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Spatial Variations and Determinants of Per Capita Household CO_2 Emissions (PHCEs) in China

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Abstract: In China, household CO_2 emissions (HCEs) are increasing due to economic development and accelerated urbanization. This paper details the spatial variations of per capita household CO_2 emissions (PHCEs) in China and the factors impacting PHCEs using spatial statistical analysis and a spatial panel data model for the period from 1997 to 2014. Our results indicate that (1) there has been high provincial variation in rates of change across China, with some provinces' PHCEs increasing by an order of magnitude from 1997 to 2014; (2) the Global Moran's I of PHCEs are above 0, and the spatial differences between PHCEs are caused by the High-High cluster and Low-Low cluster in China; (3) a 1% increase of per capita income, education level, and urbanization will result in increases in PHCEs of 0.6990%, 0.0149%, and 0.0044%, respectively, whilst a 1% increase in household size will result in a 0.0496% decrease in PHCEs. There are a large number of factors impacting CO_2 emissions, while there is little specific guidance on the spatial variations and provincial characteristics of CO_2 emissions from the perspective of household consumption.

Keywords: per capita household CO_2 emissions (PHCEs); panel data model; spatial variations; determinants; China

1. Introduction

Global climate change is primarily caused by anthropogenic greenhouse gas emissions, particularly CO_2 emissions [1,2]. China is currently the largest CO_2 emitter in the world and continues to have rapid growth in CO_2 emissions [3]. Facing fast-growing CO_2 emissions, the Chinese government established a goal of reducing its carbon intensity to 40% to 50% of 2005 levels by 2020 at the Copenhagen Climate Conference in 2009 and vowed to reach its carbon emissions peak circa 2030 and make efforts to peak early during the APEC (Asia-Pacific Economic Cooperation) Summit in 2014. While many of these emissions can be attributed to household energy usage, household consumption will account for a rising portion of emissions in the coming decades as living standards improve [4–6]. Early evaluations of carbon emission reduction efforts focused on the industrial sector and evaluated CO_2 emissions from fossil fuels, but, recently, researchers have turned to studies of CO_2 emissions from household consumption [4,6–11], with per capita household CO_2 emissions (PHCEs) being an important point for climate change mitigation efforts in the future [12].

Previous studies of household CO_2 emissions (HCEs) can be divided into three phases. During the initial phase (1990 to 2000), scholars focused on analyzing carbon emissions from residential uses [13–15]. The second phase (2001 to 2010) featured the development of a variety of assessment methods for carbon emissions from household consumption, including the Consumer Lifestyle Approach [16,17], the IPCC Reference Approach (IPCC Reference Approach for estimating CO_2 emissions) [1,18], and Input-output analysis [19,20]. In addition, household CO_2 emissions were divided into direct and indirect carbon emissions for the purpose of analysis [16,17,20]. The third phase (2011 to the present) has seen the focus shift to the analysis of factors influencing household CO_2 emissions and measures to reduce CO_2 emissions.

Studies of factors influencing HCEs have used a variety of approaches, including Logarithmic Mean Divisia Index (LMDI) models [21–23], Stochastic Impacts by Regression on Population, Affluence and Technology (STIRPAT) models [24,25], shapley decomposition [26], Structural Decomposition Analysis (SDA) models [27], self-organizing feature map (SOFM) models [28], the Adaptive Weighting Divisia (AWD) method [29], and multivariate analysis [30]. Although many scholars have explored how household carbon emissions and the factors influencing their variation vary across time, few have explored the spatial variations of PHCEs and their influencing factors. This paper contributes to the understanding of the factors influencing PHCEs by evaluating spatial patterns.

In China, there is a rich source of literature on the spatial analysis of CO_2 emissions from energy consumption [31–33]. Based on Chinese provincial energy consumption data, Chuai et al. [31] identified an increasing trend in the global spatial autocorrelation in carbon emissions. Similarly, for carbon intensity, a growing spatial agglomeration based on Moran's I has been identified [32]. However, energy usage and CO_2 emissions from the household sector accounted for 27% and 17%, respectively, of total global emissions [34]. In China, estimates of CO_2 emissions from households range from 35% [6] to 40% [4] of total emissions. To develop national and regional carbon reduction targets for the future, it is essential to analyze the factors influencing household CO_2 emissions for residents in China by using a spatial perspective.

Recently, the relationship between CO_2 emissions and the related influencing factors have been analyzed using spatial panel data models at the global level [35–39], national level [40,41], and provincial level [42–45]. There are numerous advantages to spatial panel data models, including improved efficiency with increasing degrees of freedom, the capability of controlling individual heterogeneity, and reduced the effects of collinearity among different variables [46]. Spatial panel data analysis has been used to examine the factors influencing carbon emissions both in spatial and temporal dimensions. For example, the relationship between economic development and CO_2 emissions was investigated by Du et al. [42], and the relationship between urbanization, energy consumption, and carbon emissions was examined by Wang et al. [43]. Many factors affected CO_2 emissions, including population, economic factors, and social variables. This study investigates the impacts of population, economic development, and technology on China's PHCEs by constructing different forms of spatial panel data models, including pooled regression models and variable intercepts models with both constant and variable coefficients.

In this study, we compare PHCEs at the provincial level in China and their related influencing factors (e.g., population, economic status, and technology) using a spatial panel data model. The paper asks two questions. (1) What is the current distribution of PHCEs in China? We answer this through the spatial analysis of a data set of provincial level PHCEs using measures of both global and local spatial autocorrelation. (2) What factors have influenced this distribution of PHCEs? We answer this question through use of a panel model to estimate the effects of factors likely to influence PHCEs.

The remainder of this article is organized as follows. Section 2 presents the data sources and analytical methods. Section 3 evaluates the spatial distribution of PHCEs and discusses the influencing factors based on a spatial panel data method. Finally, in Section 4, we offer some conclusions and give primary policy recommendations related to PHCEs.

2. Research Methods and Data Sources

2.1. Estimation of PHCEs

PCHEs can be divided into six parts in this work: coal, oil, gas, other fuels, electricity, heating, and household consumption. Household CO_2 emissions from coal, oil, gas, and other fuels are calculated based on the IPCC reference approach [1]. Household CO_2 emissions from electricity and heating are calculated following the IPCC Reference Approach [1] and the National Development and Reform Commission (NDRC) [47]. This follows a 'twelfth five-year' control scheme for greenhouse gas emissions and includes the first ten industries in greenhouse gas emission accounting methods and reporting guidelines [47]. Household CO_2 emissions from other household consumption are calculated by (1) Input-output analysis, which is similar to Bin and Dowlatabadi [16] and Wei et al. [17], and (2) the Consumer Lifestyle Approach, following Liu et al. [4], Zhu et al. [5], and Qu et al. [8,9]. In this work, we calculate the total amount of household CO_2 emissions in China based on the provincial unit. The formula of calculating PHCEs in each province is shown below:

$$E_T = E_{Coal} + E_{Oil} + E_{Gas} + E_{Other} + E_{Elec} + E_{Heat} + E_{HC} \tag{1}$$

where E_T is the total amount of household CO_2 emissions in each Chinese province (t CO_2); E_{Coal} is the total amount of household CO_2 emissions from coal usage (t CO_2); E_{Oil} is the total amount of household CO_2 emissions from oil usage (t CO_2); E_{Gas} is the total amount of household CO_2 emissions from gas usage (t CO_2); E_{Other} is the total amount of household CO_2 emissions from the use of other fuels (t CO_2); E_{Elec} is the total amount of household CO_2 emissions from electricity usage (t CO_2); E_{Heat} is the total amount of household CO_2 emissions from heating (heating usage in this study is the centralized heating usage in urban China; meanwhile, the centralized heating usage equals zero in rural China) (t CO_2); and E_{HC} is the total amount of household CO_2 emissions from household consumption (t CO_2).

