MEASUREMENT AND INFLUENCING FACTORS OF INDIRECT CARBON EMISSIONS FROM FOOD CONSUMPTION IN CHINA

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(Received 31st Mar 2023; accepted 18th May 2023)

Abstract. The paper selects 30 provincial units in China as the research objects, and the input-output method is used to calculate the indirect carbon emissions from food consumption. The results showed that: (1) The indirect carbon emissions reached 1.522 billion tons, of which 19.81% came from power and heat production and supply industry, 17.19% from agriculture, forestry, animal husbandry and fishery industry, and 15.14% from food processing industry; (2) The spatial differentiation of indirect carbon emissions from food consumption was significant, showing a “center-periphery” distribution characteristic. (3) The global and local correlation characteristics are positive. Eight provinces including Henan, Hubei, Hebei, Tianjin and Shandong belonged to the “high-high” cluster type, Qinghai, Gansu, Ningxia, Guangdong and Guangxi belonged to the “low-low” cluster type, while Liaoning, Jilin and Xinjiang were classified as the “high-low” cluster type; (4) Urbanization level was the main factors affecting the indirect carbon emissions of food consumption, followed by culture level of labor force, agricultural capital investment and agricultural production efficiency. Indirect carbon emissions could be reduced by decreasing the energy consumption level of the food industry chain, promoting the green transformation of agricultural development, and guiding residents to develop reasonable dietary habits.
Keywords: *carbon emission intensity, input-output method, spatial differentiation, spatial autocorrelation, spatial error model*

Introduction

Food is the material basis of human survival, and direct and indirect energy consumption triggered by the food system has a significant impact on global greenhouse gas emissions (Zhao et al., 2016; Yang et al., 2022). Overall, the impact of food consumption on carbon emissions is mainly manifested in two aspects. On the one hand, the rapid population growth has led to an increase in the demand for food consumption, resulting in a large number of carbon emissions in food production and consumption; On the other hand, with the improvement of residents’ living standard and the change of dietary structure, food consumption is developing towards diversification, and indirect carbon emissions in food processing, transportation, circulation and storage are also increasing (Pathak et al., 2010). Studies have shown that the global carbon emissions caused by the food consumption have reached about 25% of the carbon emissions generated by anthropogenic activities (Niles et al., 2018). The carbon emissions of food consumption in the United States account for 15% of the total carbon emissions, while 29% of the carbon emissions in the European Union are related to food consumption (Kim and Neff, 2009). Carbon emissions from food consumption in developed countries account for 15% to 29% of total carbon emissions (Hertwich and Peters, 2009). In fact, for the carbon emissions of the food system, the indirect carbon emissions implied in food

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2104_36913709

production, processing, transportation, circulation, storage, and other links have far exceeded the direct carbon emissions. Therefore, it is of great significance to calculate the indirect carbon emissions of food consumption from the perspective of industrial chain for building a more scientific accounting framework for carbon emissions of food consumption and comprehensively evaluating the environmental impact of food consumption under the background of the current diversified development of residents' food consumption and the sharp change of consumption structure.

Domestic and foreign scholars have carried out a lot of research around the topic of carbon emissions from food consumption, mainly focusing on accounting carbon emissions or carbon footprint of food system, food category, and dietary structure (Pathak et al., 2010; Pelletier et al., 2011; Berners-Lee et al., 2012). In terms of the food system, scholars mostly explored the carbon emissions of the whole life cycle process based on systematic thinking, revealing that the carbon emissions of the food system contributed about 1/3 to global warming. The carbon emissions of the food system in industrialized countries accounted for 24% of anthropogenic greenhouse gas emissions, while those in developing countries accounted for 39%. The carbon emissions of the food system in China, Indonesia, the United States, Brazil, the European Union, India, and other economies were large (https://news.un.org/zh/story/2021/03/1079852). Rosenzweig et al. (2020) calculated the carbon emissions of the global food system with meta-analysis method and found that the global food industry chain would produce 10.8-19.1 billion tons of carbon. Some scholars have calculated the carbon emissions from China's food system and found that indirect carbon emissions from the food system amounted to 570 million tons and direct carbon emissions were 100 million tons. Carbon emissions from the food processing industry contributed 62.7% to the carbon emissions from the food system (Zhang et al., 2022). In addition, the carbon emissions of food in the production, consumption, processing and transportation stages were different. The grain production stage (including fertilizer and other production inputs) was the main link of the current emissions of the entire grain system, and its contribution to the carbon emissions of the grain system was about 39% (Weber and Matthews, 2008). In terms of food types, scholars have found that the greenhouse gas emissions of different kinds of food vary greatly in the production process. Among them, the carbon emissions of animal food consumption were significantly higher than that of plant food, and the carbon emissions generated by the consumption of meat products per unit was about 10 times that of grain products (Tilman and Clark, 2014; Cao et al., 2020). Huang et al. (2015) analyzed the carbon emission characteristics of different types of food consumption by combining life cycle analysis with environmental input-output method, and revealed that grain, pork, aquatic products and beef made the largest contribution to the total carbon emission of food consumption, accounting for 28%, 25%, 10% and 9%, respectively. Grains, vegetables, and eggs had smaller carbon emissions per unit of calories and per unit of protein. In terms of dietary structure, some scholars have realized that residents' dietary habits were closely related to the carbon emissions, so they focused on how to achieve the carbon emission reduction goal by adjusting residents' dietary structure. For example, Alek et al. (2016) explored how to reduce carbon emissions of food consumption by building a sustainable and healthy diet model; Schösler et al. (2012) pointed out that the food structure optimization model of replacing animal protein with plant protein could effectively reduce the environmental pressure caused by human beings; Petrovic et al. (2015) proposed that the adoption of artificial breeding mode could effectively reduce the carbon emissions of livestock products. Li (2016) calculated the household food

