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Sustainable transition of food consumption in rural China: spatio-temporal patterns and drivers of carbon footprint

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Since achieving basic food security and poverty alleviation in rural areas in 2000, China has experienced rapid growth in rural residents' incomes, prompting increased scrutiny of food consumption sustainability. This study examines the transition in food consumption patterns of rural residents in China from 2001 to 2023. It quantifies their food consumption carbon footprint (FCCF) using the carbon conversion factor method and analyzes spatio-temporal patterns and drivers by integrating an extended STIRPAT framework with spatial econometric models. Three main findings emerge: First, spatio-temporal patterns reveal persistent structural imbalances in food consumption, with per capita FCCF showing a fluctuating upward trend. Second, per capita FCCF demonstrates significant spatial agglomeration, characterized by "high-high" and "low-low" clusters. Third, population, affluence, technology, trade, and food consumption structure all significantly influence per capita FCCF, albeit with notable regional variations. Identifying key drivers and their spatial spillovers offers valuable insights for tailoring region-specific policy interventions.

KEYWORDS

food consumption, carbon footprint, spatio-temporal patterns, drivers, rural China

1 Introduction

Achieving sustainable food consumption remains a global challenge, with the food system being a major contributor to greenhouse gas (GHG) emissions, responsible for approximately one-third of global emissions (Crippa et al., 2021). The Food and Agriculture Organization (FAO) defines "sustainable diets" as those with low environmental impacts which contribute to food and nutrition security and healthy life for present and future generations. These diets are protective and respectful of biodiversity and ecosystems, culturally acceptable, accessible, economically fair and affordable; nutritionally adequate, safe and healthy; while optimizing natural and human resources (FAO, 2010). Xu et al. (2015) contends that relying solely on technological solutions for mitigation is inadequate to achieve sustainable diets. Instead, a fundamental shift in food consumption patterns is necessary, particularly moving away from diets high in GHG-intensive meat and dairy products. This transition is imperative not only in developed nations but also in the long term for developing countries.

By the end of 2000, China, the world's largest developing country, had effectively solved the problem of food and clothing for its rural poor population. By reaching its Centenary Goal in 2020, China successfully attained a moderately prosperous society and eliminated absolute poverty. This achievement marks a significant advancement in global poverty alleviation and rural development efforts, signaling forthcoming economic, social, and environmental transformations as rural residents strive to elevate their living standards. Notably, a prominent transition observed in rural communities is a change in food consumption patterns, characterized by a noticeable decrease in carbohydrate intake and a substantial increase in meat consumption, which has brought rural dietary habits closer to urban or Western norms (Yuan et al., 2019; Ren et al., 2021). While this transition enhances nutritional well-being, it also increases carbon emissions linked to food consumption, posing a threat to the ecosystem. This surge in the food consumption carbon footprint (FCCF) poses profound challenges for sustainable global food consumption practices (Han et al., 2023; Han et al., 2024; Bashiri et al., 2025). Therefore, it is imperative to analyze spatial and temporal trends, and to identify the factors influencing FCCF, to develop targeted interventions and foster sustainable rural development.

This study examines the transition in food consumption patterns of rural residents in China from 2001 to 2023. It assesses their FCCF using the carbon conversion factor method and analyzes spatio-temporal patterns and driving forces by integrating an extended STIRPAT framework with spatial econometric models. The analysis reveals three key findings: First, spatio-temporal patterns indicate persistent structural imbalances in food consumption, and per capita FCCF displays a fluctuating upward trajectory. Second, per capita FCCF exhibits notable spatial clustering, characterized by "high-high" and "low-low" clusters. Third, population, affluence, technology, trade, and food consumption structure all exert significant influences on per capita FCCF, albeit with distinct regional variations. Identifying key drivers and their spatial effects provides valuable insights for designing region-specific policy interventions. Various researchers have explored the determinants of FCCF, focusing on food consumption patterns, population dynamics, and economic prosperity (Biondi et al., 2021; Dong et al., 2021; He et al., 2021; Sun et al., 2021; Khan et al., 2024; Li et al., 2024). While the body of scientific literature on FCCF is substantial and has yielded valuable insights, existing studies predominantly concentrate on national or urban contexts, with limited attention paid to FCCF in rural populations. Furthermore, the current understanding of the factors influencing FCCF lacks comprehensive and systematic coverage.

This study aims to fill two key gaps in the existing literature. First, it seeks to map FCCF patterns in rural China comprehensively. Second, it aims to analyze the distinct impacts of population, affluence, technology, trade, and dietary factors using spatial econometrics. By elucidating these aspects, this research will advance our comprehension of food consumption trends and the evolutionary trajectory of FCCF among rural Chinese residents. Such insights can inform strategies aimed at promoting sustainable rural development and mitigating the environmental impacts associated with shifts in food consumption habits. Furthermore, the findings can offer valuable lessons for other developing regions undergoing similar processes of rapid urbanization and economic advancement.

2 Research design

2.1 Theoretical framework

2.1.1 The spatial correlation of the food consumption carbon footprint

Tobler's First Law of Geography asserts that while everything is interconnected, proximity plays a key role, with closer entities exhibiting stronger relationships than those farther apart. In the context of food consumption and carbon footprint, factors such as economic ties, population movement, and cultural interchange between adjacent areas can lead to interactions impacting food consumption and carbon footprint (Zambrano-Monserrate et al., 2020). For example, neighboring regions with extensive economic integration often develop similar consumption patterns and market demands, consequently shaping comparable food consumption structures and carbon footprint. Furthermore, dietary practices from one region may diffuse to neighboring areas through population mobility, influencing their food preferences and carbon footprint. As a result, Hypothesis 1 is posited.

> *Hypothesis 1*. FCCF has positive spatial autocorrelation.

2.1.2 The drivers of the food consumption carbon footprint

The STIRPAT model provides a robust theoretical framework for analyzing environmental impact factors. It assumes that environmental impacts are a function of factors such as population, affluence, and technology. More importantly, the STIRPAT model has the flexibility to add and modify relevant influences, thereby allowing it to be extended to include more variables. This theoretical model has become a well-recognized technique and is widely used to reveal the determinants of carbon emissions (Wu et al., 2021; Qi et al., 2023; Yu et al., 2023).

Meanwhile, it is worth noting that in the context of accelerating regional integration and increasingly frequent food trade, the resource allocation effect of trade impacts FCCF through market mechanisms. If the trade factor is ignored, it is difficult to fully and accurately analyze the reasons for changes in FCCF. Besides, it is necessary to consider the impact of the food consumption structure. The carbon intensity of different food groups, including animal and plant foods, varies significantly (Xu and Lan, 2016). Rising incomes drive dietary transitions toward high-carbon options, such as increased red meat consumption, leading to an increased carbon footprint (Cao and Hao, 2018; Zhu et al., 2021). Therefore, this study modifies and extends the STIRPAT model, drawing on prior literature, to meet the research needs. Specifically, when analyzing the drivers of FCCF, this study not only focuses on the impacts of population, affluence, and technology but also considers the impacts of trade and the structure of food consumption.

First, population factors encompass household size and household structure. On the one hand, a larger household size can induce scale effects, thereby reducing the energy consumption per unit of food purchased, stored, and cooked, and thus lowering the carbon footprint; conversely, a smaller household size increases the carbon footprint due to diseconomies of scale (Underwood and Zahran, 2015). On the other hand, as the aging process intensifies, the food consumption structure of the elderly evolves, with a preference emerging for low-carbon footprint foods such as poultry, eggs, and aquatic products over livestock products (Li et al., 2024), thereby also contributing to the reduction of FCCF. Consequently, Hypothesis 2 is proposed.

> *Hypothesis 2*. Population factors have a significant impact on FCCF, with an decrease in household size and an aging population increasing and reducing FCCF, respectively.

Second, affluence factors encompass per capita disposable income and the urban–rural income gap. Generally, higher incomes are likely to lead to an increase in the consumption of high carbon footprint foods, particularly meat, thereby augmenting FCCF (Li et al., 2021; Zhu et al., 2021). As the urban–rural income gap narrows, the food consumption patterns of rural residents gradually converge with those of urban residents (Yuan et al., 2019; Ren et al., 2021). Accordingly, a reduction in the urban–rural income gap and an increase in per capita rural disposable income are likely to drive an increase in FCCF. Therefore, Hypothesis 3 is formulated.

> *Hypothesis 3*. Affluence factors have a significant impact on FCCF, with higher per capita disposable income and a narrowing of the urban-rural income gap both increasing FCCF.

