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The effect of income distribution on diet-related environmental footprints: Evidence from urban China

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Abstract

Given that income disparity is expanding and diet-related environmental footprints are increasing in urban China, this study aims to investigate the heterogeneity in these footprints across various income classes and examine the effect of income distribution on the total environmental footprints. Based on the quadratic almost ideal demand system model and taking into consideration the problems of endogeneity of food expenditure and zero expenditure, we estimate the income elasticities for 10 food categories across seven income classes and project the diet-related environmental footprints under seven scenarios for various strategies of the income distribution. The results show that per capita diet-related environmental footprints are greater for higher income classes than for lower income classes, as the former consume more animal-based food. Compared with high-income classes, income growth favouring low-income classes results in a rather significant increase in diet-related environmental footprints. With further economic growth, the lowest income group makes the greatest contribution to the increase in diet-related environmental footprints. Thus, policymakers should promote a more sustainable diet on the road to alleviating income inequality to ensure sustainable environmental development.

KEYWORDS

diet, environmental footprint, food consumption, income, QUAIDS

JEL CLASSIFICATION

Q18

1 | INTRODUCTION

Carbon footprints (CFs), water footprints (WFs) and ecological footprints (EFs) are three major categories of environmental footprints, being able to track the impact of human activities on the surrounding environment, which measure global warming potential, the use of water and biologically productive area, respectively (Galli et al., 2012; Hoekstra & Mekonnen, 2012; Wackernagel et al., 1999; Wackernagel & Rees, 1996). While extensive studies have widely discussed the role of food production in environmental footprints, increasing attention has been paid to highlighting the environmental effects of food consumption. It is estimated that food production accounts for 14%, 92% and 26% of the global average CFs, WFs and EFs, respectively (Banerjee et al., 2021; FAO, 2016; Hoekstra & Mekonnen, 2012). Although most diet-related environmental footprints are imprinted during the process of supply, these footprints are also determined by consumers. In particular, the continued growth of the population and diet transition are placing great pressure on food production systems, which will imprint larger environmental footprints (Hoekstra & Mekonnen, 2012; Mekonnen & Hoekstra, 2011, 2012). For instance, diet is expected to contribute to about 80% of the increase in global agricultural greenhouse gas (GHG) emissions by 2030 (Tilman & Clark, 2014), and water demand is estimated to increase by 55% from 2000 to 2050 (UNESCO, 2020).

Apart from the amount of total food consumed, diet structures can also matter as various foods embody different environmental footprints. Generally, animal-based food, especially ruminant meat, is related to larger environmental footprints than other foods with equivalent nutritional values (Frey & Barrett, 2007; Gaillac & Marbach, 2021; Mekonnen & Hoekstra, 2012). For example, the average WF per calorie of beef is more than 20 times that of staple foods, such as rice or wheat (Mekonnen & Hoekstra, 2012). A larger proportion of animal-based food diets could lead to an increased burden on the environment (He et al., 2018). Since developing economies are still in the process of nutrition transition, the structure of food consumption is experiencing a dramatic change; thus, it is necessary to expand our understanding of how and to what extent changing food consumption patterns could affect environmental footprints.

Income growth could contribute to diet-related environmental footprints through its impacts on both quantity and quality of food consumption. On one hand, most foods are still normal goods for most people in developing economies, with positive income elasticities, which indicates income growth could drive an increase in food consumption (Burggraf et al., 2015; Colen et al., 2018). On the other hand, income growth also promotes nutrition transition, shifting diets from high carbohydrates and fibre content towards more varied diets with a higher proportion of animal-based food (Drewnowski & Popkin, 1997; Marques et al., 2018). Taking China as an example, staple foods contributed 78% of the per capita total daily energy intake in 1961, which had halved by 2017, while the energy intake from red meats increased by 16 times during the same period (Cao et al., 2020). These shifts increased per capita diet-related environmental footprints by more than two times between 1961 and 2017 (Cao et al., 2020).

Further, income distribution could also affect national total food consumption and thus environmental footprints. Generally, the food demand for low-income classes is more elastic than that for high-income classes; hence, increasing income allocations for low-income classes drives a larger increase in the demand for all foods than a uniform percentage increase across all income classes (Pinstrup-Andersen & Caicedo, 1978; Zheng & Henneberry, 2010). Besides, as the animal-based food demand of low-income classes is more sensitive to income increases, income growth favouring these classes might result in a larger rise in the consumption of animal-based food (Li et al., 2021; Ren et al., 2018). Consequently, income distribution might also increase diet-related environmental footprints.

China is an interesting case for investigating the impact of income distribution on diet-related environmental footprints. First, as a populous and agricultural country, China is facing environmental challenges, such as high agricultural GHG emissions, limited water and arable land resources (Chen et al., 2010; FAOSTAT, 2020; MWR, 2019). Second, during the past decades, sustained income growth improved diet patterns along with increasing diet-related environmental footprints (Cao et al., 2020; Chai et al., 2020; Hawkins et al., 2018; He et al., 2021; Jiang et al., 2015; Lin et al., 2015; Zhang et al., 2022; Zheng, 2019). Third, as income growth is accompanied by expanding income disparity, China's government has formulated a series of national programmes to reduce income inequality (Fan & Cho, 2021). The extent to which various income distribution strategies significantly reshape food consumption patterns and the corresponding environmental footprints will have practical implications for improving the welfare of the low-income classes under the goal of sustainable development. Hence, against the background of continued economic growth and income inequality alleviation policies in China, it is important to analyse diet-related environmental footprints across income classes and their responses to changes in income distribution.

To the best of our knowledge, the effect of income distribution on the total diet-related environmental footprints has not been analysed in China. Many studies have calculated the CFs (Lin et al., 2015; Song et al., 2015; Zhang et al., 2022), WFs (Chai et al., 2020; He et al., 2021; Zhai et al., 2021) and EFs (Chen et al., 2010; Li et al., 2019) of both food production and household food consumption. Besides, He et al. (2019) comprehensively evaluated the environmental footprints of dietary quality improvement. Further, Cao et al. (2020) and Dong et al. (2021) analysed the main drivers of the growing environmental footprints of changing diets in China from different perspectives, such as Engel's coefficient, the children dependency ratio, education, urban–rural status, population, per capita energy intake and diet structure adjustment. Sun et al. (2021) also showed that proteinrich products, such as beef, mutton and pork, contributed most to the differences between low and high diet-related environmental footprints. Hence, based on these studies, it is worth investigating systematically the impact of income distribution on diet-related environmental footprints.

