy consumption heterogeneous at different scales; nevertheless, there are certain intrinsic patterns in the characteristics of energy consumption at similar scales [17,18].

Second, scholars have studied the factors influencing household energy consumption. Existing studies have identified household characteristics, social cultural factors, policy

mechanisms, geographical location and energy accessibility and prices as the core factors influencing household energy consumption. Jin, He, Kuang, Wan and Ning [19] explored the current status of rural household energy consumption and its influencing factors in the western region based on data from a survey of 240 farming households in 2017. The study found that modern energy consumption accounts for only a small proportion of the total energy consumption. Farmers' personal perceptions of climate change, social trust and networks and household socioeconomic and demographic factors were found to have a significant impact on rural households' biomass and commercial energy consumption. De Lauretis, Gheris and Cayla [20] analyzed the disparities in activity patterns and related energy consumptions and expenditures of households in France for a comprehensive set of everyday activities covering 24 h. The results show that the time spent in various activities has a great influence on energy consumption. Li, Zhang, Zhang and Ji [21] first assumed that households in which women play a decision-making role adopt more environmentally friendly consumption practices. The empirical results of a national survey show that in counties with higher gender inequality, households used fewer energy-efficient electrical products and were less willing to save energy. Moshiri [22] estimated the effects of the energy price reform on household consumption in Iran, and his result indicates that urban households show a stronger response to price changes than rural households. In addition, Du et al. (2015) investigated the feedback of household electricity consumption to the new pricing policy in China and found that the energy price has significant impacts on residential electricity consumption. Based on a social practice modeling framework, Yang and Liu [23] measured the quantitative distribution characteristics of household carbon emissions in different cities and analyzed the factors influencing daily energy consumption and carbon emissions in residential households, finding that space heating (in northern regions) was the largest source of CO₂ emissions; individual perceptions and household lifestyle also partially influenced energy choices and daily consumption behaviors. In addition, geographical factors, climatic conditions and energy prices are important factors that influence household energy consumption [22,24,25].

In recent years, scholars have explored the impact of dietary differences on carbon emissions. Based on representative resident survey data from the China Health and Nutrition Survey, Xiong, Zhang, Hao, Zhang, Shi and Zhang [26] analyzed urban food consumption profiles and associated greenhouse gas emissions from a life-cycle perspective. They found that meat consumption dominates the total urban GHG emissions and is the main driver of changes in total urban GHG emissions. Meanwhile, the ecological conditions of cities, including geographic climate and resource endowment, have a significant impact on urban food consumption and associated GHG emissions.

In the context of China's two targets of achieving carbon emission and carbon neutrality, we believe it is necessary to address urban household energy consumption. We carefully and meticulously examined the questionnaire data sources, after which we carried out interviews and analyzed the collected data. Finally, we made corresponding policy recommendations based on the facts of our research and the findings of existing studies. The policy recommendations are also presented separately in relation to the drivers. The framework of the paper has been showed as follow (Figure 1).

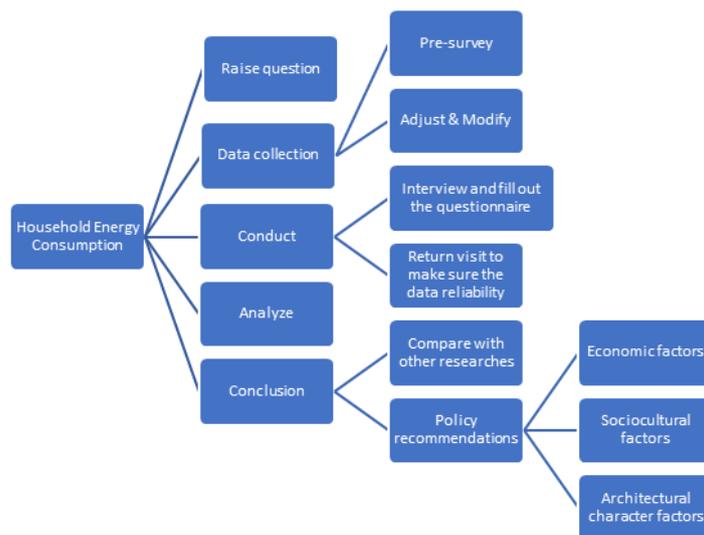


Figure 1. The framework of the paper.

3. Methodology

3.1. Research Design

This current study explores the household energy consumption patterns and carbon emissions, taking Guangzhou, China, as a study area. To achieve this goal, we collected energy data through field research on household energy consumption in 2020. Figure 2 shows the flow of our data collection and processing stages. Before starting our formal research, we conducted a pre-survey to adapt the questionnaire to the actual situation of local household consumption, such as household equipment, the size of the community, etc. After completing our formal research, we screened out some questionnaires that were not detailed, incomplete or had logical errors, and then conducted a statistical analysis of the valid questionnaires and carried out this study.

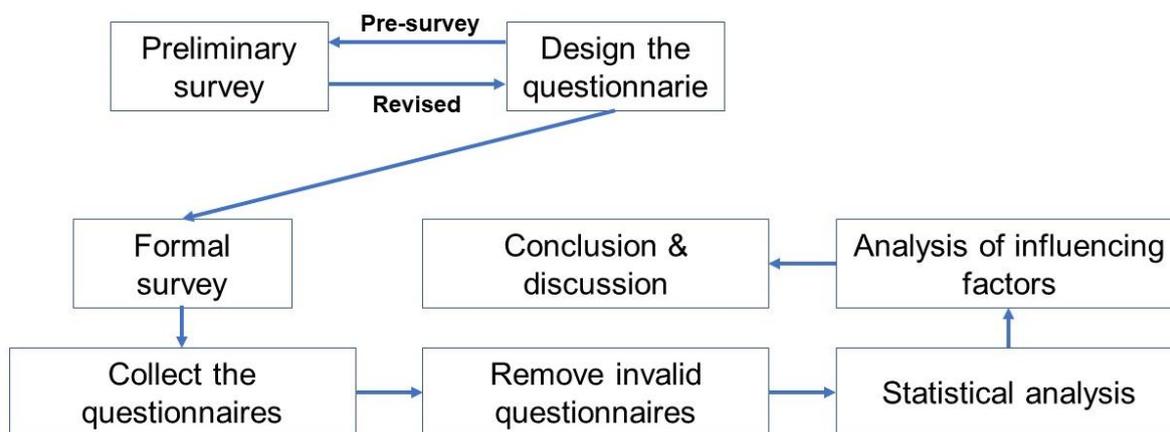


Figure 2. Steps of research.

3.2. Study Area

Guangzhou is located at 112°57′–114°3′ east longitude and 22°26′–23°56′ north latitude. Located in the subtropics and straddling the Tropic of Cancer, it has a hot summer and warm winter, with an average temperature of 15.2 °C to 28.9 °C throughout the year; Guangzhou is also one of the major cities with a small average temperature difference in China. July and August are the hottest months of the year, reaching 37 °C, followed by June and September at 35 °C. The average relative humidity is 78.4%, and the average annual precipitation is 194.67 mm. The total population of Guangzhou in 2019 was 9.54 million,

with a population density of 2111 persons/km², ranking it among the cities with the highest population densities in China. The urbanization rate of the resident population was 86.46%, which was higher than the national level of 60.60% [27]. Energy consumption by urban residents in 2019 was equivalent to 7,499,200 tons of standard coal, accounting for 72.39% of the city's total energy consumption by urban and rural residents [28]. Urban households were the main consumers of energy. Figure 3 shows the location of Guangzhou and Guangdong Province in China.

