Nutritional and Environmental Impacts of Foods on Human Health

by

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The mind is not a vessel to be filled but a fire to be kindled

- Plutarch -

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DEDICATION

This edition of *Nutritional and Environmental Impacts of Foods on Human Health* is dedicated to my beloved parents and grandparents to honor all the sacrifices they made and for setting the foundations for where and who I am. Σας ευχαριστώ!

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PREFACE

Chapter 2 (A life cycle assessment framework combining nutritional and environmental health impacts of diet: a case study on milk) has been published in 2016 at the *International Journal for Life Cycle Assessment* (nol. 21, issue 5). The full list of authors is: Katerina S. Stylianou, Martin C. Heller, Victor L. Fulgoni III, Alexi S. Ernstoff, Gregory A. Keoleian, and Olivier Jolliet.

A version of Chapter 3 (HENI: A health burden-based nutritional index for food items) is currently under review for publication. The full list of authors is: Katerina S. Stylianou, Victor L. Fulgoni III, and Olivier Jolliet. A condensed version of this chapter will be published as a conference proceeding paper at the LCA Food 2018 In Conjunction with LCA AgriFoodAsia 2018 and ICGSI 2018.

A version of Chapter 4 (Spatially-explicit characterization of the exposure and health burden of fine particulate matter in the U.S.) will be submitted for publication. The full list of authors is: Katerina S. Stylianou, Christopher W. Tessum, Julian D. Marshall, and Olivier Jolliet.

A version of Chapter 5 (Bridging the gap between environmental and nutritional sciences towards more sustainable foods: A case study on pizza) will be submitted for publication. The full list of authors is: Katerina S. Stylianou, Vy K. Nguyen, Victor L. Fulgoni III, and Olivier Jolliet. A condensed version of this chapter will be published as a conference proceeding paper at the LCA Food 2018 In Conjunction with LCA AgriFoodAsia 2018 and ICGSI 2018

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LIST OF ABBREVIATIONS

CF= characterization factor

CI = confidence interval

CONE-LCA = Combined Nutritional and Environmental Life Cycle Assessment

DANI = DALY-based Nutritional Index

DALY = disability adjusted life years

DRF = dietary risk factor

GBD = Global Burden of Disease

GHG = greenhouse gases

GW= global warming

HENI = Health Nutritional Index

iF = intake fraction

NHANES = National Health and Nutrition Examination Survey

LCA = life cycle assessment

PM = particulate matter

PUFA = polyunsaturated fatty acids

RR = risk ratio

SFA = saturated fatty acids

SSB = sugar-sweetened beverage

TFA = trans fatty acids

WWEIA = What We Eat in America

YLD = years of life disabled

YLL = years of life lost

ABSTRACT

Suboptimal diet is a major public health concern, responsible for ~10 million death/year globally associated with nutrition, plus additional deaths associated with environmental emissions from food production. Informing consumer choices is crucial and would require to consistently combine latest epidemiological evidence on the impact of diet and pollution, with life cycle assessment (LCA) of food systems to analyze relevant trade-offs.

This dissertation aims to address four critical challenges for assessing the life cycle impact and benefits of food systems on human health: (1) The failure to capture both environmental impacts and nutritional effects of foods consistently. (2) The lack of nutritional assessment metrics that evaluate the performance of individual food items based on health burden. (3) The overly simplified assessment of impacts of particulate matter ($PM_{2.5}$) on human health, which do not consider spatial variation in exposure, nor evidence for non-linear exposure-response. (4) The need for a consistent approach to evaluate multi-ingredient mixed dishes, a central component in modern diets.

Chapter 2 developed a novel Combined Nutritional and Environmental Life Cycle Assessment (CONE-LCA) framework that evaluates and compares in parallel the environmental and nutritional effects of foods or diets in a common metric, disability adjusted life years (DALYs). A proof-of-concept case study indicated that nutritional health net benefits of adding a serving of milk to the average U.S. diet exceeded environmental impacts and highlighted the need for considering nutrition as a new LCA impact category.

Chapter 3 operationalized the nutritional approach by establishing the Health Nutritional Index (HENI). This health burden-based nutritional index quantifies the health burden of one food serving in minutes of healthy life lost or gained, using epidemiological evidence for a comprehensive set of 16 dietary risks. Application to ~7,000 food items in the U.S. diet revealed substantial variability in HENI scores between and within food categories, thus the importance of informed choices at the level of individual food items.

In Chapter 4, we developed spatially-explicit intake fractions for ground-level $PM_{2.5}$, NH_3, SO_2, and NO_x emissions in the contiguous U.S. for agriculture and other relevant sectors. Using a non-linear exposure-response function and state-specific burden data, we developed the corresponding characterization factors considering a marginal and an average slope. Spatial estimates varied by three orders of magnitude, sector-specific estimates by a factor of four, and the average slope doubled estimates compared to marginal. This work stressed the importance of spatially-explicit and sector-specific estimates in LCA.

Finally, in Chapter 5 we established a new nutritional impact category for LCA, providing both inventory flows and nutritional characterization factors, and a systematic approach to decompose mixed dishes into individual components for which environmental life cycle inventory is available. Using a case study of pizzas, we quantified and compared environmental and nutritional impacts on health and found that nutrition dominates health damages. Nutritional and environmental impacts were correlated with red meat pizzas generating the highest and vegetable pizzas the lowest health damages.

This dissertation provides the foundation for evaluating nutritional and environmental impacts of foods and diets comprehensively and systematically in food sustainability assessments and LCAs. It introduces a new nutritional LCA impact category, pioneers a powerful nutritional health based index that can inform healthier dietary choices and substitutions, and improves $PM_{2.5}$ impact assessment. Findings can inform sustainable decision making for foods and diets within and beyond LCA.

CHAPTER 1
Introduction

1.1. Background

1.1.1. Dietary risks and need for an overarching framework to assess impacts of food

The Global Burden of Disease (GBD) study series report the disease risk and the health burden in deaths and in Disability Adjusted Life Years (DALYs) associated with various risk factors (Forouzanfar et al. 2016; Gakidou et al. 2017). The top five leading risk factors globally that contributed to the GBD in 2016, in decreasing impact measured in deaths, were high blood pressure, dietary risks, tobacco, air pollution, and high fasting plasma glucose (Institute for Health Metrics and Evaluation 2018a). Food items and dietary patterns are related to several of these risk factors both directly (dietary risks) and indirectly either through agricultural production practices that contribute to air pollution or metabolic risk factors such as high blood pressure and high fasting plasma glucose that can be influenced by diet. Interestingly, the large contribution of dietary risks to global deaths (~ 10 million deaths per year) and DALYs (~250 million DALYs per year) is also observed at the national level in many countries, including the U.S. Underconsumption of health beneficial foods and nutrients and overconsumption of health detrimental foods and nutrients was the leading cause of premature death for Americans in 2016, responsible for more than half a million deaths per year that corresponded to ~20% of total deaths. Air pollution, and in particular ambient fine particulate matter (PM2.5), was the leading environmental risk factors both globally and in the U.S. and was responsible for almost 3.5 million deaths globally and close to 100 thousand deaths in the U.S. (Institute for Health Metrics and Evaluation 2018a). While the GBD provides overall population estimates, there is growing interest in comparing nutritional and environmental performances at the level of food items, dietary patterns, and dietary guidelines (Tilman and Clark 2014; Springmann et al. 2016; Behrens et al. 2017; van Dooren et al. 2017; Walker et al. 2018). Very few studies have used nutritional epidemiology to evaluate the health burden associated with diets and compared them with environmental impacts (Tilman and Clark 2014; Springmann et al. 2016).

Food systems present both an ideal and challenging application of life cycle assessment (LCA) due to their complex interlink between nature and technology. LCA is a methodology that enables the evaluation of the environmental impacts associated with a product, process, or service throughout its entire life cycle, from cradle to grave, in reference to a function determined via the functional unit (International Standard Organization 2006). To estimate the environmental health impacts of a product, process, or service system in LCA we follow a two-step approach: collect life cycle inventory (LCI) for the system for the determined functional unit and characterize the damages of the LCI using life cycle impact assessment (LCIA). LCIs quantify the inputs and outputs of a given product system throughout its life cycle. LCIA links LCA to environmental damages through characterization factors calculated as the product of exposure assessment metrics and exposure-response functions (International Standard Organization 2006). Since its infancy, LCA has been used in evaluating agricultural practices and food systems (Nemecek et al. 2016), and significant progress has been made in the past decade to overcome many of the challenges of food LCAs (Roy et al. 2009; Poore and Nemecek 2018).

LCA tends to focus on environmental impacts while disregarding nutritional effects while nutritional epidemiology typically neglects environmental health impacts associated with the risk under investigation. Thus, there is a need to provide a valid and consistent approach and overarching framework for both nutrition and environment, merging LCA and epidemiology for both types of risks.

1.1.2. LCA and food - the need for a nutrition specific impact category

Food and LCA itself is a burgeoning research area that is revealing much about the environmental impacts of dietary patterns (Heller et al. 2013; Hallström et al. 2015). One of the current challenges in the field is to capture the nutritional effects associated with the “use stage” of foods (through consumption) that can induce health benefits and damages. Efforts to date to include a nutritional aspects in LCA have primarily focused on defining the functional unit (Heller et al. 2013). However, the multi-functionality of foods (e.g. human nutrition, source of energy, health, pleasure, culture etc.) generates additional complexity (Nicklas et al. 2014; Nemecek et al. 2016). Different types of functional units have been proposed: a “quality corrected functional unit” that takes into account the nutrient content of the food products (Schau and Fet 2008), a single nutritient functional unit (e.g., protein content or caloric energy) (Reijnders and Soret 2003; González et al. 2011), and nutritional indices that combine multiple positives and negatives nutritional dimensions into a single score (Smedman et al. 2010; Saarinen et al. 2017). However, an implication of using such functional units is that it forces damages in the numerator and positive outcomes (as functions) in the denominator which contradicts with the conceptual LCA framework. In addition, using functional units as a way to capture nutrition in LCA can result in inconsistencies since the choice of functional unit can greatly influence results (Kendall and Brodt 2014; Van Kernebeek et al. 2014). In the LCA framework impacts on human health are rather considered via specific impact categories as reported in the latest LCIA frameworks (Jolliet et al. 2004; Verones et al. 2017). This suggests that there is a need for considering the impact of nutrition by creating a specific impact category characterizing both nutritional impacts and benefits of food items.

To capture the nutritional impacts of food items, different approaches have been proposed: Nutritional indices such as the NRF9.x (Fulgoni et al. 2009) are often employed in order to evaluate the nutritional performance of foods and diets (van Dooren et al. 2017; Walker et al. 2018). Nutritional indices measure the dietary quality of foods or diets in relation to food and nutrient recommendation intake and adherence to dietary guidelines (Arvaniti and Panagiotakos 2008). Using such approaches however can be problematic as they are typically only indirectly associated with disease burden (McCullough and Willett 2006), they carry inherent bias associated with their structure (Drewnowski 2005), and treat components equally that restricts them from capturing the varying effect of components, typically nutrients, on health (Arvaniti and Panagiotakos 2008; Fulgoni et al. 2009). Nutritional epidemiology studies evaluate the health effects of individual nutrients (e.g., the effects of saturated fat, sodium, or dietary fiber), individual foods/food groups (e.g., the impacts of red meat or fruits and vegetables), and diets/dietary patterns (e.g., current diets vs. recommended diets), and can provide data that directly relate nutrients, food items, food groups, and dietary patterns to human health outcomes, typically expressed as disease incidence or mortality (Willett 2013). However, the GBD provides an ideal first attempt to consistently evaluate both environmental and nutritional health impacts in DALYs by utilizing epidemiology-based information. Although, a good starting point, this effort is focused on providing global burden estimates related to overall national diet rather than particular food items or functional units that would be more relevant to food LCA.

1.1.3. Improving the $PM_{2.5}$ human health impact assessment, including agriculture-specific characterization

There are also challenges associated with the environmental assessment of food systems that need to be addressed, in particular for the substantial human health impacts associated with fine particulates of diameter lower than 2.5 μm ($PM_{2.5}$). For $PM_{2.5}$ human health impacts, intake fraction (iF), the inhaled $PM_{2.5}$ per kg precursor emitted (Bennett et al. 2002), is the recommended metric to characterize exposure in LCIA (Jolliet et al. 2018). Precursors include primary $PM_{2.5}$ (aerosols directly emitted in the atmosphere), ammonia (NH_3), sulfur dioxide (SO_2), and nitrogen oxides (NO_x); NH_3, SO_2, and NO_x contribute to secondary $PM_{2.5}$ after gases are being converted to particles through photochemical reactions. Food systems and agricultural practices are the dominant sources of NH_3 atmospheric emissions (Paulot and Jacob 2014; Brunekreef et al. 2015). NH_3 is important in the secondary $PM_{2.5}$ formation mechanism, which is complex and has a non-linear chemistry (Ansari and Pandis 1998; West et al. 1999), as a limiting factor to neutralize SO_2 and NO_x (Squizzato et al. 2013; Paulot and Jacob 2014). Current iF estimates used in LCIA rely on short exposure tracking (Levy et al. 2009; Humbert et al. 2011), archetypes (Humbert et al. 2011), simplified atmospheric chemistry that fails to capture the complex non-linear chemistry (van Zelm et al. 2008; Levy et al. 2009), and low spatial resolution (van Zelm et al. 2008, 2016; Heo et al. 2016). These can lead to poor characterization of exposure (Paolella et al. 2018) and potential double counting of impacts associated with secondary $PM_{2.5}$ (Fantke et al. 2015). There are also limitations associated with the exposure-response function for $PM_{2.5}$. Current LCIA approaches are based on the linear exposure-response function by Krewski et al. (2009) (Gronlund et al. 2015; van Zelm et al. 2016), whereas recent evidence support that the integrated exposure response (IER) function for $PM_{2.5}$ between ambient $PM_{2.5}$ and ischemic heart diseases, stroke, lung cancer, and chronic obstructive pulmonary disease in adults over 25 years old and acute lower respiratory infection in children under 5 years old is non-linear (Burnett et al. 2014; Cohen et al. 2017).

1.1.4. Capturing the environmental and nutritional impacts of mixed dishes

An additional challenge of food sustainability assessment is the evaluation of mixed dishes. Mixed dishes, defined as a mixture of components with varying proportions (multi-ingredient), are an important food group to investigate as they comprise a large fraction of modern diets. For example, in 2010 mixed dishes accounted for 29% of the energy intake in the U.S. diet (Dietary Guidelines Advisory Committee 2015). For LCA in particular, it is challenging to determine of LCIs associated with mixed dishes. Mixed dishes are poorly studied in food LCA since research has mainly focused on food-related environmental impacts associated with single-component food items (e.g., beef, milk, grains, etc.) (Davis and Sonesson 2008). The few studies that have investigated mixed dishes are not harmonized since they use a distinct set of assumptions and recipes. Consequently, results are incomparable and possibly inconsistent.

1.2. Objectives and specific aims

The overarching goal of this dissertation was to improve human health impact assessment in LCA, specifically for food items and diets. In particular, this dissertation sought to establish an improved human health impact assessment for food LCA by: 1) Introducing a LCA framework of holistically assessing health impacts of food items and diets from production to consumption by accounting for potential nutritional health effects (Chapter 2), 2) Developing the parameters that will allow for a nutritional health assessment of food items in LCA and will determine a new nutritional impact category (Chapter 3), 3) Improving $PM_{2.5}$ human health impact assessment by developing spatial characterization factors based on updated intake fractions for the U.S. and a non-linear exposure-response function with agriculture-specific factors, in particular for NH_3 and secondary $PM_{2.5}$ (Chapter 4), and 4) Harmonizing the assessment of mixed dish evaluation in LCA by identifying and applying a decomposition method that will enable a consistent evaluation of environmental and nutritional human health impacts (Chapter 5).

Specific aim 1 (Chapter 2): *Develop and test a life cycle assessment (LCA) framework that evaluates and compares in parallel the environmental and nutritional effects of food items.*

There is a need and necessity for a framework in LCA that enables a comprehensive assessment of both the direct nutritional from the "use stage" and the indirect environmental effects on health from the life cycle of food items and diet on a comparable scale. To address this, we developed a novel LCA framework that allows for a parallel assessment of environmental damages and nutritional effects (positive and negative) on human health from foods and diets in a common metric, disability adjusted life years (DALYs). We demonstrate and test the proposed framework with a proof-of-concept case study that investigates the potential human health effects associated with the addition of one serving of fluid milk to the average American adult diet as well as alternative iso-caloric substitution scenarios. We followed a traditional LCA to quantify environmental health damages from global warming and particulate matter and compared them with nutritional health benefits and damages estimated using epidemiological evidence for the following health outcomes: colorectal cancer, stroke, and prostate cancer.

Specific aim 2 (Chapter 3): *Develop nutritional characterization factors for a new nutritional impact category in LCA that translates the nutritional composition of food items and diets into human health benefits or damages and apply them to ~7,000 food items in the U.S. diet to estimate overall nutritional health impact scores.*

Building on the case study from **specific aim 1** we expand the nutritional health assessment beyond milk to other dietary risk factors. In particular, this aim required to: (1) Identify a comprehensive set of dietary risk with established associations with adverse health effects and establish the Health Nutritional Index (HENI) as a framework that quantifies the nutrition-related health burden associated with a serving of food. (2) Develop dietary risk factors (DRFs) that characterize the cumulative health burden associated with a gram of dietary risk in DALYs, taking into account effect modifiers, disease burden, and disease severity in the U.S. (3) Develop nutritional profiles of the food items in grams/serving in the U.S. diet using the NHANES database (National Center for Health Statistics 2018) that align them with the definition of dietary risks. (4) Implement HENI to food items in the NHANES database and evaluate their performance.

Specific aim 3 (Chapter 4): *Develop spatially-explicit and sector-specific intake fractions and characterization factors for $PM_{2.5}$ from ground level emissions of primary $PM_{2.5}$, NH_3, SO_2, and NOx in the contiguous U.S.*

We developed updated components (*exposure, exposure-response slope, severity factors*) to inform primary and secondary $PM_{2.5}$ characterization factors (CFs) from ground level emissions, focusing on the entire contiguous U.S. and the sectors that contribute the most to each precursor's emissions. More specifically, this aim entailed: (1) Developing spatial intake fraction (*exposure*) estimates for primary $PM_{2.5}$, NH_3, SO_2, and NOx emissions in the contiguous U.S. using InMAP (Intervention Model for Air Pollution) (Tessum et al. 2017), a reduced-complexity air quality model covering the greater North America region with flexible grid resolution and spatial domain that captures the long-range exposure potential of primary and secondary $PM_{2.5}$. (2) Developing location-specific 'marginal' and 'average' $PM_{2.5}$ *exposure-response* slopes as described in Fantke et al. (2018) for each of grid cells in InMAP using cause-of-death- and age-specific inputs from the non-linear IER from Cohen et al. (2017), local $PM_{2.5}$ annual average ambient concentrations for 2016 (WHO 2016), and region-, age-, and cause-of-death-specific annual mortality estimates for 2016 (Institute for Health Metrics and Evaluation 2018b). (3) Calculating new region-, age-, and cause-of-death-specific *severity factors* in DALYs/death based on 2016 GBD (Institute for Health Metrics and Evaluation 2018b). (4) Combining updated components to estimates spatial 'marginal' and 'average' CF for $PM_{2.5}$ from ground level emissions of primary $PM_{2.5}$, NH_3, SO_2, and NOx in the contiguous U.S. (5) Characterizing the spatial extent of intake and burden as the radial distance from the source the reach certain cumulative fraction of intake fraction and characterization factors, respectively. (6) Developing emission-weighted sector-specific intake fractions and CFs for the adjoining 48 U.S. States including Washington, D.C and the U.S. for five main sectors (agriculture, fuel combustion, industrial processes, and mobile) all based on annual emission estimates from the U.S. EPA 2014 National Emissions Inventory (NEI) (U.S. Environmental Protection Agency 2018).

Specific aim 4 (Chapter 5): *Determine a decomposition method to consistently evaluate the environmental impacts of mixed dishes and compared them with nutritional health benefits and damages.*

To address the challenges of mixed dishes in LCA, we used a case study of a popular mixed dish in the U.S. diet, pizza. The specific aims were to: (1) Establish a new nutritional life cycle impact category, including both inventory flows per functional unit and nutritional characterization factors, using an adaptation of HENI (**specific aim 2**). (2) Quantify and compare the nutritional health burden associated with main types of pizzas in the U.S. diet. (3) Develop a systematic approach to decompose mixed dishes into individual components for which environmental life cycle inventory is available. (4) Evaluate the cradle-to-gate environmental impacts from global warming and $PM_{2.5}$ associated with main types of pizzas in the U.S. diet, using agriculture-specific CFs for particulate matter impacts (**specific aim 3**). (5) Compare the nutrition and environmental damages on human health for all pizzas in the U.S diet using the CONE-LCA framework (**specific aim 1**) and test for any correlations.

1.3. Dissertation Outline

This dissertation is structured according to the above Specific Aims. Following the present introductory Chapter 1, Chapters 2, 3, 4 and 5 address each of the four Specific Aims. Chapters 2-5 are formatted as journal articles accompanied by additional information available in Appendices 1, 2, 3, and 4, respectively. Finally, Chapter 6 provides an overall discussion of dissertation results and offers suggestions for future directions of this topic.

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CHAPTER 2

A life cycle assessment framework combining nutritional and environmental health impacts of diet: a case study on milk

Abstract

While there has been considerable effort to understand the environmental impact of a food or diet, nutritional effects are not usually included in food-related life cycle assessment (LCA). We developed a novel Combined Nutritional and Environmental Life Cycle Assessment (CONE-LCA) framework that evaluates and compares in parallel the environmental and nutritional effects of foods or diets. We applied this framework to assess human health impacts, expressed in Disability Adjusted Life Years (DALYs), in a proof-of-concept case study that investigated the environmental and nutritional human health effects associated with the addition of one serving of fluid milk to the present American adult diet. Epidemiology-based nutritional impacts and benefits linked to milk intake, such as colorectal cancer, stroke, and prostate cancer, were compared to selected environmental impacts traditionally considered in LCA (global warming and particulate matter) carried to the human health endpoint. Considering potential human health effects related to global warming, particulate matter and nutrition, within the context of this study, findings suggest that adding one serving milk to the current average diet could result in a health benefit for American adults, assuming that this existing foods associated with substantial health benefits are not substituted, such as fruits and vegetables. The net health benefit is further increased when considering an iso-caloric substitution of less healthy foods (sugar-sweetened beverages). Further studies are needed to test whether this conclusion holds within a more comprehensive assessment of environmental and nutritional health impacts. This case study provides the first quantitative epidemiology-based estimate of the complements and trade-offs between nutrition and environment human health burden expressed in DALYs, pioneering the infancy of a new approach in LCA. We recommend further testing of the CONE-LCA approach for other food items and diets, especially when making recommendations about sustainable diets and food choices.

2.1. Introduction

Agricultural and food product systems present both an ideal and challenging application of life cycle assessment (LCA) methods due to their complex interlink between nature and technology. Significant progress has been made in the past decade in overcoming many of the challenges of food LCAs (Roy, et al., 2009), and interest in their application has increased, as evidenced by the quality and quantity of work and growing attendance at the International Life Cycle Assessment of Foods Conference. LCA applied at the diet level is itself a burgeoning research area that is revealing much about the environmental impacts of dietary patterns (Heller et al., 2013; Hallström et al., 2014). The "use stage" nutritional effects of food – both impacts and benefits– have to date not been satisfactorily included in LCA.

Past efforts to include nutritional aspects in LCA have primarily focused on defining the functional unit (Heller et al., 2013). One review recommends a "quality corrected functional unit" that takes the nutrient content of the food products into account (Schau and Fet, 2008). Such an approach has become common in farm-level LCAs of milk production when considering fat and protein corrected milk (International Dairy Federation, 2010) and has been used to consider the effect of production practices on the protein content of wheat (Charles et al., 2006). Functional units based on a single nutritional aspect (e.g., protein content or caloric energy) are common and can be effective in particular inquiries (Gonzalez et al., 2011; Reijnders and Soret, 2003). Still others have explored the use of nutritional profiling algorithms, which aggregate multiple nutritional dimensions into a single score, as the basis for functional unit (Smedman et al., 2010; Saarinen, 2012; Heller and Keoleian, 2012). Attempting to force impacts and benefits of nutrition into the functional unit can, however, create conceptual dissonance within an LCA framework built on expressing impacts in the numerator and positive outcomes (function) in the functional unit denominator.

Within nutritional sciences, studies typically focus on the health effects related to dietary intake and rarely account for environmental impacts occurring throughout the life cycle of food production. There is a growing appreciation, however, of the need to base dietary guidelines on environmental as well as nutritional science (van Dooren et al., 2014). Nutritional studies evaluate health effects on various levels: individual nutrients (e.g., the effects of saturated fat, sodium, or dietary fiber), individual foods/food groups (e.g., the impacts of red meat or fruits and vegetables), and diets/dietary patterns (e.g., current diets vs. recommended diets). Nutritional epidemiology studies provide data that directly relate food items, nutrients, dietary patterns or dietary quality indices to human health outcomes, typically expressed as disease incidence or mortality (Willet, 2012). Such nutritional epidemiology-based information is captured by the Global Burden of Disease (GBD) studies, a large-scale and detailed scientific effort to quantify global levels and trends in health.

The 2010 GBD reports (Murray, et al., 2013; Lim, et al., 2012) detail the disease risk and impact in deaths and in Disability Adjusted Life Years (DALYs) associated with various risk factors. The top ten leading risk factors globally that contribute to the GBD, in decreasing impact measured in deaths, are dietary risks, high blood pressure, smoking, household air pollution, high body-mass index, high fasting plasma glucose, ambient particulate matter (PM) pollution, physical inactivity, alcohol use, and high total cholesterol (IHME, 2013). Food items and dietary habits are related to several of these risk factors either directly (dietary risks) or indirectly through agricultural production methods (ambient PM pollution). Interestingly, dietary risks are the largest contributor to both deaths and DALYs both globally and specifically to the U.S., and contribute to 14% of DALYs and 26% of deaths in the U.S. (IHME, 2013). Ambient PM pollution ranks 7th in terms of risk factors contributing to deaths globally, and 9th in the U.S., leading to 2.2% of total DALYs and 3.9% of total deaths in the U.S. (IHME, 2013). A full list of global and U.S. burden of disease for the top ten risk factors can be found in Appendix 1, Section A1.1 (Table A1.4).

In this paper, we first present a framework enabling a comprehensive assessment of both the direct nutritional and indirect environmental effects on human health of food items/diet in a comparable scale. We then demonstrate the proposed framework with a fluid milk case study, analyzing the potential effects of dietary substitution scenarios resulting from increased milk consumption. Focusing on human health as the "area of protection" for this case study, we utilize two relevant environmental impact categories on human health, global warming and particulate matter formation. Using the 2010 GBD and other epidemiological data, we directly compare the environmental and nutritional impacts of a specific dietary change on human health. Finally, we make recommendations for methodological and data developments necessary for a more complete comparison between environmental and nutritional health effects of food production and consumption.

2.2. Methods

2.2.1. Combined Nutritional and Environmental LCA framework of diet

Figure 2.1 schematically outlines the proposed Combined Nutritional and Environmental LCA (CONE-LCA) framework, evolving out of conceptual outlines presented in Heller et al., (2013), for harmonizing nutritional and environmental effects over food life cycles. Food items, alone or as a part of a diet, are first associated with environmental emissions occurring over the life cycle of the food item (supply, production and distribution stages), some of which may lead to population-scale health impacts. Likewise, consuming foods, the “use stage” of a food LCA, results in population-scale positive and/or negative nutritional health effects.

In this framework, the environmental assessment follows a traditional LCA approach. Starting from a common comparison basis (functional unit), emissions (e.g. N_2O, CH_4, CO_2, NH_3, $PM_{2.5}$) and important resource usages/extractions (e.g. water, land, mineral and energy) are determined, and then midpoint impacts in the most relevant categories are assessed: e.g., climate change, water consumption and quality (eutrophication), land use and respiratory impacts. These impacts can then be linked to endpoint damages on human health, ecosystem quality, resource use, and ecosystem services (Jolliet, et al., 2003; Jolliet, et al., 2004). Human health damage, which is the focus of this paper, can ultimately be expressed as an impact in DALYs using epidemiological studies.

Nutritional impacts and benefits are assessed in parallel to environmental impacts relating the “use stage” in a food life cycle framework. Published epidemiology data are used to directly relate the food in question to reported health effects expressed in DALYs. Likewise, the quantity of individual nutrients (e.g. protein, calcium, vitamin A, vitamin C, saturated fat, sodium) contained in foods can be calculated based on standard nutrient databases, and nutrients may then be associated using epidemiological data to overall health impacts or benefits.

Having both the environmental and nutritional assessment of food items or diets expressed in DALYs, as proposed by this approach, allows the addition of nutritional assessment into a life cycle impact assessment framework for a parallel comparison of effects. However, it should be emphasized that the validity of results produced by the proposed approach are contingent on the data used, their availability, level of detail, and associated uncertainty.

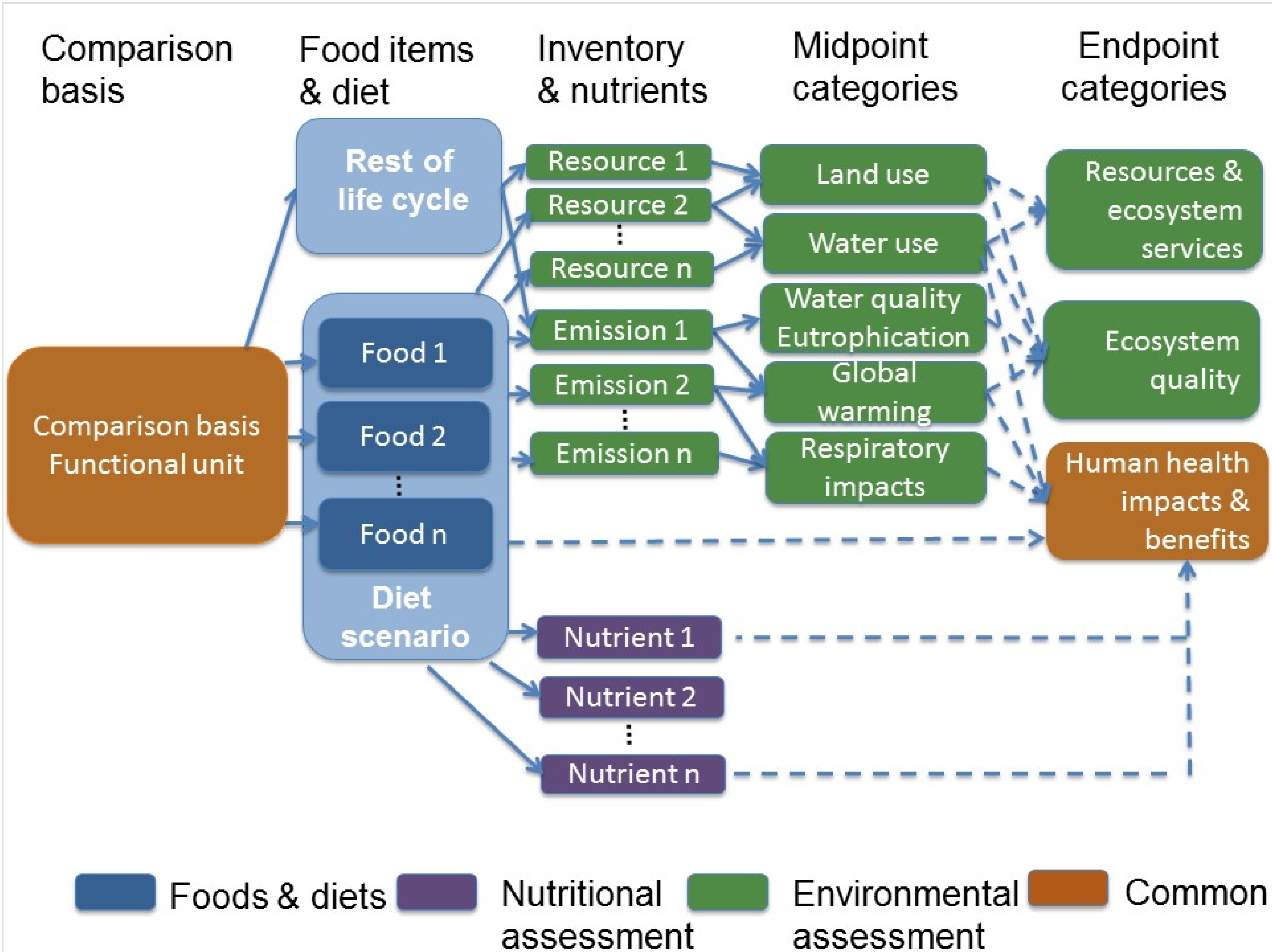

Figure 2.1. Graphical representation of the Combined Nutritional and Environmental Health Impact LCA framework. Dashed lines represent links between midpoint and endpoint categories that are useful to interpret impact scores, but whose quantification is also associated with a high degree of uncertainty.

2.2.2. Case study: Milk consumption in the U.S.

We tested the CONE-LCA framework by investigating a case study of increased fluid milk consumption in the U.S., as recommended by the *Dietary Guidelines for Americans 2010* (USDA and USHHS, 2010). Since dietary recommendations are based on nutritional health benefits, it was interesting to explore in a parallel comparison the potential trade-offs between indirect environmental health impacts and nutritional health benefits associated with increased consumption of dairy.

We focused on *two environmental midpoint impact categories* of high environmental significance to the food production sector, global warming and respiratory inorganics. Global warming (GW) impacts from the dairy industry, indicated as greenhouse gases emissions (GHGE), are largely connected to methane (CH_4) and nitrous oxide (N_2O) emissions from enteric fermentation, manure management, and feed production (Thoma et al., 2013; Asselin-Balencon et al., 2013). Ammonia (NH_3) emissions from manure management contribute to the formation of secondary PM adding to direct PM emissions from tractors and transportation (Henderson et al., 2013), and resulting in respiratory inorganic impacts. Impacts due to PM often dominate human health impacts in LCA, and PM is the most important environmental risk factor in the U.S., according to the GBD (Murray et al., 2013). Henderson et al. (2013) found that other impacts from the milk life cycle on human health, such as toxicological effects and pesticide residues detected in milk, are limited compared to PM impacts. For the nutritional health impact assessment, we focused on both positive and negative health outcomes that have been associated with milk intake in epidemiological studies.

For the purposes of this case study, we use a serving of fluid milk as a functional unit. We also consider two alternative scenarios in which milk substitutes for other food items in the diet. The sections below define the dietary scenarios evaluated, describe the current average U.S. diet baseline used in this case study, and summarize the environmental and nutritional assessment approaches used.

2.2.2.1. Dietary scenarios

The USDA-maintained 2010 Loss Adjusted Food Availability (LAFA) dataset (USDA ERS, 2012) shows that the average U.S. adult diet includes 148 g of fluid milk per day (0.61 servings) as part of the currently consumed 1.53 servings of dairy per person per day (USDA ERS, 2012), which is about half the recommended value in the *Dietary Guidelines for Americans 2010*. For this study, we defined fluid milk as the consumption weighted average (with respect to population-scale consumption frequencies) of whole, 2% reduced fat, 1% reduced fat, and non-fat milk consumed in the U.S. (detailed in Appendix 1, Section A1.2.: Table A1.5).

We investigated the total effect resulting from a one serving (244 g) increase in fluid milk consumption in the U.S. This addition led to a total daily consumption of 392 g, which is below the GBD-reported theoretical-minimum-risk exposure of 450 g/day for colorectal cancer (Lim et al., 2012). Adding one serving of fluid milk to the average adult U.S. diet may or may not substitute a compensatory dietary portion of other food or beverages. To address the possibility of a potential substitution we use a default iso-caloric equivalent basis for this case study as a first proxy and a pragmatic measure of a substitution scenario. We acknowledge that a potential substitution scenario could be based on other rationale. Ideally, data from detailed market-based surveys should be used, when available, to identify and assess more realistic substitution scenarios. Section 2.4 further discusses the selection of substitution scenario and its consequences.

One serving of fluid milk has a nutritional energy content of 119 calories. Hence, we also investigated two replacement scenarios, assuming an iso-caloric substitution of 119 calories. Starting from the current average diet as a baseline, we investigated the following per person, per day scenarios (Figure 2.2):

A. Add a serving of fluid milk, with no change to the rest of the diet. This scenario results in an increased caloric intake over the average diet baseline.

B. Add a serving of fluid milk while subtracting an equal caloric quantity from the overall average diet, excluding fluid milk. The resulting diet would be iso-caloric with the baseline average diet.

C. Add a serving of fluid milk while subtracting an iso-caloric quantity of sugar-sweetened beverages (SSB). The resulting diet would be iso-caloric with the baseline average diet.

Figure 2.2. Graphical representation of dietary replacement scenarios. The width of food groups in the average U.S. diet corresponds to their caloric contribution to the total diet.

2.2.2.2. Defining the current U.S. diet

To understand how a shift in dairy consumption may affect the overall nutritional intake, we first characterized the current U.S. diet to establish a baseline for the environmental impacts of the average U.S. diet. To define the average U.S. food consumption (average U.S. diet) we used the 2010 LAFA data series, which tracks the availability of food commodities in the U.S. marketplace (USDA ERS, 2012). In the LAFA series, the available supplies for over two hundred commodities are adjusted by percent loss assumptions at primary, retail, and consumer levels to arrive at a proxy for per capita food consumption in the U.S. The data are presented at the food commodity level (i.e., raw farm products like wheat and corn rather than consumables like bread or tortilla chips), which is far more manageable from an environmental impact perspective, since most LCA studies of food are performed at this level. LAFA data also explicitly account for supply chain losses, allowing differentiation between foods produced, which contribute to environmental impact, and foods consumed, which are responsible for nutritional health effects.

2.2.2.3. Environmental health assessment

Greenhouse gases emissions

GHGE associated with the average U.S. diet were estimated via a meta-review of food LCA studies, reported by Heller & Keoleian (2014). Several limitations were identified in this approach: many underlying studies were not specific to U.S. production scenarios; significant variability exists between studies of the same food item; and several variables (including transportation) were not treated in a consistent manner across studies. Still, this approach captured the foods in the LAFA dataset, accounting for both consumption and losses, and utilizes the most thorough collection of data currently available. For SSB, the GHGE estimate was based on an emission factor of 0.37 kg CO_2-eq/kg "soda" accounting for packaging and transportation to retail outlet (Vieux et al., 2012) and the corresponding energy content of 410 calories/ kg "Carbonated beverage" (USDA, 2011). The fluid milk GHGE emissions were obtained from a detailed LCA study specifically on U.S. milk (Thoma, et al., 2013). GHGE estimates were based on the IPCC Global Warming Potential for 100 years (IPCC, 2007). Though estimates of human health impact of GW are much more uncertain than the midpoint indicator based on radiative forcing, an initial estimate of human health impact on a 100 years horizon is 0.82 μDALY/ kg CO_2-eq (Bulle et al., 2015), which is useful for comparing on the same scale the order of magnitude of GW impacts with other environmentally induced effects on human health. The uncertainty associated with this impact factor is estimated at a GSD^2 of 4.8 with the uncertainty analysis description available in Appendix 1 (Section A1.4).

Particulate matter

Primary and secondary fine particulate matter, particles of less than 2.5 μm diameter ($PM_{2.5}$), are among the environmental contributors to human health impact of food items and agricultural systems. In a comprehensive LCA of U.S. fluid milk production, $PM_{2.5}$ was found to be the primary contributor to human health impacts, exceeding other environmental contributors considered by at least two orders of magnitude (Henderson et al., 2013).

$PM_{2.5}$ emissions and precursors (NO_x, SO_2, and NH_3) are not routinely reported in food LCA studies, hindering direct estimates of emissions associated with the average U.S. diet and SSB. To get around this limitation, we correlated PM-related emissions (primary $PM_{2.5}$, NO_x, SO_2, and NH_3) to the GW indicator measured in kg of CO_2-eq using 47 food-related Ecoinvent processes (Frischknecht, et al., 2005). Results of the correlation analysis are summarized in Table 2.1

(detailed methodology description available in Appendix 1, Section A1.3). The correlations to CO_2-eq were found to be high for NO_x (R^2=0.96), primary $PM_{2.5}$ (R^2=0.92), and SO_2 (R^2=0.65), and were thus used to estimate the corresponding emissions associated with the average diet and SSB (Table 2.1). For NH_3 we used other sources to estimate emissions since the correlation with CO_2-eq was weak (R^2=-0.02). The NH_3 emission estimate for the average diet was estimated based on food-specific emission factors by Meier and Christen (2013), while the SSB-related emissions were estimated as a proxy from an available emission factors for "sugar" from the same study. All PM-related emissions for fluid milk were based on emission factors from the Comprehensive LCA of Fluid Milk (Henderson et al., 2013). The emission estimates for each 119-calorie equivalent portion intake are available in Appendix 1 (Section A1.3: Table A1.7).

Table 2.1. Summary of results from correlation of PM related emissions to GHGE for all food-related processes in the ecoinvent database, and characterization factors for PM species.

	$PM_{2.5}$	**SO_2**	**NOx**	**NH_3**
Emission correlation analysis model: $y = b \times x$ [a]				
CO_2-eq **correlation factor**				
(kg/kg$_{CO2\text{-}eq}$)	2.4E-4	8.3E-4	2.7E-3	3.5E-3[b]
GSD^2	1.5	2.9	1.5	6.8
R^2	0.92	0.65	0.96	-0.02
Human Health Impacts per kg emitted				
Characterization factor				
(kgPM2.5 eq/kg emitted)	1.2E-3	5.2E-2	1.1E-2	1.1E-1
(DALYs/kg emitted)	3.0E-4	6.2E-5	1.3E-5	1.3E-4

[a] y =precursor, x = CO2-eq, b = CO_2-eq correlation factor
[b] Not used in this analysis

Overall $PM_{2.5}$ emissions in the U.S. are responsible for 103,000 deaths per year and 1,820,410 DALYs, mostly via cardio-pulmonary diseases (Murray et al., 2013). To link $PM_{2.5}$ emissions to human health impact, we used the framework designed by UNEP/SETAC as described by Fantke et al. (2014). A set of default human intake fractions (iF) associated with PM-related emissions (Humbert et al., 2011) was complemented with corresponding effect factors to yield characterization factors (CFs), i.e. the human health impact per kilogram of PM-related emission, accounting for cardiopulmonary and lung cancer impacts from both primary and secondary $PM_{2.5}$ (Gronlund et al., 2014). Using such epidemiological data to link midpoint ($PM_{2.5}$ formation) to endpoint impact categories (human health) supports comparability between environmental and nutritional findings in our study. The CF used to calculate health impacts for primary $PM_{2.5}$ is 3.0×10^{-4} DALYs/ kg $PM_{2.5}$ for emissions in rural areas; likewise, for secondary $PM_{2.5}$ the CF estimates for SO_2, NO_x and NH_3 are 6.2×10^{-5} DALYs/ kg SO_2, 1.3×10^{-5} DALYs/ kg NO_x, and 1.3×10^{-4} DALYs/ kg NH_3, respectively (Table 2.1). Uncertainty factors for the CFs as well as all other estimates used for the PM health impact calculation are available in Appendix 1 (Section A1.4: Table A1.10).

2.2.2.4. Nutritional health assessment

Fluid milk

There are a number of positive and negative health outcomes linked with milk consumption. One benefit of milk consumption on human health is related to a reduced risk of colorectal cancer as considered by the GBD. Another effect that we considered is stroke. Limited evidence also suggests that milk intake is associated with an increased risk of prostate cancer in males. Increased milk consumption has also been associated with a change in body mass index (BMI). However, evidence has been inconclusive with two recent meta-analyses of epidemiological studies and randomized clinical trials indicating that increased dairy consumption does not have an effect on weight (Abargouei et al., 2012) or has a modest effect on weight loss (Dougkas et al., 2011). Hence, we have decided to not include BMI change as a health outcome in our nutritional assessment. A further discussion of milk consumption-related outcomes is provided in Section 2.4.

Colorectal cancer: Milk intake has been found to reduce the risk of colorectal cancer as concluded by the World Cancer Research Fund/American Institute for Cancer Research (WCR/AICR, 2007). The hypothesized mechanism for this inverse association is related to the high calcium content of milk through two possible pathways. The first is the reduced cell proliferation in the colonic epithelium when calcium is bound to pro-inflammatory secondary bile and ionized fatty acids. The second is the enhanced cell differentiation between normal and apoptotic cells under the influence of calcium in a number of intracellular influences (Aune, et al., 2012). This inverse association between milk intake and colorectal cancer is supported by multiple meta-analyses that report a statistically significant association in a consistent manner and with almost equal risk ratio (RR) estimates (Murray et al., 2013; Aune et al., 2012). To assess the corresponding nutritional benefit, measured in avoided DALYs related to colorectal cancer, attributable to an increase of current fluid milk consumption by one serving, we used a RR of 1.11 (95% CI: 1.03-1.20) per 226.8 g/day of milk intake decrease as reported in the 2010 GBD (Murray et al., 2013), a theoretical-minimum-risk exposure of 450 g/day (Lim et al., 2012) above which it is assumed that there is no additional health benefit, and a U.S. colorectal cancer burden estimate of 1,146,830 DALYs for both sexes in 2010 (IHME, 2013)

All stroke outcomes: Evidence from a number of epidemiological studies suggests a protective effect of milk intake to all stroke outcomes (Elwood et al., 2004; Larsson etal., 2012; Ness et al., 2001). The hypothesized mechanisms of this association are linked to the influence of milk intake on hypotension (Larsson et al., 2012) and blood cholesterol levels (Elwood et al., 2004). A more recent meta-analysis of total milk intake and any stroke outcome generated a statistically significant summary association of 0.85 RR (95% CI: 0.77-0.94) comparing high (2-4 servings) versus low (0-0.5 servings) milk intake (Alexander et al., 2015), approximately corresponding to an intake difference of 541 g of milk (95% CI: 400-732). We used this RR to estimate avoided DALYs related to stroke when current fluid milk consumption is increased by one serving, assuming there is no additional benefit above an intake of 597 g, and a 2010 U.S. stroke burden of disease estimate of 1,569,720 DALYs for both sexes (IHME, 2013).

Prostate cancer: Limited evidence suggests that there could be an increased risk of prostate cancer in males associated with milk consumption, with the most cited hypothesized mechanism being that calcium may increase risk by disrupting of the circulation of vitamin D in the human body (WCR/AICR, 2007; Aune et al., 2015). Although conclusions are less established and are confounded by conflicting evidence for this health outcome, a recent meta-analysis reported a summary RR for a 200-g/day increase of milk intake of 1.03 (95% CI: 1.00, 1.06) with some indication of a nonlinear association; risk increased rapidly from 0 to 100-200 g milk/day with no further risk increase above this level (Aune et al., 2015). Hence, given a current milk intake of 148 g/day, adding one serving of fluid milk to the average U.S. diet may not result in an increase in the burden of prostate cancer according to these findings. However, we considered this health endpoint in our nutritional health assessment using the RR by Aune et al. (2015) and a 2010 U.S. prostate cancer burden of disease of 592,400 DALYs (IHME, 2013), allowing for an example of a possible negative nutritional effect of a food/diet.

Average diet

The average diet, as defined in our study, consists of numerous food items that might have positive or negative effects on human health such as fruits and vegetables and SSB, respectively. For the purposes of this case study, we assume that average diet has no effect on health and our results and conclusions are contingent on this assumption.

Sugar-sweetened beverages

One important dietary risk factor for the U.S. is "diet high in sugar-sweetened beverages (SSB)". The U.S. burden of disease for this risk factor includes health outcomes such as diabetes (75%), cardiovascular and circulatory diseases (20%), cancer and musculoskeletal disorders (3% each), as reported in the 2010 GBD (IHME, 2013). According to Lim et al. (2012), the theoretical-minimum-risk exposure for SSB is 0 g/day. Therefore, the total burden of disease related to SSB of 770,584 DALYs reported in the 2010 GBD (IHME, 2013) can be considered to be the direct outcome of the current U.S. SSB consumption, estimated at 236 calories/person/day (Han & Powell, 2013). Building on these findings, we estimated an overall SSB-related disease effect factor of 0.03 µDALYs/SSB-calorie (95% CI: 0.02-0.04).

