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A Study on the Relationship between Income Change and the Water Footprint of Food Consumption in Urban China

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Abstract: We use a threshold model to analyze the relationship between per capita income and the per capita water footprint of food consumption in the urban Guangdong Province of China, and further simulate the effect of changes in income distribution on the per capita water footprint of food consumption. The income growth of urban residents has a significant positive effect on the per capita water footprint of food consumption, where the effect varies by income stratum. The income elasticity of the per capita water footprint of food consumption for the total sample is 0.45, where the income elasticity of the low-income group (0.75) is greater than that of the high-income group (0.23), indicating that a change of income in the low-income group has a greater effect on water resources. The simulation results show that increasing the income of residents, especially that of the low-income group, significantly increases the water footprint due to food consumption for the whole society. At present, China is in a period of rapid economic growth and urbanization, comprising a period of profound change and sensitive response to the income level of urban and rural residents. Therefore, in order to reduce the effect of food consumption on the environment, sustainable food consumption management strategies should consider group differences. We should correctly guide all kinds of groups to carry out sustainable consumption, advocate healthy and reasonable diet models, reduce animal food consumption, avoid the excessive consumption of food, and strengthen the management of food waste.

Keywords: water footprint; food consumption; income change; urban residents; nonlinear relationship

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1. Introduction

Human society depends on water resources to survive, as water shortages compromise a sustainable societal development. In terms of water resource use, the agricultural sector (which is closely related to food supply) is the largest water consumption sector [1,2]. The water consumption due to agricultural production accounts for 91% of the total use of freshwater resources in the world [3]. Therefore, the sustainable use of water resources for food production has been widely considered. China is a country with limited water resources, having a per capita share of 2000 cubic meters—approximately 28% of the world average [4]. In recent years, with the development of China's urbanization and

the improvement of the income level of residents, the change in the income of urban residents has had a huge effect on food consumption, leading to an assignable influence on the demand for agricultural water resources [5–8].

Income growth can increase the quantity of consumed food, putting pressure on the sustainable use of water resources by stimulating the food supply [9–11]. On the other hand, income growth can lead to significant changes in dietary patterns, with the proportion of cereal food consumption declining and the proportion of animal food consumption increasing [12,13]. As the water requirements for animal food production are generally higher than those for plant food, the changes in dietary structure caused by income growth may increase the water requirements for future food production [14–17]. In this paper, we use urban household data to empirically analyze the relationship between water requirements for food consumption and income using the water footprint tool, paying specific attention to the effect of changes in income distribution on the water footprint of food consumption, which is used to formulate policies based on sustainable food consumption patterns to strengthen the sustainable management of water resources in China. First, because the agricultural sector, which is closely related to food supply, is the largest sector in terms of water use in China, the water footprint of food consumption is directly related to the supply security of China's freshwater resources. Second, the income level of the population has greatly increased with the development of urbanization in China, thus promoting the expansion and transformation of the food consumption of urban residents, putting more pressure on the sustainable use of water resources in the future.

To achieve this study's objective, two goals were set: The first was to estimate the response of the per capita water footprint of food consumption to per capita income changes across income strata by calculating income elasticities. More specifically, in addition to total sample estimation and non-parametric estimation, we use a threshold model to scientifically classify the urban household data into low- and high-income strata, based on the characteristics of the data themselves, and then estimate the effect of household per capita income on the per capita water footprint of food consumption in different income strata. The second objective was to predict the change in the per capita water footprint of food consumption under the assumption of changes in income and income distribution by using the estimation results of income elasticity.

Hoekstra (2002) proposed the concept of the water footprint, expanding the research perspective of water resources to the consumer field [18]. Scientifically using the water footprint tool can help to understand the complex relationships between human activities and water resources [19–21]. The water footprint has been widely applied to the study of water requirements for food consumption, profoundly affecting the evaluation and management of water resources [22–25]. The water footprint of food consumption is defined as the freshwater resources necessary for humans to maintain a certain level of food consumption over a certain period, which is used to measure the effect of human food consumption on water resources [26].

Some studies have been devoted to analyzing the effect of economic and social factors on the water footprint of food consumption [27–29]. At the global scale, Yang and Cui (2014) analyzed the effects of population, diet, and agricultural practices on the water footprint of food consumption [30]. Many studies have also analyzed the factors affecting the water footprint of food consumption in China [8,31–36]. At the national level, Liu and Savenije (2016) used Chinese food consumption data provided by the Food and Agriculture Organization (FAO) of the United Nations in order to study the effect of food consumption patterns on the water footprint in China. The results of the study indicated that the increase in per capita water requirements for food in China is largely due to an increase in the consumption of animal products [5]. Zhao and Chen (2014) used Chinese food consumption data provided by the FAO to analyze the effects of diet structure, water use efficiency, economic activity, and population factors on the water footprint of agricultural products, and believe that economic activities had a relatively significant positive effect [37]. At the urban level, Kang et al. (2017) used the Xiamen Statistical Yearbook data

to analyze the effects of population, the structure and level of food consumption, water intensity, and the population rate on the water footprint of food consumption in Xiamen [38]. Their results showed that population factors are the leading contributors to changes in the water footprint. From the perspective of previous studies, population, diet structure, income level, and urbanization are the main driving factors of changes in the water footprint of food consumption [39]. However, most of those studies used macro data—that is, at the national or city level—to analyze the factors affecting the water footprint of food consumption, while studies using micro household data are relatively rare. Similarly, some studies have focused on the issue of crop and livestock productivity [40–46]; however, they ignored the nexus of income change and water footprint of food consumption.