Given the increasing incomes and expanding income inequality among urban residents, this study aims to investigate the heterogeneity in diet-related environmental footprints across various income classes in urban China and analyse the effect of income and income distribution on the total diet-related environmental footprints. We first use the pooled data from the China Health and Nutrition Survey (CHNS) to estimate the income elasticities for 10 food commodities across seven income classes based on the quadratic almost ideal demand system (QUAIDS) model, taking into consideration the problems of endogeneity of food expenditure and zero expenditure. Based on the income elasticities, we further projected diet-related environmental footprints under seven scenarios for various strategies of income distribution. Finally, we also combined the data from the National Bureau of Statistics of China (NBSC, 2021) to project the impact of income distribution on the total diet-related environmental footprints.

Although several studies have calculated diet-related environmental footprints in China, the results of this study will help us understand the structure of such footprints across income classes in urban China, and the possible effects resulting from increasing income and changes in income distribution. Specifically, this study makes the following contributions: first, diet-related environmental footprints are linked with per capita household income changes based on income elasticities; second, we consider the heterogeneity across income classes and projected the possible influence of income distribution on diet-related environmental footprints; third, we make further projections combining the latest data from the NBSC (2021) to draw more realistic conclusions.

The remainder of this paper is organised as follows. Section 2 describes the material and methods. Sections 3 and 4 present the results and discussion, respectively. The final section concludes the study.

2 | DATA AND EMPIRICAL DESIGN

To understand the heterogeneity of diet-related environmental footprints across income classes and the effect of income distribution on these footprints in urban China, we analysed CFs, WFs and EFs for food consumption and estimated the income elasticities of 10 main food categories. The data on household food consumption and demographic characteristics were derived from the CHNS. The coefficients of the CF, WF and EF of the main food were from Lin et al. (2015), Mekonnen and Hoekstra (2011, 2012) and Cao et al. (2020), respectively. Multiple years (2004, 2006, 2009 and 2011) of CHNS data were used for estimating the QUAIDS and obtaining the income elasticities of seven income classes. Based on the elasticities, we simulated the effect of income distribution on total diet-related environmental footprints. Then, we also combined the data from the NBSC (2021) to perform the projections.

2.1 | Data

The data set for this analysis is drawn from the CHNS, which is jointly collected by the Carolina Population Centre at the University of North Carolina at Chapel Hill and the National Institute for Nutrition and Health at the Chinese Centre for Disease Control and Prevention. This survey is based on detailed individual dietary intakes (24 h recall) collected from respondents both away from home and at home for three consecutive days, that are randomly allocated over a week. More than 10 rounds of the CHNS were conducted from 1989 to 2015. As pricing information for some foods before 2004 is missing, and household food consumption data from 2015 are not made public, pooled data from 2004, 2006, 2009 and 2011 were used in this study. These data covered nine provinces (Guangxi, Guizhou, Heilongjiang, Henan, Hubei, Hunan, Jiangsu, Liaoning and Shandong) at first, and three megacities (Beijing, Chongqing and Shanghai) were added in 2011.

After dropping the observations with missing values, as well as those with quantities consumed of more than five standard deviations above the mean, and with incomes less than 1% and more than 99%, information on 6073 urban households was finally analysed in this study.[1] Based on individuals' food consumption, daily household food consumption was aggregated under 10 food categories: staple foods, beans and nuts, vegetables and fruits, pork, beef and mutton, poultry, dairy products, eggs, aquatic products and other foods. The last food group mainly includes beverages, which is regarded as the residual food category in the demand model. Besides, following the standardised approach refined by the FAO et al. (2004), an adult equivalent unit (EA) calculation was employed to account for household composition (children under 5 years old were considered equal to 0.77 EAs, children from 6 through 12 years old were assigned a value of 0.80 EAs and adolescents from 13 to 18 years old accounted for 0.88 EAs). Then, all the households were equally divided into seven income classes according to their per capita household income, specifically, the lowest (Q1), the lower (Q2), the lower middle (Q3), the middle (Q4), the upper middle (Q5), the higher (Q6) and the highest (Q7) income class.

2.2 | Price index

The free-market price for a specific food was collected at the community level. Following Khanal et al. (2016), the value-weighted price index for each food category was obtained as follows:

[1]Of the total samples, 606, 583, 594, 571, 591, 603, 610, 545, 565, 303, 201 and 301 households were from Guangxi, Guizhou, Heilongjiang, Henan, Hubei, Hunan, Jiangsu, Liaoning, Shandong, Beijing, Chongqing and Shanghai, respectively.

$$\overline{P}_i = \sum_{k=1}^{n} \frac{Q_k^i}{Q_i} \times P_k \tag{1}$$

where $\overline{P}_i$ represents the value-weighted price index of each food group i, Q_k^i is the quantity consumed of the food item k in the food group i, Q_i is the total consumption quantity of the food group i and P_k is the free-market price of the food item k. We deflated the value-weighted price and per capita household income by the Consumer Price Indices (CPIs) with 2011 as the base year. Food expenditure was computed by multiplying the quantity consumed with free-market prices, and each food group expenditure share was calculated by dividing the total studied food expenditure by each food group expenditure.

2.3 | Environmental footprint

The coefficients of the CF, WF and EF for various foods were derived from Lin et al. (2015), Mekonnen and Hoekstra (2011, 2012) and Cao et al. (2020) (Table S1), respectively. According to the sources of these environmental footprint intensities (Cao et al., 2020; Lin et al., 2015; Mekonnen & Hoekstra, 2011, 2012), the system boundary is from farm to farm gate, so the environmental footprints from transportation, storage, cooking, etc. are ignored in this study. As the last food group included many different kinds of beverages and few studies discussed their embodied environmental footprints in the agricultural production process, the per capita total diet-related CFs, WFs and EFs are aggregated by the first nine food groups and can be calculated as follows:

$$\mathrm{CF} = \sum_{i=1}^{m} \left(\mathrm{CF}_i \times q_i^0\right) \tag{2}$$

$$\mathrm{WF} = \sum_{i=1}^{m} \left(\mathrm{WF}_i \times q_i^0\right) \tag{3}$$

$$\mathrm{EF} = \sum_{i=1}^{m} \left(\mathrm{EF}_i \times q_i^0\right) \tag{4}$$

where $i = 1, 2 \ldots 9$, CF, WF and EF are the per capita total CFs, WFs and EFs of the food consumption studied, respectively. CF_i, WF_i and EF_i are the coefficients of the CF, WF and EF for the food category i, respectively.

