ABSTRACT

Title of dissertation: ENVIRONMENTAL IMPACTS OF CHANING DIETARY QUALITY

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The food sector has been recognized as a significant contributor to multiple environmental issues including GHG emissions, water shortage and contamination, ecological disruption, etc., while the malnutrition issues has been increasingly affecting global public health over the years, especially in developing countries such as China where the diet patterns have been shifting considerably over the decades. To develop a sustainable diet that can minimize the environmental impact while meeting nutritional quality targets within economic affordability and cultural acceptability, knowledge is required on how these aspects are interconnected via dietary patterns not only for different countries but also across heterogeneous subnational socio-economic status.

The overall aim of this research is to quantitatively evaluate the environmental impacts and nutritional quality of different dietary patterns characterized by socio-economic status. With this overarching question, this study explores three specific research questions that address the historical and assumed dietary patterns at different scales: 1) How have the environmental impact of the Chinese dietary patterns changed with the human nutritional quality for different socio-economic groups over the years? 2) How would an improvement in nutrition quality change the dietary environmental footprints in China? 3) How would the global adoption of healthy diets affect the environmental impacts in each country caused by agricultural production?

This dissertation is a synthesized analysis combining the environmental impact accounting and dietary quality evaluation. It links individual food consumption records with environmental impact factors and dietary recommendations to quantitatively analyze the nutrition-environmental nexus for individuals from different income groups, living areas, and countries, and compare how such nexus differ by these socio-economic features. In this way, this dissertation identifies opportunities and challenges in achieving a “win-win” solution for protecting the natural environment and improving public health jointly for individuals from various socio-economic contexts. Its findings provide implications for goal setting and cost-benefit analysis of integrative policymaking concerning joint nutrition development and environmental management.

ENVIRONMENTAL IMPACTS OF CHANING DIETARY QUALITY

by

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Chapter 1 Introduction

1.1 The food-nutrition-environment nexus

The global food system has been imposing considerable stress to the ecological environment. The agricultural production emits approximately 13% of global GHG (Tubiello, Salvatore et al. 2014). The contribution is even larger if emissions caused by land use change are considered (25%) (Intergovernmental Panel on Climate Change 2015). Meanwhile, the agricultural sector consumes more than 70% of global surface and ground water, and accounts for 92% of the global water footprint[1] (Hoekstra and Mekonnen 2012). The intensive demand for the irrigation not only imposes severe stress on the local water availability, but also causes salinization of soils by increasing salt and nutrient loading (Tilman, Fargione et al. 2001). Globally, 34Mha of agricultural land are now salinized by irrigation (FAO 2016). Other than water consumption, the usage of fertilizer and pesticides also contributes to water contamination (Tilman, Fargione et al. 2001). About 30% of water quality problems in the U.S. alone are caused by nutrients of which farming and feeding are significant sources (Zheng and Paul 2003); the pesticides have been ranked as one of the top three "worst toxic pollution problems" by realizing tremendous health problems especially in the developing countries (Blacksmith Institute 2011). In addition, land use change by cultivation is threatening ecosystems. Farming is estimated to be the direct driver for around 80% of deforestation worldwide (KissinGer and Herold 2012), and land clearing and habitat fragmentation lead to serious biodiversity loss (Dirzo and Raven 2003).

In the meantime, the inadequate patterns of food consumption are responsible for massive public health issues. About one-third of the global population are facing

[1] The water footprint is the sum of the green water (water sourced from precipitation), blue water (water sourced from surface and ground water), and grey water (the amount of fresh water required to assimilate pollutants to meet specific water quality standards). Therefore, the surface and ground water withdraw is a part of the total water footprint. A formal definition of these concepts can be viewed at http://waterfootprint.org/en/water-footprint/what-is-water-footprint/

malnutrition of different forms (Haddad, Hawkes et al. 2015). Nearly 800 million people are estimated to be chronically undernourished worldwide with the majority live in developing countries (FAO 2015), causing 3.1 million deaths of children under five annually (45% in 2011 globally) (Black, Victora et al.). On the other hand, over one third of the global population have become overweight or obese with a leading contribution of U.S., China and India (Ng, Fleming et al. 2014), with evidence showing that the unhealthy dietary habit has played a significant role (Bleich, Cutler et al. 2007, Swinburn, Sacks et al. 2009). This issue has become a major contributor to the global burden of disease by causing chronic non-communicable diseases such as type II diabetes, coronary heart disease, stroke and cancers (Hu 2011, Wang, McPherson et al. 2011). Meanwhile, 2 billion people are suffering from “hidden hunger” - the lack or inadequate intake of micronutrients causing iron-deficiency anemia and other diseases (FAO 2015, Haddad, Hawkes et al. 2015).

These outcomes are becoming increasingly critical as a result of the global dietary transition particularly in the developing countries. The world has witnessed a transition of dietary patterns towards higher consumption of processed foods, refined sugars, refined fats, oils and meats over the past decades, primarily driven by an increase of the income level and food availability during the urbanization process (Popkin, Adair et al. 2012, Tilman and Clark 2014). Such change happens more drastically in many developing countries experiencing rapid socio-economic transformation such as China, Brazil, and India, leading to increasing environmental impacts as well as health risks of multiple non-communicable disease such as diabetes, stroke and heart disease (Popkin 2001, Subramanian and Smith 2006, Subramanian, Kawachi et al. 2007, Lim, Vos et al. 2012, Haddad, Hawkes et al. 2015). For example, China has quadrupled its meat consumption per capita since 1971 (Westcott and Trostle 2014). As a result, it is estimated that the emission of three major GHGs (CO_2, NH_4, N_2O) from Chinese food chain system have grown from 489 Mt CO_2e to 732 Mt CO_2e during 1996 to 2010 (Li, Wu et al. 2015) while the rate of overweight and obesity are approaching to 30% and 11.9%, respectively (Zhai, Wang et al. 2009, National

Health and Family Planning Commission 2015). Given the worldwide ongoing socio-economic development, these outcomes will only become more critical. According to the projection of Food and Agriculture Organization (FAO), the consumption of animal products, especially meat, will be continuing to grow in both developed and developing countries (Alexandratos and Bruinsma 2012). If no measures are taken, such trend will almost surely exacerbate the ecological stress while imposing a more significant burden of diet-relevant disease that causes tremendous loss of social-welfare.

1.2 Literature review

To solve these interconnected environmental and health issues, policy makers seek for strategies of integrative management via a consumer behavior change towards diets with low environmental impacts which contribute to nutrition security and healthy life (Heller, Keoleian et al. 2013, Torres 2013). To setting up projections and develop effective strategies, understandings then become necessary about 1) how the nutritional quality and the dietary environmental impacts co-evolve as results of dietary transition within the population, and 2) the environmental and health implications of the various dietary patterns in setting policy goals of dietary change, particularly what would happen to the ecological environment if healthy diets are adopted in replacement of the current diets. So far, a growing body of literature has compared the environmental impacts and nutritional implications of different dietary patterns. While quite a few systematic literature reviews are available on this topic (Auestad and Fulgoni 2015, Hallström, Carlsson-Kanyama et al. 2015, Aleksandrowicz, Green et al. 2016), here I briefly summarize the scale and study areas, addressed dietary patterns, evaluated types of environmental impacts, and key findings of the current literature, and identify the gaps to be filled as the motivation of this research.

Scale and study area. Current evaluations of the food-health-environment nexus focus on either the global or national scale. A few studies have adopted the FAO database to examine the environmental and nutritional implications of the historical trend of global dietary transition (Tilman and Clark 2014) and various projected scenarios (Springmann, Godfray et al. 2016, Behrens, Kiefte-de Jong et al. 2017). In the meantime, country-specific case studies are prevalent, particularly for the developed countries where the high consumption of meat is identified to cause a double-loss for both the environmental sustainability and the human nutritional quality. Studies have investigated the diets in the UK (WWF 2011, Aston, Smith et al. 2012, Berners-Lee, Hoolohan et al. 2012, Macdiarmid, Kyle et al. 2012), Finland (Risku-Norja, Kurppa et al. 2009), Denmark (Saxe, Larsen et al. 2013), France (Vieux, Darmon et al. 2012, Vieux, Soler et al. 2013, WWF 2013, Masset, Vieux et al. 2014), the United States (Buzby, Wells et al. 2006, Eshel and Martin 2006, Peters, Wilkins et al. 2007, Peters, Bills et al. 2009, Peters, Bills et al. 2012), Austria (Fazeni and Steinmüller 2011, Vanham 2012), the Netherlands (Gerbens-Leenes and Nonhebel 2002, Gerbens-Leenes and Nonhebel 2005, Temme, Van Der Voet et al. 2013), Italy (Baroni, Cenci et al. 2007, Capone, Iannetta et al. 2013), Spain (WWF 2013), Germany (Meier and Christen 2012), Sweden (WWF 2013, Grabs 2015), New Zealand (Wilson, Nghiem et al. 2013), etc. Cases are much fewer for the developing countries, probably due to the limited data availability but are growing for areas with massive population and rapid socio-economic transformation. There are several evaluations on India (Pathak, Jain et al. 2010), Brazil (de Carvalho, César et al. 2013), and China (Hubacek and Sun 2001, Liu and Savenije 2008, Chen, Gao et al. 2010, Song, Li et al. 2015, Sun, Wang et al. 2015, Yu, Feng et al. 2016).

Dietary patterns. Existing studies usually focus on 1) the actual diets, 2) the projected diets characterized in specific development scenarios, 3) assumed diets based on specific food culture and dietary habitats, and 4) the dietary recommendations. The actual diets usually come from three sources: food consumption data from the FAO food balance sheets (Liu and Savenije 2008, Berners-Lee, Hoolohan et al. 2012, Kastner, Rivas et al. 2012), food consumption data from household surveys, and food intake from nutrition surveys (Buzby, Wells et al. 2006, Fazeni and Steinmüller 2011, Aston, Smith et al. 2012, Macdiarmid, Kyle et al. 2012, Temme, Van Der Voet et al. 2013, Vieux, Soler et al. 2013). The FAO food balance sheets provide consistent estimation of per capita food supply for detailed food categories at the national level during a long term, and are used in several global-scale (Tilman and Clark 2014, Springmann, Godfray et al. 2016, Behrens, Kiefte-de Jong et al. 2017) and country-scale (Liu and Savenije 2008, Berners-Lee, Hoolohan et al. 2012) studies. Nevertheless, these data do not provide information for within-country food allocation, nor do food loss and waste (FLW) at the consumption phase included. In the national-level studies, another two common data sources are the household survey and nutrition survey. The former records the household consumption of categories of food, but is unable to categorize the dining-out food consumption, indicate the within-home food distribution, or exclude the consumption-phase FLW. These restrictions make it hard to conclude nutritional implications based on accurate measurement of individual food intakes, thus limiting its use in the food-nutrition-environment evaluations except in a few cases (Feng, Cai et al.). Another data source, the nutrition survey, is much more widely used in the case studies (Buzby, Wells et al. 2006, Risku-Norja, Kurppa et al. 2009, Fazeni and Steinmüller 2011, Aston, Smith et al. 2012, Vieux, Darmon et al. 2012, Temme, Van Der Voet et al. 2013). It tracks the diet of individuals during a number of days to record their food intakes. Although potential under-reporting is possible (Tran, Johnson et al. 2000), such methods offer the most accurate data so far for quantitative assessment of nutritional quality.

Assumed diets are also included in a few studies for comparison with the habitual diets discussed above. A few global-scale studies project the dietary scenarios in the future considering how the composition and amount of food consumption change due to the population growth, socio-economic development, etc. (Springmann, Godfray et al. 2016, Röös, Bajželj et al. 2017). Other studies make simple changes to the habitual diet that can improve nutritional quality referring to the conclusions from epidemiologic studies, e.g. excluding dairy products (Risku-Norja, Kurppa et al. 2009), reducing calorie intakes (Vieux, Darmon et al. 2012), cutting down meat consumption (Vieux, Darmon et al. 2012, Temme, Van

Der Voet et al. 2013). Some conceptual styles such as Vegetarian diet (Vanham, Mekonnen et al. 2013) or Mediterranean diet (Tukker, Goldbohm et al. 2011) with assumed intake levels of specific food groups are also adopted in some evaluations. Finally, the dietary recommendations are also commonly included in the evaluations. The comparison between dietary recommendations and habitual diets gives explicit nutritional implications, and the environmental impacts are quantified for both scenarios in multiple studies to investigate whether adopting a healthy diet would bring about environmental co-benefits. The most often adopted recommendations come from national nutrition guidelines (Buzby, Wells et al. 2006, Peters, Wilkins et al. 2007, Sun, Wang et al. 2015, Behrens, Kiefte-de Jong et al. 2017) or dietary suggestions from World Health Organization (Springmann, Godfray et al. 2016).

Environmental impacts. Current studies have covered several major environmental impacts of food systems. The most widely examined is the GHG emissions (Eshel and Martin 2006, Risku-Norja, Kurppa et al. 2009, Popp, Lotze-Campen et al. 2010, Fazeni and Steinmüller 2011, Aston, Smith et al. 2012, Berners-Lee, Hoolohan et al. 2012, Macdiarmid, Kyle et al. 2012, Saxe, Larsen et al. 2013, Vieux, Soler et al. 2013, Masset, Vieux et al. 2014, Tilman and Clark 2014, Heller and Keoleian 2015, Springmann, Godfray et al. 2016, Behrens, Kiefte-de Jong et al. 2017, Röös, Bajželj et al. 2017, Song, Li et al. 2017), while the water footprint (Liu and Savenije 2008, Vanham 2012, Capone, Iannetta et al. 2013, Vanham, Mekonnen et al. 2013) and land use (Gerbens-Leenes and Nonhebel 2002, Gerbens-Leenes and Nonhebel 2005, Buzby, Wells et al. 2006, Kastner, Rivas et al. 2012, Temme, Van Der Voet et al. 2013, Alexander, Brown et al. 2016, Behrens, Kiefte-de Jong et al. 2017, Röös, Bajželj et al. 2017) are assessed in a few studies as well. Beyond these three frequently addressed impacts, several studies include ecological footprint (Chen, Gao et al. 2010, Song, Li et al. 2015), eutrophication potential (Behrens, Kiefte-de Jong et al. 2017). While most studies focus on a single type of environmental impact at a time, a few cases are accounting several aspects simultaneously (Song, Li et al. 2015, Behrens, Kiefte-de Jong et al. 2017, Röös, Bajželj et al. 2017).

Key findings. Studies show increased environmental impact due to the worldwide dietary transition over the decades, along with climbing health risks of obesity, diabetes, heart diseases, etc. (Pradhan, Reusser et al. 2013, Tilman and Clark 2014) While impacts from both sides are more critical for developed countries due to higher consumption of animal products (Springmann, Godfray et al. 2016), the developing countries are catching up rapidly with a "westernization" of dietary patterns (Du, Mroz et al. 2004, Popkin, Adair et al. 2012). Most studies agree that reduce the meat consumption or replace it with other less environmental impact intensive foods with principle of equal calories or protein can both benefit the human health and reduce the consumption-based environmental footprints in the developed or high-income countries (Gerbens-Leenes and Nonhebel 2002, Gerbens-Leenes and Nonhebel 2005, Buzby, Wells et al. 2006, Eshel and Martin 2006, Baroni, Cenci et al. 2007, Peters, Wilkins et al. 2007, Peters, Bills et al. 2009, Risku-Norja, Kurppa et al. 2009, Fazeni and Steinmüller 2011, WWF 2011, Aston, Smith et al. 2012, Berners-Lee, Hoolohan et al. 2012, Macdiarmid, Kyle et al. 2012, Meier and Christen 2012, Peters, Bills et al. 2012, Vanham 2012, Capone, Iannetta et al. 2013, Saxe, Larsen et al. 2013, Temme, Van Der Voet et al. 2013, Wilson, Nghiem et al. 2013, WWF 2013, Grabs 2015), even though the habitual dietary patterns and the dietary recommendations vary in details. For a few developing countries such as China, a win-win solution for sustainability and human health can also be observed via dietary change (Song, Li et al. 2017). For some low- and middle-income countries, however, some studies show GHG emissions, eutrophic potential, and land use (Behrens, Kiefte-de Jong et al. 2017), indicating the country-level heterogeneity of the food-nutrition-environment nexus.

Gaps in current literature. The global food system not only show diversity in food consumption patterns across countries, ethnic groups, socio-economic context, etc., but also involve a variety of climate condition, natural resources, and techniques in production, as well as country-specific food trade policies (Auestad and Fulgoni 2015, Aleksandrowicz, Green et al. 2016). As a result, dietary patterns and their change can affect the interconnected dietary environmental impact and human nutritional quality quite differently at the individual level. Due to such heterogeneity, the promotion of healthy diets can lead to distinct consequences to the environment, which affect the evaluation of cost, benefit and equality of particular food and environmental policies.

As the current literature shows some country-level difference on these topics, the heterogeneity at a more localized level in both the food consumption patterns is under-explored. Few studies compare dietary patterns for individuals and their nutritional and environmental consequences in different within-country socio-economic context. This difference can be sometimes considerable for the countries that experience rapid but uneven development such as China (Mayén, Marques-Vidal et al. 2014, Popkin 2014, Zhai, Du et al. 2014). As the country witnesses a prevalent transition from a starchy-food-dominated dietary pattern to more consumption of animal products, the pace and level of such shift differ by level of urbanization of the living area, personal income, etc. (Popkin 2014, Zhai, Du et al. 2014) As a result, the temporal joint change of nutritional quality and dietary environmental impact are differentiated by these socio-economic characteristics. Considering the ongoing population growth, urbanization, and socio-economic transformation and development, decision makers need to project the nutrition-environment nexus in various scenarios when developing effective policy strategies. Such projection thus calls for an in-depth understanding of how nutritional quality change with dietary environmental impact historically across socio-economic groups, which is seldom seen in the literature so far.

The local heterogeneity of dietary patterns is also lacking in the discussion on whether healthier diets can achieve a co-benefit for environmental sustainability. To date, the evaluations focus on developed countries where the consumption of animal products are considerably high, for which the reduction of these products leads to a reduction of both health risks and environmental impacts. While cases of developing countries are included in some studies (Springmann, Godfray et al. 2016, Behrens, Kiefte-de Jong et al. 2017), they usually focus on national-level data of food consumption with details of within-country food allocation averaged out. As a result, it remains a question whether the socio-economic heterogeneity discussed above would make a difference. Since individuals follow various dietary patterns, their malnutrition issues are also diversified, and so is the change of environmental impact due to a dietary change that eradicating such issues. In this way, healthier diets may lead to either co-benefits or trade-offs for the environment. The conclusion depends on how and to what extent a person is deviating from an adequate diet as well as how each type of malnutrition is distributed within the population, all of which are to be examined.

Finally, the heterogeneous environmental impact due to a change of agricultural production in response to a dietary shift is rarely addressed. When examine the environmental consequences of dietary change, the majority of evaluations focus their analysis on the consumption-based environmental impact, but do not explore where these environmental impacts and their change happens geographically (Gerbens-Leenes and Nonhebel 2002, Gerbens-Leenes and Nonhebel 2005, Buzby, Wells et al. 2006, Eshel and Martin 2006, Baroni, Cenci et al. 2007, Peters, Wilkins et al. 2007, Liu and Savenije 2008, Peters, Bills et al. 2009, Risku-Norja, Kurppa et al. 2009, Chen, Gao et al. 2010, Pathak, Jain et al. 2010, Fazeni and Steinmüller 2011, WWF 2011, Aston, Smith et al. 2012, Berners-Lee, Hoolohan et al. 2012, Macdiarmid, Kyle et al. 2012, Meier and Christen 2012, Peters, Bills et al. 2012, Vanham 2012, Vieux, Darmon et al. 2012, Capone, Iannetta et al. 2013, de Carvalho, César et al. 2013, Saxe, Larsen et al. 2013, Temme, Van Der Voet et al. 2013, Vieux, Soler et al. 2013, Wilson, Nghiem et al. 2013, WWF 2013, Masset, Vieux et al. 2014, Grabs 2015, Song, Li et al. 2015, Springmann, Godfray et al. 2016, Röös, Bajželj et al. 2017). However, the environmental impact of producing the same food items can be quite different provided the distinction of the endowment of natural resources and production techniques. The lack of concern about the territorial environmental change also leads to an omission of spillover effects due to the tele-connection between food production and consumption along the international supply chain. Such spillover can sometimes be considerable. For instance, the food demand in China would need additional 21% of crop land to satisfy its demand of food by 2030, among which one third come from foreign countries including Argentina, Brazil, the United States, Thailand, etc. (Yu, Feng et al. 2016)

1.3 Dissertation outline

This research aims at filling the gaps discussed above and develop an in-depth understanding of the association between dietary environmental impacts and human nutritional quality through the changing dietary patterns. In order to achieve this goal, I link food consumption and intake data to databases of environmental impact factors, and focus my analysis on different dietary scenarios, with exploration on three specific questions in the following chapters.

Question 1: How have the environmental impact of the Chinese dietary patterns changed with the human nutritional quality for different socio-economic groups over the years?

Question 2: How would an improvement in nutrition quality change the dietary environmental footprints in China?

Question 3: How would the global adoption of healthy diets affect the environmental impacts in each country caused by agricultural production?

This dissertation is structured with 5 chapters. Chapter 1 provides the general background and motivation for my overarching research topic. I summarize the growing literature in evaluating the environmental impact and nutritional quality of global and national diets, and conclude the gaps in the current literature. Based on the specified gaps, I propose the overarching question of this dissertation research and three break-down specific topics.

Chapter 2 focus on Question 1 and conduct an analysis on historical dietary records of individuals from 9 Chinese Provinces during the period of 1997-2011. It uses a product-based method to calculate the GHG emissions, water consumption, and land appropriation resulting from the intake of various food groups for each sampled individual, and conduct a Monte Carlo Simulation to measure the uncertainty of these environmental impacts. On the other hand, it detects the malnutrition issues at the individual level using a food-based dietary guideline, 2016 Chinese Dietary Guideline. In this way, the over- and under-intake of each type of food is identified. I compare the results for groups of individuals from different income levels in both urban and rural areas, and show whether the food-group-specific improvement of degradation of nutritional quality is linked with increase or reduction of environmental impacts for different groups over time.

Chapter 3 examine Question 2 with a scenario analysis comparing the three types of environmental impacts of the Chinese dietary patterns in 2011 and the healthy dietary pattern following the 2016 Chinese Dietary Guideline. It inherits the methodological framework of Chapter 2 in conducting the evaluations of environmental impacts and compare the difference of the changed environmental impacts across the socio-economic groups. Based on the micro-level results, this chapter uses national statistics to reweight individuals from different living areas and income levels to generate a nationally representative sample, and aggregate these impacts of dietary change for the whole country. It also discusses whether pursuing healthy diets result in similar change for different types of environmental impacts.

Chapter 4 explore Question 3 with an environmentally extended input-output analysis on the global diets. I estimate the change of per capita food consumption for 150 countries in pursuing healthy diets that eradicate all the malnutrition issues. Based on this quantification, I investigate the change of agriculture production and the consequential GHG emissions and land appropriation in response to such dietary change. I adopt a multi-regional input-output table, Global Trade Analysis Project (GTAP), which enables me to track the environmental impact embedded in international food trade. As the food production and consumption are becoming increasingly tele-connected along the international supply chain, this chapter provides some implications of the international environmental spillover effect of a national dietary change.

Chapter 5 summarize and conclude the entire body of work. I revisit the key findings of Chapter 2-4, and discuss how each chapter improve the understandings about the nutrition-environment nexus both in developing countries like China and worldwide. Finally, this chapter mentions the limitation of this dissertation, and develop topics for future research.

Chapter 2 The environmental impacts of rapidly changing diets and their nutritional quality in China

Abstract: China's fast-paced socio-economic transformation has been accompanied by shifting diets towards higher shares of non-starchy foods. Such trends change the dietary health risks but also potentially contribute to growing environmental problems, and thus necessitate an understanding of the links between nutritional quality and environmental impacts of Chinese diets. We assess the nutritional quality of over 21,500 individuals living in nine provinces during the 1997–2011 period and quantify their environmental footprints. Our study shows that the greenhouse gas emissions, water consumption and land appropriation of the average diet increased, driven by consumption of meat, cooking oil and other non-starchy foods. While increasing meat and oil consumption has led to an increased burden on the environment and a reduction in the nutritional quality of Chinese diets, increases in other non-starchy foods has improved nutritional quality but with increased negative environmental consequences. Our findings identify trade-offs and synergies emerging from analyzing the nutrition–environment nexus, and indicate challenges as well as opportunities in reducing environmental impacts while eliminating malnutrition.

Keywords: Dietary transition, GHG, water footprint, land use, malnutrition

2.1 Introduction

The way food is produced and consumed is affecting the environment as well as human well-being. The global food system emits about 19–29% of total global anthropogenic greenhouse gas (GHG) emissions (Vermeulen, Campbell et al. 2012), consumes more than 70% of the global surface and groundwater (Hoekstra and Mekonnen 2012, Ranganathan 2013), and occupies 37% of the earth's landmass (Ranganathan 2013). In the meantime, about one-third of the global population are facing malnutrition in various forms (Haddad, Hawkes et al. 2015). Worldwide,795 million people suffer from undernourishment (FAO 2015), while over one in three people have become overweight or obese, largely attributed to inadequate diets (Ng, Fleming et al. 2014). Two billion people are suffering from “hidden hunger” - the lack or inadequate intake of micronutrients causing iron-deficiency anemia and other diseases (Haddad, Hawkes et al. 2015).

In China as well as many other developing countries, the dietary transition from starchy food-based diets to more animal-based products has been adding new complexity to the environment-nutrition nexus. For example, China has quadrupled its pork consumption per capita since 1971 and expanded beef consumption fivefold (Westcott and Trostle 2014). Such structural change has made China a significant emitter of agricultural GHGs, with territorial food-related emissions of CO_2, NH_4, and N_2O having increased by 24% between 1996 and 2010 (Li, Wu et al. 2015), water footprint tripled from 1961 to 2003 (Liu and Savenije 2008), and agricultural land use increased by 50% between 1961 and 2014 (FAOSTAT 2016). Meanwhile, nutritional quality has improved in some aspects but worsened in others. Stunted development and undernourishment have been declining. For example, the prevalence of undernourishment decreased from 15% to 11.4% from 2002 to 2012 (World Bank 2017). But at the same time, excessive intake of energy, added sugar and fat are fueling the growth of obesity, with the rate of overweight people having surged from 22.8% to 30.1% from 2002 to 2012 (Bygbjerg 2012, National Health and Family Planning Commission 2015). Similar trends have been observed in many other developing countries undergoing rapid economic growth including India (Pathak, Jain et al. 2010), Brazil (de Carvalho, César et al. 2013), Egypt, Mexico, and South Africa (Vermeulen, Campbell et al. 2012). Amplified by the large population and its substantial growth rate (United Nations 2015), such ‘modernization’ of diets in the developing world, if continued without any intervention, will bring about significant environmental as well as health effects.

This obvious link between diets, environment, and human health necessitates an integrated perspective in decision-making (Tilman and Clark 2014). Because of inherent synergies and trade-offs between reducing environmental impacts of food consumption and eliminating malnutrition issues, ignoring such nutrition-environment nexus may lead to misguided policies and adverse effects. A growing body of literature has evaluated national or regional average per capita diets in terms of nutritional quality and environmental impacts such as greenhouse gas (GHG) emissions (Springmann, Godfray et al. 2016), water consumption (Liu and Savenije 2008), ecological footprint (Song, Li et al. 2015), and land use (Alexander, Brown et al. 2016). However, these averages miss important socio-economic heterogeneity in dietary patterns characterized by demographic and context factors such as income (Du, Mroz et al. 2004), education level (Song, Li et al. 2015), occupation (Mayén, Marques-Vidal et al. 2014), and the built-environment (Moore, Roux et al. 2008). Research has also investigated how socio-economic characteristics correlate with either diet-related environmental footprints (Song, Li et al. 2015) or nutritional quality (Du, Mroz et al. 2004) as well as their interlinkages (Behrens, Kiefte-de Jong et al. 2017), but detailed analysis at the sub-national level is still lacking. Moreover, a thorough understanding of how the interlinkages of environmental and nutritional outcomes evolve during dietary transitions, particularly for developing countries, is also missing. Given ongoing dietary transition and its considerable consequences for the environment and public health in these countries, identifying and quantifying the environmental impacts associated with nutritional improvement/degradation would enable policy makers to avail themselves of possible win-win solutions aiming for enhancement of both public health and environmental sustainability. In addition, specific tools if properly designed, such as an environmental taxation on food items, could raise fiscal income to support health policies (Springmann, Mason-D'Croz et al. 2016).

Here we investigate how the nutrition-environment nexus changes in response to rapid but highly uneven development in China. Using data from the China Health and Nutrition Survey (CHNS), we estimate the daily Chinese food intake at the individual level over 1997-2011, a period characterized by rapid dietary transition. We quantify individual's GHG emissions, water consumption and land appropriation resulting from food intake using environmental impact per gram of each food category from multiple datasets, and conduct a further Monte Carlo Simulation for uncertainty analysis. In addition, we evaluate over- or under-intake of food by comparing actual diets with a food-based rubric provided by the

Balanced Dietary Patterns from *2016 Chinese Dietary Guideline*. We then analyze the estimated impacts using a regression approach to look at the impact of urban/rural status and income. Finally, we decompose the change of environmental impacts by nutritional quality improvement/degradation to identify trade-offs and synergies between dietary environmental & nutritional impacts. To our knowledge, this is the first study to explore the environment-nutrition nexus in a developing country with micro-level data that enable us to measure with high accuracy nutritional quality and dietary environmental impacts by socio-economic status and over time. We believe that such observations help to predict the future environmental and nutritional impacts of diets for different groups not only in China but also in other developing countries with accelerated dietary transition.

2.2 Methodology and data

We associate product-based impacts with food items included in the CHNS sample to assess dietary environmental footprints. This survey tracks each individual to record the type and weight of their food intakes in three consecutive days. We take averages of the 3-day intakes, and link each food item with its per-gram environmental impact. For GHG emissions, we use average emissions per gram for different types of food from over 300 lifecycle assessment (LCA) studies covering the emissions from cradle to farm gate[2]. The "cradle" here involves the production of fertilizer and pesticides, but not the production of infrastructure and tools for agricultural production. Water consumption per gram of food comes from the water footprint database of Water Footprint Network[3] containing 1996-2005 average water consumption for 352 plant-based and 106 animal-based products. Water footprints for seafood are not included in this dataset but were calculated following the method from a previous study (Pahlow, van Oel et al. 2015). The land appropriation for plant-based food comes from the average of 1996-2005 field data the Food and Agriculture Organization Statistics (FAOSTAT) data, while we estimate this indicator for animal-based food using

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[2]The "cradle" here involves the production of fertilizer and pesticides, but not the production of infrastructure and tools for agricultural production.
[3]For more information about this dataset, visit http://waterfootprint.org/en/

conversion factors. Details on the calculations used for each of these three footprints are included in the supplementary information.

We used a Monte Carlo approach to estimate the uncertainty of the dietary environmental footprints resulting from climate conditions, technical difference, errors from evaluations, etc. The analysis was performed using 100 run Monte Carlo simulations. In each trial, environmental impact factors of each food group are generated from the assumed distribution with a specific mean and standard deviation based on information from the dataset of environmental impact factors. We assumed log normal distributions for GHG emission factors of each food group and used standard deviations based on our collection of LCA studies. For water consumption, we assume a normal distribution for each of the 352 plant-based and 106 animal-based products from the Water Footprint Network database, and a 15% of the means as the standard deviations for each product following a previous study (Zhuo, Mekonnen et al. 2014). For land appropriation, we assume normal distributions and 5% of the means from the FAOSTAT data as the standard deviations for each food group due to the observations of the flat change in productivity over time in FAOSTAT. The simulation is repeated for 100 trials. We then link these generated factors to the CHNS dataset to evaluate the individual dietary environmental impacts.

The nutritional quality is evaluated using the recommended *Balanced Dietary Patterns* from *2016 Chinese Dietary Guidelines*. The guidelines provides balanced dietary patterns that satisfy the nutrition needs of healthy individuals. These patterns provide the suggested intake of 14 food groups, each specified with for 11 different energy requirement levels ranging from 1000 kcals/day to 3000kcals/day as shown in Table A-5. To match the balanced dietary pattern with individuals of each energy requirement level, we calculate the estimated energy requirement (EER) for each person based on body weight, age, gender and physical activity. With these metrics, we evaluate the deviation of individual intakes of each food group by deducting the recommended intakes from her/his daily intakes, and identify the potential malnutrition issues for specific socio-economic groups.

To inspect the role of dietary transition, urban/rural status and income in the changing dietary environmental impacts and nutritional quality, we conduct a series of regression analysis. The individual daily intake, environmental impact, and percentage deviation from the balanced pattern of each food group are regarded as dependent variables. We regress year trend, urban/rural status, year trend*urban/rural status, per capita household income, per capita household income*year trend on each dependent variable, with age and its square controlled.

For the trade-offs and synergies, we first calculate the average environmental impact and percentage deviation from the balanced pattern of each food group for each year. Then we compare the deviation of each year with the value of 1997 to decide whether there is an improvement or degradation of nutritional quality for a specific food group, and calculate the difference of environmental impact for the same group (which can either be positive or negative). This provides four categories: increased environmental impact with nutritional quality improvement, increased environmental impact with nutritional quality degradation, decreased environmental impact with nutritional quality improvement, and decreased environmental impact with nutritional quality degradation. Finally, we sum up the difference of environmental impact in each category.

2.3 Results

Dietary transition in China and its environmental impact

Between 1997 and 2011, Chinese have changed the sources of calories considerably by replacing starchy food with meat and cooking oil, with the overall energy intake declining. The data shows that every year the average urban consumer has been reducing the consumption of refined cereal by 5.4 grams per day, while adding 3.0 grams of fruits, 1.2 grams dairy products, and a slight increase of all other non-starchy foods (Column 1-12, Table A-7 and referring text for details). By contrast, rural residents had a larger reduction in their intake of refined cereal (7.0 grams per day), and a larger increase of meat consumption (3.2 grams per day). Such trend has made the two groups more similar over time. The effect of income follows the same urban/rural pattern with higher income being correlated with a larger reduction of refined cereal and increase of non-starchy foods (see Figure 1 for age 18-30. Results for all other age groups, which follow a similar tendency, are shown in Figure A-2). Male individuals, needing more calories, have a significantly higher intake of most food groups, with the exception of fruits and dairy products intake, which is significantly lower. In general, the daily energy intake has been declining at an annual rate of 12.4 kcal per capita from the 2043.7 kcal per capita level in 1997, consistent with previous results from the literature using different Chinese surveys (Zhai, He et al. 2004, National Health and Family Planning Commission 2015).