The relationship between income and the water footprint is an important aspect of the sustainable management of water resources. In terms of research in developed countries, Feng et al. (2011) studied the relationship between income level and the water footprint of residents in different regions of the U.K. and found a linear relationship between them [47]. Longo and York (2009) found that developed countries with higher per capita income had a relatively higher water footprint of food consumption [48]. Similarly, Ivanova believed that the consumptive water footprint was unevenly distributed across regions and found that the per capita water footprint was the greatest in rich countries [49]. In terms of research in China, many studies have found regional differences in the effect of income on the water footprint of food consumption [6,50]. Huang et al. (2012) studied the effect of local grain consumption on the water resources in Beijing and found that income growth significantly increased the water footprint of food consumption and increased the pressure on water resources [51]; however, only a few previous studies have focused on the effect of income changes on the water footprint of food consumption in different income groups. Research on the effect of income distribution on the water footprint of food consumption is also relatively limited. Therefore, it is necessary to study the effect of the income changes of different income groups on the water footprint of food consumption, thus providing a reference for a more effective guidance of water resource management.

2. Data and Methods

2.1. Water Footprint Calculation

The food consumption data obtained from the Urban Household Survey from the National Bureau of Statistics of China (NBSC) that were used in this study included food consumption, expenditure at home, and food expenditure away from home. The process employed to determine the water footprint of food consumption was as follows:

First, the food groups consumed at home consisted of nine broad food categories: cereals, oils and fats, meats, poultry, eggs, aquatic products, dairy products, vegetables, and fruits. The total water footprint derived from the nine food groups is computed by multiplying the quantity of each food item consumed and the corresponding water footprint values. The water footprint of the nine foods consumed at home (*IWF*) is set as:

$$IWF = \sum_{i}^{9} Q_i \times WF_i \quad (1)$$

where Q_i is the quantity of consumed food i for households, i = 1,…,9 (in kg), and WF_i denotes the water footprint value of food i (in m^3/kg). The water footprint values for food come mainly from Mekonnen and Hoekstra's estimation of the water footprint of China's agricultural product [3,14].

Second, the ratio of the water footprint of the nine types of food to the nine types of food expenditure is expressed as $R = IWF/E_1$, where E_1 denotes the food expenditure of the nine food groups consumed at home. This ratio was applied to compute the water footprint of other food items (*OWF*), including food away from home and other food items that did not have quantity data. Based on the method of Zheng and Hennerberry (2012),

it was assumed that 50% of the food expenditure away from home is spent on food consumption [52]. Then, the water footprint of the out of home diet and other home food consumption not included in the nine food groups are expressed as $OWF = (E_2 + E_3 \times 50\%) \times R$, where E_2 denotes other food consumption expenditure at home (i.e., not included in the nine food groups) and E_3 denotes the food expenditure away from home.

Finally, the total water footprint (*TWF*) of food consumption for households is expressed as $TWF = IWF + OWF$. The per capita water footprint (*PWF*) of food consumption is expressed as $PWF = TWF/N$, where N denotes the number of household members.

2.2. Data Sources and Description

The data set used for this study was collected by the NBSC in Guangdong Province in 2009. The NBSC conducts a nationwide urban household survey annually. As an official statistical activity, the urban household survey collects extensive socioeconomic information on income, consumption, demographics, education, and asset ownership. The survey data are compiled from diaries of incomes and expenditures kept by the participating households over the course of a 12-month period. Thus, the data set used for this study reflects the actual consumption patterns of the surveyed urban households during an entire year [6,13,52–54]. After excluding the outliers of the per capita food consumption water footprint (i.e., those greater than five times the standard deviation), 2474 valid household samples were obtained.

Guangdong plays important roles in coastal economic growth and has the highest gross domestic product of any Chinese province, accounting for more than 11% of China's national GDP. The urbanization rate of Guangdong Province was 63.40% in 2009, ranking first among all provinces in China. With the acceleration of urbanization, similar to the overall situation of Chinese cities, the household income level of Guangdong has notably changed. Hence, an understanding of the effect of the changes in income on the water footprint of food consumption in urban Guangdong is expected to be useful to policymakers interested in China's agricultural water resource management.

According to the geographical location and the division of the Guangdong Provincial Bureau of Statistics, we divided Guangdong Province into four regions: Pearl River Delta, eastern Guangdong, western Guangdong, and northern Guangdong. Compared with the other regions, the residents living in the Pearl River Delta had a higher per capita income and a higher per capita water footprint of food consumption (Table 1).

