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A comparative study on the dietary ecological footprint in contemporary China

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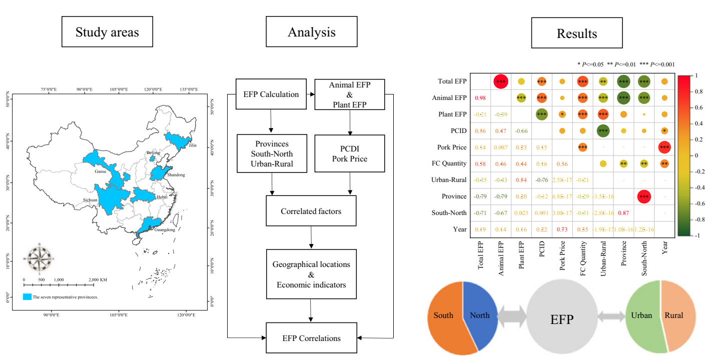
HIGHLIGHTS

- The dietary EFP in China was investigated based on the latest data.
- Southern EFP was higher than Northern EFP, urban EFP was higher than rural EFP.
- EFP was correlated with south/north areas, urban/rural status, PCDI and FC quantity.
- Geographic locations showed higher correlations with EFP than economic conditions.
- Pork price did not affect the total or animal-based EFP.

GRAPHICAL ABSTRACT



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ABSTRACT

Food consumption is increasingly impacting environmental sustainability. Building on the latest data of China Statistical Yearbook 2015–2020, this study quantified the dietary ecological footprint per capita (EFP), including animal-based and plant-based EFP, across seven provinces (representing seven regions) and between urban and rural areas of China. We further analyzed the possible correlated factors with the EFP and the strength of these correlations. The results showed that the EFP in southern areas was generally higher than that in northern areas, and the EFP in urban areas was higher than that in rural areas. The EFP was significantly correlated with per capita disposable income (PCDI), food consumption (FC) quantity, urban/rural status, southern/northern areas, and provinces. Moreover, we found geographical locations (i.e., southern/northern areas and provinces) contributed more to the total and animal-based EFP than economic conditions (i.e., urban/rural status and PCDI). Although pork price dramatically influenced the dietary patterns, it did not affect the total or animal-based EFP. These findings provide novel insights for understanding the mechanisms of the relationship between food consumption and environmental sustainability in China. The conclusions are helpful in predicting the future environmental impacts of diets in other countries with similar national conditions.

1. Introduction

Food consumption considerably impacts environmental sustainability (He et al., 2018; He et al., 2021a; Poore and Nemecek, 2018; Tilman and

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Clark, 2014; Wang et al., 2020). With the current dietary patterns, feeding 7.6 billion people worldwide is degrading terrestrial and aquatic ecosystems, depleting water resources, and driving climate change (Poore and Nemecek, 2018). Food systems driven by human consumption patterns are responsible for 38 % of terrestrial surface occupation (Song et al., 2015). Previous studies have shown complicated links between environmental degradation and food consumption (Benvenuti et al., 2019; Galli et al., 2017; Notarnicola et al., 2017; Poore and Nemecek, 2018; Tilman et al., 2011; Tilman and Clark, 2014). For instance, moving from current diets to a diet that excludes animal products can drastically reduce the land use for food by 3.1 billion ha globally, including a 19 % reduction in arable land (Poore and Nemecek, 2018). Studies exploring the environmental impacts of dietary patterns also showed that animal-based products require more land than plant-based foods, and therefore have greater environmental impacts (Okin, 2017; Su et al., 2018; Tilman et al., 2011). Hence, evaluating the environmental impacts of dietary patterns and finding strategies to avoid unsustainable eating habits are of vital importance for environmental and economic sustainability.

The ecological footprint (EF) analysis has been widely used to assess environmental impacts and measure the relationship between environmental degradation and dietary patterns (Auestad and Fulgoni, 2015; Cao et al., 2020; Sáez-Almendros et al., 2013; Veeramani et al., 2017). EF includes all natural capital that is directly or indirectly consumed by the local population (Galli et al., 2012b) and represents the area required for resource production and waste assimilation (Galli, 2015; Wackernagel and Rees, 1998; Zhen and Du, 2017). Calculating the EF from the perspective of food consumption is critical components of environmental sustainability (Galli et al., 2017; Li et al., 2019). Based on the EF model, previous research has examined the environmental impacts of food consumption from different levels and perspectives (Chen and Gao, 2010; Hasegawa et al., 2019; He et al., 2019; Li et al., 2019; Świąder et al., 2018; Xiong et al., 2022; Zambrano-Monserrate et al., 2020; Zhen and Du, 2017). For instance, He et al. (2018) analyzed the influence of urban/rural status and income on the environmental impacts of food intake and concluded that the effect of income follows the same urban/rural pattern, with higher income being correlated with a larger reduction in cereals and an increase in animal-based products.

These studies serve as a starting point for exploring possible correlated variables of the environmental impacts of food consumption. Notably, most of these studies were based on data from the China Health and Nutrition Survey (CHNS) 2011 (Bu et al., 2021; He et al., 2019; Xiong et al., 2022). The heterogeneous sample and highly informative individual-level survey data of the CHNS can accurately characterize the profile of food consumption in China (Xiong et al., 2022). However, the CHNS 2011 was conducted more than a decade ago, and China has undergone momentous changes in the past decade, especially the booming economy and rapid urbanization (Liao et al., 2020; Xiong et al., 2020). For instance, the total GDP increased by 108 %, per capita disposable income (PCDI) of urban and rural residents increased by 100.98 % and 74.22 %, and the proportion of urban population increased from 51.83 % to 63.89 % from 2011 to 2020 (NBS, 2020). Hence, analyzing people's dietary patterns based on the latest data is necessary to reflect the actual environmental impacts of food consumption in contemporary China. China is a vast country with great regional variations in demographics, economic levels, and dietary patterns (Liu and Liu, 2019; Lu et al., 2017; Wang et al., 2019; Zhang et al., 2020). In addition to the urban/rural status, the distinct south–north divide is another significant characteristic that may determine dietary patterns (Tang et al., 2020) and ultimately affect the environment. Therefore, exploring the environmental impacts of food consumption between urban/rural and southern/northern areas is vital to measure the sustainability of the Chinese food system. Furthermore, pork is the most important source of meat consumed in China (Karlova and Serova, 2020), accounting for 73.4 % of meat consumption in China, and 44.4 % of the world's total pork consumption (Cai et al., 2021; NBS, 2020). Over the past several years, pork prices experienced huge fluctuations (Ma et al., 2021). After three years of continuous decline, pork prices increased sharply in 2019 and 2020 (NBS, 2020). Consumers become more realistic when the price of meat increases; intuitively, an increase in the price of meat makes consumption less appealing (Hestermann et al., 2020; Zhang et al., 2021). Hence, including the factor of pork price in this study will also provide novel insights into the relationship between food price and the environmental impacts of food consumption.

