ARTICLE IN PRESS

Food Policy xxx (xxxx) xxx–xxx

Contents lists available at ScienceDirect

Food Policy

journal homepage: www.elsevier.com/locate/foodpol

A Comprehensive Life Cycle Assessment of Greenhouse Gas Emissions from U.S. Household Food Choices

Rebecca Boehm[a,*], Parke E. Wilde[b], Michele Ver Ploeg[c,1], Christine Costello[d], Sean B. Cash[b]

[a] Rudd Center for Food Policy and Obesity/Zwick Center for Food and Resource Policy, University of Connecticut, 1376 Storrs Road, Unit 4021, Storrs, CT 06269, United States
[b] Friedman School of Nutrition Science and Policy, Tufts University, 150 Harrison Avenue, Boston, MA 02111, United States
[c] United States Department of Agriculture, Economic Research Service, 355 E Street, SW, Washington, DC 20024-3221, United States
[d] College of Engineering, University of Missouri, W1024 Lafferre Hall, Columbia, MO 65211, United States

ARTICLE INFO

Keywords:
Diets
Food expenditures
Economic input-output life cycle assessment
Greenhouse gas emissions
Climate change

ABSTRACT

Changes in diet have been proposed as one way to reduce carbon emissions from the food system. But evidence on the implications of changing to low carbon food choices for both diet quality and food affordability are limited in the U.S. The objective of this study was to (a) estimate greenhouse gas emissions (GHGEs) from U.S. household food purchases; (b) examine the source of GHGEs across U.S. food production industries and stages of the supply chain; and (c) show the association between GHGEs and spending by food categories and household sociodemographics. GHGEs from food expenditures made by households participating in the National Household Food Acquisition and Purchase Survey were calculated using Economic Input-Output Life Cycle Assessment. Results indicate that food purchases accounted for 16% of U.S. GHGEs in 2013 and average weekly household GHGEs were 71.8 kg carbon dioxide equivalents per standard adult. 68% of average weekly household GHGEs from food spending came from agriculture and food manufacturing stages of the food supply chain. Industries that produce animal proteins accounted for 30% of average weekly household GHGEs, the largest share of any food industry. Households generating the highest levels of GHGEs spent a significantly larger share of their food budget on protein foods compared to households generating lower levels of GHGEs. White households and those with higher education levels generated more GHGEs from food spending compared to non-white and less educated households. Overall these findings inform the ongoing debate about which diets or food spending patterns in the U.S. are best for mitigating GHGEs in the food system and if they are feasible for consumers to purchase.

1. Introduction

Food production is necessary to sustain human life, but the outputs of the food system are not limited to foods for human consumption. Agricultural production, processing and manufacturing, and distribution of foods produce outputs that are harmful to the environment. Greenhouse gas emissions (GHGEs) are one such co-product of the food supply chain, and by some estimates the global food system accounts for 30% of total GHGEs (Kim and Neff, 2009). The increase in production of GHGEs by humans is causing global climate changes, which threaten the well-being of ecosystems and human societies. Reductions in GHGEs are urgently needed to ensure long-term sustainability of human societies, ecosystems, and the agricultural sector itself (IPCC, 2014). Changes in diet have been proposed as a means to reduce GHGEs from the food system (Jones and Kammen, 2011; Wynes and Nicholas, 2017).

While a large body of research has documented the life cycle GHGEs caused by the production of specific foods, uncertainty remains about the impact of different consumer dietary scenarios on reducing food system GHGEs, especially in the U.S. From a food-based perspective, beef is consistently found to be the most carbon intensive food to produce on a per mass basis; other animal products such as lamb, poultry, and dairy products are relatively more carbon intensive to produce than plant-based foods (Clark and Tilman, 2017; Costello et al., 2015; de Vries and de Boer, 2010; Garnett, 2009). Consequently, many advocates have suggested that reduced consumption of meat would significantly reduce food system GHGEs in the U.S. (Hamerschlag, 2011; Heller et al., 2013). Further, the nutrition community has also

* Corresponding author.
E-mail address: Rebecca.boehm@uconn.edu (R. Boehm).

[1] The views expressed in this paper are of the authors and should not be attributed to those of the Economic Research Services or the United States Department of Agriculture.

https://doi.org/10.1016/j.foodpol.2018.05.004
Received 22 December 2017; Received in revised form 11 May 2018; Accepted 18 May 2018

Please cite this article as: Boehm, R., Food Policy (2018), https://doi.org/10.1016/j.foodpol.2018.05.004

advocated for plant-based and vegetarian diets to simultaneously reduce GHGEs and improve health outcomes (Melina et al., 2016). While many life cycle assessment studies of individual foods have helped us to understand the climate impact of different food production systems, there needs to be additional investigation of the climate impacts of the food system from the demand side.

In taking a demand or consumption-oriented perspective we can determine if consumer mitigation of food system GHGEs, through dietary changes, affects food security and nutritional quality. Some studies have taken the consumer-oriented perspective to assess the GHGEs generated by U.S. diets and food choices, although the literature is fairly limited. Seminal work by Weber and Matthews (2008) linked food expenditure data reported in the U.S. Bureau of Labor Statistics Consumer Expenditure Survey (CEX) with an Economic Input-Output Life Cycle Assessment (EIO-LCA) to estimate GHGEs from U.S. household food purchases. However, household food purchases were examined in aggregate at the national level and individual consumer behavior was not observed. CEX data was used in a subsequent study to estimate U.S. household GHGEs from various spending categories, including food (Jones and Kammen, 2011). This study observed individual consumer behavior through use of CEX household expenditure data and estimated GHGEs of foods using an EIO-LCA model. However, GHGEs generated by household food spending were divided into only eight categories. In addition, CEX has a limited number of categories describing food for away from home (FAFH) consumption, so a detailed analysis of GHGEs from FAFH could not be conducted with these data. FAFH is important to examine in detail in the context of environmental impacts because on average U.S. households spend half of their food budget on FAFH (USDA ERS, 2018).

Other U.S. based studies have limitations that do not allow for a detailed or comprehensive accounting of GHGEs from a consumption-oriented perspective. Heller and Keoleian (2015) found that aligning U.S. diets with the 2010 Dietary Guidelines for Americans could increase diet-related GHGEs by 12%. One key limitation of this study was with the compilation of food-specific life cycle assessments used to estimate GHGEs from food consumption. While comprehensive in terms of the number of studies compiled, most of the life cycle assessments included in the meta-analysis only captured GHGEs up to the farm level (Heller and Keoleian, 2015). In another recent U.S. based study, Tom et al. (2015) used nationally aggregate loss-adjusted food availability data to estimate GHGEs of current and recommended food consumption patterns. Using nationally aggregate loss-adjusted food availability data does not allow for examination of what consumers actually purchase and consume. Two other U.S. based studies have simulated how dietary shifts may be associated with changes in nutrition quality and GHGEs (Hallström et al., 2017; Harwatt et al., 2016). While simulations are instructive because they provide baseline information about the potential for U.S. dietary choices to be aligned for nutrition and GHGE mitigation goals, they assume homogenous choices and behavior across consumers. Heller et al. (2018) went beyond analyses of simulated dietary scenarios by estimating GHGEs for self-selected diets reported in the National Health and Nutrition Examination (NHANES) diet recall survey. However, a key limitation of this study was that life cycle assessments of individual foods did not always include GHGEs occuring beyond the farm gate.

