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Spatial Patterns and Driving Factors of Urban Residential Embedded Carbon Emissions: An Empirical Study in Kaifeng, China

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Abstract

With the continuous improvement in living standards and great changes in lifestyles, more attention is being paid to the embedded carbon emissions produced by human consumption. With large sample data and high-resolution remote sensing images, we explored the spatial differentiation and influencing factors of household embedded carbon emissions within the city fine scale using the EIO-LCA model, spatial autocorrelation analysis and standard deviation ellipse, quantile regression, etc. The results indicate that the spatial dependence is more obvious than the characteristics of spatial heterogeneity; the high-value area of household embedded carbon emissions gathers in new development zones in cities that are expanding rapidly, mainly with residents in large number of newly-built commercial housing families and the relative's courtyard of institutions. The factors of family characteristics, housing characteristics, lifestyles, and consumption concept have significant effects on the embedded carbon emissions of each person. The influencing intensity of most factors showed an increasing trend with increased carbon emissions. The study verified the impact of urban sprawl on residential carbon emissions and the applicability of the situated lifestyles theory in the construction of urban low-carbon communities in China.

Keywords

Embedded Carbon Emissions, Situated Lifestyles, Community Scale, Urban Residents, Kaifeng

1. Introduction

Mitigation and adaptation to climate change are an important topic for sustainable development in the 21st century [1] [2] [3]. As an important component of greenhouse gases, CO_2 emissions and their threat to human society continue to increase [4]. Residential carbon emissions are an important part of carbon emissions and consumption by residents is also the original drive behind industrial production [5]. For the question, "How is the responsibility for carbon emissions to be distributed?", the consumption side is considered more by academia than the productive side [6] [7]. Embedded carbon emissions refer to indirect emissions caused by consumption of non-energy goods and services, such as residential clothing, food, and shelter, which are implied in the full production. Supply and disposal life cycle are far greater than the direct carbon emissions generated by the direct consumption of fossil fuels by residents, and this conclusion has become the consensus [8].

With the rapid development of China's economy and the vigorous implementation of the policy of "expanding domestic demands", the role of household consumption of economic development has become more and more prominent. However, along with the continuous improvement in living standards and the increase in income, life consumption patterns have also experienced a major and gradual shift from "subsistence-oriented" to "quality-oriented". The demand for larger quantities and diversity of goods and services is also increasing. The transformation of residents' consumption patterns will not only contribute to economic and social problems, including industry, trade, and employment, but will also increase energy consumption and the generation of carbon emissions from the conduction effect of supply and demand [9]. Therefore, to the background of urban space optimization restructuring, large rise in living standards, and the sharp changes in residents' lifestyle, realizing regional low carbon development is a scientific problem to be solved [10] [11].

The promotion of housing marketization has resulted in differences in the living environment, lifestyles, and consumption patterns of the urban residents of communities and even building scales [12]. Academic concerns for residents' carbon emissions are also gradually from the perspective of the region to the family and community, that is, from a focus on the impact on economic development to focus on lifestyle, behavior patterns, and community space form on the residents' carbon emissions [13] [14]. China has continued to promote low-carbon development in the community and began to pilot low-carbon communities in 2014. In 2016, the National Development and Reform Commission and the Ministry of Housing and Urban-Rural Development issued the *Action Plan for Adaptation to Climate Change*, which states: "To stick to 'different policies for different cities', step-by-step implementation, adopt reasonable measures, to carry out targeted adaptation actions." However, the carbon emission patterns of urban inner communities are still vague, the mechanism of the influence on residential carbon emissions is still unclear, and emission reduction indexes and models are not yet determined.

The construction of the accounting system for residential embedded carbon emissions of fine scales is the cornerstone and difficulty of the research. There are different methods and categories for the accounting of embedded carbon emissions. Among these methods, life cycle assessment (LCA) is a widely-used method that quantifies the environmental impacts on a production process [15]. Expansions of LCA include process-based (P-LCA) and input-output-based (IO-LCA).

The P-LCA method uses materials and energy data in every link in the production processes of commodities and analyzes each process in the product supply chain accordingly. The advantage of this method is the required level of refinement it can achieve, but analyzing every process in a supply chain is challenging and time-consuming, as system boundaries and categories become more and more extensive [16]. In contrast, the IO-LCA method can easily obtain the carbon emissions of the whole supply chain and eliminate cross-sectional errors but causes some uncertainty due to the degree of integration among the products and activities [17].

On the basis of the Leontief inverse matrix, Carnegie Mellon University Green Design Institute proposed the economic input-output life cycle assessment (EIO-LCA) model [18], which can analyze the environmental impact of a commodity from cradle to grave and the relationships of industries, which are widely used in current embedded carbon emission accounting [19] [20]. However, the application of this method is mainly based on the statistics of the city scale and the above [21] [22]. The data onto the community and family scales are difficult to obtain, so there is a lack of research.

There are many factors influencing residential carbon emissions, for which the mechanism is complex. At the macro level, the factors boil down to sizes of populations, economic levels, ideas and patterns of consumption, and the technical level, among the factors. The size of the population affects the level of consumption, the economic level impacts the power of consumption, ideas of consumption impact the quantity of carbon emissions, and consumption patterns affect the structure of carbon emissions, and commodity production technology influences the strength of the carbon emissions [23] [24] [25].