Based on the geographical location and per capita GDP, we selected seven provinces (Beijing, Guangdong, Hubei, Shandong, Sichuan, Jilin, and Gansu) from all the seven regions (north, south, central, east, southwest, northeast, and northwest) divided by the Administrative Division of the People's Republic of China (NBS, 2020). This study aimed to provide a benchmark assessment of the ecological footprint per capita (EFP) across seven provinces and between urban and rural areas. Furthermore, we aimed to identify the potential correlated factors. Given that there are few literatures explaining the correlation strength of these factors, we therefore explored to what extent these factors were correlated with EFP. Specifically, we first compared the EFP in contemporary China from different perspectives, that is, spatial (urban/rural, southern/northern, and seven provinces) and temporal (2015–2020). We then analyzed the possible correlated variables (i.e., PCDI, food consumption (FC) quantity, urban/rural status, southern/northern areas, provinces, and fluctuation of pork prices) of the EFP. By exploring the possible correlated variables of EFP and to what extent these factors contributed to the EFP in China based on the latest data, we can better understand the true environmental impacts of food consumption from social, economic, and geographical perspectives. The results can help predict the future environmental impacts of diets for China as well as other countries with similar national characteristics, such as the distinct urban–rural status and the southern-northern divide.

2. Materials and methods

2.1. Study areas

To observe the regional differences in the EFP, we selected Beijing, Guangdong, Hubei, Shandong, Sichuan, Jilin, and Gansu as our cases in the present study, according to the latest data on per capita GDP and geographical location. Detailed information on these seven provinces (Beijing is a municipality with a provincial status) is presented in Tables 1 and 2 and Fig. 1.

2.2. Data sources

The research period was from 2015 to 2020. Individual-level average consumption statistics were used in this study, and these statistics were derived from the China Statistical Yearbook 2015–2020; Beijing, Guangdong, Hubei, Shandong, Sichuan, Jilin, and Gansu Statistical Yearbook 2015–2020. Detailed information on each region (Tables 1 and 2), FC quantity per capita, and types of animal and plant-based food were derived from the national and local Statistical Yearbook. Further, data on national production, land use for average productivity, and equivalence factors were taken from the National Bureau of Statistics of China, the United Nations Food and Agriculture Organization (FAO), the Global Footprint Network, and published papers (Liu et al., 2017; Lu and Chen, 2017; Su et al., 2018; Wackernagel et al., 1999). These factors were used to calculate the EFP components of arable land, grazing land, and fishing grounds. The data are presented in Table 3. We employed five plant-based (cereal, oil, vegetables, fruit, and sugar) and six animal-based (beef and mutton, pork and other meat, poultry, seafood, eggs, and milk) products, according to the food categories in the National Statistical Yearbook, China.

2.3. The calculation of ecological footprint

The EF analysis is commonly used to measure the amount of natural resources required to satisfy the consumption requirements and waste assimilation needs of a given population in a defined year (Chen et al., 2010; Wackernagel and Rees, 1998). The EF categorizes six land-use types

Table 1
The basic information of the seven provinces.

Provinces	Per capita GDP (Yuan)	Per capita disposable income (Yuan)	Per capita food expenditure (Yuan)	Acreage (km^2)	Rural population (million)/%	Urban population (million)/%
Beijing	164,929	69,434	8374	16,411	2.73 (12.5)	19.17 (87.5)
Guangdong	87,899	41,029	9629	179,725	32.58 (25.8)	93.44 (74.2)
Hubei	75,226	27,881	5898	185,900	21.43 (37.1)	36.32 (62.9)
Shandong	72,027	32,886	5757	157,900	37.51 (36.9)	64.01 (63.1)
Sichuan	58,084	26,522	7026	486,000	36.21 (43.3)	47.47 (56.7)
Jilin	51,125	25,751	5022	187,400	8.99 (37.3)	15.08 (62.7)
Gansu	36,038	20,335	4769	425,800	11.95 (47.8)	13.07 (52.2)

Sourced from: The China Statistical Yearbook; Beijing, Guangdong, Hubei, Shandong, Sichuan, Jilin, and Gansu Statistical Yearbook (2020).

(i.e., arable land, grazing land, forest land, fishing grounds, built-up land, and energy land) and is often used at different scales (e.g., individuals, cities, regions, and countries) (Su et al., 2018; Wackernagel and Rees, 1998). In this study, we aimed to quantify and compare dietary EFP in China. According to the primary dietary role, we grouped the food products into 11 categories: cereals, oils, vegetables, beef and mutton, pork, poultry, seafood, eggs, milk, melons and fruits, and sugar. Three major biologically productive land types (arable land, grazing land, and fishing grounds) were used to calculate the EFP. The resource consumption in the processes of cooking, transportation, and retailing is neglected because the EFP from these processes is very small, and the omission seems unlikely to have significant effects on our results (Su and Martens, 2018; Zhen and Du, 2017). Considering the variations in population size among different provinces, the EFP was adopted for comparison. The EFP of food consumption by urban and rural residents was calculated using the bottom-up method, and the equation of EFP is as follows (Liu et al., 2017; Su et al., 2018; Zhen and Du, 2017):

$$EFP = \Sigma r_j \left(\frac{C_i}{Y_i}\right) \quad (1)$$

where *EFP* is the per capita EF (ha); r_j is an equivalence factor for the biologically productive land type j ($j = 1$ *to* 3) for arable land, grazing land, and fishing grounds; C_i is the per capita consumption of food item i (kg, $i = 1$ *to* 11), for cereal, oil, vegetables, pork, beef and mutton, poultry, seafood, eggs, milk, fruit, and sugar; Y_i is the average yield of food items i (kg/ha).

To align the measurement units, all three land types were converted using equivalence factors. The equivalence factor is the ratio of the average ecological productivity of the biologically productive land of type j in a given region to the average ecological productivity of all types of biologically productive land in this region. The equivalence factor is usually calculated using the following equation (Zhen and Du, 2017):

$$r_j = \frac{k_j}{k} \quad (2)$$

Table 2
The information of the disposable income and food expenditure in rural and urban areas.