This structural change is a major driver of environmental impacts despite the overall declining energy intake. GHG emissions from daily food intake for an average urban resident rose by about 10.0g CO_2e per year (Column 14, Table A-8), while the trend has been even more rapid for rural residents (18.0g). Such growth results in additional 3.65kg and 6.57kg of CO2e for an urban and rural resident, respectively, over a decade. Total water consumption from the daily food intake increased by 18.4 and 24.2 liters (l) per person a year based on 1997 level, for urban and rural residents, respectively (Table A-9), and the numbers are 0.03 and 0.05 m2 for land occupation (Table A-10). The Monte Carlo Simulation verifies the robustness of our results. We conduct the regressions in Column 14 of Table A-8 - Table A-10 for each trial of the simulation, and summarize the coefficients from all trials in Table A-12. Each indicator has a mean close to the original coefficient in Column 14 of Table A-8 - Table A-10 and small variation, and most indicators have the same sign for all trials. We also plot one standard deviation from the mean (i.e. the 16th and 84th percentile) of the simulation in Figure 1. Assuming our sample is representative of the whole country, and the total and urban population remains at the 1997 level[4], such trend would lead to an annual increase of 7.04 megatonnes of CO_2e (approximately an 1.1% increase of the diet-related emissions), 10.1 billion m3 water (approximately a 1.8% increase), and 19.9 billion m^2 land (approximately a 2.0% increase), for the whole

[4] The data is available at http://www.stats.gov.cn/tjsj/tjgb/ndtjgb/qgndtjgb/200203/t20020331_30011.html

country. The Monte Carlo simulation show an annual increase of 0.11%-1.5%, 1.3%-2.3%, and 1.7%-2.0% for emissions GHG total water consumption, and of land appropriation as a 5%-95% interval of all the trials, respectively. The growth of meat intake ranks as the most important contributor to all three environmental impacts (Column 8, Table A-8 - Table A-10). Due to higher meat consumption, urban and high-income dwellers are related to higher environmental impacts in general, while the footprints of their rural and low-income counterparts witnessed a steeper increase. These trends are illustrated for each age groups (Figure 1, and Figure A-3 – Figure A-5).

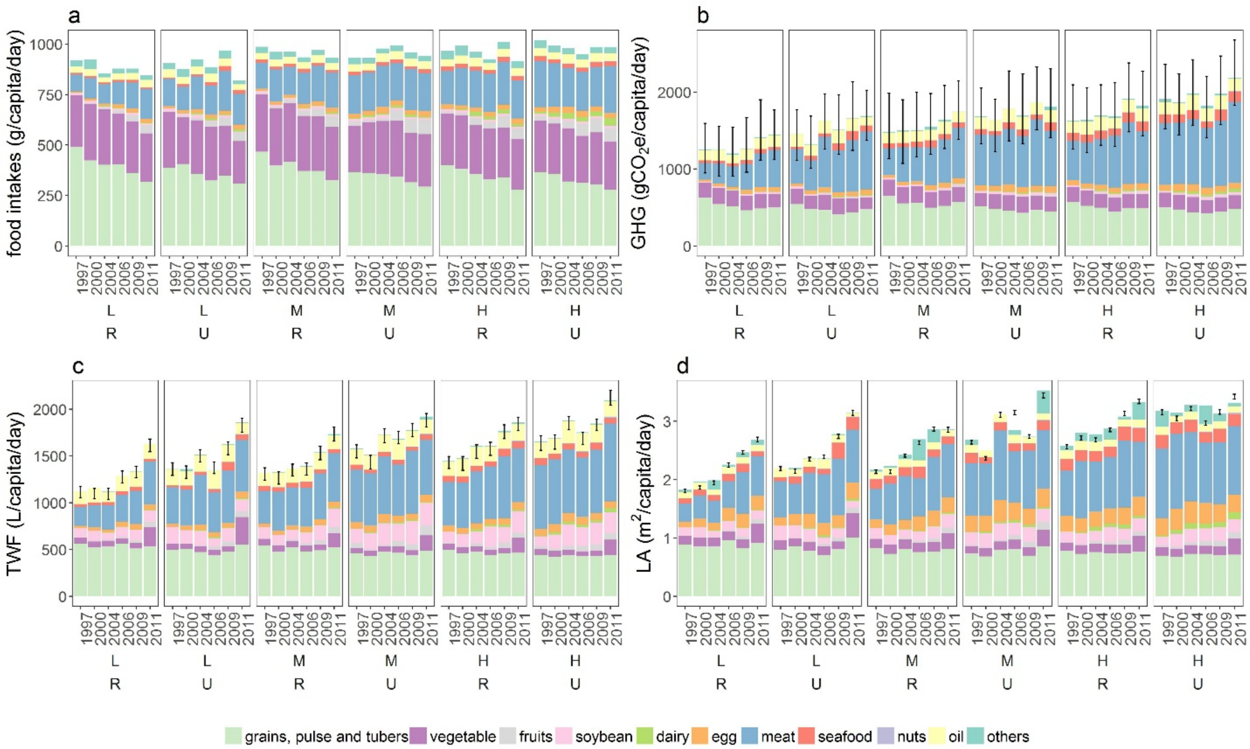

Figure 2-1 Individual daily food intake and its environmental footprints for the age group 18-30. a, Food intakes; b, GHG emissions; c, total water footprint (TWF); d, land appropriation (LA). Bars show the average food intake/environmental impact by food group represented by different colors. Error bars show one standard deviation from the mean of the average environmental impacts of each group in the 100 trials of the Monte Carlo simulation (16th and 84th percentile). R, rural; U, urban; L, low income; M, medium income; H, high income.

Nutritional quality

The Chinese suffer from a range of malnutrition issues, some of which are improving while others are worsening over time. We calculate the deviation of food intake from balanced dietary patterns for each individual with ratio of actual intakes beyond the adequate intervals divided by the boundary of the interval[5]. The socio-economic group averages are shown in Figure 2. Intake of meat, cooking oil and starchy food has been exceeding the nutritional requirement, while consumption of dairy products, fruits, nuts, seafood, eggs, vegetables and soybeans falls below recommended values (Figure A-6). Meat is the most over-consumed food: on average, individuals consume at least 100% more than they need according to the daily requirement, with middle- and high-income groups in urban areas even reaching 300%. The issue gets even worse over time for rural residents: as they were already over-consuming meat in 1997, their deviation from the balanced dietary pattern increases by 7.4% every year (Column 9, Table A-11); similar is the intake of cooking oil, with its over-intake increasing by 2.1% per year (Column 13, Table A-11). By contrast, the over-intakes of meat and oil are much more severe for urban residents, and both are increasing at a pace of 0.96% per year. At the same time, almost all groups experienced over-intake of cereal, but the over-intake had declined by 2.2% per year for rural residents and 2.3% for urban residents (Column 1, Table A-11) towards the recommended intake. The over-intake of other non-starchy foods has also slowly declined, by less than 1% a year. A considerable difference is also observed between urban and rural residents for these food groups, with the former benefiting from a more diverse diet with less deficiency of other non-starchy foods.

Richer and urban residents tend to have higher over-consumption of meat and cooking oil, lower excessive intake of cereals, and less deficiency of other non-starchy foods, and are moving closer to the recommended diet pattern over the years. Nonetheless, deficiencies of particular food groups are still prevalent: intake of coarse grains and pulses, dairy products, and nuts for all groups still close to 100% as individuals barely consume these products (Figure 2). Similar malnutrition issues and their change are also seen in other age groups (Figure A-

[5] For instance, for an individual requiring 2000kcal/day with an actual meat intake of 100g per day and a recommended meat intake of 50g per day, the deviation is (100-50)/50=100%. Similarly, if the individual has an actual dairy intake of 30g per day and a recommended dairy intake of 300g per day, the deviation is (30-300)/300=-90%.

6). In terms of gender differences, male individuals have less over-intake issues for cereal, meat, and cooking oil, and more severe deficiency of other food groups (Table A-11).

Figure 2-2 Deviation of food intake from balanced dietary patterns for the age group 18-30. The points linked by lines show averaged percentage of under-/overconsumption for each food group. The horizontal red dashed line shows balanced diets without under-/overconsumption issues; that is, points and lines on the right of this line indicate overconsumption and on the left under-consumption.

Trade-offs and synergies in the nutrition-environment nexus

From 1997-2011, increases in environmental impacts are associated with both decline and improvement of nutritional quality because of change in intake of different food groups. While increasing meat consumption above the nutritionally adequate amount leads to a loss in both environment and nutrition quality, increases of fruits, dairy products, eggs and other non-starchy foods improved nutritional quality but with negative environmental consequences. Figure 3 shows the decomposition of net changes in environmental footprint by nutritional quality changes for the age group of 18-30, rural-urban status, and level of income. The figure shows how the increasing environmental impacts due to higher consumption of meat, fruits, dairy products and other non-starchy foods tend to offset the decreasing impacts from lower cereal consumption (displays for other age groups included in Figure A-7 - Figure A-9).

The increased environmental footprints linked with a decline in nutrition quality turn out to be higher for rural and low-income groups in absolute and relative terms. For low-income, rural residents aged 18-30, there are 217.21g CO_2e/day increase of GHG emissions linked with nutrition degradation on average in 2011 compared with that in 1997, accounting for 81% of the total increase of diet-related GHGs. This is much more than their urban counterparts (195.68 g CO_2e/day, which is a 57% increase). The comparison is similar for water consumption (389 l/day, 76% increase vs. 336 l/day, 57% increase for the same groups) and land appropriation (0.51m^2/day, 61% vs. 0.48 m^2/day, 41% for the same groups). For rural, high-income residents, 116.68g CO_2e/day increased GHG emissions (60% of the total increase), 102 l/day increased water consumption (25%), and 0.12 m^2/day increased land appropriation (22%) were linked with nutrition degradation, less than half the increased environmental impacts linked with nutrition degradation of the rural, low-income group as shown above. Similar are the patterns for cross-income-group comparison in the urban area. These results can largely be attributed to a faster increase in meat and oil consumption in the rural and low-income groups. By contrast, a larger share of the increased environmental footprints for urban residents is linked with nutritional improvement as they increased intake from non-starchy foods other than meat, and in a few groups reduced intake of meat and starchy food. Generally, rural or low-income dwellers show a larger degradation of nutritional quality linked with increasing environmental impacts, while a larger share of trade-offs exist for urban residents and high-income groups.

These results reflect the distinct nutrition–environment nexus for each type of environmental footprint. The share of the increased environmental footprint that is linked to nutrition degradation is larger for GHG emissions than it is for water consumption or land appropriation (see the percentages listed above). This is essentially driven by changes in meat consumption: 1 g of meat generates more

GHG emissions than an equivalent amount of other foods, but this difference in impacts is smaller for water consumption and land appropriation (Figure A-1).

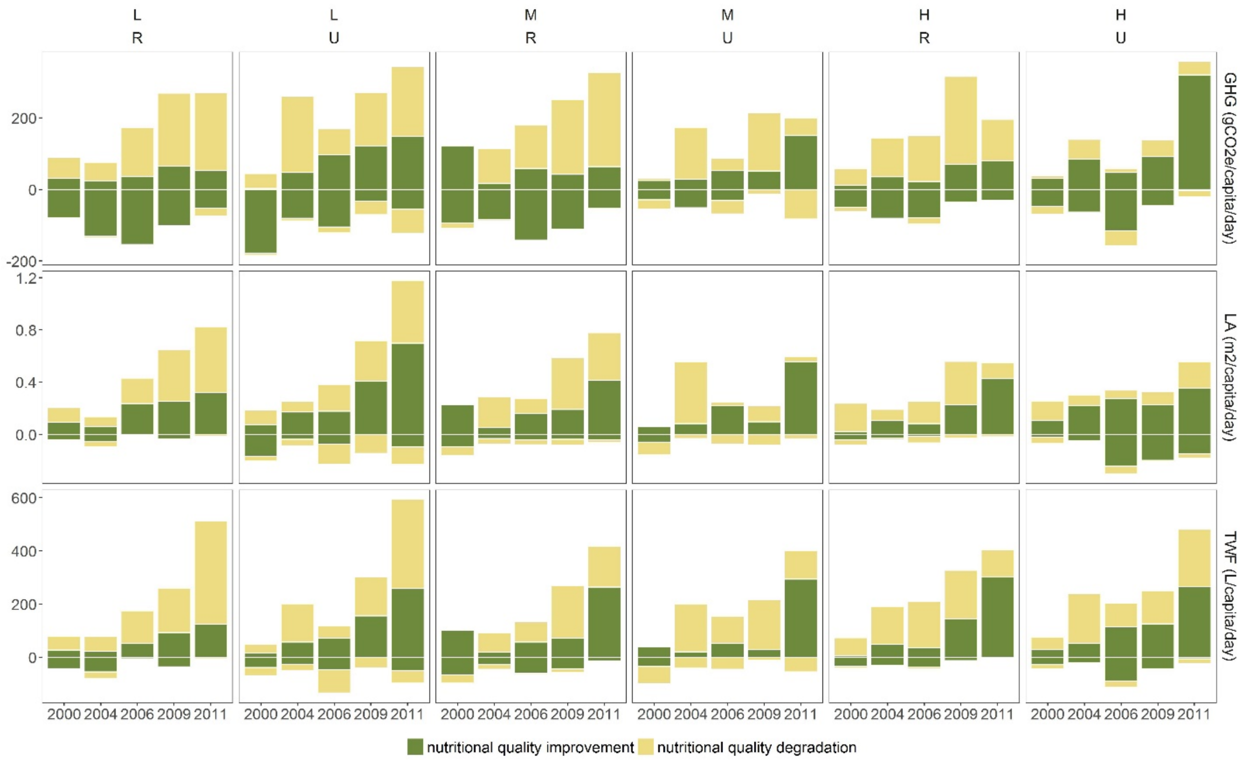

Figure 2-3 Decomposition of net changes in environmental footprints between 1997 and 2011 by nutritional quality changes for the age group 18-30. The positive bars indicate an increase in the environmental footprint and negative bars a decrease, with different colors denoting whether the nutritional quality is improved or degraded.

2.4 Discussion

The recent transition of China's diet, with its associated consequences mirrors changing lifestyles and other socio-economic developments. Because of rapid urbanization, jobs have become less physically demanding and more sedentary, while the expansion of convenient mass transport and the use of private cars have further reduced the need of consuming calories (Ng, Norton et al. 2009). Contemporaneously, high-fat and high-protein foods have become cheaper and their intake levels have increased (Popkin, Adair et al. 2012). Income growth further facilitates such increased consumption as people can afford more expensive calories from non-starchy foods, thus choose to cut down consumption of rice and flour (Du, Mroz et al. 2004). Finally, the urban food environment has also reshaped dietary patterns (Popkin, Adair et al. 2012). As more restaurants have become available and people have been adopting busier lifestyles with less time available for home cooking, dining out, which is usually characterized by the consumption of food with higher energy density and more animal products, has become a more frequent option (Zhai, Du et al. 2014).

Our results are generally in agreement with previous findings. Our estimated energy intake are close to the 2015 Chinese national survey statistics[6] (2491 kcal/day in 1982, 2328 kcal/day in 1992, 2250 kcal/day in 2002, and 2172 kcal/day 2012) (Zhai, He et al. 2004, National Health and Family Planning Commission 2015). Our estimates of diet-related individual GHG emissions are smaller than comparable estimates for developed countries. For example, in France individual GHG emission estimates based on a 2006–2007 national survey were 4.17 kgCO2e per day (Vieux, Darmon et al. 2012), and 2.94-5.93kgCO2e/day in the UK using a 1993–1999 national survey (Scarborough, Appleby et al. 2014). These differences are probably in part due to the different country-specific GHG factors used, but mostly to the higher consumption of animal products in developed countries. Our estimates are also slightly lower than some estimation for China (2.12-3.87kg CO2e/day for 2004-2009 (Song, Li et al. 2015)) largely because of different choices of emission factors. The estimated water consumption is similar to estimates from previous studies for China (1.28-1.60 m^3 per capita and day in our study vs. 1.59-2.10 m^3 per capita per day (Song, Li et al. 2015), as an example). Moreover, our estimated growth rate of dietary environmental impacts also agree with estimates from previous studies (1.3% average annual increase of per capita dietary GHG from our study vs. 1.39% of per capita dietary CO_2 in (Feng, Cai et al.)). Our results also agree qualitatively with a large body of research either based on CHNS dataset (Xu, Hall et al. 2015) or other data sources on the nutritional quality of Chinese diets (Springmann,

[6] The data from national surveys are collected by the Chinese Center For Disease Control And Prevention every ten years from a representative sample of households. Although the data from these surveys are not publicly available, results describing the state of Chinese nutrition, have been regularly released by the collecting center.

Godfray et al. 2016), which also highlight the excessive consumption of meat and lack of fruits and dairy products intake.

Our results show that there is no easy answer to whether the improvement of nutritional quality benefits the environment or not. While cutting down meat and oil consumption lead to positive environmental outcomes, increasing consumption of dairy products, seafood, eggs and other food groups needed to improve diets, results in a tradeoff between achieving the nutritional goal and protecting the environment. Specifically, the environmental impact of a dietary change depends on types and extent of individual malnutrition issues, which also varies by socio-economic status. Therefore, the environmental outcome at the country level also depends on the population structure characterized by factors that affect dietary composition and malnutrition such as age, income, and urban/rural status. Since many developing countries are often plagued with the double burden of malnutrition, that is, the coexistence of both undernourishment and over-intake of energy, animal fat and sugar (Bygbjerg 2012), the change in environmental footprints resulting from addressing both issues will depend on country-specific circumstances. More research is needed to understand the within-population differences in developing countries undergoing rapid development that drive dietary changes.

This research also stresses the necessity, because of such dietary transformations leading to sometimes conflicting, environmental and nutritional outcomes, of considering policies directed at improving nutrition and protecting the environment jointly, to take advantage of potential win–win solutions. Food policies should aim at integrating environmental sustainability considerations to guide consumers' choice, while the targets of agricultural environmental regulation should be developed based on food demand that can support healthy lives (Tilman and Clark 2014). Failure to do so could make the achievement of goals in one area negatively impact the progress of the other, and thus causes unintended policy outcomes. The need of such integrative perspectives are becoming especially urgent for not only China but also the whole developing world where a rapid dietary change is taking place. Meanwhile, more types of environmental impacts should be considered in decision making. So far, the discussion in the literature has mainly focused on GHG emissions of dietary change. While studies on water consumption (Song, Li et al. 2015), ecological footprint (Song, Li et al. 2015), and land occupation (Alexander, Brown et al. 2016) are increasing in number, most are still dealing with environmental issues in isolation. To make decisions based on more accurate estimates of cost and benefits, a wider range of environmental consequences resulted from food production and consumption would need to be considered and assessed simultaneously. By analyzing several significant nutritional and environmental consequences of food consumption, we hope that our work can serve as a starting point to develop a harmonized framework that looks at both the management of environmental impacts of the food system and nutritional adequacy for designing truly sustainable policies in all its dimensions.

Chapter 3 Environmental impacts of dietary quality improvement in China

Abstract: Global food consumption contributes significantly to not only health risks such as obesity and diabetes, but also greenhouse gas (GHG) emissions, water consumption, and land occupation. As improving nutrition quality and environmental sustainability are critical components of the Sustainable Development Goals published by United Nations, it is imperative for policymakers to understand whether initiatives towards healthier diets can also achieve a reduction of environmental impacts, particularly for developing countries such as China with rapidly changing dietary patterns and sub-national level heterogeneity in geography, socio-economic characteristics and lifestyles. We quantify the environmental impacts of individual diets from 12 provinces using the latest available data of China Health and Nutrition Survey 2011, and compare them with the environmental impacts of following the 2016 Chinese Dietary Guideline. We find that GHG emissions would decrease by 4.5% (106.5 Mt CO_2e), water consumption would increase by 36.5% (944 million m^3) and land occupation by 54.9% (2.58 billion m^2) per year in shifting to a healthy diet. Urban and high income groups have higher environmental impacts related to their diets, but could deliver larger reductions in GHG emissions with little additional water consumption and land occupation through the shift. These findings indicate a win-win opportunity in China of improving health and mitigating GHG but at the expense of increased consumption of water and land resources. They also highlight the need to focus on the effects of income inequality and urbanization in reconciling environmental impacts and human nutritional adequacy.

Key words: diet change, malnutrition, GHG, water, land, China

3.1 Introduction

The way we consume food is not only responsible for multiple malnutrition issues but also contributing to detrimental environmental impacts (Heller, Keoleian et al. 2013). Global diets have been transitioning towards a “westernized” style, which is marked by excessive intake of sugar, trans fat, and red and processed meats, as well as deficiencies of vegetables, fruits, and whole grains (Popkin, Adair et al. 2012, Micha, Khatibzadeh et al. 2015). These consumption patterns contribute to overweight or obesity in one third of the world population (Bleich, Cutler et al. 2007, Swinburn, Sacks et al. 2009, Ng, Fleming et al. 2014), inadequate intake of micronutrients ("hidden hunger") of 2 billion people (Food and Organization 2015, Haddad, Hawkes et al. 2015), and various food-related diseases including diabetes, stroke and heart disease (Lim, Vos et al. 2012). At the same time, food consumption contributes significantly directly and indirectly to global environmental impacts. The global food system accounts for 19–29% of total anthropogenic GHG emissions (Vermeulen, Campbell et al. 2012); more than 70% of the surface and ground water (Hoekstra and Mekonnen 2012, Ranganathan 2013), and uses 37% of the earth's land (Ranganathan 2013, World Bank 2016). Adverse impacts are predicted to become more severe in the near future due to further increasing consumption of animal products (Tilman and Clark 2014).

Due to the links between nutritional and environmental issues, dietary change is expected to be a promising choice to simultaneously reduce environmental impacts and eliminate malnutrition (Tilman and Clark 2014). A growing body of literature has investigated the environmental impacts of habitual diets such as GHG emissions (Eshel and Martin 2006, Risku-Norja, Kurppa et al. 2009, Popp, Lotze-Campen et al. 2010, Fazeni and Steinmüller 2011, Aston, Smith et al. 2012, Berners-Lee, Hoolohan et al. 2012, Macdiarmid, Kyle et al. 2012, Saxe, Larsen et al. 2013, Vieux, Soler et al. 2013, Masset, Vieux et al. 2014, Tilman and Clark 2014, Heller and Keoleian 2015, Springmann, Godfray et al. 2016, Song, Li et al. 2017), water consumption (Liu and Savenije 2008, Vanham 2012, Capone, Iannetta et al. 2013, Vanham, Mekonnen et al. 2013), and land appropriation (Gerbens-Leenes and Nonhebel 2002, Gerbens-Leenes and Nonhebel 2005, Buzby, Wells et al. 2006, Kastner, Rivas et al. 2012, Temme, Van Der Voet et al. 2013, Alexander, Brown et al. 2016). These studies predominantly focus on the developed world, including the United Kingdom (WWF 2011, Aston, Smith et al. 2012, Berners-Lee, Hoolohan et al. 2012, Macdiarmid, Kyle et al. 2012), Finland

(Risku-Norja, Kurppa et al. 2009), Denmark (Saxe, Larsen et al. 2013), France (Vieux, Darmon et al. 2012, Vieux, Soler et al. 2013, WWF 2013, Masset, Vieux et al. 2014), the United States (Buzby, Wells et al. 2006, Eshel and Martin 2006, Peters, Wilkins et al. 2007, Peters, Bills et al. 2009, Peters, Bills et al. 2012), Austria (Fazeni and Steinmüller 2011, Vanham 2012), the Netherlands (Gerbens-Leenes and Nonhebel 2002, Gerbens-Leenes and Nonhebel 2005, Temme, Van Der Voet et al. 2013), Italy (Baroni, Cenci et al. 2007, Capone, Iannetta et al. 2013), Spain (WWF 2013), Germany (Meier and Christen 2012), Sweden (WWF 2013, Grabs 2015), and New Zealand (Wilson, Nghiem et al. 2013). Some studies also explore whether the environmental impacts would be reduced if the study area switch to vegetarian diets (Eshel and Martin 2006, Baroni, Cenci et al. 2007, Risku-Norja, Kurppa et al. 2009, Pathak, Jain et al. 2010, Berners-Lee, Hoolohan et al. 2012, Meier and Christen 2012, Vanham 2012, Vanham, Mekonnen et al. 2013, Springmann, Godfray et al. 2016), the so-called Mediterranean diet (Wolf, Pérez-Domínguez et al. 2011, Capone, Iannetta et al. 2013, Wilson, Nghiem et al. 2013), or certain dietary recommendations (Buzby, Wells et al. 2006, Peters, Wilkins et al. 2007, Fazeni and Steinmüller 2011, WWF 2013). Most studies agree that diets with less animal products (particularly red meat) benefit both sustainability and public health (Gerbens-Leenes and Nonhebel 2002, Gerbens-Leenes and Nonhebel 2005, Buzby, Wells et al. 2006, Eshel and Martin 2006, Baroni, Cenci et al. 2007, Peters, Wilkins et al. 2007, Peters, Bills et al. 2009, Risku-Norja, Kurppa et al. 2009, Fazeni and Steinmüller 2011, WWF 2011, Aston, Smith et al. 2012, Berners-Lee, Hoolohan et al. 2012, Macdiarmid, Kyle et al. 2012, Meier and Christen 2012, Peters, Bills et al. 2012, Vanham 2012, Capone, Iannetta et al. 2013, Saxe, Larsen et al. 2013, Temme, Van Der Voet et al. 2013, Wilson, Nghiem et al. 2013, WWF 2013, Grabs 2015).

In contrast, however, there are limited studies for developing countries such as China (Lei and Shimokawa 2017, Song, Li et al. 2017). But it is important to have a stronger focus on developing countries for a range of reasons: First, diets in these countries are different from western diets. For instance, China has a much lower intake of milk but higher consumption of fruits and vegetables than many western countries (Singh, Micha et al. 2015). Furthermore, both environmental issues and malnutrition issues are worsening fast in many developing countries as their diets are westernizing with higher intake of animal products and processed foods, which create significant environmental impacts and are related to multiple diseases (Yang, Wang et al. 2013). Dietary risk factors have become the leading health risk factor in China, accounting for 16.3% of disability-adjusted life-years (DALYs) and 30.6% of deaths (Yang, Wang et al. 2013). China is suffering from obesity issues, with overweight and obesity rates reaching 30.1% and 11.9%, respectively (National Health and Family Planning Commission 2015), while deficiency of calcium is severe given the low consumption of dairy products (National Health and Family Planning Commission 2015). On the other hand, the food sector in China was responsible for 18% of direct and embedded GHG emissions (7.9-13.7% of global food-related emissions) (Chen and Zhang 2010, Vermeulen, Campbell et al. 2012), 64% of surface and ground water withdraw in 2014 (Ministry of Water Recources 2015), and 12.7% of the land use (Nath, Luan et al. 2015). All these issues are predicted to become more critical in the future, as consumption of animal products, especially meat, is expected to rise with rapid economic development and urbanization (Liu and Savenije 2008, Li, Wu et al. 2015, Yu, Feng et al. 2016). Finally, the heterogeneous socio-economic contexts within the vast population add further complexity to the nutritional and environmental impact of dietary change. In China, urban residents consumed 52% more meat than their rural counterparts in 2002 (National Health and Family Planning Commission of China 2013); the top 20% income group spent at least twice as much as the bottom 20% on food in 2011 (National Bureau of Statistics of the People's Republic of China 2012). These differences lead to distinct environmental and health outcomes as high socioeconomic status is associated with higher intake of protein, energy, and saturated fat particularly in low- and middle- income countries (Golley and Meng 2012, Eriksson, Pan et al. 2014, Mayén, Marques-Vidal et al. 2014, Wiedenhofer, Guan et al. 2016).

In this research, we explore environmental impacts of shifting to a healthy diet in China. We compare diets of 9980 individuals in 12 provinces in 2011 with the recommended 2016 Chinese Dietary Guideline to identify malnutrition issues of Chinese diets. Next, we quantify the GHG emissions, water consumption and land appropriation of their diets in two scenarios using per gram environmental impact factors from multiple databases. To capture the uncertainty of agricultural production techniques, climate conditions, as well as consumers' choice, we use a Monte Carlo simulation to evaluate uncertainties in the environmental impacts in both scenarios. We take advantage of the rich details in socio-economic characteristics in our dataset to investigate whether the results differ by income level and urban & rural status. Based on the results at the individual level, we finally extrapolate the results according to the distribution of age, sex, urban/rural status and personal income in China, and estimate the environmental impacts due to this nutritional improvement for the whole country.

3.2 Methodology and data

We derive the existing individual daily dietary patterns from the latest China Health and Nutrition Survey (CHNS) in 2011. This dataset is provided by Carolina Population Center of the University of North Carolina at Chapel Hill, and the National Institute for Nutrition and Health (NINH, former National Institute of Nutrition and Food Safety) of the Chinese Center for Disease Control and Prevention (CCDC). Aiming at obtaining nutritional information at the micro level, CHNS collects food intake, physical indicators the employment, education, and other demographic through individual surveys. It is sampled from 12 provinces of China with varying socio-economic contexts, and tracks the food intake of each individual for three continuous days and records their physical and socio-economic information including age, sex, body weight and height, physical activity, dwelling area, and income. More detailed introduction of the CHNS dataset can be found at http://www.cpc.unc.edu/projects/china. Some descriptive statistics of demographics of the sample is available in Table B-1. Although the sample is not representative at the national or provincial level, it is the most informative publicly available nutrition survey in China, and the heterogeneity of the sample can to some extent reflect the geographical difference of Chinese diets.

CHNS collects the demographic and socio-economic features from questionnaires at community, household and the individual level. The intake of other food is recorded at the individual level by 24h recall self-report for consecutive 3 days. The survey dates are randomly selected from Monday to Sunday and are almost equally balanced across the week for each sampling unit. This enables us to track all the types and weight of food intake of each individual. The intake of cooking oil and condiments are estimated by differencing the weights of these items at the beginning and the end of the survey period for each family. We follow Du et al. (Du, Mroz et al. 2004) to estimate the intake of each person. All the food items in CHNS are recorded with a food code that matches with its nutrition facts in Chinese Food Composition Tables (CFCTs) published by the National Institute for Nutrition and Health (NINH, former National Institute of Nutrition and Food Safety) at the Chinese Center for Disease Control and Prevention (CCDC). The CFCTs contain the edible portion, proximate composition and detailed nutrition content for most common food items in Chinese diets such as energy, carbohydrate, fat, protein, major mineral, vitamin, cholesterol, etc. Each food item is assigned a food code which can be directly linked to the CHNS data. There are some extraordinary large values in the food intake data. For each food group, we regard all the records that exceed 4 times of the group standard deviation as outliers and drop the corresponding individuals in our analysis.

We then construct a healthy diet for each sampled individual using the *Balanced Dietary Patterns* from *2016 Chinese Dietary Guideline*. As the latest recommendation from nutrition authorities in China, this guideline suggests a daily intake of 14 major food groups for healthy individuals, each specified for 11 different energy requirement levels ranging from 1000 kcals/day to 3000 kcals/day as shown in Table A-5. We estimate the daily energy requirement of each individual in our sample based on body weight, age, gender and physical activity, and match their diets with the balanced dietary pattern of the nearest energy level. For each food group, we regard the average of the 3-day intake taken for each individual as her/his habitual intake.

We link environmental impacts with individual daily food intake by food types to evaluate the impact of dietary patterns. As the environmental impact factors can vary due to uncertainty (e.g. changing climate) and variety (e.g. distinct techniques) of food production techniques, we adopt a Monte Carlo simulation to inspect if and how they affect our results. We assume log normal distributions for GHG emissions based on the distribution of factors of our collection, and normal distribution of water consumption and land appropriation following the current studies. Based on these assumptions, we obtain their mean and standard deviation for simulation. For GHG emissions, we collect over 300 lifecycle assessment (LCA) studies, and use the mean and standard deviation of the emission factor of each type of food to characterize the distributions. These studies cover emissions from cradle to farm gate. For water consumption, means of factors comes from the estimation provided by Water Footprint Network. The data contain 1996-2005 average water consumption for 352 plant-based and 106 animal-based products. More information about this dataset can be found at http://waterfootprint.org/en/. This dataset does not include footprints for seafood, so we estimate the factors following the method from previous studies (Pahlow, van Oel et al. 2015). However, information on the uncertainty of water footprints is rarely available. We simply assume a 15% of the means as the standard deviations for water consumption following the estimation of (Zhuo, Mekonnen et al. 2014). The means of land occupation for plant-based food is derived from the average field during 1996-2005 from the Food and Agriculture Organization Statistics (FAOSTAT); we estimate the land appropriation required in producing animal-based food using conversion factors associating quantities of feed and final animal products. Details of quantification of each environmental impact factor are included in the supporting information (SI). Similar to the water footprint, we assume 5% of the means as the standard deviations due to the lack of uncertainty analysis and the observations of the flat change in productivity over time in FAOSTAT. We also randomize the individual choice within each food group. We assume each individual independently and randomly select one item in the Chinese Food Content Tables (2002 & 2004 version) from each food group to follow the balanced dietary patterns. The probability that a specific food item is chosen is determined by the relative frequency of an individual's choice in the CHNS 2011 sample. In this way, it is assumed implicitly that they have different existing dietary patterns but similar preferences.

The simulation is repeated for 500 trials. In each trial, environmental impact factors of each food item are generated. Next, one food item from each group is picked for each individual, and its intake in following the healthy diet is calculated. As food intake is associated with a quantity of waste at the consumption phase, we inflate the intake to include such waste with the waste ratio at the consumption phase provided by FAO (Gustavsson, Cederberg et al. 2011). We also present results without the inflation in the SI to explore the role of food waste. Finally, we multiply the consumed amount of the food item with its environmental impact factors to calculate the total environmental impact. The results of all the trials compose our final sample. We calculate the percentage of deviation from the balanced dietary pattern (details included in the SI), and the total environmental impacts resulting from the dietary shift for each individual. We conduct regressions to test the effect of urban/rural status and per capita household income affect the malnutrition and dietary environmental impacts.

We finally extrapolate the environmental impact for the whole country using a reweighing method. Since the CHNS sample is not nationally representative, we generate a weight indicating the proportion of each sampled individual in the national population. The weights are constructed using another national household survey program, China Family Panel Studies (CFPS). Since 2010, this program investigates individuals from 25 provincial districts. The dataset includes individual-level demographic and socio-economic characteristics, as well as a weight for national representative estimation. We obtain the joint distribution of age, sex, urban/rural status and per capita household income in CFPS, and match the two sample using this distribution to map the weights to CHNS individuals. Details are included in the supplement information.