2.4 | Demand model

The QUAIDS model was extended by Banks et al. (1997) from the almost ideal demand system (AIDS) model (Deaton & Muellbauer, 1980). As the QUAIDS model allows for nonlinear Engel curves and has the flexibility to be applied to populations at different income levels, it is used to estimate food expenditure elasticities across income classes in this study. The budget share form in the QUAIDS is defined as follows:

$$w_i = \alpha_i + \sum_{j=1}^{n} \gamma_{ij} \ln p_j + \beta_i \ln\left[\frac{m}{a(p)}\right] + \frac{\lambda_i}{b(p)} \left\{\ln\left[\frac{m}{a(p)}\right]\right\}^2 + u_i \tag{5}$$

with the nonlinear price aggregators:

$$\ln a(p) = \alpha_0 + \sum_j^n \alpha_j \ln p_j + \frac{1}{2} \sum_i^n \sum_j^n \gamma_{ij} \ln p_i \ln p_j \tag{6}$$

and

$$b(p) = \prod_{i=1}^n p_i^{\beta_i} \tag{7}$$

where w_i is the budget share of the ith food item, $w_i = \frac{p_i q_i}{m}$; p_j is the price of the food item j; and m is the total studied food expenditure. The parameters α_i, β_i, γ_{ij} and λ_i are to be estimated, and u_i is the error term. The adding-up, homogeneity and Slutsky symmetry restrictions on the parameters are as follows:

$$\sum_i \alpha_i = 1, \ \sum_i \beta_i = 0, \ \sum_i \gamma_{ij} = 0, \ \sum_{i=1}^n \lambda_i = 0, \gamma_{ij} = \gamma_{ji} \tag{8}$$

In addition to price and income, sociodemographics also affect food consumption. Here, the method introduced by Ray (1983) and extended by Poi (2012) is used to control for the demographic effects. The budget share equation incorporating demographic variables can be written as follows:

$$w_i = \alpha_i + \sum_{j=1}^n \gamma_{ij} \ln p_j + \left(\beta_i + \eta_j' z\right) \ln\left[\frac{m}{\overline{m}_0(z) a(p)}\right] + \frac{\lambda_i}{b(p)c(p,z)} \left[\ln\left\{\frac{m}{\overline{m}_0(z) a(p)}\right\}\right]^2 + u_i \tag{9}$$

where z is a set of sociodemographic variables, including the household size, region, year and male ratio. More details can be found in Poi (2012).

As some households do not consume certain foods due to non-preference, non-availability, non-affordability or infrequent purchases, there is the problem of zero expenditure. Simply considering them as zeros in the model could lead to biased and inconsistent parameter estimates (Deaton, 1989). To address this issue, Shonkwiler and Yen (1999) proposed a consistent two-step (CTS) process. In the first step, a probit model is estimated and used to predict the cumulative distribution (Φ) and probability density functions (ϕ) for each household. In the second step, the information is used to modify Equation 9 as follows:

$$w_i^* = \hat{\Phi}_i w_i + \delta_i \hat{\phi}_i + u_i \tag{10}$$

Besides, as the food expenditure share is computed by dividing the total food expenditure by the expenditure on each food category, the expenditure might be endogenous. We followed a two-step method proposed by Blundell and Robin (1999) to address potential endogeneity. This procedure involves estimating a model for the total expenditure in each household with income as instrumental variables ($\ln y$ and $(\ln y)^2$) and then incorporating the residuals of the method as an additional control variable into Equation 9. As the error term in each equation of the demand system was heteroskedastic, we bootstrapped the standard errors for the estimated parameters, with 500 repetitions.

Due to adding-up restrictions, the covariance matrices in the complete demand system are generally singular. However, when accounting for zero expenditure shares, the demand system in Equation 9 may violate adding-up restrictions (Shonkwiler & Yen, 1999). To overcome this, following Yen et al. (2003), we estimated the first n–1 foods, regarding the last food group as a residual category. The parameters of the last food group equation are computed residually from other equations. Then, the expenditure elasticity can be calculated as follows:

$$e_i = 1 + \frac{\Phi_i}{w_i} \times \left[\beta_i + \eta_i' z + \frac{2\lambda_i}{b(p)c(p,z)} \times \ln\left(\frac{x}{\overline{x}_0(z)a(p)}\right)\right] \tag{11}$$

As we intended to predict the responses of food demand and the related environmental footprints to changes in income and income distribution, the income elasticity for food i is needed. The food expenditure model is given as follows:

$$W = \beta_0 + \beta_1 \ln y + \beta_2 (\ln y)^2 + \mu \tag{12}$$

where W is the share of total food expenditure in the total expenditure, y is per capita household income and μ is the error term. Hence, the food expenditure elasticity is calculated as follows:

$$\eta = \left(\beta_1 + 2\beta_2 \ln m\right) / W + 1 \tag{13}$$

Finally, the unconditional (income) elasticity of food i can be expressed as follows:

$$E_i = \eta \times e_i \tag{14}$$

The computed income elasticities are used to simulate the response of diet-related environmental footprints to income distribution. Before performing projections, some assumptions suggested by Zheng and Henneberry (2010) should be taken into consideration. First, consumers' preferences and the prices of foods are assumed to be unchanged for each income group. Second, the population size of each income group is assumed to be constant. Third, market development is not considered. Hence, the changes in food demand solely depend on income. Last, we assume that the environmental footprint coefficient of each food item remains the same over years. The response of the per capita food demand of each income class to income changes is estimated by the following equation:

$$\Delta Q_{i(Q)} = \left(\frac{\Delta y}{y}\right)_Q E_{i(Q)} q_{i(Q)}^0 \tag{15}$$

where $\Delta Q_{i(Q)}$ denotes the change in the per capita consumed quantity of food category i for the Qth income class; $(\Delta y / y)$ represents the change in income; $E_{i(Q)}$ is the income elasticity; and $q_{i(Q)}^0$ is the current per capita quantity consumed daily.

2.5 | Simulation scenarios

In 2021, the outline of the 14th Five-Year Plan of the People's Republic of China for National Economic and Social Development and the Vision Goal for 2035 emphasised the improvement of the income distribution structure. Hence, this study designed seven scenarios to simulate the effect of income distribution on diet-related environmental footprints. Following Zheng and Henneberry (2010), 1% of the total income of all households was set as the degree of change in each scenario (Table 1). Scenario 0 increases the incomes of all seven income classes by 1%. Scenarios 1, 2, 3 and 4 allocate the 1% increase in total income to the lowest (Q1), lower (Q2), higher (Q6) and highest income (Q7) classes, respectively. Scenarios 5 and 6 transfer 1% of the total income from the highest income class (Q7) to the lowest (Q1) and the lower (Q2) income classes, respectively. As shown in Table 1, although the lower income groups account for a larger proportion of the population than the higher income groups, the total income of the lowest income group only accounts for 2.68% of the total population income.