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN1785 0037 (Online)
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consumption and waste of Chinese residents based on the food survey data, analyzed the influencing factors of food consumption and food waste behavior, and tried to give a dietary structure that could not only meet the nutritional needs of Chinese residents but also met the minimum carbon emissions. For the research methods, scholars often used the carbon emission coefficient method based on the life cycle process to measure the carbon emissions of food consumption (Liu et al., 2011; Wu et al., 2012). Although the method was easy to operate and could be used to calculate the carbon emissions generated by different types of food consuming energy at different stages, it was difficult to obtain the energy consumption data of different types of food at the provincial level at present, and it had long ignored the impact of spatial heterogeneity on the carbon emission conversion coefficient of different food categories. As a result, the carbon emission accounting results of food consumption could hardly reflect the carbon reduction effect of technological progress on food consumption. Thus, some scholars tried to use the input-output method to measure the indirect carbon emissions from food consumption (Gao et al., 2018). The advantage of this method was that it considered the carbon reduction role played by technological progress and was used to describe the composition of carbon emissions in different industrial sectors, making the final carbon emissions assessment results of food consumption more targeted and applicable. In addition, on the basis of accounting for the direct and indirect carbon emissions of food consumption at the national, provincial and municipal, and campus scales, some scholars have adopted qualitative or quantitative methods to explore the influencing factors of carbon emissions of food consumption, and given suggestions to reduce the carbon emissions from the food consumption structure, residents' eating habits, energy efficiency as well as household population size (Wu et al., 2012; Cao et al., 2020; Zhu et al., 2020). For example, Yao et al. (2017) studied the carbon emissions of animal husbandry in China at the provincial scale and found that from 2000 to 2014, the total carbon emissions of animal husbandry grew at an average rate of 0.288%, among which the carbon emissions from livestock and poultry gastrointestinal fermentation and manure management system were the main sources.

In general, although domestic and foreign scholars have carried out a large number of studies on carbon emissions from food consumption and achieved a series of research results, including studies on the spatial structure and food category differences of carbon emissions from food consumption based on macro regional scale, and studies on direct carbon emissions from food consumption in the whole life cycle process of food production, processing, transportation and end consumption based on micro regional scale. It provides important theoretical and methodological reference for developing carbon emission accounting of food system. However, the following aspects need to be further strengthened: First, the carbon emission coefficient method based on life cycle process fails to consider the structural characteristics of indirect carbon emissions in different industries from the aspects of food production, consumption, processing and transportation, and ignores the role of economic development and technological progress in reducing carbon emissions from food consumption, leading to different degrees of deviation in the evaluation results. The input-output method can make up for this defect effectively and accurately depict the industry composition of carbon emissions from food consumption (Pairotti et al., 2015). Second, there exist correlation effects in the economic activities involved in each link of food consumption, the quantity and structure of food consumption in different regions, and the energy intensity caused by food consumption due to the differences in natural conditions, resource endowments, economic foundation,

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technological level, and dietary habits in different regions, which leads to the correlation in the spatial distribution of carbon emissions from food consumption. However, current studies on the influencing factors of carbon emissions from food consumption mainly focus on qualitative and traditional econometric methods, ignoring the role of spatial spillover effect, resulting in low accuracy of evaluation results. Therefore, the paper takes 30 provincial units in China as the research object, uses the input-output method to calculate the indirect carbon emissions of food consumption from the perspective of the industrial chain, and reveals its spatial correlation and impact mechanism. This study not only helps to build a more scientific research framework for indirect carbon emissions in the food system, further deepen the research on carbon emissions in food consumption, but also has important practical significance for assessing the environmental impact of food consumption and exploring the optimization path of the industrial chain towards carbon emission reduction under the "dual carbon" goal.

Data and methods

Data source

The paper selects 30 provincial administrative regions in China (excluding Hong Kong, Macao, Taiwan and Tibet because of the inability to obtain input-output table) as the basic regional units, and the selected time node is 2017. The data used mainly include the input-output table, energy balance table and relevant economic and social data of each province. The input-output table in 2017 comes from the Key Laboratory of Regional Sustainable Development Analysis and Simulation, Chinese Academy of Sciences (http://www.lrsd.org.cn/). The energy balance table is from the 2018 China Energy Statistical Yearbook, and the relevant economic and social data (including food consumption, energy consumption, gross domestic product, agricultural seeded area, fertilizer use, pesticide use, agricultural labor, energy consumption of different means of transportation, etc.) are from the 2018 China Statistical Yearbook and the statistical yearbooks of various provinces. It should be noted that the calculation of carbon emissions adopts the method provided by the Intergovernmental Panel on Climate Change (IPCC) of the United Nations, which is calculated by multiplying the total consumption of all kinds of energy by their average low calorific value and CO_2 emission coefficient. For some data such as the energy consumption of the agricultural cultivation, the fertilizer production, and the transportation, etc., we mainly calculate them based on energy consumption data and socio-economic data.

Research methods

Construction of theoretical framework

The carbon emissions of food system include both direct and indirect carbon emissions. Among them, the direct carbon emissions mainly refer to the carbon emissions from food cooking, final consumption, and food waste, while the indirect carbon emissions include the carbon emissions from food production, processing, transportation, circulation, and storage. The study focuses on accounting the indirect carbon emissions of food consumption. Considering the availability of data and the corresponding relationship with the input-output table, the indirect carbon emissions of food consumption are defined as the carbon emissions of food production process, processing process and storage and transportation (*Figure 1*). The production process mainly involves the consumption of

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materials and energy such as pesticides, films, seeds, seedlings, fertilizers, feed, vaccines, bait, nets, disinfectants, agricultural machinery, etc., so it mainly corresponds to agriculture, forestry, animal husbandry and fishery industry, chemical product manufacturing industry, and special equipment manufacturing industry; The processing process mainly involves food machinery, disinfection and sterilization equipment, storage equipment, power and heat and other materials and energy consumption, so it corresponds to food processing industry, accommodation, catering, retail and wholesale industry, and power and heat production and supply industry; The food transport link mainly involves the consumption of materials and energy such as various vehicles, ships and supporting equipment in the station yard, so it mainly corresponds to the transportation industry. The specific steps are as follows: First, determine the demand for corresponding inputs according to food consumption; Secondly, considering the correlation between agricultural production inputs and departments, the economic value of food consumption inputs is calculated according to the provincial and regional parameters (including the input demand per unit area or head number, such as yuan/acres, yuan/head) provided in the 2018 National Collection of Cost Benefit Data of Agricultural Products; Then, in order to separate the energy consumption caused by non-food consumption, the study calculates the energy consumption caused by food consumption based on the proportion of the economic value of food consumption inputs in different industries and the energy balance sheet; Finally, the carbon emissions of food consumption in different industries are calculated combined with the average low calorific value and carbon emission coefficient of various energy sources. It should be noted that this study does not consider soil carbon emissions during agricultural production, carbon emissions from non-commodity energy consumption and carbon emissions from energy input required for the treatment of food consumption end residues.