Table 1. Per capita income and per capita water footprint of food consumption by different cities, urban Guangdong province, China, 2009.

Region and city	Per capita income (yuan)	Per capita water footprint of food consumption (m^3)	Number of observations
Pearl River Delta	21,913	1060	1580
Guangzhou	25,506	1098	221
Shenzhen	26,643	1028	476
Zhuhai	21,571	1067	153
Zhaoqing	14,843	1006	84
Huizhou	20,760	1088	148
Foshan	23,420	1070	236
Jiangmen	14,016	1038	85

Dongguan	28,543	1089	177
Eastern Guangdong	11,470	1015	239
Jieyang	10,018	948	85
Shantou	12,923	1081	154
Northern Guangdong	12,330	970	416
Shaoguan	14,122	1021	175
Meizhou	12,193	1042	201
Qingyuan	10,674	845	40
Western Guangdong	12,606	923	239
Zhanjiang	13,379	936	201
Maoming	11,833	909	38
Total observations	19,822	1037	2474

Notes: The data come from the urban household data of Guangdong Province in 2009.

In order to observe the changes in the per capita water footprint of food consumption of different income groups, the observations were divided into five equal parts, according to the per capita income. The per capita water footprint of food consumption increased with an increase in income level, but increased at a decreasing rate (Table 2).

Table 2. Per capita income and per capita water footprint of food consumption by income groups, urban Guangdong province, China, 2009.

Income group	**Per capita Income (yuan)**	**Per capita water footprint of food consumption (m^3)**	**Number of observations**
Low-income group	684	674	495
Middle- to low-income group	11,614	941	495
Middle-income group	16,875	1090	495
Middle- to high-income group	23,633	1208	495
High-income group	40,188	1274	494
Total observations	19,822	1037	2474

Note: The data come from the urban household data of Guangdong Province in 2009.

2.3. Methods

2.3.1. The Total Sample Model

Based on the consumption function theory, food consumption can be considered a function of some economic and social characteristics of the household [52–54]. As the water footprint of food consumption is obtained by multiplying the quantity of consumed food by the water footprint conversion coefficient, the per capita water footprint can be expressed as a function of some of the economic and social characteristics of the household. Income is an important economic factor affecting the per capita water footprint of

food consumption. Per capita income growth can increase the quantity of consumed food, thus increasing the per capita water footprint of food consumption, indicating that there may be a positive relationship between the per capita water footprint of food consumption and per capita income. Second, income growth may lead to a shift in dietary structure toward animal food sources [55].

Due to the relatively higher water footprint of animal products, when the proportion of animal food consumption in the diet structure gradually increases, the water footprint of food consumption may increase. However, the awareness of healthy eating on the part of the residents continues to increase with increasing income, which may lead to a change in dietary structure toward healthy cereals. In this case, there is not necessarily a significant positive correlation between per capita income and the per capita water footprint of food consumption. To further test the relationship between per capita income and the per capita water footprint of food consumption, the following research hypothesis was proposed: There exists a non-linear relationship between per capita income and the per capita water footprint of food consumption.

According to the above analysis on the relationship between per capita income and the per capita water footprint of food consumption, the model was finally set as:

$$\ln PWF = \alpha_0 + \alpha_1 \ln I + \alpha_2 (\ln I)^2 + \alpha_3^{'} Z + \mu \quad (2)$$

where *PWF* is the per capita water footprint of food consumption for household, *I* is the household per capita disposable income, and *Z* is a matrix composed of other family social characteristics, including household size, average age of the household members, average education level, household registration, the proportion of household food expenditure away from home (FAFH), city size, and regional variables; α_0, α_1, and α_2 are unknown parameters; $\alpha_3^{'}$ is an unknown parameter matrix; and μ is the random error.

Table 3 reports summary statistics related to the sample households in urban Guangdong Province. The household per capita water footprint of food consumption is the explained variable, and its mean was 1038 m^3 in urban Guangdong.

Table 3. Summary statistics, urban Guangdong province, China, 2009.

Variables	Mean	Std. dev.	Minimum	Maximum
Per capita water footprint of food consumption (m^3)	1040	420	141	3086
Per capita disposable income (yuan)	19,800	13,300	1397	137,134
Household size	3.27	0.94	1	8
Average age (year)	37	11	15.5	83.5
Average education level	3	1	0.5	7
Ratio of FAFH expenditure	0.19	0.17	0	0.933
Census register (1 = locality, 0 = other)	0.91	0.28	0	1
City size (1 = living in a small city, 0 = other)	0.09	0.28	0	1
Pearl River Delta (1 = yes, 0 = other)	0.64	0.48	0	1
Eastern Guangdong (1 = yes, 0 = other)	0.1	0.3	0	1
Northern Guangdong (1 = yes, 0 = other)	0.17	0.37	0	1
Western Guangdong (1 = yes, 0 = other; reference)	0.1	0.3	0	1
Number of observations	2474			

Note: 1. The education level of family members is a categorical count variable, which was set to 8 categories: 0 = illiterate, 1 = primary school, 2 = junior high school, 3 = senior high school, 4 = vocational and technical school, 5 = junior college, 6 = undergraduate, and 7 = graduate.