As CHNS data are publicly available for the period before 2015, we also computed updated projections based on data from the NBSC (2021). Supposing the other conditions remained unchanged, there are dynamic changes in food demand and income elasticities with a rise in income. The NBSC divides urban households into five classes, with per capita household incomes of CNY 12,812, 22,591, 32,265, 45,106 and 78,909 per year (1 CNY = 0.21 AUD = 0.14 USD) from the first class (C1) to the fifth class (C5), respectively. According to the division criteria of the CHNS data, the income of the first (C1) and the second class (C2) is within the range of the lower middle (Q3) and the higher (Q6) income class, respectively; the third (C3), fourth (C4) and fifth (C5) classes are all within the highest income (Q7) class. Hence, we assumed the food consumption and income elasticities of C1 and C2 from the NBSC (2021) would be the same as those for Q3 and Q6 from the CHNS, respectively, and C3, C4 and C5 would be as those for Q7.

3 | RESULTS

3.1 | Summary statistics

Table 2 presents the description of daily per capita food consumption, food expenditure shares, food expenditure, household income and demographics across seven income classes in urban China. First, except for staple foods, the other foods show an upward trend with

TABLE 1 Projected distribution of households, the population and incomes by income classes under seven scenarios.

Item	Q1	Q2	Q3	Q4	Q5	Q6	Q7
Average income (CNY/day)	5.57	14.26	22.33	31.11	40.71	54.54	90.15
Household proportions (%)	14.31	14.28	14.29	14.26	14.29	14.28	14.29
Population proportions (%)	16.48	15.88	15.28	14.06	13.34	12.90	12.06
Income proportions (%)							
Original income proportions	2.68	6.60	9.94	12.75	15.83	20.51	31.70
S0 (1% increase in incomes for all classes)	2.68	6.60	9.94	12.75	15.83	20.51	31.70
S1 (1% of the total income increase received by Q1)	3.64	6.53	9.85	12.63	15.67	20.30	31.38
S2 (1% of the total income increase received by Q2)	2.65	7.52	9.85	12.63	15.67	20.30	31.38
S3 (1% of the total income increase received by Q6)	2.65	6.53	9.85	12.63	15.67	21.29	31.38
S4 (1% of the total income increase received by Q7)	2.65	6.53	9.85	12.63	15.67	20.30	32.37
S5 (transfer 1% of the total income from Q7 to Q1)	3.68	6.60	9.94	12.75	15.83	20.51	30.70
S6 (transfer 1% of the total income from Q7 to Q2)	2.68	7.60	9.94	12.75	15.83	20.51	30.70

Note: Q1—the lowest income class, Q2—the lower income class, Q3—the lower middle-income class, Q4—the middle-income class, Q5—the upper middle-income class, Q6—the higher income class, Q7—the highest income class. S0–S6 are seven projected scenarios.

Source: Authors' computations based on the CHNS (2004, 2006, 2009 and 2011).

TABLE 2 Summary statistics across income classes in urban China.

Variables	Income classes Q1	Q2	Q3	Q4	Q5	Q6	Q7
Per capita food consumed per day (g/day)							
Staple foods	451.26	438.77	441.07	420.22	402.84	400.93	389.63
	(190.94)	(166.01)	(182.45)	(171.48)	(164.28)	(158.36)	(147.33)
Beans and nuts	53.66	63.57	71.6	74.6	77.43	81.74	89.36
	(69.46)	(67.21)	(79.21)	(76.48)	(79.99)	(81.24)	(88.81)
Vegetables and fruits	394.32	416.92	440.56	458.05	451.91	461.33	478.68
	(204.94)	(207.42)	(239.09)	(252.05)	(236.33)	(243.09)	(257.73)
Pork	67.35	79.48	88.73	89.63	87.63	89.69	90.46
	(66.54)	(67.98)	(70.99)	(71.31)	(72.01)	(75.24)	(73.23)
Beef and mutton	5.33	10.32	12.01	12.02	15.21	14.88	14.47
	(16.27)	(22.75)	(25.84)	(24.40)	(28.82)	(28.06)	(27.29)
Poultry	15.24	19.26	21.85	20.06	22.84	24.7	25.37
	(33.54)	(38.42)	(40.14)	(37.43)	(39.23)	(40.79)	(42.46)
Dairy products	18.48	30.97	32.51	49.11	53.86	66.39	89.46
	(47.35)	(66.28)	(67.68)	(80.63)	(87.18)	(94.26)	(102.17)
Eggs	28.32	31.47	36.93	39.43	42.86	43.78	48.76
	(36.02)	(33.51)	(36.63)	(37.26)	(36.74)	(36.78)	(38.69)
Aquatic products	28.15	37.08	40.76	43.36	47.45	51.2	57.26
	(49.08)	(60.05)	(61.19)	(60.50)	(62.16)	(65.32)	(69.39)
Other foods	8.78	11.24	12.84	13.39	12.12	13.6	15.92
	(34.60)	(41.01)	(44.19)	(44.16)	(45.58)	(47.33)	(52.55)
Food expenditure share							
Staple foods	0.38	0.33	0.30	0.28	0.27	0.26	0.24
Beans and nuts	0.04	0.04	0.04	0.04	0.04	0.04	0.05
Vegetables and fruits	0.20	0.20	0.20	0.21	0.20	0.21	0.21
Pork	0.20	0.22	0.23	0.23	0.22	0.22	0.21
Beef and mutton	0.02	0.04	0.04	0.04	0.05	0.05	0.05
Poultry	0.04	0.04	0.05	0.04	0.05	0.05	0.05
Dairy products	0.03	0.03	0.03	0.05	0.05	0.06	0.07
Eggs	0.04	0.04	0.04	0.04	0.05	0.05	0.05
Aquatic products	0.04	0.05	0.05	0.06	0.06	0.06	0.07
Other foods	0.01	0.01	0.02	0.02	0.01	0.01	0.01
Per capita food expenditure and income (CNY/day)							
Food expenditure	6.91	7.87	8.43	8.71	8.76	9.27	9.42
	(4.83)	(4.61)	(4.82)	(5.44)	(4.74)	(6.48)	(4.41)
Income	5.57	14.26	22.33	31.11	40.71	54.54	90.15
	(3.67)	(5.47)	(7.68)	(9.87)	(11.93)	(15.04)	(31.31)

(Continues)

TABLE 2 (Continued)