The micro-scale focuses more on the incomes of residents, sizes of families, ages of family members, numbers of home and car ownership, locations of residences, and housing areas and prices [26] [27]. Finnish scholars, Heinonen *et al.*, have put forward their Situated Lifestyles Theory [28] [29], which summarize the influence mechanism from the perspectives of spatial behaviors. According to the theory, residential behaviors and ways of life are bound by the building environments and locations of residences. Residential morphology affects residence types, positions of distance, accessibility of goods and services, and the choice of social contact, pastime, which reflects on the aspect of behavior patterns, time distribution and the purchase decision, and then decided to residents' way of life. For the residential morphology affect type of residence, distance of home-work, accessibility of goods and services, the choice of social contact and way of pastime, and so on, and then decides the residential lifestyles including behavior patterns, time distribution and the purchase decision. The proposing of the theory was based on empirical research, but the theory remains to be further verified in residential areas or building scales. What are the differences in influencing strengths under different levels of carbon emissions? How is the spatial differentiation mechanism? These questions still need to be explored.

To answer these questions, we chose the city of Kaifeng as a study area where significant urban spatial changes and changes in residential lifestyle are occurring, where there are various types of urban residential areas, and where there is significant spatial differentiation in residential carbon emissions. The study is based on the theories of human-earth relationships and regional sustainable development, and follows the basic research framework of "measure-pattern-mechanism". To reveal the spatial distribution of the carbon emissions of residents on a micro-scale and explore its influence mechanisms, we constructed a carbon emissions accounting system for residential households and used multidimensional statistical methods to analyze data from a large sample questionnaire survey in conjunction with high-resolution remote sensing imagery and national economic data. This study provides a theoretical basis and data support for policy-making for the construction of low-carbon communities.

2. Study Area and Data

2.1. Study Area

Kaifeng is located at the middle and lower reaches of the Yellow River in China (Figure 1). We selected the built-up areas of Kaifeng as the research area for the following reasons. First, Kaifeng is an important central economic zone and is typical of cities with rapid urban development. From 1985 to 2015, the urban population of Kaifeng increased from 62.91 million to 160.60 million, the rate of urbanization increased from 16.2% to 44.2%, and the per capita disposable income of urban residents increased from 0.07 million yuan to 2.29 million yuan, which we can see from the statistical yearbook of Kaifeng. Second, Kaifeng has a long history, and different types of residential areas have arisen during its development and transformation. The policy of "Zheng-Kai integration" accelerated the construction of the city. There is a new development zone with high-rise buildings, as well as old urban areas of the "Eight Dynasties" with street, unit,

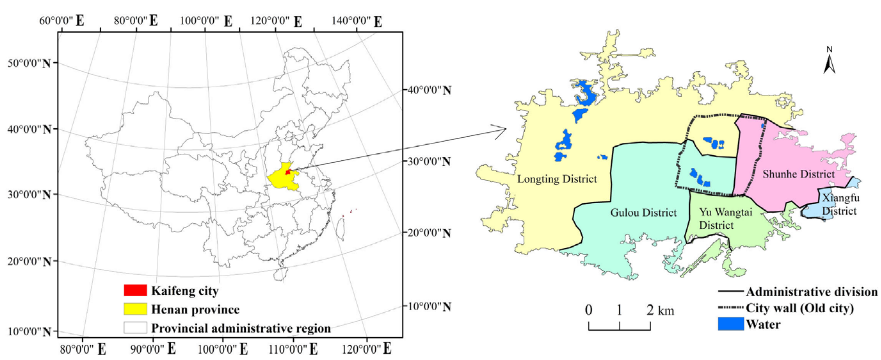

Figure 1. Study area.

policy-based housing and commercial housing communities. The communities have different locations, spatial forms, and cultural characteristics. Third, Kaifeng belongs to the group of small and medium-sized Chinese cities. These cities are numerous and will play a major role in the construction of low-carbon cities in the future, but little research into the residential carbon emissions of such cities has yet been undertaken.

2.2. Data Resources

Data collected from questionnaire surveys are the key basic source of data for this study. Initially, a pre-survey was conducted with 200 questionnaires distributed randomly for a household survey. We revised and supplemented the questions after sorting and making a preliminary analysis of the questionnaire. A large-scale sample collection was then conducted in 2015 and 2016. We mainly adopted the methods of stratified random investigation. The proportions of the questionnaire were determined according to the proportion of the population distributed in the five administrative districts of the city some questionnaires were not used due to issues such as a lack of information and inconsistent or inaccurate positioning. Of the questionnaires, 5000 were distributed randomly at various public places, 4685 were returned, and 3895, involving 14,412 residents, were used for the analysis. The distribution of the sample points is shown in Figure 2. The contents of the questionnaire are related to the household demographic characteristics of residents, consumption features, and consumption cognition and preferences.

