Food choices in the United States: opportunities for health and sustainability co-benefits

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Abstract

Evidence indicates that changing from current Western-style dietary patterns can improve health as well as reduce environmental impact from agricultural greenhouse gas emissions (GHGE). However, most studies look only at a single aggregate datapoint, and very few have been conducted on US diets. This dissertation addresses these gaps by using individual self-selected dietary data from adults ages 18+ in the nationally representative National Health and Nutrition Examination Survey (NHANES).

Paper 1 identified consumers who might be willing to change their dietary behaviors for sustainability reasons and calculated changes to diet quality, carbon footprint, and cost if these individuals were to replace beef with other protein foods. Replacing beef with poultry reduced food-related GHGE 35.7%, increased Healthy Eating Index (HEI) score by 1.7%, and reduced diet cost by 1.7%.

Paper 2 developed new commodity recipes to be able to calculate food-related GHGE over a 10-year period. US food-related carbon footprints did not change significantly between 2005-2006 and 2015-2016 (-0.14 kg CO_2-equivalents/2000kcal, p=0.18). However, there were significant differences by socioeconomic and demographic factors. Women had lower food-related emissions than men (-0.38 kg CO_2-equivalents/2000kcal, p<.001), and the Silent Generation, Millennials, and Generation Z had lower food-related emissions than Baby Boomers. These generational differences likely stem from beef consumption significantly declining in all generations except Boomers.

Paper 3 used multivariate Markov Chain Monte Carlo (MCMC) modeling to estimate usual or habitual food-related GHGE and HEI scores for the 2015-2016 NHANES. The usual distribution of food-related GHGE has substantially smaller left and right tails than previous work using 1-day dietary data. However, similar to results with 1-day dietary data, there is a significant inverse relationship (p trend = 0.010) between food-related emissions and diet quality, with the mean HEI score of low-GHGE diets being 6.5/100 points higher than high-GHGE diets.

Substantial environmental benefits are possible from dietary changes, especially those that reduce beef consumption and replace it with poultry or plant-based protein foods, and diets with these characteristics tend to have higher diet quality. However, US diets are not moving in the desired direction with respect to diet quality or climate impacts. More efforts, such as nutrition education programs, social marketing, and inclusion of sustainability in the Dietary Guidelines for Americans, are needed to achieve health and environment co-benefits.

Acronyms

Your guide to the alphabet soup:

24HR:	24-hour dietary recall
CNPP:	Center for Nutrition Policy and Promotion
CVD:	Cardiovascular disease
dataFIELD:	database of Food Impacts on the Environment for Linking to Diets
DGA:	Dietary Guidelines for Americans
DGAC:	Dietary Guidelines Advisory Committee
DHHS:	Department of Health and Human Services
EPA:	US Environmental Protection Agency
ERS:	USDA Economic Research Service
FAO:	Food and Agriculture Organization of the United Nations (UN)
FCID:	Food Commodities Intake Database
FDC:	USDA FoodData Central
FNDDS:	Food and Nutrient Database for Dietary Studies
FPED:	Food Patterns Equivalents Database
GHGE:	Greenhouse Gas Emissions (aka carbon footprint)
HEI:	Healthy Eating Index
IPR:	Income-to-poverty ratio (aka PIR)
LCA:	Life Cycle Assessment
NCD:	Noncommunicable disease
NCI:	National Cancer Institute
NHANES:	National Health and Nutrition Examination Survey
PSU:	Primary sampling unit
SR28:	USDA National Nutrient Database for Standard Reference, Release 28
UN:	United Nations
US:	United States
USDA:	United States Department of Agriculture

Background and Significance

1. Public health problem: non-communicable diseases

Non-communicable diseases (NCDs) are a leading cause of morbidity and mortality globally and in the United States (US).[1] NCDs, which include cardiovascular disease, cancer, chronic respiratory diseases, and diabetes, can result from a combination of genetic, behavioral, and environmental risk factors. Dietary intake is a modifiable risk factor for three of the major NCD categories: cardiovascular disease, cancers, and diabetes. In the US these three disease categories caused 65% of all deaths and accounted for 37% of the burden of disease (in disability-adjusted life years or DALYs) in 2019.[2]

An estimated 18% of mortality and 11% of disease burden in US adults are attributable to dietary risk factors (such as low consumption of fruits and vegetables and high consumption of red or processed meats).[3] Diet quality, combined with excess energy intake and reduced physical activity, also lead to obesity. High body mass index is an additional risk factor for NCDs, and is the second largest driver of death and disability combined in the US, eclipsed only by tobacco use.[4,5]

2. Diet and health

Measured in any number of ways—intake of food groups (e.g., fruits), intake of micronutrients (e.g., vitamin C), whole diet patterns (e.g., a Mediterranean diet), or diet quality indices (e.g., the Healthy Eating Index)—food choice is related to risk of NCDs. Evidence links dietary intake to health outcomes both directly as well as indirectly via intermediates such as blood pressure, blood sugar regulation, serum cholesterol, and obesity. See Table B-1 for a selection of relationships supported by meta-analyses.

It is a long-standing national priority to promote healthier diets in order to reduce the risk of these diseases.[31] A cornerstone of these efforts is the Dietary Guidelines for Americans (DGA), produced every five years by the USDA and the DHHS.[32] Each update of the DGA is developed based on extensive literature reviews and the input of an expert Dietary Guidelines Advisory Committee (DGAC). The DGA are used to inform nutrition education materials (e.g., MyPlate or the older MyPyramid) as well as government-run nutrition efforts such as the National School Lunch Program and the Special

Table B-1. Dietary components that reduce the risk of non-communicable diseases: selected meta-analyses

	Decreased risk of		
	CVD	**Diabetes**	**Cancer**
Food and food group intakes			
↑ Fruit	X[6]		X[6,7]
↑ Vegetables	X[6]	X[8]	X[6,7]
↑ Whole grains	X[9,10]	X[10]	X[10]
↑ Fish	X[11]		
↓ Processed meat	X[12,13]	X[12,13]	X[13]
Nutrient intakes			
↑ Omega-3 fatty acids	X[14]		
↑ Fiber	X[15]	X[16]	X[17]
↓ Saturated fats	X[9]	X[16]	X[18]
↓ Trans fats	X[19]		
↓ Cholesterol			X[20]
Diet patterns			
↑ Mediterranean diet adherence	X[21]	X[22,23]	X[24]
↑ DASH diet adherence	X[25,26]	X[25,27]	X[25,28]
↓ Western diet adherence	X[29]	X[22]	X[30]

Supplemental Nutrition Program for Women, Infants, Children (WIC).

The most recent iterations of the DGA have encouraged a focus on diet patterns as a whole, recognizing that people do not eat individual foods or nutrients in a vacuum, but rather in a variety of combinations and over time. The guidelines encourage eating an appropriate calorie level and choosing a dietary pattern that includes higher amounts of fruits, vegetables, legumes, whole grains, lean meat and poultry, nuts, seeds, and seafood, and lower amounts of red and processed meat, added sugars, and refined grains. Each new edition of the DGA drives home the continued need for interventions to improve food choice in the US. The most recent DGAC's literature review "shows that the American dietary landscape has not changed appreciably over time."[33] Most Americans are still not eating dietary patterns that reflect recommendations to reduce the risk of chronic disease. Dietary behavior is an age-old but still critical point of intervention to improve health and well-being in the US.

3. Diet, health, and environmental impacts

What is the relationship between diet and the environment?

While the impact of food choices on health is widely accepted, greater attention is being paid both by the public and by researchers to the impacts of food choice on the environment. Food choices—especially in high-income countries—create demand and drive agricultural production. Agriculture has numerous environmental impacts, including (but not limited to) emitting greenhouse gasses, consuming fresh water, using scarce land, and contributing to water pollution, to the loss of biodiversity, and to soil degradation.[34] One of the most widely studied environmental impacts is greenhouse gas emissions (GHGE), the primary driver of climate change.[35]

Agriculture accounts for 10-12% of global GHGE, which comes from clearing forests, gasses released by ruminant animals and rice production, and gasses related to manure and fertilizers.[35] Food production overall contributes an even larger share to anthropogenic GHGE when considering fossil fuel use throughout the chain, including transportation, packaging, and energy to process and refrigerate foods, as well as losses in food waste. Estimates of the total impact of global food production are difficult because elements are spread among different economic sectors (agriculture, electrical production, industry). However, the total share of global GHGE from food production is estimated at 30-34%, twice that of transportation (~14%), an area of human behavior that has been targeted to try to reduce emissions.[36-38]

Climate change is a substantial threat to human health[39,40] and to future food security.[41] Combined with the rising global population, it creates a significant challenge to producing enough food to meet dietary needs for all the world's people. It is estimated that global crop production needs to double by 2050.[42] However, this increase in yield must happen without increasing the environmental damage caused by food production.[34] This means that not only are food choices essential to better health for individuals, they can also be a mechanism to reduce global GHGE and contribute to future food security.

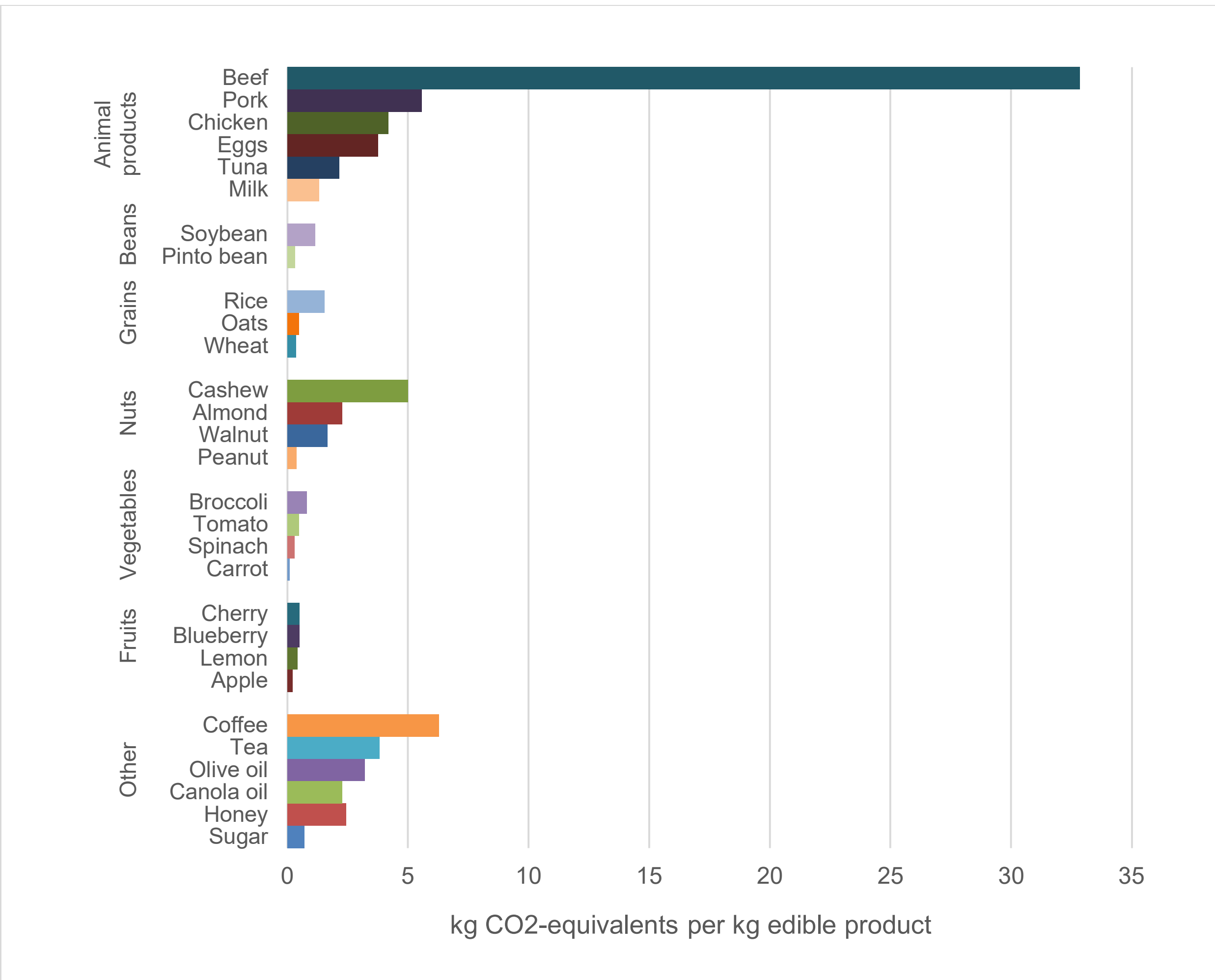
How do different foods compare on GHGE?

Broadly, animal-based foods produce higher GHGE during production than do plant-based foods. Agricultural production emits three types of greenhouse gas emissions: nitrous oxide, methane, and carbon dioxide.[43] Each of these has a different global warming potential.[44]

To measure total emissions associated with a product, the gases are standardized to the warming potential of carbon dioxide—thus the terms “carbon footprint” and “greenhouse gas emissions” are used interchangeably here. The unit for this is CO_2-equivalents (CO_2-eq).

Ruminant animals such as cattle and sheep produce methane by virtue of the fermentation in their digestive systems. In addition, since animals are higher up the food chain, their production of calories and nutrients for human consumption requires more resources than equivalent calories or nutrients directly from plant sources. Beef produces about 33 kg CO_2-eq per kg of edible product, while pork produces 6 and chicken 4 kg CO_2-eq. Meanwhile, grains, vegetables, fruits, and legumes often produce emissions an order of magnitude below that of chicken. See Figure B-1 for a comparison of several foods across different food groups. Data for the chart come from *dataFIELD*, the database of Food Impacts on the Environment for Linking to Diets, details of which have been published[45] and are also described below in the methods for Paper 1 and in Appendix 1.

Figure B-1. Greenhouse gas emissions of selected foods



What is the relationship between diet quality and environmental impacts?

As you can see from Figure B-1, a wide variety of dietary GHGE are possible depending on what a person chooses to eat in a day, in a week, and over the years of their life.

Estimates of mean daily dietary GHGE in high-income countries range from about 2 to 7 daily kg CO_2-eq per person.[45-48] Using individual, self-selected diets in the US, we found a mean of 4.7 kg CO_2-eq per person per day.[45] Diets with low GHGE can be constructed, but these will not necessarily be healthful.[49,50] They are also unlikely to be acceptable to large portions of the population: studies using linear optimization have found diets that meet nutritional requirements with 60% to 90% fewer GHGE, but the diets were very different than current eating patterns.[51-53] For example, the diet that met nutrient requirements with 90% fewer GHGE included only seven foods: "whole-grain breakfast cereal, pasta, peas, fried onions, brassicas (e.g. broccoli, cabbage), sesame seeds, and confectionary."[51]

It seems that reductions in GHGE of about 30% to 40% are the maximum before the diet starts to differ greatly from current consumption.[52-55] For example, one study found that diets with a 30% reduction in GHGE represented about a 20% deviation from the current diet in women, and a 35% deviation in men.[52] While these authors argued that such deviations were realistic policy goals, others would argue that altering the types or portions of one third of the foods you eat is not a simple objective.

Shifting to healthier diet patterns or to recommended diets can reduce food-related GHGE, albeit less than diets targeted specifically toward emissions reductions (around 5-20%).[52,56] This makes sense, since current diet patterns in many high-income countries and certainly in the US include more red and processed meats and more high-fat dairy foods than recommended patterns, and fewer whole grains, fruits, and vegetables. The former animal foods have higher production GHGE, whereas the carbon footprints of the latter plant-based foods are much lower. However, the healthiest diets are not necessarily less impactful.[57]

Communicating with consumers: sustainability in national dietary guidance

There is enough evidence for the impact of food choice on the environment, and for "win-win" scenarios—diets that are healthful and also less impactful—that the 2015 US Dietary Guidelines Advisory Committee (DGAC) suggested that sustainability be incorporated into the DGA. Their systematic review concluded that:

> *"Consistent evidence indicates that, in general, a dietary pattern that is higher in plant-based foods, such as vegetables, fruits, whole grains, legumes, nuts, and seeds, and lower in animal-based foods is more health promoting and is associated with lesser environmental impact (GHG emissions and energy, land, and water use) than is the current average U.S. diet. A diet that is more environmentally sustainable than the average U.S. diet can be achieved without excluding any food groups."*[58]

Giving attention to sustainability was not entirely new; the 2005 and 2010 DGACs had acknowledged the importance and relevance of sustainability to dietary guidance, but had not made specific recommendations. However, the scientific advisory committee does not create the final Dietary Guidelines for Americans. Despite the 2015 Committee's recommendation that sustainability be included as a consideration in the DGA, the secretaries of the agencies involved concluded that this was out of scope. This political position was strengthened in the charter for the 2020 DGAC. For the first time, USDA and DHHS defined and limited the topics that the advisory committee was to review ahead of time. Dietary sustainability was not included.

Other countries have not responded to the growing evidence of food choice and sustainability with the same avoidance. Several countries include some sustainability component in national dietary guidance. These include Canada, Sweden, Qatar, Brazil, Norway, Germany, the Netherlands, France, and the UK.[59-61] Furthermore, publications such as the Rome Declaration on Nutrition (from the UN Food and Agriculture Organization in 2014)[62] and the Decade of Action on Nutrition (from the UN in 2016)[63] show global affirmation of the need for nutrition policy and action to consider climate change and food system sustainability. Numerous scholars concur.[59,64-67]

4. Gaps in the literature

What don't we know about the nexus of diet, health, and sustainability? First of all, while most studies show some clear win-win scenarios where lower food-related GHGE diets are also healthier, this is not always true.[56] While reducing intake of high-impact animal products can usually accomplish both of these goals, the outcomes may depend on what the animal products are replaced with. One US study looking at moving the average current diet toward recommendations found that this would increase food-related emissions, likely due to the amount of dairy recommended in the DGA.[68]

Second, most studies look at aggregate diets (e.g., a national average diet, like the study just mentioned) or hypothetical diets constructed by investigators (e.g., a vegetarian or vegan diet). There is a wide variation in the GHGE of individual self-selected diets in high-income countries like the US.[45,69] Working with national averages misses this nuance. And while hypothetical diets are helpful to understand certain questions, they do not demonstrate the range of ways individuals operationalize their values and priorities into day-to-day food choices.

Third, very few studies have looked at the carbon footprint of US diets. More evidence from the US population is critical. There are certainly similarities between diets in the US and those in other high-income countries; however, food choices happen in a particular context.

This dissertation will address these gaps in the US context by using self-selected dietary intake data from a nationally representative survey and examining opportunities for lower-GHGE food choices which also improve diet quality.

There are, of course, gaps and challenges in the literature that, although they are outside the scope of the studies presented here, are still important to note. Sustainability in the diet is a multifaceted topic with many more components than just GHGE. There are additional environmental impacts (water use, land use, biodiversity loss, and more), and these metrics do not always align, presenting potential trade-offs. For example, while nuts have a lower GHGE of production than most animal foods, their water use can still be quite high.[70] Seafood is also a food group that presents challenges. Intake of high-omega-3 fish products is relatively low in the US compared to recommendations. At the same time, many of the world's fish stocks are already overfished, and aquaculture practices have unintended and sometimes harmful consequences.[71]

Sustainable diets also include social elements. Recommendations and goals for these dietary changes need to be accessible—physically and financially—as well as culturally acceptable.[72] And consumers are only one of many stakeholders involved in order to make changes to global food systems. Policy makers and those in all elements of food production must work together to achieve what some are calling “the Great Food Transformation.”[64] Evidence in all these fields continues to grow, and there is a continued need for interdisciplinary work in order to move toward the global goals of nutritious diets and future food security.

5. Overall dissertation purpose

The proposed dissertation will explore the distribution of, and covariates related to, dietary carbon footprints among US adults, with special attention given to how national dietary guidance has the potential to encourage more healthful and more sustainable diets.

Paper 1: Estimating changes to diet healthfulness, carbon footprint, and cost when motivated consumers choose different foods

1. Background

As discussed above, substantial evidence shows that shifting from more typical Western-style diets to a diet higher in plant-based foods is an opportunity to reduce food-related GHGE and improve diet quality (healthfulness). Aggregate studies from other countries are promising on the potential GHGE reductions and health improvements that might occur from this.[56]

However, not all US consumers are willing to or interested in adopting an entirely plant-based or vegetarian lifestyle. Meat eating has strong cultural associations—strength, masculinity, affluence, and even patriotism. But the 2015 DGAC scientific report makes it clear that a diet with health and sustainability co-benefits need not eliminate whole food groups.[58] Campaigns such as Meatless Monday tap into this thinking, encouraging people to eat vegetarian meals one day a week—a goal likely perceived as more achievable by many than giving up a food group entirely.[73] While there has been increased interest in sustainability in general, and in "flexitarian" type eating patterns, it is not clear how many US consumers are ready and willing to reduce the meat intake in their diet, whether that is motivated by health, sustainability, ethics, or something else. A UK study found that health and animal welfare concerns were more salient for consumers than environmental impacts when considering eating meat, and suggested improving consumer knowledge by integrating sustainability information into national dietary guidance.[74]

Even if US dietary guidance were to include sustainability considerations, not all consumers would change their behavior, or change it immediately. This study will give a realistic estimate of the daily impact US consumers could exert on food-related GHGE.

<u>Diet cost as an element of sustainability</u>

In addition, few consumers purchase food based primarily on environmental or nutritional considerations; price is a key factor in food choice.[75] So while nutritious diets with lower carbon footprint are possible, it is unlikely that these patterns would be widely adopted unless they are also economically sustainable for the individual. Higher quality diets are generally more expensive in higher-income countries.[76]

Some descriptive research using observed diets indicates that lower-carbon, healthful diets can be about the same cost or cheaper than current average diets.[77-79] No such studies exist in the US. Studies simulating optimal diets using linear programming also show broadly similar results, but the resulting diets are often complex to communicate.[51,80-82] It is important to identify realistic diets that meet the triple bottom line of health, environment, and cost in order to improve health and reduce environmental impacts from food.

This study will address these gaps in the literature by simulating nutritional, GHGE, and cost effects of diet changes in US individuals and by identifying consumers who are most likely to make these changes.

2. Research question

What are the potential effects on sustainability objectives if US dietary guidance were to recommend reducing the intake of high-impact foods? This research question was answered by addressing the following aims:

Aim 1: Identify adults in NHANES 2007-2010 who might be motivated to change their diets if dietary guidance were to include advice on how to improve sustainability.

Aim 2: Estimate the impacts on food-related GHGE, diet quality, and diet costs if these motivated consumers replaced higher-GHGE animal foods with lower-GHGE alternatives.

3. Methods

Methods: Study sample

The sample came from the 2007-2010 waves of the National Health and Nutrition Examination Survey (NHANES). This is a complex, multistage, probability-based survey designed to be representative of the civilian, non-institutionalized US population. It is conducted continuously and results are reported in two-year cycles. Survey participants undergo physical and laboratory measurements in a Mobile Examination Center (MEC) as well as completing interview modules about demographics, dietary intake, consumer behavior, and more.[83]

All individuals 18 to 65 years of age with a reliable dietary intake and with non-missing values on key demographic and behavioral variables were included, giving a sample size of 7,188. (See the next section for clarification on what constitutes reliable NHANES dietary intake, and further below for details on behavioral variables used.)

Methods: Dietary intake

Food consumption data in NHANES are based on a 24-hour dietary recall, which uses the Automated Multiple-Pass Method (AMPM) developed and validated by the United States Department of Agriculture (USDA). This system includes rigorous protocols for the collection and processing of dietary data.[84] This study used data from the Day 1 recalls, which are collected in person by trained interviewers in a Mobile Examination Center.

The dietary recall process includes 5 rounds or passes of reviewing the person's intake over the previous 24 hours. Respondents are first asked to quickly list everything they ate or drank. The following passes prompt the person to consider commonly forgotten items, organize reported items by time and eating occasion, gather full details on foods, beverages, and portion sizes, review the resulting list, and finally, prompt for any foods or eating occasions that may have been missed. A variety of aids are presented to help respondents report portion sizes. These include models, different sizes of dishware, measuring cups and spoons, images, and a ruler.

After data collection, dietary intake data are checked for quality in several ways.[85] They are only included for further research if the respondent completed at least 4 of the 5 passes in the AMPM, and if there are no missing foods. A respondent's intake data may also be labeled as unreliable based on interviewer feedback, for example, if the respondent had memory problems. Additional checks look for common reporting errors such as reporting the amount of a liquid cup of coffee using a code for dry instant coffee.

Once quality control is completed, reported intake is matched to the USDA Food and Nutrient Database for Dietary Studies (FNDDS). Unknown foods are researched and matched to existing nutrient database entries, or to new ones that are added as needed. The final NHANES individual food files are publicly available and include grams of consumption of each food item for each person, along with energy (kilocalories [kcal]), macronutrient, and micronutrient data for the reported amounts.[86]

There are 4,623 different food codes reported in the 2007-2010 NHANES. Since most environmental impact data is reported at the level of the commodity, the foods as reported in NHANES (e.g., pepperoni pizza) were converted into consumption of 332 commodity ingredients (e.g., wheat, milk, pork, etc.) using recipe files developed by the Environmental Protection Agency (EPA) for the Food Commodities Intake Database (FCID). The EPA created this database to assess pesticide exposure from food, and generated recipes for all foods consumed in the 2005-2010 NHANES.

Methods: Greenhouse gas emissions

GHGE were linked to commodity consumption using *dataFIELD* (the database of Food Impacts on the Environment for Linking to Diets). This database includes GHGE and other impacts for each FCID commodity. Built through a comprehensive literature review of life cycle assessment (LCA) studies from 2005 to 2016, *dataFIELD* includes GHGE values (kg CO_2 equivalents per kg commodity) up to the farm gate for most commodities, and up to the processor gate for the rest (for example, oils, flours, and juices). Food-related GHGE for individuals was calculated by multiplying grams of intake by GHGE per gram and summing for the day. Details of the database creation and the process of linking GHGE to diets have been published previously,[45] and are also described in detail in Appendix 1.

Methods: Diet healthfulness

The quality or healthfulness of diets was assessed using the Healthy Eating Index 2010 (HEI).[87] The HEI is a measure of how well a diet corresponds to the Dietary Guidelines for Americans. Scores range from 0 to 100 and include 12 components. Nine of the components address adequacy (total fruits, whole fruits, total vegetables, greens and beans, whole grains, dairy, total protein foods, seafood and plant proteins, and fatty acid ratio), and three are moderation components, scored higher for lower consumption (refined grains, sodium, and empty calories). An HEI score was calculated for each individual in the sample using an algorithm developed by the National Cancer Institute.[88] This algorithm makes uses of the Food Patterns Equivalents Database (FPED), which converts NHANES foods into nutrition-oriented food groups that form the basis of the HEI (e.g., cup-equivalents [c-eq] and ounce-equivalents [oz-eq]). Necessary sodium and fat values come from the Food and Nutrient Database for Dietary Studies (FNDDS). See Table 1-1 for details on the scoring from the official publication.[89]

Methods: Diet cost

Diet cost was calculated for each individual using food price data from the Center for Nutrition Policy and Promotion (CNPP) Food Prices Database. The database gives the price per

100 grams for NHANES food codes from 2003-2004 and was previously updated to the 2007-2010 time period. Diet cost for individuals was calculated by multiplying grams of intake by price per gram and summing for the day. The CNPP database prices are for food-at-home. Eating away from home is common in the US, and as such, the diet costs calculated here likely underestimate true costs.