More recently, NHANES diet recall survey data weres linked to an EIO-LCA model to estimate the level of energy required to produce current U.S. diets (Canning et al., 2017). Results indicate that more energy efficient diets would require extreme change in U.S. food choices, but notably, would also cost less than current average U.S. diets (Canning et al., 2017). However, only GHGEs from fossil fuels were estimated in this study. This study also used aggregate wholesale food prices to estimate the cost of diet recall data, which assumes that all U.S. consumers face similar food costs regardless of geographic location and wholesale prices reflect prices U.S. consumers pay for foods in retail or restaurant settings.

Recognizing the limitations of prior literature, the present study had three objectives. First total GHGEs generated by household food spending were estimated and examined by food system supply chain stage and food industry. Second, the asssociation between household GHGEs and food spending by broad categories was examined. The third objective was to examine the correlation between household sociodemographics and GHGEs generated by food spending to ascertain if some U.S. sub-populations are purchasing more carbon intensive diets than others.

To meet these objectives, actual U.S. household food expenditure data from the National Household Food Acquisition and Purchas Survey (FoodAPS) were linked to an Economic Input-Output Life Cycle Assessment (Yang et al., 2017). FoodAPS is the first U.S.-based survey to collect item-level food purchase and acquisition data from a nationally representative sample of U.S. households. The use of FoodAPS for this study allows for a major advancement of the literature on the GHGEs generated by U.S. food choices given the rich information it provides on household food choices and sociodemographic characteristics.

2. Methods

2.1. Overview of methods and EIO-LCA system boundaries

The key aspects of the methodologinclude: (1) description of GHGE data and the EIO-LCA model used to calculate GHGEs from household food expenditures; (2) description of household food expenditure survey data utilized for examining U.S. household food spending and GHGEs; (3) estimation of GHGEs of U.S. household food expenditures; (4) method for accounting for differences in caloric requirements across households; and (5) explanation of assessment of differences in household food spending by levels of GHGEs and sociodemographics.

The analyses captured GHGEs from all food system supply chain stages, including: (1) agriculture and/or food manufacturing, (2) wholesale, (3) transportation (i.e. truck, rail freight, air freight, and transport by boat), (4) retail, and/or (5) restaurant activity. GHGEs caused by household transportation to acquire foods, preparation, storage, or waste were not included in GHGE estimates. Therefore, the boundaries for the life cycle assessment of GHGEs in this analysis were from agricultural input production to consumer point of purchase.

2.2. GHGE data and EIO-LCA model

U.S. industry level GHGEs were derived from the U.S. Environmental Protection Agency (EPA) Inventory of U.S. Greenhouse Gas Emissions and Sinks report and the agency's environmentally extended economic input–output life cycle model (EIO-LCA) (Yang et al., 2017). The EIO-LCA model is used to generate Emission Intensity Factors (EIFs) that are measured in kilograms of carbon dioxide equivalents (kg CO_2e) per dollar of industry output or consumer final demand (in dollars). EIFs are generated from the EIO-LCA model for each of the 389 industries in the U.S. economy including 26 for agriculture and food manufacturing, which are referred to hereafter as production stage industries.

Ten industries in the U.S. economy represent post-food production activities in the food supply chain. The four included in this study were: wholesaling, transportation, retailing, and restaurants. Together, these 36 industries are defined by the 2007 U.S. Department of Commerce Bureau of Economic Analysis (BEA) Benchmark Input-Output Accounts representing the U.S. economy (US Department of Commerce, 2017). The EIFs for the production stage industries are listed in Table 1 and the EIFs for post-production industries are listed in Table 2. EIFs resulting from the post-production activities are calculated in the same fashion as those occurring in production stage industries.

Table 1
Emission Intensity Factors (EIFs) for 26 Agricultural Production and Food Manufacturing Industries in kg CO_2e per dollar (in 2013 dollars), listed in descending order from most carbon intensive to least carbon intensive.

Beef, pork, and other red meat	2.58
Cheese	2.01
Fluid milk, milk products, and butter	1.88
Flours and rice	1.79
Dry, condensed, and evaporated dairy	1.77
Eggs	1.21
Frozen foods	1.02
Ice cream and frozen desserts	1.00
Poultry	0.98
Fats and oils	0.92
All other foods	0.83
Canned foods	0.80
Sugar and confectionery products	0.77
Seasonings and dressings	0.77
Cookies, crackers, pasta, and tortillas	0.76
Fresh vegetables and melons	0.73
Breakfast cereal	0.67
Snack foods	0.62
Soft drinks, bottled water, and ice	0.62
Bread and bakery products	0.61
Breweries	0.59
Seafood	0.57
Coffee and tea	0.57
Fruits and tree nuts	0.54
Wineries	0.37
Distilleries	0.34

Notes: Emission Intensity Factors (EIFs) derived from the EPA EIO-LCA model (Yang et al., 2017). EIFs presented in 2013 dollars, in value received by the agricultural producer or food manufacturer. Industries are defined by the BEA and definitions of each are described in the supplementary information.

Table 2
Emission Intensity Factors (EIFs) for post-production/manufacturing industries, in kg CO_2e per dollar (2013 dollars).

Wholesale trade	0.136
Truck transportation	2.135
Rail transportation	0.688
Water transportation	1.110
Air transportation	0.920
Food and beverage stores	0.329
General merchandise stores	0.255
Full service restaurants	0.379
Limited-service restaurants	0.340
All other food and drinking places	0.449

Notes: Emission Intensity Factors (EIFs) derived from the EPA EIO-LCA model (Yang et al., 2017). EIFs presented in 2013 dollars, in value received by the producer. Industries are defined by the BEA and definitions of each are described in the supplementary information.

2.3. Household food expenditure and sociodemographic data

Food expenditure data were derived from the FoodAPS restricted use survey data. FoodAPS utilizes a nationally representative sample of U.S. households (n = 4826). Households participating in the survey recorded food acquisitions and purchases, including free items, for all family members for one 7-day period between April 2012 and January 2013. The records include both food for at-home consumption (Food at Home, FAH) and food for away from home consumption (Food Away from Home, FAFH). Each unique food purchased (~6000) by FoodAPS households was mapped to one of the 26 production stage industries listed in Table 1 to assign each item san EIF. FAFH items purchased as mixed dishes were first decomposed into their food commodity components, and then each component was mapped to one of the 26 production stage industries in Table 1. The food item mapping and decomposition process are described in the supporting information. FoodAPS participating households also reported a variety of sociodemographic characteristics and this information was used to compare household GHGEs according to race and ethnicity of the household Primary Respondent (PR, the person completing the survey and who identified as the person responsible for purchasing most of the food for the household), household monthly income, whether or not the household currently participates in the Supplemental Nutrition Assistance Program (SNAP), and education level of the PR.

The Tufts University and University of Connecticut Institutional Review Boards approved this project as human subjects research.

2.4. Estimating GHGEs generated by FoodAPS household food expenditures per household, per supply chain stage, and per production industry

Using the EPA EIO-LCA model total weekly GHGEs (in kg CO_2e) from household food expenditures were calculated by multiplying a household food spending per food (in dollars) and the EIF (in kg CO_2e/dollar) for each food purchased by production industry. Then total GHGEs for each item purchased were summed per household.

