



Spatial–temporal and structural differences in the carbon footprints embedded in households food waste in urban and rural China

Shujun Cheng¹ · Guobao Song² · Di Yang¹ · Liuyang Yao¹ · Zhide Jiang¹ · Minjuan Zhao¹

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Abstract

Household food waste (HFW) accounted for about 66% of global food waste's total carbon footprints (CF). Based on China's macro-panel food consumption data, this paper measures the urban–rural and provincial differences in the HFW CF from scale, structure, and temporal-spatial evolution perspectives. The results indicate that HFW and CF continue to grow, and the total CF and per capita HFW in urban households are higher than in rural households. The structural differences between urban and rural HFW CF vary significantly over time and spaces, which reflected that rural households in the southeastern coastal areas have higher per capita HFW CF than urban in 2019. The research results help to clarify the distribution and evolution pattern of HFW CF in China and offer new ideas for the differentiated governance of CF reduction in the food system.

Keywords Food security · Household food waste · Carbon footprint · Urban–rural differences · Spatial–temporal evolution · China

Introduction

Global food waste has proliferated over the past few decades (Giroto et al. 2015). In its latest report for 2021, the United Nations Environment Programme (UNEP) noted

that around 931 million tonnes of food waste were generated in 2019, approximately more than twice the level of consumption previously estimated by the United Nations Food and Agriculture Organization (FAO 2011). However, around 690 million people worldwide did not have enough food to eat in 2019. The COVID-19 pandemic will exacerbate global hunger (Laborde et al. 2020). The challenge of reducing food waste is a complex social, economic, and environmental issue (Liu et al. 2013). Global agriculture consumes 70% of the world's freshwater, 38% of the land area (Foley et al. 2011), and generates 26% of the world's greenhouse gas emissions (GHGs), a quarter of which comes from food that has never been eaten (Poore and Nemecek 2018). Food waste not only means the food waste but also directly leads to rising food prices, exacerbating the food supply crisis

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Highlights

- the differences of total HFW and CF become more evident, and urban households are the key areas for reducing HFW and CF.
- the per capita HFW of rural households are higher than those of urban households, but the per capita CF is lower than that of urban households.
- Although the CF of animal-based food increases, the CF of plant-based food is much higher than that of animal-based.
- the CF differences of spatial–temporal evolution are apparent in urban and rural.

✉ Minjuan Zhao
minjuan.zhao@nwafu.edu.cn

Shujun Cheng
chengsj@nwafu.edu.cn

Guobao Song
gb.song@dlut.edu.cn

Di Yang
di.yang12@outlook.com

Liuyang Yao
liuyang.yao@nwafu.edu.cn

Zhide Jiang
jiangzhide@nwafu.edu.cn

¹ College of Economics and Management, Northwest A&F University, Yangling 712100, Shaanxi, China

² Key Laboratory of Industrial Ecology and Environmental Engineering, College of Environmental Science and Technology, Dalian University of Technology, Dalian 116024, China

and increasing consumer expenditure (Jiang et al. 2018). Moreover, food waste makes the fruits of substantial socioeconomic efforts go to waste (Cheng et al. 2012), which also means inefficient use of large amounts of water, land, and energy (Garnett 2011; Xue et al. 2021).

HFW is a critical area of global food waste and GHGs emissions. Global HFW accounted for 61% of total waste (UNEP 2021), and 66% of carbon dioxide equivalent (CO_{2e}) emissions associated with food waste were caused by HFW (Tonini et al. 2018). Timely and effective quantification and monitoring of the environmental impact of HFW are more critical than ever. In 2015, the United Nations Sustainable Development Goal (UNSDG) 12.3, “Responsible Production and Consumption” urged countries to achieve a 50% reduction in per capita food waste at the retail and consumer levels globally by 2030 (UN 2015). The international community generally believed that food waste mainly occurred in developed countries in the past few decades. However, with the growth of per capita income in developing countries, there is also a large amount of food waste (UNEP 2021). Where are the potential vital areas of reducing food waste (Liu 2014). In particular, BRICS countries (Brazil, Russia, India, China, and South Africa) have less information on HFW. They are undergoing rapid changes in diet, urbanization, and household income growth, and their vast population size would lead to considerable HFW (Xue et al. 2017).

In the past 40 years, the scale and structure of urban and rural populations have undergone tremendous changes in China (Xu et al. 2020). The total population increased from 1 billion in 1981 to 1.4 billion in 2021, and the proportion of the urban population increased from 20.16 to 64.72% by 2021¹ (China National Bureau of Statistics, 1981 and 2021). Although the living standards of Chinese residents have become increasingly affluent with the sustained and rapid socio-economic development, the income gap and living standards between urban and rural areas are widening (Wang et al. 2020). There are also apparent regional and urban–rural differences in residents’ food consumption (Meng et al. 2010; Xin and Li 2018). Under such a substantial urban–rural transition and disparity in food consumption, the disparity between urban and rural areas in food waste is self-evident. China has actively responded to the UN’s global call to reduce food waste and has taken several measures to curb food waste. However, food waste was regarded as corruptive behavior for governmental officials in the beginning. After the US–China economic conflict in 2018, China realized that its food security heavily depends on the international market, particularly the USA. To reduce

strategic dependence on the global food market, China started to take strict policies to reduce food waste to enhance food security (Yu 2022). In April 2021, China passed the *Anti-Food waste Law of the People's Republic of China*,² further curbing food waste through legislation for the first time. Anti-food-waste switched its strategic focus from the governmental system to the general public (Yu 2022). However, the accurate scale of HFW and its impact in China are still poorly understood (Min et al 2020). What are the scale and structure of China’s urban–rural HFW and its CF in this context? What are the differences in the spatial–temporal distribution characteristics? We will explore these pressing issues in this article.

Since the UK (Cathcart and Murray 1939) and the USA (Adelson et al. 1961; Adelson et al. 1963) pioneered the study of HFW, developed countries, predominantly European and American countries, have carried out considerable research work in the field of HFW, which mainly involved the following aspects: metrics and scale of HFW (e.g., Harrison et al. 1975; Secondi et al. 2015); the influence of socioeconomic development on HFW (e.g., Garcia-Herrero et al. 2018; Sonesson et al. 2005); the environmental impacts of HFW (e.g., Jeswani et al. 2021; WRAP 2009); forecasting and mitigation measures of HFW (e.g., HLPE 2014); determinants of consumer behavioral willingness towards HFW (e.g., Amicarelli and Bux 2020; Barr 2007); disposal of HFW (e.g., Schott and Andersson 2015). However, there is still little scientific information about HFW in China (Li et al. 2022). Existing research in China focused on the characteristics, changing trends, and influencing factors of HFW (e.g., Qu et al. 2009; Song et al. 2018), the potential impact of HFW on the environment (e.g., Niu et al. 2022; Song et al. 2015), and the disposal of HFW (e.g., Zhang et al. 2020a). Li et al. (2017), Qi et al. (2020), Li et al. (2021), and Qian et al. (2021) focused on rural areas, while Zhang et al. (2018), Zhang et al. (2020b), and Lin and Guan (2021) focused on urban residents. Most of the existing studies are based on the China Nutrition and Health Survey (CHNS) database before 2011 (Jiang et al. 2018; Song et al. 2015), and there were also studies through field surveys (Gu et al. 2015; Wang et al. 2021). Some studies used statistical data (Li et al. 2020) and online questionnaires (Lin and Guan 2021).