Provinces	Per capita disposable income (Yuan)		Per capita food expenditure (Yuan)		Food expenditure/ disposable income (%)	
	Rural	Urban	Rural	Urban	Rural	Urban
Beijing	30,126	75,602	5968	8751	19.81	11.58
Guangdong	20,143	50,257	6992	10,795	34.71	21.48
Hubei	16,306	36,706	4305	7112	26.40	19.38
Shandong	18,753	43,726	3722	7319	19.85	16.74
Sichuan	15,929	38,253	5478	8741	34.39	22.85
Jilin	16,067	33,396	3731	6041	23.22	18.09
Gansu	10,344	33,822	3065	7068	29.63	20.90

Sourced from: The China Statistical Yearbook; Beijing, Guangdong, Hubei, Shandong, Sichuan, Jilin, and Gansu Statistical Yearbook (2020).

where k_j is the average ecological productivity of biologically productive land of type j, k is the average ecological productivity of all biologically productive land types.

Given the integrated food market in China and the diachronic character of this study, we used the equivalence factor on a national scale (Liu et al., 2017; Toth and Szigeti, 2016).

2.4. Statistical analysis

The data in this study followed a normal distribution (Shapiro–Wilk's test) and showed homogeneity of variances (Levene test). Separate one-way analysis of variances (ANOVAs) were conducted to investigate the difference in EFP across the seven selected provinces, and among different years (2015–2020). Additionally, to reduce type-I errors due to repeated testing, Fisher's procedure and the Ryan–Einot–Gabriel–Welch and Quiot (REGWQ) correction were performed. Student t-tests were carried out to investigate the differences between the mean scores (averaged for data during 2015–2020) of urban and rural, and southern and northern EFP. Pearson correlation analysis was used to explore the relationships between dietary EFP (including both animal and plant-based EFP) and related variables (including PCDI, FC quantity, urban/rural status, southern/northern areas, provinces, and pork price). Both Fisher's r-to-z transformation and the R package cocor were applied to compare the correlation coefficients (Diedenhofen and Musch, 2015; Silver and Dunlap, 1987; You and Henneberg, 2016). All results were based on two-sided tests and an alpha value of 0.05 was used for variables to be entered into the models. Statistical analyses were conducted using SPSS 24.0 statistical software and Origin 8.0 mapping software.

3. Results

3.1. The EFP across regions

The EFPs across seven regions of China from 2015 to 2020 were quantified, and the results revealed that the main sources of EFP were pork, seafood, cereal, beef, and mutton for all the seven provinces (Fig. 2). The animal-based EFP exceeded the plant-based EFP across all regions during 2015–2020. The EFP of southern China (S) was generally higher than that of northern China (N). At the regional level, the EFP of the seven selected provinces were ranked as Guangdong (S), Sichuan (S), Hubei (S), Beijing (N), Shandong (N), Jilin (N), and Gansu (N) (Fig. 3a). To further explore the differences between southern and northern China, we also quantified the EFP originating from animal and plant-based products in these regions. The animal-based EFP in southern China was higher than that in northern China ($p < 0.001$), whereas no differences were observed for the plant-based EFP ($p = 0.832$) (Fig. 3b, c).

We also quantified the temporal changes in the EFP from 2015 to 2020, and found that the EFP of six provinces did not vary significantly during the study period except for Guangdong, which showed a higher EFP of 2019–2020, compared to 2015–2018 (LSD, all $p < 0.001$) (Fig. 2 and Fig. S1).