Variables	Income classes Q1	Q2	Q3	Q4	Q5	Q6	Q7
Demographic variables							
North (0/1)	0.34	0.36	0.39	0.44	0.44	0.49	0.50
	(0.47)	(0.48)	(0.49)	(0.50)	(0.50)	(0.50)	(0.50)
Central (0/1)	0.22	0.19	0.21	0.22	0.20	0.19	0.15
	(0.42)	(0.39)	(0.41)	(0.41)	(0.40)	(0.39)	(0.35)
East (0/1)	0.06	0.12	0.11	0.14	0.20	0.18	0.24
	(0.24)	(0.32)	(0.32)	(0.35)	(0.40)	(0.39)	(0.42)
West (0/1)	0.38	0.34	0.29	0.19	0.16	0.13	0.11
	(0.49)	(0.47)	(0.45)	(0.39)	(0.36)	(0.34)	(0.32)
Wave04 (0/1)	0.21	0.21	0.21	0.21	0.21	0.21	0.21
	(0.41)	(0.41)	(0.41)	(0.41)	(0.41)	(0.41)	(0.41)
Wave06 (0/1)	0.22	0.22	0.22	0.22	0.22	0.22	0.22
	(0.41)	(0.41)	(0.41)	(0.41)	(0.41)	(0.41)	(0.41)
Wave09 (0/1)	0.22	0.22	0.22	0.22	0.22	0.22	0.22
	(0.41)	(0.41)	(0.41)	(0.41)	(0.41)	(0.41)	(0.41)
Wave11 (0/1)	0.35	0.35	0.35	0.35	0.35	0.35	0.35
	(0.48)	(0.48)	(0.48)	(0.48)	(0.48)	(0.48)	(0.48)
Household size	3.48	3.36	3.23	2.98	2.82	2.73	2.55
	(1.59)	(1.25)	(1.28)	(1.22)	(1.11)	(1.09)	(0.98)
Ratio of male	0.42	0.45	0.47	0.46	0.47	0.48	0.48
	(0.25)	(0.21)	(0.20)	(0.21)	(0.20)	(0.20)	(0.20)
Observations	869	867	868	866	868	867	868

Note: Here, per capita food expenditure refers to the total food expenditure on the studied foods. Standard variations are given in parentheses. Q1—the lowest income class, Q2—the lower income class, Q3—the lower middle-income class, Q4—the middle-income class, Q5—the upper middle-income class, Q6—the higher income class, Q7—the highest income class.

Source: Authors' computations based on the CHNS (2004, 2006, 2009 and 2011).

income increases. The highest income class consumes 4.8, 2.7 and 2.0 times as much dairy, beef and mutton and aquatic products, respectively, as the lowest income class. Second, larger shares of budgets are allocated to animal-based food with income increases. Third, there is a small difference in food expenditure but a substantial difference in per capita household income across the income classes. For example, the income of the highest income group is more than 16 times higher than that of the lowest income class. This indicates how significant inequality in terms of food consumption and household income exists across income classes in urban China.

Per capita diet-related CFs, WFs and EFs are on the rise with income increases (Figure 1). The CFs, WFs and EFs in the highest income class are 1.41, 1.39 and 1.60 times as high as those in the lowest income class, respectively. Further, the proportion of animal-source CFs, WFs and EFs also increases with higher income classes. Excluding the lowest and lower income classes, the animal-source CFs, WFs and EFs for the other income classes contribute to more than half of the total CFs, WFs and EFs.

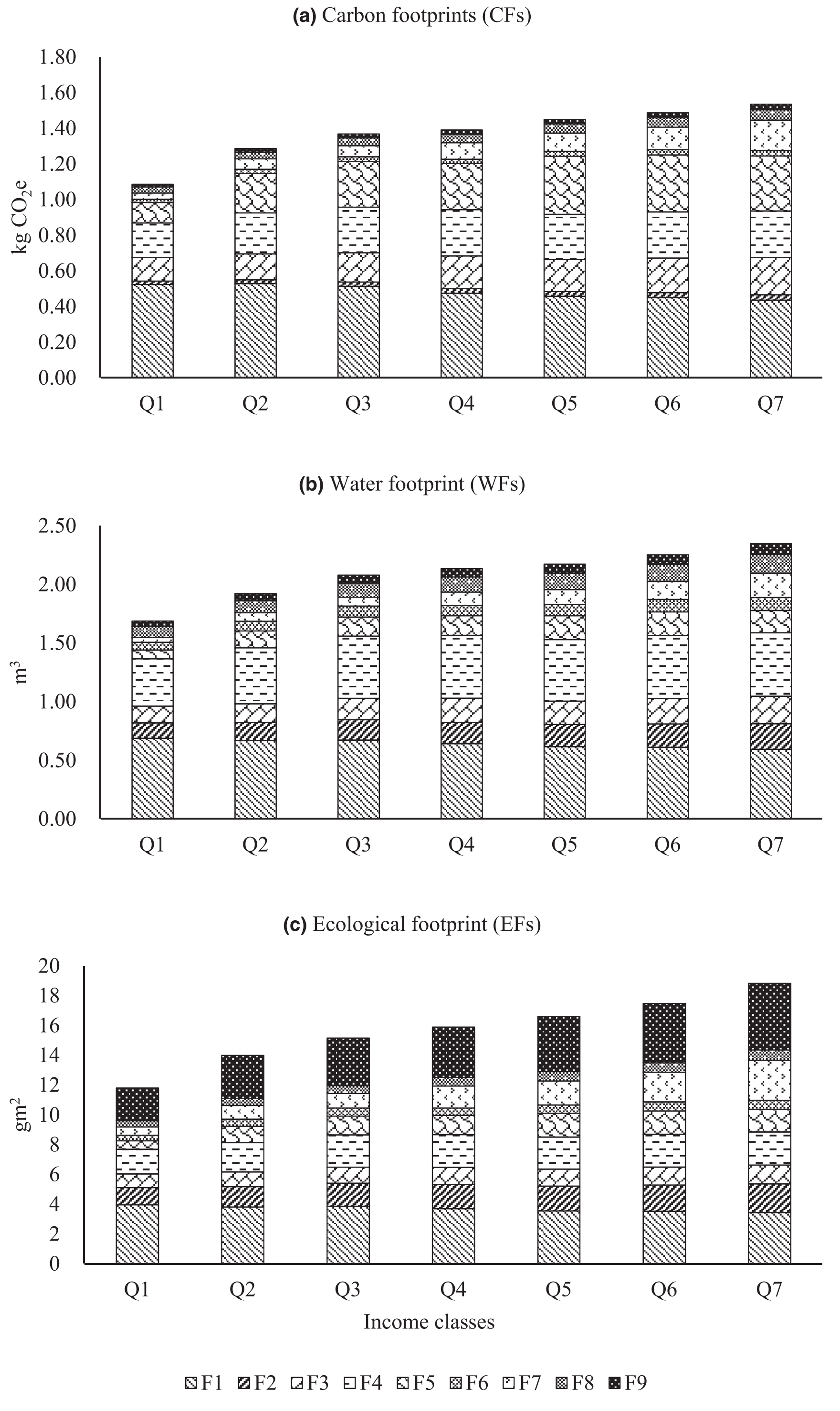

FIGURE 1 Per capita daily diet-related environmental footprints across income classes. F1 (staple foods), F2 (beans and nuts), F3 (vegetables and fruits), F4 (pork), F5 (beef and mutton), F6 (poultry), F7 (dairy products), F8 (eggs), F9 (aquatic products). Q1 = the lowest income class, Q2 = the lower income class, Q3 = the lower middle income class, Q4 = the middle income class, Q5 = the upper middle income class, Q6 = the higher income class, Q7 = the highest income class. *Source*: Authors' computations based on the CHNS (2004, 2006, 2009 and 2011).