Table 1 - 1. Healthy Eating Index 2010 Scoring (Guenther et al. 2014[87])

	Dietary component	Max Points	Standard for maximum score	Standard for zero score
Adequacy *(higher score = greater intake)*	Total Fruit	5	≥ 0.8 c-eq/1000 kcal	No fruit
	Whole Fruit	5	≥ 0.4 c-eq/1000 kcal	No whole fruit
	Total Vegetables	5	≥ 1.1 c-eq/1000 kcal	No vegetables
	Dark Greens & Legumes	5	≥ 0.2 c-eq/1000 kcal	No dark-green veggies, beans, or peas
	Whole Grains	10	≥ 1.5 oz-eq/1000 kcal	No whole grains
	Dairy	10	≥ 1.3 c-eq/1000 kcal	No dairy
	Total Protein Foods	5	≥ 2.5 oz-eq/1000 kcal	No protein foods
	Seafood & Plant Proteins	5	≥ 0.8 c-eq/1000 kcal	No seafood or plant proteins
	Fatty Acid Ratio[1]	10	(PUFAs+MUFAs)/SFAs ≥ 2.5	(PUFAs+MUFAs)/SFAs ≤ 1.2
Moderation *(higher score = lower intake)*	Refined Grains	10	≤ 1.8 oz-eq/1000 kcal	≥ 4.3 oz-eq/1000 kcal
	Sodium	10	≤ 1.1 g/1000 kcal	≥ 2.0 g/1000 kcal
	Empty Calories	20	≤ 19% of energy	≥ 50% of energy

[1]Ratio of poly- and mono-unsaturated fatty acids to saturated fatty acids.

<u>Methods: Socioeconomic and demographic variables</u>

NHANES socioeconomic and demographic variables used were age, gender, education, race/Hispanic origin, income-to-poverty ratio, and household size.

Age was categorized into four groups: 18-29, 30-49, and 50-65 years. Gender in NHANES is reported only as “male” or “female.” Highest education completed was categorized into four groups: less than high school, high school graduate or general educational development (GED), some college, and college graduate or higher.

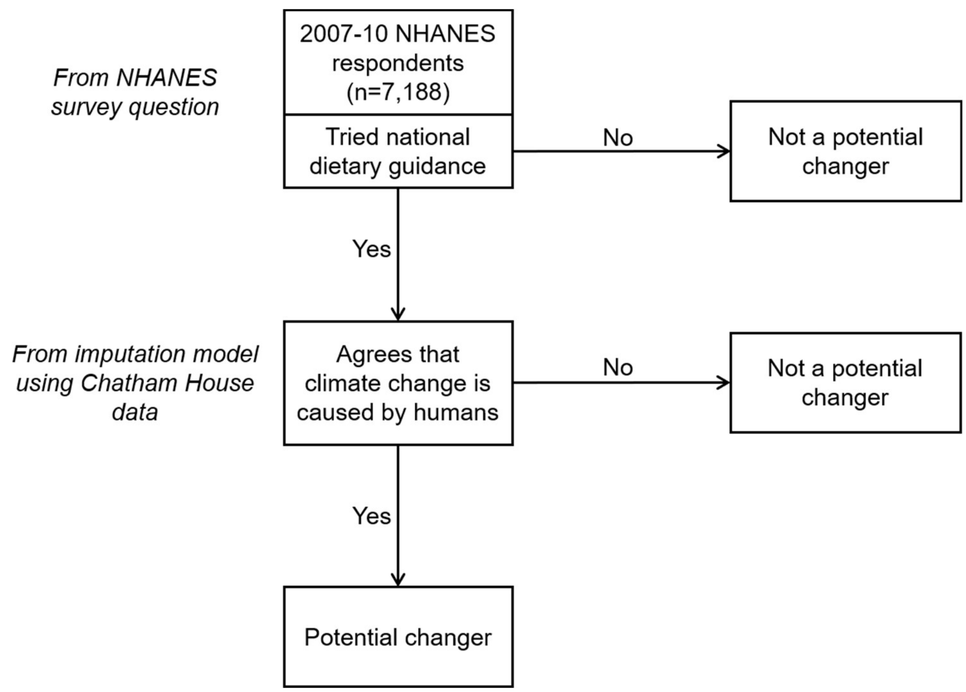
Race/Hispanic origin was recoded into four groups: Non-Hispanic White, Non-Hispanic Black, Hispanic, and Other/Multiracial. While the combination of race and ethnicity into a single variable is not ideal, it is the only option available in NHANES at this time. The categories before recoding were Non-Hispanic White, Non-Hispanic Black, Mexican American, Other Hispanic, and Other Race – Including Multi-Racial. NHANES has historically oversampled certain population groups in order to be able to calculate stable estimates for them. In the 2007-2010 years, these oversampled groups were Hispanics, Non-Hispanic Blacks, the elderly (age 80+), and those at or below 130% of the federal poverty level.[90] Asian Americans were not oversampled, nor was their race reported separately, until the NHANES wave beginning in 2011. Other categories (such as Native groups) that may be reported from other national surveys are still lumped in to “Other Race” in NHANES.

Income-to-poverty ratio (IPR) is a measure of household income divided by the poverty guideline. Poverty guidelines, calculated by the US Department of Health and Human Services, are specific to household size, state, and year.[91] An IPR of 1 means a household is at the poverty guideline. While NHANES includes a family-level IPR, for this study, IPR was estimated at the household level in order to align data with the Chatham House study (see below). IPR was categorized as <1, 1-1.99, 2-4.99, and 5 and over.

Methods: Identifying potential changers

Which individuals would change their diets if the federal government were to include information and suggestions for environmentally sustainable diets in the Dietary Guidelines for Americans? This question was the organizing framework for identifying potential changers. Potential changers were defined as individuals that: (1) have tried US dietary guidance and (2) agree that humans contribute to climate change. The first condition is reported by respondents in the NHANES. The second condition was predicted for NHANES respondents from answers by similar individuals in another nationally representative survey. Figure 1-1 gives an overview of this approach.

Figure 1 - 1. Process to identify potential changers from 2007-2010 NHANES respondents



Information on NHANES respondents' previous use of dietary guidance was obtained from the Consumer Behavior Phone Follow-up Module for Adults. A dichotomous variable was created based on three items. Individuals who answered “yes” to the question, “Have you tried to follow the (MyPyramid Plan/Pyramid plan) recommended for you?” were coded 1. Individuals who answered “no” to this question, and those who said they had not heard of the food pyramid or MyPyramid, were coded 0.

NHANES does not include questions about attitudes toward climate change, so information on the second condition was imputed using a survey commissioned by Chatham House and the Glasgow University Media Group.[92] This Chatham House survey was conducted online by Ipsos MORI across 12 countries in 2014 (US n=1,051) and asked a series of questions related to human impacts on climate change. For this study, respondents were categorized as a 1 if they answered "strongly agree" or "tend to agree" to the item, "To what extent do you agree or disagree with: Human activities contribute to climate change." Other respondents were coded 0.

To impute these attitudes to NHANES respondents, a logistic model was developed with Chatham House data using the dichotomous dependent variable described above and independent variables that are also available in NHANES: age, gender, education, household size, and income-to-poverty ratio. Coefficients from this model and observed demographic characteristics from NHANES respondents were used to calculate NHANES individuals' predicted probabilities of agreement that humans contribute to climate change. These probabilities were categorized into a dichotomous variable (1=agree, 0=does not agree), using a cut point that gave the same proportion of agreeing individuals in NHANES as in Chatham House (68.6%). See Paper 1 Appendix 1-a and Paper 1 Appendix Tables A1-1 and A1-2 for additional details.

Methods: Hypothetical diet changes

Previous research has made clear that ruminant meats like beef, sheep, and goat have a particularly high carbon footprint. While sheep and goat are not commonly consumed in the US, beef, as the marketing campaign goes, is often "what's for dinner." Because of its high impact, beef was chosen as the main food to replace in this study.

Three replacement scenarios were used, based on the types of food with which people might commonly replace beef: pork, poultry, or plant protein foods (legumes, nuts, and seeds). Substitutions were implemented at the commodity level using the FCID database.

Substitution 1: beef intake replaced with poultry
Substitution 2: beef intake replaced with plant protein foods
Substitution 3: meat intake (beef, pork, and poultry) replaced with plant protein foods.

To provide more potential options for interested consumers, the analysis looked at fully replacing the original food(s) with the alternate food(s), or instead replacing 50% or 25% of the original intake. If a respondent did not consume the substituted item (e.g. beef) on the interview day, no substitution was made.

The plant protein foods to be used as replacements for meat include 44 individual commodities and fall into three groups: legumes, nuts and seeds, and soy. To make simulations as realistic as possible, replacements will account for the proportion in which individuals reported eating these foods. For example, if a potential changer reported eating only nuts and seeds, but no legumes or soy, then any plant-based replacements for meats were 100% nuts and seeds. For potential changers who did not consume plant protein foods, mean consumption proportions from the overall sample was used for replacements. See Paper 1 Appendix 1-b and Paper 1 Appendix Tables A1-3 and A1-4 for a detailed explanation of how these and other substitutions were made on an isocaloric basis.

Substitutions were isocaloric. Averages from the National Nutrient Database for Standard Reference (SR28) were used to create conversion factors for all necessary replacements. For example, the mean energy content in 100 grams of raw beef is 188 kilocalories (kcal) and for poultry the value is 168 kcal. Therefore replacements of beef with poultry used a conversion of 1.12 to scale up the amount of poultry to the same energy value as the beef it replaced.

Since substitutions were made at the commodity level, and since there is a direct linkage from the commodity database (FCID) to the environmental database (*dataFIELD*), the effect of these substitutions on GHGE could be calculated directly. There is not, however, a one-to-one correspondence of FCID commodities to FPED foods, which are needed for calculation of the HEI. A predictive model of HEI was developed based on intakes of aggregate groups of commodities. The general linear model used calculated individual HEI scores as the dependent variable and intakes of 19 commodity groups (e.g. beef, poultry, vegetables, etc,) as well as socioeconomic and demographic characteristics, as independent variables. This model was found to be very good predictor of actual HEI ($p < 0.001$, $R^2 = 0.44$). Coefficients from this model were used with the new food commodity quantities, and demographics, to predict a post-substitution HEI for each individual.

The same approach was used for predicting the diet cost for each respondent ($p <0.001$, $R^2 = 0.32$). Paper 1 Appendix Table A1-5 shows the models used in these estimations.

Methods: Statistical analysis

In addition to the models discussed above (used to impute attitude about climate change to NHANES and those used to predict HEI and diet cost after substitutions), the following additional statistical analyses were performed.

To identify differences between potential changers and non-changers on demographic variables, Chi-squared tests were used. Student's *t* tests were used to identify differences between these groups on meat consumption variables. Paired *t* tests were used to test for differences in food-related GHGE (kg CO_2-eq), HEI scores, and cost (US dollars) between baseline and replacement diets.

All tests were two-sided with an α level of 0.05. All analyses used Stata/SE (version 13.1) survey procedures, which account for survey design and sampling weights. This meant using weights that came with the Chatham House survey, and survey strata, primary sampling units (PSU), and sampling weights available with NHANES data. NHANES provides several types of weight variables depending on the analysis to be performed. Weights specific to the dietary data account for the additional variability in dietary data (nonresponse specific to the dietary module, and day of the week) compared to the overall NHANES interview.[93] The survey weights used for this study were the Day 1 dietary weights (WTDRD1). The survey weights were adjusted for the use of multiple survey cycles according to NHANES guidance, which in this case meant dividing by two for the number of cycles used. When setting Stata up to run the survey-weighted analyses, this combined weight was treated as a probability weight.

4. Results

Results: NHANES characteristics and identifying potential changers **(Aim 1)**

Over one fifth (22%) of NHANES respondents reported trying dietary guidance. Those likely to agree that human activities contribute to climate change comprised 69% of the population. The potential changers, i.e. those in both groups, were 16% of respondents (n=1,026).

The overall sample, reflecting the US population, was slightly over half female and about two-thirds non-Hispanic White (Table 1-2). About 60% of respondents had greater than a high school education. Twelve percent of people had incomes at or below the poverty level. Only 2% (n=164) of individuals in the population were self-described vegetarians.

Compared to the rest of the population, potential changers were more likely to be female, to be more highly educated, or to have higher income. Compared to Non-Hispanic Whites, those who were of other race/Hispanic origins were less likely to be changers. There were no significant differences in age between potential changers and the rest of the population. Potential changers were more likely to describe themselves as vegetarians and, on average, consumed less beef and pork, but not poultry, than other respondents.

Results: Impacts of substitutions on diet GHGE, quality, and cost **(Aim 2)**

Baseline mean dietary GHGE among potential changers was 3.9 kg CO_2-eq per person per day (95% CI: 3.6, 4.1). Beef replacement predictions were run on the 61% of potential changers that reported eating beef on their dietary recall day, which amounted to 10% of the overall sample. Within potential changers, replacing 100% of beef intake with poultry reduced mean dietary GHGE by 1.4 kg CO_2-eq per person per day (95% CI: 1.2, 1.6) (Table 1-3). This change also increased mean estimated HEI by 0.9 points (0.8, 1.0) and decreased mean estimated dietary cost by 0.09 USD (95% CI: 0.08, 0.10). This represents a decrease in mean GHGE of 35.7%, a 1.7% increase in mean HEI, and a 1.7% decrease in mean cost. Replacing the beef with plant protein foods reduced potential changers' mean GHGE by 40.3%, increased mean HEI by 3.3%, and decreased mean dietary cost by 5.5%. Replacing less than 100% of beef intake in the potential changers resulted in similar but smaller modifications in GHGE, HEI, and diet cost. Absolute quantities of meats and plant proteins before and after replacements are presented in Paper 1 Appendix Table A1-6.

Almost all (92%, n=938) of the potential changers ate beef, pork, or poultry on their recall day, so when substituting for these meats, scenarios were run on 15% of the overall sample. Replacing 100% of beef, pork, and poultry intake in these potential changers with plant protein foods lowered mean GHGE by almost half, increased mean HEI by 8.5% (+4.5 points), and decreased dietary cost by 14.8%. Replacing only a quarter of this meat intake in the potential changers reduced mean GHGE by 12.1%, increased mean HEI by 2.0%, and decreased cost by 6.9%.

What would be the impact on the overall population of modifications made only by the potential changers? This is examined in Table 1-4. Replacing 100% of beef with either poultry or plant protein foods in only the potential changers reduced the mean GHGE in the overall population by around 5%. Replacing meat and poultry with plant proteins lowered GHGE 6.7%.

Figure 1-2 allows for examination of how changes in intakes from the different protein food groups contributed to GHGE reductions among potential changers. Beef intake represented the majority of GHGE to begin with and also the largest share of GHGE after any substitution scenario except 100% replacement. In other words, beef was still the largest emitter even when intake was reduced.

5. Discussion

Replacing beef or beef, pork, and poultry in the diets of motivated consumers reduced the GHGE associated with their diets, on average, from 9% to 50%, depending on the type and degree of substitution. Although these environmental impacts were substantial among potential changers, since they only comprised 16% of the sample (n=1,026), overall dietary GHGE changes at the population level were much smaller. Diet changes increased the healthfulness of the diets among potential changers from less than 1% to about 9%, and they reduced diet costs by less than 1% to about 15%. In general, diet quality in the US, as measured by the Healthy Eating Index, is relatively low, and the modest changes found here are in the right direction. Although the greatest reductions in emissions came from substituting plant protein foods for all beef, pork, and poultry intake, replacing just the beef intake would account for over 80% of this reduction.

These GHGE results are broadly consistent with previous research. For example, in a review of studies on the environmental impacts of dietary change, Aleksandrowicz and colleagues found decreases in GHGE from 3% to 36% when ruminant meat (e.g. beef or lamb) was replaced with monogastric meats (e.g. chicken or pork), and decreases of 15% to 58% with changes to vegetarian diets.[56] In this work, complete substitution of poultry for beef resulted in a decreased GHGE of 36% for potential changers, while shifting away from all meats to vegetarian protein foods resulted in a 50% drop. Substantial reductions in meat intakes are also recommended by recent expert committee reports.[64,94]

The results here on diet quality and cost are also consistent with the literature. Most, but not all, studies demonstrate that positive improvements with diet healthiness are concomitant with reductions in GHGE. For example, of the 37 scenarios in the review by Aleksandrowicz which shifted diets to healthy guidelines, only 4 of them had an increase in GHGE.[56] All scenarios in this work reduced GHGE and also improved diet quality. Optimization studies have shown that healthier and more sustainable diets can be obtained for modest reductions in cost (3-11%), which was similar to these results.[51,81]

The comparisons above are based on the results for potential changers. Since they account for only 16% of the sample, our overall population estimates for GHGE reductions are much smaller than other studies--only a 5% decrease for shifts from beef to chicken, and 7% from all meats to vegetable proteins. This is probably a more realistic short-term outcome for attempts to move toward more climate-friendly diets, since the entire population is not expected to make immediate changes. Still, considering the scale of these food replacements relative to other GHGE in the US, these diet scenarios produced reductions equivalent to 15 to 78 million fewer miles driven in a passenger vehicle for this one day of intake.[95]

It is clear that the transition to climate-friendly diets will require new research and new policy work. This study used a relatively weak policy lever—information from dietary guidance—to motivate change.[96,97] The assumption was that those who had tried this before and who agreed that humans caused climate change would make changes to their diets to reduce their carbon footprint, if such information was newly included in dietary guidelines. However, food choice behavior is complex and multi-faceted.[98] Taste, cultural preferences, convenience, and costs are all important factors that shape this behavior, in addition to health and environmental concerns. Moreover, there are a number of relevant aspects specific to meat-eating behavior, such as consumer attachment to eating meat and various rationalizations to justify it.[99-101] The potential changers identified here already consumed less beef and pork at baseline, but, unfortunately, there is no information about how attached they might be to eating beef. Thus, it is an open question as to how much they would reduce their beef intake, which is why several scenarios were presented.

Strengths and limitations

A major limitation of the study is the lack of data on attitudes toward climate change and sustainability in NHANES participants. The imputation method using socioeconomic and demographic variables may have missed key predictors of a person agreeing that humans cause climate change (for example, political affiliation or religious beliefs) and may therefore have mis-categorized some individuals. However, this study was not meant to estimate the proportion of climate change agreement in NHANES, but rather to provide a picture of the diet quality, carbon footprint, and cost changes that might occur if a subset of US individuals responded to the addition of sustainability in US dietary guidance. The imputation method used allowed for acceptable estimates of these outcomes even if some individuals are miscategorized.

It is also true that agreement with the anthropogenic nature of climate change does not necessarily mean an individual would feel motivated to personally take action via dietary changes. More research is needed to examine dietary behavior change in relation to sustainability beliefs and concerns.

This analysis looked at specific, fixed diet modifications of potential changers. This does not account for other dietary changes that might accompany a reduction in meat intake, or secondary effects on production, market supply, beef prices, or consumption of non-changers, either within the US or internationally. For example, reductions in GHGE described here could be muted if excess supply is shifted overseas. As such, these estimates are better thought of as potential first-order, short-run changes.

Another limitation comes from use of a single day of intake. The distribution of a single day of dietary intake data is more disperse than the distribution of people's usual, habitual intake. Please see Paper 3's background for more information on this. However, since NHANES is a nationally representative study, the single day of dietary data used here is still a valid snapshot of one day of intake in the US. While a given individual may not eat a pound of barbecue and drink 12 beers on a normal day, a few people in the country may eat that way on any given day. This study demonstrates what effects there might be if motivated individuals changed their intake on one day.

The 24-hour recalls used to collect dietary data are known to suffer from some measurement error, most often underreporting. NHANES does not collect any biomarker data by which underreporting could be identified and adjusted for. The self-reported dietary data used in this study may result in some underestimates of daily food-related GHGE or food cost; however, the comparisons of the different diet scenarios can still be made relative to one another. There is also no substitute for this nationally representative dietary dataset with rich detail of all foods and beverages.

The dietary cost estimates here are likely to be an underestimate of true costs to the consumer, since they rely on prices for food-at-home. This is usually cheaper than food prepared and/or eaten away from home. However, the costs calculated here still allow for the relative comparison of different diet scenarios.

There are some limitations related to *dataFIELD*. The database does not include impacts of foods past the farm gate (or in some cases, the producer gate; see Appendix 1 for more details). There is also variability underlying the point value for food-related GHGE associated with each commodity (for example, from studies with different production methods or in different locations). This variability is not carried forward through the whole analysis. A previous publication has addressed these issues in much more detail.[45]

The commodity recipes used to calculate food-related GHGE are from 2010, and the availability of those recipes for NHANES 2005-2010 dictated the choice of those years of dietary intake data. However, the age of these data is a limitation of this analysis. The dietary habits (or the foods that make up these diets) of US adults may have shifted over time. Using this older data allowed for studies to fill important gaps in the diet-health-environment literature using self-selected US diets. While the shifts in US diets are not expected to be major, the literature would still benefit from more updated studies that reflect current consumption (see Paper 2).

An overall strength of this research is the realistic nature of the dietary changes. Changes were made only in the portion of the population that was more likely to be motivated by this particular policy lever. Modest change scenarios are included, so complete elimination of food groups was not necessary. Changes in food groups (amounts of reductions in meat and increases in poultry, legumes, nuts, or seeds) were based on how much individuals were already eating, and replacements took into consideration the proportions in which they ate different commodities within these groups. These choices minimized the differences from potential changers' current diets, making them more likely to be acceptable to consumers. Another strength of this study was the underlying dataset developed for it. The GHGE values came from a comprehensive approach to match detailed food consumption data with the latest literature on environmental impacts.

In sum, changes in food consumption by a relatively small percentage of motivated individuals can reduce food-related GHGE and increase healthfulness of the diet without increasing cost. These changes in motivated consumers can have an effect, albeit modest, on emissions at the national level. This study provides further evidence that it is worthwhile to provide environmental sustainability as well as nutrition information to US consumers. While dietary guidance policy is one way to disseminate this information, other methods should also be considered.

Table 1 - 2. Characteristics of US adults and those categorized as potential changers, NHANES 2005-2010[1]

	Full sample (N=7,188)			Not potential changer (n=6,162)			Potential changer[2] (n=1,026)			
	n	**%**	**95% CI**	**n**	**%**	**95% CI**	**n**	**%**	**95% CI**	**p value[3]**
Female	3,828	53	(51, 54)	3,023	48	(46, 50)	805	78	(75, 81)	**<0.001**
Age										**0.100**
18-29 years	1,751	24	(22, 26)	1,515	24	(22, 27)	236	22	(19, 26)	
30-49 years	3,051	44	(42, 46)	2,613	45	(42, 47)	438	42	(38, 46)	
50-65 years	2,386	32	(30, 34)	2,034	31	(29, 33)	352	36	(32, 40)	
Race-Ethnicity										**<0.001**
Non-Hispanic White	3,208	69	(64, 74)	2,677	68	(63, 73)	531	75	(69, 80)	
Non-Hispanic Black	1,477	12	(10, 14)	1,258	12	(10, 14)	219	11	(9, 14)	
Hispanic	2,187	14	(11, 18)	1,952	15	(11, 19)	235	10	(7, 14)	
Other	316	5	(5, 7)	275	6	(5, 7)	41	5	(3, 6)	
Education										**<0.001**
Less than high school	1,875	17	(16, 19)	1,781	19	(17, 21)	94	7	(5, 11)	
High school grad/GED	1,695	24	(22, 26)	1,514	25	(23, 27)	181	16	(13, 20)	
Some college	2,141	31	(30, 33)	1,707	30	(28, 31)	434	39	(35, 43)	
College grad or higher	1,477	28	(26, 31)	1,160	26	(24, 29)	317	37	(33, 42)	
Income-to-Poverty Ratio										**<0.001**
< 1	1,336	12	(10, 14)	1,209	13	(11, 15)	127	7	(6, 9)	
1 - < 2	1,928	18	(17, 20)	1,765	20	(18, 21)	163	11	(8, 15)	
2 - < 5	2,434	38	(36, 41)	2,000	37	(35, 40)	434	42	(38, 45)	
>=5	1,490	32	(29, 35)	1,188	30	(27, 33)	302	40	(35, 46)	
Self-described vegetarian	164	2	(2, 3)	131	2	(1, 2)	33	4	(2, 6)	**0.02**
Beef consumption (mean g/d)[4]	51.3		(47.7, 54.8)	53.9		(50.2, 57.6)	37.7		(32.3, 43.0)	**<0.001**
Pork consumption (mean g/d)[4]	29.1		(26.8, 31.5)	30.9		(28.5, 33.3)	20.1		(15.8, 24.5)	**<0.001**
Poultry consumption (mean g/d)[4]	55.9		(52.4, 59.4)	56.3		(52.3, 60.3)	53.8		(49.9, 57.7)	0.350

[1]US National Health and Nutrition Examination Survey (NHANES) 2007-2010 adults (age 18 to 65) who responded to questions about trying dietary guidance (MyPyramid or MyPlate).
[2]Potential changers are individuals who had tried dietary guidance and were likely to agree that humans contribute to climate change. Probability to agree that humans contribute to climate change in NHANES was predicted using socioeconomic and demographic variables and a model from the Chatham House survey, which asks this question directly to participants. These individuals were 16% of the sample (95% CI: 15%, 17%).
[3]A chi-square statistic was used to test for association between being a potential changer (or not) and each of the categorical demographic variables. T statistics were used to test for differences between potential changers and others on each of the consumption variables.
[4]Commodity amounts of edible portion of the meats in grams per day.