2.3. Results

2.3.1. Environmental health assessment

2.3.1.1. Greenhouse gases

The GHGE associated with the current average diet of an American consumer (assuming an intake of 2534 calories/day according to LAFA data) was 5.0 kg CO_2-eq/person/day (95% CI: 2.5-9.2). To demonstrate the impact associated with our three diet modification scenarios, the bars in figure 2.3 present the GW midpoint impacts associated with a 119-calorie equivalent portion of three distinct components: fluid milk, average diet, and SSB.

Fluid milk produced the highest GW midpoint impact per calorie; a serving of fluid milk (scenario A) was associated with 0.47 kg CO_2-eq. The corresponding human health endpoint impact was estimated at 0.38 µDALY (GSD^2=4.9). In comparison the GW impacts of 119 calories of average diet amount to 0.24 kg CO_2-eq which was equivalent to 0.19 avoided µDALY (GSD^2=5.5), close to half the impact of fluid milk. Therefore the net GW impact associated with scenario B could be calculated as the difference between the impact of one serving milk and the impact of the iso-caloric substitution of average diet, i.e. 0.47-0.23=0.24 kg CO_2-eq (0.19 µDALY). Finally, 119 calories of SSB were linked to 0.19 kg CO_2-eq, equal to 0.15 avoided µDALY (GSD^2=6.5). As a result, the net difference in GW impact between milk and SSB for scenario C was 0.29 kg CO_2-eq (0.23 µDALY).

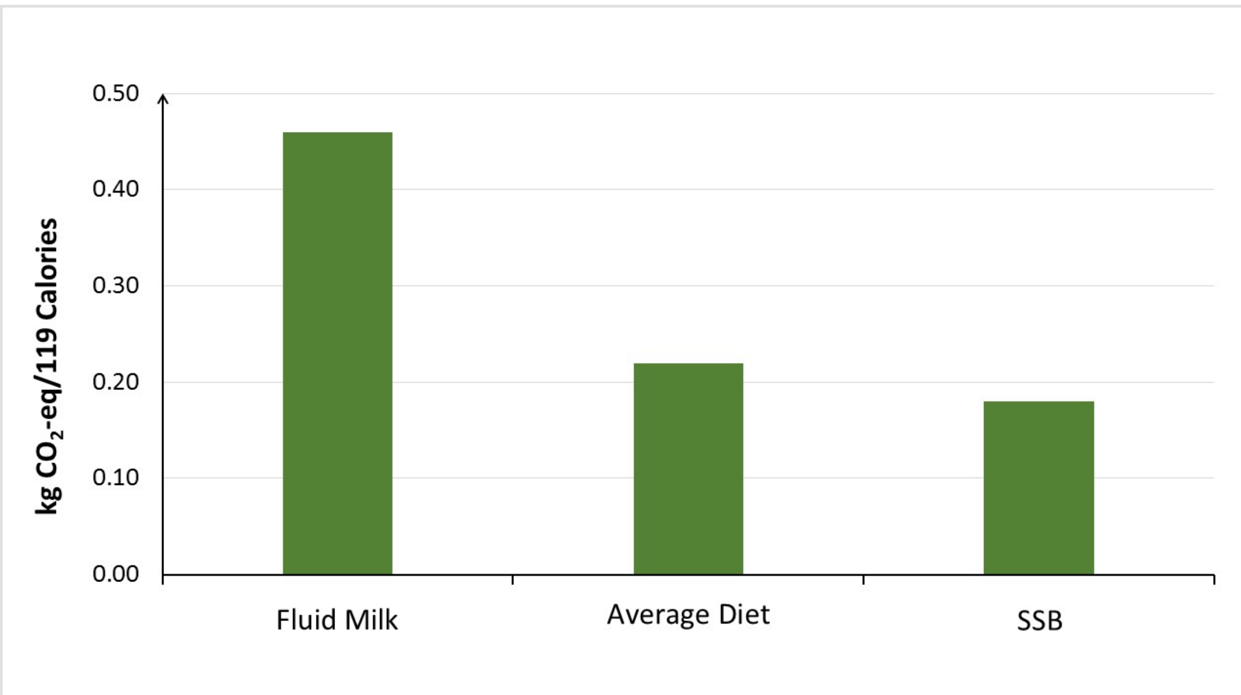

Figure 2.3. Global warming impacts measured in kg CO_2-eq associated with a 119-calorie equivalent portion of three distinct intakes: 1) fluid milk, 2) average diet, 3) sugar-sweetened beverages (SSB).

2.3.1.2. Particulate matter

The total respiratory inorganic impacts from PM-related emissions linked to the baseline U.S. diet were 2.2 g $PM_{2.5}$-eq/person/day (95% CI: 1.1-3.9). Figure 2.4 illustrates the PM-related emissions in grams (g) corresponding to 119 calorie of fluid milk, average diet, and SSB. The emissions for scenario B and C can be estimated by subtracting the emissions associated with each corresponding substitution from those of fluid milk.

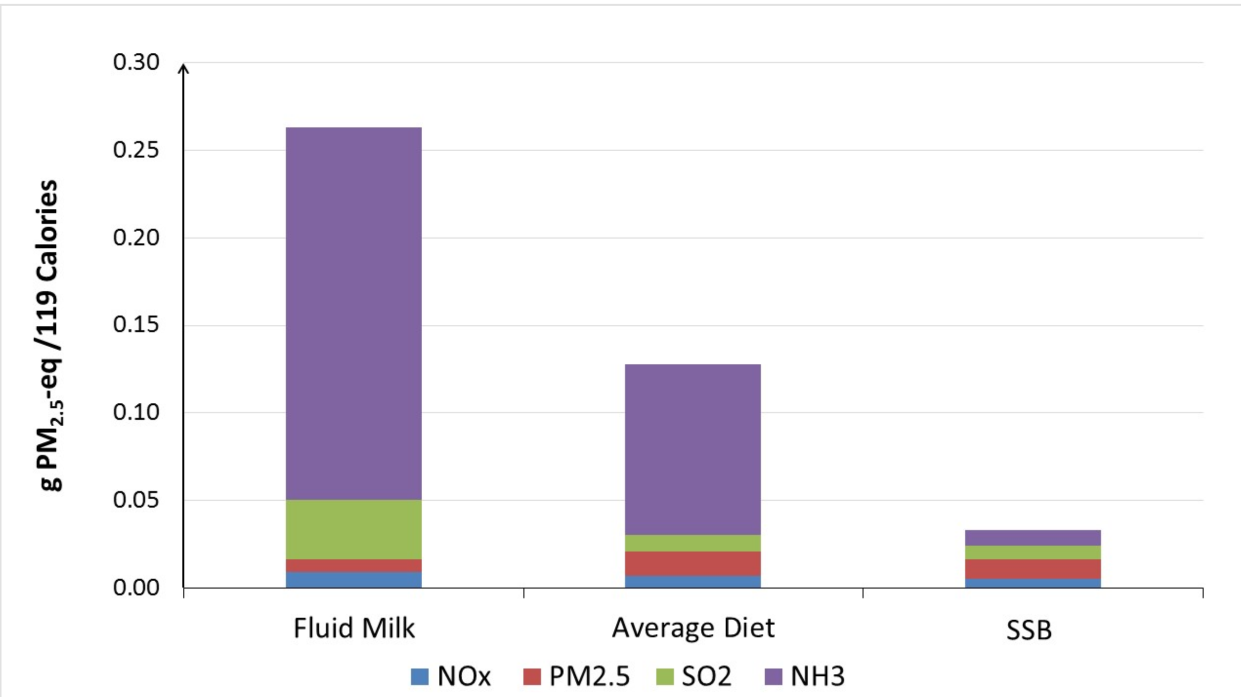

Figure 2.4. Particulate matter related emissions measured in grams (g) $PM_{2.5}$-eq associated with a 119-calorie equivalent portion of three distinct intakes: 1) fluid milk, 2) average diet, 3) sugar-sweetened beverages (SSB).

One serving of fluid milk (scenario A) was linked to total PM-related emissions of 0.26 g $PM_{2.5}$-eq, corresponding to a human health impact of 0.32 μDALY (95% CI: 0.04-0.83). This impact was predominately caused by NH_3 emissions from barn and manure management (80%) and to a lesser extent by SO_2 (13%). The iso-caloric equivalent of the average diet resulted in emissions about half of those of fluid milk. 70% of the PM-related impact for the average diet was due to NH_3, 14% was due to primary $PM_{2.5}$, and 10% was due to SO_2. The corresponding human health impact was 0.15 avoided µDALY (95% CI: 0.02-0.39). This resulted in a net PM emissions estimate of 0.13 g $PM_{2.5}$-eq, equal to 0.15 µDALY for scenario B. For the 119-calorie SSB equivalent, we estimated PM-related emissions of 0.03 g $PM_{2.5}$-eq, one third of which was attributable to primary $PM_{2.5}$ that was analogous to a human health damage of 0.04 avoided µDALY (95% CI: 0.01-0.10). As a result, the net PM-related emissions estimate for scenario C was 0.23 g $PM_{2.5}$-eq, corresponding to a health impact of 0.28 µDALY, slightly lower than scenario A.

2.3.2. Nutritional health assessment

We estimated a linear dose-response relationship between milk intake in g/person/day and the impact of colorectal cancer and stroke in DALYs/person/day (Figure 2.5A and 2.5B). For prostate cancer, the dose-response for the male population is obtained from in Aune et al. (2015).

We used these dose-response functions to estimate the expected nutritional human health burden change for each outcome as a result of a shift in fluid milk intake of one additional serving to current consumption. Not taking into account any detrimental impacts from increasing caloric intake, for colorectal cancer we found that the addition of one serving of fluid milk results in an impact of 1.10 avoided µDALY (95% CI: 0.78-1.56) while for all stroke outcomes the impact was equal to 0.95 avoided µDALY (95% CI: 0.67-1.35). In parallel, we estimated an increase in prostate cancer burden for the male population equal to 0.32 µDALY (95% CI: 0.20-0.51). To extrapolate the prostate cancer impact to the overall population, we accounted for the fraction of males in the U.S.; this resulted in an impact of 0.16 µDALY (95% CI: 0.10-0.26). Overall, we estimated that there is a net nutritional benefit for an average adult American consumer of 1.88 avoided µDALY (95% CI: 0.03-1.02) in response to the addition of one serving of fluid milk to the current diet.

The nutritional benefit from dietary changes could be further increased when food items with negative health effects such as SSB are replaced. In particular, a reduction of 119-calorie equivalent in the SSB daily intake was associated with 3.48 avoided µDALY (95% CI: 2.23-5.43). This finding demonstrates the importance of considering the added nutritional effects (positive and/or negative) of substitution scenarios when dietary changes are evaluated.

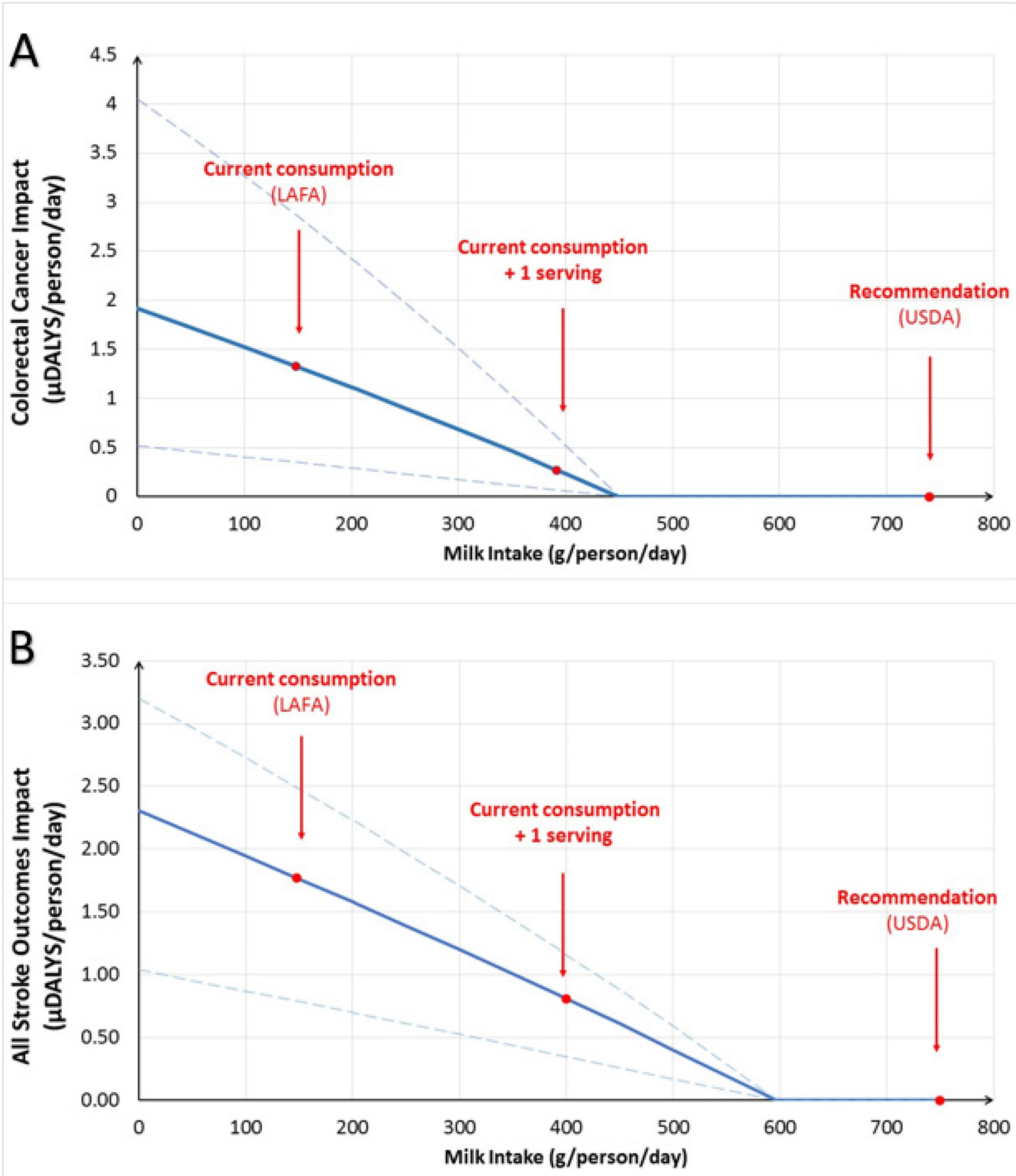

Figure 2.5. Dose-impact function for milk intake and **A)** colorectal cancer impact, **B)** stroke, with 95% confidence intervals shown as dashed lines.

2.3.3. Overall comparison

Figure 2.6 represents the overall comparison of environmental and nutritional effects for the three scenarios, all expressed at the human health endpoint level in avoided μDALYs/person/day (result summary available in Appendix 1, Section A1.5: Tables A1.12-A1.13). Based on the epidemiological evidence considered, we estimated that adding one serving of fluid milk to the present adult U.S. diet leads to an overall health improvement associated with avoided DALYs as a result of nutritional benefits. Considering no health effect associated with the average diet substitution in scenario B, all scenarios indicated an overall health benefit (positive avoided DALYs exceeded the overall health impacts measured in negative avoided DALYs). To estimate the robustness of this finding, we employed the approach by Hong et al. (2010) for each scenario to estimate the likelihood that overall benefits are greater than overall impacts, accounting for uncertainty propagation. We estimated that there was at least a 98.1% probability that overall benefits of one additional serving of fluid milk exceeded the corresponding impact in scenario A. This probability increased to 99.2% for scenario B and 100% for scenario C. When considering only outcomes reported in the 2010 GBD for the nutritional assessment, colorectal cancer for milk intake and all diseases related to SSB intake, we observed a greater likelihood variability between scenarios using this approach. . In fact, the increased consumption of fluid milk remained beneficial under all scenarios with a probability of 80.8% for scenario A, 91.4% for scenario B, and 100% for scenario C. As a sensitivity analysis, we also used this approach considering only the male U.S. population, assuming that all impact categories besides prostate cancer have an effect on males and females. This analysis resulted in a slightly reduced probability of 98.9% and 99.7% for scenario A and B, respectively, while the probability remained 100% for scenario C.

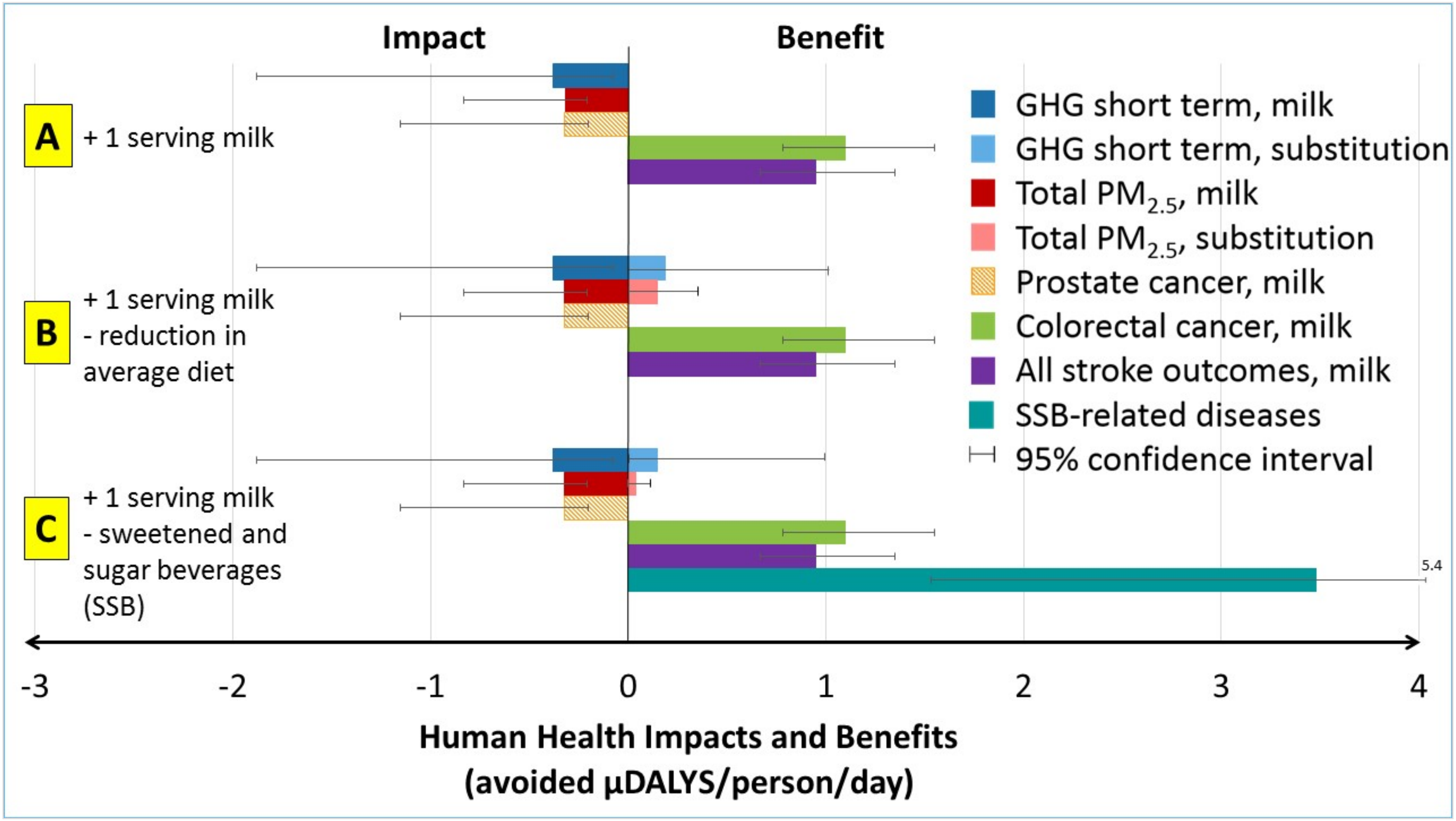

Figure 2.6. Comparison of daily environmental impacts (GHGE and PM-related emissions) with nutritional effects (milk-related disease: colorectal cancer, stroke, prostate cancer for males only and SSB-related diseases) in avoided µDALY/person/day, for three dietary changes scenarios over the average diet: 1) Add one serving of fluid milk (scenario A), 2) Add one serving of fluid milk with an iso-caloric substitution from the overall average diet (scenario B), and 3) Add a serving of fluid milk with an iso-caloric substitution from sugar-sweetened beverages (SSB, scenario C). A positive value indicates a benefit (avoided burden) while a negative value indicates an impact (induced burden). Error bars indicate the 95% confidence intervals representing a preliminary characterization of uncertainty. It should be noted that for Scenario B we assumed that substitution from the average diet has no health effects, with all observed health effects solely associated with the addition of one serving of milk.

2.4. Discussion

In this paper, we describe the CONE-LCA framework that allows for a parallel epidemiology-based assessment in LCA of environmental and nutritional effects of food items. We demonstrate this approach using a proof-of-concept case study investigating the environmental and nutritional effects associated with an increase in U.S. milk consumption. Our analysis was only focused on human health as the “area of protection,” using DALYs as a common endpoint metric, since nutritional effects only contribute to this area via the “use stage” of a food LCA. We limited our analysis to only two relevant environmental impact categories contributing to human health, namely PM and GW impacts. However, it should be emphasized that the CONE-LCA framework can be extended to other human health related environmental impact categories so that to provide a more balanced and comprehensive assessment.

Specific to this case study, nutritional human health benefits associated with the addition of one serving of fluid milk exceeded the corresponding overall impacts (environmental and nutritional) under three dietary scenarios. It should be emphasized that our findings are initial estimates and dependent on the present quality and high uncertainty level of the available data. Hence, our findings should be interpreted with caution, taking into account the scope, assumption, and limitations of this study. This is reflected in the high level of uncertainty for the different assessment categories (Appendix 1, Section A1.4: Tables A1.9-A1.11). A detailed Monte Carlo analysis of uncertainties and trade-offs would be useful in further refining these findings, as well as obtaining more accurate estimates of the uncertainty ranges for the considered impacts and benefits.

We found that one serving fluid milk has a higher impact in both environmental categories under consideration, GW on a 100 year time horizon and respiratory inorganics formation, than the iso-caloric equivalent from the average diet and SSB. This resulted in lower overall environmental impacts at the human health endpoint in DALYs associated with increased fluid milk consumption when substitutions are considered (scenario B and C), compared a no substitution case (scenario A).

The characterization factors for human health impacts due to GW are very uncertain. Hence, the corresponding human health impact estimates should only be considered as order of magnitude approximations. In future work, it would be informative to also assess the “long term” GW human health impacts beyond the 100-year time horizon.

Estimates of respiratory inorganics have wide confidence intervals, mostly due to the uncertainty on the CFs originating from variability in iF estimates. However, it should be mentioned that a fair comparison of uncertainty is often difficult since model uncertainty is hard to characterize. Additionally, there is a potential for double counting the impact on human health due to the way secondary $PM_{2.5}$ is currently handled in LCA. NO_x, SO_2, and NH_3 impacts are estimated using individual characterization factors that do not consider the interactions between these PM precursors. A better characterization of secondary $PM_{2.5}$ in LCA is therefore needed, especially for food items with high NH_3 emissions. This may be achieved through a spatially differentiated analysis of the respective effects of NO_x, SO_2 and NH_3 on the formation of secondary $PM_{2.5}$ which depend on the each precursors’ background concentrations and the location of emission, rural or urban, for which limiting factors for PM formation may differ. Finally, impact characterization depends on the shape of the exposure-response function used, which is assumed to be linear in our study. Recent evidence supports that the exposure-response is non-linear and dependent on the background $PM_{2.5}$ concentration at the location of exposure (Burnett et al. 2014a; Cohen et al. 2017) which should also be accounted for in future $PM_{2.5}$ impact characterization efforts.

Our nutritional analysis focused on health outcomes for which epidemiological evidence supports an association with milk and SSB intake. For the nutritional assessment of milk, our analysis was limited to only two beneficial (colorectal cancer and stroke) and one detrimental (prostate cancer) health outcomes. It should be noted that evidence supporting an association between milk intake and increased prostate cancer risk in males is controversial. In the study by Aune et al. (2015), whole milk appears to have a protective effect on prostate cancer whereas in the same study any milk and low-fat milk increase risk. The same study indicates a threshold effect where prostate cancer risk is flattened for intakes over 200 g/day of milk. Taking this into account, the prostate cancer burden for the male population corresponding to the addition of one serving of fluid milk over the present consumption of 146g would be increased by only 0.08 µDALY (95% CI: 0.05-0.13). However, for this case study we included the worst case scenario to avoid any overestimation of the net nutritional benefit of milk. Regarding the framework proposed in this paper, it should be emphasized that the nutritional analysis of this case study demonstrates that the CONE-LCA can evaluate foods that have both positive and negative effects on health.

In a further investigation of the nutritional health effects of milk, other health outcomes associated with milk and/or dairy product consumption should also be considered. For example, toxicological impacts due to pesticide residues detected in milk could be accounted for. However, based on data collected in 2005 from the USDA Pesticide Data Program, the estimated impact from pesticides in one serving of milk is 0.00015 µDALY (Henderson et al., 2013), dominated by the impact from dieldrin. This appears to be a negligible contribution compared to other “use stage” consumption impacts. Change in BMI is another health outcome to be considered with increased milk consumption without any compensatory decrease in caloric intake (scenario A) or increase in physical activity. Although the relationship between dairy consumption and weight loss/gain has been extensively studied, findings are inconclusive. Results from two recent meta-analyses show that increased dairy consumption does not have an effect on weight (Abargouei et al., 2012) or has a modest effect on weight loss (Dougkas et al., 2011) when controling for energy intake. Other health outcomes that could be considered are cardiovascular diseases, type 2 diabetes, hypertension, osteoporosis, and breast cancer. It would therefore be of interest to further investigate the environmental and nutritional health impacts and benefits from changes in total dairy consumption versus milk alone.

When assessing dietary changes, it is important to consider potential substitutions, especially when assessing nutritional effects, since substitutions may have positive or negative health effects. In our case study, we investigated increased milk consumption, but also considered scenarios that assumed possible iso-caloric substitutions from the average diet and SSB. Beyond the exact choices of the substitution scenario (as many could be considered), our results emphasize the importance of substitution scenarios choice when assessing dietary changes. This is apparent in scenario C where the nutritional health benefit associated with SSB reduced consumption dominated the overall health impact (Figure 2.6). It should be noted that although potentially significant, a nutritional assessment of the substituted average diet has not been performed. In this case study, average diet is defined using the 2010 LAFA dataset to primarily determine its environmental impacts of global warming and particulate matter. The composition consisted of various items that are also linked to various health outcomes with positive and negative effects. Although a single impact score of the average diet substitution could be theoretically possible by combining the effect of each single food items (consumption in average diet compared with recommended or reference values on epidemiological studies), this was beyond the scope of this study since it could potentially be problematic due to double counting resulted from the assumption of independent effect between food items and due to the limited data available. Instead, the average diet substitution was considered to have neither nutritional benefits nor impacts on human health. In a worst case scenario analysis where milk would substitute foods that are beneficial for human health, such as fresh fruits and vegetables, the overall assessment may lead to a negative health impact. Finally, we also acknowledge that the definition and iso-caloric parameterization of the substitution scenarios was pragmatic in this proof-of-concept exercise. The scenarios evaluated here are not exhaustive, and alternative approaches for selecting scenarios may be used. Ideally, detailed market-based data that capture consumer behavioral patterns should be used to determine potential substitutions resulting from dietary changes.

Finally, in this study, we have not considered the possible variations in health impacts of increased milk consumption by sex or age. The health effects of milk likely differ between men and women either by the effect magnitude or by the outcome, as evident by the nutritional assessment of prostate cancer. It is also possible that health effects might be different between age groups (younger adults versus the elderly). In this paper, we considered the general order of magnitude of potential impacts at the population-scale level for an average adult American consumer. Therefore, a possible improvement of our analysis would be the segmentation by sex and age groups to allow for more refined environmental and nutritional human health impact estimates associated with increased milk consumption.

2.5. Conclusion and recommendations

The CONE-LCA framework proposed in this paper provides the groundwork for an improved, more balanced LCA methodology that, in addition to the production-related environmental impacts of food items, also considers for the "use stage" nutritional effects resulting from consumption. The originality of this framework is that it innovatively takes dietary epidemiological evidence expressed in DALYs and compares them consistently with life cycle impact assessment human health endpoint DALYs, related to food items. Assessing environmental and nutritional human health effects of food items/diet at the DALYs level aligns well with the traditional LCA approach as well as methods used for assessing burden of disease. The need and importance of such a framework was demonstrated with a proof-of-concept case study in which we compared the environmental and nutritional effects on human health associated with the daily addition of one serving of fluid milk to the current U.S diet. Therefore, the approach proposed in this paper allows for a quantitative estimate of human health impacts by evaluating, via a common metric, the complements and trade-offs between nutritional and environmental effects of foods/diets.

However, there is a need to maintain full transparency in communicating results generated with this framework due to possible limitations emerging from the quality of data used and more specifically the uncertainties associated with the characterization of environmental and nutritional effects of food items. For the environmental assessment, it is important to differentiate the influence of each midpoint category on the endpoint and the related uncertainty. At the same time, epidemiological evidence for both environmental and nutritional effects should be used with caution as they are suggestive of correlations and do not imply causation. More specifically, it is possible that the magnitude of the effect associated to an individual risk factor is partially due to confounders, which at that point of the study were either unknown or not controlled for. For example, when estimating the effect of PM on human health it is possible that noise also contributes to that effect, since high PM levels due to traffic may be correlated to high noise exposures. The same applies to nutritional epidemiology; for instance, the burden associated with SSB might be confounded by sedentary lifestyle and/or higher consumption of less healthy food such as saturated fats, sugars, and sodium. All in all, there is a need to acknowledge uncertainties, knowledge gaps, and limitations when attempting to quantify the environmental and nutritional linkage to human health.

Despite the limitations and the exploratory character of this CONE-LCA framework proof-of-concept case study, several recommendations can already be drawn. First, our results demonstrate the potential limitations when using the established environmentally-focused LCA approaches for food items and suggest that the nutritional effects of the “use stage” should be considered in food-related LCAs. In our case study, we have shown that the nutritional effects during the “use stage” could have an effect of comparable magnitude when compared to environmental effects. Second, the study emphasized the importance and need for enhanced data availability and refinement to support this new approach. Third, when considering the human health impacts of GHGE and PM as well as nutritional impacts, results within the context of this study are suggestive of a health benefit linked with a one serving increase in milk consumption for American adults, provided that it does not substitute any health beneficial food items such as fruits and vegetables. The benefit is further increased when considering an iso-caloric substitution of less healthy beverage options. Further studies are now needed to test whether this conclusion holds within a more comprehensive assessment of environmental and nutritional health impacts, e.g. examining additional substitutions, such as the substitution of health beneficial food items such as fresh fruits and vegetables. Fourth, while not being the purpose of this paper, our results suggest that, despite the focus on GHGE of many food LCA studies, other environmental health impacts of food items, such as PM, can also be relevant. Finally, we recommend applying this CONE-LCA approach, which constitutes the infancy of a new area within food/diet-related LCA, to other food items or diets, to characterize potential trade-offs between environmental and nutritional impacts when making recommendations about sustainable diets and food choices.

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CHAPTER 3

HENI: A health burden-based nutritional index for food items

Abstract

Nutrition profiling measures the nutritional quality of foods and can inform dietary patterns that are important determinants of health; however, they rarely quantify the nutritional health performance of foods. We developed the Health Nutritional Index (HENI) that quantifies the nutrition-related health burden associated with foods. Building on the Global Burden of Disease, HENI estimates the minutes of healthy life lost or gained per food serving, based on the marginal cumulative health burden associated with 16 dietary risks (nine major food groups and seven nutrients). HENI scores are calculated as the sum of products of the amounts of dietary risks in the food and the corresponding marginal cumulative health burden per g risk, defined as dietary risk factors (DRFs in disability-adjusted life years). DRFs are estimated by coupling 6,195 risk-outcome-age group-gender-burden-specific relative risks with 4,344 U.S.-specific outcome-age group-gender-specific U.S. burden rates. We estimate HENI scores for 6,888 foods in the U.S. diet. Scores vary substantially, typically ranging from 40 minutes of healthy life lost per serving of hot dog sandwiches up to 30 minutes of healthy life gained per serving of nuts and seeds. HENI identifies nuts and seeds, legumes, fruits, and seafood as key healthy foods, whereas non-starchy vegetables and whole grains foods are also positive but to a lesser extent. Processed and red meat foods have key adverse health effects. HENI can translate complex food and nutritional information into a single health score. Thus, HENI could inform healthier dietary choices, including healthier substitutions, and can become a tool for disease prevention and public health promotion.

3.1. Introduction

Diet is fundamental for human survival and has substantial effects on human health (WHO 2003; World Cancer Research Fund and American Institute for Cancer Research 2007). According to the 2016 Global Burden of Disease (GBD) study series, suboptimal diets (over-consumption of unhealthy food and under-consumption of healthy food) are responsible for more than 500,000 deaths and 10,000,000 disability adjusted life years (DALYs) per year in the U.S. alone, due to non-communicable chronic diseases (Gakidou et al. 2017; Mokdad et al. 2018). The GBD is a remarkable effort to quantify disease burden globally for multiple risk factors. It estimates DALYs associated with both mortality and disease morbidity, covering a set of 15 dietary risks: milk, nuts and seeds, red meat, processed meat, whole grains, fruits, vegetables, legumes, sugar-sweetened beverages (SSB), omega-3, sodium, trans fatty acids (TFA), polyunsaturated fats (PUFA), calcium, fiber, plus various metabolic risks (Gakidou et al. 2017). However, the GBD focuses on population-level estimates that cannot be easily used for inferences on individual food items.

Informing and incentivizing dietary shifts from poor to healthy choices can be challenging. Dietary guidelines provide messaging to promote healthy diets. However, such efforts are not always effective, one reason being that they can be hard to interpret and use for daily food choices (Mokdad et al. 2018). To improve public health, various nutritional profiling indices have been developed to measure dietary quality in relation to food and nutrient intake recommendations and adherence to dietary guidelines (Arvaniti and Panagiotakos 2008). These indices are also used for nutrition and health claims (Fulgoni et al. 2009) and are often only indirectly associated with disease burden (McCullough and Willett 2006).

Attempts have been made to rank individual foods based on their nutrient quality (Sorenson and Hansen 1975; Drewnowski 2005; Fulgoni et al. 2009; Tharrey et al. 2017). Nutrient profiling models have a common structure with a combination of only encouraged nutrients (e.g., protein, fiber, calcium, vitamin C, iron) (Drewnowski 2005), only restricted nutrients (e.g., sodium, added sugars, and saturated fats), or both (Fulgoni et al. 2009; Drewnowski 2017). These models can have sophisticated algorithms based on up to 40 nutrients (Drewnowski 2017) that can generate continuous scores (Fulgoni et al. 2009) or assign foods into categories (Tharrey et al. 2017). Overall, nutrient profiling indices agree with general knowledge and perception of food classification and some are well correlated with diet quality metrics (Fulgoni et al. 2009). However, these models suffer from many limitations such as dependency on energy content

(Sorenson and Hansen 1975), inconsistent nutrition density definitions (Drewnowski and Fulgoni 2008), inherent bias due to the selection of considered nutrients and reference intake values used (Drewnowski 2005), and failure to capture the varying effect of nutrients on health (Arvaniti and Panagiotakos 2008; Fulgoni et al. 2009). In addition, these indices typically fail to capture synergistic effects of nutrients (Arvaniti and Panagiotakos 2008) and are not consistent with recent nutrition advancements that support focusing more on foods and dietary patterns than on nutrients (Mozaffarian 2017).

Other popular dietary indices are based on both nutrients and food groups such as the Healthy Eating Index (HEI) (Kennedy et al. 1995; Guenther et al. 2013) and the Alternate Healthy Eating Index (AHEI) (McCullough and Willett 2006). These scoring systems have shown relevance and predictability of health (Chiuve et al. 2012; Schwingshackl and Hoffmann 2015; Wang et al. 2015; Onvani et al. 2017), but limitations include that components are assumed to contribute equally to the overall score (Chiuve et al. 2012) and that both approaches do not directly relate to health burden. In addition, these indices have been primarily applied to diets which makes them hard to use by consumers for healthier choices and substitutions at the food level (US Federal Trade Commission 2004).

Despite the plethora of dietary assessment tools, we still lack a metric meeting the following essential attributes for nutrition indices (Arvaniti and Panagiotakos 2008): consider the health burden associated with each dietary risk component; expand beyond nutrients; and be applicable to all food items. To address this gap, we developed the Healthy Nutritional Index (HENI), a health burden-based continuous single score nutritional metric. HENI builds on the GBD dietary burden assessment, translating dietary risks at a population level into health burden associated with individual food items. HENI quantifies health burden in marginal minutes of healthy life gained (+) or lost (-) from all-cause premature mortality and morbidity per serving of food, based on the 15 food groups and nutrients identified as dietary risks in the GBD plus saturated fatty acids (SFA). We first determined the dietary risk factors (DRFs) to quantify the marginal burden of disease per g of each HENI dietary risk component (e.g., in $\frac{\mu DALY}{g_{red\,meat}}, \frac{\mu DALY}{g_{omega-3}}$), accounting for 50 health outcomes, and gender- and age-specific risk ratios. Using information from publically available nutritional databases (Fulgoni III et al. 2018), we combine these DRFs with the amount of each dietary risk *r* (d_r in e.g. $\frac{g_{red\,meat}}{serving}, \frac{g_{omega-3}}{serving}$) per serving of 6,888 food items consumed in the U.S. diet, to yield the HENI of each food item.

3.2. Materials and Methods

3.2.1. HENI Overview

HENI quantifies the marginal changes of healthy life per reference amount of food based on 15 dietary risks identified by the GBD (Gakidou et al. 2017) plus SFA. HENI scores are reported in minutes of healthy life gained (+) or lost (-) per serving, and alternatively per 100 kcal or 100 grams. HENI dietary risk components cover nine main food groups and seven nutrients. Food groups include milk, nuts and seeds, processed meat, red meat, SSB (mediated through body mass index), vegetables, legumes, fruits, and whole grains. The nutrients considered in HENI are calcium, fiber, seafood omega-3 fatty acids, sodium (mediated through systolic blood pressure), TFA, PUFA, and SFA (mediated through total serum cholesterol as used by GBD). Additional information and the definition and characteristics of all HENI components are available in Appendix 2, section A2.1 and Table A2.14, respectively.

The marginal HENI model is built on the assumption that the aggregated health effect from multiple dietary risk components is independent unless evidence suggests that there is a mediation mechanism between risks (WHO 2003). The joint risk effect is considered additive for small dietary changes, with the understanding that our results are primarily valid for marginal dietary changes. The HENI score in minutes of healthy life of food item *i* is calculated using:

$$HENI_i = -0.53 \cdot \sum_r DRF_{r,DALY} \cdot d_{i,r} \quad \text{(Eq. 3.1)}$$

where $DRF_{r,DALY}$ is the cumulative age- and gender-adjusted marginal dietary risk factor per g of dietary risk *r* in µDALYs/g_r , and $d_{i,r}$ is the amount of dietary risk *r* in food item *i* in g_r/$serving_i$. The constant of -0.53 represents the minutes of healthy life per µDALYs*. For the purpose of this paper, HENI is developed to produce scores for an average adult (25+ y) in the U.S.

3.2.2. Food composition

The amount of HENI components in food items ($d_{i,r}$) from the WWEIA/NHANES 2007-2014 is determined using a combination of publically available databases from the USDA that have been customized to comply with dietary risk definitions from the GBD. For food group

*1 µDALYs=1 year of healthy life lost $\cdot\, 365\frac{days}{year} \cdot 24\frac{hours}{day} \cdot 60\frac{minutes}{hour} \cdot 10^{-6}$ =- 0.53 minutes of healthy life gained dietary risks, the content of dietary risk *r* in food (in $\frac{grams_r}{100\, g\, food}$) were adapted from the Food Patterns Equivalents Database (FPED). For nutrient dietary risks, equivalent estimates were obtained by combining the Standard Reference (SR) with the Food and Nutrient Database for Dietary Studies (FNDDS). TFA estimates required special treatment since 63% of food items investigated in this paper had incomplete or missing TFA profile. We used imputed TFA values for foods with missing or incomplete profiles based on a regression model of existing data using food group and available nutrient information as predictors (R^2=0.69). For milk and yogurt, the regression model was further adapted based on the food category-specific ratio of known TFA/total fat. However, it should be emphasized that TFA has been drastically decreasing in foods, especially after the banning rule by the U.S. Food and Drug Administration (FDA), and imputed values and their corresponding impacts should be interpreted with caution. A detailed description of the methodology used in obtaining the amounts of HENI dietary risks in foods is available in Fulgoni et al. (2018).

3.2.3. Dietary risk factor model

DRFs quantify the marginal all-cause health burden benefit (-) or impact (+) from premature mortality and disease morbidity per g dietary risk *r*, expressed in µDALYs/g_r. DRFs are estimated using the attributable burden approach for marginal changes. That is, DRFs measure the health burden for an individual that would have occurred with a marginal intake shift standardized for one gram of dietary risk component, assuming that the individual's current risk intake is within an effective range (Appendix 2, Table A2.14). For intakes outside these ranges, DRFs are considered to have a neutral halth effect (DRF=0).

For each dietary risk, DRF is estimated as the age- and gender-weighted sum of the risk-outcome-burden metric-age group-gender-specific estimates, assuming that the effect from all outcomes is additive in a marginal context (model details in Appendix 2, section A2.2):

$$DRF_r = \sum_g \sum_a \sum_o \sum_b f_{a,g} \cdot DRF_{r,o,b}^{a,g} = \sum_g \sum_a \sum_o \sum_b f_{a,g} \cdot \frac{\ln(RR_{r,o,b}^{a,g})}{RI_r^{a,g}} \cdot BR_{o,b}^{a,g} \quad (Eq.3.\ 2)$$

where $DRF_{r,o,b}^{a,g}$ is the marginal DRF for outcome *o* and burden *b* due to dietary risk *r* in age group *a* and gender *g* in µDALYs/g_r, and $f_{a,g}$ is the population fraction in age group *a* and gender *g*. $RR_{r,o,b}^{a,g}$ is the relative risk (RR) for outcome *o* and burden *b* due to dietary risk *r* in age group *a* and gender g. $RI_r^{a,g}$ is the reference intake for dietary risk r in age group a and gender g reported in grams/day. $BR_{o,b}^{a,g}$ is the burden rate for outcome o and burden b in age group a and gender g in μDALYs/person-day, with burden measured in years of life disable (YLD) or years of life lost (YLL) and YLD+YLL=DALY.

For the 16 dietary risk components in HENI, we identified 479 risk-outcome RR in the 2016 GBD (Gakidou et al. 2017). Age- and gender-specific RRs were available for 15 age groups (in 5-year age groups starting from 25 years old). When an RR was available for "both" genders or "both" burden metrics (mortality and morbidity), the same RR was used in the gender-specific and burden-specific calculations, respectively. This resulted in 6,195 specific RRs considered in our analysis. Typically, dietary RRs in the GBD are reported per g/day, except for energy-related nutrients such as TFA and PUFA for which RIs are reported as fractions of daily energy intake (% kcal/day). To convert these intakes to their corresponding gram amounts, we used age- and gender-specific daily energy requirement for U.S. adults (Appendix 2, Table A2.18) and an estimate of 9.25 kcal/g_{fat}. We used disease-specific burden rates (YLL and YLD) by age group and gender (adapted from GBD Results Tool) and population distribution information for the U.S. in 2016.

Three of the dietary risks included in HENI (SSB, SFA, and sodium) are assumed to be 100% mediated through other risks (body mass index, total serum cholesterol, and systolic blood pressure, respectively). In addition, the sodium exposure is defined using daily urinary sodium in the GBD. To adjust for effect modifiers, DRFs for these dietary risks were adjusted for strata-specific associations between SSB and body mass index status, and between sodium and race and hypertension status (Gakidou et al. 2017). We describe the additional steps and data required to develop the DRFs for these mediated dietary risks in Appendix 2, section A2.3. Finally, cardiovascular effects of fiber are mediated through fruits, vegetables, legumes, and whole grains (Gakidou et al. 2017). Hence, we developed distinct DRFs for fiber for the different sources of fiber to avoid double counting, "$fiber_{other}$" representing fiber from sources other than fruits, vegetables, and whole grains; "$fiber_{f,v,l,w}$" represents fiber from fruits, vegetables, legumes, and whole grains.

There are three input parameters with characterized uncertainty in the DRF model. The first two parameters are RRs (including the effect modification RRs for sodium and SSB) and disease burden rates; the GBD studies report the 95th uncertainty interval as lower (2.5th percentile) and upper (97.5th percentile) estimates for these parameters using random draws of

1000 samples from the corresponding distributions (Gakidou et al. 2017). The third input with uncertainty is the SFA-total serum cholesterol association with an estimated standard error (SE) of 0.013 (Mensink 2016). We characterize the uncertainty of DRFs with lower and upper estimates calculated using the corresponding estimates of the uncertain input parameter for each dietary risk by assuming uniform distributions.

3.2.4. HENI score characteristics for foods

We used HENI to evaluate the performance and quantify the health burden of food items in the U.S. diet. We evaluated 6,888 food items from the What We Eat in America, National Health and Nutrition Examination Survey (WWEIA/NHANES) 2007-2014. For food items with multiple entries, we only included the most recent entry. We excluded baby foods, infant formulas, 100% fruit and vegetable juices, alcoholic beverages, water, and "other" foods. Foods were evaluated per reference amounts customarily consumed (RACC) serving, or per 100 kcal (food items with zero energy not considered) and 100 gram. Food items have been classified into 11 main groups and 48 food groups based on an adaptation of the USDA Food Coding Scheme (Appendix 2, Table A2.20).

3.3. Results

3.3.1. Dietary risk factors (DRFs).

The cumulative gender- and age-adjusted DRF estimates for U.S. adults (25+ y) vary substantially between dietary risks from -100.5 µDALY/g (95% uncertainty interval (UI): -170.4 to -39.1) for the beneficial effects of seafood omega-3 fatty acids to 11.7 µDALY/g (95% UI: 8.0 to 15.3) for the adverse health effects of sodium (Figure 3.7 and Appendix 2, Table A2.15 for uncertainty estimates). In addition to the 15 dietary risks from the GBD, we developed a DRF_{SFA} since SFA-related health burdens are captured with total serum cholesterol at the population level in the GBD, estimated at 0.70 µDALY/g (95% UI: 0.20 to 1.65).

DRFs are associated with 50 health outcomes. However, for most dietary risks the burden is dominated by years of life lost due to ischemic heart disease (IHD) mortality, except for calcium, fiber (from fruits, vegetables, legumes, and whole grains – "$fiber_{f,v,l,w}$"), and milk for which colorectal cancer mortality is the leading health burden contributor (Figure 3.7). The years of life disabled due to diabetes have substantial contributions to the burden induced by red meat (71%), processed meat (33%), and SSB (26%). Overall, the 50 to 79 years olds experience the majority of the burden associated with these dietary risks, and the burden is higher in males than females except for 85+ years olds (Appendix 2, Figure A2.21).

All cumulative DRFs are valid within a range of effective daily intakes defined by the GBD as the theoretical minimum thresholds (Appendix 2, Table A2.14). Intake estimates for the largest share of the population fall within these limits; only a small minority of the U.S. adult population have intakes above or below these thresholds (Dietary Guidelines Advisory Committee 2015). The magnitude of DRFs values are not directly comparable; meaningful comparisons need to be determined at food level (HENI), accounting for the amount of each dietary risk component in a food item.

