Relation of Dietary Healthfulness to Food Environmental Impact

RELATION OF DIETARY HEALTHFULNESS TO FOOD ENVIRONMENTAL IMPACT

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Abstract

Recent discussions in the literature have suggested that reducing the consumption of foods with high associated greenhouse gas (GHG) emissions and impacts on global water resources, such as meat and dairy foods, and replacing them with lower GHG and water resource burden associated foods, such as plant based foods, will help mitigate global cardiovascular disease, diabetes, cancer, and obesity. However, this hypothesis has not been empirically tested. The objective of this dissertation was to examine the correlation between diet-related chronic disease, obesity, and undernourishment, and the GHG emissions and Water Footprints of food.

Chapter 1 focused on obesity, and how foods found to be related to weight gain correlate with these food's GHG emissions. The Spearman correlation between a food's associated weight gain and GHG emission was 0.12 (95% CI: -0.37, 0.55). These results did not change after the removal of unprocessed red meat from the analysis. Nuts, whole grains, fruits, and vegetables exhibited lower effects on weight gain and CO_2e production.

Chapter 2 examined diet related NCDs, obesity, life expectancy, and undernutrition, and how country food supply GHG emissions associate with these particular country health outcomes. After adjustment for country socioeconomic and lifestyle characteristics, there was no association between country specific food-related GHG emissions and country specific rate of premature mortality from NCDs (β=0 [95% Confidence Interval (CI): -5, 5] deaths/100,000), life expectancy (β=0.19 [95% CI: -5, 5] years), prevalence of obesity (β=2% [95% CI: -3%, 6%]), or undernourishment (β=-7% [95% CI: -15%, 1%]). Results did not change when the association

was examined within strata of GDP per capita. However, there were large variation in country health indicators at every level of GHG emissions, and some countries had both low food-related GHG emissions and favorable health statistics.

Chapter 3 evaluated how healthfulness of diet, as measured by the Alternative Health Index, relates to food WF categories within a cohort of US women. Reservoir WF increased linearly whereas rain WF decreased linearly with increasing adherence to the AHEI. Women in the highest quintile of adherence to the AHEI had reservoir WF that was 309 liters/day (95% confidence interval (CI): 290 – 327) higher and a rain WF that was 313 liters/day (95% CI: -333, -294) liters lower than that of women in the lowest quintile of adherence to the AHEI. When both reservoir and rain WF were considered together, women on the highest quintile of adherence to the AHEI had a total WF that was 50 liters/day (95%: -81, -19) lower than that of women in the lowest quintile of adherence. The unfavorable directionality pertaining to reservoir and rain WF with healthier eating scores warrants further research, especially with progressively unequal global freshwater availability.

Although overall associations between food GHG and the health outcomes analyzed were not observed, there were variations noted that warrants further examination. However, dietary impacts on global water reservoirs should be simultaneously considered. Hence, efforts that enable the adoption of effective policies to address both dietary quality and the reduction of food GHG emissions simultaneously, without exacerbating undernutrition and water scarcity, should continue.

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IV. ACKNOWLEDGEMENTS

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V. INTRODUCTORY REMARKS

Despite the landmark international climate accord reached at the 2015 United Nations Climate Change Conference (COP21) in Paris, there is skepticism that the agreement will be enough to curb rising global greenhouse gas (GHG) emissions to a 2 degree Celsius increase in atmospheric temperature (Davenport, C., 2015). At this point, extreme weather patterns that have already been observed in recent decades, especially as they related to the global water cycle, are predicted to irreversibly worsen (Davenport, C., 2015). These include extreme drought, heavy precipitation, and hurricanes (Carrington, 2012; Grinsted, et al., 2013).

The public health consequences of further climatic change and disruptions to the water cycle are grave (Carrington, 2013; Smith, K, et al., 2014). In addition to continued direct mortality and the physical and psychological morbidity resulting from extreme weather-related catastrophes, food supply shortages, infectious disease, and food borne illnesses caused by heat, drought, and flooding are anticipated to increase (Portier, et al, 2010; Morss, et al., 2011). Furthermore, asthma and other respiratory disease exacerbations due to declining air quality (resulting from heat) are projected to rise (Kjellstrom, et al. 2010).

Additionally, cancer, cardiovascular disease, and stroke, as well as neurological and developmental disorders, are expected to be negatively affected due to increased exposures to toxic chemicals from flooding and pesticide use (for controlling increasing crop-invasive species, etc.), excessive heat events, and a decreased food supply (Portier, et al., 2010; Kjellstrom, et al., 2010). Those already afflicted with diabetes and ischemic heart disease, as well as in overweight and obese individuals, are expected to be at even greater risk of heat-related illness or death due to their associated decreased physiological compensatory mechanisms (Smith K., et al., 2014).

Furthermore, temperature increases expected under the current trends of climate change, combined with humidity, may become so high that any outdoor physical activity – including recreational endeavors and tending to food crops or husbandry – would be physiologically impossible. Such effects would begin in small land areas but expand to areas where most of the world's populace resides if climate change is left unabated (Smith, K. et al., 2014). Certainly, most plants and animals utilized for food would perish as well in such conditions. Access to whole foods and regular physical activity are paramount to chronic disease prevention and treatment, not to mention to overall survival (WHO, 2013).

While the food supply is particularly vulnerable to a changing climate and altered water cycle, agriculture, which includes the livestock sector, is reportedly the largest contributor (56%) to global anthropogenic methane and nitrous oxide release, and contributes to 10–12% of total human-derived emissions worldwide (Ripple, et al, 2014). The growing of crops and animals for food is also the largest user, 70%, of global water resources (Antonelli & Greco, 2015). CO_2 emissions resulting from fossil fuel use to power farm-related processes are not included in these GHG calculations, which would have made the contribution of agriculture to climate change even higher (Ripple, et al, 2014). (All fossil fuel power-related emissions are usually included within the energy sector's climatic burden.) Likewise, accounting for water use in the processing of food raises the global water burden of human food consumption to 86% of world water use (Hoekstra et al, 2011).

Of the total agriculturally-related non-CO_2 GHGs emissions, enteric fermentation is reported to contribute the most (32-40%), followed by soil emissions resulting from the application of manure (15%) and man-made fertilizer (12%), the cultivation of rice paddies (9-11%), the burning of biomass (6-12%), and the management of manure (7-8%) (Ripple, et al, 2014). Enteric fermentation occurs in the gastrointestinal system of ruminant animals and produces methane as a digestive by-product (Steinfeld et al., 2006). Cattle are the largest enteric fermenters worldwide (75% of the total), followed by buffalo, sheep, and goats (Smith, P. et al., 2014). Because these animals have the digestive capability for enteric fermentation, they are able to eat plant matter that is not suited for humans. In addition, ruminants can graze in areas that are not suited for farming. Hence, these animals have the ability to provide food from what would otherwise be non-food items and on land that would otherwise be out of food production, which plays a role in alleviating global hunger (Smith, P. et al., 2014).

With methane-producing enteric fermentation and the large feed-to-food ratio (many acres of feed are required to produce an edible pound of food), the agricultural-related processes involved with the production of ruminant meat, particularly cattle, has shown to have significantly higher GHG emissions and water use than with the production of other food items (Smith, P. et al., 2014; Hoekstra, A. Y., 2012). Pork, chicken meat, eggs, and dairy products on a "per protein unit" scale have lower climatic and water resource impact than ruminant meat, and generally contain less saturated fat than lamb and cattle meat when lean varieties are chosen (such as reduced-fat instead of full-fat milk, pork loin instead of bacon, etc.) (Friel et al., 2009; Vanham et al, 2013; Smith, P. et al., 2014). The production of plant food (fruits, vegetables, legumes, and grains) – which contain beneficial dietary elements that have been linked with chronic disease reduction (such as fiber, phytochemicals, and unsaturated fat) – has consistently been demonstrated to create the lowest climatic and water resource burden within the food sector (Gerbens-Leenes et al., 2013; Vanham et al, 2013; Smith, P, et al, 2014; Li, 2014; Antonelli & Greco, 2015).

Life cycle assessment (LCA) is a method commonly utilized in the evaluation of food-related GHG emissions (Audsley, 2009; Nilsson et al., 2011; Hamerschlag, 2011; Berners-Lee et al, 2012; Hoolohan et al., 2013; Iraldo et al., 2014). More specifically, it is used to approximate the amount of carbon dioxide – alone (given that it is the most abundant GHG) or (now more commonly) with other GHGs – emitted or removed during the production, utilization, and deposal of a food product (Pandey, 2011). Hence, an LCA analysis involves adding the estimated emissions released during the farming, processing, transporting, storing, packaging, consuming, and deposing of the food, depending on the boundaries set in the quantification process.

The objective of LCA is to detect areas that can be addressed for food-related climate mitigation (Pandey et al., 2011). A number of capacities within the international agricultural sector where GHG reductions have been identified (IPCC, 2014). These include innovations in livestock feeding and breeding practices (to lower enteric fermentation), as well as modifications to the management of crops and grazing land worldwide.

Although LCA has been used in the assessment of water resource use, the concept of the Water Footprint (WF), as developed by Dr. Arjen Hoekstra in 2002, has become a primary method for water resource use accounting (Antonelli & Greco,2015). The methodologies of a WF examines both direct and indirect water use by a given entity, such as a commodity or consumer, in a certain geographical location at a given time (Hoekstra et al., 2011). A total water footprint encompasses three subcategories that have been designated by a different representative color (Hoekstra, A. Y., 2016; Vanham and Bidoglio, 2012). A blue water footprint refers to water withdrawn from freshwater reservoirs: rivers, lakes, aquifers, and wetlands. A grey water footprint involves the amount of water required to dilute incoming pollutants to water safety standards in a freshwater catchment area. The green water footprint refers to the amount of rainwater used by plants for growth (Hoekstra et al, 2011). Once a WF is assessed, the goal is to alter production or consumption processes that have been identified as water intensive, or with a large WF, in order to help attain water sustainability (Hoekstra et al, 2011). As with GHG accounting, there have been several food production processes identified, particularly in relation to irrigation and fertilizer application methods, as being the most water intensive (Hoekstra, A. Y., 2012).

In addition to the global agriculture supply-side mitigation efforts, demand-side tactics to reduce food-related GHG emissions and WFs have been proposed, which will largely need to be driven by consumers transnationally increasing the selection of food products with lower GHG emissions and WFs. Changing population-level dietary patterns, as noted by the United Nation's Intergovernmental Panel on Climate Change (IPCC), is challenging, with "considerable cultural and social barriers… to be expected" (Smith, P. et al., 2014). To help break these barriers, discussions within the literature promote linking dietary climate and WF mitigation strategies with policies aimed at chronic disease reductions (Smith, P et al, 2014; Antonelli & Greco, 2015). The IPCC highlights how increased consumer health awareness about food and health has historically been shown to affect country-level food consumption patterns (Smith, P., et al, 2014). In the 1980s, concerted messages from both health professionals and food product marketers surrounding high-fat diets and increased risk for CVD were linked to the marked demand for and subsequent decrease in the fat content of animal foods within the US food supply (Daniel et al., 2011). In the United Kingdom, the shift away from red meat has been speculated to be partly the result of consumer insecurities surrounding bovine spongiform encephalopathy (also known as mad cow disease) that affected that country's cattle industry particularly hard (Kearney, 2010).

Numerous publications have highlighted potential co-benefits to be gained by replacing GHG and water intensive foods, particularly red meat, with plant based foods (Godlee, 2008; Friel, 2009; Edwards, 2009; McDermott, 2010; Breda, 2012; Macdiarmid, 2012; Reich & Gwozdz, 2012; Skouteris et al., 2013; Vanham et al, 2013; Antonelli & Greco, 2015). These proposed health co-benefits include a decreased risk of cardiovascular disease, cancer, diabetes, and obesity (Friel, et al, 2009; Hoekstra et al, 2016).

Although technological improvements in combination with reductions in animal foods have been theoretically modeled to simultaneously decrease agriculturally-related GHG emissions, WFs, and chronic disease, universal recommendations for changes in animal food consumption are cautioned against (Smith, P, et al, 2014; Antoneli & Greco, 2015). The concern is that such global recommendations could potentially lead to decreased production of, and therefore access to, ruminant meat. In regions where food availability is already limited, this would further constrain obtainable sources of protein and other nutrients (Smith, P. et al., 2014). Accessing sources of nutrition in these areas will become even more critical with the forecasted undernutrition resulting from increasing climate change events (Smith, K. et al., 2013).

The purpose of this dissertation is to relate healthfulness of diet to food impacts on climate change and global water resources. The first chapter focuses on obesity, and how foods found to be related to weight gain correlate with these food's GHG emissions. The second chapter examines diet related NCDs, obesity, and undernourishment, and how country food supply GHG emissions associate with these particular country health statistics. The third chapter examines how healthfulness of diet pertaining to chronic disease prevention, as measured by the

Alternative Health Index Score, relates to food WF. The overall goal of this work is to help guide efforts already underway in establishing food policies and dietary recommendations linking public health nutrition with environmental sustainability.

VI. CHAPTER 1: RELATION OF FOOD GREENHOUSE GAS EMISSIONS TO DIETARY FACTORS PROMOTING WEIGHT GAIN

Abstract:

Objective: It has been suggested that reducing the consumption of foods with high associated greenhouse gas (GHG) emissions, such as meat and dairy foods, and replacing them with lower GHG associated foods, such as plant based foods, will help mitigate the obesity epidemic. However, this hypothesis has not been empirically tested. The objective of this study was to examine the correlation between weight change and the GHG emissions of specific foods found earlier to affect weight status.

Design: Ecological correlations of food-based data

Results: The estimated weight change associated with specific foods ranged from 0.82 lbs lost for each 1 serving/day increase in yogurt intake to 1.61 lbs gained for each 1 serving/day increase in potato chip intake, over a 4 year period. The average GHG emissions adjusted for edible serving size ranged from 50 g CO_2e per serving of whole grains to 2360 g CO_2e per serving of unprocessed red meat. The Spearman correlation between a food's associated weight gain and GHG emission was 0.12 (95% CI: -0.37, 0.55). The results did not change after the removal of unprocessed red meat from the analysis. Nuts, whole grains, fruits, and vegetables exhibited lower effects on weight gain and CO_2e production.

Conclusion: Our results do not support the general hypothesis that a food's associated GHG emissions are related to its impact on weight change. However, a cluster of foods representative of a healthy eating pattern, such as the traditional Mediterranean Diet, appear consistent with low weight gain and low CO_2e production.