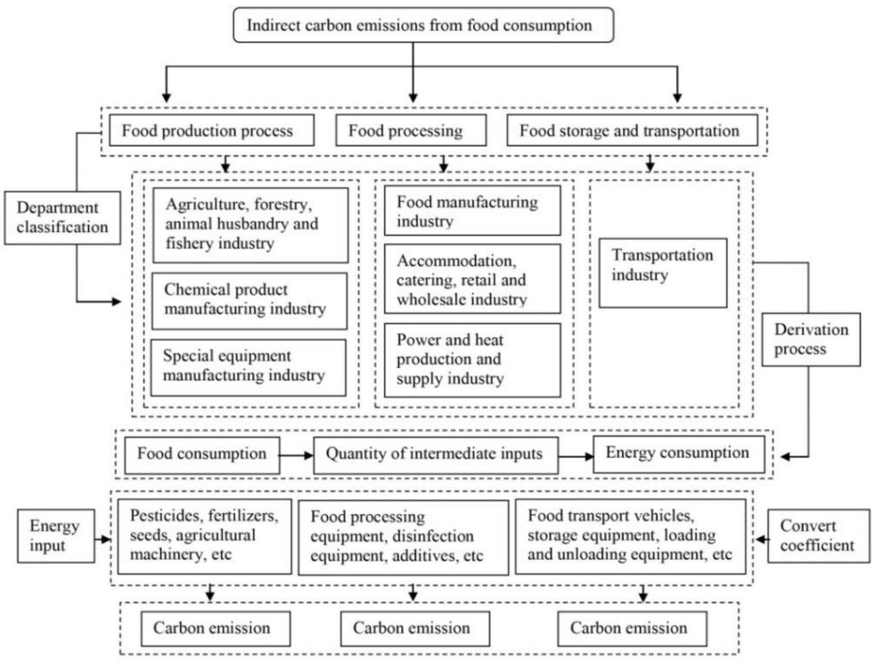

***Figure 1.** Accounting boundary of indirect carbon emissions from food consumption*

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Input-output method

The input-output method of carbon emissions from food consumption is based on the value type of input-output table prepared by the authoritative statistical department, and the energy consumption is added to construct a “value-object” mixed type carbon emissions input-output table. The formula is (Yang et al., 2019):

$$C = r_i (I - A)^{-1}\, \hat{y} \tag{Eq.1}$$

$$r_i = \frac{e_i}{x_i} \tag{Eq.2}$$

where the C represents indirect carbon emissions from food consumption, $\hat{y}$ represents the diagonal matrix of the final demand for inputs (the value of the required inputs); I is the unit matrix, A is the technical coefficient matrix; r_i is the diagonal matrix of carbon emission intensity of sector i, e_i is the carbon emission of sector i, and x_i is the total economic output of sector i (Ten thousand yuan).

Exploratory spatial data analysis method

The exploratory spatial data analysis method is used to test whether the observations of a unit have correlation characteristics with those of its adjacent units. Moran's I is used as a statistic to measure global spatial correlation, and *LISA* (Local Indicators of Spatial Association) statistic is used to represent local spatial autocorrelation. The formula is (Xie et al., 2020):

$$\begin{cases} I = \dfrac{\sum_{i=1}^{n}\sum_{j=1}^{n}(x_i - \overline{x})(x_j - \overline{x})}{s^2 \sum_{i=1}^{n}\sum_{j=1}^{n} W_{ij}} \\ I^* = \dfrac{n(x_i - \overline{x})\sum_j w_{ij}(x_j - \overline{x})}{\sum_i (x_i - \overline{x})^2} \end{cases} \tag{Eq.3}$$

where the I represents the *Moran’s I* value, and I^* represents the *LISA* value. The x_i and x_j represents the estimated carbon emissions of i th and j th unit, respectively, and the $\overline{x_t}$ represents the annual average of the measured values. The s represents the variance of carbon emissions, and the W_{ij} represents the spatial weight matrix (The paper uses a geographic adjacency matrix, where adjacent is 1, not adjacent is 0.)

Spatial econometric model

The spatial econometric model is based on the traditional econometric model, which introduces the spatial effect between variables into the model for econometric analysis. Commonly used spatial econometric models include the spatial lag model (SLM) and the spatial error model (SEM). Their formulas are as follows (Shen, 2010; Xie et al., 2022):

$$SLM\text{:}\quad y = \rho w_{ij} y + x\beta + \mu \tag{Eq.4}$$

$$SEM\text{:}\quad \begin{cases} y = x\beta + \varepsilon \\ \varepsilon = \lambda w_{ij} + \mu \end{cases} \tag{Eq.5}$$

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where the y represents the dependent variable, the x represents the explanatory variable, the W_{ij} represents the spatial weight matrix that was the same as above (where adjacent is 1, not adjacent is 0), the ρ represents a spatial lagging parameter, the β is parametric vector, the μ represents random disturbance term, the ε represents regression residual vector, and the λ represents the auto-regression coefficient.

Carbon emission accounting and difference analysis of food consumption

Industrial differences in carbon emissions of food consumption

According to the input-output table of China's provinces in 2017, the national economy related to food consumption is grouped into seven categories: power and heat production and supply industry, agriculture, forestry, animal husbandry and fishery industry, food manufacturing industry, transportation industry, accommodation, catering, retail and wholesale industry, special equipment manufacturing industry and chemical product manufacturing industry. Then, the input-output method was used to calculate the indirect carbon emissions of food consumption with the Excel software, and the industrial composition of indirect carbon emissions at the national and provincial levels was analyzed (*Figures 2 and 3*).

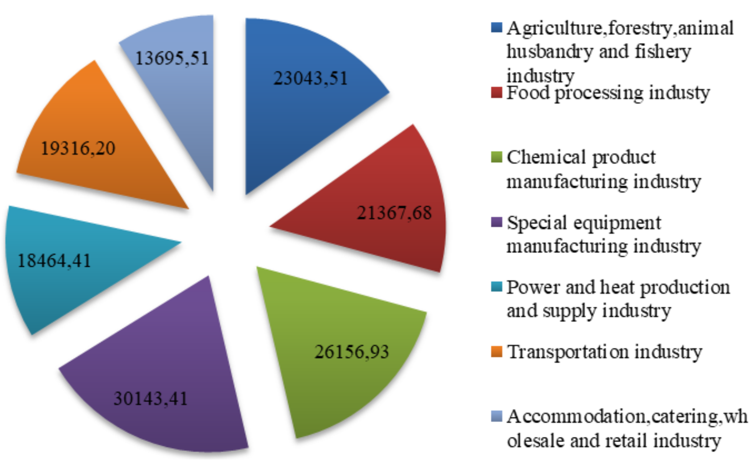

Figure 2. *Carbon emissions from different sectors of food consumption in China*

As can be seen from *Figure 2*, the carbon emissions of power and heat production and supply industry, agriculture, forestry, animal husbandry and fishery industry, and food manufacturing industry are significantly higher than those of other industries. Among them, the carbon emissions of power and heat production and supply industry reached 301,434,100 tons, accounting for 19.81% of the indirect carbon emissions of food consumption in the whole society. Carbon emissions from agriculture, forestry, animal husbandry and fishery industry reached 261,569,300 tons, accounting for 17.19% of indirect carbon emissions from food consumption. The carbon emission of food manufacturing industry was 23,435,100 tons, accounting for 15.14% of the indirect carbon emission of food consumption. The carbon emissions of transportation industry, accommodation, catering, retail and wholesale industry, special equipment manufacturing industry and chemical product manufacturing industry are relatively small,

