Article

Factors Controlling Urban and Rural Indirect Carbon Dioxide Emissions in Household Consumption: A Case Study in Beijing

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Abstract: Residential carbon dioxide emissions can be divided into a direct component caused by consumers via direct energy usage and an indirect component caused by consumers buying and using products to meet their needs, with a higher proportion caused by the latter. Based on Beijing panel data for 1993–2012, an economic boom period in China, indirect carbon dioxide emissions were separately calculated for urban and rural households using the consumer lifestyle approach (CLA) model. Then, an extended stochastic impact by regression on population, affluence, and technology (STIRPAT) model was used to analyze the influence from two aspects, social economy, and land use, with high precision. Results indicate that indirect CO₂ emissions in Beijing households display a rising trend in urban areas but a slight decrease in rural areas. Technology influences and forest land are, respectively, the most important aspects of the social economy and land use. Higher population and urbanization resulted in enhanced emissions in both urban and rural areas. The Engel coefficient presented a negative correlation with indirect CO₂ emissions for both rural and urban areas. Compared with urban areas, the per capita net income of rural areas restrained consumption. The consumption structure of urban residents was more biased toward the tertiary industry than that of rural residents. Although technical progress has proceeded, it cannot offset urban residents' indirect CO₂ emissions caused by the large amount and rapid growth of consumption. Regarding land use, urban construction land net primary productivity (NPP) was high and not an important factor contributing to indirect CO₂ emissions. Forest and lawn primarily served a recreational function and exhibited a positive impact. Water and cultivated land offered insufficient production and thus had a negative influence. For rural residents, lawn and cultivated land production is self-sufficient. Forests offer a carbon sequence effect, and construction land expansion increased the proportion of developed area, offering a scale effect that resulted in reduced carbon emissions. Based on the results, alternative carbon emission reduction policies have been proposed for each tested influence aspect to reduce emissions, including policies for optimizing industrialization quality, constructing a medium-density city, increasing space efficiency, encouraging sustainable consumption behavior, and increasing the efficiency of energy utilization.

Keywords: Beijing; urban and rural residents; indirect carbon dioxide emission; STIRPAT model; influencing factors

1. Introduction

With socio-economic development and a sharp increase in population, energy consumption is increasing worldwide. The geography of global energy consumption continues to shift toward countries experiencing rapid industrialization and urbanization, including China, which has already surpassed the United States as the largest emitter of carbon dioxide (CO₂) [1]. With a relatively more centralized population and greater anthropogenic activity, metropolitan areas are major sources of global carbon emissions [2,3]. In particular, Beijing, the capital of China, with higher CO₂ emissions and per capita CO₂ emissions than metropolises in developed countries [4], is becoming a common focus of carbon emission research [5–7].

The period between 1993 and 2012 represents an essential stage for China, especially Beijing. During this period, Beijing experienced its fastest economic growth and realized its transition from an industry-oriented to a service-oriented structure. In 2012, Chinese economic development reached a ‘new normal’ stage, which is a stage of economic development in which different degrees of decline in the national economy growth rate occur [8]. Before reaching this new normal stage, rapid urbanization and industrialization occurred in conjunction with relatively low efficiency and high energy use [9]. Therefore, examining the energy consumption and related CO₂ emissions in Beijing from 1993 to 2012 will provide details of an essential historical experience for Beijing and provide a way to construct a low-carbon city, providing a reference and inspiration allowing other developing countries to realize energy conservation and emissions reduction goals.

Current studies of energy consumption and carbon emissions mainly focus on industry sectors [10,11]. More attention should be given to household carbon emissions, especially in China. Energy consumption in households in China in 2012 accounted for 11% of the total energy consumption, and the number was 25%, considering private traveling, according to the *Chinese Residential Energy Consumption Report* (2014). Household energy consumption and related CO₂ emissions have been becoming indispensable components.

Residents’ lifestyle-relevant energy consumption and the related CO₂ emissions can be divided into a direct component caused by consumers using energy and an indirect component caused by consumers buying and using products to meet their basic needs [12]. The indirect part of Chinese households is much higher than their direct consumption [13,14]. In addition, most research on indirect household carbon emissions remains at the national level, and there are few specific studies at the city scale [15–17]. The existing studies have greatly assisted with energy conservation and emission reduction. However, because the many socioeconomic and environmental differences across regions in China increase the spatial heterogeneity of carbon emissions [16,18], research on indirect household carbon emissions at the city scale is necessary and has practical significance [19]. Moreover, a better understanding of household energy consumption and carbon emissions at the city scale is necessary for Chinese decision-makers to address energy security and local pollution mitigation.

Urban areas contain 40% of the population and account for 75% of the Chinese national economy [2]. Urban per capita energy consumption is typically 3.5 to 4 times greater than rural per capita energy consumption in China [7,20]. Considering the great difference between consumer lifestyles and the related indirect CO₂ emissions in China, urban and rural areas were separately studied in this paper.