Socio-economic data includes: 1) Yearbook data, according to the calendar year, "Kaifeng Statistical Book" and "China Urban Statistical Yearbook", which include land capacity, population, urbanization rate, and car ownership, among other aspects, to establish an overview of the level of development in specific areas of Kaifeng; and 2) Input-Output Data utilized to calculate embedded carbon intensity for residents. The input-output data of Henan Province were only

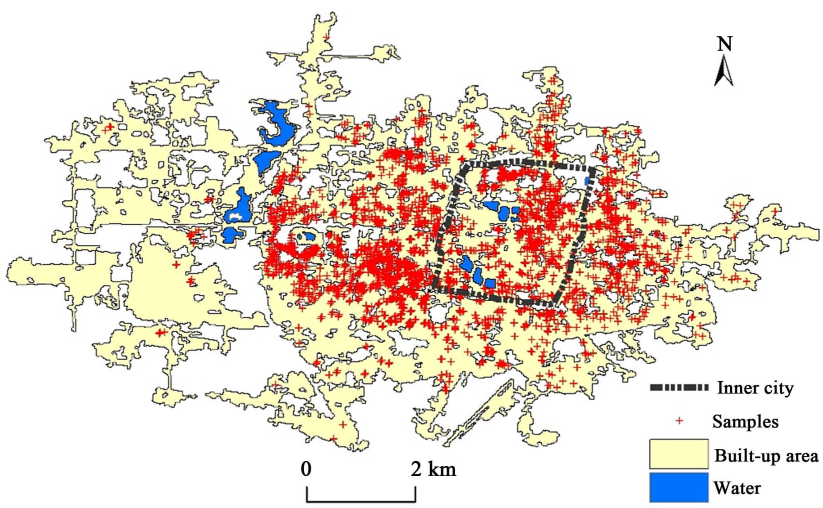

Figure 2. The spatial distribution of the samples.

available until 2012 at the time of writing, as the data are compiled every five years. These data were extracted and merged with lifestyle data to establish a final consumer spending matrix. According to international practice, the carbon emission intensities of various industries in the province represent the micro-scale carbon emission intensity in the region (Kumar *et al.*, 2016).

3. Study Methods

3.1. Calculation Method of Embedded Carbon Emissions

The EIO-LCA model, which can analyze the environmental impact of a product or service throughout the production chains from a lifecycle perspective, was used for the calculation of embedded carbon emissions [30], as given by Equation (1):

$$E = RX = R\left(I - A\right)^{-1} F \tag{1}$$

where E is the specific energy consumption CO_2 emission matrix for each sector; R is the $k \times n$ order environmental pressure matrix; element r_{ij} contained within R represents the environmental burden k (carbon emission); A is the direct demand coefficient matrix; $(I - A)^{-1}$ is the Leontief inverse matrix; X is the sum of all sector output vectors; and F is the final demand vector.

3.2. Local Space Autocorrelation

The global spatial autocorrelation method hypothesizes the spatial process is of stationarity, but in fact, this condition is difficult to satisfy. To overcome this limitation, we use the local space self-correlation method (LISA) to explore the autocorrelation characteristics of local spatial units in adjacent regions. The formula is:

$$I_i = Z_i \sum_{i=1}^{n} W_{ij} Z_j \tag{2}$$

where Z_i and Z_j are the normalized values of the observed values in the spatial units i and j, respectively. W_{ij} is the spatial weight.

3.3. Standard Deviation Ellipse

The Standard Deviation Ellipse (SDE) method can quantitatively explain the direction, spread, and centrality of the spatial distribution of geographical elements, and reveal the spatial distribution characteristics of the research objects more accurately. Specifically, the center represents the relative position of the elements in the two-dimensional spatial distribution, the azimuth indicates the direction of the main trend of the distribution, and the long axis reflects the dispersion degree of the geographical elements in the direction of the main trend.

The formula for the angle of rotation is:

$$\tan\theta = \frac{\left(\sum_{i=1}^{n} \tilde{x}_i^2 - \sum_{i=1}^{n} \tilde{y}_j^2\right) + \sqrt{\left(\sum_{i=1}^{n} \tilde{x}_i^2 - \sum_{i=1}^{n} \tilde{y}_i^2\right)^2 + 4\left(\sum_{i=1}^{n} \tilde{x}_i \tilde{y}_i\right)^2}}{2\sum_{i=1}^{n} \tilde{x}_i \tilde{y}_i} \tag{3}$$

where $\tilde{x}_i$ and $\tilde{y}_i$ are the deviations of the coordinate of xy to the mean center.