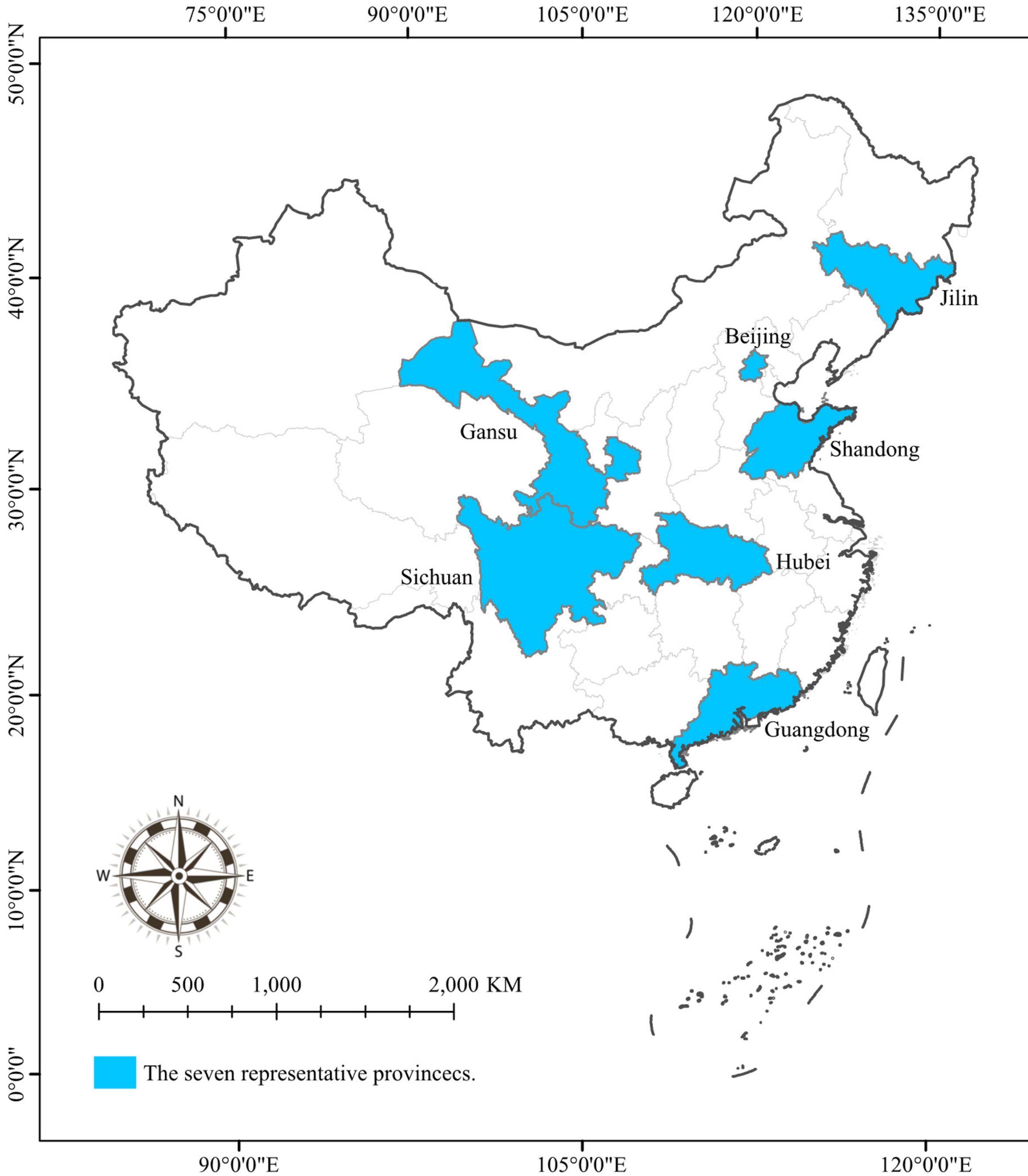

Fig. 1. Location map of the study area: provinces of Beijing, Guangdong, Hubei, Shandong, Sichuan, Jilin, and Gansu. According to the regional division in China, the selected provinces respectively represent Northern China (Beijing), Southern China (Guangdong), Central China (Hubei), Eastern China (Shandong), Southwest China (Sichuan), Northeast China (Jilin), and Northwest China (Gansu). Further, provinces of Guangdong, Sichuan, and Hubei belong to Southern China, while provinces of Beijing, Jilin, Shandong, and Gansu belong to Northern China. The analyses of the regional differences were based on this classification.

3.2. The EFP between urban and rural areas

The EFPs of urban areas were higher than those of rural areas, except for Guangdong and Beijing, which had higher PCDI values (Fig. 4, Fig. S2). We further found that the EFPs of urban and rural areas in southern China were higher than the urban and rural equivalences in northern China (both $p < 0.001$) (Fig. S3). In addition, we quantified animal-based and plant-based EFPs between urban and rural areas across seven provinces, and the results showed a higher animal-based EFP (except Guangdong) and a lower plant-based EFP (except Beijing) in urban areas than in rural areas (all $p < 0.05$). The findings also demonstrated that the animal-based EFP of Guangdong was the highest (all $p < 0.001$) and the plant-based EFP of Beijing was the lowest (all $p < 0.05$) (Fig. 5a, b).

3.3. The correlative factors of the dietary EFP

Correlations among EFP, animal-based EFP, plant-based EFP, PCID, FC quantity, year, urban/rural status, southern/northern areas, and provinces were explored. Given the great fluctuation in pork prices during the study period, we specifically included pork prices as a potential correlative factor.

Table 3
The annual average productivity and equivalence factor of different land types.

Items	Annual average productivity (kg/hm^2)	Equivalence factor	Land type
Beef and mutton	33	0.46	Grazing land
Pork	74	0.46	Grazing land
Poultry	200	0.46	Grazing land
Fish	44	0.37	Fishing grounds
Oil	1856	2.49	Arable land
Sugar	18,000	2.49	Arable land
Egg	400	0.46	Grazing land
Milk	502	0.46	Grazing land
Cereal	3077	2.49	Arable land
Vegetable	16,846	2.49	Arable land
Fruit	5709	2.49	Arable land

Note: The equivalence factor is the ratio of the biological productivity of a certain type of land to the average productivity of all productive land in the region.

The results showed that the total EFP was highly correlated with animal-based EFP ($p < 0.001$) but not with plant-based EFP ($p = 0.054$). Both total EFP ($p = 0.001$) and animal-based EFP ($p < 0.001$) were positively correlated with the PCDI, whereas plant-based EFP was negatively correlated with the PCDI ($p < 0.001$). Additionally, the total EFP and animal and plant-based EFP were positively correlated with FC quantity ($p < 0.001$). The total EFP and animal-based EFP were significantly correlated with geographical location. For instance, southern residents showed higher total EFP ($p < 0.001$) and animal-based EFP ($p < 0.001$) than northern residents. Urban residents showed higher total EFP ($p = 0.001$) and animal-based EFP ($p < 0.001$) than rural residents. Conversely, rural residents showed higher plant-based EFP than urban residents ($p < 0.001$). Pork price fluctuated strongly during the study period and was significantly correlated with FC quantity ($p = 0.001$). However, neither the total EFP ($p = 0.206$) nor the animal-based EFP ($p = 0.433$) showed significant correlations with the pork price (Fig. 6).

Based on the results of Fisher's r-to-z transformation and cocor, we found that the correlation coefficient of southern/northern areas and EFP (both total and animal-based) and the correlation coefficient of provinces and EFP were higher than the correlation coefficient of urban/rural status and EFP and the correlation coefficient of PCDI and EFP (all $p < 0.05$) (Fig. 6).