Household per capita disposable income is the core explanatory variable. The mean per capita income of the sample households in urban Guangdong was 19,822 yuan. Controlling other economic and social factors is crucial in the estimation of the model. The number and structural characteristics of household members are closely related to the level of food consumption, which affects the per capita water footprint of food consumption. Therefore, household size and the average age of household members were added to the model, with averages of 3.27 and 37, respectively. The level of education may be

closely related to the kind of food that people choose to consume, thus affecting the per capita water footprint of food consumption. Therefore, the model incorporated the average level of education for household members. The education level of each member is a categorical count variable, which was set to eight categories, according to the level of education, where the average education level of household members was 3. We used the proportion of FAFH to reflect the effect of eating out on the water footprint of food consumption, with an average of 19%. To control the influence of registered residence differences, whether the head of a household had the virtual variables of local household registration was added. The statistical results showed that the proportion of households with local household registration was 91.1%. As the level of urbanization affects the convenience of food purchase, whether the family lives in a small city was added to the model as a control variable. Small cities are defined as cities with less than half a million permanent residents. The statistical results showed that 8.9% of the sample households lived in small cities. The number of observations in the Pearl River Delta was relatively large, accounting for 63.9% of the total observations.

2.3.2. Threshold Model

To accurately analyze the possible non-linear relationship between the water footprint of food consumption and income, and to estimate the extent of the effect of income on the food consumption water footprint in different income groups, the threshold model was used to scientifically group the samples. Differently from the subjective set critical point, the threshold model is characterized by the endogenous determination of structural abrupt points by non-linear methods, which not only can estimate the threshold value but also statistically test the significance of the threshold [48]. Therefore, the threshold model can determine the demarcation points in a more objective way in the measurement method, such that the bias caused by the subjective demarcation point can be effectively alleviated. The threshold model was set as follows:

$$\begin{cases} \ln PWF = \beta_0 + \beta_1 \ln I + \beta_2 (\ln I)^2 + \beta_3' Z + \varepsilon, I \le \gamma \\ \ln PWF = \theta_0 + \theta_1 \ln I + \theta_2 (\ln I)^2 + \theta_3' Z + \mu, I > \gamma \end{cases} \quad (3)$$

where the per capita income I is the threshold variable, γ is the threshold value, $\beta_0, \beta_1, \beta_2$ and $\theta_0, \theta_1, \theta_2$ are unknown parameters, β_3' and θ_3' are unknown matrices, and ε、μ are random errors.

After the optimal threshold was determined, two hypothesis tests were carried out. One determined whether the threshold effect existed, and the second assessed whether the threshold estimate was equal to the actual value. The purpose of the first hypothesis test was to test whether the model estimation parameters of the two sets of samples divided by the threshold significantly differed. Therefore, the null hypothesis was H_0: $\beta_i = \theta_i$, while the alternative hypothesis was H_1: $\beta_i \neq \theta_i$. The Lagrange Multiplier (*LM*) statistic was constructed as:

$$F = \frac{S_0 - S_1(\gamma)}{\hat{\sigma}^2} \quad (4)$$

where S_0 and S_1 are the sum of squared residuals under the null hypothesis and alternative hypothesis, respectively. Under the null hypothesis, the threshold value γ was not recognized, and the distribution of the F statistic was a "non-standard and non-similar distribution", which led to the critical value of the distribution not being obtained in an analog manner. Hansen obtained a gradual distribution of statistics through the bootstrap method and constructed a progressively effective probability value (p-value) [56].

After the threshold effect was determined, the confidence interval of the threshold was further determined. We tested the null hypothesis (H_0: $\gamma = \hat{\gamma}$) using likelihood ratio (LR) statistics:

$$LR_1(\gamma) = \frac{S_1(\gamma) - S_1(\hat{\gamma})}{\hat{\sigma}^2} \quad (5)$$

The distribution of $LR_1(\gamma)$ was non-standard. Hansen has provided a simple formula to calculate its non-rejection domain [56]. The principle is that, when the significance level is α and $LR_1(\gamma) \le c(\alpha) = -2\ln(1-\sqrt{1-\alpha})$, the null hypothesis cannot be rejected. $c(\alpha)$ = 7.35 at the 95% confidence level.