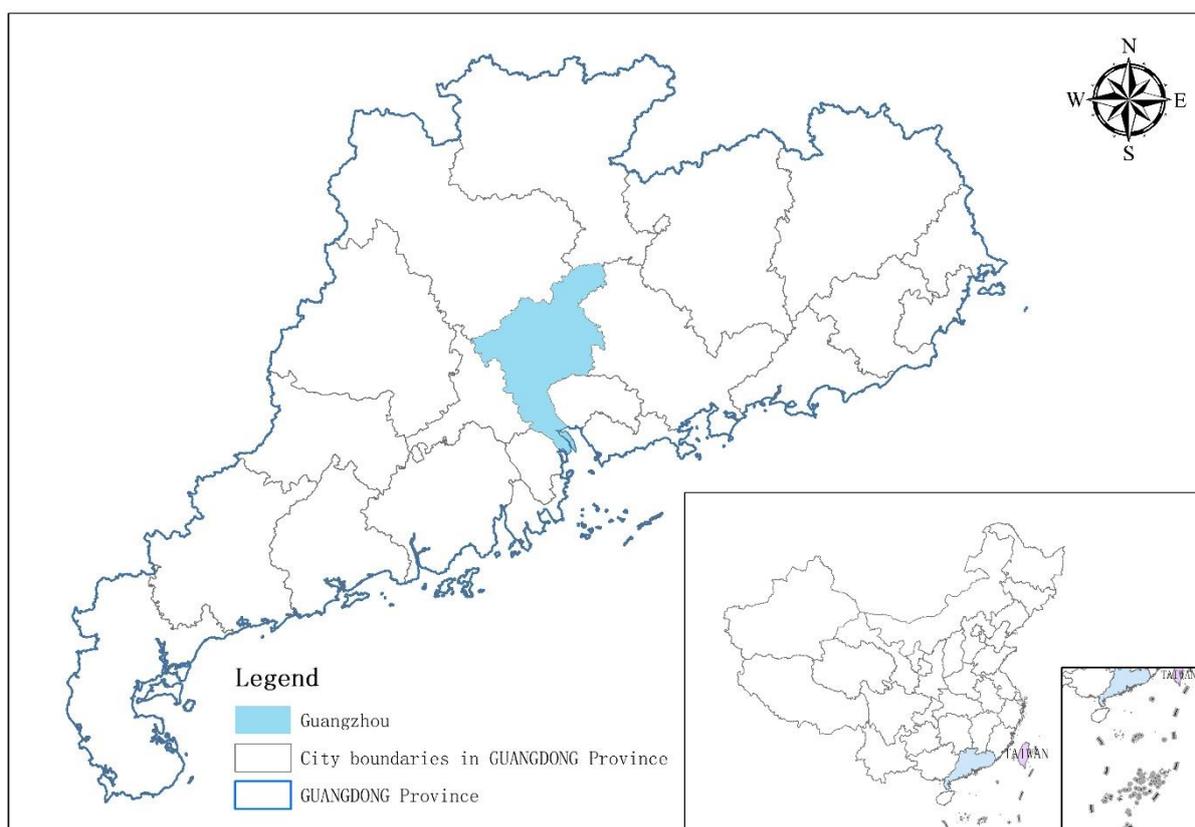


Figure 3. The location of Guangzhou.

3.3. Data Collection

The data for the study were mainly derived from field research. The research team conducted research in 2020 within the Guangzhou municipal area (excluding Zengcheng, Huadu and Conghua) by means of structured interviews at the household level. In this study, a social class evaluation system and calculation method proposed by Wang, which considers “five levels + eight classes + three perspectives” [29], was applied to assess the subdistricts of Guangzhou. The valid sample points were distributed in four types of areas: old cities, core areas, central cities and suburban areas. The total sample setting used for the research was based on Equation (1), i.e., the maximum error of the sample data representing the total dataset was $\pm 2.83\%$ (within a 95% confidence interval), with an acceptable margin of error of $\pm 5\%$. In practice, this sampling design is relatively dependent on the error requirements after segmentation. The questionnaire mainly covered basic information about the respondent's household (the population, genders, education levels and annual household incomes of household members), household energy consumption and housing situation. Information about and indicators of direct household energy consumption were mainly obtained from questions related to the following topics: frequency and average length of use of cooking equipment; number, energy efficiency frequency of use and other relevant factors of domestic appliances such as refrigerators and televisions; length and

frequency of use and number of water heaters and refrigeration equipment; number and length of use of lighting equipment; etc.

$$\theta = \pm Z_{\frac{\alpha}{2}} \sqrt{\frac{p \times 1 - p}{n}} \quad (1)$$

where $Z = 1.96$ (95% confidence interval), $p = 0.5$ and θ is the sample error.

The spatial vector data used for the data visualization process in this study are the Guangzhou Administrative Region Vector Map (WGS84 Coordinate System (Review No. GS (2019)1822)) and the Guangzhou Administrative Map (Standard Map Service of the Guangzhou Municipal Bureau of Planning and Natural Resources), which were imported into ArcMap 10.3 software and aligned using the georeferencing tool. Street base maps of the study area were created under the condition that the root mean square residuals of all alignments were guaranteed to be less than 0.001 (Figure 4).

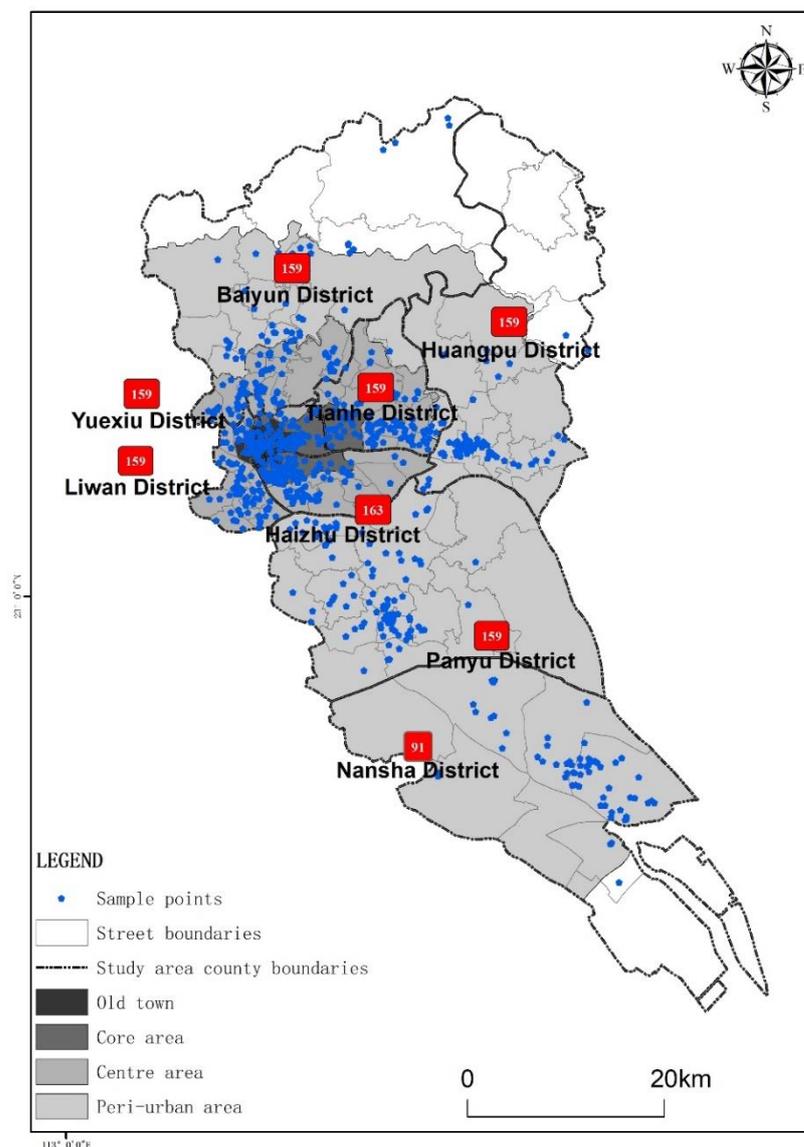


Figure 4. Spatial distribution of samples.

3.4. Analysis

3.4.1. The Carbon Emissions from Household Energy Consumption

The main categories of energy consumed by households addressed in this research are natural gas, electricity and gas. The accounting method described in the IPCC GHG inventory guidelines was adopted to estimate carbon emissions from energy consumption; the formula for estimating carbon emissions is as follows:

$$C_T = \sum E_i \times N_i \times C_i \times O_i \times \frac{44}{12} \quad (2)$$

where C_T denotes the total carbon emissions from energy consumption, E_i denotes the consumption of the i th energy source, N_i denotes the net heat generation value of the i th energy source, C_i denotes the carbon content of the i th energy source, O_i denotes the oxidation rate of the i th energy source, and i refers to the energy category (i.e., natural gas, electricity and gas). The power-related carbon emission factor (0.8042 kg CO₂/kWh) from the Southern Regional Grid of Guangdong Province [30] was used to calculate the carbon emissions from energy consumption by power-related equipment. When calculating the carbon emissions of energy consumed by water heaters and kitchen equipment, the carbon emission factors for natural gas and gas were derived from values reported by Wu [31]. Natural gas, electricity and gas were equalized to standard coal in the summary analysis of energy statistics, and the accounting of carbon emission data was based on the energy use questions of the questionnaire. Since the use of solar energy and other energy sources does not produce carbon emissions per se, the carbon emissions of solar water heaters and other household appliances that use solar energy were recorded as zero. The calculation methods and carbon-emission-related parameters used for the specific household energy consumption devices assessed in this study are shown in Tables 1 and 2.

Table 1. The methods of assessing household energy consumption and direct carbon emissions of equipment.