By reviewing the existing literature, we find the following problems and shortcomings. First, most of the studies were carried out in industrialized countries, and there is a considerable lack of research in developing countries (Xue et al. 2017). Second, the difficulty in obtaining data is a common problem worldwide (Vázquez-Rowe et al. 2021). In

¹ The National Bureau of Statistics of China, 1981, 2021, China’s urban and rural population, <https://data.stats.gov.cn/easyquery.htm?cn=C01>

² Chinese People’s Congress, 2021. *Anti-foods Waste Law of the People's Republic of China*. Law Press, China, Beijing.

China, most of the existing research was based on the CHNS database, which contains only 12 provinces in eastern and central China, and available data only updated to 2009. With the changes in the dietary consumption structure of Chinese residents, the database has been unable to provide accurate and time-sensitive data for research (UNEP 2021; Xin and Li 2018). It is undeniable that the database has contributed to a number of excellent studies in this field, and making timely adjustments to this database is an up-to-date approach to in-depth research. Third, most of the existing research started from a micro perspective, focusing on a few economically developed cities in a traditional bottom-up manner, and there is very little research on food waste in rural areas (Qian et al. 2021), which makes it difficult to make differentiated comparisons among provinces and between urban and rural areas. Fourth, the use of cross-sectional data for a single year is widespread in this field, and the existing researches rarely consider the dynamic changes in HFW (Parizeau et al. 2015). The research results vary widely (Huang 2021). The analysis of the evolution of HFW over time and space in China is urgently needed. Finally, relatively little research focused on HFW specifically. Given the importance of HFW, it is necessary to target this critical source for further research.

This paper uses the official statistical panel data of food consumption in urban and rural households in the “China Statistical Yearbook (2015–2019)” (after this abbreviated as the yearbook) from a macro perspective. Our analysis combined the results of scholars’ calculation of different food waste rates in urban and rural areas in China with the carbon footprints coefficients in the Double Food-Environment Pyramid (DFEP) database. This paper measures the urban–rural differences from the aspect of scale, structure, and temporal-spatial evolution of the HFW with a unified caliber. Our research results make up for the lack of understanding about the HFW and its embedded CF in urban and rural inter-provincially and help to understand the distribution pattern and environmental impact of HFW in China. We expect to provide decision-making reference for differentiated governance of GHGs emission reduction in the food system and contribute to the sustainable development of the food system.

Data and methods

Study area and data source

The study areas cover 31 provincial-level administrative divisions in mainland China. Due to the lack of data, Hong Kong, Taiwan, and Macau are not included in the study. Primary data of foods consumption: the annual data on the per capita consumption of different foods in urban and rural

households comes from the China Statistical Yearbook (2015–2019).³ The National Bureau of Statistics of China adjusted and unified the statistical caliber of urban–rural residents’ food consumption in the “Urban–Rural Integrated Household Income Expenditure and Living Survey” in 2013, and the data achieved the same statistical caliber among provinces since 2015. We define the research period from 2015 to 2019. Primary data of food waste rates: this paper uses the urban and rural waste rate coefficients of various foods calculated by Song et al. (2015) based on the CHNS database. CHNS database is the only available inter-provincial data in China, which contains both urban and rural food waste data. The calculation of food waste rates here is more consistent with Chinese dietary habits. By combining the above two data sets, we make up for the lack of macro-statistical data on food waste since 2010 in urban and rural China. Furthermore, we use the carbon footprint coefficients of various foods from the DFEP database (DFEP 2013).

The scale of urban and rural household food waste

With the changes in household food consumption in China, this paper studies the regional characteristics, evolution, and differences in urban and rural HFW. Referring to the definition in the CHNS database, we define the HFW as the food waste that occurs in households’ living places after food harvesting and processing, excluding food waste caused by household members in restaurants and cafeterias. The national households’ food waste is made up of the food wasted by urban and rural residents in all provinces, autonomous regions, and municipalities (referred to as provinces for short). Calculations are as follows:

$$fW_{ij(r,u)} = fC_{ij(r,u)} \times \mu_{i(r,u)} \quad (1)$$

$$FW_{j(r,u)}^{\text{percapita}} = \sum_{i=1}^{19} fW_{ij(r,u)} \quad (2)$$

$$FW_{j(r,u)}^{\text{province}} = FW_{j(r,u)}^{\text{percapita}} \times N_{j(r,u)} \quad (3)$$

$$FW_{(r,u)}^{\text{total}} = \sum_{j=1}^{31} FW_{j(r,u)}^{\text{province}} \quad (4)$$

$fW_{ij(r,u)}$ is the urban and rural annual per capita waste (kg) of the i th type foods in the j th province (municipalities and autonomous region). $fC_{ij(r,u)}$ is the urban and rural annual per capita consumption (kg) of the i th type foods in

³ The National Bureau of Statistics of China, 2016–2020: China Statistical Yearbook, China Statistics Press, Beijing, China.

Table 1 Per capita household food waste rate in urban and rural areas in China (%), and average (minimum, maximum) of CF coefficients (kg CO₂e kg⁻¹)

Types	U	R	CF	Types	U	R	CF
Rice	1.14	2.83	2.51 (0.19–6.40)	Other cereals	1.09	2.39	1.33 (0.36–3.90)
Wheat	0.70	0.91	0.94 (0.37–1.71)	Pork	2.10	2.82	4.19 (1.45–8.26)
Maize	4.28	7.30	0.66	Beef	0.92	0.58	21.36 (2.21–83.50)
Legumes	1.26	2.70	1.00 (0.10–5.40)	Lamb	0.76	0.98	10.44 (5.33–15.50)
Tubers	3.18	4.71	0.18 (0.08–0.35)	Poultry	4.95	6.05	3.41 (0.80–8.72)
Vegetable oil	41.17	13.11	2.97 (0.49–9.66)	Aquatic products	4.72	7.98	3.85 (0.07–20.86)
Vegetables	4.58	7.17	0.93 (0.04–4.92)	Eggs	1.94	2.44	3.23 (0.67–5.80)
Dried fruit	2.45	4.40	2.25 (0.72–3.57)	Milk	0.16	0.31	1.43(0.77–8.48)
Fresh fruit	4.83	5.54	0.67 (0.06–5.12)	Other Meats	6.79	7.78	12.10 (0.08–83.50)
Sugar	0.85	4.62	0.52 (0.21–0.96)				