2.3.3. The Projection Model

The income elasticity of the per capita food consumption water footprint represents the percentage of the per capita food consumption water footprint change caused by a 1% per capita income change. The second goal of this study is to use the calculated income elasticities from Equation (3) to project the water footprint of food consumption resulting from hypothetical changes in incomes and income distribution. Changes in the water footprints due to food consumption are virtually assumed to be brought about only by changes in income and income distribution. As a result, the change in the water footprint of food consumption in income stratum n due to income changes in that stratum is given by

$$\Delta PWF_n = (\Delta y / y)_n \times e_n \times PWF_n^0 \quad (6)$$

where $\triangle PWF_n$ denotes the change in the per capita water footprint of food consumption for households in stratum n due to changes in incomes in that stratum, $(\triangle y/y)_n$ is the rate of change in income in stratum n, e_n is the per capita income elasticity of per capita water footprint in stratum n, and PWF_n^0 is the current average quantity of the per capita water footprint of food consumption for each household in stratum n.

3. Results

3.1. Total Sample Estimation

In order to judge whether to add the square term of per capita income into the model, we first estimated the model for the total sample with and without the income squared term based on Equation (2); the parameter estimates are reported in Table 4. Comparing the estimation results of Models 1 and 2, we found that the income squared term of Model 2 was estimated to be significant, indicating that the regression model of the total sample should be added to the income squared term, which also suggests that the relationship between income and the per capita water footprint of food consumption was non-linear, and hence consistent with the research hypothesis. There is no significant difference in the size and significance of the estimated control variable coefficients in Models 1 and 2, indicating that the model estimation was robust. Therefore, according to the estimation coefficient of Model 2, the income elasticity of the per capita water footprint of food consumption was calculated, in order to observe the effect of income change on the per capita water footprint of food consumption. According to the estimated control variable coefficient, the relationship between the per capita water footprint of food consumption and the control variables was analyzed.

Table 4. Parameter estimates of the total sample, urban Guangdong province, China, 2009.

Variables	Total Sample	
	Model 1 [a]	**Model 2**
Ln(Per capita disposable income)	0.49 *** [b]	3.11 ***
	(0.01)	(0.20)
Ln(Per capita disposable income)^2		−0.14 ***
		(0.01)
Household size	−0.07 ***	−0.08 ***
	(0.01)	(0.01)
Average age	0.003 ***	0.003 ***
	(0.00)	(0.00)
Average education level	−0.02 **	−0.02 *
	(0.01)	(0.01)
Ratio of FAFH expenditure	−0.45 ***	−0.38 ***
	(0.05)	(0.05)
Census register	0.12 ***	0.11 ***
	(0.02)	(0.02)
City size	0.02	−0.00
	(0.02)	(0.02)
Pearl River Delta	−0.08 ***	−0.08 ***
	(0.02)	(0.02)
Eastern Guangdong	0.10 **	0.10 ***
	(0.03)	(0.03)
Northern Guangdong	0.07 *	0.06 *
	(0.03)	(0.03)
Intercept	2.34 ***	−10.12 ***
	(0.14)	(0.96)
Observations	2 474	2 474
Adjusted R-squared	0.450	0.486

Notes: Estimated using the 2009 China's National Bureau of Statistics urban household survey data for Guangdong province. [a] Model 2 contains the square of per capita income, while Model 1 does not. Single, double, and triple asterisks (*, **, ***) denote statistical significance at the 10%, 5%, and 1% levels, respectively. The number in brackets is the standard error.

The income elasticity was 0.45, and the significance level was 1%, indicating that income had a significant positive effect on the per capita water footprint of food consumption for all sample households. Meanwhile, the income elasticity results indicated that, when the per capita income increases by 1%, the household per capita water footprint of food consumption will increase by 0.45%.

Household size had a significant negative effect on the per capita water footprint of food consumption. The possible reason for this is that there is an economy of scale in the water footprint of food consumption for the household; that is, as the number of household members increases, the shared consumption pattern among household members may cause the per capita water footprint of food consumption to decline. Further, there existed a significant positive relationship between the average age of household members and the per capita water footprint of food consumption. The level of education had a significant negative effect on the per capita water footprint . Census registers had a positive effect on the per capita water footprint of food consumption, indicating that the per capita water footprint of food consumption for households with locality census registers was higher than that of households with non-local census registers. The proportion of FAFH had a significant negative effect on the per capita water footprint of food consumption. In

addition, three regional variables were estimated to be significant, indicating regional differences in the per capita water footprint of food consumption.

3.2. Threshold Estimation

3.2.1. Non-Parametric Estimation

To visually observe the relationship between the per capita water footprint of food consumption and per capita income, we used locally weighted scatterplot smoothing to estimate the relationship between them (Figure 1). The non-parametric estimation curve showed that the per capita water footprint of food consumption increased at a higher rate with the increase in per capita income at the beginning; however, this upward trend became slower after a certain threshold. There was a non-linear relationship between the per capita water footprint of food consumption and per capita income, consistent with the estimation results of the overall sample.