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and their carbon emissions account for 14.04%, 12.69%, 12.13% and 9.00% of the indirect carbon emissions of food consumption in the whole society, respectively. It is found that food production and processing require a large amount of heat and electricity, and the production of heat and electricity will consume diesel, crude oil, coal, natural gas and other fossil energy and release carbon dioxide, so the production and supply of power and heat have the highest carbon emissions. As a traditional agricultural production country, agriculture, forestry, and fishery occupy a larger proportion in our national economy. The process of digestion of livestock, processing process of livestock and poultry manure, crop growth process, agricultural machinery using process will also cause carbon emission, so agricultural, forestry and fishery carbon emission is higher. With the rapid development of economy and the improvement of people's living standards, residents' food consumption demand is developing in a diversified and personalized direction, resulting in the continuous extension of the food industry chain and the continuous expansion of the level of food deep processing. In this process, a large amount of carbon dioxide will be emitted. Therefore, the carbon emissions of the food manufacturing industry account for a large proportion. The transformation and upgrading of residents' food consumption and the progress of food storage technology have greatly increased the distance of food transportation, resulting in an increase in the carbon emissions of food transportation. Therefore, the carbon emissions of transportation industry also account for a certain proportion. Catering and wholesale and retail are important components of the service industry, among which, the catering industry will emit carbon dioxide in the deep processing of food. The booming development of online shopping and logistics industry promotes the increasing carbon emission of wholesale and retail industry, so the carbon emission of catering and wholesale and retail industry is also an important part of the indirect carbon emission of the food system. Special equipment manufacturing and chemical product manufacturing can provide agricultural machinery, fertilizers, mulch, pesticides, and other intermediate inputs needed in the food production process, and these intermediate inputs will inevitably emit carbon dioxide in the use process. From this perspective, the carbon emissions of special equipment manufacturing, and chemical product manufacturing accounted for a lower proportion of the total carbon emissions of food consumption.

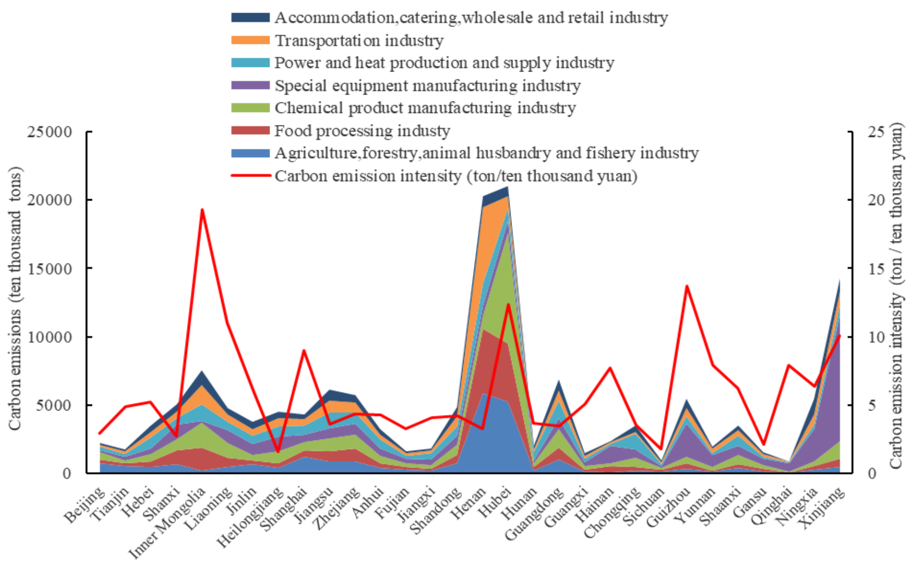

Figure 3. *Carbon emissions of food consumption in different regions of China*

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Total carbon emissions mainly refer to the total carbon emissions generated by the food industry chain, namely indirect carbon emissions from food consumption. Due to the large gap in the economic development level between different provinces and regions, it is not comprehensive enough to describe regional differences by using the simply absolute quantity index of total carbon emission. Therefore, it is necessary to introduce the relative quantity index of carbon emission intensity to measure regional differences. It should be noted that carbon intensity mainly refers to the indirect carbon emissions produced per unit of GDP. According to *Figure 3*, there are significant differences in indirect carbon emissions and carbon emission intensity of food consumption among Chinese provinces, showing the coexistence of industry composition differences and regional differences. From the perspective of total indirect carbon emissions, the average amount of carbon emissions from food consumption in 30 provinces of China is about 50.72 million tons. Hubei, Henan, and Xinjiang lead the way in indirect carbon emissions from food consumption, reaching 210.32 million tons, 202.59 million tons and 243.01 million tons. Specifically, the indirect carbon emissions from food consumption in accommodation, catering, wholesale and retail, transportation and food manufacturing accounted for 79.8% of the indirect carbon emissions from food consumption in Henan, which was the main reason for the high carbon emissions from food consumption. Carbon emissions from agriculture, forestry, animal husbandry and fishery accounted for a large proportion of indirect carbon emissions from food consumption in Hubei, which was the cause of huge carbon emissions from food consumption. The carbon emissions from power and heat production and supply industry account for 56.3% of indirect carbon emissions from food consumption in Xinjiang, which is the reason for the high carbon emissions from food consumption The indirect carbon emissions of food consumption in Inner Mongolia, Jiangsu, Zhejiang, Guangdong, Guizhou, and Ningxia were all above the average, and the proportion of industry composition was generally in a balanced state. The indirect carbon emissions from food consumption in Beijing, Tianjin, Hebei, Shanxi, Liaoning, Jilin, Heilongjiang, Shanghai, Anhui, Fujian, Jiangxi, Shandong, Hunan, Guangxi, Hainan, Chongqing, Sichuan, Yunnan, Shaanxi, Gansu, and Qinghai are lower than the national average, and the industrial composition is more balanced. The measures to reduce carbon emissions from food consumption could be developed from multiple sectors simultaneously in the future. The provinces with the highest carbon emissions from food consumption were 24 times as much as the provinces with the lowest carbon emissions, indicating that the indirect carbon emissions from food consumption differed greatly among different provinces. Hubei, Henan, Xinjiang, Inner Mongolia, Jiangsu, Zhejiang, Guangdong, Guizhou, and Ningxia were the key regions to reduce indirect carbon emissions from food consumption. It is difficult to accurately reflect the carbon emission reduction potential of provinces based solely on the absolute index of indirect carbon emission from food consumption due to the differences in land area, industrial structure, crop type, population size and economic base of provinces in China. In terms of carbon emission intensity, the average indirect carbon emission intensity in China is 6.1 tons/ten thousand yuan. Specifically, Inner Mongolia, Guizhou, Hubei, and Xinjiang have the highest carbon emission intensity of food consumption, reaching 19.3, 13.7, 12.3 and 10.0 tons/ten thousand yuan. The carbon emission intensity of food consumption in Jilin, Shanghai, Hainan, Yunnan, Shaanxi, Qinghai, and Ningxia was higher than the national average level and below 10.0 tons/ten thousand yuan while the carbon intensity of Beijing, Tianjin, Hebei, Shanxi, Liaoning, Jilin and Heilongjiang provinces was lower than the national average. It is not difficult to find that there are significant differences in