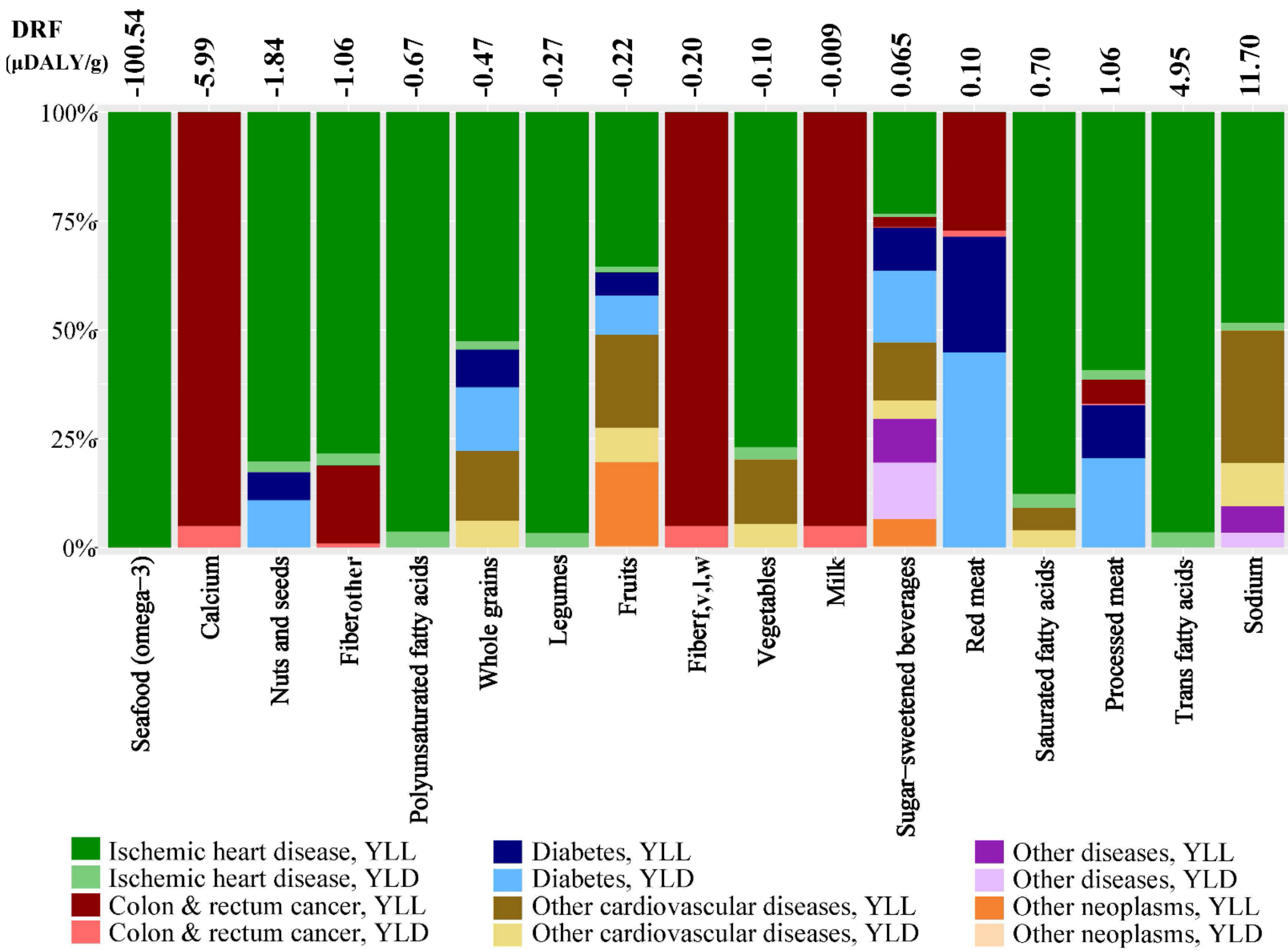

Figure 3.7. Cumulative gender- and age-adjusted dietary risk factor (DRFs) estimates for US adults (25+ y) in µDALY/g and disease contribution (%) by burden measure, including morbidity in years of life disabled (YLD) and mortality in years of life lost (YLL). $Fiber_{f,v,l,w}$=fiber from fruit, vegetables, legumes, and whole grains. $Fiber_{other}$= fiber from sources other than fruits, vegetables, legumes, and whole grains.

3.3.2. HENI for foods

From the 6,888 food items in the WWEIA/NHANES 2007-2014 database, processed and red meat dishes, as well as sweetened beverages, have a lower health performance compared to nuts and seeds, legumes, fruits, and seafood (Figure 3.8). In particular, the food categories with the five lowest HENI medians are hot dog sandwiches (-42 minutes of healthy life/serving, interquartile range-IQR: -48 to -37), cured meats (-31 minutes of healthy life/serving, IQR: -33 to -28), breakfast sandwiches (-16 minutes of healthy life/serving, IQR: -24 to -11), burgers (-9 minutes of healthy life/serving, IQR: -15 to -6), and sweetened beverages (-7 minutes of healthy life/serving, IQR: -10 to 0). The food categories with the highest HENI medians are nuts and seeds (+30 minutes of healthy life/serving, IQR: +28 to +31), legumes (+11 minutes of healthy life/serving, IQR: +2 to +12), fruits (+11 minutes of healthy life/serving, IQR: +7 to+16), seafood (+9 minutes of healthy life/serving, IQR: +4 to +22), and seafood mixed dishes (+6 minutes of healthy life/serving, IQR: +2 to +12).

Foods in the categories of milk and dairy (excluding cheese), oils, non-alcoholic beverages (excluding sweetened beverages), and sugars tend to have an overall net neutral health effect per serving. Interestingly, only a few food categories have HENI scores of all their foods entirely positive or entirely negative, thus the importance to identify which food items have high or low HENI scores within each food category.

In the U.S., nutrition labeling is based on RACC serving sizes established by the U.S. FDA, and thus this unit served as the primary comparison basis in our analysis (Drewnowski et al. 2009). Nevertheless, HENI can also be determined per 100 kcal or 100 g. The 100 kcal-based HENI leads to a somewhat similar food category rankings as the serving-based results (Appendix 2, Figure A2.22), but with less extreme HENI scores for food items with high energy density (e.g., nuts, meat) and higher scores for lower energy content food items (e.g., fruit and non-starchy vegetables), see Appendix 2, Figure A2.24A. HENI per 100 g scores could result in considerable food category ranking differences, especially for foods with small serving size such as fats, oils, sugars, snacks, sweets, condiments, nuts, seeds, and cheese (Appendix 2, Figures A2.23 & A2.24B). However, 100 g-based HENI scores should be interpreted with caution as these foods are typically consumed in much lesser quantities than 100 g within conventional diets.

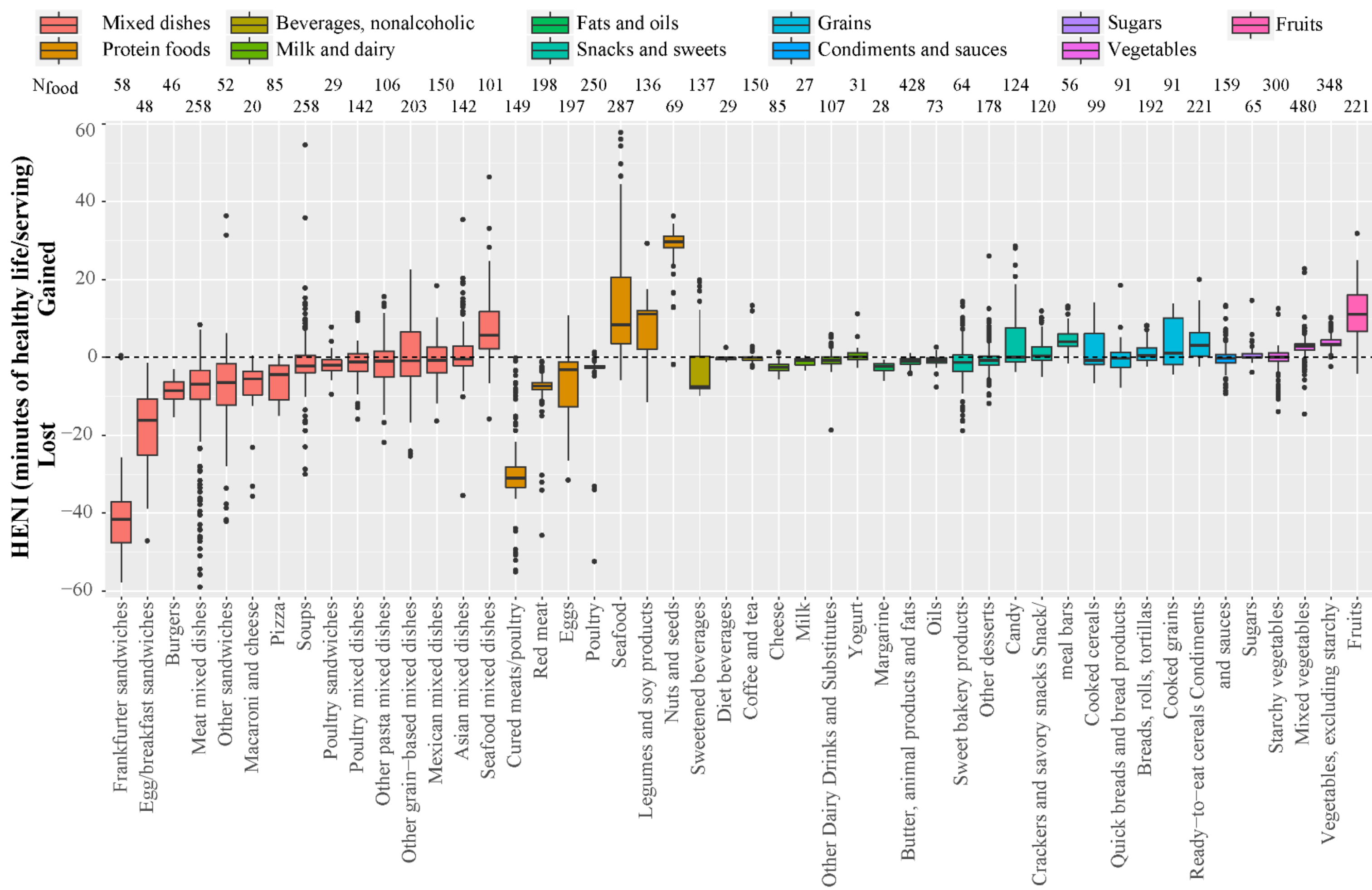

Figure 3.8. Distribution of HENI in minutes of healthy life per serving for 6,888 foods in the WWEIA/NHANES 2007-2014 by food category. Positive HENI values indicate health benefits. Boxes represent the interquartile range (IQR), horizontal lines represent the medians, whiskers extend to 1.5 times the IQR, and data points represent outliers. 16 outliers fall outside the HENI range in this figure. The dotted line represents the neutral health effect score (HENI=0). N_{food} represents the number of foods in each category. See also Appendix 2, Table A2.16.

3.3.3. HENI composition.

HENI scores show considerable inter- and intra-food category variability that could not be explained by food characteristics such as energy density and serving size (Appendix 2, Figure A2.25). To better understand the drivers of HENI we analyzed the contribution of each component by food group for five foods, representative* of the minimum, 25th percentile, median, 75th percentile, and maximum of the food group HENI range (Figure 3.9 and Appendix 2, Figure A2.26). For *mixed dishes* (Figure 3.9A), the lowest HENI scores (88 minutes of healthy life lost/serving) were associated with high levels of processed meat, while the highest HENI scores (119 minutes of healthy life gained/serving) were associated with high seafood omega-3 fatty acids, a tendency also observed for *protein foods* (Appendix 2, Figure A2.26A). Mexican dishes and vegetable soups tend to have neutral scores, with the positive effect of vegetables being offset by sodium and SFA. For *dairy products* (Figure 3.9B), cheeses have the lowest scores with higher levels of sodium and SFA leading to moderately detrimental scores (-5 minutes of healthy life/serving). For milk, HENI scores improve as its fat content reduces while maintaining the health benefits of milk on colorectal cancer. The best dairy score is associated with fruits in low-fat yogurt, mostly due to the health benefits of fruits. *Snacks and sweets* show substantial HENI variation (Figure 3.9C), between 16 minutes lost/serving for foods high in TFA (e.g., fritters and doughnuts) and 29 minutes of life gained/serving for nut-based snacks. For *vegetables* (Figure 3.9D), HENI score differences between starchy (corn, potato) and non-starchy vegetables are due to the GBD definition of vegetables that excludes starchy vegetables (Gakidou et al. 2017). Sodium added during cooking lowers the HENI score of certain vegetable dishes. *Grains* show increasing benefits (Figure 3.9E), up to 14 minutes of healthy life gained/serving, as the whole grain content increases. For the rest of the food groups (Appendix 2, Figure A2.26), low HENI scores are driven by a single detrimental dietary risk component such as processed meat (protein foods), SSB (nonalcoholic beverages), SFA (sauces), and TFA (fats). Similarly, the highest HENI scores are linked with high levels of a single dietary risk such as seafood omega-3 fatty acids (protein foods), fruits (nonalcoholic beverages and sugars), and nuts and seeds (sauces). The HENI score for fruits increases with the content of fruits per serving and is positively correlated with serving size ($\rho=0.85$, $p<0.0001$, Appendix 2, Table A2.17 and Figures A2.4B and A2.6F). Additional

*Selected as the nearest food item within one percentile that best represented the food composition in each food category.

correlations are discussed in Appendix 2, section A2.6. Finally, sodium has a small adverse health effect in most foods in comparison with other dietary risk components. However, the small contributions of sodium at the food level can accumulate to a substantial intake at the diet level.

In a sensitivity analysis, we evaluated the addition of added sugars as a HENI dietary risk component since it is not included in the GBD but has been associated with adverse health effects (Appendix 2, section A2.4). Assuming 50% the effect of SSB, added sugars has little influence on the HENI scores of foods, except for candy with a median $HENI_{added\ sugars}$ of 4.4 minutes of healthy life lost/serving (Appendix 2, Figure A2.28). We also investigated in more detail the influence of TFA and SFA on HENI since their contributions could be refined in the future (Appendix 2, section A2.5). TFA appears to have a relatively small impact overall, with the largest influence observed in margarine with a median of 2.2 minutes of healthy life lost/serving (Appendix, Figure A2.29). The contribution of SFA on HENI is slightly higher than TFA, especially for animal-based food categories (Appendix 2, Figure A2.30).

We also quantify the disease composition of the net health burden associated with each food (Appendix 2, Figure A2.27). IHD mortality dominates the net health burden of foods in most categories as observed is the DRF disease repartition. “Other cardiovascular diseases” and “other neoplasms” mortality also play an essential role for fruits.

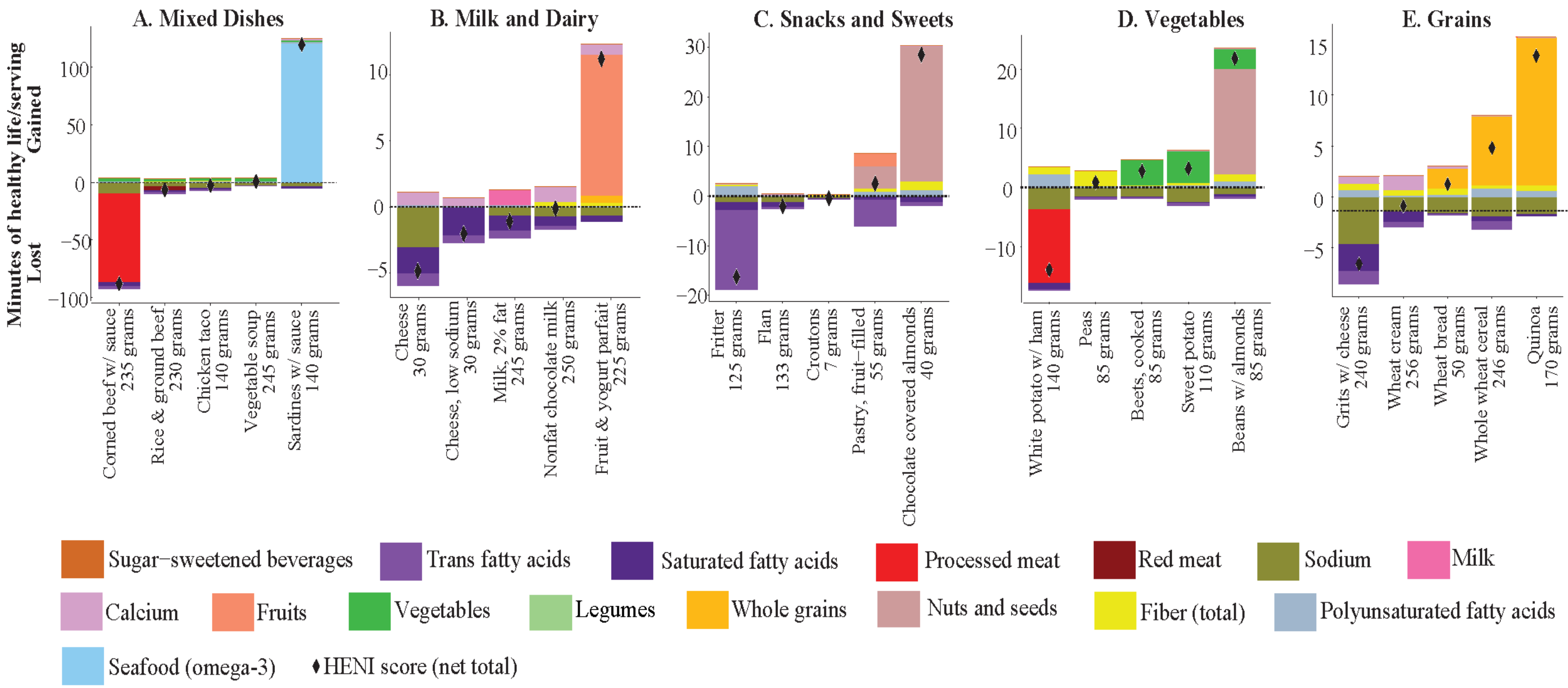

Figure 3.9. Dietary risk contribution to HENI for select food groups: **A.** Mixed dishes, **B**. Milk and Dairy, **C.** Snacks and Sweets, **D.** Vegetables, **E.** Grains. The foods are representative of the min, 25th percentile, median, 75th percentile, and max scores within the food group (within one percentile). The black diamond represents the HENI score per serving. The dotted line represents the neutral health effect score (HENI=0). For the remaining food groups, see Appendix 2, Figure A2.26.

3.4. Discussion

HENI evaluates the marginal health burden-based nutritional quality of foods and satisfies the characteristics of a proper nutrition evaluation index (Arvaniti and Panagiotakos 2008). HENI is the first nutritional index to directly link individual food items to health impacts and benefits in a single continuous score. The model is based on the most recent epidemiological evidence from more than 100 risk-health outcome pairs that meet the World Cancer Research Fund criteria of causality (Gakidou et al. 2017). Moving away from the nutrient-based indices (Mozaffarian 2017), HENI is based on both nutrients and food groups with established beneficial and adverse associations with cardiovascular, cancer, and metabolic health. This approach is consistent with recent dietary recommendations (Dietary Guidelines Advisory Committee 2015). Furthermore, model components are weighted (via the DRFs) using information on the magnitude of health effect, type of disease affects, disease prevalence, and diseases severity in the population, addressing a major limiting factor in previous indices where components contributed equally to the overall performance (Arvaniti and Panagiotakos 2008). Using the risk ratio and burden rate uncertainty characterizations from the GBD, and assuming uniform distributions, the high-end DRF uncertainty estimates confirm the significance of each dietary risk, with typical variations between 30% to 87% around the best estimates. This preliminary uncertainty analysis can serve as an input for more advanced Monte Carlo simulations in the future. As a whole, HENI can translate a complex nutritional food evaluation to a simple but powerful score expressed in minutes of healthy life lost or gained. This metric is easy to understand and relevant to consumers, stakeholders, and academics (Kunkel and McKinley 2007). Thus, HENI can be used in decision-making towards healthier choices and substitutions within and between food groups.

Our evaluations of almost 7,000 foods consumed in the U.S. diet using HENI supports that foods can have a broad range of scores, extending from -88 (Corned beef with tomato sauce and onion) up to 119 (Sardines with tomato-based sauce) minutes of healthy life/serving. Our approach is consistent with increasing evidence that dietary choices based on food quality might be a better health promoter than calorie-dependent approaches (Mozaffarian 2017). The broad range of HENI scores illustrates the index's ability to assess extreme food items adequately while also providing more general recommendations at the food group level (e.g., nuts and seeds, legumes, fruits, seafood, and non-starchy vegetables induce health benefits while processed and red meat foods induce adverse effects). The general trends of food group performance with HENI are in line with other nutritional indices (Fulgoni et al. 2009; Chiuve et al. 2012). However, wide variability within food groups suggests that selection solely based on the food group could be problematic. This variability emphasizes the complexity of dietary assessments and the need to make inferences at the food level and not at the food category level.

The HENI composition can shed light on the drivers and hidden health risks and benefits associated with food, especially in mixed foods which are popular in the U.S. diet. HENI not only quantifies the magnitude of health burden associated with food but also identifies the component with the highest contribution to health burden as well as the health outcome affected the most. For example, the highest HENI scores are typically linked with high levels of nuts and seeds or seafood omega-3 fatty while foods with the lowest HENI scores are high in processed meat. Our analysis supports that IHD mortality is responsible for the majority of the health burden associated with most foods, followed by other cardiovascular diseases mortality, neoplasm mortality, and diabetes morbidity. This granularity feature of HENI helps the differentiation and allows for the identification of foods within a category with maximum beneficial components and minimum detrimental components. This level of information could help advise disease prevention programs.

The validity of our results relies on a number of assumptions and limitations. First, this work investigates the health burden associated with food items in a marginal context, assuming that for marginal changes the model components have an independent and additive joint health effect. However, large diet-level shifts may not satisfy this marginality condition and will require considering the synergistic effect of multiple foods within the diet and treating the combined risk effects as multiplicative (Arvaniti and Panagiotakos 2008). HENI is valid under the assumption of isocaloric changes. Additional health benefits or impacts associated with changes in calories could be considered in complementary diet level approaches.

Second, our estimates were developed using U.S.-specific data for background disease prevalence and disease severity in adults, and for food composition. An additional validity condition of this work is that current consumption levels in the U.S. exceed the GBD minimum levels of intake for detrimental dietary risks and are below GBD maximum levels of intake for beneficial dietary risks. This condition is satisfied for the vast majority of the U.S. population as shown by estimates from a representative sample (Dietary Guidelines Advisory Committee 2015), although, certain individuals might not fall within such minimum or maximum levels.

Third, the TFA content of 63% of foods in our analysis was imputed using a regression model. Although the regression analysis used had a relatively good fit (R^2=0.69), the rather small contributions of TFA to HENI scores should be interpreted with caution as TFA levels from partially hydrogenated oils are declining in food since FDA has ruled their elimination from food earlier this year. Finally, our analysis fails to capture possible additional damaging health effects linked with cooking methods (Liu et al. 2018) and discretionary salt added at the dining table.

We also want to stress out that since our model builds on the work of the GBD, our results depend on the accuracy of the estimates provided and are limited to risk-outcomes pairs considered in that work. While the approach implemented by the GBD to identify risk-outcome pairs and quantify pooled association estimates is rigorous and comprehensive, estimates have not considered the growing evidence of additional associations and effect modifiers of dietary risks. Such evidence includes, but are not limited to, the direct (Slattery and Randall 1988) and food-specific (De Oliveira Otto et al. 2012) effect of SFA on cardiovascular disease, the protective effect of fiber on chronic kidney disease (Chiavaroli et al. 2015), the joint effect of sodium and potassium on cardiovascular and all-cause mortality (Yang et al. 2011), the inverse association between coffee consumption and diabetes (Ding et al. 2014) as well as cardiovascular and all-cause mortality (Crippa et al. 2014). Thus, HENI scores in this paper could underestimate the total health burden of foods studied here. However, as new data are developed, HENI can be easily updated and expand beyond the work of the GBD. Such an expansion was partly illustrated by the inclusion of SFA in HENI, a dietary risk component not directly considered in the GBD. Similarly, HENI could be further expanded and consider nutrients of public health concern (e.g., vitamin D and potassium) and shortfall nutrients (e.g., magnesium, vitamin C) as identified by the U.S. Department of Agriculture (USDA) that are not included in the GBD studies (Dietary Guidelines Advisory Committee 2015).

3.5. Conclusion

HENI is a nutritional index that uses epidemiological evidence to provide health intelligence to inform healthier food choices and substitutions. Reporting nutrition-related health information at the food level in a relatable and straightforward unit such as minutes of healthy life, HENI could become a powerful tool to guide disease prevention associated with diet, an important public health challenge. Future studies are needed to investigate whether HENI can improve the understanding of food healthiness in consumers and help them achieve adherence to a healthy diet.

Our analysis could uniquely complement growing efforts to evaluate the relationship between environmental impacts from food production and nutrition (Springmann et al. 2016; van Dooren et al. 2017; Walker et al. 2018). With growing interest on sustainable diets (Tilman and Clark 2014; Drewnowski 2017), HENI can be integrated into ongoing efforts to develop sustainability indicators that would measure and document the progress of the trade-offs between environmental impacts from agricultural production and nutrition health effects of foods and diets (Stylianou et al. 2016). In this context, HENI can characterize the nutritional pathway within a new life cycle impact subcategory, evaluating health impacts of foods in parallel with their ‘cradle to grave’ environmental impacts. Combining environmental and nutritional health effects of foods and diets in a comparable manner using a common metric (e.g., DALYS or minutes of healthy life) would result in a comprehensive sustainability index, which is needed for optimizing sustainable dietary recommendations (Drewnowski 2017). Overall, HENI can help inform healthier dietary choices and substitutions, assist with nutrition promotion and education, and expand towards a sustainable diet indicator that can tackle both nutritional and environmental dietary challenges.

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CHAPTER 4

Spatially-explicit characterization of the exposure and health burden of fine particulate matter in the U.S.

Abstract

The growing literature on regionalized life cycle impact assessments (LCIA) has highlighted the need to develop spatial estimates to characterize exposure and health damage from pollutants. In this paper we develop spatially-explicit intake fraction (iF- fraction of the emission taken in by population) and characterization factors (CF – impact per kg precursor emitted) for fine particulate matter ($PM_{2.5}$) from ground level emissions of $PM_{2.5}$, NH_3, SO_2, and NO_x in the U.S. We calculate iFs for 43,304 locations in the contiguous U.S. using a reduced-form chemical transport model, the Intervention Model for Air Pollution (InMAP), with high spatial resolution in urban settings and large spatial domain. For each source location, we integrate iFs multiplied by a non-linear exposure-response function and region-specific burden estimates at each receptor location to derive cumulative location-specific CF estimates. We finally investigate the spatial extent of exposure and impacts by quantifying the radial distance from the source to reach 25%, 50%, and 95% of the cumulative exposure and burden. The emission-weighted national average cumulative iF is 0.8 parts per million (ppm) for primary $PM_{2.5}$, 0.4 ppm for NH_3, 0.3 ppm for SO_2, and 0.1 ppm for NO_x, with location-specific estimates varying up to 3 orders of magnitude across the U.S. The corresponding CFs using a marginal slope of the exposure-response are 103 μDALYs/kg for primary $PM_{2.5}$, 48.4 μDALYs/kg for NH_3, 36.3 μDALYs/kg for SO_2, and 18.5 μDALYs/kg for NO_x, with the estimates using the average slope being about twice as large. The location-specific estimates show considerable variability of about three orders of magnitude that is higher for SO_2 and NO_x. Urban emissions result in higher iF and CF estimates and have a spatial extent about a factor 10 lower than rural emissions. We also report estimates for four distinct sectors (agriculture, fuel combustion, industrial processes, and mobile) that account for the spatial distribution of the corresponding emissions, in order to provide exposure and health damage characterizations that are more accurate for processes in life cycle assessment (LCA) studies. This

work informs LCIA, helping quantify sector-specific health damages from $PM_{2.5}$–related emissions, using the current state of knowledge for $PM_{2.5}$ exposure and health effect.

4.1. Introduction

Ambient fine particulate matter ($PM_{2.5}$) emissions can be released to the environment throughout the life cycle of a product or a process. In life cycle assessment (LCA), a tool that evaluates product- or process-related damages associated with emissions, $PM_{2.5}$ often dominates human health impacts. The adverse health effects of $PM_{2.5}$ include cardiovascular impacts, cancer impacts, respiratory impacts, and premature mortality (Künzli et al. 2000; Lipsett et al. 2011; Pope et al. 2011; Lepeule et al. 2012; Smith et al. 2014). According to the Global Burden of Disease (GBD), $PM_{2.5}$ is the leading environmental health risk and it is estimated that in 2016 ambient $PM_{2.5}$ was responsible for more than 100 million disability adjusted life years (DALYs) globally and about 1.7 million DALYs in the U.S. (Institute for Health Metrics and Evaluation (IHME) 2018).

A critical input in life cycle impact assessment (LCIA) approaches is characterization factors (CFs). CFs quantify the damage associated with a marginal unit emission of a pollutant. Human health CFs are measured in disability adjusted life years (DALYs) per kg pollutant emitted and are estimated by combining information on *exposure characterization*, *exposure to health response relationships*, and *disease severity*. For $PM_{2.5}$ CFs, these metrics are influenced by precursor (exposure), emission location (exposure), population density (exposure) and age distribution (exposure-response, disease severity), as well as background mortality rates (exposure-response, disease severity), all variables that show important spatial variations. With recent evidence supporting that the integrated exposure response (IER) function for $PM_{2.5}$ is non-linear (Burnett et al. 2014; Cohen et al. 2017), background ambient $PM_{2.5}$ concentration levels also influence CFs estimates. Since the initial $PM_{2.5}$ CFs by Hofstetter (1998), significant improvements have been implemented to account for some of these factors of influence (van Zelm et al. 2008, 2016; Gronlund et al. 2015; Tang et al. 2015). However, we lack CFs that combine all the attributes mentioned above, while accounting for the spatial variation in each of the influential parameters.

Intake fraction (iF), the inhaled $PM_{2.5}$ by the exposed population per kg precursor emitted in $kg_{PM2.5,inhaled}/kg_{precursor,emitted}$ (Bennett et al. 2002), is the recommended metric to characterize $PM_{2.5}$ *exposure* in LCIA (Jolliet et al. 2018). There are four $PM_{2.5}$ precursors of interest: primary $PM_{2.5}$ (aerosols directly emitted in the atmosphere), ammonia (NH_3), sulfur dioxide (SO_2), and nitrogen oxides (NO_x). The three latter, when released in the atmosphere, produce aerosols through photochemical reactions and contribute to secondary $PM_{2.5}$ that accounts for up to 50% of the ambient $PM_{2.5}$ concentrations and have long-range travel distance (Hand et al. 2012; Brunekreef et al. 2015). Past studies have shown that source characteristics such as location (van Zelm et al. 2008, 2016; Humbert et al. 2011; Apte et al. 2012; Fantke et al. 2017; Lamancusa et al. 2017), stack height (Wang et al. 2006; van Zelm et al. 2008; Humbert et al. 2011), and type (e.g., industry, mobile) (Wang et al. 2006; Zhou et al. 2010) are key determinants of $PM_{2.5}$ iF. Seasonality is equally important (Zhou et al. 2010; Heo et al. 2016a; Lamancusa et al. 2017). The majority of these studies have heavily focused on characterizing exposure from primary $PM_{2.5}$, leading to secondary $PM_{2.5}$ being poorly studied (Heo et al. 2016a; Fantke et al. 2017). This was primarily due to the complex and non-linear relationship between precursors and secondary $PM_{2.5}$ causing computational challenges (Ansari and Pandis 1998; West et al. 1999). The limited studies that investigate secondary $PM_{2.5}$ exposure suffer from several limitations including short exposure travel distance tracking (Levy et al. 2009; Humbert et al. 2011), small number of source locations (Lamancusa et al. 2017), archetypes that may produce results of lower precision (Humbert et al. 2011), simplified atmospheric chemistry that fails to capture the complex non-linear formation chemistry (van Zelm et al. 2008; Levy et al. 2009), and low spatial resolution (van Zelm et al. 2008, 2016; Heo et al. 2016a) that does not allow for proper characterization of exposure disparities between sources (Paolella et al. 2018). In addition, the studies that investigated differences in source types have not developed iFs for the agricultural sector, the dominant source of NH_3 atmospheric emissions (Paulot and Jacob 2014; Brunekreef et al. 2015).

Recent epidemiological evidence support that the integrated *exposure to health response* function, IER, between ambient $PM_{2.5}$ and ischemic heart diseases, stroke, lung cancer, and chronic obstructive pulmonary disease in adults over 25 years old and acute lower respiratory infection in children under 5 years old is non-linear (Cohen et al. 2017). The slope of IER quantifies the annual mortality (all-cause or disease-specific) per unit $PM_{2.5}$ inhaled (in $death/kg_{PM2.5,inhaled}$). Previous LCIA approaches have primarily used linear exposure-response from large epidemiological studies in the U.S. that utilized region-specific estimates to adjust for the background ambient $PM_{2.5}$ concentrations (van Zelm et al. 2008, 2016; Gronlund et al. 2015). Spatially-explicit estimates of global IER slopes based on the non-linear function produced results with similar central tendency as previous estimates. However, quantification of location-specific exposure-response estimates enabled the identification of differences between locations, with the leading factors of influence being background ambient $PM_{2.5}$ concentrations and mortality rates. The non-linear IER function also showed flexibility within a LCA context as it could be tailored towards consequential ('marginal' IER slope) and attributional ('average' IER slope) studies, which emphasized the importance of the shape of the IER function (Fantke et al. 2018).

To address limitations from previous estimates, this paper aims to develop updated exposure and human health factors for primary and secondary $PM_{2.5}$ CFs from ground level emissions, focusing on the entire contiguous U.S. and the sectors that contribute the most to each precursor's emissions. The specific objectives were:

1. Develop spatial iF for $PM_{2.5}$ from ground level emissions of the four main precursors (primary $PM_{2.5}$, NH_3, SO_2, and NO_x) for about 43,000 source locations in the entire contiguous U.S. using InMAP (Intervention Model for Air Pollution) (Tessum et al. 2017), a reduced-complexity air quality model covering the greater North America region with flexible grid resolution that captures the long-range exposure potential of primary and secondary $PM_{2.5}$ (*exposure*). Derive sector- and state-specific estimates for the 48 adjoining U.S. States plus Washington, D.C.
2. Determine location-specific 'marginal' and 'average' $PM_{2.5}$ *exposure-response* slopes as described in Fantke et al. (2018) for each of grid cells in InMAP using cause-of-death- and age-specific inputs from the non-linear IER from Cohen et al. (2017), local $PM_{2.5}$ annual average ambient concentrations (WHO 2016), and region-, age-, and cause-of-death-specific annual mortality estimates (Institute for Health Metrics and Evaluation 2018).
3. Calculate new region-, age-, and cause-of-death-specific *severity* factors in DALYs/death based on 2016 GBD for each of grid cells in InMAP and combine them with IER slopes to derive region-, age-, and cause-of-death-specific effect factors (EF), the annual health burden (all-cause or disease-specific) per unit $PM_{2.5}$ inhaled (in $DALYs/kg_{PM2.5,inhaled}$).
4. Calculate spatial CF for $PM_{2.5}$ from ground level emissions of the four main precursors (primary $PM_{2.5}$, NH_3, SO_2, and NO_x) for about 43,000 source locations in the entire contiguous U.S., as well as sector- and state-specific estimates for the 48 adjoining U.S.

states plus Washington, D.C, by combining updated *exposure*, *exposure-response*, and *severity* estimates.

5. Analyze the spatial distribution of exposure and burden associated with an emitter by quantifying for the 43,000 source locations the distance from the source (travel distance) at which ground-level emissions affect that exposure ('intake travel distance') and health burden ('burden travel distance').

4.2. Materials and methods

4.2.1. Intake fraction

Intake fraction (iF) is an exposure metric that links environmental emissions to population exposure, defined as the fraction of precursor emission that is eventually inhaled as $PM_{2.5}$ by the exposed population integrated over space and time ($kg_{PM2.5,inhaled}/kg_{precursor,emitted}$). The cumulative iF of precursor i in source location j ($iF_{i,j}$) was calculated as follows:

$$iF_{i,j} = \sum_w iF_{i,j\to w} = \sum_w \frac{BR \cdot Pop_w \cdot f_{year\to s} \cdot \Delta C_{PM2.5,i,j\to w}}{E_{i,j}} \qquad (Eq.\ 4.1)$$

where BR is the annual volumetric breathing rate ($m^3/person$), Pop_w is the population in 2015 at location w, $E_{i,j}$is the marginal unit emission flow of precursor i in source location j ($\mu g/s$), $f_{year\to s}$ is a years-to-seconds conversion factor, and $\Delta C_{PM2.5,i,j\to w}$ is the change in the annual average concentration of $PM_{2.5}$ at receptor location w from a marginal unit emission of precursor i in source location j ($\mu g/m^3$).

There are different approaches that can be used in estimating change in ambient concentration of a pollutant after the emission of a precursor such as box models (Humbert et al. 2011; Apte et al. 2012), Gaussian plume dispersion models (Wang et al. 2006; Levy et al. 2009), and Eulerian chemical transport models (CTMs) (Zhou et al. 2010; Heo et al. 2016a; van Zelm et al. 2016; Lamancusa et al. 2017). CTMs are considered the state-of-the-art in air pollution modeling, however, they can be computationally expensive and typically are used in evaluating limited number of emission scenarios (Heo et al. 2016b). In addition, CTMs could compromise high spatial resolution across large regions that are necessary to adequately characterize exposure differences between sources (Paolella et al. 2018). Reduced-form CTMs are computationally efficient but often suffer from low spatial resolution (Heo et al. 2016b; Paolella et al. 2018), unless they work on adaptive scales with higher resolution in areas of higher exposure and lower resolution in the more remote area, while covering an entire continent.

We used the source-receptor matrix InMAP Source-Receptor Matrix (ISRM) from the reduced-form CTM Intervention Model for Air Pollution (InMAP) to obtain information on the change in $PM_{2.5}$ ambient concentration from marginal primary $PM_{2.5}$, NH_3, SO_2, and NO_x emissions (Tessum et al. 2017). InMAP is based on simplified runs from a state-of-the-art CTM, WRF-Chem, using emissions and atmospheric conditions from 2005. The spatial domain of the model is the greater North America region that covers the contiguous U.S., adjacent portions of Canada and Mexico, and the islands of Cuba and the Bahamas. The spatial domain is large enough to capture the long travel distance of $PM_{2.5}$, particularly important for secondary $PM_{2.5}$. Unlike other reduced-form CTMs, InMAP has a flexible spatial resolution (grid cell dimensions: 48-, 24-, 12-, 4-, 2- and 1-km per side depending on population density) that allows for high resolution when necessary such as population-dense urban centers. This resolution results in 52,411 grid cells (43,304 located in the U.S.) that serve as both emission and receptor locations in InMAP. To develop the ISRM, InMAP was run thousands of times with each run modeling a 1 µg⁄s change from a single grid cell and characterizing the corresponding change on ambient annual $PM_{2.5}$ concentrations at every receptor cell. Although InMAP has three emission levels (0-57 m, 57-379 m, and >379 m), we focused on ground level emissions (0-57 m) as this emission height is the most relevant for NH_3 emissions, primarily from agriculture, which has a critical role in secondary $PM_{2.5}$ formation (Paulot and Jacob 2014).

For the breathing rate we used a combined indoor and outdoor annual population average of 11.68 m^3/d (Fantke et al. 2018). Population estimates in each grid cell were estimated using U.N. adjusted population counts in 2015 from the Center for International Earth Science Information Network (CIESIN 2017).

4.2.2. Effect factor

4.2.2.1. Exposure-response function

We followed the approach from the GBD, as recommended for LCIA (Jolliet et al. 2018), and used the exposure-response function (ERF) by Cohen et al. (2017), deriving a non-linear integrated exposure-response (IER) function between $PM_{2.5}$ and ischemic heart diseases, stroke, lung cancer, and chronic obstructive pulmonary disease in adults over 25 years old and acute lower respiratory infection in children under 5 years old. Age was an effect modifier for ischemic heart diseases and stroke.

Building on this work, Fantke et al. (2018) developed updated model parameters for the non-linear IER function and for a given background $PM_{2.5}$ concentration proposed two approaches to derive a slope for the IER that can serve different types of LCA studies. A 'marginal' slope specific to the background $PM_{2.5}$ ambient levels is more suitable for consequential LCA studies interested in characterizing the change in morbidity and mortality likely to follow a small change in exposure, whereas an 'average' slope between the background $PM_{2.5}$ ambient levels and the level of minimum risk (defined as the theoretical minimum risk exposure level by the GBD) better fits the scope of attributional LCA studies, attempting to determine the fraction of air pollution mortality impacts attributable to total emissions from a source or class of sources. Unlike Fantke et al (2018), here we use state-specific instead of national mortality estimates. The ERF for the two approaches at location *w* for disease *e* and age group *k* ($ERF_{w,e,k}^{marginal}$, $ERF_{w,e,k}^{average}$) are calculated as follows:

$$ERF_{w,e,k}^{marginal} = \begin{cases} 0 & \text{for } C < C_0 \\ \frac{\left(RR_{e,k}(C_w+\Delta C)-RR_{e,k}(C_w)\right)\cdot M_{e,k,region_w}}{\Delta C\cdot RR_{e,k}(C_{region_w})\cdot Pop_{k,region_w}\cdot BR\cdot f_{\text{kg}\to\text{µg}}} & \text{for } C \geq C_0 \end{cases} \qquad (Eq.\ 4.\ 2a)$$

$$ERF_{w,e,k}^{average} = \begin{cases} 0 & \text{for } C < C_0 \\ \frac{\left(RR_{e,k}(C_w)-1\right)\cdot M_{e,k,region_w}}{(C_w-C_0)\cdot RR_{e,k}(C_{region_w})\cdot Pop_{k,region_w}\cdot BR\cdot f_{\text{kg}\to\text{µg}}} & \text{for } C \geq C_0 \end{cases} \qquad (Eq.\ 4.2b)$$

where $RR_{e,k}(C)$is the relative risk for disease *e* and age group *k* at $PM_{2.5}$ ambient concentration *C*, $M_{e,k,region_w}$is the annual mortality for disease *e* and age group *k* at the *region* of location *w*, $Pop_{k,region_w}$ is the population of age group *k* at the *region* of location *w*, BR is the annual volumetric breathing rate per capita, and $f_{\text{kg}\to\text{µg}}$ is the kg-to-µg conversion factor. C_w and C_{region_w} denote the annual average ambient $PM_{2.5}$ concentration at location *w* and in the *region* of location *w*, respectively, while C_0 represent the theoretical minimum risk exposure level for $PM_{2.5}$. In this study, for grid cell falls in the U.S. *region* represents a U.S. State while for grid cells with centroids in Canada, Mexico, Cuba, and the Bahamas *region* represents the country.

We obtained C_0 and $RR_{e,k}(C)$ estimates from Fantke et al (2018). For ischemic heart disease and stroke RR estimates were reported separately for 12 age groups (25-29, 30-34, 35-39, 40-44, 45-49, 50-54, 55-59, 60-64, 65-69, 70-74, 75-79, and ≥80 years), while for lung cancer and chronic obstructive pulmonary disease RRs were reported for adults above 25 years old. For acute lower respiratory infection, RRs were reported for children below the age of 5 years. The corresponding annual mortality estimates in 2016 for the U.S. States, Canada, Mexico, Cuba, and the Bahamas were obtained from the results of the 2016 GBD study (Institute for Health Metrics and Evaluation 2018). Regional and grid cell-specific $PM_{2.5}$ annual average ambient concentrations were estimated to reflect population distribution in the respective area (population-weighted averages) using estimates for 2016 from the World Health Organization (WHO 2016). Age-specific national population estimates for 2016 were obtained from the GBD (Global Burden of Disease Collaborative Network 2017). To determine the population by age in each U.S. State, we estimated the fraction of U.S. population in each state for 2015 and applied them to the national estimates, assuming that the population distribution by State is equal for all age groups.

4.2.2.2. Severity factors

Severity factors (SF) characterize the health burden in DALYs associated with a death, accounting for both morbidity and mortality. For each *region* in this study (U.S. States, Canada, Mexico, Cuba, and the Bahamas) we calculated the age- and disease-specific SF ($SF_{e,k,region}$) as the ratio of the corresponding annual total health burden in DALYs and annual total mortality in deaths for the year 2016 using estimates from the GBD (Institute for Health Metrics and Evaluation 2018).

4.2.2.3. Effect factor model

Effect factors (EFs) quantify the annual change in health burden associated with a unit change in population exposure in $DALYs/kg_{PM2.5,inhaled}$. EFs are calculated as the product of the exposure-response function (ERF) slope that reflects the annual change in mortality (all-cause or disease-specific) per unit change in population exposure in $death/kg_{PM2.5,inhaled}$ and the respective severity factor (SF) that characterizes the health burden of a death in $DALYs/death$. We estimated all-cause age-adjusted EF at location *w* for marginal or average slope *s* (EF_w^s) as follows:

$$EF_w^s = \sum_{e,k} fr_{k,region_w} \cdot ERF_{w,e,k}^s \cdot SF_{e,k,region_w} \qquad (Eq.\ 4.3)$$

where $ERF^{s}_{w,e,k}$ is the ERF calculated using slope s at location w for health outcome e and age group k in $death/kg_{PM2.5,inhaled}$, $SF_{e,k,region_w}$ is the SF for health outcome e and age group k at the *region* of location w in $DALYs/death$, and $fr_{k,region_w}$ is the fraction of the population in age group k at the *region* of location w. We calculated $fr_{k,region_w}$ using population estimates by age for U.S., Canada, Mexico, Cuba, and the Bahamas for 2016 from the GBD (Global Burden of Disease Collaborative Network 2017).

4.2.3. Characterization factor

Characterization factors (CFs) quantify the annual cumulative health burden associated with $PM_{2.5}$ exposure due to a unit emission. The cumulative CF for an emission of precursor i in source location j assume an ERF slope s ($CF^{s}_{i,j}$) in $DALYs/kg_{precursor,emitted}$ was calculated as:

$$CF^{s}_{i,j} = \sum_{w} iF_{i,j\to w} \cdot EF^{s}_{w} \qquad (Eq.4.4)$$

where $iF_{i,j\to w}$ is the cumulative iF for $PM_{2.5}$ from precursor i emitted in location j at location w ($kg_{PM2.5,inhaled}/kg_{precursor,emitted}$) and EF^{s}_{w} is the all-cause age-adjusted EF for $PM_{2.5}$ at location w based on ERF slope s ($DALYs/kg_{PM2.5,inhaled}$).

4.2.4. Travel Distance

Determining the spatial extent of the effect of an emission can provide an additional layer of information in characterizing the associated exposure and health burden. (Greco et al. 2007) We developed intake travel distance (ITD_x) and burden travel distance (BTD_x) estimates that represent the radial distance from the source to achieve x fraction of the cumulative iF and cumulative CF, respectively (Greco et al. 2007; Wannaz et al. 2018).

To estimate $ITD_{i,j,x}$ and $BTD_{i,j,x}$ we developed the cumulative radial distribution of $iF_{i,j,}$ and $CF_{i,j}$ using 1 km- width rings that were centered at the location of emission. We used these distributions to determine the percentage of the cumulative $iF_{i,j}$ and $CF_{i,j}$ reached as a function of the distance from the source. We then estimated for each emission location j, the travel distances at which iF reaches fractions of 25%, 50%, and 95% of the cumulative $iF_{i,j}$.