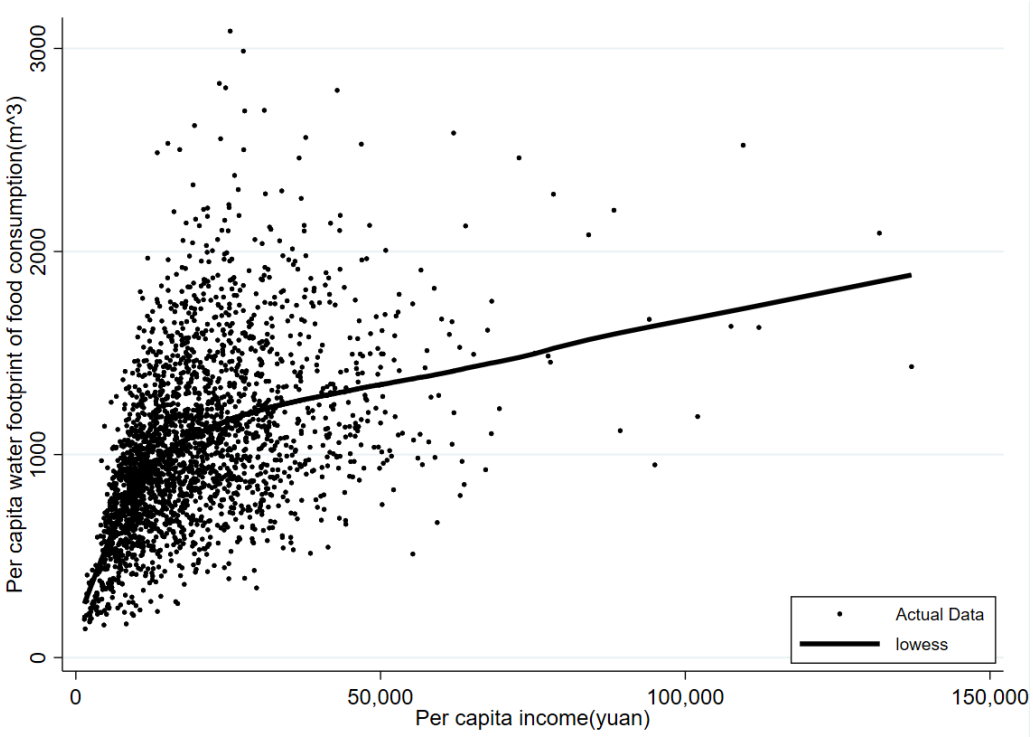

Figure 1. per capita water footprint of food consumption vs. per capita income.

Although non-parametric estimates could identify the non-linear relationship between the water footprint and income, they failed to account for the effects of control variables and did not estimate the extent to which income levels affect the water footprint of different income groups. Therefore, it is necessary to use threshold regression to estimate the effect of per capita income on the water footprint of different income groups, and then to obtain the income elasticity by income stratum.

3.2.2. Determination of the Optimal Threshold

Table 5 reports the test results of the threshold effect. Per capita income was chosen as the threshold variable. First, the first round of threshold selection was made using Equation (3). The test results indicated that the optimal threshold value of income was 15,054 yuan, the *LM* statistic level of the threshold was 1%, and the 95% confidence interval was (13,950, 16,093). Second, the next round of the threshold effect test was performed for samples smaller than the threshold value and samples larger than the threshold value. The test results showed that the threshold effect was not significant at all and, so, the two sub-samples were not further segmented. The above test results showed that there was a

significant threshold relationship between the per capita water footprint of food consumption and per capita income in the overall sample.

Table 5. Test results of the threshold effect.

Variable	Threshold value of income (yuan)	*LM* statistics	95% confidence interval
Water footprint of food consumption	15,054	186 ***	(13,950, 16,093)

Notes: Three asterisks (***) denote statistical significance at the 1% level.

The estimated threshold value of per capita income for the per capita water footprint of food consumption was close to the average disposable income of urban residents in Zhaoqing city (15,063 yuan) and Shaoguan city (16,288.7 yuan) in 2009; slightly higher than the average disposable income of the middle-lower households of urban residents in Guangdong (14,127.5 yuan) [57]. Therefore, the estimated threshold value of income had a high degree of credibility. Next, based on the estimated threshold value of per capita income, the data sample was scientifically divided into a low-income group (i.e., below the threshold) and high-income group (i.e., above the threshold), and the income elasticity was then estimated by income stratum.

3.2.3. Effects of Income on the Per Capita Water Footprint of Food Consumption for Different Income Strata

After determining the optimal threshold value of income, the model estimates of the low- and high-income groups were constructed, by adding or not adding the income square term, respectively. The results are reported in Table 6. The income squared items in Models 4 and 6 were not significantly estimated, indicating that the regression models for the low- and high-income groups should not include the income squared term. Therefore, the estimation results of Models 3 and 5 were analyzed.

Table 6. Parameter estimates of different income groups, urban Guangdong province, China, 2009.