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the carbon emission intensity among provinces. Reducing the carbon emission intensity in Inner Mongolia, Guizhou, Hubei, Xinjiang, Jilin, Shanghai, Hainan, Yunnan, Shaanxi, Qinghai and Ningxia is conducive to reducing the indirect carbon emissions of food consumption.

Spatial differentiation characteristics of indirect carbon emissions

Spatial distribution characteristics of indirect carbon emissions from food consumption

The study uses the natural breakpoint classification method to classify them into four categories, so as to analyze the distribution pattern of indirect carbon emissions and carbon emission intensity from food consumption (*Figure 4*).

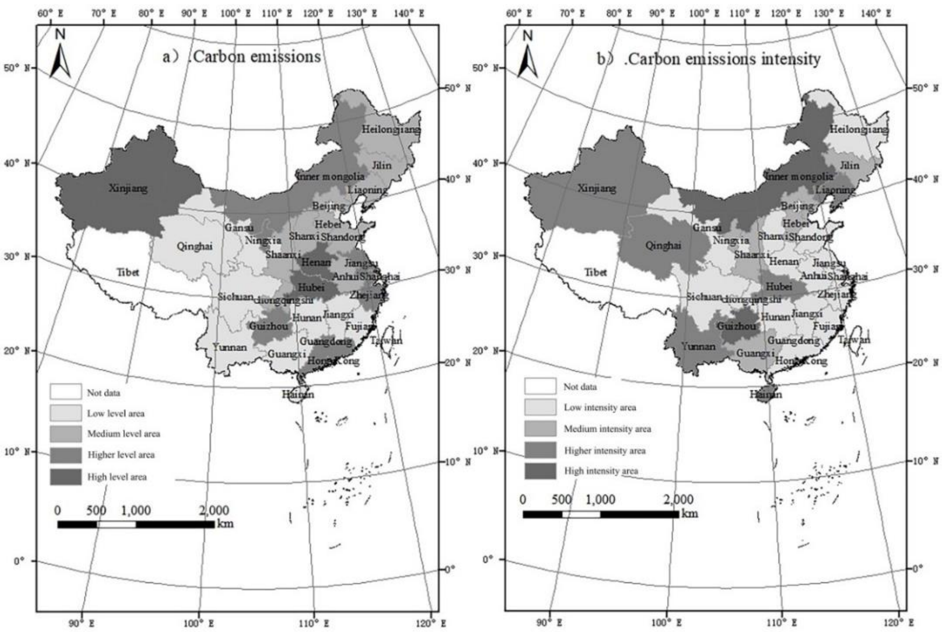

Figure 4. *Carbon emissions and carbon emission intensity of food consumption*

According to *Figure 4a*, the spatial distribution of indirect carbon emissions generally presents a “center-periphery” layout feature, and the high value areas are mainly concentrated in central and eastern provinces. Specifically, the high value areas of indirect carbon emissions from food consumption are mainly distributed in Henan, Hubei and Xinjiang; The higher level type areas are mainly distributed in Inner Mongolia, Ningxia, Jiangsu, Zhejiang, Guizhou and Guangdong; The provinces in the middle level include Heilongjiang, Jilin, Liaoning, Hebei, Shandong, Shanxi, Shaanxi, Chongqing and Anhui; Gansu, Qinghai, Sichuan, Yunnan, Guangxi, Hainan, Hunan, Jiangxi and Fujian are low value areas of indirect carbon emissions from food consumption. On the whole, the areas with high and higher indirect carbon emissions of food consumption are mainly distributed in central and eastern regions such as Henan, Hubei, Jiangsu, Zhejiang and Guangdong, showing a spatial layout structure of “high center and low periphery”. The reason for this phenomenon is that there are a large number of people in the central and eastern regions, the demand for food is huge, and the residents have a strong desire to consume personalized food. In addition, the level of agricultural mechanization is high, the transportation infrastructure is developed, the food industry chain is relatively

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complete, and the degree of food fine processing and deep processing is high. Therefore, food needs to consume a lot of fossil energy in each industrial chain link, which will inevitably cause carbon emissions in this process. This is the reason for the large indirect carbon emissions of food consumption in central and eastern provinces. *Figure 4b* reflects the spatial distribution pattern of carbon emission intensity of food consumption. It can be found that the areas with high carbon emission intensity are located in Inner Mongolia and Guizhou; Higher level areas are distributed in Shanghai, Hubei, Liaoning, Hainan, Yunnan, Qinghai, Ningxia and Xinjiang; The provinces in the middle type include Tianjin, Hebei, Jilin, Guangxi and Shaanxi; Beijing, Shanxi, Heilongjiang, Jiangsu, Zhejiang, Anhui, Fujian, Jiangxi, Shandong, Henan, Hunan, Guangdong, Chongqing, Sichuan and Gansu belong to low carbon emission intensity areas. In general, the provinces with high carbon emission intensity of food consumption are mainly economically underdeveloped regions, while economically developed regions have low carbon emission intensity. The reason for the phenomenon is that the industrial structure of economically developed regions is dominated by the tertiary industry, and the proportion of agriculture, animal husbandry and food processing industry is small. In addition, the urbanization level is high, the foundation of economic development is solid, the people have a strong sense of environmental protection, and the economic development is less dependent on fossil energy, which helps these regions to adopt advanced technology and improve the intensive utilization level of resources and energy, so the amount of carbon dioxide emitted per unit of GDP is less.

