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Case Report

Driving Forces of Food Consumption Water Footprint in North China

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Abstract: The water footprint (WF) vividly links water resources with virtual water of food, providing a novel perspective on food demand and water resources management. This study estimates the per capita WF of food consumption for six provinces in North China. Then, the study applies the logarithmic mean Divisia index method to decompose the driving forces of their WF changes. Results show that the per capita WF of food consumption in Beijing, Tianjin, and Inner Mongolia increases significantly in 2005–2017, whereas that in the other three provinces in North China varies slightly. All provinces have shown the same trend of food structure changes: the grain decreased, whereas the meat increased. In general, the urban effect was positive, and the rural effect was negative for all regions. The urban effects in Beijing and Tianjin played a leading role, whereas the rural effects in the other four provinces played a leading role from 2005–2009. However, the urban effects in all provinces played a leading role in 2010–2017. The WF efficiency increased in each province, and the effect in urban areas is stronger due to the higher water use efficiency. For most provinces, the consumption structure was positive because the diet shifted toward more meat consumption. The food consumption per capita effect was the major driving force in Beijing and Tianjin due to the increased consumption level, whereas the population proportion effect exerted a weak effect. To alleviate the pressure on water resources, further improving water use efficiency in food production and changing the planting structure should be emphasized for all regions in North China.

Keywords: driving force; water footprint; food consumption; LMDI method; North China

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1. Introduction

As a basic resource for human survival and economic development, freshwater is essential for human well-being and sustainable social and economic development. The occupation of freshwater resources and water pollution caused by human activities has brought tremendous pressure to the water system. In addition, the uneven distribution of natural water has caused serious water shortages in some areas [1,2]. With the rapid economic development and the continuous deepening of urbanization, the problem of water shortage has become increasingly prominent. As a major water consumer, the food production process consumes approximately 70% of the world's freshwater [3,4], it has the largest share in the total water consumption (61.2%) of China [5]. In addition, changes in the structure and quantity of the food consumption system of urban and rural residents have increased the pressure on water resources.

In addition to direct water use, a large amount of water is consumed through goods and services [6]. This part of the water can be characterized by virtual water [7]. The water footprint (WF) refers to the total amount of direct or indirect water resources that the research group consumes in a certain period of time for products and services [8]. WF can well describe the close relationship between human activities and water shortage and also provides an innovative method for comprehensive water resources management. The calculation methods of WF usually include two types, namely, top-down input–output and bottom-up process analysis methods. The top-down WF calculation method is based on the input–output model [9], and the research includes the utilization of the input–output method to calculate the national WF [10]. The multiregional input–output model analysis is used to calculate the interprovincial virtual water flow [11]. This method can allocate all direct water use to various sectors of the entire economic activity to reflect the water flow among various sectors [12]. This method is only suitable for calculating the WF at the macro industrial sector level due to the high degree of aggregation, in which conducting specific evaluations on certain specific products or technologies is impossible. Inversely, the bottom-up WF calculation method is based on the growth process [13]. Considering its low computational complexity and high data accessibility, the calculation of the WF of crops and animal products is suitable. The production tree method is used to calculate the WF of crops, which is based on CropWat software (developed by the Food and Agriculture Organization (FAO), Rome), combined with meteorological data and unit area crop yield data to calculate crop virtual water [7,8,14].

The changes in the WF should be linked to social, economic, and environmental factors to solve the water scarcity [15]. Decomposition analysis has been successfully applied to the research on the driving factors of WF changes [16]. In addition, they are connected by establishing mathematical formulas between the research object and the socio-economic factors. Common decomposition methods include the structure and exponential decomposition methods. The latter is more widely used in decomposition research due to the simplicity and availability of data, and Divisia and Laspeyres indexes are the two most common methods [17]. The logarithmic mean Divisia index (LMDI) is usually the preferred method [18], which can handle zero values and has no unexplainable remaining terms [19]. This method has been widely used in the field of energy consumption, carbon dioxide emissions [20–22], and sulfur dioxide emissions [23]. In the food system, some scholars studied the driving force of the nitrogen input, creatively evaluated and compared the driving forces of nitrogen input into food systems at different city levels [24]. Research on WF includes the following: on a global scale, Yang and Cui analyzed sub-continental dynamics of the WF of consumption from 1961–2009, and highlighted that population growth is the main driving factor; diet change is likely to overtake population growth as the main factor in the future [25]. Qian examined the evolution of virtual water trade in relation to agricultural products between China and Belt and Road Initiative countries during 2000−2016, and revealed the driving factors of trade imbalance and virtual water export [26]. Tamea reconstructed the value of the international virtual water trade from 1986–2010, and then analyzed the impact of population, Gross Domestic Product(GDP), arable land, virtual water embedded, and the geographic distance between countries on the virtual water fluxes. The results show that population, GDP, and geographic distance are the main driving forces [27]. Wan et al. used the structural decomposition analysis method to study the driving factors of the virtual flow of gray water from 1995–2009 under globalization, and concluded that the evolution of the globalized economic system and consumption structure, as well as the consumption volume made positive contributions [28]. On the national scale, Gerveni used the structural decomposition method to highlight the factors at the origin of the increase in water use in crop production across EU countries. The results indicate that the change in total water use was driven mostly by the technology effect and, within it, by a change in domestic sales [29]. The changes on China agricultural WF was divided into four effects, namely, diet structure, economic activity, efficiency, and population, and pointed out that economic activity effect was the largest positive contributor [30]. On the regional scale, Vanham calculated the WF of food consumption in 13 Mediterranean cities and analyzed the diet patterns in the Mediterranean, emphasizing that if urban residents want to save water, they need to pay attention to their diet [31]. Sun took the greater capital region of China, decomposed the WF per capita changes of province-level cities and pointed out that urbanization and consumption levels were the main driving forces of water footprint growth [32]. In the scale of the city, the driving forces of food consumption WF in Xiamen were analyzed; research showed that population effects were the leading drivers of WF growth [33]. In general, these studies put forward many driving factors of WF changes and provided references for establishing a connection between WF and influencing factors. However, most of the above studies analyze the driving forces of WF changes for one region, whereas few studies analyzed and compared the driving forces of per capita WF changes for different regions considering urban and rural effects.

North China is an important production base of grain and agricultural products in China, which is of vital importance to ensure the country's grain and food security. However, North China is an area with severe water shortages, which uses only 6% of the country's water resources to support 18% of the country's arable land and produces 23% of the country's food [34]. The shortage of water resources has brought many negative effects on the ecological environment and has restricted social and economic development, posing a great threat to water resources security. There have been some empirical analyses of WF for some specific areas in North China, including Beijing, Tianjin, Hebei, Shandong, Shanxi, and Inner Mongolia [32,35]. However, there are few studies decomposing the WF of food consumption from both rural and urban perspectives in these areas. Comparing with above-mentioned literature, this study aims to analyze and compare the driving forces of per capita WF changes in the six regions, including detailed urban and rural effects from the aspects of different provinces and crops. This research might help to improve the structure of residents' food consumption and provide valuable information to optimize agricultural production and relieve water stress. The rest of this paper is further presented as follows. Section 2 presents the methodology and data sources. Section 3 shows the calculation results and quantification of driving forces based on the LMDI decomposition method, which is followed by Section 4 that further highlights the policy implications. Finally, Section 5 summarizes the findings of this study.