Variables	Low-Income Stratum		High-Income Stratum	
	Model 3 [a]	Model 4	Model 5	Model 6
Ln(Per capita disposable income)	0.75 *** [b]	2.02 **	0.23 ***	1.32
	(0.03)	(0.67)	(0.03)	(0.86)
Ln(Per capita disposable income)^2		−0.07		−0.05
		(0.04)		(0.04)
Household size	−0.02 *	−0.03 *	−0.14 ***	−0.14 ***
	(0.01)	(0.01)	(0.01)	(0.01)
Average age	0.004 ***	0.004 ***	0.001	0.001
	(0.00)	(0.00)	(0.00)	(0.00)
Average education level	−0.04 **	−0.04 **	−0.01	−0.01
	(0.01)	(0.01)	(0.01)	(0.01)
Ratio of FAFH expenditure	−0.43 ***	−0.41 ***	−0.34 ***	−0.34 ***
	(0.08)	(0.08)	(0.06)	(0.06)
Census register	0.15 ***	0.15 ***	0.11 ***	0.11 ***
	(0.04)	(0.04)	(0.03)	(0.03)
City size	−0.04	-0.04	0.01	0.01
	(0.06)	(0.06)	(0.02)	(0.02)
Pearl River Delta	−0.10 ***	−0.09 **	−0.02	−0.02
	(0.03)	(0.03)	(0.04)	(0.04)
Eastern Guangdong	0.04	0.04	0.26 ***	0.26 ***
	(0.03)	(0.03)	(0.05)	(0.05)

Northern Guangdong	0.04	0.04	0.09 *	0.09 *
	(0.03)	(0.03)	(0.05)	(0.05)
Intercept	−0.26	−5.83 *	5.04 ***	−0.56
	(0.24)	(2.93)	(0.26)	(4.42)
Observations	1 069	1 069	1 405	1 405
Adjusted R-squared	0.484	0.486	0.249	0.250

Notes: Estimated using the 2009 China's National Bureau of Statistics urban household survey data for Guangdong province. [a] Models 4 and 6 contain the square of per capita income, while Models 3 and 5 do not. [b] Single, double, and triple asterisks (*, **, ***) denote statistical significance at the 10%, 5%, and 1% levels, respectively. The number in brackets is the standard error.

The most important finding was that the effect of per capita income on the per capita water footprint of food consumption varied by income stratum. When the household per capita income was below the threshold value of 15,054.32 yuan, the income elasticity of the per capita water footprint of food consumption was 0.75 and the significance level was 1%. However, when the household per capita income crossed the income threshold value, the income elasticity was converted to 0.23 and the significance level was 1%. The above analysis showed that, as per capita income increases, the positive effect of income on the per capita water footprint of food consumption becomes weaker. In other words, the effect of income on the per capita water footprint of food consumption varied according to the income level, which was consistent with the research hypothesis. The income elasticity of the per capita water footprint of food consumption for the low-income group was larger than that for the high-income group, indicating that, when the income increased by the same proportion, the per capita water footprint of food consumption for the low-income group increased more.

It is worth noting that there were some differences in the effects of control variables on low- and high-income groups. First, household size had a significant negative effect on the per capita water footprint of low- and high-income groups, but had a relatively larger effect on the high-income groups. Second, the average age and average education level had a significant effect on the per capita water footprint of the low-income group, while their estimates were not significant in the high-income group. In addition, the census register variable had a significant positive effect on the per capita water footprint of the low- and high-income groups, where the effects were basically the same. The proportion of FAFH had a negative effect on the water footprint of both the low- and high-income groups.

3.3. Projection Results

In order to simulate the effect of changing incomes and income distribution on the per capita water footprint of food consumption, four scenarios were considered. Each scenario involved hypothetically changing incomes and income distribution patterns from existing levels and estimating the effects on the per capita water footprint of food consumption. For comparison, it was assumed that the per capita income of each household increased by 10%. During 2009–2020, the income of urban residents in China has increased from 18,858 yuan to 43,834 yuan, with an average annual growth rate of 12% [58]. In the same period, the per capita income of urban residents in Guangdong Province has increased from 23,897.8 yuan to 50,257 yuan, with an average annual growth rate of 10% [57]. Therefore, setting a 10% income change can reflect the annual growth rate of per capita income of urban residents. A 10% change in the per capita income of each household in the total sample translates into a change of 47.73% and 12.65% for low- and high-income strata, respectively.

We can provide a more specific distribution of income under the four simulation scenarios: Scenario A involves the per capita income of all sample households increasing by 10%. Scenario A involves increasing the per capita incomes of both income strata at the

same rate, while keeping the current population income distribution pattern constant. Scenario B involves the per capita income of households in low-income stratum alone increasing by 47.73%. Scenario C involves the per capita income of families in high-income stratum alone increasing by 12.65%. Scenarios B and C involve increasing the incomes of the low- and high-income strata, respectively, while keeping the income of the other stratum constant. Scenario D involves the per capita income of high-income families decreasing by 12.65%, while the per capita income of low-income families increases by 47.73%. Scenario D involves redistributing current incomes from the high-income stratum to the low-income stratum, in such a way that the total population incomes remain constant. The effect of changes in income distribution on the per capita water footprint of food consumption is estimated based on Equation (6). Table 7 presents the hypothetical income distribution patterns under the simulated scenarios and results.