Spatial correlation characteristics of indirect carbon emissions from food consumption

The indirect carbon emissions of food consumption are used as variables, and the spatial weight matrix is determined based on Rook proximity criterion in the study. Then, the global Moran'I index of carbon emissions of food consumption is calculated using Geoda software. The results show that the overall Moran'I index is 0.1265 and the Z value is 2.732, indicating that the spatial distribution of indirect carbon emissions from food consumption is mainly positive correlation and significant at the 1% critical value level, showing a trend of agglomeration development. In order to analyze the difference in local space of indirect carbon emissions in more detail, the study analyzes the local correlation characteristics of the spatial distribution of carbon emissions with the help of LISA cluster map and significance map (*Figure 5*).

Figure 5a shows that the local correlation characteristics of the spatial distribution of indirect carbon emissions of food consumption are mainly “high-high”, “low-low” and “high-low” clusters. Specifically, the “high-high” cluster areas are mainly distributed in Henan, Hubei, Hebei, Tianjin, Shandong, Jiangsu, Anhui, and Beijing. These provinces are the traditional major grain producing regions in China. Agriculture, forestry, animal husbandry and fishery account for a large proportion in the national economy, and they emit more carbon dioxide in food production. At the same time, the transportation infrastructure of the above provinces is complete, the food deep processing level is high, and the economic activities are frequently linked, which will lead to carbon emissions in the food processing and transportation links, which is the main reason for creating a “high-high” cluster area. Qinghai, Gansu, Guangdong, Guangxi, and other provinces belong to the “low-low” cluster type. The level of agricultural mechanization and food deep processing in this region is low, the proportion of food related industries in the national economy is small, and the proportion of fossil energy consumed by food consumption is low. In addition, food consumption is mainly imported from other regions,

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DOI: http://dx.doi.org/10.15666/aeer/2104_36913709

so the carbon emissions in food production, processing and transportation are low, which is the reason why Qinghai, Gansu, Guangdong, and Guangxi have become “low-low” cluster areas. Liaoning, Jilin, and Xinjiang belong to the “low-high” cluster area, but the reasons for the phenomenon are different. Among them, Liaoning, Jilin, and other provinces are located in the Northeast Plain of China, with a high proportion of planting and food processing industries, resulting in more fossil energy input in food production, processing, transportation and other links related to food consumption. As a result, the carbon emissions of Liaoning and Jilin residents are relatively high, forming a “low-high” cluster area with surrounding provinces. The energy structure of Xinjiang is dominated by fossil energy, the energy utilization rate is low, and the carbon emissions of power and heat production and supply industries in food production, processing and transportation are high, which is the main reason for the high carbon emissions of food consumption, so Xinjiang is also a “low-high” cluster area. *Figure 5b* shows the significance of local spatial correlation of indirect carbon emissions from food consumption. It can be found that the spatial agglomeration types in Hebei, Tianjin, Shandong, Jiangsu, Anhui, Beijing, Qinghai, Gansu, Liaoning and Jilin are significant at the 5% critical level, while those in Henan, Hubei, Guangdong, Guangxi and Xinjiang are significant at the 1% critical level.

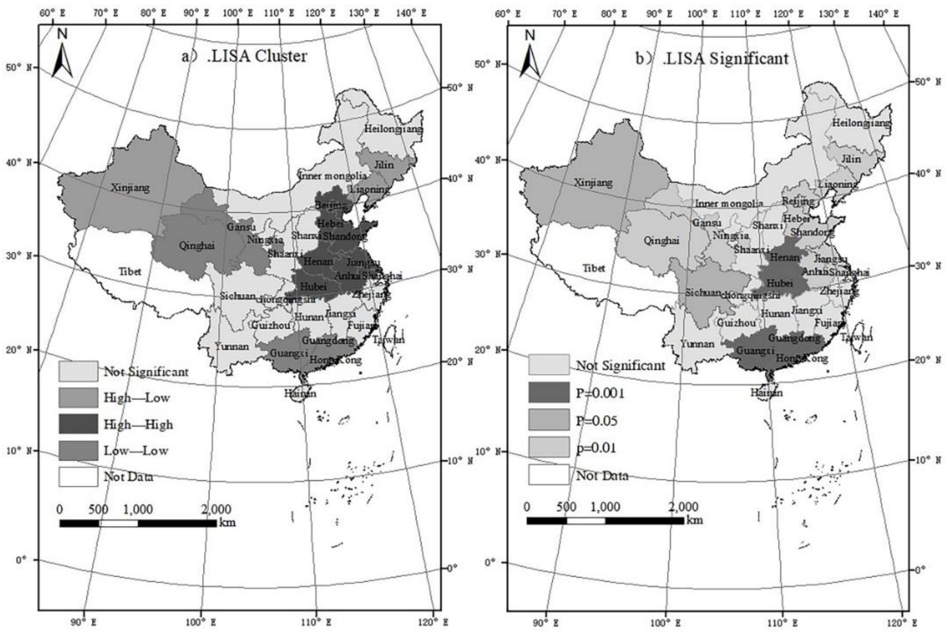

Figure 5. *LISA cluster and significance diagram of the spatial distribution of carbon emissions*

Analysis of the influencing factors of indirect carbon emissions from food consumption

Selection of evaluation indicators of influencing factors

On the basis of accounting for indirect carbon emissions of food consumption, the study builds an evaluation index system of factors affecting indirect carbon emissions of food consumption from the aspects of economic development level, agricultural production efficiency, agricultural capital investment, agricultural industrial structure, labor culture level, urbanization (*Table 1*). Indicators were selected for the following reasons: (1) There is a close relationship between carbon emissions and economic

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development, so GDP per capita is selected as the indicator of regional economic development level (Feng et al., 2022). (2) The carbon emission of food production stage is the main source of carbon emission of food consumption (Weber and Matthews, 2008). The study uses the ratio of the total output value of agriculture, forestry, animal husbandry and fishery to the total agricultural population to characterize the regional agricultural production efficiency. (3) Regional economic links will lead to capital flow, which will cause the carbon transfer of food consumption in different regions, and then affect the carbon emissions of food consumption in different regions (Yi et al., 2019). In this study, the ratio of agricultural fixed asset investment to agricultural population represents the agricultural capital investment index. (4) The adjustment of agricultural industry will promote the change of food carbon emissions in the region and have a spatial spillover effect on the industrial structure of surrounding areas. Therefore, the ratio of the total output value of agriculture and animal husbandry to the total output value of agriculture, forestry, animal husbandry and fishery is used to represent the agricultural industrial structure. (5) The culture level of labor force directly determines the ability of employees to master new technologies and the level of environmental awareness, which indirectly affects the carbon emissions of food consumption. The number of employees above junior middle school in agriculture accounts for the number of agricultural employees is selected as the indicator of the cultural level of labor force. (6) The urbanization process can help reduce the number of agricultural employees, change food consumption habits, improve energy efficiency, and thus affect the carbon emissions from food consumption. Therefore, the study selects the urbanization rate as the indicator to reflect the urbanization level.