3.3 Results

Deviation from balanced dietary patterns. Chinese diets show a combination of over- and under-intake of important food categories. As shown in Figure 1, there is a significant over-intake of meat, refined cereal, and cooking oil, compared to the guidelines. We also summarize how much individuals are over-consuming each group of food in Table B-2 in the supporting information, which indicates that individuals consume on average 175% more meat, 71% more refined cereal and 43% more cooking oil than in the healthy diet per day, respectively. In the meantime, the consumption of other types of food is not enough to sustain a healthy diet. For example, the intake of dairy products is on average 93% lower than the recommended amount; the deficit is 88% for coarse grains and pulse, 86% for nuts, 80% for fruits, 73% for tubers, and 71% for seafood 71%. Such unbalanced diet can result in significant health risks: The over-intake of meat and low consumption of milk are both correlated to colon and rectum cancers, the dearth of nuts is associated with ischemic heart disease, and lack of fruits and vegetables is likely to cause multiple types of cancer and strokes (Lim, Vos et al. 2012). These malnutrition issues have made the dietary risks the leading health risks in China by 2010 (Yang, Wang et al. 2013).

The diets across socio-economic groups, urban vs. rural, income groups and age groups show surprisingly similar patterns of malnutrition for each food group. However, there are interesting differences to point out. We present the malnutrition patterns for each income and urban/rural group in Figure 1, further separate the groups by age in Figure B-2, and regress the socio-economic factors on the deviation from the balanced pattern for each food group in Table B-3. Urban dwellers have a smaller over-intake level of cereal and less deficit of other non-starchy food (10.4% less deficiency of milk, 11.6% less deficiency of egg, 12.9% less deficiency of seafood than their rural counterparts as shown in Table B-3), but show a more severe (44.1%) over-intake of meat. The per capita household income plays a similar role: an increase of every 10 thousand RMB leads to a decline of the deficiency of dairy products by 1.7%, egg by 3.7%, and seafood by 4.2%, but also leads to additional 11.8% of over-intake of meat. On the other hand, age play a role for all the food groups except meat according to the significance of its coefficients in Table B-3. Its effect is particularly critical for several food groups. Figure B-2 and Table B-3 shows that the elders tend to have more serious over-intake issue of refined grains and cooking oils, but less insufficiency of vegetables and soybeans. This may reflect the distinction of dietary habitat across different generations.

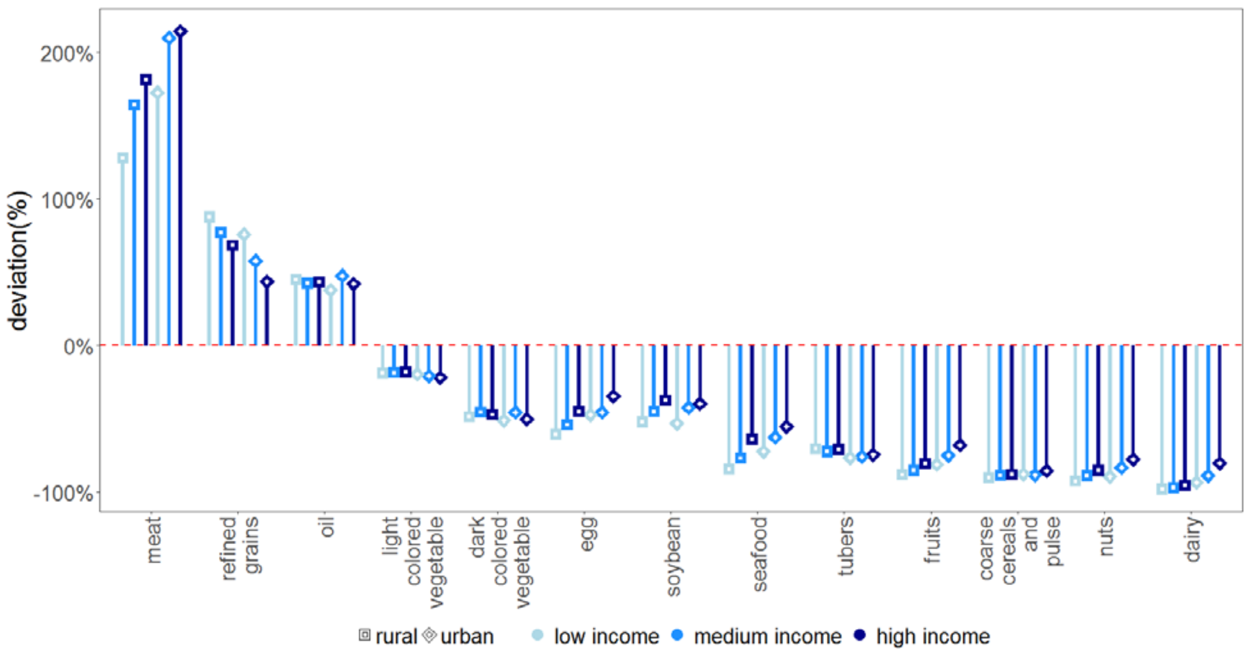

Figure 3-1 Deviation of food intake from balanced dietary patterns in percentage. Food groups on the x axis are ranked by the level of malnutrition from the most severe over-intake to the most severe under-intake. The points and lines show average percentage of under-/over-intake of each food group for each socio-economic group. The horizontal red dashed line shows balanced diets without under-/over-intake issues. We conduct t-tests on the percentage deviation from the balanced dietary patterns, and all of them turn out statistically significant.

Environmental impacts of dietary change. In order to achieve a healthy diet as laid out in the 2016 Chinese Dietary Guideline, all the socio-economic groups would have to reduce the intake of refined grains, meat, as well as cooking oil, and increase the intake of other food groups. Such dietary adjustments toward a healthy diet would create a different set of environmental impacts. The environmental impacts required to support a healthy diet would lead to a decrease of GHG by 4.5% (i.e. 106.5 Mt CO2e), 36.5% (944 million m^3) more water, and 54.9% (2.58 billion m^2) more land. We test if impacts are statistically significant conduct t-tests on all the simulation trials to detect whether the increase/decrease are statistically significant. It turns out that the average decrease of GHG emissions is only significant at the 10% significance level, while the increase of water and land are significantly positive at the 1% significance level, indicating possible trade-offs between nutrition and environment.

These results indicate that shifting to healthy diets does not necessarily benefit the environment, as was found in developed countries. The direction of change for each of these environmental impacts is dependent on the current patterns of consumption and thus the required change for each of the food groups and the respective environmental impacts of each food group. Since meat is the major over-consumed food group and has high impacts in comparison to the insufficiently consumed food groups, the environmental outcomes would depend on how high its per-gram impact is compared to those other groups. As shown in Figure A-1, the per-gram-meat GHG emission is much larger than other foods; for water consumption and land occupation, however, the contrast is weaker. Therefore, when individuals shift to healthy diets by reducing meat consumption, it would lead to a significant reduction of GHG emissions that is large enough to cancel out the increased emissions caused by increasing intake of dairy product, nuts, fruits, seafood, and other insufficiently consumed food items. For water and land, however, the benefit from the reduction of meat is more than compensated by the increased intake of other food groups.

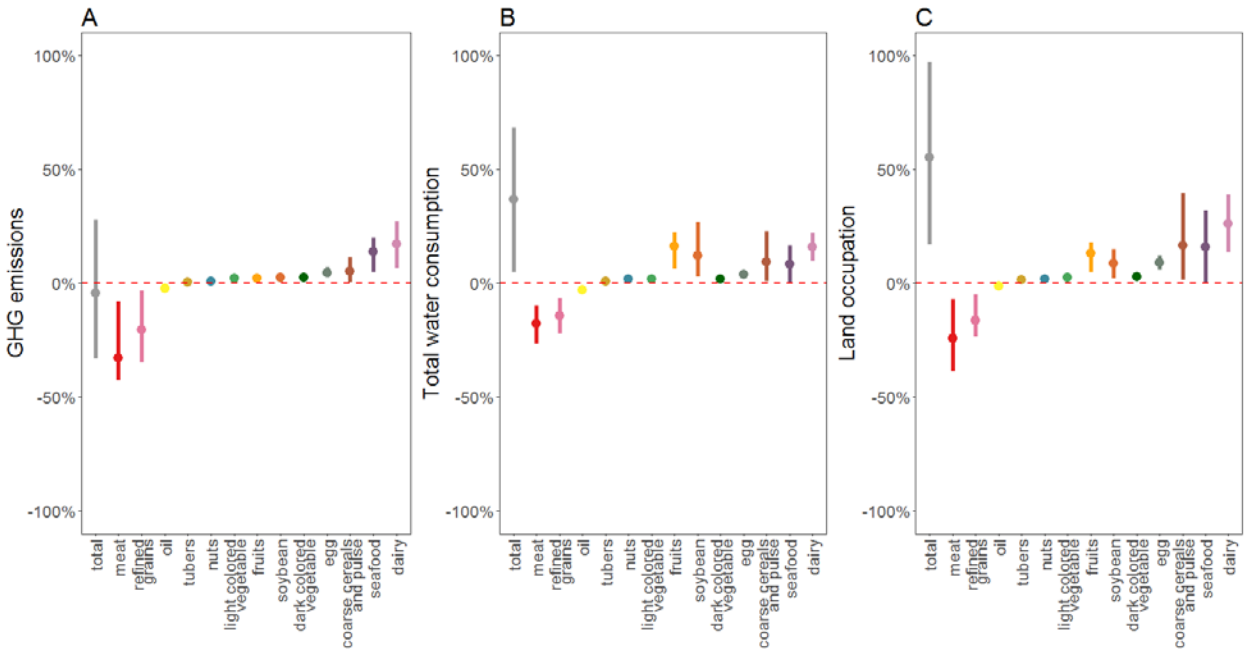

Figure 3-2 Change of environmental impacts respect to existing diet in percentage. Food groups (on the x axis) are ranked by average from the lowest to the highest. (A) GHG emissions; (B) Total water footprint; (C) Land appropriation. The points show the average, and the line shows one standard deviation from the mean (16% and 84%).

Individuals of different socio-economic groups contribute differently to environmental impacts. We display environmental impacts of the current diet and the dietary change in Figure 2, and explore the role of socio-economic status in Table B-3. Both the urban/rural status and per capita income have significantly negative coefficients when regressed on the change of the respective environmental impact, meaning that urban dwellers and high income groups are usually related to a lower increase (for water consumption and land occupation) or a higher decrease (for GHG emissions). This is a result of their higher intake level of non-starchy foods, especially animal products. On one hand, these individuals consume more meat, thus the adjustments would result in larger environmental benefits; on the other hand, they do not need as much food as their counterparts to make up for intake deficiency, especially of non-meat animal products such as eggs and dairy products. The results vary by age as well. For example, youth show a smaller decrease of GHG emission but a larger increase of water consumption and land occupation due to children and adolescents having less plant-based food groups such as tubers, soybean, and vegetables, which result in small GHG emissions but larger water consumption and land occupation. By contrast, their over-intake of meat is lower than adults'. Therefore, the net benefit in cutting GHG emissions become smaller for the youth when shifting to the healthy diet, whereas water and land use experience a larger increase for the same group.

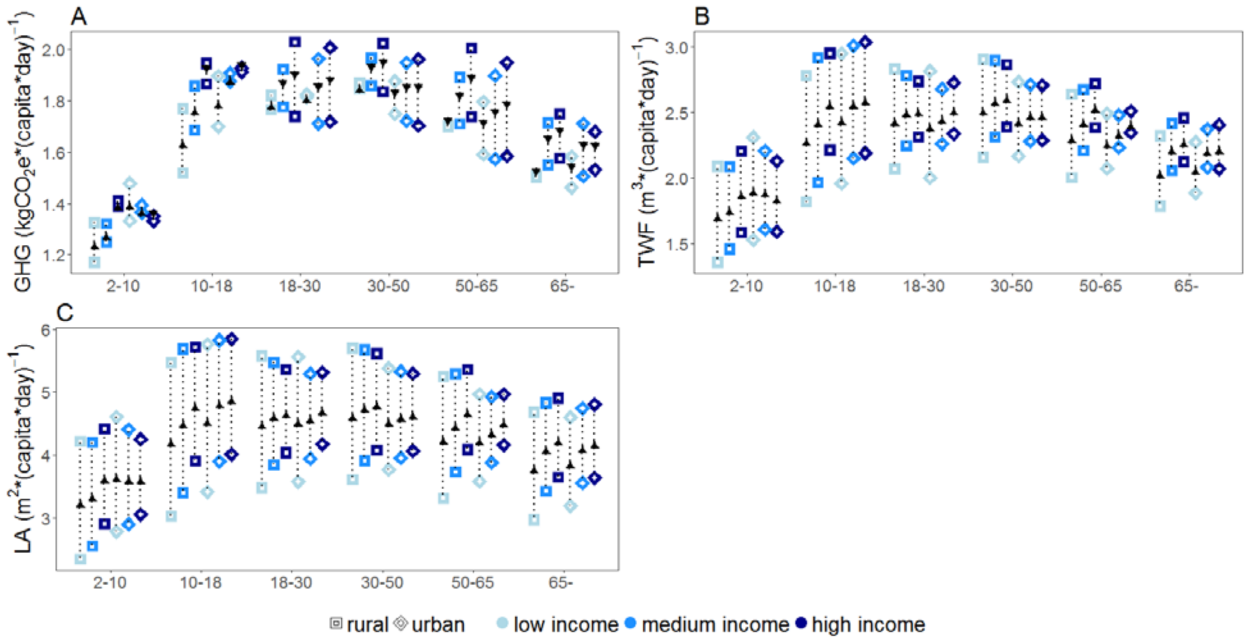

*Figure 3-3 Environmental impacts of existing and healthy diet for different socio-economic*age groups, average at the individual level. Age groups on the x axis. (A) GHG emissions; (B) Total water footprint; (C) Land appropriation. GHG=greenhouse gas, TWF=total water footprint, LA=land appropriation. The points show the average level, and the arrows show the direction of change (increase/decrease).*

3.4 Discussion

Our results add to the discussion on whether improving nutritional dietary quality leads to environmental benefit or loss. To date, research has predominantly focused on developed countries, with most concluding that a change in food consumption behavior would be a competitive, low-cost means of realizing environmental sustainability and positive health outcomes (Gerbens-Leenes and Nonhebel 2002, Gerbens-Leenes and Nonhebel 2005, Buzby, Wells et al. 2006, Eshel and Martin 2006, Baroni, Cenci et al. 2007, Peters, Wilkins et al. 2007, Peters, Bills et al. 2009, Risku-Norja, Kurppa et al. 2009, Fazeni and Steinmüller 2011, WWF 2011, Aston, Smith et al. 2012, Berners-Lee, Hoolohan et al. 2012, Macdiarmid, Kyle et al. 2012, Meier and Christen 2012, Peters, Bills et al. 2012, Vanham 2012, Capone, Iannetta et al. 2013, Saxe, Larsen et al. 2013, Temme, Van Der Voet et al. 2013, Wilson, Nghiem et al. 2013, WWF 2013, Grabs 2015). However, the conclusion of these studies is based on the fact that the developed countries need to cut down more animal products, particularly meat, than Chinese to follow a healthy diet. Although typical Western diets are generally deficient in food groups such as vegetables and fruits, increasing the intake of these foods does cancel out the environmental benefits from reducing meat intake. By contrast, over-consumption of meat is less severe in China while the deficiency of dairy products is more critical (Lim, Vos et al. 2012). Along with other insufficiently consumed foods, their increase cancels out the environmental benefits from reducing meat consumption. This result shows that the environmental impact of dietary quality improvement may not always be positive as in the case of developed countries, but depend on existing dietary patterns that individuals pursue. To date, there are very few studies examining the synergies between the environmental and nutritional consequences of dietary change in developing countries, partly due to lack of micro-level data.

Our results are different from the previous global-level study of Springmann et al. involving China (Springmann, Godfray et al. 2016). In the Springmann study, the scenario of the healthy diet is constructed according to dietary recommendations from the World Health Organization (WHO), which does not impose constraints on the intake of dairy products and seafood. These foods are rich sources of calcium and essential omega-3 fatty acid, respectively, but are rare in Chinese diets and lead to the insufficiency of the two nutrients (Lim, Vos et al. 2012), and increasing the intake of both would introduce considerable environmental impacts as shown in our results. Meanwhile, the study adopts dietary projections from FAO estimates as a business-as-usual scenario, which estimates per capita food supply based on national statistics but not micro-level individual dietary records (Details of FAOSTAT data preparation are included in Food Balance Sheets: A Handbook available at http://www.fao.org/docrep/003/X9892E/X9892E00.htm.) Such data differences may affect the evaluation results as well. So far, what composes a healthy diet is still an open question, and it is agreed that there is more than one way to practice dietary recommendations (Committee 2016). As more research attempts evaluating the environmental impact of adopting healthy diets, scholars should put more emphasis on the question of how different definitions of healthy diets affect the conclusions with important implications for designing dietary guideline and other food policy.

The findings of this research highlight the necessity of a holistic perspective in addressing the two interconnected objectives of nutritional quality and ecological sustainability. Previous studies have connected the nutritional and environmental outcomes of diets predominantly by focusing on a single type of environmental impact (Gerbens-Leenes and Nonhebel 2002, Gerbens-Leenes and Nonhebel 2005, Buzby, Wells et al. 2006, Eshel and Martin 2006, Baroni, Cenci et al. 2007, Peters, Wilkins et al. 2007, Peters, Bills et al. 2009, Risku-Norja, Kurppa et al. 2009, Fazeni and Steinmüller 2011, WWF 2011, Aston, Smith et al. 2012, Berners-Lee, Hoolohan et al. 2012, Macdiarmid, Kyle et al. 2012, Meier and Christen 2012, Peters, Bills et al. 2012, Vanham 2012, Capone, Iannetta et al. 2013, Saxe, Larsen et al. 2013, Temme, Van Der Voet et al. 2013, Wilson, Nghiem et al. 2013, WWF 2013, Grabs 2015). However, multiple environmental impacts from dietary adjustment can be different in directions, and looking at each in isolation would lead to misleading conclusions and incomplete understanding. Studies have shown that when human activities can lead to more than one environmental outcomes, lack of integrated perspectives can lead to inconsistent policies and inefficient use of resources and erroneous estimation on the cost and benefit (Howells, Hermann et al. 2013, Gingerich, Sun et al. 2017). As shown in this case, shifting to a healthy diet can result in synergies and trade-offs with different types of environmental impacts. This fact calls for integrative consideration of significant, if not all, environmental elements affected by dietary choice in managing the food-health-environment nexus. The Chinese government has developed national goals of improving nutrition quality (China General Office of the State Council 2014) as well as five year plans of abating GHG emissions (The State Council of China 2016), promoting water saving (National Development and Reform Commission 2017), and conserving the ecological sustainability during land development (Ministry of Land and Resources of the People's Republic of China 2016). The food-health-environment nexus thus provides a framework to systematically evaluate trade-offs across policy arenas.

Our findings also suggest that policy makers should look into socio-economic diversity when addressing the nutrition-environment nexus. The differences across lifestyles and other socio-economic variables help explain diverse malnutrition issues and environmental impacts. Such differences have been observed across countries (Tilman and Clark 2014, Alexander, Brown et al. 2016, Springmann, Godfray et al. 2016, Springmann, Mason-D'Croz et al. 2016), but still need more attention within countries or even regions given socio-economic heterogeneities. As urban and high-income consumers pursue more westernized diets in China, policies that improve their nutritional quality may result in co-benefits with regards to reducing GHG emissions as well as slowing the inevitable increase of water and land use. Available policy tools such as campaigns promoting healthy diets and food price adjustment can result in different distributional environmental and nutritional outcomes given disparities in behavioral responses and price elasticities among various socio-economic groups (Andreyeva, Long et al. 2010). While these issues should be addressed in future research, we hope this study would provide a starting point for recognizing their importance.

Chapter 4 National environmental impacts of reducing global dietary health risks

Abstract: Global food consumption is transitioning in a way that not only imposes pressure on the ecological environment but also adds to health risks. While scholars have been discussing whether shifting to healthy diets also realize a co-benefit in reducing environmental impacts, the spatial distribution of such change and the spillover effects due to the globalization of the food supply chain is under-explored. In this study, we evaluate the national greenhouse gas (GHG) emissions and land appropriation of shifting to dietary patterns at the global level. We compare the diet of each country in 2011 with the dietary recommendation from Global Burden of Disease Study to identify the change of food consumption in eradicating dietary health risks. Next, we adopt the environmentally-extended input-output analysis to quantify the GHG emissions and land appropriation resulting from the change of food consumption. We further track backward the international trade network to map the distribution of territorial environmental impacts due to the change of agricultural production, with a separation of domestic and exported impacts. We find that shifting to healthy diets lead to a reduction of GHG

increased from 4875 Mt CO2e to 4295 Mt CO2e by about 12%

emission from 4874.1 Mt CO_2e to 4294.0 Mt CO_2e (by 11.9%, and 1.9% of the all-sector emissions) and land appropriation of 2.62 billion m^2 to 2.12 billion m^2 (by 19.1%, and 8.1% of the all-sector appropriation) per year, mainly driven by cutting down the consumption of meat, cereal, oil, and sugar. The change is heterogeneous across countries with all but a few countries in South Asia and Africa reducing both their consumption-based and production-based environmental impacts. The largest changes in environmental impacts happen in the countries where diets also change. Changes in diets can however also affect the environment in other countries through the supply chain. Countries affected this way include Brazil, United States, China, and Australia. Our findings reveal

the importance of local heterogeneity in evaluations on the environmental impact caused by promoting healthy diets, and provide policy implications in mediating the global food-health-environment nexus through domestic food consumption, international trade network, and consumer behavior change.

Key words: dietary environmental footprint, nutrition adequacy, sustainable diet

4.1 Introduction

The global food consumption patterns are not only placing a significant burden of disease but also resulting in significant environmental impacts. The inadequate diets low in fruits, vegetables, whole grains, and nuts and seeds but high in sweetened beverage, and red and processed meat are causing multiple non-communicable diseases (NCDs) including obesity, diabetes, heart disease, strokes, etc.(Lim, Vos et al. 2012) In the meantime, such food consumption patterns are responsible for about 19%–29% of total global anthropogenic GHG emissions (Vermeulen, Campbell et al. 2012), more than 70% of global surface and ground water (Hoekstra and Mekonnen 2012, Ranganathan 2013), 37% of the earth's landmass occupation (Ranganathan 2013). Both issues are becoming even more critical as most countries, particularly the developing world, have been experiencing a rapid dietary transition towards excessive intake of animal products and foods rich in saturated fat and added sugar (Popkin, Adair et al. 2012, Tilman and Clark 2014).

These alerting issues have led to a discussion on whether public health improvement through dietary change can also lead to an environmental co-benefit. A growing body of literature has compared the environmental impact and nutritional implications of various dietary patterns. Studies are conducted for multiple developed countries including the United Kingdom (WWF 2011, Aston, Smith et al. 2012, Berners-Lee, Hoolohan et al. 2012, Macdiarmid, Kyle et al. 2012), Finland (Risku-Norja, Kurppa et al. 2009), Denmark (Saxe, Larsen et al. 2013), France (Vieux, Darmon et al. 2012, Vieux, Soler et al. 2013, WWF 2013, Masset, Vieux et al. 2014), the United States (Buzby, Wells et al. 2006, Eshel and Martin 2006, Peters, Wilkins et al. 2007, Peters, Bills et al. 2009, Peters, Bills et al. 2012), Austria (Fazeni and Steinmüller 2011, Vanham 2012), the Netherlands (Gerbens-Leenes and Nonhebel 2002, Gerbens-Leenes and Nonhebel 2005, Temme, Van Der Voet et al. 2013), Italy (Baroni, Cenci et al. 2007, Capone, Iannetta et al. 2013), Spain (WWF 2013), Germany (Meier and Christen 2012), Sweden (WWF 2013, Grabs 2015), and New Zealand (Wilson, Nghiem et al. 2013), while cases of developing countries such as India (Pathak, Jain et al. 2010), Brazil (de Carvalho, César et al. 2013), and China (Hubacek and Sun 2001, Liu and Savenije 2008, Chen, Gao et al. 2010, Song, Li et al. 2015, Sun, Wang et al. 2015, Yu, Feng et al. 2016) are increasing. Despite the difference of dietary patterns across the countries, most studies agree that shifting to healthy diets that contain less meat but more fruits and vegetables help to reduce GHG emissions, water consumption, ecological footprints, etc. Global-level evaluations also conclude a reduction of GHG emissions (Springmann, Godfray et al. 2016, Behrens, Kiefte-de Jong et al. 2017, Röös, Bajželj et al. 2017), land appropriation (Alexander, Brown et al. 2016, Behrens, Kiefte-de Jong et al. 2017, Röös, Bajželj et al. 2017), and eutrophication potential (Behrens, Kiefte-de Jong et al. 2017) of dietary change in the total amount.

While the current literature shows an extensive coverage of geographical areas, how the environmental impacts due to such dietary change distribute across the countries is under-explored. The majority of studies focus their accounting on the consumption-based environmental footprints but do not discern where these footprints are generated (Gerbens-Leenes and Nonhebel 2002, Gerbens-Leenes and Nonhebel 2005, Buzby, Wells et al. 2006, Eshel and Martin 2006, Baroni, Cenci et al. 2007, Peters, Wilkins et al. 2007, Liu and Savenije 2008, Peters, Bills et al. 2009, Risku-Norja, Kurppa et al. 2009, Chen, Gao et al. 2010, Pathak, Jain et al. 2010, Fazeni and Steinmüller 2011, WWF 2011, Aston, Smith et al. 2012, Berners-Lee, Hoolohan et al. 2012, Macdiarmid, Kyle et al. 2012, Meier and Christen 2012, Peters, Bills et al. 2012, Vanham 2012, Vieux, Darmon et al. 2012, Capone, Iannetta et al. 2013, de Carvalho, César et al. 2013, Saxe, Larsen et al. 2013, Temme, Van Der Voet et al. 2013, Vieux, Soler et al. 2013, Wilson, Nghiem et al. 2013, WWF 2013, Masset, Vieux et al. 2014, Grabs 2015, Song, Li et al. 2015, Springmann, Godfray et al. 2016, Röös, Bajželj et al. 2017), while studies addressing this issue cover only a limited number of countries or regions (Hubacek and Sun 2001, Sun, Wang et al. 2015, Alexander, Brown et al. 2016, Yu, Feng et al. 2016, Behrens, Kiefte-de Jong et al. 2017). This leads to an omission of the regional heterogeneity of impacts in producing the same foods due to the distinction of technology, climate condition, etc. It also fails to include the spillover effects due to the tele-connection between food production and consumption along the international supply chain. Such spillover can sometimes be considerable. For instance, the food demand in China would need additional 21% of crop land to satisfy its demand of food by 2030, among which one third come from foreign countries including Argentina, Brazil, the United States, Thailand, etc. (Yu, Feng et al. 2016) As a result, it is unclear whether and how international trade may play a role in reallocating agriculture production to further optimize resource use and reduce environmental impacts while advocating healthy diets, particularly if local ecological stress increases due to an improvement of nutritional quality.

Here we present an evaluation of the national environmental impacts in eradicating global malnutrition issues. We compare the current diet of each country and the global dietary recommendations from the Global Burden of Disease Project to find out the change of food consumption in shifting to healthy diets. Next, we adopt the environmentally-extended input-output analysis to quantify the GHG emissions and land appropriation resulting from such change. We further track backward the international trade network to map the territorial environmental impacts due to the adjustment of agricultural production, with a separation of domestic and exported impacts. The evaluation cover 150 countries and regions, more than the existing global-level studies that we are aware of (Alexander, Brown et al. 2016, Springmann, Godfray et al. 2016, Behrens, Kiefte-de Jong et al. 2017, Röös, Bajželj et al. 2017). By linking the food consumption to agricultural production and investigate the national difference of environmental impacts from both sides, we provide implications for comprehensive policy design to support sustainable food systems with a combination of consumer behavior change, production technical progress, and international food trade.

4.2 Methodology and data

Food consumption in following the current diets

We retrieve the per capita consumption of different food groups for each country from the Global Expanded Nutrient Supply (GENuS) database. Developed by nutritionists from Harvard University and Tufts University, this dataset contains individual daily supply of 225 food categories as well as 23 nutrients[7] for 26 demographic groups (13 age group with an interval of 5 years, each separated for male and female) in 150[8] countries and regions in 2011. The food supply data are constructed based on the food supply data from Food and Agriculture Organization Statistics (FAOSTAT), and are further disaggregated referring to the food intake data from Global Dietary Database[9]. The supply of nutrient is estimated using the food content tables from each country. The method of constructing the database has been validated through a comparison with the independent estimates by the USDA for historical US nutrition which shows good agreement. Details of the methodology in developing and validating the database can be found from (Smith, Micha et al. 2016).

We exclude the food waste in the consumption phase using the food waste ratio from FAO to obtain the food intakes. Similar with FAOSTAT from which its data is estimated, GENuS describe the food supplies available for human consumption at the retail level, i.e. before the food enters the household (FAO 2001), which is

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[7] Including calories, fat, protein, carbohydrates, dietary fiber, vitamin C, vitamin A, folate, thiamin, riboflavin, niacin, total B6, calcium, iron, zinc, potassium, copper, magnesium, selenium, phosphorus, saturated fatty acids, monounsaturated fatty acids, and polyunsaturated fatty acids.

[8] There are 175 countries in the introductive paper of the GENuS dataset Smith, M. R., et al. (2016). "Global expanded nutrient supply (genus) model: A new method for estimating the global dietary supply of nutrients." PLoS ONE **11**(1): e0146976. However, 15 of them are with 0 values for all the 225 food categories, and 2 are with extraordinary values that are too far away from the FAOSTAT. We exclude these 17 countries from the evaluation.

[9] The GDD provides per capita intakes of major food groups for demographic groups of each country. The data comes from the collection of national nutritional surveys.

usually higher than the actual food intake considering the possible food waste during the household storage and food preparation. To exclude such waste, we adopt the waste ratio from FAO (Gustavsson, Cederberg et al. 2011). These ratios provide food group and region-specific percentage of the food wasted in the consumption phase, each linked with the food categories in GENuS. The details of linking the two datasets are included in the supporting information.

Food consumption in following the healthy diets

We adopt an optimization method to obtain the food intake for individuals from each sex and age group in every country in following healthy diets. This technique has long been used in designing dietary patterns that satisfies the requirement of nutritional quality (Macdiarmid, Kyle et al. 2012, Moraes, Wilen et al. 2012, Tyszler, Kramer et al. 2015, van Dooren, Tyszler et al. 2015, Gephart, Davis et al. 2016, Horgan, Perrin et al. 2016). In an optimization, a programming, either linear or nonlinear, is conducted in searching for the intake levels of each food categories as an optimal solution that can maximize/minimize the objective function while meeting the constraints on the adequate intake levels of specific nutrients and/or food categories. Various objective functions are used in the optimization studies, including minimizing the environmental impacts (Macdiarmid, Kyle et al. 2012, Gephart, Davis et al. 2016), minimizing the individual deviation from existing dietary patterns following several previous studies (Tyszler, Kramer et al. 2015, Horgan, Perrin et al. 2016), etc. In this study, we assume that individuals consume foods in a way that conform as close as possible to familiar and socially acceptable dietary patterns, and seek for the food consumption that leads to the smallest change from their current diet without hurting the nutritional quality with

$$\min \| C - C_0 \|$$

$$s.t. NC < b$$

In which C implies a to-be-solved vector of food consumption in following a healthy diet, and C_0 is the food consumption in following the current diet retrieved from the GENuS dataset. $\| C - C_0 \|$ implies the Euclidean distance between the two calculated by $\sqrt{\sum_i (c_i - c_{0i})^2}$, where c_i and c_{0i} are the consumption of food category i in C and C_0, respectively. $NC < b$ are a set of constraints on the intakes of specific food categories and nutrients.

We refer to the nutritional recommendations from the Global Burden of Disease (GBD) Project (Lim, Vos et al. 2012) to set up $NC < b$. Based on previous studies, the GBD project conclude the causal associations between specific foods (e.g. fruits, vegetables, red meat, etc.) or nutrients (e.g. dietary fiber, calcium, etc.) and diseases, and provide recommendations on adequate intake of these foods and nutrients that can minimize the diet-related health risks. For each food or nutrient, the adequate intake is indicated by an interval, which we adopt as constraints of food and nutrient intakes in following healthy diets[10]. A detailed list of each food category/nutrient and their constraints included in the supporting information. Moreover, these recommendations only apply to adults above 25 years old, so we refine the population of study accordingly and leave the dietary patterns for the children and adolescents untouched.

In addition to the GBD recommendations, we include consideration of total daily calorie intake for evaluation of nutritional quality. Excessive calorie intake more than the physical requirement is suspect to be a reason of overweight and obesity, (citation) while insufficient intakes lead to starving and undernourishment. As the GBD study doesn't provide a quantitative recommendation on total daily energy intakes, here we restrict the total calorie intakes to equal to the daily calorie requirement. These requirements are retrieved from the Average Dietary Energy Requirement (ADER), a proper normative reference for adequate calorie intake in the population, provided by FAOSTAT. It is computed based on the distribution

[10] The bounds of these intervals can involve some variation. For instance, fruit intake of no lower than a mean of 300g/day with a standard deviation of 30g/day is identified to be adequate, meaning that the lower bound of fruit intake can vary by individuals with a standard deviation of 30g/day while the mean threshold turns to be 300g/day. Here we adopt the means to evaluate the nutritional quality.

of body height, body weight, and physical activity level of the population. More details about the estimation of ADER can be found from (FAO/WHO/UNU 2004).

Environmental impact of food consumption

We conduct an environmentally extended input-output (EEIO) analysis to evaluate both the GHG emission and land appropriation of the food consumption. The input-output analysis has been widely applied in accounting the embedded environmental impact in food products generated in each phase of the supply chain (Yu, Feng et al. 2016, Behrens, Kiefte-de Jong et al. 2017, Hadjikakou 2017). Through matrix manipulation, it captures the total environmental impacts of consuming foods produced by different sectors. Moreover, a multi-regional input-output (MRIO) table enable us to track the international trade flow and locate such embedded environmental impacts to the geographical area where they take place. As a result, we can readily tell the environmental impacts based on both consumption, i.e. the impact realized by the dietary change in each country, and production, i.e. the territorial impact in each country due to the dietary change in itself and other regions.

The IO table and the environmental impact factors come from the Global Trade Analysis Project (GTAP) database (version 9). With the latest reference year of 2011, the GTAP database features 140 regions for all 57 production sectors, covering the majority of the global economic activities. Among the 57 sectors, there are 20 food sectors covering both primary and processed products of crops, livestock, poultry, and fish. Compared with other IO database in which the agricultural sectors are highly aggregated, this detailed disaggregation enables us to quantitatively evaluate specific environmental impacts of major food groups. GTAP 9 also provides data of GHG emissions including CO_2, CH_4, and N_2O normalized in CO_2 equivalent for each sector in all the regions. For land use, the data of cropland, grazing, and forest lands for agricultural sectors of each region are available. For non-agricultural sectors, we retrieve the data of commercial and residential land collected by the World Resources Institute in 2007 (World

Resource Institute 2000), and further disaggregate them by sectors following the method from (Yu, Feng et al. 2013). Along with the highly disaggregated sectors and detailed environmental impact factors, the 140 regions included in the database cover more than 99% of the global population with a range of development levels, more than other IO databases with high disaggregation of agricultural sectors (such as EXIOBASE). Such inclusiveness allows us to tell the national heterogeneity of agricultural production techniques, food trade networks, and dietary patterns in resulting from country-specific environmental impacts, and investigate how the development level has affected the environmental impacts from food consumption and production through these factors.