4.2.5. Spatial aggregation by sector

We estimated $iF_{i,j}$, $CF_{i,j}$, $ITD_{i,j,x}$, and $BTD_{i,j,x}$ for 52,411 emission locations i identified as grid cells in the spatial domain of InMAP. However, since the specific location of emissions is often unknown in LCA studies, we aggregated results to derive emission-weighted total, sector-specific national and state-specific estimates for the 48 adjoining U.S. states plus Washington, D.C. (N_{grid}=43,304) using the U.S. EPA 2014 National Emissions Inventory (NEI) (U.S. Environmental Protection Agency 2018). When estimates are aggregated, it is important that the spatial variability of the considered estimates be carried forward as uncertainty.

From the 60 sectors available in the dataset, we first selected four main sectors directly relevant to life cycle inventory emissions, namely: agriculture, fuel combustion, industrial processes, and mobile. We also considered the overall emission (referred to as "all sectors" or "national emission-weighted" in this paper) of primary $PM_{2.5}$, NH_3, SO_2, and NO_x, that also include the remaining of emission sectors associated with dust, fires, miscellaneous, solvent and "other" sectors (N=16), dust and fire being sectors associated with major emission at national level. Since emission estimates in NEI are reported per county and the InMAP resolution is higher than the county level in regions with high population density, we employed two approaches to aggregate $iF_{i,j,}$ and $CF_{i,j}$ from grid cell to counties, each approach related to different sectors. For the fuel combustion, industrial processes, and mobile sectors, we used population count from 2015 (CIESIN 2017) as a proxy for emissions and estimated population-weighted country estimates. For the agricultural sector, land use was a better surrogate for emissions. To determine agriculture-related land use, we used land use and land cover geospatial information from FAO (FAO; Nachtergaele and Petri 2013), adjusting for the level of livestock density (Appendix 3, Table A3.21). For the all-sector estimates, we used the agriculture-related land aggregation approach to calculate county estimates for NH_3 and the population count approach for the rest of the precursors.

4.3. Results

4.3.1. Intake fraction

4.3.1.1. iF spatial variability

Figure 4.10 shows maps of location-specific of $PM_{2.5}$ intake fractions (iFs) in the greater North America region for four precursors: primary $PM_{2.5}$, NH_3, SO_2, and NO_x. The spatial variability of iFs is precursor dependent. For $PM_{2.5}$ and NH_3, emissions close to population centers lead to substantially higher exposure estimates.

Figure 4.11 shows the distribution of iFs by state and nationally by precursors along with their respective emission-weighted sector-specific estimates. Emissions from primary $PM_{2.5}$ and NH_3 result in exposures with the most varying magnitude, with the upper and lower bounds having more than two orders of magnitude difference. The iF estimates for primary $PM_{2.5}$ emissions in the U.S. range from 3.0×10^{-2} to 58.4 ppm whereas for NH_3 emissions from 2.7×10^{-2} to 36.9 ppm. The median state-specific estimates of $iF_{primary\ PM2.5}$ typically range from 0.07 ppm in Montana to 9.1 ppm in New Jersey (Appendix 3, Table A3.28). NH_3 emissions result in similar state-specific median estimates with approximately the same ranking between states.

Exposure estimates in the U.S. from SO_2 (1.4×10^{-2} to 2.7 ppm) and NO_x (3.6×10^{-3} to 1.2 ppm) emissions are of substantially lower magnitude compared to primary $PM_{2.5}$ and NH_3 (Figure 4.11). Estimates for these precursors show a lower spatial variability that is less affected by population centers (Figure 4.10), as exposure occurs further away from the source location (higher travel distances as demonstrated later in Figure 4.14a). The lowest spatial variability is observed for SO_2 emissions for which the majority of iFs fall within one order of magnitude for most states, with median state-specific estimates ranging between 0.05 ppm (Montana) and 1.2 ppm (New Jersey). NO_x emissions result in the lowest exposures, with state-specific median estimates ranging from 0.03 ppm (Maine) up to 3.9 ppm (California). Interestingly, the ranking between states for NO_x and SO_2 differs substantially from $PM_{2.5}$, which is linked to each precursor's dependency on population clusters. The correlation between the fraction of population in urban areas in a state (defined as areas with >386 people/km^2) and median state iF is 0.84 for $PM_{2.5}$, 0.80 for NH_3, and 0.54 for NO_x and SO_2.

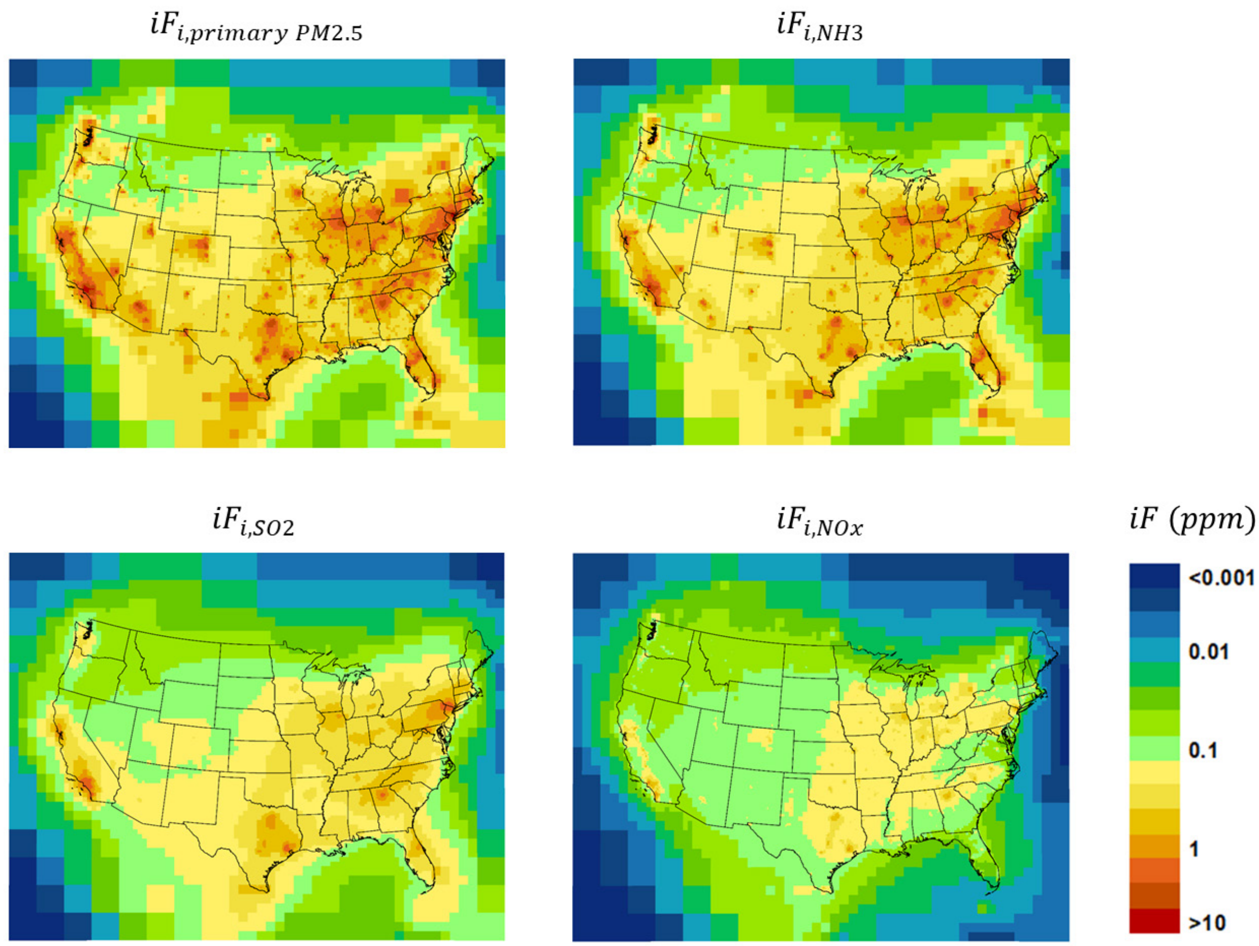


Figure 4.10. $PM_{2.5}$ Intake fraction estimates for ground-level emissions of primary $PM_{2.5}$, NH_3, SO_2, and NO_x in parts per million (ppm, $\mu g_{PM2.5,inhaled}/kg_{precursor,emitted}$). Each point estimate represents the cumulative intake per marginal precursor emission released at the point.

4.3.1.2. Weighted-average and sector-specific iFs

Using annual emission estimates from 2014, we estimate emission-weighted sector-specific iF estimates by state and nationally (Figure 4.11 and Appendix 3, Table A3.22). The national emission-weighted average (all sectors) is 0.8 ppm for primary $PM_{2.5}$, 0.4 ppm for NH_3, 0.3 ppm for SO_2, and 0.1 ppm for NO_x (Appendix 3, Table A3.23). The $PM_{2.5}$ estimate is relatively low due to the inclusion of fire and dust emissions that represent a substantial part of the overall national emissions (fire 33%, dust 16%) and primarily occur in areas with low population density.

For all four pollutants, iFs from four sectors (agriculture, fuel combustion, industrial processes, and mobile) follow a similar spatial variability distribution as the central tendency of estimates in each state. Agriculture-specific estimates are obtained only for primary $PM_{2.5}$ and NH_3 emissions, and estimates for these precursors show sector dependency. For $PM_{2.5}$ emissions, agriculture iFs are substantially lower than estimates for other sectors, representing emissions at rural locations. We observe a factor ~5 difference between agriculture iFs (weighted average of 0.4 ppm, range: 0.07-1.5 ppm) and the mobile-sector iFs (weighted average of 1.8 ppm, range: 0.08-6.1 ppm), the sector with typically the highest estimate in most states. This difference can be negligible (West Virginia) or as high as a factor of 13 (Nevada) depending on the state. For states with substantial fire emissions such as California (19%), Oregon (9%), and Washington (8%), the all-sectors weighted average of $PM_{2.5}$ is substantially lower than the industry and mobile sources by a factor of 3.

For NH_3 emissions, agriculture- and all-sector estimates are similar - ranging between 0.07-2.1 ppm and 0.07-2.3 ppm, respectively - since agriculture emissions make up the majority of total emissions and produce the lowest sector-specific iFs. Compared to agriculture, mobile (weighted-average 1.4 ppm, range: 0.08-4.3 ppm), fuel combustion (weighted average 1.3 ppm, range: 0.08-4.1), and industrial (weighted-average 1.0 ppm, range: 0.09-9.3 ppm) are substantially higher in most states. There is little variability between sectors for SO_2 and NO_x with estimates around 0.3 ppm and 0.1 ppm, respectively.

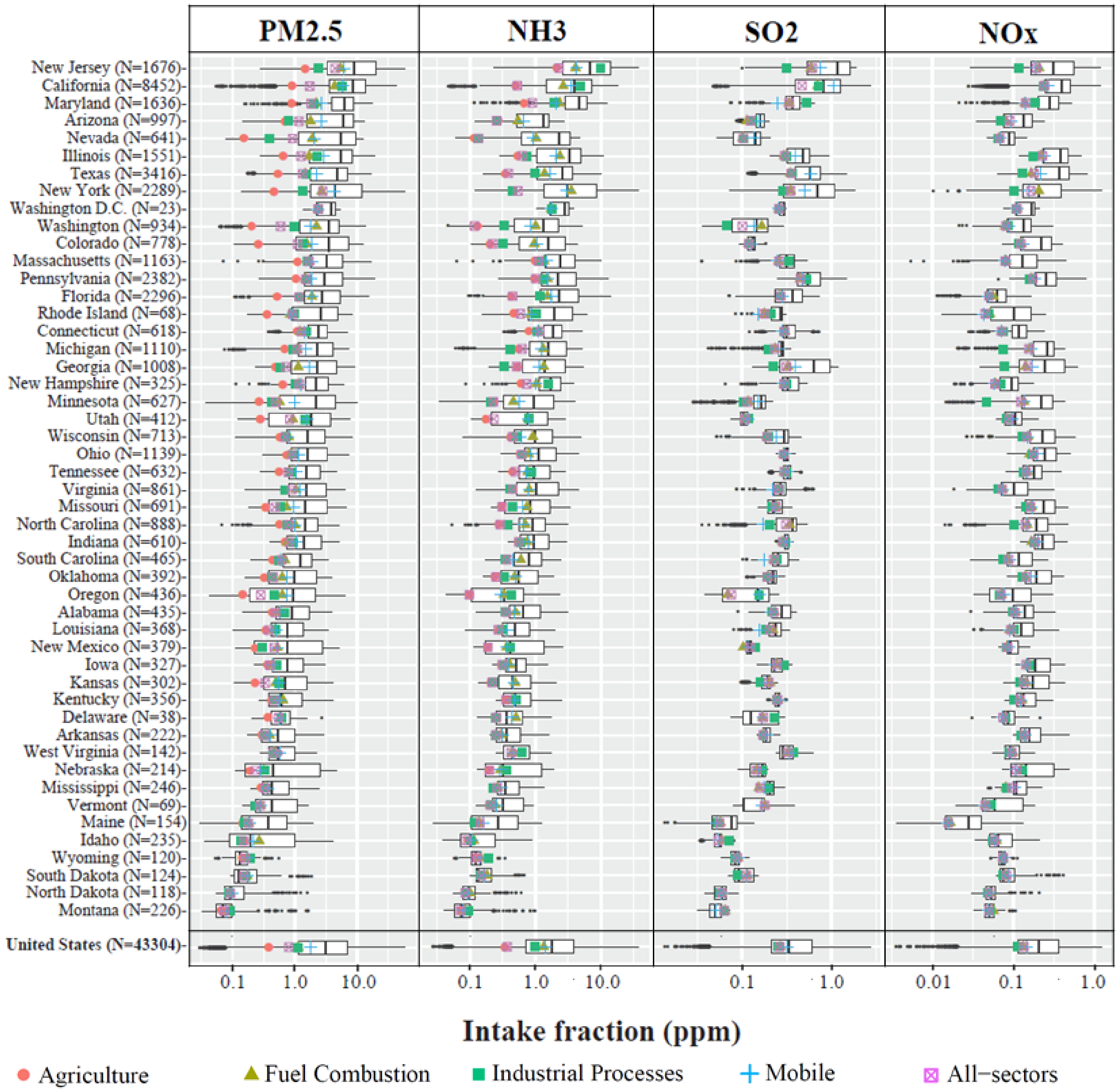


Figure 4.11. Distribution of cumulative $PM_{2.5}$ intake fraction (iF) in parts per million (ppm) from ground level primary $PM_{2.5}$, NH_3, SO_2, and NO_x emission in 43,304 emission locations in the contiguous U.S. Boxes represent the interquartile range (IQR), vertical lines represent the medians, whiskers extend to 1.5 times the IQR, and data points represent outliers. Markers represent the sector-specific emission-weighted iF estimates using annual emission estimates from NEI 2014 from agriculture, fuel combustion, industrial processes, mobile, and all-sectors. States are ranked by decreasing median for primary $PM_{2.5}$ emissions. Data are available in Appendix 3, Table A3.28.

4.3.2. Characterization factors

4.3.2.1. CFs spatial variability

Figure 4.12 maps the spatial variability of the location-specific characterization factors (CFs) for $PM_{2.5}$ from ground level emissions of primary $PM_{2.5}$, NH_3, SO_2, and NO_x in the greater North America region using a 'marginal' and an 'average' exposure-response effect factor (EF). The magnitude of CFs is strongly correlated with the magnitude of iFs with higher CFs estimates for emissions released in urban areas (Appendix 3, Table A3.23), highlighting the influence of population. This correlation is more prominent for primary $PM_{2.5}$ and NH_3. Overall, CFs calculated using the average slope (slope between background $PM_{2.5}$ ambient concentration at the location of emission and theoretical minimum risk level) are about twice as large as the CFs calculated based on the marginal slope at the background $PM_{2.5}$ ambient concentration. This can be explained by the EF estimates (Appendix 3, Figure A3.31). The population-weighted average EF for the spatial domain of our model (North America) is 144 DALYs/$kg_{PM2.5\ inhaled}$ (27-941 DALYs/$kg_{PM2.5\ inhaled}$) for the marginal and 288 DALYs/$kg_{PM2.5\ inhaled}$ (59-941 DALYs/$kg_{PM2.5\ inhaled}$) for the average slope, with the concave shape of the non-linear dose-response leading to higher EFs in regions of low $PM_{2.5}$ concentrations and lower EFs in regions of high $PM_{2.5}$ exposure.

Figure 4.13 summarizes the CFs distribution by state and nationally and illustrates the comparison with the respective distributions of emission-weighted sector-specific estimates. The spatial variability of CFs from both approaches is about three orders of magnitude for primary $PM_{2.5}$, NH_3, and NO_x and two orders of magnitude for SO_2. The variability of $CF^{marginal}$ in the U.S. is 3.5-4,960 μDALYs/$kg_{emitted}$ for primary $PM_{2.5}$, 2.9-3,140 μDALYs/$kg_{emitted}$ for NH_3, 2.2-205 μDALYs/$kg_{emitted}$ for SO_2, and 0.3-1,252 μDALYs/$kg_{emitted}$ for NO_x. Background ambient $PM_{2.5}$ concentrations that influence the value of EFs inherently influence CFs but the correlation is moderate, more evident in marginal than in average CFs. For $CFs^{average}$ the influence of population on iFs is partly compensated by higher $EF^{average}$ estimates associated with lower background $PM_{2.5}$ ambient concentrations for which the effect is regional rather than local.

For primary and NH_3 emissions, there is substantial variability of the central tendency of state-specific CFs, primarily reflecting differences in population density. The median state-specific $CF^{marginal}$ spans from 14.7 (North Dakota) to 911 (Arizona) μDALYs/$kg_{emitted}$ for primary $PM_{2.5}$ and 13.6 (North Dakota) to 564 (New Jersey) μDALYs/$kg_{emitted}$ for NH_3 (Appendix 3, Table A3.29). In some cases, the effect of high iFs is further enhanced by higher EFs associated with lower background $PM_{2.5}$ ambient concentrations (e.g., CFs from primary $PM_{2.5}$ in Arizona which ranks among the highest CFs). Within state variability of CFs ranges from about a factor 10 in states with lower CFs such as Wyoming and South Dakota, up to more than two orders of magnitude in states with diverse population density throughout the state, such as New York. These trends are similar but twice higher for $CF^{average}$ estimates.

On the contrary, the two exposure-response slopes produce different state-specific estimates for SO_2 and NO_x. For SO_2, the state-specific median CFs range from 8.5 (North Dakota) to 90.3 (Georgia) $\mu DALYs/kg_{emitted}$ for the marginal slope whereas for the average slope CFs vary between 15.6 (Montana) and 197.5 (New Jersey). NO_x emissions result in about half the marginal burden of SO_2 but follow similar trends. The within state variability for both SO_2 and NO_x emissions is relatively narrow, except for densely populated states on the northeast coast.

4.3.2.2. Weighted average and sector-specific CFs

The emission-weighted average (all-sector) for an emission in the contiguous of U.S. for the marginal (average) CF is 103 (209) $\mu DALYs/kg_{emitted}$ for primary $PM_{2.5}$, 48.4 (99.1) $\mu DALYs/kg_{emitted}$ for NH_3, 36.3 (75.2) $\mu DALYs/kg_{emitted}$ for SO_2, and 18.5 (38.0) $\mu DALYs/kg_{emitted}$ for NO_x. Sector-specific estimates are available in Appendix 3, Table A3.24. The emission-weighted sector-specific CF estimates by state (Figure 4.13, also see Appendix 3, Tables A3.29-A3.30) follow similar trends with the central tendencies of each precursor for both marginal and average estimates. While SO_2 and NO_x show negligible differences between sectors in most states, for $PM_{2.5}$ and NH_3 agriculture CFs are typically lower by a factor of 2 compared to the sector with the highest CFs, for both marginal and average slopes.

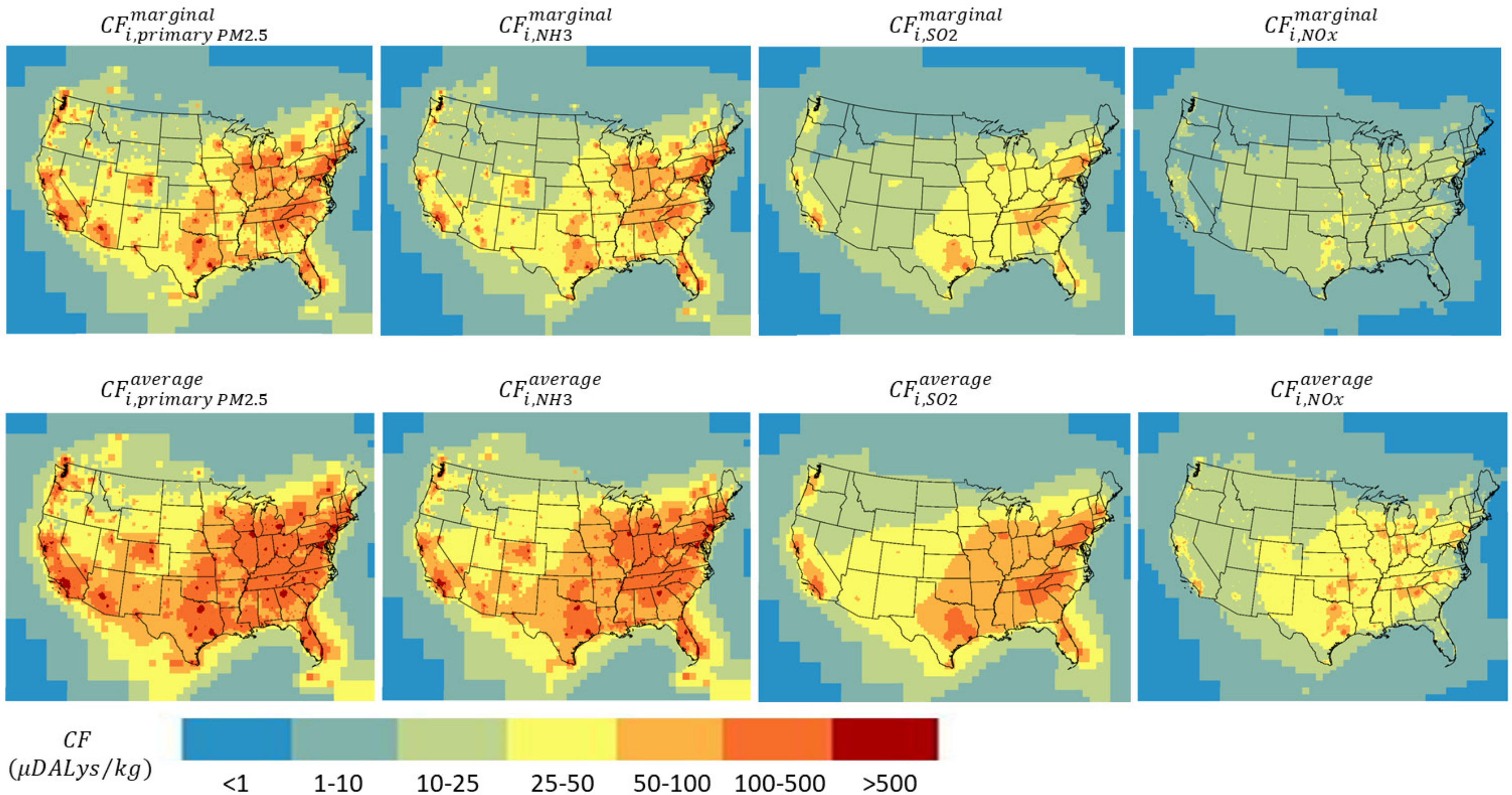
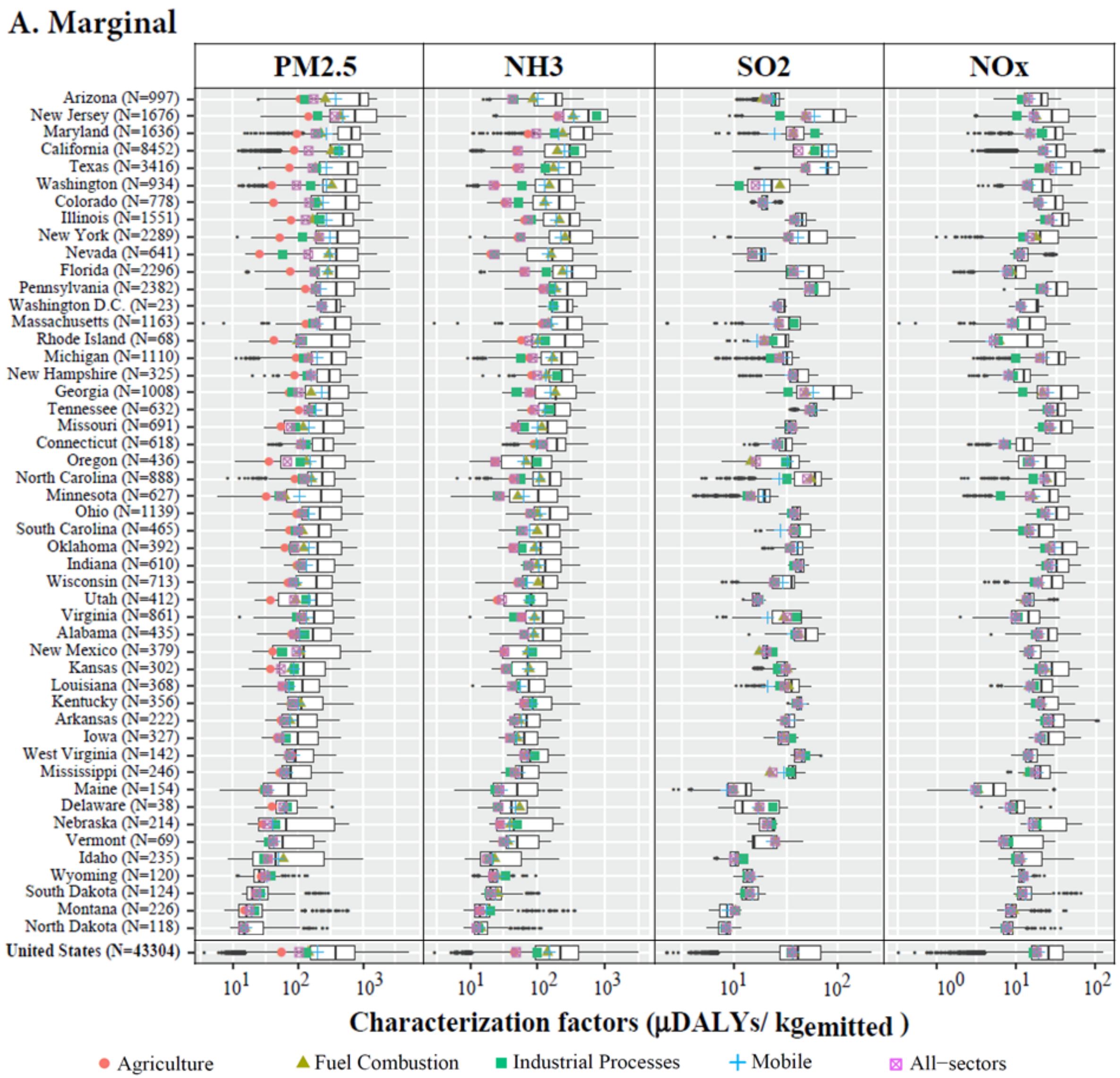


Figure 4.12. Characterization factors (CF) for $PM_{2.5}$ from ground-level emissions of primary $PM_{2.5}$, NH_3, SO_2, and NO_x in $\mu DALYs/kg_{precursor,emitted}$ for two types of exposure-response slope approaches: 'marginal' and 'average'. Each point estimate represents the cumulative health burden per marginal precursor emission released at the point.


A. Marginal
PM2.5
NH3
SO2
NOx
Arizona (N=997)
New Jersey (N=1676)
Maryland (N=1636)
California (N=8452)
Texas (N=3416)
Washington (N=934)
Colorado (N=778)
Illinois (N=1551)
New York (N=2289)
Nevada (N=641)
Florida (N=2296)
Pennsylvania (N=2382)
Washington D.C. (N=23)
Massachusetts (N=1163)
Rhode Island (N=68)
Michigan (N=1110)
New Hampshire (N=325)
Georgia (N=1008)
Tennessee (N=632)
Missouri (N=691)
Connecticut (N=618)
Oregon (N=436)
North Carolina (N=888)
Minnesota (N=627)
Ohio (N=1139)
South Carolina (N=465)
Oklahoma (N=392)
Indiana (N=610)
Wisconsin (N=713)
Utah (N=412)
Virginia (N=861)
Alabama (N=435)
New Mexico (N=379)
Kansas (N=302)
Louisiana (N=368)
Kentucky (N=356)
Arkansas (N=222)
Iowa (N=327)
West Virginia (N=142)
Mississippi (N=246)
Maine (N=154)
Delaware (N=38)
Nebraska (N=214)
Vermont (N=69)
Idaho (N=235)
Wyoming (N=120)
South Dakota (N=124)
Montana (N=226)
North Dakota (N=118)
United States (N=43304)
10^1 10^2 10^3
10^1 10^2 10^3
10^1 10^2
10^0 10^1 10^2
Characterization factors (µDALYs/ kgemitted)
Agriculture
Fuel Combustion
Industrial Processes
Mobile
All−sectors

B. Average

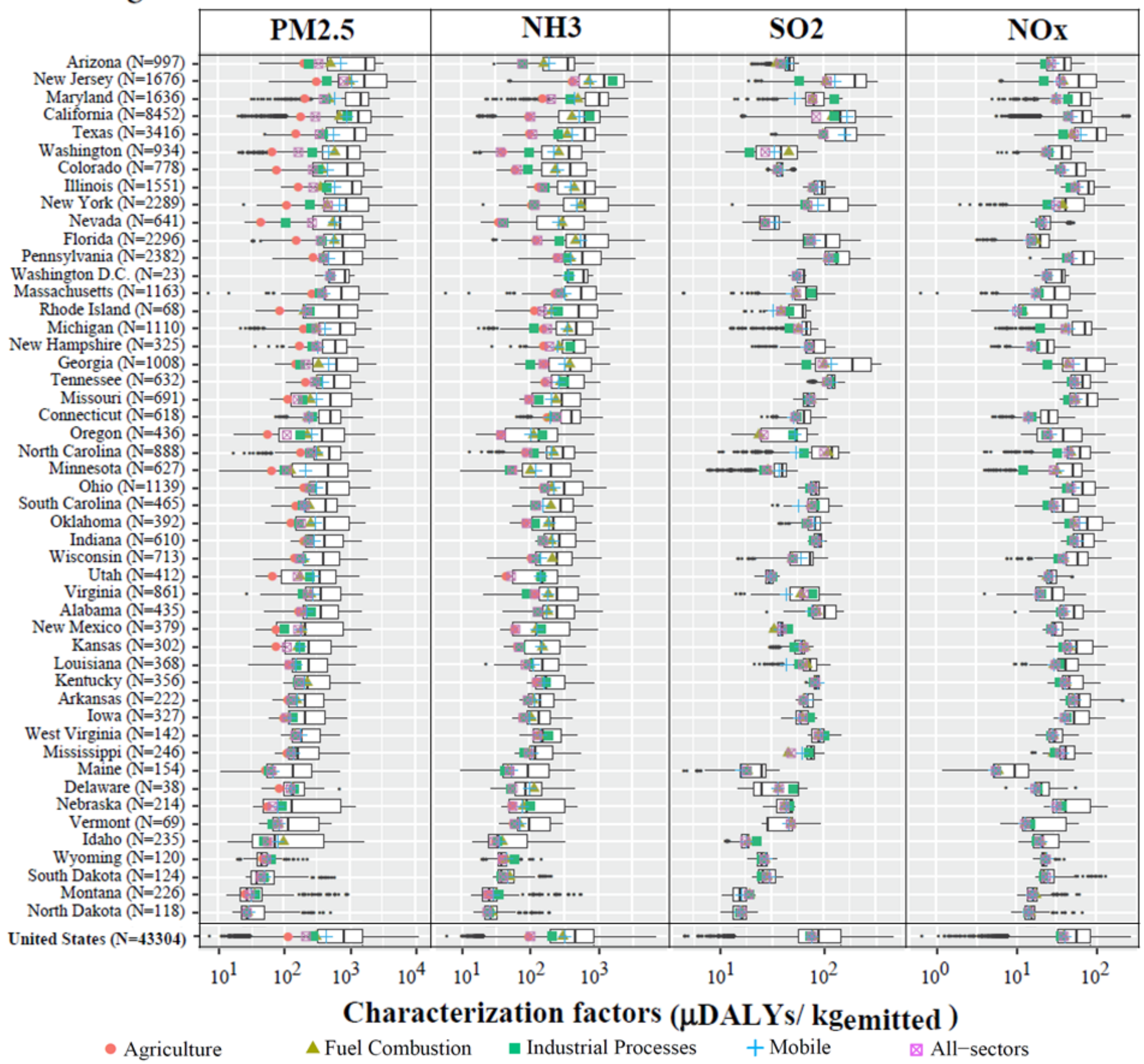


Figure 4.13. Distribution of cumulative $PM_{2.5}$ characterization factors (CF) in µDALYs/$kg_{emitted}$ from ground level primary $PM_{2.5}$, NH_3, SO_2, and NO_x emission in 43,304 emission locations in the contiguous U.S based on (**A**) a marginal slope of a non-linear exposure-response function, and (**B**) an average slope of a non-linear exposure-response function. Boxes represent the interquartile range (IQR), vertical lines represent the medians, whiskers extend to 1.5 times the IQR, and data points represent outliers. Markers represent the sector-specific emission weighted iF estimates using annual emission estimates from NEI 2014 from agriculture, fuel combustion, industrial processes, mobile, and all-sectors. States are ranked by decreasing median for primary $PM_{2.5}$ emissions. Data are summarized in Appendix 3, Tables A3.29-A3.30.

4.3.3. Spatial extent of exposure and burden

The spatial extent of exposure and burden is quantified by the intake travel distance (ITDx) and burden travel distance (BTDx), respectively. We investigate the radial distance from the source required to reach 25%, 50%, and 95% of the cumulative exposure and burden for all precursors. Figure 4.14 summarizes the distribution of ITD estimates for rural and urban sources separately, using the rural and urban classification from the U.S. Census 2010 (U.S. Census Bureau 2015) (urban areas must have a population density of at least 386 people per km^2). For emissions released in areas with high population density, the majority of exposure and consequently burden is in short distance from the source, often within a few km except for SO_2 emissions. In particular, 50% of the cumulative exposure and burden from urban emissions is achieved within a median of 5 km from the source for primary $PM_{2.5}$ and NH_3, whereas for NO_x (~10 km) and SO_2 (~20 km) the travel distance is longer. The longer travel distance of SO_2 is primarily linked with the time required to covert the gas into sulfates (secondary $PM_{2.5}$) that allows the exposure (and burden) to affect populations living downwind from the emission origin. Meeting 50% of exposure and burden from emissions in rural areas requires substantially longer travel distances, with median ranges between about 10 km for primary $PM_{2.5}$ and NH_3 and 180 km for SO_2. Our results support that secondary $PM_{2.5}$ have a longer spatial extent than primary $PM_{2.5}$ and have the ability to affect populations as far as 3,000 km downwind from the source, signifying that secondary $PM_{2.5}$ can induce health impacts at continental levels. The spatial variability of travel distances are mapped in Figures A3.32 and A4.33, respectively, in Appendix 3, confirming the short travel distances for highly urbanized areas. BTDs follow similar trends.

The emission-weighted average of ITDx and BTDx by sectors for the contiguous of the U.S. are summarized in Tables A3.22 and A3.24 in Appendix 3. Overall, the travel distance for burden is slightly shorter than the travel distance for exposure, with very similar marginal and average BTDs. However, the difference between ITDs and BTDs increases at higher fractions of cumulative exposure and burden. The spatial extent to meet 50% of all-sector emissions is ~150 km for primary $PM_{2.5}$, against ~300 km for secondary $PM_{2.5}$. The spatial extent of agriculture emissions is significantly larger compared to the other sectors (rural emissions), with half of the effect occurring within 300 km for primary $PM_{2.5}$ and 400 km for NH_3. In all sectors, NO_x has the longest emission-weighted spatial extent with the distance to meet 95% of the cumulative exposure and burden estimated at approximately 1,500 km from the sources.

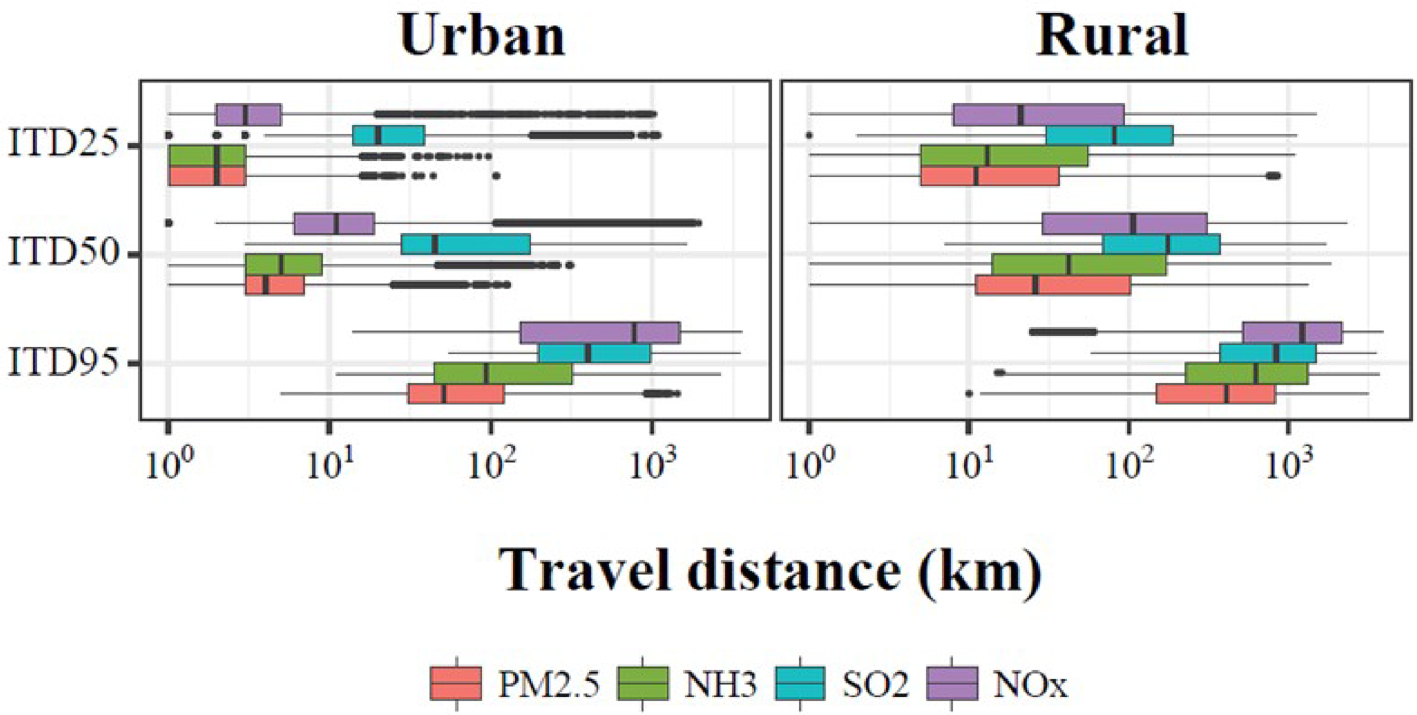


Figure 4.14. 25%, 50%, and 95% intake (ITD) for urban and rural ground level emissions of primary $PM_{2.5}$, NH_3, SO_2, and NO_x in the contiguous U.S. ITDx represents the radial distance from the source to meet x% of the cumulative iF. Boxes represent the interquartile range (IQR), vertical lines represent the medians, whiskers extend to 1.5 times the IQR, and data points represent outliers. The data of this figure is summarized in Tables A3.25 (Rural) and A3.26 (Urban) in Appendix 3.

4.4. Discussion

Using source-receptor matrices based on a reduced-form CTM, we were able to investigate the magnitude of marginal exposure (intake factions) associated with $PM_{2.5}$ from ground level emissions of primary $PM_{2.5}$, NH_3, SO_2, and NO_x in more than 43,000 locations of the contiguous U.S., including transboundary impacts that occur beyond the U.S. border. For each source location, we integrated location-specific iFs with marginal and average EF estimates based on a non-linear exposure-response function to derive characterization factors. The high resolution in urban locations of the underlying model, InMAP, and its large spatial domain covering the greater North America region allowed us to explore the spatial distribution of the impacts associated with these emissions. In addition, were able to track the long-range transport of air pollution, and calculate intake and burden travel distance in order to characterize the spatial extent of emissions. Our analysis resulted in iFs, CFs, ITDs, and BTDs with large heterogeneity, with the values across source locations having three to four orders of magnitude difference that was primarily associated with the population density near the source. This highlights the need for high-resolution spatially explicit estimates when evaluating $PM_{2.5}$-related human health impacts in LCA. However, since the specific source location is often unknown in LCA, U.S. state-specific averages or emission-weighted sector-specific estimates offer interesting alternatives as long as the uncertainty related to the spatial variability is carried forward.

We find that across all sources in the U.S., there is considerable spatial variability between iF estimates that is precursor-specific ranging from 0.03-58.4 ppm for primary $PM_{2.5}$, 0.03-36.9 ppm for NH_3, 0.01-2.7 for SO_2, and 0.004-1.2 ppm for NO_x. Table 4.2 compares our archetype-specific and national estimates for the U.S. with those from the literature. Our archetype estimates fall in the range of other studies and show comparable trends for most substance-archetype combinations. However, the magnitude of estimates between archetypes and pollutants can show differences that are primarily linked with underlying assumptions and air pollution model used in each study. For urban areas, our estimates fall within a factor 2 from previous estimates for all precursors expect for the $PM_{2.5}$ estimate from Humbert et al. (2011), which is a factor 7 higher than ours, and NOx for which our estimate is 26 times lower than Lamancusa et al. (2017) and 5-fold lower than Greco et al. (2007). For rural emissions, our estimates are consistently lower than others; our median estimates of $PM_{2.5}$ (0.6 ppm) and NO_x (0.1 ppm) are five times lower than Humbert et al. (2011) and Lamancusa et al. (2017), respectively. In contrast, for the remote archetype, we report estimates that are substantially higher (between a factor 3 for SO_2 and 9 for NO_x) compared to Humbert et al. (2011) and similar to Lamancusa et al. (2017) for all precursors but NO_x for which we observe a 6-fold difference. The difference in the iF definition could explain the higher estimates by Lamancusa et al. (2017); here we only consider the particulate sulfates and nitrates, respectively, while in Lamancusa et al. (2017) iF estimates consider not only sulfates and nitrates $PM_{2.5}$ but also the intake of the precursor themselves and other degradation products. In addition, we model annual iFs whereas in their study iFs are calculated by season which better captures the influence of temperature and relative humidity in the formation mechanism of nitrates (Dassios and Pandis 1999; Fountoukis and Nenes 2007). Our national emission-weighted estimates were also comparable with those reported in other studies. In particular, emission-weighted national estimates from van Zelm et al. (2016) and Greco et al. (2007) are similar to ours for all precursors, except for NO_x for which we estimate iF values 2-3 times higher. Our population-weighted national estimates fall within the range of estimates from other studies, but are substantially higher than the emission-weighted estimates.

As expected, we found that the magnitude of exposure was directly related to the proximity of densely populated areas for $PM_{2.5}$ and NH_3. NO_x and SO_2 are the least influenced by populations since it takes longer to partition from gas to solid phase and therefore exposure affects population living downwind rather than close to a source. This was supported by the ITD estimates that clearly illustrate a considerable difference in the spatial extent of emissions in urban and rural areas and a longer travel distance for secondary $PM_{2.5}$. We estimate that for urban ground level emissions, the majority of exposure occurs within a radial distance of 20 km from the source for all precursors, which is comparable with previous estimates, (Lamancusa et al. 2017) while for rural emissions the spatial extent is an order of magnitude higher. However, this trend is not observed for SO_2 that shows minor differences in the spatial extent between the two source archetypes. Furthermore, the spatial extent of SO_2 is considerably longer compared to other precursors, especially for urban emissions. While typically the majority of exposure occurs close to the source, our results also indicate that the exposure extent can be continental with exposure reaching populations livings as far as 2,000-3,000 km away from the source for some sources, with SO_2 having on average the longest extend. This finding was also shown in the work by Greco et al. (2007).

Table 4.2. Comparison of intake fraction in parts per million (ppm) by archetype from selected studies to the present study

Study		*Archetype* [a]			*National*		
		Urban	**Rural**	**Remote**	**Population-weighted**	**Emission-weighted**	**Mobile emission-weighted**
Humbert et al. (2011)	$PM_{2.5}$ [b]	39.53	3.41	0.09	22.46		
	NH_3	1.53	1.53	0.09	1.53		
	SO_2	0.89	0.71	0.04	0.80		
	NO_X	0.18	0.15	0.01	0.16		
Lamancusa et al. (2017) [c]	$PM_{2.5}$	6.69	0.86	0.65	2.95		
	NH_3	3.30	0.21	0.17	1.04		
	SO_2	2.57	0.52	0.35	1.38		
	NO_X	7.95	0.61	0.50	2.85		
Van Zelm et al. (2016) [d]	$PM_{2.5}$					1.42	
	NH_3					0.47	
	SO_2					0.16	
	NO_X					0.04	
Greco et al. (2007) [e]	$PM_{2.5}$	5.72	1.05			0.70	1.46
	NH_3	0.99	0.30			0.24	0.39
	SO_2	0.06	0.13			0.04	0.07
Present study [f]	$PM_{2.5}$	5.61	0.61	0.57	4.70	0.80	1.81
	NH_3	3.04	0.44	0.35	2.75	0.37	1.43
	SO_2	1.24	0.24	0.15	0.44	0.27	0.32
	NO_X	0.31	0.12	0.08	0.24	0.13	0.14

[a] Archetypes defined according to Humbert et al. (2011) classification: Urban (>386 people/km^2), Rural (1<x<100 people/km^2), Remote (<1 people/km^2)
[b] Reflect ground level emissions
[c] Represent the median of a total of 25 source locations and archetype classification considered in the study
[d] Represent national estimates
[e] Represent the median of county-level estimates for mobile sources and archetype classification considered in the study
[f] Archetype-specific estimates reflect median estimates
* All estimates have been adjusted for a breathing rate of 11.68 m3/d for comparability with the present study

To estimate CFs, we followed recent recommendations for LCIA and combined iFs with EFs based on the non-linear integrated exposure-response function by Cohen et al. (2017) and compatible health burden estimates from the GBD to estimate the marginal change in health burden associated with $PM_{2.5}$ (Jolliet et al. 2018). This non-linear exposure-response depends on the background $PM_{2.5}$ ambient levels and has been used widely in estimating the health burden associated with ambient $PM_{2.5}$ exposure (Lelieveld et al. 2015; Forouzanfar et al. 2015; Gakidou et al. 2017). Our location-specific CF estimates illustrate considerable spatial variability on the magnitude of CFs between U.S. sources, with average slope-based estimates being about two times higher than marginal slope-based estimates due to differences of the corresponding EFs. In particular, the marginal CFs ranged between 3.5-4,960 µDALYs/$kg_{emitted}$ for primary $PM_{2.5}$, 2.9-3,140 µDALYs/$kg_{emitted}$ for NH_3, 2.2-205 µDALYs/$kg_{emitted}$ for SO_2, and 0.3-125 µDALYs/$kg_{emitted}$ for NO_x. Estimates follow a similar spatial distribution and spatial extent with iFs.