Table 7. Estimated increase in the per capita water footprint of food consumption under various incomes and income distribution scenarios.

Scenario	Change in the per capita water footprint of food consumption	
	Quantity of change (m^3)	Rate of change (%)
Scenario A	42.36	4.08
Scenario B	127.40	12.28
Scenario C	19.83	1.91
Scenario D	107.57	10.37

The Scenario A results showed that a 10% increase in the per capita income of each household resulted in a 4.08% increase in the per capita water footprint of food consumption for all sample households, compared with the current water footprint level. The Scenario B results showed that only increasing the per capita income of households in the low-income group would lead to an increase of 12.28% in the per capita water footprint of food consumption for all sample households, which was higher than the growth results for all other scenarios. Therefore, the income growth mode of narrowing the income gap may significantly affect the per capita water footprint of the food consumption of the whole society. The Scenario C results showed that only increasing the per capita income of households in the high-income group would lead to an increase of 1.91% in the per capita water footprint of food consumption for all sample households, indicating that the income growth pattern of widening the income gap would slightly increase the societal per capita water footprint of food consumption. The Scenario D results showed that the transfer of income from the high-income stratum to the low-income stratum, maintaining constant total household incomes, would increase the per capita water footprint of food consumption for all sample households by approximately 10.37%. Therefore, the income transfer from the high-income stratum to the low-income stratum would also significantly increase the societal per capita water footprint of food consumption, even if there was no increase in the average per capita income.

4. Discussion and Conclusions

In this paper, we calculated the per capita water footprint of food consumption based on data of urban households in Guangdong Province. The influence of income change on the per capita water footprint of food consumption was analyzed by calculating the elasticity. We projected the per capita water footprint of food consumption under hypothetical changes in income and income distribution.

The income growth of urban residents had a significant positive effect on the per capita water footprint of food consumption, where the effect varied by income stratum. The income elasticity of the per capita water footprint of food consumption for the total sample was 0.45, while the income elasticity of the low-income group (0.75) was greater

than that of the high-income group (0.23), indicating that the change in income in the low-income group had a greater effect on water resources. Previous studies have confirmed the effects of food consumption patterns, population size, and urbanization on the per capita water footprint of food consumption. The difference of income elasticity was closely related to the change of food consumption structure in different income groups. Increasing income can push the food consumption pattern of low-income groups in the direction of higher water consumption due to a higher animal food consumption. The water footprint of food consumption in the high-income group had already reached a very high level, and the growth rate was small. Therefore, in order to reduce the effect of food consumption on the environment, sustainable food consumption management should consider group differences. We should correctly guide all kinds of groups to carry out sustainable consumption, advocate healthy and reasonable diet models, reduce animal food consumption, avoid the excessive consumption of food, and strengthen the management of food waste. In future research, we should explore the relationship between income and the water footprint of specific food, as well as study sustainable food consumption management from the perspective of the water footprint.

The simulation results for Scenarios A and B showed that the increase in the per capita water footprint of food consumption for the total sample of households would be considerably larger if the total increase in income was received by the low-income stratum, rather than a uniform percentage distribution of the additional income across each income stratum. Therefore, revenue growth by narrowing the income gap will considerably increase the water footprint of food consumption for the whole society. Meanwhile, the simulation results for Scenario D showed that the redistribution of income would significantly increase the per capita water footprint of food consumption, even if there was no increase in the average per capita income. However, the simulation results of Scenario C showed that the income growth pattern of the widening income gap would slightly increase the per capita water footprint of food consumption for all sample households. At present, China is in a period of rapid economic growth and urbanization, a period of profound change and sensitive response to the income level of urban and rural residents. The simulation results showed that increasing the income of residents, especially of low-income groups, will significantly increase the water footprint of food consumption of the whole society. This prospect is expected to have an effect on the sustainable food consumption and water resources management in China. In future research, when analyzing the water demand due to food consumption in China, the expected changes in income growth and income distribution should be fully considered.

This paper analyzed the effect of income on water resources for food consumption from the perspective of the water footprint, which is of great significance to promote sustainable food consumption and sustainable water resources management. The research results showed that changes in income and income distribution can affect the water footprint of food consumption of urban households in China. In this paper, the complex relationship between human activities and natural resources was simplified by using the water footprint tool, which has some limitations. First, we estimated the amount of water resources needed to produce food, according to the amount of food consumed, and failed to consider the environment, location, and other factors of food production. Future food water footprint research should consider the regional distribution of food production and the flow of water footprint among regions. Second, we analyzed the relationship between income growth and water footprint of food consumption at the micro level using household data, which has certain limitations when used as a reference in formulating macro policies at the national scale. In the future, we should strengthen the macro level research and carry out research on the differences and flows of water footprint among regions, countries, and provinces, which will be more conducive to the formulation of macro policies at the national scale.

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