3.2 | Expenditure and income elasticities

The results of the QUAIDS are reported in Table S2. As we focus on the effects of income and income distribution on the total diet-related environmental footprints, our interpretation rests on income elasticities (Table 3). Expenditure elasticities, own- and cross-price elasticities across income classes can be found in Tables S3–S10. All the expenditure and income elasticities are positive, and statistically significant at 0.01% except for the last food group, which indicates that all the foods are normal goods for urban households. The food expenditure elasticities vary across the seven income groups, which means their consumer preferences are heterogeneous. Meanwhile, the elasticity gap across the income groups is quite small for most foods. This may reflect more equal distribution in terms of food expenditures than income distribution across the various income classes. Besides, beef and mutton, dairy products and beans and nuts have the highest expenditure elasticities for all the income classes.

Unlike the food expenditure elasticities (Table S3), there are substantial differences in the income elasticities across the income classes (Table 3). The income elasticities display an inverted 'U' as income increases. The lowest income group has the lowest income elasticities, and the middle income class has the highest income elasticities for all the studied foods. This means that a 1% increase in income will lead to a greater increase in food demand for the middle-income class than for the lowest or highest income class. Among the studied foods,

TABLE 3 Income elasticities across income classes.

Food groups	Q1	Q2	Q3	Q4	Q5	Q6	Q7
Staple foods	0.178***	0.385***	0.409***	0.445***	0.341***	0.318***	0.243***
	(0.005)	(0.012)	(0.015)	(0.017)	(0.015)	(0.015)	(0.014)
Beans and nuts	0.275***	0.646***	0.719***	0.812***	0.638***	0.620***	0.501***
	(0.020)	(0.053)	(0.057)	(0.065)	(0.049)	(0.049)	(0.040)
Vegetables and fruits	0.208***	0.487***	0.542***	0.616***	0.484***	0.472***	0.391***
	(0.007)	(0.018)	(0.020)	(0.020)	(0.017)	(0.017)	(0.014)
Pork	0.265***	0.622***	0.688***	0.789***	0.629***	0.614***	0.515***
	(0.010)	(0.022)	(0.024)	(0.028)	(0.024)	(0.024)	(0.019)
Beef and mutton	0.316***	0.697***	0.775***	0.900***	0.666***	0.665***	0.565***
	(0.030)	(0.063)	(0.068)	(0.089)	(0.055)	(0.063)	(0.059)
Poultry	0.259***	0.608***	0.665***	0.778***	0.598***	0.586***	0.485***
	(0.022)	(0.067)	(0.066)	(0.091)	(0.060)	(0.062)	(0.056)
Dairy products	0.287***	0.678***	0.810***	0.843***	0.639***	0.618***	0.507***
	(0.019)	(0.050)	(0.072)	(0.066)	(0.040)	(0.041)	(0.034)
Eggs	0.247***	0.574***	0.636***	0.708***	0.549***	0.529***	0.431***
	(0.019)	(0.049)	(0.056)	(0.067)	(0.049)	(0.051)	(0.042)
Aquatic products	0.234***	0.541***	0.599***	0.673***	0.526***	0.511***	0.421***
	(0.022)	(0.061)	(0.067)	(0.077)	(0.054)	(0.056)	(0.044)
Other foods	0.037	0.099	0.221***	0.266***	0.069	0.098	0.099*
	(0.046)	(0.106)	(0.093)	(0.104)	(0.116)	(0.113)	(0.087)

Note: Standard errors are given in parentheses. Q1—the lowest income class, Q2—the lower income class, Q3—the lower middle-income class, Q4—the middle-income class, Q5—the upper middle-income class, Q6—the higher income class, Q7—the highest income class.

*$p<0.10$; ***$p<0.01$.

Source: Authors' computations based on the CHNS (2004, 2006, 2009 and 2011).

the income elasticities of staple foods are the lowest, while those of beef and mutton and dairy products are relatively high for all the income classes. This implies that income growth tends to drive a larger increase in beef and mutton and dairy product consumption in urban China.

3.3 | Projections

3.3.1 | Projections using the CHNS data

The projected total food demand and diet-related environmental footprint changes are aggregated with those from each income class (Table 4). S0 leads to a rise in demand for each food (0.13%–0.68%). S1 and S2 drive a larger increase in food demand than S0. Interestingly, S2 increases the consumption of most foods more than S1, except for staple foods and vegetables and fruits. This result may be explained by the fact that the food demand for the lower income class is more income elastic, and the original quantities of most food consumption are also more than that for the lowest income class. As expected, S3 and S4 drive a much smaller increase in food demand than S0, S1 and S2. Similar to S1 and S2, S5 and S6 also drive a relatively high increase in food demand. Simultaneously, the increased food demand under various scenarios leads to a rise in diet-related environmental footprints.

Meanwhile, preferences regarding the foods studied vary under the seven scenarios (Table 4), which indicates changes in diet structure along with income distribution. S0, S3 and S4 cause an increase in the consumption of beef and mutton, dairy products and beans and nuts. S1 and S5 lead to a rise in the consumption of pork, beans and nuts and staple food, whereas S2 and S6 drive growth in terms of the consumption of beef and mutton, pork and beans and nuts. As the environmental footprint intensities of various foods are different, these diet structure changes also affect the total diet-related environmental footprints.

Further, we computed the projected increases in the total diet-related environmental footprints (Table 5). S0 increases the environmental footprints by about 0.5%, while S1, S2 and S6 increase them by more than 1%. Notably, the largest increases in CFs, WFs and EFs take place under S2, where they grow by 1.19%, 1.20% and 1.18%, respectively, which is 2.38, 2.38

TABLE 4 Projected increases in food consumption and diet-related environmental footprints.