Three estimation methods have been used to measure indirect household energy consumption: A hybrid energy analysis [21], the family metabolic method, and the consumer lifestyle approach (CLA) method [22]. Hybrid energy analysis and the family metabolic method treat consumption the item as a basic unit. They first calculate the energy consumption of each item and then add all consumption items up to get the household energy consumption and related emissions [21]. Although these two methods provide relatively elaborate results, they require very detailed data. Moreover, these two methods are more suitable for micro-scale calculation, like a household or a community, but not for macro-scale, like estimating household CO₂ emissions in whole Beijing because the data volume would be significant and the calculation would be extremely complex. Compared with these two methods,

the CLA method, which uses more accessible data, is commonly used to calculate indirect energy consumption and carbon emissions and was applied in this study [23,24].

Additionally, one of the keys to controlling CO₂ emissions is analyzing its influencing factors, and various methods have been used for this, including input–output models [25], LEAP models and Urban-RAM models [11], panel regression [26], and Holos models [27]. These models are primarily applied to analyses of the impact of macro-level factors, such as GDP, industry sector, and energy intensity. They are province (or province city) level data and regard the urban and rural as a whole, thus it is not suitable for analyzing urban and rural separately [28,29]. The stochastic impact by regression on population, affluence, and technology (STIRPAT) model, another common factor decomposition model, was first applied in this area by York et al. [30], and then broadly used based on panel or cross-sectional data [16,31–33]. In this study, the STIRPAT model was utilized.

Currently, although utilization of the STIRPAT model can resolve many problems, there are areas where its application could be improved. First, regarding the spatial and temporal scales, Brantley Liddle collected 28 articles based on the STIRPAT model at macroscopic scales and argued that the STIRPAT model should be applied to smaller spatial scales and longer time scales [31]. Second, regarding the study area, recent studies have mainly focused on developed countries, while little attention has been given to developing countries [31]. Finally, the STIRPAT model focuses less on changes in the extension of urban land use [28,34]. However, the process of urbanization not only involves a change in industrial structure and a shift in lifestyle but also includes transitions in the land-utilization. Urbanization leads to urban expansion into fertile and productive lands. This process not only directly decreases carbon storage but also releases more CO₂ [35,36], dramatically altering ecosystem functions and processes [37,38].

Net primary productivity (NPP), a sensitive indicator of the energy and material cycles of ecosystems [39,40], has been used to quantify the impact of land transformation on an ecosystem [36,41], determine the anthropogenic activities' ecological impact, and reflect the impact of different lifestyles on the environment [42]. Most of the existing research on the relationship between CO₂ emissions and NPP uses cross-sectional data, and studies analyzing inter-annual variations commonly use NPP of one year [16], which leads to low precision. In this paper, based on the Carnegie–Ames–Stanford Approach (CASA) model and MODIS remote sensing data, the NPP of Beijing from 2001 to 2012 was calculated at a resolution of 250 meters by 250 meters to provide accurate results. Therefore, in addition to widely used social-economic factors [34], the land-use factors based on the NPP were added to the analysis.

To address the aforementioned issues, first, Indirect CO₂ emissions in urban and rural households in Beijing between 1993–2012, an economic boom period before 'new normal', are calculated. Second, land use influence factors are added to the widely used factors: Population, affluence, technology in STIRPAT analysis. Additionally, rather than using the annual data, net primary production is calculated using remote sensing data for each year to improve the accuracy of the results. Finally, policy suggestions are proposed. This research is expected to improve the analyses of the comprehensive influence of indirect CO₂ emissions from households in other metropolises during rapid economic booms and the realization of energy conservation and emission reduction goals.

2. Study Area and Data

2.1. Study Area

Beijing, a high-consumption city and the capital of China, was selected as the study area (Figure 1). During the period from 1993 to 2012, the urban population (11.12 million by the end of 1993 and 20.69 million by the end of 2012) increased rapidly, accompanied by a tenfold increase in per capita disposable income, unstable growth, and a rapid transition in the consumption structure (Figures 2 and 3, data from 1993 to 2012 *Beijing Statistical Yearbook*), resulting in increased energy consumption in households and related CO₂ emissions. As a result, household energy consumption and related CO₂ emissions are a critical component of overall carbon emissions.

Figure 1. The location of the study area.

Figure 2. Per capita disposable income growth since the reform and opening-up.

Figure 3. The Engel coefficient since the reform and opening-up.

2.2. Data

Data on gross output and energy consumption for different sectors, consumption expenditures by urban and rural households, demographics, per capita income, GDP, Engle coefficient, energy intensity, and mechanical harvest area proportion are taken from 1993 to 2012 (missing data for 2004) *Beijing Statistical Yearbook*. Carbon emission coefficients are taken from the *2006 IPCC Guidelines for National Greenhouse Gas Inventories*. To avoid error caused by price fluctuations, urban per capita disposable income, and rural per capita net income are adjusted to a 1993 constant according to the GDP index and the consumer price index. The meteorological data are taken from the China meteorological science data-sharing service (<http://cdc.cma.gov.cn/>). Fraction of photosynthetically active radiation (FPAR)

and the data needed to calculate the temperature and water stress coefficients are taken from the NASA server (ladsweb.nascom.nasa.gov). The ground biomass data are taken from a field sampling of the Tibetan Plateau in 2012 and 2013 and Inner Mongolia.

3. Methodology

Figure 4 presents the methods used in this paper and their functions.

Figure 4. The methods utilized in this paper and their functions.