Table 1 - 3. Results of hypothetical meat reductions among potential changers (n=1,026): Dietary greenhouse gas emissions, Healthy Eating Index, and dietary cost[1]

	Food-Related Greenhouse Gas Emissions (kg CO_2-equivalents person^{-1} day^{-1})[2]				Estimated Healthy Eating Index[2]				Estimated Diet Cost (US dollars person^{-1} day^{-1})[2]			
	Mean[3]	95% CI[3]	p value[4]	% Change in mean[5]	Mean[3]	95% CI[3]	p value[4]	% Change in mean[5]	Mean[3]	95% CI[3]	p value[4]	% Change in mean[5]
Original	3.88	(3.64, 4.12)	--	--	52.65	(51.97, 53.32)	--	--	5.24	(5.16, 5.32)	--	--
100% beef replaced:												
With poultry	-1.38	(-1.58, -1.19)	<0.001	-35.7	0.88	(0.76, 1.00)	<0.001	1.7	-0.09	(-0.10, -0.08)	<0.001	-1.7
With plant protein[6]	-1.56	(-1.79, -1.34)	<0.001	-40.3	1.74	(1.40, 2.08)	<0.001	3.3	-0.29	(-0.33, -0.25)	<0.001	-5.5
50% beef replaced:												
With poultry	-0.69	(-0.79, -0.59)	<0.001	-17.8	0.44	(0.38, 0.50)	<0.001	0.8	-0.05	(-0.05, -0.04)	<0.001	-0.9
With plant protein[6]	-0.78	(-0.89, -0.67)	<0.001	-20.1	0.87	(0.70, 1.04)	<0.001	1.7	-0.14	(-0.17, -0.12)	<0.001	-2.8
25% beef replaced:												
With poultry	-0.35	(-0.40, -0.30)	<0.001	-8.9	0.22	(0.19, 0.25)	<0.001	0.4	-0.02	(-0.03, -0.02)	<0.001	-0.4
With plant protein[6]	-0.39	(-0.45, -0.34)	<0.001	-10.1	0.44	(0.35, 0.52)	<0.001	0.8	-0.07	(-0.08, -0.06)	<0.001	-1.4
100% beef, pork, poultry replaced:												
With plant protein[6]	-1.93	(-2.14, -1.71)	<0.001	-49.6	4.46	(3.93, 4.98)	<0.001	8.5	-0.78	(-0.82, -0.74)	<0.001	-14.8
50% beef, pork, poultry replaced:												
With plant protein[6]	-0.96	(-1.07, -0.86)	<0.001	-24.8	2.17	(1.91, 2.43)	<0.001	4.1	-0.50	(-0.53, -0.47)	<0.001	-9.6
25% beef, pork, poultry replaced:												
With plant protein[6]	-0.48	(-0.54, -0.43)	<0.001	-12.1	1.03	(0.90, 1.16)	<0.001	2.0	-0.36	(-0.39, -0.34)	<0.001	-6.9

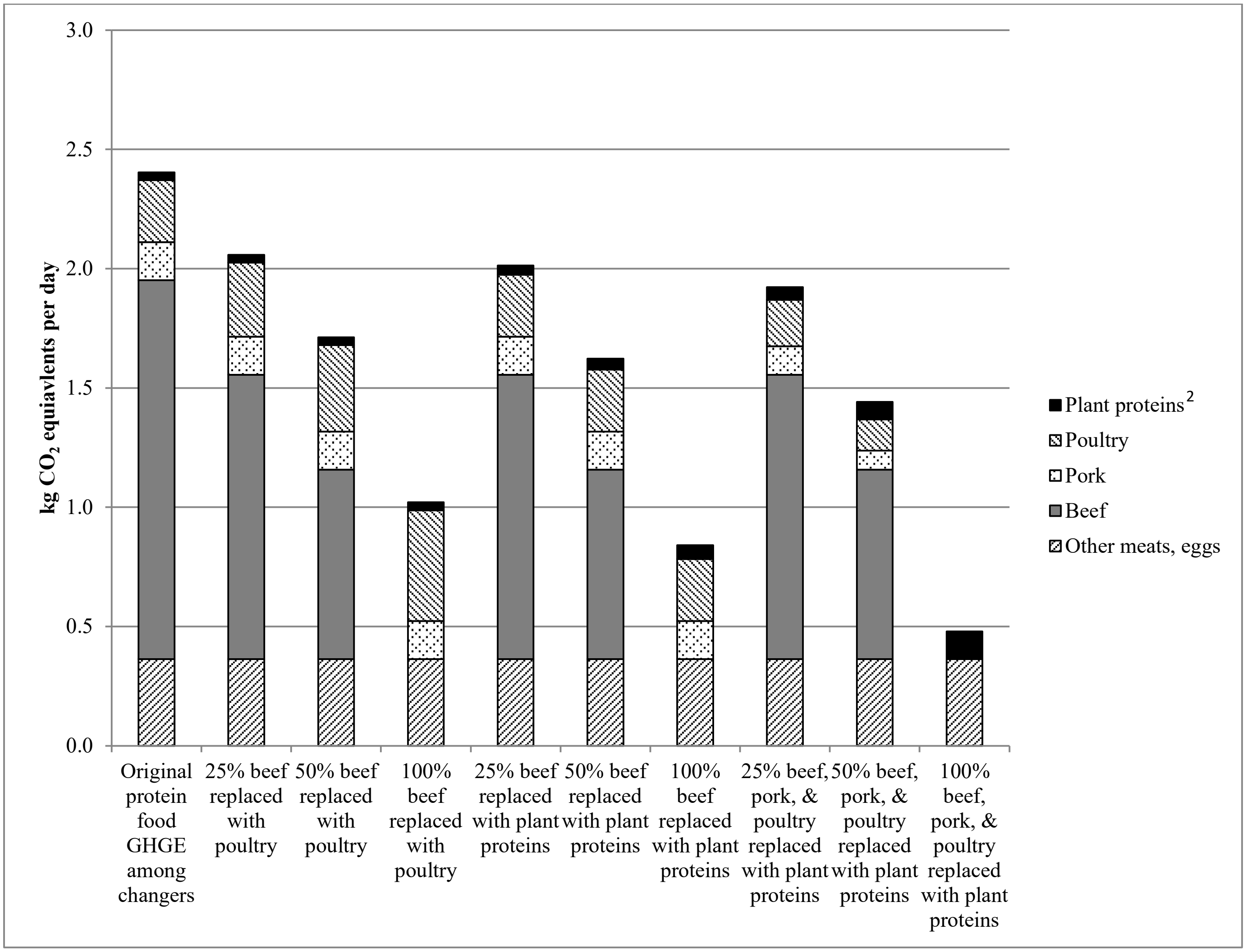
[1]Potential changers (n=1,026) are individuals who had tried dietary guidance and were likely to agree that humans contribute to climate change. Probability to agree that humans contribute to climate change in NHANES was predicted using socioeconomic and demographic variables and a model from the Chatham House survey, which asks this question directly to participants. These individuals were 16% of the sample (95% CI: 15%, 17%). All replacements were made in equal calorie amounts, as estimated from the National Nutrient Database for Standard Reference (SR28). Replacements were only made if individuals consumed the meats in question: 645 (61%) ate beef, and 938 (92%) ate beef, pork, or poultry, but mean changes included all likely changers, whether a replacement was made or not.
[2]Food-related greenhouse gas emissions (GHGE) were calculated based on commodity intakes using dataFIELD. Mean results are based on calculations of substitutions at the individual level, with variability due to sampling error in NHANES (CI=Confidence Interval). Healthy Eating Index (HEI) and diet cost results are means of person-level predicted values and associated confidence intervals. Predictions were based on commodity intakes and socioeconomic and demographic variables (See Appendix Table 4).
[3]Values in the first row of the tables are mean and 95% CI at baseline. Subsequent rows show the mean difference from baseline, and 95% CI for that difference.
[4]A paired t test was used to test the hypothesis that the mean difference between the substituted diet and the original ≠ 0.
[5]Values are percent change in the mean value compared to baseline (original).
[6]Plant proteins are legumes, nuts, and seeds. Diet changes for each potential changer reflected the individual's actual reported intakes of these three food groups. Replacements were made in the same ratio as the individual reported eating the three food groups. If the individual did not eat any of the food groups, the overall average ratio in the sample was used to distribute the new intake, specifically: 0.405 legumes other than soy, 0.336 nuts/seeds, and 0.259 soy.

Table 1 - 4. Total US food-related greenhouse gas emissions after hypothetical changes in meat intake among potential changers[1]

	Mean per person per day (N=7,188)				Population-level impact per day[2]	
	Mean[3] (kg CO_2-equivalents)	95% CI[3]	p value[4]	% Change in mean[5]	Total (Mg CO_2-equivalents)	Equivalent difference in passenger vehicle miles[6]
Original	4.64	(4.48, 4.80)	--	--	475,410	--
100% beef replaced:						
With poultry	-0.22	(-0.26, -0.19)	<0.001	-4.8	-22,939	-56,224,538
With plant protein[7]	-0.25	(-0.29, -0.21)	<0.001	-5.4	-25,906	-63,496,294
50% beef replaced:						
With poultry	-0.11	(-0.13, -0.09)	<0.001	-2.4	-11,469	-28,112,269
With plant protein[7]	-0.13	(-0.15, -0.11)	<0.001	-2.7	-12,953	-31,748,147
25% beef replaced:						
With poultry	-0.06	(-0.07, -0.05)	<0.001	-1.2	-5,734	-14,056,134
With plant protein[7]	-0.06	(-0.07, -0.05)	<0.001	-1.4	-6,476	-15,874,074
100% beef, pork, poultry replaced:						
With plant protein[7]	-0.31	(-0.35, -0.27)	<0.001	-6.7	-31,916	-78,225,536
50% beef, pork, poultry replaced:						
With plant protein[7]	-0.16	(-0.18, -0.13)	<0.001	-3.4	-15,958	-39,112,768
25% beef, pork, poultry replaced:						
With plant protein[7]	-0.08	(-0.09, -0.07)	<0.001	-1.6	-7,979	-19,556,384

[1]Potential changers (n=1,026) are individuals who had tried dietary guidance and were likely to agree that humans contribute to climate change. Probability to agree that humans contribute to climate change in NHANES was predicted using socioeconomic and demographic variables and a model from the Chatham House survey, which asks this question directly to participants. These individuals were 16% of the sample (95% CI: 15%, 17%). All replacements were made in equal calorie amounts, as estimated from the National Nutrient Database for Standard Reference (SR28). Replacements were only made if individuals consumed the meats in question: 645 (61%) ate beef, and 938 (92%) ate beef, pork, or poultry.
[2]Population-level values are calculated using the probability weights (expansion factors) supplied with the NHANES dataset. These represent the size of the population at the mid-point of the survey years being used. In the case of NHANES 2007-2010 this is 153,731,402 individuals.
[3]Values in the first row of the tables are baseline (original diets). Subsequent rows show the difference from baseline.
[4]A paired t test was used to test the hypothesis that the mean difference between the substituted diet and the original ≠ 0.
[5]Values are percent change in the mean value compared to baseline (original).[6]Calculated using https://www.epa.gov/energy/greenhouse-gas-equivalencies-calculator (accessed July 2018).
[7]Plant proteins are legumes, nuts, and seeds. Diet changes for each potential changer reflected the individual's actual reported intakes of these three food groups. Replacements were made in the same ratio as the individual reported eating the three food groups. If the individual did not eat any of the food groups, the overall average ratio in the sample was used to distribute the new intake, specifically: 0.405 legumes other than soy, 0.336 nuts/seeds, and 0.259 soy.

Figure 1 - 2. Greenhouse gas emissions from protein foods in potential changers before and after hypothetical changes[1]



[1]Potential changers (n=1,026) are individuals who had tried dietary guidance and were likely to agree that humans contribute to climate change. Probability to agree that humans contribute to climate change in NHANES was predicted using socioeconomic and demographic variables and a model from the Chatham House survey, which asks this question directly to participants. These individuals were 16% of the sample (95% CI: 15%, 17%). All replacements were made in equal calorie amounts, as estimated from the National Nutrient Database for Standard Reference (SR28). Replacements were only made if individuals consumed the meats in question: 645 (61%) ate beef, and 938 (92%) ate beef, pork, or poultry.
[2]Plant proteins are legumes, nuts, and seeds. Diet changes for each potential changer reflected the individual's actual reported intakes of these three food groups. Replacements were made in the same ratio as the individual reported eating the three food groups. If the individual did not eat any of the food groups, the overall average proportions in the sample were used to distribute the new intake, specifically: 0.405 legumes other than soy, 0.336 nuts/seeds, and 0.259 soy.

6. Paper 1 Appendix

a. Imputing climate change agreement to NHANES data

To impute an attitude on climate change to NHANES respondents, a logistic regression model was developed with the US subsample (n=1,051) of the Chatham House data using a dichotomous dependent variable (i.e., agrees or not that humans contribute to climate change) and all independent variables that were also available in NHANES: age, gender, education, household size, and income-to-poverty ratio. Coefficients from this model (Paper 1 Appendix Table A1-1) and observed demographic characteristics from NHANES respondents were used to calculate NHANES individuals' predicted probabilities of agreement that humans contribute to climate change (see Appendix Figure A1-1).

Appendix Table A1 - 1. Coefficients used to predict agreement that humans contribute to climate change in Chatham House Survey[1]

	Coefficient	**Standard Error**	**P>|z|**
Female	0.483	0.240	0.04
Age			
18-29 years			
30-49 years	0.436	0.405	0.28
40-49 years	-0.524	0.420	0.21
50-65 years	-0.457	0.355	0.20
Education			
Less than high school			
High school grad/GED	0.319	0.536	0.55
Some college	0.491	0.529	0.35
College grad or higher	0.272	0.533	0.61
Income-to-Poverty Ratio			
1 - < 2			
2 - < 5	0.531	0.330	0.11
5 - < 10	0.415	0.382	0.28
>=10	0.376	0.713	0.60
Household Size	-0.227	0.103	0.03
Intercept	0.740	0.572	0.20
N	939		
Wald chi-squared	22.56		
P > chi-squared	0.02		
Pseudo R^2	0.063		

[1]The model was a multi-variable logistic regression run on all US survey participants with complete socioeconomic and demographic data (939 of 1,051) between 18 and 65 years old. The outcome variable was equal to 1 if the respondent agreed (strongly agreed or tended to agree) that humans contribute to climate change and equal to 0 otherwise. All independent variables in the model are shown in the table.

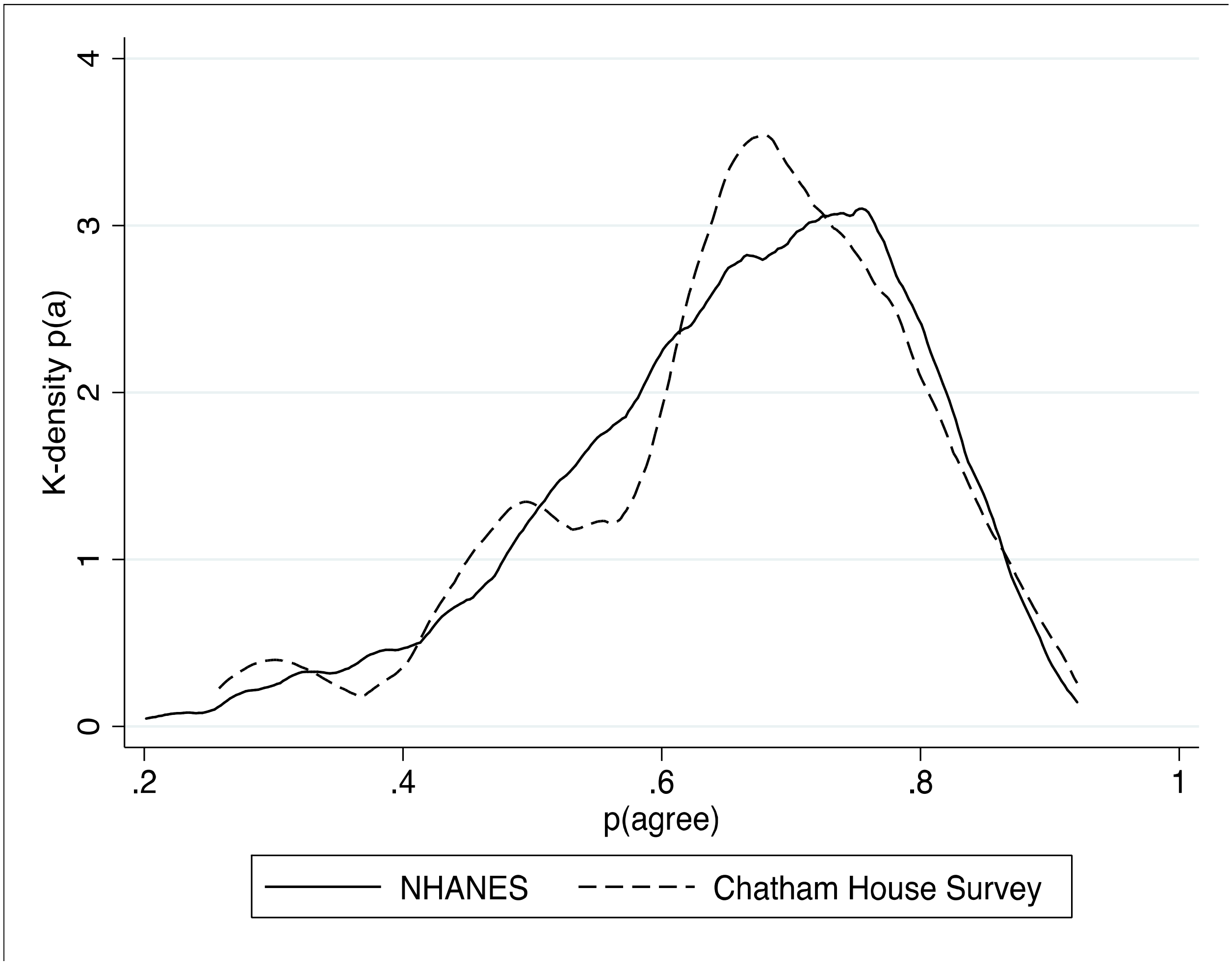
These predicted probabilities were categorized into a dichotomous variable equal to 1 if the probability was greater than 0.615. We used this cut point to create the same proportion of agreeing individuals in NHANES as in Chatham House (69%, n=715), since both are nationally representative samples of the US adult population. The distribution of socioeconomic and demographic characteristics differs between the Chatham House dataset and NHANES.

Therefore, before imputation, the Chatham House data were reweighted using entropy balancing weights. This multivariate reweighting method calibrates unit weights for Chatham House to balance covariate means between it and the NHANES dataset (Paper 1 Appendix Table A1-2).[102]

Appendix Table A1 - 2. Entropy balancing process: Covariate means with original dataset sample weights and with entropy weights

	NHANES			Chatham House: Sample weights			Chatham House: Entropy balanced weights		
	Mean	**Var.**	**Skew.**	**Mean**	**Var.**	**Skew.**	**Mean**	**Var.**	**Skew.**
Age [18,30)	0.260	0.192	1.096	0.225	0.175	1.317	0.260	0.192	1.096
Age [30,40)	0.230	0.177	1.285	0.166	0.139	1.796	0.230	0.177	1.285
Age [40,50)	0.306	0.212	0.843	0.394	0.239	0.435	0.306	0.213	0.843
Household size	3.201	2.359	0.610	2.587	1.816	0.898	3.201	2.847	0.572
Male	0.487	0.250	0.051	0.494	0.250	0.026	0.487	0.250	0.051
Less than high school	0.243	0.184	1.200	0.182	0.149	1.652	0.243	0.184	1.201
High School grad/GED	0.311	0.214	0.815	0.375	0.235	0.515	0.311	0.215	0.815
Some College	0.263	0.194	1.077	0.417	0.243	0.337	0.263	0.194	1.076
Employed	0.701	0.210	-0.878	0.608	0.239	-0.442	0.701	0.210	-0.877
Unemployed	0.129	0.113	2.210	0.101	0.091	2.652	0.129	0.113	2.210
Student	0.041	0.040	4.614	0.107	0.096	2.537	0.041	0.040	4.603
Retired	0.071	0.066	3.345	0.114	0.101	2.434	0.071	0.066	3.343
Homemaker	0.029	0.028	5.607	0.010	0.010	10.050	0.029	0.028	5.609
Income-to-Poverty Ratio (0,1]	0.129	0.112	2.218	0.142	0.122	2.047	0.129	0.112	2.216
Income-to-Poverty Ratio (1,2]	0.187	0.152	1.606	0.214	0.168	1.396	0.187	0.152	1.606
Income-to-Poverty Ratio (2,5]	0.369	0.233	0.544	0.434	0.246	0.266	0.369	0.233	0.544
Income-to-Poverty Ratio (5,10]	0.238	0.182	1.228	0.198	0.159	1.514	0.238	0.182	1.229

Appendix Figure A1 - 1. Predicted probabilities to agree that humans contribute to climate change in Chatham House and in NHANES[1]



[1]Predicted probabilities of agreement [p(agree)] are calculated for all individuals using coefficients of the logistic regression model depicted in Supplemental Table 1 and observed values of socioeconomic and demographic variables. This figure depicts the distribution of probabilities in the original Chatham House data compared to the distribution of probabilities imputed to NHANES respondents.

b. Isocaloric replacement of meats

All substitutions employed in this research were isocaloric. Averages from the National Nutrient Database for Standard Reference (SR28) were used to create conversion factors for all necessary replacements. For example, the mean energy content in 100 grams of raw beef was 188 kilocalories (kcal) and for poultry the value was 168 kcal. Therefore, replacements of beef with poultry used a conversion of 1.12 to scale up the amount of poultry to the same energy value as the beef it replaced.

Nutrient content from all analytic entries of the following food groups was extracted from the National Nutrient Database for Standard Reference (SR28): beef products, pork products, poultry products, legumes and legume products, and nut and seed products. "Composite" items such as 'Beef, composite of trimmed retail cuts, separable lean and fat, trimmed to 0" fat, all grades, raw,' are aggregations of other SR28 entries. As such, these were excluded. Items missing nutrient information were also excluded (5 cured beef items). Coconut entries were excluded from the nuts and seeds category in order to align with commodity groupings from FCID. Peanuts were included as nuts, not legumes. The legumes group included soy products. Items that could be commonly used as plant-based protein sources were included (e.g. tofu and soymilks). Highly processed entries such as soy creamers were excluded.

Mean kilocalories per 100 grams were calculated for all categories: raw beef products, raw pork products, raw poultry products, raw legumes, soy, and raw nuts and seeds. See Appendix Table A1-3.

Appendix Table A1 - 3. Mean energy content per 100 grams in SR28 entries

	Kilocalories	95% CI	Count
	188.1	(179.1, 197.1)	408
Raw pork products	209.1	(177.5, 240.8)	95
Raw poultry products	167.7	(154.3, 181.1)	154
Raw legume products, excluding soy	344.7	(339.1, 350.2)	33
Soy products, excluding highly processed	120.2	(95.5, 144.9)	91
Raw nuts and seeds	479.2	(413.9, 544.6)	34

To calculate conversion factors for replacements, the average nutrient value in the food to be replaced was divided by the average nutrient value in the replacement food. For example, the mean energy content in 100 grams of raw beef was 188 kilocalories (kcal) and for poultry the value was 168 kcal. Therefore, replacements of beef with poultry used a conversion of 1.12 to scale up the amount of poultry to the same energy value as the beef it replaced. Appendix Table A1-4 shows conversion factors for iso-caloric replacements for all food groups.

Appendix Table A1 - 4. Isocaloric substitution factors (grams needed to replace 1 gram of the column food)

	Beef	**Pork**	**Poultry**
Poultry	1.12	..	..
Legumes, excluding soy	0.55	0.61	0.49
Nuts and seeds	0.39	0.44	0.35
Soy	1.57	1.74	1.39

For changes including legumes, nuts, and seeds replacements, the following calculations were done at the individual level. The grams of beef (or of beef, of poultry, and of pork) to be replaced was calculated. For example, if the person ate 80 grams of beef, 40 grams would need to be replaced under the 50% scenario. Those 40 grams would be allocated among the legumes, soy, and nuts/seeds categories according to the ratios in which that person ate those foods. For the 8% of changers who did not consume any of these foods (n=106), their replacement grams were allocated at the overall ratios for the population: 0.405 legumes other than soy, 0.336 nuts/seeds, and 0.259 soy. To replace the 40 grams of beef using these proportions, for example, the amounts would be as follows:

- Legumes other than soy: 40 grams * 0.405 * 0.55 = 8.91 grams
- Nuts/seeds: 40 grams * 0.336 * 0.39 = 5.24 grams
- Soy: 40 grams * 0.259 * 1.57 = 16.27 grams

Appendix Table A1 - 5. Coefficients used to predict Health Eating Index and diet cost in NHANES[1]

	Model to predict Health Eating Index			Model to predict diet cost		
	Coef.	**Std. Err.**	**P>|z|**	**Coef.**	**Std. Err.**	**P>|z|**
Crop Group: Beef	-0.015	0.002	<0.0001	0.001	0.000	<0.0001
Crop Group: Other ruminant meat	-0.023	0.008	0.02	0.003	0.001	0.00
Crop Group: Pork	-0.021	0.004	<0.0001	0.001	0.000	0.01
Crop Group: Poultry	0.007	0.002	<0.0001	0.001	0.000	<0.0001
Crop Group: Other nonruminant meat	0.282	0.020	<0.0001	0.006	0.001	<0.0001
Crop Group: Fish & Seafood	0.024	0.003	<0.0001	0.005	0.000	<0.0001
Crop Group: Eggs	-0.009	0.004	0.03	-0.001	0.000	<0.0001
Crop Group: Dairy	0.006	0.001	<0.0001	0.000	0.000	<0.0001
Crop Group: Oils	-0.022	0.008	0.01	-0.011	0.001	<0.0001
Crop Group: Solid (plant) fats	-0.016	0.069	0.84	0.006	0.003	0.05
Crop Group: Vegetables & Juices	0.011	0.004	<0.0001	0.001	0.000	<0.0001
Crop Group: Fruits & Juices	0.016	0.001	<0.0001	0.000	0.000	<0.0001
Crop Group: Legumes	0.051	0.009	<0.0001	-0.002	0.000	<0.0001
Crop Group: Nuts & Seeds	0.096	0.017	<0.0001	-0.002	0.001	0.01
Crop Group: Soy	0.027	0.005	<0.0001	0.001	0.000	<0.0001
Crop Group: Grains	-0.010	0.002	<0.0001	0.001	0.000	<0.0001
Crop Group: Beverages	0.000	0.000	0.01	0.000	0.000	0.01
Crop Group: Sweeteners	-0.040	0.002	<0.0001	-0.002	0.000	<0.0001
Crop Group: Other	0.014	0.018	0.42	0.008	0.001	<0.0001
Women	1.146	0.407	0.00	0.103	0.022	<0.0001
Household size	0.143	0.127	0.30	-0.015	0.008	0.08
Age [30,40)	0.662	0.527	0.18	0.048	0.038	0.20
Age [40,50)	1.276	0.525	0.04	0.068	0.042	0.06
Age [50,65)	3.264	0.558	<0.0001	0.101	0.044	0.01
High School grad/GED	0.737	0.569	0.29	0.047	0.043	0.20
Some College	2.043	0.571	<0.0001	0.073	0.031	0.05
College	4.134	0.674	<0.0001	0.098	0.040	0.02
Income-to-Poverty Ratio (2,5]	0.852	0.429	0.04	0.065	0.028	0.03
Income-to-Poverty Ratio (5,10]	1.011	0.563	0.18	0.108	0.036	0.00
Income-to-Poverty Ratio>10	1.501	0.926	0.12	0.204	0.044	<0.0001
Hispanic	0.719	0.463	0.32	-0.166	0.032	<0.0001
Black	-0.774	0.432	0.11	-0.137	0.035	<0.0001
Other race	-0.032	0.817	0.97	-0.219	0.050	<0.0001
Intercept	42.044	1.036	<0.0001	2.358	0.060	<0.0001
N	7,188			7,188		
R^2	0.4371			0.3183		

[1] Coefficient estimates in this table are the results of two separate multi-variable regressions models, one with Healthy Eating Index as the dependent variable, and one with Diet Cost as the dependent variable. All variables in the respective models are included in the table.