The GTAP IO table provides z_{ij}^{pq}, i.e. the direct monetary flow from sector i in country p to sector j in country q. $\sum_i z_{ij}^{pq}$ thus gives vector X, with each of its element x_j^q indicating the total output of sector j in country q. In this way, we can obtain the technical coefficient matrix A, in which each element is calculated with z_{ij}^{pq} / x_j^q. Meanwhile, the matrix of final demand, Y, composed by y_i^{pq}, the final consumption in country q from sector of country p, is also available in the database. In this way, we have

$$X = AX + Y$$

Solving X gives

$$X = (I - A)^{-1} Y$$

With the data of direct environmental impacts resulting from the production activity of each sector in each country, g_j^q, we can construct a vector F, with each element g_j^q / x_j^q indicating the impacts per unit output. The total environmental impacts embedded in the consumption from each sector and country can then be calculated as

$$E = F \cdot (I - A)^{-1} Y$$

In this way, the environmental impact of the dietary change can be quantified as

$$\Delta E = F \cdot (I - A)^{-1} \Delta Y$$

We link the food consumption in following the current and healthy diets with the GTAP database to evaluate the environmental impacts of dietary change for each country following (Behrens, Kiefte-de Jong et al. 2017). First, each of the 225 food categories from the GENuS dataset that we develop is associated with a sector in the GTAP MRIO table as its output. The concordance of the food items in the food balance sheet and the MRIO sectors is included in the supporting information. Next, we sum up the consumption of food categories that are linked to the same sector in each country, and regard this aggregated amount as the total output (in quantities) in each sector for a country to follow the current diet. As the GTAP provide the monetary values of such consumption in Y , the basic price of foods from each sector can be obtained by dividing Y by such quantities of total output. Finally, we estimate ΔY with the basic prices and the change of food consumption in quantities, and use the equation above to calculate the consequential environmental impacts.

4.3 Results

Dietary adjustment

The majority of countries suffer from similar dietary health risks, with the extents varying with income levels. We plot the Gross National Income (GNI) per capita (in log) and the change of consumption in each food group approaching healthy diets for each country in Figure 1. There is a widespread over-intake of meat and sugar in global diets. All the countries need to cut their consumption of these foods, with an average of 47.40g for red meat, 22.66g for poultry, and 59.46g for sugar. Meanwhile, 122 out of 148 countries should reduce consumption of cereal (63.69g on average globally), while 110 countries need to cut oil consumption (25.37g on average). In the meantime, the deficiency of vegetables, fruits, dairy products, seafood, as well as nuts is common. The intake of milk is far below the recommended value for most countries so that they need to increase

164.16g*(capita*day)$^{-1}$ on average. Similarly, 131.34g fruits, 48.03g nuts, 15.33g seafood, and 223.08g vegetable should be added to plates.

There is some heterogeneity by development levels, however, in this malnutrition pattern. The two variables show a positive correlation between starchy foods include cereal and tuber. The distribution of points on both sides of the horizontal line of zero, along with the intersection of this line with the linear trend, indicates an excessive intake of carbohydrate in low-income countries as well as a need of replacing other foods with cereal and tuber in several high-income countries. Meanwhile, a downward trend is seen for not only animal products including red meat, poultry, dairy products, and eggs, but also oil and sugar. Although most countries are located on the same side of the horizontal line, the over-consumption of meat, sugar and oil seems to become more severe as income level rises, while the insufficiency of dairy products declines. These results align with the observations that human diets advance to patterns with less intake of carbohydrate but more animal-based proteins and added sugars. There are no specific trends for fruits, vegetable and seafood with small and insignificant correlation coefficients, showing a common deficiency of these foods in the global diet.

The change of dietary patterns also shows some geographical difference as well. We regress the dummies of regions and per capita GNI on the change of food consumption in Table C-3. There is a significant across regions particularly for starchy foods, dairy products, meat, and seafood. Most regions need to reduce their intake of cereal compared with the North America (which actually show an increase of cereal in demand), with the largest reduction happening in the Middle East & North Africa. Similarly, regions other than Europe & Central Asia show a requirement of more dairy products than North America, specifically East Asia & Pacific where such food is less popular. Compared with North America, the other regions also show a smaller reduction of oil and red meat and a smaller increase of seafood. These difference may reflect the disparities in dietary culture for each region.

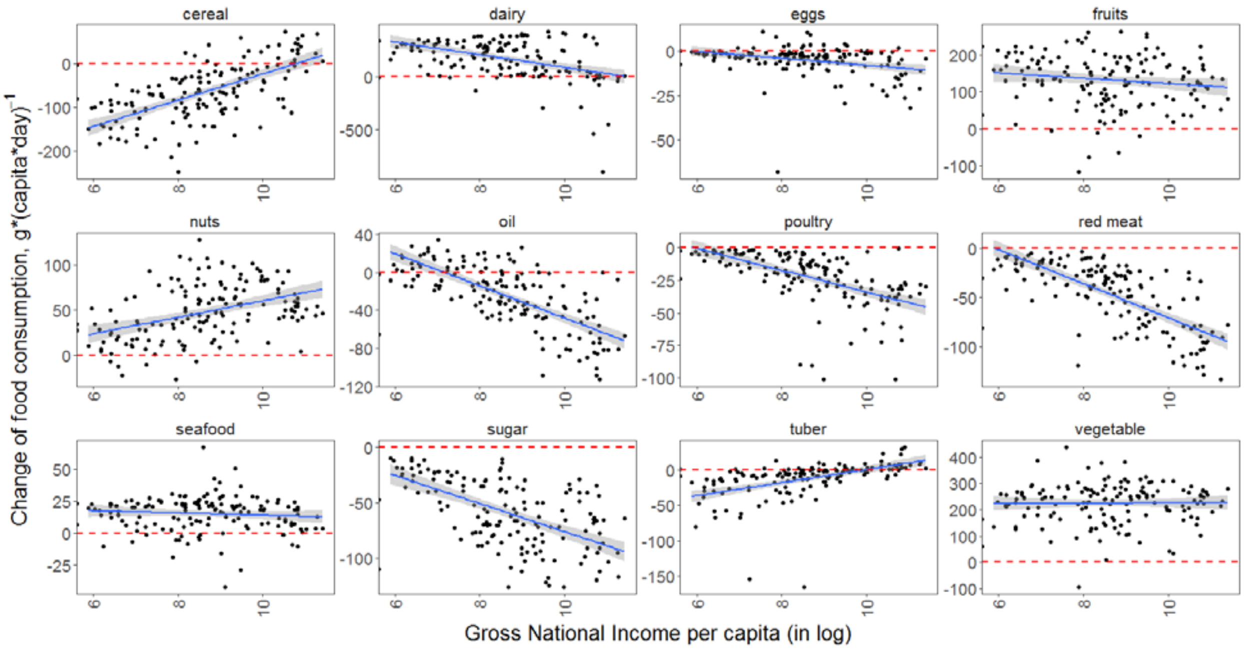

Figure 4-1 Relationship between gross national income per capita and the change of food consumption towards healthy diets. The red dashed lines show the balanced level of healthy diet; positive y coordination indicates that an increase of consumption is in need and negative y coordination indicates a decrease in need. The blue solid lines show a linear trend between the two variables and the bands denote 95% confidence level interval.

Consumption-based environmental impact

Shifting to a healthy diet result in a slight decrease of the environmental footprints at the global level. The GHG emission from food consumption decreases from 4874.1 Mt CO_2e to 4294.0 Mt CO_2e (by 11.9%, and 1.9% of the total impact) per year, while the values are from 2.62 billion m^2 to 2.12 billion m^2 (by 19.1%, and 8.1% of the total impact) for land appropriation. This change is a result of the reduced impacts from meat, sugar, cereal, etc. partly compensated by the additional footprints from dairy products, fruits, vegetables, and nuts. Globally, the most critical reduction comes from red meat (-72.0% of the change of GHG emissions and -56.5% of land appropriation), oil (-69.7% and -44.6%, respectively), and cereal (-40.7% and -22.4%), which is compensated by a significant increase of dairy products (41.5% and 13.7%) and vegetable (38.9% and 17.8%). The contribution of each food group differs by the type of environmental impact. Animal products, including meat, eggs, dairy products, and seafood, resulting in a higher impact for GHG and land by per gram than for land.

The change of environmental impacts differs by the geographical region and income level. We plot the change of environmental impacts in each food group for geographical regions in Figure 2, and regress per capita GNI on the change of environmental impacts per capita with region-specific factors controlled in Table C-4 and Table C-5. For all the regions except for South Asia, the dietary change leads to a decrease of GHG emissions and land appropriation due to a large reduction of meat and oil consumption. The dummies of regions also show the geographical difference in the regression results. Moreover, the GNI is significant for cereal, dairy product, oil, poultry, red meat, and vegetable for the regressions of GHG emissions, and is significant for cereal, nuts, poultry, and red meat for the regressions of land appropriation. The signs of the coefficient are consistent with the results of regressions on the food consumption. Taken together, the GNI is significantly and negatively correlated with both environmental impacts in the total amount.

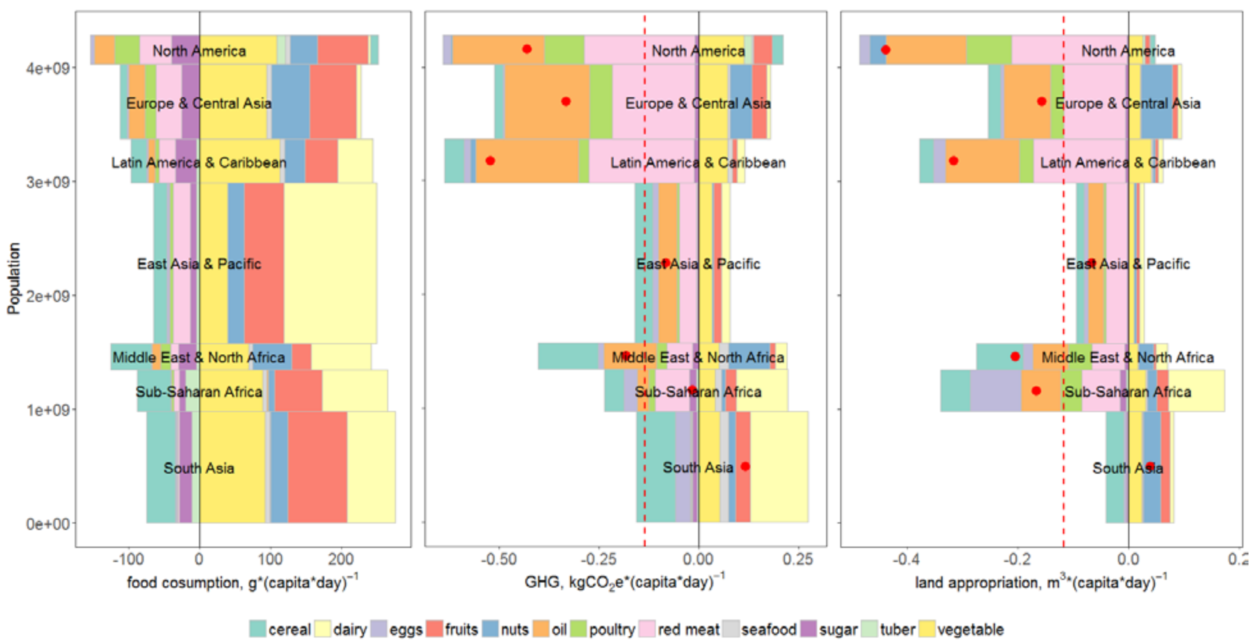

Figure 4-2 Change of food consumption and environmental impacts by regions. The vertical axis shows the cumulative population in each region above age 25, and the horizontal axes show the change of food consumption and environmental impact by food groups in each region.

Spatial distribution of environmental impact

For most countries, the environmental impacts are reduced due to the dietary change, the major of which happens domestically. We plot the production-based change of environmental impacts in Figure 3, with more than half of the evaluated area have reduced either GHG emission or land appropriation from agricultural production. The major reduction of GHG concentrates in Brazil (-118.77 Mt CO_2e), the United States (-104.156 Mt CO_2e), and China (-83.98 Mt CO_2e). Taken together, the three countries are responsible for 40.13% of the total reduction. Followed are Russia, Canada, and a series of European countries such as France and Spain. On the other hand, two countries in South Asia, India and Pakistan, bear the largest increase of GHG emission (66.84 Mt CO_2e and 22.85 Mt CO_2e, respectively). Other countries in South Asia such as Nepal and Bangladesh, as well as several countries in Africa, like Ethiopia and Ghana, also experience an increase of GHG emission. The reduction of land appropriation mainly locates in the United States (-0.106 billion m^2, 17.14% of the total reduction), Australia (-0.061 billion m^2, 9.78% of the total reduction), China (-0.055 billion m^2, 8.86% of the total reduction), Brazil (-0.045 billion m^2, 7.31% of the total reduction), etc. Mongolia (0.018 billion m^2), Ghana (0.015 billion m^2), and Nepal (0.014 billion m^2) rank the top for the increase of land appropriation. A considerable proportion of change of environmental impacts happens domestically. We map the consumption-based change of environmental impacts in Figure 3, which, compared with the production-based change, shows similar patterns of spatial distribution. In fact, more than half of countries or regions have over 80% of their changed environmental impacts locate in their own territories.

Nevertheless, the change of exported environmental impacts plays a role in some countries. The changed environmental impact embedded in the international trade flows are included in Figure C-1-Figure C-2. Brazil has the largest reduction of GHG emission attributable to reduced imports from other countries (15.78 Mt CO_2e), the majority of which comes from meat export to a variety of countries. Australia (reducing an exported emission of 7.19 Mt CO_2e), and Argentina (7.03 Mt CO_2e), and United States (5.29 Mt CO_2e) also have a considerable reduction, also mainly driven by the meat export. Meanwhile, there is a significant increase of the exported emission happening in China (7.26 Mt CO_2e) which primarily results from the additional international requirement of vegetable products. For land appropriation, Australia shows a substantial reduction (0.0259 billion m^2) due to less demand for cereal, meat, and sugar. The change is slighter for other countries.

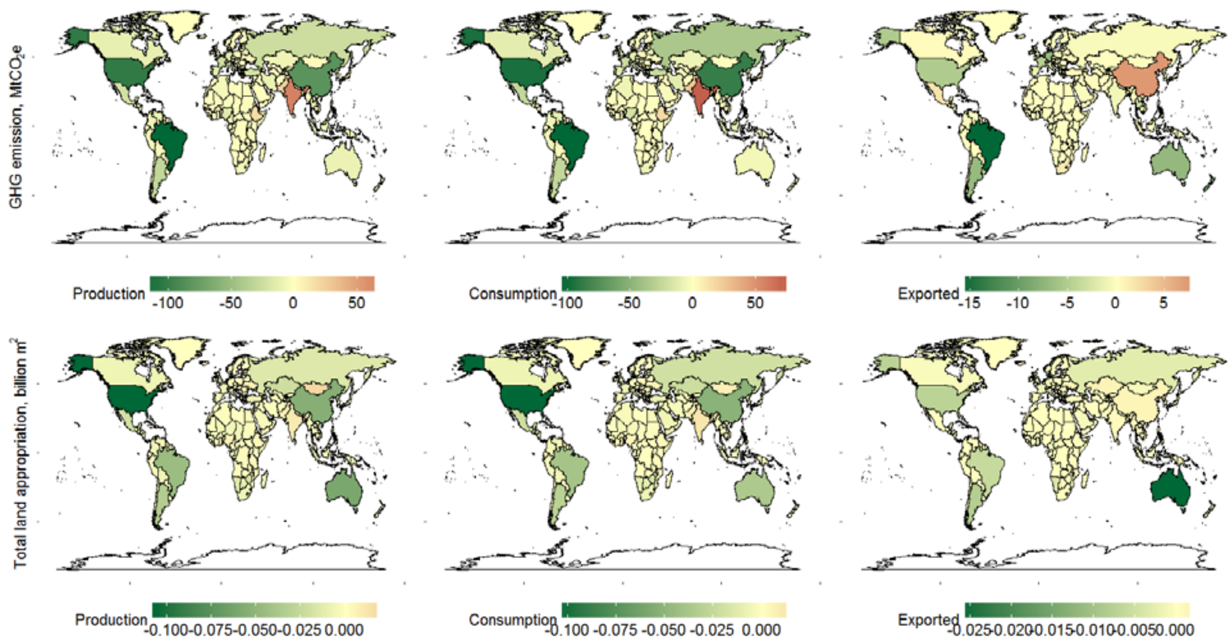

Figure 4-3 Change of environmental impacts.

4.4 Discussion

Our results add to the discussion on whether shifting to healthy diet leads to environmental benefit both globally and locally. Several global-level studies have concluded that adapting to healthy diets requires a reduction of red meat and increase of vegetable and fruits. Taken together, these changes lead to a reduction of GHG emissions (Springmann, Godfray et al. 2016, Behrens, Kiefte-de Jong et al. 2017, Röös, Bajželj et al. 2017), land appropriation (Alexander, Brown et al. 2016, Behrens, Kiefte-de Jong et al. 2017, Röös, Bajželj et al. 2017), and eutrophication potential (Behrens, Kiefte-de Jong et al. 2017). Springmann et.al. estimate that healthy diet recommended by WHO leads to 29% reduction of GHG compared with the reference scenario of 2050 (Springmann, Godfray et al. 2016).

This estimation is larger than ours (11.9%) as the GBD standard requires a larger intake of vegetable and fruits, the increase of which compensate the reduced emission from less meat consumption. The heterogeneous change of GHG emission and land appropriation is also seen in Behrens et.al., which observe an increase of both in poorer middle-income nations such as India by following the national dietary recommendation, a decrease of the two in upper-middle-income nations such as China, and high-income nations such as West European countries and the United States (Behrens, Kiefte-de Jong et al. 2017).

Our key findings provide implications for decision makers in mediating the environmental impacts of the improvement of nutritional quality. As most countries realize a reduction of territorial environmental impacts through shifting to healthy diets, changing food consumption patterns brings a direct win-win solution concerning the environmental quality. Therefore, measures that promote dietary change becomes more beneficial and thus should be put on the agenda of policy designs. This solution is even more attractive for the countries that suffer from limited land availability and ecological issues resulting from the agricultural activities. As we only address GHG emissions and land appropriation, further studies may involve other major environmental impacts such as water consumption and pollution, nitrogen use, etc., and push the evaluation further to the end-point of environmental damage and pressure. Meanwhile, several countries in South Asia and Sub-Sahara Africa shall consider how to diminish the negative environmental impacts resulted from health initiatives through dietary change. Particularly, a lot of these countries belong to the developing world that is faced with increasing environmental impacts from other socio-economic activities due to the rapid population growth, urbanization, and economic development. Governments of these countries need to figure out ways in mediating the nutritional requirement of their people and the rising environmental stress through higher production efficiency, conservative agricultural techniques, optimized reallocation of food supply chain, etc.

In the meantime, the spillover effect from the exported environmental impact is overall minute, but still play a role in countries such as Brazil, United States, China, and Australia, most of which experience a considerable reduction of environmental impacts, it then becomes a question of whether there is a chance for them to help relieve the increased environmental pressure in other countries through a reallocation of agricultural production. While the international food trade depends on multiple factors such as economic comparative advantage, political consideration of food security, etc., to boost healthy diets and meet challenges of environmental sustainability jointly can certainly be a motivation. In this way, the potential of trade policy in facilitating sustainable diet is to be investigated in future research.

Chapter 5 Conclusion

5.1 Major findings

As the food system results in significant environmental impacts and public health issues, decision makers are eager to design policies that can address these interconnected problems together. In this way, knowledge is needed on how human nutritional quality and the dietary environmental impacts are associated with different scenarios, and how the change of the former affect the later. While literature is growing on this topic, this dissertation fills the gaps of current research in exploring the heterogeneity of dietary patterns and geographically distributed environmental impacts. In Chapter 2 and 3, it focuses on the case of China and provides detailed quantitative analysis on how the GHG emissions, water consumption, and land appropriation change with the nutritional quality over time for different socio-economic groups historically over more than one decade, and how these impacts would vary if individuals shift to healthy diets. In Chapter 4, a global-scale evaluation is conducted to explore the change of production-based environmental impacts in pursuing healthy diets.

Chapter 2 finds that Chinese diet has been transitioning from a starchy-food-dominant style to more consumption of animal products and diverse compositions. As a result, the dietary environmental impact has increased. In the meantime, the nutritional quality experienced a mixture of changes, including an improvement as over-intake of cereal and under-intake of several food groups such as vegetable and fruits is relieved, and a degradation as the over-intake of meat and cooking oil is worsened. Therefore, there is no easy answer to whether the improvement of nutritional quality benefits the environment or not with a co-existence of double-win, double-loss, and trade-offs between the two aspects. Across the socio-economic groups, there is a similar temporal trend of changing dietary environmental impacts, malnutrition issues, and patterns of nutrition-environment association. However, urban and high-income groups are more advanced in the track of dietary transition, with overall higher environmental impacts and generally more balanced diets. Meanwhile, the rural and low-income counterparts catching up, with rapid increase of environmental impacts due to growing meat consumption.

Chapter 3 finds that shifting to healthy diets would lead to different change for each type of environmental impact. While there is a possible win-win for GHG emission, a trade-off is more likely the case for water and land. This change is a combination of the benefit of reduced meat and refined cereal balanced out by the requirement of dairy products, seafood, soybean, etc. Meanwhile, the change of environmental impacts differ by socio-economic status: urban and high-income groups are responsible for higher impact in following the current diet due to more animal product consumption, therefore can achieve larger benefit for the reduction of GHG emissions and less increase of water consumption and land appropriation when shifting to a healthy diet.

Chapter 4 identifies a worldwide prevalent pattern of malnutrition issues, including the over-consumption of starchy food, meat, oil, and sugar, as well as the insufficient intake of dairy products, vegetable, fruits, seafood, and nuts. The level of malnutrition is correlated with economic development level: countries with higher per capita GNI have less insufficiency but more severe over-consumption issues. Therefore, shifting to healthy diets lead to a reduction of GHG emission and land appropriation at the global level, mainly driven by cutting down the consumption of meat, cereal, oil, and sugar. The change is heterogeneous across countries, with all but a few countries in South Asia and Africa reducing both their consumption-based and production-based environmental impacts. The major change happens territorially, while the change of exported environmental impacts reduces considerably in Brazil, United States, and Australia, but increases in some countries such as China.

5.2 Future research

Substantial work is required in constructing databases of environmental impact factors in food production. Among the major environmental impacts of food systems, there is a thorough database only for water footprint (http://waterfootprint.org/en/resources/water-footprint-statistics/) covering national or even sub-national specific values for different food items, which is however outdated by providing averaged values during the period of 1996-2005. For other impacts, the data either does not have a wide coverage (e.g. GHG emission) or are not life-cycle based (e.g. land appropriation). In Chapter 2 and 3, I collect the GHG emissions from multiple LCA studies, with very rare cases focus on food production in China as my study area. The land appropriation adopted in this and many other studies are retrieved from the same FAOSTAT database, which involves only the direct land occupied for agricultural production. As studies are growing on the environmental impacts of food consumption, accurate quantification requires data that can be representative and updated for the regional and even national difference of production technique and climate condition. For now, a few global LCA database with a focus on food items are either available (http://esu-services.ch/data/fooddata/) or under construction (https://quantis-intl.com/), but their inclusiveness are yet to be further improved.

Future evaluations also requires better measurements of nutritional quality. The majority of studies to date do not specify a measurement of nutritional quality and compare various dietary patterns in a quantitative way. Rather, they cite conclusions from research on the diet-related health risks, and qualitatively assume specific dietary patterns are superior in the sense of nutrition than the others. Based on these assumptions, they develop discussion about whether healthier diets lead to less environmental impacts. Other studies, including this dissertation research, regard the dietary recommendations and guidelines as the rubric of healthy diets, and focus on the comparison of environmental impacts between these diets and the other dietary patterns. In this sense, however, this method does not provide a direct measurement of nutritional quality, and it is still unclear whether reducing per gram meat consumption lead to larger health benefits than increasing per gram of vegetable consumption. In the lack of a comprehensive indicator that translate the nutritional quality of different aspects (i.e. for different food categories or nutrients) to be comparative, it is hard to conclude which dietary patterns are of high nutritional quality. In fact, such indicators have been developed, such as the healthy eating index (HEI) that applies to the diets in the United States (Guenther, Casavale et al. 2013) and the Chinese healthy eating index (CHEI) that is constructed in a similar way but is adapted to the Chinese diet (Yuan, Li et al. 2017). These indices score dietary patterns in examining whether the intakes of specific foods and nutrients are within the adequate intervals, and evaluate the overall quality of dietary patterns with their sum. These indices convert the nutrition adequacy of various aspects into a normalized indicator. Future research can adopt these indices as they offer a clearer way to express the synergies and trade-offs between environmental impact reduction and nutritional quality improvement and the consequential policy implications.

Future research should also test the outcomes of more practical policy initiatives for comprehensive cost-benefit analysis. This research, along with quite a few others, has shown how the nutritional quality and dietary environmental food prints are interconnected as a result of food consumption behavior. Nevertheless, how and to what level such behavior can be changed by specific policy tools, such as dietary education, environmental tax for food items, obesity tax, and other specific food or environmental policies still requires deliberate inspection. In Chapter 3, I examine the outcome of adapting to dietary guidelines, which can be can be regarded as a policy tool in educating individuals to adopt a healthy and sustainable diet as argued in (Behrens, Kiefte-de Jong et al. 2017). However, I make a simple assumption that the recommendations are fully adopted, which is almost surely not the case in practice. There are some evaluations focus on the actual consumer behavior change, such as (Springmann, Mason-D'Croz et al. 2016) that examines the health effect of a carbon tax on food commodities at the global scale. However, more studies in various policy tools and areas are still needed for policy makers to compare the cost and benefit of each choice within specific socio-economic settings. In addition, individual behavior change can be heterogeneous given the distinct income level, living environment, educational level, and many other socio-economic characteristics. Therefore, studies should focus on household or individual level assessment in order to not only improve the accuracy in quantifying how their health and environmental footprints are affected as outcomes of such behavior change, but also involve the consideration of social justice in policy making by investigating the unequal responsibility of environmental impact and health risks.

Another topic that calls for further exploration is how the food-nutrition-environment nexus would change in the future. The scenarios analyzed in this research are based on either historical records or current situation. However, the proceeding of dietary transition will be continuing as a result of ongoing urbanization and economic development at the global scale and especially for the developing countries (Alexandratos and Bruinsma 2012, Belahsen 2014, Tilman and Clark 2014). In the meantime, factors including population growth, the progress of agriculture production techniques, and climate change also contribute to the changing food availability and demand, and the environmental impact of the future food system. As a result, the estimation of cost and benefit of specific policies discussed above shall take in consideration of the environmental and nutritional outcomes in different development scenarios. To date, projections are available at the global level on the future food consumption patterns (Alexandratos and Bruinsma 2012), and the consequential environmental impacts (Springmann, Godfray et al. 2016, Röös, Bajželj et al. 2017) and health effects (Springmann, Godfray et al. 2016). These studies help for identifying regional-specific policy intervention in mediating the outcomes of food consumption, but more scenarios are still in need to make the findings conclusive, and involve the consideration of climate change which is so far beyond research design. Meanwhile, analysis at the subnational-level is lacking. Such research is however an urgent need for countries with considerable nutritional and environmental impacts from food consumption due to the mass population, disparities in food distribution and consumption across socio-economic groups, and rapid but unequal socio-economic development, such as India and China.

Appendix A: Supplement information for Chapter 2

Environmental footprint assessment

The GHG emissions

We collect the GHG emission per gram of food for different types of food from more than 300 LCA studies on 24 food categories[11]. Ideally, LCA results from Chinese cases should be used as most food consumed in China is domestically produced. However, the availability of such data is quite limited, thus we shift to an average of all the available GHG footprint studies from different countries instead following (Springmann, Godfray et al. 2016). To keep all the LCA data with a consistent boundary, we only include assessments covering the emissions from cradle to farm gate[12], meaning that the emissions from transportation and retailing phase are excluded. Nevertheless, the production phase has already accounted for a dominant proportion of the total GHG emission for most food items according to the cases from several countries (Garnett 2008, Sonesson, Davis et al. 2009);, the post-production emission in China is likely to be small due to the short supply chain and the prevalence of wet markets. Therefore, these data should be able to capture the major difference between food items. We also refine our selection within studies with major kinds of GHG emissions (CO_2, CH_4, N_2O, O_3, and CFCs) aggregated as CO2e.

Water footprints

Water consumption per gram of food comes from the water footprint database provided by the Water Footprint Network[13]. This database includes the water consumption for 352 crops and processed crop products, and 106 animal products, each indicated by a 1996-2005 average. Country specific data are available, so we adopt the footprints for the food produced in China. Water Footprint Network adopts a grid-based dynamic water model to quantify the water demand in

[11] A category here is more detailed than a food group that we use for analysis. For instance, the food group "aquatic animal product" includes the category "fish" and "shrimp".
[12] The "cradle" here involves the production of fertilizer and pesticides, but not the production of infrastructure and tools for agricultural production.
[13] For more information about this dataset, visit http://waterfootprint.org/en/

producing the plant-based products (Mekonnen and Hoekstra 2011), which includes water consumption for irrigation between different food items but not the water used for any upstream process such as fertilizer production. For animal products, both the water required for feed production and the direct water demand including the drinking water and the service water are considered (Mekonnen and Hoekstra 2012). For the processed products, the water footprints are calculated based on the product and value fractions of the relevant unprocessed crop/animal products and water footprints of processing steps following the method from (Aldaya, Chapagain et al. 2012). The water consumption is separated into green water footprint, i.e. the water from the precipitation, and the blue water footprint, i.e. the water from the surface and groundwater. We include both in our evaluation.

For the seafood, the water footprints are not included in this dataset, and we conduct our own calculation following the method from (Pahlow, van Oel et al. 2015). According to this study, the water footprints for aquatic products are defined as the water consumed for aquaculture production for the farming fishery. Specifically, the water footprints for the seafood are calculated with

$$Water\ footprint_m = Perfeed_m \cdot FCR_m \cdot \sum_s (Per_{ms} \cdot Water\ footprint_{ms})$$

In which $Water\ footprint_m$ is the unit water footprint (either green or blue water) for food item m (kg water/kg product). $Perfeed_m$ is the proportion of aquaculture in the total production of this item. FCR_m is the feed conversion ratio (kg of feed/kg of product) of the item, indicating the weight of feed needed in producing per unit of item. In the aquaculture, the feed is often a mixture of different component such as soybean, maize, etc. Therefore, the water footprint of the feed is calculated by weighting the unit water footprint of each feed component m, $Water\ footprint_{ms}$ (g water/g product), by the percentage of the component in per unit of feed, Per_{ms}. $Perfeed_m$ is available in the FAO fishery statistics (Fisheries 1997-2006), and we adopt the FCR_m and Per_{ms} for Chinese aquaculture from (Weimin and Mengqing 2007). $Water\ footprint_m$ comes from the database of the Water Footprint Network. As the available species from the FAO fishery statistics are not fully matched with the food items in our sample, we use the data of the nearest species for the items lack of data. In accordance with the water footprints of other products, we take the 1996-2005 average as the final $Water\ footprint_m$ of each item.

Land occupation

The land use associated with each item was estimated using FAOSTAT data. FAO provides the harvest field and the production of the main crops produced in each country, and we obtain the unit annual land occupation for these products by taking the ratio of the two. For the primary livestock and poultry products, we calculate the land occupation for the concentrated production and grazing production separately, and take the average of the two weighted by the fraction of each in the total production. For concentrated feeding, we assume a zero direct land occupation for the concentrated production; thus the land occupation only comes from the land used for feed production. For the grazing production, the land occupation equals to the grazing land used for production. For aquatic products, only the land occupied for feed production in aquaculture is accounted for. For the processed crop, livestock and poultry products, the production and value fraction method is again adopted with the similar equation for the water footprints.

Specifically, the land occupation of the unprocessed food products is calculated with

$$LO_m = PerCP_m \cdot FCR_m \cdot \sum_s (Per_{ms} \cdot LO_{ms}) + GLO_m / PrdW_m$$

In which LO_m is the land occupation of animal product m. Here we consider six main unprocessed animal product: pork, poultry, milk, egg, beef, and goat &

sheep. The first term denotes the land occupation of the concentrated production. $\sum_s (Per_{ms} \cdot LO_{ms})$ calculates the land occupation of the feed, in a way similar as we deal with the aquaculture, with LO_{ms} to be the land occupation of feed component s in producing m, and Per_{ms} and FCR_m defined as above. $PerCP_m$ is the proportion of concentrated production in the total production of m. The second term captures the land occupation for the grazing production. GLO_m is the total grazing land used for producing m in one year, and $PrdW_m$ is the total production weight[14] of the product m. We obtain $PerCP_m$ and FCR_m from (Mekonnen and Hoekstra 2010), and Per_{ms} from (Sa 2002). LO_{ms} comes from the land occupation of the main crop products that we calculated. The FATSTAT provides GLO_m and $PrdW_m$.

For aquatic products, only the land occupied for feed production in aquaculture is accounted for, with

$$LO_m = Perfeed_m \cdot FCR_m \cdot \sum_s (Per_{ms} \cdot LO_{ms})$$

With all the parameters defined in a similar way as in the calculation of the aquaculture water footprints. The data source are identical as well, except that the LO_{ms} comes from our calculation of the land occupation of main crops.

[14] The total production weight here accounts for both the concentrated production and grazing production, as the proportion of the grazing production is cancelled out. To see why, remember that the land occupation for per unit of m from grazing production is calculated with $GLO_m / (PrdW_m \cdot (1 - PerCP_m))$; in each unit of m that reaches the consumers, $(1 - PerCP_m)$ comes from grazing production, so the land occupation from grazing for per unit of m is $GLO_m / (PrdW_m \cdot (1 - PerCP_m)) \cdot (1 - PerCP_m) = GLO_m / PrdW_m$.

For the processed crop, livestock and poultry products, the production and value fraction method similar as for water footprint in (Aldaya, Chapagain et al. 2012) is adopted, with

$$LO_m = fv_m \cdot \sum_s \frac{LO_{ms}}{fp_{ms}}$$

In which LO_m is the land occupation of the food item m; LO_{ms} is the land occupation of the root product s of m. fv_m is the value fraction of m, which is defined as the ratio of the market value of this item to the aggregated market value of all the items produced from the root products. fp_{ms} is the product ration of item m, which is defined as the quantity of item m obtained per quantity of its root product s. The database of the water footprint provides the root products and the two fractions of each food item, thus we can obtain LO_m by plugging in LO_{ms}.