Third, technology factors, which reflect the level of agricultural production technology, encompass the rate of agricultural mechanization and the per capita output value of agriculture, forestry, animal husbandry, and fishery. Innovations in agricultural production technologies have significantly enhanced the yield, quality, and accessibility of low-carbon foods (e.g., plant-based foods and alternative proteins), facilitating a consumer transition away from high-carbon foods (e.g., red meat) toward low-carbon alternatives (Xu et al., 2015; McClements et al., 2021). Therefore, Hypothesis 4 is proposed.

> *Hypothesis 4*. Technology factors have a significant impact on FCCF, with an increase in the rate of agricultural mechanization and a rise in the per capita output value of agriculture, forestry, animal husbandry, and fishery both reducing FCCF.

Fourth, trade factors encompass the level of agricultural trade and the food retail price index. Agricultural trade facilitates the optimal allocation of resources across regions, a process that enhances the diversity of food supplies available to households (Xu et al., 2020). Such enhanced diversity in food supplies significantly drives the diversification of household food consumption (Dithmer and Abdulai, 2017; Krivonos and Kuhn, 2019). A more diversified consumption structure is inclined to reduce dependence on high-carbon foods (e.g., red meat), thus contributing to lower FCCF (Dou and Liu, 2024). Besides, the food retail price index can be interpreted as the cost of consumer purchases. An increase in the food retail price index usually indicates an increase in the cost of consumer purchases and a decrease in consumer purchases of food, thus reducing FCCF. Consequently, Hypothesis 5 is formulated.

> *Hypothesis 5*. Trade factors have a significant impact on FCCF, with an increase in the level of agricultural trade and a rise in the food retail price index both reducing FCCF.

Fifth, the structure of food consumption encompasses the proportion of livestock and poultry consumption, as well as the proportion of eggs, dairy, and aquatic products. It has been widely demonstrated that elevated meat consumption significantly increases FCCF; conversely, an increase in the consumption of foods such as eggs leads to a decrease in the consumption of other animal foods, thereby reducing FCCF (Xu and Lan, 2016; González et al., 2020). Accordingly, the structure of food consumption is also a key factor influencing FCCF. Therefore, Hypothesis 6 is proposed.

> *Hypothesis 6*. The structure of food consumption has a significant impact on FCCF, with an increase in the proportion of livestock and poultry consumption, as well as an increase in the proportion of eggs, dairy, and aquatic products increasing and decreasing FCCF, respectively.

Furthermore, it is crucial to recognize that, due to the significant disparities in economic development levels, resource endowments, dietary customs, and policy environments across different regions, regional heterogeneity inevitably manifests in the extent and manner in which factors such as population, affluence, technology, trade, and food consumption structure influence FCCF. Therefore, we further propose Hypothesis 7.

> *Hypothesis 7*. There is regional heterogeneity in the impact of factors such as population, affluence, technology, trade, and the structure of food consumption.

2.2 Data sources

Given that the subsistence problem for China's poor was essentially resolved by the end of 2000, the period since then has been a peak period for policy deepening and a golden age for result accumulation. This period has not only witnessed a historic leap from subsistence to comprehensive well-being but has also revealed a profound transformation in the lifestyles and food consumption patterns of rural residents. Therefore, this study selected the period from 2001 to 2023 as the study interval. Meanwhile, to ensure data completeness, this study excludes regions with significant data gaps, including Tibet, Hong Kong, Macau, and Taiwan. Consequently, the analysis is confined to 30 provinces and municipalities in mainland China.

The data used in this paper encompass three main components: food consumption, carbon footprint, and drivers. First, the primary dataset, which focuses on food consumption among rural residents in China, is sourced from authoritative publications, including the "China Statistical Yearbook," "China Rural Statistical Yearbook," and "China Yearbook of Rural Household Survey." This dataset provides detailed information on the consumption of 12 major food categories.

Second, the FCCF comprises both direct and indirect carbon footprint. The parameters required for the calculation include the integrated carbon conversion factors for various food items, the direct carbon conversion factors for different foods, and the meat conversion ratios for animal-based products. These parameters are obtained from the research of Khan et al. (2024). Additionally, the specific carbon conversion factors for cooking and processing are obtained from the research of Cao and Hao (2018). For a comprehensive and detailed overview, see Table 1.

Third, the factors influencing the FCCF of rural residents are analyzed across five critical dimensions: population, affluence, technology, trade, and food consumption structure. Each dimension comprises two indicators, forming a comprehensive set of 10 indicators. These indicators are as follows: (1) average family size; (2) the percentage of rural residents aged 65 and above in the total population; (3) per capita rural disposable income; (4) the urban–rural income gap, measured as the ratio of urban to rural per capita disposable income; (5) the agricultural mechanization rate; (6) per capita output value of agriculture, forestry, animal husbandry, and fishery; (7) the food retail price index; (8) the level of agricultural trade, represented by the ratio of total agricultural trade value to the added value of the primary sector; (9) the proportion of pork, beef, mutton, and poultry in total food consumption; and (10) the proportion of eggs, dairy, and aquatic products in total food consumption. Data for these indicators were obtained from the "China Population and Employment Statistics Yearbook," "China Population Statistics Yearbook," "China Yearbook of Household Survey," "China Rural Statistical Yearbook," "China Statistical Yearbook," and provincial statistical yearbooks. When individual data points are missing, the interpolation technique is employed to ensure data completeness.

2.3 Methods

2.3.1 Measuring the food consumption carbon footprint

The FCCF includes direct and indirect carbon footprint. Among them, the direct carbon footprint is calculated using the carbon conversion factor method, which determines the carbon footprint by converting the consumption of various food items into their corresponding carbon emissions based on specific conversion factors (Khan et al., 2024). It is founded on residents' consumption of various food types and their respective comprehensive carbon conversion factors. The specific calculation formula is as follows.

$$CF_i = Q_i \times R_i = Q_i \times \left(r_i + m_i \times r_1\right) \tag{1}$$

$$CF_d = \sum_{i=1}^{12} CF_i \tag{2}$$

In Equations 1, 2, CF_i denotes the per capita direct carbon footprint of food category i. Q_i is the per capita consumption; R_i is the integrated carbon conversion factor; r_i is the direct carbon conversion factor; m_i is the meat conversion ratio; r_1 is the direct carbon conversion factor of cereal consumption. CF_d is the sum of the per capita direct carbon footprint of 12 categories of food consumption.

Following Yang (2022), we quantify the indirect carbon footprint from food storage and cooking. In the storage segment, the carbon footprint of food refrigeration's electricity consumption is calculated using the following equation, which is derived from the number of refrigerators in the household and their average annual electricity consumption.

$$FS = EC \times SF \times ER \times \frac{N}{100 \times H} \tag{3}$$

In Equation 3, FS is the per capita carbon footprint of electricity consumption of refrigerated food in residential households. EC is the average annual electricity consumption of each refrigerator, which is 507.37 kWh according to the Maximum Allowable Values of the Energy Consumption and Energy Efficiency Grade for Household Refrigerators. SF is the coefficient of standardized coal conversion of electricity, which is taken as the value of 0.1229 kg ce/kWh. ER is the carbon footprint coefficient of electricity consumption, taking the value of 2.2132 kg C/kg ce. N is the number of refrigerators owned by each 100 households. H is the average number of permanent residents per household.

The carbon footprint of cooking is calculated by multiplying the carbon conversion factor for cooking and processing by food consumption. It should be noted that since fruits are mostly consumed directly without additional cooking and processing, the carbon conversion factor for cooking and processing is recorded as zero. The same is true for sugar.

$$FC = \sum_{i=1}^{12} Q_i \times k_i \tag{4}$$

TABLE 1 Overview of carbon conversion factors for various food types (unit: kg CO_2 eq/kg).

Types and classification of food		Integrated carbon conversion factor (R_i)	Direct carbon conversion factor (r_i)	Meat conversion ratio (m_i)	Carbon conversion factor for cooking and processing (k_i)
Plant-based food	Cereals	0.3269	0.3269	(NA)	0.1090
	Vegetables	0.0276	0.0276	(NA)	0.0109
	Fruits	0.0498	0.0498	(NA)	(NA)
	Sugar	0.3966	0.3966	(NA)	(NA)
	Vegetable oil	1.1588	0.7666	1.20	0.6540
Animal-based food	Pork	1.1892	0.2546	2.86	0.1588
	Beef	1.3658	0.2546	3.41	0.1908
	Mutton	1.3658	0.2546	3.41	0.1908
	Poultry	1.0063	0.2546	2.31	0.1363
	Eggs	0.9025	0.1511	2.30	0.0545
	Dairy	0.4255	0.0628	1.11	0.0164
	Aquatic products	0.7316	0.1432	1.81	0.0818

$$CF_{ind} = FC + FS \tag{5}$$

In Equation 4, FC is the per capita carbon footprint from the energy consumption of food cooking and processing in rural households. k_i is the carbon conversion factor of cooking and processing of food type i. In Equation 5, CF_{ind}, FC and FS are the per capita indirect carbon footprint from food consumption, per capita carbon footprint from energy consumption for food cooking and processing, and per capita carbon footprint from electricity consumption for food refrigeration, respectively.