3.4. Quantile Regression

Least squares estimation can achieve the Best Linear Unbiased Estimation only when the former meet very strict assumptions (such as the random error term's obeying the same variance, no autocorrelation, normal distribution, no linear relations among different explanatory variables, etc.) In fact, the above conditions are extremely difficult to achieve, especially the social and economic problems with complex influencing mechanisms, and the robustness of the model becomes greatly reduced. In addition, the limitation of the conditions of the OLS average does not allow the response variable regression model to fully describe the conditions of different quantile functions, but only the average in the sense of dependence. What's more, the OLS regression model cannot fully describe the quantile functions of the different conditions of response variables but can only describe the dependence relationship of the sense of the mean value, so the problem cannot be explained completely or precisely. Therefore, Koenker and Bassett proposed the current Quantile Regression (QR) method based on the Median Regression method [31], which has some advantages in the study of residential carbon emissions, because it does not make any distribution assumptions and the estimated results are stable [27]. In essence, the model adjusts the position and direction of the quantile regression plane by selecting different values of the points on 0 - 1, so as to estimate the dependent variables at different points with multiple covariates. The basic principle is:

$$\sum w_\tau \left|y_t - \alpha\right| = -\sum_{i:y_i<\alpha}^{T} (1-\tau)(y_t - \alpha) + \sum_{i:y_i\geq\alpha}^{T} \tau(y_t - \alpha) \tag{4}$$

where $\hat{y}_{(\tau)t}$ refers to the quantile regression estimator of y_t, w_τ refers to the weight, and $\sum w_\tau \left|y_t - \alpha\right|$ refers to the sum of the absolute value of the weighted deviation for y_t to any value α. When $\alpha = \hat{y}_{(\tau)t}$, $\left[\tau \in (0,1)\right]$, its value can be minimum.

4. Results

4.1. Basic Characteristics of Residential Embedded Carbon Emissions in Kaifeng

According to the input-output table of Henan Province and Equation (1), the embedded carbon emission intensity of 40 departments related to household consumption is calculated, as shown in **Table 1**.

When calculating the main living consumption category of residential embedded CO_2 emission intensity, if a kind of consumption category corresponds to several industries, the weights of different industries are the proportion of its expenditure on the total expenditure of this category (**Table 2**).

According to EIO-LCA, the average household embedded carbon emissions in Kaifeng are 22.19 kg/day. The basic statistical characteristics of different types of embedded carbon emissions are shown in **Figure 3**. From higher to lower, the

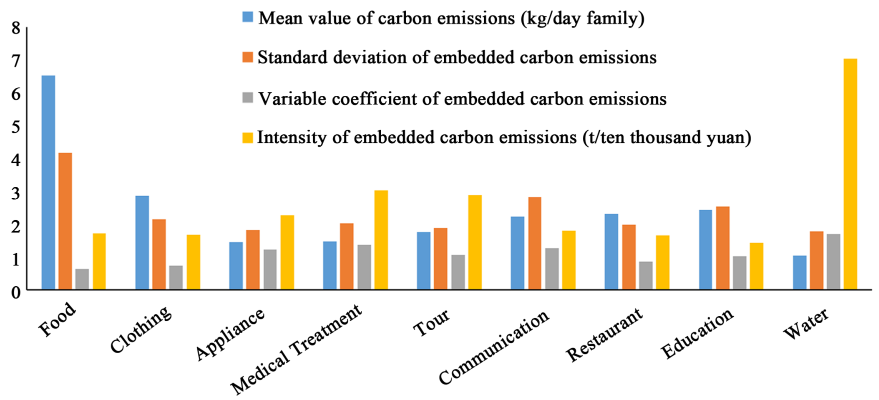

Figure 3. The basic statistical characteristics of embedded carbon emissions in Kaifeng.

Table 1. Embedded CO_2 emission intensity in related industries.

Department	CO_2 emission intensity (t/ten thousand yuan)	Department	CO_2 emission intensity (t/ten thousand yuan)
Agricultural and forestry animal husbandry and fishery products	1.2574	Other manufactured products	2.2814
Coal mining products	13.9944	Scrap waste	4.2222
Oil and gas exploration products	4.3262	Electricity, thermal production, and supply	16.8435
Metal mining products	3.6089	Gas production and supply	6.9308
Non-metallic ore and other mining products	2.5483	Production and supply of water	7.0528
Food and tobacco	1.7200	Building	2.6830
Textiles	1.7424	Transportation, warehousing, and postal services	4.1294
Clothing, shoes, hats, and leather down and its products	1.6325	Wholesale and retail	0.9042
Wood processing and furniture	1.7394	Accommodation and catering	1.6740
Papermaking and teaching sports articles	2.7962	Information transmission, software, and information technology services	1.2380
Petroleum, coking products, and nuclear-fuel-processed products	10.8082	Financial	1.4791
Chemical products	4.2135	Real estate	0.5766
Non-metallic mineral products	3.6932	Leasing and business services.	1.5293
Metal smelting and rolling processing	4.7729	Scientific research and technical services	1.9375
Metal products	3.6374	Water conservancy, environment, and public facilities management	1.3142
Special equipment	2.8886	Resident services, repairs and other services	1.3271
Transport equipment	2.9068	Education	1.0536
Electrical machinery and equipment	2.6543	Health and social work	3.0443
Communications, computers, and other electronic equipment	2.2277	Culture, sports and entertainment	1.4828
Instruments and meters	2.2936	Public administration, social security, and social organization	1.6846

Table 2. The industry corresponding to the main living consumption categories of residents and their embedded CO_2 emission intensity.