Food categories	FC (kg)	CFs (kg)	WFs (m^3)	EFs (gm^2)	S0 (%)	S1	S2	S3	S4	S5	S6
Staple foods	0.423	0.487	0.645	3.715	0.33	1.17	0.96	0.19	0.09	1.08	0.88
Beans and nuts	0.072	0.024	0.176	1.548	0.61	1.26	1.37	0.44	0.24	1.03	1.14
Vegetables and fruits	0.440	0.170	0.188	1.097	0.46	1.14	1.11	0.31	0.16	0.98	0.95
Pork	0.084	0.243	0.503	2.066	0.60	1.31	1.42	0.41	0.21	1.10	1.20
Beef and mutton	0.012	0.252	0.160	1.239	0.68	0.88	1.48	0.53	0.26	0.62	1.21
Poultry	0.021	0.025	0.091	0.515	0.58	1.16	1.34	0.43	0.22	0.93	1.12
Dairy products	0.046	0.088	0.108	1.391	0.63	0.71	1.09	0.56	0.37	0.33	0.72
Eggs	0.038	0.046	0.125	0.549	0.53	1.13	1.14	0.38	0.21	0.92	0.93
Aquatic products	0.043	0.023	0.070	3.341	0.51	0.95	1.13	0.39	0.21	0.73	0.92
Other foods	0.012				0.13	0.16	0.22	0.07	0.05	0.11	0.17

Note: FC, CFs, WFs and EFs represent food consumption, carbon footprints, water footprints and ecological footprints, respectively. S0–S6 are seven projected scenarios.

Source: Authors' computations based on the CHNS (2004, 2006, 2009 and 2011).

TABLE 5 Projected increases in total diet-related environmental footprints.

Environmental footprints		S0	S1	S2	S3	S4	S5	S6
		(%)						
CFs	1.358 (kg)	0.50	1.10	1.19	0.35	0.18	0.92	1.01
WFs	2.065 (m^3)	0.51	1.15	1.20	0.35	0.18	0.97	1.02
EFs	15.461 (gm^2)	0.51	1.08	1.18	0.37	0.20	0.88	0.98

Note: CFs, WFs and EFs represent carbon footprints, water footprints and ecological footprints, respectively. S0–S6 are seven projected scenarios.

Source: Authors' computations based on the CHNS (2004, 2006, 2009 and 2011).

TABLE 6 Projected increases in diet-related environmental footprints across income classes.

Environmental footprints	Income classes	S0	S1	S2	S3	S4	S5	S6
CFs (kg)	Q1	0.002	0.091				0.091	
	Q2	0.007		0.102				0.102
	Q3	0.008						
	Q4	0.009						
	Q5	0.008						
	Q6	0.008			0.037			
	Q7	0.006				0.020	−0.020	−0.020
WFs (m^3)	Q1	0.004	0.144				0.144	
	Q2	0.010		0.156				0.156
	Q3	0.012						
	Q4	0.014						
	Q5	0.011						
	Q6	0.012			0.056			
	Q7	0.010				0.031	−0.031	−0.031
EFs (gm^2)	Q1	0.027	1.015				1.015	
	Q2	0.076		1.151				1.151
	Q3	0.092						
	Q4	0.108						
	Q5	0.089						
	Q6	0.091			0.445			
	Q7	0.081				0.256	−0.256	−0.256

Note: CFs, WFs and EFs represent carbon footprints, water footprints and ecological footprints, respectively. S0–S6 are seven projected scenarios. Q1—the lowest income class, Q2—the lower income class, Q3—the lower middle-income class, Q4—the middle-income class, Q5—the upper middle-income class, Q6—the higher income class, Q7—the highest income class.

Source: Authors' computations based on the CHNS (2004, 2006, 2009 and 2011).

and 2.30 times as much as those under S0. As expected, S6 results in a much small increase in diet-related environmental footprints.

As shown in Table 6, the inequality of diet-related environmental footprints across income classes also varies under various scenarios. S0 leads to a rise in environmental footprints for each income class, but the greatest increase is observed for the middle-income class. S1 and S2 only increase the environmental footprints for the lowest and lower income classes, respectively, while S3 and S4 only increase the environmental footprints for the higher and highest income class, respectively. S5 and S6 drive the same increase in environmental footprints as S1 and S2 for the lowest and lower income classes, respectively, while they reduce the environmental footprint of the highest income class at the same time. This indicates that S0, S3 and S4 worsen the inequality status across income classes, while S1, S2, S5 and S6 improve the inequality status to some extent.

3.3.2 | Projections using the NBSC data

Table 7 presents the projected increases in food consumption and diet-related environmental footprints based on the NBSC (2021). Compared with Table 4, the consumption of staple foods decreased, while that of the other food categories increased. Similar to the results from the survey data, S1 and S2 drive a larger increase in food demand and related environmental footprints than S3 and S4. The difference is that the increased effect is stronger under S1 than under S2 based on the NBSC (2021). The reason might be that the food consumption and income elasticities for the lowest income class rise with additional income increases.

Table 8 displays the simulated changes in the total diet-related environmental footprints based on the NBSC (2021). All the distribution scenarios would increase the environmental

TABLE 7 Projected increases in food consumption and diet-related environmental footprints based on the NBSC (2021).

	Year 2020									
	FC	**CF**	**WF**	**EF**	**S0**	**S1**	**S2**	**S3/S4**	**S5**	**S6**
Food categories	**(kg)**	**(kg)**	**(m^3)**	**(gm^2)**	**(%)**					
Staple foods	0.402	0.454	0.614	3.544	0.29	1.34	0.54	0.11	1.23	0.42
Beans and nuts	0.084	0.029	0.206	1.812	0.56	1.83	1.02	0.26	1.57	0.76
Vegetables and fruits	0.468	0.197	0.219	1.215	0.44	1.53	0.79	0.19	1.33	0.6
Pork	0.090	0.260	0.539	2.211	0.57	2.03	1.04	0.25	1.78	0.79
Beef and mutton	0.014	0.301	0.187	1.468	0.62	1.98	1.19	0.28	1.7	0.91
Poultry	0.025	0.029	0.106	0.601	0.54	1.77	1	0.24	1.53	0.76
Dairy products	0.073	0.140	0.170	2.204	0.55	1.07	0.95	0.3	0.77	0.65
Eggs	0.045	0.054	0.149	0.654	0.48	1.55	0.87	0.22	1.32	0.64
Aquatic products	0.053	0.028	0.086	4.127	0.47	1.38	0.84	0.22	1.16	0.62
Other foods	0.015				0.12	0.57	0.15	0.05	0.52	0.1

Note: FC, CFs, WFs and EFs represent food consumption, carbon footprints, water footprints and ecological footprints, respectively. S0–S6 are seven projected scenarios.