Table A1 - 1. Mean grams of commodity intake by potential changers under various meat replacement scenarios[1]

	Beef		Pork		Poultry		Legumes		Nuts/Seeds	
	Mean	95% CI	Mean	95% CI	Mean	95% CI	Mean	95% CI	Mean	95% CI
Baseline diet	37.7	(32.3, 43.0)	20.1	(15.8, 24.5)	53.8	(49.9, 57.7)	19.4	(14.7, 24.1)	10.3	(8.8, 11.8)
100% beef replaced:										
With poultry	0.0				96.0	(90.6, 101.4)				
With plant protein[2]	0.0						44.5	(36.5, 52.6)	15.8	(14.3, 17.3)
50% beef replaced:										
With poultry	18.8	(16.2, 21.5)			74.9	(71.2, 78.6)				
With plant protein[2]	18.8	(16.2, 21.5)					32.0	(26.1, 37.8)	13.1	(11.6, 14.5)
25% beef replaced:										
With poultry	28.2	(24.2, 32.3)			64.4	(60.9, 67.8)				
With plant protein[2]	28.2	(24.2, 32.3)					25.7	(20.6, 30.7)	11.7	(10.3, 13.1)
100% beef, pork, poultry replaced:										
With plant protein[2]	0.0		0.0		0.0		96.4	(80.7, 112.1)	24.8	(22.6, 27.0)
50% beef, pork, poultry replaced:										
With plant protein[2]	18.8	(16.2, 21.5)	10.1	(7.9, 12.2)	26.9	(24.9, 28.9)	57.9	(48.5, 67.3)	17.6	(15.9, 19.3)
25% beef, pork, poultry replaced:										
With plant protein[2]	28.2	(24.2, 32.3)	15.1	(11.8, 18.4)	40.4	(37.4, 43.3)	38.6	(32.0, 45.2)	14.0	(12.4, 15.5)

[1]Commodity amounts of edible portion of the different meats and plant foods in grams per day. Blank cells under replacement scenarios represent no change in commodity consumption from baseline.

[2]Plant proteins are legumes, nuts, and seeds. Diet changes for each potential changer reflected the individual's actual reported intakes of these three food groups. Replacements were made in the same ratio as the individual reported eating the three food groups. If the individual did not eat any of the food groups, the overall average ratio in the sample was used to distribute the new intake, specifically: 0.405 legumes other than soy, 0.336 nuts/seeds, and 0.259 soy.

Paper 2: Assessing the change in US food-related greenhouse gas emissions (GHGE) over 10 years

1. Background

Previous work in the US has looked at the distribution of food-related greenhouse gas emissions using dietary data from 2005-2010.[45,69] However, diet patterns may have changed in the years since then. To address this issue, this paper looks at change in diet-related GHGE over time.

Diets change over time for various reasons, such as war rationing, changes in agricultural practices, and cultural trends. How we eat can change on many dimensions. For example, in an analysis of NHANES data from 1971 to 2010, researchers found that over time, respondents have mentioned fewer traditional meal occasions (breakfast, lunch, dinner), “snacks” have become more likely to replace meals, and the average clock time of breakfast and lunch has gotten later.[103] Energy density of reported foods has also increased (1971-2002), paralleling a national rise in the prevalence of obesity.[104]

Meat intakes in the US have shifted considerably over time. Between NHANES 1999-2000 and 2015-2016, overall unprocessed red meat intakes decreased.[105] Within this unprocessed red meat category, beef intakes decreased, pork intakes remained the same, and “other” red meat increased. (Defining red meat as meat from mammal muscle, this “other” category could include lamb, goat, venison, or other large game.) During the same time, poultry intakes increased. Fish/seafood and processed meat intakes did not change.[105] Despite the reduction in beef intakes, the US remains one of highest per capita consumers of meat in the world.[106] In addition, the USDA estimates that intakes will rise between now and 2030.[107]

When looking at potential trends in food-related GHGE over time, meats and especially beef will probably be the largest drivers. However, changes in other food groups will also play a role. Sustainability or environmental-friendliness of foods is a growing motivation in many US consumers.[108] But are US diets becoming more sustainable over time, in terms of their carbon footprint?

One recently published study looked at US food-related GHGE from 2003 to 2018.[109] Similar to the present study, Bassi et al. used NHANES dietary data translated to commodity intakes using FCID, and used *dataFIELD* as their source of GHGE of commodities. However, Bassi et al. did not account for the structural changes to the USDA Food and Nutrient Database for Dietary Studies (FNDDS) after the 2011-2012 NHANES wave. This results in many foods from 2013-2014 onward not having commodity recipes from which to calculate food-related carbon footprint. Essentially, their analysis assigns these foods zero emissions. Their results show a steep decline in US food-related GHGE starting in 2013-2014, illustrating the impact of these missing foods. It is a necessity to update FCID recipes to match all foods reported in any NHANES waves used to explore questions of dietary carbon footprint using *dataFIELD*. The present study addresses this gap.

A handful of studies outside the US look at change in food-related GHGE over time. One Swedish study[110] found a significant decline in food-related GHGE overall, as well as in all age groups, over a similar time frame to the present study (2001-2004 to 2014-2018). A second Swedish study[111] was longitudinal, the only study of that type that has looked at this question. They found that dietary GHGE tended to be slightly lower at participants’ second visit than at their first (going from 3.43 kg to 3.30 CO_2-eq/1000kcal over the 10-year time period). However, they did not present statistical testing of this difference. In addition, their graphical results show food-related carbon footprints to be quite stable (~±0.2 CO_2-eq/1000kcal) in the sample over the course of the study (1996-2016).

This mirrors a study from China.[112] While the authors found substantial changes in the makeup of food intakes and the carbon footprint of those intakes from 1980 to 2000, the changes from 2000 to 2017 do not appear to be statistically significant (they do not report these results in a table, only in a bar chart, and do not present any statistical testing).

It is clear that more research is needed in this area, and the results may differ by country context. It is also critical that the correct methods be applied when calculating food-related emissions. This paper addresses the question of whether food-related GHGE has changed over time in the US context.

The results of this study will be informative whether or not trends toward a lower carbon footprint diet are found. If there is a decreasing trend, this shows that US consumers can make dietary changes that improve sustainability. This “positive deviance” behavior can be highlighted, as it shows that more sustainable diets are real, possible, and already acceptable to some consumers. If no trend is found, or even an increase in the carbon footprint of diets over time, this further underscores the need for incorporating sustainability into nutrition education and national dietary guidance.

2. Research question

How has the food-related carbon footprint of US diets changed over time? This research question was answered by addressing the following aims:

Aim 1: Develop and implement a method to calculate individual food-related GHGE for NHANES participants from 2015-2016.

Aim 2: Assess the trend in overall food-related carbon footprint in US adults from 2005-2006 to 2015-2016.

Aim 3: Examine how this trend varies by socio-economic and demographic characteristics.

Aim 4: Assess changes in intakes of different food groups that account for these trends.

3. Methods

Methods: Building new commodity recipes **(Aim 1)**

Previous work with the database *dataFIELD* has resulted in food-related GHGE values for NHANES respondents from 2005-2010, but not for any of the NHANES waves since. See Paper 1 Methods and dissertation Appendix 1 for additional details.

Commodity recipes were composed for all additional foods eaten by respondents in the 2015-2016 wave of NHANES. New recipes followed existing FCID recipes and standards as closely as possible. This ensured that newly added foods did not systematically differ from the original items in their ingredient makeups, and therefore their GHGE values. For example, a nutrition-oriented person might see a dish that is "cooked in oil" and assume that commodity recipe should include olive oil. However, FCID uses a selection of several common vegetable oils (based on market share) whenever an item is cooked "with oil." New recipes followed these and other similar standards to minimize the impact of investigator decision making. Nutrient profiles and ingredient data from USDA's FoodData Central (FDC) provided additional guidance on the makeup of new foods.

Many new foods were matched directly to an existing FCID recipe. This is due to structural changes made to the USDA's Food and Nutrient Database for Dietary Studies (FNDDS). The FNDDS is gives nutrient information for foods reported in NHANES, and is released on the same two-year cycle. First, modification codes were eliminated from the FNDDS between the 2011-2012 and 2013-2014 waves of NHANES. This means that some of the "new" foods that needed recipes in NHANES 2015-2016 were simply items that had been a modification in the past. For example, a "new" food might be "Egg omelet or scrambled egg, made with butter." This could be matched directly to the existing FCID recipe for "Egg omelet or scrambled egg, fat added in cooking" with a modification code that specified the cooking fat was butter.

Second, while some FNDDS items now describe the source of the food, the GHGE from production would not vary across these scenarios. For example, the foods "Chicken breast, baked or broiled, skin eaten, from pre-cooked" and "Chicken breast, baked or broiled, skin eaten, from fast food / restaurant" were both matched to the existing recipe for "Chicken, breast, roasted, broiled, or baked, skin eaten."

Recipes for foods without clear matches or previous recipes were developed based on judgement and informed from discussions with the research team. All new recipes were categorized by development type based on the source of the base recipe used, and the complexity of any changes made. See Paper 2 Appendix Table A2-1 for detailed criteria for these types.

Newly created recipes were reviewed for accuracy and consistency. This meant consistency within category (for example, making sure that recipes for coffee drinks with "non-dairy" milk all used the same commodity to represent that item), as well as consistency across categories (e.g., making sure that the commodity used for "non-dairy milk" in coffee drinks was the same as that used for non-dairy yogurt).

<u>Methods: Study sample</u>

The study sample was adults aged 18 years and older with reliable Day 1 and 2 dietary intake data from NHANES 2005-2006 and 2015-2016. The total sample size was 8,927.

<u>Methods: Calculating 2015-2016 individual-level food-related GHGE **(Aim 1)**</u>

Once all new recipes were completed, GHGE for each commodity ingredient was calculated using emissions values from *dataFIELD* and the ingredient amount per recipe. Emissions per ingredient in a recipe were summed to give kg CO_2-eq per 100g of each food (i.e., NHANES or USDA food code). This created a new version of what was referred to as the "bridge" file (bridging commodities and as-eaten foods) in the earlier section on *dataFIELD* methods. (More detail in dissertation Appendix 1.)

Dietary data were appended into one file, which contained respondents from both waves: 2005-2006 and 2015-2016. Food-related GHGE was calculated for each person's foods in the amounts they reported eating on both days. Finally, emissions were summed for each person to get a dataset of all respondents and their food-related GHGE for each day.

Intakes in grams of six commodity groups were also calculated for each respondent and averaged over the two days of dietary intake data. These groups were beef, pork, poultry, fish and seafood, eggs, and dairy.

Methods: Socioeconomic and demographic variables

Variables for age, gender, race/Hispanic origin, education, and IPR were used. These were coded as described above in Paper 1, with the exception of age. Instead of chronological age, for this analysis respondents were categorized based on which generation they fell into (Table 2-1).

Also of note: while a Non-Hispanic Asian category exists in NHANES 2015-2016, respondents who might fall into that category are not disaggregated in 2005-2006, so the same four categories were used as in Paper 1: Non-Hispanic White, Non-Hispanic Black, Hispanic, and Other/Multiracial.

Table 2 - 1 Generational Age Category Definitions

Generation	Birth Years	Estimated age (years) in 2006	Estimated age (years) in 2016
Silent[1]	1945 and earlier	61 and older	71 and older
Baby Boomer	1946 – 1964	42 to 60	52 to 70
X	1965 – 1980	26 to 41	36 to 51
Millennial	1981 – 1996	18 to 25	20 to 35
Z	1997 and later	--	18 to 19

[1]The age variable in NHANES 2005-2006 was top-coded at 85 years, but the following waves used 80 years. Although some members of the Greatest Generation (born ~1928 to 1944) are likely present in the sample, they cannot be distinguished at the second time point. Therefore, for this analysis, they were not separated from the Silent Generation at either time point.

Statistical analysis: new commodity recipes **(Aim 1)**

For newly created commodity recipes, descriptive statistics were calculated to show the frequency of each new recipe development type.

Statistical analysis: change in dietary GHGE, differences by socioeconomic and demographic characteristics **(Aims 2 & 3)**

All analyses were appropriate for the complex survey structure of NHANES. For the main analysis—did US dietary GHGE change over time—the outcome variable was food-related GHGE (kg CO_2-eq) per 2000 kilocalories averaged over the two days of dietary recall data (Day 1 GHGE per 2000kcal plus Day 2 GHGHE per 2000kcal, divided by two). This is effectively the GHGE concentration or density in the diet, and eliminates differences in carbon footprint that would come from respondents simply eating a lot or a little on the sample day.

General linear models were used. First, a crude model tested change in food-related GHGE over time (essentially a survey-weighted Student's *t* test). A fully adjusted model included time and all socioeconomic and demographic variables. To see if the trend varied by socioeconomic or demographic characteristics, two-way interaction terms were tested (e.g., generation*time). Interactions were only left in the model if they were statistically significant.

<u>Statistical analysis: Socioeconomic differences in commodity food groups **(Aim 4)**</u>

Additional models explored differences in intake of commodity food groups by socioeconomic or demographic characteristics. For each of these models, the outcome variable was 2-day average consumption in grams per 2000kcal of that commodity group (e.g., beef or dairy). Again, two-way interactions between time and socioeconomic and demographic variables were tested and only left in the model if significant. Adjusted consumption by generation and time were calculated from the regression equation, holding gender, race/Hispanic origin, educational attainment, and income-to-poverty ratio constant at their means. The following differences were tested, controlling for multiple comparisons with a Bonferonni correction: (1) Baby Boomers compared to each other generation, controlling for time (2) Baby Boomers compared to each other generation in 2015-2016.

All analyses used strata, PSU, and sampling weights provided in NHANES. The weights used were the 2-day dietary weights (WTDR2D). These survey weights were adjusted for the use of multiple survey cycles according to NHANES guidance, which in this case meant dividing by two for the number of cycles used. All tests were two-sided with an α level of 0.05. Analyses were conducted in Stata/SE Version 17.

4. Results

<u>Results: Building new commodity recipes **(Aim 1)**</u>

A total of 2,239 new commodity recipes were developed in order to calculate GHGE for foods consumed by NHANES participants in 2015-2016. Of these new recipes, 44.1% were directly matched with (i.e., copied from) existing FCID recipes (see Table 2-2). Relatively few items were classified as complex modifications or as "other" types of recipes.

<u>Results: Socioeconomic and demographic characteristics and change over time</u>

The sample, reflecting the US population, was largely Non-Hispanic White (68.2% overall), and more than half female (52.1%). Table 2-3 shows that over half of respondents (61.1%) had completed some education beyond high school. While those from the Silent Generation made up a fifth of the population (22.5%) in 2005-2006, their proportion declined and that of Millennials increased in 2015-2016. The distribution of age did not differ significantly over time. The distribution of race/Hispanic origin shifted over time, with respondents in 2015-2016 more likely to be Hispanic (10.7% in 2005-2006 vs. 15.1% in 2015-2016) or Other/Multiracial (5.0% vs 9.6%). However, the difference was only statistically significant for the Other/Multiracial group.

<u>Results: Changes in energy intake over time</u>

Reported energy intake (two-day average of kcal) decreased significantly over time in both crude and adjusted models (Paper 2 Appendix Table A2-2). Compared to Baby Boomers, the Silent Generation reported significantly fewer calories and Gen X and Millennials reported significantly more. Non-Hispanic Black and Other/Multiracial respondents reported fewer calories than Non-Hispanic Whites.

<u>Results: Food-related GHGE in 2005-2006 vs 2015-2016 **(Aims 2 & 3)**</u>

The mean food-related carbon footprint in 2005-2006 was 4.57 kg CO_2-eq per 2000 kcal, and in 2015-2016 it was 4.42. This reduction was not statistically significant in either the crude or the fully adjusted model (Table 2-4). There were no significant interactions between time and socioeconomic or demographic variables.

<u>Results: Socioeconomic and demographic differences in overall food-related GHGE</u>

However, there were significant differences in overall food-related carbon footprint by socioeconomic and demographic characteristics in the full model, that is, using observations from both time periods. Even adjusting for energy intake, women had lower food-related GHGE than men (-0.373, $p<0.001$). Non-Hispanic Black respondents had lower food-related GHGE than Non-Hispanic White respondents (-0.301, $p=0.009$). And those with education beyond a high-school diploma had lower food-related carbon footprint compared to those with a high school diploma or less.

And finally, the Silent Generation, Millennials, and Generation Z had lower dietary carbon footprints than Baby Boomers. There was no significant difference between Baby Boomers and Generation X.

<u>Results: Commodity consumption differences by generation **(Aim 4)**</u>

Compared to Baby Boomers, controlling for time and all other socioeconomic and demographic variables, respondents from the Silent Generation consumed significantly less poultry (-13.8%) and more eggs (+20.5%) and dairy (+20.1%) (Table 2-5). Gen Xers ate more poultry (+10.9%) and fewer eggs (-14.3%). Millennials consumed less pork (-25.9%) and dairy (-9.3%) and more poultry (+19.5%). Gen Z respondents ate less fish and seafood (-52.8%).

There was a significant interaction between time and generation for consumption of beef, fish & seafood, and eggs. Figure 2-1 shows the very different trajectories of beef consumption by generation and time. By 2015-2016, Baby Boomers were consuming 23.0% more beef than the Silent Generation and 21.0% more than Millennials (see Paper 2 Appendix Table A2-3 for regression models and A2-4 for adjusted consumption values). In addition, the Silent Generation ate 20.5% more egg than Boomers in 2015-2016.

5. Discussion

The food-related carbon footprint of individual, self-selected diets in the US did not significantly change between 2005-2006 and 2015-2016. While there were interesting differences in food-related GHGE by socioeconomic and demographic characteristics, the main result indicates that the US is not decreasing with regard to its environmental impact in this area.

These results are similar to work in China[112] and in Sweden.[111] Although these studies did not present statistical testing, the graphical results show food-related GHGE remaining relatively stable over time periods similar to the one in this study. However, a different Swedish study[110] found that dietary GHGE (measured as CO_2-eq / total grams of food from an 86-item FFQ) declined over time in all age groups. It may be that the results from this second Swedish study are not generalizable. The data came from an intervention program aimed at cardiovascular disease prevention in one county that invited participants to come to their primary care center for screenings, and the study had a relatively high non-response rate (about 60%).

The results of the present study do not agree, as expected, with the US study by Bassi et al.,[109] who found a sharp decline in dietary GHGE over time but neglected to account for new foods in NHANES from 2013-2014 onward. The authors do not report mean food-related GHGE numerically, but from their graphs it appears that they calculated 4.3 kg CO_2-eq per person per day in 2005-2006 and 2.5 in 2015-2016 (they did not adjust for energy intake). For comparison, the mean values unadjusted for energy intake in the present study are 4.8 kg CO_2-eq per person per day for 2005-2006 and 4.4 for 2015-2016. Bassi et al. account only for losses at the consumer level and not at the retail level, which could explain the discrepancy between their values and the present study in 2005-2006. The dramatic difference between the two studies' values in 2015-2016 demonstrates the large number of foods attributed a zero impact in Bassi et al.

The present study found that the dietary carbon footprint of Baby Boomers was higher than that of respondents from the Silent Generation, Millennials, or Gen Z. This is likely due to declining beef intake among all the generations except Baby Boomers. Few nutrition-related studies look at consumption behavior or diet quality by generation. However, one US study that found that compared to the previous generation (those referred to as the Silent Generation in this study, born before 1946), Boomers consumed more total calories and higher amounts of fat and cholesterol.[113]

Baby Boomers are the second largest generational cohort in the US, numbering around 71.6 million, with the Millennial generation (72.1 million) only recently surpassing Boomers in size.[114] Boomers suffer from chronic disease at higher rates than previous generations at the same age and this presents a substantial burden to the present and future health care system.[113,115] Targeting modifiable risk factors such as diet, especially beef intake, could have benefits in the disease risk of this group as well as reducing environment impacts.

A recent report by the Pew Research Center indicates that Millennials and Gen Z are more engaged both online (e.g., social media posts) and offline (e.g., donating money) with the issue of climate change, and are more supportive of prioritizing policies to address climate change (e.g., phasing out gas-powered vehicles), compared to older generations.[116] Large majorities of Gen Z (76%) and Millennials (75%) say that addressing climate change is an important concern to them personally, compared to smaller majorities of Baby Boomers (and older, 64%) or Gen X (67%).

Over one third of all generations surveyed said that they are more motivated to take action on climate change when they see people like themselves urging it, meaning that social marketing efforts may be an effective method of delivering nutrition and sustainability messaging. Overall, there was surprisingly high support in the Pew Research Center study for some diet-related behaviors: 81% of respondents said that they reduced their food waste and 40% said that they ate less meat to help protect the environment (responses were not reported by generation and these were the only two diet-specific behaviors in the list). This suggests potential responsiveness to education or social marketing with messages relating to the climate benefits of reducing meat consumption—especially if those messages were targeted by generation and delivered by a member of that generation.

Some argue that chronological age, not generational cohort, is a more influential determinant of eating behavior.[117] The most recent iteration of the Dietary Guidelines for Americans focuses on nutrition and wellness across the life course.[32] Regardless of any age or generational targeting, food sustainability information could be incorporated into nutrition education materials and national dietary guidance. Given that a majority within all the generations studied by the Pew Research Center indicated that addressing climate change was a personal concern, increasing consumer awareness about the GHGE of different foods could increase the chances of dietary change, compared to simply giving health-related information about food.

Strengths and limitations

NHANES is a nationally representative dataset with rich detail about foods consumed by respondents. However, it is cross-sectional. This study cannot show whether *individuals* have changed their diets over time, and what factors might have affected that.

The commodity recipes used to calculate the food-related carbon footprint in 2015-2016 were based on the original 2005-2010 recipes, with the addition of new recipes that follow the methods and choices of these older recipes. It is possible that there are differences in the makeup of foods consumed more recently, and these are not captured by using the original recipe structure. However, using the same makeup of commodity recipes for the whole study sample is a strength that allows for the comparison of the effects of changes in dietary choices alone. The GHGE of food production may also change over time, but that is beyond the scope of *dataFIELD* and this analysis. More research is needed to understand the evolving impact of dietary choices in light of changes in food production and formulation, as well as any changes in consumer choices or other market forces.

As above in Paper 1, the limitations of 24-hour recalls still apply here. Using the average of two days of dietary intake data helped reduce in-person variation. Also, all analyses here adjusted for reported energy intake, as suggested for the interpretation of self-reported dietary data.[118] This eliminated variation that might have occurred if reported energy intakes changed over the decade the study, which they did (see Paper 2 Appendix Table A2-2 for details). In addition, dietary data are often right-skewed (see Paper 3), making analyses vulnerable to the influence of extreme large values. Additional analyses should explore the effect of outliers and/or transformation of the outcome variables to better approximate a normal distribution.

In conclusion, the food-related GHGE of US diets did not decline between 2005-2006 and 2015-2016. More effort is needed to address the climate impacts of food choice in the US. These efforts could include nutrition education and social marketing targeted demographically as well as inclusion of sustainability information in national dietary guidance.

Table 2 - 2. NHANES 2015-2016 new recipe development types and frequencies

New recipe development type	N	%	Example
Direct match to FCID[1]	988	44.1	"Chicken drumstick, fried, coated, skin / coating eaten, from pre-cooked" (food code 24147310): matched to existing recipe for "Chicken, drumstick, coated, baked or fried, prepared with skin, skin/coating eaten" (24147210). "Egg, whole, fried with animal fat or meat drippings" (food code 31105060): matched to recipe for "Egg, whole, fried w/ animal fat or meat drippings" (31105000, modification code 205034).
Simple modification of FCID recipe	896	40.0	"Corn with peppers, red or green, cooked, made with butter" (food code 75303022): replaced the fat components of the existing recipe "Corn with peppers, red or green, cooked, NS as to fat added in cooking" (75303000) with milk commodity ingredients using proportions from "Butter, NFS" (81100500).
Complex modification of FCID recipe	147	6.6	"Pasta with tomato-based sauce, poultry, and added vegetables, restaurant" (food code 58146341): used "Pasta with meat sauce" (53146110) as a base, replacing meat with poultry items in the same proportions as "Spaghetti sauce with poultry, home-made style" (27141030), and added vegetables in the proportions from "Macaroni, creamed, with vegetables" (58147350).
Direct from FoodData Central[2] ingredient list	13	0.6	"Kefir, NS as to fat content" (food code 11115400): used FoodData Central entry to determine proportions of FCID dairy commodities: milk fat, milk nonfat solids, and milk water.
Simple modification of FoodData Central ingredient list	6	0.3	"Edamame, cooked" (food code 41420020): took kcal per 100g from the FoodData Central entry. Used this value to scale SR Legacy item "Soybeans, mature seeds, raw" and find the commodity amount of soybeans needed for 100g cooked edamame. (Edamame are not mature seeds, but FCID has no commodity for immature soybeans.)
Complex modification of FoodData Central ingredient list	98	4.4	"Rice, white, with cheese and/or cream based sauce, NS as to fat added in cooking" (food code 58164500): proportions of cooked rice, vegetable oil, and prepared cheese sauce came from FoodData Central. FCID had existing recipes for those three items: cooked rice (56205000), cheese sauce (14650100), and vegetable oil (82101000).
Other	91	4.1	"Bean chips" (food code 41310900): started with existing FCID recipe for "Soy chips" (41410015) and replaced soy beans in this recipe with black beans. Consulted online listings for popular brand "Beanitos" and added brown rice and cassava to match the brand's ingredient list.
Total	2,239		

[1]Food Commodity Intake Database from the US Environmental Protection Agency.

[2]FoodData Central, a search tool from the US Department of Agriculture that combines several food and nutrient databases, including the Food and Nutrient Database for Dietary Studies and the National Nutrient Database for Standard Reference Legacy Release.