Energy-Consuming Items	Formula	Description
Kitchen equipment	$Energy_{Kitchen\ equipment}$ = Energy consumption per hour * operating hours	The amount of energy consumed mainly by cooking equipment, which included cooking devices that rely on natural piped gas, tank gas, induction, etc.
Large appliances such as refrigerators, washing machines and televisions	$Energy_{Large\ appliances}$ = Equipment power * operating hours * energy efficiency (according to the label)	The power required for large appliances was determined by calculating the average size of the washing machine, the volume of the refrigerator and the size of the TV screen and overlaying the value with data from the shopping market.
Refrigeration equipment	$Energy_{Refrigeration\ equipment}$ = Equipment power * operating hours * energy efficiency (according to the label) * operating frequency	Including air conditioners, electric fans, etc. Some samples were discarded due to logical errors made during the calculation of air conditioner energy consumption.
Water heaters	$Energy_{Water\ heaters}$ = Equipment power * operating hours * energy efficiency (according to the label) * operating frequency	Water heaters that use solar energy, solar energy and electricity and electricity as their main energy sources were classified as water storage water heaters, while others were classified as instant water heaters.
Lighting equipment	$Energy_{Lighting\ equipment}$ = \sum_i^3 Equipment power * operating hours	The three main categories of lighting equipment in the database were fluorescent lamps (fluorescent tubes), energy-saving lamps (LEDs) and ordinary incandescent lamps, with i indicating the type of equipment.
Total E_T	$E_T = \sum Energy_j'$	Note: $Energy_j'$ is the result of the conversion of $Energy_j$ to standard coal by the corresponding energy discount factor; j is kitchen equipment, large appliances, water heaters, lighting equipment, etc.

Note: Some information was collected from some households without concern for energy efficiency coefficients; in these cases, the sample energy efficiency coefficients were determined by comparison with similar samples with corresponding usage frequencies.

Table 2. Carbon emission coefficients of household energy consumption by energy category.

Energy Category	Average Low-Level Heat Generation (PJ/10 ⁸ m ³)	Emission Factors (tC/TJ)	Oxidation Rate	Emission Factors (kg CO ₂ /kg)
Natural gas	5.14	15.32	0.99	2.8603
Coal gas	1.67	13.58	0.98	0.8162

Note: electricity CO₂ emissions factor: 0.8042 kg CO₂/(kwh), 1 PJ = 1000 TJ. Factors are from [32,33].

3.4.2. Spatial Autocorrelation Analysis

Spatial autocorrelation analysis can be used to reveal the spatial relationships among carbon emissions in Guangzhou, and there are two main types of spatial autocorrelation analysis: global autocorrelation analysis and local autocorrelation analysis. In this study, a global autocorrelation analysis, Moran's index (Moran's *I*) and local indices of spatial association (LISA) aggregation map were adopted to characterize the relationship between carbon emissions generated directly by household energy consumption in Guangzhou. As the dataset contains information on the geographical locations corresponding to the samples, the locations of the samples were found in the Baidu coordinate selection system. The obtained latitude and longitude coordinates were converted into a WGS-84 coordinate system consistent with the vector map and imported into ArcMap 10.3 for visualization.

Global Spatial Autocorrelation

The results of global autocorrelation analysis (Moran's *I*) can reflect whether the distribution of regional attribute values is aggregated, discrete or random. Moran's *I* is calculated as follows:

$$I = \frac{n \sum_{i=1}^n \sum_{j=1}^n W_{ij} (x_i - \bar{x})(x_j - \bar{x})}{\sum_{i=1}^n \sum_{j=1}^n W_{ij} \sum_{i=1}^n (x_j - \bar{x})^2} \quad (3)$$

where W_{ij} is the spatial weight matrix, n is the number of samples, x_i denotes the carbon intensity of sample i , x_j denotes the carbon intensity of sample j and $i \neq j$ and \bar{x} denotes the mean carbon intensity. In general, the range of I is $[-1,1]$, with I values greater than zero indicating a positive correlation and I values less than zero indicating a negative correlation; the closer the absolute value of Moran's *I* is to 1, the stronger the correlation. The significance of Moran's *I* was tested by z values.

$$z = \frac{I - E(I)}{\sqrt{Var(I)}} \quad (4)$$

where $E(I)$ is the mathematical expectation $E(I) = \frac{1}{(N-1)}$ and $Var(I)$ is the coefficient of variation.

Additionally, using the global G coefficient, we specified whether the aggregation of the samples was characterized by the agglomeration of high values or low values. The global G coefficient was calculated as follows:

$$Gd = \frac{\left(\sum_{i=1}^n \sum_{j=1}^n w_{ij}(d) x_i x_j \right)}{\sum_{i=1}^n \sum_{j=1}^n x_i x_j}$$

$$Z = \frac{(G(d) - E(d))}{\sqrt{Var(G(d))}}$$

where d is the intersample distance, $w_{ij}(d)$ is the distance weight of point i, j ; $Z > 0$ indicates high-value agglomeration, and $Z < 0$ indicates low-value agglomeration.

Local Spatial Autocorrelation

The local autocorrelation (LISA) aggregation plot reflects the degree of aggregation of the samples. The data aggregation was classified into four types according to the scat-

ter plot: high–high (HH), high–low (HL), low–high (LH) and low–low (LL), where HH (LL) agglomeration indicates positive spatial autocorrelation between adjacent points and a high (low) spatial agglomeration of carbon intensity and LH (HL) indicates negative spatial autocorrelation between adjacent samples, with high (low) carbon emission samples surrounded by low (high) carbon emission samples [34]. The HH, LL, HL and LH clustering patterns of the samples were determined by importing the carbon emission vector file into GeoDa software, establishing a k-nearest neighbor spatial weight matrix and performing local autocorrelation analysis on the sample carbon emission data. These clustering patterns were exported to a vector file from the LISA clustering map and loaded into ArcMap 10.3 software to view and compare their distribution characteristics. The distribution characteristics of the clusters were compared in ArcMap 10.3.

3.4.3. Standard Deviation Ellipse (SDE)

The SDE method proposed by Lefever [35] is a spatial statistical method that quantitatively describes the overall characteristics of the spatial distribution of a study object and its spatial and temporal evolution processes using the center, main axis (long axis), auxiliary axis (short axis) and azimuth as the basic parameters. The spatial distribution range of SDEs indicates the main area of the spatial distribution of geographical elements, the center of gravity indicates the relative position of the spatial distribution of geographical elements, and the azimuth reflects the main trend in the direction of the distribution of geographical elements (i.e., the angle formed by a clockwise rotation in the due north direction to the long axis of the ellipse). The long and short axes of the ellipse can indicate the degree of dispersion of geographical elements in the main and secondary directions. The relevant parameters are calculated as follows.

Center of gravity:

$$(\overline{XY}) = \left(\frac{\sum_{i=1}^n w_i x_i}{\sum_{i=1}^n w_i}, \frac{\sum_{i=1}^n w_i y_i}{\sum_{i=1}^n w_i} \right) \quad (5)$$

Azimuth:

$$\frac{((\sum_{i=1}^n w_i^2 \tilde{x}_i^2 - \sum_{i=1}^n w_i^2 \tilde{y}_i^2) + \sqrt{(\sum_{i=1}^n w_i^2 \tilde{x}_i^2 - \sum_{i=1}^n w_i^2 \tilde{y}_i^2)^2 - 4 \sum_{i=1}^n w_i^2 \tilde{x}_i \tilde{y}_i})}{2 \sum_{i=1}^n w_i^2 \tilde{x}_i \tilde{y}_i} \quad (6)$$

X axis standard deviation:

$$\sigma_x = \sqrt{\frac{\sum_{i=1}^n (w_i \tilde{x}_i \cos \theta - w_i \tilde{y}_i \sin \theta)^2}{\sum_{i=1}^n w_i^2}} \quad (7)$$

Y axis standard deviation:

$$\sigma_y = \sqrt{\frac{\sum_{i=1}^n w_i \tilde{x}_i \sin \theta - w_i \tilde{y}_i \cos \theta^2}{\sum_{i=1}^n w_i^2}} \quad (8)$$

x_i and y_i are the coordinates of the centers of the cells in the study area; w_i is the weight of the study unit; \overline{X} and \overline{Y} are the coordinates of the center of gravity; θ is the elliptical azimuth, i.e., the angle formed by a clockwise rotation in the due north direction to the long axis of the ellipse; \tilde{x}_i and \tilde{y}_i are the coordinate deviations from the center coordinates of each study cell to the center of gravity, respectively; and σ_x and σ_y are the standard deviations along the x- and y-axes, respectively.