$$E_{Coal} + E_{Oil} + E_{Gas} + E_{Other} = \sum_{i=1} F_i \times NCV_i \times CC_i \times OF_i \times \frac{44}{12} \tag{2}$$

where F_i denotes the fuel consumption of the average household (10^4 t/10^8 m^3) (i = coal, oil, gas, and other fossil fuels); NCV_i is the Net Calorific Value of the i^{th} fuel (TJ/10^4 t/10^8 m^3); CC_i denotes the Carbon Emission Factor of the i^{th} fuel (t C/TJ); OF_i expresses the fraction of carbon oxidized for the i^{th} fuel; and *44/12* is the ratio of molecular weight of CO_2/C.

$$E_{Elec} + E_{Heat} = F_{\mathrm{Elec}} \times C_{\mathrm{Elec}} + F_{\mathrm{Heat}} \times C_{\mathrm{Heat}} \tag{3}$$

where F_{Elec} is the electric power consumption (MWh); C_{Elec} is the CO_2 emission factor of the electricity sector (t CO_2/MWh) from different provinces in 2010, which comes from the Baseline Emission Factor for provincial power grids in China [48]; F_{Heat} (GJ) is the heating power consumption; and C_{Heat} is the CO_2 emissions factor of the heating sector (t CO_2/GJ), which is derived from the NDRC [47].

$$E_{HC} = \sum_{j=1} F_{HC} \times C_{HC} = \sum_{j=1}^{j=n} \left(\frac{E_j}{P_j} \times (I - A) - 1 \times F_{Ij}\right) \tag{4}$$

where $C_{HC} = C_{Dj}(I - A)^{-1}$ and $C_{Dj} = E_j/P_j$, F_{Ij} is the consumption of the household (10^4 RMB); C_{HC} is the CO_2 emissions factor from household consumption (t CO_2/10^4 RMB); j is the household consumption category (i.e., food, clothing, residence, household equipment, transportation and communication, cultural and educational entertainment, medical care, and other goods); C_{Dj} is the direct energy carbon emissions intensity from the j^{th} category (t CO_2/10^4 RMB); E_j is the direct energy carbon emissions from the j^{th} category (t CO_2, E_j is calculated based on Equation (2); P_j is the total output value of the j^{th} category (10^4 RMB); A is the direct requirement matrix; I is the identity matrix; and $(I - A)^{-1}$ is Leontief inverse square matrix.

$$\text{PHCEs} = \frac{E_T}{P} \tag{5}$$

where *PHCEs* is the per capita household CO_2 emissions (t CO_2/person) and P is the population size of each province in China.

2.2. The Spatial Statistical Analysis

2.2.1. Global Spatial Autocorrelation

Spatial autocorrelation and spatial regression analyses have long been employed in studies of energy consumption and the related carbon emissions [31–33]. In this study, changing trends in regional spatial patterns of PHCEs are evaluated by Global Moran's I and Local Indicators of Spatial Association (LISA) by using ArcGIS10.3 and GeoDa software, respectively.

The formulas of Global Moran's I are shown below [49]:

$$I = \frac{n\sum_{i=1}^{n}\sum_{j\neq i}^{n} w_{ij}(x_i-\overline{x})(x_j-\overline{x})}{\sum_{i=1}^{n}\sum_{j\neq i}^{n} w_{ij}\sum_{i=1}^{n}(x_i-\overline{x})^2} = \frac{\sum_{i=1}^{n}\sum_{j\neq i}^{n} w_{ij}(x_i-\overline{x})(x_j-\overline{x})}{S^2\sum_{i=1}^{n}\sum_{j\neq i}^{n} w_{ij}} \tag{6}$$

where $S^2 = \frac{1}{n}\sum_i (x_i-\overline{x})^2$; n is the total number of provinces; x_i and x_j are the household carbon emissions of the i^{th} and j^{th} provinces, respectively; $\overline{x}$ is the average of all observational values; and w_{ij} is the spatial weight matrix. In this study, we use the z value as Moran's I statistic test, calculated as $z = (I - E(I))/\sqrt{var(I)}$.

The Global Moran's I measures the degree of global spatial autocorrelation for PHCEs in China, with values ranging between −1 and 1. Spatial autocorrelation is positive if the value is > 0, indicating more agglomeration, and negative for values < 0, indicating more scattered data. There is no spatial autocorrelation when the value is equal to 0 [49].

2.2.2. Cluster and Outlier Analysis

In addition to global spatial autocorrelation, this article examines the Local Indicators of Spatial Association (LISA) [49], expressed as:

$$I_i = \frac{(x_i-\overline{x})}{S^2}\sum_{j\neq i}^{n} w_{ij}(x_i-\overline{x}) \tag{7}$$

where $S^2 = \frac{1}{n}\sum_i (x_i-\overline{x})^2$ and $z_i = (I_i - E(I_i))/\sqrt{var(I_i)}$.

LISA makes every local spatial unit a target item, which indicates the presence or absence of significant spatial clusters or outliers for every local spatial pattern. The Moran scatterplot can identify relationships between a local province and its adjacent provinces. By composing four quadrants [49], the upper right quadrant, termed High-High (H-H), and the lower left quadrant, termed Low-Low (L-L), indicate that there is a conglomeration effect of high values and low values between the province and its adjacent provinces, respectively. The upper left quadrant, termed High-Low (H-L), and the lower right quadrant, termed Low-High (L-H), indicate that the province itself has a high value with low values in adjacent provinces and that the province itself has a low value with high values in adjacent provinces, respectively.