(Food waste rate comes from author's calculations based on CHNS database, and CF coefficients based on the database of the Double Food-Environmental Pyramid. "U" is the abbreviation for "Urban," and "R" is the abbreviation for "Rural")

the j th province in the yearbook. We combine the "Chinese Food Nutrition Composition Table 2009" with this study and divide 19 food types into nine categories, namely grains (including rice, wheat, maize, other grains, legumes, and tubers), vegetable oil, vegetables, meat (pork, beef, lamb, poultry and other meats), aquatic products, eggs, milk, fruits, and sugar. $\mu_{i(r,u)}$ is the urban and rural waste rate of i th type foods (see Table 1). Due to the difficulty in measuring the wasted vegetable oil, there is a significant error in the waste rate of vegetable oil in urban areas. We replace this rate with the urban–rural average value. $FW_{j(r,u)}^{\text{per capita}}$ is the annual per capita total waste amount (kg) of 19 types of foods in j th province. $FW_{j(r,u)}^{\text{province}}$ is the annual total amount of food waste in the j th ($j=1, 2, 3, \dots, 31$) province (kg). $N_{j(r,u)}$ is the urban and rural population at the end of the year (in units of 10,000 people) in j th province in the yearbook. $FW_{(r,u)}^{\text{total}}$ is the annual total amount of food wasted nationwide (kg). Since the provincial statistics in the yearbook lack specific subdivision data for grain, we calculate the consumption of cereals, legumes, and tubers by the average proportion of the national consumption in each province. Due to China's low proportion of self-consumed agricultural products, this study only counts purchased food products. Plant-based foods include rice, wheat, maize, legumes, tubers, vegetable oil, vegetables, dried and fresh fruits, sugar, and other cereals. Animal-based foods refer to pork, beef, lamb, poultry, aquatic products, eggs, milk, and other meats.

The calculation of carbon footprints

China has a vast territory and a large population, with substantial dietary differences among provinces. This paper draws on the definition of the carbon footprints from FAO (2013), which refers to the total amount of GHGs emitted

by foods throughout their life cycle, expressed in CO_{2e}. The specific formulas for calculating the carbon footprints of household food waste in China are as follows:

$$CF_{j(r,u)}^{\text{per capita}} = \sum_{i=1}^{19} (f_{w_{ij(r,u)}} \times \sigma_i) \quad (5)$$

$$CF_{j(r,u)}^{\text{province}} = CF_{j(r,u)}^{\text{per capita}} \times N_{j(r,u)} \quad (6)$$

$$CF_{(r,u)}^{\text{total}} = \sum_{j=1}^{31} CF_{j(r,u)}^{\text{province}} \quad (7)$$

σ_i is the CF coefficient of the i th type food (kg CO_{2e} kg⁻¹) (see Table 1). $CF_{j(r,u)}^{\text{per capita}}$ is the per capita total CF of 9 types in the j th province in the current year (kg CO_{2e}). $CF_{j(r,u)}^{\text{province}}$ is the total food waste CF (kg CO_{2e}) in the j th ($j=1, 2, 3, \dots, 31$) province. $N_{j(r,u)}$ is the urban and rural population at the end of the year (in units of 10,000 people) in j th province in the yearbook. $CF_{(r,u)}^{\text{total}}$ is the annual total amount of CF of HFW in China (kg CO_{2e}).

This paper combines the measurement and the analysis of distribution characteristics of HFW and its CF among provinces. Drawing on the classification method of Zhou et al. (2019), we divide the amount of HFW and its CF in each province as follows. For the total CF, we divide four criteria: the low-level type with CF below 50% of the average nationwide; low-to-medium level type with CF between 50 and 100% of the average; medium to high type with CF between 100 and 150% of the average; high-level type with CF 150% higher than the average. For the total differences, we divide "urban more than rural" and "urban less than rural" into two categories. In the category of "urban more than rural," there are six subcategories: "urban CF is [1, 2) times than that of rural", "urban CF is [2, 3]) times than that of rural", "urban

Table 2 Scale, differences, and trends of HFW and its CF in urban and rural China from 2015 to 2019 (10,000 tons, kg; 10,000 tons CO₂e; kg CO₂e)

Category		2015	2016	2017	2018	2019	Growth rate	Trend		
Total	National	HFW	2007.12	2121.48	2121.98	2068.20	2144.82	6.86		
		CF	3898.68	4216.98	4228.16	4112.32	4229.79	8.49		
	Urban	HFW	1124.98	1244.64	1272.49	1250.59	1315.60	16.94		
		CF	2327.34	2664.15	2713.61	2628.24	2726.78	17.16		
	Rural	HFW	882.14	876.84	849.49	817.61	829.22	-6.00		
		CF	1571.34	1552.83	1514.55	1484.09	1503.01	-4.35		
	Differences	HFW	1.28	1.42	1.50	1.53	1.59	24.41		
		CF	1.48	1.72	1.79	1.77	1.81	22.49		
	Per capita	National	HFW	14.51	15.24	15.16	14.72	15.21	4.83	
			CF	28.18	30.29	30.20	29.26	30.00	6.43	
Urban		HFW	14.19	15.19	15.09	14.47	14.88	4.88		
		CF	29.35	32.52	32.17	30.41	30.84	5.07		
Rural		HFW	14.95	15.30	15.26	15.11	15.77	5.52		
		CF	26.62	27.10	27.21	27.43	28.58	7.37		
Differences		HFW	0.95	0.99	0.99	0.96	0.94	-0.61		
		CF	1.10	1.20	1.18	1.11	1.08	-2.14		

(Data comes from author’s calculation)

CF is [3, 4) times than that of rural”, “urban CF is [4, 5) times than that of rural”, “urban CF is [5, 6) times than that of rural”, “urban CF is [5, 6) times than that of rural”, “urban CF is [6, 9) times than that of rural”. For the per capita, we divide four criteria: low-level type with CF below 25% of the average nationwide; low-to-medium level type with CF between 75 and 100% of the average; medium to high type CF between 100 and 125% of the average; high-level type with CF 125% higher than the average. For the per capita differences, we divide two types “urban more than rural” and “urban less than rural.” We then use ArcGIS 10.2 software to make categorize maps to reflect urban–rural and provincial differences.