4. Results

4.1. Sample Characteristics

Ultimately, 1208 questionnaires were distributed in Guangzhou, and the samples covered eight districts, including Tianhe District (159), Yuexiu District (159), Haizhu District (163), Panyu District (159), Liwan District (159), Huangpu District (159), Nansha

District (91) and Baiyun district (159). A total of 1097 valid questionnaires were returned, for an effective rate of 91%. In terms of personal characteristics, 50.5% of the interviewees were male and 49.5% were female; the age of the interviewees ranged from 18 to 60 years old, with the highest percentage of respondents in the 36 to 45 age group (35.1%). Educational attainment was mainly dominated by tertiary education, accounting for 24.9%. In terms of household characteristics, 34.8% of the households had a permanent household size of three persons. A total of 65.2% of households had a workforce of two; a total of 19.8% had an annual income of CNY 100,000 to 150,000. In terms of housing characteristics, 43.6% of the households were in a multistory building (fewer than nine stories, no elevator); a total of 43.6% of households were in a house that had been under construction for 10 to 20 years; and 37.1% of households had a housing area of 50 to 70 square meters. In terms of regional characteristics, the samples were distributed in all eight administrative districts; a total of 22.5% of the samples were collected in Guangzhou's urban villages.

4.2. Energy Consumption

According to the Guangzhou household energy consumption statistics (Table 3), the average household in Guangzhou consumes 1.9827 kgce/day (standard coal equivalent). Energy consumption varies among households, indicating variation in the potential to save energy. In terms of the equipment used in homes, water heating equipment, kitchen equipment and refrigeration equipment were the three types of appliances with the highest energy consumption. Water heating equipment ranked first in energy consumption, accounting for 37.79% of the total energy consumption, with an average household energy consumption of 0.7493 kgce/day for water heaters; this differs from the findings for most other cities. Kitchen equipment and refrigeration equipment accounted for 36.10% and 20.51% of the total energy use, respectively, which is similar to the results of existing studies, with heating, cooling and cooking being the main components of carbon emissions from household energy use [36,37]. In addition, this study found that the share of energy consumed by large household appliances in Guangzhou was lower than expected. The highest coefficient of variation was observed for lighting, followed, in descending order, by kitchen equipment, refrigeration equipment, water heaters and large appliances, further illustrating the variability in energy-consuming equipment and the differences in carbon emissions from energy use among households.

Table 3. Residential energy consumption by equipment type (kgce/day).

Energy-Consuming Appliance	Proportion of Total Energy Consumption	Average Value	Standard Deviation	Coefficient of Variation	Maximum Value	Minimal Value
Water heaters	37.79%	0.7493	0.6642	0.8863	3.4720	0.1361
Kitchen equipment	36.10%	0.7157	0.7244	1.0121	5.8320	0
Refrigeration equipment	20.51%	0.4067	0.4058	0.9978	4.9269	0
Large appliances	4.26%	0.0844	0.0399	0.4733	0.3629	0
Lighting	1.34%	0.0265	0.0330	1.2453	0.3687	0
Total	100%	1.9827	1.1927	0.6016	10.0250	0.1766

In terms of the types of energy consumed by households (Table 4), the highest proportion of households relied on electric energy, followed by natural gas (59.34% of users), which was mainly used to fuel natural gas stoves in households. The lowest proportion of users relied on gas. Field research found that gas was used relatively frequently in Guangzhou, with gas tanks and pipes mainly supplying kitchen equipment and water heaters, respectively.

Table 4. Household energy consumption by energy source.

Energy Consumption	Electricity	Natural Gas	Gas
Percentage of users	100%	59.34%	43.94%
Proportion of total energy consumption	42.95%	29.30%	27.75%

4.3. Spatial Distribution Characteristics

4.3.1. The Spatial Patterns of Energy Consumption and Carbon Emissions

The carbon emission data were calculated based on the previous formula and energy consumption data. We found that the average household carbon emission in Guangzhou was 15.31 kg/day, and the per capita carbon emission was 4.49 kg/day. Due to the different attributes of various aspects of households, there was a significant difference in the carbon emissions among Guangzhou households. The ratio of above-average carbon emissions to below-average carbon emissions was close to 3:5. Figure 5a,b was created by linking the carbon emission results obtained from the energy consumption data with the existing points to compare the spatial distribution characteristics of carbon emissions from average household domestic energy use and per capita domestic energy use. The results show that there were distinctive features in the locations of the samples with high values of average household carbon emissions; most of the high-value samples were clustered in and scattered around the central city, especially in Yuexiu, Haizhu and Baiyun districts. The number of samples with low carbon emissions was high, and these samples covered various social subdivisions and administrative areas, mainly around the central city boundary, with a significant number of samples with low values within the peri-urban area. The sample distribution of per capita carbon emissions was similar to that of average household carbon emissions, but due to the large sizes of some of the households in the sample, the number of high-value samples of per capita carbon emissions was lower than the number of high-value samples of average household carbon emissions. However, most of the high-value samples were still clustered in and around the central city, and the number of low-value samples increased.

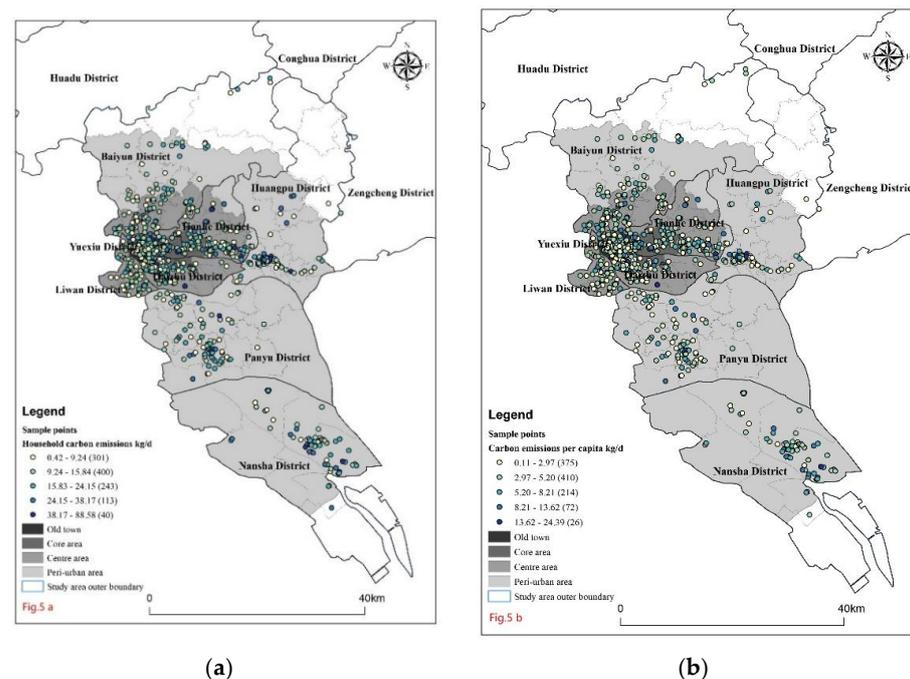


Figure 5. Spatial distribution of household carbon emissions in Guangzhou. (a) Household carbon emissions per day. (b) Carbon emissions per capita per day.

4.3.2. Global Autocorrelation Variance Analysis

The analysis of the global autocorrelation of carbon emissions among the sample data was calculated according to Moran's I formula and tested according to the Z value. As shown in Table 5, both the global and local Moran indices were significantly greater than 0 at a confidence level of 99%, rejecting the original hypothesis of a random distribution; that is, the carbon emissions of the sample data were not randomly distributed, with high values adjacent to high values and low values adjacent to low values. By calculating the global Getis–Ord general G values of the sample data, we found that both observations were larger than the expected values, indicating high clustering (as in Table 5), and there were hotspots of clustering within the study area at a 95% confidence level.

Table 5. Estimation of Moran's I and general G for household energy consumption in Guangzhou.

	Moran's I	$Z(I)$	$P(I)$	$G(d)$	$E(d)$	$Z(d)$	$P(d)$
Carbon emissions from average household energy use	0.0762	3.8448	0.002	0.002	0.001	3.3049	0.0009
Carbon emissions from energy use per capita	0.0823	4.2316	0.001	0.0019	0.0016	2.0720	0.038

4.3.3. Local Autocorrelation Variance Analysis

(1) Local differences in the total carbon emissions from direct household energy consumption

As shown in Figure 6, the sites with high values of carbon emissions were mainly clustered in and around the central city of Guangzhou, with a small number in the central and southern parts of the study area, which marks the current level of development of Guangzhou. Statistically, the aggregation of samples with high carbon emissions was generally consistent with Guangzhou households with high incomes and relatively large living areas. This is evidenced by the high annual gross household income of the samples in areas with high carbon emissions, with 83.3% of those households earning over CNY 100,000 annually. In addition, there were more samples with high carbon emissions in city centers than in peri-urban areas, urban villages and suburbs, and 75% of the samples in aggregates of high carbon emissions represented houses of 70 square meters or more. Most of the households in the high–high aggregation samples were local to Guangzhou, and 79.17% of those households were more than 5 years old. The same method was applied to visualize carbon emissions per capita; the results show that high–high samples were distributed within the central city and southward, while the low–low samples were mainly distributed around the core area.