Introduction

The relation of climate change mitigation strategies to obesity treatment and prevention policies has been of considerable interest in recent years (McMichael, et al, 2007; Godlee, F, 2008; Michaelowa & Dransfeld, 2008; Friel, et al, 2009; Edwards & Roberts, 2009; McDermott, R. A., 2010; Breda, J, 2010; Macdiarmid, et al, 2012; Reisch & Gwozdz, 2011; Skouteris, et al, 2013; Tipple, et al., 2014; McCoy, et al., 2014; Lowe, M, 2014). This interest stems from hopes that interdisciplinary efforts by public health professionals and environmentalists will be effective in curbing both of these global crises simultaneously. Reducing red meat and dairy consumption has been identified as a possible intervention target that could concurrently address both concerns (McMichael, et al, 2007; Godlee, F, 2008; Michaelowa & Dransfeld, 2008; Friel, et al, 2009; Edwards & Roberts, 2009; McDermott, R. A., 2010; Breda, J, 2010; Macdiarmid, et al, 2012; Reisch & Gwozdz, 2011; Skouteris, et al, 2013; Tipple, et al., 2014; McCoy, et al., 2014; Lowe, M, 2014). Greenhouse gas (GHG) emissions resulting from the production of foods from ruminant animal origin (red meat and dairy) are higher than those derived from other meat sources (such as poultry) and plants (grains, legumes, nuts/seeds, vegetables, and fruits) (McMichael, et al, 2007; Godlee, F, 2008; Michaelowa & Dransfeld, 2008; Friel, et al, 2009; Edwards & Roberts, 2009; McDermott, R. A., 2010; Breda, J, 2010; Macdiarmid, et al, 2012; Reisch & Gwozdz, 2011; Skouteris, et al, 2013; Tipple, et al., 2014; McCoy, et al., 2014; Lowe, M, 2014). It has been postulated that reducing intake of these foods at a population level could curtail the obesity epidemic through an associated decrease in calories and saturated fat (Godlee, 2008, Michaelowa, 2008; Berners-Lee, H.C., 2012; Lowe, et al., 2014).

Empirical evidence supporting this possible strategy, however, is lacking. Furthermore, the associated underlying assumption that the foods most strongly linked to weight gain are the same foods most strongly contributing to GHG emissions may not be as strong as it may appear. Mozaffarian et al. (2011) evaluated the prospective association between intake of more than 130 foods and weight change over a 20-year period among 121,000 US adults and found that foods more strongly related with weight change were not exclusively animal-based foods (Mozaffarian et al, 2011). Specifically, the foods associated with the highest amount of long term weight gain included foods with high GHG emission associated to their production (unprocessed red meats, processed meats, and butter), but also foods with a much lower GHG emission impact such as potato and potato products (French fries, chips), sugar-sweetened beverages, refined grains, and fruit juice (Mozaffarian, et al, 2011).

The purpose of this study was to quantify the GHG emission impacts of foods related to long-term weight gain, as reported by Mozaffarian et al. (2011), using the food greenhouse gas emission factors as calculated by Hoolohan et al. (2013).

Methods

Foods significantly associated with long-term weight gain, and the estimated weight change associated with their consumption over a 4 year period were obtained from Mozaffarian et al. (2011). The nutrient composition of each food for its specified portion size was obtained from the Harvard T. H. Chan School of Public Health, Nutrition Department's Food Composition Database (https://regepi.bwh.harvard.edu/health/nutrition/index.html, which is primarily based on the United States Department of Agriculture (USDA) food composition database with additional data obtained from food manufacturers.

Greenhouse gas emissions for individual food items were obtained from Hoolohan et al. (2013), in units of Carbon Dioxide Equivalents, CO_2e, kilograms emitted per kilogram of food. Carbon Dioxide Equivalents are measures of the potential of a mass of a greenhouse gas to warm the planet through its associated radiative force properties, as compared to the same mass of carbon dioxide over a specified time period (McElroy, 2002). Hoolohan et al. utilized the 100 year, global warming potential (GWP) of the three principal GHGs associated with the food system - carbon dioxide, nitrous oxide, and methane - in their CO_2e estimates.

Food categories from Hoolahan et al. (2013) were paired as closely as possible with the foods associated with weight change from Mozaffarian et al (2011). Since the foods associated with weight gain were in quantities of food consumed while the CO_2e factors were published as quantities at the point of purchase (the retail store), conversions were made to the CO_2e factors to reflect the average percent of food yield after preparation. These conversion factors were obtained from the USDA's Agricultural Research Service (ARS) (Matthews & Garrison, 1975). The average percent of food yield after preparation for the specific foods listed in the Mozaffarian et al. (2011) publication were averaged for each food grouping as needed.

After food unit conversions were completed, variable distributions were inspected. To account for non-normality of data, we calculated Spearman correlation coefficients, and their 95% confidence intervals, between a foods' impact on long term weight change with its' impact on GHG emissions. To explore whether the large GHG value of unprocessed red meat would unduly influence results, an additional subanalysis was performed with the meat CO_2e and weight values removed. To directly address the proposed hypothesis that decreasing caloric and saturated fat intake by decreasing the consumption of animal meats and milk could also decrease GHG emission (McMichael, et al, 2007; Godlee, F, 2008; Friel, et al, 2009), we also calculated

Spearman correlations of a food's caloric and saturated fat content with its GHG emissions. Analyses were conducted in SAS 9.3 (SAS, Cary, NC).

Results

Selected nutritional characteristics of the foods found to significantly predict long term weight change by Mozaffarian et al (2011) are presented in Tables 1.1 and 1.2. The estimated weight change associated with these foods ranged from 0.82 pounds lost over a 4 year period for each additional yogurt serving consumed, to 1.61 pounds gained over a 4 year period for each additional potato chips serving consumed (Table 1.1). The average GHG emissions ranged from 50 g CO_2e per serving of whole grains to 2360 g CO_2e per serving of unprocessed red meat (Table 1.2).

Overall, there was no association found between a food's impact on long term weight gain and its GHG emissions (Table 1.3, Figure 1.1). The Spearman correlation between these two food characteristics was 0.12 (95% CI: -0.37, 0.55). Results did not change after removal of unprocessed red meat from the analyses (Table 1.3). Food's caloric and saturated fat content was also unrelated with its GHG emissions in the main analysis and in the sensitivity analysis eliminating unprocessed red meats (Table 1.3). Of the foods that displayed lower GHG emissions, nuts, whole grains, fruits, and vegetables also exhibited lower effects on weight gain (Figure 1.1).

Table 1.1: Food-Associated Weight Change (lb), Calories, & Saturated Fat (g) Per Avg Edible Food Serving			
Food List	**Avg Weight Gain (lb) per Daily Edible Food Serving***	**Avg Calories per Avg Edible Food Serving**	**Avg Saturated Fat (g) per Avg Edible Food Serving**
Nuts	-0.57	174	2
Fruits	-0.49	64	0
Vegetables	-0.22	36	0
Processed Meats	0.93	94	2
Unprocessed Red Meats	0.95	346	9
Whole Grains	-0.37	104	0
Refined Grains	0.39	212	1
Sweets	0.41	162	2
Sugar-sweetened Beverages	1.00	151	0
Potatoes or fries	1.28	311	2
Potato chips	1.69	143	2
Whole Milk	-0.06	146	5
Butter	0.30	36	3
Cheese	0.02	97	3
Low-fat Milk	0.06	102	2
Yogurt	-0.82	212	2
Fruit Juice	0.31	93	0
Alcohol	0.41	120	0

* Mozaffarian et al (2011). Changes in weight are over a 4 –year follow-up.

Table 1.2: Food GHG Emissions Per Avg Edible Food Serving				
Food List	**Avg CO_2e (kg) per Food Item (kg) at Retail***	**CO_2e after Food Preparation (kg/kg edible food)**	**Avg Food Serving Size (g)****	**Avg CO_2e (g) per Avg Edible Food Serving**
Nuts	4.26	6.66	28	190
Fruits	1.97	2.55	110	280
Vegetables	3.10	3.41	78	270
Processed Meats	11.95	18.67	44	820
Unprocessed Red Meats	15.79	21.63	109	2360
Whole Grains	2.32	0.48	96	50
Refined Grains	3.16	2.41	87	210
Sweets	3.54	3.94	60	240
Sugar-sweetened Beverages	0.90	0.90	368	330
Potatoes or fries	2.10	2.15	174	370
Potato chips	4.09	4.09	28	110
Whole Milk	1.64	1.64	244	400
Butter	11.08	11.08	5	60
Cheese	8.76	8.76	48	420
Low-fat Milk	1.64	1.64	244	400
Yogurt	3.87	3.87	227	880
Fruit Juice	1.61	1.61	196	320
Alcohol	2.31	2.31	209	480

* Hoolahan et al (2013). Mitigating the greenhouse gas emissions embodied in food through realistic consumer choices.
**Mozaffarian et al (2011). Changes in weight are over a 4 –year follow-up.

Figure 1

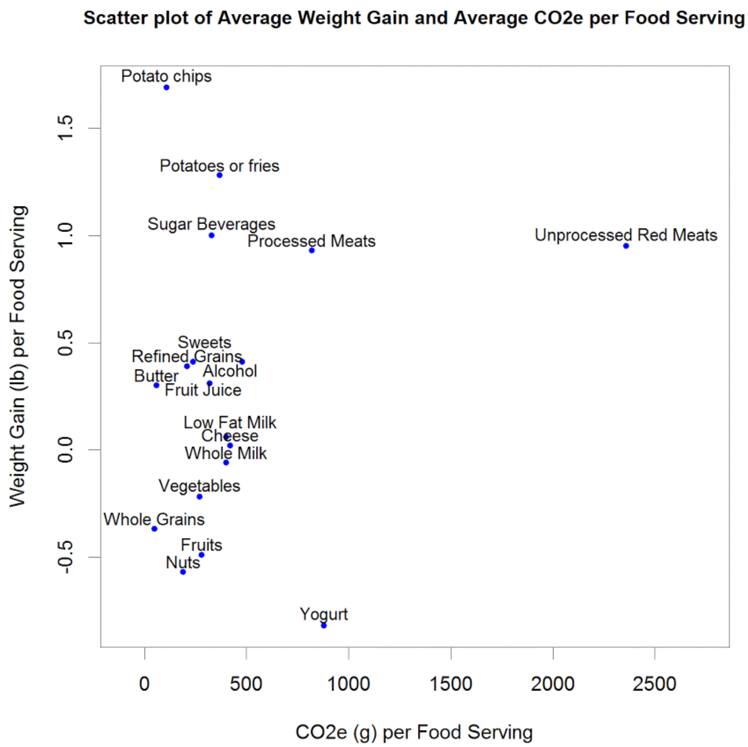

Table 3. Spearman Correlations between Foods' Weight Impact, Caloric and Saturated Fat Content with its GHG Emissions.				
Variable	**With Variable**	**Spearman Correlation Coefficient**	**P-value**	**95% Confidence Limits**
Avg Weight Change (lb) per Avg Food Serving	**Avg CO_2e (g) per Avg Food Serving**	0.12	0.65	(-0.37, 0.55)
Calories per Avg Food Serving	**Avg CO_2e (g) per Avg Food Serving**	0.25	0.31	(-0.25, 0.64)
Saturated Fat (g) per Avg Food Serving	**Avg CO_2e (g) per Avg Food Serving**	0.29	0.24	(-0.21, 0.66)
Subanalysis: Without Unprocessed Meat				
Avg Weight Change (lb) per Avg Food Serving	**Avg CO_2e (g) per Avg Food Serving**	0.03	0.92	(-0.46, 0.50)
Calories per Avg Food Serving	**Avg CO_2e (g) per Avg Food Serving**	0.11	0.68	(-0.40, 0.56)
Saturated Fat (g) per Avg Food Serving	**Avg CO_2e (g) per Avg Food Serving**	0.05	0.77	(-0.42, 0.54)

Discussion

We evaluated the association between foods' impact on long-term weight gain with its GHG emission impact and found no relation between these food characteristics. These findings do not support the general hypothesis that population-wide dietary changes that decrease foods from ruminants can simultaneously mitigate both the obesity and climate crises. This lack of association is explained by the fact that some foods with the greatest impact on long-term weight gain (potato, potato products, and sugar sweetened beverages) had low GHG impacts while some foods with the greatest GHG impact (meat and dairy) had minimal, if not beneficial, impacts on long-term weight gain.

Although our general analysis did not reveal a direct correlation between the foods' associated effect on weight gain and GHG emissions, meaningful overlaps were observed. Figure 1 displays a cluster of foods that have low impacts on weight and CO2e production, specifically whole grains, whole fruits, vegetables, and nuts. The consumption of these foods are consistent with healthy eating patterns, such as the traditional Mediterranean Diet. Hence, it is possible to develop a diet that reduces GHG emissions and obesity premised primarily on the careful selection of whole plant based foods.

To our knowledge, this is the first study to directly evaluate the popular hypothesis that decreasing consumption of foods with the greatest climatic impact could have the added benefit of tackling obesity. Although Friel et al (2009) highlighted obesity reduction as a potential dual health benefit of decreasing consumption of GHG intensive ruminant meat and dairy foods, their health modeling focused solely on ischemic heart disease, not obesity. Other published works may have based their conclusion of this potential benefit on inaccurate assumptions. For example, Michaelowa and Dransfeld (2008) correctly noted that there has been a global increase in the consumption of meat and dairy products that is correlated with rising obesity rates. They then conclude that the global obesity epidemic has greatly stemmed from a worldwide increase of dietary fat. Noting a widespread increase in "cheap food with high-fat content, especially of animal origin," these authors call for policies that "control the fat content in manufactured food as well as shift from high-fat to low fat food" for mitigating both obesity and further climate change. However, multiple studies using individual level data, including a multitude of randomized trials, have indicated that macronutrient content composition of diet is not an overall contributor of obesity (Howard, et al, 2006; Sacks, et al., 2009; Crino, et al., 2015) or that higher carbohydrate, not fat, intake may contribute more to becoming overweight (Tobias, et al, 2015). Additionally, many of the specific foods convincingly linked to weight gain and obesity, such as sugar-sweetened beverages (Malik & Hu, 2012), have low associated GHG emissions.

Limitations of this study involved the different levels of food categorization between the two publications used for this analysis. In the Hoolohan et al. (2013) publication, some food items were aggregated into broad categories, such as "dried fruit and vegetables, nuts, and seeds." In the Mozaffarian et al (2011) study, categorized foods followed traditional food groups, such as fruits, vegetables, and nuts (separately). Hence, misclassification could have biased the correlation coefficients.

A future study should include an analysis of how a particular food item changes in relation to other foods, and how GHG emissions correspond to this. That is, if one food item is increased, there will most likely be other items in the diet that increase or decrease as well. Quantifying the GHG emissions of the total dietary consumption profile in relation to weight change, or other health outcomes, would be interesting. Additionally, a future study should take into account the increased energy requirements, and hence, increased food intakes, required to support a higher weight once it has been attained.

While it is too late to prevent climate change from continuing in the relative near term (the warming that is continuing into this new century is the result of past emissions, as some greenhouse gases stay in the atmosphere for decades), measures can be taken to lessen the severity of future impacts (Karl, T. M., 2009). And, while it is difficult to treat obesity once it has ensued, measures also can be taken to lessen increases in prevalence (Gortmaker, S. S, 2011). Although the GHG emissions associated with a single food item or simplified food categories were not strongly correlated with those associated with weight gain, further research involving climate change and obesity prevention is worth pursuing. When doing so, however, the importance of presenting evidence-based, food-related messages to the public should be kept at the forefront.