The geographic divisions adopted in this paper are based on the research of Chen et al. (2018), following the principles of comprehensiveness, relative consistency of natural environment, economic and social development, continuity of spatial distribution, and administrative divisions. We also combine “China’s Natural Geography” with our study and divide geographic regions into eight human geographic regions: East China, including Shanghai (SH), Jiangsu (JS), Zhejiang (ZJ), and Anhui (AH); North China, including Beijing (BJ), Tianjin (TJ), Shandong (SD), Shanxi (SX), Hebei (HE), and Neimenggu (NM); Central China, including Jiangxi (JX), Henan (HA), Hubei (HB), and Hunan (HN); South China, including Guangdong (GD), Guangxi (GX), Hainan (HI), and Fujian (FJ); Southwest China, including Sichuan (SC), Guizhou (GZ), Yunnan (YN), and Chongqing (CQ); Northwest China, including Shaanxi (SN), Gansu (GS), Ningxia (NX), Xinjiang (XJ); Northeast Region, including Heilongjiang (HL), Jilin (JL), Liaoning (LN);

Qingzang Region, including Qinghai (QH) and Xizang (XZ). The regional abbreviation here is consistent with Niu et al. (2022).

Results and discussion

The scale differences of HFW between urban and rural households

With the residents’ foods consumption structural transformation in China, the total amount of HFW rose in volatility from 20.07 million tons in 2015 to 21.44 million tons in 2019, with an accumulative increase of 6.86% (see Table 2). Based on the per capita annual food demand of 399 kg (Gong and Yin 2018), the total HFW in 2019 could feed about 53.73 million people. The total amount of HFW in urban households rose rapidly, with an accumulative increase of 16.94% in five years, and the share of national food waste increased from 56% in 2015 to 61% in 2019. In contrast, the total HFW in rural households decreased by 6% in five years. In terms of per capita HFW, the per capita HFW in urban and rural areas were 14.88 kg and 15.77 kg in 2019, with accumulative increases of 4.88% and 5.52% compared with 2015, respectively. The calculation result of per capita HFW is close to the calculation result of Qi et al. (2020) (14.9 kg yr⁻¹) and far lower than the per capita HFW in Australia (102 kg/year), Canada (79 kg/year), the USA (59 kg/year), and 64 kg/year in East Asia published by the UNEP (2021). In terms of differences, we divide the

data of total urban HFW by rural HFW. The results show that the total HFW of urban households is much higher than that of rural households, with the ratio increasing rapidly from 1.28 times to 1.59 times. However, it is worth noting that rural households' per capita HFW is always higher than urban households. The per capita gap between urban and rural areas is widening, which may be related to the lack of household food storage knowledge in rural areas (Min et al. 2020) and the relatively low popularity of food refrigeration equipment. The per capita HFW in rural overgrew, while the total HFW decreased rapidly, directly related to the continuous reduction of the rural population.

The scale differences of the CF between urban and rural households

From 2015 to 2019, the total CF of HFW in China increased from 38.99 million tons CO₂e to 42.30 million tons CO₂e, with an accumulative increase of 8.49% (see Table 2). The total HFW CF in 2019 amounted to 6.34% of China's agricultural total carbon emissions (667.45 Mt) in that year (FAO STAT 2019). The total CF in urban households increased by 17.16% in five years, while the total CF in rural households decreased by 4.35% in the same period. The proportion of urban households CF increased from 60 to 64%. In terms of per capita CF, the CF were 30.84 kg and 28.58 kg, in urban and rural households in 2019, with accumulative increases of 5.07% and 7.37% compared with 2015. The calculation results are slightly lower than Song et al. (2015) per capita measurement result of 50 kg CO₂e yr⁻¹. A possible reason is that the provinces selected in the CHNS database are mainly economically developed, and people eat more high-carbon foods there, while this research involves a broader scope of China, covering more economically underdeveloped areas. It is worth noting that the total and per capita CF in urban were consistently higher than those in rural households, and the total amount increased from 1.48 times to 1.81 times the total HFW in rural. The urban–rural disparity in per capita CF was narrowing. With the continuous improvement of China's urbanization rate, it is expected that the urbanization rate will be more than 70% around the year 2030, which means nearly 1 billion people will live in cities (Hou et al. 2021). The key to reducing HFW and its CF lies in urban areas.

Structural differences of the CF between urban and rural households

There are apparent structural differences in urban and rural HFW CF. Although the proportions of animal-based HFW CF show upward trends in urban and rural areas, plant-based foods are still the most critical contributor to the urban–rural HFW CF (see the purple part of Table 3, and light blue

represents the classification of different foods). Vegetable oil (urban) and grain (rural) had the highest CF, followed by meat and vegetables. Vegetable oil and meat had the largest per capita CF in urban households in 2019, accounting for 35% and 25%, respectively. We use pink to represent towns and green to represent rural areas, and the depth of each color represents the proportion of this food in the year's food waste in turn. The darker the color, the greater the proportion. Only the top three food types are shown here. The per capita CF proportion of vegetables rose in volatility, and the CF proportion of vegetable oil decreased yearly. At the same time, the per capita CF of dried and fresh fruits and vegetables increased in urban households, while the per capita CF of grain decreased year by year. It has to be admitted that the per capita HFW of vegetable oil in China's urban households had a very high CF. For rural households, a significant change was that the per capita CF of meat proliferated from the third-largest source to the most significant source, followed by grain and vegetables, and pork dominated the CF of meat (light grey represents the food type with the largest share of waste in the category).

The per capita CF of various HFW in urban and rural households varied little over time, while there were considerable differences among different food types. Vegetable oil had the most considerable CF differences in per capita CF, and the per capita CF of vegetable oil in urban households was about 3.2 times that of rural. In contrast, grain and sugar's per capita CF were significantly higher in rural households than in urban. It is worth noting that the CF from the waste of aquatic products was also prominent in both urban and rural households (see the light yellow part of Table 3).