3.1. The CLA Model

In the late 1980s, researchers brought the concept of lifestyle into the study of personal energy consumption [43]. Then CLA was proposed by Bin and Dowlatabadi [12] to decompose all of the components of lifestyle and then break down the total energy consumption of households across the variety of lifestyle areas [16,23]. Based on the classification of direct and indirect carbon emissions, Chinese consumer behaviors are classified, as shown in Table 1.

Table 1. Residents' living behavior categorization for CO₂ emissions.

Residents' Living Behavior	Residents' Living Behavior Categorization	
Direct CO ₂ emission behaviors	Household CO ₂ emission behavior	Cooling, heating Lighting Heating, cooking Recreation and other similar behaviors
	Personal travel	Long-distance travel by plane, ship, and automobile Short-distance travel by private automobile, motorcycle, and public transportation
Indirect CO ₂ emission behaviors		Food
		Clothing
		Household
		Facilities and services
		Medical and medicine
		Transport and communication services
		Education, culture, recreation
		Other commodities and services

According to the classification of production in Beijing's statistical yearbook and existing research [16], production sectors are merged into eight indirect carbon consumption behaviors (Table 2).

Table 2. Sectors related to household consumer behavior.

Residents' Indirect Carbon Behavior	Related Sectors
Food	Processing of Food from Agricultural Products, Manufacture of Foods, Manufacture of Wines, Beverage, and Refined Tea
Clothing	Manufacture of Textiles, Manufacture of Textile Wearing Apparel and Ornament, Manufacture of Leather, Fur, Feather, and its Products
Household	Production and Supply of Electric Power and Heat, Production and Distribution of Gas, Production and Distribution of Water, Manufacture of Non-metallic Mineral Products, Manufacture of Fabricated Metal Products
Facilities and services	Processing of Timber, Manufacture of Wood, Bamboo, Rattan, Palm, and Straw Products, Manufacture of Furniture, Manufacture of Rubber and Plastic Products, Manufacture of Electrical Machinery and Equipment
Medical and medicine	Manufacture of Medicines
Transport and communication services	Manufacture of Motor Vehicles, Manufacture of Railway Locomotives, Building of Ships and Boats, Manufacture of Air and Spacecraft and Other Transportation Equipment, Manufacture of Computer, Communication Equipment, and Other Electronic Equipment
Education, culture, and recreation services	Manufacture of Paper and Paper Products, Printing, Reproduction of Recording Media, Manufacture of Articles for Culture, Education, Artwork, Sports, and Entertainment Activity
Other commodities and services	Manufacture of Cigarettes and Tobacco

Based on Table 2, the CLA can be used to calculate indirect CO₂ emissions in urban and rural areas as follows:

$$CO_2 = \sum_i (CI_i \times X_i) \times N \quad (1)$$

$$CI_i = C_i / G_i \quad (2)$$

where CO₂ refers to the indirect CO₂ emissions of urban (rural) residents in Beijing. CI_i refers to the CO₂ intensity of sector i , which is equal to the sum of CO₂ emissions for the industries in sector i (C_i) divided by the sum of the value added of the industries in sector i (G_i). X_i refers to the per capita expenditure on consumption for products from sector i . N refers to the permanent population in the urban (rural) areas of Beijing.

3.2. The STIRPAT Model

The central concept of the STIRPAT model can be traced back to 1970, when Paul Ehrlich demonstrated that environmental pollution is connected to population size, per capita consumption, and environmental impact per unit of production [44]. The STIRPAT model is derived from the IPAT model ($I = PAT$) proposed by [45], where I represents environmental impact, P represents population, A is affluence, and T is technology level. There are two deficiencies in the IPAT model. First, the model is based on an identity equation and cannot be directly used to indicate a single factor's impact on the environment. The other is that the model assumes that the factors of population, affluence, and technology have the same elasticity in their impact on the environment, which does not occur in reality [46]. To solve these problems, Dietz and Rosa obtained the STIRPAT model [46],

$$I = a P^b A^c T^d e \quad (3)$$

where I , P , A , and T have the same meaning as in the IPAT model, but a represents the model coefficient, and b , c , and d represent exponential terms to be estimated for the population, affluence, and technology

factors, respectively, e represents random error. In addition, the STIRPAT model is usually estimated in logarithmic form:

$$\ln I = a + b(\ln P) + c(\ln A) + d(\ln T) + e \quad (4)$$

b , c , and d in the formula can be regarded as the percentage change in the environmental impact caused by a 1% change in the population, affluence, or technology, respectively. As the STIRPAT model is extendable, the explanatory variables can be increased or decreased according to different research purposes.

The PLS Method

The partial least squares regression (PLS) method was used to solve the multicollinearity problem. The PLS concept can be traced back to the 1960s [47]. The ideas and statistical principles of PLS had remained unsolved until 1983 when PLS was applied in stoichiometric chemistry [48]. The PLS model is mainly applied to solve multicollinearity in a multiple regression where the sample size is limited, and the degrees of freedom are relatively low [47]. In this study, Simca-P 11.5 was adopted to perform the PLS calculations.