Accordingly, the per capita FCCF equals the sum of the per capita direct carbon footprint and the per capita indirect carbon footprint. The expression is shown in Equation 6.

$$CF = CF_d + CF_{ind} \tag{6}$$

2.3.2 Spatial correlation test

Spatial correlation reveals the spatial cluster or dispersion of spatial unit attributes. To investigate the spatial pattern of FCCF among rural Chinese residents, global Moran's I and local Moran's I are used to identify local clusters and estimate the effects at each location. The global Moran's I is expressed as follows.

$$I = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}\left(x_i - \overline{x}\right)\left(x_j - \overline{x}\right)}{S^2 \sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}} \tag{7}$$

$$S^2 = \frac{1}{n}\sum_{i=1}^{n}\left(x_i - \overline{x}\right)^2 \tag{8}$$

In Equations 7, 8, n is the number of research regions, indexed by i and j; x is the variable of interest; $\overline{x}$ is the mean of x; x_i and x_j denote the per capita FCCF among rural Chinese residents in the research regions i and j; and w_{ij} is an element of the binary spatial weight matrix. Moran's I ranges from -1 to 1. At a given significance level, the larger the absolute value of global Moran's I, the higher the degree of spatial correlation. Specifically, when Moran's I is close to 1, there is a significant positive spatial correlation among provinces; when Moran's I is close to -1, there is a significant negative spatial correlation. Moreover, it shows no spatial correlation if Moran's I is equal to zero, which means the FCCF on the province level is randomly distributed. The significance of the spatial correlation is usually judged using the normalized statistic z with the following formula.

$$Z(I) = \frac{I - E(I)}{\sqrt{\mathrm{VAR}(I)}} \tag{9}$$

In Equation 9, $E(I)$ is the expected value of I, and $VAR(I)$ is the variance of I.

However, the global Moran's I can only reflect the generally spatial correlation, which cannot provide information about the degree of spatial correlation on the provincial level. To solve this problem, we use local Moran's I to identify the local spatial clusters and estimate the effects among provinces. The local Moran's I can be expressed as follows.

$$I_i = \frac{\left(x_i - \overline{x}\right)}{S^2}\sum_{j=1}^{n} w_{ij}\left(x_j - \overline{x}\right) \tag{10}$$

In Equation 10, I_i is Moran's I of the i space unit, and the other variables are identical to those in Equations 7, 8. The meaning of the local Moran's I is similar to the global Moran's I. A positive I_i means that the high (low) values of region i are surrounded by the high (low) values of the surrounding region; a negative I_i means that the high (low) values of region i are surrounded by the low (high) values of the surrounding region.

2.3.3 Evaluating drivers of the food consumption carbon footprint

Given that the FCCF of provincial administrative regions may exhibit spatial spillover effects (e.g., cross-regional trade), these effects must be captured through a spatial weight matrix to reflect the influence of neighboring areas. Therefore, subsequent analysis will use spatial econometric methods to analyze the drivers of FCCF. Compared with traditional econometric models, spatial econometric models incorporate spatial interaction terms, which can reflect the spatial effects among different regions. Typically, spatial econometric models primarily consist of three types: the Spatial Error Model (SEM), which examines the impact of errors in neighboring areas on regional observations and accentuates the spatial lag effect of omitted variables; the Spatial Lag Model (SLM), which explores whether variables display a diffusion phenomenon within the same region, concentrating on the spatial lag of the dependent variable; and the Spatial Durbin Model (SDM), which takes into account both SEM and SLM and effectively captures the spatial spillover effects of variables. The general form of the spatial econometric model is as follows.

$$CF_{it} = \alpha + \beta X_{it} + \rho\sum_{j=1}^{n} w_{ij} CF_{jt} + \theta\sum_{j=1}^{n} w_{ij} X_{jt} + \mu_{it} \tag{11}$$

$$\mu_{it} = \varphi\sum_{j=1}^{n} w_{ij}\mu_{jt} + \varepsilon_{it} \tag{12}$$

In Equations 11, 12, CF_{it} represents the dependent variable FCCF; X_{it} represents the independent variable; w_{ij} is an element of the binary spatial weight matrix; α is the constant term; β stands for the spatial regression coefficient of the independent variable; ρ stands for the spatial regression coefficient of the dependent variable; θ stands for the spatial regression coefficient of control variable; φ stands for the spatial error regression coefficient; and ε_{it} stands for the random error term. When $\rho = 0, \theta = 0, \varphi \neq 0$, this model is SEM; when $\rho \neq 0, \theta = 0, \varphi = 0$, this model is SLM; when $\rho \neq 0, \theta \neq 0, \varphi = 0$, this model is SDM.

3 Results

3.1 Basic characteristics of changes in food consumption

From 2001 to 2023, the consumption of animal-based foods increased significantly, whereas that of plant-based foods decreased (Figure 1). In 2023, the per capita consumption of animal-based foods amounted to 82.4 kilograms, representing 2.9 times the level recorded in 2001 (28.6 kilograms). Specifically, in 2023, the per capita consumption of livestock and poultry products, eggs, dairy, and aquatic products was 46.6 kg, 14.2 kg, 9.3 kg, and 12.4 kg, respectively. These values were 2.7, 2.9, 5.8, and 2.7 times higher than those in 2001. In contrast, the total per capita consumption of plant-based foods (including cereals and vegetables) decreased from 339.5 kg in 2001 to 266.5 kg in 2023, representing a 21.5% decrease, with a particularly pronounced decline in cereal consumption.

Meanwhile, the food consumption structure has become increasingly diversified. However, plant-based foods, particularly cereals, continued to account for a substantial proportion. Specifically, the per capita consumption of plant-based foods accounted for 92.8% of the total consumed in 2001. Although this proportion declined to 80.0% in 2023, it remained dominant. The per capita consumption of cereals decreased from 58.4% in 2001 to 37.8% in 2023. And the consumption of other plant-based foods, such as vegetables and fruits, remained relatively stable. Over the same period, the proportion of livestock and poultry products in the consumption of animal-based foods, a crucial food category for rural residents, decreased from 61.2% in 2001 to 56.5% in 2023. Conversely, the proportion of poultry eggs, dairy, and aquatic products in the consumption of animal-based foods increased by 4.6 percentage points.

To further assess the nutritional adequacy of rural residents' food consumption, this study compares the recommended intakes of major food types specified in the Chinese Dietary Guidelines (2022) with the actual food consumption patterns of rural residents over the years. Additionally, considering the systematic influence of China's five-year planning system (The Five-Year Plan, an important part of China's national economic planning, is a long-term plan, and the period from 2001 to 2005 is the time frame for the implementation of the first Five-Year Plan of the 21st Century (referred to as the Tenth Five-Year Plan).) on socioeconomic development and food consumption, cross-sectional data from representative five-year intervals (2001, 2006, 2011, 2016, 2021, and 2023) were analyzed (see Table 2). Despite a downward trend, cereal consumption remained above recommended thresholds. Daily consumption of livestock and poultry products has grown consistently and surpassed recommended allowances. Meanwhile, the consumption of eggs and aquatic products, although rising, remained below recommended levels. Notably, the recommended dairy intake (300–500 g/person·day) far exceeded actual consumption in 2023 (25.4 g/person·day). The insufficient consumption of vegetables and fruits also indicated a deviation from the dietary nutritional requirements.

3.2 Spatio-temporal patterns of the food consumption carbon footprint

3.2.1 Spatio-temporal distribution characteristics of carbon footprint

From 2001 to 2023, the total FCCF in rural China generally decreased, while the per capita FCCF exhibited a fluctuating upward trend (Figure 2). Specifically, the per capita FCCF increased from 160.74 kg CO_2 eq/person in 2001 to 237.51 kg CO_2 eq/person in 2023, indicating an increasing environmental impact of food consumption by rural residents. This underscores the need for attention and appropriate measures to mitigate FCCF. The total FCCF remains relatively stable, with slight fluctuations, indicating that the increase in per capita FCCF does not result in a significant change to the total FCCF. This may be attributed to rural population migration driven by rapid urbanization and industrialization.