VII. CHAPTER 2: RELATION OF NATIONAL FOOD GREENHOUSE GAS EMISSIONS TO MORTALITY FROM NONCOMMUNICABLE DISEASES, OBESITY, LIFE EXPECTANCY, AND UNDERNUTRITION

Abstract:

Objective: Global policies promoting decreased animal food production and consumption have been proposed to reduce the global of noncommunicable diseases (NCD) while simultaneously reducing greenhouse gas emissions (GHG) emissions. However, some have cautioned that the universal adoption of such policies could exacerbate undernutrition. We examined the relationship between country-specific food related greenhouse gas emissions (GHG) and mortality from diabetes, heart disease, and cancer; life expectancy; obesity and undernutrition.

Design: Ecological study of country level data

Results: Food-related GHG emissions ranged from 0.05 kg CO2e/ kg for sugar beets to 20.42 kg CO2e/ kg for mutton on an absolute scale, and from 0.03 kg CO2e/kcal for maize germ oil and peas (tied) to 9.93 kg CO2e/kcal for mutton when expressed as emissions per 1000 calories of edible food. The per capita availability of red meats, milk, and poultry explained more than 93% of the variation in global food-related GHG emissions. After adjustment for country socioeconomic and lifestyle characteristics, there was no association between country specific food-related GHG emissions and country specific rate of premature mortality from NCDs (β=0 [95% Confidence Interval (CI): -5, 5] deaths/100,000), life expectancy (β=0.19 [95% CI: -5, 5] years), prevalence of obesity (β=2% [95% CI: -3%, 6%]), or undernourishment (β=-7% [95% CI: -15%, 1%]). Results did not change when the association was examined within strata of GDP per capita. However, there were large variation in country health indicators at every level of GHG

emissions, and some countries had both low food-related GHG emissions and favorable health statistics.

Conclusion: Overall, national GHG emissions are not associated with diet-related NDC death rates nor undernutrition frequency. However, it appears possible to consume diets that concurrently reduce food climatic and NCD burden, without furthering malnutrition.

Introduction

In 2000, the World Health Organization (WHO) released its Global Strategy for the Prevention and Control of Noncommunicable Diseases(NCD) in recognition of the rapidly increasing global prevalence of cardiovascular disease (CVD), diabetes, cancer, and chronic obstructive respiratory disease (COPD), collectively known as the major noncommunicable diseases (NCDs), and the resulting detriment to public, societal, and economic health. The strategy centered largely on the need for an international reduction of the well-documented modifiable NCD risk factors, which include unhealthy diets (Director-General, 2000). To assist with implementation, the WHO released the 2008-2013, and the recently updated 2013-2020, Action Plan<s> for the Global Strategies for the Prevention and Control of Noncommunicable Diseases. The latter extends an array of policy suggestions to garner more unified worldwide cooperation believed to be required for ceasing the continued global growth of avoidable NCD-related morbidity, disability, and mortality (Director-General, 2000). By focusing on the major NCDs, the goal also is for decreased occurrence of other diseases and disorders that afflict world health and share overlapping modifiable risk factors (WHO, 2013).

At the 2011 High-level Meeting of the (United Nations) General Assembly on the Prevention and Control of Noncommunicable Diseases, the heads and representatives of states and governments drew upon the 2010 WHO Global Status Report on Noncommunicable Diseases and other resources to foster discussion of the global burden and challenges posed from NCDs, especially in low- to middle-income countries where the prevalence of NCDs is rapidly rising (Wagner et al., 2012; WHO, 2013). The event culminated in the adoption of a Political Declaration that outlined conclusions and recommended measures for universal NCD curtailment (Assembly, 2011). Within this declaration, the General Assembly (2011) articulated a "deep concern" over the "increasing challenges posed by climate change" – in addition to the strains brought about by the global economic crises, unpredictable cost of energy and food, unstable food supplies, and loss of biodiversity (all of which are exacerbated by a changing climate) – and the ability of nations to control and prevent NCD. The document emphasized the necessity for "prompt and robust, coordinated and multisectoral efforts to address <these> impacts, while building on efforts already under way" (Assembly, 2011).

In 2014, the United Nations' Intergovernmental Panel on Climate Change (IPCC) projected with "very high confidence" that human health will be affected by climate change, and noted the substantial impact of the agricultural sector (driven largely by the livestock industry) on anthropogenic climate change (Smith, K. et al, 2014; Smith P. et al, 2014). The panel also warned that immediate, forceful, and synchronized GHG mitigation efforts are required to stem the increasing threat to the public wellbeing (Smith K. et al., 2014; Smith P. et al, 2014; Stocker et al, 2013). They proposed both sweeping technical improvements and global average consumer reductions in animal food intake to lessen GHGs stemming from food (Smith P. et al, 2014).

The IPCC additionally highlighted the potential public health co-benefits from replacing animal foods, particularly red meat, with plant-based foods in countries where animal food consumption is high (Smith, P. et al, 2014). These potential health benefits include a decreased risk of cardiovascular disease (assuming animal saturated fat is replaced with plant polyunsaturated oils), cancer, and type 2 diabetes (Pan et al, 2012; Smith, P. et al., 2013; Willett, 2013; Turesky, 2011).

Although there appears to be substantial health co-benefits pertaining to NCD reduction with food-related climate change mitigation tactics, the IPCC cautioned against universal recommendations for animal food consumption change. The panel noted that such recommendations could potentially lead to decreased production of, and therefore access to, ruminant meat. In regions where food availability is already limited, this would further constrain obtainable sources of protein and other nutrients (Smith, P. et al., 2014). Accessing sources of nutrition in these areas will become even more critical with the forecasted undernutrition resulting from increasing climate change events (Smith, K. et al., 2013). Hence, the IPCC noted a need for more research regarding the health co-benefits from climate change mitigation tactics, particularly in low-income countries (Smith P. et al, 2014). To date, there are no known reported analyses of the association between food-related climate change impact and health outcomes.

The purpose of this study was to quantify the relationship between country specific food-related greenhouse gas (GHG) emissions and major health indicators including NCD mortality, life expectancy, obesity and undernutrition at an ecological level.

Methods

Existing countries in 2009 served as the population group in this study. We obtained food supply data from the 177 countries included in the United Nation (UN)'s Food and Agriculture Organization (FAO) database: *FAOSTAT* (http:// faostat.fao.org). For this analysis, 2009 food supply data, in kilogram quantities per capita year and kcal per capita day, were acquired. Food kilogram per capita year was then converted to daily per capita amounts.

Outcome measures included health metrics obtained from the World Health Organization (WHO)'s *Global Health Observatory Data Repository, World Health Statistics* (http://apps.who.int/gho/data/node.main) and the World Bank's *Open Data* (http://data.worldbank.org/inidicator). Specifically from the WHO's *World Health Statistics*, we obtained 2008 country specific mortality rates (deaths per 100,000 population) from cardiovascular disease (CVD) and diabetes; cancer; and premature deaths due to NCDs (defined as death between 30 and 70 years of age from CVD, cancer, diabetes, or chronic respiratory disease); as well as the prevalence of overweight (BMI=25.0-29.9) and obesity (BMI >= 30.0) among adults. From the World Bank's *Open Data*, we obtained the 2009 country specific prevalence of undernourishment (defined as the percent of the population that cannot continually meet their basic caloric requirements) and life expectancy at birth (total years).

We used the processed-based, life-cycle assessment (LCA) tool*, Food Carbon Scope* (Clean Metrics, Inc., Portland, OR) to provide an estimate of GHG emissions for foods included in the *FAOSTAT* database, expressed as Carbon Dioxide Equivalents (CO_2e) per kilogram of food. Carbon Dioxide Equivalents measures the capacity of a mass of a greenhouse gas to warm the planet through its associated radiative forcing properties, as compared to the same mass of carbon dioxide over a specified time period (McElroy, 2002). This warming capacity is also referred to as the Global Warming Potential (GWP). Because of the commodity-based nature of the FAO food consumption data, the boundary in the LCA process was set at the production level.

Food Carbon Scope meets the internationally recognized standards for LCA accounting as outlined in the International Standards Organization (ISO) 14040 series and the British Publically Available Specification 2050 (PAS 2050) (Amani & Schiefer, 2011). *Food Carbon Scope* also utilizes the 2007 IPCC Task Force on National Greenhouse Gas Inventories (TFI) 100-year GWP standardization factors for carbon dioxide, methane, nitrous oxide, and hydrofluorocarbon HFC-134a (a refrigerant) in the calculation of a CO_2e per food item.

Country foods listed in *FAOSTAT* were matched directly with those in the *Food Carbon Scope* database. We calculated the median food GHG values of the different country-specific food GHG values that were listed. For consistency of data quality, we used CO_2e values from conventional production methods only (conventional production have been the most extensively researched and there are uncertainties associated with GHG measures pertaining to organic methods). For FAO commodity groups, such as tree nuts, a list of associated foods contained within the *Food Carbon Scope* database, such as almonds, pistachios, pecans, and walnuts, was obtained. Median values for each commodity category were then calculated. For items not listed directly within the *Food Carbon Scope* database, CO_2e values (kg/kg food) were found in the literature. For food items not listed directly in *Food Carbon Scope* or in the literature, similar food items within *Food Carbon Scope* were used as proxy values. Once a CO_2e kg per food was determined, a CO_2e kg per capita day was established for each food item within each country.

To convert the GHG emission values per food supply weight (measured in kilograms) to food supply energy density, CO_2e kg per edible food calorie was quantified utilizing data from the US Department of Agriculture Agricultural Research Service's (USDA ARS) *National Nutrient Database for Standard Reference, Release 28*. Food items selected for this analysis were those listed as "raw, edible" to be as comparable as possible to the commodity-level foods listed in *FAOSTAT*, but still indicative of caloric amount typically consumed. Median caloric values of individual foods within broad FAO food categories were computed and scaled to 1,000 calorie units for better interpretability, to create a CO_2e kg per 1,000 kcals of edible food supply item.

We obtained country-specific data on physical inactivity, smoking, literacy, existence of national policies for the prevention of NCDs, per-capita total caloric intake, and GDP per-capita from the WHO's *Global Health Observatory Data Repository, World Health Statistics* (http://apps.who.int/gho/data/node.main), the FAO's *FAOSTAT*, the UN's *National Accounts Main Aggregates Database* (http://unstats.un.org/unsd/snaama/introduction.asp), and published literature. Specifically from the WHO's *World Health Statistics*, we acquired age-standardized data on physical inactivity and tobacco use. From *FAOSTAT*, total daily food availability calories per capita values were obtained. From the UN's *National Accounts Main Aggregates Database,* 2009 country GDP per capita (current international prices, US $) was accessed. From the literature, age-standardized, mean country BMI (sexes averaged) was obtained from Finucane, et al. (2011), and age-standardized, estimated mean sodium intake (g per day) was taken from Powles, et al. (2013).

Stepwise linear regression was used to identify which foods contributed the most to food-related GHG emissions. The association between food-related GHG emissions and country level health indicators was evaluated using median multivariate regression to account for the non-normally distributed health outcome variables Regression models for health outcomes were adjusted for physical inactivity, smoking, literacy rate, existence of national policies for the prevention of NCDs, per-capita total caloric intake, and GDP per-capita with the exception of models for overweight, obesity and undernourishment which were not adjusted for daily per capita caloric intake. Because a country's economic status affects the availability the overall health of its populace in many ways, each country was categorized as being either a low, middle, or high income country and multivariable models were additionally fit within each of these three strata. All analyses were conducted in SAS 9.4. (SAS Institute, Cary, NC).

Results

The GHG emissions of the FAO food supply items are listed in Table 2.1. Animal based foods had the highest GHG emissions whereas plant based foods had the lowest. Mutton and goat meat had the highest GHG emissions (20.44 CO_2e kg per kg food), followed by bovine meat (15.15 CO_2e kg/kg food), and butter (10.37 CO_2e kg/kg food). On the other hand, apples, pineapples, and onions had the lowest GHG emissions per food weight (0.07, 0.08, and 0.08 CO_2e kg/kg food, respectively) (Table 2-1). These relations were similar when expressed as GHG emissions per 1,000 kcal of edible food (Table 2.1).

Bovine meat accounted for more than half of food-related GHG emission variations and 3 food categories, namely red meats, milk and poultry, explained more than 90% of the variation in GHG emissions (Table 2.2). Marine fish, butter and ghee, freshwater fish, molluscs (other than mussels and oysters), cocoa beans, and vegetables (excluding tomatoes and onions), yams, and coconut together contributed less than 2% of the global variation (Table 2.2).

Univariate analyses showed statistically significant moderate-to-strong relationships between country food GHG emissions and all country health related models (Table 2.3). Specifically, food-related GHG emissions were inversely related to CVD and diabetes mortality, premature mortality by NCD, and undernourishment; and positively related to cancer mortality, life expectancy, adult obesity, and adult overweight. Adjustment for per capita caloric intake did not change the results. All of the associations, however, disappeared after adjustment for population lifestyle and socioeconomic indicators, with the exception for the positive association between food-related GHG emissions and cancer mortality which remained despite adjustments (Table 2.3). Also, when models were fit within strata of GDP per capita, food-related GHG emissions were not related to any of the outcomes examined (Table 2.3). However, there were large variation in country health indicators at every level of GHG emissions, and some countries had both low food-related GHG emissions and favorable health statistics.

Discussion

Overall, national GHG emissions were not associated with diet related NDC death rates. Our examination also did not reveal a relationship between country food GHG emissions and under nutrition frequency. Furthermore, there did not appear to be an association with country food GHG emissions and life expectancy, or adiposity. However, some countries had both low GHG emissions and favorable health statistics. Hence, it appears possible to consume diets that concurrently reduce food climatic and NCD burden, without furthering malnutrition.