Table 1. *Evaluation index system of factors affecting carbon emission of food consumption*

Variable	Specific indicators	Variable abbreviation
Economic development level	GDP per capita	Eco
Agricultural production efficiency	Total output value of agriculture, forestry, animal husbandry and fishery/total agricultural population	A-eco
Agricultural capital investment	Total investment in agricultural fixed assets/total agricultural population	Invest
Agricultural industrial structure	Total output value of agriculture and animal husbandry/total output value of agriculture, forestry, animal husbandry and fishery	Stru
Culture level of labor force	Number of agricultural employees above junior high school/number of agricultural employees	Edu
Urbanization level	urbanization rate	Urban

Estimation results of spatial econometric model

The previous content has confirmed that the global and local correlation characteristics of the spatial distribution of indirect carbon emissions are mainly positive correlation, while the traditional OLS (ordinary least square) regression model is based on independent and random assumptions of variables and does not consider the impact of the spatial spillover effect of variables on the analysis results of the model, resulting in limited accuracy of the evaluation results. Therefore, the study takes the carbon emissions

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN1785 0037 (Online)
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of food consumption as the dependent variable, and takes economic development level, agricultural production efficiency, agricultural capital investment, agricultural industrial structure, culture level of labor force, and urbanization level as the dependent variables. In order to eliminate the impact of variable statistical caliber differences on the model results, the paper conducts bilateral logarithmic processing on variable data. Then, the GeoDa software is used to perform LM (Lagrange Multiplier) test on the regression model (*Table 2*).

Table 2. *LM test results of spatial error model and spatial lag model*

LM test	Value	Prob
LM (Lag)	1.2534	0.8255
Robust LM (Lag)	0.9875	0.7532
LM (Error)	9.3251	0.0029
Robust LM (Error)	11.3281	0.0015

It can be seen from *Table 2* that the spatial lag model has not passed the significance test, and the Prob value of the spatial error model is 0.0029, less than 0. 01, indicating that the spatial error model is significant at the critical value level of 1%. Therefore, the study is suitable to use the spatial error model to analyze the influencing factors of indirect carbon emissions from food consumption. *Table 3* shows the estimation results of influencing factors of carbon emissions from food consumption obtained by using the spatial error model in the study.

Table 3. *Estimation results of spatial error model*

Variable	Coefficient	Z-value	P-value
Constant	3.860	0.253	0.863
Ln Eco	0.145***	2.312	0.000
Ln A-eco	0.312***	4.683	0.000
Ln Invest	0.367	3.125	0.008
Ln Stru	0.249	2.964	0.025
Ln Edu	-0.412**	-3.621	0.004
Ln Urban	0.945**	2.823	0.000
R-squared	0.948	-	-
F-statistic	82.292	-	-

Note: "*, ** and ***" means significant at the critical value level of 10%, 5% and 1% respectively; "-" means that the item does not exist

Table 3 shows that the R^2 of the spatial error model is 0.9480, indicating that the spatial error model constructed in the paper can explain the influencing factors of indirect carbon emissions of food consumption to 94.80%, and the overall estimation effect of the regression model is good. In terms of the estimated values of model parameters, the economic development level, agricultural production efficiency, agricultural capital investment, agricultural industrial structure, culture level of labor force, and urbanization level have a significant impact on the carbon emissions. Specifically, economic development level, agricultural production efficiency, agricultural capital investment,

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agricultural industrial structure, and urbanization level have a positive impact on indirect carbon emissions of residents' food consumption, and have passed the significance test of 1%, 1%, 5%, 1%, and 1% threshold levels, respectively. The coefficient of economic development level is 0.145, indicating that for every 1% increase in per capita GDP, the indirect carbon emissions from food consumption will also increase by 0.145%. The coefficient of agricultural production efficiency is 0.312, indicating that the indirect carbon emissions of food consumption will increase 0.312% for every 1% increase in agricultural production efficiency. The coefficient of agricultural capital investment is 0.367, indicating that the indirect carbon emissions of food consumption will increase by 0.367% when agricultural capital investment increases by 1%. The coefficient of agricultural industrial structure is 0.249, indicating that the indirect carbon emissions of food consumption will increase by 0.249% for every 1% increase in agricultural industrial structure. The coefficient of urbanization level is 0.945, indicating that the indirect carbon emissions of food consumption will increase by 0.945% for every 1% increase of urbanization rate. The coefficient of the labor culture level is -0.412, and it has passed the significant test of the 5% threshold level, which means that every 1% increase in the culture level of labor force will reduce the indirect carbon emissions by 0.412%. To sum up, the urbanization level has the greatest impact on indirect carbon emissions from food consumption, followed by the culture level of labor force, agricultural capital investment and agricultural production efficiency. The agricultural production structure and economic development level have less impact on indirect carbon emissions. Some measures such as controlling the size of urban population, improving the cultural level of labor force, and optimizing the agricultural structure can be considered to reduce indirect carbon emissions from food consumption.

Discussion and policy implications

Discussion

The study accounted for the indirect carbon emissions from food consumption and analyzed the influencing factors of indirect carbon emissions from food consumption, which is helpful to comprehensively assess the environmental impact of food consumption and formulate targeted measures to reduce carbon emissions from food consumption. However, the study also has the following problems: First, the study focuses on measuring the carbon emissions of food production, processing, and circulation from the perspective of the industrial chain. It relatively ignores the carbon emissions of food terminal consumption and food waste treatment, which will lead to the incomplete results of carbon emissions accounting of food consumption and weaken the application value to a certain extent. However, it should also be noted that the indirect carbon emissions of food consumption obtained by the input-output method in the study is 1.522 billion tons, which is significantly greater than the direct carbon emissions (472 million tons) of food consumption calculated by Cao et al. (2020), which verifies the conclusion that the indirect carbon emissions of food consumption are far greater than the direct carbon emissions. Wu et al. (2012) also confirmed that the indirect carbon emissions of food consumption in Beijing were 22.39 million tons, while the direct carbon emissions of food consumption were 4.77 million tons. The result verified that the indirect carbon emissions of food consumption were far greater than the direct carbon emissions of food consumption. In addition, carbon emissions from food consumption also have significant regional differences. For example, Yu et al. (2020) found that the direct and