This calculation can be represented by the following equation:

$$\mathrm{GHGE}_j = \exp_j \cdot \mathrm{EIF}_j + \sum_s \exp_{js} \cdot \mathrm{EIF}_s \tag{1}$$

where GHGE_j represents total life cycle emissions for foods categorized to the *j* agricultural or food manufacturing production industry listed in Table 1. Exp_j is the proportion of total expenditure per food allocated to one of the *j* production stage industries, and EIF_j is the EIF for production stage industry *j*. Exp_{js} represents the proportion of total expenditure on each food allocated to each post-production industry *s*. EIF_s represents the EIF for each of the post-production industries listed in Table 2. Allocation of the expenditure on each food to one of the *j* production industries and to each *s* post-production industry is derived from 2007 BEA input–output data on the production (agricultural and/or manufacturing), transportation, wholesale, retail, and restaurant costs required to deliver foods to consumers at point of purchase for each *j* production stage industry (US Department of Commerce, 2017). Further details on the calculation of $\exp_j$ and $\exp_{js}$ can be found in the supporting information. Total weekly household GHGEs are calculated as the sum of GHGEs from foods purchased from each *j* production stage industry. Once each household's total weekly GHGEs were estimated using equation 1, average weekly household GHGEs attributable to each supply chain stage and food industry were estimated by calculating the mean CO_2e by supply chain stage and industry across households.

It should be noted that the most recent year BEA published data on transportation by mode (i.e. truck, water, rail, and air) was in 2002. For 2007, BEA only released transportation mode data by industry in aggregate. As a result, the share of transportation by mode used for each of the 26 food-related production/manufacturing industries are derived from the 2002 BEA data. Using these data assumes that the mix of transportation modes by food industry used to deliver food to consumers has not changed since 2002.

2.5. Calculating the number of standard adult equivalents per household

Standard Adult Equivalents (SAE) per household were calculated to permit comparisons of total weekly GHGEs across sub-groups of households in the FoodAPS sample. The definition of an SAE comes from the USDA Center for Nutrition Policy and Promotion (CNPP) which provides average calorie requirements per day by activity level, age, and gender groups for children, men, women, and women who are pregnant or breastfeeding (Center for Nutrition Policy and Promotion, 2010). Each household members' age, gender, activity level (i.e. sedentary, low-active, and active) and pregnancy/breastfeeding status were used to estimate daily individual and household energy

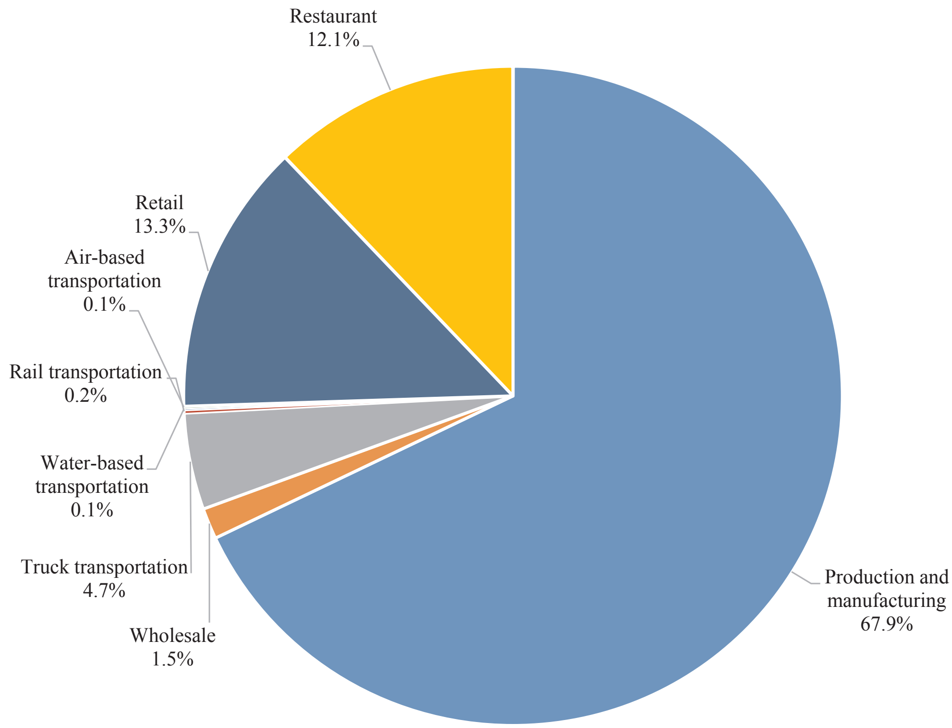

Fig. 1. Average weekly household GHGEs per SAE by supply chain stage. (n = 4723 households).

requirements using CNPP guidelines. All household members were assumed to be sedentary for this analysis.

2.6. Household food expenditure shares and sociodemographics by GHGE levels

To compare food spending patterns by GHGEs generated, households were divided into quintiles based on total household GHGEs per SAE. Households in the very low GHGE quintile (n = 951) generated < 20th percentile of the within-sample average weekly household GHGEs per SAE; households in the low GHGE quintile (n = 943) generated ≥20th and < 40th percentile of the within-sample average weekly household GHGEs; households in the medium quintile (n = 943) generated ≥40th and < 60th percentile of the within-sample average weekly household GHGEs per SAE; households in the high quintile (n = 943) generated ≥60th and < 80th percentile of the within sample average weekly household GHGEs per SAE; and households in the very high quintile (n = 943) generated ≥80th percentile of the within-sample average weekly household GHGEs per SAE.

To compare food spending across GHGE quintiles, individual food expenditures were categorized into mutually exclusive broad categories. These categories are similar to those defined by the 2015 U.S. Dietary Guidelines for Americans, thus provide some indication of the nutritional quality of household food expenditures (U.S. Department of Health and Human Services and U.S. Department of Agriculture, 2015). The categories included: (1) milk and dairy products, (2) red meat, poultry, fish, eggs, and beans, called protein foods (3) mixed dishes, (4) grains, (5) sweets and snacks, (6) fruits and vegetables, (7) beverages, and (8) fats, oils, condiments, and sugars. Then, the share of spending per household in each category was calculated by dividing total expenditure per category by total household food spending for the FoodAPS reporting week.

Differences in average expenditure share by food category, average total weekly GHGEs per household (in kg CO2e), average GHGE intensity per dollar of household food expenditures and average GHGE intensity per dollar of household total monthly income were compared using Analysis of Variance (ANOVA). Post hoc unpaired t-tests were used to compare individual means and a Bonferroni correction was made to account for inflation of type 1 error rate due to multiple comparisons.

Ordered logistic regression was used to assess the association between membership to GHGE quintile (dependent variable) and sociodemographic characteristics (independent variables). Sociodemographic characteristics assessed included: race of household PR (including White, Black, Asian, and other/multiple race); ethnicity of household PR (Hispanic or not Hispanic); level of education of household PR (less than a high school graduate; high school graduate/equivalent degree; some college completed; college graduate; master's degree or higher); total household monthly income (in dollars per SAE); and household participation in the Supplemental Nutrition Assistance Program (SNAP).

All analyses were adjusted for complex survey design features of FoodAPS using Stata complex survey design prefix commands. Information on the FoodAPS survey sample design can be found at the USDA Economic Research Service (ERS) FoodAPS website and in Cole and Baxter (2016).

3. Results

3.1. GHGEs per household and for the U.S. by supply chain stage and food industry

3.1.1. GHGEs per U.S. household and total contribution to U.S. GHGEs

On average households generated 71.8 kg CO_2e per SAE per week (95% CI: 68.6, 75.3; n = 4723). In total U.S. households generated 899 billion kg CO_2e from food spending in 2013. This represents 16.3% of total U.S. GHGEs in the same year (EPA, 2014).