To our knowledge, this is the first study to examine directly the correlation between country food-GHG emissions and country health outcome statistics. Briggs et al (2015) forecasted a potential decrease in NCD premature death in the UK after a hypothetical carbon tax applied to GHG intensive foods. Tillman and Clark (2014) predicted that the largest decrease in global food related GHG emissions could be obtained if nations across all economic strata adopted a mostly vegetarian, Mediterranean, or pescetarian way of eating, while offering potential health benefits to these countries. Earlier works looked at individual food items and

Table 2.1 (1 of 3): GHG Emissions (CO_2e) of FAO Food Supply Items

Item	CO_2e kg / food kg at farm*	CO_2e kg / 1000 kcals of raw, edible item**
Cereals – Excluding Beer		
Wheat	0.35	0.11
Rice (Milled Equivalent)	2.25	0.62
Barley	0.31	0.09
Maize	0.32	0.09
Rye	0.25	0.07
Oats	0.29	0.07
Millett	0.32	0.08
Sorghum	0.42	0.13
Cereals, other	0.32	0.09
Starchy Roots		
Cassava	0.31	0.19
Potatoes	0.18	0.23
Sweet Potatoes	0.43	0.50
Yams	0.43	0.36
Roots, other	0.09	0.08
Sugarcrops		
Sugar Cane	0.85	0.22
Sugar & Sweeteners (total)		
Sugar (Non-Centrifugal)	3.94	1.04
Sugar (Raw Equivalent)	2.14	0.57
Honey	1.00	0.33
Sweeteners, other	0.33	0.11
Pulses		
Beans	0.75	0.22
Peas	0.10	0.03
Treenuts	**1.39**	**0.25**
Oilcrops		
Soyabeans	0.56	0.12
Groundnuts	0.57	0.10
Sunflowerseed	0.88	0.15
Rape/Mustardseed	0.89	0.17
Palmkernels	0.33	0.06
Olives	0.18	0.12
Coconuts (including copra)	0.57	0.16
Sesame	0.57	0.10
Oilcrops, other	0.57	0.11

* Based on *Food Carbon Scope* LCA at farm production (farm-gate) level
** Based on USDA ARS's *National Nutrient Database for Standard Reference Release 27* median caloric data for raw, edible portions

Table 2.1 (continued, 2 of 3): GHG Emissions (CO_2e) of FAO Food Supply Items

Item	CO_2e kg / food kg at farm*	CO_2e kg / 1000 kcals of raw, edible item**
Vegetable Oils		
Soyabean Oil	1.48	0.17
Groundnut Oil	3.90	0.44
Sunflowerseed Oil	1.48	0.17
Rape/Mustard Oil	1.70	0.19
Palmkernel Oil	0.91	0.11
Palm Oil	0.44	0.05
Maize Germ Oil	0.25	0.03
Cottonseed Oil	1.48	0.17
Coconut Oil	1.48	0.17
Sesameseed Oil	1.48	0.17
Olive Oil	2.57	0.29
Ricebran Oil	1.48	0.17
Oilcrops Oil, other	1.75	0.20
Vegetables		
Tomatoes	0.66	0.75
Onions	0.08	0.20
Vegetables, other	1.18	0.68
Fruits (excluding wine)		
Oranges, Mandarines	0.20	0.39
Lemons, Limes	0.09	0.30
Grapefruit	0.15	0.47
Citrus, other	0.70	1.65
Bananas	0.29	0.33
Plaintain	0.29	0.24
Apples	0.07	0.13
Pineapples	0.08	0.16
Dates	0.62	0.22
Grapes	0.55	0.81
Fruits, other	0.15	0.31
Stimulants		
Coffee and products	2.51	--
Tea	0.70	--
Cocoa Beans	0.57	0.09

* Based on *Food Carbon Scope* LCA at farm production (farm-gate) level
** Based on USDA ARS's *National Nutrient Database for Standard Reference Release 27* median caloric data for raw, edible portions

Table 2.1 (continued, 3 of 3): GHG Emissions (CO_2e) of FAO Food Supply Items

Item	CO_2e kg / food kg at farm*	CO_2e kg / 1000 kcals of raw, edible item**
Alcoholic Beverages		
Wine	0.44	0.53
Beer	0.38	0.88
Bev Fermented	0.41	0.65
Bev, Alcoholic	2.74	1.84
Meat		
Bovine Meat	15.15	5.46
Mutton Meat	20.44	8.93
Pigmeat	4.95	2.29
Poultry Meat	4.11	1.69
Meat, other	10.05	7.39
Offals (edible)	10.05	8.55
Animal Fats		
Butter, Ghee	10.37	1.45
Cream	0.18	0.05
Fats, animal, raw	5.28	0.59
Eggs	**2.06**	**1.44**
Milk (excluding butter)	**1.02**	**2.00**
Fish & Seafood		
Freshwater Fish	8.86	4.04
Demersal Fish	3.68	3.58
Pelagic Fish	2.39	1.50
Marine Fish, other	6.98	4.89
Crustaceans	5.73	7.44
Cephalopods	5.40	5.87
Molluscs, Other	5.49	7.84
Aquatic Plants	**0.12**	**0.34**
Spices		
Pepper	2.50	--
Pimento	3.20	0.01
Cloves	1.60	--
Spices, other	1.60	--

* Based on *Food Carbon Scope* LCA at farm production (farm-gate) level
** Based on USDA ARS's *National Nutrient Database for Standard Reference Release 27* median caloric data for raw, edible portions

Table 2.2: Foods Contributing to 2009 Country Food Greenhouse Gas Emissions Variation Based on Daily Per Capita Food Supply Weight (kg)			
Food Item	**Stepwise Regression Model R^2**	**Stepwise Regression Model Cumulative R^2**	**P-value**
Bovine meat	0.60	0.60	<.0001
Milk (excl. butter)	0.15	0.75	<.0001
Poultry meat	0.07	0.82	<.0001
Mutton & goat meat	0.04	0.86	<.0001
Pig meat	0.07	0.93	<.0001
Rice	0.05	0.98	<.0001
Marine fish, other (sea bass)	<0.01	0.98	<.0001
Butter, ghee	<0.01	0.99	<.0001
Freshwater fish	<0.01	0.99	<.0001
Molluscs, other (mussels, oysters)	<0.01	0.99	<.0001
Cocoa beans	<0.01	0.99	<.0001
Vegetables, other (excl. tomatoes, onions)	<0.01	0.99	<.0001
Yams	<0.01	0.99	<.0001
Coconuts (incl. copra)	<0.01	1.00	<.0001

Table 2.3: Spearman Correlation and Median Regression Statistics Overall and By Country Economic Development

	Explanatory Variable: Food GHG Emissions Based on Daily Per Capita Food Supply Weight (CO_2e kg / Food Kg)				
	Correlation	Unadjusted Regression	Adjusted for Total Daily Per Capita Calories	Adjusted for Covariates	Adjusted for Total Daily Per Capita Calories & Covariates
Health Outcome Variables:	**Rho (95% CI)**	**Beta (95% CI)**	**Beta (95% CI)**	**Beta (95% CI)**	**Beta (95% CI)**
CVD & diabetes deaths*	-0.55 (-0.65, -0.44)	-200 (-245, -155)	-172 (-234, -112)	-38 (-174, 97)	-29 (-172, 115)
- High Income Countries	-0.66 (-0.78, -0.48)	-237 (-318, -155)	-231 (-318, -144)	-151 (-301, -2)	-151 (-332, 30)
- Medium Income Countries	0.06 (-0.21, 0.31)	74 (-134, 282)	34 (-268, 335)	30 (-931, 991)	34 (-1235, 1304)
- Low Income Countries	-0.25 (-0.47, 0.02)	-74 (-173, 25)	-46 (-163, 71)	79 (-160, 320)	47 (-204, 298)
Cancer deaths**	0.50 (0.37, 0.61)	28 (18, 38)	27 (12, 42)	44 (10, 77)	43 (9, 77)
- High Income Countries	-0.19 (-0.43, 0.08)	-9 (-34, 16)	-10 (-35, 16)	-7 (-42, 27)	-7 (-48, 34)
- Medium Income Countries	0.51 (0.29, 0.68)	49 (12, 86)	51 (11, 92)	68 (-107, 243)	3 (-246, 251)
- Low Income Countries	0.22 (-0.04, 0.46)	36 (8, 63)	36 (-3, 73)	43 (-21, 107)	62 (-3, 138)
Premature death by NCD***	-0.57 (-0.66, -0.45)	-5 (-7, -4)	-4 (-5, -2)	0 (-5, 5)	0 (-5, 5)
- High Income Countries	-0.60 (-0.74, -0.39)	-5 (-7, -3)	-4 (-6, -2)	-3 (-9, 2)	-3 (-11, 4)
- Medium Income Countries	0.02 (-0.24, 0.27)	-1 (-7, 5)	1 (-7, 8)	10 (-107, 27)	11 (-50, 72)
- Low Income Countries	-0.17 (0.41, 0.10)	0 (-4, 4)	0 (-4, 4)	-3 (-13, 8)	1 (-8, 11)
Life expectancy ₸	0.80 (0.74, 0.85)	7 (6, 8)	3 (2, 5)	2 (-3, 7)	0.19 (-5, 5)
- High Income Countries	0.56 (0.34, 0.72)	3 (2, 4)	2 (1, 4)	1 (-6, 8)	1 (-7, 10)
- Medium Income Countries	0.46 (0.21, 0.64)	3 (0.3, 6)	4 (1, 7)	2 (-79, 84)	2 (-91, 95)
- Low Income Countries	0.54 (0.32, 0.70)	7 (0.16, 14)	7 (-1, 15)	1 (-12, 14)	3 (-12, 17)

*CVD and diabetes, deaths per 100,000 (2008 age-standardized estimate, both sexes, sourced from the WHO). Covariates: Mean country BMI (age-standardized, 2008, sexes averaged, Finucane et al.); Percent of adult population insufficiently active (age-standardized estimate, ages 15+, 2008, WHO); Current smoking of any tobacco product (age-standardized prevalence, ages 15+, 2009, WHO); Mean sodium intake (age-standardized, ages 20 +, 2010,Powles, et al.), Existence of operational policy/strategy/action plan for cancer (2010, WHO); Literacy rate among adults aged 15 years + (%, 1990-2010, WHO); and GDP per capita, (current prices US $, 2009, United Nations).

** Cancers, deaths per 100,000 (2008, age-standardized estimate, both sexes, 2008, WHO). Covariates used in analysis: Mean country BMI (age-standardized, 2008, sexes averaged, Finucane et al.); Percent of adult population insufficiently active (age-standardized estimate, ages 15+, 2008, WHO); Current smoking of any tobacco product (age-standardized prevalence, ages 15+, 2009, WHO); Mean sodium intake (age-standardized, ages 20 +, 2010,Powles, et al.), Existence of operational policy/strategy/action plan for diabetes (2010, WHO); Existence of operational policy/strategy/action plan for cardiovascular diseases (2010, WHO); Literacy rate among adults aged 15 years + (%, 1990-2010, WHO); and GDP per capita (current prices US $, 2009, United Nations).

***Probability of dying between exact ages 30 and 70 from any of CVD, cancer, diabetes, or chronic respiratory (%, 2008, WHO). Covariates used in analysis: Mean country BMI (age-standardized, 2008, sexes averaged, Finucane et al.); Percent of adult population insufficiently active (age-standardized estimate, ages 15+, 2008, WHO); Current smoking of any tobacco product (age-standardized prevalence, ages 15+, 2009, WHO); Existence of operational policy/strategy/action plans for CVD, diabetes, cancer, overweight and obesity, and respiratory disease (2010, WHO); Literacy rate among adults aged 15 years + (%, 1990-2010, WHO); and GDP per capita (current US prices $, 2009, United Nations).

₸ Life expectancy at birth (total years, 2009, World Bank). Covariates used in analysis: Mean country BMI (age-standardized, 2008, sexes averaged, Finucane et al.); Percent of adult population insufficiently active (age-standardized estimate, ages 15+, 2008, WHO); Current smoking of any tobacco product (age-standardized prevalence, ages 15+, 2009, WHO); Existence of operational policy/strategy/action plans for CVD, diabetes, cancer, overweight and obesity, and respiratory disease (2010, WHO); Literacy rate among adults aged 15 years + (%, 1990-2010, WHO); and GDP per capita (current prices US $, 2009, United Nations)

Table 2.3 (continued): Spearman Correlation and Median Regression Statistics Overall and By Country Economic Development

	Explanatory Variable: Food GHG Emissions Based on Daily Per Capita Food Supply Weight (CO_2e kg / Food Kg)				
	Correlation	Unadjusted Regression	Adjusted for Total Daily Per Capita Calories	Adjusted for Covariates	Adjusted for Total Daily Per Capita Calories & Covariates
Health Outcome Variables:	**Coeff (95% CI)**	**Beta Coeff (95% CI)**	**Beta Coeff (95% CI)**	**Beta Coeff (95% CI)**	**Beta Coeff (95% CI)**
Adult obesity ‡	0.51 (0.39, 0.62)	7 (5, 9)	--	2 (-3, 6)	--
- High Income Countries	-0.18 (-0.42, 0.09)	-1 (-4, 3)	--	1 (-4, 6)	--
- Medium Income Countries	0.33 (0.11, 0.56)	3 (-2, 8)	--	6 (-17, 28)	--
- Low Income Countries	0.16 (-0.11, 0.40)	3 (-1, 7)	--	4 (-0.2, 9)	--
Adult overweight ‡‡	0.51 (0.39, 0.62)	11 (8, 15)	--	3 (-4, 10)	--
- High Income Countries	-0.13 (-0.38, 0.14)	-1 (-5, 3)	--	3 (-4, 9)	--
- Medium Income Countries	0.36 (0.08, 0.54)	5 (-1, 11)	--	7 (-28, 42)	--
- Low Income Countries	0.16 (-0.11, 0.40)	7 (-5, 20)	--	9 (-4, 22)	--
Undernourishment ŦŦ	-0.68 (-0.77, -0.57)	-10 (-14, -5)	--	-7 (-15, 1)	--
- High Income Countries	-0.28 (-0.62, 0.15)	0 (-3, 3)	--	0 (-3, 3)	--
- Medium Income Countries	-0.56 (-0.73, -0.32)	-8 (-16, 1)	--	-12 (-22, -2)	--
- Low Income Countries	-0.52 (-0.69, -0.29)	-13 (-30, -2)	--	-15 (-32, 2)	--

‡ Percent of adult population with obesity (BMI >= 30.0, age standardized, age 20+, both sexes, 2008,WHO). Covariates used in analysis: Mean country BMI (age-standardized, 2008, sexes averaged, Finucane et al.); Percent of adult population insufficiently active (age-standardized estimate, ages 15+, 2008, WHO); Current smoking of any tobacco product (age-standardized prevalence, ages 15+, 2009, WHO); Existence of operational policy/strategy/action plans for overweight and obesity (2010, WHO); Literacy rate among adults aged 15 years + (%, 1990-2010, WHO); and GDP per capita (current prices US $, 2009, United Nations).

‡‡ Percent of adult overweight population (BMI=25.0-29.9, age standardized, age 20+, both sexes, 2008, WHO). Covariates used in analysis: Mean country BMI (age-standardized, 2008, sexes averaged, Finucane et al.); Percent of adult population insufficiently active (age-standardized estimate, ages 15+, 2008, WHO); Current smoking of any tobacco product (age-standardized prevalence, ages 15+, 2009, WHO); Existence of operational policy/strategy/action plans for overweight and obesity (2010, WHO); Literacy rate among adults aged 15 years + (%, 1990-2010, WHO); and GDP per capita (current prices US $, 2009, United Nations).

Ŧ Life expectancy at birth (total years, 2009, World Bank). Covariates used in analysis: Mean country BMI (age-standardized, 2008, sexes averaged, Finucane et al.); Percent of adult population insufficiently active (age-standardized estimate, ages 15+, 2008, WHO); Current smoking of any tobacco product (age-standardized prevalence, ages 15+, 2009, WHO); Existence of operational policy/strategy/action plans for CVD, diabetes, cancer, overweight and obesity, and respiratory disease (2010, WHO); Literacy rate among adults aged 15 years + (%, 1990-2010, WHO); and GDP per capita (current prices US $, 2009, United Nations)

ŦŦ Undernourishment prevalence (% of population, 2009, World Bank). Covariates used in analysis: Literacy rate among adults aged 15 years + (%, 1990-2010, WHO); and GDP per capita (current prices US $, 2009, World Bank).

surmised that improvements in global health could potentially be obtained from reducing meat and dairy foods (Aston et al., 2012; Hamerschlag, 2011; Audsley et al., 2009; Friel et al., 2009; Smith, P. et al., 2014; Blake, 2012).