This is the first study to reporting location-specific CFs for the U.S. Hence, we can only compare our emission-weighted national estimates with estimates reported in the literature (Figure 4.15). Unlike our study which uses spatially differentiated non-linear exposure-response factors, previous studies estimated CFs using on a linear exposure-response from a single study (Krewski et al. 2009). Since previous studies only report population-weighted estimates (using population as a proxy for emissions), we report both population-weighted and all-sector emission-weighted national estimates. Our population-weighted $CF^{marginal}$ estimates ($PM_{2.5}$: 469 µDALYs/$kg_{emitted}$; NH_3: 276 µDALYs/$kg_{emitted}$; SO_2: 48.6 µDALYs/$kg_{emitted}$; and NO_x: 28.6 µDALYs/$kg_{emitted}$) are comparable with the estimates reported by van Zelm et al. (2016), although the study only used severity factors that reflected only disease burden from premature mortality (years of life lost) instead of disease burden from morbidity and premature mortality (DALYs). Compared to Gronlund et al. (2015), marginal CFs are also comparable, except from primary $PM_{2.5}$ for which the authors report an estimate almost four times higher than ours that can be explained by the higher underlying iF used from Humbert et al. (2011). We also observe up to a factor four differences in secondary $PM_{2.5}$ estimates compared to both studies. These differences cannot be fully explained by the underlying differences of iFs and are associated with differences in EFs. Although EFs between the three studies are similar on a national level (Fantke et al. 2018), the use of location-specific estimates based on a non-linear exposure-response at different background $PM_{2.5}$ levels explains the minor precursor-specific differences observed. Our $CF^{average}$ estimates are a factor of 1.2 to 8 higher than estimates from both studies, except for the $PM_{2.5}$ estimate by Gronlund et al. (2015).

We also estimate emission-weighted CF estimates that are substantially lower than population-weighted estimates reported in previous studies regardless of approach (marginal/average). This finding suggests that using population as a proxy for emissions might not be appropriate, particularly in countries were dust and fire emissions can be substantial. This also stresses the importance of using sector-specific estimates corresponding to the considered processes rather than global averages in LCA. Therefore, it is recommended to use emission-weighted estimates when available. In Table A3.27, Appendix 3, we also summarize the comparison of archetype-specific CFs between Gronlund et al. (2015) and the present study.

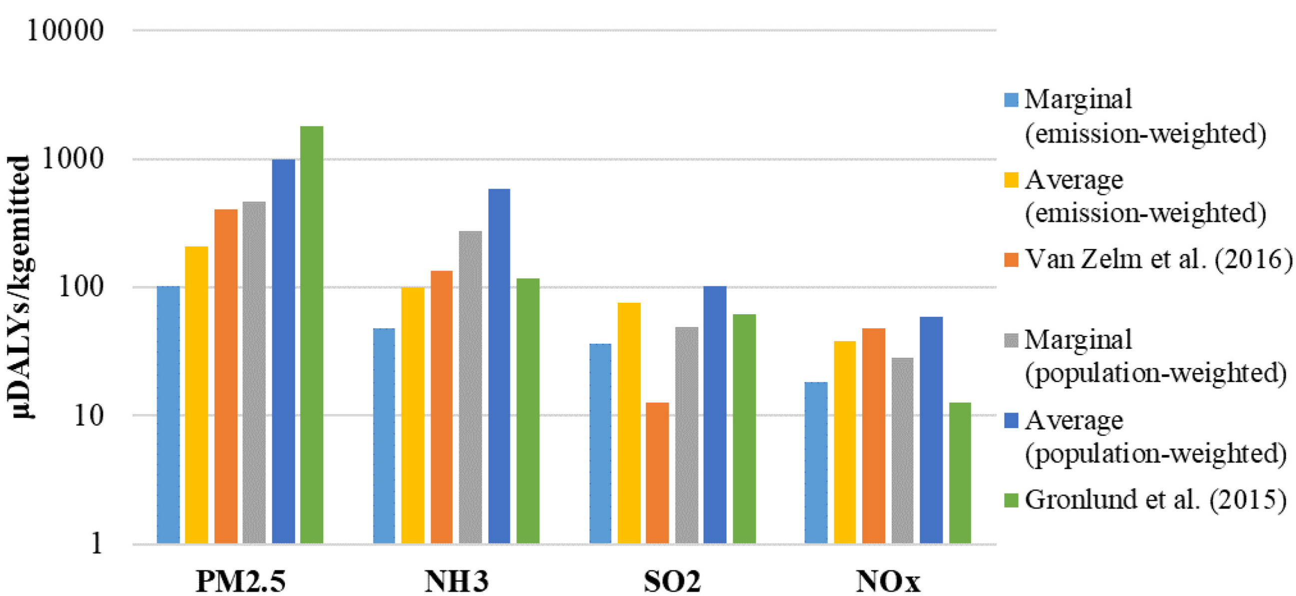


Figure 4.15. Comparison of national characterization factor in $\mu DALYs/kg_{emitted}$ for the U.S. from selected studies to the present study. Estimates have been adjusted for a breathing rate of 11.68 m^3/d for comparability with the present study.

Our analysis and results depend on a number of assumptions and limitations. For exposure estimates were calculated using the ISRM and the underlying air pollution model, InMAP. The model is a reduced-complexity CTM with high spatial resolution in urban areas and a great spatial domain that allows tracking long-range air pollution. As a reduced-form CTM, InMAP relies on chemistry and transportation simplifications. Tessum et al. (2017) showed that InMAP under-predicts primary $PM_{2.5}$ at fine resolution grids, which means that the corresponding exposure estimates in urban settings in our analysis might be underestimated. More recently, Paolella et al. (2018) evaluated the performance of InMAP at different spatial resolutions and showed good predictability for SO_2 at fine resolution (Paolella et al. 2018). The model estimates marginal annual changes in $PM_{2.5}$ concentrations from precursor emissions. This might be a limitation for our study since temporal resolution is important for secondary $PM_{2.5}$. In addition to the limitations associated with exposure estimates, there are additional limitations associated with burden. First, we assume that particles from different precursors have equal toxicity. Second, the non-linear exposure-response curve is associated with high uncertainty that currently does not account for model uncertainty. Third, estimates are dependent on the shape of the exposure-response curve which relies on evidence synthesis and at low concentrations is driven by the $PM_{2.5}$ minimum risk level that is itself uncertain. Furthermore, since the curve is non-linear, there is additional uncertainty associated with the slope of the curve at the level of exposure in locations of interest. Estimates based on a marginal slope are the least robust as the slope is very steep for low exposure levels (in some cases reaching infinity) and relatively low for high exposure levels. Temporal resolution limitations might can also affect the burden estimates of this work since local background concentrations used to determine the working point on the exposure-response curve might change with time, especially for forest fire emissions. Finally, we limited our analysis to ground level emissions, primarily since we were interested in developing iFs and CFs for NH_3 that is primarily release at ground level through agricultural processes. However, our approach could be extended to other the other emissions heights available in InMAP, combining them with the stack height information on point sources available in the NEI since 2011.

4.5. Conclusion

In this study, we propose comprehensive and consistent intake fraction and characterization factor estimates for primary and secondary inorganic $PM_{2.5}$ for the U.S. based on spatially explicit estimates of ground-level precursor emissions. Using a reduced-form air pollution model with high resolution in urban settings, we are able to improve from previous studies and characterize exposure more accurately for a large number of source locations as well as sector-specific archetypes. Since the spatial domain of the model covers the greater North America region, our estimates capture the health damage that occurs within the U.S. and in adjoined countries. Following recommendations to characterize the health burden associated with $PM_{2.5}$ exposure in LCIA using a non-linear exposure-response function and burden estimates from the GBD, we implement an integrated approach and estimate location-specific CFs taking into considerations the background ambient $PM_{2.5}$ concentrations and background state-specific mortality at the receptor location.

Our analysis highlights the importance of spatial estimates in LCA, as both iF and CF estimates may vary by three orders of magnitude between sources that cover the contiguous U.S. The magnitude of exposure and consequently health damage is associated with the proximity of emission source to population centers, with urban emissions resulting in considerably higher estimates. For secondary $PM_{2.5}$ population density is not as an important determinant of exposure and burden as in primary $PM_{2.5}$, and in particular for NO_x and SO_2 emissions. This finding was further supported by the characterization of the spatial extent of emissions, which provides an additional layer of information in regards to the exposure and health burden associated with emissions. We find that the majority the effect of emissions can span from ~20 km (urban $PM_{2.5}$ emissions) up to 3,000 km (rural SO_2 emissions). In general, NO_x and SO_2 share the longest spatial extent.

We aggregate the results of our analysis and report emission-weighted state-specific and national estimates for the U.S. In addition, we report for the first time iF and CF estimates for four distinct sectors (agriculture, fuel combustion, industrial processes, and mobile). These estimates can be used in LCA studies to quantify the health burden associated with primary $PM_{2.5}$, NH_3, SO_2, and NO_x emissions.

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CHAPTER 5

Bridging the gap between environmental and nutritional sciences towards more sustainable foods: A case study on pizza

Abstract

Food systems are complex and pose several challenges for assessing food sustainability and their impacts and benefits on human health. Three major challenges in assessing the effects of food on human health are the lack of nutritional health impact consideration in methods such as Life Cycle Assessment, inconsistencies in the environmental assessment of mixed dishes, the lack of data comparing environmental and nutritional health impacts of foods. Here we address these issues by developing an approach to evaluate and compare nutritional and harmonized environmental impacts on health from pizzas in the U.S. diet. First, we developed the DALY Nutritional Index (DANI), an epidemiology-based nutritional index covering 16 dietary risks for major food groups and nutrients, serving as a new life cycle nutritional impact category in LCA. DANI was used to quantify the health burden associated with different pizza types in disability adjusted life years (DALYs). Second, we determined the Standard Reference (SR) as a decomposition methodology to harmonize the environmental impacts of mixed dishes after evaluating the performance of four difference approaches. Using SR, we quantified the global warming and particulate matter impacts for different pizza types using Impact World+ and U.S. spatially- and sector-explicit characterizations factors for $PM_{2.5}$, respectively. Third, we compared human health damages from nutritional and environmental impacts using the Combined Nutritional and Environmental LCA framework for all pizzas in the National Health and Nutrition Examination Survey. We found that nutritional impacts dominate the health performance of pizzas, with the most nutritional healthy options typically being the environmentally friendliest. Our analysis showed great variability in health damages for all impact categories, with nutritional impacts dominating with estimates one to two orders of magnitude higher than environmental estimates. Health impacts ranged between -1.6 and 28.5 µDALYs/serving pizza for nutrition, 0.20-0.88 for global warming, and 0.04-0.24 for particulate matter. We found a significant positive

correlation between environmental and nutritional health impacts for pizzas, with the highest damages associated with red meat pizzas and the lowest with vegetable pizzas. This case study supports that nutrition can dominate health damages and should be considered as in impact category in LCA. This approach can be used as a benchmark for a comprehensive assessment of all food items and mixed dishes in LCA and help to inform sustainable dietary food choices and substitutions.

5.1. Introduction

Food systems are undergoing drastic transformations. Population growth and economic growth have increased food demand that poses risks to food security (FAO 2017). At the same time, convenience, price, and increased accessibility to processed and manufactured foods have contributed to radical increases of empty calories and less healthy food (Popkin et al. 2012; Stuckler et al. 2012; Rao et al. 2013; Gakidou et al. 2017). Furthermore, increased environmental emissions result in environmental changes and especially climate change that threaten food systems (FAO 2017), while at the same time compromising the nutrient profiles of foods (Myers et al. 2016). All these challenges threaten the sustainability of food systems contributing to an urgent need to understand and quantify the tradeoffs between environmental and nutritional impacts of food systems (Tilman and Clark 2014).

Life cycle assessment (LCA) is a methodology that enables the evaluation of the environmental impacts associated with a product, process, or service throughout its entire life cycle, from cradle to grave, in reference to a function (International Standard Organization 2006). For close to 40 years, LCA has been used to study food systems and evaluate the environmental performance of foods and diets (Nemecek et al. 2016), within a food sustainability assessment context. Granting significant progress in food sustainability assessment and food LCA (Roy et al. 2009), several challenges still remain to be addressed in relation to the evaluation of foods and diets (Castellani et al. 2017). A fundamental limitation, particularly in food LCA, is that nutritional health effects from the "use stage" of food systems are often neglected or unsatisfactorily addressed when evaluating their environmental performance (Stylianou et al. 2016a). This is of particular importance for human health damages, as dietary risks are the leading cause of premature death and disease morbidity, contributing to more than 10 million disability adjusted life years (DALYs) per year globally (Institute for Health Metrics and Evaluation (IHME) 2018). The need to address this limitation is evident in a recent movement in LCA that promotes the consideration of benefits within human health impact assessments in LCA (Arvidsson et al. 2016; Schaubroeck and Rugani 2017), emphasizing the need for a new impact category to assess the nutritional life cycle impact of food items on human health.

An additional challenge for both food sustainability assessments and LCA is the limited availability of necessary environmental data to evaluate mixed dishes. Mixed dishes are defined as a mixture of components with varying proportions (multi-ingredient). Mixed dishes currently comprise a large fraction of modern diets. Environmental information, such as life cycle inventories (LCIs) in LCA that quantify the inputs and outputs of a given product system throughout its life cycle (International Standard Organization 2006) are primarily available for main individual agricultural commodities. This has led practitioners to not only understudy mixed dishes but possibly underestimate their impacts in the limited number of studies available in the literature due to a variety of simplifications (Davis and Sonesson 2008; Pernollet et al. 2017). In addition, mixed dishes evaluation studies rely on different decomposition methods causing incomparable and possibly inconsistent results that highlight the need to harmonize the environmental evaluation of mixed dishes.

Using a case study on pizza in the U.S. diet, this work aims to address these limitations and evaluate the environmental impacts of foods with multiple ingredients by: 1) Establishing a new nutritional life cycle impact category, including both inventory flows per functional unit and health burden-based nutritional characterization factors ($CF_{Nutrition}$). 2) Quantifying and comparing the nutritional health burden associated with main types of pizzas in the U.S. diet. 3) Evaluating the potential use of four decomposition methods in LCA to determine a systematic approach to decompose mixed dishes into individual components for which environmental life cycle inventories are available. 4) Assessing the cradle-to-gate environmental impacts from global warming and particulate matter associated with main types of pizzas in the U.S. diet. 5) Analyzing the magnitude and potential correlations of nutritional and environmental health damages between all pizzas in the U.S diet.

To achieve these goals, we first use the Healthy Nutritional Index (HENI) developed in Chapter 3 to determine the DALY Nutritional Index (DANI) as a new nutritional impact category in LCA. DANI evaluates the nutritional health benefits and damages of foods in a marginal context in DALYs per functional unit using a health-based approach based on 16 dietary risks (9 main food groups and 7 nutrients). Then we explore the potential of four publically available databases as methods to deconstruct mixed dishes. In particular, we evaluate their environmental performance in reconstructing the daily consumption of pizzas in the U.S. diet and their applicability within an LCA framework. Based on the results of these analyses, we use the most appropriate method to evaluate first the nutritional and then the environmental impacts of different pizza types in the U.S. diet as reported in the National Health and Nutrition Examination Survey (NHANES) database. Finally, we employ the Combined Nutritional and Environmental LCA framework (CONE-LCA) from Chapter 2 to compare environmental human health damages from global warming and particulate matter with nutritional human health effects associated with pizzas in a common metric, DALYs.

5.2. Material and methods

5.2.1. Pizza in the U.S. diet

We determined the U.S. consumption of various pizzas types using the What We Eat in America/National Health and Nutrition Examination Survey (WWEIA/NHANES) 2007-2014 database (National Center for Health Statistics 2018). This is a nationally representative, cross-sectional survey administered every two years to U.S. citizens. For determining the population average of the daily pizza consumption, we combined data for the various survey cycles (2005-2008) for participants older than 19 years old, excluding pregnant women.

To identify all the pizza types that could possibly be consumed in the U.S. diet, we searched the database for foodcodes with the description that included the word "pizza," and excluded pizzas with multiple entries in the database. In addition, we excluded foodcodes described as "pizza toppings" as they represented individual ingredients and we considered that a comparison with these items would be unfair. We also eliminated entries identified as "calzones" and "rolls." The final 78 identified pizzas were classified into six main categories ("Red Meat pizza", "Vegetable pizza", "Cheese pizza", "Chicken pizza", "Seafood pizzas", and "Other pizza") based on their main components (Appendix 4, Table A4.31).

5.2.2. Life cycle assessment framework

We implemented the Combined Nutritional and Environmental Life Cycle Assessment (CONE-LCA) framework to compares the environmental and nutritional effects of foods on human health (Stylianou et al. 2016a). The functional unit (FU) for this work is defined as the reference amounts customarily consumed (RACC) serving sizes that have been established by the U.S. Food and Drug Administration (FDA) (U.S. Food and Drug Administration 2017). For all pizzas, RACC is defined at 140 g. The system boundaries for the life cycle assessments were cradle to farm or processing facility gate and did not include impacts from packaging.

5.2.3. Nutritional assessment

We adapted the HENI developed in chapter 3 to the LCIA framework and produced the

DALY Nutritional Index (DANI) as a new nutritional impact category in LCA. DANI quantifies the marginal health burden from all-cause premature mortality and disease morbidity associated with food items for U.S. adult age 25+ years, expressed in disability adjusted life years (DALYs) per functional unit. DANI evaluates the nutritional performance of foods based on 15 dietary risks identified by the Global Burden of Disease (GBD) plus saturated fatty acids (Stylianou et al. 2018a). The dietary risks include nine main food groups (milk, nuts and seeds, processed meat, red meat, sugar-sweetened beverages, vegetables, legumes, fruits, and whole grains) and six nutrients (calcium, fiber, seafood omega-3 fatty acids, sodium, trans fatty acids, and polyunsaturated fatty acids).

The DANI for food i is calculated in DALYs/FU as the sum of products of the inventory flows of the 16 dietary risk components in the food, e.g., the risk factor components per functional unit ($d_{i,risk\ component}$ in $kg_{risk\ component}$/FU), and the corresponding nutritional characterization factors, defined as dietary risk factors ($CF_{Nutrition,risk\ component}$ in DALY/$kg_{risk\ component}$):

$$DANI_i = \sum_{risk\ component} CF_{Nutrition,risk\ component} \cdot d_{i,risk\ component} \qquad \textit{(Eq. 5.1)}$$

$CF_{Nutrition}$ are based on epidemiological evidence from 6,195 risk-outcome-age group-gender-burden stratum and U.S.-specific burden rates obtained from the GBD (Gakidou et al. 2017; Institute for Health Metrics and Evaluations 2018). The methodology followed to develop these CFs is described in Stylianou et al. (2018a), and estimates are available in Appendix 4, Table A4.32.

The nutritional inventory flows of the 16 dietary risk components are determined in a multistep approach through a combination of multiple publically available databases. First, foods are identified from the WWEIA/NHANES database. To determine inventory flows for food groups we adapt estimates reported in food group serving-eq/100 g food from the Food Patterns Equivalents Database (FPED) and obtain estimates of food group kg/FU (Bowman et al. 2013). Adaptations include both conversions from serving equivalents to masses and customization of food groups to align definitions between FPED and the GBD. This process is informed by the Standard Reference (SR) database that details the ingredients of foods by relative weight (SR28 2016). The inventory flows of nutrients are estimated as the sum of products of ingredients in foods as identified by the SR and the nutritional profile of SR ingredients reported in the Food and

Nutrient Database for Dietary Studies (FNDDS) (USDA 2014). The inventory flow for trans fat, as it was incomplete in FNDDS for the majority of ingredients, was imputed at the food level using regression models. The transfat regression model and the full methodology to determine the inventory flows for this work is as described by Fulgoni et al. (2018).

5.2.4. Environmental assessment

5.2.4.1. Decomposition methods

To evaluate the environmental impacts of foods with multiple ingredients, we first need to establish a consistent method to decompose (or deconstruct) mixed dishes in order to identify their composition and quantify the amounts of each individual food components (in kg) that can then be related to available LCI unit processes. This is a different and more detailed breakdown of foods into components compared to the nutritional assessment; for nutrition, the breakdown is related to the health effect associated with components (e.g., dietary risks) which is at a higher level, for example, the nutritional health benefits of a kg of strawberries is equal to that of a kg of apples. However, environmental impacts can differ substantially between ingredients (e.g., global warming impacts from one kg strawberries in the U.S. are three times higher than the impacts of one kg of apples produced in the U.S.). In addition, impacts are influenced by production systems (e.g., there is a 5- to 10-fold difference in the global warming impacts of strawberry produced in open fields compared to those produced in green houses). Hence, there is a need for a high-level disaggregation of mixed dishes to components from an environmental perspective in order to capture these differences.

Recently, a few studies have evaluated diet-level environmental impacts and have used two different approaches to decompose diets. Heller et al. (2018) used the Food Commodity Intake Database (FCID) to estimate environmental impacts of dietary patterns reported in NHANES. Conrad et al. (2018) used the same database to investigate diet-level nutritional and environmental trade-offs associated with food losses. Finally, Tichenor Blackstone et al. (2018) used the Food Intakes Converted to Retail Commodities Database (FICRCD) to quantify environmental impacts associated with different dietary patterns recommended in U.S. dietary guidelines. However, these databases have never been used to evaluate environmental impacts associated with individual foods. Therefore, using the U.S. population average of daily pizza consumption reported in g/d by the WWEIA/NHANES 2005-2008 based on 57 pizzas reported as consumed, we evaluate the potential of these methods along with methods used in the nutritional assessment, namely FPED and SR, as decomposition approaches. Descriptions of the four methods are available in Table 5.3.

We based our evaluation on the following criteria:

a) Ability to determine component quantity expressed in mass/FU
b) Ability to reconstitute the total daily intake of pizza from NHANES
c) Resolution that enables a disaggregation into components that identify the appropriate environmental dataset accurately (e.g., type of meat or dairy product)
d) Applicability and frequency of updates that follow the NHANES cycles

5.2.4.2. Environmental life cycle inventory

All components identified by the four decomposition methods have been linked with environmental life cycle inventory (LCI) datasets. LCIs quantify the inputs and outputs of a given product system throughout its life cycle (International Standard Organization 2006). We use these datasets to quantify food-related life cycle environmental emissions (e.g., CO2, CH4, and $PM_{2.5}$).

We employed three databases to maximize the coverage of LCIs in our analysis. Listed in the order of priority, we obtained LCIs from the Ecoinvent v3.2 (Wernet et al. 2016), the World Food LCA Database v3.1 (Nemecek et al. 2015), and the ESU World food LCA database (ESU). If a direct match was not available, we used proxies either by production system similarities or by developing "average" component LCIs that represented the average of the food group that the component belongs to. Since we are investigating environmental impacts of foods in the U.S. diet, we assume that all ingredients used in pizzas are produced in the U.S., so we link them with US-specific LCIs, when available. Otherwise, global LCIs are selected that represent the market-weighted average of LCIs for the specific ingredient.

Since retail levels are more consistent to be connected with life cycle inventories than consumption amounts (as they partially account for supply chain food losses), and the FICRCD method only allows for a decomposition at the retail level, we applied consumption-to-retail conversion factors reported in the database to all deconstruction methods for comparability.

5.2.4.3. Environmental life cycle impact assessment

We estimated environmental impacts using Impact World+ v1.4 (Bulle et al., 2018) at the midpoint and endpoint level. Midpoint impacts quantify changes in the natural environmental whereas endpoint impacts quantify damages on ecosystems, human health, and resource use. Human health damages from short-term global warming were calculated using the work by De

Schryver (2009). Human health damages from particulate matter were tabulated separately by multiplying inventory data for primary $PM_{2.5}$, NH_3, NO_x, and SO_2 emissions with spatially-explicit characterization factors (CFs) for the U.S. from Stylianou et al. (2018b). For primary $PM_{2.5}$ and NH_3 we used agriculture-specific national CFs and for NO_x, and SO_2 we used the emission-weighted national CFs (Appendix 4, Table A4.34). CFs have been estimated using a marginal slope from the non-linear exposure-response function by Cohen et al. (2017).

5.3. Results

5.3.1. Nutritional assessment of pizzas

5.3.1.1. Nutritional Decomposition by risk factors

Table A4.32, in Appendix 4, provides a summary of the nutritional profiles per serving pizza (e.g., the $d_{i,risk\ component}$) for seven select pizza types in the U.S. diet with distinct composition. From the 16 dietary risks in our approach, only seven are present in all pizza types in varying amounts and additional four were identified within specific pizza types. The amounts of the seven dietary exposures varied by as much as a factor of 8 depending on the type of pizza: calcium (0.02-0.4 g/serving), transfat (0.3-0.7 g/serving), sodium (0.35-0.91 g/serving), saturated fats (1.2-10 g/serving), total fiber (2-3 g/serving), polyunsaturated fatty acids (1.9-3.9 g/serving), and vegetables (33-54 g/serving). For example, the composition (in g/serving) of a 'pizza with extra meat' consisted of vegetables (33.6), processed meat (14.4), saturated fats (10), red meat (3.5), polyunsaturated fats (3.9), fibers (total: 2.0), sodium (0.9), transfat (0.7), and calcium (0.3). In comparison, for the 'pizza with extra vegetables', the composition for beneficial dietary risks increased between 6% (calcium) and 60% (vegetables), except for polyunsaturated fats, while the amount of detrimental dietary risks reduced up to a factor 2 (transfat) in addition to no meat. However, meaningful comparisons of pizzas needs to account for the health effect of dietary risks, e.g., using DANI scores.

5.3.1.2. Nutritional impact of pizzas

Figure 5.16 presents the nutritional performance of the select pizza types with distinct composition, differentiating the contribution of each DANI dietary risk component. In all seven pizza types investigated here, we found contributions from both detrimental and beneficial dietary risk components (negative impact). However, in most pizzas health damages exceed benefits leading to net positive and therefore health-damaging DANI scores (Figure 5.16 – diamonds).

Interestingly, the damage score of sodium in most pizzas (except those without cheese) was nearly constant at around ~9 μDALY/serving pizza. A similar trend was observed for saturated fats. Polyunsaturated fatty acids (2.1 avoided μDALY/serving pizza), total fiber (1.8 avoided μDALY/serving pizza), and calcium (1.5 avoided μDALY/serving pizza) also showed relative uniform contributions to the health benefits of pizzas.

The highest nutritional health damage was estimated for "pizza with extra meat" with a DANI score of 27.2 μDALY/serving pizza. The dietary exposures that contributed the most to damages were processed meat (56%), sodium (39%), and saturated fats (26%). Reducing the amount of processed meat improved the nutritional health performance of pizzas as lower net DANI scores indicate that the food is better for human health. Compared to the "pizza with extra meat", meatless pizzas had lower DANI scores by at least a factor 4 (e.g. "pizza with extra cheese") for which damages were associated with the detrimental health effects of sodium and saturated fats primarily from cheese, and only partly compensated by the health benefit from calcium. DANI scores further reduce as the quantity of vegetables and legumes increases with the beneficial health effect associated with these ingredients compensating for the detrimental impacts of cheese. The "pizza with beans and vegetables" produced an almost neutral score of 0.5 μDALY/serving pizza. A better score was estimated for cheeseless pizzas (0.04 avoided μDALY/serving pizza) with the detrimental effects of sodium halved and negligible damages associated with saturated fats compared to other pizza types. Finally, the presence of fruits on a pizza results in the best DANI score at 0.7 *avoided* μDALY/serving pizza (indicating health benefit) due to the substantial beneficial health effects of fruits.

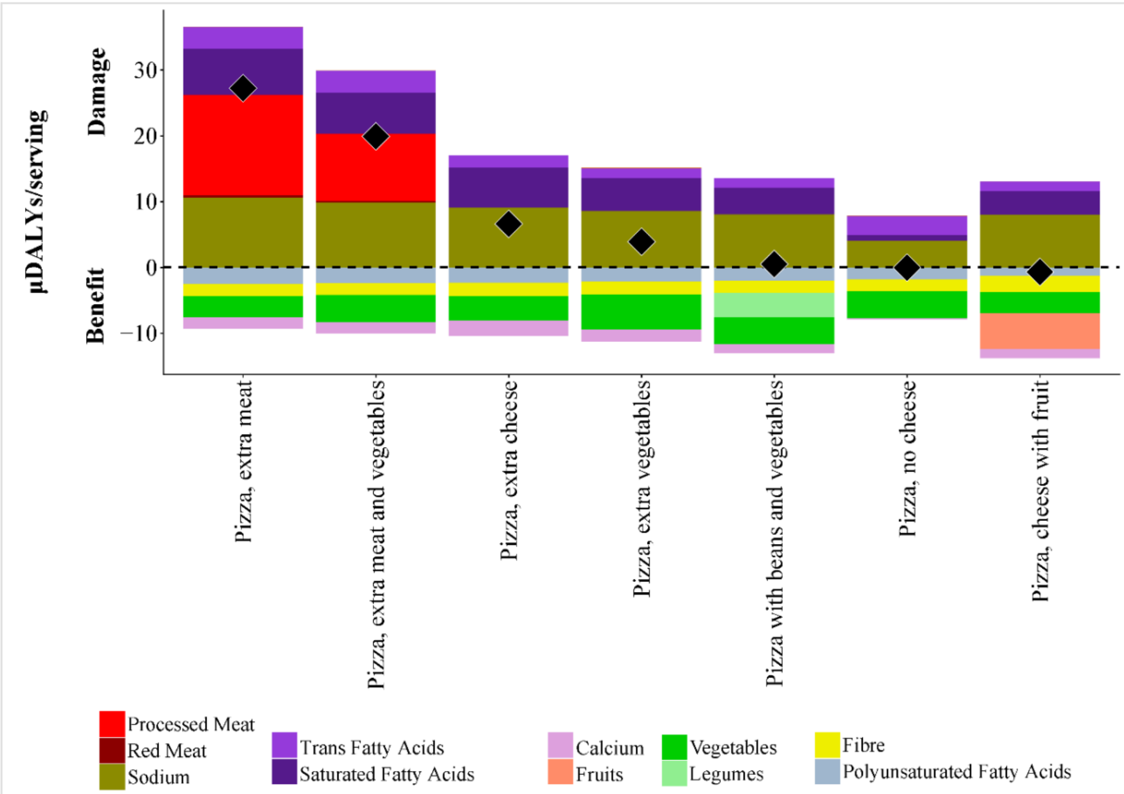

Figure 5.16. Dietary risk contribution to DANI scores measured in µDALY/serving for select pizza types. The black diamond represents the DANI score. The dotted line represents the neutral health effect score (DANI=0).

5.3.2. Environmental assessment of pizzas

5.3.2.1. Decomposition approach evaluation

<u>a) Environmental decomposition</u>

57 pizza items have been reported to be consumed in the WWEIA/NHANES 2005-2008. On average, the daily consumption of pizza in the U.S. diet of adults is estimated at 31.4 g/d that amounts to 4.2% of the total energy intake (Appendix 4, Table A4.35). There is a large discrepancy in the number of components identified by each decomposition method. With the FPED, the 57 pizzas were decomposed into 14 food categories, with FICRCD into 20 commodities, with FCID into 61 components, and with SR into 47 ingredients.

Figure 5.17 illustrates the repartition and total of intake and retail amounts (accounting for FICRCD loss factors for all methods) obtained by each decomposition method. An accurate decomposition should obtain an intake equal to the total intake of 31.4 g/d reported by NHANES. The highest disaggregation is offered by the SR that is the food composition database in NHANES and directly reports quantities for each component in g. Therefore, SR perfectly matches NHANES (estimates intake 31.4 g/d) and can constitute a reference to compare the reconstruction of daily pizza intake from other approaches. The most recent version of SR have introduced multi-ingredient components that can be challenging as LCIs are typically single-ingredient foods. The way we addressed this limitation was by referencing multi-ingredients items in the SR with single ingredient items from previous versions of the database, a process that when implemented for all multi-ingredient components of SR can be meticulous and time-consuming. However, due to similarities of multi-ingredient items that could nearly be classified into several food groups, we can use proxies to address this limitation.

The FPED method estimated a pizza intake of 41.0 g/day, overestimating it by 30%. This difference was attributable primarily to twice higher estimates of grains and, to a lesser extent, four times higher estimates of fats. As FPED repartitions foods in food equivalents, differences are possibly due to the approach we used to convert serving equivalents to masses (Appendix 4, Table A4.33), which is one of the requirements for a decomposition method. It should also be mentioned that unlike SR, FPED does not contain water as a decomposition component that explains the difference observed in ingredients categorized as 'other.'

FCID slightly underestimated intake (30.8 g/d); however, this approach produced a substantially different repartition compared to SR. Compared to the SR, FCID overestimated oils in pizzas by a factor of seven, dominated by the estimate of soybean oil, and grains by 35%. At the same time, this approach underestimated meats by 33% and water that falls under the 'other' category by a factor of 3.5. Although FCID reports water as a component, estimates represent indirect sources of water such as ingredient moisture. Interestingly, this approach offers a less than ideal decomposition of dairy products as it was intended to capture pesticide residue that is linked to fat content in ingredients. Hence, dairy products are decomposed into 'Milk, fat', 'Milk, nonfat solids', and 'Milk, water'. This decomposition does not enable the identification of the dairy product used in a mixed dish, especially when multiple dairy products are used.

Finally, FICRCD estimated the retail level of daily pizzas intake at 45.8 g/d and could not provide an intake estimate. This estimate was ~20% higher than the corresponding retail-level estimate of SR, derived using consumption-to-retail factors from FICRCD. In addition, this approach yielded a considerably different repartition compared to SR. More specifically, FICRCD overestimated oils by a factor 4, sugars by a factor 2, dairy by 70%, vegetables by 40%, and grains by 20%. Similar to the other decomposition approaches, FICRCD does not characterize well the water in foods and in fact does not cover any beverages beyond fruits juices and milk. Although from an environmental perspective, water is not anticipated to have substantial contributions, when evaluating decomposition methods on a mass basis, lack of water that is typically used in larger amounts, might hide overestimated quantities of other ingredients.

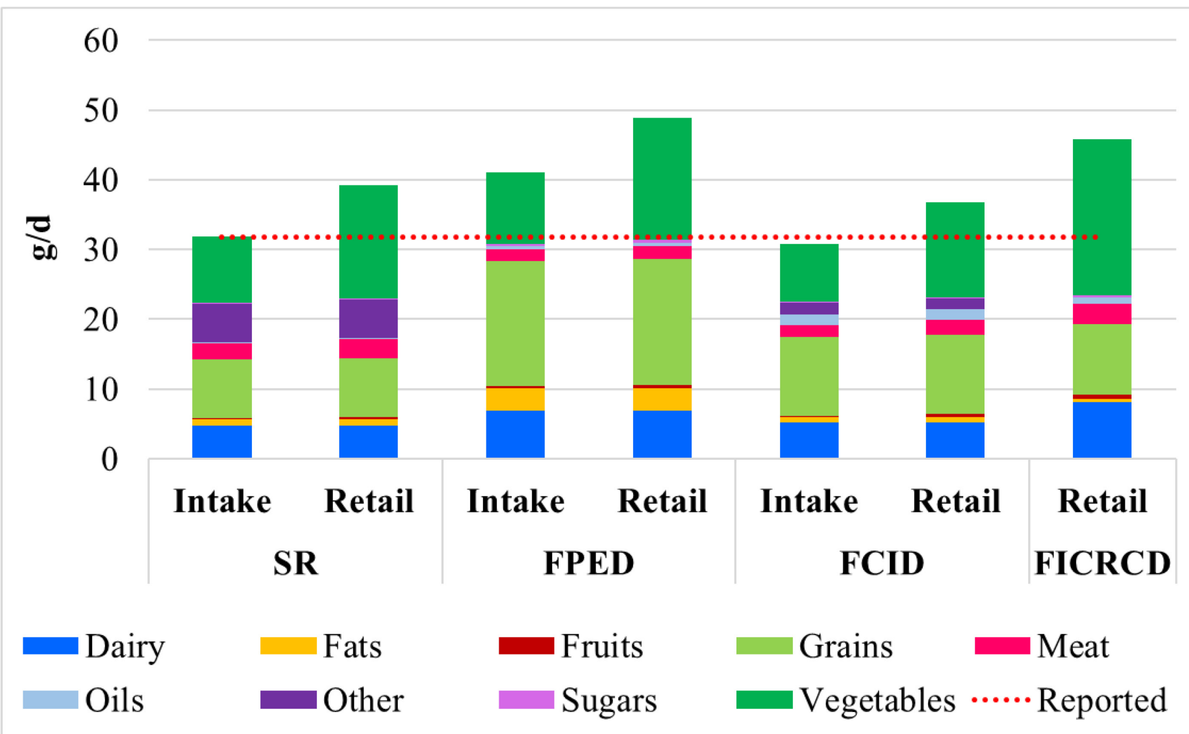

Figure 5.17. Reconstruction of daily pizza intake reported by WWEIA/NHANES 2005-2008 by deconstruction method in consumed (intake) and retail amounts. Retail estimates were obtained by applying conversions factors available in the FICRCD database and capture mass lost or gained during preparation, cooking, and other processing, as well as mass losses from non-edible parts of foods. Components have been aggregated to main food group categories as described in Tables A4.36-A9, in Appendix 4.

b) Environmental impacts of pizzas

Figure 5.18 presents the midpoint global warming scores associated with the retail-level amounts of daily pizza consumption from each deconstruction method. The method produced varying estimates that span from 47.8 g CO2 eq/d for SR (which is our reference) up to 117.4 g CO2 eq/d for FICRCD, showing that the decomposition method really matters and can strongly influence results. According to the SR, dairy - in particular cheese - was responsible for nearly 40% of greenhouse gas emissions (GHG), followed by meat with a 30% contribution. Adjusting for the retail amounts associated with each approach, we produced the first estimate of the carbon footprint of one kg of pizza. The highest estimate was derived with the FICRCD approach at 2.2 kg CO2 eq/kg_{pizza} that was almost twice higher than the lowest from SR at 1.2 kg CO2 eq/kg_{pizza}.

FPED generated a GHG estimate 50% higher than SR at 71.9 g CO2 eq/d (retail level) and substantially different relative and absolute contributions for some components. More specifically, this approach resulted in relative contributions of dairy to total impacts (36%) similar to those of SR. However, in absolute values dairy components produced 50% higher impacts in FPED than in SR. The method identified substantial impact contributions from grains (20%), vegetables (17%), and at lower degree meat (14%). Compared to SR, the absolute contributions of these components differed by a factor of 2-3. The overestimation of fats with FPED from the decomposition was further enhanced in the environmental assessment with GHG associated with fats in FPED being seven times higher than in SR. Adding to the decomposition limitations discussed, FPED is also limited in its ability to link decomposed components to LCIs. The approach covers mainly food groups and has a low resolution that required aggregation of LCIs into 'average components' that might over- (e.g., vegetables) or under-estimate (e.g., meat) the impacts associated with certain components (Appendix 4, Table A4.40).

Using FCID, the midpoint global warming of the average daily pizza at the retail level was 80.4 g CO2 eq/d. Almost half of the impact (44%) was attributable to meat and in particular beef (32%). Although compared to SR this approach was in relative agreement with the quantity of meat in the average pizza (Figure 5.17), environmental impacts are 2.5 times higher for FCID. This is associated with the resolution differences between the two approaches for meats (as well as other products, e.g., dairy). While for FCID we were able to identify the different meet types in pizza (e.g., pork and beef), in SR meat ingredients were more descriptive which allowed us to match them with more representative LCIs. For example, the beef identified in the SR was "ground beef, 75% lean, 25 fat" for which we developed a new LCI that reflects this composition (Appendix 4, Table A4.40). Compared to the beef LCI used in FCID, the new LCI resulted in 15% lower impacts per kg; when combined with composition information this difference in LCIs resulted in a 4-fold difference with the estimate from FCID being the highest. The same was observed for pork; SR identifies the pork content primarily in the form of sausage for which an LCI is available and results in a carbon footprint three times lower than the pork LCI used in FCID. Discrepancies were also observed for oils due to decomposition differences. Finally, although we mentioned that dairy product decomposition is limited with FCID, in our case we assumed that all dairy FCID components represent cheese. However, such an assumption would not be possible if we were investigating multi-ingredient foods that contain different types of dairy such as pasta, pastries, and desserts.

Finally, the FICRCD approach provided the highest estimate of midpoint global warming impacts at 117.4 g CO2 eq/d, more than twice higher than SR. This was driven by an almost 4-fold overestimation the impacts from meat and vegetable. For meat, the difference was due to the underlying meat types quantities in each approach; sausages that are a mixture of beef and pork make up 83% of the meat in SR, whereas in FICRCD 64% of the meat is beef, with the LCIs matched with these two components generating carbon footprint estimates that differ by a factor 7. The difference between impacts from vegetables was due to a 2-part difference in disaggregating tomatoes between the two approaches. First, in the decomposition of pizza at the retail level, the mass of tomatoes in FICRCD was twice higher than in SR. Second, in SR we were able to identify distinct tomato products (e.g., fresh, pure, canned) for which LCIs were available. In contrast, FICRCD does not allow for such resolution, and hence we used an 'average tomato' LCI, estimated as the mean of all LCIs identified as tomato products, that was more than three times higher than any of the LCIs used in SR.

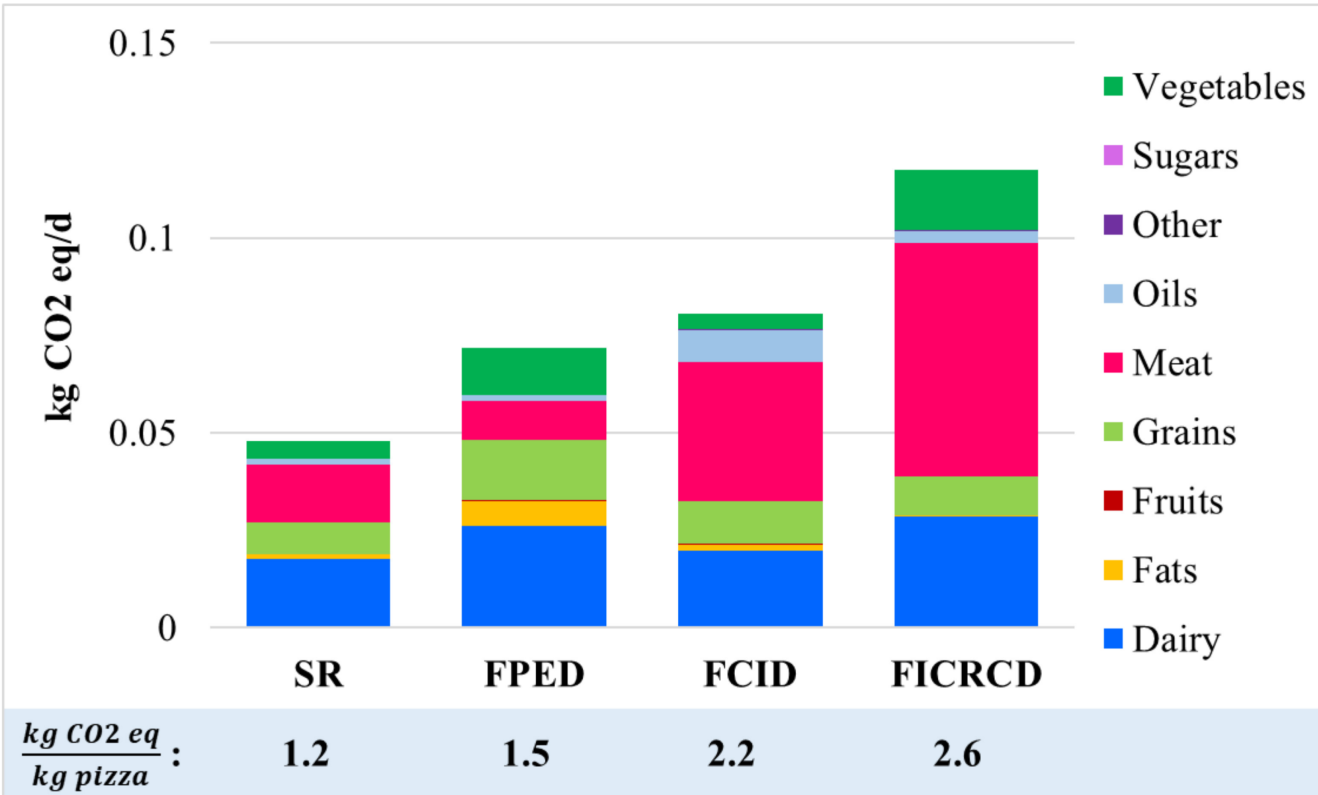

Figure 5.18. Carbon footprint associated with daily pizza consumption at the retail level by deconstruction method. Detailed information on the underlying environmental LCIs used for each approach is available in Appendix 4, Tables A4.36-A4.40.

c) Overall evaluation

Table 5.3 summarizes the overall performance of the four decomposition methods evaluated in this work as decomposition methods for mixed dishes. The different approaches differ by scope and resolution, but all suffer from limitations linked to their ability to accurately repartition mixed dishes into components in mass that align well with environmental information. Several limitations have already been discussed for each approach. However, additional attributes of each approach need to be considered for a comprehensive and fair comparison. For example, while the SR and FPED databases are being frequently updated and reflect updated in the WWEIA/NHANES cycles, the FCID and FICRCD databases have not been updated for nearly 10 years. This limits their ability to capture changes in the food composition over time properly (e.g., the same foodcode in NHANES can have different meat content between cycles) and fails to provide information on newly introduced foods.

The recommended approaches to be used in evaluating mixed dishes is the SR. This approach showed the best performance according to the criteria of this evaluation. It can provide exact masses of components, capture the variability of environmental information very well, and is consistent with the nutritional decomposition. The limitation of SR in relation to multi-ingredient components can be addressed using either foodcode proxies or reference previous SR versions. The FPED can be used as a systematic check mechanism of these proxies as the two databases work in conjunction. In addition, attributes from the FICRCD (retail-to-intake losses) and FCID (cooking processes), can complement the SR when the system boundary of LCAs is cradle-to-fork.

Table 5.3. Evaluation summary of the potential of four database as decomposition methods for mixed dishes in LCA

Description & criteria	***Standard Reference (SR)*** *(SR28 2016)*	***Food Patterns Equivalents Database (FPED)*** *(Bowman et al. 2013)*	***Food Commodity Intake Database (FCID)*** *(U.S. EPA 2018)*	***Food Intakes Converted to Retail Commodities Database (FICRCD)*** *(USDA 2017).*
Description	SR is the core composition databases in WWEIA/NHANES. It reports the relative weight of ingredients per food. Contains ~ 8,000 ingredients, excluding baby food and formulas (~40% reported consumed)	FPED reports the pattern of foods in WWEIA/NHANES using 37 components measured in serving equivalents defined as standardized portion units that may vary by food type (e.g. milk in cup equivalents and meat in ounce equivalents).	The FCID was developed to assess dietary exposure to pesticides. The database converts consumed amounts of food in WWEIA/NHANES into over 500 commodities	FICRCD links consumed amounts of foods in WWEIA/NHANES with 65 retail-level commodities, accounting for masses lost or gained during preparation, cooking, other processing, and non-edible parts of foods
Accuracy in amount compared to NHNAES	Excellent Reports exact components in mass	Low Requires conversion of serving equivalents into masses that differ by food type Overestimation of grains and fats Water content missing	Good Reports of components in mass Overestimation of oils and grains Water content only from moisture	Moderate Reports retail-level commodities Overestimation of sugars, dairy, grains, meats, and vegetables Water content missing
Disaggregation level and match with environmental data	Very high resolution Detailed component description allows for best possible match with LCIs Problem with multi-ingredient components Possibility to decompose multi-ingredient components based on past version of SR or equivalent components from FPED	Low resolution Requires aggregation of LCIs for most components	High resolution but related to pesticide exposure (disaggregation of single-ingredient into multiple agricultural commodities to reflect lipophilicity differences) Problem with dairy products and meats	Moderate resolution Requires aggregation of LCIs for certain components
Update frequency	Latest update: 2018 Always reflects updates in NHANES	Latest update: 2017 Always reflects updates in NHANES	Latest updated: 2010 Does not reflect recent cycles of NHANES and cannot be used for newly introduced foods	Latest update: 2008 Does not reflect recent cycles of NHANES and cannot be used for newly introduced foods
Useful attributes	Recommended as backbone decomposition Consistent with nutritional decomposition	Useful to check multi-ingredients components from SR Consistent with nutritional decomposition	Complementary information on cooking processes	Captures retail-to-intake losses that are relevant for LCA

5.3.2.2. Environmental assessment of pizzas

Figure 5.19 presents the midpoint global warming and particulate matter impacts for the seven select pizza types. "Pizza with extra meat" produced the highest impacts in both categories with a serving associated with 0.64 kg CO2 eq and 0.28 g $PM_{2.5}$ eq. Reducing the amount of meat in pizza substantially reduced impacts by a factor of 1.5 for carbon footprint and 1.7 for particulate matter. The absence of meat reduced GHG by at least a factor of 2, with the pizza without cheese generating the lowest estimate of 0.18 kg CO2 eq. For particulate matter, the deduction was more evident, with estimates of all meatless pizzas around 0.07 g $PM_{2.5}$ eq/serving, more than 4 times lower than the extra meat pizza. Ammonia emission had the highest contribution to particulate matter impacts of ~83% for pizzas with meat and ~70% for meatless pizzas.