3.1.2. GHGEs per U.S. household by supply chain stage

Fig. 1 shows average weekly household GHGEs in kg CO_2e per SAE across supply chain stages of the food system. Agricultural production and manufacturing account for 67.9% of average weekly household GHGEs from food spending. The restaurant and retail sectors combined accounted for 25.4% of GHGEs from household food spending, followed by truck transportation (4.7%) and wholesale trade (1.5%). All other

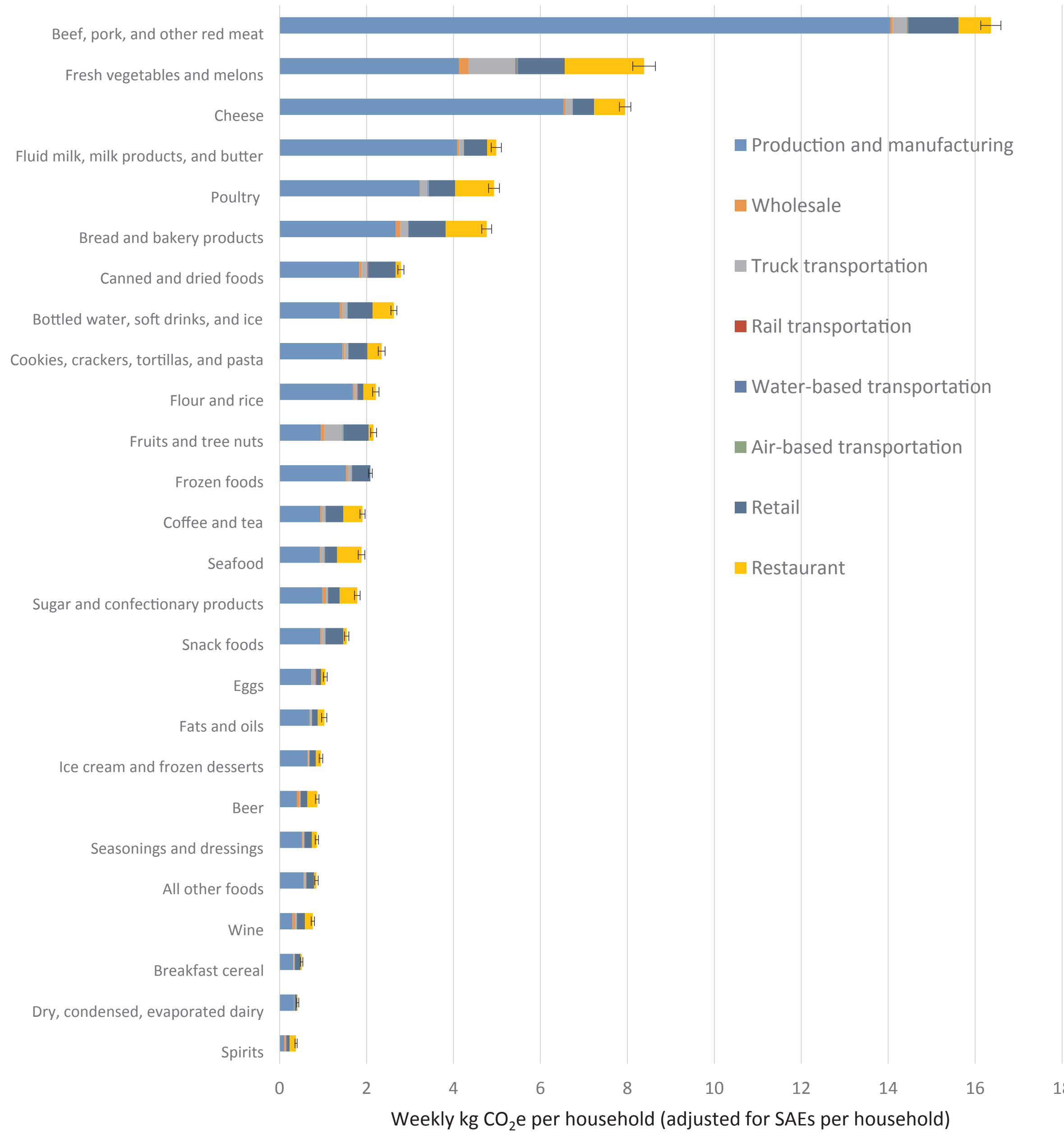

Fig. 2. Average weekly household GHGEs per SAE by food system industries, decomposed by supply chain stages (n = 4723 households). Means and standard errors are adjusted for complex survey design. Black bars indicate one standard error of the estimated mean. Note: See supplementary information for a definition of each industry and description of how household food purchases were categorized to each industry.

forms of transportation (i.e. water-based, rail-based, and air-based) accounted for a combined 0.4% of average weekly household GHGEs.

Fig. 2 shows average weekly household GHGEs per SAE from food spending both by supply chain stages and by the 26 food industries that produce and manufacturing foods for purchase by U.S. households. The share of GHGEs from supply chain stages varied across food industries. GHGEs from industries producing beef, pork, and other red meat; cheese; and fluid milk, milk products, and butter were concentrated in the production and manufacturing stages (86%, 82%, and 82%, respectively). Conversely, production and manufacturing of products from the spirits; wine; and fruits and tree nuts industries generated the least amount of GHGEs compared to other industries (28%, 38%, and 44%, respectively). Across all industries, wholesale accounted for no more than 8% of total GHGEs per industry. Truck transportation accounted for 19% of GHGEs from the fruits and tree nuts industries and 13% from the fresh vegetables and melon industries. Compared to all other industries, these two industries had the largest share of GHGEs coming from truck transportation. Rail, water, and air transportation accounted for no more than 1.4% of the share of total GHGEs per industry. The largest share of retail GHGEs were generated by the fruits and tree nuts (27%), snack foods (27%), and breakfast cereal (25%) industries. Finally, the largest share of restaurant GHGEs were from the purchase of spirits (39%), seafood (30%), and beer (26%).

3.1.3. GHGEs per U.S. household by industry

As illustrated in Fig. 2, the industries that produce beef, pork, and other red meat generated the largest share of GHGEs from U.S. household food purchases, approximately 21%. Industries that produce fresh vegetables and melons accounted for 11% of average weekly household GHGEs, followed by cheese industries (10%), and the fluid milk, milk products, and butter industries (7%). These four industries combined accounted for 49% of average weekly household GHGEs from

Table 3
Average weekly household expenditure shares by food category, total weekly GHGEs, total weekly food expenditures, and GHGE expenditure and income intensity values by GHGE quintile (standard errors reported in parentheses).