For all the products, we take the 1996-2005 average as the final land occupation of each food item.

Nutritional quality evaluation

<u>Food weight equivalent</u>

According to the food content table, the nutrition composition of food items from the same food group can vary considerably. For instance, lean pork contains more proteins and less fat than the same amount of fatty pork, and a gram of strawberry has less calories than grapes. Even for the same type of food, the nutrition composition can differ between boiled and uncooked per gram. For example, one gram of rice contains less carbohydrate and proteins but far more water after being cooked. The way of cooking also affects the nutrition, e.g., cooked rice and rice congee. These different types of foods and different preparations are all coded and recorded as different items in the food content table as well as the CHNS database.

With such within-food-group variation, the evaluation would be problematic with the raw weight. For example, 250g rice congee (in the group of “cereal, pulse and tubers” in Table A-1) may not be sufficient for a person requiring 2000kcal/day, and 50g fatty pork (in the group pf “livestock and poultry”) may provide too much fat.

To avoid such problems, the dietary guideline provides instructions on standardizing the food items for dietary quality evaluation. This normalization is based on the “key nutrients for standardizing” as we list in Table S1. Generally, a most frequently consumed products by Chinese residents within each food group is selected as the reference item, which is used for standardizing the food weight with the rules listed below:

1. Cereals containing 80g carbohydrate are defined as 100g standardized cereals ;
2. Tubers containing 40g carbohydrate are defined as 100g standardized tubers;
3. Eggs containing about 14g protein are defined as 100g standardized eggs;
4. Soybean products containing about 35g protein are defined as 100g standardized soybean products ;
5. Livestock and poultry containing about 140kcal are defined as 100g standardized livestock and poultry;
6. Aquatic products containing about 100kcal are defined as 100g standardized aquatic products;
7. Nuts containing about 50g fat are defined as 100g standardized nuts.
8. Fruits containing about 50kcal are defined as 100g standardized fruits.

There are no specific rules for vegetables. They are converted based on the uncooked edible part as required by the guideline. The “nutrient for standardizing” for other food groups are also evaluated based on the uncooked edible parts.

The weight equivalent is then calculate with

$$Weight\ equivalent_{ml} = Weight_{ml} \cdot edible\ part_{ml} \cdot \frac{Key\ nutrient\ in\ the\ item_{ml}}{Key\ nutrient\ in\ the\ reference\ item_{l}}$$

$Weight_m$ indicates the weight of intakes of item m in food group l from the CHNS records. $edible\ part_m$ is the weight percentage of the food items that is edible. The key nutrient denotes the nutrient that that plays a key role in supporting physical health and is mainly contributed by the food group. For instance, the cereals, pulse and tubers are the main sources of the carbohydrate, thus the carbohydrate would be adopted as the key nutrient for this group. The reference items and the key nutrients vary by food groups as shown in (Chinese Nutrition Society 2016). $edible\ part_m$ and $Key\ nutrient\ in\ the\ item_{ml}$ can be attained from the Chinese Food Content Tables (the detailed introduction is in the data session).

Table A-1 The key nutrient and its content of the representative food items

Food groups	Standard item	key nutrient for standardizing	Content	Energy
Cereals and pulse	Uncooked rice	Carbohydrate	80g/100g	267-360kcal/100g
Tubers	Potato	Carbohydrate	20g/100g	80-113kcal/100g
Livestock and poultry	Lean pork	Energy	140kcal/100g	140kcal/100g
Egg and egg product	Chicken egg	Protein	14g/100g	130-200kcal/100g
Soybean and soybean products	Soybean	Protein	35g/100g	260-400kcal/100g
Dairy products	Uncondensed milk	Protein	3g/100g	22-55 kcal/100g
Aquatic products	Fish	Energy	100kcal/100g	100kcal/100g
Nuts	Sunflower seed	Fat	50g/100g	400-550kcal/100g
Fruits	Apple	Energy	50kcal/100g	50kcal/100g
Vegetables	Normalized only based on the edible part			15-35 kcal/100g

Calculating the (EER)

EERs are calculated with the methods adopted by 2013 DRIs. The equations differ for children, adults and elders. For health adults aged 18-49 whose Body Mass Index (BMI)[15] are within the normal range (18.5-24 according to *2016 Chinese Dietary Guideline*), the EER can be calculated with:

$$EER_i = BEEperW \cdot BW_i \cdot PAL_i$$

EER_i denote the estimated energy requirement (kcal/day) of individual i ; $BEEperW$ is the basal energy expenditure per unit of body weight (kcal/kg*day), indicating the energy needed for fundamental metabolic functions. This expenditure differs by age and sex groups, as shown in Table A-2. BW_i is the body weight of individual i available from the CHNS data. The product of BEE and BW_i gives the energy required per day in supporting the basic metabolism for a human being with particular body weight, and the EER_i is then calculated by inflating this basic energy need with the Physical Activity Level, PAL_i. PAL_i is a non-dimensional factor, and a higher PAL_i indicates more intensive physical activities and higher energy demand. DRIs 2013 provides the PALs in three levels (light, moderate and heavy) according to the life-style and profession. In the CHNS data, the variable of PALs are directly available for each person in 6 levels determined by the profession[16]. We associate these levels with the classification of

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[15] BMI is an indicator showing whether one is underweight, overweight or obese which is defined as the body mass divided by the square of the body height. It is argued that the standards in diagnosing underweight/overweight/obese differs by ethnicity. In *2016 Chinese Dietary Guideline*, the standards for Chinese are: BMI<18.5 for underweight, 18.5≤BMI<24 for normal weight, 24≤BMI<28 for overweight, and BMI≥28 for obese.

[16] CHNS also contains the information on time assigned to various types of non-occupational activities to estimate the total physical activity level. However, the missing rate for such data is usually very high (around 90%), so we do not include these data for the analysis. Nevertheless, occupational activity is the major source of activity for adults in China since leisure time activity and sports are not yet as prevalent as in the more developed nations Bell, A. C., et al. (2001). "Weight gain and its predictors in chinese adults." International Journal of Obesity & Related Metabolic Disorders **25**(7).. In 2015, 18.7% of Chinese adults report regular exercise National

PALs in DRIs 2013, as shown in Table A-3. For adults aged above 49, the BEE is lowered down compared with the group aged 18-49 as shown in Table A-2. For adults aged above 80, the PAL is lowered down by 0.05. The same equation applies for calculation.

For people who are underweight, overweight or obese, the energy requirement can be different for adjusting to normal BMI. Since there is no available equation from DRIs 2013, we calculate the EER that suits the normal weight of these people. For underweight individuals, we use the equation

$$BWnorm_i = BMI_{lb} \cdot Height_i^2$$

Where BMI_{lb} is the lower bound of the normal weight (18.5), $Height_i$ is the body height of individual i, and $BWnorm_i$ is the normal weight of individual i according to her/his body height. Finally, the EER is calculated with $BWnorm_i$. The EER for the overweight and obese individuals are calculated accordingly, but with the upper bound of the BMI (24).

Table A-2 The BEEs by sex-age groups (kcal/kg body weight per day)

	18-49	**50-65**	**65-80**	**80-**
Male	22.7	21.5	21.4	21.5
Female	21.4	20.1	20.1	20.1

Table A-3 The association of the PALs in DRIs and CHNS

Intensity of physical activities	**PALs for adults in DRIs 2013**	**PAL classes in CHNS**
Light	1.50	No working ability
		Very light physical activities
		Light physical activities
Moderate	1.75	Moderate physical activities
Heavy	2.00	Heavy physical activities
		Very heavy physical activities

Health and Family Planning Commission (2015). 2015 report on chinese nutrition and chronic disease.

For young children and adolescents, the EER include both the energy in supporting daily activities and the energy for growth and development, which is calculated with

$$EER_i = f_{BEE}(BW_i) \cdot PAL_i + dBW_i \cdot EGD_i$$

Where $f_{BEE}(BW_i)$ is the basal energy expenditure of individual i as a linear function of the body weight. $dBW_i \cdot EGD_i$ denotes the energy for growth and development, with dBW_i to be the daily increased body weight and EGD_i to be the energy requirement in supporting such increase. The other terms are the same as above. $f_{BEE}(BW_i)$, PAL_i, dBW_i and EGD_i vary by sex and age, and all the parameters are shown in Table A-4 as below. The calculation for underweight, overweight and obese groups are similar as for the same adult groups.

Table A-4 Parameters for calculating EERs for young children and adolescents

age	$f_{BEE}(BW_i)$ [17]		dBW_i		PAL_i [18]		
	male	**female**	**male**	**female**	**light**	**moderate**	**heavy**
2	0.255 BW_i -0.141	0.246 BW_i -0.0965	5.5	5.5		1.35	
3	0.0937 BW_i +2.15	0.0842 BW_i +2.12	5.5	5.5	-	1.45	-
4	0.0937 BW_i +2.15	0.0842 BW_i +2.12	5.5	5.5	-	1.45	-
5	0.0937 BW_i +2.15	0.0842 BW_i +2.12	6.8	5.5	-	1.45	-
6	0.0937 BW_i +2.15	0.0842 BW_i +2.12	9.6	8.2	1.35	1.55	1.75
7	0.0937 BW_i +2.15	0.0842 BW_i +2.12	8.2	6.8	1.35	1.55	1.75
8	0.0937 BW_i +2.15	0.0842 BW_i +2.12	9.6	8.2	1.4	1.6	1.8
9	0.0937 BW_i +2.15	0.0842 BW_i +2.12	9.6	12.3	1.4	1.6	1.8
10	0.0769 BW_i +2.43	0.0465 BW_i +3.18	11	11	1.45	1.65	1.85
11	0.0769 BW_i +2.43	0.0465 BW_i +3.18	12.3	12.3	1.45	1.65	1.85

[17] The equation comes from Henry, C. (2005). "Basal metabolic rate studies in humans: Measurement and development of new equations." Public health nutrition **8**(7a): 1133-1152.
[18] The data comes from Sasaki, S. (2008). "Dietary reference intakes (dris) in japan." Asia Pacific journal of clinical nutrition **17**(S2): 420-444. There is no difference on PAL for children under 6 years old.

12	$0.0769\,BW_i$ +2.43	$0.0465\,BW_i$ +3.18	15.1	9.6	1.45	1.65	1.85
13	$0.0769\,BW_i$ +2.43	$0.0465\,BW_i$ +3.18	12.3	6.8	1.45	1.65	1.85
14	$0.0769\,BW_i$ +2.43	$0.0465\,BW_i$ +3.18	8.2	4.1	1.45	1.65	1.85
15	$0.0769\,BW_i$ +2.43	$0.0465\,BW_i$ +3.18	5.5	2.7	1.55	1.75	1.95
16	$0.0769\,BW_i$ +2.43	$0.0465\,BW_i$ +3.18	5.5	2.7	1.55	1.75	1.95
17	$0.0769\,BW_i$ +2.43	$0.0465\,BW_i$ +3.18	13.7	11	1.55	1.75	1.95

The suggested energy requirement and dietary patterns can be different for the infants under 24 months and women who are pregnant or breastfeeding, thus we exclude these groups in this study. Since no information is available from the survey to identify these groups either directly or indirectly (e.g. information on religious beliefs)[19], we do not exclude the potential vegetarians and vegans.

[19]It is estimated that there are 50 million vegetarian in China according to the statistics in *2106 Chinese Dietary Guideline*. The reference year of this statistic is not provided. By contrast, the total population is about 1.37 billion by the end of 2014 according to the statistics from the National Bureau of Statistics of China. Therefore, there are roughly 3.6% of people in China are vegetarian or vegan. Another estimation comes from media (http://www.pri.org/stories/2013-06-27/vegan-lunch-going-meatless-beijing) is 4-5% (the report was in 2013 but no reference year is available for this statistic).

Balanced Dietary Patterns from Chinese Dietary Guideline 2016

Table A-5 The balanced dietary patterns from Chinese dietary guideline 2016

	energy requirement levels										
food groups	1000	1200	1400	1600	1800	2000	2200	2400	2600	2800	3000
cereal, pulse and tubers	85	100	150	200	225	250	275	300	350	375	400
whole grain and legume	Appropriate (>25)			50-150							
tubers	appropriate(>25)			50-100					125	125	125
vegetables	200	250	300	300	400	450	450	500	500	500	600
dark vegetables	half of the vegetable intake										
fruits	150	150	150	200	200	300	300	350	350	400	400
livestock and poultry	15	25	40	40	50	50	75	75	75	100	100
eggs	20	25	25	40	40	50	50	50	50	50	50
aquatic products	15	20	40	40	50	50	75	75	75	100	125
dairy products	500	500	350	300	300	300	300	300	300	300	300
soybean products	5	15	15	15	15	15	25	25	25	25	25
nuts	-	Appropriate (10)		10	10	10	10	10	10	10	10
cooking oil	15-20	20-25			25	25	25	30	30	30	35
salt	<2	<3	<4	<6	<6	<6	<6	<6	<6	<6	<6

Only the energy requirement levels that are equal or larger than 1600kcal/day are used for matching with the individual EERs as 1600kcal/day is the lowest energy requirement level for adults in DRIs 2013. For the food groups with an interval provided (e.g. whole grain and pulse), the positive deviation is calculated with the upper bound and the negative deviation the lower bound. The intervals are not provided for whole grain and legume for energy requirement levels above 2600kcal/day, and we adopt the same values as for 1800-2200 kcal/day. For young children with an estimated energy requirement levels of 1000-1400 kcal/day (we regard this group as children between 2-10 referring to the description in 2016 guideline), there is no explicit recommendation on the intake of whole grain and legume, tubers and nuts, so we exclude these terms in evaluating the nutritional quality for this age group. Nevertheless, it is possible that individuals from other age group are matched with these energy requirement levels. For these individuals, we also adopt the same values as for 1800-2200 kcal/day.

The assignment of the cooking oil and condiment data

To estimate the daily individual intakes of the oil and condiment, we need to 1) assign the cooking oil and condiment consumption data at the household level to each individual that have meals during the surveyed 3 days, and 2) estimate the intakes when the individual have outside-home meals. For 1), we first exclude the intakes of guests who are not involved in our sample. As CHNS data include the number of person*meals for each day, we and calculate a "guest ratio", with

$$guest\ ratio = \frac{\sum_{i=1}^{m} person\ meal_i \cdot PAL\ factor_i}{\sum_{i=1}^{N} person\ meal_i \cdot PAL\ factor_i}$$

In which $i = 1, 2, ..., m$ are guests, and $i = m+1, \mathrm{m}+2, ..., N$ are family members. $person\_meal_i$ is the number of meals that person i has in the surveyed family during the 3 days. We assume that the heavier the physical activity level, the higher intakes of the cooking oil and condiment, and adjust $person\ meal_i$ with a factor, $PAL\ factor_i$ (shown in Table A-3). In this way, we obtain the cooking oil and condiment that is consumed by the family members, with

$$household\ member\ intake = total\ household\ intake \cdot (1 - guest\ ratio)$$

In which $total\ household\ intake$ is the total consumption of the cooking oil and condiment at the household level. Next, we assign the intakes with

$$assigned\ intake_i = household\ member\ intake \cdot \frac{total\ food\ intake_i}{\sum_{i=m+1}^{N} total\ food\ intake_i}$$

In which $total\ food\ intake_i$ is the total weight of the food intake other than cooking oil and condiment of person i. $person\_meal_i$, PAL, $total\ household\ intake$ and $total\ food\ intake_i$ all come from CHNS dataset.

Regression analysis

To inspect the role of dietary transition, urban/rural status and income in the changing dietary environmental impacts and nutritional quality, we conduct a series of regression analysis with equation:

$$\begin{aligned}Y_{ilt} &= \beta_0 + \beta_1 yeartrend_t + \beta_2 urban_{it} + \beta_3 urban_{it} \cdot yeartrend_t + \beta_4 income_{it} \\ &+ \beta_5 income_{it} \cdot yeartrend_t + \beta_6 age_{it} + \beta_7 age_{it}{}^2 + \varepsilon_{ijt}\end{aligned};$$

where $yeartrend_t$ is a year trend with 1996=0, 1997=1, …. $urban_{it}$ indicates the urban/rural status of individual i during wave t, with urban=1. The CHNS sample include four classes: cities, suburban, town or county capital city, and rural village. We treat the first two as urban areas and the last two as rural, the same as classified in the CHNS. $income_{it}$ denotes the per capita household income (in 1,000 RMB) for individual i during wave t. We also include age_{it} and its square to control for its impact on the food intakes and its consequences. Y_{ijlt} is the outcome variable of food l for individual i during wave t. We first inspect how the independent variable affect the food and energy intake as shown in Table A-7. In Column 1-13, we use the intakes (in gram) of each type of food. The CHNS sample include food intakes for each individual during three days, and we regard the average of this survey period as the chronic dietary pattern of each individual. We also include the result for total energy intake in Column 14. In Table A-8-Table A-10 we regard GHG emissions, total water consumption, and land occupation from each type of food as dependent variables. Finally in Table A-11 we regard the deviation of each type of food from its balanced pattern (in percentage) as the dependent variables.

CHNS dataset and descriptive statistics

Food intake, individual characteristics and regional socio-economic factors come from the China Health and Nutrition Survey (CHNS)[20]. This dataset is provided by Carolina Population Center of the University of North Carolina at Chapel Hill, and the National Institute for Nutrition and Health (NINH, former National Institute of Nutrition and Food Safety) of the Chinese Center for Disease Control and Prevention (CCDC). Aiming at obtaining nutritional information at the micro level, CHNS collects food intakes, physical indicators the employment, education, and other demographic through individual surveys. It is sampled from 9 provinces[21] of China considering the spatial heterogeneity in terms of physical geography and socio-economic characteristics. (The surveyed regions is shown in Figure 1). The survey adopts a multistage random cluster strategy based on the consideration of regional income per capita and urban/rural status. Started from 1989, 9 waves of the survey has been conducted, including the years of 1989, 1991, 1993, 1997, 2000, 2004, 2006, 2009, and 2011. The survey tracks individuals from previously surveyed households over the years, although there are some attrition[22] and several untrackable communities being replaced. Due to the information limitation of the sample frame, it is not feasible to generate a set of weights for CHNS to be representative at the national or provincial level. Nevertheless, it is the most informative publicly available nutrition survey in China, and the heterogeneity of the sample can to some extent reflect the geographical difference of Chinese diets.

[20] For more detailed introduction of the CHNS dataset, visit http://www.cpc.unc.edu/projects/china

[21] The map of Survey Regions can be found at http://www.cpc.unc.edu/projects/china/about/proj_desc/chinamap.Beijing, Shanghai and Chongqing were added to the sample in 2011. As they are highly urbanized metropolitans in which the lifestyle can be very different (usually with less physical activity level and less carbohydrate intake as shown in the following sections), the observations from these areas may drive the estimations of 2011 to be incomparable with other waves. Therefore, we drop the records from these cities.

[22] The attrition rate is between 8%-65% between the contiguous waves according to Liang, Y. (2011). "Research on the success tracking rates in panel survey: Sample attrition in the context of social transition." Sociological Studies (In Chinese)(6): 132-153.

CHNS collects the demographic and socio-economic features from questionnaires at community, household and the individual level. The intake of other food is recorded at the individual level by 24h recall self-report for consecutive 3 days. The survey dates are randomly selected from Monday to Sunday and are almost equally balanced across the week for each sampling unit. This enables us to track all the types and weight of food intake of each individual. The intake of cooking oil and condiments are estimated by differencing the weights of these items at the beginning and the end of the survey period for each family. We follow Du et al. (Du, Mroz et al. 2004) to estimate the intake of each person (the details are included in the supporting information). All the food items in CHNS are recorded with a food code that matches with its nutrition facts in Chinese Food Composition Tables (CFCTs) published by the National Institute for Nutrition and Health (NINH, former National Institute of Nutrition and Food Safety) at the Chinese Center for Disease Control and Prevention (CCDC). The CFCTs contain the edible portion, proximate composition and detailed nutrition content for most common food items in Chinese diets such as energy, carbohydrate, fat, protein, major mineral, vitamin, cholesterol, etc. Each food item is assigned a food code which can be directly linked to the CHNS data. The recording of the CHNS data adopts multiple versions of CFCTs. The data for 1989, 1991 and1993 are linked with the 1981 CFCT including more than 600 items; the data for 1997 and 2000 are associated with 1991 version with more than 1,000 items; the latter waves adopt a combination of 2002 and 2004 CFCT for coding, which contains over 2,200 food items in total. As the coding in 1981 CFCT is not yet publicly available, we conduct the analysis for the years 1997 to 2011. There are some extraordinary large values in the food intake data. For each food group, we regard all the records that exceed 4 times of the group standard deviation as outliers and drop the corresponding individuals in our analysis.

We include descriptive statistics on the demographic characteristics in Table A-6. After data processing, we get more than 20,000 records for every year, containing the food intake of 3 continuous days and socio-economic characteristics for more than 6,000 adults aged 18-65. The composition of the sample remains stable in terms of key characteristics such as province, urban/rural status, and gender across the years. About one-third sampled individuals are from urban areas and the other two-thirds rural areas. In contrast, the national population census shows a 73.77%, 63.08% and 49.73% of rural population in 1990, 2000 and 2010 respectively. This indicates that urban area is possibly under-represented in the latter waves. The individuals are about evenly distributed in each province[23] and by gender. A transition to less physical activity, higher average income level and higher age can be observed. Indeed, if we plot the age distribution, we see a shift of the whole curve towards right, reflecting the fact that CHNS has been tracking the same communities and households.

[23] In 1997, Liaoning is not sampled.

Table A-6 Descriptive statistics of the sample

		1997	2000	2004	2006	2009	2011
Records (NO.)[24]		9,451	9,483	8,227	8,194	8,218	7,635
Province (NO.)	Liaoning	-	902	822	664	699	761
	Heilongjiang	958	962	897	815	821	641
	Jiangsu	1,128	903	714	824	816	748
	Shandong	1,088	1,019	827	862	812	696
	Henan	1,131	1,163	1,030	1,031	1,043	1,047
	Hubei	1,269	1,067	810	769	815	696
	Hunan	1,185	1,096	895	951	987	932
	Guangxi	1,415	1,291	1,235	1,182	1,231	1,151
	Guizhou	1,277	1,080	997	1,096	994	963
Urban/rural areas (NO.)	urban	2,944	2,845	2,514	2,590	2,528	2,275
	rural	6,507	6,638	5,713	5,604	5,690	5,260
Sex (NO.)	male	4,453	4,513	3,786	3,787	3,814	3,469
	female	4,998	4,970	4,441	4,407	4,404	4,166
Age (NO.)	2-10	1,212	876	709	711	691	662
	10-18	1,412	1,462	858	691	615	460
	18-30	1,564	1,395	919	721	774	619
	30-50	2,907	3,155	2,746	2,701	2,620	2,375
	50-65	1,428	1,591	1,870	2,094	2,166	2,120
	65-	928	1,004	1,125	1,276	1,352	1,399
Net household income (RMB, inflated to 2011)	mean	4042.223	5213.802	6996.574	8092.075	11339.09	13115.54
	s.d.	3270.995	5539.031	7564.15	10483.62	14362.38	14819.54

[24] As *CHNS tracks the same individuals and include additional samples due to attrition, same individuals can appear in multiple waves. In total, the sample size we use for final analysis is 21,504 individuals, and 51,208 individual*years.*

Supplementary Figures and Tables

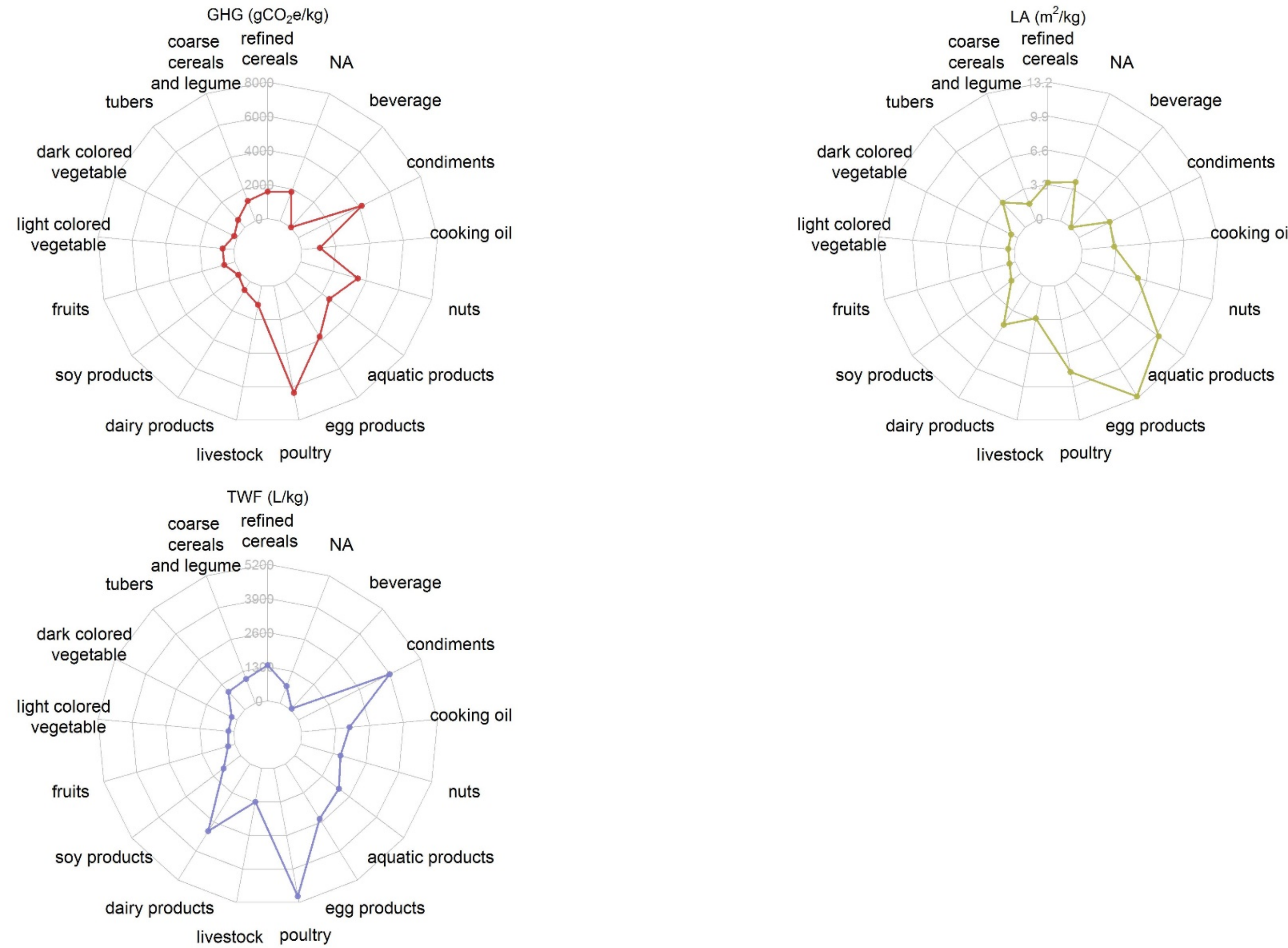

Figure A-1 Environmental footprint of each food group per kg. The calculation is weighted by individual daily intake. In our calculation, aquatic products are more environmentally friendly than other animal products, because capture fishery do not consume water and land directly but only from feed either by aquaculture or capture fishery; also, its conversion factor is lower than other animals so that the same amount of feed can support more fish, shrimp or other *aquatic animals than livestock or poultry. The environmental performance of aquatic animal products is also relevant to the high farming rates of Chinese fisheries. Compared with capture fishery, farming fisheries consume much less energy, and the total GHG emissions is lower even though the indirect emissions from feed are included. A higher farming rate, however, leads to higher water consumption and land occupation since the capture fishery is exempt from feed production.*

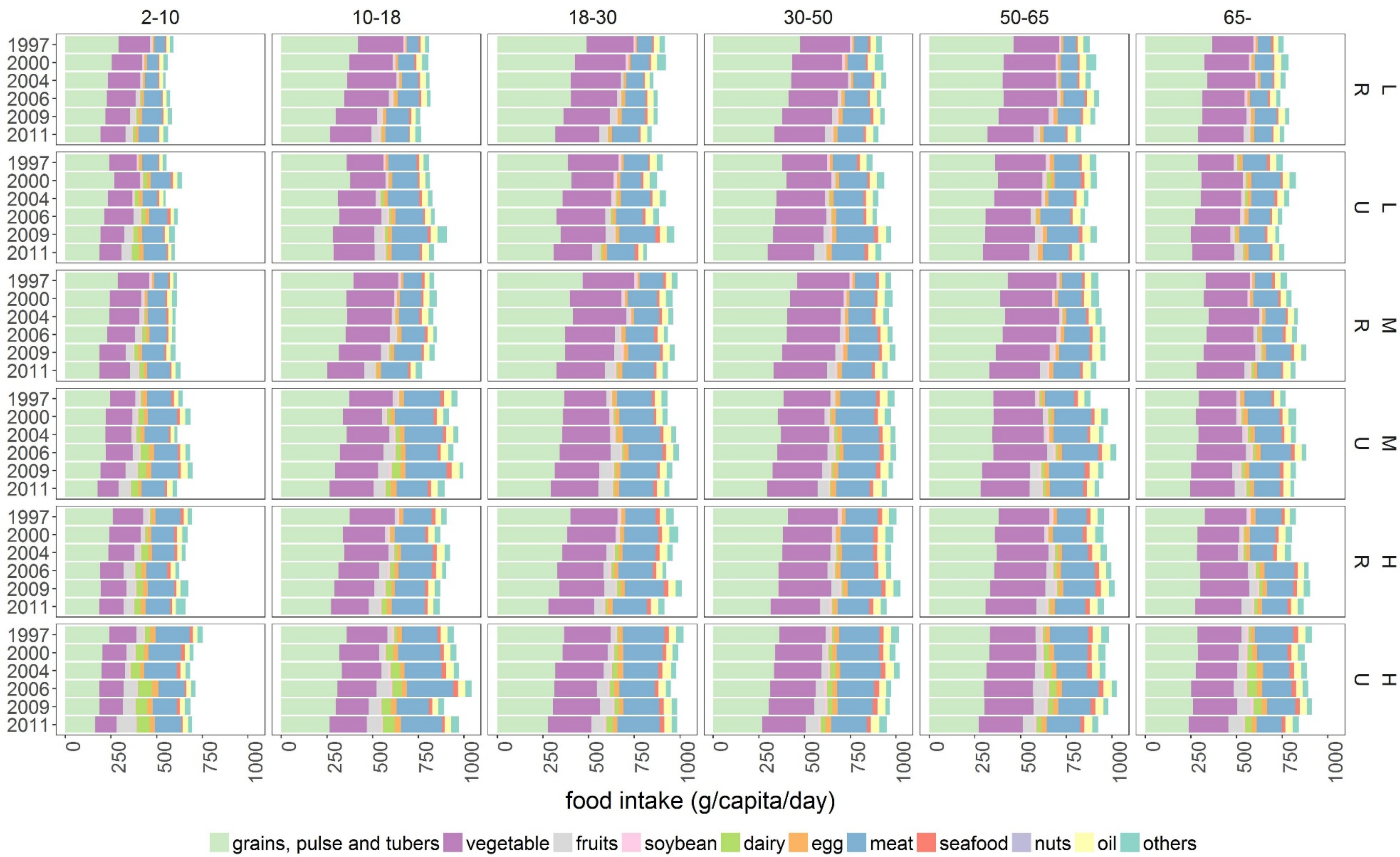

Figure A-2 Food intakes of individual daily food intakes, all age groups. R=rural, U=urban, L=low income, M=medium income, H=high income. Bars show the average of the food intake/environmental impact by food groups denoted by different colors in the legend.

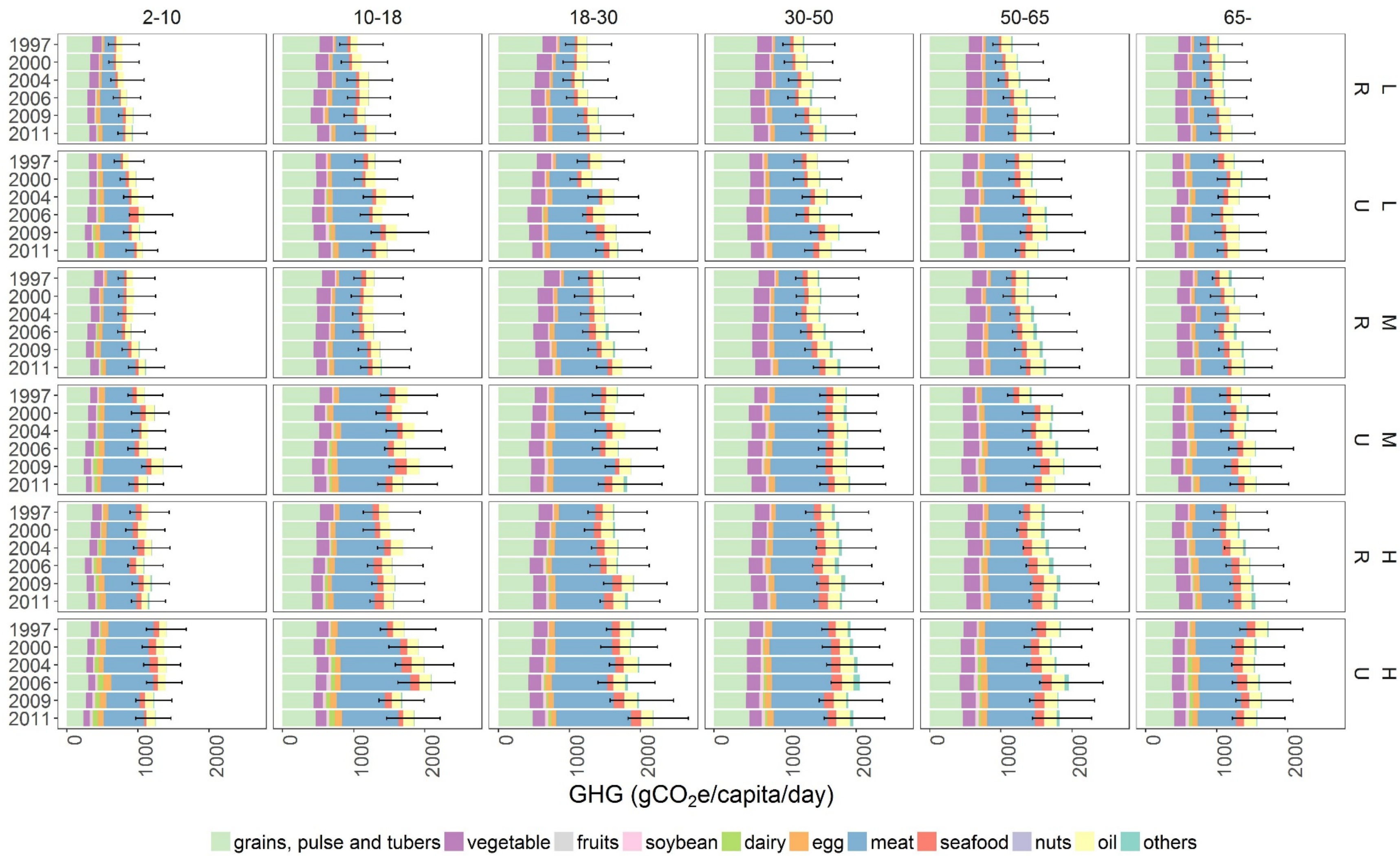

Figure A-3 GHG emissions of individual daily food intakes, all age groups. R=rural, U=urban, L=low income, M=medium income, H=high income. Bars show the average of the environmental impact by food groups denoted by different colors in the legend, and error bars show one standard deviation from the mean of the average environmental impacts of each group in the 100 trials of Monte Carlo simulation (16th and 84th percentile).