3.3. Net Primary Production

The CASA model [49] was used to calculate NPP:

$$NPP = SOL \times 0.5 \times FPAR \times \varepsilon_{max} \times Ts \times W \quad (5)$$

where SOL represents total solar radiation, calculated using the climatology method [50]. $FPAR$ is the proportion of the photosynthetically active radiation absorbed by vegetation. The $FPAR$ data of MODIS level four production MCD15A2H derived from vegetation canopy light are used in this study. ε_{max} represents the greatest energy conversion from vegetation photosynthesis multiplied by the temperature stress coefficient (Ts) and water stress coefficient (W) to capture light utility efficiency. W is computed based on existing research [51], and the near-infrared and shortwave infrared reflectivity data are taken from MOD09A1 and MOD09Q1. T is computed based on existing research [6], and precipitation data are interpolated from station data. Finally, net primary production is the result of NPP multiplied by the land area of the corresponding land use type.

4. Empirical Study

4.1. Urban and Rural Household's Indirect CO₂ Emissions

Using the CLA method, the carbon intensity of all types of industry sectors in Beijing were calculated for 1993–2012 (Table 3). With the development of science and technology, industrial carbon emissions intensity presented an obvious decreasing trend. Using the industry sectors' carbon emissions intensity, the household indirect CO₂ emissions of Beijing urban and rural residents from 1993 to 2012 were calculated (Figure 5). Since 1993, some fluctuations in the indirect CO₂ emissions in Beijing have occurred: the indirect CO₂ emissions of urban residents exhibited a trend of rapid growth, while the indirect CO₂ emissions of rural residents exhibited a trend toward small decreases. There were major differences between the indirect CO₂ emissions of urban and rural residents. In addition, there was a slight fluctuation in the difference between urban and rural residents' indirect CO₂ emissions, with an overall increasing inter-annual trend.

Figure 5. Calculated urban and rural indirect CO₂ emissions and the difference between them.

Table 3. The calculated carbon dioxide intensity of different sectors for 1993–2012 (t CO₂/10⁴ Yuan).

Items	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002
Food	1.30	1.42	1.07	0.99	0.80	0.96	1.07	0.88	1.00	0.89
Clothing	1.48	1.07	1.04	1.42	1.30	1.24	1.38	1.12	1.15	0.92
Residence	21.52	11.04	15.83	13.50	11.80	3.83	5.06	3.85	4.04	4.48
Household facilities, articles, and services	1.87	1.30	1.24	1.20	1.19	0.83	0.89	0.69	0.88	0.80
Medicine and medical services	2.05	1.38	1.43	1.05	1.02	0.87	0.80	0.61	0.63	0.44
Transport and communications services	0.86	0.66	0.69	0.46	0.35	0.28	0.28	0.18	0.18	0.17
Education, cultural, and recreation services	1.92	1.50	1.39	1.24	1.28	0.92	1.04	0.95	1.02	0.79
Miscellaneous commodities and services	0.56	0.45	0.58	0.50	0.46	0.45	0.44	0.43	0.41	2.29
Items	2003	2005	2006	2007	2008	2009	2010	2011	2012	
Food	0.85	0.69	0.68	0.59	0.51	0.47	0.44	0.42	0.38	
Clothing	0.84	0.68	0.66	0.58	0.52	0.51	0.42	0.16	0.45	
Residence	4.29	2.21	1.68	1.33	1.07	1.00	0.76	0.62	0.49	
Household facilities, articles, and services	0.55	0.59	0.43	0.38	0.34	0.24	0.23	0.24	0.25	
Medicine and medical services	0.42	0.43	0.40	0.33	0.26	0.24	0.21	0.57	0.17	
Transport and communications services	0.16	0.11	0.10	0.09	0.09	0.09	0.08	0.10	0.12	
Education, cultural, and recreation services	0.82	0.81	0.71	0.62	0.56	0.56	0.55	0.66	0.54	
Miscellaneous commodities and services	0.21	0.17	0.16	0.12	0.11	0.11	0.10	0.10	0.10	

4.2. An analysis of Influencing Factors

4.2.1. Socioeconomic influences

Variable Selection

Nine indicators are selected as explanatory variables (Table 4).

- (1) **Population.** Urban and rural permanent populations were chosen to assess the effects of the population on indirect CO₂ emissions. Furthermore, urbanization rate, a characteristic that can indirectly reflect urban population lifestyle and consumption, which exhibits different impacts on CO₂ emissions at different stages of development [31,33] was selected.
- (2) **Affluence.** Because the research objective is to measure the indirect CO₂ emissions of urban and rural residents, the widely used indicator GDP [31] was replaced by consumption ability (urban residents' per capita disposable income and rural per capita net income) and consumption structure (the Engel coefficient of urban and rural residents). In general, high-income families have a higher consumption ability, resulting in greater indirect CO₂ emissions. The Engel

coefficient reflects the proportion of food consumption in total consumption, revealing the consumption structure transition trend and the influence of household consumption on indirect energy consumption.

- (3) Technology. A less specific definition of “technology” makes the selection of technical indicators complex. This variation was proxied by four indexes: Secondary industry proportion, tertiary industry proportion, mechanical harvest area proportion, and energy intensity. The mechanical harvest area proportion, which reflects agricultural mechanization levels, was combined with the other widely used indicators that have been shown to have a profound influence on carbon emissions [16,31,34] and can reflect the industry structure, advancing level, and energy utilization efficiency.