Table 2 - 3. Characteristics of NHANES 2005-2006 and 2015-2016[1] adults and tests of demographic change over time

	Overall (N=8,927)		2005-2006 (n=4,527)		2015-2016 (n=4,400)		N	χ^2 p value	Logistic Regression[3]	
	%	CI	%	CI	%	CI			OR	p value
Gender										
Male	47.9	(46.7, 49.2)	47.2	(45.6, 48.8)	48.6	(46.7, 50.5)	4,224	0.261	(reference)	
Female	52.1	(50.8, 53.3)	52.8	(51.2, 54.4)	51.4	(49.5, 53.3)	4,703		0.96	0.431
Generation										
Silent	17.1	(15.0, 19.4)	22.5	(18.8, 26.6)	12.3	(10.3, 14.5)	1,871		0.64	**0.002**
Boomer	31.6	(29.5, 33.7)	33.3	(31.4, 35.3)	30.0	(26.6, 33.7)	2,543		(reference)	
Gen X	27.6	(25.6, 29.7)	29.3	(26.2, 32.7)	26.0	(23.6, 28.6)	2,272	**<0.001**	0.96	0.698
Millennial	22.3	(20.4, 24.3)	14.9	(13.2, 16.8)	28.9	(26.0, 32.0)	2,041		2.04	0.261
Gen Z[2]	1.4	(1.1, 1.8)	--	--	2.7	(2.2, 3.4)	200		--	--
Race/Hispanic Origin										
Hispanic	13.0	(10.2, 16.4)	10.7	(8.4, 13.5)	15.1	(10.3, 21.5)	2,378		1.45	0.174
Non-Hispanic White	68.2	(63.0, 73.0)	72.6	(66.0, 78.2)	64.3	(56.1, 71.7)	3,755	0.067	(reference)	
Non-Hispanic Black	11.4	(8.6, 14.8)	11.8	(8.1, 16.8)	11.0	(7.3, 16.2)	2,011		0.93	0.815
Other	7.4	(5.9, 9.3)	5.0	(3.9, 6.5)	9.6	(7.1, 13.0)	783		1.73	**0.015**
Highest Education										
Less than HS	15.1	(13.1, 17.4)	16.7	(14.4, 19.3)	13.7	(10.6, 17.4)	2,167		0.79	0.062
HS grad or equivalent	23.8	(22.1, 25.5)	25.7	(23.2, 28.4)	22.0	(19.7, 24.4)	2,184	0.093	(reference)	
Some college	32.6	(30.8, 34.5)	32.0	(30.0, 34.1)	33.2	(30.3, 36.2)	2,612		1.23	**0.014**
College grad or higher	28.5	(25.0, 32.3)	25.5	(21.4, 30.1)	31.2	(25.7, 37.3)	1,962		1.62	**0.005**
Income-to-Poverty Ratio										
<1	11.6	(10.0, 13.5)	10.5	(8.9, 12.4)	12.6	(10.0, 15.9)	1,666		1.08	0.509
1 - <2	19.4	(17.8, 21.1)	19.2	(17.2, 21.4)	19.6	(17.3, 22.2)	2,142		(reference)	
2 - <5	38.6	(36.1, 41.3)	41.6	(39.8, 43.5)	35.9	(31.3, 40.8)	3,043	**0.019**	0.80	0.051
5+	24.7	(21.5, 28.3)	25.2	(21.2, 29.6)	24.3	(19.4, 29.9)	1,466		0.81	0.282
Missing income data	5.6	(4.8, 6.6)	3.5	(2.8, 4.2)	7.6	(6.1, 9.3)	610		2.09	**<0.001**
Age										
18-29 years	21.6	(19.3, 24.1)	20.9	(18.5, 23.6)	21.2	(19.5, 23.0)	2,153			
30-49 years	37.7	(33.5, 42.1)	33.1	(30.0, 36.4)	35.3	(32.7, 38.0)	2,773	0.154	*Not included in model*	
50-65 years	24.6	(22.1, 27.2)	27.3	(25.1, 29.5)	26.0	(24.4, 27.7)	2,111			
66-80 years[4]	16.1	(13.4, 19.3)	18.7	(15.9, 21.9)	17.5	(15.5, 19.7)	1,890			

[1]All calculations account for survey design parameters and sampling weights.
[2]Generation Z respondents only reached adulthood, and therefore were only included, in the 2015-2016 wave. Since being in Gen Z perfectly predicts being in the 2015-2016 wave, it was excluded from the logistic regression model.
[3]Outcome was a dummy variable equal to 0 for respondents from 2005-2006 and 1 for respondents from 2015-2016. Predictors included all the characteristics in this table.
[4]Age is top-coded to 85 in NHANES 2005-2006, and 80 in 2015-2016. For this study, any respondent with an age 81-85 years in 2005-2006 was recoded to 80.

Table 2 - 4. Mean food-related greenhouse gas emissions (kg CO_2-equivalents per 2000kcal) by socioeconomic and demographic characteristics and time

	Overall		2005-2006		2015-2016		Crude Model		Fully Adjusted	
	Mean	**CI**	**Mean**	**CI**	**Mean**	**CI**	**Coefficient[1]**	**P**	**Coefficient[1]**	**P**
Overall	4.49	(4.39, 4.59)	4.57	(4.45, 4.68)	4.42	(4.26, 4.57)	-0.149	0.124	-0.137	0.181
Gender										
Male	4.69	(4.54, 4.83)	4.78	(4.63, 4.93)	4.60	(4.37, 4.84)			(reference)	
Female	4.31	(4.19, 4.43)	4.38	(4.21, 4.55)	4.24	(4.08, 4.41)			-0.373	**<0.001**
Generation										
Silent	4.42	(4.28, 4.57)	4.54	(4.39, 4.69)	4.23	(3.96, 4.51)			-0.261	**0.024**
Boomer	4.64	(4.47, 4.80)	4.62	(4.43, 4.82)	4.65	(4.38, 4.92)			(reference)	
Gen X	4.51	(4.31, 4.70)	4.63	(4.35, 4.90)	4.38	(4.10, 4.66)			-0.123	0.292
Millennial	4.34	(4.14, 4.53)	4.37	(4.07, 4.67)	4.32	(4.08, 4.56)			-0.308	**0.021**
Gen Z[2]	4.10	(3.63, 4.58)	--	--	4.10	(3.63, 4.58)			-0.594	**0.027**
Race/Hispanic Origin										
Hispanic	4.58	(4.40, 4.76)	4.77	(4.43, 5.10)	4.46	(4.25, 4.67)			0.010	0.949
Non-Hispanic White	4.50	(4.37, 4.63)	4.58	(4.46, 4.71)	4.42	(4.18, 4.65)			(reference)	
Non-Hispanic Black	4.23	(4.06, 4.40)	4.17	(3.97, 4.37)	4.29	(4.03, 4.55)			-0.301	**0.009**
Other	4.62	(4.34, 4.90)	4.87	(4.26, 5.48)	4.50	(4.20, 4.80)			0.178	0.226
Highest Education										
Less than HS	4.69	(4.47, 4.91)	4.66	(4.45, 4.87)	4.73	(4.33, 5.13)			0.179	0.253
HS grad or equivalent	4.51	(4.38, 4.63)	4.56	(4.42, 4.71)	4.44	(4.24, 4.65)			(reference)	
Some college	4.50	(4.37, 4.63)	4.52	(4.33, 4.71)	4.48	(4.30, 4.65)			-0.019	0.795
College grad or higher	4.36	(4.22, 4.51)	4.57	(4.37, 4.77)	4.21	(4.00, 4.41)			-0.201	**0.028**
Income-to-Poverty Ratio										
<1	4.48	(4.33, 4.64)	4.66	(4.41, 4.91)	4.35	(4.15, 4.55)			-0.031	0.779
1 - <2	4.52	(4.36, 4.68)	4.62	(4.46, 4.79)	4.43	(4.17, 4.68)			(reference)	
2 - <5	4.42	(4.29, 4.55)	4.49	(4.33, 4.65)	4.35	(4.14, 4.56)			-0.100	0.344
5+	4.51	(4.31, 4.71)	4.58	(4.32, 4.84)	4.44	(4.14, 4.74)			-0.003	0.985
Missing income data	4.79	(4.46, 5.12)	4.90	(4.45, 5.36)	4.75	(4.32, 5.17)			0.308	0.115

[1]The coefficient in the first row is the one for time: a dummy variable where NHANES 2005-2006 respondents are coded 0 and 2015-2016 respondents are coded 1.

[2]Generation Z respondents only reached adulthood, and therefore were only included, in the 2015-2016 wave.

Table 2 - 5. Adjusted[1] consumption of animal-based food groups by generation with differences compared to Baby Boomers

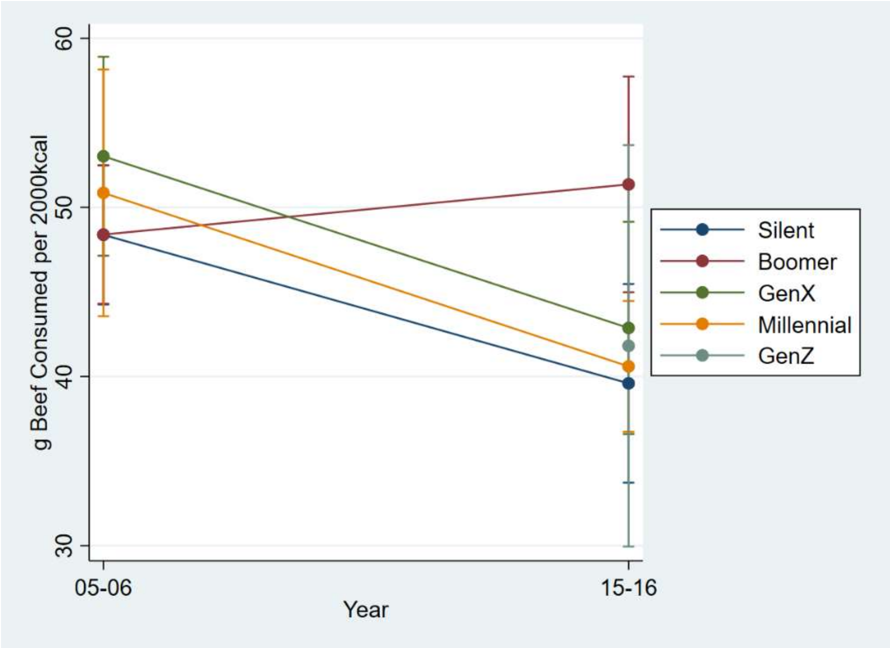
	Boomers		Silent Generation				Gen X				Millennial				Gen Z			
	g per 2000 kcal	**SE**	**g per 2000 kcal**	**SE**	**Abs. Diff.**	**% Diff.**	**g per 2000 kcal**	**SE**	**Abs. Diff.**	**% Diff.**	**g per 2000 kcal**	**SE**	**Abs. Diff.**	**% Diff.**	**g per 2000 kcal**	**SE**	**Abs. Diff.**	**% Diff.**
Beef	50.0	1.8	43.8	1.9	n.s.[2]	n.s.	47.7	2.1	n.s.	n.s.	45.5	2.0	n.s.	n.s.	41.8	5.8	n.s.	n.s.
Pork	30.5	1.3	28.4	1.2	n.s.	n.s.	27.0	1.7	n.s.	n.s.	22.6	1.2	-7.9***	-25.9***	29.2	9.0	n.s.	n.s.
Poultry	52.2	2.4	45.0	1.8	-7.2**	-13.8**	57.9	1.7	+5.7*	+10.9*	62.4	2.5	+10.2***	+19.5***	55.7	7.5	n.s.	n.s.
Fish & Seafood	19.7	1.7	20.9	1.5	n.s.	n.s.	20.2	1.7	n.s.	n.s.	14.7	1.5	n.s.	n.s.	9.3	3.2	-10.4*	-52.8*
Eggs	29.3	1.0	35.3	1.2	+6.0**	+20.5**	25.1	1.3	-4.2*	-14.3*	25.1	1.6	n.s.	n.s.	25.5	4.2	n.s.	n.s.
Dairy	220.0	6.0	264.2	6.9	+44.2***	+20.1***	214.7	9	n.s.	n.s.	199.6	7.7	-20.4*	-9.3*	234.3	25.6	n.s.	n.s.

[1]Predicted values based on regression models controlling for time, generation, gender, race/Hispanic Origin, education, and income-to-poverty ratio. An interaction between time and gender was statistically significant and therefore included in the models for beef, fish & seafood, and eggs. Post-tests for difference compared to Baby Boomers used a Bonferroni correction for multiple tests.

[2]*p<0.05; **p<0.01, ***p<0.001 for adjusted Wald test comparing to Baby Boomers.

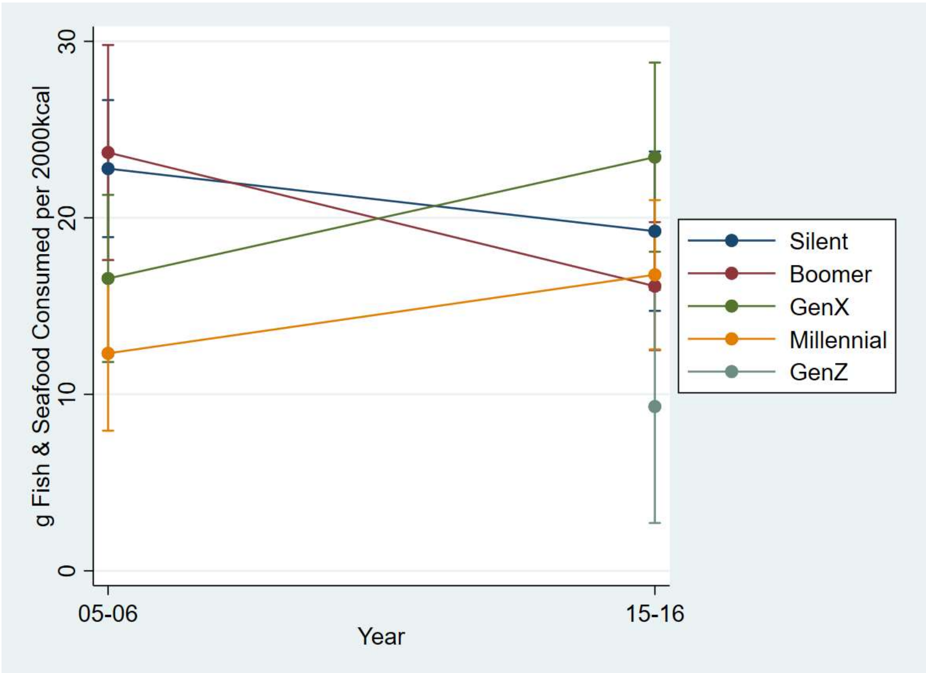
n.s.: difference was not statistically significant.

Figure 2 - 1. Adjusted[1] beef consumption by time and generation



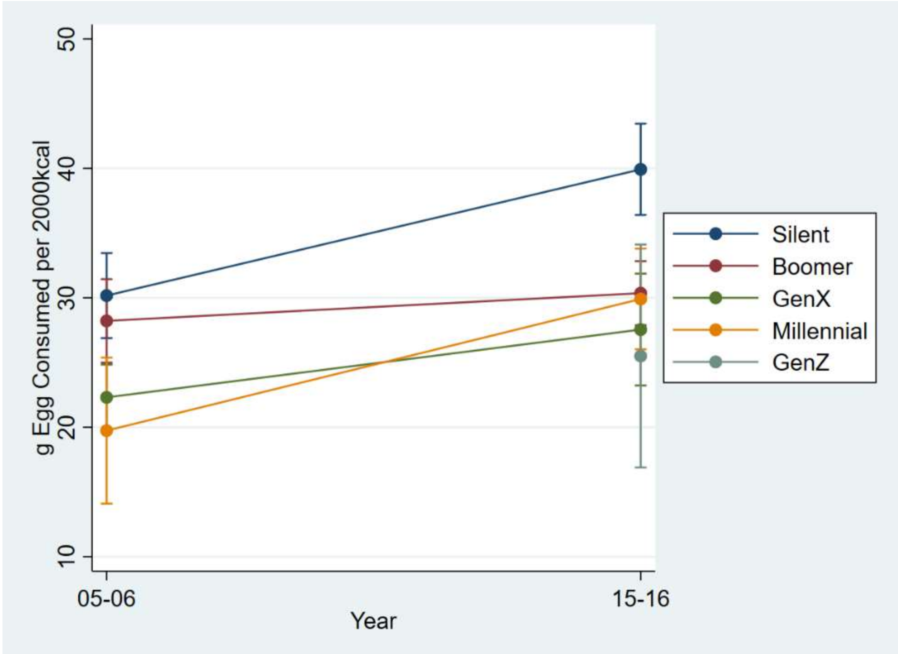
[1]Predicted values based on regression models including time, generation, time*generation, gender, race/Hispanic origin, education, and income-to-poverty ratio.

Figure 2 - 2. Adjusted[1] fish & seafood consumption by time and generation



[1]Predicted values based on regression models including time, generation, time*generation, gender, race/Hispanic origin, education, and income-to-poverty ratio.

Figure 2 - 3. Adjusted[1] egg consumption by time and generation



[1]Predicted values based on regression models including time, generation, time*generation, gender, race/Hispanic origin, education, and income-to-poverty ratio.

6. Paper 2 Appendix

Appendix Table A2 - 1. Criteria and documentation details for commodity recipe types

Code	Description	Base recipe comes from	Examples	Info to include in Recipe tab
1	Direct match to FCID[1]	FCID		Food code and modification code of the recipe used.
2	Simple modification of FCID recipe	FCID	One base FCID recipe modified with info from a second recipe. Or could be an average of two recipes. Could be an FCID recipe modified with info from an FDC item.	Food code and modification code of the main FCID used. Either food code + mod code or FDC ID of the second item, as appropriate. If you modified an FCID recipe using some reasoning that is in your notes, but doesn't necessarily come from another recipe/item, you just need to include food code + mod code of the base recipe.
3	Complex modification of FCID recipe	FCID	Combinations of 3 or more existing recipes, where the primary recipe is an FCID one. Modifying items could be FCID recipes or FDC items.	Food code and modification code of the main FCID used. Either food code + mod code or FDC ID of the additional items, as appropriate and as space is available. So for example if you have an FCID recipe that you modified using another FCID food and an FDC food, you would fill in Food Code/Mod Code 1, Food Code/Mod Code 2, and FDC ID 1.
4	Direct from FoodData Central ingredient list	FDC	This is not a direct match in the same way that code #1 is, because FDC foods are not made up of FCID commodity ingredients. So what this means is something like the Kefir example from our practice items: one FDC food was used to create a recipe of FCID commodity ingredients.	FDC ID of the item used.
5	Simple modification of FoodData Central ingredient list	FDC	A recipe based on an FDC item, with modifications or additions from another FDC item or from an existing FCID recipe.	FDC ID of the main item used. Either food code + mod code or FDC ID of the second item, as appropriate.
6	Complex modification of FoodData Central ingredient list	FDC	Combinations of 3 or more existing recipes, where the primary recipe is an FDC item. Modifying items could be FCID recipes or FDC items.	FDC ID of the main item used. Either food code + mod code or FDC ID of the additional item, as appropriate and as space allows.
7	Other	Other	Use sparingly--we want most of our work to fall in line with existing FCID recipes. Check with Amelia about recipes that don't fit the above categories.	

[1]Food Commodities Intake Database from the US Environmental Protection Agency.

Appendix Table A2 - 2. Regression coefficients for models of change in energy intake over time

	Day 1 kcal		Day 2 kcal		Two-day avg kcal	
	Crude	**Adjusted**	**Crude**	**Adjusted**	**Crude**	**Adjusted**
Constant	2198.6	2625.7	2062.0	2416.0	2130.3	2520.8
2015-2016 vs 2005-2006	-99.5*	-150.9***	-64.9	-111.1**	-82.2*	-131.0***
Gender						
Male						
Female		-714.3***		-633.4***		-673.8***
Generation						
Silent		-331.6***		-247.9***		-289.7***
Boomer		(reference)		(reference)		(reference)
Gen X		176.7***		89.8*		133.3***
Millennial		188.2***		124.6**		156.4***
Gen Z		-90.4		15.7		-37.3
Race/Hispanic Origin						
Hispanic		-17.6		-25.0		-21.3
Non-Hispanic White		(reference)		(reference)		(reference)
Non-Hispanic Black		-73.4*		-121.2**		-97.3**
Other		-150.3***		-99.9		-125.1**
Highest Education						
Less than HS		-67.8		-36.8		-52.3
HS grad or equivalent		(reference)		(reference)		(reference)
Some college		-8.7		81.3*		36.3
College grad or higher		-0.8		89.3*		44.3
Income-to-Poverty Ratio						
<1		-64.4		-116.2*		-90.3*
1 - <2		(reference)		(reference)		(reference)
2 - <5		-10.2		-27.6		-18.9
5+		-30.3		-7.6		-18.9
Missing income data		-118.5		-108.6		-113.5
N	8927	8925	8927	8925	8927	8925
F	6.4549	62.2877	2.6463	49.0375	5.0510	82.9376
p	0.0165	0.0000	0.1143	0.0000	0.0321	0.0000

Appendix Table A2 - 3. Regression coefficients for models predicting 2-day average g animal food group consumption per 2000kcal

Variable		Beef		Pork		Poultry		Fish & Seafood		Eggs		Dairy	
		Crude	Full	Crude	Full	Crude	Full	Crude	Full	Crude	Full	Crude	Full
Generation:	Silent	-3.8	0.0	-1.3	-2.1	-10.1***	-6.7**	0.0	-0.9	4.5**	2.0	55.2***	44.2***
	Boomer	(base)	(base)	(base)	(base)	(base)	(base)	(base)	(base)	(base)	(base)	(base)	(base)
	GenX	-1.5	4.6	-3.5	-3.5	6.2*	5.5*	0.4	-7.1	-3.3*	-5.9*	-8.9	-5.3
	Millennial	-4.6*	2.5	-6.8***	-7.9***	12.8***	11.7***	-4.2	-11.4**	-1.2	-8.5**	-31.2***	-20.4*
	GenZ	-3.0	-9.5	0.8	-2.7	6.6	1.0	-10.7**	-6.8*	-2.4	-4.9	-7.0	30.9
Survey wave:	2005-2006		(base)		(base)		(base)		(base)		(base)		(base)
	2015-2016		3.0		2.8		5.3		-7.6*		2.1		-35.1**
Time-generation interaction:[1]													
	2015-2016#Silent		-11.7*						4.0		7.6**		
	2015-2016#Boomer		(base)						(base)		(base)		
	2015-2016#GenX		-13.1*						14.4**		3.1		
	2015-2016#Millennial		-13.2*						12.0**		8.0*		
	2015-2016#GenZ		(omitted)						(omitted)		(omitted)		
Gender:	Male		(base)		(base)		(base)		(base)		(base)		(base)
	Female		-12.1***		-6.6***		0.7		3.2		2.1		28.2***
Race/Hispanic origin:	Hispanic		2.0		-4.6*		9.1**		5.3*		5.9**		-28.6**
	Non-Hispanic White		(base)		(base)		(base)		(base)		(base)		(base)
	Non-Hispanic Black		-2.9		-1.5		24.5***		6.9***		0.3		-98.2***
	Other/Multiracial		2.6		-0.1		8.2*		12.0***		2.0		-37.6**
Income-to-poverty ratio:	<1		-0.2		1.0		5.6		-2.0		3.3*		-5.3
	1 - <2		(base)		(base)		(base)		(base)		(base)		(base)
	2 - <5		0.5		0.9		5.9*		-3.2		0.2		-19.2
	5+		-1.4		-3.7		11.9**		1.9		-3.8		-23.1
	Missing		4.5		-1.9		5.7		-0.1		-2.6		-2.8
Education:	Less than HS		4.7		2.3		-1.3		-2.7		1.7		7.5
	HS grad or equivalent		(base)		(base)		(base)		(base)		(base)		(base)
	Some college		-1.3		-3.3		-0.7		-0.1		2.8		17.7*
	College grad or higher		-7.9***		-3.9*		-0.1		3.8*		3.1		21.3*
	N	8927	8925	8927	8925	8927	8925	8927	8925	8927	8925	8927	8925
	F	1.2203	9.9761	6.4893	5.8517	24.8670	9.5174	6.2656	7.7206	4.2045	7.8389	19.1546	29.6467
	p	0.3254	0.0001	0.0009	0.0007	0.0000	0.0000	0.0011	0.0004	0.0090	0.0004	0.0000	0.0000

[1]Interactions were tested for each food group, but only left in if the term was statistically significant. Adjusted Wald test p value for interactions: beef p=0.043, fish & seafood p=0.033, eggs p=0.003.
*p<0.05; **p<0.01, ***p<0.001

Appendix Table A2 - 4. Adjusted[1] consumption (g/2000kcal) of all commodity food groups by generation and time

	Silent Generation						Boomer					
	Overall	**SE**	**0506**	**SE**	**1516**	**SE**	**Overall**	**SE**	**0506**	**SE**	**1516**	**SE**
Beef	43.8	1.9	48.4	2.0	39.6*	2.9	50.0	1.8	48.4	2.0	51.4	3.1
Pork	28.4	1.2	26.9	1.2	29.7*	1.6	30.5	1.3	29.1	1.5	31.9	1.5
Poultry	45.0**	1.8	44.1	2.3	45.8	2.9	52.2	2.4	52.1	3.3	52.2	3.7
Fish & Seafood	20.9	1.5	22.8	1.9	19.2	2.2	19.7	1.7	23.7	3.0	16.1	1.8
Eggs	35.3**	1.2	30.2	1.6	39.9***	1.7	29.3	1.0	28.2	1.6	30.4	1.2
Dairy	264.2***	6.9	282.7	8.5	247.6***	8.7	220.0	6.0	238.4	8.6	203.4	7.3

	Gen X						Millennial						Gen Z[2]	
	Overall	**SE**	**0506**	**SE**	**1516**	**SE**	**Overall**	**SE**	**0506**	**SE**	**1516**	**SE**	**1516**	**SE**
Beef	47.7	2.1	53.0	2.9	42.9	3.1	45.5	2.0	50.9	3.6	40.6**	1.9	41.8	5.8
Pork	27.0	1.7	25.6	1.9	28.4	1.9	22.6***	1.2	21.1	1.5	23.9***	1.4	29.2	9.0
Poultry	57.9*	1.7	54.4	2.5	61.0	2.3	62.4***	2.5	54.5	3.4	69.6**	3.5	55.7	7.5
Fish & Seafood	20.2	1.7	16.6	2.3	23.4	2.6	14.7	1.5	12.3	2.1	16.8	2.1	9.3	3.2
Eggs	25.1*	1.3	22.3	1.2	27.5	2.1	25.1	1.6	19.7	2.8	29.9	1.9	25.5	4.2
Dairy	214.7	9.0	233.1	13.2	198.0	7.1	199.6*	7.7	218.0	11.0	182.9	7.5	234.3	25.6

[1]Predicted values based on regression models controlling for time, generation, gender, race/Hispanic Origin, education, and income-to-poverty ratio. An interaction between time and generation was statistically significant and therefore included in the models for beef, fish & seafood, eggs. Post-tests for difference compared all other generations to Baby Boomers both overall (i.e., controlling for time) and in 2015-2016, using a Bonferroni correction for multiple tests.
*p<0.05; **p<0.01, ***p<0.001 for adjusted Wald test comparing to Baby Boomers.
[2]Gen Z fish & seafood consumption differed from Baby Boomers in total (controlling for time), but not compared to 2015-2016 Baby Boomer values.