2.2.3. The Standard Deviational Ellipse

The Standard Deviational Ellipse (SDE) is a Geographic Information Systems (GIS) tool for delineating the dispersion of univariate features around its center [50], which was initially put forward by Lefever [51]. We use the SDE to calculate the gravity center of PHCEs in China following Lefever [51] and Zhao and Zhao [50]. The center of SDE is calculated as:

$$
\begin{aligned}
SDE_x &= \sqrt{\frac{\sum_{i=1}^{n}(x_i - \overline{X})}{n}} \\
SDE_y &= \sqrt{\frac{\sum_{i=1}^{n}(y_i - \overline{Y})}{n}} \\
\tan\theta &= \frac{\left(\sum_{i=1}^{n}\widetilde{x}_i^2 - \sum_{i=1}^{n}\widetilde{y}_i^2\right) + \sqrt{\left(\sum_{i=1}^{n}\widetilde{x}_i^2 - \sum_{i=1}^{n}\widetilde{y}_i^2\right)^2 + 4\left(\sum_{i=1}^{n}\widetilde{x}_i\widetilde{y}_i\right)^2}}{2\sum_{i=1}^{n}\widetilde{x}_i\widetilde{y}_i} \\
\delta_x &= \sqrt{2}\sqrt{\sum_{i=1}^{n}\frac{(\widetilde{x}_i\cos\theta - \widetilde{y}_i\sin\theta)^2}{n}} \\
\delta_y &= \sqrt{2}\sqrt{\sum_{i=1}^{n}\frac{(\widetilde{x}_i\sin\theta - \widetilde{y}_i\cos\theta)^2}{n}}
\end{aligned}
\tag{8}
$$

where x_i and y_i are the space coordinates of each feature; $\overline{X}$ and $\overline{Y}$ are the arithmetic average centers; SDE_x and SDE_y are the center of SDE; and θ, δ_x, and δ_y represent the angle of rotation, the length of X, and the length of Y of the SDE, respectively.

2.3. Spatial Panel Data Models

A spatial panel data analysis is used in this paper is to estimate the relationships between PHCEs and factors predicted to influence PHCEs. There are three types of panel data analytic models based on different parameters, as shown in Figure 1; pooled regression models ($y_{it} = a + bx_{it} + \varepsilon_{it}$), variable intercepts and constant coefficient models ($y_{it} = a_i + bx_{it} + \varepsilon_{it}$), and variable intercepts and variable coefficient models ($y_{it} = a_i + b_i x_{it} + \varepsilon_{it}$) [46]. In Figure 1, y_{it} is the index for the dependent variable; x_{it} is the index for the independent variable; a_i and b_i are expressed as fixed effects or random effects; and ε_{it} is the error term. Baltagi [46] has shown that the Hausman test is the most appropriate analytic to select the suitability of spatial panel data models. In this work, we use the Hausman test to decide which model is most suitable for analyzing the factors influencing PHCEs in China.

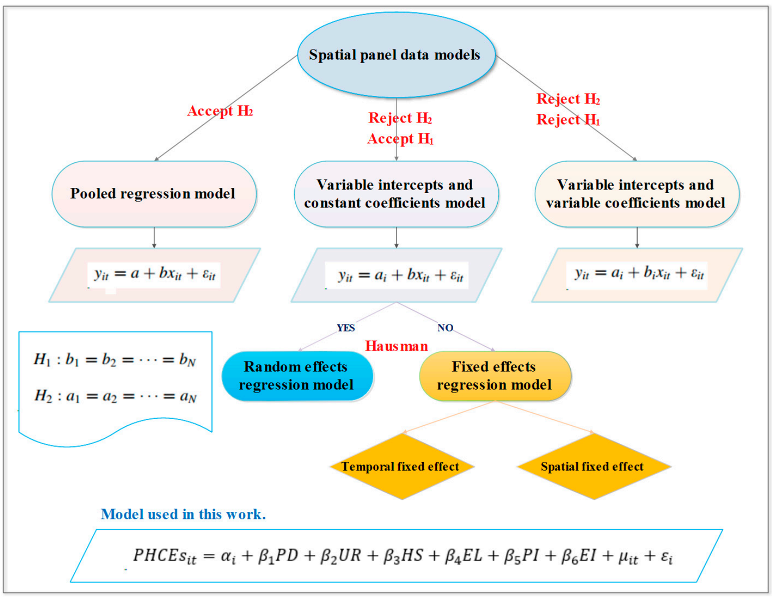

Figure 1. Flowchart of the methodology for the spatial panel data model.

Based on the Hausman test, two main hypotheses are used to confirm which specific model should be selected. The formulas are shown as below [46]:

$$H_1: \ b_1 = b_2 = \ \ldots \ = b_N$$

$$H_2: \ a_1 = a_2 = \ \ldots \ = a_N \quad b_1 = b_2 = \ \ldots \ = b_N$$

$$F_2 = \frac{(S_3 - S_1)/[(N-1)(k+1)]}{S_1/(NT - N(k+1))} \sim F[(N-1)(k+1), N(T-k-1)]$$

$$F_1 = \frac{(S_2 - S_1)/[(N-1)k]}{S_1/(NT - N(k+1))} \sim F[(N-1)k, N(T-k-1)] \quad (9)$$

where F_2 is the statistic for H_2; F_1 is the statistic for H_1; S_1, S_2, and S_3 are the residual sums of the squares of the three spatial panel data models above, respectively; and N, T, and k are the number of entities, time points, and explanatory variables, respectively.

Based on these two hypotheses, if H_2 is accepted, we should choose the pooled regression model. If H_2 is rejected but H_1 is accepted, we should choose the variable intercepts and constant coefficients model. If both H_2 and H_1 are rejected, we should choose the variable intercepts and variable coefficients model [46].

We selected a variety of variables that have been shown to be related to PHCEs in previous research for the spatial data model. Two variables were chosen to represent urbanization and population density, which in previous studies have been shown to influence PHCEs [8–11]. Population per km^2 (PD) was chosen to represent the average population density of a province. This is distinct from the rate of urbanization (UR) which represents the portion of the population living in urban areas. For example, Sichuan has a relatively high population density, while it has a moderate rate of urbanization. A final demographic variable that has been shown to influence PHCEs is average household size (HS) [8–11]. Per capita income (PI) was chosen as a metric of economic affluence [21], since personal income is likely to have the most direct impact on PHCEs, relative to other measures such as per capita GDP. Personal income data is also readily available for both urban and rural China, while GDP data is only available at the provincial level. Education has also been identified as an important factor influencing HCEs [8,9]; its effect has been debated. This effect appears to be independent of measures of relative wealth, which is often correlated with income. The relative level of technological development plays an important role in HCEs yet is difficult to define. We have chosen energy intensity (measures in t ce/10^4 RMB) to represent technological development [5].

The spatial panel data model used in this work is shown as follows:

$$PHCEs_{it} = \alpha_i + \beta_1 PD + \beta_2 UR + \beta_3 HS + \beta_4 EL + \beta_5 PI + \beta_6 EI + \mu_{it} + \varepsilon_i \quad (10)$$

where α_i represents the intercept for specifying cross-section fixed or period fixed effects; μ_{it} is the error term; and the factors influencing *PHCEs* are shown in Table 1.

Table 1. The factors influencing per capita household CO_2 emissions (PHCEs) in this work.