Table 4. The definition of variables and measurement methods.

Variable	Symbol	Variable Declaration	Unit
Indirect CO ₂ emission	I	Indirect CO ₂ emissions through daily consumption in households	10 ⁴ tons
Population size	P	Urban (rural) permanent population	Ten thousand people
Urbanization level	U	The proportion of the urban resident population in the total resident population	%
Per capita income	A	Urban per capita disposable income (Rural per capita net income)	Yuan per capita, constant 1993 RMB Yuan
Engel coefficient	E	The proportion of food consumption out of total consumption	%
Secondary industry proportion	S	The share of the secondary industry output value over the total GDP	%
Tertiary industry proportion	TI	The share of the tertiary industry output value over the total GDP	%
Energy intensity	EI	Energy use per constant 1993 PPP Yuan GDP	Tons of standard coal per ten thousand 1993 PPP Yuan
Mechanical harvest area proportion	M	The mechanical harvest area proportion	%

Collinearity Diagnostics

The correlation between the variables was tested via SPSS19.0 for urban and rural separately (Tables 5 and 6). There are significant correlations between every two of the following seven independent variables, which are population size, urbanization level, per capita income, Engel coefficient, secondary industry proportion, tertiary industry proportion, and energy intensity, suggesting the presence of multicollinearity in the variables. Traditional least squares regression modeling can be influenced by multicollinearity and cannot guarantee the accuracy and reliability of the model. Therefore, the PLS method was used to construct the STIRPAT model.

Table 5. Correlation between variables for urban residents.

	ln(I)	ln(P)	ln(U)	ln(A)	ln(E)	ln(S)	ln(TI)	ln(EI)	ln(M)
ln(I)	1	0.857 ^a	0.817 ^a	0.866 ^a	−0.869 ^a	−0.818 ^a	0.781 ^a	−0.901 ^a	0.152
ln (P)	−	1	0.978 ^a	0.992 ^a	−0.849 ^a	−0.981 ^a	0.596 ^a	−0.971 ^a	−0.203
ln(U)	−	−	1	0.986 ^a	−0.865 ^a	−0.978 ^a	0.558 ^b	−0.951 ^a	−0.284
ln(A)	−	−	−	1	−0.897 ^a	−0.983 ^a	0.599 ^a	−0.982 ^a	−0.191
ln(E)	−	−	−	−	1	0.863 ^a	−0.625 ^a	0.910 ^a	0.019
ln(S)	−	−	−	−	−	1	−0.618 ^a	0.971 ^a	0.315
ln(TI)	−	−	−	−	−	−	1	−0.708 ^a	0.014
ln(EI)	−	−	−	−	−	−	−	1	0.129
ln(M)	−	−	−	−	−	−	−	−	1

a. Significant at the 1% level. b. Significant at the 5% level.

Table 6. Correlation between variables for rural residents.

	ln(I)	ln(P)	ln(U)	ln(A)	ln(E)	ln(S)	ln(TI)	ln(EI)	ln(M)
ln(I)	1	0.777 ^a	−0.563 ^b	−0.467 ^b	0.325	0.540 ^b	−0.472 ^b	0.426	0.583 ^a
ln (P)	−	1	−0.614 ^a	−0.474 ^b	0.360	0.497 ^b	−0.449	0.388	0.518 ^b
ln(U)	−	−	1	0.982 ^a	−0.836 ^a	−0.978 ^a	0.953 ^a	−0.951 ^a	−0.284
ln(A)	−	−	−	1	−0.841 ^a	−0.974 ^a	0.944 ^a	−0.966 ^a	−0.187
ln(E)	−	−	−	−	1	0.840 ^a	−0.897 ^a	0.887 ^a	0.013
ln(S)	−	−	−	−	−	1	−0.981 ^a	0.971 ^a	0.315
ln(TI)	−	−	−	−	−	−	1	−0.979 ^a	−0.250
ln(EI)	−	−	−	−	−	−	−	1	0.129
ln(M)	−	−	−	−	−	−	−	−	1

a. Significant at the 1% level. b. Significant at the 5% level.

PLS Model Validation

Two types of figures were used to explain the applicability of the PLS Method: The t_1/u_1 scatter plot and t_1/t_2 scatter plot (Figures 6 and 7). It can be clearly seen that the t_1/u_1 relationship was nearly linear, with an R^2 above 0.7, demonstrating that t_1 and u_1 can represent the variation in the dependent and independent variables to some extent and that the model was appropriate. In Figure 7, all of the sample points were in uniform distribution and included in the oval, a confidence level of 95%, showing that the sample data were homogeneous and acceptable. In addition, Figure 8 reflects a near-linear relationship between the predicted value and the observed value, showing that the regression model had high precision. The variable importance in projection (VIP) in Figure 9 reflects the potential of each independent variable for explaining each dependent variable. A VIP value of more than 1 indicates that the variable is important, and a variable with a VIP less than 0.5 is unimportant. The interval between 1 and 0.5 is a gray zone, where the importance level depends on the VIP value [52]. Each independent variable had an important role in explaining the growth of indirect CO₂ emissions. Therefore, the PLS model was effective.