Paper 3: Carbon footprint and diet quality of usual diets in the US

1. Background

Issues in dietary measurement

In nutrition research, it is typical to study the relationship between dietary intake and a health outcome. In infectious disease like food-borne parasites, the lag time between intake and a change in health may be quite short. When studying noncommunicable diseases, however, it is the long-term average (i.e., usual) intake that contributes to future health outcomes. Despite this, in research food intake is often measured at only one point or a few points in time.

In a 24-hour dietary recall (24HR), respondents are asked to report everything they ate or drank over the last 24-hour period. Many details of consumption are recorded, including portion sizes and method of preparation. Diet recalls may be administered by a trained interviewer (as in NHANES, described in Paper 1 Methods) or by using validated self-assessment methods (e.g., the National Cancer Institute's Automated Self-Administered Recall system [ASA24]). Recalls are structured to include probing questions that help respondents remember commonly forgotten items, and visual guides assist respondents in reporting portion sizes.

Despite these strict protocols, it is possible for 24-hour recalls to suffer from measurement error related to respondent underreporting. This may be systematic. Certain groups have been found to misreport intake, such as those who are obese or elderly. Social desirability bias may also occur, with respondents reporting smaller portions or excluding foods that they know are unhealthy.

Despite these potential limitations 24-hour dietary recalls are useful and important tools to understand diets.[118] Since respondents report their intake retrospectively, they will not have changed what they ate because they knew they were being tracked. And most importantly, 24HRs give researchers rich detail about all the different foods and beverages consumed for the previous day, including preparation methods. This allows for the most accurate and complete calculation possible of food and nutrient intake using available analytic databases.

Measuring "usual" intake

A single 24HR is adequate to describe the average intake of a population.[119] However, one day of eating does not necessarily represent a person's typical intake.

Dietary measurements using a single day of intake data tend to be more disperse than true usual intakes over time. In other words, the 1-day distribution of intakes tends to have more of the study sample in the extreme parts of the distribution. To assess adequacy in relation to a recommended standard, or to understand the true relationship between diet and a health outcome, a method is needed to get an accurate usual intake over time. Simply averaging multiple recalls does not fix these issues; the distributions are still wider than true usual intake.

Biostatistics researchers have developed a series of complex methods to estimate usual intake from 2 or more days of 24-hour dietary recalls. The earliest versions of these methods could only model usual intake for nutrients that were consumed daily by everyone (i.e., no zero consumption values allowed), and they could not account for complex survey design or issues related to 24-hour recalls. The latest models can be used for both ubiquitously and episodically consumed foods and nutrients. They can also be used with complex survey data, and models account for various elements of 24-hour recalls: time-in-sample (the order of the recall days), seasonality, day of the week (weekday versus weekend), and the relationship between probability of consumption and amount of consumption. Covariates related to consumption, such as age and sex, can also be added to improve the models.

The effect of modeling usual intake versus 1-day diets or simply averaging multiple dietary recalls is shown in Figures 3-1 and 3-2. Figure 3-1 shows three distributions of total fruit and vegetable intake in the US from 1994-1996.[120] The distribution overall is right-skewed, as dietary intake data often is. The line with long dashes represents a single day of dietary intake data. Substantially more of the population fell into the lowest and highest parts of this curve compared to the usual intake curve (solid line). The within-person mean distribution (short-dashed line) is intermediate between the single day of intake and the usual intake. However, this would still overestimate the proportion of the population with very low or very high intakes, as the figure illustrates with the shaded area under the curve showing which proportion of the population would be categorized as consuming below one serving of fruits and vegetables per day.

Figure 3 - 1. Comparing the distribution of dietary intakes using different estimation methods: a commonly consumed food (Dodd et al, 2006)

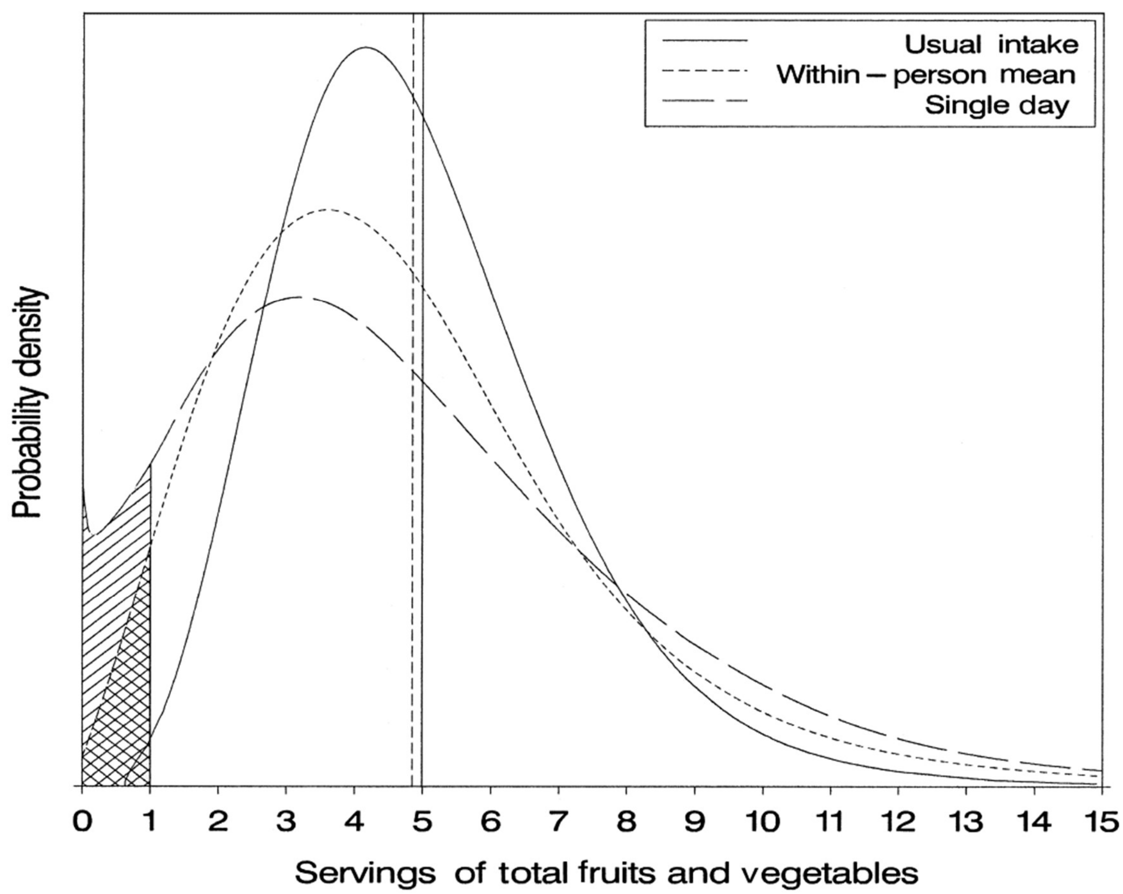
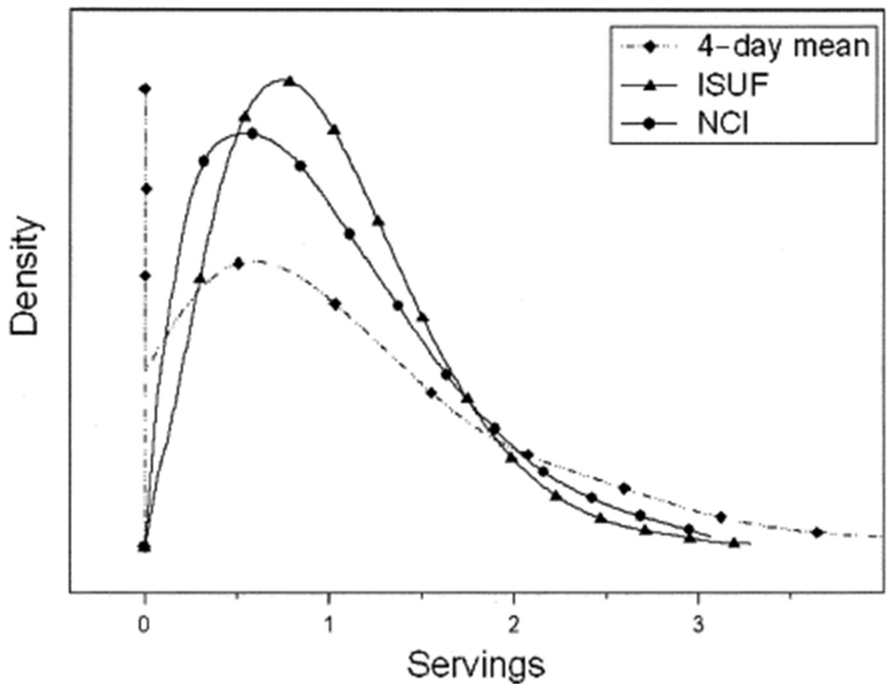


Figure 3-2 illustrates the additional challenge of episodically-consumed foods, or a food that is not usually consumed by all people every day, by looking at whole grain consumption in women.[121] There is a large spike of values at zero (7.5% of the distribution) when dietary recalls are simply averaged (dotted line). The usual intake estimation methods (solid lines) produce distributions that are shifted to the right and that account for the large amount of non-consumption.

Figure 3 - 2. Comparing the distribution of dietary intakes using different estimation methods: an episodically-consumed food (from Tooze et al, 2006)



Note: The present study uses the NCI (National Cancer Institute) method; more details are in the Methods below.

In summary, methods are available to address common pitfalls in accurately analyzing 24-hour dietary recall data. These usual intake methods are especially important when the research question of interest includes looking at particularly high- or low-consumption ends of the distribution.

<u>Food-related greenhouse gas emissions and usual intake</u>

One such question pertains to the carbon footprint or food-related GHGE of foods. GHGE can be thought of like a nutrient: just as different foods have different levels of fat, they also have different carbon footprints. We would expect the distribution of food-related GHGE to be right-skewed, similar to the nutrients shown in Figure 3-1. Research into the overlap between healthier diets and diets that have a lower carbon footprint necessarily means looking at the tails of this distribution. For example, what are the characteristics of the diets highest in GHGE versus those lowest in GHGE?

To answer this question, an accurate analysis of which diets are truly “high” and “low” in GHGE is needed. This presents the same set of issues as other dietary components when the data come from only one day of intake. The distribution from one day of intakes can be expected to be more disperse than the true usual food-related GHGE of the population. The distribution may overestimate the proportion of diets that are extremely high in GHGE, or extremely low.

While few studies have looked at the distribution of food-related greenhouse gas emissions (GHGE) from individual diets, earlier work using NHANES 2005-2010 confirms the expectation of a large right tail.[45] Examining this 1-day distribution revealed that diets in the highest quintile of food-related GHGE produced eight times the emissions of those in the lowest quintile. If everyone in the highest quintile shifted to a diet with average emissions, the GHGE savings would be substantial. But whether the magnitude of these findings hold when looking at GHGE of usual diets instead of 1-day intakes is unknown.

The key issue in sustainable nutrition research is finding “win-win” dietary scenarios that provide adequate human nutrition with lower environmental impact. While the relationship between healthfulness of diet and food-related GHGE has been examined for 1-day US diets, the relationship has not been investigated using usual diets. It is usual intake over time that leads to both diet-related health outcomes and to the cumulative environmental impacts of food. The research here addresses this gap.

2. Research question

Are usual diets with a lower carbon footprint healthier than those with a higher carbon footprint? This research question was answered by addressing the following aims:

Aim 1: Assess the difference in distribution of food-related GHGE in usual versus 1-day diets.

Aim 2: Test the difference in diet quality (Healthy Eating Index) between high-GHGE usual diets and low-GHGE usual diets.

Aim 3: Examine differences in HEI component scores to determine which components contribute to any differences found in overall HEI score.

3. Methods

<u>Methods: Study sample</u>

The study sample was adult respondents (aged 18 years and older) from NHANES 2015-2016 with one or two reliable 24HRs. Respondents who were pregnant or breastfeeding, and those who had zero kilocalories or zero food-related GHGE on either of their dietary recall days, were excluded.

<u>Methods: Socioeconomic and demographic variables</u>

Variables for age, gender, race/Hispanic origin, education, and IPR were used. Age was categorized into four groups: 18-29, 30-49, 50-65, and 66+ years. The coding of the race/Hispanic origin variable differed from that of the previous papers. NHANES 2015-2016 included Non-Hispanic Asian as a category, and this was used in the present study, for a total of five groups: Non-Hispanic White, Hispanic, Non-Hispanic Black, Non-Hispanic Asian, and Other/Multiracial. Education and IPR categories were the same as Papers 1 and 2.

Methods: Greenhouse gas emissions

Food-related GHGE were calculated for individuals in the sample using *dataFIELD* (as described in the Methods of Paper 1 and in more detail in Appendix 1) as well as the commodity recipes for new foods developed as described in Paper 2's methods.

Methods: Diet healthfulness

The healthfulness (quality) of diets was assessed using the Healthy Eating Index 2015 (HEI). The methods are very similar to those described for calculating the HEI-2010 in Paper 1. However, the HEI-2015 is the correct version to use for these data, as it measures adherence to the 2015 DGA. The main differences are that in the HEI-2015, saturated fats and added sugars are assessed separately, legume intake is counted as both a vegetable and a protein source, and alcohol is not included in the scoring (though it is still included in total calories). See Appendix 2 for a comparison of HEI-2010 and HEI-2015 components and scoring. The food group intake variables for these calculations come from the USDA's Food Patterns Equivalents Database (FPED). This database converts NHANES foods into nutrition-oriented food groups with common units (e.g., cup-equivalents [c-eq] and ounce-equivalents [oz-eq]). Sodium and fat values come from the Food and Nutrient Database for Dietary Studies (FNDDS).

Methods: Statistical analysis

Usual food-related GHGE (kg CO_2-eq) and usual intakes of food groups were estimated using the NCI method, which is a multivariate Markov Chain Monte Carlo (MCMC) method.[122-124] This method fits a two-part model that allows for correlated person-specific effects. The first part estimates the probability of consuming a food, and the second part uses the 24HR data to get the amount consumed on a consumption day. Both parts of the model allow for multiple covariates, which here included socioeconomic and demographic characteristics of the individual, as well as information about the two 24HRs (see Table 3-1 for a full list of variables). The modelling also includes NHANES survey design variables and sampling weights.

Intakes of quite a few food groups and nutrients are needed to calculate HEI for each person. For the multivariate MCMC to run correctly, all food groups must be run in their most disaggregated form and the groups must not overlap. For example, while the HEI-2015 scoring includes legume consumption in both the Total Vegetable and Seafood and Plant Protein component scores, legumes were run as a separate variable in the multivariate MCMC. Re-aggregations necessary for HEI scoring were done afterward.

Table 3-1 lists all the variables that were included. First, all of the food group intake variables were checked to determine whether they should be included in the multivariate MCMC models as ubiquitous or commonly consumed foods, or as episodically consumed foods. Food groups with less than 5% nonconsumption (zero consumption) were categorized as ubiquitous. Food groups with greater nonconsumption were categorized as episodic. See Paper 3 Appendix Table A3-1 for details on variables' nonconsumption rates.

The multivariate MCMC models produce a population of pseudo-people (100 for each original NHANES respondent), the means of which are the same as those of the original observed population, and the distribution of which reflects the usual intake of the modeled components. Usual food-related emissions per 2000kcal were calculated for this pseudo-population, as were quintile cut points. Estimates of usual intakes of food groups were used to calculate HEI-2015 scores for each pseudo-person.

Table 3 - 1. Variables included in usual intake multivariate Markov Chain Monte Carlo models

Intake variables		**Covariates**
Ubiquitous[1]	**Episodic**	
• Total food-related GHGE • Total energy (kcal) • Saturated fat • Monounsaturated fat • Polyunsaturated fat • Sodium • Non-dark-green vegetables • Dairy • Refined grains • Added sugars	• Meat • Poultry • Cured and organ meats • Seafood • Legumes • Whole fruits • Fruit juice • Dark green vegetables • Whole grains	Elements of 24HR • Day of the week • Order of the two recalls Demographic/Socioeconomic • Age • Gender • Race/Hispanic origin • Income-to-Poverty ratio • Educational attainment

[1]For details on classification of intake variables as episodic or ubiquitous, see Paper 3 Appendix Table A3-1.

<u>Statistical analysis: difference in 1-day and usual diet GHGE distributions **(Aim 1)**</u>

Density curves were plotted for one-day, two-day mean, and usual food-related GHGE per 2000kcal distributions. Using NHANES weights, food-related GHGE per 2000kcal was summed to represent the total population level emissions contributed by each quintile. These results were multiplied by 365 to get total emissions for a year. These values were translated to equivalent passenger vehicles driven for a year using the Environmental Protection Agency's GHGE Equivalencies Calculator.[95] Values of GHGE/2000 kcal were calculated at different percentiles of each distribution. These were compared across distributions and compared to values from previously published work.

<u>Statistical analysis: relationship between HEI and food-related GHGE **(Aim 2)**</u>

General linear models were used with quintile of usual food-related GHGE as a categorical predictor and usual HEI score as the outcome. A second model included a quadratic term to test for any non-linear relationship. Models included the following covariates, all of which have been found to be associated with diet quality:[125] age, gender, race/Hispanic origin, education, and IPR. Standard errors were calculated using Fay's modified balanced repeated replications (BRR) technique.[126] This is instead of the Taylor Series Linearization method for variance estimation, which is recommended for standard NHANES analysis and was used for Papers 1 and 2. Sixteen replicate weights were generated for NHANES 2015-2016 respondents (based on the two-day dietary weights, WTDR2D), and the multivariate MCMC models were run for each replicate, in addition to the base run that used the original NHANES weights.

Statistical analysis: relationship between HEI component and food-related GHGE **(Aim 3)**

The same process was repeated, with a model for each HEI component score. Since HEI component scores for protein foods combine foods with a wide variety of production GHGE, additional models were run with FPED food groups as the outcome variable.

All tests were two-sided with an α level of 0.05. All analyses accounted for the complex survey design of NHANES, incorporating strata, PSU, and sampling weights.Analyses used SAS Version 9.4 for the multivariate MCMC models, HEI scoring, regressions, and BRR standard errors. Stata/SE Version 17 was used for all other analyses.

4. Results

Results: Population characteristics

The population was slightly more than half female (50.6%), and over one third non-White (35.5%) (Table 3-2). Almost two-thirds of respondents (64.1%) had completed some education beyond high school. The mean energy intake reported on Day 2 recalls was lower (-100kcal) than that of Day 1 recalls. While the mean food-related GHGE per day for Day 2 recalls was slightly lower than that of Day 1 recalls (-0.24 kg CO_2-eq), the food-related GHGE per 2000kcal on Day 2 was higher (+0.13 kg CO_2-eq).

Results: Comparing 1-day and usual distributions of food-related GHGE **(Aim 1)**

Figure 3-3 shows density curves for 1-day, 2-day mean, and usual food-related GHGE in NHANES 2015-2016 adults. While the difference is small between the curves for 1-day and 2-day average diets, the usual dietary GHGE has a dramatically different distribution. Both tails are shifted noticeably inward, and while the distribution is still right-skewed, that is much less pronounced.

Table 3-3 compares the distributions numerically. Quintile cut points that might be used to classify diets as high- or low-carbon footprint are substantially different between the usual and one-day distributions. For example, the lowest 20% of diets in the usual distribution had food-related GHGE below 3.40 kg CO_2-eq per 2000kcal. However, this same cut point would include nearly half of the one-day distribution (one-day median = 3.46 kg CO_2-eq per 2000kcal). See Paper 3 Appendix Table A3-1 for additional percentile values, as well as percentiles for kg CO_2-eq per day unadjusted for energy intake.

Previous work using NHANES 2005-2010 indicated that the top quintile of one-day food-related GHGE represented 5.1 times the total emissions contributed by the lowest quintile (41% versus 8% of total emissions).[69] Using quintiles based on usual food-related GHGE in NHANES 2015-2016, this difference was attenuated: 28% versus 14% (Table 3-4).

However, substantial reductions in food-related GHGE are still possible if individuals with usual diets like those in the top quintiles were to eat more like those with diets in the lower quintiles. Table 3-4 shows the magnitude of these potential reductions in both metric tons (kilograms / 1000) CO_2-eq per year and the equivalent number of gas-powered passenger vehicles driven for a year. If individuals with usual diets like those in quintiles 4 or 5 were to eat diets at the mean of quintile 3 (4.22 kg CO_2-eq/2000kcal), it would be equivalent to taking over 9 million gas-powered passenger vehicles off the road. With a more dramatic dietary shift, if individuals with the top 80% of usual dietary GHGE were to eat diets with the mean GHGE of quintile 1 (2.95 kg CO_2-eq/2000kcal), this would be equivalent to eliminating almost 26 million passenger vehicles for a year, or 6.2% of the US's new GHGE reduction target of 50-52% below 2005 levels.

Results: Relationship between usual diet quality and food-related GHGE **(Aims 2 & 3)**

The mean HEI score for the sample was 56.8 (Table 3-5). Adjusting for all socioeconomic and demographic factors, the mean score for diets in the top quintile of usual food-related GHGE was 6.5 points lower than that of the diets in the lowest quintile. Controlling for demographic and socioeconomic characteristics, there was a statistically significant (p=0.010) inverse relationship between usual food-related GHGE quintile and overall Healthy Eating Index score.

Several HEI component scores also differed significantly across quintiles of usual food-related GHGE. As expected, the total protein foods score was significantly higher in higher quintiles of dietary GHGE. However, the mean component scores even in the lowest quintile of dietary GHGE were not particularly low (4.6 out of a possible 5 points). The component score for seafood and plant protein did not differ across quintiles of GHGE.

Higher usual dietary GHGE were significantly associated with lower scores on the total fruit, whole grain, saturated fat, fatty acid ratio, and sodium components. Higher GHGE were associated with a higher score on the added sugars component. (Recall that sodium and added sugars are reverse-scored, so higher scores equal lower consumption.)

Results: Usual consumption of food groups and relationship with usual diet GHGE (lagniappe)

Differences in the usual consumption of food groups shine light on the source of some of the differences in usual HEI component scores (Table 3-6). Usual intakes of meat (i.e., beef, pork, lamb, veal, and game), cured and organ meats, and eggs were positively associated with usual food-related GHGE. However, usual intakes of poultry, seafood, and plant-based protein foods (legumes, soy, nuts, and seeds) did not differ across quintiles of GHGE.

The significant difference in the fatty acid ratio component score was driven by differences in usual monounsaturated and saturated fat intakes; usual polyunsaturated fatty acid intake did not differ by quintile of usual food-related GHGE. While no significant difference was seen in the HEI component score for vegetables, usual intake of vegetables was significantly lower in lower-GHGE diets (-0.08 cup equivalents per 1000kcal for the lowest quintile compared to the highest).

There were no remarkable quadratic effects of quintile of usual food-related GHGE on usual HEI or on usual consumption of any food group.

5. Discussion

The distribution of usual food-related greenhouse gas emissions in the US differs substantially from that of one-day food-related GHGE. However, usual food-related GHGE is still inversely related to diet quality, strengthening the body of evidence showing that nutritious diets are possible at lower impact to the planet.

Results from the present study differ from previous studies using one-day food-related GHGE from NHANES 2005-2010. The threshold used by Rose et al.[69] and Pollock et al.[127] to designate low-GHGE diets (2.27 kg CO_2-eq per 2000kcal) would apply to only 1% of the population when looking at usual food-related GHGE (1st percentile = 2.29 kg CO_2-eq per 2000kcal). While Rose et al. calculated that individuals in the top 20% of food-related GHGE were responsible for 5.1 times the emissions of those in the bottom 20%, using usual food-related GHGE, the difference is more modest, with the top quintile being responsible for twice the emissions of those in the lowest quintile. The present study focused on food-related GHGE standardized by energy intake. However, change in proportion of total food-related emissions contributed by each quintile in one-day versus usual distributions was more pronounced when looking at GHGE not standardized by energy intake. Heller et al. found that the top quintile of diets produced 7.9 times the food-related GHGE of the bottom quintile using one-day dietary intakes.[45] Using usual food-related GHGE, this difference would be 3.1 times (see Paper 3 Appendix Table A3-3 for percent of total emissions coming from each quintile). These previous studies used one-day intakes from NHANES 2005-2010, while the present study estimated usual food-related GHGE using NHANES 2015-2016. It is unlikely that the differences in one-day and usual distributions come from a change in food-related GHGE over time, since no significant change was found between 2005-2006 and 2015-2016 in Paper 2.

The present study found that diets with higher usual food-related GHGE had lower Healthy Eating Index scores. This finding adds to the growing body of literature with similar results using different types of dietary data and different measures of diet quality or health outcomes.[46,51,52,57,128] The total HEI score difference between the lowest quintile of usual food-related GHGE and the highest was 6.5 points. This difference is not only statistically significant, but it falls above the range of 5-6 points identified by Kirkpatrick et al.[129] as a meaningful difference in diet quality between groups.

These results differ from those in Rose et al.,[69] where the finding was a difference of 2.3 points between top and bottom quintiles of one-day food-related GHGE distribution. That the narrower usual food-related GHGE distribution should produce a larger HEI difference is unexpected. While Rose et al. used the HEI-2010 and the present study used the HEI-2015, this is unlikely to be the source of the differences. The evaluation study for the HEI-2015 found that the correlation between the two versions of the index when applied to the same sample is very high (r=0.96).[130] The GHGE per 2000kcal of diets from the second and fourth quintiles in Rose et al. have emissions closer to the first and fifth quintiles of the usual distribution. The difference in HEI scores from Q2 to Q4 in Rose et al. was 3 points, and the highest HEI was found in Q3. There was a significant quadratic trend in HEI across food-related GHGE quintiles in Rose et al., whereas the trend was linear in the present study. The HEI scores in the present study were also higher overall and in all quintiles (5-9 points higher) than in Rose et al. This likely comes from the process of estimating usual diets, where less commonly consumed foods (legumes, dark green vegetables, whole grains) that might not have shown up often in the one-day diets had higher estimated usual consumption, resulting in higher HEI scores. See Appendix Tables A3-4 and A3-5 for comparisons of total HEI, HEI component score, and food group results from Rose et al.[69] and the present study.

<u>Strengths and limitations</u>

This study presents a novel application of statistical methods for estimating usual dietary intakes to food-related GHGE. No other study, whether in the US or elsewhere, has done this. (One study labeled its analyses as “usual” food-related carbon footprint, but they were simply describing the use of a one-time food frequency questionnaire.[131]) Another strength of this work is that the food-related GHGE come from a comprehensive literature review of life cycle assessments of foods.