2. Methodology and Data Sources

2.1. WF Accounting

This study adopts a bottom-up process analysis method. The per capita WF of food consumption is obtained by multiplying the amount of per capita food consumed and the virtual water content coefficient per unit product. In the calculation, only blue water and green water are considered. The WF calculation formula is as follows:

$$WF_{food,cons,per} = \sum_{n}(VWC_i \times C_i) \quad (1)$$

In the formula, $WF_{food,\ cons,\ per}$ represents the per capita WF of food consumption (m^3/year/person); VWC_i represents the virtual water content per unit mass of each category crop or animal product (m^3/kg); C_i represents the consumption of each category of crop products or animal products (kg/year), and i refers to the numbers of categories (i = 1,2,3, . . .).

The virtual water content of crop products can be calculated by the ratio of the water demand per unit area of the crop to the yield per unit area. The water demand per unit area is calculated using the CropWat software which is a decision support tool developed by the Land and Water Development Division of FAO; the meteorological data of six provinces in North China involved in the calculation process use the observation data in the Climwat software (FAO, Rome, Italy). Besides, the virtual water content of animal products adopts the research results of Chapagain on China's WF.

The calculation scope of the WF in this study is as follows: crop products include grain, vegetables, edible oil, fruits, sugar, and wine; animal products include pork, beef, mutton, aquatic products, poultry, eggs, and milk.

2.2. Decomposition of per Capita WF of Food Consumption

This study is based on the LMDI method to analyze the per capita WF of food consumption influencing factors in North China. The basic idea is to decompose the target values into several main factors based on mathematical identity transformation [36]. According to existing research results, the per capita WF of food consumption has an important relationship with food production water requirements and climatic conditions (temperature, precipitation), planting area, food consumption per capita level, regional food consumption structure, and urbanization process [37–39]. In order to quantify the factors that affect the changes in the per capita WF of food consumption, two consumer groups in urban and rural areas are considered, and each is divided into water footprint intensity (interpreted as the amount of water consumed to produce 1 kg of food), consumption structure, food consumption per capita, and proportion of population (ratio of the urban/rural population to the total population of the region). The exponential decomposition formula of the per capita WF of food consumption is shown as follows:

$$WF = \frac{\sum_i WF_u^i \cdot P_u + \sum_i WF_r^i \cdot P_r}{P} = \sum_i \frac{WF_u^i}{C_u^i} \cdot \frac{C_u^i}{C_u} \cdot \frac{C_u}{P_u} \cdot \frac{P_u}{P} + \sum_i \frac{WF_r^i}{C_r^i} \cdot \frac{C_r^i}{C_r} \cdot \frac{C_r}{P_r} \cdot \frac{P_r}{P} = \sum_i I_u^i \cdot S_u^i \cdot V_u \cdot U + \sum_i I_r^i \cdot S_r^i \cdot V_r \cdot U', \quad (2)$$

where WF (m^3) is the per capita WF of food consumption, and WF_u^i (m^3) and WF_r^i (m^3) are the WF of food i consumption per capita in urban and rural, respectively. C_u^i (kg) and C_r^i (kg) represent the consumption per capita of food i in urban and rural residents, respectively. C_u (kg) and C_r (kg) represent the total per capita consumption of agricultural products in urban and rural residents, respectively. P_u (person) and P_r (person) are the numbers of urban and rural residents, respectively, and P is the total population. I_u^i and I_r^i represent the urban and rural water footprint intensity of food i, respectively. S_u^i and S_r^i respectively refer to the urban and rural consumption structures. V_u and V_r are the per capita food consumption in urban and rural areas, respectively. U is the proportion of the urban population, and U' is the proportion of the rural population. Here, $U + U' = 1$.

According to the LMDI method, the change in WF consumption between base year 0 and target year t can be decomposed into the following formula:

$$\Delta WF = WF^t - WF^0 = \Delta WF_u(I) + \Delta WF_u(S) + \Delta WF_U(V) + \Delta WF_u(U) + \Delta WF_r(I) + \Delta WF_r(S) + \Delta WF_r(V) + \Delta WF_r(U') \quad (3)$$

where $\Delta WFu(I)$, $\Delta WFu(S)$, $\Delta WFU(V)$, and $\Delta WFu(U)$ are the four factors that affect the changes in the WF of urban residents. They refer to water footprint intensity, consumption structure, food consumption, urban population ratio, and population. The factors $\Delta WFr(I)$, $\Delta WFr(S)$, $\Delta WFr(V)$, and $\Delta WFr(U')$ represent the factors that affect the changes in the WF of rural residents. The contribution of each effect to changes in the per capita WF of food consumption can be calculated using the following formula:

$$\Delta WF_u(I) = \sum_i \frac{\left(WF_u^i \cdot P_u/P\right)^t - \left(WF_u^i \cdot P_u/P\right)^0}{ln\left(\left(WF_u^i \cdot P_u/P\right)^t\right) - ln\left(\left(WF_u^i \cdot P_u/P\right)^0\right)} \cdot ln\left(\frac{I_u^{i,t}}{I_u^{i,0}}\right), \quad (4)$$

$$\Delta WF_u(S) = \sum_i \frac{\left(WF_u^i \cdot P_u/P\right)^t - \left(WF_u^i \cdot P_u/P\right)^0}{ln\left(\left(WF_u^i \cdot P_u/P\right)^t\right) - ln\left(\left(WF_u^i \cdot P_u/P\right)^0\right)} \cdot ln\left(\frac{S_u^{i,t}}{S_u^{i,0}}\right), \quad (5)$$

$$\Delta WF_u(V) = \sum_i \frac{\left(WF_u^i \cdot P_u/P\right)^t - \left(WF_u^i \cdot P_u/P\right)^0}{ln\left(\left(WF_u^i \cdot P_u/P\right)^t\right) - ln\left(\left(WF_u^i \cdot P_u/P\right)^0\right)} \cdot ln\left(\frac{V_u^t}{V_u^0}\right), \quad (6)$$

$$\Delta WF_u(U) = \sum_i \frac{\left(WF_u^i \cdot P_u/P\right)^t - \left(WF_u^i \cdot P_u/P\right)^0}{ln\left(\left(WF_u^i \cdot P_u/P\right)^t\right) - ln\left(\left(WF_u^i \cdot P_u/P\right)^0\right)} \cdot ln\left(\frac{U_u^t}{U_u^0}\right), \quad (7)$$

$$\Delta WF_r(I) = \sum_i \frac{\left(WF_r^i \cdot P_r/P\right)^t - \left(WF_r^i \cdot P_r/P\right)^0}{ln\left(\left(WF_r^i \cdot P_r/P\right)^t\right) - ln\left(\left(WF_r^i \cdot P_r/P\right)^0\right)} \cdot ln\left(\frac{I_r^{i,t}}{I_r^{i,0}}\right), \tag{8}$$

$$\Delta WF_r(V) = \sum_i \frac{\left(WF_r^i \cdot P_r/P\right)^t - \left(WF_r^i \cdot P_r/P\right)^0}{ln\left(\left(WF_r^i \cdot P_r/P\right)^t\right) - ln\left(\left(WF_r^i \cdot P_r/P\right)^0\right)} \cdot ln\left(\frac{V_r^t}{V_r^0}\right), \tag{9}$$

$$\Delta WF_r(S) = \sum_i \frac{\left(WF_r^i \cdot P_r/P\right)^t - \left(WF_r^i \cdot P_r/P\right)^0}{ln\left(\left(WF_r^i \cdot P_r/P\right)^t\right) - ln\left(\left(WF_r^i \cdot P_r/P\right)^0\right)} \cdot ln\left(\frac{S_r^{i,t}}{S_r^{i,0}}\right), \tag{10}$$

$$\Delta WF_r(U) = \sum_i \frac{\left(WF_r^i \cdot P_r/P\right)^t - \left(WF_r^i \cdot P_r/P\right)^0}{ln\left(\left(WF_r^i \cdot P_r/P\right)^t\right) - ln\left(\left(WF_r^i \cdot P_r/P\right)^0\right)} \cdot ln\left(\frac{U_r^t}{U_r^0}\right). \tag{11}$$