(2) Local differences in energy consumption by and carbon emissions of water heaters and kitchen cooking equipment

This paper focuses on the distribution of carbon emissions from water heaters and kitchen appliances, which account for 73.89% of total carbon emissions. As shown in Figure 7a, the samples with high values of per capita carbon emissions from water heaters (>8.38 kg/day) were mainly located near the central city, while HH aggregation samples were aggregated mainly in Huangpu District, Tianhe District and Nansha District, which are all on the edge of or outside the central city. The samples with low values of carbon emissions (<0.84 kg/day) were distributed in all regions, while a low-value aggregation of samples (LL) was basically centered in Yuexiu District within the central city, with more low-value aggregations in Liwan District, Haizhu District and Tianhe District. As shown in Figure 7b, the samples with high values (>6.71 kg/day) of per capita carbon emissions from kitchen cooking equipment were mainly distributed in and around the central urban area, while the HH aggregations were mainly scattered within the central urban area, mainly in Liwan, Yuexiu, Haizhu and Tianhe districts. Samples with low values of carbon emissions (<0.64 kg/day) were distributed in all regions, while aggregations of samples with low values (LL) generally surrounded the boundaries and periphery of the central

city. Low-value aggregations of samples were mainly distributed in the Haizhu, Tianhe and Huangpu districts. Among the samples with HH aggregations, 88.89% of the samples represented Guangzhou households, and 11.11% were from within the province; among the districts with LL aggregations, only 42.86% represented Guangzhou households, and the rest were non-Guangzhou households from outside or within the province.

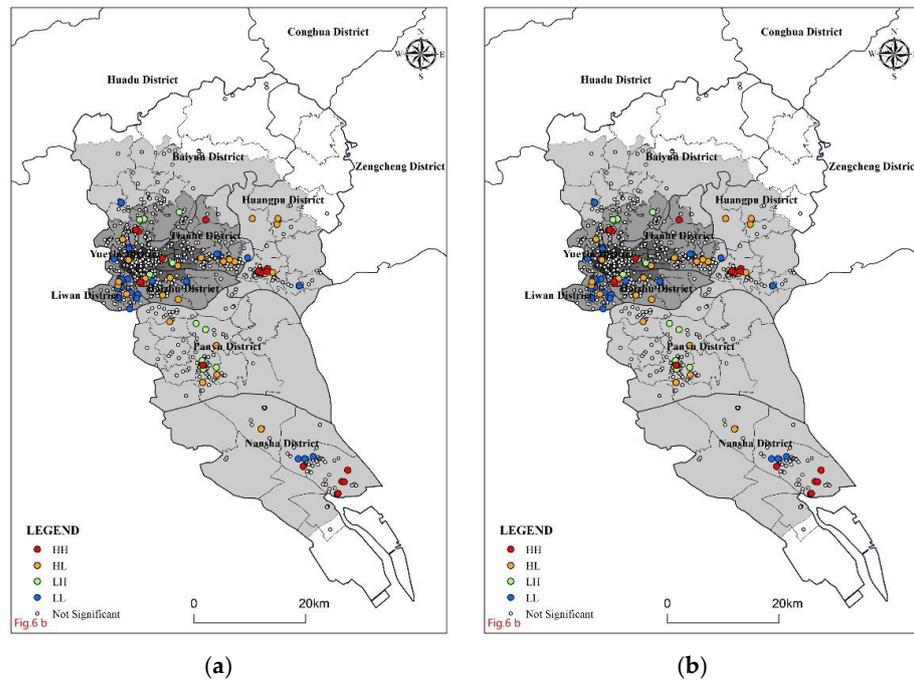


Figure 6. LISA cluster maps of household carbon emissions in Guangzhou. (a) LISA cluster map of household carbon emissions. (b) LISA cluster map of carbon emissions per capita.

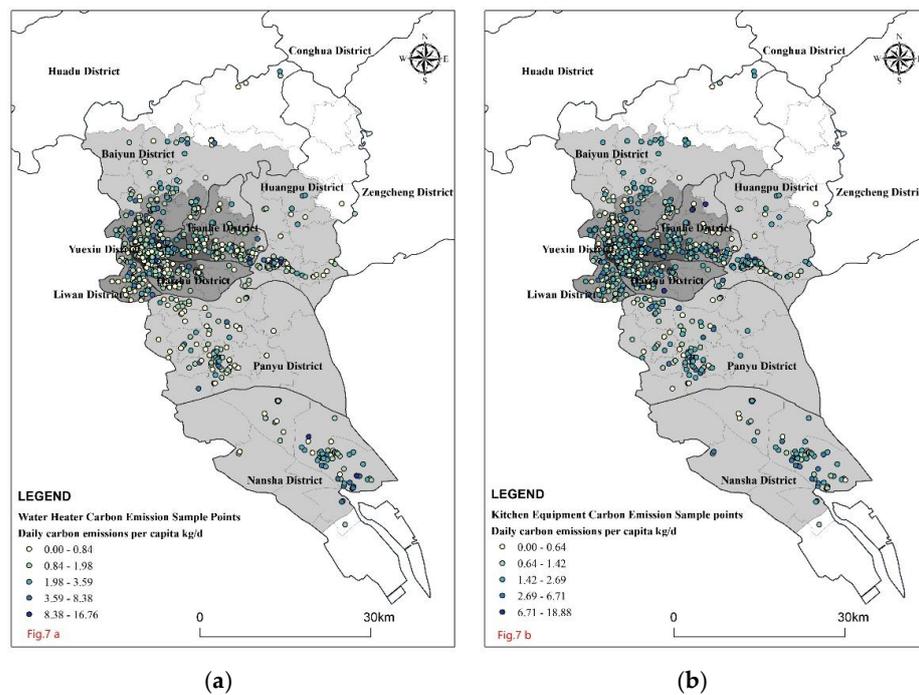


Figure 7. LISA cluster maps of carbon emissions from household equipment in Guangzhou. (a) Carbon emissions from water heaters per capita. (b) Carbon emissions from kitchen equipment per capita.

4.3.4. Spatial Variance Analysis Using Standard Deviation Ellipses (SDEs)

To investigate whether the characteristics of the carbon emission aggregations had a clear directional and distributional range, the standard deviation ellipse tool was applied to analyze kitchen equipment, water heating equipment, refrigeration equipment, large appliances and lighting equipment according to HH and LL aggregations; the results of these analyses are shown in Table 6. In addition, according to the results of the SDE analysis of carbon emissions in Guangzhou city (Figure 8), the SDEs of the aggregations of high and low values of total carbon emissions and per capita carbon emissions had similar shapes. A comparison of the respective areas of the ellipses (Table 7) showed that the areas of both the HH and LL aggregations of per capita carbon emissions increased compared to the total carbon emissions, and the elliptical flatness corresponds to an increase, i.e., the distribution of per capita carbon emissions had a larger range and more pronounced directional trend than the total carbon emissions.

Table 6. LISA clustering data of per capita carbon emissions by equipment type.

	Kitchen Equipment	Water Heaters	Refrigeration Equipment	Large Appliances	Lighting
Moran's I	0.0729	0.0999	0.0749	0.0992	0.0360
$Z(I)$	3.8878	5.2305	3.7701	5.0521	1.9911

Note: kitchen equipment, water heaters, refrigeration equipment and large appliances all had Z values greater than 2.58 and passed the 99% confidence test; lighting equipment had a Z value greater than 1.65 and passed the 90% confidence test.