Use of usual intake methods for 24-hour dietary recalls depends on certain assumptions about those recalls, namely that the recall is an unbiased measure of usual intake. For episodically consumed foods, further assumptions are that the dietary recall (1) correctly identifies consumption and non-consumption, and (2) is an unbiased measure for how much was eaten if consumption is reported. A limitation of this study is that these assumptions may not be accurate. Underreporting of energy has been identified in 24-hour dietary recalls, and it may be systematic by food type and/or by certain characteristics such as participants' weight status. It is not possible to know which foods are being misreported, or to know by how much.

However, there are currently no better methods to address this potential error in NHANES. NHANES does not collect biomarkers on a subset of the sample, which would then allow for adjustment for underreporting, and there is currently no other methodology available to ascertain "true" energy intake. The dietary constituents used here—carbon footprint and HEI scores—are both adjusted for reported energy intake, which is the recommended way to deal with this issue.[118]

The age of the data is also a potential limitation. This could be problematic because either dietary habits, or the foods that make up the diets (for example, the fats people might choose to cook with), may have changed over time. The findings from Paper 2 showed that US dietary GHGE did not significantly change from 2005-2006 to 2015-2016, but some commodity intakes did. It is unknown if trends in commodity intakes, like the reduction in beef intakes of some respondents, has continued to the present. Future work could build on these results using newer data.

Finally, HEI is an excellent indicator of how well a diet corresponds with US national dietary guidance. It does not, however, detect micronutrient inadequacies in the diet. Future work could look at relationship between usual food-related GHGE and other measures of diet quality, such as the Total Nutrient Index.[132]

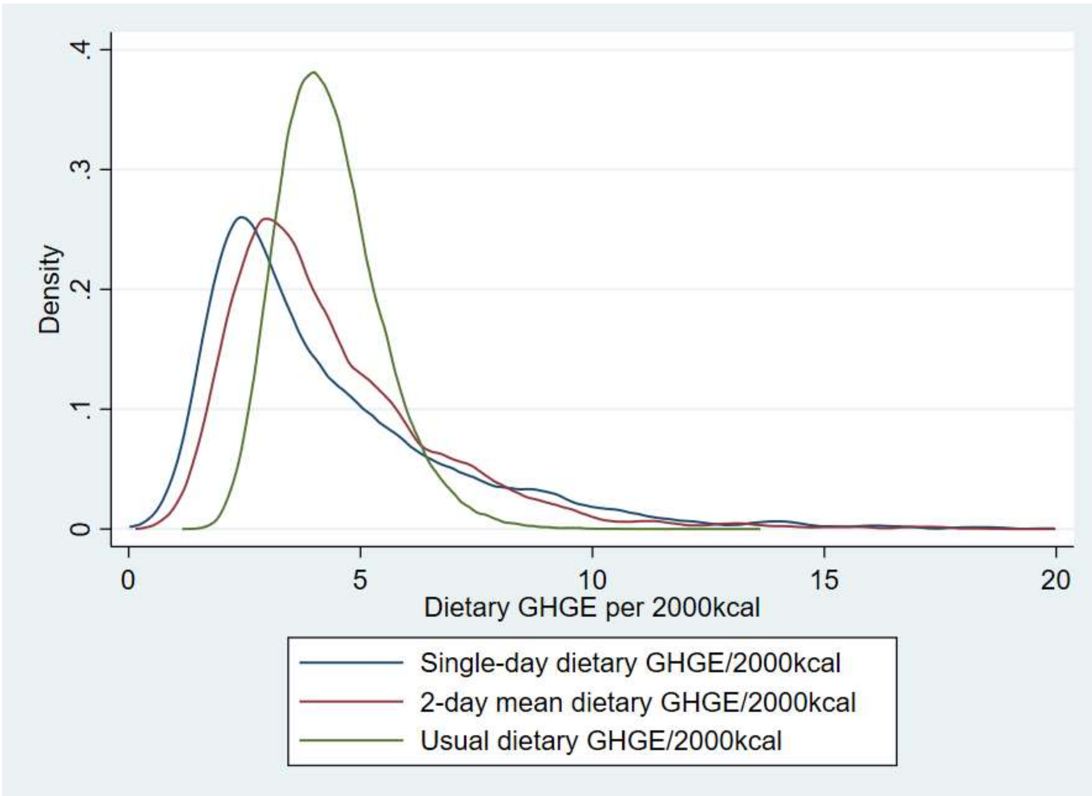
In summary, the distribution of usual dietary carbon footprint differs substantially from that of one-day carbon footprints in the US. Nevertheless, in concordance with previous studies, diet quality was significantly lower in diets with higher usual food-related GHGE. Reducing usual dietary carbon footprints could yield benefits equivalent to 6.2% of the current US emissions target.

Table 3 - 2. Characteristics of NHANES 2015-2016 adult respondents with 1 or 2 days of reliable dietary recalls

	Full Sample (N=5,175)		
	n	**%**	**95% CI**
Gender			
Female	2,632	50.6	(48.4, 52.7)
Male	2,543	49.4	(47.3, 51.6)
Age			
18-29 years	1,031	20.2	(17.4, 23.2)
30-49 years	1,644	33.1	(29.8, 36.6)
50-65 years	1,374	27.7	(25.4, 30.1)
66+ years	1,126	19.1	(16.1, 22.4)
Race/Hispanic Origin			
Non-Hispanic White	1,734	64.5	(56.0, 72.2)
Non-Hispanic Black	1,111	11.0	(7.2, 16.4)
Hispanic	1,598	14.9	(10.0, 21.7)
Non-Hispanic Asian	538	5.7	(3.5, 9.1)
Other	194	3.9	(2.8, 5.3)
Education[1]			
Less than high school	1,219	13.7	(10.6, 17.5)
High school grad/GED	1,204	22.2	(19.9, 24.6)
Some college	1,516	33.2	(30.1, 36.4)
College grad or higher	1,234	30.9	(25.2, 37.3)
Income-to-Poverty Ratio			
< 1	1,040	12.5	(9.8, 15.9)
1 - < 2	1,271	19.8	(17.3, 22.4)
2 - < 5	1,602	35.8	(31.2, 40.8)
>=5	755	24.3	(19.4, 29.9)
Missing income	507	7.6	(6.1, 9.5)
	n	**Mean**	**95% CI**
Energy intake (kcal)			
Day 1	5,175	2103	(2058, 2148)
Day 2	4,323	1998	(1942, 2055)
2-day average	4,323	2048	(2003, 2094)
Food-related GHGE (kg CO_2) per day			
Day 1	5,175	4.61	(4.40, 4.82)
Day 2	4,323	4.37	(4.16, 4.59)
2-day average	4,323	4.46	(4.27, 4.64)
Food-related GHGE (kg CO_2) per 2000kcal			
Day 1	5,175	4.36	(4.20, 4.52)
Day 2	4,323	4.49	(4.24, 4.74)
2-day average	4,323	4.43	(4.25, 4.60)

[1]Two respondents were missing education information.

Figure 3 - 3. Distribution of food-related greenhouse gas emissions (kg CO_2-equivalents per 2000kcal) in NHANES 2015-2016 adults



Note: The x axis is truncated at 20 kg CO_2-eq/2000kcal to allow for more visual detail of the right tails from 10 to 15 kg CO_2-eq/2000kcal. The maximum values for each distribution are as follows: 60.7 kg CO_2-eq/2000kcal for single-day diets, 36.1 for 2-day average diets, and 13.6 for usual diets. See Paper 3 Appendix Figure A3-1 for a version with the full right tail.

Table 3 - 3. US food-related GHGE distribution: percentile comparison among one-day intake, 2-day mean intake, and usual intake

Value	Food-Related GHGE ($kg\ CO_2$-eq) per 2000kcal			
	1-day	2-day mean	Usual	Rose et al. 2019[1]
Mean	4.41	4.43	4.34	4.42
20th percentile[2]	2.23	2.62	3.40	2.27
40th percentile	2.99	3.35	3.95	2.99
Median	3.46	3.82	4.22	--
60th percentile	4.16	4.29	4.50	4.12
80th percentile	6.20	5.84	5.21	6.25

[1]Rose D, Heller MC, Willits-Smith AM, Meyer RJ. Carbon footprint of self-selected US diets: Nutritional, demographic, and behavioral correlates. Am J Clin Nutr. 2019;109(3):526-534. This publication used quintiles per 1000kcal of dietary carbon footprint to categorize low- versus high-GHGE diets. The first quintile was designated low-GHGE, and the fifth quintile was designated high-GHGE. To make this table, the quintile cut points were doubled to match the per-2000kcal basis used in the present study. Rose et al. 2019 used dietary data from NHANES 2005-2010.

[2]Percentiles are calculated using NHANES weights corresponding to the number of days of data and the number of waves used. NHANES 2015-2016 is one wave, so day 1 values used one-day weights and 2-day and usual values used 2-day weights (adjusted by the multivariate MCMC for use with the pseudo-people in the resulting dataset). For NHANES 2005-2010, weights were divided by 3 to account for the use of multiple waves.

Table 3 - 4. Total yearly US food-related GHGE by quintile

	Quintile 1	Quintile 2	Quintile 3	Quintile 4	Quintile 5	Total
Mean usual kg CO_2-eq per 2000kcal	2.96	3.68	4.22	4.82	6.02	4.34
Metric tons yearly CO_2 -eq at population level	51,021,646	63,604,789	72,982,128	83,699,809	104,633,089	375,941,461
Percent of total emissions	13.6%	16.9%	19.4%	22.3%	27.8%	100%
Change if everyone ate at mean of Q3				-10,488,049	-31,345,947	-41,833,997
Change if everyone ate at mean of Q1		-12,673,919	-21,975,570	-32,509,893	-53,390,466	-120,549,847
Equivalent passenger vehicles driven for a year	10,993,595	13,704,875	15,725,403	18,034,734	22,545,211	81,003,818
Change if everyone ate at mean of Q3				-2,259,852	-6,754,087	-9,013,939
Change if everyone ate at mean of Q1		-2,730,840	-4,735,059	-7,004,882	-11,504,002	-25,974,783

Table 3 - 5. Healthy Eating Index 2015 component scores by quintile of usual food-related greenhouse gas emissions

Component	Max Points	Overall	Quintile 1 Mean (SE)	Quintile 2 Mean (SE)	Quintile 3 Mean (SE)	Quintile 4 Mean (SE)	Quintile 5 Mean (SE)	P value for linear trend Crude	P value for linear trend Adjusted[1]
Total Fruit	5	2.58 (0.09)	2.93 (0.23)	2.74 (0.14)	2.60 (0.10)	2.45 (0.10)	2.21 (0.14)	0.126	**0.034**
Whole Fruit	5	3.02 (0.10)	3.29 (0.26)	3.15 (0.15)	3.03 (0.11)	2.90 (0.11)	2.71 (0.16)	0.255	0.108
Total Vegetables	5	3.55 (0.06)	3.42 (0.11)	3.53 (0.08)	3.57 (0.07)	3.59 (0.07)	3.61 (0.09)	0.415	0.067
Dark Greens & Legumes[1]	5	2.99 (0.13)	3.07 (0.27)	3.03 (0.16)	3.00 (0.13)	2.96 (0.13)	2.91 (0.18)	0.757	0.830
Whole Grains	10	2.95 (0.08)	3.47 (0.28)	3.16 (0.13)	2.97 (0.09)	2.74 (0.11)	2.43 (0.21)	0.097	**0.010**
Dairy	10	5.43 (0.08)	4.92 (0.23)	5.27 (0.11)	5.47 (0.10)	5.62 (0.14)	5.85 (0.25)	0.148	0.085
Total Protein Foods[2]	5	4.82 (0.02)	4.64 (0.03)	4.77 (0.02)	4.84 (0.02)	4.90 (0.02)	4.96 (0.01)	**<0.001**	**<0.001**
Seafood & Plant Proteins[2]	5	4.06 (0.08)	4.17 (0.18)	4.10 (0.10)	4.06 (0.08)	4.02 (0.10)	3.95 (0.20)	0.630	0.419
Fatty Acid Ratio[3]	10	4.72 (0.14)	5.41 (0.26)	4.96 (0.16)	4.69 (0.14)	4.45 (0.15)	4.07 (0.19)	**0.007**	**0.001**
Refined Grains	10	6.71 (0.09)	6.83 (0.37)	6.75 (0.17)	6.71 (0.11)	6.64 (0.16)	6.60 (0.37)	0.818	0.624
Sodium	10	3.70 (0.13)	5.26 (0.28)	4.26 (0.13)	3.66 (0.13)	3.08 (0.21)	2.24 (0.32)	**<0.001**	**<0.001**
Added Sugars	10	6.98 (0.11)	6.06 (0.33)	6.72 (0.18)	7.07 (0.11)	7.35 (0.11)	7.69 (0.21)	**0.017**	**0.001**
Saturated Fats	10	5.33 (0.13)	6.45 (0.24)	5.77 (0.13)	5.33 (0.13)	4.93 (0.18)	4.18 (0.29)	**<0.001**	**<0.001**
Overall HEI	100	56.83 (0.60)	59.91 (1.85)	58.22 (1.00)	56.98 (0.62)	55.62 (0.64)	53.40 (1.21)	0.105	**0.010**

[1]Adjusting for age, gender, race/Hispanic origin, educational attainment, and income-to-poverty ratio
[2]HEI-2015 scores include all legume consumption in all the possible categories: Total Vegetables, Dark Green Vegetables or Legumes, Total Protein Foods, and Seafood and Plant Proteins.
[3]Ratio of poly- and mono-unsaturated fatty acids to saturated fatty acids.

Table 3 - 6. Usual food group consumption by quintile of usual food-related greenhouse gas emissions

	Unit	Quintile 1 Mean (SE)	Quintile 2 Mean (SE)	Quintile 3 Mean (SE)	Quintile 4 Mean (SE)	Quintile 5 Mean (SE)	P value for linear trend	
							Crude	Adjusted[1]
Fruit	cup eq/1000 kcal	0.60 (0.05)	0.56 (0.03)	0.53 (0.02)	0.50 (0.02)	0.46 (0.04)	0.184	0.066
Vegetables	cup eq/1000 kcal	0.79 (0.03)	0.82 (0.02)	0.84 (0.02)	0.85 (0.03)	0.87 (0.03)	0.342	**0.023**
Whole grains	oz eq/1000 kcal	0.54 (0.05)	0.47 (0.03)	0.44 (0.02)	0.40 (0.03)	0.34 (0.04)	0.101	**0.011**
Refined grains	oz eq/1000 kcal	2.75 (0.11)	2.79 (0.06)	2.81 (0.04)	2.84 (0.06)	2.85 (0.12)	0.813	0.621
Protein foods: total	oz eq/1000 kcal	3.01 (0.1)	3.18 (0.05)	3.32 (0.05)	3.49 (0.05)	3.86 (0.08)	**<0.001**	**<0.001**
Meat[2]	oz eq/1000 kcal	0.50 (0.06)	0.66 (0.04)	0.78 (0.04)	0.92 (0.04)	1.19 (0.08)	**<0.001**	**<0.001**
Cured meat, organ meat[3]	oz eq/1000 kcal	0.32 (0.04)	0.38 (0.03)	0.41 (0.02)	0.45 (0.03)	0.51 (0.04)	**0.020**	**0.010**
Poultry	oz eq/1000 kcal	0.85 (0.08)	0.81 (0.05)	0.80 (0.04)	0.79 (0.04)	0.81 (0.05)	0.648	0.739
Seafood	oz eq/1000 kcal	0.31 (0.04)	0.33 (0.02)	0.34 (0.03)	0.36 (0.04)	0.40 (0.05)	0.547	0.236
Eggs	oz eq/1000 kcal	0.27 (0.03)	0.31 (0.02)	0.34 (0.02)	0.37 (0.02)	0.42 (0.03)	**0.048**	**0.008**
Legumes, soy, nuts, seeds	oz eq/1000 kcal	0.77 (0.1)	0.69 (0.05)	0.65 (0.03)	0.60 (0.03)	0.53 (0.07)	0.332	0.117
Total dairy	cup eq/1000 kcal	0.57 (0.04)	0.61 (0.02)	0.63 (0.01)	0.65 (0.02)	0.69 (0.03)	0.141	0.081
Monounsaturated fat	g/1000 kcal	13.12 (0.28)	13.52 (0.18)	13.80 (0.16)	14.06 (0.16)	14.59 (0.26)	**0.025**	**<0.001**
Polyunsaturated fat	g/1000 kcal	9.02 (0.2)	9.03 (0.12)	9.05 (0.09)	9.07 (0.1)	9.14 (0.16)	0.998	0.690
Saturated fat	% of kcal	10.28 (0.23)	10.82 (0.12)	11.19 (0.1)	11.51 (0.13)	12.16 (0.24)	**<0.001**	**<0.001**
Added sugars	% of kcal	13.75 (0.66)	12.26 (0.35)	11.48 (0.25)	10.82 (0.34)	10.00 (0.65)	**0.020**	**0.002**

[1]Adjusting for age, gender, race/Hispanic origin, educational attainment, and income-to-poverty ratio.
[2]The Food Patterns Equivalents Database (FPED) meat group includes beef, pork, lamb, veal, and game, but excludes organ and cured meats.
[3]Includes organs from any animal, and cured beef, pork, or poultry (e.g., bacon or lunch meats).

6. Paper 3 Appendix

Table A3 - 1. Food and nutrient nonconsumption analysis and classification of variables as episodic or ubiquitous for multivariate MCMC

Component	Stratum	Percent days with 0	Percent 0 on all days	Classified episodic vs. not episodic	Number with 2 non-zero recalls
Fish and seafood	Male	83.8	74.5	Episodic	103
	Female	81.5	70.5	Episodic	121
Dark green vegetables	Male	78.5	68	Episodic	182
	Female	72.4	59.7	Episodic	279
Legumes	Male	76.8	65	Episodic	187
	Female	77.6	65.6	Episodic	182
Fruit juice	Male	66.7	54	Episodic	375
	Female	65.1	51.5	Episodic	419
Soy, nuts, and seeds	Male	64.4	52.1	Episodic	436
	Female	60.3	45.7	Episodic	500
Organ and cured meats[1]	Male	51.8	36.1	Episodic	612
	Female	58.4	41.6	Episodic	486
Poultry	Male	56.5	38.5	Episodic	455
	Female	54.5	36.1	Episodic	529
Meat[2]	Male	48.3	29.7	Episodic	613
	Female	56.3	37.2	Episodic	471
Whole grains	Male	51.1	39.1	Episodic	719
	Female	49	34.2	Episodic	747
Whole fruit	Male	48.1	35.2	Episodic	760
	Female	40	26.8	Episodic	988
Eggs	Male	32.1	17.7	Episodic	1055
	Female	32	17.2	Episodic	1124
Dairy	Male	9.5	4.2	Not Episodic	1761
	Female	7.6	2.5	Not Episodic	1923
Non-dark green vegetables	Male	7.5	2.4	Not Episodic	1810
	Female	6.6	1.9	Not Episodic	1956
Refined grains	Male	2.6	0.5	Not Episodic	1989
	Female	3.1	1	Not Episodic	2102
Added sugars	Male	2.2	0.8	Not Episodic	2015
	Female	1.4	0.4	Not Episodic	2169
Total kilocalories	Male	0	0	Not Episodic	2096
	Female	0	0	Not Episodic	2227
Saturated fat	Male	0	0	Not Episodic	2094
	Female	0	0	Not Episodic	2226
Sodium	Male	0	0	Not Episodic	2095
	Female	0	0	Not Episodic	2227
Food-related GHGE	Male	0	0	Not Episodic	2096
	Female	0	0	Not Episodic	2227
Monounsaturated fat	Male	0	0	Not Episodic	2094
	Female	0	0	Not Episodic	2226
Polyunsaturated fat	Male	0	0	Not Episodic	2094
	Female	0	0	Not Episodic	2226

[1]Includes organs from any animal, and cured beef, pork, or poultry (e.g., bacon or lunch meats).

[2]Includes beef, pork, lamb, veal, and game, but excludes organ and cured meats.[117]

Figure A3 - 1. Distribution of food-related greenhouse gas emissions (kg CO2-equivalents per 2000kcal) in NHANES 2015-2016 adults with full right tails

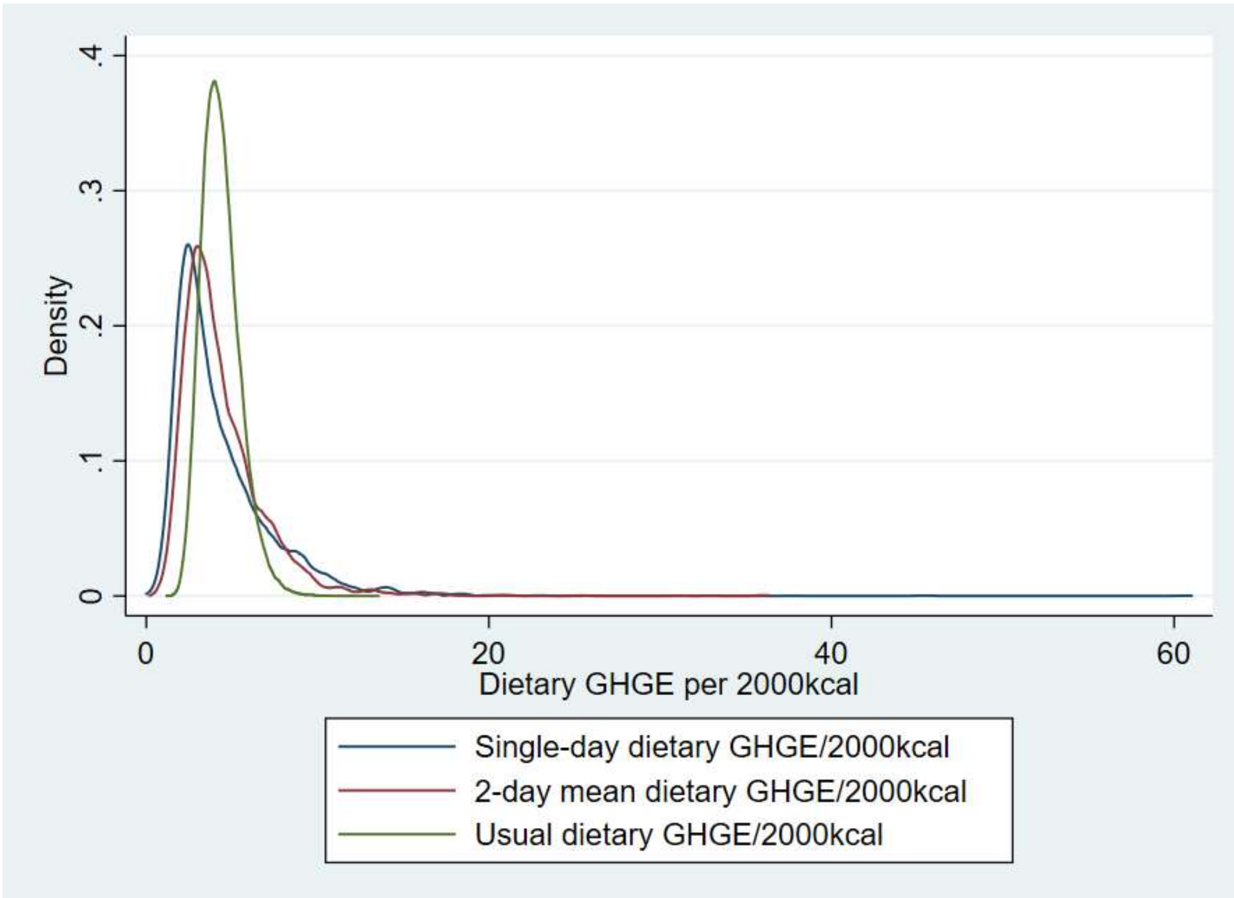


Table A3 - 2. US food-related GHGE distribution percentile comparison: one-day intake, 2-day mean intake, usual intake, and previous studies' findings

Value or percentile	Food-Related GHGE ($kg\ CO_2$-eq) per 2000kcal				Food-Related GHGE ($kg\ CO_2$-eq) per day			
	1-day	2-day mean	Usual	Rose et al. 2019[1]	1-day	2-day mean	Usual	Heller et al. 2018[2]
Mean	4.41	4.43	4.34	4.42	4.61	4.46	4.61	4.72
Minimum	0.34	0.47	1.23		0.07	0.10	0.57	
p1[3]	1.09	1.31	2.29		0.57	0.81	1.63	
p5	1.54	1.88	2.75		1.06	1.36	2.16	
p10	1.84	2.17	3.03		1.36	1.69	2.51	
p20	2.23	2.62	3.40	2.27	1.88	2.26	3.01	1.94
p25	2.42	2.81	3.55		2.15	2.52	3.22	
p40	2.99	3.35	3.95	2.99	2.91	3.19	3.84	2.95
p50	3.46	3.82	4.22		3.54	3.78	4.27	
p60	4.16	4.29	4.50	4.12	4.30	4.41	4.75	4.32
p75	5.49	5.43	4.99		5.89	5.72	5.65	
p80	6.20	5.84	5.21	6.25	6.63	6.32	6.03	6.91
p90	8.22	7.38	5.81		9.09	8.07	7.18	
p95	9.95	8.73	6.35		11.70	9.69	8.21	
p99	14.76	13.25	7.51		18.07	13.64	10.47	
Maximum	60.71	36.05	13.55		78.78	40.05	24.49	
IQR	3.07	2.62	1.45		3.74	3.20	2.42	

[1]Rose D, Heller MC, Willits-Smith AM, Meyer RJ. Carbon footprint of self-selected US diets: Nutritional, demographic, and behavioral correlates. Am J Clin Nutr. 2019;109(3):526-534. This publication used quintiles per 1000kcal of dietary carbon footprint to categorize low- versus high-GHGE diets. The first quintile was designated low-GHGE, and the fifth quintile was designated high-GHGE. To make this table, the quintile cut points were doubled to match the per-2000kcal basis used in the present study. Rose et al. 2019 used dietary data from NHANES 2005-2010.
[2]Heller MC, Willits-Smith A, Meyer R, Keoleian GA, Rose D. Greenhouse gas emissions and energy use associated with production of individual self-selected US diets. Environ Res Lett. 2018;13(4):044004. This publication used NHANES 2005-2010 data.
[3]Percentiles are calculated using NHANES weights corresponding to the number of days of data and the number of waves used. NHANES 2015-2016 is one wave, so day 1 values used one-day weights and 2-day and usual values used 2-day weights (adjusted by the multivariate MCMC for use with the pseudopeople in the resulting dataset). For NHANES 2005-2010, weights were divided by 3 to account for the use of multiple waves.

Table A3 - 3. Percent of total US food-related GHGE from each quintile

	NHANES 2015-2016		NHANES 2005-2010	
Quintile	Usual food-related GHGE per 2000kcal	Usual food-related GHGE per day	One-day food-related GHGE per 2000kcal (Rose et al. 2019 [69])	One-day food-related GHGE per day (Heller et al. 2018 [45])
	% of total emissions	% of total emissions	% of total emissions	% of total emissions
1	13.6%	10.4%	8.2%	6%
2	16.9%	14.7%	11.8%	10%
3	19.4%	18.5%	15.8%	15%
4	22.3%	23.2%	23.1%	23%
5	27.8%	33.2%	41.1%	46%

Table A3 - 4. Comparison of relationship between HEI and quintile of food-related GHGE per 2000kcal: present study and Rose et al.