Figure 6. $t1/u1$ scatter plot of urban and rural residents.

Figure 7. $t1/t2$ scatter plot of urban and rural residents.

Figure 8. Observed vs. predicted plot of urban and rural residents.

Figure 9. VIP histogram of urban and rural residents.

Analysis of Regression Results

The regression coefficients of the PLS method are shown in Table 7. For urban residents, tertiary industry proportion and mechanical harvest area proportion showed higher influence, whose coefficients were 0.265 and 0.290 respectively, followed by Engel coefficient (−0.188), energy intensity (−0.157), population size (0.131), per capita income (0.131), urbanization level (0.096) and secondary industry proportion (−0.088). For rural residents, population size (0.428) and mechanical harvest area proportion (0.351) were domain factors, followed by secondary industry proportion (0.085), Engel coefficient (−0.050), tertiary industry proportion (−0.031), per capita income (−0.029), energy intensity (0.012) and urbanization level (−0.010).

Table 7. Regression coefficient for urban and rural socioeconomic factors.

Variables	Standardized Coefficient	
	Urban	Rural
Constant	26.933	21.643
ln(P)	0.131	0.428
ln(U)	0.096	−0.010
ln(A)	0.131	−0.029
ln(E)	−0.188	−0.050
ln(S)	−0.088	0.085
ln(TI)	0.265	−0.031
ln(EI)	−0.157	0.012
ln(M)	0.290	0.351

The positive coefficient of population indicated that population and urban expansion increased the pressure on the environment and became the main element contributing to rural indirect CO₂ emissions in households (with the largest standardized coefficient). In the stage of rapid urbanization and industrialization, Beijing attracted many people. The non-native population increase became an indispensable component, causing great environmental pressure. According to the data of the 6th National Population Census in 2010, Beijing's permanent population reached 19.6 million (an increase of 44.5% over the 5th National Population Census in 2000), among which 7.045 million were non-native individuals. Furthermore, according to data obtained from the Beijing municipal bureau of statistics, since 1990, the permanent population, especially the non-native population, routinely moved to marginal areas. From 2000 to 2010, the non-native population in the central city and the suburban decreased by 3.8% and 7.8%, respectively. Only the non-native population of the outer suburbs increased (12.5%).

The urbanization process can be represented by three aspects. First is the transformation from rural residents to urban residents. With the process of urbanization, a large number of rural residents, especially the young, migrate to urban areas. Their lifestyle becomes urbanized, causing greater energy consumption and CO₂ emissions. Second is the change in the industry. Urbanization promotes the development of the secondary and tertiary industry, thus increasing energy consumption and indirect CO₂ emissions. Third is the expansion of construction land. Compared with grassland or farmland, construction land generates more carbon emissions and reduces carbon absorption [53]. Thus, urbanization showed a positive impact on urban household CO₂ emission but a negative role in rural household CO₂ emission.

Per capita net income positively contributed to urban residents' indirect CO₂ emissions. However, it exhibited a negative contribution in rural areas. In the rapid development stage, the income gap between urban and rural residents expanded annually. For example, the Beijing urban per capita disposable income in 1993 was 1.78 times that of rural areas, and the proportion increased to 2.21 times in 2012 (using constant 1993 RMB Yuan). Therefore, in this period, for urban residents, increased income can stimulate consumption, but rural per capita net income constrains rural residents' consumption.

The Engel coefficient indicated a positive influence and a stronger influence on urban indirect CO₂ emissions than seen in rural areas. With improvements in economic growth and living standards, consumer attitudes transitioned from basic material satisfaction to more diverse commodities and spiritual enjoyment. Urban residents enjoyed relatively more diverse commodities and services, and the upgraded consumption structure imposed environmental pressure.

The transition of consumption structure can also be reflected in the consumption of commodities from different industrial sectors. The results show that the consumption structure of urban residents was more biased toward the tertiary industry than that of rural residents. As for the regression results for the mechanical harvest area proportion, they show that improvements in agricultural mechanization will improve urban and rural residents' indirect CO₂ emissions, because China's agricultural production is neither large-scale nor intensive, leading to low efficiency and high energy consumption [54].

Energy density was found to be negatively related to urban residents' indirect CO₂ emissions and positively correlated to rural residents'. During the economic development stage in Beijing, although every industry had realized different degrees of energy intensity declines triggered by industrial structure optimization and technological progress, the technology level was unable to offset urban residents' indirect CO₂ emissions.

4.2.2. The Influence of Different Land Uses

Net Primary Production Calculation and Validation

The mean absolute error between the simulation value and the measured value of NPP was 27.99 g C·m⁻²·a⁻¹, and most of the relative errors were within 20%, being relatively small. Along with the change in the sample NPP, the change in the trend of the simulation value and measured value exhibited good consistency. Additionally, they had a significant correlation ($R^2 = 0.90$, $P < 0.01$, and $n = 61$) (Figure 10). From the above, the result simulated by the CASA model was acceptable. In addition, based on the NPP, the net primary production was calculated (Table 8).

(a) Difference between measured values and simulated values of NPP

(b) The correlation analysis of measured value and simulation value

Figure 10. Precision evaluation of CASA model.