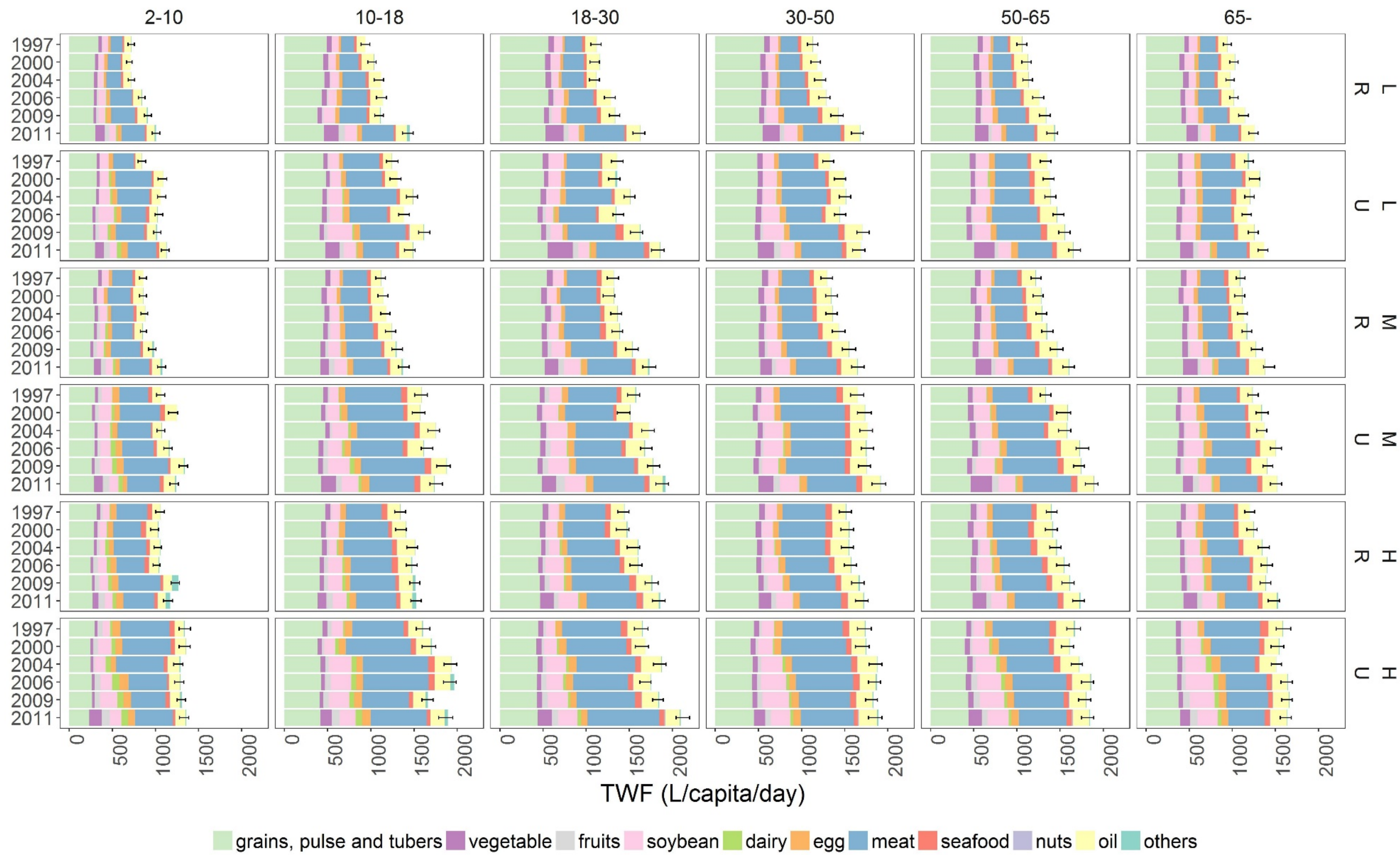

Figure A-4 Total water footprint of individual daily food intakes, all age groups. R=rural, U=urban, L=low income, M=medium income, H=high income. Bars show the average of the environmental impact by food groups denoted by different colors in the legend, and error bars show one standard deviation from the mean of the average environmental impacts of each group in the 100 trials of Monte Carlo simulation (16th and 84th percentile).

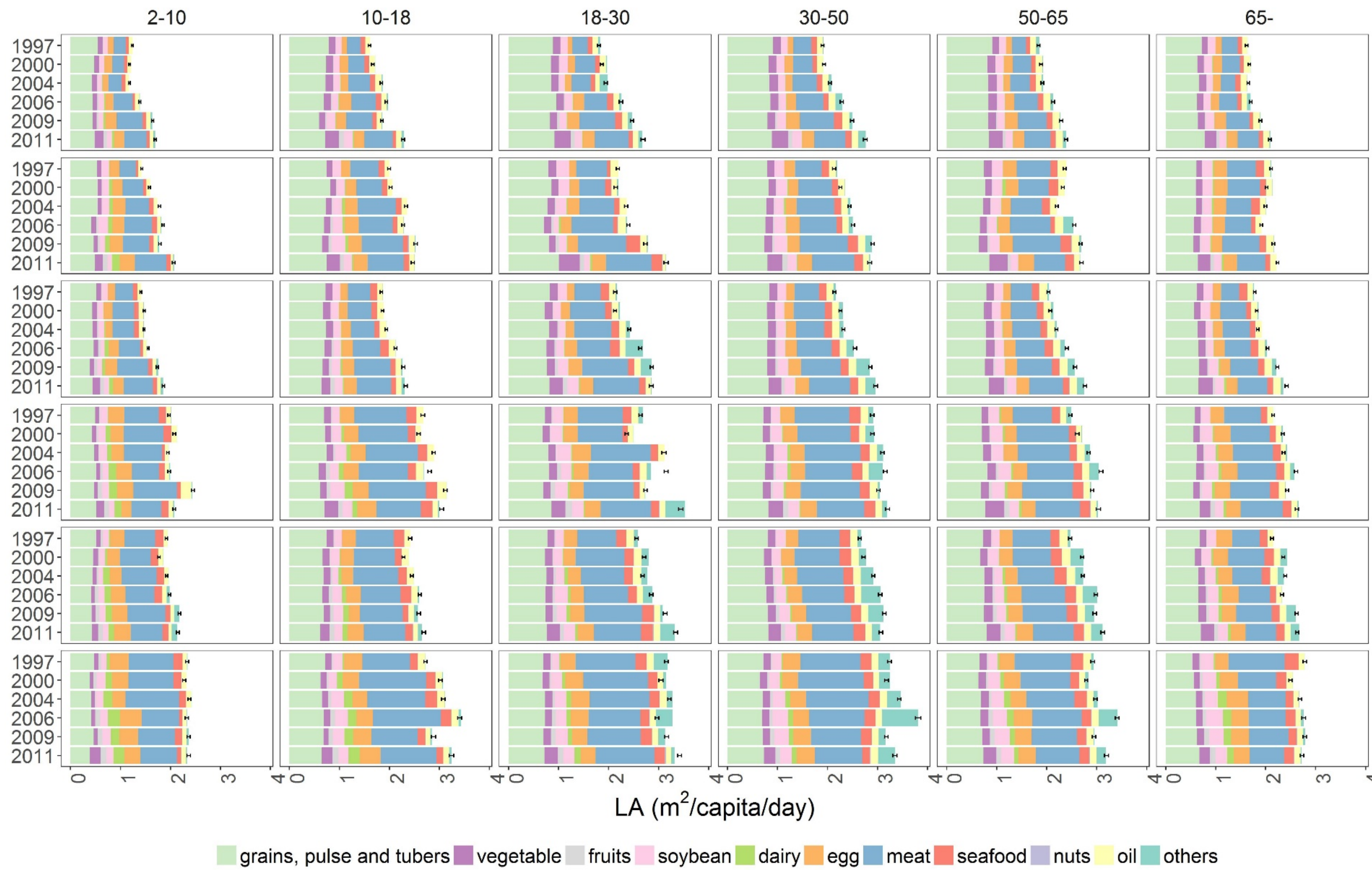

Figure A-5 Land appropriation of individual daily food intakes, all age groups. R=rural, U=urban, L=low income, M=medium income, H=high income. Bars show the average of the environmental impact by food groups denoted by different colors in the legend, and error bars show one standard deviation from the mean of the average environmental impacts of each group in the 100 trials of Monte Carlo simulation (16th and 84th percentile).

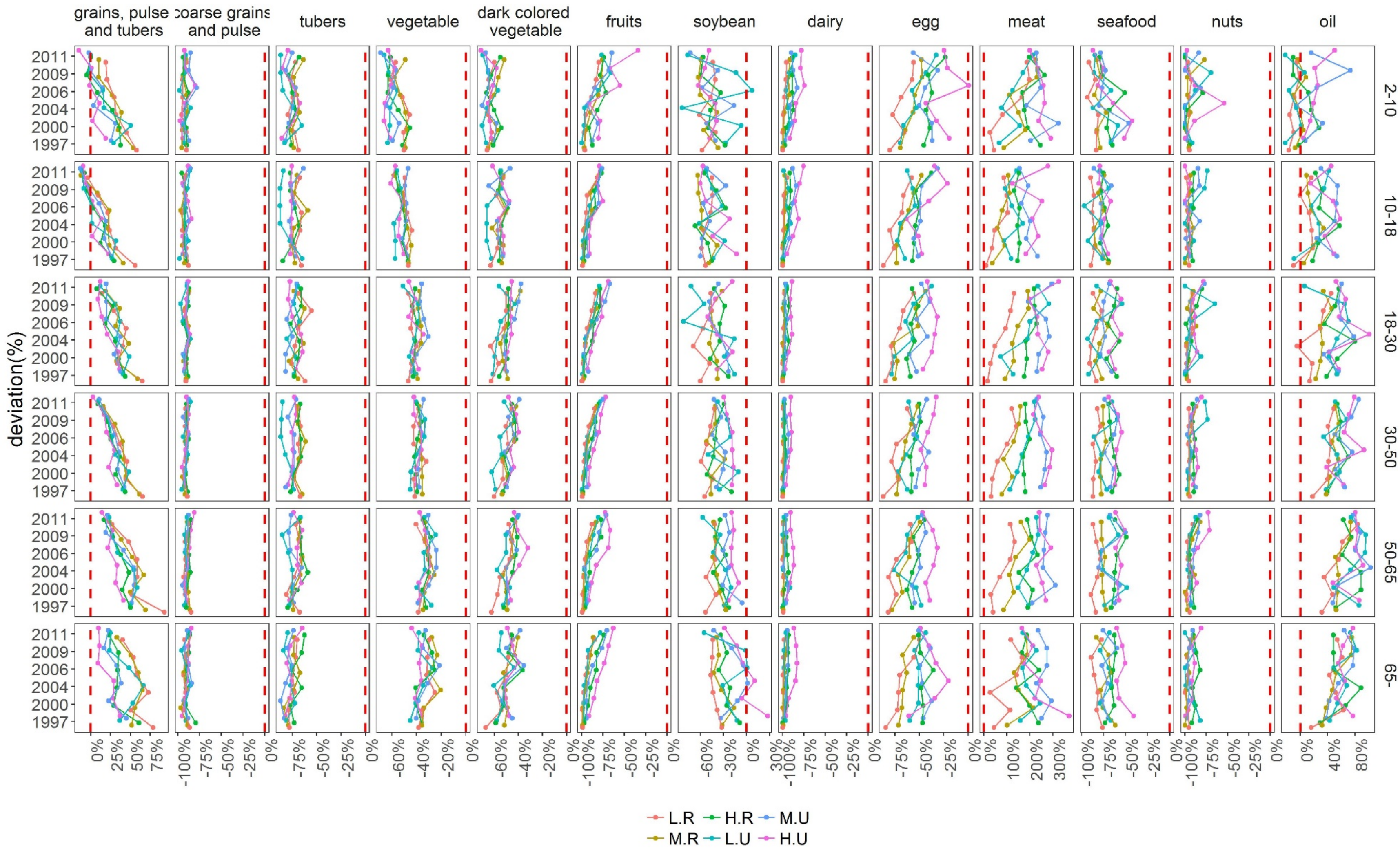

Figure A-6 Deviation of food intakes from balanced dietary patterns, all age groups. R=rural, U=urban; L=low income, M=medium income, H=high income. The points and line show averaged percentage of under-/over-intakes of each food group. The vertical red dashed line shows balanced diets without under-/over-intake issues, i.e. points and lines on the right of this line indicates over-intakes and the left under-intakes.

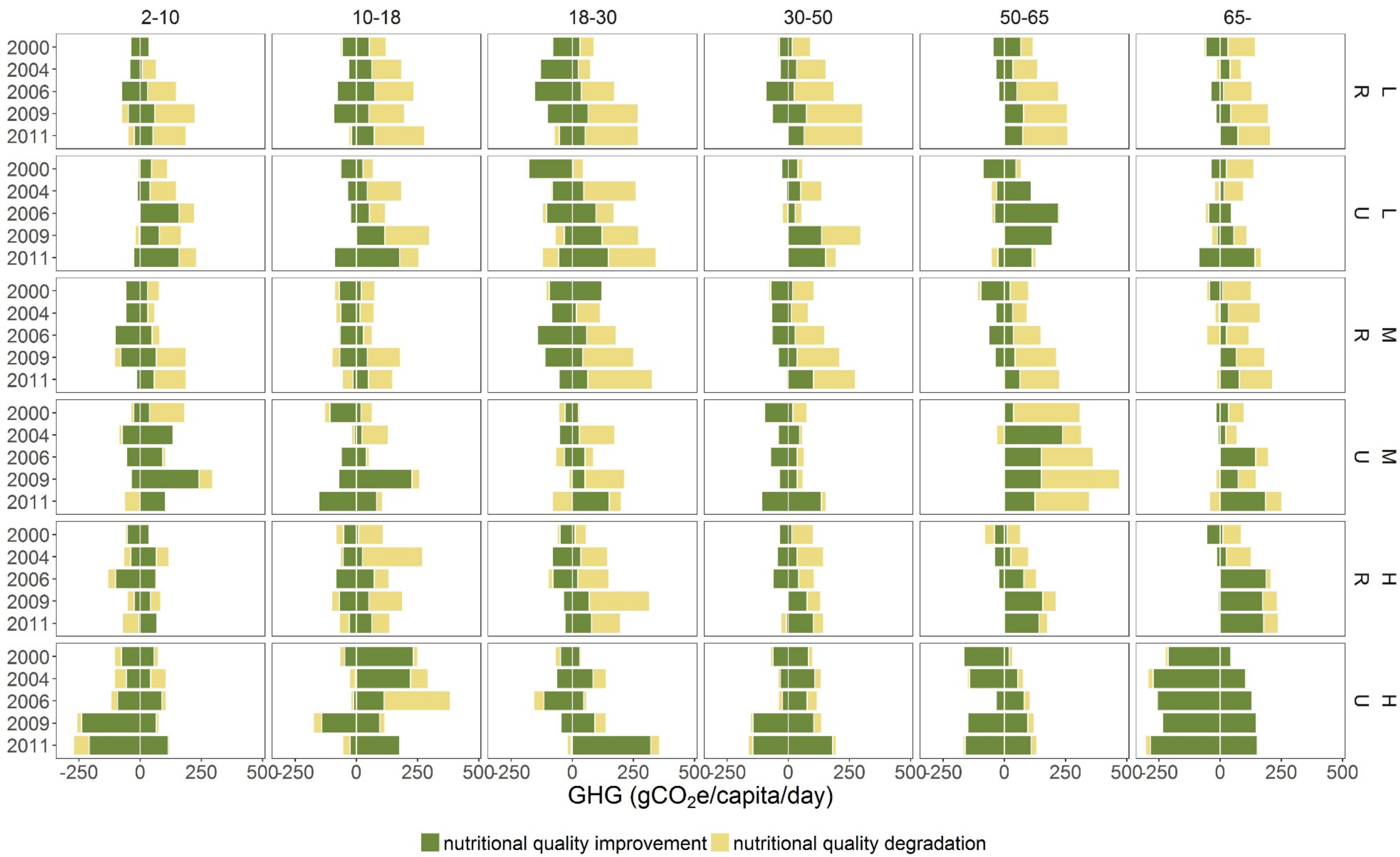

Figure A-7 Decomposition of net changes in GHG emissions between 1997 and 2011 by nutritional quality changes for all age groups. R=rural, U=urban, L=low income, M=medium income, H=high income. The positive bars indicate an increase of the environmental footprints and negative bars a decrease, with different colors denoting whether the nutritional quality is improved or degraded.

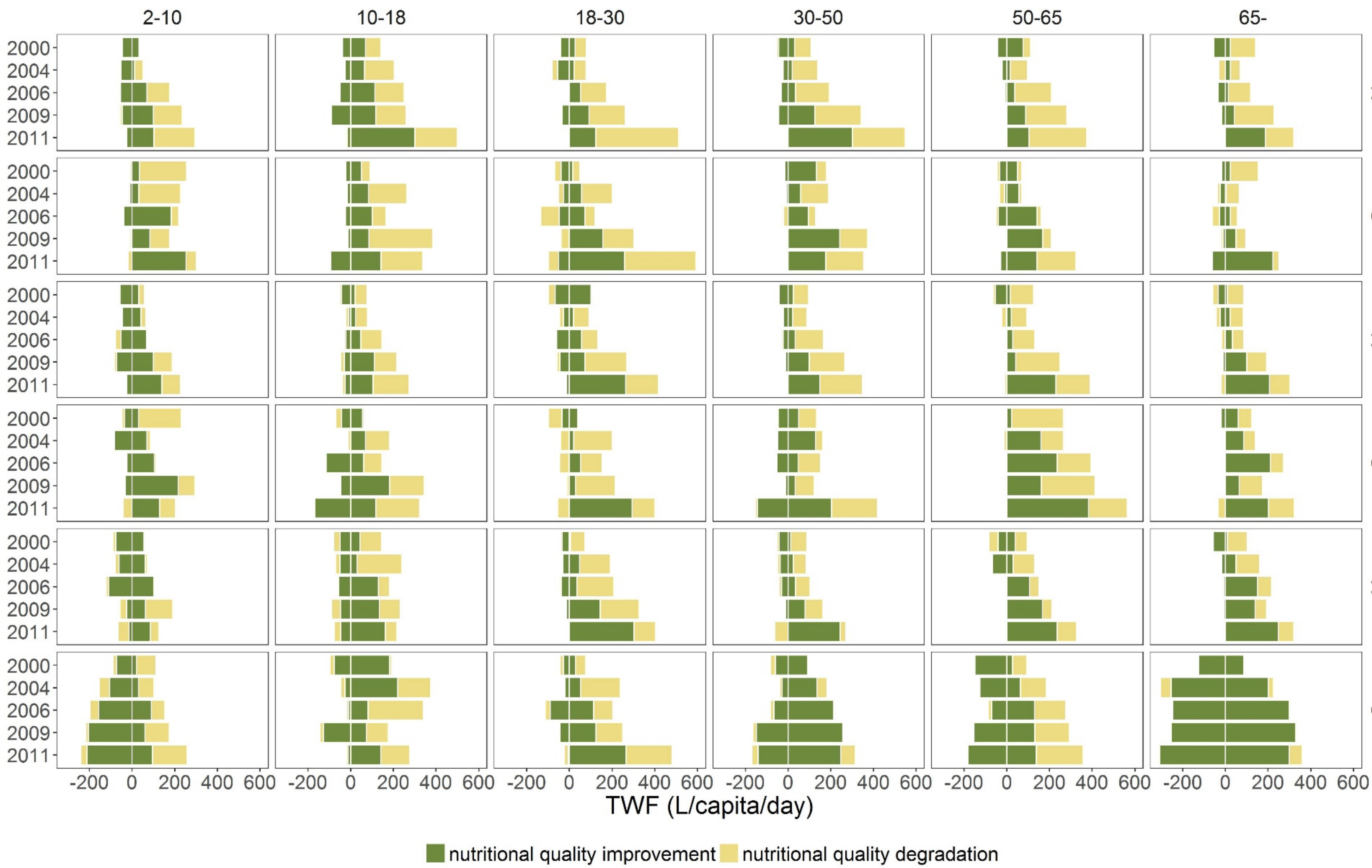

Figure A-8 Decomposition of net changes in water consumption between 1997 and 2011 by nutritional quality changes for all age groups. R=rural, U=urban, L=low income, M=medium income, H=high income. The positive bars indicate an increase of the environmental footprints and negative bars a decrease, with different colors denoting whether the nutritional quality is improved or degraded.

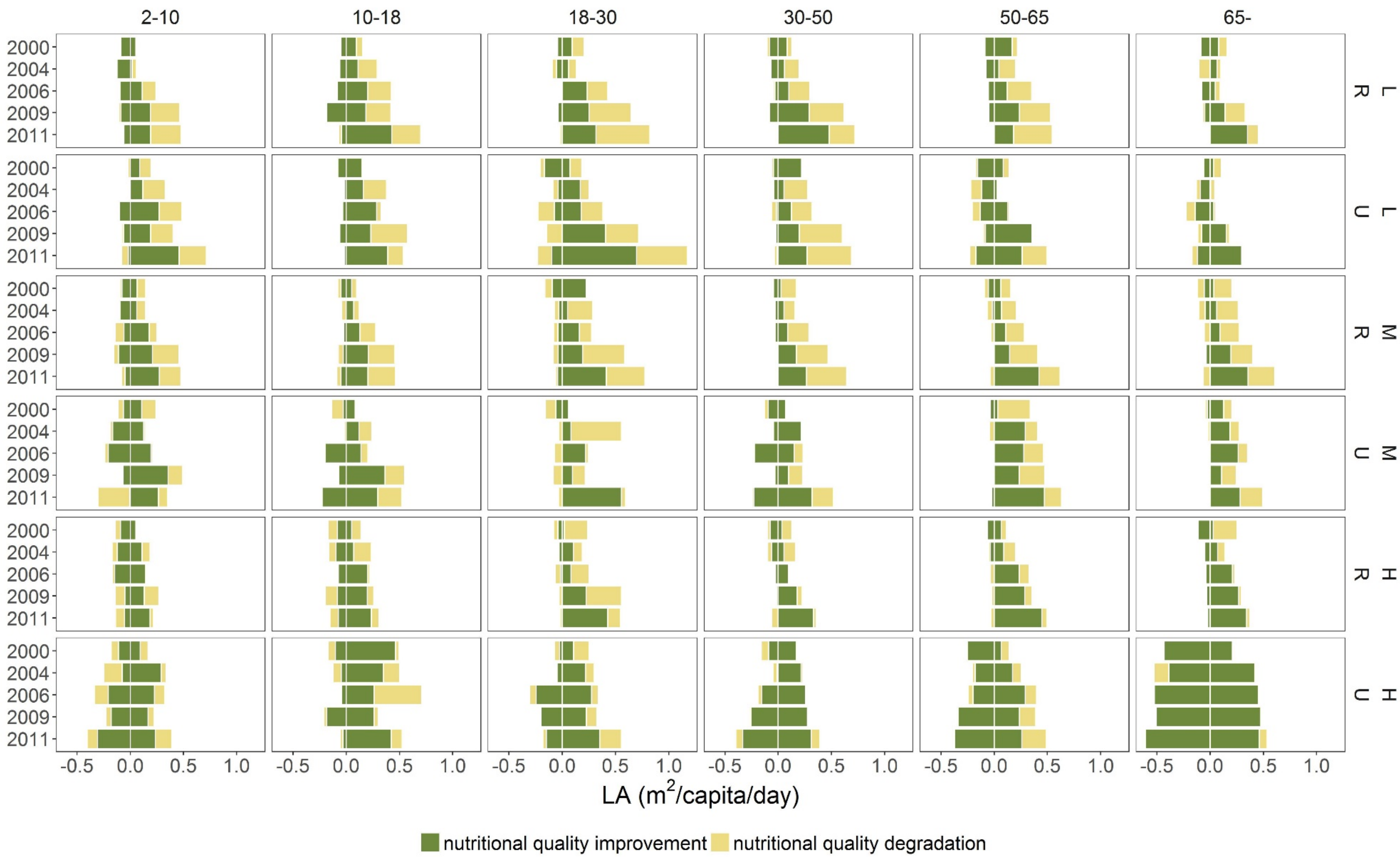

Figure A-9 Decomposition of net changes in land occupation between 1997 and 2011 by nutritional quality changes for all age groups. R=rural, U=urban, L=low income, M=medium income, H=high income. The positive bars indicate an increase of the environmental footprints and negative bars a decrease, with different colors denoting whether the nutritional quality is improved or degraded.

Table A-7 Regression results for food intakes from each food group and the total energy intake

	(1) Refined grains	(2) Coarse grains and pulse	(3) Tubers	(4) Vegetable	(5) Fruits	(6) Soybean	(7) Dairy	(8) Meat	(9) Egg	(10) Seafood	(11) Nuts	(12) Oil	(13) Others	(14) Total energy intakes
year trend	-6.977***	-0.058**	0.143**	2.285***	2.214***	-0.043**	0.719***	3.205***	0.687***	0.166***	0.026***	0.376***	-0.921***	-13.393***
	(0.149)	(0.023)	(0.057)	(0.133)	(0.078)	(0.021)	(0.048)	(0.168)	(0.031)	(0.035)	(0.004)	(0.038)	(0.058)	(0.747)
urban	-50.122***	-1.818***	-5.168***	1.726	8.517***	2.528***	9.493***	65.552***	8.758***	3.190***	0.108*	1.964***	-1.552*	-41.616***
	(2.031)	(0.296)	(0.749)	(1.782)	(0.889)	(0.304)	(0.737)	(2.583)	(0.473)	(0.534)	(0.064)	(0.549)	(0.808)	(10.566)
urban*year	1.544***	0.209***	-0.122	-0.821***	0.737***	-0.105***	0.443***	-3.132***	-0.297***	0.076	0.012	0.038	0.151*	2.894**
	(0.212)	(0.032)	(0.077)	(0.187)	(0.124)	(0.031)	(0.087)	(0.263)	(0.050)	(0.056)	(0.008)	(0.062)	(0.084)	(1.141)
income	-2.990***	-0.030	-0.153**	1.194***	0.918***	0.112***	1.582***	5.190***	0.784***	0.969***	0.018***	0.402***	-0.009	4.222***
	(0.202)	(0.026)	(0.062)	(0.157)	(0.117)	(0.028)	(0.109)	(0.248)	(0.052)	(0.061)	(0.006)	(0.048)	(0.061)	(0.922)
income*year	0.163***	0.007***	0.010**	-0.085***	-0.017*	-0.005**	-0.086***	-0.336***	-0.047***	-0.056***	-0.000	-0.028***	0.005	-0.252***
	(0.015)	(0.002)	(0.005)	(0.012)	(0.010)	(0.002)	(0.008)	(0.019)	(0.004)	(0.005)	(0.001)	(0.004)	(0.005)	(0.074)
age	7.779***	0.102***	0.550***	3.302***	-0.203***	0.176***	-0.706***	2.506***	0.058***	0.363***	0.015***	0.849***	0.629***	43.996***
	(0.083)	(0.012)	(0.031)	(0.072)	(0.043)	(0.012)	(0.038)	(0.098)	(0.019)	(0.020)	(0.003)	(0.022)	(0.031)	(0.457)
age^2	-0.089***	-0.001***	-0.007***	-0.036***	0.001*	-0.002***	-0.008***	-0.031***	-0.001**	-0.004***	-0.000***	-0.009***	-0.006***	-0.495***
	(0.001)	(0.000)	(0.000)	(0.001)	(0.001)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.006)
male	43.172***	0.045	0.845**	6.982***	-5.141***	1.011***	-0.772**	22.940***	0.841***	1.843***	-0.003	3.502***	2.829***	239.364***

	(0.971)	(0.147)	(0.380)	(0.900)	(0.487)	(0.141)	(0.355)	(1.185)	(0.216)	(0.249)	(0.032)	(0.271)	(0.398)	(5.189)
Constant	242.048***	4.847***	18.116***	47.776***	3.782***	6.643***	6.636***	38.002***	8.260***	2.773***	0.073	14.067***	21.191***	1217.663***
	(2.013)	(0.297)	(0.758)	(1.735)	(0.944)	(0.276)	(0.752)	(2.266)	(0.441)	(0.478)	(0.057)	(0.493)	(0.730)	(10.497)
N	50399	50399	50399	50399	50399	50399	50399	50399	50399	50399	50399	50399	50399	50399
R^2	0.229	0.005	0.010	0.045	0.089	0.011	0.065	0.063	0.042	0.031	0.006	0.039	0.015	0.186

Notes: Standard errors in parentheses are robust to heteroskedasticity. * p<0.1, ** p<0.05, *** p<0.01. For each food group, the dependent variables are in log form; for the total value, the dependent variable is the absolute value. Independent variables include year trend, urban* year trend, household income per capita (1,000 RMB), household income per capita* year trend, and age and its square. Fur urban/rural status, the sample include four classes: cities, suburban, town or county capital city, and rural village. We treat the first two as urban areas and the last two as rural, the same as classified in the CHNS.

Table A-8 Regression results for GHG emissions from each food group and the total value

	(1) Refined grains	(2) Coarse grains and pulse	(3) Tubers	(4) Vegetable	(5) Fruits	(6) Soybean	(7) Dairy	(8) Meat	(9) Egg	(10) Seafood	(11) Nuts	(12) Oil	(13) Others	(14) Total GHG emissions
year trend	-1.803***	0.042	0.064***	-0.566***	0.468***	0.294***	0.838***	12.755***	1.907***	1.544***	0.063***	1.559***	0.784***	17.946***
	(0.343)	(0.029)	(0.013)	(0.115)	(0.018)	(0.040)	(0.055)	(0.610)	(0.096)	(0.200)	(0.010)	(0.156)	(0.180)	(0.923)
urban	-68.783***	-1.625***	-0.583***	-20.140***	1.517***	6.152***	7.985***	321.150***	27.532***	19.199***	0.150	8.159***	2.900	303.612***
	(3.935)	(0.322)	(0.191)	(1.598)	(0.190)	(0.565)	(0.784)	(10.617)	(1.485)	(2.846)	(0.117)	(2.281)	(2.528)	(13.903)
urban*year	3.813***	0.202***	-0.078***	0.638***	0.140***	0.262***	0.747***	-12.211***	-0.957***	0.121	0.057***	0.159	-0.841***	-7.948***
	(0.489)	(0.045)	(0.019)	(0.170)	(0.028)	(0.065)	(0.098)	(1.068)	(0.154)	(0.315)	(0.019)	(0.259)	(0.286)	(1.439)
income	-4.881***	-0.099***	-0.025*	-0.163	0.142***	0.394***	1.723***	22.821***	2.434***	5.721***	0.004	1.670***	1.344***	31.084***
	(0.359)	(0.030)	(0.014)	(0.132)	(0.025)	(0.065)	(0.122)	(1.109)	(0.161)	(0.415)	(0.011)	(0.201)	(0.282)	(1.623)
income*year	0.402***	0.013***	0.002	-0.002	-0.000	-0.019***	-0.091***	-1.438***	-0.146***	-0.307***	0.003***	-0.117***	-0.067***	-1.768***
	(0.031)	(0.003)	(0.001)	(0.010)	(0.002)	(0.005)	(0.009)	(0.081)	(0.012)	(0.032)	(0.001)	(0.016)	(0.023)	(0.120)
age	12.384***	0.103***	0.132***	4.666***	-0.015	0.415***	-0.771***	9.866***	0.173***	1.765***	0.033***	3.523***	1.780***	34.054***
	(0.176)	(0.014)	(0.007)	(0.066)	(0.010)	(0.023)	(0.042)	(0.360)	(0.059)	(0.111)	(0.006)	(0.093)	(0.094)	(0.516)
age^2	-0.143***	-0.001***	-0.002***	-0.049***	-0.000	-0.004***	-0.009***	-0.131***	-0.002***	-0.020***	-0.000***	-0.036***	-0.017***	-0.396***
	(0.002)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.001)	(0.004)	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)	(0.006)

male	73.293***	-0.029	0.248***	11.172***	-0.986***	2.100***	-0.676*	85.470***	2.572***	9.096***	-0.140*	14.540***	39.449***	236.109***
	(2.164)	(0.181)	(0.089)	(0.805)	(0.114)	(0.287)	(0.403)	(4.545)	(0.665)	(1.399)	(0.074)	(1.125)	(1.434)	(6.339)
Constant	289.200***	3.687***	3.817***	106.751***	0.439**	7.343***	6.922***	52.963***	26.934***	2.937	0.039	58.398***	-42.220***	517.209***
	(4.138)	(0.334)	(0.176)	(1.557)	(0.214)	(0.520)	(0.839)	(8.450)	(1.367)	(2.702)	(0.112)	(2.048)	(2.395)	(12.283)
N	50399	50399	50399	50399	50399	50399	50399	50399	50399	50399	50399	50399	50399	50399
R^2	0.102	0.006	0.010	0.089	0.070	0.032	0.064	0.092	0.040	0.036	0.010	0.039	0.025	0.152

Notes: Standard errors in parentheses are robust to heteroskedasticity. * p<0.1, ** p<0.05, *** p<0.01. For each food group, the dependent variables are in log form; for the total value, the dependent variable is the absolute value. Independent variables include year trend, urban* year trend, household income per capita (1,000 RMB), household income per capita* year trend, and age and its square. Fur urban/rural status, the sample include four classes: cities, suburban, town or county capital city, and rural village. We treat the first two as urban areas and the last two as rural, the same as classified in the CHNS.