	Very low GHGE quintile (n = 951)		Low GHGE quintile (n = 943)		Medium GHGE quintile (n = 943)		High GHGE quintile (n = 943)		Very High GHGE quintile (n = 943)		F statistic	P value
	Average or medians reported (standard errors in parentheses)											
Expenditure share category												
Milk and Dairy	6.2%	(0.8%)	5.9%	(0.3%)	5.2%	(0.2%)	5.5%	(0.2%)	5.1%	(0.2%)	1.20	0.3303
Protein foods	18.0%^{VH}	(0.9%)	18.7%^{VH}	(0.6%)	20.4%	(0.8%)	20.4%	(0.7%)	21.4%$^{VL, L}$	(0.6%)	3.47	0.0200
Mixed dishes	21.3%	(1.5%)	22.6%	(0.9%)	23.3%	(0.8%)	22.7%	(1.0%)	23.1%	(0.6%)	0.47	0.7573
Grains	7.8%$^{H, VH}$	(0.6%)	6.8%	(0.3%)	6.7%	(0.5%)	6.1%^{VL}	(0.3%)	5.9%^{VL}	(0.2%)	3.65	0.0200
Sweets and snacks	9.5%	(0.5%)	8.7%	(0.4%)	9.4%	(0.3%)	9.3%	(0.4%)	9.0%	(0.3%)	1.01	0.4138
Fruits and vegetables	13.3%	(0.9%)	14.3%	(0.6%)	14.1%	(0.5%)	14.8%	(0.4%)	13.9%	(0.2%)	1.20	0.3320
Beverages	18.9%^{H}	(0.9%)	17.2%	(0.7%)	15.9%	(0.7%)	15.8%^{VL}	(0.5%)	16.6%	(0.5%)	4.47	0.0062
Fats, oils, condiments and sugars	4.1%^{H}	(0.4%)	5.7%	(0.5%)	4.9%	(0.3%)	5.4%^{VL}	(0.2%)	5.0%	(0.2%)	3.56	0.0175
Emissions, food expenditures, and emissions intensities												
Total weekly GHGEs (kg CO_2e)	**13.94**	**(0.42)**	**32.85**	**(0.24)**	**50.29**	**(0.34**	**73.56**	**(0.38)**	**136.33**	**(3.23)**	2629.79	< 0.001
Total weekly food expenditures ($)	**18.20**	**(0.58)**	**41.49**	**(0.65)**	**61.96**	**(0.61**	**87.15**	**(0.95)**	**160.95**	**(4.21)**	1674.63	< 0.001
GHGEs/total weekly food expenditures (kg CO_2e/$)	0.82$^{H, VH}$	(0.01)	0.83$^{H, VH}$	(0.01)	0.85	(0.01	0.87$^{VL, L}$	(0.01)	0.88$^{VL, L}$	(0.01)	8.27	< 0.001
Median GHGEs/household monthly income (kg CO_2e/$)*	**0.008**	**(0.001)**	**0.021**	**(0.001)**	**0.028**	**(0.001)**	**0.035**	**(0.001)**	**0.043**	**(0.002)**	1139.95	< 0.001

Notes: Total n = 4723; F-statistic and p-value reported for Analysis of Variance (ANOVA) test on expenditure shares for each food category by all GHGE quintiles. Post-hoc t-tests adjusted for multiple comparisons with a Bonferroni correction; sub-scripts indicate which means are statistically different from one another (VL = very low GHGE quintile; L = low GHGE quintile; M = medium GHGE quintile; H = high GHGE quintile; VH = very high GHGE quintile). Bold values indicate when all values are statistically different from all other values.

* Median values compared across quintiles given the skewness of household monthly income using Kruskal-Wallis test; Pearson design-adjusted chi-squared test statistic and p-value reported. n = 4,624 since 99 households did not report monthly income.

food purchases. The remaining 21 industries accounted for 51% of average weekly household GHGEs from food purchases.

Industries producing animal proteins, which include beef, pork, lamb, other red meats, poultry, and seafood, accounted for 30% of average household weekly GHGEs per SAE. Industries that produce dairy products and eggs accounted for 20% of average household weekly GHGEs. 14% of average weekly household GHGEs came from fruit and vegetable industries, 13% from grain industries, 6% from canned and frozen foods industries, 6% from non-alcoholic beverage producing industries, 4% from industries producing sweets and salty snack foods, 2% from industries producing alcoholic beverages, 1% from industries producing fats and oils, and 2% for all other foods.

3.2. Differences in household food expenditure shares and sociodemographics across GHGE quintiles

Table 3 shows average weekly household food expenditure shares by broad food categories and GHGE quintile. Households in the very high GHGE quintile spent 19% more of their food budget on protein foods compared to households in the very low and low GHGE quintiles. Compared to households in the very low GHGE quintile, households in the high and very high GHGE quintile spent 21% and 24% less of their food budget on grains, respectively. Households in the high GHGE quintile spent 16% less of their food budget on beverages compared to households in the very low GHGE quintile. Households in the high GHGE quintile spent 32% more of their food budget on fats, oils, condiments, and sugars compared to households in the very low GHGE quintile. Share of food spending on milk and dairy products; fruits and vegetables; sweets and snacks; and mixed dishes was not statistically different across GHGE quintiles.

Table 3 also reports average weekly household GHGEs (in kg CO_2e), weekly food expenditures (in dollars) and GHGEs generated per dollar of food expenditure and per dollar of household monthly income (kg CO_2e divided by total weekly food expenditures, and kg CO_2e divided by household total monthly income). Households in the very high GHGE quintile generated on average 9.8 times more GHGEs than households in the very low GHGE quintile. Households in the very high GHGE quintile spent on average 8.8 times more on food per week compared to households in the very low GHGE quintile. Emissions intensities per dollar of food expenditure were 7.3% and 6.1% higher for households in the very high GHGE quintile compared to households in the very low and low quintiles, respectively. Emissions intensity per dollar of household monthly income also varied substantially across GHGE quintiles. Households in the very high GHGE quintile had an emissions intensity per dollar of income that was 5.4 times the emissions intensity of households in the very low GHGE quintile.

Table 4 presents summary statistics of household and PR sociodemographic characteristics by GHGE quintiles. 83.8% of households in the very high GHGE quintile had a White PR, compared to only 64.5% in the very low GHGE quintile. Conversely, the share of households with a Black, Asian or other/multiple race PR decreased when moving from very low to very high GHGE quintile. SNAP participation was inversely associated with GHGE quintile membership; 23.9% of households in the very low GHGE quintile participated in SNAP compared to only 9.2% in the very high GHGE quintile. Educational attainment of the household PR was also inversely correlated with GHGE quintile level. Mostly notably, 26.4% of households of the very high GHGE quintile had a PR with a college degree, compared to only 11.8% of households in the very low GHGE quintile. There were also more households in the very high GHGE quintile with a master's degree or higher compared to the very low GHGE quintile. Average household monthly income was positively associated with household membership to GHGE quintile.

Table 5 reports results from the ordered logistic regression predicting household membership to higher GHGE quintiles by sociodemographic characteristics. Household PR race, ethnicity, educational

Table 4
Summary statistics of household sociodemographics by GHGE quintile (n = 4620).

	Very low GHGE quintile (n = 922)	Low GHGE quintile (n = 916)	Medium GHGE quintile (n = 927)	High GHGE quintile (n = 929)	Very high GHGE quintile (n = 926)
	Estimated proportions or means reported (standard errors in parentheses)				
Race					
% White	64.51	71.66	74.29	80.41	83.77
	(4.211)	(2.556)	(2.777)	(2.444)	(1.966)
% Black	22.35	15.11	12.13	9.279	8.051
	(4.296)	(2.116)	(2.229)	(1.668)	(1.322)
% Asian	4.109	4.072	5.314	3.338	2.977
	(1.171)	(1.020)	(1.361)	(0.960)	(0.958)
% Other race or multiple races	9.035	9.162	8.264	6.970	5.207
	(1.550)	(1.660)	(1.595)	(1.118)	(0.995)
Ethnicity					
% Hispanic	17.12	18.08	13.24	13.62	6.756
	(3.005)	(3.238)	(2.822)	(4.220)	(1.028)
% SNAP participants	23.89	14.92	13.39	10.15	9.198
	(2.460)	(1.321)	(1.585)	(1.215)	(1.158)
Education					
% Less than high school graduate	17.59	13.86	10.02	6.269	4.880
	(2.462)	(1.919)	(1.413)	(1.375)	(1.016)
% High School Grad/equivalent	29.73	25.43	25.89	27.15	18.54
	(2.673)	(2.798)	(2.540)	(3.071)	(1.978)
% Some college	30.30	39.79	33.72	34.99	30.22
	(2.328)	(4.170)	(2.126)	(3.008)	(2.013)
% College graduate	11.83	14.13	20.62	23.84	26.43
	(2.771)	(2.340)	(1.498)	(2.358)	(2.885)
% Master's degree or higher	10.54	6.783	9.743	7.753	19.94
	(2.167)	(1.827)	(1.402)	(1.435)	(2.058)
Household monthly income ($) per SAE	$2020.18	$2109.27	$2242.01	$2570.94	$3954.84
	(209.02)	(146.49)	(138.14)	(126.74)	(356.02)

Notes: Of the 4723 households with estimated GHGEs in the sample, 3 did not report the educational level of their Primary Respondent (PR), 99 did not report total monthly income, and 2 did not report whether or not they participated in SNAP.