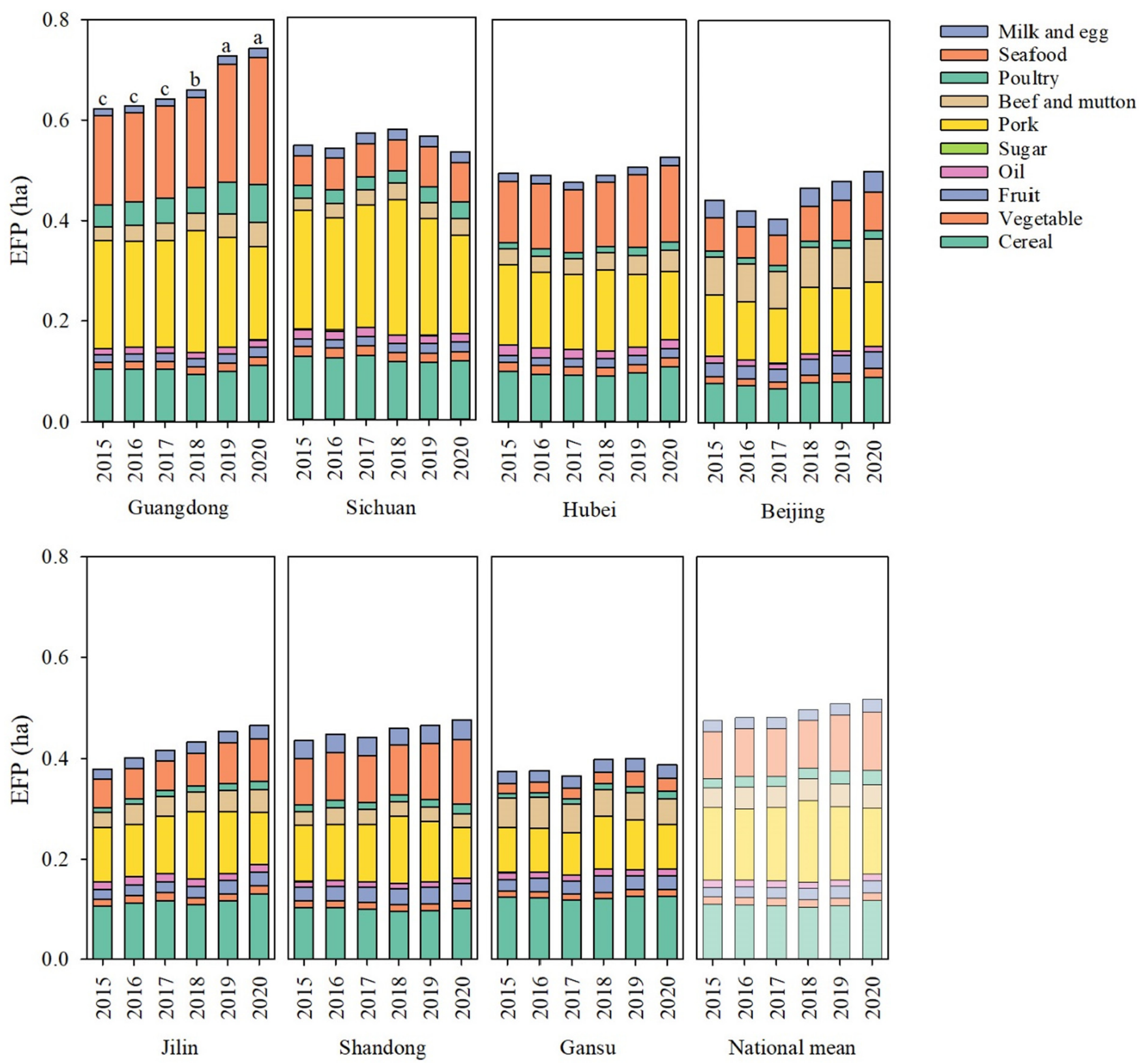

Fig. 2. The total EFP with ten food types across seven provinces during 2015–2020. The temporal differences in each province were tested using one-way ANOVA. Different letters indicate significance at the $p < 0.05$ level, while the same letters indicate no significant difference. The three letters "a-c" indicate significant differences of total EFP during 2015–2020 in Guangdong province. Note that no letters were shown if there were no significance in a given province. The national mean data (bars with 50 % transparency) were also included as a general reference.

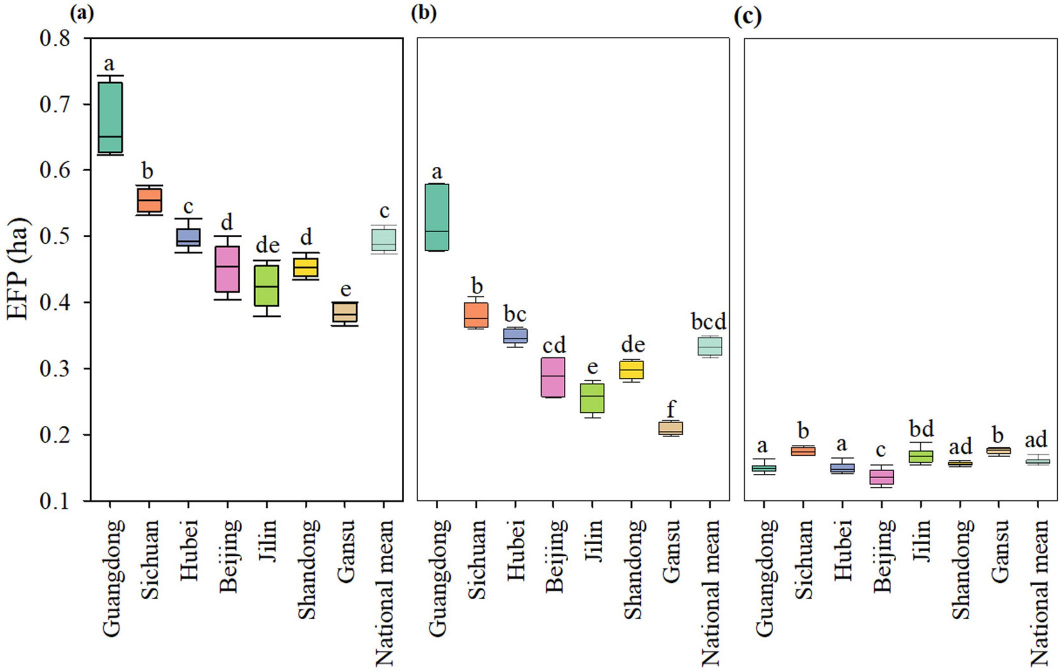

Fig. 3. The comparisons of the total EFP (a), animal-based EFP (b), and plant-based EFP (c) across seven provinces. The letters above bars correspond to the results from one-way ANOVA tests. Different letters indicate significance at the $p < 0.05$ level, while the same letters indicate no significant difference. The lowercases letters in each panel indicate significant differences of total EFP (a), animal-based (b) and plant-based EFP (c) across seven provinces at the p < 0.05 level.

4. Discussion

Dietary choices have a considerable impact on environmental sustainability (Okin, 2017). The dietary EFPs of both urban and rural residents were calculated in seven representative provinces of China (i.e., Beijing, Guangdong, Hubei, Shandong, Sichuan, Jilin, and Gansu) during 2015–2020. The southern-northern divide, urbanization, and increasing income dramatically altered the dietary patterns in contemporary China and consequently affected dietary EFP. For instance, southern and urban residents and those with higher PCDI showed higher total EFP and animal-based EFP than their counterparts did. Conversely, rural residents and those with a lower PCDI showed a higher plant-based EFP.

Our results, together with previous findings (He et al., 2018; Okin, 2017; Poore and Nemecek, 2018; Su et al., 2018; Tilman and Clark, 2014) demonstrate that dietary patterns could contribute directly and significantly to dietary EFP, and animal-based diets have greater environmental consequences in terms of land use than plant-based diets (Xu and Lan, 2016). This study highlights the dominant role of meat consumption, especially pork and seafood, in dietary patterns, suggesting that China has entered an era dominated by animal-based products. India, as another fast-developing country with the second-largest population, however, did not consume much meat, fish, or eggs (Green et al., 2018; Tak et al., 2019). This resulted in a relatively lower environmental footprint for Indian people than for Chinese people (Galli et al., 2012a; Gill et al., 2015). The dietary choice is a personal matter; however, owing to the increasing environmental concern, individuals are motivated to change their dietary patterns (Mao et al., 2016; Rose et al., 2019). Previous research has shown that the environmental impacts of the lowest-impact animal products typically exceed those of vegetable substitutes, providing new evidence for the importance of dietary change (Poore and Nemecek, 2018). A transition that eats less meat would therefore reduce the negative environmental impacts. According to the 2020 national FC consumption, replacing animal-based products with cereal has transformative potential, reducing EFP by 0.29 ha (a 55.8 % reduction), while replacing only pork meat with cereal could reduce EFP by 0.12 ha (a 22.1 % reduction). However, it is impossible to replace all animal products or pork meat with plant-based foods, especially given the nutritional requirements for human health. Hence, we recommend an alternative scenario that halves consumption of animal-based products by replacing them with cereal equivalents, which will reduce land use by 27.9 %.