2.3. Study Area

North China (including Beijing, Tianjin, Hebei, Shandong, Shanxi, and Inner Mongolia, Figure 1) is an important agricultural production and commercial grain base in China. In 2018, North China has 275,89 million people, accounting for 19.76% of the country's population, and a gross domestic product accounting for 21.74% of the country. Urbanization is developing rapidly, and the urbanization rate has risen from 42.38% in 2005 to 62.87% in 2018, having an increase of 48.34%, which is higher than the national average. Particularly, the urbanization levels of Beijing and Tianjin are 86.50% and 83.15%. Cultivated land accounts for 20.82% of the country, and the annual output value of agriculture and animal husbandry accounts for 15.24% of the country. The grain output in 2018 was 1.42×10^8 t, accounting for 21.58% of the country's total. Among grain crops, wheat and corn are the main sources of raw grain production in North China, accounting for 90% of the total grain output. North China dominates China's wheat production. In 2018, the sown area and output of wheat accounted for 31.70% and 33.56% of the country's total, respectively. The wheat yield was 0.574 kg/m^2, which was higher than the national average of 0.542 kg/m^2. The amount of water resources in study area only accounts for 4.17% of the total water resources in the country, and the per capita water resources are lower than the national average [34]. In the future, with the development of urbanization in these areas, food consumption will bring greater pressure on sustainable agricultural development and water consumption. Therefore, improving the structure of food consumption and increasing water efficiency is urgently needed to achieve sustainable agricultural development and water resources management.

2.4. Data and Materials

The main data used in this study include urban/rural food consumption per capita data (12 types of food), population data, and main crop production data in each region from 2005–2017 in six provinces (municipalities) in North China. The main sources of data include China Statistical Yearbook (2006–2018), six provinces and municipality (including Beijing, Tianjin, Hebei, Shandong, Shanxi, Inner Mongolia) Statistical Yearbook (2006–2018), China Environment Statistical Yearbook, Food Consumption Statistical Yearbook, and Rural Statistical Yearbook, and others. More details of the data and calculation process can be found in Figure 2.

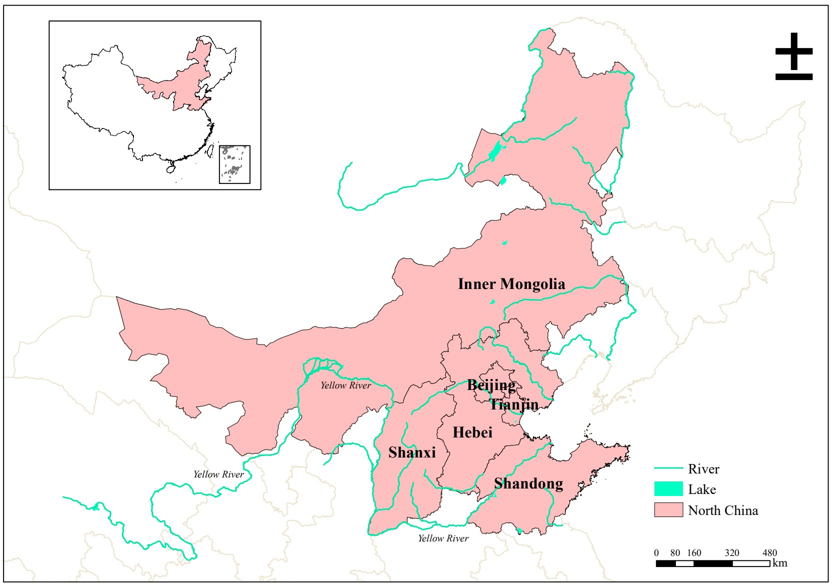

Figure 1. Location of the study area and distribution of watershed.

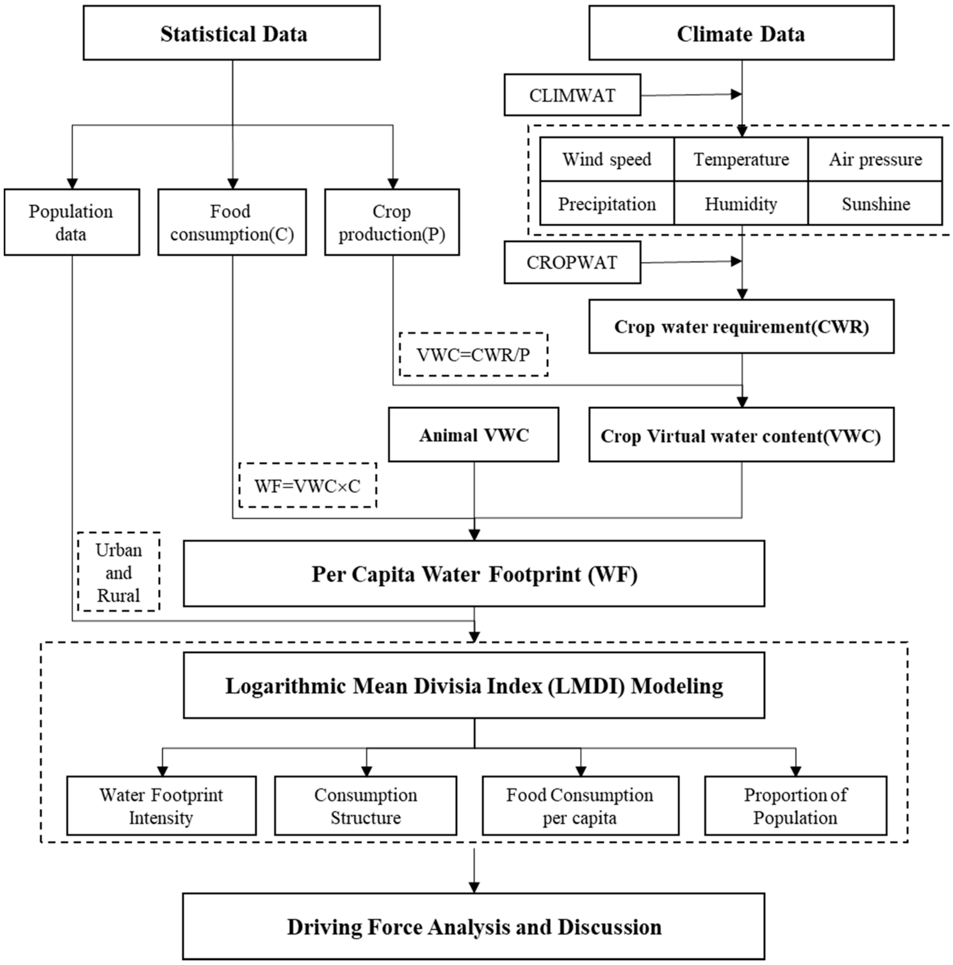

Figure 2. Major data sources and conceptual framework.