Variables	Implication	Interpretation	Unit	Sources
PHCEs	**Per capita household CO_2 emissions**	Total household CO_2 emissions/total population	t CO_2/person	Calculated by above formulas
PD	**Per km^2 areas population (Population density)**	Administrative area/total population	person/km^2	China Statistical Yearbooks (1998–2015)
UR	**Urbanization**	The proportion of urban population	%	China Statistical Yearbooks (1998–2015)
HS	**Household size**	Average person in each household	Person/household	China Population Statistical Yearbooks (1998–2015)

Table 1. *Cont.*

Variables	Implication	Interpretation	Unit	Sources
EL	**Education level**	The proportion of college educated people and/or higher educational level students in the population	%	China Statistical Yearbooks (1998–2015)
PI	**Per capita income**	Total income/total population	10^4RMB/person	China Statistical Yearbooks (1998–2015)
EI	**Energy intensity**	Total Energy usage/Total GDP	t ce/10^4RMB	China Statistical Yearbooks (1998–2015)

2.4. Data Sources

Annual data for household energy usage were obtained from the China Energy Statistical Yearbooks (1998 to 2015) [52]. Annual data for household consumption were obtained from the China Statistical Yearbooks (1998 to 2015) [53]. Data for calculating CO_2 emissions factors from household consumption were obtained from China's Input-Output tables (1999, 2007, 2009, 2015) [54], the extended input-output tables [53], and the China Energy Statistical Yearbooks (1998–2015). In addition, data for factors influencing PHCEs were obtained from the China Population Statistical Yearbooks (1998 to 2015) [55] and the China Statistical Yearbooks (1998 to 2015) [53]. To control for inflation, annual data for household consumption was indexed to the year 2005. Due to the lack of comparable data for the Taiwan, Hong Kong, and Macao Special Administrative Regions and the Tibet Autonomous Region, this work took no account of these regions.

3. Results and Discussions

3.1. Comparing PHCEs in China

Figure 2 illustrates the temporal-spatial evolution of China's PHCEs for each province in 1997, 2002, 2007, and 2014. The PHCEs of different provinces range from 0.60 t CO_2/person in 1997 to 6.18 t CO_2/person in 2014, differing by one order of magnitude. We classify the PHCEs of different provinces into five groups: lowest (less than 1.00 t CO_2/person), low (1.01–2.00 t CO_2/person), mid (2.01–3.00 t CO_2/person), high (3.01–4.00 t CO_2/person), and highest (more than 4 t CO_2/person). In 1997, all provinces' PHCEs were no more than 3.00 t CO_2/person; thus they were classified into the lowest three groups. Of these, 16 provinces were in the lowest-level PHCEs, including northwest China, central China and southeast China. The 12 provinces with low-level PHCEs were concentrated in northeast China, the Qinghai-Tibet area, the Bohai Sea Region, and the Yangtze River Delta Economic Zone. By 2014, PHCEs in all provinces were more than 1.00 t CO_2/person, constituting the top four groups. Only four provinces had low-level PHCEs in 2014, and these were among the poorest provinces: Gansu, Jiangxi, Guangxi, and Yunnan. The 16 provinces with mid-level PHCEs in 2014 were concentrated in the Qinghai-Tibet area, central China, and northern China. Six provinces that were either relatively wealthy (Guangdong, Fujian, Jiangsu) or had coal resources and a higher concentration of energy industries (Heilongjiang, Liaoning, and Inner Mongolia) had high-level PHCEs. Four of China's wealthiest provinces, Beijing, Shanghai, Tianjin, and Zhejiang, had the highest-level PHCEs.

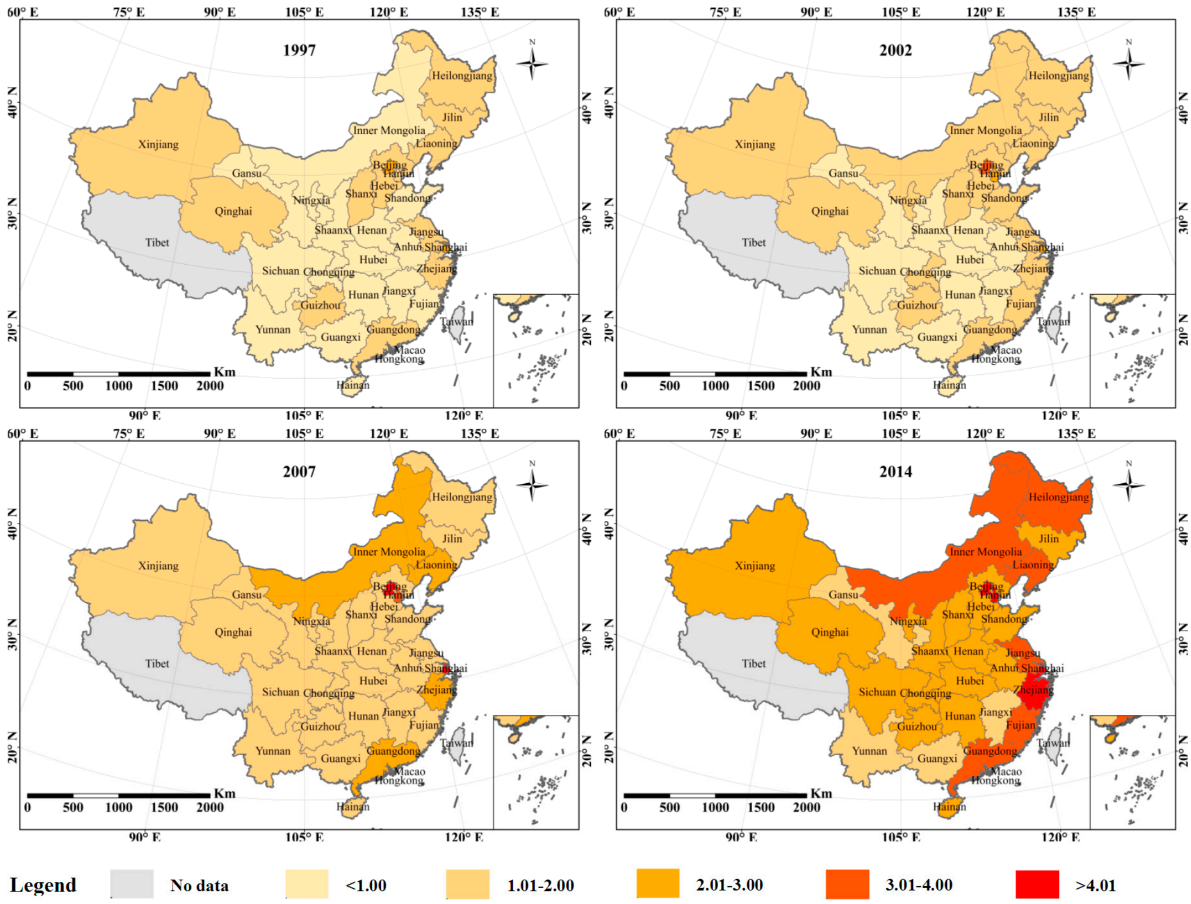

Figure 2. The distribution of China's total PHCEs in 1997, 2002, 2007, and 2014.