Rising incomes and urbanization are driving a global dietary transition in which traditional diets are replaced by diets higher in refined fats and meats (Tilman and Clark, 2014). This trend is especially significant in developing countries like China (Xiong et al., 2022), Nigeria (Olabisi et al., 2021), India (Green et al., 2018), Indonesia (Colozza and Avendano, 2019), and Mexico (Lares-Michel et al., 2022). The gap between urban and rural areas, particularly the significant difference in the PCDI, is one of the most significant characteristics in contemporary China (Li et al., 2019; Su et al., 2018). This gap could directly influence household lifestyles, including food consumption patterns (Zhou et al., 2014). Accordingly, we found that urban and wealthy residents consumed more animal-based products, resulting in a higher EFP compared to rural and poor residents in China. This finding confirmed previous research conducted in Sub-Saharan Africa showing that diets diversified in source and form, and consequently the wealthy people tended to consume more animal-based products, resulting in a more serious environmental degradation (Steyn and Mchiza, 2014; Udemba, 2020). However, according to diminishing marginal utility (Easterlin, 2005), the consumption percentage of animal-based products may decrease with a significant increase in PCDI (Lee and Simpson, 2016). Hence, improving people's incomes, from a long-term perspective is an effective way to reduce dietary EFP. Notably, although the economic conditions (i.e., PCDI and urban/rural status) significantly influenced the animal-based EFP, they did not influence the EFPs of pork and poultry (Fig. S5). The prices of pork and poultry are lower than those of beef, mutton, and seafood. Therefore, rural and poor residents prefer to consume pork and poultry, resulting in a similar consumption quantity of pork and poultry between urban and rural residents and between wealthy and poor residents. Notably, we found that the EFP was similar between urban and rural areas in Guangdong and Beijing, which had a higher PCID, indicating that higher disposable income may narrow the urban-rural gap in die-induced environmental impacts. Nonetheless, future studies with more cases are warranted to confirm this hypothesis.

China is a vast country, and its ecological contexts, including climate conditions and resource endowments, are heterogeneous in different

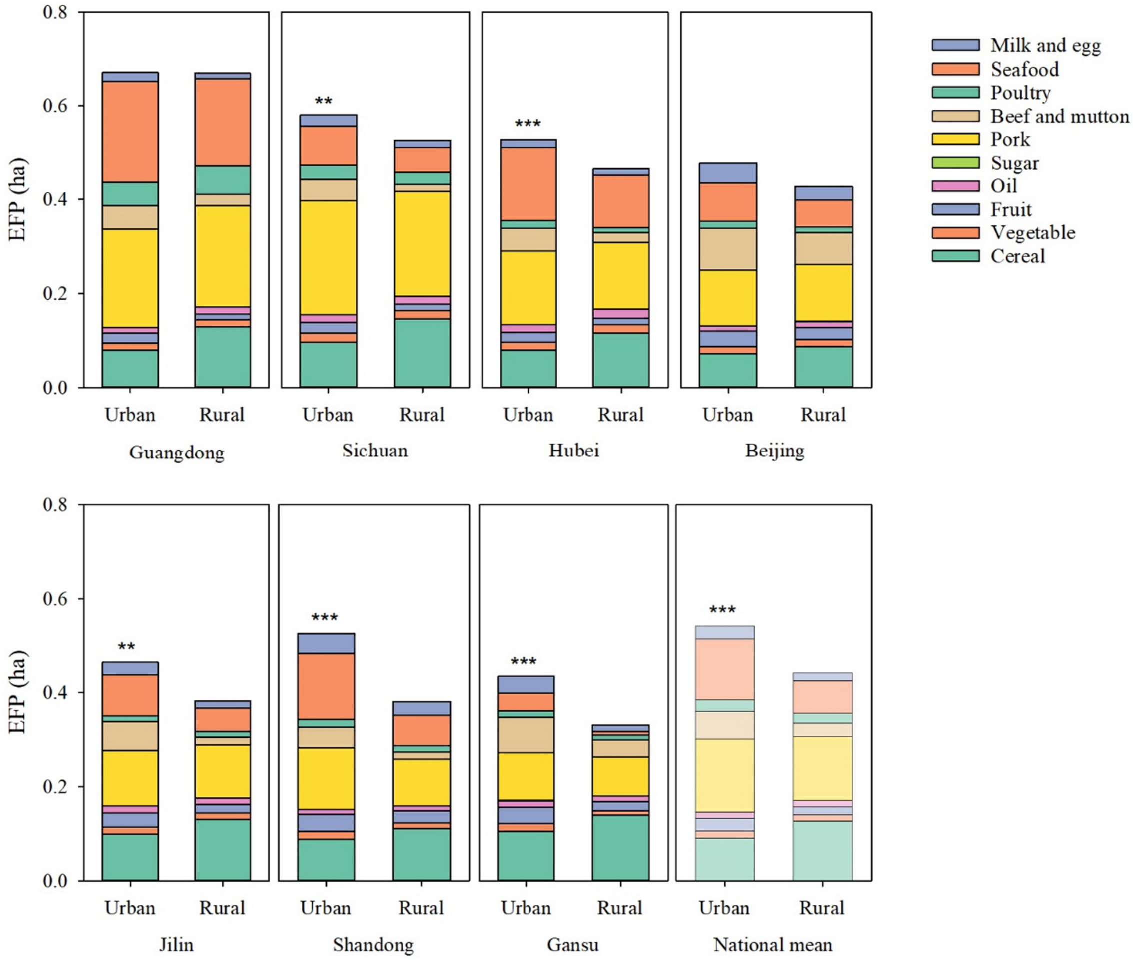

Fig. 4. The total EFP with ten food types between urban and rural areas in seven provinces and the national averages. The statistical differences of total EFP between urban and rural areas within each province and national mean were tested and the asterisks (*** < 0.001, ** < 0.01) indicate the significant difference of total EFP between urban and rural areas.