Quintile of usual food-related GHGE/2000kcal
NHANES 2015-2016
GHGE cut point: 3.40 3.95 4.50 5.21

HEI-2015 Component[1]	Max Pts	Q1 Mean[2]	Q2 Mean	Q3 Mean	Q4 Mean	Q5 Mean	P value for linear trend Crude	P value for linear trend Adj[3]	P value for quadratic trend Crude	P value for quadratic trend Adj[3]	Diff. high - low[4]
Total Score	100	59.91	58.22	56.98	55.62	53.4	0.105	**0.010**	0.563	0.759	-6.5
Total Fruit	5	2.93	2.74	2.6	2.45	2.21	0.126	**0.034**	0.736	0.917	-0.7
Whole Fruit	5	3.29	3.15	3.03	2.9	2.71	0.255	0.108	0.796	0.896	-0.6
Total Vegetables[5]	5	3.42	3.53	3.57	3.59	3.61	0.415	0.067	0.365	0.556	+0.2
Dark Greens & Legumes[5]	5	3.07	3.03	3	2.96	2.91	0.757	0.83	0.931	0.743	-0.2
Whole Grains	10	3.47	3.16	2.97	2.74	2.43	0.097	**0.01**	0.906	0.894	-1.0
Dairy	10	4.92	5.27	5.47	5.62	5.85	0.148	0.085	0.388	0.502	+0.9
Total Protein Foods[5]	5	4.64	4.77	4.84	4.9	4.96	**<0.001**	**<0.001**	0.133	**0.049**	**+0.3**
Seafood & Plant Proteins[5]	5	4.17	4.1	4.06	4.02	3.95	0.63	0.419	0.994	0.605	-0.2
Fatty Acid Ratio	10	5.41	4.96	4.69	4.45	4.07	**0.007**	**0.001**	0.654	0.410	**-1.3**
Refined Grains	10	6.83	6.75	6.71	6.64	6.6	0.818	0.624	0.924	0.658	-0.2
Sodium	10	5.26	4.26	3.66	3.08	2.24	**<0.001**	**<0.001**	0.325	0.143	**-3.0**
Added Sugars	10	6.06	6.72	7.07	7.35	7.69	**0.017**	**0.001**	0.204	0.114	**+1.6**
Saturated Fats	10	6.45	5.77	5.33	4.93	4.18	**<0.001**	**<0.001**	0.678	0.306	**-2.3**
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Quintile of one-day food-related GHGE/2000kcal
NHANES 2005-2010
(Rose et al. 2019[69])
GHGE cut point: 2.27 2.99 4.12 6.25

HEI-2010 Component[1]	Max Pts	Q1 Mean	Q2 Mean	Q3 Mean	Q4 Mean	Q5 Mean	P val. Linear trend Crude	P val. Quad trend Crude	Diff. high - low[4]
Total score	100	50.25	51.22	50.46	48.22	48.00	**<0.001**	**0.012**	**-2.3**
Total Fruit	5	2.04	2.4	2.33	2.06	1.91	**0.003**	**<0.001**	**-0.1**
Whole Fruit	5	2.06	2.31	2.21	2.01	1.77	**<0.001**	**<0.001**	**-0.3**
Total Vegetables[6]	5	2.8	2.94	3.08	3.07	3.18	**<0.001**	0.200	**+0.4**
Dark Greens & Legumes[6]	5	1.14	1.21	1.27	1.23	1.19	0.494	**0.041**	+0.1
Whole Grains	10	2.74	2.62	2.34	1.99	1.77	**<0.001**	0.254	**-1.0**
Dairy	10	4.03	5.83	6.02	5.51	4.83	**<0.001**	**<0.001**	**+0.8**
Total Protein Foods[6]	5	3.56	3.96	4.19	4.41	4.87	**<0.001**	0.255	**+1.3**
Seafood & Plant Proteins[6]	5	2.38	2.08	1.96	1.85	1.6	**<0.001**	0.493	**-0.8**
Fatty Acid Ratio	10	6.91	5.15	4.33	4.11	3.59	**<0.001**	**<0.001**	**-3.3**
Refined Grains	10	5.22	5.81	6.35	6.27	7.05	**<0.001**	0.537	**+1.8**
Sodium	10	5.57	4.68	4.13	4.07	3.99	**<0.001**	**<0.001**	**-1.6**
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Empty Calories[7]	20	11.81	12.23	12.26	11.64	12.26	0.558	0.669	+0.4

[1]For summary of differences between HEI-2015 and HEI-2010 scoring, see Appendix 2.
[2]Standard errors removed for space. Available in original Table 3-5, and supplement of Rose et al. 2019.
[3]Adjusted for age, gender, race/Hispanic Origin, educational attainment, and income-to-poverty ratio.
[4]Bold values correspond to p<0.05 on linear trend in the crude model.
[5]Includes legumes.
[6]Legumes included in protein food scores until maximum score is met; remainder is included in vegetable components.
[7]Calories from solid fats, added sugars, and alcohol. For alcohol, intakes ≤ 13 grams/1000kcal do not influence scoring.

Table A3 - 5. Comparison of relationship between food group intakes and quintile of food-related GHGE per 2000kcal: present study and Rose et al.

Quintile of usual food-related GHGE/2000kcal NHANES 2015-2016												Quintile of one-day food-related GHGE/2000kcal NHANES 2005-2010 (Rose et al. 2019[69])									
GHGE cut point: 3.40 3.95 4.50 5.21												GHGE cut point: 2.27 2.99 4.12 6.25									
Food Group	Unit per 1000 kcal	Q1	Q2	Q3	Q4	Q5	P value for linear trend		P value for quadratic trend		Diff. high - low[3]	Food Group	Unit per 1000 kcal	Q1	Q2	Q3	Q4	Q5	P val. Linear trend	P val. Quad trend	Diff. high – low[3]
		Mean[1]	Mean	Mean	Mean	Mean	Crude	Adj[2]	Crude	Adj[2]				Mean	Mean	Mean	Mean	Mean	Crude	Crude	
Fruit	cup eq	0.6	0.56	0.53	0.5	0.46	0.184	0.066	0.953	0.755	-0.1	Fruit	cup eq	0.49	0.57	0.60	0.49	0.46	**0.018**	**<0.001**	**-0.0**
Vegetable	cup eq	0.79	0.82	0.84	0.85	0.87	0.342	**0.023**	0.380	0.697	+0.1	Vegetable	cup eq	0.71	0.78	0.83	0.80	0.84	**<0.001**	**0.033**	**+0.1**
Whole grain	oz eq	0.54	0.47	0.44	0.4	0.34	0.101	**0.011**	0.983	0.793	-0.2	Whole grain	oz eq	0.51	0.45	0.39	0.32	0.28	**<0.001**	0.608	**-0.2**
Refined grain	oz eq	2.75	2.79	2.81	2.84	2.85	0.813	0.621	0.916	0.648	+0.1	Refined grains	oz eq	3.09	2.82	2.61	2.65	2.35	**<0.001**	0.198	**-0.7**
Protein foods: total	oz eq	3.01	3.18	3.32	3.49	3.86	**<0.001**	**<0.001**	0.057	0.008	**+0.9**	Protein foods: total	oz eq	2.37	2.77	3.14	3.19	4.17	**<0.001**	**<0.001**	**+1.8**
Meat[4]	oz eq	0.5	0.66	0.78	0.92	1.19	**<0.001**	**<0.001**	0.118	0.015	**+0.7**	Meat[6]	oz eq	0.11	0.21	0.47	0.96	2.26	**<0.001**	**<0.001**	**+2.2**
Cured, organ meat[5]	oz eq	0.32	0.38	0.41	0.45	0.51	**0.020**	**0.010**	0.790	0.920	**+0.2**	--	--	--	--	--	--	--	--	--	--
Poultry	oz eq	0.85	0.81	0.8	0.79	0.81	0.648	0.739	0.110	0.077	-0.0	Poultry	oz eq	0.85	1.02	0.94	0.57	0.33	**<0.001**	**<0.001**	**-0.5**
Seafood	oz eq	0.31	0.33	0.34	0.36	0.4	0.547	0.236	0.885	0.150	+0.1	Seafood	oz eq	0.21	0.30	0.33	0.30	0.41	**<0.001**	0.741	**+0.2**
Eggs	oz eq	0.27	0.31	0.34	0.37	0.42	**0.048**	**0.008**	0.804	0.489	**+0.2**	--	--	--	--	--	--	--	--	--	--
Legume, nut, seed	oz eq	0.77	0.69	0.65	0.6	0.53	0.332	0.117	0.761	0.903	-0.2	Legume, nut, seed	oz eq	0.81	0.54	0.47	0.45	0.37	**<0.001**	**<0.001**	**-0.4**
Total dairy	cup eq	0.57	0.61	0.63	0.65	0.69	0.141	0.081	0.498	0.650	+0.1	Total dairy	cup eq	0.54	0.84	0.93	0.84	0.72	**<0.001**	**<0.001**	**+0.2**
MUFA	g	13.12	13.52	13.8	14.06	14.59	**0.025**	**<0.001**	0.606	0.247	**+1.5**	--	--	--	--	--	--	--	--	--	--
PUFA	g	9.02	9.03	9.05	9.07	9.14	0.998	0.690	0.950	0.538	+0.1	--	--	--	--	--	--	--	--	--	--
Saturated fat	% of kcal	10.28	10.82	11.19	11.51	12.16	**<0.001**	**<0.001**	0.645	0.297	**+1.9**	--	--	--	--	--	--	--	--	--	--
Added sugar	% of kcal	13.75	12.26	11.48	10.82	10	**0.020**	**0.002**	0.220	0.129	**-3.8**	--	--	--	--	--	--	--	--	--	--
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[1]Standard errors removed for space. See Table 3-6, and supplement of Rose et al. 2019.
[2]Adjusted for age, gender, race/Hispanic Origin, educational attainment, income-to-poverty ratio
[3]Bold values correspond to p<0.05 on linear trend in the crude model.
[4]Beef, pork, lamb, veal, game
[5]Cured beef, pork, or poultry; organs of any animal
[6]Includes organ and cured meats

Conclusions and Future Directions

This dissertation used self-selected dietary data from a nationally representative US sample to examine food-related greenhouse gas emissions, diet quality, and potential efforts to reduce environmental impacts of food in the US. The three studies here reinforce themes in the existing sustainable nutrition literature: food choice is a powerful mechanism to reduce greenhouse gas emissions, and diets with a lower carbon footprint can be more healthful.

Substantial environmental benefits are possible from dietary changes, especially those that reduce beef consumption and replace it with poultry or plant-based protein foods, and diets with these characteristics tend to have higher diet quality. However, US diets are not moving in the desired direction with respect to diet quality or climate impacts. More efforts, such as nutrition education programs, social marketing, and inclusion of sustainability in the Dietary Guidelines for Americans, are needed to achieve health and environment co-benefits.

These studies were only possible because of the foundation of cross-disciplinary work in the development of *dataFIELD* and its application to NHANES dietary data. Continued collaboration across multiple disciplines (nutrition, life cycle assessment, agriculture, economics, etc.) and stakeholders (researchers, governments, etc.) is critical in efforts to improve human health and combat climate change.

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Dissertation Appendix

1. Detailed methods for the creation of *dataFIELD*

Food-related GHGE will be calculated using a previously described database, *dataFIELD*. *DataFIELD* was created from an exhaustive literature review of life cycle assessment (LCA) studies published from 2005 to 2016. The database includes a variety of information about the compiled studies, including environmental impact values (GHGE or cumulative energy demand), boundary conditions of the study, location of the study, and specific species or production information.

Next, the available LCA data for food production was mapped to a list of 354 commodity foods in the Food Commodities Intake Database. The FCID was created by the EPA to assess pesticide exposure. It was chosen here because it allows for foods reported in national dietary studies to be broken down into commodity constituents. For example, a cheeseburger would have a commodity "recipe" including beef, wheat, milk, tomato, lettuce, etc. This is important because LCA studies are most often focused on production of commodities like wheat, soybeans, or beef.

Not all of the 354 commodities[*] had perfect matches from the LCA literature compiled into *dataFIELD*. In these cases, a proxy value was assigned using botanically similar commodities. For example, an average of available citrus fruit values was used as a proxy for uncommon citrus fruits in the FCID list. While many foods in the FCID are commodities, some entries include some processing, such as flours, oils, and fruit juices. These were matched to primary LCA data where possible. Where not possible, appropriate conversion factors were applied.

In addition, there were some LCA studies for foods that were not represented in the FCID. Since FCID was created to assess pesticide exposure, its construction did not always provide commodity recipes that would best describe the environmental impact of a food. For example, the "recipe" for beer was simply a small amount of hops. Recipes for diet soda were empty. When possible, to better account for these impacts, LCA study values were directly connected to NHANES foods: tofu, cheese, yogurt, beer, liquor, and soft drinks (check this list).

Recipes for cocktails did not include any liquor component, but only mixers such as juice. A separate recipe file was created for these drinks based on the ingredient breakdowns in the National Nutrient Database for Dietary Studies (check name), also known as the Standard Reference (version 28). The recipes included both commodity items from the FCID list (such as orange juice or sugar) and directly connected impacts (such as liquor and soft drinks).

There were still a few foods or ingredients that did not have associated GHGE even after assigning LCA values to FCID commodity recipes, and assigning LCA values directly to certain foods, and applying new cocktail recipes. For example, artificial sweeteners, supplements, and salt are not assessed in the FCID. Nor were there LCA studies of these items collected in *dataFIELD*. So in essence these parts of foods were assessed a zero impact, although they are not in truth without emissions or energy use in their production.

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[*] If you see a different number of commodities listed somewhere else: we often use the number 332 in descriptions of the database, because some commodities are component breakdowns of the same item: e.g., "Milk, fat," "Milk, nonfat solids," and "Milk, water." The smaller number reflects these aggregations.

The above process was used to create a “bridge file,” bridging commodities and LCA study values with NHANES as-consumed foods, via the FCID recipe database. Each FCID recipe represented the commodity inputs needed to create 100g of an as-eaten food. Commodity GHGE and CED were added to the recipes and impacts were calculated for the amount of commodity used in each recipe. Then the impacts for a 100g recipe were summed, to get the total GHGE or CED of the food.

It is important that the environmental impact per kg of food have the correct weight basis. For example, if the GHGE of one kg walnuts in the shell is __, then the GHGE of one kg of walnuts without the shell must come from a larger amount of walnuts to begin with, and must necessarily be assigned a larger impact value. The FCID commodity list accounts for primary food waste—things such as deboning meat, shelling nuts, and peeling citrus fruit. When the source LCA studies did not give these conversions, three USDA resources were used to find appropriate conversion factors.: the Food Intakes Converted to Retail Commodities Databases (FICRCD), Loss-Adjusted Food Availability (LAFA) data, and the National Nutrient Database for Standard Reference (SR) version 28.

However, so called primary waste is not the only type of food waste. Losses of edible food occur along the chain of production, transportation, retail, and consumption. For example, some portion of foods carried in a grocery store will spoil before they are sold. In addition, consumers may purchase some items that they do not use before they spoil, or choose to throw them out. Consumers may also cook a meal and not eat everything on their plate, throwing away the leftovers.

To estimate the additional impact of wasted food, data from the 2010 USDA Loss-Adjusted Food Availability (LAFA) dataset were used to assign edible loss values to each FCID commodity. LAFA breaks down losses into primary, retail, and consumer levels. However, LAFA contains fewer foods than FCID. When possible, commodity items were matched directly to a LAFA entry (e.g. oranges to oranges). If this was not possible, the FCID commodity was matched to a similar LAFA entry (e.g. nectarines to peaches), or to an average of entries. Averages were of two types: those already in LAFA, and new ones created as needed. LAFA has summary rows in all of its sections (fruits, meats, and so on). So the chickpea commodity was matched to the LAFA entry “Beans, dry, other.” However, these summary rows did not always provide breakdowns of losses between retail and consumer levels. When necessary, we created our own averages. For example, several grain commodities (such as amaranth, buckwheat, and millet) were given loss values based on an average of all relevant grain entries from LAFA (wheat flour, rye flour, barley products, oat products, and corn meal).

Since primary waste was already accounted for within the FCID commodities’ weight basis, we used only the latter two categories. LAFA is constructed such that the retail and consumer losses are stacked or cumulative. In the case of an orange, the retail loss is given as 11.6% and the consumer loss as 36%. However, what this means is this means is that an estimated 36% of the remaining 100 – 11.6 = 88.4% is lost. If you were to add together 11.6 and 36, you would get an inflated estimate of the edible losses of oranges. In order to accurate apply the loss factors, we used an adjusted consumer loss factor that can be summed together with retail losses without duplication. It was calculated as (100 – retail loss %) * (consumer loss % / 100). In the above case of an orange, that yields a consumer edible loss of 31.8%.

This bridge file was merged with dietary intake data from the 2005-2010 National Health and Nutrition Examination Survey (NHANES). NHANES collects dietary intake in the form of two 24-hour dietary recalls. The first is collected in person in the Mobile Examination Center. The second is conducted in a phone follow up (check this). Diet recalls are collected using the Automated Multiple Pass Method (AMPM) developed by UDSA. The process includes asking the respondent about all foods and beverages consumed in the last day, using several rounds, specific prompts to help remember forgotten items, and props to show portion sizes so the respondent can accurately describe amounts consumed.

Dietary recall data are then subject to review; recalls may be deemed unreliable if recall was incomplete, or the interviewer noted certain things about the session (such as the respondent having memory problems). The final resulting dataset with reliable diet recalls is a source of rich detail for investigators. In it we have all foods and beverages the person consumed through the day, along with specific amounts and other metadata like what meal they called it and what day of the week the recall represents.

It is to this detailed list of foods and drinks that the environmental impact data are connected, via the above-described bridge file. GHGE and CED were calculated for each item, in the amount that the respondent reported consuming it. This includes calculating impacts for the items directly connected to LCA study values. Finally, the impacts were summed to calculate GHGE and CED values for respondents' full recall day.

Strengths and limitations of *dataFIELD*

This database is the first of its kind and the first to be built to link commodity life cycle assessment data to US dietary intake data. It is founded on a thorough search of all available literature at the time.

The food-related GHGE linked in this work only account for emissions up to the farm gate (for most foods, and up to the processor gate for a few). There are several reasons for this. First of all, this is the boundary condition most often set in life cycle assessment (LCA) studies. Second, this was the boundary that made the most sense given that diet recipes were constructed from commodity foods with minimal or no processing. Lastly, NHANES 24-hour dietary recalls do not include information that could allow for addition of other food production stages (e.g. transportation). The recalls do not include details such as where the food item was produced, how it was packaged, how long the item was refrigerated at home, and other relevant factors. Previous findings have estimated that packaging and processing could increase impacts about 27% from cradle-to-farm gate impacts. While this is a limitation of the findings, the majority of GHGE related to food happen during production (up to the farm gate). An important strength of using these data is that they come from an up-to-date literature search that includes all possible LCA studies of food.

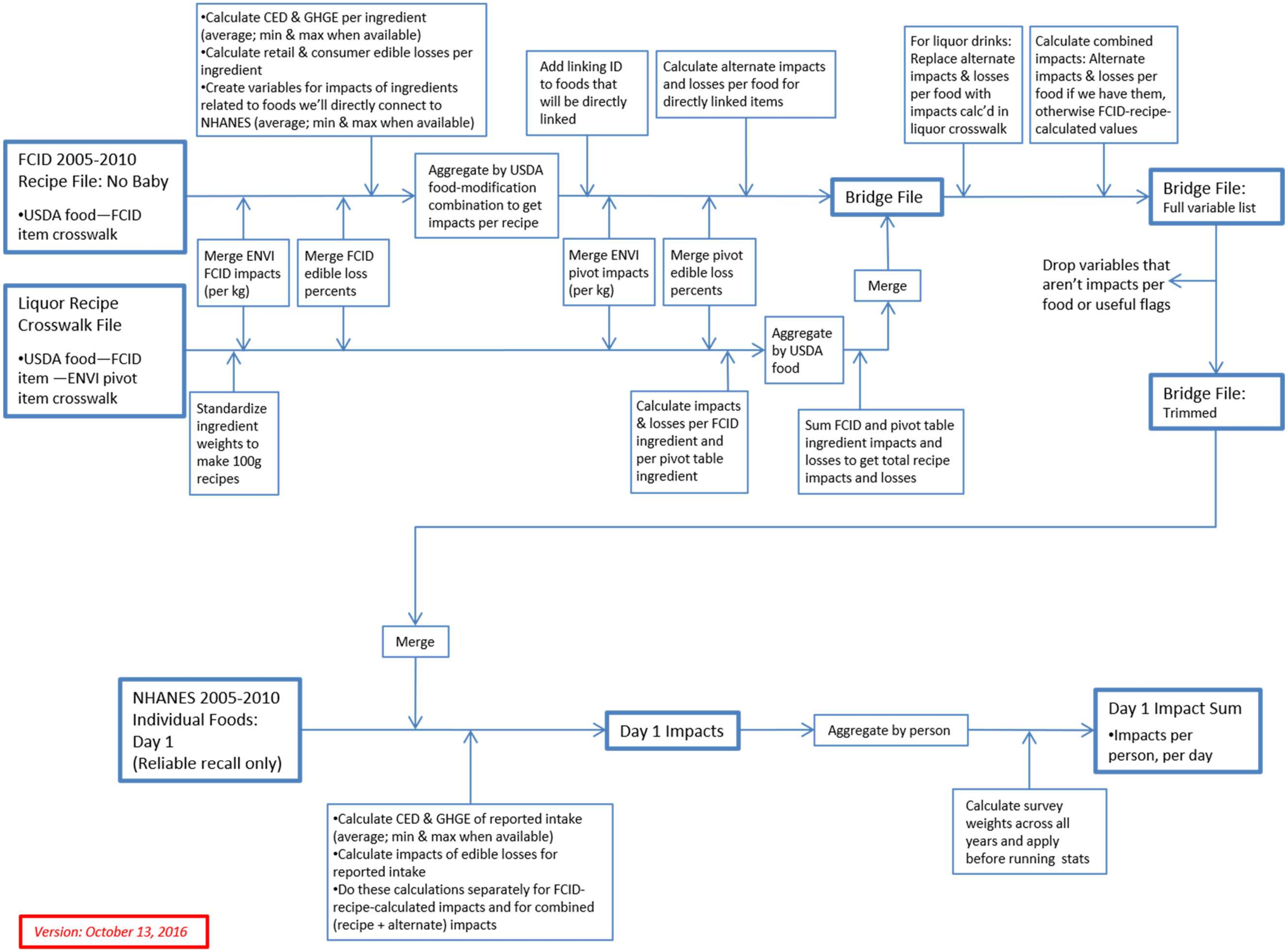
However, there are limitations. While the FCID commodity recipes allow for NHANES foods to be broken down into commodity components, the original design of the database was to assess pesticide exposure. Therefore, the recipes do not account for some things that we may care about in terms of environmental impacts (for example, alcohol). We did our best to account for these issues. In the case of alcohol, we created our own recipes that included alcohol as an ingredient.

The FCID recipe construction sometimes treats water idiosyncratically. The recipes only specify water amounts if that water is added by the consumer, not if it is added by a manufacturer. For example, homemade soup recipes contain water, but canned soup recipes do not. Another example is soft drinks. Since the water is added by the manufacturer, the only FCID ingredient is sugar. For soft drinks and beer, we directly linked these NHANES foods with LCA results, rather than using the FCID recipes, therefore addressing the lack of water in the recipes. However, for other foods like the soup example, this was not possible. The result is that for some foods, the calculated impact (GHGE, CED) is a small underestimate due to the missing water.

Some items are missing altogether from FCID: salt, alternative sweeteners, yeast, and many spices or herbs. The first three were considered to not be a concern for pesticide residue. For spices and herbs, there are several herbs in the list, and a commodity for "Spices, other." While there may be environmental impacts for all these items, they are either given for "free" in our database, or in the case of spices, their impact is estimated by a aggregate of the small number of available LCA studies. *[mention other things like dyes?]*

In short, while the FCID is the best tool to bridge between as-eaten NHANES foods and commodity-level environmental impacts, it was not designed specifically for this work, and this should be remembered in interpreting results.

Figure A - 1. Steps in using dataFIELD[1] to calculate environmental impacts of NHANES 2005-2010 diets



[1]*dataFIELD* is referred to in the figure as ENVI ("environmental impacts").

2. HEI-2010 and HEI-2015 scoring comparison

From the National Cancer Institute: https://epi.grants.cancer.gov/hei/comparing.html.

	Dietary component	Max Points	Standard for maximum score		Standard for zero score	
			2010	2015	2010	2015
Adequacy *(higher score = greater intake)*	Total Fruit	5	≥ 0.8 c-eq/1000 kcal		No fruit	
	Whole Fruit	5	≥ 0.4 c-eq/1000 kcal		No whole fruit	
	Total Vegetables	5	≥ 1.1 c-eq/1000 kcal		No vegetables	
	Dark Greens & Legumes[1]	5	≥ 0.2 c-eq/1000 kcal		No dark-green veggies, beans, or peas	
	Whole Grains	10	≥ 1.5 oz-eq/1000 kcal		No whole grains	
	Dairy	10	≥ 1.3 c-eq/1000 kcal		No dairy	
	Total Protein Foods[1]	5	≥ 2.5 oz-eq/1000 kcal		No protein foods	
	Seafood & Plant Proteins[1]	5	≥ 0.8 c-eq/1000 kcal		No seafood or plant proteins	
	Fatty Acid Ratio[2]	10	(PUFAs+MUFAs)/SFAs ≥ 2.5		(PUFAs+MUFAs)/SFAs ≤ 1.2	
Moderation *(higher score = lower intake)*	Refined Grains	10	≤ 1.8 oz-eq/1000 kcal		≥ 4.3 oz-eq/1000 kcal	
	Sodium	10	≤ 1.1 g/1000 kcal		≥ 2.0 g/1000 kcal	
	Empty Calories[3]	20	≤ 19% of energy		≥ 50% of energy	
	Added Sugars	10		≤6.5% of energy		≥26% of energy
	Saturated Fats	10		≤8% of energy		≥16% of energy

[1]2010 scores include legumes as protein foods until the maximum score is met. Any legumes left over after this are counted as vegetables. HEI-2015 scores add include all legume consumption in all the possible categories: Total Vegetables, Dark Green Vegetables or Legumes, Total Protein Foods, and Seafood and Plant Proteins

[2]Ratio of poly- and mono-unsaturated fatty acids to saturated fatty acids.

[3]Calories from solid fats, added sugars, and alcohol