Table A-9 Regression results for total water consumption from each food group and the total value

	(1) Refined grains	(2) Coarse grains and pulse	(3) Tubers	(4) Vegetable	(5) Fruits	(6) Soybean	(7) Dairy	(8) Meat	(9) Egg	(10) Seafood	(11) Nuts	(12) Oil	(13) Others	(14) Total water consumption
year trend	-1.045***	0.409***	0.449***	2.593***	2.689***	2.778***	0.831***	10.080***	1.839***	0.358***	0.102***	2.613***	0.469***	24.164***
	(0.227)	(0.058)	(0.018)	(0.197)	(0.098)	(0.266)	(0.054)	(0.569)	(0.093)	(0.128)	(0.018)	(0.183)	(0.061)	(0.810)
urban	-53.004***	-2.742***	0.048	-6.270***	14.072***	39.569***	9.643***	274.846***	26.544***	9.848***	0.172	9.953***	3.721***	326.400***
	(2.759)	(0.577)	(0.258)	(1.452)	(1.638)	(3.675)	(0.781)	(10.445)	(1.433)	(2.065)	(0.223)	(2.661)	(0.654)	(12.705)
urban*year	2.167***	0.411***	-0.212***	0.430	0.266	3.248***	0.565***	-11.417***	-0.912***	-0.102	0.138***	0.078	-0.459***	-5.799***
	(0.331)	(0.091)	(0.027)	(0.295)	(0.193)	(0.457)	(0.096)	(1.002)	(0.149)	(0.210)	(0.035)	(0.297)	(0.088)	(1.324)
income	-4.844***	-0.181***	0.113***	-2.301***	0.938***	2.829***	1.714***	18.591***	2.345***	2.161***	-0.002	2.901***	0.322***	24.586***
	(0.282)	(0.060)	(0.020)	(0.170)	(0.133)	(0.442)	(0.118)	(0.932)	(0.155)	(0.195)	(0.021)	(0.250)	(0.075)	(1.341)
income*year	0.330***	0.024***	-0.011***	0.196***	-0.019*	-0.123***	-0.092***	-1.182***	-0.140***	-0.132***	0.006***	-0.208***	-0.010	-1.362***
	(0.022)	(0.005)	(0.002)	(0.019)	(0.011)	(0.035)	(0.009)	(0.069)	(0.012)	(0.015)	(0.002)	(0.020)	(0.006)	(0.101)
age	11.131***	0.220***	0.209***	1.697***	-0.286***	2.554***	-0.795***	8.330***	0.169***	1.236***	0.060***	3.844***	-0.039	28.328***
	(0.124)	(0.029)	(0.011)	(0.078)	(0.060)	(0.162)	(0.042)	(0.336)	(0.057)	(0.072)	(0.010)	(0.109)	(0.040)	(0.466)
age^2	-0.127***	-0.002***	-0.003***	-0.018***	0.001**	-0.026***	0.009***	-0.110***	-0.002**	-0.014***	-0.001***	-0.039***	0.000	-0.332***

	(0.002)	(0.000)	(0.000)	(0.001)	(0.001)	(0.002)	(0.000)	(0.004)	(0.001)	(0.001)	(0.000)	(0.001)	(0.000)	(0.006)
male	62.680***	-0.082	0.414***	4.444***	-5.752***	12.289***	-0.817**	74.249***	2.470***	6.740***	-0.311**	16.426***	5.808***	178.559***
	(1.470)	(0.379)	(0.139)	(0.980)	(0.643)	(1.971)	(0.393)	(4.206)	(0.642)	(0.912)	(0.129)	(1.318)	(0.391)	(5.546)
Constant	261.263***	3.277***	2.152***	22.393***	4.496***	33.515***	7.551***	72.901***	25.981***	12.334***	0.113	52.500***	0.164	498.640***
	(2.902)	(0.636)	(0.249)	(1.739)	(1.246)	(3.442)	(0.826)	(7.841)	(1.320)	(1.692)	(0.197)	(2.411)	(0.708)	(10.718)
N	50399	50399	50399	50399	50399	50399	50399	50399	50399	50399	50399	50399	50399	50399
R^2	0.162	0.011	0.020	0.043	0.062	0.042	0.065	0.074	0.040	0.014	0.012	0.038	0.009	0.166

Notes: Standard errors in parentheses are robust to heteroskedasticity. * p<0.1, ** p<0.05, *** p<0.01. For each food group, the dependent variables are in log form; for the total value, the dependent variable is the absolute value. Independent variables include year trend, urban* year trend, household income per capita (1,000 RMB), household income per capita* year trend, and age and its square. Fur urban/rural status, the sample include four classes: cities, suburban, town or county capital city, and rural village. We treat the first two as urban areas and the last two as rural, the same as classified in the CHNS.

Table A-10 Regression results for land occupation from each food group and the total value

	(1) Refined grains	(2) Coarse grains and pulse	(3) Tubers	(4) Vegetable	(5) Fruits	(6) Soybean	(7) Dairy	(8) Meat	(9) Egg	(10) Seafood	(11) Nuts	(12) Oil	(13) Snacks and drinks	(14) Total land occupation
year trend	-0.001***	0.001***	0.000***	0.004***	0.004***	0.001***	0.002***	0.020***	0.008***	0.001***	0.000***	0.000	0.008***	0.049***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.002)
urban	-0.065***	-0.009***	-0.001*	-0.010***	0.012***	0.046***	0.023***	0.446***	0.109***	0.027***	0.000	-0.003	0.048***	0.623***
	(0.006)	(0.002)	(0.001)	(0.002)	(0.001)	(0.004)	(0.002)	(0.017)	(0.006)	(0.006)	(0.000)	(0.003)	(0.018)	(0.028)
urban *year	0.003***	0.001***	-0.000***	0.000	0.001***	0.001**	0.002***	-0.019***	-0.004***	0.000	0.000***	-0.000	-0.005**	-0.020***
	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.002)	(0.001)	(0.001)	(0.000)	(0.000)	(0.002)	(0.003)
income	-0.007***	-0.000**	-0.000**	-0.003***	0.001***	0.003***	0.005***	0.037***	0.010***	0.007***	-0.000	0.001***	0.010***	0.063***
	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.002)	(0.001)	(0.001)	(0.000)	(0.000)	(0.002)	(0.004)
income*year	0.001***	0.000***	0.000	0.000***	-0.000	-0.000***	-0.000***	-0.002***	-0.001***	-0.000***	-0.000***	-0.000***	-0.000***	-0.004***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
age	0.017***	0.001***	0.000***	0.004***	-0.000***	0.003***	-0.002***	0.014***	0.001***	0.004***	0.000***	0.003***	0.009***	0.053***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)
age^2	-0.000***	-0.000***	-0.000***	-0.000***	0.000	-0.000***	-0.000***	-0.000***	-0.000**	-0.000***	-0.000***	-0.000***	-0.000***	-0.001***

	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
male	0.093***	0.000	0.001***	0.009***	-0.008***	0.017***	-0.002	0.116***	0.010***	0.020***	-0.000**	0.012***	0.174***	0.444***
	(0.003)	(0.001)	(0.000)	(0.001)	(0.001)	(0.002)	(0.001)	(0.007)	(0.003)	(0.003)	(0.000)	(0.001)	(0.011)	(0.014)
Constant	0.402***	0.011***	0.014***	0.060***	0.004***	0.070***	0.020***	0.091***	0.107***	0.035***	-0.000	0.064***	-0.238***	0.639***
	(0.006)	(0.002)	(0.001)	(0.002)	(0.002)	(0.004)	(0.002)	(0.014)	(0.005)	(0.005)	(0.000)	(0.002)	(0.018)	(0.027)
N	50399	50399	50399	50399	50399	50399	50399	50399	50399	50399	50399	50399	50399	50399
R^2	0.099	0.010	0.010	0.059	0.074	0.026	0.063	0.073	0.040	0.016	0.011	0.015	0.011	0.111

Notes: Standard errors in parentheses are robust to heteroskedasticity. * p<0.1, ** p<0.05, *** p<0.01. For each food group, the dependent variables are in log form; for the total value, the dependent variable is the absolute value. Independent variables include year trend, urban* year trend, household income per capita (1,000 RMB), household income per capita* year trend, and age and its square. Fur urban/rural status, the sample include four classes: cities, suburban, town or county capital city, and rural village. We treat the first two as urban areas and the last two as rural, the same as classified in the CHNS.

Table A-11 Regression results for deviation from the balanced dietary pattern (in percentage)

	(1) Grains, pulse and tubers	(2) Coarse grains and pulse	(3) Tubers	(4) Vegetable	(5) Dark colored vegetable	(6) Fruits	(7) Soybean	(8) Dairy	(9) Meat	(10) Egg	(11) Seafood	(12) Nuts	(13) Oil
year trend	-2.235***	-0.058*	0.278***	0.112***	0.974***	0.790***	-0.135	0.147***	7.379***	1.751***	0.226***	0.226***	2.059***
	(0.080)	(0.031)	(0.064)	(0.042)	(0.045)	(0.031)	(0.124)	(0.014)	(0.336)	(0.073)	(0.064)	(0.049)	(0.153)
urban	-16.889***	-1.852***	-5.947***	-0.007	8.980***	3.434***	16.990***	2.171***	162.510***	20.531***	11.130***	0.839	25.073***
	(0.994)	(0.386)	(0.753)	(0.517)	(0.555)	(0.304)	(1.578)	(0.169)	(4.579)	(0.932)	(0.883)	(0.587)	(1.962)
urban*year	-0.088	0.282***	-0.095	-0.053	-0.613***	0.356***	-0.591***	0.272***	-6.419***	-0.978***	0.125	0.170**	-1.095***
	(0.101)	(0.040)	(0.077)	(0.055)	(0.057)	(0.043)	(0.161)	(0.021)	(0.479)	(0.100)	(0.092)	(0.071)	(0.220)
income	-0.836***	0.004	0.004	-0.056	0.306***	0.340***	0.508***	0.495***	7.505***	1.569***	1.409***	0.184***	1.399***
	(0.085)	(0.035)	(0.062)	(0.045)	(0.051)	(0.048)	(0.163)	(0.035)	(0.454)	(0.112)	(0.103)	(0.065)	(0.195)
income*year	0.046***	0.006**	0.002	-0.001	-0.020***	-0.006	-0.021*	-0.027***	-0.481***	-0.092***	-0.082***	-0.005	-0.099***
	(0.007)	(0.003)	(0.005)	(0.004)	(0.004)	(0.004)	(0.013)	(0.003)	(0.035)	(0.009)	(0.008)	(0.005)	(0.015)
age	0.483***	0.050***	0.304***	0.717***	0.597***	-0.264***	0.124*	-0.210***	-0.883***	-0.368***	0.072*	0.157***	2.329***
	(0.050)	(0.017)	(0.032)	(0.025)	(0.024)	(0.021)	(0.074)	(0.012)	(0.232)	(0.050)	(0.043)	(0.031)	(0.094)
age^2	-0.001**	-0.000	-0.004***	-0.006***	-0.006***	0.003***	0.002*	0.002***	0.013***	0.005***	0.000	-0.002***	-0.020***
	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.003)	(0.001)	(0.001)	(0.000)	(0.001)
male	-12.834*	-0.285	-1.961**	-6.072**	-2.057**	-4.120**	-7.237**	-0.168	-29.760*	-2.279**	-4.935**	0.086	-3.278**

	**		*	*	*	*	*		**	*	*		*
	(0.472)	(0.189)	(0.374)	(0.268)	(0.273)	(0.197)	(0.778)	(0.115)	(2.256)	(0.479)	(0.442)	(0.333)	(1.058)
Constant	52.714***	-91.801***	-75.480***	-55.967***	-72.866***	-95.453***	-51.723***	-98.334***	41.548***	-76.261***	-86.631***	-99.533***	-37.812***
	(1.186)	(0.412)	(0.816)	(0.578)	(0.603)	(0.410)	(1.736)	(0.226)	(4.964)	(1.092)	(1.001)	(0.683)	(2.015)
N	50399	50399	50399	50399	50399	50399	50399	50399	50399	50399	50399	46174	50399
R^2	0.087	0.006	0.009	0.053	0.037	0.094	0.013	0.070	0.070	0.042	0.035	0.006	0.035

Notes: Standard errors in parentheses are robust to heteroskedasticity. * p<0.1, ** p<0.05, *** p<0.01. For each food group, the dependent variables are in percentage. Independent variables include year trend, urban* year trend, household income per capita (1,000 RMB), household income per capita* year trend, and age and its square.

Table A-12 Summary of Monte Carlo simulation on total dietary environmental impacts

Variable	Obs	Mean	Std. Dev.	Min	Max	t-stat, min	t-stat, max
GHG emissions							
year trend	50,399	15.486	8.758	-44.155	32.275	-6.283	30.470
urban	50,399	236.875	166.650	-1003.707	437.304	-10.073	25.754
urban*year	50,399	-4.823	8.869	-12.170	64.428	-7.034	6.110
income	50,399	27.701	8.141	0.737	64.851	0.087	19.753
income*year	50,399	-1.561	0.437	-3.633	-0.345	-15.458	-0.524
age	50,399	39.114	29.681	20.903	272.600	31.247	79.014
age2	50,399	-0.444	0.307	-2.862	-0.248	-72.435	-30.347
male	50,399	234.636	75.116	144.632	795.299	15.945	39.111
Constant	50,399	649.436	731.329	223.987	6431.448	12.002	69.162
Total water consumption							
year trend	50,399	24.028	4.051	12.245	32.957	15.416	41.010
urban	50,399	322.855	24.563	267.048	394.552	21.753	28.765
urban*year	50,399	-6.036	1.328	-8.557	-2.314	-6.350	-1.874
income	50,399	23.962	2.059	19.910	29.128	16.347	19.601
income*year	50,399	-1.327	0.135	-1.674	-1.046	-15.022	-11.169
age	50,399	27.853	1.213	25.663	30.726	53.595	64.283
age2	50,399	-0.325	0.014	-0.359	-0.299	-62.342	-52.313
male	50,399	174.360	8.506	156.560	198.157	28.516	33.524
Constant	50,399	489.164	38.169	412.032	582.812	37.494	57.458
Land appropriation							
year trend	50,399	0.051	0.002	0.046	0.055	23.369	27.987
urban	50,399	0.619	0.014	0.589	0.670	20.948	23.003
urban*year	50,399	-0.020	0.001	-0.023	-0.018	-6.819	-5.903
income	50,399	0.062	0.001	0.059	0.066	16.336	17.659
income*year	50,399	-0.003	0.000	-0.004	-0.003	-13.044	-11.833
age	50,399	0.053	0.001	0.051	0.056	47.517	51.038
age2	50,399	-0.001	0.000	-0.001	-0.001	-48.899	-45.434
male	50,399	0.439	0.009	0.417	0.465	29.533	31.053
Constant	50,399	0.611	0.022	0.568	0.665	20.279	25.491

Notes: Presented are the summary statistics of the coefficients in the regressions as same as Column 14 in Table S8-S10. The mean, standard deviation, min, and max of each estimator in the 100 trials are shown in the table.

Appendix B: Supplement information for Chapter 3

Nutritional quality evaluation

The nutritional quality evaluation of Chapter 3 follows the same methodology used in Chapter 2.

Monte Carlo simulation

As shown in Figure 3, the Monte Carlo simulation is processed in 3 steps:

1) Environmental impacts per gram of food is determined with reference data from literature and the assumed distributions.
2) Individual choices of food is randomized. Each individual independently and randomly select one food item within each food group from the Chinese Food Content Tables (2002 & 2004 version) to correct the deviation from *Balanced Dietary Patterns*. Probabilities of being chosen is constructed by intake frequencies of each food item to project the dietary preference of our sample. In other words, we implicitly assume that they have different existing dietary patterns but similar preference.
3) Deviations *Balanced Dietary Patterns* are multiplied with environmental impacts per gram of the selected food to calculate the environmental impacts of dietary change.

10000 trials including these three steps are run for each individual. In the final results, we plot the combined simulation results for all the individuals.

Figure B-1 Monte Carlo simulation for calculating environmental impacts of dietary change

Environmental footprint distribution construction

The GHG emissions by food categories

Evidence is rarely conclusive on what distribution the environmental footprint of products should be. For GHG emission, some studies adopt triangle distributions (Penman 2000, Song, Li et al. 2015), and others denotes that the environmental footprints are not normally distributed but with positive skewness (Pradhan, Reusser et al. 2013). Here we assume the distributions of all the environmental footprints per gram of food follow log normal distribution, which exhibit the non-negative nature and the long-tail quality of environmental footprints. The means and standard deviations are derived by our collection of over 300 LCA studies on 25 food categories.

Table B-1 GHG emissions of each food category (gCO2e/g product)

categories	GHG emission	categories	GHG emission
wine	2.5054	**juice**	1.06
barley	0.770714	**pulse**	0.58419
beef	19.28516	**potato**	0.18328
egg	2.518055	**sugar**	0.233
fish	4.268423	**vegetable**	0.839539
fruit	0.13311	**carrot**	0.117727
sheep	11.26746	**flour**	0.2615
maize	0.36267	**wheat**	0.603486
milk	1.148019	**nut**	1.073692
cheese	5.371067	**butter**	4.3
mushroom	0.00468	**yogurt**	1.17
oil	4.151519	**beer**	1.25
pork	5.274014	**spirit**	1.55
poultry	6.049611	**soda**	0.32775
rice	1.698058	**tea**	0.089
shrimp	9.296667	**honey**	0.795

Water footprints

Similar as GHG emissions, variation and uncertainties for multiple types of food are seldom measured with identical quantitative strategies. Following the only study that address this case to our knowledge (Zhuo, Mekonnen et al. 2014), we assume a normal distribution of water footprints, with standard deviations to be

15% of the mean. The intuition behind this assumption is that the larger the footprint is, the larger uncertainty and variation its production process has, and the more conservative we should be in drawing conclusions.

The water footprints for the aquatic (animal) products are calculated with

$$Water\ footprint_m = Perfeed_m \cdot FCR_m \cdot \sum_s (Per_{ms} \cdot Water\ footprint_{ms})$$

In which $Water\ footprint_m$ is the unit water footprint (either green or blue water) for food item m (kg water/kg product). $Perfeed_m$ is the proportion of aquaculture in the total production of this item. FCR_m is the feed conversion ratio (kg of feed/kg of product) of the item, indicating the weight of feed needed in producing per unit of item. In the aquaculture, the feed is often a mixture of different component such as soybean, maize, etc. Therefore, the water footprint of the feed is calculated by weighting the unit water footprint of each feed component m, $Water\ footprint_{ms}$ (g water/g product), by the percentage of the component in per unit of feed, Per_{ms}. $Perfeed_m$ is available in the FAO fishery statistics (Fisheries 1997-2006), and we adopt the FCR_m and Per_{ms} for Chinese aquaculture from (Weimin and Mengqing 2007). $Water\ footprint_m$ comes from the database of the Water Footprint Network. As the available species from the FAO fishery statistics are not fully matched with the food items in our sample, we use the data of the nearest species for the items lack of data. In accordance with the water footprints of other products, we take the 1996-2005 average as the final $Water\ footprint_m$ of each item.

Land appropriation

We adopt a similar method as for water footprint to calculate the land appropriation. The land occupation of the unprocessed food products is calculated with

$$LO_m = PerCP_m \cdot FCR_m \cdot \sum_s (Per_{ms} \cdot LO_{ms}) + GLO_m / PrdW_m$$

In which LO_m is the land occupation of animal product m. Here we consider six main unprocessed animal product: pork, poultry, milk, egg, beef, and goat & sheep. The first term denotes the land occupation of the concentrated production. $\sum_s (Per_{ms} \cdot LO_{ms})$ calculates the land occupation of the feed, in a way similar as we deal with the aquaculture, with LO_{ms} to be the land occupation of feed component s in producing m, and Per_{ms} and FCR_m defined as above. $PerCP_m$ is the proportion of concentrated production in the total production of m. The second term captures the land occupation for the grazing production. GLO_m is the total grazing land used for producing m in one year, and $PrdW_m$ is the total production weight[25] of the product m. We obtain $PerCP_m$ and FCR_m from (Mekonnen and Hoekstra 2010), and Per_{ms} from (Sa 2002). LO_{ms} comes from the land occupation of the main crop products that we calculated. The FATSTAT provides GLO_m and $PrdW_m$.

For aquatic products, only the land occupied for feed production in aquaculture is accounted for, with

$$LO_m = Perfeed_m \cdot FCR_m \cdot \sum_s (Per_{ms} \cdot LO_{ms})$$

[25] The total production weight here accounts for both the concentrated production and grazing production, as the proportion of the grazing production is cancelled out. To see why, remember that the land occupation for per unit of m from grazing production is calculated with $GLO_m / (PrdW_m \cdot (1 - PerCP_m))$; in each unit of m that reaches the consumers, $(1 - PerCP_m)$ comes from grazing production, so the land occupation from grazing for per unit of m is $GLO_m / (PrdW_m \cdot (1 - PerCP_m)) \cdot (1 - PerCP_m) = GLO_m / PrdW_m$.

With all the parameters defined in a similar way as in the calculation of the aquaculture water footprints. The data source are identical as well, except that the LO_{ms} comes from our calculation of the land occupation of main crops.

For the processed crop, livestock and poultry products, the production and value fraction method similar as for water footprint in (Aldaya, Chapagain et al. 2012) is adopted, with

$$LO_m = fv_m \cdot \sum_s \frac{LO_{ms}}{fp_{ms}}$$

In which LO_m is the land occupation of the food item m; LO_{ms} is the land occupation of the root product s of m. fv_m is the value fraction of m, which is defined as the ratio of the market value of this item to the aggregated market value of all the items produced from the root products. fp_{ms} is the product ration of item m, which is defined as the quantity of item m obtained per quantity of its root product s. The database of the water footprint provides the root products and the two fractions of each food item, thus we can obtain LO_m by plugging in LO_{ms}.

Reweighing the CHNS sample

As shown in our analysis on individual diets, environmental impacts of dietary change differ by characteristics such as age, urban/rural status, income levels. Although distribution of these characteristics are summarized in yearbooks and census dataset, no information is available for a joint distribution. Here we solve this problem by using another micro-level dataset, the China Family Panel Studies (CFPS). Launched by the Institute of Social Science Survey (ISSS) of Peking University, the CFPS is designed to collect individual-, family-, and community-level longitudinal data in contemporary China[26]. This dataset contains weights to adjust the sample to be nationally representative, indicated by the number of individuals represented by the sampled interviewee. The initial collection of

[26] More information is available from http://www.isss.edu.cn/cfps/EN/

CFPS is completed in 2010. We thus assume that the population is unchanged till the launch of 2011 CHNS, and take four steps to map these weights to CHNS data:

1) We separate individuals from the two samples into groups with key diet-affecting characteristics, including urban/rural status, income, age, and sex. Bins are adopted for continuous variables: for age, we adopt the same bins as presented in (Figure); for income, we obtain quintiles from CFPS (the income is inflated to 2011 level). This gives us 2(urban/rural status)*5(income bins)*5(age bins)*2(sex)=100 groups in both samples.
2) The number of individual in each group is counted for both dataset so that how many CFPS individual is represented by a CHNS individual is known.
3) The CFPS weight is summed up within groups and then divided by the number of CHNS individuals in the same group. In this way, how many individuals in the population is represented by a CHNS individual is obtained.
4) In the CFPS data, the sum of all the weights (approximately 0.9 billion) is smaller than Chinese population above age 2 (approximately 1.3 billion) according to the 2010 census. Thus, we multiply each weight by 1.3/0.9 as a simple inflation in the final step.

Supplementary results

Table B-2 Descriptive statistics of deviation from the balanced dietary pattern

	mean	sd	t stat	N
Refined cereals	0.71	1.34	52.98	10,222
Coarse grains and pulse	-0.88	0.21	-430.00	10,222
Tubers	-0.73	0.38	-200.00	10,222
Dark colored vegetable	-0.48	0.29	-170.00	10,222
Light colored vegetable	-0.20	0.24	-80.78	10,222
Fruits	-0.80	0.32	-250.00	10,222
Soybean	-0.45	0.78	-58.68	10,222
Dairy	-0.93	0.19	-490.00	10,222

Meat	1.75	2.53	69.96	10,222
Egg	-0.49	0.55	-90.20	10,222
Seafood	-0.71	0.50	-140.00	10,222
Nuts	-0.86	0.49	-170.00	10,222
Oil	0.43	1.28	34.28	10,222

Standard errors in parentheses. * p<0.1, ** p<0.05, *** p<0.01. For each food group, the percentage of deviation from the recommended value is summarized, and hypothesis test on whether the average of each equals 0 is tested.

Table B-3 Regression results for deviation from the balanced dietary pattern (in percentage)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
	Refined cereals	Coarse grains and pulse	Tubers	Dark colored vegetable	Light colored vegetable	Fruits	Soybean	Dairy	Meat	Egg	Seafood	Nuts	Oil
urban	-0.230***	0.016***	-0.042***	-0.021***	-0.029***	0.109***	0.006	0.104***	0.441***	0.116***	0.129***	0.066***	-0.025
	(0.019)	(0.004)	(0.008)	(0.006)	(0.005)	(0.007)	(0.016)	(0.004)	(0.052)	(0.012)	(0.011)	(0.011)	(0.027)
income	-0.049***	0.007***	-0.002	-0.004*	-0.005***	0.024***	0.023***	0.017***	0.118***	0.037***	0.042***	0.013***	-0.008
	(0.006)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.006)	(0.002)	(0.016)	(0.004)	(0.005)	(0.003)	(0.009)
age	-0.030	0.002	0.008	0.063***	0.045***	-0.035***	0.066***	-0.046***	-0.078	-0.034***	0.034***	0.045***	0.224***
	(0.020)	(0.004)	(0.006)	(0.005)	(0.004)	(0.006)	(0.013)	(0.004)	(0.050)	(0.012)	(0.009)	(0.009)	(0.023)
age^2	0.012***	0.000	-0.001	-0.006***	-0.002***	0.004***	-0.005***	0.005***	0.008	0.004***	-0.003***	-0.005***	-0.017***
	(0.002)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.000)	(0.006)	(0.001)	(0.001)	(0.001)	(0.003)
Constant	0.694***	-0.909***	-0.725***	-0.606***	-0.319***	-0.811***	-0.669***	-0.898***	1.555***	-0.530***	-0.892***	-0.998***	-0.128***
	(0.039)	(0.007)	(0.013)	(0.010)	(0.007)	(0.012)	(0.025)	(0.007)	(0.097)	(0.023)	(0.017)	(0.017)	(0.039)
N	9964	9980	9980	9980	9980	9980	9980	9980	9980	9980	9980	9101	9980
R^2	0.050	0.006	0.003	0.022	0.052	0.049	0.009	0.114	0.014	0.025	0.040	0.010	0.022

Standard errors in parentheses. * p<0.1, ** p<0.05, *** p<0.01. For each food group, the dependent variables are in percentage. Independent variables include year trend, household income per capita (1,000 RMB), household income per capita, and age and its square. Fur urban/rural status, the sample include four classes: cities, suburban, town or county capital city, and rural village. Here we treat the first three as urban areas, while the last as rural.

Table B-4 Regression results for environmental impacts of dietary shifts

	(1) GHG	(3) TWF	(5) LA
urban	-0.101***	-0.123***	-0.365***
	(0.016)	(0.018)	(0.031)
income	-0.045***	-0.052***	-0.124***
	(0.005)	(0.006)	(0.011)
age	-0.127***	-0.070***	-0.038
	(0.013)	(0.015)	(0.026)
age^2	0.012***	0.002	-0.003
	(0.002)	(0.002)	(0.003)
Constant	0.264***	0.889***	2.108***
	(0.024)	(0.028)	(0.050)
N	9980	9980	9980
R^2	0.029	0.032	0.043

Standard errors in parentheses. * p<0.1, ** p<0.05, *** p<0.01. For each food group, the dependent variables are in percentage. Independent variables include urban/rural status, household income per capita (1,000 RMB), and age and its square (10 years).

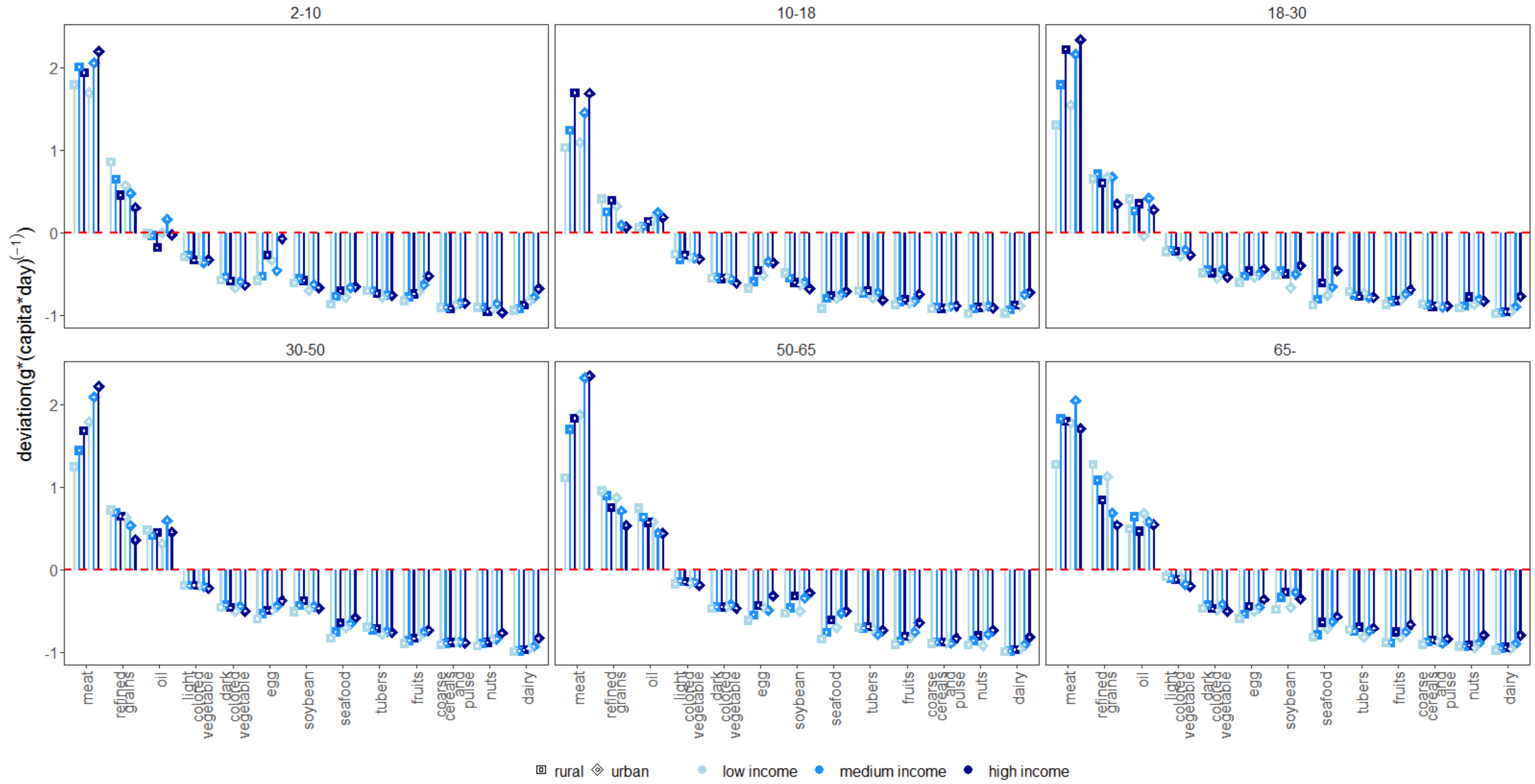

Figure B-2 Deviation of food intake from balanced dietary patterns in quantity by age groups. Food groups on the x axis are ranked by the level of malnutrition from the most severe over-intake to the most severe under-intake. The points and lines show averaged quantities of deviation. We conduct t-tests on the percentage deviation from the balanced dietary patterns, and all of them turn out statistically significant.