While this manuscript represents the first empirical evaluation of the hypothesis that reducing food-related GHG emissions could simultaneously address global health concerns related to NCDs, it is not without limitations. A careful consideration of the study's strengths and limitations is critical for interpreting our findings. An important strength is the large number of food items aggregated to derive at our food CO_2e estimations. We additionally utilized GHG estimates from average global food production data (Supplementary Table 2.2, 2.3). The magnitude of our CO_2e values were consistent with other published analyses (Hoolahan et al., 2013; Aston et al., 2012; Hamerschlag, 2011; Audsley et al., 2009; and Friel et al., 2009; MORE REFS to be inserted here). Hence, our results can additionally be viewed with even greater certainty than had we only utilized a smaller number of food items that were based on GHG estimates coming from one country, but assumed to be globally representative.

It must be noted, however, that any GHG food value given to a specific food should be viewed cautiously. Although life cycle assessment has been the standard procedure to estimate an item's GHG emissions, there are limitations to LCA that have been reviewed in detail elsewhere, particularly when applied to the food industry (Shau & Fet, 2008; Wardenaar et al, 2012; Pryshlakivsky & Searcy, 2013; Thoma et al, 2014; Curran, 2014). The most noted of such limitations revolve around the allocation of environmental impacts to different foods that are derived from a common source (Shau & Fet, 2008; Pryshlakivsky & Searcy, 2013; Thomas et al, 2014). For example, cream had low associated CO_2e emissions in this analysis. However, cream is one of several items within the *Food Carbon Scope* database that originated from liquid milk. These items included butter, cheese, ice cream, and yogurt. As a result, the CO_2e value for cream was, as is done in all LCA software tools, derived from a composite of assumed, albeit well sourced, fractions. Therefore, comparing the associated GHG emission of cream (0.18 kg CO_2e / kg cream, or 0.05 kg CO_2e / 1000 calories of cream) to other items that are unilaterally produced, such as honey (1.00 kg CO_2e / kg honey, or 0.33 kg CO_2e / 1000 calories of honey) or dates (0.63 kg CO_2e / kg date, or 0.22 kg CO_2e / 1000 calories of edible, raw dates) in this study and beyond, should be prudently interpreted.

An important limitation of this study is its ecological nature. Food GHG emissions were based on the FAO's Food Balance Sheets (FBS) within *FAOSTAT* whose shortcomings have been previously discussed (FAO, 2001; Naska, 2009). Likewise, nationally reported health statistics are prone to measurement error, especially in low-income countries that lack sophisticated monitoring systems (FAO, 2013). Thus, the use of a FBS and country derived health statistics in an analysis can potentially lead to residual or unmeasured bias. However, the magnitude of such biases and the resulting direction of effect on estimates are difficult to determine.

Using cross-sectional country-level data also poses serious challenges to causal inference. Most NCDs have long latency periods, some of them even starting in early life (Balbus et al, 2013). Although this analysis only considered concurrent food related GHG emission and health related outcomes from circa 2009, the results of this study may nevertheless provide a reasonable associative relationship between country food GHG emissions and the country health profiles analyzed. Overall country intake averages have been reported to be typically stable over several decades (Willett, 2013). Hence, this study approximates a relatively lengthy period of estimated country consumption prior to the health event outcomes analyzed.

Our analyses adjusted for national lifestyle and socioeconomic indicators that are important to include in any evaluation involving dietary consumption. If one was to merely look at the crude analysis, it would seem to suggest that decreasing food GHG emissions would lead to more, not less, mortality from CVD and diabetes, as well as greater premature death from a NCD, as examples. However, when other factors found previously to be related to the health outcomes analyzed were added to the regression models, and, in the case of country GDP, stratified upon, the significance of these associations disappeared. Hence, a lack of consideration for confounding by other potentially influential variables would have led to erroneous conclusions.

Although we did not observe overall associations between national per capita food related CO_2e emissions and health statistics, our analysis identified some countries with relatively low food GHG emissions and positive health outcomes. Further examination of diets within these countries is warranted as they may provide models for sustainable diets. Hence, efforts that enable the adoption of effective policies to address both dietary quality and the reduction of food GHG emissions simultaneously, without exacerbating undernutrition, should continue.

VIII. CHAPTER 3: RELATION OF HEALTHFULNESS OF DIET TO FOOD WATER FOOTPRINT AMONG US WOMEN

Abstract:

Objective: It has been suggested that diets that are conducive to good health have lower impacts, or smaller water footprints (WF), on global water resources. However, this hypothesis has not been empirically tested. The purpose of this study was to quantify the relationship of food water footprint and quality of diet, in terms of chronic disease prevention, within a cohort of US women in the Nurses' Health Study I.

Design: Cross sectional study

Results: Over 400 foods were given three WF values for the total, reservoir, and rain water used in their production, as produced domestically in, or internationally for importation into, the US. As a measure of diet quality, the Alternative Healthy Eating Index (AHEI) score was calculated for the 53,817 participants based on their reported diets. Reservoir WF increased linearly whereas rain WF decreased linearly with increasing adherence to the AHEI. Women in the highest quintile of adherence to the AHEI had reservoir WF that was 309 liters/day (95% confidence interval (CI): 290 – 327) higher and a rain WF that was 313 liters/day (95% CI: -333, -294) liters lower than that of women in the lowest quintile of adherence to the AHEI. When both reservoir and rain WF were considered together, women on the highest quintile of adherence to the AHEI had a total WF that was 50 liters/day (95%: -81, -19) lower than that of women in the lowest quintile of adherence.

Conclusion: Our results do not support the hypothesis that eating more healthfully will result in substantially lower impacts on global water resources. On the contrary, doing so may place more burden on global reservoir supply.

Introduction

The Water Footprint (WF) concept was developed as a means to measure the water use of modern society (Hoekstra et al, 2011). It examines both direct and indirect water use by a given entity, such as a commodity or consumer, in a certain geographical location at a given time (Hoekstra et al, 2011). A total water footprint encompasses three subcategories that have been designated by a different representative color (Hoekstra et al, 2016; Vanham and Bidoglio, 2014). A *blue water footprint* refers to water withdrawn from freshwater reservoirs: rivers, lakes, aquifers, and wetlands. A *grey water footprint* involves the amount of water required to dilute incoming pollutants to water safety standards in a freshwater catchment area. The *green water footprint* refers to the amount of rainwater used by plants for growth (Hoekstra et al., 2011). Once a WF is assessed, the goal is to alter production or consumption processes that have been identified as water intensive, or with a large WF, in order to help attain water sustainability (Hoekstra A.Y., 2013).

Studies involving food-related water footprints have shown that the animal foods have larger water footprints than those of plant foods (Hoekstra, 2014). Hence, consuming a vegetarian diet has been linked with a lesser burden on global water resources than a diet consisting of meat and dairy foods (Renault and Wallender, 2000; Lui and Savenije, 2008; Marlow et al., 2009; Vanham and Bidoglio, 2014; Vanham et al., 2013; Jalava et al., 2014). A potential co-benefit of adopting diets that emphasize more plant based foods, it is theorized, would be improvements in health (Marlow et al., 2009; Hoeskstra, A.Y., 2012; Vanham and Bidoglio, 2013; Vanham et al., 2013). Although the consumption of meat and dairy is associated with an increased risk of cardiovascular disease, diabetes, certain cancers, and mortality, animal foods represent only one of several complex dietary components related to health (Pan et al., 2011; Pan et al., 2012; Willett, 2013; Abid et al., 2014; McGrane & Lyon, 2014).

In 2015, Hess et al. modeled the impact of five different diet scenarios on global blue water resources. Each diet was developed theoretically to meet the United Kingdom's (UK) *Dietary Reference Values* for essential nutrients recommended for adult women within the recommended consumption patterns of the UK National Health Services, '*The eatwell plate*". Utilizing UK trade data, they found modestly negative influences of the different healthy eating scenarios on global blue water resources. These researchers concluded that the promotion of healthier eating may increase worldwide water stress (Hess et al, 2015).

The purpose of this study was to quantify the relationship of food water footprint and healthfulness of diet, in terms of its potential for chronic disease prevention, within a cohort of US women.

Methods

Study Population

The Nurses' Health Study I (NHS I) is an ongoing prospective, US-based, cohort study consisting of 121,700 US female registered nurses from the ages of 30 to 55 years when the study began in 1976. The nurses have provided details pertaining to their health, lifestyle, place of residence, and demographics at baseline and every two years since. Height and weight were provided in 1976, and weight has since been updated at these two year intervals.

In 1984, the study survey questionnaire was lengthened to include information regarding their consumption frequency of various food items over the year prior. In 1986 and every four years after (1990, 1994, 1998, 2002, 2006, 2010, and 2014), repeated food frequency questionnaires (FFQ) were sent to track the nurses' dietary intake patterns. The validity of the FFQ as a measure of average consumption has been thoroughly reviewed (Willett, 2013).

This study included women who provided dietary information on the 2002 FFQs to correspond with average food water footprint values assessed by Mekonnen and Hoekstra (2010) for the years 1996-2005. Exclusion criteria included those with reported cancer (except for non-melanoma skin cancer), diabetes, and cardiovascular disease, those nurses who left more than 70 items unanswered, or where calculated total calories to be below 500 or above 3500 calories per day.

Explanatory Variable: Healthy Eating Index

The Alternative Healthy Eating Index (AHEI) is a measure of diet quality that incorporates food characteristics associated with prevention of major chronic diseases (McCullough & Willett, 2006). It was devised as an alternative to the US Department of Agriculture's (USDA) Healthy Eating Index (HEI), which was developed to assess compliance with the Dietary Guidelines for Americans (McCullough et al., 2002). The AHEI includes specific scoring criteria for intake of the Healthy Eating Index's fruits, vegetables, nuts, legumes, processed red meat, sodium, trans fats, long chain (n-3) fats (EPA and DHA), polyunsaturated fat, and alcohol (Chiuve et al., 2012). Research comparing both indices have indicated that high adherence to the AHEI is associated more strongly with lower risk of major chronic disease more than adherence to the HEI, especially for coronary heart disease and diabetes (McCullough & Willett, 2006; Chiuve et al, 2010).

Total AHEI scores were calculated for each study participant as previously described (Chiuve et al., 2012). Specifically, intakes of each of the components in the score, as described above, were ranked and assigned. Points for each category ranging from 0 (intake associated with highest disease risk) to 10 (intakes consistent with chronic disease prevention), based on usual frequency of consumption. Total AHEI scores ranged from 0 (no adherence) to 110 (maximum adherence) (Chiuve et al, 2012).

After the participants total daily AHEI score were determined, these values were adjusted for calories utilizing the residual method. Total AHEI scores were calculated for each study participant by the following, as designed by Chiuve et al (2012). Each food item on the 2002 FFQ was designated to one of the nine 2010 AHEI categories (noted above) according to the food's corresponding nutrient profile. Points for each category ranged from 0 (no intake) to 10 (intakes consistent with chronic disease prevention), based on usual frequency of consumption as reported on the subject's FFQ. Typical consumption frequencies vary from "never" to "more than 6 times per day" over the period of the previous year. AHEI scores from each category were summed for a total AHEI value. Total AHEI scores ranged from 0 (no adherence) to 110 (maximum adherence) (Chiuve et al, 2012).

After the participants' total daily 2010 AHEI scores were determined, these values were adjusted for calories utilizing the residual method (Willett, 2013). Median daily caloric intake of the study population were utilized for this conversion. Adjustment for caloric intake provides for more refined analyses by removing any extraneous variation of AHEI scores due to differing caloric intakes. Thus, the AHEI scores given to each nurse were those that reflect what would be attained if she were to consume 1650 calories per day.

Outcome Variables: Food Water Footprints

Three food water footprint variables were used as the outcome variables in this study. The first was a *Total WF* variable which was the sum of the food's blue (water withdrawn from freshwater reservoirs), green (amount of rainwater used by plants for growth), and grey (the amount of water required to dilute incoming pollutants to water safety standards in a water catchment area) WF values. The second WF variable was *Reservoir WF,* which was the sum of the food's blue and grey WF values. The third WF variable was *Rain WF,* which was the food's green WF values only.

Each item included in the FFQ was given green, blue, and grey WF values for every food producing country worldwide. Blue and grey WF values were then combined into the category of Reservoir WF (as noted above) to better reflect water stress to globally stored freshwater. Country WF data were derived from Mekonnen and Hoekstra (2010). For specific food items listed on the NHS FFQ that were not listed in the Mekonnen and Hoekstra (2010) publications, general WF values were obtained from other publications. For example, WF values for soda were obtained from Ercin et al (2011). Pizza WF values were acquired from Aldaya and Hoekstra (2010), and potato chip WF values were attained from Hoekstra and Chapagain (2007). For recipe items that lacked published WF values, individual WF values per ingredient were proportionally summed for a total recipe WF score. Recipes were accessed from the Harvard T. H. Chan School of Public Health, Nutrition Department's Food Composition Database (https://regepi.bwh.harvard.edu/health/nutrition/index.html), which is primarily based on the United States Department of Agriculture (USDA) food composition database with additional data obtained from food manufacturers. Whether coming from the literature or from recipe ingredient aggregation, all WF values were scaled to cubic meters of water used per ton of food (m^3/ton) for consistency with units listed in Mekonnen and Hoekstra (2010).

To assess the global water resource impact of study participant dietary consumption, 2002 tonnages of food imported into the US from different countries were obtained from the United Nations Food and Agriculture Organization's database, *FAOSTAT*. If a 2002 import country lacked WF data from the Mekonnen and Hoekstra (2010) publications, a regional average was implemented for that country. The regional average was a weighted average of countries belonging to a certain region, as defined by the FAO. The weighted average was calculated using individual country production data from the years 1996-2005 and averaged for the 10 years. If a regional average could not be obtained due to lack of production data, the world weighted average was used instead, as given by Mekonnen and Hoekstra (2010).

Domestic (US) food production was also factored into the WF scores. Domestic production food tonnage for 2002 was obtained from the FAO. If production numbers were negative due to the use of stocks for 2002, US production was not included in the final WF values.

Food codes given by Mekonnen and Hoeskstra (2010) were matched with FAO import and production codes. WF values took into account the differing 2002 import country and domestically-provided food quantities. Further calculations were performed to adjust raw tonnage of food into quantities conducive to actual edible portions. Such conversion factors were obtained from the USDA's Agricultural Research Service (Matthews & Garrison, 1975). The final WF values were in units of liters per 100 edible grams of food (liters/100 grams).

Each study participant was provided a total *Total WF*, *Reservoir WF,* and *Rain WF* value by multiplying the designated WF given to a serving size of each FFQ item by the study participants' reported frequency of consumption.