It is worth noting that by the end of 2020, nearly 100 million poor rural people in China had been lifted out of poverty, marking that the major country accounting for nearly one-fifth of the world's population had completely lifted out of absolute poverty, undoubtedly contributed to the realization of UNSDG 1 "No Poverty." However, as one of the countries with the scarcest protein intake globally, the Chinese should intake more protein nutrients. According to OECD data, China's per capita meat consumption has been far lower than that of European and American countries for a long time. In 2021, China's per capita meat consumption was 45.2 kg, compared with 101.2 kg in the USA and 89.2 kg in Australia. Among them, the per capita consumption of beef and poultry in the USA was 26.1 kg and 50.8 kg, respectively, much higher than China's 4.1 kg and 14.0 kg. With the continuous development of China's economy, Chinese residents will inevitably consume more high-quality protein to enhance their health, and the proportion of meat-based foods is gradually increasing (Sheng et al. 2021). According to the prediction of OECD, China's per capita meat consumption in 2029 will be

Table 3 Urban and rural comparison of per capita HFW CF structure in China from 2015 to 2019 (g CO₂e; %)

	2015		2016		2017		2018		2019	
	U	R	U	R	U	R	U	R	U	R
Grain	2157 (7.35)	7142 (26.83)	2139 (6.58)	7019 (25.91)	2097 (6.52)	6907 (25.39)	2102 (6.91)	6606 (24.08)	2106 (6.83)	6862 (24.01)
Rice	1680 (5.72)	6191 (23.25)	1662 (5.11)	6063 (22.38)	1630 (5.07)	5968 (21.94)	1633 (5.37)	5684 (20.72)	1628 (5.28)	5878 (20.56)
Wheat	254 (0.87)	488 (1.83)	252 (0.77)	478 (1.76)	247 (0.77)	471 (1.73)	247 (0.81)	448 (1.63)	247 (0.80)	464 (1.62)
Maize	82 (0.28)	206 (0.77)	81 (0.25)	202 (0.75)	79 (0.25)	199 (0.73)	80 (0.26)	189 (0.26)	79 (0.26)	196 (0.69)
Legumes	112 (0.38)	178 (0.67)	115 (0.35)	197 (0.73)	111 (0.34)	192 (0.70)	111 (0.36)	208 (0.76)	120 (0.39)	245 (0.86)
Tubers	12 (0.04)	23 (0.09)	13 (0.04)	25 (0.09)	13 (0.04)	24 (0.09)	14 (0.05)	25 (0.09)	15 (0.05)	27 (0.09)
Fruit	1834 (6.25)	1310 (4.92)	1933 (5.94)	1492 (5.51)	1993 (6.20)	1560 (5.74)	2050 (6.74)	1625 (5.92)	2207 (7.16)	1766 (6.18)
Fresh fruit	1614 (5.50)	1103 (4.14)	1701 (5.23)	1255 (4.63)	1756 (5.46)	1303 (4.79)	1824 (6.00)	1348 (4.91)	1970 (6.39)	1459 (5.10)
Dried fruit	220 (0.75)	208 (0.78)	231 (0.71)	237 (0.88)	237 (0.74)	257 (0.95)	226 (0.74)	277 (1.01)	237 (0.77)	307 (1.07)
Vegetable oil	12228 (41.67)	3583 (13.46)	12961 (39.86)	3622 (13.37)	12595 (39.15)	3583 (13.17)	10883 (35.79)	3505 (12.78)	10638 (34.50)	3505 (12.26)
Vegetables	3999 (13.63)	5913 (22.21)	4397 (13.52)	5980 (22.07)	4367 (13.57)	5899 (21.68)	4218 (13.87)	5707 (20.81)	4325 (14.02)	5813 (20.34)
Sugar	6 (0.02)	31 (0.12)	6 (0.02)	34 (0.12)	6 (0.02)	34 (0.12)	6 (0.02)	31 (0.11)	5 (0.02)	34 (0.12)
Plant-based	20224 (68.92)	17979 (67.54)	21436 (65.92)	18147 (66.98)	21058 (65.46)	17983 (66.10)	19259 (63.33)	17474 (63.70)	19281 (62.53)	17980 (62.91)
Meat	5753 (19.60)	5748 (21.59)	7684 (23.63)	5946 (21.94)	7703 (23.94)	6219 (22.86)	7834 (25.76)	6866 (25.03)	7761 (25.17)	6866 (24.02)
Poultry	1586 (5.40)	1464 (5.50)	1721 (5.29)	1629 (6.01)	1637 (5.09)	1629 (5.99)	1653 (5.44)	1650 (6.02)	1923 (6.24)	2062 (7.22)
Pork	1765 (6.02)	2304 (8.65)	1792 (5.51)	2209 (8.15)	1809 (5.62)	2304 (8.47)	1994 (6.56)	2717 (9.91)	1783 (5.78)	2387 (8.35)
Beef	474 (1.61)	100 (0.38)	494 (1.52)	112 (0.41)	513 (1.60)	112 (0.41)	533 (1.75)	137 (0.50)	573 (1.86)	150 (0.52)
Lamb	119 (0.41)	92 (0.34)	143 (0.44)	112 (0.41)	127 (0.39)	102 (0.37)	119 (0.39)	102 (0.37)	111 (0.36)	102 (0.36)
Aquatic products	2672 (9.10)	2212 (8.31)	2690 (8.27)	2304 (8.50)	2690 (8.36)	2273 (8.36)	2599 (8.55)	2396 (8.74)	3035 (9.84)	2949 (10.32)
Eggs	659 (2.25)	654 (2.46)	672 (2.07)	670 (2.47)	684 (2.13)	702 (2.58)	678 (2.23)	662 (2.41)	722 (2.34)	757 (2.65)
Milk	40 (0.13)	28 (0.10)	38 (0.12)	29 (0.11)	38 (0.12)	30 (0.11)	38 (0.13)	30 (0.11)	39 (0.13)	32 (0.11)
Animal-based	9124 (31.08)	8642 (32.46)	11084 (34.09)	8949 (33.02)	11115 (34.55)	9224 (33.91)	11149 (36.67)	9954 (36.29)	11557 (37.48)	10604 (37.10)

Other grains and meats are not listed here due to space limitations and tiny proportions. “U” is the abbreviation for “Urban,” and “R” is the abbreviation for “Rural”

(Data comes from author’s calculations)

52.8 kg, compared with 101.1 kg in the USA. Due to the enormous carbon footprint coefficient of meat-based food, China’s food system will inevitably lead to more GHGs emissions. Our findings provide solid evidence that people

waste enormous amounts of meat. We must realize that targeted intervention in foods with high carbon coefficients is an important channel for the food system to mitigate GHGs emissions.