Figure 3 presents the increment and the increase rate of PHCEs from 1997 to 2014 for each province. All provinces' PHCEs increased by more than 1.00 t CO_2/person between 1997 and 2014. Twenty-two provinces had relatively low increases of PHCEs, from 1.00–2.00 t CO_2/person. These provinces were relatively poor and were found in China's southwest, northwest, and central regions. The two provinces with high increments of PHCEs, from 3.01 to 4.00 t CO_2/person, were the rich provinces, Shanghai and Beijing. However, patterns in the rates of increase are somewhat different. Thirteen provinces had low rates of increase in PHCEs by one to two times. These can be divided into two groups; (1) relatively wealthy provinces, including Guangdong, Beijing, Shanghai, and other provinces with large PHCEs but with low rates of increase, and (2) relatively poor provinces with both low PHCEs and low rates of increase. Seven provinces had PHCEs more than double from 1997 to 2014. These included provinces with low PHCEs but high rates of increase (e.g., Anhui and Hainan) and provinces with both relatively high PHCEs and rates of increase (e.g., Zhejiang, Shandong, and Inner Mongolia).

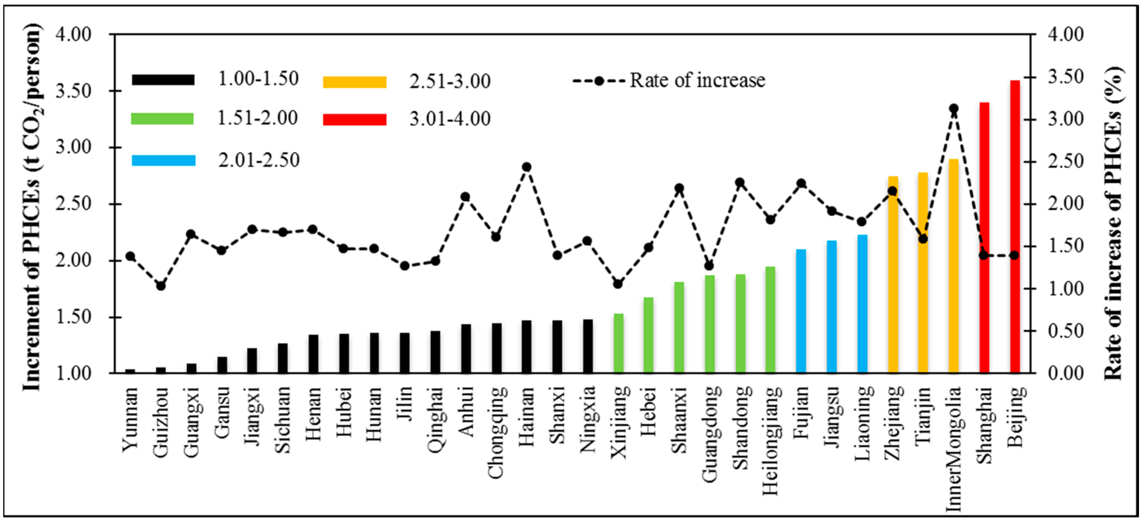

Figure 3. Increment and rate of increase of PHCEs in China from 1997 to 2014.

3.2. Spatial Evolution Analysis of PHCEs in China

3.2.1. Results of Global Spatial Autocorrelation

While a regional pattern is clear from our descriptive analysis, we quantified this correlation using Moran's I to evaluate the global spatial autocorrelation of PHCEs at the provincial level from 1997 to 2014. Table 2 shows that the Global Moran's I of PHCEs in China for all years was above 0, indicating spatial clustering, and all are significant at a 95% confidence interval level based on the Z test. While the values of Moran's I vary from year to year, over the study period, there was a general rising pattern from values in the low 0.2 range (0.22 in 1997) to the mid 0.3 range (0.37 in 2014). This pattern of increasing Moran's I was matched by increasing statistical significance levels, from the 95% confidence range in 1997 to greater than 99% confidence by 2014. This indicates that there is significant and rising spatial autocorrelation for PHCEs in China.

Table 2. Changes of the Global Moran's I of PHCEs in China (1997–2014).

Year	I	Z	P
1997	0.22	1.98	0.04
1998	0.24	2.12	0.03
1999	0.26	2.12	0.04
2000	0.28	2.27	0.03
2001	0.27	2.07	0.04
2002	0.28	2.29	0.03
2003	0.29	2.58	0.02
2004	0.25	2.12	0.03
2005	0.29	2.34	0.02
2006	0.32	2.62	0.02
2007	0.32	2.45	0.02
2008	0.34	2.51	0.02
2009	0.35	2.65	0.02
2010	0.34	2.54	0.01
2011	0.34	2.56	0.01
2012	0.33	2.53	0.02
2013	0.37	2.78	0.01
2014	0.37	2.81	0.01

3.2.2. Cluster and Outlier Analysis

We analyzed local spatial autocorrelation [31–33] using LISA for 1997, 2002, 2007, and 2014. Figure 4 reveals the characteristics of significant local spatial agglomeration in the distribution of PHCEs in China. Three significant patterns stand out. Firstly, the LL type of local spatial autocorrelation, which indicates provinces with low PHCEs that are also surrounded by provinces with low PHCEs, was present in central and southwest China for all years. This pattern can be seen in the provinces of Hubei, Hunan, Guizhou, and Yunnan for all years, as well as Sichuan, Chongqing, and Guangxi for all years except 1997 and 2002. Secondly, Guangdong, a manufacturing powerhouse located in the Southeast, has the HL pattern in 1997, indicating that Guangdong's PHCEs are high whilst those of the surrounding provinces are low. However, Guangdong has no significant pattern in 2002, 2007, and 2014, indicating a convergence between Guangdong's PHCEs and the surrounding provinces such as Fujian. Thirdly, in the Bohai region (Beijing, Tianjin, and Hebei), a notable shift occurred during the study period. Early in the study period (1997 and 2002), Beijing and Tianjin exhibited the HH pattern, indicating high PHCEs surrounded by provinces with high PHCEs. However, for 2007 and 2014, the adjacent Hebei province began to show a significant LH pattern, indicating low PHCEs surrounded by higher PHCEs. It is likely that this divergence during the course of the study period was driven by diverging PHCEs patterns within the Bohai region, with PHCEs rising rapidly in Beijing and Tianjin. Finally, it is worth noting that, in many regions of China, there were no significant patterns of local spatial autocorrelation, which is important to note in light of the significant patterns of global spatial autocorrelation. Most of northwest and northeastern China had no patterns of PCHEs spatial autocorrelation, nor did the Yangtze River Delta centered on Shanghai, Jiangsu, and Zhejiang. The latter example was particularly notable because the Yangtze River Delta, along with the Bohai region and Guangdong, was one of China's most economically developed regions with relatively high PHCEs, yet, unlike the other two urban metropolises, the Yangtze Delta exhibited no patterns of local spatial autocorrelation in PHCEs.