Statistical Analysis

Spearman correlation statistics between an individual's AHEI score and her WF were calculated. Univariate and multivariate median regression models were used to evaluate the association between dietary AHEI index and dietary WF variables. The AHEI was modeled as a continuous variable or as quintiles of intake. Multivariate median regression analysis were adjusted for age and total daily caloric intakes.

Results

Over 400 foods were given *Total WF*, *Reservoir*, and *Rain WF* values. The number of participants in this analysis was 53,817. Their median age was 67 years, their median daily calorie was 1650 kcal before energy adjustment, and their median AHEI score was 55.83, on a scale of 0 to 100. Median daily food related WF values were: *Total WF*, 3055 liters; *Reservoir WF*, 698 liters, and *Rain WF*, 3055 liters (Table 3-1).

AHEI scores were weakly related to WF measures (Tables 3-2 & 3-3). The Spearman correlations between the AHEI score and each WF variable were -0.02 (95% CI: -0.02, -0.01) for *Total WF*; 0.20 (CI: 0.19, 0.20) for *Reservoir WF*; and -0.15 (CI: -0.15, -0.14) for *Rain WF* (Table 3-2). *Reservoir WF* increased linearly whereas *Rain WF* decreased linearly with increasing adherence to the AHEI. Women in the highest quintile of adherence to the AHEI had a *Reservoir WF* that was 309 liters/day (CI: 290 – 327) higher and a rain WF that was 313 liters/day (CI: -333, -294) liters lower than that of women in the lowest quintile of adherence to the AHEI. When both reservoir and rain WF were considered together, women on the highest quintile of adherence to the AHEI had a total WF that was 50 liters/day (CI: -81, -19) lower than that of women in the lowest quintile of adherence (Table 3-3). Adjustment for the women's age and calories did not change the magnitude, significance, nor directionality of these associations, regardless of whether the AHEI score was modeled as a continuous or categorical variable (Table 3-3).

Table 3.1: Study Population Characteristics	
Year: 2002; Size: 53,817*	
Variable	**Median (10 - 90 %iles)**
Age (years)	67 (58 – 77)
Calories Consumed (daily)	1650 (1049 – 2442)
AHEI Score (calorie adjusted, daily)**	55.83 (41.2 – 72.5)
Total Water Footprint (daily liters)***	3055 (1731 – 5404)
Reservoir Water Footprint Values (daily liters)****	698 (355 – 2346)
Rain Water Footprint (daily liters)*****	2178 (1250 – 3457)
AHEI Score (calorie adjusted, daily), categorized	**Mean (SD)**
Quintile 1	40.09 (4.6)
Quintile 2	49.38 (2.0)
Quintile 3	55.83 (2.0)
Quintile 4	62.59 (2.1)
Quintile 5	73.88 (6.0)
Total Water Footprint (daily liters), categorized	
Quintile 1	1665 (336)
Quintile 2	2439 (178)
Quintile 3	3057 (183)
Quintile 4	3810 (272)
Quintile 5	5705 (1252)
Reservoir Water Footprint (daily liters), categorized	
Quintile 1	342 (68)
Quintile 2	512 (45)
Quintile 3	707 (74)
Quintile 4	1160 (203)
Quintile 5	2527 (1010)
Rain Water Footprint (daily liters), categorized	
Quintile 1	1201 (124)
Quintile 2	1756 (125)
Quintile 3	2180 (125)
Quintile 4	2664 (163)
Quintile 5	3624 (598)

*Excluded RNs with reported CVD, diabetes, and cancer (except for non-melanoma skin cancer); with no returned 2002 FFQ; with returned FFQs with more than 70 items left blank; or with returned FFQs with calculated total calories to be below 500 or above 3500 calories per day.
**Calorie adjusted using the residual method.
*** Total Water Footprint includes the impact of dietary consumption on global water resources from the use of fresh water for irrigation, rain water, and the amount of fresh water needed to dilute incoming pollutants from food production.
****Fresh Water Footprint includes the impact of dietary consumption on global fresh water resources for irrigation and dilution of incoming agricultural pollutants from food production.
*****Rain Water Footprint includes the impact of dietary consumption on global rain water for food production.

Table 3.2: Spearman Correlation Coefficients		
Variables	**r_s (95% CI)**	**p-value**
AHEI Score (calorie adj) vs. Total Water Footprint (liters)	-0.02 (-0.02, -0.01)	0.0004
AHEI Score (calorie adj) vs. Reservoir Water Footprint (liters)	0.20 (0.19, 0.20)	<0.0001
AHEI Score (calorie adj) vs. Rain Water Footprint (liters)	-0.15 (-0.15,-0.14)	<0.0001

Table 3.3: Univariate and Multivariate Median Regression Results						
	Outcome: Total Water Footprint					
Explanatory Variable	**Unadjusted**		**Adjusted for Age**		**Adjusted for Age & Calories**	
	Beta (95% CI)	**p-value**	**Beta (95% CI)**	**p-value**	**Beta (95% CI)**	**p-value**
AHEI Score (calorie adjusted), continuous	-2 (-3, -1)	<0.0001	-3 (-4, 2)	<0.0001	-2 (-3, -1)	<0.0001
AHEI Score (calorie adjusted), categorical		**p-value for trend**		**p-value for trend**		**p-value for trend**
Quintile 1 (ref)		0.03		0.0001		0.002
Quintile 2	-119 (-157, -81)		-113 (-150, -76)		-31 (-59, -2)	
Quintile 3	-105 (-141, -68)		-101 (-137, -65)		-20 (-48, 8)	
Quintile 4	-104 (-146, -61)		-120 (-162, -77)		-37 (-68, -7)	
Quintile 5	-45 (-88, -2)		-69 (-106, -32)		-50 (-81, -19)	
	Outcome: Reservoir Water Footprint					
Explanatory Variable	**Unadjusted**		**Adjusted for Age**		**Adjusted for Age & Calories**	
	Beta (95% CI)	**p-value**	**Beta (95% CI)**	**p-value**	**Beta (95% CI)**	**p-value**
AHEI Score (calorie adjusted), continuous	9 (9, 9)	<0.0001	8 (8, 9)	<0.0001	8 (7, 8)	<0.0001
AHEI Score (calorie adjusted), categorical		**p-value for trend**		**p-value for trend**		**p-value for trend**
Quintile 1 (ref)		<0.0001		<0.0001		<0.0001
Quintile 2	12 (0.3, 23)		14 (3, 25)		18 (12, 25)	
Quintile 3	89 (74, 103)		88 (75, 100)		65 (56, 74)	
Quintile 4	162 (143, 180)		161 (143, 179)		131 (118, 145)	
Quintile 5	299 (280, 317)		295 (276, 315)		309 (290, 327)	
	Outcome: Rain Water Footprint					
Explanatory Variable	**Unadjusted**		**Adjusted for Age**		**Adjusted for Age & Calories**	
	Beta (95% CI)	**p-value**	**Beta (95% CI)**	**p-value**	**Beta (95% CI)**	**p-value**
AHEI Score (calorie adjusted), continuous	-11 (-12, -10)	<0.0001	-12 (-12, -11)	<0.0001	-11 (-12, -11)	<0.0001
AHEI Score (calorie adjusted), categorical		**p-value for trend**		**p-value for trend**		**p-value for trend**
Quintile 1 (ref)		<0.0001		<0.0001		<0.0001
Quintile 2	-133 (-165, -101)		-117 (-143, -93)		-60 (-80, -41)	
Quintile 3	-203 (-230, -176)		-196 (-220, -173)		-134 (-154, -115)	
Quintile 4	-249 (-280, -218)		-252 (-277, -227)		-201 (-220, -182)	
Quintile 5	-301 (-329, -272)		-317 (-341, -293)		-313 (-333, -294)	

Discussion

We evaluated the association between the healthfulness of diet, as captured by the AHEI, and its water footprint. Overall healthier diets had a negative, albeit small, impact on water resources. This weak inverse relationship, however, resulted from the combination of a strong positively impact on rainwater resources and a strong negative (although somewhat less in magnitude than rainwater) impact on reservoir water resources. Sustaining universal reservoir water supply is of most concern in regards to water sustainability. Hence, this analysis does not support the hypothesis that healthier diets have lesser burden on global water resources.

The assumption of plant based foods as being both uniformly healthy and less water intensive appears to have been oversimplified. For example, high fructose corn syrup (HFCS) is derived, as the name indicates, from corn. HFCS has been the primary sweetener utilized in sugar sweetened beverages over the couple of decades (Ventura et al, 2010; Goran, 2013). It has also been widely used in sweetened processed food items, such as store-bought chips, crackers, cookies, and cakes (Ventura et al, 2010; Fitch et al, 2012). The 2010 AHEI scoring system applied points for vegetable, fruit, whole grain, and nut and seed consumption, while deducting points for sugar sweetened beverage consumption. Furthermore, no points were given for sweetened snack foods (Chiuve et al, 2012). Hence, the more a nurse identified to have consumed a sweetened processed food or drink, the less her healthy eating score was.

On the other hand, corn appears to have limited impacts on global fresh water resources. According to the USDA's 2002 Census of Agriculture, irrigation for corn was only 14% of harvested corn acreage in the United States in 2002. Thus, corn is a primarily rain-fed crop. Alternatively, for example, most, 77%, of harvested berry acreage was irrigated (USDA, 2004). Assuming irrigation patterns were similar globally in 2002, eating, in this case, processed sweetened foods and beverages with HFCS, compared to naturally sweetened fruit, cost more in terms of fresh water resources during the time of this study.

To our knowledge, our analyses was the first to have designated WF values to foods actually consumed by individuals in a cohort. Hess et al (2015) also found slightly negative influences of healthy eating on overall global blue water resources based on commodity foods with consumption patterns premised on national surveys. Unlike Hess et al (2015), our work included the impact of pollutants generated in the food production processes that impacts global water reservoirs. Furthermore, our study capitalized on the food scoring methods of Chuive et al (2010) premised on the large body of dietary-related scientific literature findings pertaining to chronic disease prevention, while Hess et al's (2015) food groupings were in relation to the UK dietary guidelines, based, in large part, on the United States' *Dietary Guidelines for Americans*. (For example, similar to the US national recommendations, dairy foods were given more emphasis in the UK dietary guidelines than was found to be supportive of health through the work of Chuive et al (2012). Additionally, we assigned WF values to the largest numbers of foods found in existing literature and captured the global impact of the nurses' consumption patterns in accordance with extensive 2002 food importation and domestic production data. Although diet consumption was self-reported, the validity of the FFQ as a measure of average consumption has been validated by comparison with more detailed methods, biomarkers, and ability to predict health outcomes (Willett, 2013). Hence, our results can be viewed to be reasonably representative of the impact of dietary consumption on global water resources.

A limitation of this study was that it only utilized 2002 trade and domestic production figures. It would also be interesting to analyze the impact of consumption patterns within different demographic groups on global water resources to get a broader understanding of the relation of food water footprint and diet healthfulness.

The results of this study seem to indicate that care must be taken when advising the public to eat more healthfully for chronic disease prevention. The unfavorable directionality pertaining to reservoir and rain WF with healthier eating scores warrants further investigation, especially as we face an uncertain future of climate change and progressively unequal freshwater availability worldwide.

IX. CONCLUDING REMARKS

This dissertation examined how food GHG emissions and food WF were associated with a range of health indicators. The first chapter focused on obesity, and found no association between a foods' associated weight gain and GHG emission. However, meaningful overlaps were observed. There were a cluster of foods that have low impacts on weight and CO_2e production, specifically whole grains, whole fruits, vegetables, and nuts. The consumption of these foods are consistent with healthy eating patterns, such as the traditional Mediterranean Diet. Hence, it appears possible to develop a diet that reduces GHG emissions and obesity premised primarily on the careful selection of whole plant based foods.

The second chapter examined diet related NCDs, obesity, life expectancy, and undernutrition, and how country food supply GHG emissions associate with these particular country health outcomes. After adjustment for country socioeconomic and lifestyle characteristics, there were no associations found for any of the health outcomes. However, there were large variation in country health indicators at every level of GHG emissions, and some countries had both low food-related GHG emissions and favorable health statistics. Further examination of diets within these countries is warranted, as they may provide models for sustainable diets.

The third chapter evaluated how healthfulness of diet pertaining to chronic disease prevention, as measured by the Alternative Health Index Score, relates to food WF categories within a cohort of US women. Minimal associations were found, but the directionality of the relationship with reservoir WF and rain WF were not in the direction that would be favorable in a world of growing water scarcity. Healthier diet scores had slightly more negative impacts on global water reservoirs, which is of most importance in relation to water sustainability. There were also indications of slightly less rain water with healthier consumption. In an ideal world, all crops would be rain fed. The observation that less rain was related to diets that were conducive to health is troublesome. Hence, these results do not seem to indicate that healthier eating will trend with sustainable food water footprints.

In summary, the three chapters of this dissertation reveal that further work is warranted. Efforts that will enable the adoption of effective policies to address both dietary quality and the reduction of food carbon footprints simultaneously, without exacerbating undernutrition or global water reservoir scarcity, should continue. The importance of such work is paramount as we face an uncertain future of climate change and progressively unequal freshwater availability worldwide.