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indirect carbon emissions of urban residents were higher than those of rural residents by analyzing carbon emissions from food consumption of urban and rural residents in Anhui Province. Second, input-output tables provide important support for calculating indirect carbon emissions from food consumption. Since Chinese government have not yet published the latest input-output table (the input-output table in 2022), the input-output table in 2017 was used to calculate indirect carbon emissions from food consumption. It should be noted that the measurement results of indirect carbon emissions from food consumption are mainly completed based on the input-output table and the income data of Chinese agricultural products. Although the input-output tables of 2017, 2012, 2007 and 2002 are available, we cannot obtain the income data of China's agricultural products in 2013 and before. As a result, we cannot compare the changes of carbon emissions from food consumption of different sectors from the perspective of time series. Undeniably, above defects will inevitably weaken the timeliness and applicability of the evaluation results. In the future, the latest input-output tables and time series variation should be adopted to calculate and analyze the indirect carbon emissions of food consumption. In addition, there is no unified standard for boundary division when calculating carbon emissions from food consumption and the difference of accounting boundary will also lead to different calculation results, which will affect the formulation of policies. For this study, the accounting boundary of indirect carbon emission from food consumption is divided into power and heat production and supply industry, agriculture, forestry, animal husbandry and fishery, food manufacturing industry, transportation industry, catering and wholesale and retail industry, special equipment manufacturing industry, chemical product manufacturing industry and other industries, but Huang et al. (2021) divide it into agriculture, forestry, animal husbandry and fishery, food processing industry, transportation and postal warehousing industry, accommodation and catering industry, wholesale and retail industry and other industries, how to establish a unified accounting boundary is the key to enhance the comparability between different research results (Zhang et al., 2022). Third, the establishment of the evaluation index system for the impact factors of carbon emissions from food consumption is a complex system process because it involves both quantitative and qualitative evaluation indexes. The study mainly constructs an evaluation index system from the perspective of data availability, and to some extent ignores the role played by hard-to-quantify indicators, such as transportation costs, eating habits, cultural customs, and behavioral preferences, etc. For example, Zhu et al. (2012) found that changes in residents' consumption level and food consumption structure were the main factors affecting carbon emissions from food consumption. Yue et al. (2017) argue that better agricultural management and changes in diet consumption could go a long way toward reducing China's greenhouse gas emissions. Long et al. (2022) revealed that internal migration had a positive impact on national carbon emissions, which increased by 16% between 2001 and 2016. How to combine the quantitative indicators with non-quantitative indicators needs to be broken through in the future.

Policy implications

According to the results of indirect carbon emissions of food consumption and its influence factors, the following policy implications are proposed in the study: First, reduce the energy consumption level of the food industry chain. The traditional food supply chain is long, and the level of energy consumption remains high. On the one hand, we can start with reducing the food circulation links, establish new food trading cooperation organizations, promote food information sharing, and improve the efficiency

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of the supply chain; On the other hand, cleaner production technology can be promoted in food production, processing, transportation, and other links to reduce the consumption of fossil energy. Second, promote a green transformation of agricultural development. Agricultural growth depends on the increase of intermediate inputs such as chemical fertilizers, pesticides, agricultural films, diesel oil. The proportion of crops and livestock with high carbon emissions in planting and animal husbandry should be appropriately reduced, and the project of returning farmland to forests and grasslands should be implemented to enhance the carbon absorption capacity of the agricultural ecosystem, develop green agriculture and low-carbon agriculture, and achieve the sustainability of agricultural development. Third, establish a scientific and reasonable diet. Reducing the carbon emissions of food consumption needs to start from the production side, and from the supply side. The carbon emissions of food consumption can be reduced by guiding residents to increase the proportion of plant food in the diet structure, reduce the proportion of animal food (especially for pig, beef and mutton) in the diet structure, prepare meals on demand to reduce food waste, and select appropriate cooking methods.

Conclusions

The paper uses the input-output method to calculate the indirect carbon emissions of food consumption, and uses the spatial analysis method to discuss the spatial differentiation characteristics and influencing factors of carbon emissions of food consumption, and draws the following conclusions:

(1) The indirect carbon emissions from food consumption reached 1.522 billion tons. Among them, 19.81% came from power and heat production and supply industry; 17.19% from agriculture, forestry, animal husbandry and fishery industry; 15.14% from food processing industry; 14.04% from transportation industry; 12.69% from catering, wholesale, and retail industry; 12.13% from special equipment manufacturing industry; and 9.00% from chemical product manufacturing industry.

(2) The spatial distribution of carbon emissions from food consumption is generally in the form of “center-periphery”. The carbon emissions intensity of food consumption in economically underdeveloped regions is significantly higher than that in economically developed regions. The high carbon emission areas are mainly distributed in Henan, Hubei, Anhui, Hunan, Sichuan and other provinces, while the high carbon emission intensity areas are mainly distributed in Inner Mongolia, Xinjiang, Yunnan and other provinces.

(3) The global correlation characteristics of the spatial distribution of carbon emissions from food consumption are positive correlation, and the local correlation characteristics are mainly “high-high”, “low-low”, and “high-low” clusters. Henan, Hubei, Hebei, Tianjin, Shandong, Jiangsu, Anhui, Hunan and Beijing belong to the “high-high” cluster type, while Qinghai, Gansu, Ningxia, Guangdong and Guangxi belong to the “low-low” cluster type; Liaoning, Jilin and Xinjiang belong to the "high-low" cluster type.

(4) Urbanization level, culture level of labor force, agricultural production efficiency and economic development level and other factors have significant differences in the intensity and direction of indirect carbon emissions from food consumption. In terms of effect intensity, the urbanization level is the primary factor affecting the carbon emissions, followed by the culture level of labor force, agricultural capital investment and agricultural production efficiency. The agricultural industrial structure and economic development level have little impact on the carbon emissions. In terms of effect direction,

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other factors play a positive role except that the cultures level of labor force plays a negative role in indirect carbon emissions.

Funding. This research was supported by Natural Science Foundation of China (No. 41971241, 42277325), Open Fund of Key Laboratory of Geospatial Technology for the Middle and Lower Yellow River Regions (Henan University), Ministry of Education (Grant No. GTYR202201).

Disclosure statement. No potential conflict of interests was reported by the authors.

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