Source: Authors' computations based on the CHNS (2004, 2006, 2009 and 2011) and the NBSC (2021).

TABLE 8 Projected increases in total diet-related environmental footprints based on the NBSC (2021).

		S0	**S1**	**S2**	**S3/S4**	**S5**	**S6**
Environmental footprints	**Year 2020**	**(%)**					
CFs	1.492 (kg)	0.47	1.62	0.87	0.21	1.40	0.65
WFs	2.276 (m^3)	0.47	1.63	0.86	0.21	1.42	0.65
EFs	17.836 (gm^2)	0.48	1.54	0.87	0.22	1.32	0.65

Note: CFs, WFs and EFs represent carbon footprints, water footprints and ecological footprints, respectively. S0–S6 are seven projected scenarios.

Source: Authors' computations based on the CHNS (2004, 2006, 2009 and 2011) and the NBSC (2021).

footprints to a different extent. If a 1% total income increase is received by the lowest income groups (S1), the diet-related CFs, WFs and EFs increase by 1.62%, 1.63% and 1.54%, respectively, which are more than two times higher than in S0 and almost seven times higher than those under S3 or S4. Compared with Table 5, the effect of the increase under S0, S2, S3, S4 and S6 is smaller, while the effect under S1 and S5 is greater. This indicates that at times of economic growth, increasing the incomes of the lowest income classes is the main contributor to the increase in diet-related environmental footprints.

4 | DISCUSSION

China is undergoing marked economic growth and diet transition while attempting to narrow the income inequality gap. This study analysed diet-related environmental footprints across income classes and projected their responses to changes in income distribution in urban China. Consistent with He et al. (2019), as well as research in Australia (Reynolds et al., 2015), Argentina (Arrieta et al., 2021) and India (Harris et al., 2017), our results show that per capita daily diet-related environmental footprints increase with income. However, in contrast to findings in other countries (Arrieta et al., 2021; Harris et al., 2017; Reynolds et al., 2015), we found that there is no evident difference in plant-source environmental footprints, while the proportion of animal-source environmental footprints increases with income. This is in accordance with the NBSC (2012), which shows that the highest income class consumes more than twice as much animal-source food than the lowest income class.

Income elasticities also vary across income classes and food groups. First, we find that the lowest income class does not have the highest income elasticities for most foods, and income elasticities decline with an increase in income from the rest income groups. This differs from previous results (Zheng & Henneberry, 2010), as well as findings in India (Kumar et al., 2011), which found the lowest income class has the highest income elasticities. A possible explanation for this might be that we categorised sample households into more groups. Second, similar to previous results (Ren et al., 2018; Yen et al., 2004; Zheng & Henneberry, 2010), our findings show that staple foods are insensitive, while beef and mutton and dairy products are sensitive to income changes, especially for low-income classes. This indicates how income growth tends to increase the demand for beef and mutton and dairy products. In turn and especially for beef and mutton, which embody relatively high environmental footprints, the increased demand causes a greater environmental pressure. In addtion, the impact of income distribution on demand for beef and mutton is different under various scenarios, which accords with earlier observations in Colombia (Pinstrup-Andersen & Caicedo, 1978). For example, the demand for beef and mutton would increase by 0.68% if all incomes are increased by 1%, and 1.42% if the same total income is received by the lower income class. The preferred food categories change under the seven scenarios due to heterogeneous demand characteristics across the various income classes. If the income allocations of high-income classes are increased, their food preferences shift to dairy products beef and mutton, while the same is true of pork, beans and nuts and staple foods for the lowest income class, and mutton and beef, pork and beans and nuts for the lower income class.

Our projections present how income growth experienced by the low-income (the lowest and lower income) classes drives a larger increase in diet-related environmental footprints than a uniform percentage increase in all income classes. Additionally, income transfer from high- to low-income classes leads to a smaller rise in total diet-related environmental footprints than direct income growth. This finding is similar to that of Zheng and Henneberry (2010), who found that changes in income redistribution have a considerable impact on food demand. At times of economic growth, the lowest income class replaces the lower income class in terms of contributing the largest increase in total diet-related environmental footprints. This implies that any policy aimed at increasing the income of the lowest income class in urban China will drive more growth in food demand and diet-related environmental footprints. In the future, it is expected that China will experience sustained economic growth and will try to alleviate income inequality. This will significantly increase food demand and improve the country's nutrition status but will also result in a greater environmental pressure.

A more sustainable diet structure should be urgently promoted in China. Going beyond increasing diet-related environmental footprints, many studies also found that increased food demand and diet structure changes might also increase the rates of obesity and non-communicable diseases (McMichael et al., 2007; Popkin, 2014; Xu & Lan, 2016). Regarding this, researchers have come up with various suggestions. For example, Lei and Shimokawa (2020) claimed that following the Chinese Dietary Guidelines could improve both diet quality and environmental sustainability. Western researchers proposed a carbon-based tax to guide an environment-friendly and healthy diet (Edjabou & Smed, 2013; Feng et al., 2010; IPCC, 2015; Tilman & Clark, 2014). Synergies are emerging from improving health and reducing diet-related environmental footprints (He et al., 2018).

5 | CONCLUSION

This study investigated diet-related environmental footprints across income classes and their responses to changes in income distribution in urban China. The QUAIDS model was employed to estimate the income elasticities of 10 food categories for seven income classes, handling the issues of endogeneity of food expenditure and zero expenditure. Based on the income elasticities, the impacts of income distribution on food demand and the corresponding environmental footprints were analysed under seven scenarios.

The results indicate that higher income groups contribute more diet-related environmental footprints and that increasing their incomes drives a slight increase in such footprints. However, any policy designed to increase incomes targeted at low-income groups will result in a larger rise in environmental footprints, while transferring the income from high-income class to low-income class can mitigate the effect. Further, along with economic growth, a rise in income favouring the lowest income group will contribute the largest proportion to increasing diet-related environmental footprints. This will be a great challenge for sustainable agriculture development in China.

Going beyond income inequality, China, is also facing environmental challenges. In recent years, China's government has been paying more and more attention to environmental protection and has formulated a series of policies to reduce GHG emissions, to save agricultural water resources and to protect arable land areas. However, our findings imply that income growth, especially for low-income groups, will be accompanied by increasing food demands and diet transition, which emit more agricultural GHG emissions and demand more agricultural water resources and arable land areas. Hence, on the road to poverty elimination or inequality alleviation, policymakers should come up with win-win solutions to both improve nutrition and protect the environment through, for example, promoting and guiding more sustainable diet structures.

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DATA AVAILABILITY STATEMENT

The data were derived from public domain resources: https://www.cpc.unc.edu/projects/china. However, the community data are not publicly available.

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SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

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