Table 8. Net primary production of different land use types (unit: $10^4 \text{ t C} \cdot \text{a}^{-1}$).

Year	Water	Forest	Lawn	Cultivated Land	Construction Land
2000	0.28	330.42	150.88	305.27	15.79
2001	0.88	250.54	79.85	157.10	15.63
2002	0.92	215.69	52.85	211.09	15.28
2003	0.87	210.12	53.51	202.79	14.56
2004	0.50	227.15	41.28	246.50	15.93
2005	1.08	250.34	74.34	175.00	15.69
2006	0.82	311.68	68.95	196.14	16.79
2007	2.38	330.31	94.53	201.72	18.83
2008	1.48	335.84	79.69	201.84	18.47
2009	1.93	347.70	110.29	184.38	18.65
2010	0.62	331.08	103.77	165.18	17.02
2011	0.81	345.18	108.98	158.48	17.29
2012	0.64	365.58	95.35	165.54	17.86

PLS Model Validation

The PLS was used to build the STIRPAT model and to analyze the relationship between land patterns and household indirect carbon emissions. In particular, when urban household CO₂ emissions were modeled, the data for 2002 and 2003 were eliminated because they were abnormal in the t_1/u_1 test. The R^2 values of the final models for urban and rural residents were 0.69 and 0.71, respectively, and the four figures shown in 4.2.1.3 were used for model validation (Figures 11–14). Therefore, the biological production and carbon absorption abilities represented by net primary production explained the indirect CO₂ emissions in household consumption to some extent.

Figure 11. t_1/u_1 scatter plot of urban and rural residents.

Figure 12. t_1/t_2 scatter plot of urban and rural residents.

Figure 13. Observed vs. predicted plot of urban and rural residents.

Figure 14. VIP histogram of urban and rural residents.

Analysis of Regression Results

The regression coefficients are shown in Table 9. For urban residents, forest and water NPP showed higher influence, whose coefficients were 0.60 and -0.50 respectively, followed by lawn (0.092) and cultivated land (-0.076). Construction land NPP is not a significant factor. For rural residents, forest NPP (-0.85) showed the greatest influence, followed by lawn (0.36), construction land (-0.29), and lawn (0.03).

- (1) Water. Water provides aquatic product used to meet residents' consumption needs. Based on the model results, the water NPP exhibited a negative influence on the indirect CO_2 emissions of urban residents. Although there was an increasing trend in aquatic product output in Beijing, it still could not meet demand. The aquatic products consumed in Beijing were mainly from the exterior (*Beijing Statistic Yearbook*). Meanwhile, water NPP was not an important indicator of rural resident indirect CO_2 emissions, as the per capita consumption of aquatic products increased by only 0.62 kg from 2001 to 2012, reflecting the difference between urban and rural residents' consumption structure: Urban residents tend to have more diverse food consumption.
- (2) Forest. Forests have a production function of providing forest products and timber, an ecological function of absorbing carbon emissions, and can be regarded as tourist destinations. However, the forest resources protection and management regulations of Beijing prohibit cutting down trees, limiting the production function. Therefore, the forest ecological function caused its NPP to be negatively correlated with rural resident CO_2 emissions, although this did not offset the rapidly increasing urban CO_2 emissions. Furthermore, almost all of the forests in Beijing are distributed in rural areas, which may affect urban residents' train travel and driving behaviors, along with indirect CO_2 emissions.
- (3) Lawns. Lawns in Beijing usually have a production function of supporting livestock products and an ecological function of absorbing carbon emissions. However, the carbon sequestration quantity of herbaceous plants was limited, and clipping may have increased CO_2 emissions [55]. As the result shows, with a higher positive coefficient, native livestock products were mainly supplied to rural residents.
- (4) Cultivated land. The regression results show that cultivated land net primary production was negatively correlated with urban residents' indirect CO_2 emissions and had a weak positive correlation with rural residents' indirect CO_2 emissions. Due to the rapid industrial structural transformation, Beijing has limited ability to produce grain, and yet it is the largest grain-consuming region in northern China [56]. The native grain production cannot satisfy the daily consumption of urban residents and can meet the needs of rural residents' consumption to only a minimal degree.
- (5) Construction land. With high land urbanization, new construction land was limited and mainly concentrated in suburban and outer suburban areas (*China's Urban and Rural Construction Statistics Yearbook*). Thus, its net primary production had an unimportant influence on urban resident

indirect CO₂. Additionally, new construction land increased the density of developed areas in the mature urbanized district, and as discussed by Satoshi et al., medium-density usually causes minimum energy consumption [57]. Thus, the spatial expansion of construction land would to some extent help ease the carbon emissions caused by excessively high density and its related congestion.

Table 9. Regression coefficients for urban and rural land use factors.