Table 5
Ordered logistic regression results predicting membership to GHGE quintile by household sociodemographic characteristics.

	GHGE Quintile
Race (White is the reference group)	
Black	0.480*
	(0.0869)
Asian	0.555*
	(0.0971)
Other race/multiple race	0.895
	(0.117)
Hispanic (Non-Hispanic is the reference group)	0.778*
	(0.0673)
Education (Less than high school is reference group)	
High school graduate/equivalent	1.469*
	(0.187)
Some College	1.850*
	(0.237)
College Graduate	3.054*
	(0.513)
Master's Degree or higher	3.568*
	(0.780)
Log(household monthly income, $, per SAE)	1.203*
	(0.0245)
Household participating in SNAP	0.891
	(0.104)
Observations	4619
F-statistic	17.65
p(F)	< 0.00001

Notes: Statistical significance indicated by $^{*}p < 0.01$. Of the 4723 households with estimated GHGEs in the sample, 3 did not report the educational level of their Primary Respondent (PR), 99 did not report total monthly income, and 2 did not report whether or not they participated in SNAP.

attainment, and household income werestrongly associated with membership to GHGE quintiles. Households with a White PR had between 1.8 and 2.1 greater odds of being in higher GHGE quintiles compared to households with a Black or Asian PR. Non-Hispanic households had 1.3 greater odds of being in a higher GHGE quintile compared to Hispanic households. Households with a PR with higher educational attainment had higher odds of being in a higher GHGE quintile compared to households with lower educational attainment. In particular, households with a PR who attained a Master's degree or higher had 3.6 greater odds of being in a higher GHGE quintile compared to households with a PR who was not a high school graduate. Higher household monthly income was also associated with increased odds of being in a higher GHGE quintile. No association was found between GHGE quintile membership and household SNAP participation status.

4. Discussion and conclusions

A key strength of this study is that it provides the most comprehensive estimate of GHGEs generated by U.S. consumer food purchasing to date. Table 6 reports estimates of GHGE per capita per day, comparing prior study estimates to the present study's results. Prior studies reported in Table 6 did not capture GHGEs from the entire food supply chain or did not disaggregate foods beyond very coarse categories. Other studies were limited because life cycle assessments only captured emissions beyond the farm gate. Consequently, the estimates provided in this study of daily GHGE per capita represents a major advancement in our understanding of the magnitude of life cycle GHGEs generated by food purchasing in the U.S.

The results of this study indicate that emissions generated from U.S. household food spending are substantial. At the household level, the average amount of GHGEs generated in a week from food spending are equivalent to traveling 174 miles in an average U.S. passenger vehicle (EPA, 2016). However, GHGEs generated by food purchases vary substantially across households, in some instances by a factor of 10, which suggests that changes to food purchasing patterns could contribute to reduced GHGEs from the food system. The variation in emissions intensity per dollar of food expenditure and household income across GHGE quintiles further indicates that GHGEs could be mitigated through changes in U.S. household food purchasing. At the economy level, GHGEs resulting from U.S. household food spending account for almost one-fifth of total U.S. GHGEs. For comparison, according to EPA 2015 estimates of U.S. GHGEs by broad economic sectors, commercial/residential activity accounted for 12% and industrial activity accounted for 21% of total U.S. GHGEs (EPA, 2016). Therefore, changes in food consumption can be a key area for reducing GHGEs in the U.S.

GHGEs resulting from U.S. household food purchases were concentrated at the agricultural and manufacturing stages of the food supply chain. However, the proportion of GHGEs by supply chain stage varied by the food industry from which a food product originated. In particular, the share of GHGEs from post-production industries (i.e. wholesale, transportation, retail and restaurants) is highest for the production of fresh vegetables and melons. This specific finding suggests that eating locally grown fruits and vegetables may be an effective strategy to meaningfully reduce food system GHGEs from transportation.

After the production stage of the food supply chain, the combined retail and restaurant stages account for the second largest share (25%) of GHGEs generated from U.S. household food expenditures. Numerous life cycle assessment studies have focused on GHGEs from the production stage of the food supply chain and have mostly omitted estimates of post-farm gate GHGEs (Heller and Keoleian, 2015; Soret et al., 2014). This is particularly true for the retail and restaurant stages of the food supply chain. While Canning (2010) estimated energy use in the wholesale, retail and restaurant supply chain stages, as well energy used by households for cooking and storage of food, there was not an

Table 6
Comparison of estimates of GHGEs generated by U.S. diet or food expenditures.

Study	Study Year	kg CO_2e/capita/day	Method used to estimate GHGEs	Food system boundaries	Food data used
Weber and Matthews	2008	8.4	EIO-LCA	Cradle to consumer[c]	1997 Benchmark Input-Output Accounts
Jones and Kammen	2011	5.6[a]	EIO-LCA	Cradle to consumer	1997 Benchmark Input-Output Accounts
Soret et al.	2014	2.6[a]	Compilation of LCA studies	Variable	Survey based, consumption
Heller and Keoleian	2015	3.6	Compilation of LCA studies	Variable	2010 Loss-Adjusted Food Availability
Canning et al.	2017	6.7[b]	EIO-LCA	Cradle to consumer	2007–2008 NHANES
Heller et al.	2018	4.7	Compilation of LCA studies	Variable	2005–2010 NHANES
Current study estimate	2018	10.3	EIO-LCA	Cradle to consumer	FoodAPS

[a] Midpoint was computed and reported here when a range of values were reported in the original study.
[b] Only includes fossil fuel use in the food system, including consumer/household energy use, but no other sources of GHGEs.
[c] Cradle to consumer indicates that the boundaries of analysis include input and production stages to consumer point of purchase.

estimation of the resulting GHGEs from these stages of the food supply chain (Canning et al., 2010). Based on the results of this study efforts to reduced GHGEs from the food supply chain could be more focused on retailers and restaurants.

Results show that the purchase and consumption of meat is a large contributor to GHGEs from the U.S. food system and household food spending. Industries producing red meat, poultry, and fish constituted the largest share of weekly household GHGEs. This is consistent with previous life cycle assessments that found that meat and animal products are the most GHGEs intensive foods to produce (Eshel and Martin, 2006; Garnett, 2009; Hamerschlag, 2011; Steinfeld et al., 2006; Weber and Matthews, 2008). Relatedly, plant-based diets have proven in some studies to be less GHGEs intensive than higher meat diets (Scarborough et al., 2014; Soret et al., 2014). However, results of this study also indicate that industries producing fresh vegetables and melons account for the second largest share of GHGEs from U.S. household food expenditures. This is likely due to the fact that this industry represents the production of many more unique foods than other industries, and not because fresh vegetables or melons are particularly carbon intensive to produce, as noted in prior life cycle assessments of such products (Heller and Keoleian, 2015). Additionally, the significant share of post-production emissions from the fresh vegetables and melons industry points to the need for efficiency gains in the post-production supply chain for such products, specifically in transportation and among retailers and restaurants.