Table 4 Ranking of HFW CF by the province in 2019 (kg CO₂e; 10,000 kg CO₂e)

	Per capita						Total					
	U		R		Diff.		U		R		Diff.	
Highest	XZ	50.28	SH	41.27	XZ	2.99	GD	318768	GD	140336	BJ	6.62
	CQ	36.98	GD	41.08	XJ	1.40	JS	193591	SC	121464	SH	6.41
	NX	22.35	QD	16.93	ZJ	0.98	QH	8011	QH	4117	GX	1.09
Lowest	GZ	21.21	XZ	16.81	NX	1.01	XZ	6264	XZ	3974	YN	1.06

Only the upper two provinces and the lower two provinces are shown due to space limitations. “U” is the abbreviation for “Urban,” and “R” is the abbreviation for “Rural”

(Data comes from author’s calculation)

Structural-provincial differences in the CF between urban and rural households

There were evident provincial differences in the CF of HFW in China. In 2019, there were 4.59 million tons of CO₂e in Guangdong (10.85% of the total), 3.00 million tons of CO₂e in Shandong (7.12%), and 2.83 million tons of CO₂e in Sichuan (6.70%), which were the highest three total CF of HFW, while Qinghai (0.12 million tons of CO₂e) and Xizang (0.10 million tons of CO₂e) had the least. The total CF in Guangdong was about 45 times that of Xizang. In terms of per capita CF, Xizang (37.80 kg CO₂e), Guangdong (37.35 kg CO₂e), and Chongqing (36.42 kg CO₂e) had higher CF, while Qinghai (20.80 kg CO₂e) and Guizhou (20.06 kg CO₂e) had the lowest. From the perspective of urban–rural differences (see Table 4), the per capita HFW CF differences were mainly extensive in the western region. Xizang had the largest per capita HFW CF in urban (see the green part of Table 4), while its rural households’ per capita HFW CF was the lowest nationwide, which made Xizang the most significant differences between urban and rural households. Regarding total CF differences, Guangdong was still the region with the highest total urban and rural CF with its large population base (see the light yellow part of Table 4). We notice that the economically developed cities, such as Beijing and Shanghai, had significant CF differences in urban and rural (See the pink part of Table 4). In contrast, southwest China, where the economy is relatively backward, had minor differences.

Due to the inter-provincial population differences, the characteristics of total CF differences were apparent. The most significant CF provinces were Guangdong, Shandong, and Sichuan. In urban or rural areas, fruits, eggs, and milk had the highest CFs in SD, and meat and aquatic products had the highest CF in GD. However, for grain, vegetable oils, and sugar, GD had the highest CF in urban areas, while SC had the highest CF in rural areas.

Provincial differences also appeared in the per capita CF of different food types (see Table 5). For example, Guangdong’s urban and rural households had the highest per capita CF from wasted meat. On the one hand, this phenomenon is closely related to the carnivorous diet culture of Guangdong

residents. On the other hand, because Guangdong is located in the southeast coastal area of China, the temperature is high all year long, and the high temperature often accelerates the propagation of bacteria in meat food, which is not conducive to the storage and storage of meat. Tianjin had the highest per capita CF from wasted eggs and fruits. The per capita CF from wasted vegetables in Sichuan (urban) and Chongqing (rural) were the largest. The CFs of wasted grain in Xizang were common problems between urban and rural households, inseparable from Xizang’s unique plateau food culture that prefers staple food. In urban households, Xizang had the most prominent and quickest per capita CF increase from wasted vegetable oil. It is worth noting that urban households in Xizang and rural households in Shanghai gradually became the places with the largest per capita CF of total types of foods. This change in Xizang largely depends on the rapid increase in residents’ income driven by urban tourism development in recent years. It is worth noting that both areas are essential mitigation areas for carbon management in the food system.

Spatial–temporal evolution differences of the CF between urban and rural households

The spatial distribution pattern of the total HFW CF between urban and rural China changed little from 2015 to 2019. The urban households’ CF was mainly concentrated in the eastern region and Sichuan, especially the relatively high CF in coastal cities (Shandong, Zhejiang, Jiangsu, and Guangdong) (see Fig. 1(a)). In terms of growth rate, the total CF of urban in Xizang and Gansu grew the fastest, increasing by 101.82% and 41.93%, respectively. However, due to their small population base, the total CF were still small. At the same time, the total CF of urban in five provinces (Beijing, Tianjin, Hubei, Heilongjiang, and Shanghai) showed negative growth. Beijing and Tianjin had the most significant decrease (11.01% and 9.03%).

The rural HFW CFs mainly concentrated in the central, eastern, and southern regions, especially the inland areas west of Bohai Bay and the Yellow Sea (see Fig. 1(b)). Only the HFW CF in Hubei and Jiangsu dropped significantly nationwide. Other provinces did not change significantly.

Table 5 The regional distribution of the largest per capita CF of various types of HFW in urban and rural from 2015 to 2019 (g).

	Urban					Rural				
	2015	2016	2017	2018	2019	2015	2016	2017	2018	2019
Grain	XZ (3017)	XZ (2943)	XZ (3646)	XZ (4012)	XZ (3545)	XZ (14269)	XZ (14911)	XZ (14519)	XZ (9575)	NM (9626)
Vegetable oil	HB (17608)	XJ (17486)	XZ (23477)	XZ (18708)	XZ (29102)	HB (5920)	HL (5803)	HL (5881)	HL (5413)	HL (5569)
Vegetables	CQ (5435)	SC (5694)	SC (5702)	SC (5290)	SC (5363)	CQ (8821)	TJ (9620)	CQ (9954)	CQ (9444)	CQ (9262)
Fruits	NX (2560)	TJ (2711)	TJ (2865)	TJ (2913)	GS (3049)	TJ (2706)	TJ (3163)	TJ (3324)	TJ (3148)	TJ (3540)
Sugar	CQ (11)	XZ (12)	CQ (11)	XZ (15)	XZ (18)	XZ (84)	XZ (89)	CQ (77)	XZ (110)	XZ (134)
Meat	GD (9342)	GD (10316)	GD (10409)	GD (10340)	XZ (12090)	GD (11097)	GD (11648)	GD (12265)	GD (12893)	GD (13563)
Aquatic products	HI (5743)	HI (5616)	HI (5343)	HI (5343)	HI (5961)	HI (6605)	SH (6820)	SH (6851)	SH (7619)	HI (6605)
Eggs	SD (1080)	TJ (1149)	TJ (1168)	TJ (1143)	TJ (1180)	TJ (1190)	TJ (1222)	TJ (1316)	TJ (1206)	TJ (1348)
Milk	BJ (67)	NM (68)	XJ (70)	XJ (70)	XJ (76)	XZ (102)	XZ (95)	XZ (101)	BJ (70)	NM (67)
Total	CQ (36377)	CQ (39549)	CQ (40342)	XZ (37605)	XZ (50277)	GD (35497)	TJ (37423)	GD (37558)	SH (40182)	SH (41270)

The use of colors in the table makes the patterns more apparent, and each province has its unique color to distinguish it (Data comes from author's calculation)