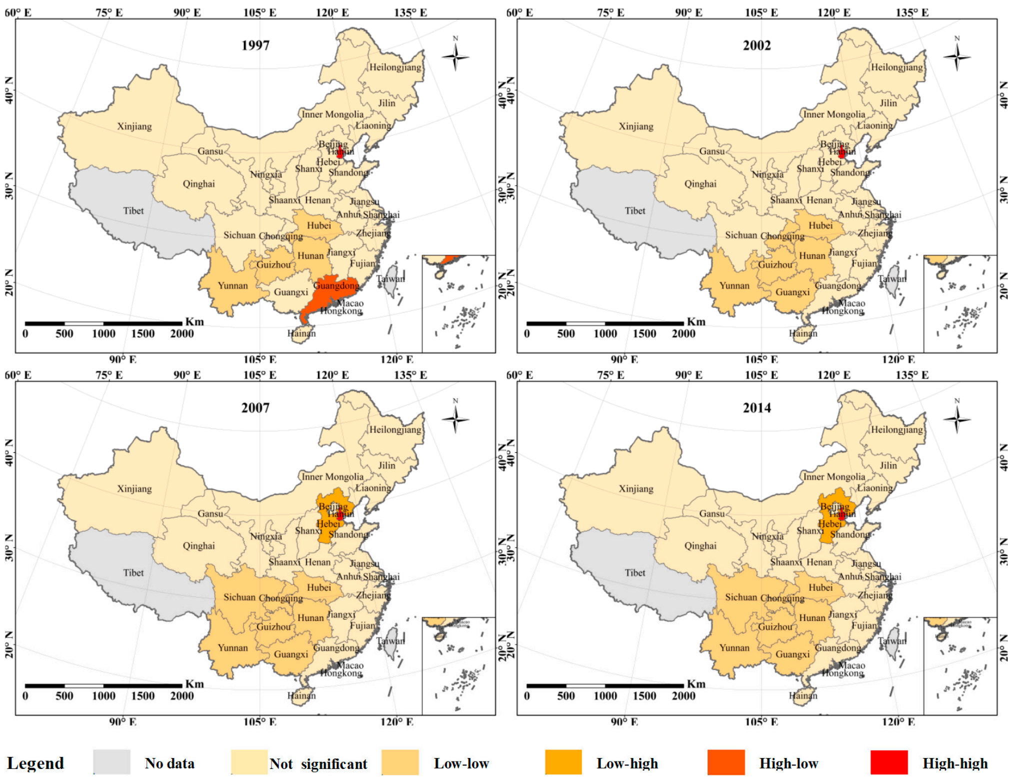

Figure 4. Spatial Moran's I scatterplots of China's PHCEs in 1997, 2002, 2007, and 2014.

3.2.3. Geographical Distribution of PHCEs in China

We used ArcGIS10.3 to analyze the gravity center of PHCEs in China following Zhao and Zhao [50]. The semi-major axis of the SDE represents the direction of distribution, whilst the short half axis of the SDE represents the range distribution. The greater the gap between the semi-major and short half axis, the more obvious the direction of distribution. If the length of the half shaft is completely equal to that of the semi-major axis, this means there is no direction characteristic [48]. As shown in Figure 5a, we can find that the gap between the semi-major axis and the short half axis of the SDE was not large in any year, which means that the gravity center offset of PHCEs in China is not obvious. Although there was little directional orientation to the location of PHCEs in China, important temporal trends did emerge. As shown in Figure 5b, the center of PHCEs in China during the study period was located between 34°30′–34°50′ N and 112°50′–113°50′ E. The movement of the SDE in PHCEs can be divided into three stages: firstly, from 1997 to 2003, it was located where the gravity center of PHCEs varied within a relatively small area; secondly, from 2004 to 2007, it was located where the gravity center of PHCEs moved approximately 60 km southeast; and thirdly, from 2007 to 2012, it was located where the center of PHCEs moved approximately 40 km to the northwest. As important as the individual patterns, it is worth noting that at all times during the study period, with the exception of 2003, 2004, 2013, and 2014, there was a relatively consistent pattern of movement in the center of gravity.

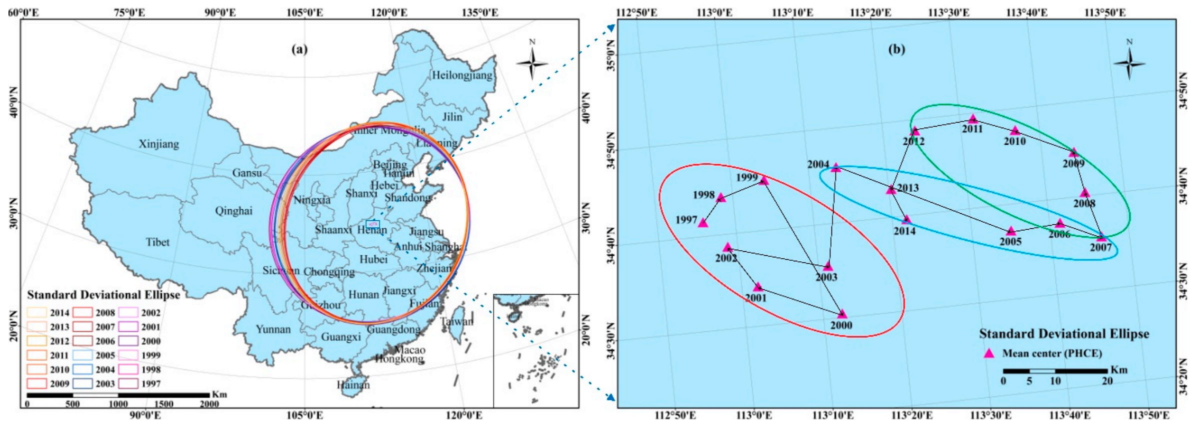

Figure 5. The geographical distribution trend of PHCEs in China (**a**); and the gravity center of PHCEs in China (**b**).

3.3. *Spatial Panel Data Model of PHCEs in China*

Based on the Hausman test, H_2 was rejected while H_1 was accepted, indicating that a variable intercept and constant coefficients model is most suitable [46]. Since the variables used in this work are co-integrated, the results for the four-type spatial panel data models (pooled regression model, spatial fixed effect, time period fixed effect, and spatial and time period fixed effect) are presented in Table 3. Comparing the estimators of R-squared, Adjusted R-squared, Log likelihood, Probability (F-statistic), and the Akaike info criterion in these four spatial panel data models, R-squared (0.97), Adjusted R-squared (0.96), and Log likelihood (200.47) are all higher and the Akaike info criterion (−0.55) is lower in the spatial and time period fixed effect than the other three models. Hence, the spatial and time period fixed effect model should be considered a fit model in this work. Based on the spatial and time period fixed effect model (Table 3), the parameter estimations of individual variable coefficients have important but slightly different influences on PHCEs in China.

As shown in Figure 6, PI (Per capita income), EL (Education level), and UR (Urbanization) have a positive impact on PHCEs. HS (Household size) and EI (Energy intensity) have a negative impact on PHCEs. Based on the spatial panel data model, of the factors influencing PHCEs in China, PI (Per capita income) has a positive impact and the highest regression coefficient of 0.6990, followed by EL

(Education level), and UR (Urbanization). As shown in Table 3, a 1% increase in PI, EL, and UR will result in 0.6990%, 0.0149%, and 0.0044% increases in PHCEs, respectively. HS (Household size) has a negative impact, with the highest regression coefficient of −0.0496, followed by PD (Population density). A 1% increase in HS and PD will result in 0.0496% and 0.0003% decreases in PHCEs, respectively. However, the coefficient of EI (Energy intensity) is not significant at the 5% level. Of the factors influencing PHCEs, we find that PI, EL, and UR have a positive influence, HS has a negative influence, and PD has a statistically significant negative influence, although very slight. The influence of EI on PHCEs, while negative, is not significant at the 5% level.