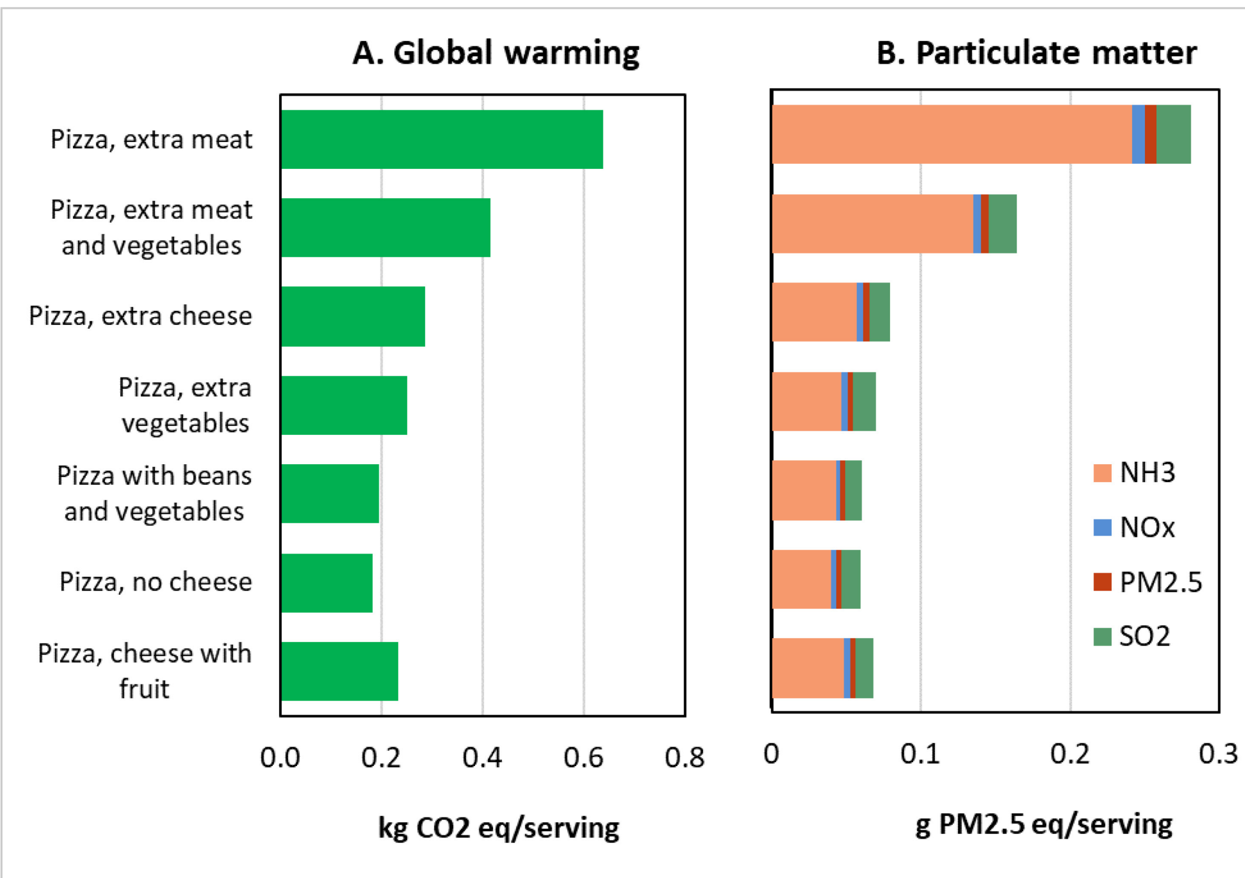

Figure 5.19. Midpoint environmental impacts of global warming (**A**) and particulate matter (**B**) per serving of select pizza types.

5.3.3. Comparison of environmental and nutritional impacts on health

Following the CONE-LCA framework proposed by Stylianou et al. (2016a), we compared the environmental and nutritional impacts on health from all pizzas (N=78) in the WWEIA/NHANES database in a common metric, DALYs, using the damage level scores for the environmental impacts. Figure 5.20 compares global warming health damages and $PM_{2.5}$-related health damages with nutritional DANI scores.

We found that nutritional impacts dominate the health performance of pizzas, with most nutritional healthy options also typically being environmentally friendliest. Results, showed variability in all impact categories that could be explained by the type of pizza. The highest variability was observed for nutritional impacts with DANI scores ranging from -1.6 up to 28.5 μDALYs per serving pizza. Environmental human health impacts from global warming and $PM_{2.5}$ also varied between pizzas but were on average one to two orders of magnitude lower than nutritional impacts. This suggests that for pizzas, when evaluated from the perspective of human health, the nutritional costs are so dominant that it is not necessary to consider the environmental health impacts. Just for a context, for global warming, estimates associated with a serving of pizza ranged from 0.20-0.88 μDALYs, while for $PM_{2.5}$ estimates varied by a factor of 6, from 0.04-0.24 μDALYs per serving pizza. The regression analysis shows significant positive correlations between the environmental health damages investigated in this study and the nutritional health impacts for pizzas, with Pearson correlation coefficients estimated at 0.68 (p-value$<$0.001, R^2=0.46) for global warming and 0.67 (p-value$<$0.001; R^2=0.45) for $PM_{2.5}$. For the latter, we performed a correlation analysis for the impacts associated with each precursor separately. The highest correlation was observed for NH_3-induced impacts which dominates particulate matter impacts (p=0.67, p-value$<$0.001; R^2=0.46) and the lowest for NO_x (p=0.18, p-value$<$0.001; R^2=0.03).

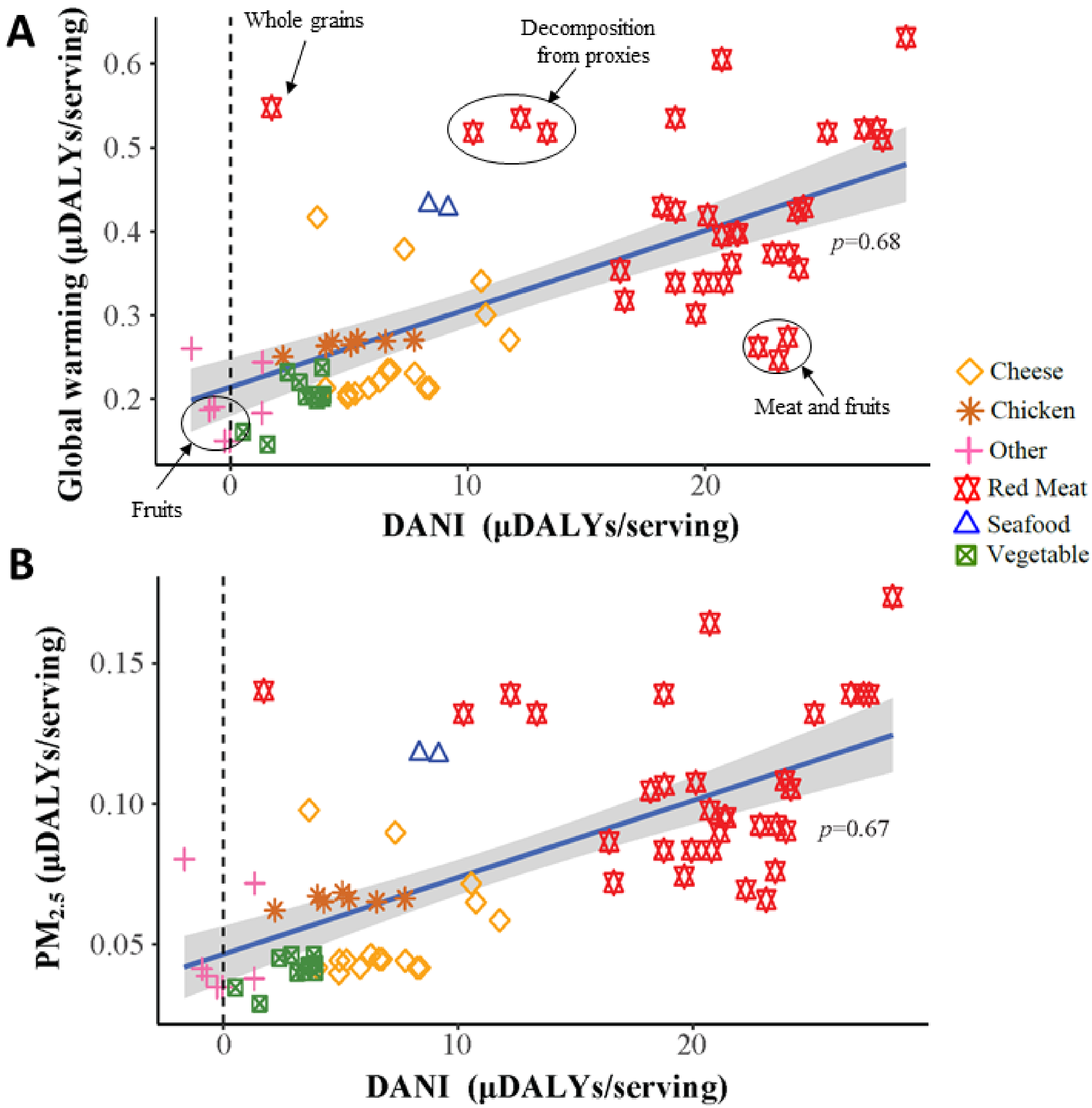

Figure 5.20. (**A**) Global warming and (**B**) Particulate matter human health damages as a function of nutritional health impacts estimated by DANI scores, for 78 pizzas in the WWEIA/NHANES database, classified into four main classes based on their main component. Blue lines represent the linear fit between impacts and shaded areas the corresponding 95% confidence interval. Positive DANI scores indicate health damages.

Red meat pizzas typically generated the highest health damages in all impact categories (19.7, 0.42, and 0.11 μDALYs/serving pizza for nutritional, global warming, and $PM_{2.5}$ health damages, respectively), associated with processed and red meat that increase health risk from a nutritional perspective and higher environmental emissions associated with beef production from an environmental perspective. .Red meat pizzas containing fruits generate considerably lower environmental health damages, especially for global warming (0.23 μDALYs/serving pizza). On the contrary, for a "pizza with a whole grain crust" Figure 5.20 shows high environmental health impacts but low nutritional damages due to health benefit from whole grains compensate for the detrimental health effects of processed meat, sodium, and saturated fats. We also observed this for a cluster of red meat pizzas "from restaurant or fast food". The shared commonality of these pizzas was that we used proxies from previous versions of the SR database to decompose multi-ingredient components, the predicted quantity of meat from past years being substantially higher than the amount of meat from most recent FPED that informs the nutritional assessment. This discrepancy suggests that using earlier versions of the SR might not reflect the current composition of foods and in our case lead to overestimating the amount of red meat and the corresponding environmental damages. Finally, from all the protein-containing pizzas, poultry pizzas generate the lowest impact estimates of 5.02, 0.27, and 0.07 μDALYs/serving pizza for nutritional, global warming, and $PM_{2.5}$ health damages, respectively.

For meatless pizzas, intermediary levels of impacts were observed for cheese pizzas with average health damage estimates of 6.99, 0.25, 0.05 μDALYs/serving pizza for nutrition, global warming, and $PM_{2.5}$, pizzas with "extra cheese" having higher environmental impacts and cheese pizzas without vegetables generating higher nutritional damages. Vegetable pizzas and a cluster of "other pizzas" that contain fruits generated the lowest overall impacts. The mean estimates for nutritional, global warming, and $PM_{2.5}$ health damages for vegetable pizza was 2.9, 0.20, and 0.04 μDALYs/serving, respectively. Fruit-containing pizzas produced on average similar environmental health damages (global warming: 0.19 μDALYs/serving, $PM_{2.5}$: 0.04 μDALYs/serving). In contrast to all other pizzas, the presence of fruit generated net nutritional health benefits, with a DANI score of 0.8 *avoided* μDALYs/serving.

Interestingly, the pizza crust influenced the damage scores for all impact categories. Regular crust pizzas produced on average a DANI score of 10.4 μDALYs/serving with health damage estimates of 0.03 μDALYs/serving for global warming and 0.07 μDALYs/serving for $PM_{2.5}$. Other crust types had higher damage estimates some for nutritional and some for environmental impacts. The most evident differences were observed for stuffed-crust pizzas that had on average ~60% higher DANI scores, while for environmental had higher impacts of only 10%. For thin and thick crust pizzas, impacts were up to 15% higher. However, we found that for thick crust pizzas highest differences were linked with nutritional impacts whereas for thin crust pizzas impacts were higher for environmental impacts.

For all pizzas, health impacts from both nutritional and environmental perspective predominantly induce health burden associated with cardiovascular diseases, in principle affecting premature mortality.

5.4. Discussion

In this paper, we propose DANI as a new nutritional impact category in LCA. DANI is a health burden-based nutritional assessment tool based on a comprehensive set of 16 dietary risks that cover main food groups and nutrients in the diet. Using epidemiological and disease burden evidence, DANI evaluates the cumulative marginal nutritional health benefits and damages associated with foods in DALYs that is compatible with the LCA concept. In this work, we illustrated that DANI has the ability to evaluate the nutritional performance of both simple food item such as milk and complex dishes such as pizzas, and can be used to identify the dominant dietary risks, an important attribute that can be useful in hotspot analysis.

Several limitations of this approach should be acknowledged. First, the nutritional characterization factors used in this work were developed using U.S.-specific data and are valid under the assumption that present intake levels of each dietary risks fall within ranges that do not exceed levels of minimum risk (Gakidou et al. 2017). According to estimates from USDA, this condition is met by the majority of the Amercian population (Dietary Guidelines Advisory Committee 2015). Second, the contributions of transfats in DANI should be interpreted with caution as, for more than half foods in the NHANES database, transfat values have been imputed with a linear regression (Fulgoni III et al. 2018; Stylianou et al. 2018a)and as artificial transfat is being eliminated from the food supply chain. Finally, the current dietary risks and their corresponding characterization factors used in DANI are based on evidence developed by the GBD and are affected by any inherent limitations of this data. Even though the GBD follows a rigorous and comprehensive framework to determine health risks and their magnitude, emerging evidence might offer room for refinement. The underlying DANI methodology used to produce nutritional characterization factors is flexible and can be easily updated and expanded as associations between dietary risks and health outcomes are being developed (Stylianou et al. 2018a).

In this paper, we also addressed the lack of environmental inventory data for mixed dishes. We evaluated the potential use of four publically databases as sources of consistent reference flows for mixed dishes. We showed that the choice of the decomposition method has a substantial influence on results, and that all approaches suffer from some limitations. We nevertheless identified the SR method as the most appropriate decomposition approach to link consistently U.S. foods with LCIs. SR having the highest resolution enables the differentiation of ingredient with different environmental impacts and quantifies ingredient amounts accurately. Since the SR resolution is currently higher than available LCIs, the use of proxies will be required for several food items (of lower consumption levels in most cases). In addition, this approach contains multi-ingredient components that entail further decomposition that can be time- and resource consuming. We were able to address this limitation by using previous versions of the SR, complemented by the FPED for a systematic check of changes in the composition of multi-ingredient items between WWEIA/NHANES and SR cycles. The FPED itself had the lowest resolution, overestimated the daily average pizza intake; this and could lead to substantial errors of environmental impacts in LCA. For certain food groups, FICRCD has a moderate resolution that does not enable to account for important LCIs variability within food groups. In addition, it reports consumed food amount only in retail-level commodity amounts that might be inappropriate for certain LCAs. The FCID approach has a satisfactory resolution but is unsuitable for certain food groups such as dairy products, preventing the identification of the dairy product present in the food.

Using the SR decomposition method, we compared nutritional and environmental impacts of pizzas. Using the CONE-LCA framework we compared health damages from nutrition using DANI scores, with health damages from global warming and particulate matter, in a common metric (DALYs). $PM_{2.5}$ health damages were estimated using spatially explicit characterization factors for the U.S. for $PM_{2.5}$, NH_3, SO_2, and NO_x emissions. Characterization factors were sector-specific; we used agriculture estimates for $PM_{2.5}$ and NH_3, and national emission-weighted estimates from NO_x and SO_2. The estimates used reflected a marginal non-linear exposure-response slope and state-specific severity factors derived from data in the GBD. It should also be mentioned that endpoint global warming estimates are associated with high uncertainty and should be interpreted with caution (De Schryver et al. 2009).

Our analysis showed that for an evaluation of pizzas based on human health, it is only necessary to evaluate nutrition, as this is the dominant pathway for impacts being one to two orders of magnitude higher than global warming and $PM_{2.5}$-related health damages, respectively. This highlighted the importance of considering nutritional impacts and benefits in food LCA. Similar trends have been found for milk (Stylianou et al. 2016a), and fruits and vegetables (Stylianou et al. 2016b). We also found that health damages are pizza type-dependent for all impact categories investigated in this study, with nutritional damages positively correlated with environmental impacts. Red meat pizzas generated the highest DANI scores and induced the highest environmental health impacts, while at the opposite end of the range for all impact categories we found vegetable pizzas, with cheese pizzas being in between. One limitation is that the system boundary used in this study was cradle to farm or processing facility gate and environmental impacts reported here did not capture impacts from distribution, packaging, and cooking nor they accounted for supply chain food losses, which can have substantial contributions to impacts, especially for vegetables (Heller and Keoleian 2015; Pernollet et al. 2017). This could be addressed by complementing our approach with FCID that provides cooking information and the Loss-Adjusted Food Availability (LAFA) database that reports food losses throughout the supply chain for the U.S. (USDA 2015). However, considering the substantially higher human health damages associated with nutrition, these added environmental impacts would probably have little influence on the overall health damages of pizzas.

5.5. Conclusion

This study addresses important gaps in food sustainability assessment and food LCA. Using a case study on pizzas in the U.S. diet, a popular food group with a complex composition, we were able to illustrate an approach that evaluates and compares nutritional and environmental damages on human health using DALYs as a common unit. This approach uniquely uses consistent GBD epidemiological data for assessing both $PM_{2.5}$- and nutritional-related health impacts. The analysis illustrated that nutritional impacts can dominate human health impacts for certain foods such as pizza. We also found that for pizzas, nutritional damages were strongly correlated with environmental impacts. The type of pizza was a key determinant of impacts with the red and processed meat generating the highest damages. To the best of our knowledge, this is the first study to produce consistent environmental and nutritional health impact estimates for pizzas in the U.S.

From an impact assessment perspective, DANI can be a powerful nutritional assessment tool that translates health burden in a single score for individual foods and can serve as a new impact category in LCA. The DRFs can serve as nutritional characterization factors available for 16 dietary risks along with the corresponding inventory flows for about 7,000 food items in the WWEIA/NHANES database. Including DANI in LCA will allow for a more comprehensive assessment of foods and diets. Such an accomplishment could lead to a holistic metric that could be used as a solution to "fixing" the food systems (Sukhdev 2018) and answer needs in assessing human health impacts within social LCA (Arvidsson et al. 2016; Schaubroeck and Rugani 2017). This approach could be used as a benchmark to evaluate foods and diets comprehensively. Implementation of such broader and inclusive methodologies could help inform stakeholders not only in making science-based quantitative comparisons between foods but also by identifying food items and substitutions that optimize public and planetary health by minimizing environmental impacts and maximizing nutritional benefits.

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CHAPTER 6
Conclusion

The overarching goal of this dissertation was to improve human health impact assessment in food sustainability assessment and life cycle assessment of food systems in particular, in order to inform more healthy and sustainable diet choices. As defined in Chapter 1, the dissertation sought to: 1) Develop and test a life cycle assessment (LCA) framework that evaluates and compares the environmental and nutritional effects of food items on health (Chapter 2). 2) Develop nutritional characterization factors for a new nutritional impact category in LCA that translates the nutritional composition of food items and diets into human health benefits or damages and apply them to ~7,000 food items in the U.S. diet to estimate overall nutritional health impact scores (Chapter 3). 3) Develop spatially explicit intake fractions and characterization factors for $PM_{2.5}$ from ground level emissions of primary $PM_{2.5}$, NH_3, SO_2, and NO_x in the contiguous U.S. for agriculture and other relevant sectors (Chapter 4). 4) Determine a decomposition method to consistently evaluate the environmental impacts of mixed dishes and compare them with nutritional health benefits and damages (Chapter 5).

The findings of this dissertation propose a new nutritional impact category as well as promising methodological and inventory data improvements for agricultural processes, food systems, and diets in sustainability assessment and LCA. For each chapter, the summary, conclusions, limitations, and recommendations for future research are listed below.

6.1. LCA framework to assess and compare environmental and nutritional health impacts of food items

Chapter 2 described the development of a novel Combined Nutritional and Environmental Life Cycle Assessment (CONE-LCA) framework that evaluates and compares the environmental and nutritional health effects of foods or diets in a common metric, disability adjusted life years. The framework was demonstrated in a proof-of-concept case study investigating the addition of one serving of fluid milk to the current average diet of U.S. adults. Considering health impacts from global warming, particulate matter, and nutrition, preliminary results suggested a net health benefits that was associated with nutrition-related risk reduction of colorectal cancer; the health benefit further increased when the milk was an iso-caloric substitute for less healthy foods. This case study was the first to quantify trade-offs between nutrition and environment human health burden, expressed in DALYs, which highlighted the importance to consider nutrition as an impact category in LCA.

The CONE-LCA framework pioneers an improved and more comprehensive approach in LCA. Going forward, there is a need for evaluation of additional impact pathways linked with human health burdens in relation to foods such as dietary energy loss through water use (Motoshita et al. 2014), chemical exposure through pesticides (Fantke and Jolliet 2016), and chemical migration from packaging into food (Ernstoff et al. 2017a). Future research is recommended using this framework to provide sustainability information on dietary guidelines and substitution options. However, it is essential to base such work on carefully selected and realistic scenarios (Ernstoff et al. 2017b).

6.2. Nutritional characterization factors for a new nutritional impact category in LCA

Chapter 3 detailed the development of a new nutritional assessment tool, the Health Nutritional Index (HENI). HENI, unlike other nutritional indices, links individual foods to health burden measured in minutes of healthy life lost or gained per serving. HENI is based on 16 dietary risks using epidemiological evidence. The originality of this index is that it weights component contributions based on health burden, an attribute not considered in other nutritional indices. An implementation of HENI to ~7,000 food items in the U.S. diet revealed substantial variability of scores between and within food categories, signifying the importance of evaluating nutritional performance at the food level rather than the food group. This work offers a unique opportunity for science communication as it can be used as a resource to educate and inform the public. More specifically, HENI scores could translate nutritional information to a simple score or color-coded scale for consumers through a smartphone *app* or a food-labeling scheme.

HENI could be further refined to include epidemiological evidence covering a broader set of dietary risks and health outcomes and expanded to other countries or regions. The latter would be particularly useful in developing countries facing an epidemic of diet-related chronic diseases due to drastic dietary pattern changes that converge towards western diets. For such endeavors, there should be a focus on diet not solely individual foods. To be effective, HENI would need to be adapted to account for the multiplicative joint effect of dietary risks.

6.3. Spatially-explicit intake fractions and characterization factors for $PM_{2.5}$ from ground level emissions of primary $PM_{2.5}$, NH_3, SO_2, and NO_x in the contiguous U.S. for agriculture and other relevant sectors

Chapter 4 illustrated the development of estimates to characterize exposure (intake fraction, iFs) and burden (characterization factors, CFs) of $PM_{2.5}$ in LCA. Spatial estimates were calculated for ground-level primary $PM_{2.5}$, NH_3, SO_2, and NO_x emissions in the U.S. using the current state of knowledge for $PM_{2.5}$ exposure and health effect that can help inform life cycle impacts assessment (LCIA). Marginal burden estimates were calculated using recent epidemiological evidence supporting a non-linear exposure-response for $PM_{2.5}$. As emission location is often unknown in LCA, results were aggregated using emission weighted-averages by state, sector, and nationally. Our analysis highlighted the importance of spatially-explicit and emission-weighed sector-specific estimates in LCA (Seppälä et al. 2004; Azevedo et al. 2013). In addition, it revealed the importance of the influence that the shape of the exposure-response function has on burden estimates. Interestingly, we found that the aggregation method produces considerably different national estimates. Population-weighted estimates that is the most commonly approach used in LCA produces higher national estimates compared to emission-weighted estimates, suggesting that population might not be a good surrogate for emissions. We recommend that emission-weighted sector-specific estimates be used when available. In this work, we characterized not only the magnitude of exposure and burden but also their spatial extent. When combined, these data improve our understanding of where, who, and how much impact is associated with $PM_{2.5}$ emissions from an emitter-perspective. As such, these estimates can also inform risk assessment.

As our estimates only cover ground-level emission, future work should focus on developing iF and CF estimates for different stack heights, a factor that can influence iF (Humbert et al. 2011). Such estimates would improve this work and allow for estimates applicable to more refined sector (e.g., power plants that have high stacks). This could be achieved by combining information from the second atmospheric layer of InMAP and sector-specific stack height data made recently available in the U.S. National Emission Inventory (NEI) database. A higher sector granularity would also be useful since in the present work we have aggregated several sectors into "main sectors" (e.g., industrial processes), including a sector that reports unclassified emissions with substantial contributions in certain areas, and may influence results and lack of specificity is not useful for LCA (U.S. Environmental Protection Agency 2018). Another improvement of this work would be to expand the approach spatially and develop global estimates. Both iF and CF estimates are calculated using parameters that vary substantially between regions. iFs are influenced by population density (Apte et al. 2012; van Zelm et al. 2016), and non-linear exposure-response slopes are influenced by background $PM_{2.5}$ ambient concentrations (Fantke et al. 2018).

6.4. Determine a decomposition method to consistently evaluate the environmental impacts of mixed dishes and compare them with nutritional health benefits and damages

In Chapter 5, we demonstrated the application of the findings in Chapters 2-4 by comparing nutritional and environmental health damages for mixed dishes. In this work, we established the DALY Nutritional Index (DANI), an adaptation of HENI (Chapter 3) for the damage-oriented LCIA field, measuring the nutritional health impacts of foods in DALYs. After evaluating four methods, we recommended the use of the Standard Reference (SR) databases as the best decomposition methods for mixed dishes. SR offered the highest resolution that could identify components with varying environmental impacts and quantify the exact amount of components in mixed dishes. Using the CONE-LCA framework from Chapter 2, we compared health damages from global warming, particulate matter, and nutritional for pizzas in the U.S. diet, with particulate matter estimates calculated using CFs from Chapter 4. We found that nutritional impacts dominate the health performance of pizzas, with most nutritional healthy pizza options also typically being environmentally friendliest and red meat pizzas inducing the highest damages. This study is the first to consistently quantify and compare complex foods using a common metric, DALYs,

The system boundary of this work would benefit if expanded to consider cradle-to-fork impacts. Such an expansion would improve the environmental impact assessment as it would consider additional impacts from food waste throughout the supply chain and cooking processes, which can be an important source of environmental impacts for foods (Heller and Keoleian 2015; Pernollet et al. 2017). Furthermore, the application of this work to other mixed dishes of different composition is required to test whether the correlation between the nutritional and environmental performance of pizzas that we observed in this work is valid for other food groups as well.

6.5. General application and outlook

Overall, the interdisciplinary collaboration with an outstanding expert in the field of nutrition, Dr. Victor Fulgoni, and thinking outside the box has enabled us to address critical challenges in food system and diet evaluation. Diverging from the traditional norms of environmental and nutritional sciences, we developed frameworks, methodologies, and data that bridge the gap between the two fields and empower a comprehensive evaluation of food systems and diets in a common metric, aiming to make hidden health risks visible.

This multi-angled inclusive approach to evaluate food systems has potential implication for public health policies and sustainable dietary guidelines. Every five years the USDA develops dietary guidelines for Americans based on the current state of knowledge in nutrition. These guidelines have never been evaluated as to the health benefit they could generate. Future adaptations of HENI for diets, would allow such an evaluation and could provide key insights on the magnitude of health benefits and simultaneously help dentify areas for improvement. In the 2015-2020 dietary guidelines, there was a qualitative discussion about food sustainability and the sustainability of particular foods (Dietary Guidelines Advisory Committee 2015). However, the current state of knowledge on the topic is far more advanced. Using the findings from this dissertation could inform dietary guidelines using science-based quantitative data that account for both the nutritional and environmental impacts on health. Such an undertaking will enable the optimization of guidelines in a way that maximizes health benefits and minimizes environmental impacts. Even if a small fraction of Americans follow such guidelines, it would yield benefits in public health, health care, communities, and ecosystems.

HENI, as a stand-alone product of this dissertation, has the potential to be used as a decision-making tool that could guide consumers towards healthier dietary choices and substitutions. HENI can translate complex nutritional food evaluation to a simple but powerful score expressed in minutes of healthy life lost or gained that is easy to understand and relevant to consumers, stakeholders, and academics (Kunkel and McKinley 2007). The past summer, we partnered with Innovation Studio at the University of Michigan School of Public Health for a 12-week internship aiming to explore the potentials of HENI in improving public health and having a social impact. This collaboration revealed a great deal of exciting and promising feedback received from stakeholders. One potential use of HENI is the development of a nutritional *app* that can inform consumers for healthy and environmentally friendly dietary options at grocery stores, restaurants, and during meal preparation. Other potential applications of HENI include a food labeling system answering the recent call for new methods to inform 'health' claims from the U.S. Food and Drug Administration as part of their nutrition innovation strategy, a scoring system which evaluates the social impact of food manufacturers that could also quantifying their public health impacts under a corporate social responsibility regime, and an evaluation tool that enables nutritional programs like SNAP and organizations like Food Banks determine their social impact by quantifying the health benefit they generate to the populations they serve.

Personal preferences, socio-economic status, education, culture, taste, and health status are some of the factors that affect dietary patterns. In addition, food price is an important determinant of diet , with healthier diets typically costing more (Rao et al. 2013). Future efforts to improve this work should account for these determinans. In particular, our environmental and nutritional approach could be integrated with food cost databases to develop and generate optimized dietary recommendations at different budget levels that also consider personal preference (e.g., a diet optimized for vegetarians with a low budget for groceries). Eventually, disease history and genetic traits could also be incorporated in our approach to provide personalized health responses to nutritional or environmental risks.

In all, this work has been an exciting endeavor that has propelled substanital advances in the rapidly evolving field of food sustainability. Food systems are at the nexus of a systemic crisis in diets, public health, and ecosystems. I hope that with this dissertation, we have laid the foundation for the development and implementation of more inclusive approaches to inform decision-making for lifestyles choices with long-term benefits for good public and planetary health.

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APPENDICES

APPENDIX 1
A life cycle assessment framework combining nutritional and environmental health impacts of diet: a case study on milk

A1.1. 2010 Global Burden of Disease

Table A1.4 lists the top 10 risk factors for the total (all cause) global and U.S. burden of disease measured in both deaths and disability adjusted life years (DALYs) for the year 2010 (IHME 2013).

Table A1.4. 2010 Global and U.S. burden of disease

Global			United States (U.S.)		
Risk factor	**Deaths (Millions)**	**DALYs (Millions)**	**Risk factor**	**Deaths (Millions)**	**DALYs (Millions)**
Dietary risks	11.4	230.2	Dietary risks	0.7	11.5
High blood pressure	9.4	173.6	Tobacco smoking	0.5	9.7
Tobacco smoking	6.3	156.8	High blood pressure	0.4	6.4
Household air pollution from solid fuels	3.5	108.1	High body-mass index	0.4	8.9
High body-mass index	3.4	93.6	Physical inactivity and low physical activity	0.2	4.3
High fasting plasma glucose	3.4	89.0	High fasting plasma glucose	0.2	4.8
Ambient particulate matter pollution	3.2	76.2	High total cholesterol	0.2	2.8
Physical inactivity and low physical activity	3.2	69.3	Ambient particulate matter pollution	0.1	1.8
Alcohol use	2.7	97.2	Alcohol use	0.1	3.6
High total cholesterol	2.0	40.9	Drug use	0.03	2.4

A1.2. Defining fluid milk

In this study, when referring to milk we use the term fluid milk. This was defined as the consumption weighted average (with respect to population-scale consumption frequencies) of whole, 2% reduced fat, 1% reduced fat and non-fat milk consumed in the U.S. based on sales data from Thoma et al. (2013) and milk energy values available in USDA Standard Reference 27 database (USDA, 2011) as summarized in Table A1.5. This resulted an energy content estimate for a serving (244 g) of fluid milk equal to 119 calories.

Table A1.5. Average national fluid milk consumption in the U.S.

Milk type	Total Sales (million kg)	Energy content per serving (Calories)
Whole milk	7398	149
Reduced fat milk (2%)	8742	122
Low fat milk (1%)	5257	102
Fat free milk	3971	83

A1.3. Defining PM-related Emissions

To estimate particulate matter (PM) related emissions for the average diet and sugar-sweetened beverages (SSB) we extrapolated from greenhouse gases emissions (GHGE) using correlation factors since there were no available data in the literature. To do so, we performed a correlation analysis between $PM_{2.5}$, NO_x, SO_2, and NH_3 emissions (in kg pollutant) from 47 food-related ecoinvent processes (Frischknecht et al. 2005) with their corresponding global worming potential for a 100 year time horizon (in kg CO2-eq). The list of the ecoinvent processes included in the analysis are presented in Table A1.6.

The analysis supported a strong linear correlation for $PM_{2.5}$ (correlation coefficient=+0.96), NO_x (correlation coefficient=+0.98), and SO_2 (correlation coefficient=+0.83) with GHGE, while NH_3 showed a weaker association (correlation coefficient=+0.62). We then performed a regression analysis using the model (eq. A1.1):

$$log_{10}(pollutant) = a \times log_{10}(CO_2 - eq) + b \qquad Eq.\ A1.1$$

for which all but the one for SO_2 a estimates were not statistically different than 1 (for SO_2 the estimate was lower but close to 1). Therefore, we forced a=1 for all models for a more parsimonious model to capture these correlations. As beta (b) estimates we used the $median\left(log\ _{10}\frac{pollutant}{CO_2-eq}\right)$ that was then used to estimate correlation factors as summarized in Table 2.1. For NH_3 we used emission factors by Meier and Christen (2013). These emission factors were used to estimate emissions related to all three 119 caloric equivalent portion of intake: fluid milk, average diet, and SSB. Finally, PM-related emission factors for fluid milk were retrieved from the Comprehensive LCA of Fluid Milk (Henderson et al. 2013). All emissions estimates associated with the three distinct 119 caloric equivalent portion of intake used in our analysis are summarized in Table A1.7.

Table A1.6. Food-related ecoinvent processes

Dataset-ID	Name	Location
190	barley grains extensive, at farm	CH
191	barley grains IP, at farm	CH
192	barley grains organic, at farm	CH
196	fava beans IP, at farm	CH
197	fava beans organic, at farm	CH
200	grain maize IP, at farm	CH
201	grain maize organic, at farm	CH
216	potatoes IP, at farm	CH
217	potatoes organic, at farm	CH
218	protein peas, IP, at farm	CH
219	protein peas, organic, at farm	CH
220	rape seed extensive, at farm	CH
221	rape seed IP, at farm	CH
222	rye grains extensive, at farm	CH
223	rye grains IP, at farm	CH
224	rye grains organic, at farm	CH
230	soy beans IP, at farm	CH
231	soy beans organic, at farm	CH
234	sugar beets IP, at farm	CH
235	sunflower IP, at farm	CH
236	wheat grains extensive, at farm	CH
237	wheat grains IP, at farm	CH
238	wheat grains organic, at farm	CH
6215	rape seed, organic, at farm	CH
6258	sugar cane, at farm	BR
6528	corn, at farm	US
6576	rape seed conventional, at farm	DE
6577	rye grains conventional, at farm	RER
6659	soybeans, at farm	US
6711	sweet sorghum grains, at farm	CN
6955	protein peas conventional, Saxony-Anhalt, at farm	DE
6956	barley grains conventional, Saxony-Anhalt, at farm	DE
6957	rape seed conventional, Saxony-Anhalt, at farm	DE
6958	wheat grains conventional, Saxony-Anhalt, at farm	DE
6959	protein peas conventional, Castilla-y-Leon, at farm	ES
6960	barley grains conventional, Castilla-y-Leon, at farm	ES
6961	sunflower conventional, Castilla-y-Leon, at farm	ES
6962	wheat grains conventional, Castilla-y-Leon, at farm	ES
6963	protein peas conventional, Barrois, at farm	FR
6964	barley grains conventional, Barrois, at farm	FR
6965	rape seed conventional, Barrois, at farm	FR
6966	wheat grains conventional, Barrois, at farm	FR
6968	potatoes, at farm	US
6969	rape seed, at farm	US
6970	rice, at farm	US
6972	wheat grains, at farm	US
6976	sheep for slaughtering, live weight, at farm	US

Table A1.7. Emissions for each of the 119 caloric equivalent portion of intake (kg)

	CO_2-eq*	NOx	$PM_{2.5}$	SO_2	NH_3†
Fluid milk	4.7E-01	8.6E-04‡ below	2.8E-05‡	6.6E-04‡	2.0E-03
Average diet	2.3E-01	6.2E-04	5.5E-05	1.9E-04	9.0E-04
SSB	1.8E-01	4.9E-04	4.4E-05	1.5E-04	8.2E-05

A1.4. Characterizing Uncertainty

To calculate uncertainty, represented by squared geometric standard deviation (GSD^2), in our analysis we employed the approach by MacLeod et al. (2002) which is based on a Taylor series expansion and is given in equation A1.2:

$$GSD_O^2 = \exp[S_{I_1}^2(\ln GSD_{I_1}^2)^2 + S_{I_2}^2(\ln GSD_{I_2}^2)^2 + \ldots S_{I_n}^2(\ln GSD_{I_n}^2)^2]^{1/2} \qquad Eq.A1.2$$

where, S_i is a sensitivity factor describing how sensitive is the outcome (O) to each input (I_i) parameter calculated by:

$$S_i = \frac{\frac{\Delta O}{O}}{\frac{\Delta I}{I}} \qquad Eq.\ A1.3$$

Although this approach assumes linearity, we applied eq. A1.1 even in cases where the assumption was violated in order to generate an initial proxy for uncertainty.

* Based on the meta-analysis by Heller and Keoleian (2014)

† Based on Meier and Christen (2013)

‡ Based on the Comprehensive LCA of Fluid Milk by Henderson et al. (2013)

A1.4.1. Global warming

The input parameters used in the uncertainty analysis for the global warming endpoint estimate was calculated as the product of emissions and the global warming human health damage factor (Bulle et al. 2015). For the milk and average diet emissions uncertainty was obtained from Thomas et al. (2013) and from Heller and Keoleian (2014), while for SSB the emission uncertainty was calculated based on the range of emission available in the literature as summarized in Table A1.8 that reflect differences in packaging. Table A1.9 summarizes the global warming uncertainty estimates.

Table A1.8. Summary of GHGE estimates for SSB

		Estimate (kg CO_2-eq/kg)			
Source	**Commodity**	**Min**	**Max**	**Arithmetic Mean**	**GSD^{2*}**
Vieux et al., (2012)	Soda	0.30	0.44	0.37	1.21
Amienyo et al., (2013)	Carbonated soft drink	0.14	0.36	0.25	1.59
Coca Cola (2015)	Coca Cola	0.25	1.09	0.67	2.09
Updated estimate		**0.14**	**1.09**	**0.37**	**2.80**

[*] Calculated as $\sqrt{\frac{Max}{Min}}$

Table A1.9. Uncertainty estimates associated with the global warming impact assessment (GSD^2)

		Milk	**Av. diet**	**SSB**
Emission		1.2	1.9	2.8
Impact factor	$CF_{GHG} = GWP_{GHG} \times \frac{\Delta T_{int}}{\Delta GWP_{GHG}} \times \frac{\Delta risk}{\Delta T_{int}} \times Burden$			
Midpoind Impact	GWP_{GHG}	1.5 (S=0.6[+])		
Climate sensitivity parameter	$\frac{\Delta T_{int}}{\Delta GWP_{GHG}}$	1.5		
Human Health	$\frac{\Delta risk}{\Delta T_{int}}$	1.8		
Burden (human health)		4.0[++]		
Total		4.8		
Total		**4.9**	**5.5**	**6.5**

[+] Accounting for the impact of CH4 and N20. The sensitivity estimate is the contribution of these two gases to GHGE for fluid milk according to Thoma et al. (2013).

[++] Determined to reflect uncertainty associated with global warming health impacts that are not currently being considered and outcomes occurring beyond the 100 year time horizon.

A1.4.2. Particulate Matter

The input parameters used in the uncertainty analysis for the PM endpoint estimate calculated as the additive impact of the product of emissions and characterization factors (Gronlund et al. 2014) of $PM_{2.5}$, NO_x, SO_2, and NH_3 are summarized in Table A1.10.

The emission uncertainty is divided between fluid milk and average diet/SSB because of the methodology followed. For fluid milk we used GSD^2 estimates from the ecoinvent database (The ecoInvent Databse: Overview and Methodological Framework, 2005) from which the processes used in the work by Henderson et al (2013) were originated. For average diet/SSB, eq. A1.2 was used considering uncertainty from the correlation analysis that accounted for the model uncertainty and the uncertainty of GHGE (assuming S=1 for both parameters).

Characterization factors are a product of intake fraction (iF), dose response (DR), and severity factor (SF). To estimate uncertainty we used eq. A1.2 with a GSD^2_{DR} of 2.2 and GSD^2_{SF} of 1.4 as reported in Gronlund et al. (2014) and low and high uncertainty factors for $PM_{2.5}$, NO_x, SO_2, and NH_3 based on the work by Humbert et al. (2011).

For the human health damage we first calculated the total GSD^2 (low and high) for each of the three distinct intakes as the product of emissions and CFs for each PM-related pollutant. To estimate the total impact associated with each food item intake we combined the resulting PM-related pollutant GSD^2 accounting for their contribution as an input sensitivity (S_i) when using eq. A1.2.

Table A1.10. Uncertainty estimates associate with the particulate matter impact assessment (GSD^2)

Emission	*Fluid Milk*		*Av. Diet/SSB*
$PM_{2.5}$	3.0		1.5
SO_2	1.1		2.9
NO_X	1.5		1.5
NH_3	1.5		1.5
Intake fractions	*Low*		*High*
$PM_{2.5}$	2.0		5.0
SO_2	10.0		2.0
NO_X	10.0		10.0
NH_3	10.0		2.0
Characterization factors	*Low*		*High*
$PM_{2.5}$	3.0		6.2
SO_2	11.7		3.0
NO_X	11.7		11.7
NH_3	11.7		3.0
Contribution (S_i x10^{-1})	Fluid milk	Average diet	SSB
$PM_{2.5}$	0.3	0.5	3.3
SO_2	1.3	1.1	2.4
NO_X	0.4	0.8	1.6
NH_3	8.0	7.6	2.7
Total health damage	Fluid milk	Average diet	SSB
Low	7.5	6.9	3.0
High	2.6	2.6	2.4

A1.4.3. Nutritional Assessment

The total effect of nutrition for the different endpoints considered associated with 119 calories of intake was calculated as an attributable burden. Therefore, the uncertainty of the effect was a combination of uncertainty associated with the risk ratio (RR) and the burden estimate. For the SSB nutritional assessment, uncertainty is linked to the SSB daily intake estimate. The input parameters used in the uncertainty analysis for the nutritional assessment are summarized in Table A1.11.

Table A1.11. Uncertainty estimates associate with the nutritional impact assessment (GSD^2)

	Colorectal cancer	**Stroke**	**Prostate cancer**	**SSB-related diseases**
RR	1.1	1.1	1.0	-
Burden	1.4	1.4	1.6	1.4
Intake	-	-	-	1.3
Total	1.4	1.4	1.6	1.6

A1.5. Overall comparison

Table A1.12. Environmental human health impact for each of the 119 caloric equivalent portion of intake (μDALYs)

	CO_2-eq	**NOx**	**$PM_{2.5}$**	**SO_2**	**NH_3**
Fluid milk	3.84E-01	1.11E-02	8.46E-03	4.06E-02	2.55E-01
Average diet	1.88E-01	8.07E-03	1.66E-02	1.18E-02	1.17E-01
SSB	1.50E-01	6.42E-03	1.32E-02	9.42E-03	1.07E-02

Table A1.13. Environmental and nutritional human health impacts and benefits under each scenario (avoided μDALYs)[§]

<table>
<tr><th></th><th colspan="3">Impacts</th><th colspan="3">Benefits</th><th></th></tr>
<tr><th></th><th>CO_2-eq</th><th>Total $PM_{2.5}$</th><th>Prostate[**] cancer</th><th>Colorectal cancer</th><th>All stroke outcomes</th><th>SSB-related disease</th><th>Net</th></tr>
<tr><td>Scenario A</td><td>-3.84E-01</td><td>-3.15E-01</td><td rowspan="3">-1.64E-01</td><td rowspan="3">+1.10E+00</td><td rowspan="3">+9.50E-01</td><td></td><td>+1.18E+00</td></tr>
<tr><td>Scenario B</td><td>-1.96E-01</td><td>-1.62E-01</td><td></td><td>+1.53E+00</td></tr>
<tr><td>Scenario C</td><td>-2.34E-01</td><td>-2.75E-01</td><td>+3.48E+00</td><td>+4.85E+00</td></tr>
</table>

[§] Impacts are indicative of induced burden (negative values) while benefits are indicative of avoided burden (positive values).
[**]Impact weighted with the male population fraction so as to reflect an impact for the overall population

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APPENDIX 2
HENI: A health burden-based nutritional index for food items

A2.1. HENI components description

The Health Nutritional Index (HENI) is a single score dietary assessment tool that quantifies changes in total all-cause disease burden per serving, mass, or energy content of foods, measured in gain (+) or loss (-) of minutes of healthy life. The score attributes healthiness to the marginal consumption of a food item. HENI is based on a 16-component model, with components selected based on the work by the Global Burden of Disease (GBD) study series by which they have been identified as dietary risks (Gakidou et al. 2017). First published in 1996, the GBD study series is an ongoing effort aiming to quantify the disease burden of premature death and disability on a global, regional, and national scale and constitutes the most comprehensive and consistent approach to evaluate behavioral, environmental, occupational, and metabolic health risk factors simultaneously (Gakidou et al. 2017).

HENI dietary risk components fall under the behavioral cluster of health risks in the 2016 GBD and are composed of nine food groups and six nutrients. Food groups include fruits, vegetables, legumes, red meat, processed meat, milk, whole grains, nuts and seeds, and sugar-sweetened beverages (SSB). The nutrient components include calcium, fiber, polyunsaturated fatty acids (PUFA), omega-3 fatty acids, sodium, and trans fatty acids (TFA). Each dietary risk components has been positively or negatively associated with one to 38 disease outcomes in adults aged 25 years and up, covering a total of 50 health outcome. The selection of risk-outcome pairs in the GBD is based on four criteria. These criteria are: 1) the importance of risk factor to disease burden and/or policy; 2) availability of sufficient risk factor exposure data; 3) support of a causal relationship based on epidemiological studies and ability to estimate effect magnitude per exposure unit increase; and 4) evidence supporting that the association can be generalized (Gakidou et al. 2017). To evaluate these criteria, the GBD has adopted the World Cancer Research Fund (WCRF) grading system, and risk-outcome pairs are included only when it is determined that they have of convincing or probable evidence (Gakidou et al. 2017). According to WCRF (World Cancer Research Fund and American Institute for Cancer Research 2007), convincing evidence is defined as evidence with a high robustness that is unlikely to be modified with new evidence. In particular, convincing evidence should be based on numerous good quality epidemiological studies (prospective observational and randomized control trials) that show consistent direction and magnitude of the effect, with limited or no studies with opposing findings. The evidence should be supported by biological plausibility. Evidence is defined as probable if there is fair support of a probable causal relationship based on epidemiological studies that suffer from some limitations. Limitations could include a small number of studies, availability of evidence with opposite effects, and lower quality studies. The evidence should be supported by experimental studies and by biological plausibility. New evidence is evaluated with each update of the GBD study series.