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XI. SUPPLEMENTAL MATERIAL

Supplementary Table 2.1 (1 of 5): Total Country Food GHG Emissions Based on Daily Food Supply Weight Per Capita

Rank	Country	CO_2e per Daily Capita Food Weight (kg / daily capita kg)
1	Luxembourg	4.64
2	Australia	4.41
3	United States of America	4.36
4	Mongolia	4.32
5	New Zealand	4.26
6	Iceland	3.85
7	Argentina	3.85
8	Bermuda	3.82
9	French Polynesia	3.78
10	Sweden	3.66
11	France	3.66
12	Canada	3.61
13	Greece	3.60
14	Denmark	3.59
15	Turkmenistan	3.56
16	Kuwait	3.51
17	Ireland	3.49
18	Austria	3.45
19	Finland	3.42
20	Switzerland	3.41
21	Italy	3.39
22	Brazil	3.34
23	Norway	3.34
24	United Kingdom	3.31
25	Bahamas	3.30
26	Portugal	3.29
27	Belgium	3.22
28	Slovenia	3.20
29	Germany	3.20
30	Netherlands	3.17
31	Israel	3.13
32	Spain	3.07
33	Kazakhstan	3.03
34	Malta	2.96
35	Lithuania	2.87
36	Samoa	2.85

Supplementary Table 2.1 (continued, 2 of 5): Total Country Food GHG Emissions Based on Daily Food Supply Weight Per Capita

Rank	Country	CO_2e per Daily Capita Food Weight (kg / daily capita kg)
37	Netherlands Antilles	2.88
38	Estonia	2.86
39	United Arab Emirates	2.82
40	Belarus	2.77
41	Antigua and Barbuda	2.77
42	Albania	2.77
43	Lebanon	2.70
44	Venezuela	2.69
45	Romania	2.67
46	Barbados	2.67
47	Czech Republic	2.64
48	Russia	2.63
49	Montenegro	2.62
50	Brunei Darussalam	2.61
51	Dominica	2.59
52	Croatia	2.54
53	Armenia	2.53
54	New Caledonia	2.53
55	China	2.51
56	Saint Vincent & the Grenadines	2.50
57	Costa Rica	2.49
58	Saint Lucia	2.49
59	Poland	2.48
60	Cyprus	2.44
61	Myanmar	2.43
62	Viet Nam	2.43
63	Japan	2.41
64	Panama	2.39
65	Chile	2.34
66	South Korea	2.33
67	Hungary	2.33
68	Kyrgyzstan	2.31
69	Mexico	2.31
70	Uruguay	2.31
71	Latvia	2.3
72	Cuba	2.17

Supplementary Table 2.1 (3 of 5): Total Country Food GHG Emissions Based on Daily Food Supply Weight Per Capita

Rank	Country	CO_2e per Daily Capita Food Weight (kg / daily capita kg)
73	Colombia	2.16
74	Bolivia	2.14
75	Saint Kitts and Nevis	2.12
76	Ecuador	2.10
77	Fiji	2.10
78	Laos	2.10
79	Ukraine	2.06
80	Azerbaijan	2.06
81	Mauritius	2.01
82	South Africa	2.00
83	Jamaica	2.00
84	Uzbekistan	1.98
85	Malaysia	1.96
86	Cambodia	1.96
87	Grenada	1.95
88	Iran	1.94
89	Slovakia	1.94
90	Serbia	1.93
91	Mauritania	1.93
92	Guyana	1.90
93	Bosnia and Herzegovina	1.89
94	Dominican Republic	1.87
95	Macedonia	1.84
96	Egypt	1.84
97	Saudi Arabia	1.83
98	Thailand	1.83
99	Philippines	1.79
100	Bulgaria	1.78
101	Jordan	1.76
102	Cape Verde	1.76
103	Turkey	1.74
104	Suriname	1.71
105	Mali	1.70
106	Syrian Arab Republic	1.69
107	Trinidad and Tobago	1.68
108	Paraguay	1.68

Supplementary Table 2.1 (4 of 5): Total Country Food GHG Emissions Based on Daily Food Supply Weight Per Capita

Rank	Country	CO_2e per Daily Capita Food Weight (kg / daily capita kg)
109	Libya	1.67
110	Central African Republic	1.65
111	Bangladesh	1.61
112	Sudan	1.59
113	Vanuatu	1.58
114	Belize	1.58
115	Gabon	1.56
116	Tunisia	1.55
117	Niger	1.55
118	Algeria	1.54
119	Seychelles	1.54
120	Pakistan	1.52
121	Djibouti	1.51
122	Kiribati	1.47
123	Madagascar	1.47
124	Swaziland	1.45
125	Indonesia	1.44
126	El Salvador	1.43
127	Honduras	1.41
128	Guinea	1.41
129	Morocco	1.41
130	Senegal	1.40
131	Georgia	1.39
132	Namibia	1.38
133	Moldova	1.34
134	Nepal	1.34
135	Solomon Islands	1.33
136	Kenya	1.32
137	Peru	1.28
138	Guinea-Bissau	1.26
139	Sao Tome and Principe	1.26
140	Nicaragua	1.24
141	Sri Lanka	1.17
142	Botswana	1.16
143	Benin	1.16
144	India	1.13

Supplementary Table 2.1 (5 of 5): Total Country Food GHG Emissions Based on Daily Food Supply Weight Per Capita

Rank	Country	CO_2e per Capita Food Supply Weight (kg / kg daily capita)
145	Palestine	1.13
146	Côte d'Ivoire	1.12
147	Cameroon	1.05
148	North Korea	1.05
149	Tajikistan	1.04
150	Guatemala	1.04
151	Tanzania	1.03
152	Comoros	1.02
153	Sierra Leone	1.02
154	Liberia	1.02
155	Angola	1.01
156	Nigeria	1.01
157	Burkina Faso	1.01
158	Ghana	1.01
159	Haiti	0.98
160	Chad	0.98
161	Timor-Leste	0.97
162	Gambia	0.97
163	Uganda	0.95
164	Zimbabwe	0.94
165	Yemen	0.90
166	Togo	0.83
167	Lesotho	0.81
168	Mozambique	0.75
169	Rwanda	0.71
170	Malawi	0.68
171	Zambia	0.68
172	Congo	0.66
173	Burundi	0.66
174	Eritrea	0.57
175	Ethiopia	0.57
176	Ethiopia	0.57
177	Eritrea	0.57

Supplementary Table 2.2 (1 of 6): *Food Carbon Scope* Modeled Food Items

Food Item	Food Carbon Footprint (CO_2e kg / food kg)
Cereals - Excluding Beer	
Wheat (median)	**0.35**
Wheat, winter, conventional, USA	0.41
Wheat, winter wheat, conventional, intensive, UK	0.39
Wheat, conventional (conservation tillage), OH, USA	0.35
Wheat, conventional, for grain, CA, USA	0.32
Wheat, Hard Red Spring Wheat, conventional, Eastern ID, USA	0.35
Wheat, Hard Red Spring Wheat, conventional, Northern ID, USA	0.48
Wheat, Soft White Spring, conventional, Southcentral ID, USA	0.34
Wheat, Hard Red Winter Wheat, conventional (lower rainfall dryland), Eastern ID, USA	0.69
Wheat, Hard White Spring Wheat, conventional (lower rainfall dryland), Eastern ID, USA	0.41
Wheat, Hard White Spring Wheat, conventional, Eastern ID, USA	0.34
Wheat, winter wheat, conventional, Sweden	0.30
Wheat, Winter Wheat, conventional,Southwestern ID, USA	0.22
Rice (median)	**2.25**
Rice, brown, conventional (long term continuous rice culture, intermittently flooded), CA, USA	2.16
Rice, brown, conventional (rice only rotation, continuously flooded), CA, USA	2.99
Rice, brown, conventional (two year crop rotation, intermittently flooded), CA, USA	2.15
Rice, brown, conventional (long term continuous rice culture, intermittently flooded), CA, USA	2.16
Rice, conventional, USA	2.07
Rice, white, conventional (long term continuous rice culture, intermittently flooded), CA, USA	2.35
Rice, white, conventional (rice only rotation, continuously flooded), CA, USA	3.25
Rice, white, conventional (two year crop rotation, intermittently flooded), CA, USA	2.34
Rice, brown, conventional (long term continuous rice culture, intermittently flooded), CA, USA	2.16
Rice, brown, conventional (rice only rotation, continuously flooded), CA, USA	2.99
Barley (median)	**0.31**
Barley, conventional, Sweden	0.37
Barley, Malting Barley, conventional (higher rainfall dryland), Eastern ID, USA	0.30
Barley, Malting Barley, conventional, Blaine/Lincoln, Southcentral ID, USA	0.35
Barley, Malting Barley, conventional, Eastern ID, USA	0.28
Barley, Malting Barley, conventional, Magic Valley, Southcentral ID, USA	0.31
Maize (median)	**0.32**
Corn, conventional, Midwest, USA	0.25
Corn, conventional, Switzerland	0.17
Corn, conventional, Upper Midwest, USA	0.23
Corn, conventional, USA	0.33
Corn, Field Corn, conventional, for grain, Sacramento Valley, CA, USA	0.33
Corn, Sweet Corn (early season), conventional (small farm, full till, hand harvested), PA, USA	0.35
Corn, Sweet Corn (mid to late season), conventional (small farm, no till, machine harvested), PA, USA	0.31
Corn, Sweet Corn (mid to late season), conventional, (small farm, no till, hand harvested), PA, USA	0.33
Corn, Sweet Corn (mid to late season), conventional, (small farm, no till, hand harvested), PA, USA	0.33
Corn, Sweet Corn, conventional (hand harvested, for retail), OH, USA	0.19
Corn, Sweet Corn, conventional (machine harvested, for wholesale), OH, USA	0.19
Corn, Sweet Corn, conventional, for fresh eating, CA, USA	0.35
Rye	**0.25**
Rye, conventional, Switzerland	0.25
Oats (median)	**0.29**
Oats, conventional, Northern ID, USA	0.31
Oats, conventional, Switzerland	0.27
Sorghum (median)	**0.42**
Sorghum, conventional, for grain, CA, USA	0.28
Sorghum, conventional, USA	0.56
Millet (median value from cereals group**)**	**0.32**
Cereals, other (median value from cereals group**)**	**0.32**
Maize (median)	**0.32**
Corn, conventional, Midwest, USA	0.25
Corn, conventional, Switzerland	0.17
Corn, conventional, Upper Midwest, USA	0.23
Corn, conventional, USA	0.33

Supplementary Table 2.2 (continued, 2 of 6): *Food Carbon Scope* Modeled Food Items

Food Item	Food Carbon Footprint (CO₂e kg / food kg)
Starchy Roots	
Cassava (median value of starchy roots group**)**	**0.31**
Potatoes (median)	**0.18**
Potatoes, conventional, autumn/winter, Sweden	0.09
Potatoes, conventional, CA, USA	0.33
Potatoes, conventional, early summer, Sweden	0.15
Potatoes, conventional, Switzerland	0.08
Potatoes, conventional, USA	0.19
Potatoes, Russet Burbank, conventional (no storage), Eastern ID, USA	0.18
Potatoes, Russet Burbank, conventional (on-farm storage), Eastern ID, USA	0.23
Sweet Potatoes	**0.43**
Sweet Potatoes, conventional, CA, USA	0.43
Yams (assumed same as sweet potatoes)	**0.43**
Roots, other (median)	**0.09**
Beets, red, conventional, irrigated, Sweden	0.09
Daikon Radish, conventional (small farm), CA, USA	0.16
Carrots, conventional, for fresh eating, CA, USA	0.11
Carrots, conventional, integrated, Sweden	0.04
Carrots, conventional, Sweden	0.08
Sugarcrops	
Sugar Cane (median)*	**0.85**
Sugar, raw, cane, Brazil	1.51
Sugar, raw, cane, Mauritius	0.18
Sugar Beet (median)	**0.05**
Beets, Sugarbeets, conventional, CA, USA	0.05
Beets, sugarbeets, conventional, Sweden	0.06
Beets, sugarbeets, conventional, Switzerland	0.05
Sugar & Sweeteners	
Sugar, non-centrifugal	**3.94**
Sugar, refined, cane, Brazil	3.94
Sugar (raw equivalent, median value of sugar & sweetener group)	2.14
Sweeteners, other	**0.33**
Corn Syrup, conventional, Midwest, USA	0.33
Pulses	
Beans (median)	**0.75**
Beans, Baby Lima, conventional, CA, USA	0.63
Beans, Blackeye, conventional (double cropped), CA, USA	0.56
Beans, Blackeye, conventional (single cropped), CA, USA	0.56
Beans, common dry varieties, conventional (double cropped), Sacramento Valley, CA, USA	1.03
Beans, common dry varieties, conventional (double cropped), San Joaquin Valley North, CA, USA	0.95
Beans, Dry Beans, conventional (concrete ditch & siphon tube irrig.), Southwestern ID, USA	0.75
Beans, Dry Beans, conventional, Southcentral ID, USA	0.80
Beans, Dry Beans, conventional, Switzerland	0.29
Beans, Large Lima, conventional, CA, USA	1.15
Beans, Lima/Blackeye, conventional (single cropped), CA, USA	0.76
Dry Beans, conventional, USA	0.82
Garbanzos (chick-peas), conventional, Northern ID, USA	0.64
Lentils, conventional, Northern ID, USA	0.53
Peas (median)	**0.10**
Peas, green, conventional, Sweden	0.10
Peas, green, conventional, Switzerland	0.10
Peas, Spring Peas, conventional, Northern ID, USA	0.29
Treenuts (median)	**1.39**
Pecans, conventional (flood irrig.), CA, USA	1.61
Pistachios, conventional (low-volume irrig.), CA, USA	1.11
Almonds, conventional (flood irrig.), CA, USA	1.89
Almonds, conventional (low-volume sprinkler irrig.), CA, USA	2.45
Almonds, conventional (micro-sprinkler irrig.), San Joaquin Valley North, CA, USA	2.47
Almonds, conventional (micro-sprinkler irrig.), San Joaquin Valley South, CA, USA	1.39
Walnuts, conventional (micro-sprinkler irrig.), CA, USA	0.76
Walnuts, Chandler Variety, conventional (small farm/homesite), CA, USA	0.49
Walnuts, English Variety, conventional (sprinkler irrig.), CA, USA	0.90

Supplementary Table 2.2 (continued, 3 of 6): *Food Carbon Scope* Modeled Food Items

Food Item	Food Carbon Footprint (CO2e kg / food kg)
Oilcrops	
Soyabeans (median)	**0.56**
Soybeans, conventional (round-up ready, no tillage), OH, USA	0.56
Soybeans, conventional, Major States, USA	0.59
Soybeans, conventional, Switzerland	0.51
Groundnuts	**0.57**
Peanuts, conventional, CA, USA	0.57
Sunflowerseed	**0.88**
Sunflower Seed, conventional, France	0.88
Rape and Mustardseed (median)	**0.89**
Rape Seed, summer rape, conventional, Sweden	0.89
Rape Seed, winter rape, conventional, Sweden	0.58
Yellow Mustard, conventional, Northern ID, USA	1.01
Palmkernels	**0.33**
Palm Kernels, conventional, Malaysia	0.33
Olives	**0.18**
Olives, conventional, CA, USA	0.18
Cottonseed (median value of oilcrops group)	**0.57**
Coconuts, including copra (median value of oilcrops group)	**0.57**
Sesame (median value of oilcrops group)	**0.57**
Oilcrops, other (median value of oilcrops group)	**0.57**
Vegetable Oils	
Soyabean Oil (median)	**1.48**
Soybean Oil, Argentina	1.47
Soybean Oil, USA	1.48
Groundnut Oil	**3.90**
Peanut Oil, conventional, USA	3.90
Sunflowerseed Oil	**1.48**
Sunflower Oil, Europe	1.48
Rape and Mustard Oil	**1.70**
Rapeseed/Canola Oil, Europe	1.70
Palmkernel Oil	**0.91**
Palm Kernel Oil, conventional, Malaysia	0.91
Palm Oil	**0.44**
Palm Oil, conventional, Malaysia	0.44
Maize Germ Oil	**0.25**
Corn Oil, conventional, Midwest, USA	0.25
Coconut Oil (median value from vegetable oils group)	**1.48**
Sesameseed Oil (median value from vegetable oils group)	**1.48**
Ricebran Oil (median value from vegetable oils group)	**1.48**
Oilcrops Oil, Other	**1.75**
Cooking/Salad Oil, USA	1.75
Vegetables	
Tomatoes (median)	**0.12**
Tomatoes, Cherry, conventional, (small farm, from transplants), Califorina, USA	0.07
Tomatoes, conventional (direct seeded), for processing, CA, USA	0.10
Tomatoes, conventional (from transplants), for processing, CA, USA	0.08
Tomatoes, conventional (furrow irrig., from transplants), CA, USA	0.24
Tomatoes, conventional (smal farm, drip irrig.), PA, USA	0.50
Tomatoes, conventional, Spain	0.18
Tomatoes, conventional, USA	0.12
Onions (median)	**0.08**
Onions, conventional, for dehydrating, Southeast Interior, CA, USA	0.08
Onions, conventional, Southeast Interior, CA, USA	0.08
Vegetables, Other (median)	**0.19**
Artichokes, conventional, CA, USA	0.26
Asparagus, conventional (small farm, drip irrig.), PA, USA	0.88
Beans, green, conventional, irrigated, Sweden	0.14
Broccoli, conventional, CA, USA	0.36
Broccoli, conventional, irrigated, Sweden	0.37
Brussels Sprouts, conventional, USA	0.26
Cabbage, conventional, USA	0.10
Cabbage, white, conventional, irrigated, Sweden	0.10
Celery, conventional, CA, USA	0.12
Cucumber, conventional, irrigated, Sweden	0.05
Garlic, conventional (small farm, drip irrig.), PA, USA	0.95
Lettuce, crisp-head , conventional, Sweden	0.13
Lettuce, Iceberg, conventional, CA, USA	0.19
Lettuce, Romaine Hearts, conventional, CA, USA	0.92