Table 3. Estimation of influencing factors on PHCEs in by the spatial panel data model.

Panel Data Model	Pooled Regression Model	Spatial Fixed Effect	Time Period Fixed Effect	Spatial & Time Period Fixed Effect
C		1.7756 ***	0.4784 ***	**1.2156 *** **
PD	0.0001 ***	0.0001	0.0000 *	**0.0003 *** **
UR	0.0214 ***	0.0091 ***	0.0182 ***	**0.0044 ** **
HS	0.0559 ***	0.3087 ***	0.1903 ***	**0.0496 ** **
EL	0.0421 ***	0.0199 **	0.0413 ***	**0.0149 ** **
PI	0.4989 ***	0.5921 ***	0.6557 ***	**0.6990 *** **
EI	0.1241 **	0.0237 *	0.1263 ***	**0.0697 * **
R-squared	**0.92**	**0.96**	**0.93**	**0.97**
Adjusted R-squared	**0.92**	**0.96**	**0.93**	**0.97**
Log likelihood	**−39.44**	**131.46**	**5.96**	**200.47**
Prob(F-statistic)	**0.00**	**0.00**	**0.00**	**0.00**
Akaike info criterion	**0.19**	**−0.35**	**0.07**	**−0.55**

Notes: * Significant at the 10% level; ** Significant at the 5% level; *** Significant at the 1% level.

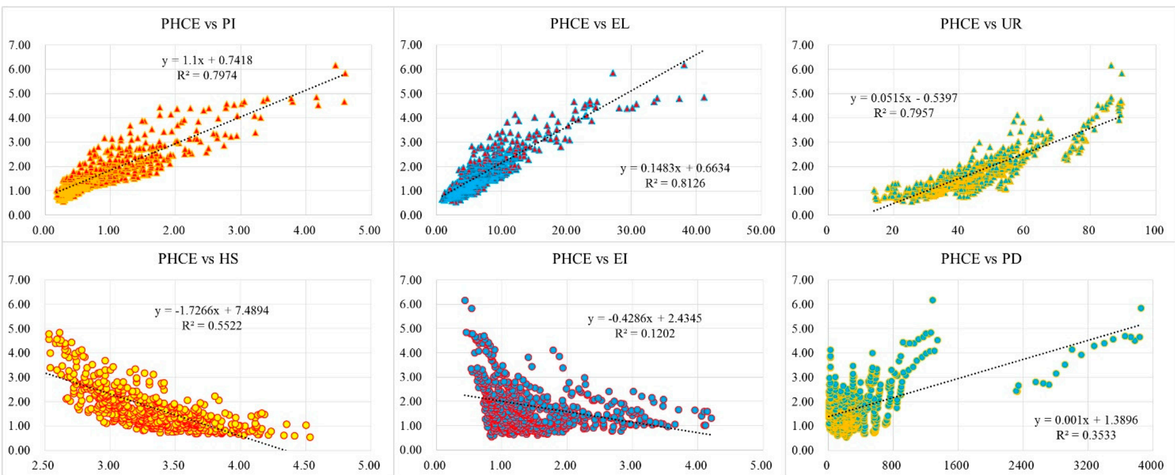

Figure 6. The relationship between PHCEs and the related influencing factors (Per capita income (PI), Education level (EL), Urbanization (UR), Household size (HS), Energy intensity (EI), and Population density (PD)).

3.4. Discussions

Base on the movement of the SDE in PHCEs, the gravity center moves eastward first and then moves westward. There are two main reasons for this movement. First, economic development has a positive impact on PHCEs; meanwhile, the economic development in the East of China has been faster than in the West. Residents living in the East of China are relatively richer than those who live in the West of China. They have better living conditions, use more energy, and purchase more goods. This is why the gravity center moved eastward in the preliminary study period. Second, technology development has a substantial impact on PHCEs. The technological development in the East of China is also much faster than in the West. People that live in the East of China can get more information about renewable energy and clean energy, so they can enjoy the green energy welfare such as purchasing more energy-saving products. This is why the gravity center moved westward in the later study period.

After reviewing the spatial distribution and influencing factors of PHCEs in China, with an eye towards reducing PHCEs in China, we identify several trends.

First, PI has an important impact on PHCEs. The result that PI has a positive impact on PHCEs is similar with previous studies. Feng et al. [56] and Han et al. [26] showed that per capita income has a significant positive association with per capita CO_2 emissions. As regions experience economic growth, household expenditure can be expected to rise, resulting in higher household consumption and associated emissions. PHCEs levels increase with both regional development and income level in this work.

Second, UR, and EL are also important factors that affect PHCEs in China in this analysis. The results in this work indicate that the rapid development of urbanization has increased household consumption and the related CO_2 emissions. Zhang and Lin [57] pointed out that urbanization was positively related to energy consumption and the CO_2 emissions in China based on a STIRPAT model and a spatial panel data model, respectively. Li et al. [58] revealed that there was a unidirectional causal relationship between urbanization and household carbon emissions. A 1% increase in urbanization may result in a 2.9% and 1.1% increase in direct and indirect household carbon emissions, respectively. Currently, China's urbanization rate is projected to increase by 1.5% annually. Reducing PHCEs in the face of rapid urbanization presents a challenge and will require the decoupling of urbanization and PHCEs. With rapid urbanization in China, people's lifestyles and habits have changed greatly. China's urbanization rate is projected to increase, and this will further challenge the goal of carbon emissions reduction. Such challenges can be overcome through policy and changes in consumer behavior. Yang et al. [59] suggested that sustainable urban development should be highlighted and that enforcement of the law should be strengthened in 'China's new Environmental Protection Law' [59]. Moreover, the advancement of technology can reduce carbon intensity and also save CO_2 emissions. Therefore, technology should be improved to reduce environmental damage and develop more energy-saving products to cut carbon emissions.

The relationship between education and PHCEs has had mixed evaluations in the literature. Some have found that persons with higher education levels have higher emissions [60], while others claim that persons with higher education will help reduce carbon emissions [61,62]. There is ample grounding for both positions. The theory that higher education levels will reduce emissions is grounded in the belief that those with higher education levels are more aware of the adverse consequence of fossil fuel consumption and will adopt low carbon practices. The notion that higher education levels will lead to higher PHCEs is grounded in the belief that persons with higher education levels will purchase more modern products such as mobile phones, computers, and automobiles, thus resulting in more carbon emissions. Such consumer preference is also corroborated by the fact that those with higher education levels also have higher incomes. Our results indicate that the education level of household members positively, but only slightly, influences consumption attitudes and consumption habits, even when controlling for income. This influence is small in magnitude but significant at the 95% confidence level. We cannot, in this case, rule out the possibility of a latent variable, and the relationship between education and PHCEs is a likely venue for finer grained analysis.