3. Results and Discussions

3.1. Changes of per Capita WF of Food Consumption in 2005–2017

Figure 3 shows the per capita WF of food consumption in North China from 2005 to 2017. The per capita WF of food consumption in Beijing has been growing before 2014 but has been decreasing after 2014, with an average annual growth rate of 4.76% and −5.79% in these two periods, respectively. The per capita WF of food consumption in Tianjin and Inner Mongolia has been growing over time, with an average annual growth rate of 4.88% and 1.69%, respectively. Inner Mongolia has the highest proportion of beef and mutton consumption, as it is located in ethnic minority settlements and is a typical livestock area. However, Beijing and Tianjin have a more balanced food consumption structure. The per capita WF of Hebei, Shandong, and Shanxi is relatively stable. The grain has a higher proportion in these three provinces, but the pro-portion has been gradually decreasing over time. Given the local noodle-based dietary characteristics, the grain consumption in Shanxi has the highest proportion, exceeding 50%. For all six regions, the WF of grain decreased, and the WF of meat increased in the composition of food consumption from 2005–2017, the trend is similar to the change of China's food consumption WF structure from 1992–2012 [6].

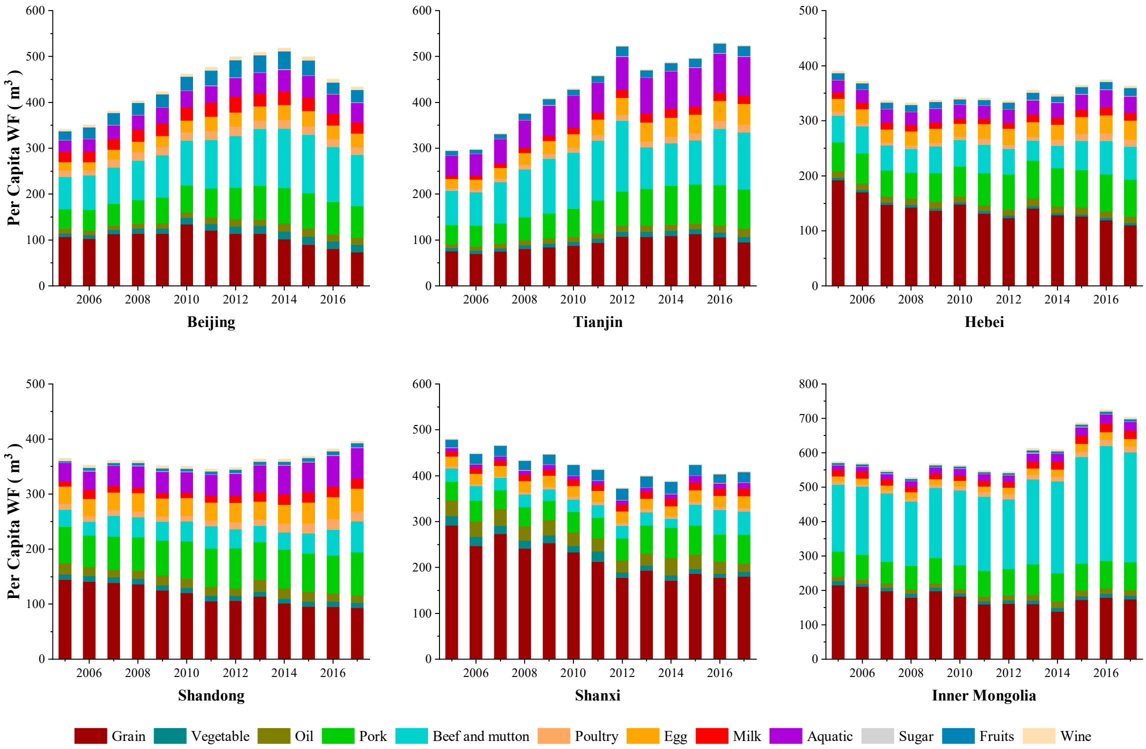

Figure 3. Per capita water footprint (WF) of food consumption in North China (2005–2017).

3.2. Decomposition Results from Three Periods

Based on the decomposition analysis, Figure 4 shows the changes in per capita WF of food consumption and the contribution values of eight related factors, and the numerical results are shown in Table A1 (Appendix A). Here, the decomposition results will be demonstrated from the three four-year periods as follows.

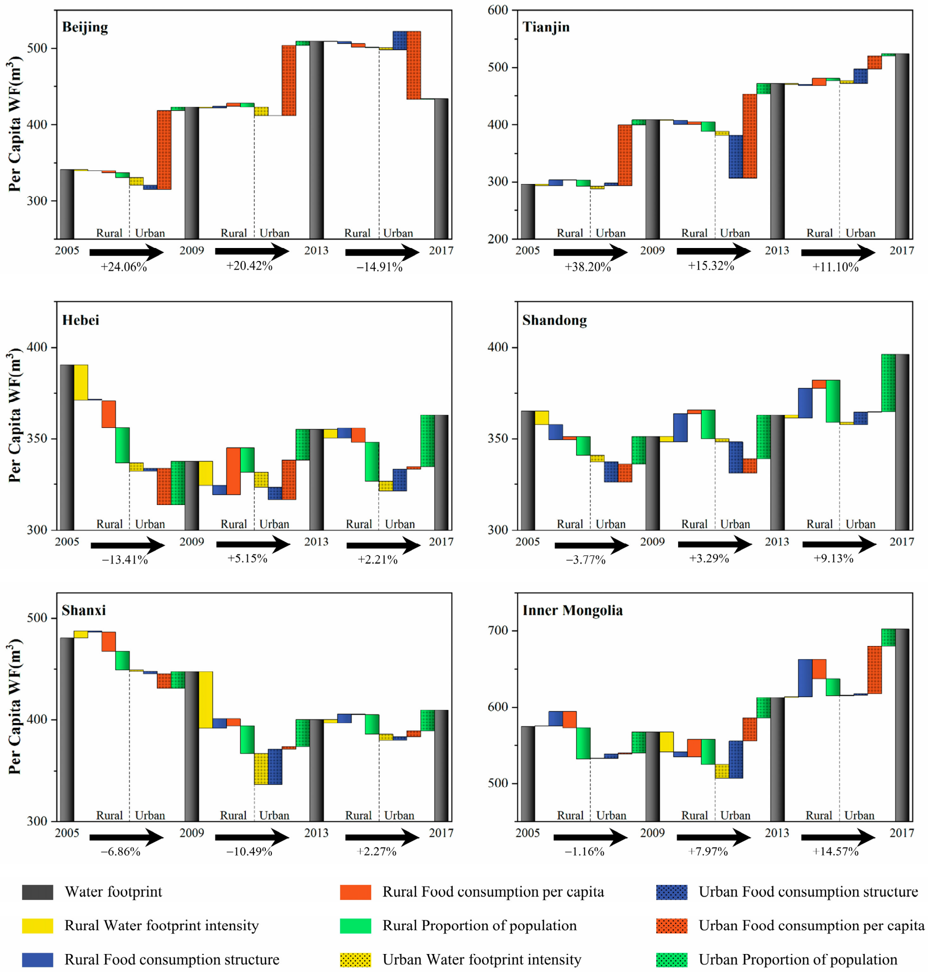

Figure 4. Driving forces to per capita WF change of food consumption in six regions during three periods.