Due to correlations between dietary risks, the effects of a few components in HENI is mediated either by other dietary risks or by other factors such as metabolic risks. In particular, cardiovascular effects associated with fiber are mediated through fruits, vegetables, and whole grains. Other dietary risk components are 100% mediated through metabolic risks such as SSB and sodium that are mediated via body mass index (BMI) and systolic blood pressure (SBP), respectively (Gakidou et al. 2017). The burden associated with SSB and sodium is estimated in a two-step process. First, the dietary risk (e.g., SSB) is linked to a change in the metabolic risk (e.g., BMI). Second, the corresponding metabolic risk change (e.g., BMI) is linked to a disease burden (e.g., diabetes). As a result, SSB and sodium are indirectly associated with all the health outcomes that their respective metabolic risks have effects on.

Since SFA-related health burdens are captured with total serum cholesterol at the population level in the 2016 GBD, HENI also considers the health effects of saturated fatty acids (SFA) in individual food items. Studies support that SFA increase the risk for ischemic heart disease (IHD) mortality (Slattery and Randall 1988). The direct effect of SFA, as with other fatty acids, is dependent on the substitution and some studies have found that reduction of SFA could increase carbohydrate intake that might not improve health (Slattery and Randall 1988; Mensink 2016). However, increased consumption of SFA induces higher concentrations of serum cholesterol, which is identified as a metabolic risk factor in the GBD (Hu et al. 2001; Mensink 2016; Gakidou et al. 2017). Therefore, HENI also considers the indirect effect of SFA mediated via cholesterol as described in the section A2.3 focusing on mediated dietary risk factors.

Table A2.14 summarizes the HENI dietary risk components and provides their description and characteristics.

Table A2.14. Definition, description, and characteristics of HENI indicators

Dietary risk component	Description*	Effective intake*	Health effect	Health outcomes
Calcium	Calcium from all sources	<1.25 g/day	Positive	1
Fiber	Fiber from all sources	<23.5 g/day	Positive	2
Polyunsaturated fats	Omega-6 fatty acids from all sources	<11% total energy intake	Positive	1
Seafood omega-3 fats	Eicosapentaenoic & docosahexaenoic acids	<250 mg/day	Positive	1
Sodium†	Dietary sodium from all sources	>3.49 g/day	Negative	15
Saturated fatty acids‡	Saturated fat from all sources		Negative	2
Trans fatty acids	Trans fat from all sources	>0.5% total energy intake	Negative	1
Fruits	Fresh, frozen, cooked, canned, or dried, excluding fruit juices and salted or pickled fruits	< 250 g/day	Positive	10
Milk	Milk (including non-fat, low-fat, and full-fat milk) but excluding plant derivatives	<435 g/day	Positive	1
Nuts and seeds	Nut and seed foods	<20.5 g/day	Positive	2
Processed meat	Meat preserved by smoking, curing, salting, or addition of chemical preservatives	>2 g/day	Negative	3
Legumes	Fresh, frozen, cooked, canned, or dried legumes	<60 g/day	Positive	1
Red meat	Beef, pork, lamb, and goat but excluding poultry, fish, eggs, and all processed meats	>22.5 g/day	Negative	2
Sugar-sweetened beverages§	Beverages >50 kcal per 226.8 g serving, including carbonated beverages, sodas, energy drinks, and fruit drinks, but excluding 100% fruit and vegetable juices	>2.5 g/day	Negative	38
Vegetables	Fresh, frozen, cooked, canned, or dried vegetables, excluding legumes, salted or pickled vegetables, juices, and starchy vegetables	<360 g/day	Positive	3
Whole grains	Whole grains from breakfast cereals, bread, rice, pasta, biscuits, muffins, tortillas, pancakes, and other sources	<125 g/day	Positive	4

*Description obtained from Gakidou et al. 2017

†Based on "Diet high in sodium" described as 24 h urinary sodium in g/day. All health effects are mediated through systolic blood pressure. Effective intake calculated as $3\frac{\text{grams}_{\text{urinary sodium}}}{\text{day}}/0.85\frac{\text{grams}_{\text{dietary sodium}}}{\text{grams}_{\text{urinary sodium}}}=3.49\,\frac{\text{grams}_{\text{dietary sodium}}}{\text{day}}$

‡All health effects are mediated through total serum cholesterol

§ All health effects are mediated through body mass index

A2.2. Dietary risk factors model

To calculate the health effects of marginal dietary changes per dietary risk component, we adapted the Comparative Risk Assessment (CRA) used in the GBD (Murray et al. 2003; Gakidou et al. 2017). CRA entails determining the fraction of each disease attributable to changes in intakes from a baseline to a counterfactual, known as population attributable fraction (PAF). Since we are interested in marginal intake changes, we estimate PAF(Δx) for a marginal difference between the baseline and counterfactual intake ($\Delta x \rightarrow 0$). In addition, we assume a log-linear dose-response relationship for the epidemiological associations (Gakidou et al. 2017).

Therefore, the generic model for dietary risk factors (DRFs) for marginal dietary changes is given by:

$$\mathrm{DRF} = \lim_{\Delta x \to 0} \mathrm{PAF}(\Delta x) \cdot \frac{1}{\Delta x} \cdot \mathrm{BR} = \lim_{\Delta x \to 0} \left(\frac{\mathrm{RR}^{\Delta x/\mathrm{RI}} - 1}{\mathrm{RR}^{\Delta x/\mathrm{RI}}} \right) \cdot \frac{1}{\Delta x} \cdot \mathrm{BR}$$

$$\xRightarrow{\text{Taylor expansion series}} \mathrm{DRF} = \frac{\ln(\mathrm{RR})}{\mathrm{RR}} \cdot \mathrm{BR} \qquad \textit{(Eq. A2.1)}$$

where RR is the relative risk, RI is the reference intake for the corresponding RR, and BR is the burden rate of the disease associated with the risk represented by the RR.

A2.3. Mediated dietary risk factors

A2.3.1. Sodium

The GBD studies define sodium exposure using 24-hour urinary sodium estimates using a crosswalk adjustment between data from dietary and urinary surveys (Gakidou et al. 2017). 24-h urinary sodium is considered the most reliable method to measure sodium intake (WHO 2006), averting measurement errors present in dietary estimates due to under- or over-reporting (Willett 2001). Evidence supports that the health effect of sodium is mediated through systolic blood pressure (SBP) (Aburto et al. 2013; Gakidou et al. 2017). Race (black versus non-black) and hypertension status (hypertensive versus non-hypertensive) have been found as significant effect modifiers for this relationship (Mozaffarian et al. 2011).

The DFR_{sodium} accounts for the mediation mechanism in grams of dietary sodium and adjusts for effect modifiers such as age, gender, race, and hypertension, as follows:

$$\mathrm{DRF_{Sodium}} = \sum_{s_{sodium}} \sum_{g} \sum_{a} \sum_{o} \sum_{b} \mathrm{f}_{a,g,s_{sodium}} \cdot \frac{\ln \mathrm{RR}^{a,g}_{\mathrm{SBP},o,b}}{10\ \mathrm{mmHg}} \cdot \frac{\mathrm{SBP}^{a,g,s_{sodium}}\ \mathrm{mmHg}}{2.3\ \mathrm{g_{urinary}}} \cdot 0.86 \frac{\mathrm{g_{urinary}}}{\mathrm{g_{dietary}}} \cdot \mathrm{BR}^{a,g}_{o,b}$$

(*Eq. A2. 2*)

$\mathrm{f}_{a,g,s_{sodium}}$ is the fraction of the 2016 US population in age group *a* and gender *g* and strata s_{sodium} obtained by combining information from the US 2016 population distribution by the GBD and race and hypertension information from the National Health and Nutrition Examination Survey (NHANES) 2015-2016. $\mathrm{RR}^{a,g}_{r,o,b}$ is the relative risk (RR) for outcome *o* and burden *b* due to SBP in age group *a* and gender *g* for a reference of 10 mmHg (Gakidou et al. 2017). $\mathrm{SBP}^{a,g,s_{sodium}}$ represents the systolic blood pressure shifts in mmHg per 2.3 grams of urinary sodium in age group *a* and gender *g* and strata s_{sodium}. We assume that 86% (standard error (SE): 1.6%) of dietary sodium ingested is excreted in urine (Rhodes et al. 2013). $\mathrm{BR}^{a,g}_{o,b}$ is the burden rate for outcome *o* and burden *b* in age group *a* and gender *g* in µDALYs/person-day, with burden measured in years of life disable (YLD) or years of life lost (YLL) and YLD+YLL-DALY. BR estimates are adapted from the US estimates from GBD 2016 (Institute for Health Metrics and Evaluation 2018).

A2.3.2. Sugar-sweetened beverages

According to the GBD, SSB health effects are mediated via body mass index (Gakidou et al. 2017). Body mass index status (BMI>25 vs. BMI<25) is reported to modify this relationship (Mozaffarian et al. 2011; Malik et al. 2013; Gakidou et al. 2017). To address this, the updated DRF_{SSB} model is:

$$\mathrm{DRF_{SSB}} = \sum_{s_{BMI}} \sum_{g} \sum_{a} \sum_{o} \sum_{b} \mathrm{f}_{a,g,s_{BMI}} \cdot \frac{\ln \mathrm{RR}^{a,g}_{\mathrm{BMI},o,b}}{5\,\frac{\mathrm{kg}}{\mathrm{m}^2}} \cdot \frac{\frac{\mathrm{weight}^{a,g,s_{BMI}}}{\mathrm{height}^{a,g}}\frac{\mathrm{kg}}{\mathrm{m}^2\cdot\mathrm{serving}}}{226.8\frac{\mathrm{grams}}{\mathrm{serving}}} \cdot \mathrm{BR}^{a,g}_{o,b}$$

(Eq. A2.3)

$\mathrm{f}_{a,g,s_{BMI}}$ is the fraction of the 2016 US population in age group *a* and gender *g* and strata s_{BMI} obtained by combining information from the US 2016 population distribution by the GBD and BMI status from the National Health and Nutrition Examination Survey (NHANES) 2015-2016. $\mathrm{RR}^{a,g}_{r,o,b}$ is the relative risk (RR) for outcome *o* and burden *b* due to BMI in age group *a* and gender *g* for a reference of $5\frac{\mathrm{kg}}{\mathrm{m}^2}$ (Gakidou et al. 2017). $\mathrm{Weight}^{a,g,s_{BMI}}$ represents the weight gain in kg per serving SSB (226.8 grams/serving) in age group *a* and gender *g* and strata s_{BMI} which when divided by height estimates in m^2 ($\mathrm{height}^{a,g}$) results in a BMI increase per serving SSB. $\mathrm{Weight}^{a,g,s_{BMI}}$ estimates are obtained from the 2016 GBD (Gakidou et al. 2017) and $\mathrm{height}^{a,g}$ estimates are derived using the National Health and Nutrition Examination Survey (NHANES) 2015-2016. $\mathrm{BR}^{a,g}_{o,b}$ is the burden rate for outcome *o* and burden *b* in age group *a* and gender *g* in μDALYs/person-day, with burden measured in years of life disable (YLD) or years of life lost (YLL) and YLD+YLL-DALY. BR estimates are adapted from the US estimates from GBD 2016 (Institute for Health Metrics and Evaluation 2018).

A2.3.3. Saturated fatty acids

The GBD recognizes high total serum cholesterol as an important metabolic risk factor for cardiovascular diseases (Gakidou et al. 2017). Evidence supports an association between SFA and total serum cholesterol, with the relationship influenced by the nutrient substitution (e.g., carbohydrates versus PUFA replaced with SFA) (Mensink 2016), thus the importance for a food-based index to capture SFA-related health burdens as mediated by serum cholesterol. To capture the effect of saturated fats on health in HENI, we use the 2016 GBD metric, i.e., total serum cholesterol as a proxy.

We use the work by the World Health Organization (WHO) in 2016 to associate SFA with total serum cholesterol. WHO reports that a 1% energy increase from SFA replacing carbohydrates results in a total cholesterol increase of 0.045 mmol/L (95% confidence interval (CI): 0.038 to 0.051) (Mensink 2016). As a result, the SFA DRF is estimated using:

$$\mathrm{DRF_{SFA}} = \sum_{g}\sum_{a}\sum_{o}\sum_{b} \mathrm{f_{a,g}} \cdot \frac{\ln \mathrm{RR^{a,g}_{total\ cholesterol,o,b}}}{1\,\frac{\mathrm{mmol}}{\mathrm{L}}} \cdot \frac{0.045\frac{\mathrm{mmol}}{\mathrm{L}} \cdot 9.25\frac{\mathrm{kcal}}{\mathrm{grams_{fat}}}}{0.01 \cdot \mathrm{EER^{a,g}}\frac{\mathrm{kcal}}{\mathrm{day}}} \cdot \mathrm{BR^{a,g}_{o,b}}$$

(*Eq. A2.4)*

where $\mathrm{f_{a,g}}$ is the fraction of the 2016 US population in age group *a* and gender *g* (Global Burden of Disease Collaborative Network 2017), $\mathrm{RR^{a,g}_{r,o,b}}$ is the relative risk (RR) for outcome *o* and burden *b* due to total serum cholesterol in age group *a* and gender *g* for a reference of $1\,\frac{\mathrm{mmol}}{\mathrm{L}}$ (Gakidou et al. 2017). $\mathrm{EER^{a,g}}$ represents the physical activity adjusted estimated energy requirement (EER) in age group *a*, gender *g* (Table A3.18). $\mathrm{BR^{a,g}_{o,b}}$ is the burden rate for outcome *o* and burden *b* in age group *a* and gender *g* in μDALYs/person-day, with burden measured in years of life disable (YLD) or years of life lost (YLL) and YLD+YLL-DALY. BR estimates are adapted from the US estimates from GBD 2016 (Institute for Health Metrics and Evaluation 2018).

According to the GBD, total serum cholesterol can have adverse effects on health for individuals with total cholesterol above 3.1 mmol/L (119.9 mg/dL) (Gakidou et al. 2017). Current total cholesterol levels exceed by far this limit (Benjamin et al. 2017). As a result, the adverse health effects of SFA are valid at any intake level.

A2.4. Sensitivity analysis: Addition of added sugars in HENI

Added sugars are defined as free, mono- and disaccharides sugars added to foods and beverages during manufacturing, processing, cooking or consumption. Dietary guidelines propose the restriction of added sugars to <10% of total daily energy (Brouns 2015; Dietary Guidelines Advisory Committee 2015). Although not consistent (Khan and Sievenpiper 2016), evidence supports an association between added sugars and weight gain (Te Morenga et al. 2012), diabetes (Basu et al. 2013), and cardiovascular diseases (Yang et al. 2014). Since the GBD only considers SSB and does not consider added sugars as a dietary risk, we performed a sensitivity analysis to determine the additional health damage that could occur if the health effect of added sugars was to be added in the HENI framework. First, we developed a $DRF_{Added\ sugar}$ assuming that added sugar has 50% the effect of SSB[1], which resulted in an estimate of 4.6×10^{-1} μDALY/g. Using the added sugar density of food items from the Food Patterns Equivalents Database (FPED) we estimated the $HENI_{added\ sugar}$ per serving (Figure A2.28).

Under the assumptions listed above, our analysis suggests that added sugar is not a major influential contributor to health burden for most food categories. Candy is the category affected the most on average, with a median health burden of added sugars of -4.4 minutes of healthy life/serving. For about 80% of all food items, added sugars induce a health loss lower than a minute of healthy life/serving. However, for specific food items with high added sugar density in food categories such as sweet baked products, other desserts, and yogurts, added sugars may induce a health burden up to 10 minutes of minutes lost per serving. It should be noted that the effect of added sugars was not evaluated for sweetened beverages to avoid double counting.

A2.5. Sensitivity analysis: Contribution of trans and saturated fatty acids to HENI

We also evaluated the influence of TFA and SFA on HENI in a separate sensitivity study. TFA contributions to HENI scores should be interpreted with caution for three main reasons. First, the TFA content for about 60% of the food items in our analysis is based on imputing values using a regression described by Fulgoni et al. (Fulgoni III et al. 2018). Second, TFA has been eliminated or reduced in many food products since 2013 when US FDA determined TFA to be "no longer generally recognized as safe" (US Food and Drug Administration 2013), which makes keeping up-to-date values of TFA in foods a virtually impossible task. Third, recent evidence support that the effect of TFA on health could by source-specific with natural ruminant TFA, and especially conjugated linoleic acids and trans-palmitoleic acid, compensating for some of the adverse effects of other TFA (Astrup et al. 2016; Kleber et al. 2016; Kuhnt et al. 2016).

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[1] $DRF_{added\ sugars} = \frac{0.5 \cdot DRF_{SSB}}{grams\ added\ sugar\ in\ 1\ gram\ SSB}$. We applied an estimate of 0.07 $\frac{grams_{added\ sugar}}{grams_{SSB}}$ based on the mean sugar content of the sweetened beverages in WWEIA/NHANES (Table A2.6)

We investigate the contribution of TFA on HENI for all food items by food category (Figure A2.29). TFA appears to have a relatively small impact in all food categories with the median effect varying from 0.02 minutes of healthy life lost/serving for candy to up to 2.2 minutes of healthy life lost/serving for margarine. Very few foods have substantial health effects due to TFA (> 5 minutes of healthy life lost/serving), with the majority of them belonging to the sweet bakery products food category, which are typically high in industrial TFA. For foods high in natural ruminant TFA such as red meat, cheese, and milk the median contribution of TFA to HENI is 0.5, 0.3, and 0.2 minutes of healthy life lost/serving, respectively.

The contribution of SFA on HENI is slightly higher than TFA, especially for animal-based food categories (Figure A2.30). The median $HENI_{Saturated\ fat}$ ranges from 0 to 3 minutes of healthy life lost per serving of diet beverages and burgers, respectively. SFA-related health damages tend to be higher for red meat-based foods. Extreme estimates of $HENI_{Saturated\ fat}$ (<-5 minutes of healthy life/serving) include primarily grain-based foods that with high levels of coconut milk (coconut milk has the highest $HENI_{Saturated\ fat}$= -19 minutes of healthy life/serving). The high content of SFA in coconut products is well known, however, evidence support that coconut-SFA may not share the detrimental impact as SFA from other sources (Bengmark 2017; Nagashree et al. 2017). Similarly, emerging evidence supports a food-dependent effect of SFA on health, with SFA from dairy having cardiovascular neutrality/protection (De Oliveira Otto et al. 2012; Astrup 2014; Astrup et al. 2016). Based on these results, if we were to exclude the health effects of TFA and SFA for dairy and coconut products, their HENI scores would improve substantially, with the majority of milk and yogurt foods having positive HENI scores ($Median_{milk}$= 0.6 minutes of healthy life gained/serving, IQR_{milk}=-0.01 to 0.7; $Median_{yogurt}$= 0.7 minutes of healthy life gained/serving, IQR_{yogurt}= 0.6 to 2.7)

A2.6. HENI correlation analyses

HENI scores per serving revealed that the performance of food might vary both between and within food groups. We performed various correlation analysis to evaluate whether this variability is associated with food characteristics and food components.

Differences in energy density (Figure A2.25A) or serving size (Figure A2.25B) could not explain most of the variability between food categories. However, a Pearson correlation analysis by food group revealed a statistically significant strong positive correlation between HENI scores for fruits and serving size (ρ=0.85, p <0.0001, Table A2.17). A weak but statistically significant positive correlation was identified between milk and dairy and serving size (ρ=0.38, p <0.0001). We also found weak inverse associations between energy density and the HENI score for mixed dishes and vegetables, with statistically significant correlation coefficients of -0.37 (p<0.0001) and -0.49 (p<0.0001), respectively.

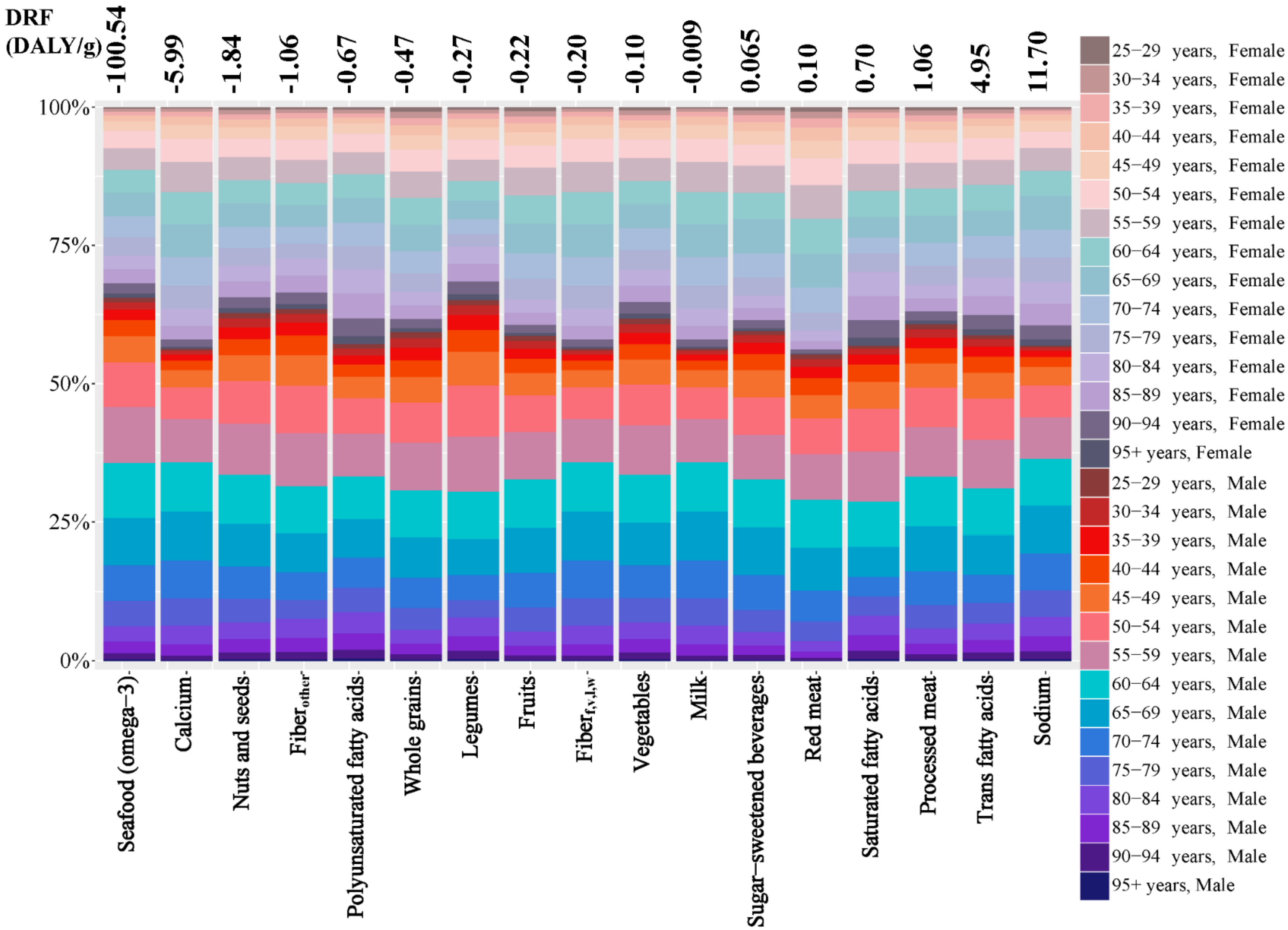


Figure A2.21. Cumulative gender- and age-adjusted dietary risk factor (DRFs) estimates for US adults (25 years and older) in µDALY/g and age group contribution (%) by gender. Fiber$_{f,v,l,w}$=fiber from fruit, vegetables, legumes, and whole grains. Fiber$_{other}$= fiber from sources other than fruits, vegetables, legumes, and whole grains.

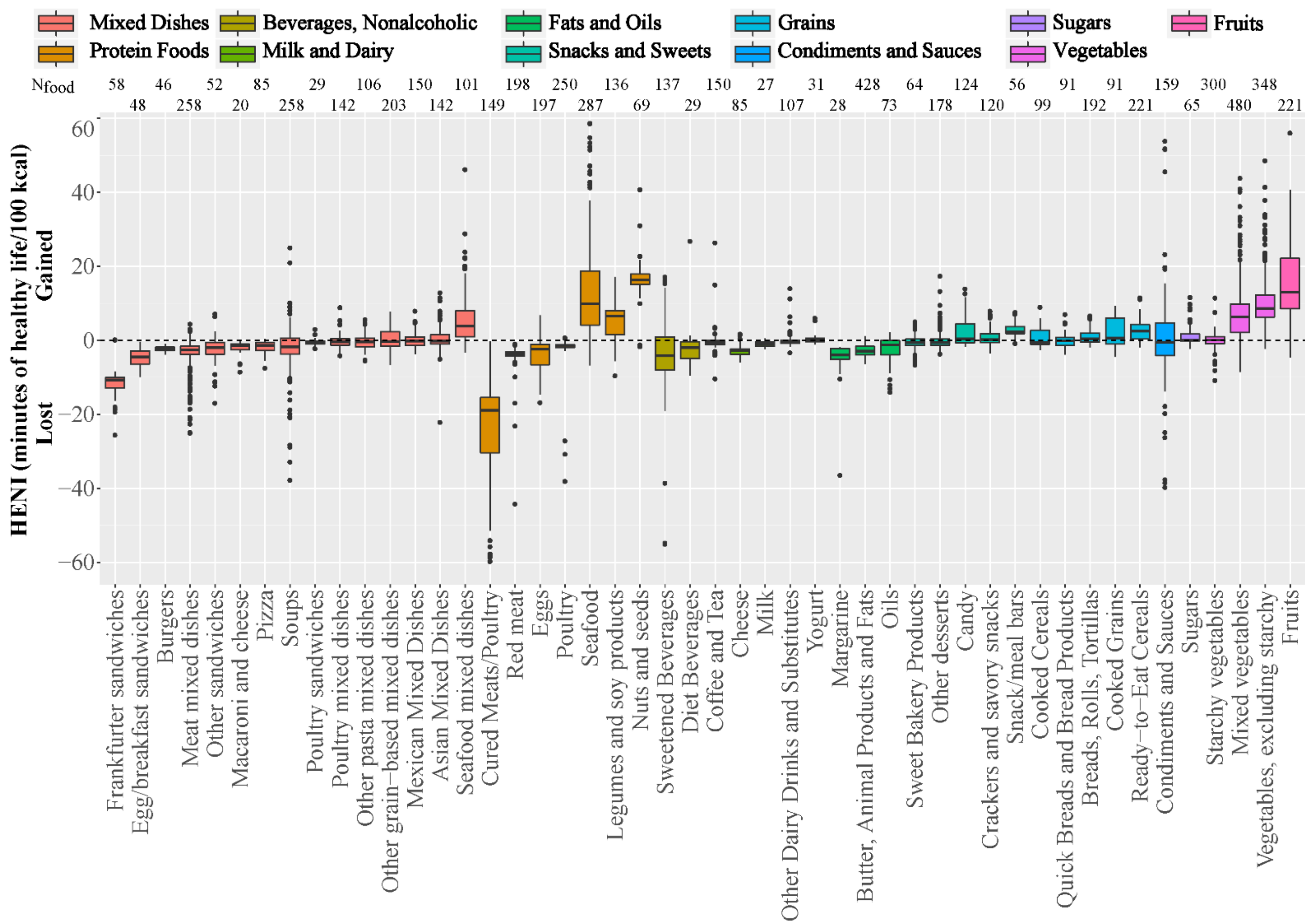


Figure A2.22. Distribution of HENI in minutes of healthy life per 100 kcal for 6,870 foods in the WWEIA/NHANES 2007-2014 by food category. Positive HENI values indicate health benefits. Boxes represent the interquartile range (IQR), horizontal lines represent the medians, whiskers extend to 1.5 times the IQR, and data points represent outliers. 18 food items with zero calories were not included in the analysis, and 11 outliers fall outside the HENI range in this figure. The dotted line represents the neutral health effect score (HENI=0). N_{food} represents the number of foods in each category.

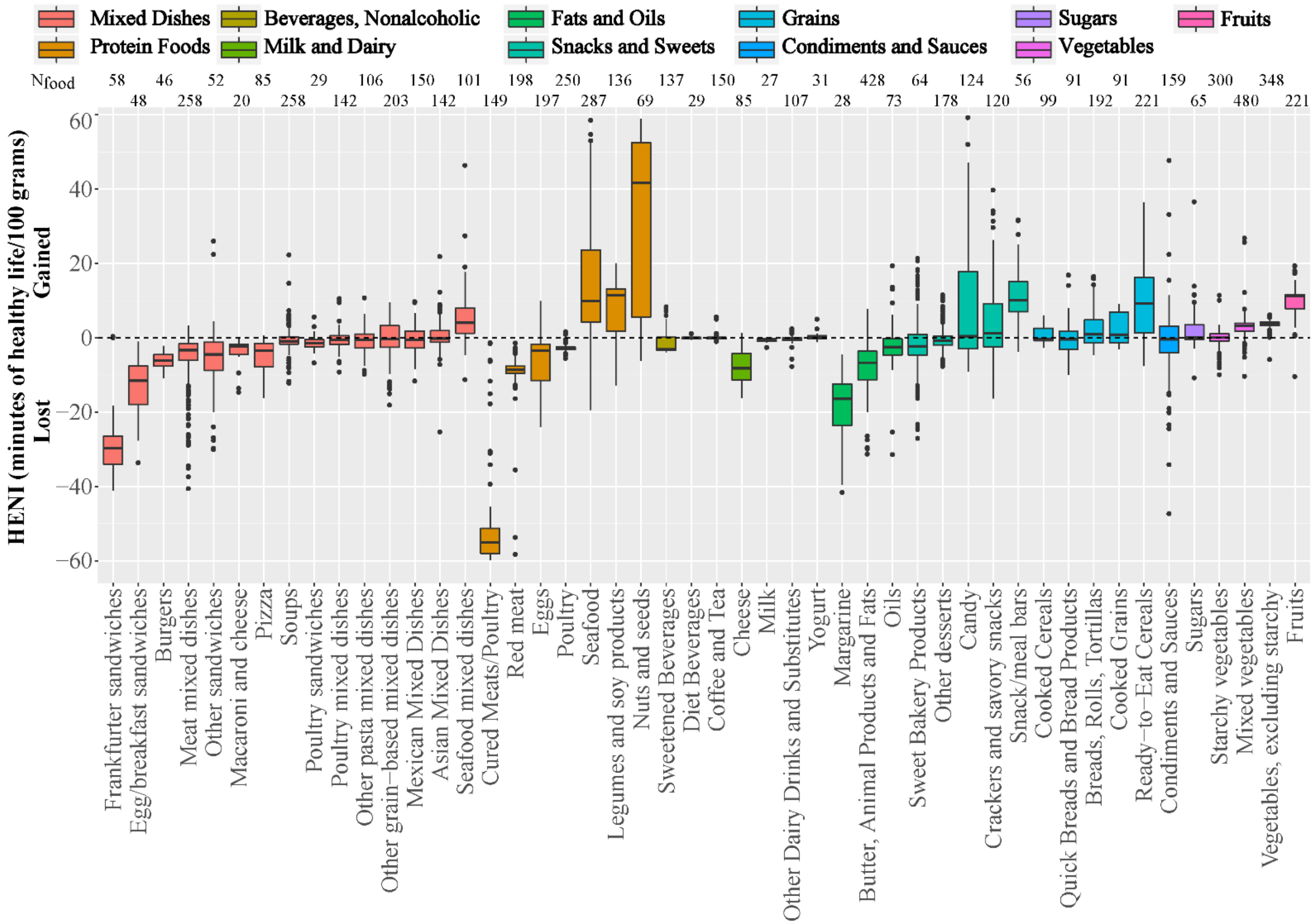


Figure A2.23. Distribution of HENI (minutes of healthy life/100 g) for 6,888 foods in the WWEIA/NHANES 2007-2014 by food category. Positive HENI values indicate health benefits. Boxes represent the interquartile range (IQR), horizontal lines represent the medians, whiskers extend to 1.5 times the IQR, and data points represent outliers. 132 outliers fall outside the HENI range in this figure. The dotted line represents the neutral health effect score (HENI=0). N_{food} represents the number of foods in each category.

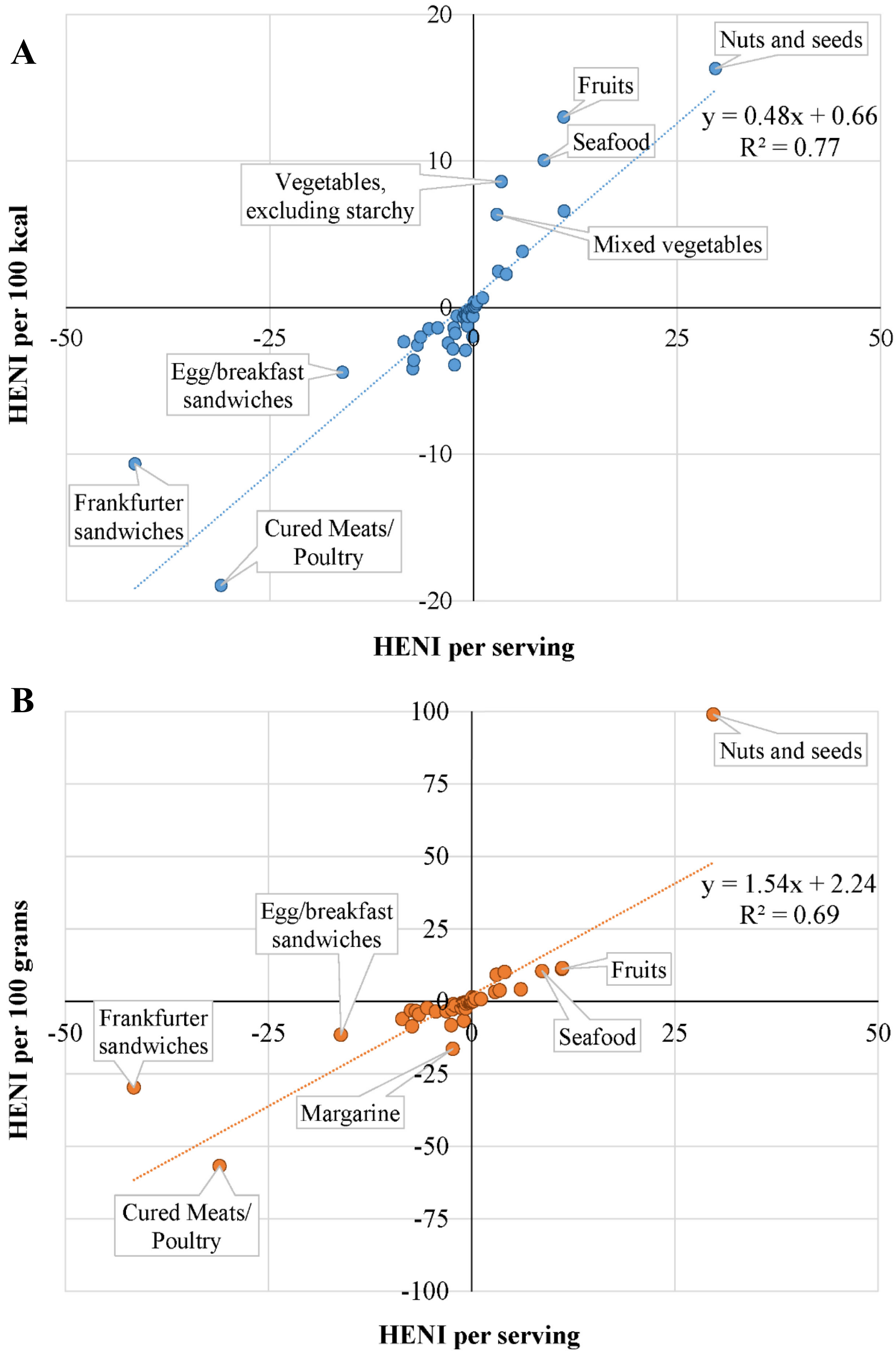


Figure A2.24. Association between and median HENI scores per serving by food category and (**A**) median HENI scores per 100 kcal, and (**B**) median HENI scores per 100 grams.

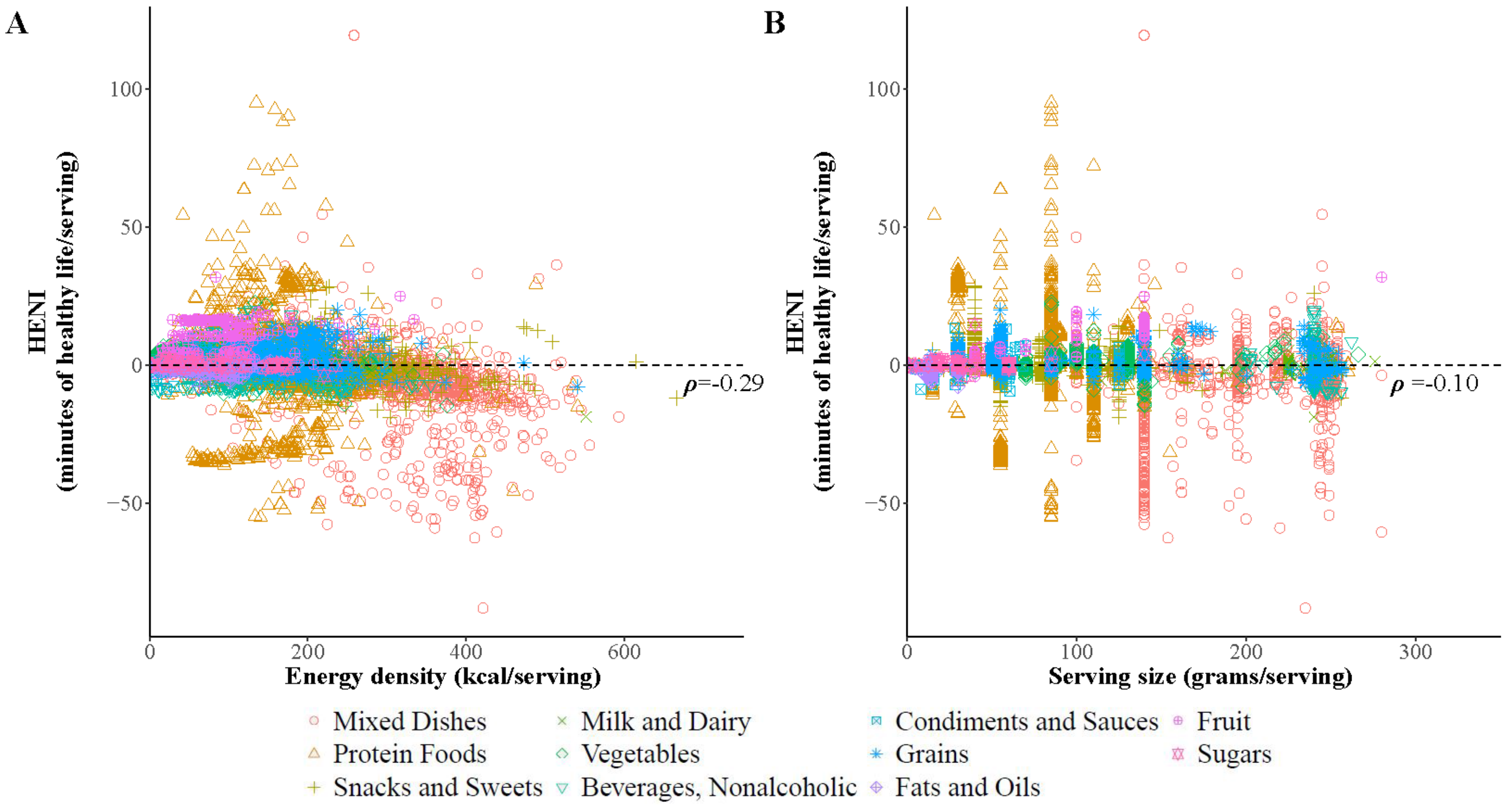


Figure A2.25. HENI per serving as a function of energy density (**A**) and serving size (**B**) by food group for 6,888 food items in the US diet. ρ represents the Pearson's correlation coefficient.

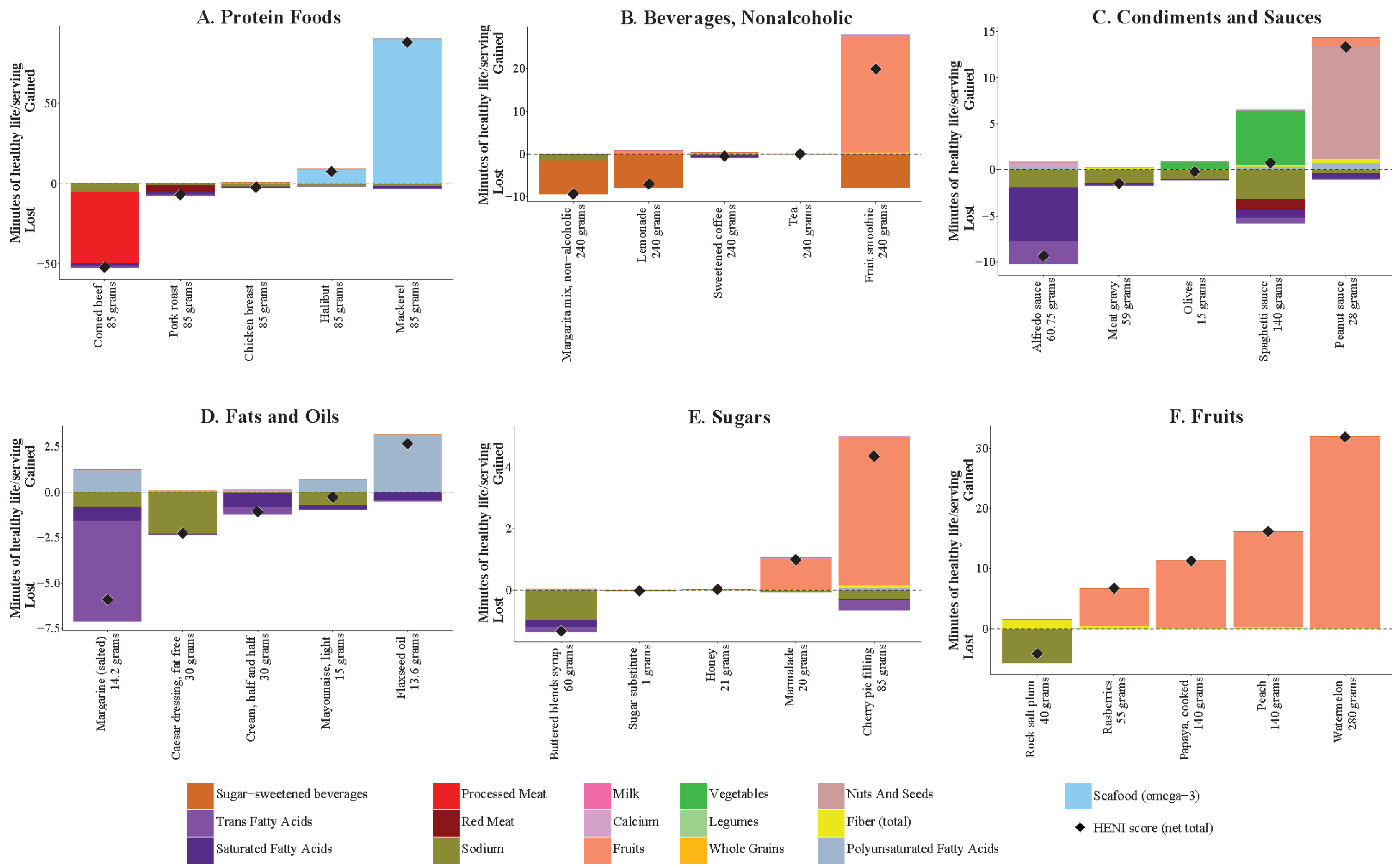
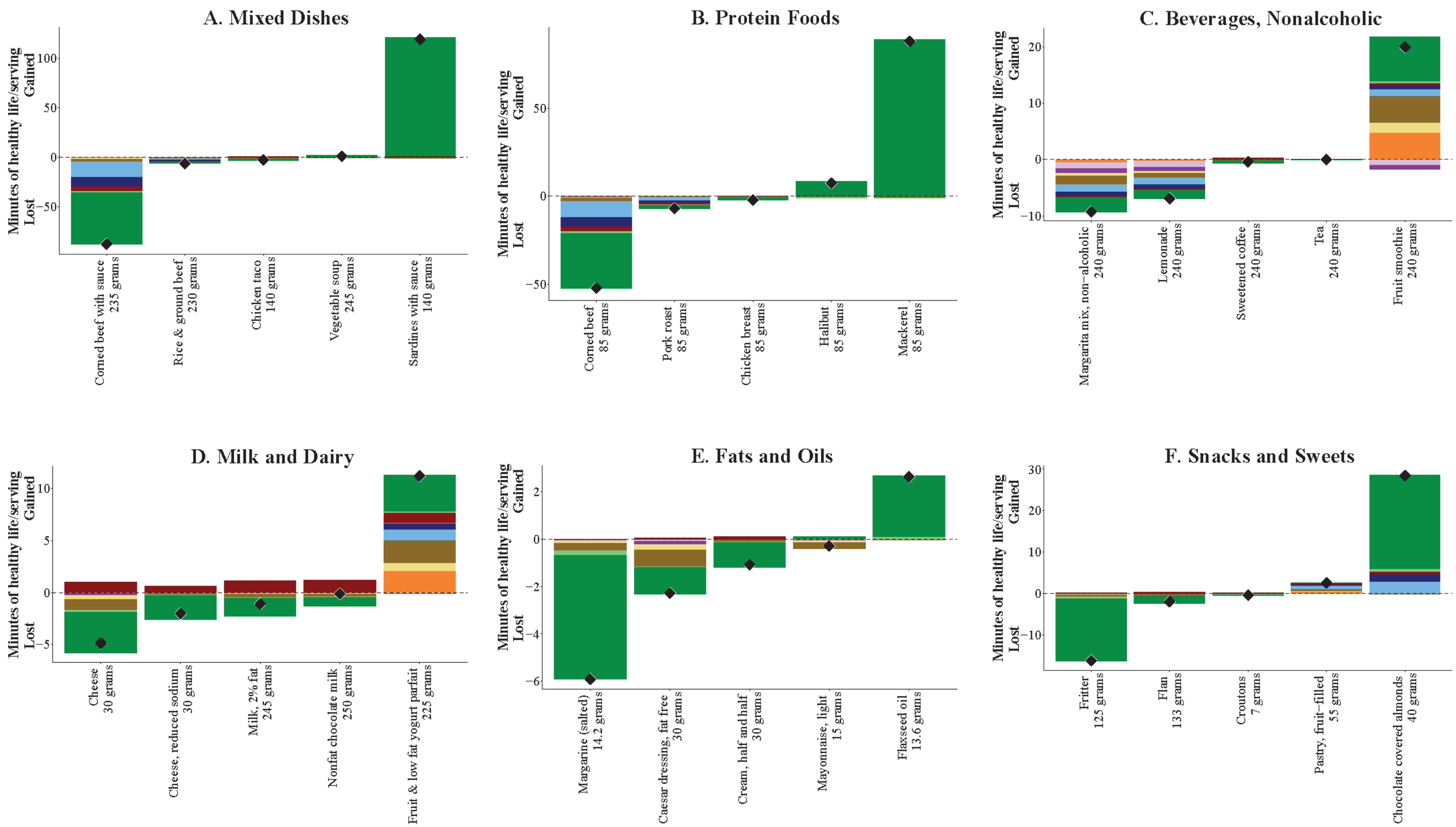


Figure A2.26. Dietary risk contribution to HENI for food group (complementary of Figure 3.3): **A.** Protein Foods, **B**. Beverages, Nonalcoholic, **C.** Condiments and Sauces, **D.** Fats and Oils, **E.** Sugars, **F.** Fruits). The five foods are representative of the min, 25th percentile, median, 75th percentile, and max scores within the category (within one percentile). The black diamond represents the HENI score per serving. The dotted line represents the neutral health effect score (HENI=0).