Appendix C: Supplement information for Chapter 4

Matching the food groups

Table C-1 food groups from GENuS database, FAO food waste groups, and GTAP

Food	Discarded % by weight (USDA)	Food waste group from FAO	Food group for nutritional quality evaluation	GTAP food production sector
Wheat	0	Cereals	cereal	Wheat
Rice (Milled Equivalent)	0	Cereals	cereal	Processed rice
Barley	0	Cereals	cereal	Cereal grains nec
Maize	0	Cereals	cereal	Cereal grains nec
Rye	0	Cereals	cereal	Cereal grains nec
Oats	0	Cereals	cereal	Cereal grains nec
Millet	0	Cereals	cereal	Cereal grains nec
Sorghum	0	Cereals	cereal	Cereal grains nec
Buckwheat	0	Cereals	cereal	Cereal grains nec
Fonio	0	Cereals	cereal	Cereal grains nec
Triticale	0	Cereals	cereal	Cereal grains nec
Mixed grain	0	Cereals	cereal	Cereal grains nec
Cereals; nes	0	Cereals	cereal	Cereal grains nec
Popcorn	0	Cereals	cereal	Cereal grains nec
Quinoa	0	Cereals	cereal	Cereal grains nec
Canary seed	0	Cereals	cereal	Cereal grains nec
Cassava	16	Roots and tubers	tuber	Vegetables; fruit; nuts
Potatoes	25	Roots and tubers	tuber	Vegetables; fruit; nuts
Sweet Potatoes	28	Roots and tubers	tuber	Vegetables; fruit; nuts
Yams	14	Roots and tubers	tuber	Vegetables; fruit; nuts
Yautia (cocoyam)	14	Roots and tubers	tuber	Vegetables; fruit; nuts
Taro (cocoyam)	14	Roots and tubers	tuber	Vegetables; fruit; nuts

Roots and tubers; nes	19.2	Roots and tubers	tuber	Vegetables; fruit; nuts
Flour of roots and tubers	0	Roots and tubers	tuber	Vegetables; fruit; nuts
Sugar Cane	0	Roots and tubers	sugar	Sugar cane; sugar beet
Sugar; Non-Centrifugal	0	Roots and tubers	sugar	Sugar
Sugar (Raw Equivalent)	0	Roots and tubers	sugar	Sugar
Sweeteners; Other	0	Roots and tubers	sugar	Sugar
Honey	0	Roots and tubers	sugar	Animal products nec
Beans	0	Oilseeds and pulses	vegetable	Vegetables; fruit; nuts
Peas	0	Oilseeds and pulses	vegetable	Vegetables; fruit; nuts
Broad beans; horse beans; dry	0	Oilseeds and pulses	vegetable	Vegetables; fruit; nuts
Chick peas	0	Oilseeds and pulses	vegetable	Vegetables; fruit; nuts
Cow peas; dry	0	Oilseeds and pulses	vegetable	Vegetables; fruit; nuts
Pigeon peas	0	Oilseeds and pulses	vegetable	Vegetables; fruit; nuts
Lentils	0	Oilseeds and pulses	vegetable	Vegetables; fruit; nuts
Bambara beans	25	Oilseeds and pulses	vegetable	Vegetables; fruit; nuts
Vetches	0	Oilseeds and pulses	vegetable	Vegetables; fruit; nuts
Lupins	0	Oilseeds and pulses	vegetable	Vegetables; fruit; nuts
Pulses; nes	0	Oilseeds and pulses	vegetable	Vegetables; fruit; nuts
Flour of pulses	0	Oilseeds and pulses	vegetable	Vegetables; fruit; nuts
Brazil nuts; with shell	49	Oilseeds and pulses	nuts	Vegetables; fruit; nuts
Cashew nuts; with shell	28	Oilseeds and pulses	nuts	Vegetables; fruit; nuts
Chestnuts	20	Oilseeds and pulses	nuts	Vegetables; fruit; nuts
Almonds; with shell	60	Oilseeds and pulses	nuts	Vegetables; fruit; nuts
Walnuts; with shell	65.5	Oilseeds and pulses	nuts	Vegetables; fruit; nuts
Pistachios	47	Oilseeds and pulses	nuts	Vegetables; fruit; nuts
Kolanuts	0	Oilseeds and pulses	nuts	Vegetables; fruit; nuts
Hazelnuts; with shell	59	Oilseeds and pulses	nuts	Vegetables; fruit; nuts
Areca nuts	0	Oilseeds and pulses	nuts	Vegetables; fruit; nuts
Nuts; nes	55	Oilseeds and pulses	nuts	Vegetables; fruit; nuts
Prepared nuts (exc. groundnuts)	4.7	Oilseeds and pulses	nuts	Vegetables; fruit; nuts

Soyabeans	0	Oilseeds and pulses	nuts	Oil seeds
Groundnuts (Shelled Eq)	0	Oilseeds and pulses	nuts	Oil seeds
Sunflowerseed	46	Oilseeds and pulses	nuts	Oil seeds
Rape and Mustardseed	0	Oilseeds and pulses	nuts	Oil seeds
Cottonseed	0	Oilseeds and pulses	nuts	Oil seeds
Coconuts - Incl Copra	48	Oilseeds and pulses	nuts	Crops nec
Sesameseed	0	Oilseeds and pulses	nuts	Oil seeds
Palmkernels	0	Oilseeds and pulses	nuts	Oil seeds
Olives	0	Oilseeds and pulses	nuts	Vegetables; fruit; nuts
Oilcrops; Other	22	Oilseeds and pulses	nuts	Oil seeds
Soyabean Oil	0	Oilseeds and pulses	oil	Vegetable oils and fats
Groundnut Oil	0	Oilseeds and pulses	oil	Vegetable oils and fats
Sunflowerseed Oil	0	Oilseeds and pulses	oil	Vegetable oils and fats
Rape and Mustard Oil	0	Oilseeds and pulses	oil	Vegetable oils and fats
Cottonseed Oil	0	Oilseeds and pulses	oil	Vegetable oils and fats
Palmkernel Oil	0	Oilseeds and pulses	oil	Vegetable oils and fats
Palm Oil	0	Oilseeds and pulses	oil	Vegetable oils and fats
Coconut Oil	0	Oilseeds and pulses	oil	Vegetable oils and fats
Sesameseed Oil	0	Oilseeds and pulses	oil	Vegetable oils and fats
Olive Oil	0	Oilseeds and pulses	oil	Vegetable oils and fats
Ricebran Oil	0	Oilseeds and pulses	oil	Vegetable oils and fats
Maize Germ Oil	0	Oilseeds and pulses	oil	Vegetable oils and fats
Oilcrops Oil; Other	0	Oilseeds and pulses	oil	Vegetable oils and fats
Tomatoes	9	Fruits and vegetables	vegetable	Vegetables; fruit; nuts
Onions	10	Fruits and vegetables	vegetable	Vegetables; fruit; nuts
Cabbages and other brassicas	25.9	Fruits and vegetables	vegetable	Vegetables; fruit; nuts
Artichokes	60	Fruits and vegetables	vegetable	Vegetables; fruit; nuts
Asparagus	47	Fruits and vegetables	vegetable	Vegetables; fruit; nuts
Lettuce and chicory	17	Fruits and vegetables	vegetable	Vegetables; fruit; nuts
Spinach	28	Fruits and vegetables	vegetable	Vegetables; fruit; nuts

Cassava leaves	0	Fruits and vegetables	vegetable	Vegetables; fruit; nuts
Cauliflowers and broccoli	50	Fruits and vegetables	vegetable	Vegetables; fruit; nuts
Pumpkins; squash; and gourds	21.3	Fruits and vegetables	vegetable	Vegetables; fruit; nuts
Cucumbers and gherkins	3	Fruits and vegetables	vegetable	Vegetables; fruit; nuts
Eggplants (aubergines)	19	Fruits and vegetables	vegetable	Vegetables; fruit; nuts
Chillies and peppers; green	16.6	Fruits and vegetables	vegetable	Vegetables; fruit; nuts
Onions (inc. shallots); green	17	Fruits and vegetables	vegetable	Vegetables; fruit; nuts
Garlic	13	Fruits and vegetables	vegetable	Vegetables; fruit; nuts
Leeks; other alliaceous veg.	28	Fruits and vegetables	vegetable	Vegetables; fruit; nuts
Beans; green	12	Fruits and vegetables	vegetable	Vegetables; fruit; nuts
Peas; green	34	Fruits and vegetables	vegetable	Vegetables; fruit; nuts
Leguminous vegetables; nes	3	Fruits and vegetables	vegetable	Vegetables; fruit; nuts
String beans	12	Fruits and vegetables	vegetable	Vegetables; fruit; nuts
Carrots and turnips	11	Fruits and vegetables	vegetable	Vegetables; fruit; nuts
Okra	14	Fruits and vegetables	vegetable	Vegetables; fruit; nuts
Maize; green	64	Fruits and vegetables	vegetable	Vegetables; fruit; nuts
Mushrooms and truffles	3	Fruits and vegetables	vegetable	Vegetables; fruit; nuts
Chicory roots	18	Fruits and vegetables	vegetable	Vegetables; fruit; nuts
Vegetables; fresh; nes	24	Fruits and vegetables	vegetable	Vegetables; fruit; nuts
Vegetables; dried; nes	2.1	Fruits and vegetables	vegetable	Vegetables; fruit; nuts
Vegetables; dehydrated	0	Fruits and vegetables	vegetable	Vegetables; fruit; nuts
Vegetables in vinegar	0	Fruits and vegetables	vegetable	Vegetables; fruit; nuts
Vegetables; preserved; nes	0	Fruits and vegetables	vegetable	Vegetables; fruit; nuts
Vegetables; frozen	3.1	Fruits and vegetables	vegetable	Vegetables; fruit; nuts
Vegetables in tem. preservatives	0	Fruits and vegetables	vegetable	Vegetables; fruit; nuts
Vegetables prepared or preserved; frozen	2.6	Fruits and vegetables	vegetable	Vegetables; fruit; nuts
Homogenous vegetables prepared	0	Fruits and vegetables	vegetable	Vegetables; fruit; nuts
Watermelons	48	Fruits and vegetables	fruits	Vegetables; fruit; nuts
Other melons (inc. cantaloupes)	47.7	Fruits and vegetables	fruits	Vegetables; fruit; nuts

Coffee substitutes; cont. coffee	0	Fruits and vegetables	fruits	Crops nec
Oranges; Mandarines	25.3	Fruits and vegetables	fruits	Vegetables; fruit; nuts
Lemons; Limes	31.5	Fruits and vegetables	fruits	Vegetables; fruit; nuts
Grapefruit	47	Fruits and vegetables	fruits	Vegetables; fruit; nuts
Citrus; Other	7	Fruits and vegetables	fruits	Vegetables; fruit; nuts
Bananas	36	Fruits and vegetables	fruits	Vegetables; fruit; nuts
Plantains	35	Fruits and vegetables	fruits	Vegetables; fruit; nuts
Apples	10	Fruits and vegetables	fruits	Vegetables; fruit; nuts
Pineapples	49	Fruits and vegetables	fruits	Vegetables; fruit; nuts
Dates	9	Fruits and vegetables	fruits	Vegetables; fruit; nuts
Grapes	16.7	Fruits and vegetables	fruits	Vegetables; fruit; nuts
Pears	10	Fruits and vegetables	fruits	Vegetables; fruit; nuts
Quinces	39	Fruits and vegetables	fruits	Vegetables; fruit; nuts
Apricots	7	Fruits and vegetables	fruits	Vegetables; fruit; nuts
Sour cherries	10	Fruits and vegetables	fruits	Vegetables; fruit; nuts
Cherries	8	Fruits and vegetables	fruits	Vegetables; fruit; nuts
Peaches and nectarines	6.5	Fruits and vegetables	fruits	Vegetables; fruit; nuts
Plums and sloes	6	Fruits and vegetables	fruits	Vegetables; fruit; nuts
Stone fruit; nes	7.3	Fruits and vegetables	fruits	Vegetables; fruit; nuts
Pome fruit; nes	20.2	Fruits and vegetables	fruits	Vegetables; fruit; nuts
Strawberries	6	Fruits and vegetables	fruits	Vegetables; fruit; nuts
Raspberries	4	Fruits and vegetables	fruits	Vegetables; fruit; nuts
Gooseberries	0	Fruits and vegetables	fruits	Vegetables; fruit; nuts
Currants	2	Fruits and vegetables	fruits	Vegetables; fruit; nuts
Blueberries	5	Fruits and vegetables	fruits	Vegetables; fruit; nuts
Cranberries	2	Fruits and vegetables	fruits	Vegetables; fruit; nuts
Berries; nes	0.8	Fruits and vegetables	fruits	Vegetables; fruit; nuts
Figs	1	Fruits and vegetables	fruits	Vegetables; fruit; nuts
Mangos; mangosteens; guavas	25.5	Fruits and vegetables	fruits	Vegetables; fruit; nuts
Avocados	26	Fruits and vegetables	fruits	Vegetables; fruit; nuts

Persimmons	17	Fruits and vegetables	fruits	Vegetables; fruit; nuts
Cashewapple	0	Fruits and vegetables	fruits	Vegetables; fruit; nuts
Kiwi fruit	25	Fruits and vegetables	fruits	Vegetables; fruit; nuts
Papayas	38	Fruits and vegetables	fruits	Vegetables; fruit; nuts
Fruit; tropical fresh; nes	30.5	Fruits and vegetables	fruits	Vegetables; fruit; nuts
Fresh fruit; nes	25	Fruits and vegetables	fruits	Vegetables; fruit; nuts
Fruit dried; nes	14.3	Fruits and vegetables	fruits	Vegetables; fruit; nuts
Fruit juice; nes	0	Fruits and vegetables	fruits	Vegetables; fruit; nuts
Fruit; prepared; nes	1.2	Fruits and vegetables	fruits	Vegetables; fruit; nuts
Homogenized; cooked fruit prepared	0	Fruits and vegetables	fruits	Vegetables; fruit; nuts
Coffee	0	Fruits and vegetables	other	Crops nec
Cocoa Beans	0	Fruits and vegetables	other	Crops nec
Tea	0	Fruits and vegetables	other	Crops nec
Pepper	0	Fruits and vegetables	other	Crops nec
Pimento	0	Fruits and vegetables	other	Crops nec
Cloves	0	Fruits and vegetables	other	Crops nec
Vanilla	0	Fruits and vegetables	other	Crops nec
Cinnamon (canella)	0	Fruits and vegetables	other	Crops nec
Nutmeg; mace; and cardamoms	0	Fruits and vegetables	other	Crops nec
Anise; badian; fennel; coriander	0	Fruits and vegetables	other	Crops nec
Ginger	0	Fruits and vegetables	other	Crops nec
Spices; nes	10.1	Fruits and vegetables	other	Crops nec
Wine	0	Milk	other	Beverages and tobacco products
Beer	0	Milk	other	Beverages and tobacco products
Beverages; Fermented	0	Milk	other	Beverages and tobacco products
Beverages; Alcoholic	0	Milk	other	Beverages and tobacco products
Bovine Meat	19	Meat	red meat	Bovine meat products
Mutton & Goat Meat	11.5	Meat	red meat	Bovine meat products
Pigmeat	18	Meat	red meat	Meat products nec

Poultry Meat	30.5	Meat	poultry	Meat products nec
Bird meat; nes	9.4	Meat	poultry	Meat products nec
Horse meat	0	Meat	red meat	Bovine meat products
Meat of asses	0	Meat	red meat	Bovine meat products
Meat of mules	0	Meat	red meat	Bovine meat products
Camel meat	0	Meat	red meat	Bovine meat products
Rabbit meat	0	Meat	red meat	Meat products nec
Meat of other rodents	0	Meat	red meat	Meat products nec
Meat of other camelids	0	Meat	red meat	Bovine meat products
Game meat	0	Meat	poultry	Meat products nec
Meat; dried; nes	0	Meat	red meat	Meat products nec
Meat; nes	6.7	Meat	red meat	Meat products nec
Snails; not sea	0	Meat	poultry	Animal products nec
Offals of cattle; edible	10.7	Meat	red meat	Bovine meat products
Offals of sheep; edible	8.4	Meat	red meat	Bovine meat products
Offals of goats; edible	0	Meat	red meat	Bovine meat products
Offals of pigs; edible	6.4	Meat	red meat	Meat products nec
Offals; liver; chicken	0	Meat	red meat	Animal products nec
Offals; liver; geese	0	Meat	red meat	Animal products nec
Offals; liver; duck	0	Meat	red meat	Animal products nec
Offals; nes	7.8	Meat	red meat	Meat products nec
Butter; cow milk	0	Milk	oil	Dairy products
Ghee; butteroil of cow milk	0	Milk	oil	Dairy products
Butter of buffalo milk	0	Milk	oil	Dairy products
Ghee oil of buffalo milk	0	Milk	oil	Dairy products
Butter; ghee of sheep milk	0	Milk	oil	Dairy products
Cream	0	Milk	oil	Dairy products
Fats; Animals; Raw	0	Meat	oil	Bovine meat products
Fish; Body Oil	0	Fish and seafood	oil	Bovine meat products
Fish; Liver Oil	0	Fish and seafood	oil	Bovine meat products

Hen eggs; in shell	12	Fish and seafood	eggs	Animal products nec
Eggs; liquid	12	Meat	eggs	Animal products nec
Eggs; dried	0	Meat	eggs	Animal products nec
Other bird eggs; in shell	11.3	Meat	eggs	Animal products nec
Cow milk; whole; fresh	0	Milk	dairy	Dairy products
Buffalo milk; whole; fresh	0	Milk	dairy	Dairy products
Sheep milk; whole; fresh	0	Milk	dairy	Dairy products
Goat milk; whole; fresh	0	Milk	dairy	Dairy products
Camel milk; whole; fresh	0	Milk	dairy	Dairy products
Product of natural milk constit.	0	Milk	dairy	Dairy products
Ice cream and edible ice	0	Milk	dairy	Dairy products
Freshwater Fish	0	Fish and seafood	seafood	Fishing
Demersal Fish	0	Fish and seafood	seafood	Fishing
Pelagic Fish	0	Fish and seafood	seafood	Fishing
Marine Fish; Other	0	Fish and seafood	seafood	Fishing
Crustaceans	0	Fish and seafood	seafood	Fishing
Cephalopods	0	Fish and seafood	seafood	Fishing
Molluscs; Other	0	Fish and seafood	seafood	Fishing
Aquatic Animals; Others	0	Fish and seafood	seafood	Fishing
Aquatic Plants	0	Fruits and vegetables	vegetable	Fishing
Miscellaneous + (Total)	0	Cereals	other	Cereal grains nec
Wheat Flour	0	Cereals	cereal	Wheat
Corn Flour	0	Cereals	cereal	Cereal grains nec
Millet Flour	0	Cereals	cereal	Cereal grains nec
Sorghum Flour	0	Cereals	cereal	Cereal grains nec

The optimization of the dietary intakes

Table C-2 nutrition constraints

Food & nutrients	restriction	benchmarks
Vegetable	>	400g/day
Fruits	>	300g/day
Whole grains	>	125g/day
Nuts and seeds	>	114g/week
Milk	>	450g/day
Red meat	<	100g/week
Processed meat	=	0g/day
Sweetened beverage	=	0g/day
Fiber	>	30g/day
Calcium	>	1200mg/day
Omega-3 fatty acid	>	250mg/day
Polyunsaturated fatty acid	>	12% energy intake
Trans fatty acid	<	0.5% energy intake
Sodium	<	1000mg/day
Fatty acid	<	30% energy intake
Seafood	>	32g/day
Energy intake	=	2500kcal/day

Supplement results

Table C-3 The effect of income level and geographical regions on the change of food consumption

	(1) cereal	(2) dairy	(3) eggs	(4) fruits	(5) nuts	(6) oil	(7) poultry	(8) red meat	(9) seafood	(10) sugar	(11) tuber	(12) vegetable
lnGNI	22.643***	-30.817**	-1.990***	-10.417**	2.565	-13.060***	-7.761***	-13.080***	-2.632***	-10.728***	3.323*	-0.150
	(3.334)	(13.553)	(0.736)	(4.892)	(2.328)	(1.975)	(1.178)	(1.803)	(0.934)	(1.714)	(1.750)	(6.419)
East Asia & Pacific	-48.488**	207.972***	-1.400	-1.776	-10.529	49.309***	22.593**	12.816	-20.923***	11.114	-26.446**	-39.442
	(18.688)	(64.161)	(3.737)	(22.608)	(8.251)	(14.128)	(11.426)	(14.028)	(5.980)	(18.123)	(10.769)	(27.888)
Europe & Central Asia	-5.971	-47.842	0.701	-9.532	3.564	25.581*	19.758**	-1.500	-4.247*	10.597	-12.359	-26.822**
	(10.820)	(38.264)	(2.883)	(17.900)	(6.621)	(13.768)	(9.865)	(9.108)	(2.205)	(16.897)	(8.587)	(12.230)
Latin America & Caribbean	-25.117**	165.498***	2.763	-57.133***	-5.506	51.846***	16.212	25.219**	-3.130	-8.988	-18.028*	18.343
	(12.436)	(38.960)	(3.057)	(19.838)	(8.487)	(14.047)	(11.365)	(9.845)	(3.341)	(17.312)	(9.205)	(16.787)
Middle East & North Africa	-102.348***	167.487***	-1.688	-77.833***	13.187	28.818**	9.317	32.054***	-9.467***	-0.611	-20.945**	-93.217***
	(15.068)	(42.862)	(4.341)	(26.220)	(8.594)	(13.869)	(11.383)	(10.722)	(2.496)	(18.087)	(9.113)	(22.027)
South Asia	-63.197***	143.328*	-0.210	19.119	-14.205	47.459***	25.063**	37.421***	-18.337***	7.272	-27.175**	-25.983
	(19.758)	(78.391)	(3.601)	(26.641)	(17.755)	(16.358)	(10.537)	(11.437)	(6.665)	(17.981)	(10.939)	(31.511)
Sub-Saharan Africa	-53.578***	138.153**	0.033	-37.341	-33.663***	46.004***	19.907*	22.065**	-14.228***	20.580	-46.107***	-34.038
	(16.856)	(53.985)	(3.658)	(27.854)	(10.771)	(15.080)	(10.729)	(10.969)	(4.516)	(17.686)	(14.077)	(25.546)
Constant	-223.185***	339.075**	11.371	252.550***	33.304	49.260**	26.288	50.162**	46.812***	26.555	-17.370	252.663***
	(36.895)	(146.312)	(8.290)	(54.681)	(25.609)	(24.888)	(15.989)	(21.184)	(10.084)	(24.648)	(20.617)	(69.365)
N	146	146	146	146	146	146	146	146	146	146	146	146
R^2	0.607	0.428	0.121	0.171	0.339	0.618	0.388	0.656	0.173	0.452	0.412	0.166

Notes: Standard errors in parentheses are robust to heteroskedasticity. * p<0.1, ** p<0.05, *** p<0.01. The area of North America is set as the reference group.

Table C-4 The effect of income level and geographical regions on the change of GHG emissions

	(1) cereal	(2) dairy	(3) eggs	(4) fruits	(5) nuts	(6) oil	(7) poultry	(8) red meat	(9) seafood	(10) sugar	(11) tuber	(12) vegetable	(13) total
lnGNI	0.017**	-0.027***	-0.008	0.016	-0.006	-0.077**	-0.022***	-0.050***	-0.002	0.001	-0.006	0.035**	-0.128**
	(0.008)	(0.009)	(0.010)	(0.013)	(0.004)	(0.038)	(0.005)	(0.010)	(0.001)	(0.002)	(0.005)	(0.014)	(0.049)
East Asia & Pacific	0.093**	0.005	-0.043	-0.048*	0.013	-0.102**	-0.031***	-0.021	0.011***	0.001	0.002	-0.063*	-0.182*
	(0.040)	(0.011)	(0.056)	(0.028)	(0.023)	(0.050)	(0.010)	(0.038)	(0.003)	(0.006)	(0.006)	(0.033)	(0.104)
Europe & Central Asia	0.057	0.053	-0.063	-0.054*	-0.045***	0.076	-0.096***	-0.098*	0.019***	-0.003	-0.006	-0.036	-0.197
	(0.040)	(0.048)	(0.061)	(0.030)	(0.014)	(0.415)	(0.030)	(0.050)	(0.005)	(0.006)	(0.006)	(0.034)	(0.452)
Latin America & Caribbean	-0.027	0.005	-0.056	-0.056*	0.015	-0.007	-0.022**	0.034	0.015***	-0.005	-0.005	-0.046	-0.153
	(0.044)	(0.012)	(0.060)	(0.030)	(0.029)	(0.044)	(0.010)	(0.038)	(0.005)	(0.006)	(0.006)	(0.040)	(0.106)
Middle East & North Africa	0.078**	0.035*	-0.035	-0.067**	-0.016	-0.046	-0.018	-0.016	0.011***	0.002	0.020	-0.073*	-0.125
	(0.039)	(0.018)	(0.051)	(0.033)	(0.012)	(0.101)	(0.024)	(0.059)	(0.004)	(0.008)	(0.013)	(0.038)	(0.121)
South Asia	0.044	0.110	-0.094	0.018	-0.004	-0.049	-0.024*	0.022	0.028*	0.003	-0.019*	0.037	0.071
	(0.047)	(0.105)	(0.071)	(0.042)	(0.024)	(0.083)	(0.014)	(0.042)	(0.016)	(0.007)	(0.011)	(0.050)	(0.161)
Sub-Saharan Africa	0.059	0.073*	-0.138*	0.036	-0.016	-0.096	-0.055***	-0.073	0.004	-0.011	-0.041	0.043	-0.217
	(0.050)	(0.041)	(0.080)	(0.067)	(0.018)	(0.082)	(0.018)	(0.048)	(0.004)	(0.008)	(0.027)	(0.070)	(0.161)
Constant	-0.240***	0.254***	0.111	-0.070	0.074*	0.577*	0.177***	0.329***	0.016	-0.021	0.057	-0.189	1.076**
	(0.089)	(0.082)	(0.128)	(0.122)	(0.042)	(0.343)	(0.045)	(0.094)	(0.011)	(0.018)	(0.047)	(0.133)	(0.462)
N	145	145	145	145	145	145	145	145	145	145	145	145	145
R^2	0.248	0.112	0.109	0.088	0.052	0.016	0.203	0.278	0.141	0.041	0.084	0.106	0.029

Notes: Standard errors in parentheses are robust to heteroskedasticity. * p<0.1, ** p<0.05, *** p<0.01. The area of North America is set as the reference group.

Table C-5 The effect of income level and geographical regions on the change of land appropriation

	(1) cereal	(2) dairy	(3) eggs	(4) fruits	(5) nuts	(6) oil	(7) poultry	(8) red meat	(9) seafood	(10) sugar	(11) tuber	(12) vegetable	(13) total
lnGNI	0.014***	-0.000	-0.269	0.000	-0.010**	-0.030	-0.064*	-0.094*	-0.001	0.001	0.000	0.005	-0.447**
	(0.004)	(0.006)	(0.175)	(0.003)	(0.005)	(0.046)	(0.033)	(0.056)	(0.001)	(0.006)	(0.000)	(0.004)	(0.215)
East Asia & Pacific	0.024	-0.012	-0.304	-0.011	0.028	0.027	0.032	0.193	0.004	0.010	-0.001	-0.017	-0.030
	(0.018)	(0.012)	(0.438)	(0.008)	(0.033)	(0.080)	(0.033)	(0.143)	(0.003)	(0.009)	(0.002)	(0.012)	(0.350)
Europe & Central Asia	0.018	0.017	-0.541	-0.013	-0.012	0.511	-0.055*	0.056	0.001	0.009	-0.002	-0.002	-0.014
	(0.016)	(0.020)	(0.471)	(0.009)	(0.011)	(0.548)	(0.032)	(0.153)	(0.001)	(0.009)	(0.002)	(0.013)	(0.648)
Latin America & Caribbean	-0.047*	0.022	-0.493	-0.016	0.013	0.020	-0.071	0.095	0.001	0.007	-0.002	-0.014	-0.484
	(0.024)	(0.028)	(0.464)	(0.010)	(0.017)	(0.073)	(0.061)	(0.157)	(0.001)	(0.009)	(0.002)	(0.014)	(0.374)
Middle East & North Africa	0.012	-0.014	0.030	-0.013	-0.017	0.021	0.081	0.236	0.003	0.010	0.001	-0.019	0.329
	(0.015)	(0.014)	(0.474)	(0.009)	(0.015)	(0.114)	(0.066)	(0.164)	(0.002)	(0.014)	(0.003)	(0.014)	(0.476)
	0.027	0.003	-0.962	0.007	0.156	0.068	-0.099	0.045	0.001	0.015	-0.003	0.012	-0.730
South Asia	(0.019)	(0.023)	(0.637)	(0.012)	(0.149)	(0.103)	(0.073)	(0.199)	(0.003)	(0.014)	(0.002)	(0.018)	(0.571)
Sub-Saharan Africa	-0.010	0.074	-1.723*	0.018	-0.006	-0.144	-0.324**	-0.286	-0.000	-0.026	-0.007***	0.028	-2.406**
	(0.021)	(0.050)	(0.919)	(0.015)	(0.015)	(0.153)	(0.163)	(0.308)	(0.002)	(0.024)	(0.002)	(0.020)	(1.017)
Constant	-0.159***	0.018	2.857	0.019	0.099**	0.141	0.553*	0.617	0.013	-0.025	-0.001	-0.007	4.124**
	(0.045)	(0.056)	(1.758)	(0.028)	(0.045)	(0.406)	(0.303)	(0.556)	(0.009)	(0.053)	(0.003)	(0.037)	(2.004)
N	145	145	145	145	145	145	145	145	145	145	145	145	145
R^2	0.266	0.063	0.124	0.235	0.063	0.027	0.127	0.088	0.033	0.053	0.327	0.136	0.122

Notes: Standard errors in parentheses are robust to heteroskedasticity. * p<0.1, ** p<0.05, *** p<0.01. The area of North America is set as the reference group.

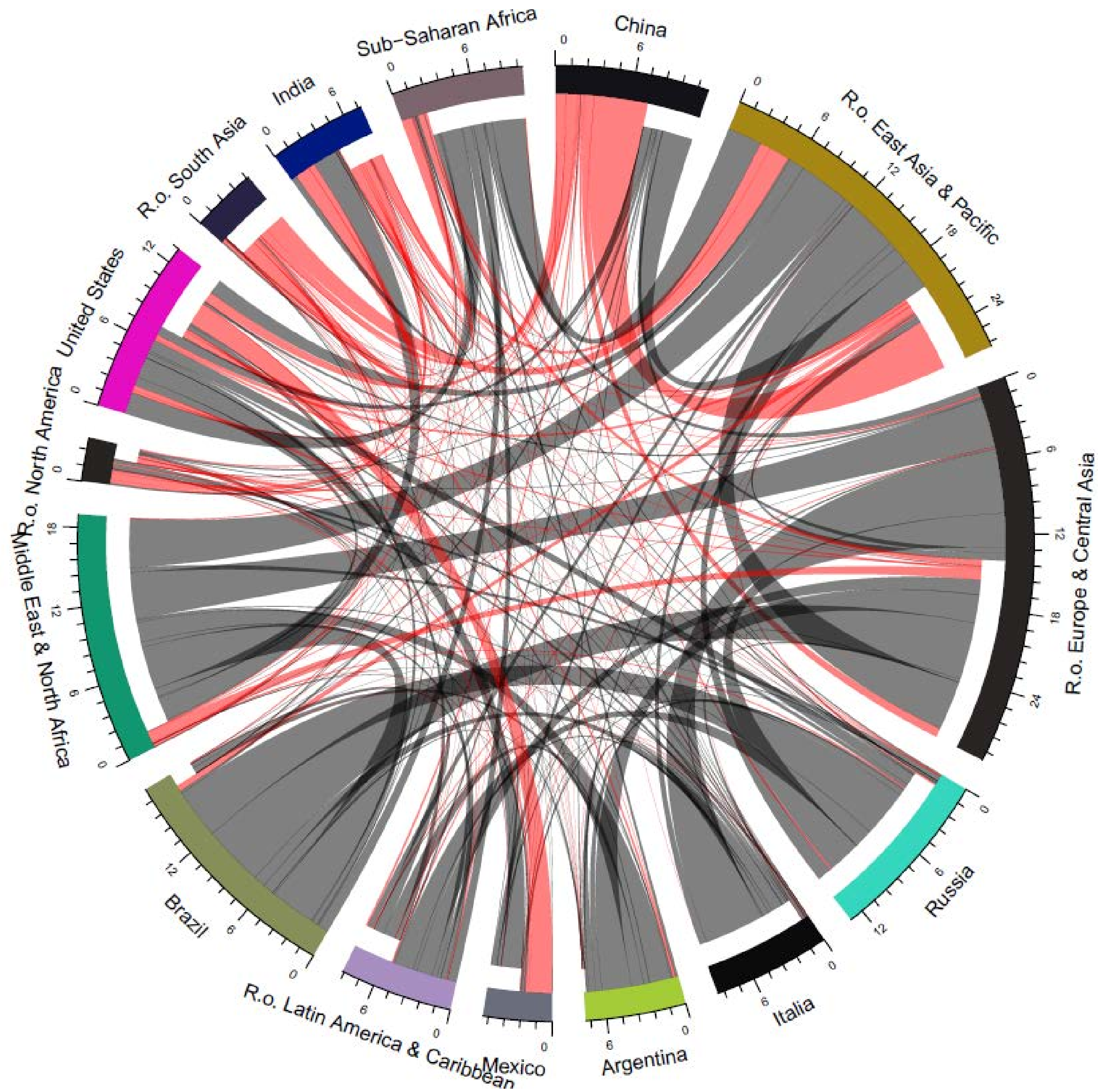

Figure C-1 Changed GHG embedded in trade flows between countries and areas (MtCO$_2$ equivalent). The red flows indicates the increase of embedded GHG while the grey ones indicates the decrease. The flows with lags indicate the exports and the ones without lags indicate the imports.

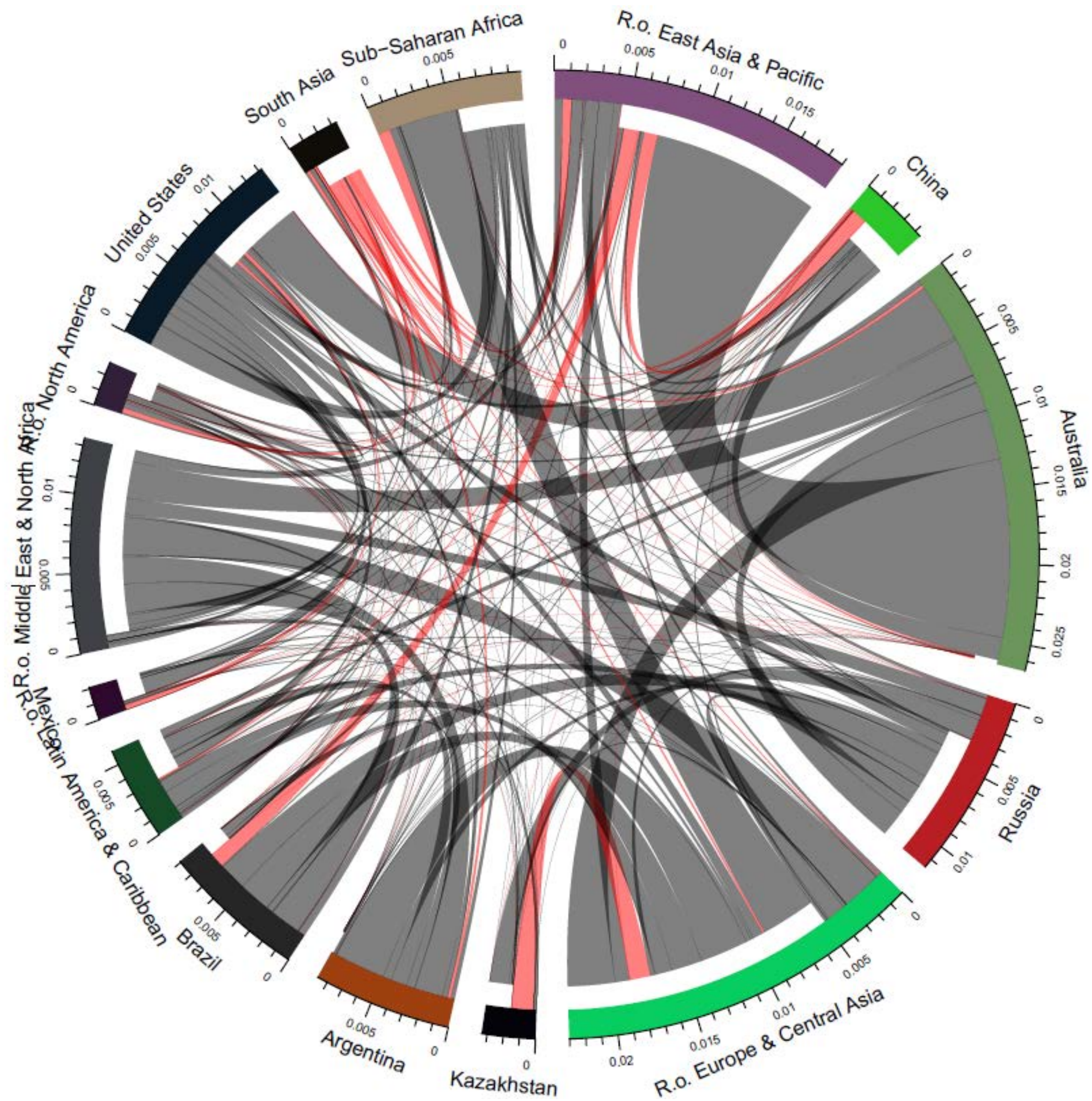

Figure C-2 Changed land appropriation embedded in trade flows between countries and areas (billion m²). The red flows indicates the increase of embedded land appropriation while the grey ones indicates the decrease. The flows with lags indicate the exports and the ones without lags indicate the imports.

Abbreviations

GHG	Greenhouse gas
TWF	Total water footprint
LA	Land appropriation
CCDC	Chinese Center for Disease Control and Prevention
CHNS	China Health and Nutrition Survey
CFCT	Chinese Food Composition Tables
FAO	Food and Agriculture Organization
GBD	Global Burden of Disease
GENuS	Global Expanded Nutrient Supply
GTAP	Global Trade Analysis Project
MRIO	Multi-Regional Input-Output

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