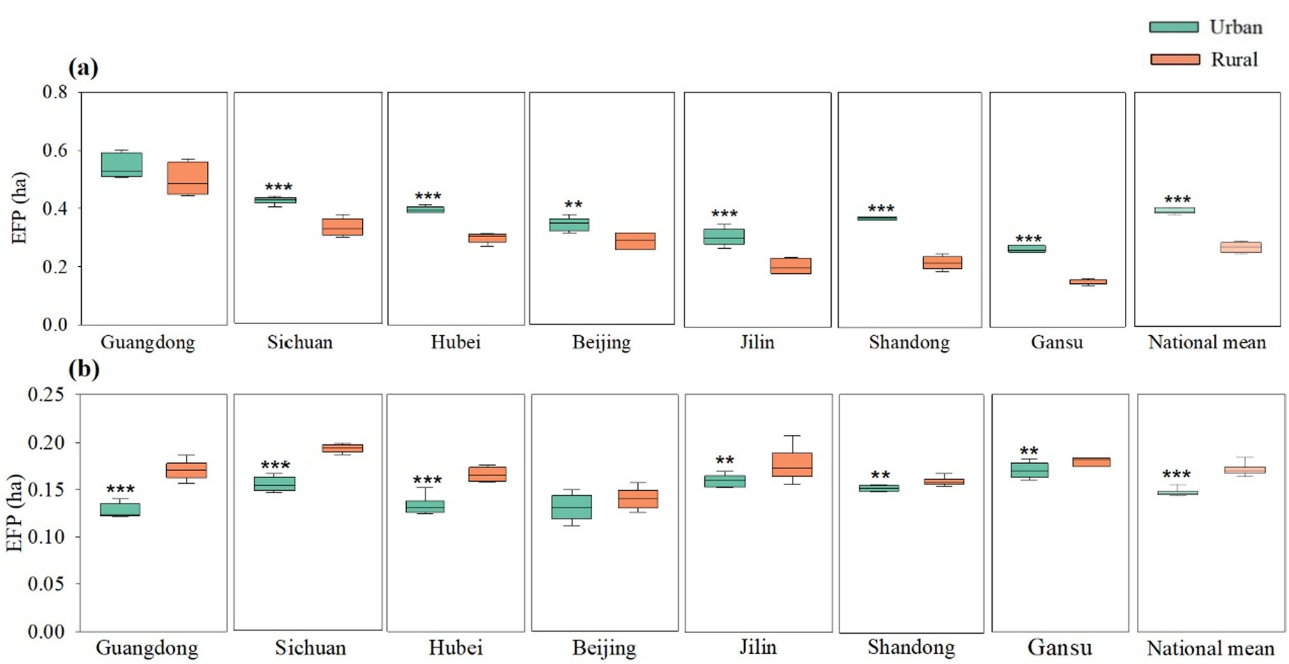

Fig. 5. The comparisons of animal-based EFP (a), and plant-based (b) EFP between urban and rural areas in seven provinces. The asterisks (*** < 0.001, ** < 0.01) indicate a significant difference of animal-based (a) and plant-based EFP (b) between urban and rural areas.

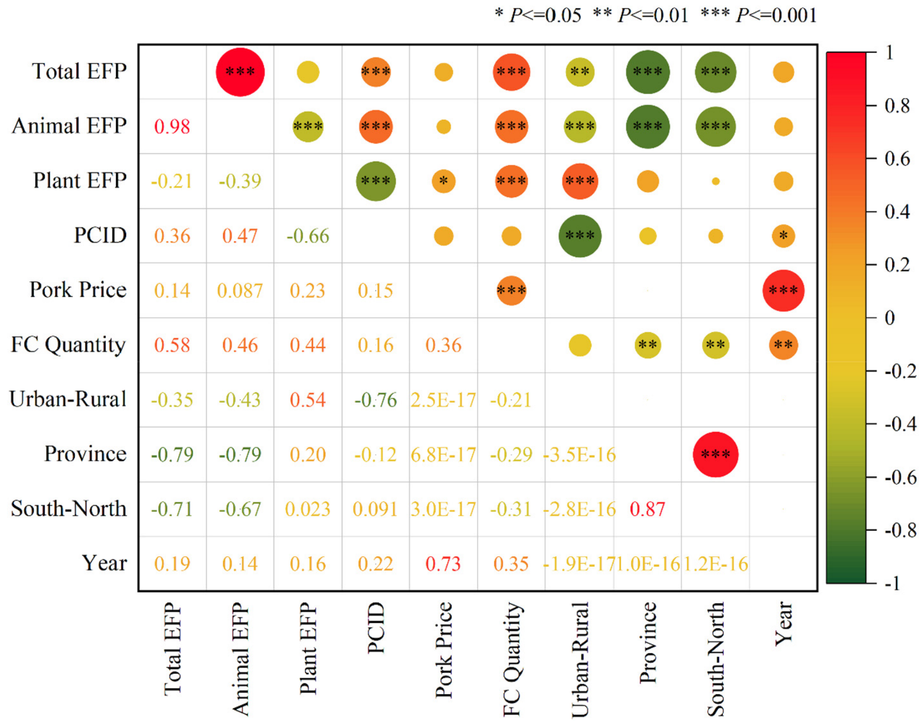

Fig. 6. The correlogram of the total EFP, animal-based EFP, plant-based EFP, PCID, pork price, FC quantity, urban-rural areas, provinces, south-north areas, and year. Positive correlation is displayed in red, while negative correlation is shown in green. At the lower left corner of the figure, the numbers represent the correlation coefficients, and color intensity of the numbers is directly linked to the magnitude of correlation coefficient as shown in the legend. At the upper right corner of the figure, the circles denote the correlation for two factors and the asterisks in the circles indicate the significant levels of the correlations. Color intensity and circle size are proportional to correlation coefficient. Thus, the larger of circles, the higher correlation coefficients between two given variables.