Consumption category	Corresponding industry (weight)	CO_2 emission intensity (t/ten thousand yuan)
Food	Food manufacturing and tobacco processing industry (1)	1.7200
Dress	Textile industry (0.5) + Clothing, and leather down and its products (0.5)	1.6874
Home Appliances	Electrical, mechanical and equipment manufacturing (0.6) + timber Processing and furniture (0.4)	2.2883
Medical	Health, social security, and social welfare (1)	3.0443
Tourism	Tourism (1)	2.9017
Communications	Communication equipment, computer, and other electronic equipment, Manufacturing (0.8) + postal service, information transmission service (0.2)	1.8163
Dining	Catering industry (1)	1.6740
Schools	Information transmission, computer services, and software (0.2) + culture, sports, and entertainment (0.8)	1.4338
Water	Production and supply of water (1)	7.0528

proportions of the different kinds of embedded carbon emissions are: food 29.43%, clothing 12.99%, education 11%, dining out 10.51%, communication 10.03%, tourism 7.97%, medical treatment 6.72%, home appliances 6.62%, and water 4.72%. In addition, the intensities of the carbon emissions of water, medical treatments, and tourism are high. Meanwhile, the coefficients of variation of all kinds of embedded carbon emissions are very high, among them, the data dispersion degree of the carbon emissions from water, medical, communication, home appliance and child education are significant.

According to the spatial distribution patterns of embedded carbon emissions (Figure 4), the different levels of the carbon emission value are distributed in different regions, but there are significant differences among different regions. On the one hand, the density of the low value is high in the central and eastern areas, and the area east of the old city. On the other hand, the density of the high-value points gradually increases from the western region of the old city to the new development zone. Most samples around Zheng-Kai Road are high-value points. In addition, we found that the high and low values are mixed in the outer layers of the eastern, southern, and northern regions.

4.2. The Spatial Differences of Residential Embedded Carbon Emissions

From the results and the map of LISA regarding household embedded carbon emissions (Figure 5), we can see that 7.02% of the total sample points have significant spatial autocorrelation effects, of which the high concentration values (HH) accounted for 31.93%, high-low concentration values (HL) accounted for 21.08%, low-high concentration values (LH) accounted for 10.84%, and low concentration values (LL) accounted for 31.15%. As can be seen from the

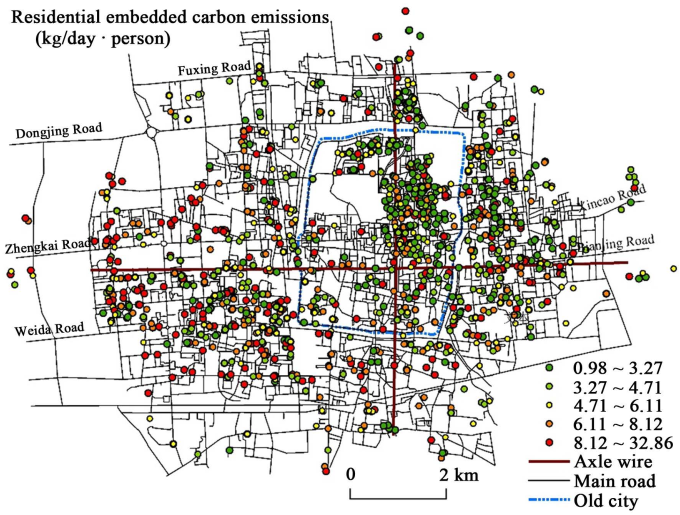

Figure 4. The spatial distribution pattern of residential embedded carbon emissions.

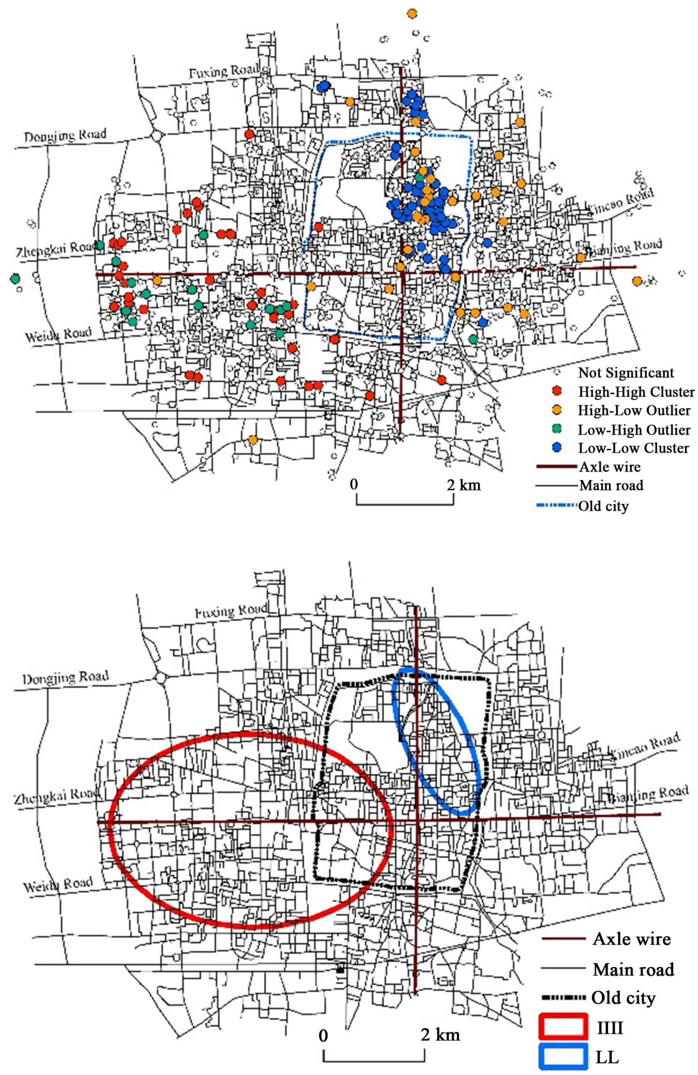

Figure 5. LISA cluster map and results of standard deviation ellipse for embedded carbon emissions distribution.