3.2.1. Driving Forces of per Capita WF Change in 2005–2009

The WF of Beijing and Tianjin increased by 24.06% and 38.20%, respectively. The rural effect drove the WF to decrease by 3.17% and 1.34%, and the urban effect drove the WF to increase by 27.23% and 39.54%, respectively. The urban effect played a leading role. Among the rural effects, the food structure effect promoted a 0.17% and 0.62% increase in the WF. The water footprint intensity, food consumption per capita, and proportion of population effects restrained the growth of the WF: the water footprint intensity effect reduced the WF by 0.62% and 0.34%. Food consumption per capita reduced WF by 0.99% and 0.09%. The decrease in the proportion of rural population reduced the per capita WF by 1.12% and 3.78%. Among the urban effects, the food consumption per capita effect was the main driving factor, driving the WF to increase by 30.32% and 36.00%. The increase in the proportion of urban population contributed to the WF growth of 1.44% and 3.24%. In addition, Tianjin's consumption structure drove a WF growth of 1.80%. The consumption structure effects of Beijing restrained the growth of the total WF, reducing the WF by 1.54%.

The WF of Hebei, Shandong, Shanxi, and Inner Mongolia decreased by 13.41%, 3.77%, 6.86%, and 1.16%, respectively. The rural effect was negative, whereas the urban effect was positive. In addition, the rural effect played a leading role. Among the rural effects, the proportion of the rural population and the per capita food consumption effects were the main reasons for the decline in the WF. Notably, during this period, the water footprint intensity effect of Shanxi increased WF by 1.52%, which is contrary to the rule that the water footprint intensity effect was negative. According to statistics, Shanxi was affected by natural disasters (floods in 2007 and drought in 2009), which led to a decline in food crop production. The consumption structure effect in Shandong drove the WF down by

1.55%, whereas this effect was positive in other regions. Among the urban effects, the food consumption effect of Hebei and Shanxi drove the decline of the WF, and the effect on Hebei was the strongest, reducing the WF by 5.07%. The effect of consumption structure was negative in Hebei and Inner Mongolia, driving the WF down by 0.39% and 0.98%. However, the impact on Shandong and Shanxi was positive, driving the WF to increase by 3.13% and 0.58%. The proportion of urban population effect drove the WF to increase by 6.11%, 4.12%, 3.40%, and 4.90%, respectively, compared with Beijing and Tianjin, in which the intensity was stronger.

3.2.2. Driving Forces of per Capita WF Change in 2010–2013

Considering the impact of natural disasters in Shanxi in 2005–2009, the intensity of the WF at this stage included the effects of productivity recovery and productivity improvement. The water footprint intensity effect in rural and urban caused the WF to go down by 12.42% and 6.73%, respectively. From the data, the water footprint intensity effect was the main driving force for the decline of Shanxi's WF. However, considering the particularity of this factor during this period, on the basis of removing this factor, the changes of WF in Shanxi and its driving force will be reconsidered.

In 2010–2013, the WF of Beijing and Tianjin increased by 20.42% and 15.32%, respectively. The rural effect reduced the WF by 0.1% and 5.1%, and the urban effect increased the WF by 20.51% and 20.43%. The overall effect of the rural effect was relatively weak, whereas that of the rural population proportion was the strongest, driving the WF down by 1.27% and 3.91%. Among the urban effects, the food consumption per capita effect was the main reason for the increase in the WF, increasing the WF by 21.70% and 35.90%, respectively. Furthermore, the proportion of the urban population promoted the WF increase by 1.4% and 4.54%. The food structure effect in Beijing increased the WF by 0.62%, whereas the food structure effect in Tianjin reduced the WF by 1.72%. In addition, the water footprint intensity effect reduced the WF by 2.59% and 1.75%.

The WF of Hebei, Shandong, Shanxi, and Inner Mongolia increased by 6.35%, 4.79%, 7.68%, and 8.55%, respectively, during this period. The growth rate was weaker than that of Beijing and Tianjin. The rural effect was negative, whereas the urban effect was positive. In addition, the urban effect played a leading role. Among the rural effects, the water footprint intensity and the proportion of rural population effects reduced the WF. The food consumption per capita effect reduced the WF of Shanxi by 1.57%, whereas that of the WF of Hebei, Shandong, and Inner Mongolia increased by 7.62%, 0.53%, and 4.03%, respectively. The food structure effect reduced the WFs of Hebei and Inner Mongolia by 1.53% and 1.08% and increased the WFs of Shandong and Shanxi by 4.51% and 2.11%, respectively. Among the urban effects, the effects of per capita food consumption and the proportion of the urban population were positive. Hebei had the strongest food consumption per capita effect, promoting a 6.35% increase in WF. In addition, Shandong had the strongest proportion of urban population effect, promoting a 6.80% increase in WF. The food structure effect was negative in Hebei and Shandong, which reduced the WF by 1.97% and 4.79%, whereas in Shanxi and Inner Mongolia it was positive, which promoted the increase in WF by 7.68% and 8.55%. The water footprint intensity effects were all negative, driving the WFs of Hebei, Shandong, and Inner Mongolia to decrease by 2.42%, 0.55%, and 3.12%, respectively.

3.2.3. Driving Forces of per Capita WF Change in 2014–2017

In 2014–2017, Beijing's per capita WF dropped by 14.91%, and Tianjin's per capita WF increased by 11.10%. The rural and urban effects of Beijing reduced the WF by 1.77% and 13.14%, respectively. The rural and urban effects of Tianjin increased the WF by 1.18% and 9.92%, respectively. The urban effect was the dominant factor. Among the rural effects, the water footprint intensity and population proportion effects of Beijing and Tianjin still restrained the growth of the WF, compared with those in 2010–2013, where the water footprint intensity effect was weakened by 76.01% and 10.91%, respectively. The proportion of rural population effects was weakened by 87.16% and 75.56%, respectively. The food structure effect drove down the WF by 0.67% and 0.50%, respectively. Among the urban effect, Beijing's food consumption per capita decreased, resulting in a decrease of 17.50%. This factor is the main driving factor for changes in Beijing's WF. Tianjin's consumption per capita continued to grow, but the impact intensity weakened by 84.49%. The food consumption structure of the two places promoted the increase of WF by 4.73% and 5.26%. The proportion of urban population effect promoted the increase of WF, and the intensity weakened by 86.12% and 74.78%. The water footprint intensity effect is negative, and the intensity weakened by 75.07% and 22.66%, respectively.

The WFs of Hebei, Shandong, Shanxi, and Inner Mongolia increased by 2.21%, 9.13%, 2.27%, and 14.57%, respectively. The rural effect in Inner Mongolia was positive, whereas in other regions it was negative. The urban effects in the four provinces were all positive. Among the rural effects, the food structure effect increased the WF by 1.51%, 4.58%, 2.16%, and 7.93%, and the proportion of rural population effect reduced the WF by 5.99%, 6.31%, 4.64%, and 3.54%, respectively. The water footprint intensity effect was negative, and the impact intensity became weaker. Food consumption per capita decreased in Hebei and Inner Mongolia, reducing the WF by 2.22% and 4.13%, and increased in Shandong and Shanxi, increasing the WF by 1.16% and 0.15%. Among the urban effects, the food consumption per capita effect promoted the growth of the WF, the Inner Mongolia effect was the strongest, increasing the WF by 10.11%. The proportion of urban population effect also promoted the growth of the WF, increasing by 7.98%, 8.61%, and 4.98% in Hebei, Shandong, and Shanxi. Food structure effects promoted the growth of WF, but the intensity was weaker.