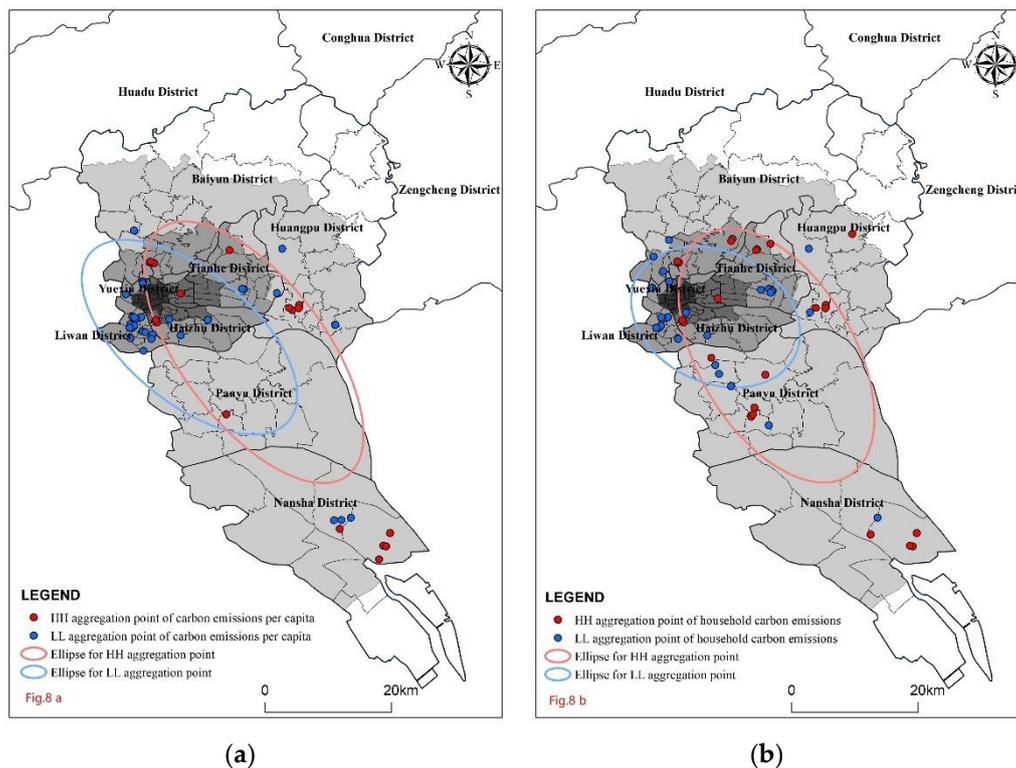
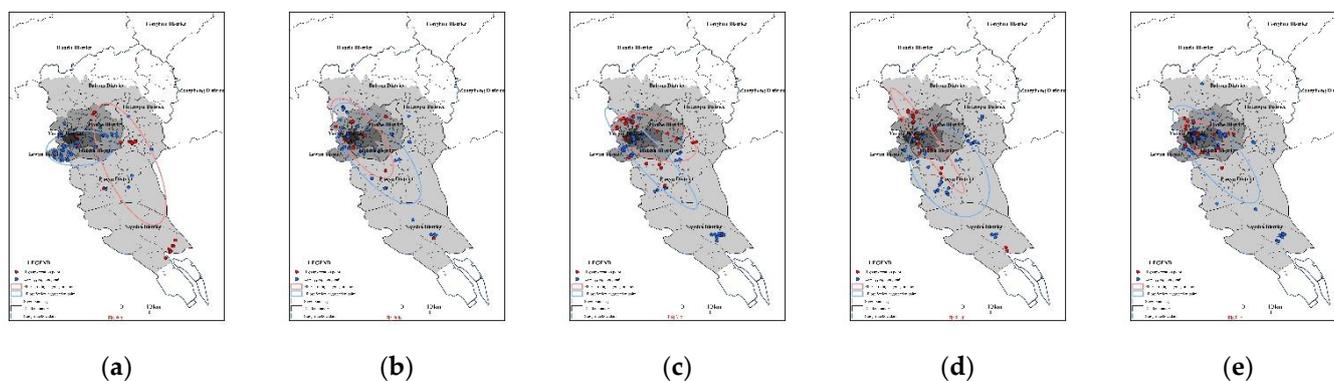


Figure 8. The SDEs of carbon emissions in Guangzhou. (a) The standard deviation ellipses (SDEs) per capita. (b) The SDEs of carbon emissions household carbon emissions.

Table 7. Standard deviation ellipse parameters of total carbon emissions and per capita carbon emissions.

	Perimeter	Area	Length of X-axis	Length of Y-axis	Angle	Flatness of the Ellipse
Total carbon emissions (HH)	0.999708	0.069758	0.201052	0.110455	149.599478	0.450614766
Total carbon emissions (LL)	0.694436	0.037128	0.125961	0.093858	116.475692	0.254864601
Carbon emissions per capita (HH)	1.052959	0.07137	0.221484	0.102594	143.170724	0.53678821
Carbon emissions per capita (LL)	0.898379	0.053865	0.1856	0.09239	130.477083	0.502209052

More specifically, in Figure 9a,b, which shows the results of the SDE analysis of the standard deviation of carbon emissions from household equipment in Guangzhou, the distribution of the aggregations of low-value samples from kitchen equipment and lighting equipment almost covered the distribution of the aggregations of high-value samples; the aggregations were distributed in different directions, but they included both the old city and core areas. The results of the SDE analysis of the standard deviation of carbon emissions for types of equipment in Guangzhou are shown in Figure 9c–e. The ellipse of the high-value aggregation of samples and the ellipse of the low-value aggregation of samples for water heater equipment, large appliances and refrigeration equipment covered different ranges and directions. In addition, the direction and area of the SDE of the HH aggregation of water heating equipment were most similar to those of the HH zone of per capita carbon emissions, which is a result of the highest proportion of carbon emissions being caused by water heating equipment and the large variation in carbon emission values among the HH samples. The pattern of carbon emissions from water heating equipment determines the pattern of carbon emissions from total domestic energy use. In terms of the shapes of the ellipses, both the HH zone for large appliances and the LL zone for refrigeration equipment had a “pike” shape, which indicates that the distributions of these zones had less concentrated centers of gravity, while the distributions of the HH zones for lighting equipment and the LL zone for water heaters had more concentrated centers of gravity and therefore smaller areas.

**Figure 9.** The standard deviation ellipses for carbon emissions from equipment in Guangzhou: (a) water heating equipment; (b) kitchen equipment; (c) refrigeration equipment; (d) large household appliances; (e) lighting equipment.

5. Discussion

After analyzing the structure, spatial distribution and drivers of carbon emissions from urban households at the community scale based on field data from Guangzhou, we attempt to explain the influencing factors behind these phenomena:

(1) Economic factors

According to the distribution of samples, samples with a higher total household income (>CNY 100,000) accounted for a higher number of the samples in the HH aggregation of carbon emissions per capita, with 66.67% of the sample households having an income above CNY 100,000 and only 15.15% of the sample households having an income below CNY 50,000. Based on our experience in Guangzhou, there are two main reasons for this

finding: On the one hand, the increase in income has led to a higher demand for energy use in households in addition to meeting basic energy needs. On the other hand, differences in household economic levels lead to variation in the extent to which households pay attention to the amount of energy consumed in the home. Households with lower incomes are more concerned about energy expenditure and tend to conserve energy, often cutting off the power supply after using electrical equipment. In contrast, as income increases, the proportion of household energy consumption to household income decreases, and concern for household energy savings decreases, a finding that is generally consistent with previous results [38]. In addition, with housing being a part of the economic attributes of a household, studies have found that an increase in house size may lead to an increase in the level of carbon emissions per capita. Among the samples with a high concentration of carbon emissions per capita, the number of samples with a housing area above 70 square meters is greater than the number of samples with smaller housing areas, with 57.58% of the samples having housing areas greater than 70 square meters and only 15.15% of the samples having housing areas of less than 50 square meters. These findings prove that the larger a dwelling is, the higher the demand for cooling and heating will be, with a corresponding increase in electricity-consuming equipment leading to a higher energy demand [39,40]. In addition, Estiri [41] proved that household characteristics affect energy consumption simultaneously due to their direct impact on energy behaviors. This study further explored the factors related to economic conditions and found that the samples from urban villages in which residential areas are located had lower levels of carbon emissions per capita than the samples located in the city center; among the samples with high concentrations of carbon emissions per capita, the number of samples from urban villages was only 1/5 of the number of samples from the city center. This view is also supported by Ling, Li and Xing [42].