To delve deeper into the changes in the per capita FCCF across provinces, cross-sectional data from representative five-year intervals (2001, 2006, 2011, 2016, 2021, and 2023) were analyzed (see Figure 3). The results indicate that provincial trends generally aligned with the national average. Despite this consistency, the spatio-temporal analysis reveals two distinct patterns: (1) coastal-inland disparities in per capita FCCF, and (2) "high-high" and "low-low" clustering confirmed by Moran's I. The figure visualizes the east–west gradient in FCCF, with hotspots concentrated in economically developed coastal provinces (e.g., Guangdong, Shanghai).

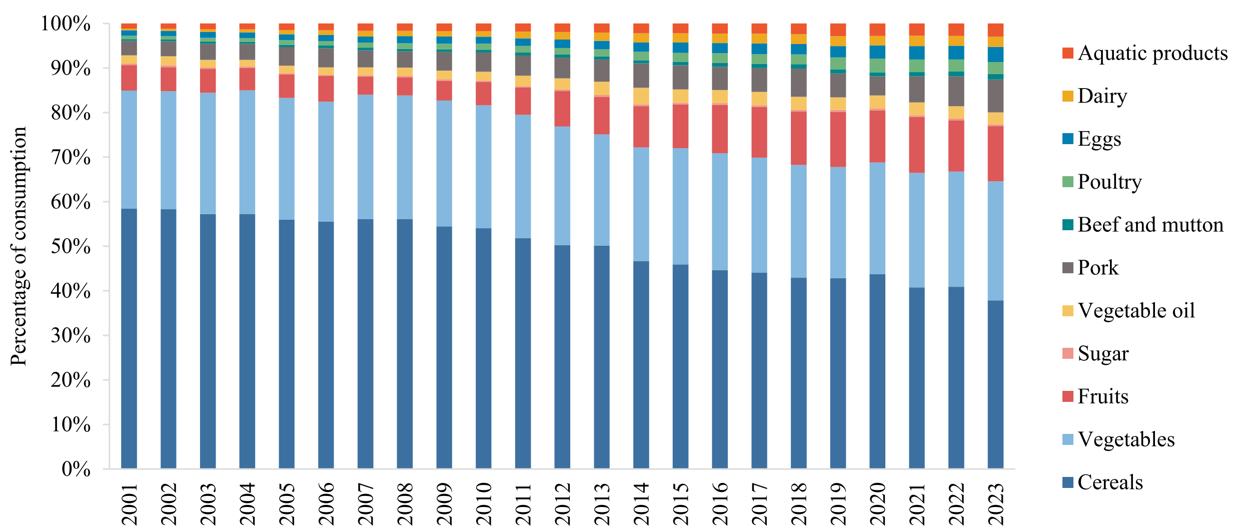

FIGURE 1
Rural Chinese residents' per capita food consumption structure (2001–2023).

TABLE 2 Dietary compliance analysis: recommended vs. actual food intake (unit: g/person·day).

Types and classification of food	Recommended appropriate intake	2001	2006	2011	2016	2021	2023
Cereals	200–300	639.8	546.6	458.1	425.2	463.1	427.9
Vegetables	300–500	290.3	265.2	244.3	249.3	292.2	302.3
Fruits	200–350	62.5	56.2	53.8	103.5	142.8	140.2
Livestock and poultry products	40–75	47.9	57.7	58.8	78.2	109.6	127.7
Aquatic products	40–75	12.6	15.2	16.3	21.8	31.3	33.9
Eggs	40–50	13.4	13.6	15.2	21.9	33.8	38.9
Dairy	300–500	4.4	10.5	13.2	20.2	26.6	25.4
Vegetable oil	25–30	20.2	16.4	20.9	28.2	32.7	30.8

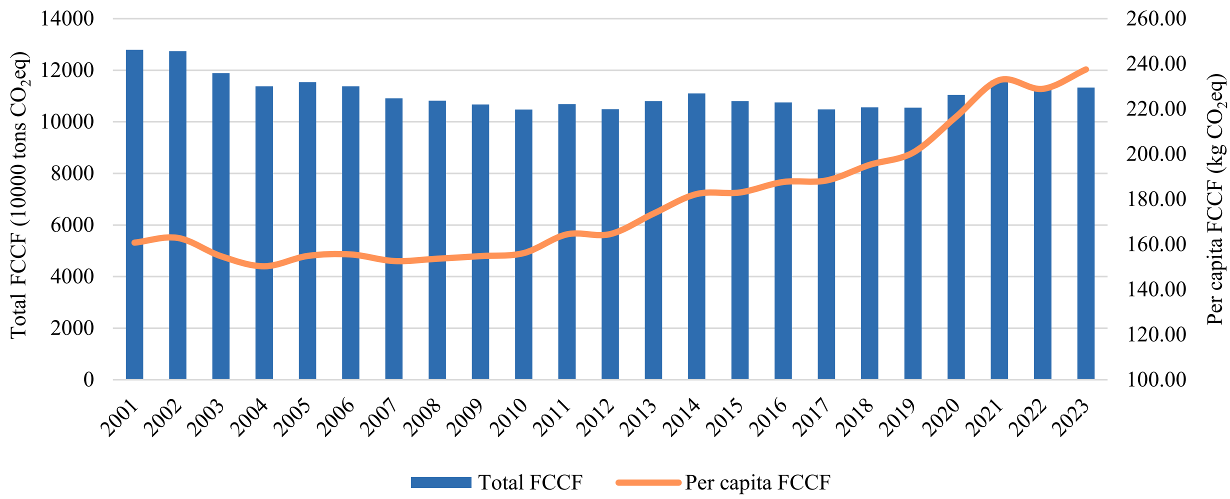

FIGURE 2
Temporal trends in the FCCF of rural Chinese residents (2001–2023).

3.2.2 Spatial agglomeration characteristics of carbon footprint

The global Moran's I, Z-value, and *p*-value for the per capita FCCF of rural Chinese residents are presented in Table 3. The global Moran's I for the per capita FCCF was predominantly greater than zero and passed the significance test. This result suggests that the distribution of FCCF exhibited significant positive spatial correlation, characterized by spatial dependence and agglomeration effects in neighboring regions. That is, provinces with high carbon footprint values tended to neighbor provinces with similarly high carbon footprint values, while provinces with low carbon footprint values tended to be adjacent to provinces with similarly low carbon footprint values. It is notable, however, that despite being greater than zero, Moran's I did not pass the significance test between 2011 and 2020. This indicates that the spatial agglomeration state is relatively unstable, characterized by a "significant—insignificant—significant" development pattern.

Further research was conducted on the local spatial distribution of clustering. Moran's I scatter plots of the FCCF of rural residents in China for 2001, 2006, 2011, 2016, 2021, and 2023 were plotted (see Figure 4). The x-axis represents the FCCF of rural residents in each province, while the y-axis represents the spatial lag value. The four quadrants correspond to different local spatial correlations. Specifically, the first quadrant (upper right) represents a high-high agglomeration type, indicating that the region is a high-value center surrounded by similar high-value areas. The second quadrant (upper left) represents a low-high agglomeration type, indicating that the region is a low-value center surrounded by dissimilar high-value areas. The third quadrant (lower left) represents a low-low aggregation type, while the fourth quadrant (lower right) represents a high-low type, exhibiting analogous meanings to the first two quadrants.

The spatial agglomeration of FCCF for rural residents in China is primarily concentrated in high-high agglomeration areas and low-low agglomeration areas. Compared with other regions, areas with rapid economic development and abundant resources are more likely to form high-high agglomeration areas. For example, Jiangsu, Shanghai, Zhejiang, Fujian, and Guangdong fall into this category. Areas with relatively underdeveloped economies are more prone to forming low-low agglomeration areas. Shanxi, Henan, Ningxia, and Gansu are typical examples.