In summary, the WF of Beijing and Tianjin showed an increasing trend, and the main driving force is food consumption per capita. The WF of Hebei, Shandong, Shanxi, and Inner Mongolia showed a downward trend from 2005–2009, and the WF showed an increasing trend after 2010. For the entire North China region, the urban effect was positive, and the increase in the urban population proportion caused the WF to continue to grow. The rural effect was negative, and the decrease in the rural population proportion caused the WF to continue to decline. The reason is that urbanization has contributed to the growth of water footprint [32]. The effect of water footprint intensity on rural and urban was almost negative. The reason is that the advancement of agricultural science and technology and the substantial improvement of agricultural infrastructure conditions have realized the continuous increase of agricultural output under the conditions of reduced total agricultural water consumption [34].

3.3. Effects of Driving Factors on WF Changes

Figure 5 shows the impact of driving factors on changes in the WF of each region, and the numerical results are shown in Table A2 (Appendix A). The contribution of the decomposition is demonstrated by eight driving factors to facilitate the comparison among regions and the analysis of driving forces. The driving factors are further re-fined according to food types to deeply explore the internal reasons for the changes in driving factors.

3.3.1. Water Footprint Intensity Effect

The water footprint intensity represents the efficiency of food production. If food production efficiency is high, then the negative effect of water footprint intensity is strong. From Figure 4, the rural and urban water footprint intensity effects over the three periods are as follows: The water footprint intensity in each region has a negative effect on the changes of WF, which means that the WF efficiency continues to increase over time. The effect is the strongest in 2009–2013, and after 2013, the degree of changes in the WF gradually weakens. The water footprint intensity effect of Hebei and Shandong provinces, which are more developed in agriculture [12], has been reduced by 64.77% and 93.32%, respectively. In addition, the water footprint intensity effect in urban is stronger than that in rural, specifically in Beijing and Tianjin, which varies among provinces mainly due to the higher water use efficiency in urban.

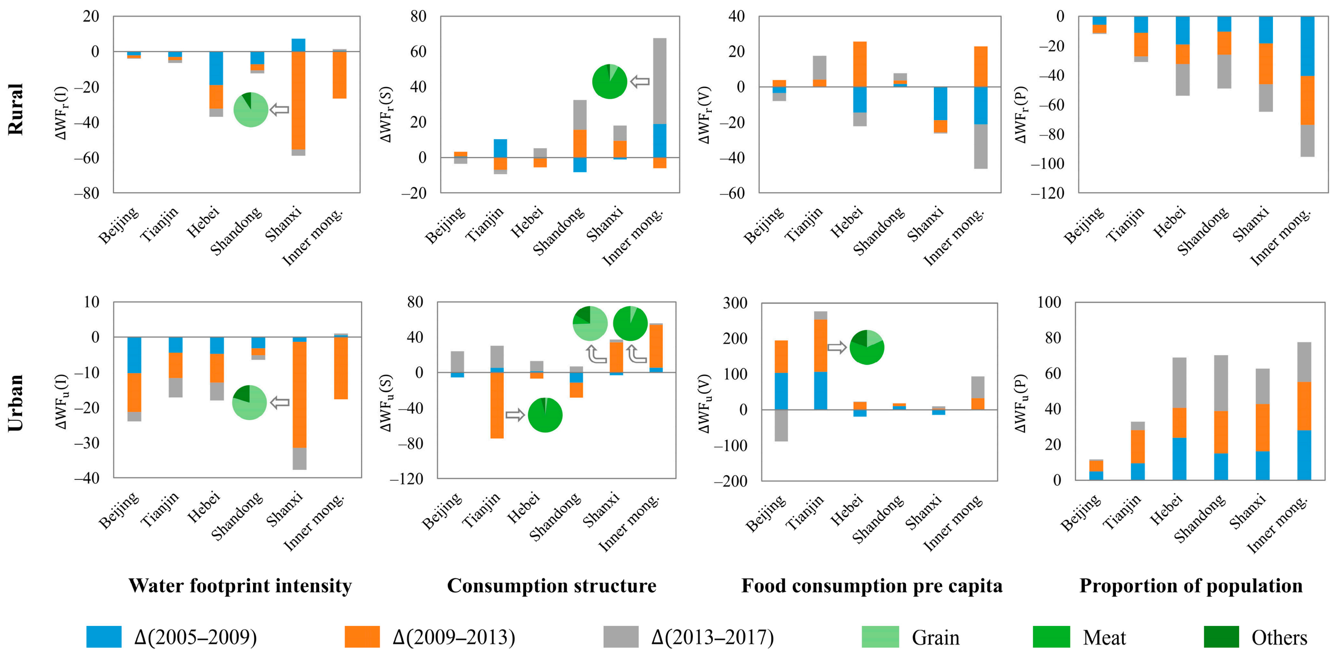

Figure 5. Decomposed contributions to the six provinces in North China's WF changes in 2005–2017. Note: Inner Mong. (Inner Mongolia). Meat includes pork, beef, mutton, poultry, and aquatic. Others include vegetables, oil, egg, milk, sugar, fruits, and wine.

3.3.2. Consumption Structure Effect

Different foods contain various virtual water contents. This notion is the root cause of the changes in the WF caused by the food structure. For example, meat contains more virtual water than grain. For the rural, the effect of changes in WF caused the food structure in general to have a strong impact on Shandong and Inner Mongolia, and a weaker impact on other regions. The negative effect of the influence of food structure in Shandong Province before 2009 turned into a positive one mainly because the proportion of meat consumption increased. As the proportion of meat consumption continued to rise, and the structural effect gradually strengthened. The change in food structure in Mongolia had the strongest impact in 2013–2017 mainly due to the highest change in the proportion of meat consumption. For the urban, the consumption structure changed weakly in 2005–2009. From 2009–2013, changes in the food structure drove Tianjin's WF to drop by 74.72 m^3, specifically due to the decline in meat structure. Shanxi and Inner Mongolia increased their WFs by 34.37 m^3 and 48.58 m^3 due to the increase in the proportion of grain and meat, respectively. During this period, the consumption structure effect became the main driving factor of the WF changes in the three provinces, and the other three provinces were less affected by this effect. From 2013–2017, the effects of changes in food structure were all positive, but the degree of impact was weakened.

3.3.3. Food Consumption per Capita Effect

Not only the structure of food consumption but also food consumption has changed. In addition, the improvement of living standards and the advocacy of dietary structure have affected food consumption. For the rural, the food consumption per capita showed a positive effect in Tianjin, Hebei, and Shandong. On the contrary, the per capita WF in other regions decreased. For the urban, the consumption level increased for most provinces. Except in Shanxi, the food consumption effect drove the per capita WF to increase particularly in meat consumption WF. This effect was the major driving factor for Beijing and Tianjin but exerted less in the other four provinces.