proportion of HH and LL, the spatial dependence characteristics of family embedded carbon emissions are relatively obvious. On the one hand, the high-value agglomeration area of the embedded carbon emissions mainly exists in the western new development zone, mainly with a large number of new commercial housing community residents and family member courtyards of administrative departments and institutions, where most of the communities were built in recent years with high housing prices and perfect facilities. On the other hand, the low-value agglomeration areas are mainly in the northeastern area of the old city and the area east of the old town, mainly with the old commercial houses and the street communities. This shows that residential embedded carbon emissions have a high correlation with household income.

The standard deviation ellipse (SDE) method can further reflect the distribution center and trend of different agglomeration areas. The long axis represents the maximum diffusion direction, the short axis represents the minimum diffusion direction, and the area represents the discrete degree. The smaller the area, the greater is the concentration of the center. From the SDE result of household embedded carbon emissions (**Figure 5**), we can see that for the high-value agglomeration standard deviation ellipse, the area is 16.36 km^2, the length of the x-axis is 3.09 km, the length of the y-axis is 1.69 km, and the angle of rotation of the x-axis is 94.25˚. For the low-value agglomeration standard deviation ellipse, the area is 2.85 km^2, the length of the x-axis is 1.42 km, the length of the y-axis is 0.64 km, and the x-axis angle of rotation is 154.33˚. The HH ellipse center household per capita embedded carbon emissions are in the positive western direction and the dispersion degree is higher. The LL ellipse is located in the northeastern corner of the old city, and the agglomeration degree is high.

4.3. Influencing Factors of Residential Embedded Carbon Emissions

According to a related study, the influencing factors of embedded carbon emissions includes two main aspects: 1) the production system, which includes energy-saving technology, production efficiency, energy efficiency, etc.; 2) the consumption system, which includes income level, consumption habits and preferences, population sizes, etc. The product system determines the carbon emission coefficient (*i.e.*, the carbon intensity of different consumer products), which is generally analyzed in the research at the macro scale according to the relevant statistical data, but the focus of this study is how micro-level improves the behavior of the residential preferences, consumption structure, and other relevant economic and social measures to reduce residential embedded carbon emissions, so we have chosen the influencing factors of the consumption system.

4.3.1. The Comprehensive Influence Mechanism of Residential Embedded Carbon Emissions

According to the relevant indexes mentioned in the literature review, the actual situation of local residential consumption, the family monthly income, building area, number of family members and the property of housing are used to characterize the family characteristics. The concept of low-carbon consumption is characterized by frugality, emphasis on low carbon consumption, timely suppression of family waste, the number of home-cooked meals, the number of trips per year, and the number of monthly beauty and healthcare products are used to characterize the family lifestyle. Consuming as little meat as possible, saving and reusing water, update cycle of furniture and household appliances, avoiding purchases of luxury goods, controlled consumption of mobile telephones and communications are used to represent behavioral preferences. Because of the large multi-items involved, we adopted the stepwise regression method to remove independent variables and chose embedded carbon emissions per capita as dependent variables to reflect the fairness of responsibility for the terminal emissions. The independent variables in the final model of residential embedded carbon emissions are shown in **Table 3**.

According to the results of the regression (**Table 4**), the whole equation passes the F significance test, showing that the regression equation has good statistical significance, as problems of complex social and economic fields with the big samples; the results have been able to reveal related issues [32]. Family characteristics, lifestyle, behavior habit, and the thought idea has significant influence on the embedded carbon emissions, among them, family income, and building area has a positive effect on embedded carbon emissions per capita, while number of family members, the housing property, number of cooking at home, consumption preference without luxury goods, emphasis of low carbon consumption and frugal purpose for saving money has a significant negative effect on embedded carbon emissions per capita.

Table 3. Descriptions of variables and statistical characteristics of embedded carbon emissions.