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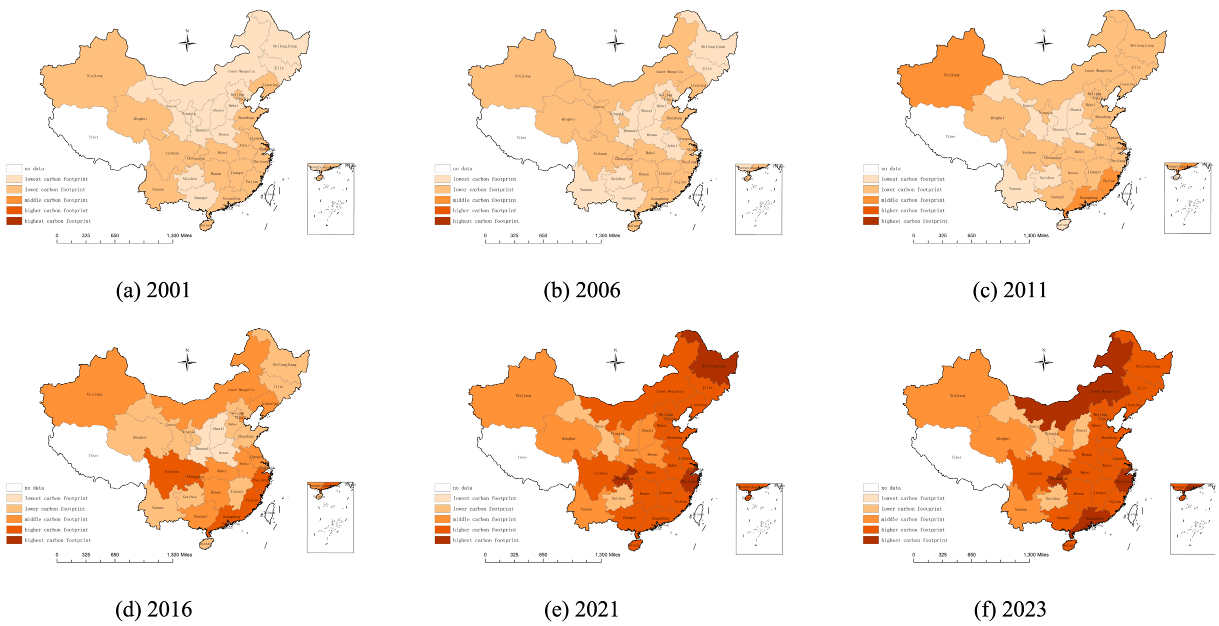

FIGURE 3
Spatial distribution of per capita FCCF in different periods **(a–f)** respectively represent the spatial distribution of per capita FCCF for the years 2001, 2006, 2011, 2016, 2021, and 2023.

TABLE 3 Global Moran's I for per capita FCCF of rural Chinese residents (2001–2023).

Year	Moran's I	*Z*-value	*p*-value
2001	0.473	4.154	0.000
2002	0.379	3.481	0.001
2003	0.370	3.281	0.001
2004	0.321	2.868	0.004
2005	0.246	2.268	0.023
2006	0.353	3.174	0.002
2007	0.374	3.352	0.001
2008	0.270	2.507	0.012
2009	0.232	2.157	0.031
2010	0.206	1.962	0.050
2011	0.138	1.402	0.161
2012	0.050	0.687	0.492
2013	0.034	0.559	0.576
2014	0.132	1.333	0.182
2015	0.119	1.231	0.218
2016	0.071	0.848	0.397
2017	0.066	0.806	0.420
2018	0.109	1.153	0.249
2019	0.132	1.336	0.181
2020	0.160	1.567	0.117
2021	0.321	2.858	0.004
2022	0.290	2.614	0.009
2023	0.339	3.000	0.003

3.3 Drivers of the food consumption carbon footprint

3.3.1 Descriptive statistics

To further identify the primary factors driving the FCCF of rural residents, this study integrates the extended STIRPAT model with the spatial econometric model to examine the effects of population, affluence, technology, trade, and food consumption structure. Descriptive statistics for the specific variables are presented in Table 4.

3.3.2 Selection of spatial econometric model

Pre-diagnostic tests, including the Lagrange Multiplier (LM) test, the Likelihood Ratio (LR) test, the Wald test, and the Hausman test, were performed before spatial econometric modeling. Results presented in Table 5 validate the appropriateness of the SDM with a fixed-effects specification for subsequent analysis.

3.3.3 Analysis of SDM regression result

Table 6 presents the estimation results for the drivers of rural residents' FCCF. It can be observed that the coefficients of the spatial lag terms of SDM under time-fixed and spatial-fixed effects are significant, at least at the 5% significance level with a positive direction, except in the case of both-fixed effects. This suggests a positive spatial spillover effect of rural residents' FCCF across regions.

Furthermore, the SDM under the both-fixed effects has the smallest AIC and BIC; therefore, the subsequent analysis mainly focuses on this model. Due to the existence of the spatial lag term, the regression coefficients in the model no longer indicate the actual effect of the explanatory variables on the explained variables (Elhorst, 2014). Thus, the spatial effects of the variables are further decomposed using the partial differential method, as shown in Table 7.

In terms of direct effects, spatial regression identifies three dominant drivers: aging population, income growth, and meat

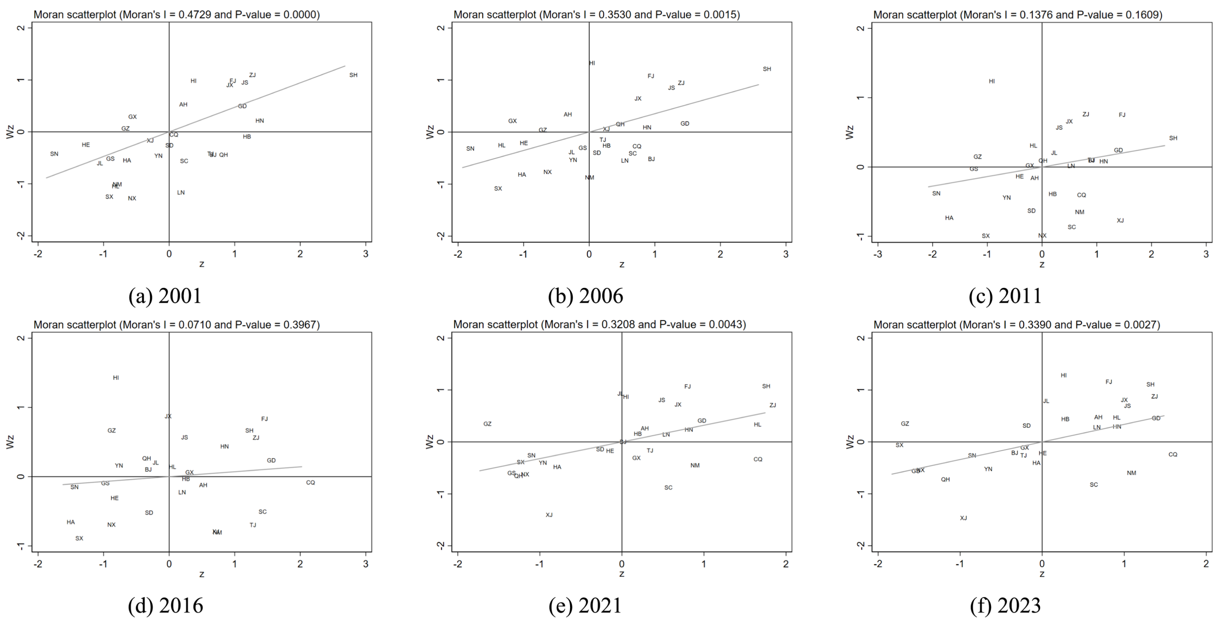

FIGURE 4
Moran's I scatter plot of per capita FCCF in different periods. **(a–f)** respectively represent the Moran's I scatter plots of per capita FCCF for the years 2001, 2006, 2011, 2016, 2021, and 2023.

consumption share. Among them, the proportion of the rural population aged 65 and above in the total population and the proportion of pork, beef, mutton, and poultry in total food consumption have the most significant impacts, with coefficients of 0.011, signifying that an increase of one percentage point in these two proportions increases the per capita FCCF of local rural residents by 1.1 percentage points. Furthermore, the coefficient of per capita rural disposable income is 0.285. Specifically, every 1% increase in per capita rural disposable income can drive the per capita FCCF of local rural residents to increase by 0.285 percentage points. The coefficients of average family size (Pop_1) and agricultural trade level (Com_2) are negative and significant at the 10% significance level, indicating that the above factors negatively impact the FCCF of local rural residents. For every unit increase in average household size, the per capita FCCF of local rural residents decreases by 1.1 percentage points. Moreover, it can be seen that an increase in the level of agricultural product trade helps to mitigate the growth of the per capita FCCF of local rural residents.