3.3.4. Proportion of Population Effect

The decline in the proportion of rural population drives a decline in the per capita WF of food consumption. The proportion of the urban population continues to increase, driving the per capita WF of food consumption to rise. The proportion of population effect (whether rural or urban) in Beijing and Tianjin exerts a weak effect because both have higher urbanization rates and lower annual growth rates [40]. However, this proportion has a strong effect on Hebei, Shandong, Shanxi, and Inner Mongolia because the urbanization levels of other regions are in a rapid development stage. The urbanization rate of the four provinces increased by 45.96%, 46.95%, 36.17%, and 31.39%, respectively in 2005–2017.

In general, the effect of driving factors on the per capita WF changes shows that the water footprint intensity in each region has a negative effect on the changes of WF. Moreover, the intensity effect is gradually weakening, which is restricted by the level of agricultural technology and management measures. For most provinces, the consumption structure has a positive effect mainly due to the increasing proportion of meat. The food consumption per capita is the major driving factor for Beijing and Tianjin. Naturally, the proportion of the rural population effect was negative, whereas that of the urban population effect was positive.

4. Conclusions

This study used bottom-up process analysis to estimate the per capita WF of food consumption for six regions in North China. In addition, the LMDI method was used to analyze the driving force of the per capita WF changes, covering the effects of water footprint intensity, consumption structure, food consumption per capita, and proportion of the population from urban and rural aspects. The research results cannot only help to improve the structure of residents' food consumption but can also provide valuable information to optimize agricultural production and relieve water stress. The main results are as follows:

1. Beijing's per capita WF of food consumption was the highest in 2014 and then began to decline. Tianjin and Inner Mongolia showed an increasing trend, whereas other regions vary slightly. In terms of the food consumption structure changes, the grain WF of the six provinces in North China has shown a downward trend, whereas the meat WF has shown an upward trend.
2. For Beijing and Tianjin, the urban effect played a major role, and the main driving force was the per capita food consumption effect from 2005 to 2017, indicating the increasing consumption levels of these two regions. For Hebei, Shandong, Shanxi, and Inner Mongolia, the rural effect was stronger than the urban effect in 2005–2009 mainly due to the decreasing rural population proportion and food consumption per capita. However, the urban effect played a major role in 2010–2017. In general, the main driving forces of per capita WF increase were the increase in the proportion of the urban population and per capita food consumption. Furthermore, the urban effect was positive, but the rural effect was negative for all regions.
3. The WF efficiency increased in each province, in which the effect in urban was stronger due to the higher water use efficiency. Except in Tianjin and Shandong, the consumption structure effect was positive due to the increasing proportion of meat. Food consumption per capita effect was the major driving force in Beijing and Tianjin but exerted less in the other four provinces. Naturally, the rural population proportion effect was negative, whereas the urban population proportion effect was positive. Beijing and Tianjin have less population proportion effect because of their strict population control measures.

At present, in most parts of the world, the per capita WF has decreased even if diets have become richer due to the increase in water use efficiency in food production [25]. Changes in dietary structure drive an increase in the WF, which has a significant impact in Asia [41]. The traditional Mediterranean diet is regarded as a healthy and sustainable lifestyle [42]. Compared with the Chinese dietary structure, the WF needs to be increased by

22%. Specifically, it requires more consumption of milk, vegetables, and fruits. Population growth has contributed to an increase in the WF, which has a more substantial effect in areas with rapid economic development [27].

Thus, for a healthy diet, increasing the proportion of vegetables, fruits, and milk in the food structure and reducing food waste should be promoted. Considering the greater water stress in the future, improving water use efficiency in food production and changing the planting structure should be emphasized, specifically developing new irrigation technologies and alternate sources, such as rainfall harvest.

5. Policy Implications

5.1. Improving Water Use Efficiency in Food Production

Improving water use efficiency is of great significance for all regions in North China. At the technical level, by developing new irrigation technologies and alternative resources such as rainfall harvesting from small reservoirs [43] to improve water use efficiency and the resistance and recovery of food production areas from natural disasters. At the management level, the serious problem of groundwater over-exploitation in North China can be addressed by changing the planting structure [44], optimizing the allocation of water and soil resources, and strengthening the control of groundwater exploitation [45]. In addition, the import of virtual water is also a key way to solve the shortage of water resources in North China [46]. Through virtual water trade with water-rich regions, the local water consumption in North China might be reduced.

5.2. Advocating Healthy and Sustainable Food Consumption Structure

The living standard improvement and the healthy eating promotion will gradually tend to a "healthy and sustainable" diet, which will closely link human health with environmental sustainability. For this structural system transformation, the EAT-Lancet Commission board proposed a global sustainable food production-personal diet framework ("Planetary Health Diet") [47]. In addition, China proposed the "Chinese Resident Dietary Guidelines (2016)" using the food structure proposed in the guide as a standard to calculate the WF of food consumption. In Figure 6, the histogram shows the WF of various food consumptions, and the map shows the gap between the total food consumption WF and the standard food structure WF. According to the histogram, the proportion of milk, fruit, and vegetable consumptions are low, but those of meat and grain consumptions are relatively high. The difference in structural characteristics of Inner Mongolia is the largest. The food structure should increase the proportion of milk, vegetable, and fruit consumptions and reduce the proportion of meat consumption.

5.3. Increasing Food Consumption but Reducing Food Waste

Based on the WF standards proposed by the Guidelines (Figure 5), except in Inner Mongolia, the total per capita WF in North China has not yet reached the standard requirements. From the perspective of food categories, the consumption of milk, fruits, and vegetables is generally low in North China, and that of meat and grains meets the requirements. It is suggested to increase the consumption of milk, fruits, and vegetables under the premise of ensuring a stable consumption of meat and grains. However, considering the multi-ethnic integration in North China, differences in diet, and the particularity of policies, food consumption standards should be proposed based on the actual situation in that region. In addition, food waste brings a considerable loss of WF. The global average food waste is about 178 g per capita per day, and the average food waste is about 276 g per capita per day in China, accounting for about 13.24% of food consumption [48]. Considering the limited ability of agriculture to increase production, reducing food waste is also an important way to save WF of food consumption in the future.