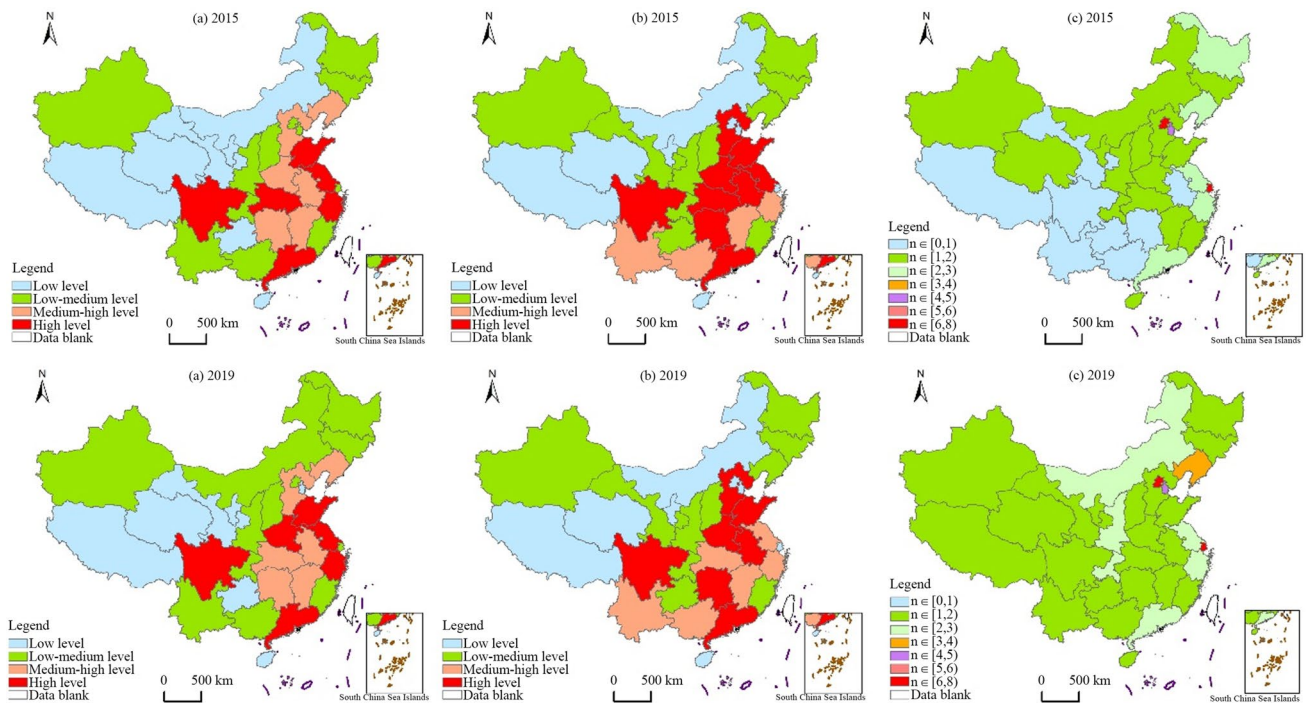


Fig. 1 Spatial-temporal evolution of total HFW CF. (a) Urban; (b) Rural; (c) Differences. (Figures come from the author)

In terms of growth rate, the total CF of rural households in Hainan and Shanghai grew the fastest, increasing by 19.05% and 13.69%, respectively. The total CF of rural households in 21 provinces showed negative growth because of the massive loss of the rural population. In these CF declining provinces, Guizhou and Xizang experienced the most significant decrease of 24.68% and 20.41%, respectively.

Figure 1(c) shows that the differences in the total HFW CF in urban and rural households changed significantly from 2015 to 2019. The differences between urban and rural households in 2015 mainly reflected that the total CF in urban households were lower than that in rural southwest China, which was contrary to other regions. However, the urban CF were higher than the rural in 2019. Moreover, the total HFW CF varied significantly between urban and rural households in Beijing, Shanghai, and Tianjin. Neimenggu, Liaoning, Shaanxi, Chongqing, and Anhui significantly widened the urban–rural HFW CF gap, while Heilongjiang narrowed the gap. The spatial patterns of total HFW CF in urban and rural households in the same year were generally similar combined with Fig. 1(a) and (b), and the differences in Fig. 1(c) were mainly located in the southern border areas (such as Yunnan and Guangxi).

The inter-provincial and urban–rural differences of the per capita HFW CF in China were relatively small over time. From 2015 to 2019, the overall distribution of urban households' per capita CF was mainly concentrated in China's land border and central provinces such as Sichuan,

Chongqing, Hunan, and Hubei (see Fig. 2(a)). The highest per capita CF province changed from Chongqing to Xizang. Seven provinces' HFW CF in urban households, including Xizang, Shanxi, Beijing, Jilin, and Anhui, rose significantly in the national rankings. In contrast, Chongqing, Ningxia, Hubei, and Fujian dropped. Regarding per capita growth rates, Xizang, Gansu, and Henan had the highest accumulative growth rates of 54.34%, 24.54%, and 16.37%. However, the per capita HFW CF of urban households in 11 provinces showed negative growth, of which Hubei and Beijing experienced the most significant decline, with accumulative decreases of 14.06% and 11.75%, respectively.

The overall distribution of per capita HFW CF in rural households is mainly located in southern China (south of the Qinling Mountains-Huaihe River). In 2019, the top three provinces with the largest per capita CF were Chongqing, Shanghai, and Guangdong. The national rankings of rural households in Heilongjiang, Beijing, and Shanxi rose, while Xinjiang, Xizang, Gansu, Tianjin, Liaoning, and Guizhou dropped significantly (see Fig. 2(b)). Regarding growth rates, Neimenggu and Hainan had the fastest growth, with 28.16% and 25.48%, respectively. At the same time, per capita, HFW CF in six rural provinces showed negative growth, with Xinjiang, Guizhou, and Xizang having the most significant decreases of 14.77% and 30.91%, respectively. The spatial patterns of the per capita HFW CF in urban and rural households were very different in the same year (combined with Fig. 1(a) and (b)).