Regarding indirect effects, the coefficients of the proportion of rural residents aged 65 and over in the total population (Pop_2) and urban–rural income gap (Aff_2) are both positive and reach the 1 and 10% significance levels, respectively. This indicates that the two above variables have positive spillover effects on rural residents' FCCF in neighboring provinces. An increase of one percentage point in the local proportion of rural residents aged 65 and over in the total population will increase the per capita FCCF among rural residents of neighboring provinces by 1.2 percentage points. Every unit increase in the local urban–rural income gap will increase the per capita FCCF among rural residents of neighboring provinces by 8.4 percentage points. These results underscore the importance of being vigilant about the environmental impacts of population aging and urban–rural income inequality, particularly their spillover effects on neighboring regions. The coefficients of per capita output value of agriculture, forestry, animal husbandry, and fishery ($Tech_2$) and the proportion of eggs, dairy, and aquatic products in total food consumption (Str_2) are significantly negative, at least at the 10% level. A high per capita output value of agriculture, forestry, animal husbandry, and fishery means that the region has advanced technology, which can drive the upgrading of the production structure of neighboring areas through a technology diffusion mechanism, thereby helping to improve food consumption structures and reduce the per capita FCCF. Additionally, due to the geographical proximity between regions, an increase in the proportion of consumed eggs, dairy, and aquatic products can generate a demonstration effect on the food consumption structure of neighboring provinces, which in turn can have a negative spillover effect on their FCCF.

As for total effects, the proportion of rural residents aged 65 and over in the total population (Pop_2), per capita rural disposable income (Aff_1), as well as the proportion of pork, beef, mutton, and poultry in total food consumption (Str_1) positively influence rural residents' FCCF, with population aging playing the most significant role. The per capita output value of agriculture, forestry, animal husbandry, and fishery ($Tech_2$) negatively affects FCCF.

3.3.4 Robustness checks

To enhance the reliability of regression outcomes, robustness checks were conducted using two approaches: 1% tail truncation and time horizon truncation. Specifically, all variables were winsorized at the 1% level, and regression analysis was performed again. Meanwhile, given that 2020 was the first year of major public health emergencies, during which the economy and people's livelihoods were severely affected, the data for 2020 were removed, and regression analysis was performed once more. The regression results are presented in Table 8. A comparison with the original regression results indicates that the coefficients are generally consistent in size, direction, and significance level, thereby demonstrating the robustness of the above findings.

TABLE 4 Descriptive statistics of variables.

Variable	Definition	Mean	SD	Min	Max
ln*CF*	Per capita carbon footprint of food consumption (kg/person)	5.166	0.197	4.670	5.667
Pop_1	Average family size (person/household)	3.242	0.612	0.470	8.770
Pop_2	The ratio of rural residents aged 65 and over in the total population (%)	11.604	4.613	4.342	28.119
ln Aff_1	Per capita rural disposable income (yuan/person)	8.935	0.781	7.277	10.669
Aff_2	Urban–rural income gap	2.700	0.500	1.718	4.459
$Tech_1$	Agricultural mechanization rate (kilowatts/hectare)	5.732	2.553	1.390	13.940
ln$Tech_2$	Per capita output value of agriculture, forestry, animal husbandry, and fishery (yuan/person)	9.315	0.851	7.168	11.074
lnCom_1	Retail price index of food commodities	5.167	0.352	4.579	5.765
Com_2	The level of agricultural trade	0.762	2.709	0.005	25.503
Str_1	The proportion of pork, beef, mutton, and poultry in total food consumption (%)	7.173	3.221	1.315	19.530
Str_2	The proportion of eggs, dairy, and aquatic products in total food consumption (%)	5.566	2.978	0.416	14.081
690					

TABLE 5 Test results of spatial econometric model.

Test	Statistic	*p*-value
LM-error	39.770	0.000
LM-lag	5.235	0.022
Robust LM-error	47.356	0.000
Robust LM-lag	12.821	0.000
LR-error	24.760	0.006
LR-lag	25.140	0.005
Wald-error	24.870	0.006
Wald-lag	25.630	0.004
Hausman	473.580	0.000

3.3.5 Heterogeneity analysis

Given the differences in resource endowment and economic development among provinces, it is challenging to prescribe targeted measures for managing FCCF in different regions based solely on the regression results of the whole sample. Therefore, this study undertakes a comprehensive analysis of the heterogeneous drivers of rural FCCF. Thirty provinces are categorized into four regions: eastern, central, western, and northeastern, according to the official regional classification of the National Bureau of Statistics (see Table 9).

As shown in Table 10, there are variations in the drivers of the per capita FCCF across different regions. The analysis begins by examining the role of population factors. The direct effect of household size is significantly negative in the eastern and western areas and significantly positive in the central and northeastern regions. Moreover, there are positive spillover effects in the central and northeastern areas. These results reflect the heterogeneous impact of household size on the per capita FCCF in different regions. The direct effect of the aging level is significantly positive in the western and northeastern areas, and there is a positive spillover effect in the northeast region. However, they are not significant in either the eastern or central areas. This suggests that the contribution of aging to the per capita FCCF is limited to the western and northeastern rural regions.

The analysis of affluence effects follows. The direct impact of per capita rural disposable income is positive in the central and western regions, yet there is no significant promotion in the eastern and northeastern areas. Rural disposable income has a positive spillover effect in the eastern region and a negative one in the western and northeastern areas. Furthermore, the influence of the narrowing of the urban–rural income gap on rural residents' FCCF in different places is complex. In the eastern and northeastern regions, narrowing the urban–rural income gap contributes to the increase in the FCCF of rural residents. Conversely, it has a dampening effect in the central area. Such changes also impact FCCF in other regions through inter-regional spillover effects.

The level of agricultural mechanization exerts a significant dampening effect on the per capita FCCF of rural residents in the northeast region. Also, it has a positive spillover effect in the east and northeast regions and a negative spillover effect in the central region. The growth in per capita output value of agriculture, forestry, animal husbandry, and fishery has an inhibitory effect on the per capita FCCF of rural residents in the western region. However, it is not conducive to carbon reduction in the central and northeastern areas. In addition, the per capita output value of agriculture, forestry, animal husbandry, and fishery has a positive spillover effect in the western and northeastern regions. This indicates significant differences in the

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TABLE 6 Estimation results of the spatial Durbin model.

Variable	Spatial fixed	Time fixed	Spatial and time fixed
Pop_1	−0.013**	−0.006	−0.011**
	(0.006)	(0.007)	(0.005)
Pop_2	0.011***	0.010***	0.012***
	(0.002)	(0.002)	(0.002)
$\ln Aff_1$	0.286***	0.201***	0.277***
	(0.075)	(0.027)	(0.078)
Aff_2	−0.061**	−0.076***	−0.033
	(0.027)	(0.015)	(0.027)
$Tech_1$	0.002	−0.007***	0.001
	(0.003)	(0.002)	(0.003)
$\ln Tech_2$	−0.027	0.013	−0.016
	(0.020)	(0.012)	(0.022)
$\ln Com_1$	0.107	−0.205	0.142
	(0.225)	(0.284)	(0.217)
Com_2	−0.003	−0.002	−0.004*
	(0.002)	(0.002)	(0.002)
Str_1	0.009**	0.019***	0.010***
	(0.004)	(0.002)	(0.004)
Str_2	0.009**	0.006**	0.004
	(0.004)	(0.003)	(0.004)
$W \times Pop_1$	−0.005	0.003	−0.003
	(0.008)	(0.010)	(0.008)
$W \times Pop_2$	0.009***	−0.001	0.013***
	(0.003)	(0.004)	(0.004)
$W \times \ln Aff_1$	−0.201**	−0.188***	−0.031
	(0.079)	(0.055)	(0.134)
$W \times Aff_2$	−0.092***	0.028	0.085
	(0.034)	(0.032)	(0.052)
$W \times Tech_1$	0.003	0.000	0.006
	(0.006)	(0.004)	(0.007)
$W \times \ln Tech_2$	−0.100***	−0.051**	−0.076*
	(0.029)	(0.024)	(0.042)
$W \times \ln Com_1$	−0.292	−0.065	−0.346
	(0.235)	(0.475)	(0.361)
$W \times Com_2$	−0.002	−0.002	−0.006
	(0.005)	(0.004)	(0.006)
$W \times Str_1$	−0.003	−0.004	0.010
	(0.005)	(0.004)	(0.006)
$W \times Str_2$	0.007	0.003	−0.016*
	(0.007)	(0.006)	(0.008)
rho	0.111**	0.196***	−0.064
	(0.052)	(0.054)	(0.056)
sigma2_e	0.004***	0.007***	0.004***
	(0.000)	(0.000)	(0.000)
N	690	690	690
R-sq	0.644	0.756	0.748
AIC	−1786.435	−1438.165	−1854.772
BIC	−1686.628	−1338.358	−1754.965

*, **, *** denote significance levels of 10, 5, and 1%, respectively.

impacts of agricultural mechanization and per capita output value of agriculture, forestry, animal husbandry, and fishery on the per capita FCCF of rural residents in different regions. These differences may be influenced by the region's stage of economic development.