(2) Sociocultural factors

The study found that Lingnan culture has a significant impact on household energy consumption in Guangzhou. First, the traditional “soup-making” culture, which is unique to the Lingnan region, has a significant impact on energy consumption, leading to high carbon emissions from kitchen equipment and water heating equipment. Field research found that the frequency of soup making in Guangzhou, especially in Guangzhou households, is more than four times a week, and the time spent making soup is approximately 45 minutes or more each time; thus, the consumption of energy by kitchen equipment is higher in Guangzhou than in other regions. Brouwer’s research also showed that local climatic conditions can also affect household energy consumption [43]. Second, the attributes of the households and residents in different administrative districts led to different carbon emission characteristics. According to the statistics, the number of household samples with high per capita carbon emissions from Guangzhou was greater than the number of household samples with high per capita carbon emissions from other cities of Guangdong Province, which was followed by the number of household samples outside Guangdong Province; a total of 96.97% of the samples in the HH area of per capita carbon emissions belong to households in Guangdong Province, among which 75% are located in Guangzhou. According to the results of the field research, residents of the old urban areas and the core area tend to have households registered in Guangzhou and own their own property; therefore, they do not worry about rent and other costs that tenants have, which leads to a significant difference in their energy consumption and carbon emissions. Simanaviciene, Dirma and Simanavicius [44] also found that changing routine behavior of a community or a group will have an effect on energy consumption. In addition, the length of residence in Guangzhou may affect the level of carbon emissions per capita, with longer residence durations being associated with higher levels of carbon emissions. In the HH aggregation zone of per capita carbon emissions, 87.88% of the residents sampled had lived in Guangzhou for 5 years or more, while only 12.12% had lived there for less than 5 years, which also indicates that long-term residents are more likely than short-term residents to be influenced by the Lingnan food culture.

(3) Architectural character factors

The timing of house construction (i.e., age of the building) is very indicative of the samples in the HH zones of per capita carbon emissions. A total of 63.64% of the samples from HH aggregations were built over 10 years ago, with 23.81% of the samples being 20 years old or older and only 15.15% of the samples being less than 5 years old. Different construction standards applied to houses built in different eras may affect household energy consumption levels [45]; in the future, houses built under the new standards will be more energy-efficient than those built under the old construction standards. The type of housing also has an impact on household energy consumption. The higher the ratio of new standard homes is, the lower the domestic energy consumption [46]. In fact, the residential area of Guangzhou in 2000 amounted to 79,520,500 square meters; however, due to many factors, such as the levels of awareness, structural development and economic development at that time, residential buildings constructed around 2000 were less likely to adopt energy-saving measures, and most of them consume high levels of energy [47], resulting in high overall energy consumption.

6. Conclusions

In this paper, we first combed through our research data to estimate household energy consumption based on factors such as the power and hours of use of different devices, and later we calculated their carbon emissions. The relevant influencing factors were explored through spatial autocorrelation and standard deviation ellipsoid methods of analysis. We came to the following conclusions:

- (1) The average household carbon emission in Guangzhou amounted to 15.31 kg/day, and the per capita carbon emission was 4.49 kg/day. The main sources of energy consumption in Guangzhou households were water heating equipment, kitchen equipment and refrigeration equipment. Unlike other cities, water heaters account for the largest share of household energy consumption in Guangzhou, and carbon emissions from water heaters are the main drivers of the spatial pattern of carbon emissions per capita in the city.
- (2) There is a clear spatial heterogeneity in carbon emissions from household domestic energy use in Guangzhou. The aggregations of samples with high levels of carbon emissions were mainly created by Guangzhou households with high incomes and relatively large living areas. Moreover, the carbon emissions from Guangzhou's household domestic energy consumption were globally spatially autocorrelated, while local areas also had high-low and low-high clusters, indicating that carbon emissions from household domestic energy consumption are a complex issue with dynamic spatial patterns.
- (3) Economic factors, sociocultural factors and the level of building decarbonization were the main drivers of the spatial characterization of household energy consumption and carbon emissions. Along with the overall increase in income and the pursuit of quality of life, the demand for household energy consumption will grow further in the future, especially in areas such as cooling and hot water needs.

The effects of global warming are increasing, leading to an increase in the demand for household energy and posing a challenge to achieving carbon neutrality targets. Based on the findings of this paper, we recommended that policies be optimized according to the energy needs of people in different regions to reduce carbon emissions from household energy consumption. In the central part of the city, the demands of urban residents for energy for water heaters and refrigeration due to rising living standards are likely to increase, as are the demands for energy due to the food-based culture and the possible temperature increases due to global climate change. Therefore, it is important that households in the central part of the city be guided to transition to low-carbon energy sources such as solar energy and natural gas through the promotion of energy efficiency and the introduction of clean energy for residents. In addition, stronger promotion of energy-efficient equipment, such as water heaters, refrigeration and cooking equipment, is recommended, thus reducing carbon

emissions from direct household energy consumption. In other areas, particularly urban villages and urban border areas, the focus should be on addressing the issue of inadequate energy use. Migrant populations play an important role in the economic development of large cities, and they often have less capacity to consume energy. We need to focus on the cooling and hot water needs of this group to meet their basic energy consumption needs and achieve equity in urban energy use. In addition, as building type has a significant impact on residential energy consumption, low-carbon standards for energy efficiency and energy consumption in new buildings should be improved in the future, and the transition of existing buildings to low-carbon structures should be prioritized.

Even though we were able to arrive at conclusions that were fairly good for the purpose of the study, we should admit that a single city study may not be enough to reflect the situation of the whole country, nor to make appropriate national policy recommendations tailored to local conditions. Therefore, we plan to carry out further research in central, western and northeast China in accordance with carbon neutrality goals, to study the relationship between household energy consumption, carbon emissions and the economy in the megacities, and finally form systematic and reliable national recommendations in the future.

Author Contributions: Conceptualization, L.J. and C.L.; methodology, B.D. and X.S.; software, B.D.; validation, L.J., B.D. and X.S.; formal analysis, B.D. and X.S.; investigation, L.J. and Y.C.; resources, L.J.; data curation, L.J.; writing—original draft preparation, B.D. and X.S.; writing—review and editing, L.J., B.D. and X.S.; visualization, B.D.; supervision, L.J.; project administration, L.J.; funding acquisition, L.J. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by the National Natural Science Foundation of China (42001130), the National Natural Science Foundation of Qinghai Province (2022-ZJ-937Q), and GDAS' Project of Science and Technology Development (2021GDASYL-20210103002).

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Informed consent was obtained from all subjects involved in the study.

Data Availability Statement: Not applicable.

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

References

1. IEA. *World Energy Balances 2018*; International Energy Agency: Paris, France, 2018. [CrossRef]
2. Mi, Z.; Zheng, J.; Meng, J.; Ou, J.; Hubacek, K.; Liu, Z.; Coffman, D.M.; Stern, N.; Liang, S.; Wei, Y.-M. Economic development and converging household carbon footprints in China. *Nat. Sustain.* **2020**, *3*, 529–537. [CrossRef]
3. Committee TCC. Central People's Government of the People's Republic of China. 2021. Available online: <http://openstd.samr.gov.cn/bz/gk/gb/newGbInfo?hcn=53D1440B68E6D50B8BA0CCAB619B6B3E> (accessed on 1 February 2022).
4. Liu, J.; Murshed, M.; Chen, F.; Shahbaz, M.; Kirikkaleli, D.; Khan, Z. An empirical analysis of the household consumption-induced carbon emissions in China. *Sustain. Prod. Consum.* **2021**, *26*, 943–957. [CrossRef]
5. Yang, Z.; Fan, Y.; Zheng, S. Determinants of household carbon emissions: Pathway toward eco-community in Beijing. *Habitat Int.* **2016**, *57*, 175–186. [CrossRef]
6. Xie, L.; Yan, H.; Zhang, S.; Wei, C. Does urbanization increase residential energy use? Evidence from the Chinese residential energy consumption survey 2012. *China Econ. Rev.* **2020**, *59*, 101374. [CrossRef]
7. Sun, C.; Ouyang, X.; Cai, H.; Luo, Z.; Li, A. Household pathway selection of energy consumption during urbanization process in China. *Energy Convers. Manag.* **2014**, *84*, 295–304. [CrossRef]
8. Li, S.-m.; Hou, Q.; Chen, S.; Zhou, C. Work, home, and market: The social transformation of housing space in Guangzhou, China. *Urban Geogr.* **2010**, *31*, 434–452. [CrossRef]
9. Jiang, L.; Xing, R.; Chen, X.; Xue, B. A survey-based investigation of greenhouse gas and pollutant emissions from household energy consumption in the Qinghai-Tibet Plateau of China. *Energy Build.* **2021**, *235*, 110753. [CrossRef]
10. Zheng, X.; Wei, C.; Qin, P.; Guo, J.; Yu, Y.; Song, F.; Chen, Z. Characteristics of residential energy consumption in China: Findings from a household survey. *Energy Policy* **2014**, *75*, 126–135. [CrossRef]
11. Wang, X.H.; Li, K.Q.; Li, H.; Bai, D.; Liu, J.R. Research on China's rural household energy consumption—Household investigation of typical counties in 8 economic zones. *Renew. Sustain. Energy Rev.* **2017**, *68*, 28–32. [CrossRef]