Variable	Type	Instruction	Mean	Standard Deviation
Monthly household income	Classification	Below ¥2999 = 1; ¥3000 - 5999 = 2; ¥6000 - 8999 = 3; ¥9000 - 11,999 = 4; ¥More than 12,000 = 5	2.59	1.23
Building area	Continuous	Housing construction area size (m^2)	120.94	55.30
Number of family members	Continuous	The number of members who live together in a house	4.02	1.91
Housing property	Classification	Whether it is affordable housing: Yes = 1; No = 0	0.17	0.38
Cook at home	Continuous	Average home cooking times per day	2.29	0.75
Frugal purpose for saving money	Classification	We are frugal in household management mainly to save money: Very consistent = 5; Consistent = 4; General = 3; Not very consistent = 2; It does not fit at all = 1	3.67	1.33
Emphasis of low carbon consumption	Classification	Family adults can focus on low-carbon consumption: Very consistent = 5; Consistent = 4; General = 3; Not very consistent = 2; It does not fit at all = 1	4.30	0.87
Consumption without luxury	Classification	Family adults do not pursue luxury goods: Very consistent = 5; Consistent = 4; General = 3; Not very consistent = 2; It does not fit at all = 1	3.94	1.13

Table 4. The gradual regression results for influencing factors of embedded carbon emissions per capita.

Independent variables	Coefficient	Standard error	Significant
(Constant)	9.892	0.663	0.000
Monthly household income	0.529	0.075	0.000
Number of family members	−0.372	0.048	0.000
Housing property	−0.246	0.056	0.000
Building area	0.005	0.001	0.000
Cook at home	−0.242	0.124	0.050
Consumption without luxury	−0.213	0.105	0.042
Emphasis of low carbon consumption	−0.426	0.082	0.000
Frugality	−0.175	0.068	0.011

Adjusted $R^2 = 0.372$; F test 29.516 (sig. = 0.000).

4.3.2. The Differences in Influence Mechanisms under Different Embedded Carbon Emission Levels

For a more detailed depiction of the dynamic mechanism of residential embedded carbon emissions, according to the theory of quantile regression, in combination with the results of stepwise regression analysis, we did the quantile regression estimate under 0.1, 0.2, 0.3, ⋯, 0.9 quantile points. The estimated coefficients represent the marginal effect of the explanatory variable to the interpreted variable on the specific points.

From the quantile regression results (Figure 5), the influence strength of the monthly family income on embedded carbon emissions per capita has an increasing trend with the increase in carbon emissions. Most quantiles estimated coefficients are within the confidence interval of OLS estimates (Figure 5(a)).

The influence strength (absolute value of the negative influence) of the number of family members on carbon emissions has the trend of increasing first, then decreasing. The coefficient under 0.6 quantile is the turning point and the coefficient on 0.9 cannot pass the test of significance of 10%, reflecting that the family size is not the main influencing factor for the families of the highest carbon emissions. In addition, the absolute value of its coefficient in the OLS estimates is less than in the quantile regression in most quantile points. Therefore, the OLS method has the possibility for estimating the role played by the number of family members on the carbon emissions (Figure 5(b)).

There are similar trends for the influence of family housing types, times of cooking at home, the extent of consumption without luxury, and emphasis of low carbon consumption on per capita carbon emissions. The absolute value of negative influence has an increasing trend. Most quantile estimated coefficients are within the confidence interval of the OLS estimate except the indicator of emphasis of low carbon consumption whose estimated values are in confidence interval of OLS estimates only at the 0.5, 0.6, 0.7 quantile points and the coefficients of both sides of the median are symmetrical (Figure 5(c), Figures 5(e)-(g)).

The influence strength of the family building area on embedded carbon emissions per capita also has an increasing trend with the increase in carbon emissions, but the estimated results do not pass the test of significance of 10% on the quantiles of 0.1 - 0.3. That illustrates building area will have a significant impact to carbon emissions only for the group of high embedded carbon emissions, and the higher the level of carbon emissions, the greater the influencing strength of building area (Figure 6(d)).

There is a stable trend of influence of frugality on embedded carbon emissions per capita. The quantile estimated coefficients are generally within the confidence interval of OLS estimates. It explains that the influence of cognitive preference of low carbon on embedded carbon emissions were not significantly difference under different emission levels (Figure 6(h)).

5. Conclusion and Discussions

Using large sample questionnaire survey data, high-resolution remote sensing data, and the ESDA and SDE methods, we measured the spatial patterns of