Analysis of the variation in household food expenditure shares by GHGEs levels provides additional evidence that animal proteins are the main driver of carbon emissions resulting from U.S. household food choices. Compared to households in the lowest GHGE quintile, households in the highest quintile spent a significantly larger share of their food budget on animal proteins. This implies that reducing food-related GHGEs will require households to spend less on animal proteins. As noted before, animal proteins are more carbon intensive to produce on a per mass basis, as numerous life cycle assessments at the food product-level have shown (Garnett, 2009). This analysis offers evidence that at the diet level, increased purchase of animal protein foods is associated with more emissions intensive household food expenditures. However, future research should examine in more detail how GHGEs from food choices change when households substitute animal proteins with other foods.

Results of this analysis also indicate that reducing GHGEs generated by food purchasing could have some adverse consequences for diet quality. Households with the lowest GHGEs spent a significantly larger share of their food budget on grains and beverages. These categories included refined grains, alcohol, and sugary drinks. This result confirms a prior study on the connection between GHGEs and the nutrient density of foods, which found that more energy dense, refined-grain foods are lower in GHGEs per gram and calorie (Drewnowski et al., 2015). Further research is warranted to determine how diet quality is affected by reduced spending on animal protein foods.

The association between household sociodemographics and GHGEs suggest that educational efforts could be targeted to more highly educated and affluent U.S. consumers to encourage more climate friendly food choices. These results can also be used to inform dietary guidance. In 2015, leading researchers on dietary sustainability and members of the U.S. Dietary Guidelines Advisory Committee indicated that addressing food sustainability was “essential to ensure a healthy food supply will be available for future generations” (Department of Health and Human Services, 2015). Priority recommendations from this report included (1) in-depth evaluations of U.S. domestic dietary patterns and (2) research on whether sustainable diets are affordable and accessible to all income groups in the U.S. Results in our analysis identify new knowledge in these two priority areas, and can provide critical information for the next round of the formation of the Dietary Guidelines for Americans when the scientific advisory committee is convened next.

This study is not without limitations. First, USDA analyses of FoodAPS data found underreporting of food purchases and acquisitions among households participating in the survey, due in part to a decrease in food reporting toward the end of the household’s seven-day reporting period. Fifty-four percent of individuals in participating households reported food acquisitions on day one of reporting, but only 40% reported a food acquisition on the seventh day of reporting (USDA ERS, 2013). Consequently, estimates of average weekly GHGEs could be considered conservative. Additionally, USDA also found that compared to households with a White PR, households with a Black/African American PR were less likely to report FAH purchasing events (with White PR as referent, Odds Ratio: 0.85, 95% CI: 0.75, 0.97) (Hu et al., 2017). While this difference may attenuate the association between race/ethnicity and membership to GHGEs quintile, the effect would be limited given the relatively small difference in probability of reporting FAH events between the two racial groups. Second, in using the EIO-LCA methodology to calculate emissions, food purchases could not be disaggregated beyond the 26 agricultural and food manufacturing industries defined by the BEA Benchmark accounts. In particular, GHGEs from beef and pork could not be estimated separately. This is important because beef has a much higher carbon footprint than pork on a per weight and per calorie basis (Garnett, 2009; Hamerschlag, 2011). Third, the EIO-LCA methodology estimates GHGEs of food expenditures in monetary units not physical units, such as pounds of edible food. As a result, foods containing the same physical units (a pound of beef) with different prices will generate different levels of GHGEs using the EIO-LCA methodology. This limitation of EIO-LCA has been discussed in detail elsewhere (Soret et al., 2014; Weisz and Duchin, 2006). Fourth, mixed dishes could not be disaggregated for the comparison of of food expenditure shares and GHGEs. It is unclear how much meat and animal products are contained in this food category.

There are also limitations to how EIO-LCA modeling estimates GHGEs of imported foods. For this analysis it was assumed that imported foods generate the same level of GHGEs as domestically-produced foods. Approximately 7.3% of the U.S. food supply (in dollars) was imported in 2013 (Behrens et al., 2017; USDA ERS, 2018) and there is evidence that U.S. imports represent a relatively small share of the embodied GHGEs generated by food production (Behrens et al., 2017). Taken together these facts indicate that results of this study may only be minimally affected by differences in food production systems for imported foods. A hybrid LCA approach could be used in future studies to account for differences in production systems for imported foods.

Another limitation of this study is that GHGEs generated by agricultural and food manufacturing for processed food items were not disaggregated. While this is a limitation, a strength of this study is that post-agricultural production GHGEs were included in emission estimates. This enhances our understanding of how post-production influences the GHGE profile of foods, which has been a major limitation of prior studies (Heller and Keoleian, 2015; Soret et al., 2014). Finally, nutritional quality of household food expenditures was not examined in detail. Future research should examine simultaneously nutritional quality and the cost of food in the U.S. to determine if low carbon food expenditures are compatible with both food security and public health nutrition goals.

This study adds new information to the literature on the contribution of U.S. food choices to climate change. The source of GHGEs from household food spending have been examined comprehensively by food supply chain stages and industries that produce food for human consumption. This analysis also provides an overview of GHGEs in the U.S. food system so that the carbon hotspots can be pinpointed for decreasing demand and improving the production efficiency of high carbon foods. The association between the mix of spending on different types of foods and the carbon footprint of U.S. household food expenditures has been examined for the first time. These findings provide evidence on the composition of actual low carbon diets that are already being purchased in the U.S. and what implications these diets might have for food costs and diet quality. Overall this study informs the ongoing debate about which diets or food spending patterns in the U.S. are best for mitigating GHGEs in the food system and if they are feasible for consumers to purchase in terms of both cost and nutrition.

Acknowledgements

The authors thank the following individuals for their support in the preparation of this work: Lisa Mancino, USDA ERS; Jessica Todd, USDA ERS; Rigoberto A. Lopez, University of Connecticut; Giulia Tiboldo, University of Connecticut; Bhavik R. Bakshi, The Ohio State University.

Funding

This work was funded by the Friedman Family Foundation Doctoral Fellowship and the Tufts University Institute of the Environment.

Conflicts of interest

The authors report no conflicts of interest.

Appendix A. Supplementary material

Supplementary data associated with this article can be found, in the online version, at http://dx.doi.org/10.1016/j.foodpol.2018.05.004.

References

Behrens, P., Jong, J.C.K., Bosker, T., Rodrigues, J.F.D., de Koning, A., Tukker, A., 2017. Evaluating the environmental impacts of dietary recommendations. PNAS 201711889. http://dx.doi.org/10.1073/pnas.1711889114.

Canning, P., Charles, A., Huang, S., Polenske, K.R., Waters, A., 2010. Energy use in the US food system (No. 94). United States Department of Agriculture Economic Research Service, Washington, D.C.

Canning, P., Rehkamp, S., Waters, A., Etamadnia, H., 2017. The Role of Fossil Fuels in the U.S. Food System and the American Diet (No. 224). USDA Economic Research Service, Washington, D.C.

Center for Nutrition Policy and Promotion, 2010. Estimated Calorie Needs per Day by Age, Gender, and Physical Activity Level. USDA, Washington, D.C.

Clark, M., Tilman, D., 2017. Comparative analysis of environmental impacts of agricultural production systems, agricultural input efficiency, and food choice. Environ. Res. Lett. 12, 064016. http://dx.doi.org/10.1088/1748-9326/aa6cd5.

Cole, N., Baxter, C., 2016. Lessons Learned from the Design and Implementation of the National Household Food Acquisition and Purchase Survey (FoodAPS). Mathematica Policy Research, Washington, D.C.