12. Gao, B.; Yuan, H.L.; Geng, L.W.; Tang, J. Analysis on rural household energy consumption in Hebei province. In Proceedings of the 5th International Conference on Energy and Environmental Protection (ICEEP), Shenzhen, China, 17–18 September 2016; pp. 501–504.
13. Jiang, L.; Yu, L.; Xue, B.; Chen, X.; Mi, Z. Who is energy poor? Evidence from the least developed regions in China. *Energy Policy* **2020**, *137*, 111122. [[CrossRef](#)]
14. Sun, M.; Chen, G.; Xu, X.; Zhang, L.; Hubacek, K.; Wang, Y. Reducing Carbon Footprint Inequality of Household Consumption in Rural Areas: Analysis from Five Representative Provinces in China. *Environ. Sci. Technol.* **2021**, *55*, 11511–11520. [[CrossRef](#)] [[PubMed](#)]
15. Mashhoodi, B. Spatial dynamics of household energy consumption and local drivers in Randstad, Netherlands. *Appl. Geogr.* **2018**, *91*, 123–130. [[CrossRef](#)]
16. Jones, P.H.; Taylor, N.W.; Jennison Kipp, M.; Knowles, H.S. Quantifying household energy performance using annual community baselines. *Int. J. Energy Sect. Manag.* **2010**, *4*, 593–613. [[CrossRef](#)]
17. Yuan, R.; Rodrigues, J.F.D.; Behrens, P. Driving forces of household carbon emissions in China: A spatial decomposition analysis. *J. Clean. Prod.* **2019**, *233*, 932–945. [[CrossRef](#)]
18. Wang, X.H.; Feng, Z.M. Common factors and major characteristics of household energy consumption in comparatively well-off rural China. *Renew. Sustain. Energy Rev.* **2003**, *7*, 545–552. [[CrossRef](#)]
19. Jin, J.; He, R.; Kuang, F.; Wan, X.; Ning, J. Different sources of rural household energy consumption and influencing factors in Dazu, China. *Environ. Sci. Pollut. Res.* **2019**, *26*, 21312–21320. [[CrossRef](#)]
20. De Lauretis, S.; Ghersi, F.; Cayla, J.M. Energy consumption and activity patterns: An analysis extended to total time and energy use for French households. *Appl. Energy* **2017**, *206*, 634–648. [[CrossRef](#)]
21. Li, J.; Zhang, J.; Zhang, D.; Ji, Q. Does gender inequality affect household green consumption behaviour in China? *Energy Policy* **2019**, *135*, 111071. [[CrossRef](#)]
22. Moshiri, S. The effects of the energy price reform on households consumption in Iran. *Energy Policy* **2015**, *79*, 177–188. [[CrossRef](#)]
23. Yang, T.; Liu, W. Inequality of household carbon emissions and its influencing factors: Case study of urban China. *Habitat Int.* **2017**, *70*, 61–71. [[CrossRef](#)]
24. Ping, X.; Li, C.; Jiang, Z. Household energy consumption patterns in agricultural zone, pastoral zone and agro-pastoral transitional zone in eastern part of Qinghai-Tibet Plateau. *Biomass Bioenergy* **2013**, *58*, 1–9. [[CrossRef](#)]
25. Li, J.; Huang, X.; Yang, H.; Chuai, X.; Li, Y.; Qu, J.; Zhang, Z. Situation and determinants of household carbon emissions in Northwest China. *Habitat Int.* **2016**, *51*, 178–187. [[CrossRef](#)]
26. Xiong, X.; Zhang, L.; Hao, Y.; Zhang, P.; Shi, Z.; Zhang, T. How urbanization and ecological conditions affect urban diet-linked GHG emissions: New evidence from China. *Resour. Conserv. Recycl.* **2022**, *176*, 105903. [[CrossRef](#)]
27. Guangzhou Municipal Statistics Bureau. *Guangzhou Statistical Yearbook*; China Statistics Press: Beijing, China, 2020.
28. Guangzhou Municipal Statistics Bureau. *Guangdong Provincial Bureau of Statistics. Guangdong Provincial National Economic and Social Development Statistical Bulletin*; China Statistics Press: Beijing, China, 2020.
29. Wang, Y.; Yue, X.; Zhang, H.o.; Su, Y.; Qin, J. Relationship between Urban Floating Population Distribution and Livability Environment: Evidence from Guangzhou’s Urban District, China. *Sustainability* **2021**, *13*, 13477. [[CrossRef](#)]
30. MINISTRY OF ECOLOGY AND ENVIRONMENT THE PEOPLE’S REPUBLIC OF CHINA. Baseline Emission Factors of China’s Regional Power Grids for Emission Reduction Projects in 2019. 2019. Available online: https://www.mee.gov.cn/ywgz/ydqhbh/wsqtgz/202012/t20201229_815386.shtml (accessed on 29 December 2020).
31. Wu, S.; Zheng, X.; Wei, C. Measurement of inequality using household energy consumption data in rural China. *Nat. Energy* **2017**, *2*, 795–803. [[CrossRef](#)]
32. General Rules for Calculation of the Comprehensive Energy Consumption. GB/T 2589-2020. Standardization Administration of the P.R.C.: Beijing, China, 2020.
33. Shan, Y.; Huang, Q.; Guan, D.; Hubacek, K. China CO₂ emission accounts 2016–2017. *Sci. Data* **2020**, *7*, 465–474. [[CrossRef](#)]
34. Cheng, Y.; Wang, Z.; Ye, X.; Wei, Y.D. Spatiotemporal dynamics of carbon intensity from energy consumption in China. *J. Geogr. Sci.* **2014**, *24*, 631–650. [[CrossRef](#)]
35. Lefever, D.W. Measuring geographic concentration by means of the standard deviational ellipse. *Am. J. Sociol.* **1926**, *32*, 88–94. [[CrossRef](#)]
36. Yu, H.; Tang, B.-J.; Yuan, X.-C.; Wang, S.; Wei, Y.-M. How do the appliance energy standards work in China? Evidence from room air conditioners. *Energy Build.* **2015**, *86*, 833–840. [[CrossRef](#)]
37. Martin Arrieta, E.; Daniel Gonzalez, A. Energy and carbon footprints of food: Investigating the effect of cooking. *Sustain. Prod. Consum.* **2019**, *19*, 44–52. [[CrossRef](#)]
38. Golley, J.; Meng, X. Income inequality and carbon dioxide emissions: The case of Chinese urban households. *Energy Econ.* **2012**, *34*, 1864–1872. [[CrossRef](#)]
39. Min, J.; Hausfather, Z.; Lin, Q.F. A high-resolution statistical model of residential energy end use characteristics for the United States. *J. Ind. Ecol.* **2010**, *14*, 791–807. [[CrossRef](#)]
40. Karatasou, S.; Santamouris, M. Socio-economic status and residential energy consumption: A latent variable approach. *Energy Build.* **2019**, *198*, 100–105. [[CrossRef](#)]

41. Estiri, H. Building and household X-factors and energy consumption at the residential sector A structural equation analysis of the effects of household and building characteristics on the annual energy consumption of US residential buildings. *Energy Econ.* **2014**, *43*, 178–184. [[CrossRef](#)]
42. Ling, J.H.; Li, Q.; Xing, J.C. The influence of apartment location on household space heating consumption in multi-apartment buildings. *Energy Build.* **2015**, *103*, 185–197. [[CrossRef](#)]
43. Brouwer, I.D.; Wijnhoven, T.M.A.; Burema, J.; Hoorweg, J.C. Household fuel use and food consumption: Relationship and seasonal effects in central Malawi. *Ecol. Food Nutr.* **1996**, *35*, 179–193. [[CrossRef](#)]
44. Simanaviciene, Z.; Dirma, V.; Simanavicius, A. Psychological factors influence on energy efficiency in households. *Oecon. Copernic.* **2017**, *8*, 681–694. [[CrossRef](#)]
45. Song, Q.; Duan, H.; Yu, D.; Li, J.; Wang, C.; Zuo, J. Characterizing the essential materials and energy performance of city buildings: A case study of Macau. *J. Clean. Prod.* **2018**, *194*, 263–276. [[CrossRef](#)]
46. Wang, J.; Yi, F.; Zhong, Z.; Qiu, Z.; Yu, B. Diversity and causality of university students' energy-conservation behavior: Evidence in hot summer and warm winter area of China. *J. Clean. Prod.* **2021**, *326*, 129352. [[CrossRef](#)]
47. Zhan, J.; Liu, W.; Wu, F.; Li, Z.; Wang, C. Life cycle energy consumption and greenhouse gas emissions of urban residential buildings in Guangzhou city. *J. Clean. Prod.* **2018**, *194*, 318–326. [[CrossRef](#)]