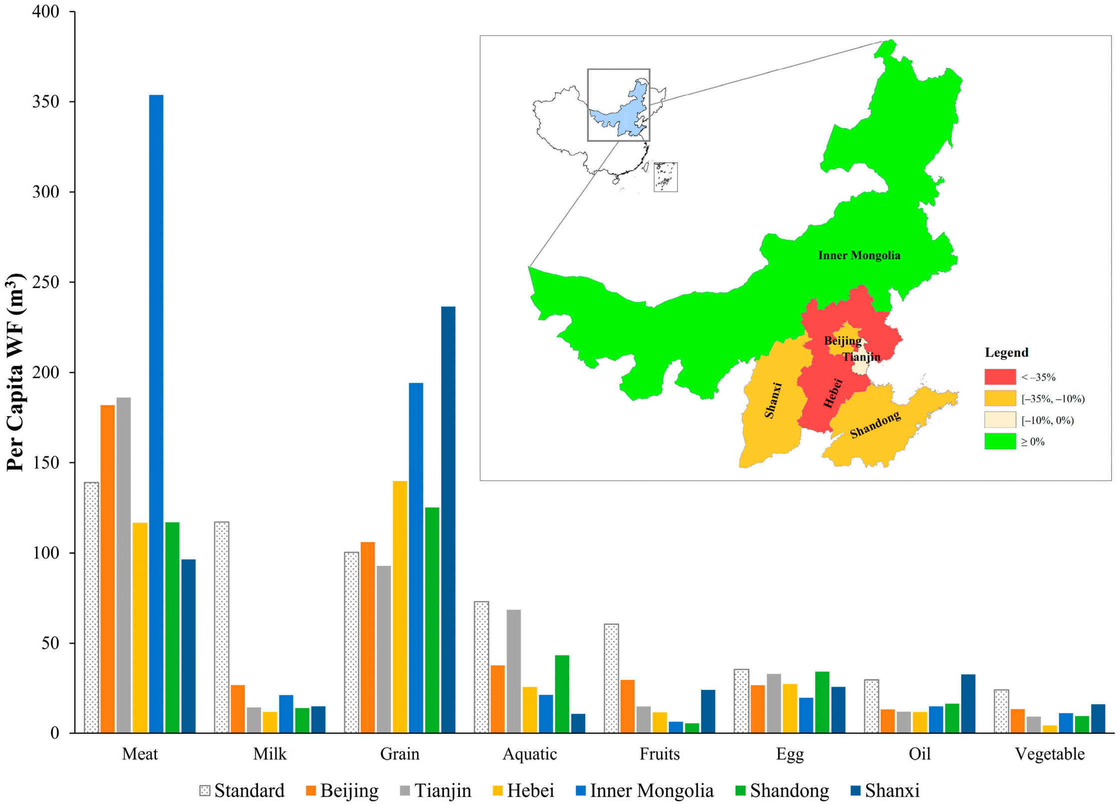

Figure 6. Comparison of actual and standard WF of food consumption by food types in North China. Note: The actual WF is the food consumption WF in 2017; the standard WF is calculated based on the food consumption recommended by the Chinese Dietary Guidelines.

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Appendix A

Table A1. Details of decomposition of WF attributable in North China (m^3).

Period	Region	Rural				Urban			
		$\Delta WFu(I)$	$\Delta WFu(S)$	$\Delta WFU(V)$	$\Delta WFu(U)$	$WFr(I)$	$\Delta WFr(S)$	$\Delta WFr(V)$	$\Delta WFr(U')$
2005–2009	Beijing	−2.13	0.58	−3.39	−5.86	−10.25	−5.24	103.49	4.92
	Tianjin	−2.92	10.41	−0.27	−11.18	−4.45	5.34	106.57	9.60
	Hebei	−18.97	−0.50	−14.39	−19.27	−4.76	1.50	−19.80	23.84
	Shandong	−7.25	−8.28	1.68	−10.45	−3.21	−11.42	10.13	15.05
	Shanxi	7.29	−1.12	−18.84	−18.54	−1.31	−2.79	−13.99	16.35
	Inner Mong	0.47	19.01	−21.16	−40.51	0.50	5.61	1.22	28.17

Table A1. *Cont.*

Period	Region	Rural				Urban			
		Δ*WFu*(*I*)	Δ*WFu*(*S*)	Δ*WFU*(*V*)	Δ*WFu*(*U*)	*WFr*(*I*)	Δ*WFr*(*S*)	Δ*WFr*(*V*)	Δ*WFr*(*U*′)
2009–2013	Beijing	−1.43	2.61	3.80	−5.39	−10.97	0.02	91.86	5.93
	Tianjin	−1.90	−7.04	4.07	−16.02	−7.14	−74.72	146.86	18.58
	Hebei	−13.36	−5.16	25.76	−13.31	−8.17	−6.64	21.45	16.83
	Shandong	−3.33	15.85	1.86	−15.68	−1.94	−16.85	7.75	23.90
	Shanxi	−55.56	9.46	−7.01	−27.61	−30.11	34.37	3.11	26.42
	Inner Mong	−26.71	−6.13	22.88	−33.34	-17.73	48.58	30.72	26.99
2013–2017	Beijing	−0.34	−3.41	−4.60	-0.69	−2.74	24.12	−89.19	0.82
	Tianjin	−1.69	−2.37	13.54	-3.91	−5.52	24.84	22.78	4.69
	Hebei	−4.71	5.36	−7.88	-21.28	−5.10	11.74	1.33	28.37
	Shandong	−1.74	16.63	4.20	-22.92	−1.27	6.90	0.08	31.26
	Shanxi	−3.43	8.67	−0.59	-18.60	−6.36	3.13	6.34	19.93
	Inner Mong	0.89	48.63	-25.31	-21.68	0.51	1.80	61.99	22.52

Note: Inner Mong: Inner Mongolia.

Table A2. The contribution value of each factor to the six provinces in North China's WF changes (m^3).

Factors	Region	Rural				Urban			
		Δ(2005–2009)	Δ(2009–2013)	Δ(2013–2017)	Total	Δ(2005–2009)	Δ(2009–2013)	Δ(2013–2017)	Total
Water Footprint Intensity	Beijing	−2.13	−1.43	−0.34	−3.90	−10.25	−10.97	−2.74	−23.96
	Tianjin	−2.92	−1.90	−1.69	−6.51	−4.45	−7.14	−5.52	−17.11
	Hebei	−18.97	−13.36	−4.71	−37.04	−4.76	−8.17	−5.10	−18.03
	Shandong	−7.25	−3.33	−1.74	−12.33	−3.21	−1.94	−1.27	−6.42
	Shanxi	7.29	−55.56	−3.43	−51.69	−1.31	−30.11	−6.36	−37.78
	Inner Mong	0.47	−26.71	0.89	−25.34	0.50	−17.73	0.51	−16.72
Consumption Structure	Beijing	0.58	2.61	−3.41	−0.22	−5.24	0.02	24.12	18.90
	Tianjin	10.41	−7.04	−2.37	1.00	5.34	−74.72	24.84	−44.55
	Hebei	−0.50	−5.16	5.36	−0.30	1.50	−6.64	11.74	6.61
	Shandong	−8.28	15.85	16.63	24.20	−11.42	−16.85	6.90	−21.37
	Shanxi	−1.12	9.46	8.67	17.01	−2.79	34.37	3.13	34.71
	Inner Mong	19.01	−6.13	48.63	61.50	5.61	48.58	1.80	56.00
Food Consumption Per Capita	Beijing	−3.39	3.80	−4.60	−4.19	103.49	91.86	−89.19	106.15
	Tianjin	−0.27	4.07	13.54	17.35	106.57	146.86	22.78	276.21
	Hebei	−14.39	25.76	−7.88	3.48	−19.80	21.45	1.33	2.98
	Shandong	1.68	1.86	4.20	7.74	10.13	7.75	0.08	17.96
	Shanxi	−18.84	−7.01	−0.59	−26.45	−13.99	3.11	6.34	−4.54
	Inner Mong	−21.16	22.88	−25.31	−23.59	1.22	30.72	61.99	93.93
Proportion of Population	Beijing	−5.86	−5.39	−0.69	−11.95	4.92	5.93	0.82	11.67
	Tianjin	−11.18	−16.02	−3.91	−31.11	9.60	18.58	4.69	32.88
	Hebei	−19.27	−13.31	−21.28	−53.86	23.84	16.83	28.37	69.03
	Shandong	−10.45	−15.68	−22.92	−49.04	15.05	23.90	31.26	70.21
	Shanxi	−18.54	−27.61	−18.60	−64.75	16.35	26.42	19.93	62.69
	Inner Mong	−40.51	−33.34	−21.68	−95.54	28.17	26.99	22.52	77.67

Note: Inner Mong: Inner Mongolia.

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