Supplementary Table 2.2 (continued, 4 of 6): *Food Carbon Scope* Modeled Food Items

Food Item	Food Carbon Footprint (CO_2e kg / food kg)
Vegetables, Other (cont.)	
Mushrooms, Portabella/Button, conventional, USA	0.00
Peppers, Bell, conventional (drip irrig.), CA, USA	0.26
Pumpkins, conventional (small farm, drip irrig.), PA, USA	0.14
Squash, conventional, irrigated, Sweden	0.06
Fruits - Excluding Wine	
Oranges, Mandarines (median)	**0.20**
Mandarin Oranges, Murcott Variety, conventional, CA, USA	0.19
Mandarin Oranges, Satsuma, conventional, CA, USA	0.21
Oranges, Blood Oranges, conventional (low volume irrig.), CA, USA	0.17
Oranges, conventional, USA	0.10
Oranges, Minneola (Tangelo), conventional (low volume irrig.), CA, USA	0.12
Oranges, Navel/Valencias, conventional (low volume irrig.), CA, USA	0.13
Oranges, Valencia, conventional (drip irrig., w/o canker-greening), for processing, Southwest FL, USA	1.46
Oranges, Valencia, conventional (drip irrig., with canker-greening), for processing, Southwest FL, USA	1.69
Oranges, Valencia, conventional (microsprinkler irrig., w/o canker-greening), for processing, Central FL, USA	1.35
Oranges, Valencia, conventional (microsprinkler irrig., with canker-greening), for processing, Central FL, USA	1.62
Lemons, Limes	**0.09**
Lemons, Lisbon Variety, conventional (low volume irrig.), CA, USA	0.09
Grapefruit (median value of citrus fruits)	**0.15**
Bananas (median)	**0.29**
Bananas, conventional, Hawaii	0.28
Bananas, conventional, New South Wales, Australia	0.30
Plaintain (assuming equivalent value to bananas)	**0.29**
Pineapples (median)	**0.08**
Pineapple, conventional, Costa Rica	0.08
Dates (median)	**0.62**
Fruits/Berries:Dates, Deglet Noor (Grade B - "US Choice"), conventional (flood irrig.), CA, USA	0.88
Fruits/Berries:Dates, Deglet Noor (Grade C - "US Standard"), conventional (flood irrig.), CA, USA	0.36
Grapes (median)	**0.55**
Grapes, conventional (small farm), for processing, OH, USA	0.29
Grapes, conventional (small farm, with on-farm storage), for processing, OH, USA	0.55
Grapes, Thompson Seedless, conventional (continuous tray-dried), for raisins, CA, USA	0.67
Grapes, conventional (small farm), for table grapes, OH, USA	0.83
Grapes, conventional (small farm, with on-farm storage), for table grapes, OH, USA	1.57
Grapes, Thompson Seedless, conventional, for table grapes, CA, USA	0.20
Grapes, Redglobe, conventional, for table grapes, CA, USA	0.17
Apples (median)	**0.07**
Apples, conventional, France	0.03
Apples, conventional, New Zealand	0.07
Apples, conventional, Sweden	0.07
Apples, conventional, UK	0.26
Apples, conventional, USA	0.16
Apples, conventional (small farm), for fresh eating, CA, USA	0.23
Apples, conventional (small farm), for processing, CA, USA	0.01
Fruits, Other (median)	**0.15**
Apricots, conventional (micro-sprinkler irrig.), for fresh eating, CA, USA	0.23
Apricots, conventional (micro-sprinkler irrig.), for processing, CA, USA	0.15
Apricots, conventional (micro-sprinkler irrig., small farm), for drying, CA, USA	0.15
Cantaloupe, conventional (mid bed trench irrig.), CA, USA	0.14
Cantaloupe, conventional (slant bed irrig.), CA, USA	0.14
Cherries, conventional, CA, USA	0.18
Cherries, conventional, Switzerland	0.24
Melon, Watermelon, conventional (small farm, drip irrig.), PA, USA	0.03
Melons, Cantaloupe/watermelon/honeydew/specialty, conventional (small farm), CA, USA	0.14
Pineapple, conventional, Costa Rica	0.08
Peaches, conventional, CA, USA	0.22
Plums, conventional (furrow irrig.), CA, USA	0.22

Supplementary Table 2.2 (continued, 5 of 6): *Food Carbon Scope* Modeled Food Items

Food Item	Food Carbon Footprint (CO_2e kg / food kg)
Coffee	**2.51**
Coffee, roasted and ground (from Brazilian beans), USA	2.51
Cocoa Beans	**0.57**
Cocoa Beans, conventional, Ghana	0.57
Wine (median)	**0.44**
Medium White Wine, CA, USA	0.44
New Red Wine, CA, USA	0.43
Premium Red Wine, CA, USA	0.43
Premium White Wine, CA, USA	0.44
Beer	**0.38**
Beer, USA	0.38
Beverages, Fermented (median value of beer & wine)	**0.41**
Beverages, Alcoholic	**2.74**
Malt Whisky, USA	2.74
Bovine Meat (median)	**15.15**
Beef Meat, conventional, fresh, New Zealand	11.16
Beef Meat, conventional, fresh, UK	15.90
Beef Meat, Conventional, ration fed, AL, USA	12.76
Beef Meat, Conventional, ration fed, ID, USA	14.39
Beef Meat, Conventional, ration fed, NE, USA	17.12
Beef Meat, Pasture fed (hypothetical), ID, USA	15.99
Mutton & Goat Meat (median)	**20.44**
Lamb Meat, conventional, fresh, New Zealand	31.30
Lamb Meat, conventional, fresh, UK	17.57
Lamb Meat, Conventional, ration fed, 150% crop, OH, USA	20.44
Lamb Meat, Conventional, ration fed, 175% crop, OH, USA	18.42
Lamb Meat, Conventional, ration fed, ID, USA	24.38
Pig Meat (median)	**4.95**
Pork Meat, conventional, fresh, UK	6.35
Pork Meat, Conventional, full confinement, average production, MI, USA	4.60
Pork Meat, Conventional, full confinement, high production, MI, USA	4.27
Pork Meat, Conventional, full confinement, IA, USA	4.95
Pork Meat, Conventional, pasture access, IA, USA	5.60
Poultry Meat (median)	**4.11**
Chicken Meat (broiler), Large-scale, confinement, BC, Canada	3.09
Chicken Meat (broiler), Large-scale, confinement, commercial ration, BC, Canada	3.25
Chicken Meat (broiler), Small-scale, free-range, BC, Canada	5.12
Chicken Meat (broiler), Small-scale, free-range, KS, USA	7.52
Chicken, at farm, Denmark	1.66
Poultry Meat, conventional, fresh, UK	6.28
Turkey Meat (Hens), Small-scale, confinement, PA, USA	4.19
Turkey Meat (Toms), Small-scale, confinement, PA, USA	4.02
Meat, other (median value of meat group)	**10.05**
Offals, total (median value of meat group)	**10.05**
Animal Fats	
Butter, Ghee (median)	**10.57**
Butter, conventional, UK	12.40
Butter, conventional, WI, USA	1.17
Butter, organic, UK	14.29
Butter, UK, 2004	10.37
Cream (median)	**0.18**
Cream, sour, conventional, WI, USA	0.22
Cream, whipped fluid, conventional, WI, USA	0.14
Fats, animal, raw (median value of animal fats group)	**5.28**
Fish, body oil (median value of animal fats group)	**5.28**
Fish, liver oil (median value of animal fats group)	**5.28**
Eggs (median)	**2.06**
Eggs (Grade A, X Large, Jumbo, and Medium), Large-scale, free-range, BC, Canada	2.06
Eggs (Grade A, X Large, Jumbo, and Medium), Large-scale, free-range, commercial ration, BC, Canada	2.43
Eggs (Jumbo, X Large, Large, Medium, Small), Large-scale, confinement, commercial ration, NJ, USA	1.89
Eggs (X Large, Jumbo, Large, and Medium), Small-scale, free-range, PA, USA	1.93
Eggs, conventional, UK	5.64
Eggs, Denmark	1.64

Supplementary Table 2.2 (continued, 6 of 6): *Food Carbon Scope* Modeled Food Items

Food Item	Food Carbon Footprint (CO_2e kg / food kg)
Milk - Excluding Butter (median)	**1.02**
Milk, whole, conventional, New Zealand, 2004	0.75
Milk, whole, conventional, UK	1.04
Milk, whole, conventional, UK, 2004	0.86
Milk, whole, raw, Conventional, ration fed, ID, USA	1.11
Milk, whole, raw, Conventional, ration fed, high productivity, WI, USA	1.03
Milk, whole, raw, Conventional, ration fed, low productivity, WI, USA	1.17
Fish & Seafood	
Freshwater Fish (median)	**8.86**
Arctic Char, farmed, Canada	9.73
Arctic Char, farmed, filleted, Canada	17.92
Catfish, farmed, filleted, Louisiana, USA	8.86
Catfish, farmed, Louisiana, USA	4.22
Catfish, farmed, filleted, Louisiana, USA	8.86
Common Carp, farmed, filleted, Israel	9.06
Common Carp, farmed, Israel	4.81
Trout, freshwater, farmed, Denmark	2.02
Trout, freshwater, farmed, filleted, Denmark	3.93
Silver Carp, farmed, filleted, Israel	9.06
Silver Carp, farmed, Israel	4.81
Tilapia, farmed, filleted, Israel	10.07
Tilapia, farmed, Israel	4.81
Demersal Fish (median)	**3.68**
Atlantic Cod, Europe	2.22
Atlantic Cod, filleted, Europe	4.77
Flatfish, Europe	2.58
Flatfish, filleted, Europe	5.49
Pelagic Fish (median)	**2.39**
Herring, Europe	0.75
Mackerel, Europe	0.65
Mackerel, filleted, Europe	1.43
Tuna, filleted, Europe	2.95
Atlantic Salmon, farmed, based on aggregate data, Canada	2.29
Atlantic Salmon, farmed, based on aggregate data, Chile	2.64
Atlantic Salmon, farmed, based on aggregate data, filleted, Canada	4.38
Atlantic Salmon, farmed, based on aggregate data, filleted, Chile	5.04
Atlantic Salmon, farmed, based on aggregate data, filleted, Norway	3.61
Atlantic Salmon, farmed, based on aggregate data, Norway	1.89
Atlantic Salmon, farmed, Canada	2.39
Atlantic Salmon, farmed, filleted, Canada	4.57
Marine Fish, Other (median)	**6.98**
Sea Bass, farmed, filleted, Thailand	9.22
Sea Bass, farmed, Thailand	4.74
Crustaceans (median)	**5.73**
Shrimp, farmed, Thailand	12.40
Shrimp, farmed, USA	6.57
Shrimp/Prawn, Europe	4.08
Norway Lobster, Europe	4.89
Molluscs, Other (median)	**5.49**
Mussels, Europe	0.04
Oyster, farmed, Hawaii, USA	10.94
Aquatic Products, Other	
Meat, Aquatic Mammals (median value of fish & seafood)	**5.61**
Aquatic Animals, Others (median value of fish & seafood)	**5.61**
Aquatic Plants (median value of vegetables)	**0.12**
Miscellaneous (median value of all foods, including those from the literature)	**0.70**

Supplementary Table 2.3: Food CO_2e Values (Seed to Farm Production) from the Literature

Food Item	Food Carbon Footprint (CO_2e kg / food kg)	Source
Tea	0.70	Soret, S., Mejia, A., Batech, M., Jaceldo-Siegl, K., Harwatt, H., & Sabaté, J. (2014). Climate change mitigation and health effects of varied dietary patterns in real-life settings throughout North America. *The American Journal of Clinical Nutrition*, ajcn-071589.
Olive Oil	2.57	Iraldo, F., Testa, F., & Bartolozzi, I. (2014). An application of Life Cycle Assessment (LCA) as a green marketing tool for agricultural products: the case of extra-virgin olive oil in Val di Cornia, Italy. *Journal of Environmental Planning and Management*, *57*(1), 78-103.
Honey	1.00	Scarborough, P., Appleby, P. N., Mizdrak, A., Briggs, A. D., Travis, R. C., Bradbury, K. E., & Key, T. J. (2014). Dietary greenhouse gas emissions of meat-eaters, fish-eaters, vegetarians and vegans in the UK. *Climatic Change*, 1-14.
Pimento	3.20	Scarborough, P., Appleby, P. N., Mizdrak, A., Briggs, A. D., Travis, R. C., Bradbury, K. E., & Key, T. J. (2014). Dietary greenhouse gas emissions of meat-eaters, fish-eaters, vegetarians and vegans in the UK. *Climatic Change*, 1-14.
Pepper	2.50	Scarborough, P., Appleby, P. N., Mizdrak, A., Briggs, A. D., Travis, R. C., Bradbury, K. E., & Key, T. J. (2014). Dietary greenhouse gas emissions of meat-eaters, fish-eaters, vegetarians and vegans in the UK. *Climatic Change*, 1-14.
Spices, other	1.60	Scarborough, P., Appleby, P. N., Mizdrak, A., Briggs, A. D., Travis, R. C., Bradbury, K. E., & Key, T. J. (2014). Dietary greenhouse gas emissions of meat-eaters, fish-eaters, vegetarians and vegans in the UK. *Climatic Change*, 1-14.
Citrus, other	0.70	Scarborough, P., Appleby, P. N., Mizdrak, A., Briggs, A. D., Travis, R. C., Bradbury, K. E., & Key, T. J. (2014). Dietary greenhouse gas emissions of meat-eaters, fish-eaters, vegetarians and vegans in the UK. *Climatic Change*, 1-14.
Cephalopods	5.40	Scarborough, P., Appleby, P. N., Mizdrak, A., Briggs, A. D., Travis, R. C., Bradbury, K. E., & Key, T. J. (2014). Dietary greenhouse gas emissions of meat-eaters, fish-eaters, vegetarians and vegans in the UK. *Climatic Change*, 1-14.