Third, PHCEs decrease with increasing household size. This finding is similar to the findings of Qu et al. [8,9], who pointed out that PHCEs decreased as household size increased in northwest China. Large families, specifically extended families living together, presented a promising way to save energy and reduce CO_2 emissions [8,9]. The same conclusion is found in Ireland [63]. When comparing per capita CO_2 emissions between one-person households, two-person households, and any other household size, Lyons found that a larger household size will produce fewer per capita emissions than a lower household size.

The Chinese government has pledged to cut carbon intensity by 40% to 45% by 2020 from 2005 levels and to achieve peak CO_2 emissions around 2030, which will result in more CO_2 emissions from household consumption. These goals will be challenging in the face of rising income and urbanization levels, two factors that we have identified as influential for PHCEs. International comparisons point towards this difficulty, with CO_2 emissions rising with increased income in Ireland [63] and China [21,26]. Thus, it is important to introduce policies to decouple increased household spending from rising emissions.

This could be accomplished through government policies that encourage consumers to use low-carbon products such as eco-labeling [64,65] and helping the producers of consumer goods to produce energy-saving products. However, it is ultimately consumers who must transition from luxurious to more frugal consumption activities [17] such as purchasing fuel-efficient cars and using more environmental-friendly home appliances. Consumers, as the drivers of markets for many energy-consuming items, should choose 'green' products to achieve a reduction in carbon emissions. Carbon labelled products should be considered important in this choosing process [64–68]. Increasing the ratio of renewable energy and clean energy in the total household energy usage in the future is also a very important measure to reduce CO_2 from the household sector. These findings also highlight the importance of funding research into household emission mitigation measures.

Finally, although the connection between education level and emissions in general is ambiguous, education activities surrounding climate change should be publicized in schools and public places, especially in some rural areas, to explain individuals' impact on climate change.

Although many findings highlighting the importance of this research on carbon reduction mitigation measures, a minor uncertainty in the results of accounting for PHCEs exists, owing to the inaccuracy or uncertainty of statistical data. First, heating usage in this study only includes the centralized heating usage in urban China. Centralized heating is only used in urban China so the centralized heating usage equals zero in rural China. Residents living in rural China mainly utilize small coal stoves (by using coal or gas) for heating in winter. Second, the emissions factors used to calculate CO_2 emissions from the electricity sector (t CO_2/MWh) for each province are based on data from 2010. The mix of electric generating sources changes constantly, which varies the carbon intensity of generation for two reasons; increasing the efficiency of fossil fuel (primarily coal) fired plans and changes in the mix of renewable and non-renewable sources. Data for electric emissions were selected for 2010 due to data being available for all provinces. Both of these sources of uncertainty could have a slight influence on our results.

Based on the aforementioned research results, the first way to reduce PHCEs is to narrow the difference of provincial PHCEs in China. Policy-makers should consider provincial differences when making policies impacting household emissions. China's rapid development of urbanization has a great impact on PHCEs and thus policy-makers should; (1) consider the different urbanization ratios of different provinces and (2) seek ways to decouple urbanization from an increase in PHCEs. Provinces with higher PHCEs in China should have more responsibility to reduce emissions by taking on different responsibilities in a domestic form.

4. Conclusions

4.1. Conclusions

In this paper, we have investigated the spatial variations and determinants of per capita household CO_2 emissions (PHCEs) in China. By analyzing the distributions of PHCEs in China, we examine the influencing factors of PHCEs using a spatial panel data model.

PHCEs at the provincial level grew rapidly from 1997 to 2014, with certain spatial patterns of variation enduring while others changed. The PHCEs of provinces ranged from 0.60 t CO_2/person in 1997 to 6.18 t CO_2/person in 2014, differing by one order of magnitude. Higher PHCE emitting regions are concentrated in eastern China, including Beijing, Shanghai, Zhejiang, and Tianjin. Lower PHCEs emitting regions are predominately in northwest and central China, including Guangxi, Anhui, Hainan, Qinghai, Gansu, and Ningxia. While individual provinces differed in their ranks in specific years, regional patterns of higher and lower PHCEs did not change during the study period. To lessen regional disparities and realize balanced development, regional compensation mechanisms, distinct development, and regional energy supply and demand must also be balanced.

To analyze the factors influencing PHCEs, geographically spatial dependence cannot be ignored. Based on the global Moran's I index, we find a significant spatial autocorrelation of provincial PHCEs in China. We also reveal that the regions with high PHCEs tend to be adjacent to other regions with high PHCEs; regions with low PHCEs are also adjacent to each other. However, the gravity center offset of PHCEs in China is not obvious. The gravity center of PHCEs in China has moved between 34°30′–34°50′ N and 112°50′–113°50′ E, showing a distinct eastward movement between 2002 and 2007, with westward movement from 2007 to 2014.

We analyzed factors influencing PHCEs across Chinese provinces by using panel datasets. Our results show that PHCEs are increased by per capita income (PI), education level (EL), and urbanization (UR). A 1% increase in per capita income, education level, and urbanization will result in 0.6990%, 0.0149%, and 0.0044% increases in PHCEs, respectively. Household size (HS) has a negative impact with the highest regression coefficient of -0.0496, followed by population density (PD).

4.2. Policy Recommendations

Household CO_2 emissions (HCEs) are increasing in China due to economic development and accelerated urbanization. Per capita income (PI) will keep growing in China, which will result in more CO_2 emissions from household sector. Based on the results of spatial panel data model in this study, per capita income has a great impact on per capita household CO_2 emissions (PHCEs). As regions experience different economic growth, policy makers should consider the impact of issues of increasing income and income disparity on PHCEs. It is urgent to introduce policies to decouple increased household spending from rising emissions.

Urbanization (UR) also has a positive impact on PHCEs in China and is likely to continue to do so in the future. One problem facing China is how to reduce carbon emissions in the face of rapid urbanization progress. It is necessary to guide residents to change their lifestyles and habits, yet there are positive signs in this regard. The proliferation of bike sharing services in China has increased the use of bike riding within close ranges, and the purchasing low-carbon and energy-saving products has increased. Education plays an important role in carbon reduction awareness. Our results reveal that an individual's education level slightly influences their attitudes towards consumption and consumption habits, so it is very important to emphasize education in different regions. Education activities surrounding climate change should be publicized in schools and public places, especially in some rural areas, to promote environmental awareness to address climate change.

Although China's PHCEs are much lower than those of developed countries, it is also important to prevent further increases of PHCEs. To achieve peak CO_2 emissions around 2030, it is suggested to advance technology and establish a carbon emission trading system to reduce carbon intensity and reduce CO_2 emissions from household consumption.

There are many factors affecting household CO_2 emissions, including population, economic development, and demographic traits, all of which are identified by our spatial panel data model, which can give some suggestions for meaningful theoretical and policy implications. Measures for household carbon emission abatement should be proposed at the government and consumer levels. These findings also highlight the importance of funding research into household emission mitigation measures.

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