The retail price index of food commodities has a significantly positive direct effect in the northeast. This suggests that in the northeast, an increase in the food retail price index could contribute to an increase in the per capita FCCF of local rural residents. Furthermore, the rise in the food retail price index would be transmitted to adjacent regions via market mechanisms. Nevertheless, this positive spillover effect in the western region is not apparent, probably due to differences in economic conditions and consumption habits. Additionally, it is noteworthy that the level of agricultural product trade has a contributory influence on the per capita per capita FCCF of local rural residents in the northeast region, which diverges from the results of the benchmark regression. A possible reason for this is that, although the demand for food consumption increases as living standards rise, the food access conditions of rural residents in the northeast region are restricted, making it challenging to fully meet the consumption demand. With the development of agricultural trade, food availability has increased, which has contributed to the growth of the per capita FCCF of rural residents in the northeast region.

Lastly, the analysis focuses on the effects of food consumption structure. Increases in livestock and poultry consumption shares in central and western rural areas significantly augment per capita FCCF. However, it is interesting to note that in the rural areas of the eastern region, the increase in the share of livestock and poultry consumption reduces the per capita FCCF. Moreover, there is a negative spillover effect associated with the share of livestock and poultry consumption. With a relatively stable food supply, livestock and poultry consumption in local and neighboring areas showed a seesaw trend. It was also found that changes in the consumption share of eggs, dairy, and aquatic products had different impacts on the per capita FCCF in various regions. In the western region, an increase in the share leads to a rise in the per capita FCCF, while in the northeastern region, it has a negative effect and contributes to a decrease in the per capita FCCF.

4 Discussion

By the year 2000, China had primarily addressed the fundamental food and clothing needs of its rural populace. However, the subsequent rapid increase in income has raised concerns about the sustainability of rural food consumption. This research empirically examines the changes in dietary patterns and their associated carbon footprint among rural residents from 2001 to 2023. The findings demonstrate a significant transition: a decrease in plant-based food consumption,

TABLE 7 Decomposition of spatial effects.

Variable	Direct effect	Indirect effect	Total effect
Pop_1	−0.011*	−0.003	−0.013
	(0.006)	(0.008)	(0.009)
Pop_2	0.011***	0.012***	0.024***
	(0.002)	(0.004)	(0.003)
$\ln Aff_1$	0.285***	−0.057	0.229*
	(0.075)	(0.121)	(0.123)
Aff_2	−0.033	0.084*	0.050
	(0.027)	(0.049)	(0.051)
$Tech_1$	0.001	0.005	0.006
	(0.003)	(0.006)	(0.007)
$\ln Tech_2$	−0.015	−0.069*	−0.084*
	(0.021)	(0.041)	(0.046)
$\ln Com_1$	0.151	−0.318	−0.167
	(0.231)	(0.352)	(0.299)
Com_2	−0.004*	−0.005	−0.009
	(0.002)	(0.006)	(0.006)
Str_1	0.011***	0.008	0.019***
	(0.004)	(0.006)	(0.005)
Str_2	0.005	−0.016**	−0.011
	(0.004)	(0.008)	(0.009)

*, **, *** denote significance levels of 10, 5, and 1%, respectively.

accompanied by a notable increase in animal-based food consumption. This trend aligns with previous studies by Zhou et al. (2020) and Li et al. (2021), indicating that as rural residents' living standards improve, they tend to favor animal products over grain-based items due to the higher income elasticity of animal products. Despite this dietary shift, disparities persist, including excessive cereal consumption that surpasses recommended levels of livestock and poultry intake, as well as inadequate consumption of eggs, dairy, aquatic products, and fruits compared to nutritional guidelines. Moreover, the per capita carbon footprint associated with food consumption in rural China has increased over the past two decades, partly due to the transition towards animal-based foods, which inherently have higher carbon intensities than plant-based alternatives (Xu and Lan, 2016). The spatial–temporal trends and drivers analysis collectively suggest that effective mitigation of carbon footprint from food consumption necessitates: (1) dietary modifications in regions with high carbon footprint, as well as (2) the dissemination of technologies and the improvement of trade flows.

Spatial analysis reveals significant regional variations in FCCF. Provinces with strong economies, such as Guangdong, Shanghai, and Zhejiang, exhibit higher FCCF levels due to factors including population concentration resulting from migration, substantial investments in food-related infrastructure, and increased consumption associated with economic development. The presence of positive spatial autocorrelation in FCCF supports Hypothesis 1, indicating the clustering of regions with high carbon footprint, consistent with previous spatial clustering findings (Yang, 2022). This spatial distribution offers valuable insights for prioritizing targeted mitigation strategies.

Utilizing spatial econometric models, the research identifies key determinants of FCCF. Factors such as the aging population ratio, per capita disposable income, and the proportion of livestock and poultry consumption have a positive impact on FCCF; while household size has a negative influence, aligning with prior studies on the challenges faced by single households in decarbonization efforts (Huang et al., 2024). Notably, these findings contradict Hypothesis 2, which suggested that aging decreases FCCF due to reduced consumption of red meat. A plausible explanation could be the compensatory rise in poultry, egg, and aquatic product consumption among older demographics (Li et al., 2024). Furthermore, an uptick in the share of livestock and poultry consumption notably boosts per capita FCCF, partially supporting Hypothesis 6 and aligning with prior research (Yang, 2022), underscoring the need to enhance food consumption patterns for sustainable development (Reisch et al., 2013; Hedenus et al., 2014). Additionally, an increase in rural residents' per capita disposable income is linked to higher per capita FCCF, partially validating Hypothesis 3. Income significantly influences food consumption, with the income elasticity of animal products generally exceeding that of other product categories (Ren et al., 2018; Li et al., 2021). Consequently, the per capita disposable income of rural residents plays a crucial role in increasing per capita food consumption expenditure. However, it is essential to note that as residents' income and living standards increase, the income elasticity of food consumption decreases (Yu, 2018; Li et al., 2021), potentially leading to a reduction in the impact of income on per capita food consumption expenditure. As a result, the positive influence of income is relatively less pronounced compared to other contributing factors.

In contrast to prior research, which primarily examined population, affluence, and dietary patterns when analyzing factors influencing FCCF, this study enhances the existing literature by incorporating technology and trade considerations. Our empirical findings indicate that increased agricultural trade has a detrimental impact on local rural per capita FCCF, partially supporting Hypothesis 5. This outcome may be attributed to enhanced efficiency in food production and distribution systems (Xu et al., 2020), suggesting that facilitating resource flows could be an effective strategy for FCCF mitigation. Moreover, the per capita output value of agriculture, forestry, animal husbandry, and fishery demonstrates significant adverse spillover effects on neighboring rural FCCF. This phenomenon is likely due to the presence of advanced technologies in areas with high per capita output values in agriculture-related sectors. These technologies, through technology diffusion mechanisms, enhance production structures in adjacent regions and optimize dietary patterns (McClements et al., 2021), thereby contributing to a decrease in per capita FCCF. This finding provides partial support for Hypothesis 4. The geographical proximity of regions can lead to changes in food consumption patterns in adjacent provinces. An increase in the consumption of eggs, dairy, and aquatic products can impact the food consumption structure of neighboring areas, consequently reducing their per capita FCCF. Additionally, the study identified significant regional variations in the drivers of FCCF, confirming Hypothesis 7. This highlights the need for region-specific policies to mitigate the environmental impacts of food consumption.

TABLE 8 Robustness test in tail-shortening treatment and shortening the time window.

Variable	Tail-shortening treatment			Shortening the time window		
	Direct effect	Indirect effect	Total effect	Direct effect	Indirect effect	Total effect
Pop_1	−0.024***	0.015	−0.009	−0.010*	−0.001	−0.012
	(0.009)	(0.014)	(0.013)	(0.006)	(0.008)	(0.009)
Pop_2	0.011***	0.011***	0.022***	0.011***	0.013***	0.024***
	(0.002)	(0.004)	(0.003)	(0.002)	(0.004)	(0.003)
$\ln Aff_1$	0.266***	−0.050	0.216*	0.318***	−0.027	0.291**
	(0.074)	(0.121)	(0.123)	(0.076)	(0.120)	(0.120)
Aff_2	−0.041	0.079	0.038	−0.021	0.083*	0.062
	(0.028)	(0.051)	(0.052)	(0.028)	(0.049)	(0.050)
$Tech_1$	0.002	0.005	0.007	0.001	0.006	0.006
	(0.003)	(0.006)	(0.007)	(0.003)	(0.006)	(0.007)
$\ln Tech_2$	−0.019	−0.082**	−0.101**	−0.017	−0.074*	−0.091**
	(0.021)	(0.041)	(0.046)	(0.021)	(0.040)	(0.045)
$\ln Com_1$	0.150	−0.279	−0.129	0.202	−0.317	−0.115
	(0.232)	(0.357)	(0.305)	(0.242)	(0.359)	(0.304)
Com_2	−0.005*	−0.007	−0.012*	−0.004*	−0.004	−0.008
	(0.003)	(0.007)	(0.007)	(0.002)	(0.006)	(0.006)
Str_1	0.010***	0.007	0.017***	0.009**	0.011*	0.020***
	(0.004)	(0.006)	(0.005)	(0.004)	(0.006)	(0.005)
Str_2	0.005	−0.014*	−0.009	0.003	−0.017**	−0.014
	(0.004)	(0.008)	(0.008)	(0.004)	(0.008)	(0.009)

*, **, *** denote significance levels of 10, 5, and 1%, respectively.