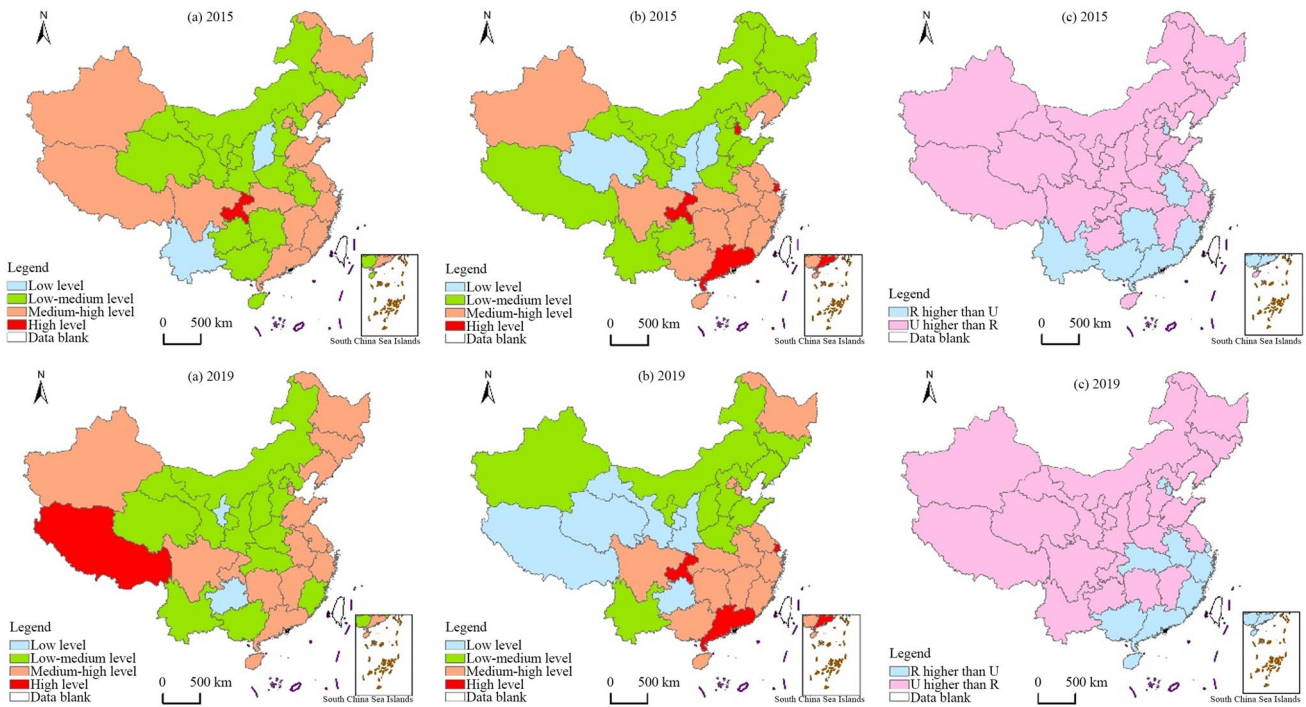


Fig. 2 Spatial–temporal evolution of per capita HFW CF. (a) Urban; (b) Rural; (c) Differences. (“U” is the abbreviation for “Urban,” and “R” is the abbreviation for “Rural”, figures come from the author)

Figure 2(c) shows that the urban–rural differences in the per capita HFW CF changed significantly from 2015 to 2019. In 2015, the differences mainly reflected that rural households’ per capita CF in the southern land border provinces were higher than that of urban, and the opposite was true in other areas. However, in 2019, the main differences were that the per capita CF of rural households in the southeastern coastal areas were higher than that in urban areas (such as Hubei, Anhui, Zhejiang, and Fujian). The per capita HFW CF in urban Yunnan and Hunan were gradually higher than that in rural. In contrast, the rural households in Beijing, Zhejiang, Hubei, and Hainan provinces were gradually higher than urban households.

Conclusions and policy implications

From a macro perspective, this paper uses China’s official statistical panel data from 2015 to 2019 and unified accounting methods to quantitatively calculate and analyze the scale, structure, and spatial–temporal differences of HFW CF in urban and rural households under the background that the food consumption structure of residents has undergone significant changes. The main conclusions of this study are as follows.

First, with the changes in the food consumption structure of Chinese residents, the total amount of HFW and

CF rose rapidly in volatility. The total HFW and CF differences became more evident with the dual structures between urban and rural households. Urban households are the central front for reducing HFW and CF.

Second, urban and rural China’s per capita HFW and CF fluctuated and increased yearly. The per capita rural households’ HFW and its growth rate of were higher than those of urban households. However, the per capita CF of rural households was still lower than that of urban households, although the per capita CF grew fast in rural households.

Third, the structures of HFW CF in urban and rural households varied significantly over time and space. Although the per capita CF of animal-based foods in urban and rural both increased yearly, the CF of wasted plant-based foods were still much higher than that of animal-based foods. Affected by the population base, the total CF of various wasted foods concentrated in Guangdong, Shandong, and Sichuan provinces.

Fourth, the HFW CF differences in spatial–temporal evolution characteristics were apparent in urban and rural China. The differences between urban and rural areas in 2015 were that the total CF of urban households in the southwestern region was lower than that in rural areas. However, in 2019, the total CF of all urban areas was higher than that of rural areas. The per capita HFW CF in urban areas is mainly concentrated in China’s land border provinces, showing a

surrounding shape. The province with the highest per capita CF in urban households changed from Chongqing to Xizang.

In the context of the UNSDG 12.3 and China's era of "Carbon Peak, Carbon Neutrality" and "Shared Prosperity," this study helps to promote sustainable dietary awareness in urban and rural households and provides scientific support for the differentiated governance of HFW and CF between urban and rural. First, China should increase the monitoring and tracking of food waste in urban households and actively popularize scientific awareness of food storage among rural residents. Second, given the heterogeneity of food waste characteristics in different regions and urban–rural areas, policymakers should consider setting some provinces and regions with vast amounts of food waste as pilot areas to curb food waste further. Third, due to the differences in the dietary habits of various regions and urban–rural residents, corresponding policies should carry out targeted governance combined with residents' food preferences. We must minimize food waste at the household level in China and reduce the negative environmental impact of the food system.

However, this article is not exempted from criticism. First, due to the insufficiency of our data, we treat food waste rates as constant, which does not account for differences between locations and time. This shortcoming will cause bias in the spatial estimation results. However, lack of data is a common problem in estimating food waste. The food waste rates calculated from the CHNS database are the most detailed data available at the provincial level, including urban and rural households. The method of estimating the whole country's HFW by survey data is a common way at present. For example, Xue et al. (2021) used field survey data from rural Shandong and urban Zhengzhou, respectively, to infer the level of wasted food nationwide. Second, due to the relatively late start of research in the field of CF in China, the CF coefficients used in this paper are the global average. Further efforts are to conduct more specific research on the waste rates of various foods based on the economic development status of different provinces and to build a CF accounting system in line with China's existing food system as soon as possible.

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Author contribution Shujun Cheng: Formal analysis; Methodology; Data curation; Writing—original draft; Writing—review and editing. Guobao Song: Data curation; Software; Writing—original draft. Di Yang: Visualization; Writing—original draft. Liuyang Yao: Conceptualization; Writing—review and editing. Zhide Jiang: Conceptualization; Writing—review and editing; Supervision.

Minjuan Zhao: Writing—review and editing; Funding acquisition; Project administration; Supervision.

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Data availability The data used in this paper come from the primary data of food consumption per capita in China's National Statistical Yearbook, and the coefficients come from existing research results of scholars. Specific data sources are explained in detail in the method section of the paper.

Declarations

Ethical approval Not applicable.

Consent to participate Not applicable.

Consent for publication This submission has been approved by all co-authors. This paper is not considered for publication elsewhere and has never been published anywhere.

Competing interests The authors declare no competing interests.

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