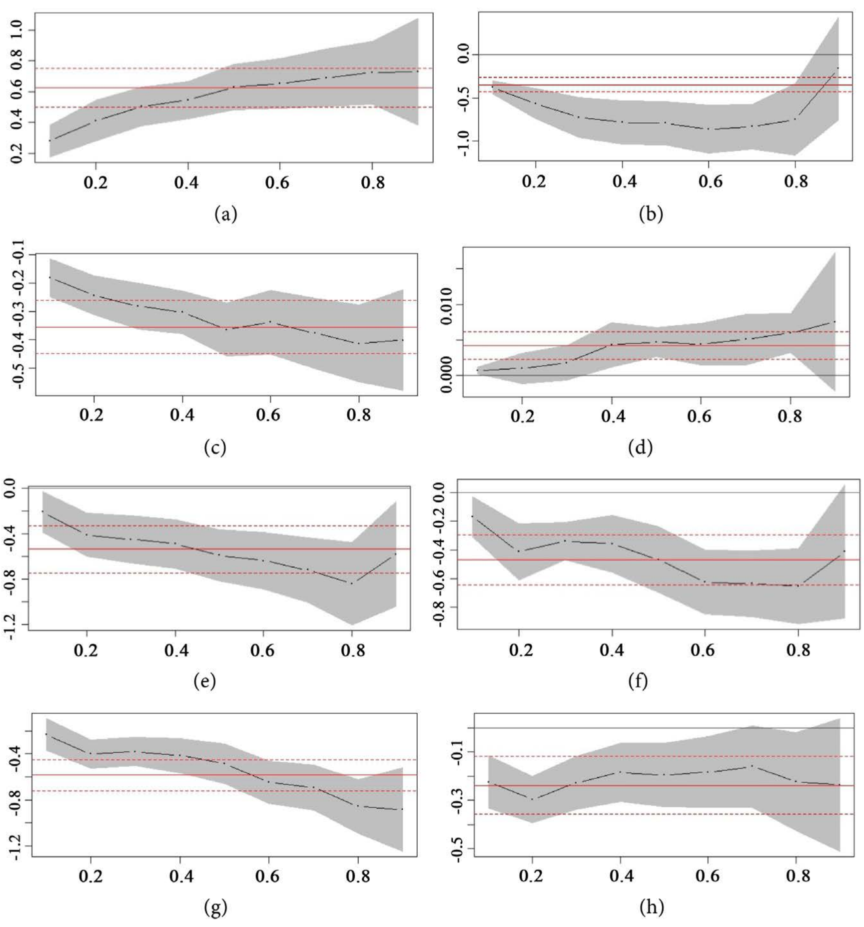

Figure 6. The quantile regression results for residential embedded carbon emissions. (a) Monthly household income; (b) Number of family members; (c) Housing property; (d) Building area; (e) Times of cooking at home; (f) Consumption without luxury; (g) Emphasis of low carbon consumption; (h) Frugal purpose for saving money.

urban residential embedded carbon emissions on an internal fine scale in Kaifeng. Using the OLS and QR methods, we explored its comprehensive effect mechanism and the influencing differences at different levels of carbon emissions. The contribution of this research is that we calculated the indirect carbon emissions generated by residents' consumption in the fine scale through large sample survey and economic input-output life cycle assessment model, and clarified the spatial distribution pattern within the urban area and the reasons for its formation.

The spatial dependency characteristics of household embedded carbon emission are more obvious than the spatial heterogeneity characteristics. The cluster areas of high value of the embedded carbon emissions mainly exist in the urban newly built development zone with a large number of residents in new commercial housing communities and employees of administrative departments and institutions whose construction times are late, housing prices are high, and facilities are perfect. The low-value agglomeration area is mainly in the northeastern area and eastern areas of the old city, which are mostly the old commercial houses and street communities. At present, the area with the greatest development effort is the development zone in the western of the city where spreading quickly to the provincial capital Zhengzhou, and because of the advantages of geographic location, the house prices are relatively high, so residents there need to have certain economic basis, it also determines its various consumptions which may be higher than in other districts. Correspondingly, the outer layers of east, south, and north are in the developing state, so that the commercial housing of different levels, housing placement, and self-establish buildings in the rural-urban continuum are blended together, so the rule is not obvious.

We can see from a lot of high and low carbon emission mixed areas that the problem of residential embedded carbon emissions is complicated. Families with the same geographical locations, living environments, and spatial patterns may produce vastly different carbon emissions due to different family characteristics, lifestyles, and behavioral preferences. The regression result of influencing factors shows that the characteristics of family, lifestyle, behavior, and ideology all affect the embedded carbon emissions. The application of the quantile regression (QR) method can more accurately reveal the different mechanisms of various influencing factors under different distribution functions and overcome the estimation error of the least square method on the mean level. The estimated results show that the influence strength of the remaining factors on embedded carbon emissions per ca-pita showed a trend of increase with the increase in carbon emissions, but the influencing strength of housing types and frugal purpose for saving money has the tendency of zigzag fluctuation. To a certain extent, the result emphasized the necessity of specific emissions reduction measures for high carbon emissions groups.

The conclusions are verified and supplemented for case application of situated lifestyle theory in Chinese cities from the perspective of residential carbon emissions, but there are limitations to the study. On the one hand, because of the fine scale of research, the data acquisition is difficult. This study only analyzes the spatial distribution of one time section. If the tracking survey of household consumption on a time dimension could be implemented or household energy and the public consumption statistic platform could be set up in the future, a richer conclusion will be obtained. On the other hand, further exploration of the influence mechanism of residential embedded carbon emissions is also the work to be carried out in future research.

Though we had calculated the indirect carbon emissions generated by residents' consumption in a fine scale, due to the difficulty in data acquisition, we only analyzed the spatial differentiation of one time section. In the future, if the tracking survey of the time dimension of household consumption is realized or the public platform of household energy and commodity consumption is effectively established, richer conclusions may be drawn. In addition, further exploration of the complex impact mechanism of resident embedded carbon emission is also the work to be carried out in the future research.

Highlights

Economic input-output life cycle assessment (EIO-LCA) model can be used for calculating the residential embedded carbon emissions.

There is obvious spatial dependence of residential embedded carbon emissions.

The high-emissions gather in new development zones that are expanding rapidly.

Specific emissions reduction measures for high emissions group are necessary.

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Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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