regions. These differences may result in a regional divergence in food culture and dietary patterns (Xiong et al., 2022). Our results confirmed that food consumption of animal-based products (especially pork and poultry) of the southern residents was higher than that of the northern residents (Mao et al., 2016; Yao and Zhang, 2001), which underlies the higher animal-based EFP and total EFP of the southern provinces than that of the northern provinces. Similar trends have been observed in India, for example, residents from southern and eastern states of India have more diverse diets and consequently a larger EFP than those from northern and western regions (Green et al., 2016; Tak et al., 2019). These findings also indicated the large regional heterogeneities in diets call for regionally differentiated strategies (Tak et al., 2019). Additionally, previous research has shown that urban/rural status and income are significantly correlated with dietary EFP in China (Gao et al., 2018; He et al., 2018; Xiong et al., 2022). Here, we found similar patterns in which urban/rural status and PCID were correlated with EFP, including both animal and plant-based EFP. This finding revealed that the economic conditions were still significantly correlated with the EFP, although China has undergone momentous changes in the past decade, for example, the booming economy and rapid urbanization. Moreover, we further demonstrated that the geographical locations (i.e., south/north areas and provinces) showed stronger correlations with the EFP and animal-based EFP than with economic conditions (i.e., urban/rural status and PCDI). This finding revealed that factors (e.g., differences in cultures, eating habits, and the composition of nationalities) that highly related to the south-north divide may impact EFP, and such impacts may be even stronger than economic indicators, such as the urban/rural status and PCID. It may also suggest that with the increasing PCDI, economic conditions will be less strongly correlated with the EFP than a decade ago. Therefore, the environmental outcome at the country level will be more likely to depend on the geographical structure characterized by factors that affect dietary composition, such as provinces and south/north areas.

China has the largest meat market worldwide, accounting for 46 % of the global pork production and 44.4 % of the global pork consumption (Cai et al., 2021; Zhang et al., 2018). This study demonstrated the dominant role of pork in correlating EFP and animal-based EFP in China. Pork prices[1] in China have experienced great volatility during the last few years. Therefore, we initially speculated that pork price fluctuations would influence dietary patterns and ultimately influence dietary EFP. We found that the continuous decline in pork prices from 2016 to 2018 stimulated pork consumption. When pork prices increased sharply in 2019 and 2020 (54.61 % and 134.98 % compared to 2018), pork consumption decreased markedly (10.99 % and 22.03 %, respectively, compared to 2018). Surprisingly, decreased pork consumption did not result in lower animal-based EFP. This is because the decline in pork consumption has been offset by other animal-based products, mainly poultry and seafood. This finding, on the other hand, revealed that the consumption of poultry and seafood was more likely to be influenced by pork price than the consumptions of beef and mutton. Furthermore, pork price fluctuations changed the EFPs of both urban and rural residents, yet the amplitude of the EFP changes in rural areas was much higher than that in urban areas. This illustrates that the impact of food price on the dietary EFP of urban residents is limited, and rural society is associated with a higher instability regarding price fluctuations and food consumption than urban society.

The present study compared the EFP and dietary patterns from different perspectives in contemporary China and demonstrated that the EFP was shaped by factors such as PCDI, FC quantity, urban/rural status, and geographical location (i.e., southern/northern areas, provinces). However, the proprietary nature and incredible variety of human food makes a thorough calculation impossible. Therefore, a household tracking survey is needed to obtain further information and fill the gaps in this research.

[1] The pork prices from 2015 to 2020 were 24.26, 28.67, 25.09, 21.90, 33.86, and 51.46 in China; Unit: Yuan/Kg; Data were from the National Statistical Yearbook

Additionally, this study highlighted the spatial perspective (i.e., southern and northern areas, provinces, and urban and rural areas) of food consumption. To make the results clearer and to reserve more orientation information, we only focused on the analysis of dietary EFP. Another interesting avenue for future research is integrating EFP analysis with other evaluation approaches (e.g., carbon footprint and water footprint) (He et al., 2018; Wang et al., 2020) to measure the environmental impacts of food consumption and maximize the environmental sustainability of China and the world.

5. Policy implications

Currently, the ideas of advocating healthy and resource-saving dietary patterns and reducing the environmental impacts of food production are partially reflected in the Food Safety Law, Consumer Protection Law, Law of Quality and Safety of Agricultural Products, and Animal Industry Act in China. For instance, the Consumer Protection Law clearly declared that "The State advocates civilized, healthy consumption patterns that conserve resources and protect the environment, and opposes waste" (Chapter 1, Article 5). We showed China has entered an era dominated by animal-based products, and diminishing the environmental impacts of rising meat consumption has always been the concern of policymakers (Godfray et al., 2018). Our results emphasize more-specific policy interventions to address the larger EFP of meat consumption. For example, we found that food price had a larger effect on the dietary patterns of rural residents than on those of urban residents. Therefore, food price regulation strategies may function better in rural areas to diminish the environmental impacts of food consumption, and governmental subsidies and preferential policies can be geared towards rural communities. Similar to previous findings (Godfray et al., 2018; He et al., 2018; He et al., 2021b), we also showed that increasing income promoted the consumption of meat. However, according to the diminishing marginal effect (Li et al., 2021), the environmental impacts of food consumption would decrease with increasing income from a long-term perspective. Therefore, promoting the national economic development, reducing the regional gap, and improving individuals' income may benefit future environmental outcomes. Furthermore, we demonstrated the dietary EFP in China had strong correlations with geographical locations. Therefore, more attention should be paid to the regional heterogeneities in both ecological conditions and dietary cultures, and the regional-specific dietary guidelines and policies should be put forward. It is unquestionable that cutting down the consumption of meat has a considerable impact on the decrease of dietary EFP. Considering the over-consumption of meat in contemporary China (He et al., 2018), enabling the Chinese Dietary Guidelines 2022 known to the public via awareness campaigns and education is vital to driving behavioral changes.

6. Conclusions

In this study, we quantified the dietary EFP across seven provinces of China, and analyzed the relationships between EFP and geographical locations as well as economic conditions. We found that both geographical locations and economic conditions were significantly correlated with the EFP, but the former contributed more to the EFP than the latter. These findings suggest that beside the economic conditions, further attention should be paid to the regional differences and the related eating habits when discussing the environmental footprint of food consumption. In light of the continually increasing income, diversity dietary cultures, and dietary transitions, the impacts on environmental resources would be severe. Hence, incentives focus on improving people's awareness of sustainable dietary patterns. The framework in this study provided novel insights for understanding the mechanisms of the relationship between dietary transition and environmental sustainability not only in China but also in other countries with rapid economic development and distinct southern-northern divide.

CRediT authorship contribution statement

Conceptualization: Bingtao Su; Methodology: Chao Zhang, Bingtao Su; Formal analysis: Bingtao Su; Data curation: Bingtao Su; Writing—original draft preparation: Bingtao Su; Writing—review and editing: Chao Zhang, Pim Martens and Xianqiang, Cao; Supervision: Pim Martens and Xianqiang Cao; All authors have read and agreed to the published version of the manuscript.

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Data availability

Data will be made available on request.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.scitotenv.2022.158289.

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