Variables	Standardized Coefficients	
	Urban	Rural
Constant	62.04	22.09
Water	−0.50	−
Forest	0.60	−0.85
Lawn	0.092	0.36
Cultivated land	−0.076	0.03
Construction land	−	−0.29

5. Conclusions and Recommendations

Residents' indirect household CO₂ emissions fluctuate, showing a rising trend in urban areas but a small decrease in rural areas. The indirect CO₂ emissions of urban residents are much higher than that of rural residents, reflecting the differences between urban and rural residents' consumption modes, with the former causing higher indirect CO₂ emissions. Compared to the factor analyzing results with studies in other regions, Beijing shows special characteristics. Studies in Finland and Thailand show urbanization is not strongly related with CO₂ emissions, and the indirect CO₂ emission produced by urban residents is slightly less than those of rural people [15,58]. As for the studies of different regions in China, the population was regarded as the primary driver, which is the same with rural Beijing [58,59]. For urban Beijing, technology and consumption structure shows greater influence. Moreover, secondary industry proportion showed a positive influence in current studies, however, it has a negative influence on indirect household CO₂ emission in urban Beijing [5,60]. Considering the dense population, significant urban-rural difference, and advanced consumption level, it is necessary to provide targeted carbon emission reduction policies.

Industrialization: The results showed that during the process of industrialization, the consumption of urban residents has a quicker reformation, i.e., the consumption structure of urban residents is more biased toward the tertiary industry than that of rural residents. Beijing, which has experienced a rapid economic boom, focused heavily on the pace of industrialization, resulting in a high ratio of tertiary industry output value but unbalanced and under-graded industrialization. Optimizing the industrialization quality will play an important role in increasing energy efficiency and realizing energy conservation and emissions reduction. For energy-intensive industries, the government should control the scale to prevent overcapacity and plan to phase them out. For the tertiary industry, the government should implement effective policies to encourage them to import materials. Moreover, the Chinese government should take advantage of the agglomeration effect to improve production efficiency, for example, encourage sectors to become specialized and build an inter-sector industrial chain to realize emission reduction.

Urbanization of population: Beijing, with its superior economic status and high degree of urbanization, similar to other metropolises around the world, has become a center of population aggregation for not only its rural residents but also immigrants from other provinces and even other countries. Aiming to become a low-carbon city, Beijing must reasonably control the population of permanent residents, especially the scale of its urban population, to improve the quality of urbanization and decrease population density.

Urbanization of land: As for urban residents' indirect CO₂ emissions, construction land NPP, which has been maintained at a high level, is not a crucial factor. Forests and lawns should be given

priority given their recreational function and positive impact, and water and cultivated land show insufficient production, which has a negative influence. As for rural residents' indirect CO₂ emissions, lawn and cultivated land production can be self-sufficient. Forests provide a carbon sequestration effect, and construction land expansion reduces density, leading to carbon emissions reduction. Beijing urgently needs to formulate policies that design the appropriate scale and reasonable layout to increase energy use efficiency and realize indirect CO₂ reductions. Beijing should focus on protecting forests and maintaining their rational distribution, especially in urban areas. Based on the result, the forest lands, especially those in urban areas, showed a significant positive role in emission reduction. Moreover, scientific management and clipping are important. The city should be constructed at a medium density to balance the use intensity of urban and rural construction land. The government can plan and provide more accessibility to the shared-used spaces and resources, making households less obligated to own everything and increase the efficiency of land utilization and frequency of the equipment usage.

Consumption behavior: The Engel coefficient presents a negative correlation with indirect CO₂ emissions for both urban and rural residents. Per capita net income presents a positive correlation with urban residents' CO₂ emissions but a negative one with rural residents' emissions. This result means that compared with urban residents, rural per capita net income and lifestyle have become an important constraint of rural residents' consumption. On the one hand, considering the stimulus of economic development to household consumption, it is imperative for Beijing to encourage rational and green consumption. On the other hand, the government should always be alert to avoid disproportionately economic pressure caused by environmental protection on the lower-income rural residents and reduce inequality. Meanwhile, Beijing needs to intensify publicity to raise awareness of saving energy and protecting the environment. Studies have shown that raising awareness on environmental-friendly consumption has great potential to benefit sustainable development. Installation of energy and emission metering devices can provide the residents regular and effective feedback to change their behavior and live a sustainable life [61].

Efficiency of energy utilization: Technology was proved to be the most important factor for indirect household CO₂ emissions, within which, energy intensity has less of an effect and mechanical harvest area proportion has a greater positive influence for both urban and rural residents. The result suggested that Beijing should pay more attention to improving output per energy unit and cutting down the per-unit energy use. From the energy source perspective, China must formulate policies to increase the usage of renewable energy rather than high carbon coal, which accounted for nearly 66% of the total energy supply in 2012 (data from *U.S. Energy Information Administration*). From the energy consumption perspective, the government should encourage industrial intensivism. Especially for agricultural production, the government should encourage cooperation between farmers or villages, forming large-scale and intensive agricultural production, thus increase efficiency and reduce energy consumption.

Although this study contributes to a better understanding of urban and rural indirect CO₂ household emissions in Beijing and their influence factor from socio-economic factors and land-use aspects during an economic boom period, it has some limitations. A future study should analyze CO₂ emissions in the "new normal" stage, when different degrees of decline in the national economic growth rate occur. Studying and analyzing the CO₂ emissions characteristics and how their influence factors work, have the potential to propose targeted policy recommendations.

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Abbreviations

CO ₂	carbon dioxide
CLA	Consumer Lifestyle Approach
STIRPAT	Stochastic Impact by Regression on Population, Affluence, and Technology
PLS	Partial Least Squares Regression
NPP	Net Primary Productivity

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