Costello, C., Xue, X., Howarth, R.W., 2015. Comparison of production-phase environmental impact metrics derived at the farm- and national-scale for United States agricultural commodities. Environ. Res. Lett. 10, 114004. http://dx.doi.org/10.1088/1748-9326/10/11/114004.

de Vries, M., de Boer, I.J.M., 2010. Comparing environmental impacts for livestock products: a review of life cycle assessments. Livestock Sci. 128, 1–11. http://dx.doi.org/10.1016/j.livsci.2009.11.007.

Department of Health and Human Services, 2015. Scientific Report of the 2015 Dietary Guidelines Advisory Committee. (No. Part D. Chapter 1: Food and Nutrient Intakes, and Health: Current Status and Trends). Dietary Guidelines Advisory Committee, Washington, D.C.

Drewnowski, A., Rehm, C.D., Martin, A., Verger, E.O., Voinnesson, M., Imbert, P., 2015. Energy and nutrient density of foods in relation to their carbon footprint. Am. J. Clin. Nutr. ajcn.092486. doi: 10.3945/ajcn.114.092486.

EPA, 2016. Greenhouse Gas Emission Sources [WWW Document]. URL http://www.epa.gov/climatechange/ghgemissions/sources.html (accessed 5.5.14).

EPA, 2014. U.S. Greenhouse Gas Inventory Report [WWW Document]. URL http://www.epa.gov/climatechange/ghgemissions/usinventoryreport.html (accessed 5.4.14).

Eshel, G., Martin, P.A., 2006. Diet, energy, and global warming. Earth Interact. 10, 1–17. http://dx.doi.org/10.1175/EI167.1.

Garnett, T., 2009. Livestock-related greenhouse gas emissions: impacts and options for policy makers. Environ. Sci. Policy, Special Issue: Food Security and Environmental Change Food Security and Environmental Change: Linking Science, Development and Policy for Adaptation 12, 491–503. http://dx.doi.org/10.1016/j.envsci.2009.01.006.

Hallström, E., Gee, Q., Scarborough, P., Cleveland, D.A., 2017. A healthier US diet could reduce greenhouse gas emissions from both the food and health care systems. Climat. Change 1–14. http://dx.doi.org/10.1007/s10584-017-1912-5.

Hamerschlag, K., 2011. Meat Eaters Guide to Climate Change and Health. Environmental Working Group.

Harwatt, H., Sabate, J., Eshel, G., Soret, S., Ripple, W., 2016. Eating away at climate change – substituting beans for beef to help meet US climate targets. FASEB J 30, 894. 3-894.3.

Heller, M.C., Keoleian, G.A., 2015. Greenhouse gas emission estimates of U.S. dietary choices and food loss. J. Indust. Ecol. 19, 391–401. http://dx.doi.org/10.1111/jiec.12174.

Heller, M.C., Keoleian, G.A., Willett, W.C., 2013. Toward a life cycle-based, diet-level framework for food environmental impact and nutritional quality assessment: a critical review. Environ. Sci. Technol. 47, 12632–12647. http://dx.doi.org/10.1021/es4025113.

Heller, M.C., Willits-Smith, A., Meyer, R., Keoleian, G.A., Rose, D., 2018. Greenhouse gas emissions and energy use associated with production of individual self-selected US diets. Environ. Res. Lett. 13, 044004. http://dx.doi.org/10.1088/1748-9326/aab0ac.

Hu, M., Gremel, G.W., Kirlin, J.A., West, B.T., 2017. Nonresponse and underreporting errors increase over the data collection week based on paradata from the national household food acquisition and purchase survey. J. Nutr. 147, 964–975. http://dx.doi.org/10.3945/jn.116.240697.

IPCC, 2014. Summary for policymakers: Impacts, Adaptation, and Vulnerability, Climate Change 2014: Impacts, Adaptation, and Vulnerability. Part A: Global and Sectoral Aspects. Intergovernmental Panel on Climate Change, United Kingdom and New York, NY, USA.

Jones, C., Kammen, D.M., 2011. Quantifying carbon footprint reduction opportunities for U.S. households and communities. Environ. Sci. Technol. 45, 4088–4095. http://dx.doi.org/10.1021/es102221h.

Kim, B., Neff, R., 2009. Measurement and communication of greenhouse gas emissions from U.S. food consumption via carbon calculators. Ecol. Econ. 69, 186–196. http://dx.doi.org/10.1016/j.ecolecon.2009.08.017.

Melina, V., Craig, W., Levin, S., 2016. Position of the academy of nutrition and dietetics: vegetarian diets. J. Acad. Nutr. Diet. 116, 1970–1980. http://dx.doi.org/10.1016/j.jand.2016.09.025.

Scarborough, P., Appleby, P.N., Mizdrak, A., Briggs, A.D.M., Travis, R.C., Bradbury, K.E., Key, T.J., 2014. Dietary greenhouse gas emissions of meat-eaters, fish-eaters, vegetarians and vegans in the UK. Climat. Change 125, 179–192. http://dx.doi.org/10.1007/s10584-014-1169-1.

Soret, S., Mejia, A., Batech, M., Jaceldo-Siegl, K., Harwatt, H., Sabaté, J., 2014. Climate change mitigation and health effects of varied dietary patterns in real-life settings throughout North America. Am. J. Clin. Nutr. 100, 490S–495S. http://dx.doi.org/10.3945/ajcn.113.071589.

Steinfeld, H., Gerber, P., Wassenaar, T.D., Castel, V., de Haan, C., 2006. Livestock's long shadow: environmental issues and options. Food & Agriculture Org.

Tom, M.S., Fischbeck, P.S., Hendrickson, C.T., 2015. Energy use, blue water footprint, and greenhouse gas emissions for current food consumption patterns and dietary recommendations in the US. Environ. Syst. Decis. 1–12. http://dx.doi.org/10.1007/s10669-015-9577-y.

US Department of Commerce, B.E.A., 2017. Bureau of Economic Analysis [WWW Document]. URL http://www.bea.gov/iTable/index_industry_io.cfm (accessed 5.12.14).

U.S. Department of Health and Human Services and U.S. Department of Agriculture, 2015. 2015-2020 Dietary Guidelines for Americans, eighth ed., U.S. Department of Health and Human Services and U.S. Department of Agriculture, Washington, D.C.

USDA ERS, 2018. U.S. Food Expenditure Data [WWW Document]. Food Expenditures. https://www.ers.usda.gov/data-products/food-expenditures.aspx (accessed 4.30.18).

USDA ERS, 2013. USDA Economic Research Service – FoodAPS National Household Food Acquisition and Purchase Survey [WWW Document]. http://www.ers.usda.gov/data-products/foodaps-national-household-food-acquisition-and-purchase-survey.aspx (accessed 3.23.16).

Weber, C.L., Matthews, H.S., 2008. Food-miles and the relative climate impacts of food choices in the United States. Environ. Sci. Technol. 42, 3508–3513. http://dx.doi.org/10.1021/es702969f.

Weisz, H., Duchin, F., 2006. Physical and monetary input–output analysis: what makes the difference? Ecol. Econ. 57, 534–541. http://dx.doi.org/10.1016/j.ecolecon.2005.05.011.

Wynes, S., Nicholas, K.A., 2017. The climate mitigation gap: education and government recommendations miss the most effective individual actions. Environ. Res. Lett. 12, 074024. http://dx.doi.org/10.1088/1748-9326/aa7541.

Yang, Y., Ingwersen, W.W., Hawkins, T.R., Srocka, M., Meyer, D.E., 2017. USEEIO: a new and transparent United States environmentally-extended input-output model. J. Clean. Prod. 158, 308–318. http://dx.doi.org/10.1016/j.jclepro.2017.04.150.