TABLE 9 Regional division.

Region	Provinces
Eastern China	Beijing, Tianjin, Hebei, Shandong, Jiangsu, Shanghai, Zhejiang, Fujian, Guangdong, and Hainan
Central China	Shanxi, Henan, Anhui, Hubei, Hunan, and Jiangxi
Western China	Inner Mongolia, Guangxi, Chongqing, Sichuan, Guizhou, Yunnan, Shaanxi, Gansu, Ningxia, Qinghai, and Xinjiang
Northeastern China	Liaoning, Jilin, and Heilongjiang

The results of this paper hold significant policy implications for advancing sustainable food consumption in rural China. First, it is imperative to advocate for a transition toward sustainable dietary practices, including a reduction in the consumption of carbon-intensive animal-based products and an increase in the consumption of plant-based foods. Public awareness initiatives and nutritional education programs are crucial in promoting healthier and more environmentally conscious dietary habits. Second, considering the combined impact of population dynamics and dietary patterns, centralized feeding models such as communal dining facilities for the rural elderly not only serve as livelihood initiatives to address the aging population but also have the potential to enhance the nutritional well-being of rural residents and potentially lower FCCF. Third, policies to enhance trade flows and promote technological advancements in agriculture can help mitigate FCCF. Lastly, policymakers should consider the region-specific driver heterogeneity and spatial spillover effects identified in this study when developing strategies to ensure that interventions align with the local economic environment, resource endowments, and demographics, thereby maximizing sustainability outcomes.

This study nevertheless has certain limitations. First, this study draws on aggregated provincial-level data, which may obscure local-scale variations in food consumption and carbon emissions. Future research could utilize more granular data at the household or individual level to better capture the heterogeneity in food consumption patterns and their associated environmental impacts. Second, this study focuses on the carbon footprint of food consumption but does not account for other environmental impacts, such as water consumption or land utilization. Future studies could employ a more integrated approach by incorporating multiple ecological metrics to provide a holistic evaluation of food consumption sustainability. Lastly, this study primarily examines the role of population, affluence, technology, trade, and dietary structure in driving changes in FCCF. Future research should explore in depth the cultural and psychological factors that influence dietary choices and their associated environmental consequences. A better understanding of these factors can inform the design of more effective interventions to promote sustainable food consumption.

TABLE 10 Heterogeneity test in four geographic divisions.

Variable	Eastern China			Central China		
	Direct effect	Indirect effect	Total effect	Direct effect	Indirect effect	Total effect
Pop_1	−0.020***	−0.009	−0.029**	0.043***	0.044**	0.086***
	(0.007)	(0.009)	(0.013)	(0.014)	(0.018)	(0.025)
Pop_2	0.001	−0.001	−0.001	0.008	0.006	0.014
	(0.003)	(0.005)	(0.005)	(0.007)	(0.010)	(0.009)
$\ln Aff_1$	0.196	0.512**	0.708***	0.731***	0.598	1.329***
	(0.149)	(0.228)	(0.262)	(0.149)	(0.372)	(0.321)
Aff_2	−0.210***	−0.023	−0.233**	0.183**	−0.225*	−0.042
	(0.061)	(0.084)	(0.113)	(0.073)	(0.127)	(0.120)
$Tech_1$	−0.001	0.018***	0.016**	0.000	−0.038***	−0.038***
	(0.004)	(0.006)	(0.008)	(0.004)	(0.007)	(0.007)
$\ln Tech_2$	0.039	−0.068	−0.030	0.122**	−0.076	0.046
	(0.029)	(0.052)	(0.064)	(0.061)	(0.086)	(0.112)
$\ln Com_1$	−0.295	0.809*	0.514	−0.601	2.090***	1.489***
	(0.349)	(0.485)	(0.443)	(0.439)	(0.539)	(0.421)
Com_2	0.001	0.005	0.006	−0.447	−0.163	−0.610
	(0.003)	(0.005)	(0.007)	(0.329)	(0.532)	(0.611)
Str_1	−0.032***	0.028***	−0.004	0.024***	−0.027**	−0.003
	(0.007)	(0.010)	(0.010)	(0.006)	(0.011)	(0.010)
Str_2	−0.000	−0.007	−0.007	−0.017	−0.018	−0.034**
	(0.008)	(0.012)	(0.014)	(0.011)	(0.018)	(0.016)

Variable	Western China			Northeast China		
	Direct effect	Indirect effect	Total effect	Direct effect	Indirect effect	Total effect
Pop_1	−0.017*	0.006	−0.011	0.129***	0.088***	0.217***
	(0.010)	(0.013)	(0.012)	(0.036)	(0.032)	(0.066)
Pop_2	0.012***	0.004	0.016***	0.016***	0.019**	0.035***
	(0.004)	(0.007)	(0.006)	(0.005)	(0.009)	(0.010)
$\ln Aff_1$	0.558***	−0.648***	−0.090	−0.145	−1.348***	−1.493***
	(0.122)	(0.200)	(0.208)	(0.263)	(0.400)	(0.479)
Aff_2	0.002	−0.077	−0.075	−0.086*	−0.516***	−0.603***
	(0.032)	(0.067)	(0.068)	(0.051)	(0.114)	(0.108)
$Tech_1$	0.002	−0.029	−0.027	−0.019*	0.031*	0.011
	(0.010)	(0.018)	(0.020)	(0.011)	(0.016)	(0.022)
$\ln Tech_2$	−0.115***	0.225***	0.110*	0.518***	0.503***	1.021***
	(0.038)	(0.058)	(0.066)	(0.058)	(0.068)	(0.112)
$\ln Com_1$	0.134	−0.253	−0.119	1.963***	2.082***	4.044***
	(0.309)	(0.407)	(0.280)	(0.340)	(0.458)	(0.652)
Com_2	0.349	−0.251	0.098	0.834***	−0.036	0.798***
	(0.231)	(0.455)	(0.404)	(0.109)	(0.165)	(0.201)

(Continued)

TABLE 10 (Continued)

Variable	Western China			Northeast China		
	Direct effect	Indirect effect	Total effect	Direct effect	Indirect effect	Total effect
Str_1	0.021***	−0.014*	0.006	0.003	−0.024	−0.021
	(0.005)	(0.007)	(0.008)	(0.011)	(0.015)	(0.020)
Str_2	0.020***	0.017	0.037***	−0.037***	0.077***	0.041
	(0.006)	(0.012)	(0.014)	(0.014)	(0.017)	(0.026)

*, **, *** denote significance levels of 10, 5, and 1%, respectively.

5 Conclusion

This paper investigates the sustainable transition of food consumption in rural China, with a specific emphasis on the spatio-temporal patterns and drivers of the FCCF. It reveals that, despite the gradual diversification of rural food consumption structures among rural residents in China, significant room for improvement remains. The increasing per capita FCCF, driven by rising incomes, population aging, and transitions in food consumption towards livestock and poultry products, underscores the need for sustainable food consumption policies. The spatial heterogeneity of FCCF further emphasizes the importance of region-specific strategies for addressing the environmental impacts of food consumption. By advancing technological innovation, optimizing trade patterns, refining dietary structures, and addressing regional disparities, policymakers can help reduce the FCCF and contribute to the sustainable development of rural China. Additionally, the findings of this research will provide valuable practical insights and policy recommendations for other developing regions facing similar challenges, thereby contributing to global sustainable development.

Data availability statement

The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding author.

Author contributions

HQ: Supervision, Writing – review & editing, Validation, Conceptualization, Formal analysis, Project administration. YG: Visualization, Software, Conceptualization, Formal analysis, Data curation, Writing – review & editing, Validation, Methodology, Writing – original draft. PJ: Visualization, Methodology, Software, Writing – original draft. FL: Funding acquisition, Writing – review & editing, Conceptualization. JZ: Funding acquisition, Conceptualization, Writing – review & editing.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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