A. Mixed Dishes
Minutes of healthy life/serving
Gained
Lost
Corned beef with sauce 235 grams
Rice & ground beef 230 grams
Chicken taco 140 grams
Vegetable soup 245 grams
Sardines with sauce 140 grams
B. Protein Foods
Corned beef 85 grams
Pork roast 85 grams
Chicken breast 85 grams
Halibut 85 grams
Mackerel 85 grams
C. Beverages, Nonalcoholic
Margarita mix, non-alcoholic 240 grams
Lemonade 240 grams
Sweetened coffee 240 grams
Tea 240 grams
Fruit smoothie 240 grams
D. Milk and Dairy
Cheese 30 grams
Cheese, reduced sodium 30 grams
Milk, 2% fat 245 grams
Nonfat chocolate milk 250 grams
Fruit & low fat yogurt parfait 225 grams
E. Fats and Oils
Margarine (salted) 14.2 grams
Caesar dressing, fat free 30 grams
Cream, half and half 30 grams
Mayonnaise, light 15 grams
Flaxseed oil 13.6 grams
F. Snacks and Sweets
Fritter 125 grams
Flan 133 grams
Croutons 7 grams
Pastry, fruit-filled 55 grams
Chocolate covered almonds 40 grams

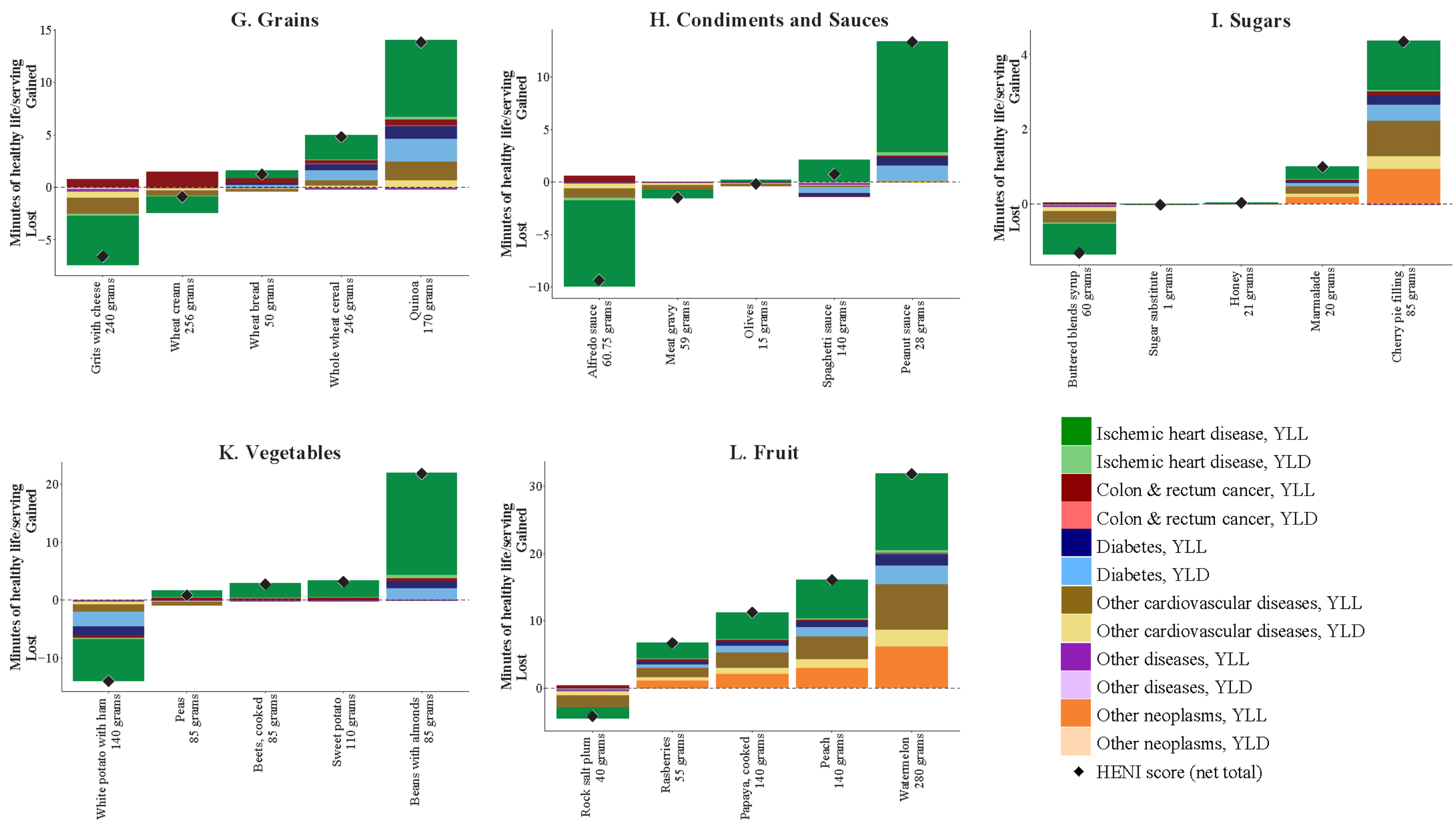


Figure A2.27. Disease composition of HENI by food group: **A.** Mixed dishes, **B.** Protein foods, **C.** Milk and Dairy, **D.** Snacks and Sweets, **E.** Vegetables, **F.** Nonalcoholic Beverages, **G.** Condiments and Sauces, **H.** Fats and Oils, **I.** Grains, **J.** Sugars, **K.** Fruits). The five foods are representative of the min, 25th percentile, median, 75th percentile, and max scores within the category (within one percentile). The black diamond represents the HENI score per serving. The dotted line represents the neutral health effect score (HENI=0). YLD= years of life disabled, YLL= years of life lost

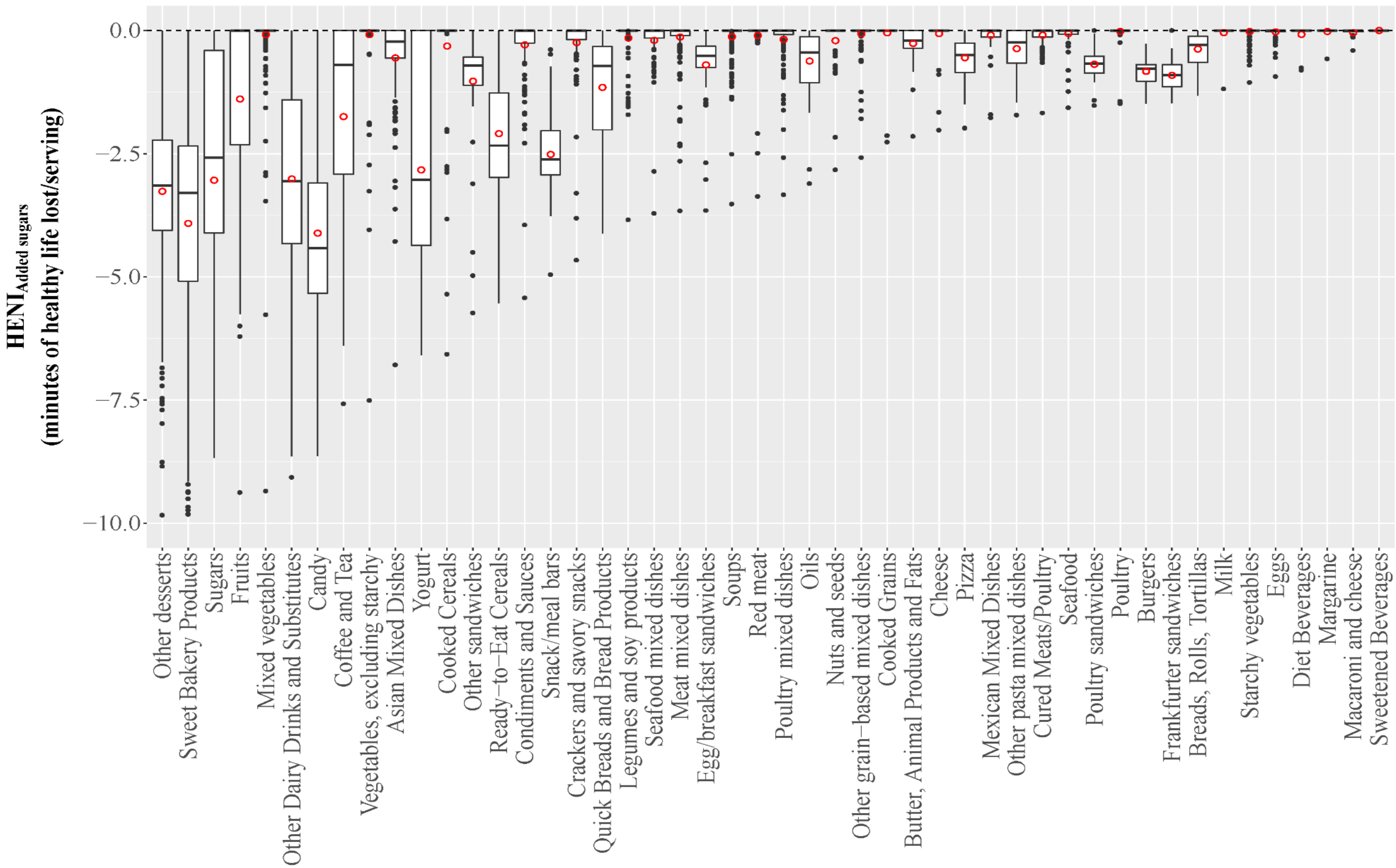


Figure A2.28. Risk-specific HENI estimates in minutes of healthy life per serving by food category for 6,888 food items in the WWEIA/NHANES 2007-2014 for added sugars. Results were estimated based on $DRF_{added\ sugars}$=4.6 × 10^{-1} µDALY/g, assuming that added sugars have 50% of the effect of SSB. The health effect of added sugars was not evaluated for SSBs to avoid double counting. Nine outliers fall outside the HENI range in this figure.

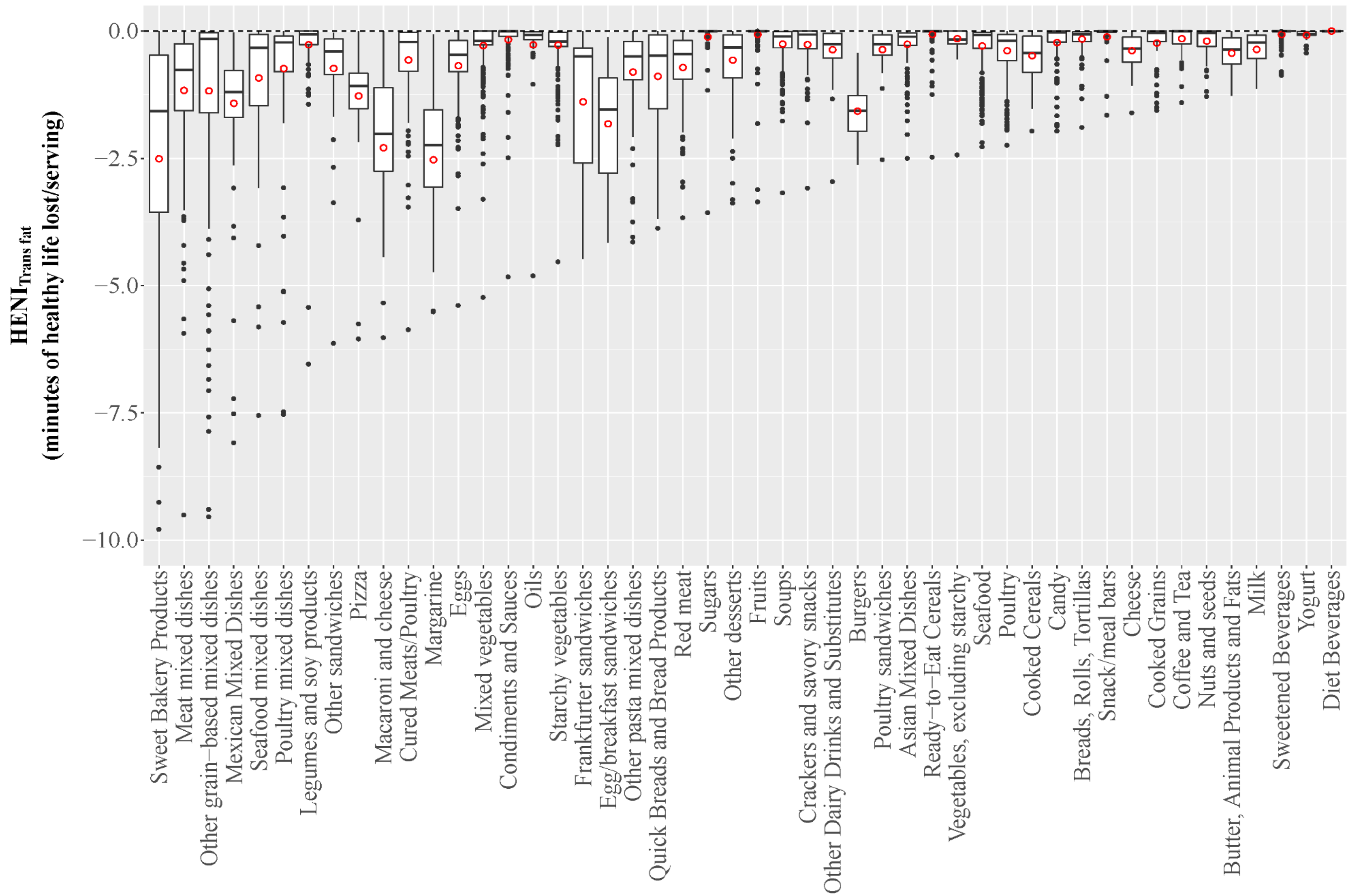


Figure A2.29. Risk-specific HENI estimates in minutes of healthy life per serving by food category for 6,888 food items in the WWEIA/NHANES 2007-2014 for trans fatty acids. 16 outliers fall outside the HENI range in this figure.

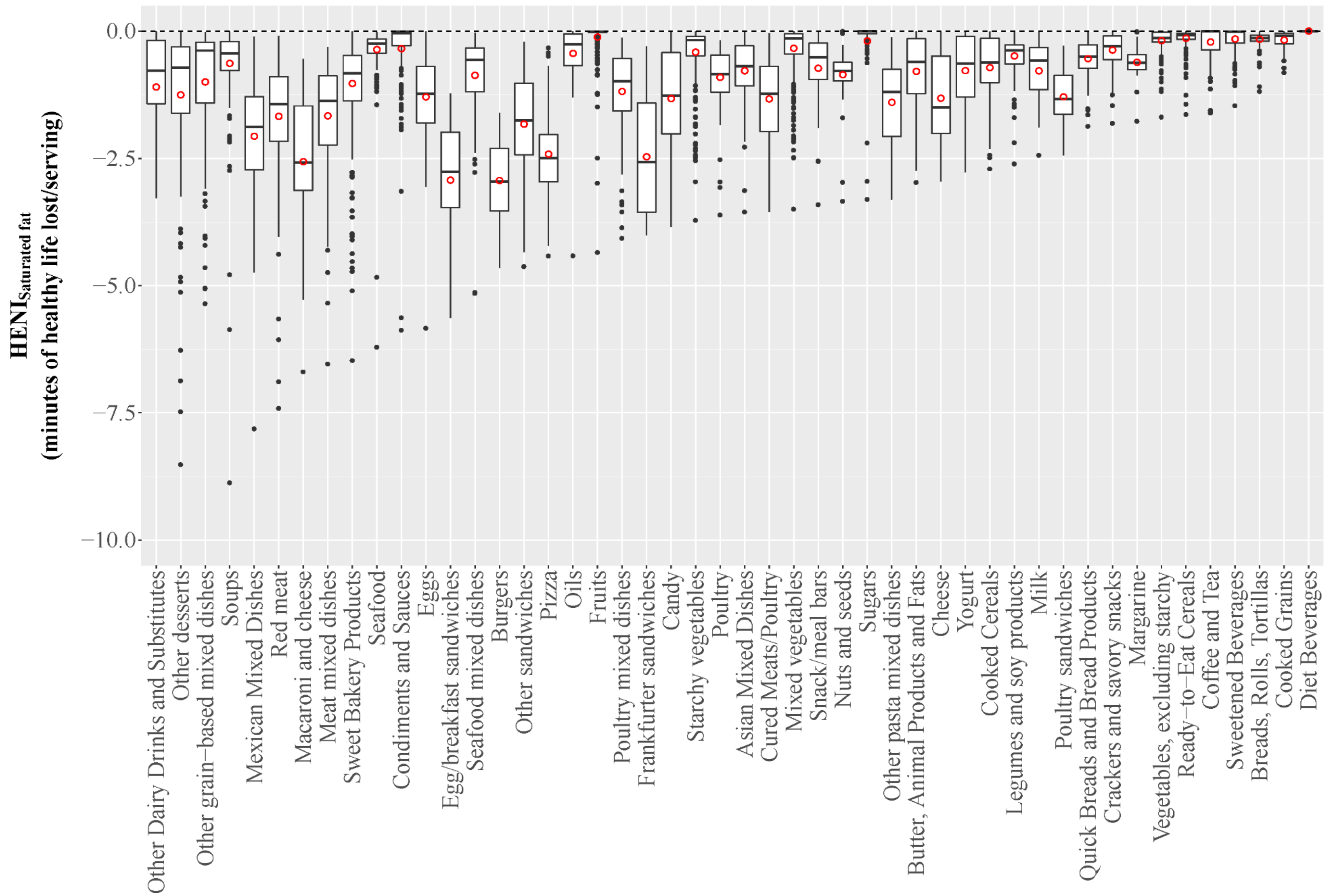


Figure A2.30. Risk-specific HENI estimates in minutes of healthy life per serving by food category for 6,888 food items in the WWEIA/NHANES 2007-2014 for saturated fatty acids. Three outliers fall outside the HENI range in this figure.

Table A2.15. 95% uncertainty interval (UI) characterization of dietary risk factors (DRFs) in μDALYs/g

Dietary risk	**DRF (μDALYs/g)**	**Lower**	**Upper**
Seafood (omega-3)	-100.54	-170.35	-39.11
Calcium	-5.988	-8.022	-4.195
Nuts and seeds	-1.837	-2.830	-1.031
$Fiber_{other}$	-1.063	-1.551	-0.652
Polyunsaturated fatty acids	-0.665	-1.120	-0.250
Whole grains	-0.470	-0.735	-0.262
Legumes	-0.266	-0.449	-0.104
Fruits	-0.215	-0.390	-0.076
$Fiber_{f,v,l,w}$	-0.201	-0.304	-0.110
Vegetables	-0.098	-0.178	-0.033
Milk	-0.0089	-0.016	-0.0030
Sugar-sweetened beverages	0.065	0.020	0.164
Red meat	0.102	0.013	0.213
Saturated fatty acids	0.704	0.195	1.653
Processed meat	1.060	0.199	1.902
Trans fatty acids	4.945	3.381	6.757
Sodium	11.70	7.959	15.34

$Fiber_{other}$= fiber from sources other than fruits, vegetables, legumes, and whole grains
$Fiber_{f,v,l,w}$=fiber from fruit, vegetables, legumes, and whole grains

Table A2.16. HENI score summary statistics per serving for 6,888 food items in the WWEIA/NHANES 2007-2014 by HENI category

HENI categories	N	Min	Q1 (25th percentile)	Median	Q3 (75th percentile)	Max	Mean
Frankfurter sandwiches	58	-57.66	-47.57	-41.56	-37.06	0.48	-40.49
Cured Meats/Poultry	149	-55.08	-33.37	-31.00	-28.07	-0.11	-28.60
Egg/breakfast sandwiches	48	-47.10	-25.10	-16.09	-10.61	-1.39	-18.35
Burgers	46	-15.28	-10.64	-8.55	-6.28	-3.02	-8.59
Sweetened Beverages	137	-9.75	-8.00	-7.45	0.26	19.91	-3.63
Red meat	198	-45.68	-8.30	-7.33	-6.48	-0.99	-8.06
Meat mixed dishes	258	-87.98	-10.94	-6.88	-3.36	8.38	-11.38
Other sandwiches	52	-42.10	-12.23	-6.48	-1.61	36.36	-8.61
Macaroni and cheese	20	-35.64	-9.58	-5.47	-3.55	0.56	-9.12
Pizza	85	-14.97	-10.88	-4.40	-2.05	0.87	-6.10
Eggs	197	-31.51	-12.67	-3.11	-1.16	10.84	-6.83
Cheese	85	-5.65	-3.42	-2.51	-1.76	1.34	-2.46
Poultry	250	-52.40	-2.73	-2.39	-2.11	1.36	-2.93
Margarine	28	-5.91	-3.34	-2.33	-1.59	-0.67	-2.73
Soups	258	-30.02	-3.95	-2.23	0.60	54.56	-1.37
Poultry sandwiches	29	-9.48	-3.39	-2.01	-0.63	7.79	-1.93
Sweet Bakery Products	428	-18.83	-3.61	-1.23	0.62	14.38	-1.41
Poultry mixed dishes	142	-15.86	-3.55	-1.12	0.98	11.35	-1.31
Other pasta mixed dishes	106	-21.82	-5.09	-0.97	1.64	15.64	-1.57
Butter, Animal Products and Fats	73	-4.25	-1.69	-0.96	-0.29	1.17	-1.15
Other grain-based mixed dishes	203	-25.37	-4.87	-0.81	6.55	22.57	-0.04
Milk	27	-3.32	-1.90	-0.79	-0.27	0.46	-1.10
Cooked Cereals	99	-6.58	-1.79	-0.74	6.13	14.16	1.33
Oils	64	-7.62	-1.40	-0.74	-0.07	2.63	-0.88
Mexican Mixed Dishes	150	-16.32	-3.95	-0.72	2.60	18.41	-0.84
Other Dairy Drinks and Substitutes	107	-18.66	-1.61	-0.69	0.11	5.90	-0.55

HENI categories	N	Min	Q1 (25th percentile)	Median	Q3 (75th percentile)	Max	Mean
Other desserts	178	-11.83	-1.96	-0.69	0.36	26.03	-0.13
Asian Mixed Dishes	142	-35.47	-2.10	-0.42	2.98	35.40	1.22
Quick Breads and Bread Products	91	-7.72	-2.53	-0.21	1.29	18.50	-0.18
Condiments and Sauces	159	-9.34	-1.45	-0.17	0.81	13.35	-0.18
Diet Beverages	29	-1.13	-0.52	-0.10	-0.04	2.57	-0.18
Coffee and Tea	150	-2.50	-0.73	-0.04	-0.01	13.35	-0.12
Sugars	65	-3.83	-0.03	0.01	0.99	14.62	0.69
Starchy vegetables	300	-13.95	-0.98	0.05	1.14	12.56	-0.30
Candy	124	-3.60	-1.13	0.09	7.58	28.58	3.96
Yogurt	31	-2.63	-0.55	0.24	1.19	11.21	0.68
Crackers and savory snacks	120	-4.89	-0.71	0.37	2.74	11.91	1.42
Breads, Rolls, Tortillas	192	-2.33	-0.68	0.48	2.41	8.23	1.28
Cooked Grains	91	-4.39	-1.78	1.14	10.12	13.84	3.64
Mixed vegetables	480	-14.53	1.86	2.88	3.44	22.77	2.68
Ready-to-Eat Cereals	221	-2.26	0.39	3.06	6.41	20.01	3.92
Vegetables, excluding starchy	348	-2.34	3.04	3.44	4.53	10.26	3.76
Snack/meal bars	56	-1.49	2.80	4.05	6.03	13.15	4.83
Seafood mixed dishes	101	-15.81	2.28	6.04	12.44	119.40	9.81
Seafood	287	-5.84	3.70	8.67	21.99	95.04	15.40
Fruits	221	-4.18	6.70	11.10	16.08	31.84	11.47
Legumes and soy products	136	-11.46	2.13	11.16	11.99	29.29	7.61
Nuts and seeds	69	-1.85	28.16	29.73	31.15	36.31	28.07

Table A2.17. Pearson correlation coefficient between HENI per serving and energy density by the main food group

Main Food Group Description	Energy density (kcal/serving)	Serving size (g/serving)
Mixed Dishes	-0.37 ****	0.09 ***
Protein Foods	-0.12 ****	-0.03
Snacks and Sweets	-0.15 ****	-0.2 ****
Milk and Dairy	-0.16 **	0.38 ****
Vegetables	-0.49 ****	-0.01
Beverages, Nonalcoholic	-0.21 ***	-0.07
Condiments and Sauces	-0.08	0.11
Grains	0.09 *	-0.04
Fats and Oils	0.04	0.03
Fruit	0.21 **	0.85 ****
Sugars	0.09	0.14

p-value < .0001 '****'; p-value < .001 '***', p-value < .01 '**', p-value < .05 '*'

Strong +
Moderate +
Weak +
Weak -
Moderate -
Strong -

Table A2.18. Physical activity adjusted estimated calorie needs per pay (kcal/day), by Age and Sex. Estimated daily calorie needs are obtained from the 2015-2020 Dietary Guidelines for Americans and physical activity distribution information from US estimates in 2008-2010 (Schoenborn et al. 2013)

Age group	Male	Female
25-29	2662	2018
30-34	2662	1956
35-39	2586	1956
40-44	2494	1956
45-49	2418	1931
50-54	2418	1781
55-59	2355	1781
60-64	2249	1731
65-69	2198	1704
70-74	2198	1704
75-79	2103	1657
80-84	2103	1657
85-89	2103	1657
90-94	2103	1657
95+	2103	1657

Table A2.19. Added sugar density of sweetened beverages in the WWEIA/NHANES database. Information obtained from the Food Patterns Equivalents Database (FPED)

Food Description	Added sugars (g/100 g)
Orange Julius	1.44
Fruit smoothie drink, made with fruit or fruit juice and dairy products	10.20
Instant breakfast, powder, milk added	5.80
Meal supplement or replacement, commercially prepared, ready-to-drink	6.09
High calorie beverage, canned or powdered, reconstituted	8.44
Meal supplement or replacement, milk-based, high protein, liquid	7.43
Meal replacement or supplement, milk based, ready-to-drink	7.43
Licuado / Batido (milk fruit drink)	4.91
Fruit smoothie, NFS	3.06
Meal replacement or supplement, soy- and milk-base, powder, reconstituted with water	0.00
Nutritional supplement for people with diabetes, liquid	7.43
Ensure with fiber, liquid	3.32
Ensure Plus liquid nutrition	11.97
Energy Drink	10.08
Fluid replacement, electrolyte solution	2.44
Fruit smoothie drink, made with fruit or fruit juice only (no dairy products)	4.13
Fruit nectar, NFS	10.08
Apricot nectar	10.08
Banana nectar	9.98
Cantaloupe nectar	12.41
Guava nectar	13.46
Mango nectar	6.51
Peach nectar	9.95
Papaya nectar	11.55
Passion fruit nectar	11.98
Pear nectar	11.26
Soursop (Guanabana) nectar	7.64
Full Throttle Energy Drink	12.10
Ensure liquid nutrition	0.00
Soft drink, NFS	9.16
Coconut water, unsweetened (liquid from coconuts)	0.00
Coconut water, sweetened	5.05
Soft drink, fruit flavored, caffeine containing	10.21
Soft drink, ale type	8.06
Fruit juice drink	10.17
Fruit punch, made with fruit juice and soda	4.35
Fruit punch, made with soda, fruit juice, and sherbet or ice cream	6.54

Food Description	**Added sugars (g/100 g)**
Fruit flavored drink (formerly lemonade)	11.28
Citrus fruit juice drink, containing 40-50% juice	6.42
Frozen daiquiri mix, frozen concentrate, not reconstituted	48.43
Frozen daiquiri mix, from frozen concentrate, reconstituted	11.07
Pina Colada, nonalcoholic	21.07
Fruit flavored drink, with high vitamin C	12.99
Fruit juice drink, with high vitamin C	11.30
Vegetable and fruit juice drink, with high vitamin C	0.88
Fruit juice drink, with high vitamin C, plus added calcium	5.69
Fruit flavored drink, reduced sugar, with high vitamin C, plus added calcium	7.89
Horchata beverage, made with rice	9.10
Horchata beverage, NFS	12.97
Sugar cane beverage, Puerto Rican	6.95
Atole (corn meal beverage)	11.74
Nonalcoholic malt beverage	8.06
Shirley Temple	13.18
Meal replacement or supplement, liquid, soy-based	0.00
Soft drink, cola-type, with higher caffeine	10.58
Mavi drink	10.38
Wine, nonalcoholic	0.00
Monster Energy Drink	11.26
Mountain Dew AMP Energy Drink	12.10
Powerade sports drink	6.09
Carbonated juice drink, NS as to type of juice	0.00
Boost, nutritional drink, ready-to-drink	3.99
Boost Plus, nutritional drink, ready-to-drink	3.99
Carnation Instant Breakfast, nutritional drink, regular, ready-to-drink	5.67
Ensure, nutritional shake, ready-to-drink	3.99
Ensure Plus, nutritional shake, ready-to-drink	17.98
Glucerna, nutritional shake, ready-to-drink	2.02
Kellogg's Special K Protein Shake	4.49
Muscle Milk, ready-to-drink	0.00
Muscle Milk, light, ready-to-drink	0.00
Slim Fast Shake, meal replacement, regular, ready-to-drink	1.39
Slim Fast Shake, meal replacement, high protein, ready-to-drink	0.00
Nutritional drink or meal replacement, ready-to-drink, NFS	3.99
Nutritional drink or meal replacement, high protein, ready-to-drink, NFS	0.00
Nutritional drink or meal replacement, high protein, light, ready-to-drink, NFS	3.99
Nutritional drink or meal replacement, liquid, soy-based	3.99
Red Bull Energy Drink	10.08
NOS Energy Drink	11.26

Food Description	**Added sugars (g/100 g)**
Rockstar Energy Drink	12.26
SoBe Energize Energy Juice Drink	10.00
XS Energy Drink	0.00
Fruit smoothie, with whole fruit and dairy	3.06
Fruit smoothie, with whole fruit and dairy, added protein	3.30
Fruit smoothie juice drink, with dairy	0.00
Vault Energy Drink	12.98
Fruit smoothie, with whole fruit (no dairy)	0.00
Fruit smoothie, with whole fruit (no dairy), added protein	0.00
Fruit smoothie juice drink (no dairy)	0.36
Fruit smoothie, light	0.00
Fruit smoothie, bottled	0.00
Soft drink, cola	9.95
Soft drink, cola, reduced sugar	5.17
Soft drink, cola, decaffeinated	10.58
Soft drink, pepper type	9.95
Soft drink, pepper type, decaffeinated	10.58
Fruit and vegetable smoothie	0.00
Fruit and vegetable smoothie, added protein	0.00
Fruit and vegetable smoothie, bottled	0.00
Soft drink, cream soda	13.31
Soft drink, fruit flavored, caffeine free	8.99
Soft drink, ginger ale	8.90
Soft drink, root beer	10.58
Soft drink, cola, fruit or vanilla flavored	9.95
Fruit juice drink, citrus, carbonated	0.00
Fruit juice drink, noncitrus, carbonated	0.00
Tamarind drink (Refresco de tamarindo)	13.41
Margarita mix, nonalcoholic	21.42
Fruit flavored smoothie drink, frozen (no dairy)	7.56
Cranberry juice drink, with high vitamin C	9.87
Sunny D	12.10
Fruit flavored drink, powdered, reconstituted	6.50
Fruit flavored drink, with high vitamin C, powdered, reconstituted	9.75
Fruit juice drink, with high vitamin C, light	2.60
Fruit juice drink, diet	0.00
Cranberry juice drink, with high vitamin C, light	2.60
Orange juice beverage, 40-50% juice, light	0.00
Vegetable and fruit juice drink, with high vitamin C, light	0.00
Soft drink, chocolate flavored	10.71
Sunny D, reduced sugar	0.00

Food Description	Added sugars (g/100 g)
Lemonade, fruit juice drink	11.68
Lemonade, fruit flavored drink	6.50
Fruit flavored drink	15.83
Capri Sun, fruit juice drink	7.01
Sunny D, added calcium	6.01
Refresco de avena (oatmeal beverage with water)	9.34
Fruit juice drink, light	7.01
Atole de avena (oatmeal beverage with milk)	11.86
Grape juice drink, light	0.00
Atole de chocolate / Champurrado (cornmeal beverage with chocolate and milk)	14.45
Apple juice beverage, 40-50% juice, light	4.79
Lemonade, fruit juice drink, light	5.00
Horchata beverage, made with water	8.04
Horchata beverage, made with milk	8.76
Gatorade G sports drink	5.25
Sports drink, NFS	5.25
Slim Fast Shake, meal replacement, sugar free, ready-to-drink	1.39
Energy drink, sugar free	0.00

Table A2.20. Correspondence table between USDA food coding scheme and HENI food categories

Main Group Description	Subgroup Description	Category Description	Final Categories
Alcoholic Beverages	Alcoholic Beverages	Beer	Alcoholic Beverages
Alcoholic Beverages	Alcoholic Beverages	Liquor and cocktails	Alcoholic Beverages
Alcoholic Beverages	Alcoholic Beverages	Wine	Alcoholic Beverages
Beverages, Nonalcoholic	100% Juice	Citrus juice	100% Juice
Beverages, Nonalcoholic	100% Juice	Other fruit juice	100% Juice
Beverages, Nonalcoholic	100% Juice	Apple juice	100% Juice
Beverages, Nonalcoholic	100% Juice	Vegetable juice	100% Juice
Beverages, Nonalcoholic	Coffee and Tea	Coffee	Coffee and Tea
Beverages, Nonalcoholic	Coffee and Tea	Tea	Coffee and Tea
Beverages, Nonalcoholic	Diet Beverages	Diet soft drinks	Diet Beverages
Beverages, Nonalcoholic	Diet Beverages	Other diet drinks	Diet Beverages
Beverages, Nonalcoholic	Diet Beverages	Diet sport and energy drinks	Diet Beverages
Beverages, Nonalcoholic	Sweetened Beverages	Smoothies and grain drinks	Sweetened Beverages
Beverages, Nonalcoholic	Sweetened Beverages	Nutritional beverages	Sweetened Beverages
Beverages, Nonalcoholic	Sweetened Beverages	Fruit drinks	Sweetened Beverages
Beverages, Nonalcoholic	Sweetened Beverages	Soft drinks	Sweetened Beverages
Beverages, Nonalcoholic	Sweetened Beverages	Sport and energy drinks	Sweetened Beverages
Condiments and Sauces	Condiments and Sauces	Dips, gravies, other sauces	Condiments and Sauces
Condiments and Sauces	Condiments and Sauces	Pasta sauces, tomato-based	Condiments and Sauces
Condiments and Sauces	Condiments and Sauces	Soy-based condiments	Condiments and Sauces
Condiments and Sauces	Condiments and Sauces	Mustard and other condiments	Condiments and Sauces
Condiments and Sauces	Condiments and Sauces	Olives, pickles, pickled vegetables	Condiments and Sauces
Condiments and Sauces	Condiments and Sauces	Tomato-based condiments	Condiments and Sauces
Fats and Oils	Fats and Oils	Cream and cream substitutes	Butter, Animal Products and Fats
Fats and Oils	Fats and Oils	Cream cheese, sour cream, whipped cream	Butter, Animal Products and Fats
Fats and Oils	Fats and Oils	Butter and animal fats	Butter, Animal Products and Fats
Fats and Oils	Fats and Oils	Margarine	Margarine
Fats and Oils	Fats and Oils	Mayonnaise	Butter, Animal Products and Fats

Main Group Description	Subgroup Description	Category Description	Final Categories
Fats and Oils	Fats and Oils	Salad dressings and vegetable oils	Oils
Fruit	Fruits	Citrus fruits	Fruits
Fruit	Fruits	Dried fruits	Fruits
Fruit	Fruits	Other fruits and fruit salads	Fruits
Fruit	Fruits	Apples	Fruits
Fruit	Fruits	Bananas	Fruits
Fruit	Fruits	Melons	Fruits
Fruit	Fruits	Grapes	Fruits
Fruit	Fruits	Peaches and nectarines	Fruits
Fruit	Fruits	Berries	Fruits
Grains	Breads, Rolls, Tortillas	Yeast breads	Breads, Rolls, Tortillas
Grains	Breads, Rolls, Tortillas	Rolls and buns	Breads, Rolls, Tortillas
Grains	Breads, Rolls, Tortillas	Bagels and English muffins	Breads, Rolls, Tortillas
Grains	Breads, Rolls, Tortillas	Tortillas	Breads, Rolls, Tortillas
Grains	Cooked Cereals	Grits and other cooked cereals	Cooked Cereals
Grains	Cooked Cereals	Oatmeal	Cooked Cereals
Grains	Cooked Grains	Pasta, noodles, cooked grains	Cooked Grains
Grains	Cooked Grains	Rice	Cooked Grains
Grains	Quick Breads and Bread Products	Biscuits, muffins, quick breads	Quick Breads and Bread Products
Grains	Quick Breads and Bread Products	Pancakes, waffles, French toast	Quick Breads and Bread Products
Grains	Ready-to-Eat Cereals	Ready-to-eat cereal, lower sugar (=<21.2g/100g)	Ready-to-Eat Cereals
Grains	Ready-to-Eat Cereals	Ready-to-eat cereal, higher sugar (>21.2g/100g)	Ready-to-Eat Cereals
Milk and Dairy	Cheese	Cheese	Cheese
Milk and Dairy	Cheese	Cottage/ricotta cheese	Cheese
Milk and Dairy	Dairy Drinks and Substitutes	Milk substitutes	Other Dairy Drinks and Substitutes
Milk and Dairy	Dairy Drinks and Substitutes	Milk shakes and other dairy drinks	Other Dairy Drinks and Substitutes
Milk and Dairy	Flavored Milk	Flavored milk, whole	Other Dairy Drinks and Substitutes
Milk and Dairy	Flavored Milk	Flavored milk, nonfat	Other Dairy Drinks and Substitutes
Milk and Dairy	Flavored Milk	Flavored milk, reduced fat	Other Dairy Drinks and Substitutes

Main Group Description	Subgroup Description	Category Description	Final Categories
Milk and Dairy	Flavored Milk	Flavored milk, lowfat	Other Dairy Drinks and Substitutes
Milk and Dairy	Milk	Milk, reduced fat	Milk
Milk and Dairy	Milk	Milk, whole	Milk
Milk and Dairy	Milk	Milk, lowfat	Milk
Milk and Dairy	Milk	Milk, nonfat	Milk
Milk and Dairy	Yogurt	Yogurt, regular	Yogurt
Milk and Dairy	Yogurt	Yogurt, Greek	Yogurt
Mixed Dishes	Mixed Dishes - Asian	Stir-fry and soy-based sauce mixtures	Asian Mixed Dishes
Mixed Dishes	Mixed Dishes - Asian	Fried rice and lo/chow mein	Asian Mixed Dishes
Mixed Dishes	Mixed Dishes - Asian	Egg rolls, dumplings, sushi	Asian Mixed Dishes
Mixed Dishes	Mixed Dishes - Grain-based	Rice mixed dishes	Other grain-based mixed dishes
Mixed Dishes	Mixed Dishes - Grain-based	Turnovers and other grain-based items	Other grain-based mixed dishes
Mixed Dishes	Mixed Dishes - Grain-based	Pasta mixed dishes, excludes macaroni and cheese	Other pasta mixed dishes
Mixed Dishes	Mixed Dishes - Grain-based	Macaroni and cheese	Macaroni and cheese
Mixed Dishes	Mixed Dishes - Meat, Poultry, Fish	Meat mixed dishes	Meat mixed dishes
Mixed Dishes	Mixed Dishes - Meat, Poultry, Fish	Poultry mixed dishes	Poultry mixed dishes
Mixed Dishes	Mixed Dishes - Meat, Poultry, Fish	Seafood mixed dishes	Seafood mixed dishes
Mixed Dishes	Mixed Dishes - Mexican	Burritos and tacos	Mexican Mixed Dishes
Mixed Dishes	Mixed Dishes - Mexican	Other Mexican mixed dishes	Mexican Mixed Dishes
Mixed Dishes	Mixed Dishes - Mexican	Nachos	Mexican Mixed Dishes
Mixed Dishes	Mixed Dishes - Pizza	Pizza	Pizza
Mixed Dishes	Mixed Dishes - Sandwiches	Other sandwiches	Other sandwiches
Mixed Dishes	Mixed Dishes - Sandwiches	Burgers	Burgers
Mixed Dishes	Mixed Dishes - Sandwiches	Chicken/turkey sandwiches	Poultry sandwiches
Mixed Dishes	Mixed Dishes - Sandwiches	Frankfurter sandwiches	Frankfurter sandwiches
Mixed Dishes	Mixed Dishes - Sandwiches	Egg/breakfast sandwiches	Egg/breakfast sandwiches
Mixed Dishes	Mixed Dishes - Soups	Soups	Soups

Main Group Description	Subgroup Description	Category Description	Final Categories
Other	Other	Not included in a food category	Other
Other	Other	Protein and nutritional powders	Other
Protein Foods	Cured Meats/Poultry	Cold cuts and cured meats	Cured Meats/Poultry
Protein Foods	Cured Meats/Poultry	Bacon	Cured Meats/Poultry
Protein Foods	Cured Meats/Poultry	Frankfurters	Cured Meats/Poultry
Protein Foods	Cured Meats/Poultry	Sausages	Cured Meats/Poultry
Protein Foods	Eggs	Eggs and omelets	Eggs
Protein Foods	Meats	Beef, excludes ground	Red meat
Protein Foods	Meats	Ground beef	Red meat
Protein Foods	Meats	Pork	Red meat
Protein Foods	Meats	Lamb, goat, game	Red meat
Protein Foods	Meats	Liver and organ meats	Red meat
Protein Foods	Plant-based Protein Foods	Beans, peas, legumes	Legumes and soy products
Protein Foods	Plant-based Protein Foods	Processed soy products	Legumes and soy products
Protein Foods	Plant-based Protein Foods	Nuts and seeds	Nuts and seeds
Protein Foods	Poultry	Chicken, whole pieces	Poultry
Protein Foods	Poultry	Chicken patties, nuggets and tenders	Poultry
Protein Foods	Poultry	Turkey, duck, other poultry	Poultry
Protein Foods	Seafood	Fish	Seafood
Protein Foods	Seafood	Shellfish	Seafood
Snacks and Sweets	Candy	Candy not containing chocolate	Candy
Snacks and Sweets	Candy	Candy containing chocolate	Candy
Snacks and Sweets	Crackers	Crackers, excludes saltines	Crackers and savory snacks
Snacks and Sweets	Crackers	Saltine crackers	Crackers and savory snacks
Snacks and Sweets	Other Desserts	Ice cream and frozen dairy desserts	Other desserts
Snacks and Sweets	Other Desserts	Pudding	Other desserts
Snacks and Sweets	Other Desserts	Gelatins, ices, sorbets	Other desserts
Snacks and Sweets	Savory Snacks	Tortilla, corn, other chips	Crackers and savory snacks
Snacks and Sweets	Savory Snacks	Pretzels/snack mix	Crackers and savory snacks
Snacks and Sweets	Savory Snacks	Popcorn	Crackers and savory snacks

Main Group Description	Subgroup Description	Category Description	Final Categories
Snacks and Sweets	Savory Snacks	Potato chips	Crackers and savory snacks
Snacks and Sweets	Snack/Meal Bars	Nutrition bars	Snack/meal bars
Snacks and Sweets	Snack/Meal Bars	Cereal bars	Snack/meal bars
Snacks and Sweets	Sweet Bakery Products	Cakes and pies	Sweet Bakery Products
Snacks and Sweets	Sweet Bakery Products	Doughnuts, sweet rolls, pastries	Sweet Bakery Products
Snacks and Sweets	Sweet Bakery Products	Cookies and brownies	Sweet Bakery Products
Sugars	Sugars	Jams, syrups, toppings	Sugars
Sugars	Sugars	Sugars and honey	Sugars
Sugars	Sugars	Sugar substitutes	Sugars
Vegetables	Vegetables, excluding Potatoes	Vegetable mixed dishes	Mixed vegetables
Vegetables	Vegetables, excluding Potatoes	Other vegetables and combinations	Mixed vegetables
Vegetables	Vegetables, excluding Potatoes	Other starchy vegetables	Starchy vegetables
Vegetables	Vegetables, excluding Potatoes	Dark green vegetables, excludes lettuce	Vegetables, excluding starchy
Vegetables	Vegetables, excluding Potatoes	Lettuce and lettuce salads	Vegetables, excluding starchy
Vegetables	Vegetables, excluding Potatoes	Carrots	Vegetables, excluding starchy
Vegetables	Vegetables, excluding Potatoes	Other red and orange vegetables	Vegetables, excluding starchy
Vegetables	Vegetables, excluding Potatoes	Tomatoes	Vegetables, excluding starchy
Vegetables	Vegetables, excluding Potatoes	String beans	Vegetables, excluding starchy
Vegetables	Vegetables, excluding Potatoes	Corn	Starchy vegetables
Vegetables	Vegetables, excluding Potatoes	Onions	Vegetables, excluding starchy
Vegetables	White Potatoes	White potatoes, baked or boiled	Starchy vegetables
Vegetables	White Potatoes	Mashed potatoes and white potato mixtures	Starchy vegetables
Vegetables	White Potatoes	French fries and other fried white potatoes	Starchy vegetables
Water	Flavored or Enhanced Water	Flavored or carbonated water	Water
Water	Flavored or Enhanced Water	Enhanced or fortified water	Water
Water	Plain Water	Tap water	Water
Water	Plain Water	Bottled water	Water

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APPENDIX 3
Spatially-explicit characterization of the exposure and health burden of fine particulate matter in the U.S.

A3.1. Land use and land cover for agriculture

We used land use and land cover geospatial data from FAO to estimate agriculture scores for InMAP grid-U.S. county cells (N=123,000) (FAO; Nachtergaele and Petri 2013). To estimate agricultural scores we grouped the 36 land use and land cover categories into agriculture and non-agriculture land use (Table A3.21). Since agriculture is primarily contributing to ammonia (NH3) emissions, with livestock activities leading emissions (Paulot and Jacob 2014), we further disaggregated agriculture land use into four categories that reflect varying levels of livestock activity and assigned higher weights to land use with higher livestock activity. We supplemented land use with livestock density geospatial data from FAO (FAO).

Table A3.21. Grouping and weighting of the land cover categories from GeoNetwork (FAO) into agriculture and non-agriculture categories.

Category	*Description*	*GeoNetwork Category*	*Weight*
Non-agriculture	Non-agriculture land use	*Livestock density* = "No data", "None", "Water"	0
		Land cover and land use = "Forest virgin", "Forest protected", "Grasslands unmanaged", "Grasslands protected", "Shrub cover unmanaged", "Shrub cover protected", "Urban areas", "Wetlands unmanaged", "Wetlands protected", "Wetlands mangroves", "Sparse areas unmanaged", "Sparse areas protected", "Bare areas unmanaged", "Bare areas protected", "Water unmanaged", "Water protected", "Water inland fisheries"	
Agriculture	Other agriculture-related land use	*Land cover and land use* = "Forest with agriculture activities", "Rainfed Agriculture (Subsistence/commercial)","Agriculture Large scale irrigation", "Agriculture protected", "Wetlands with agriculture activities"	1
	Land use with low livestock density	*Livestock density* = "Low livestock"	2
		Land cover and land use = "Grasslands low livestock density", "Shrub cover low livestock density", "Sparse areas with low livestock density", "Bare areas with low livestock density"	
	Land use with moderate livestock density	*Livestock density* = "Moderate livestock"	3
		Land cover and land use = "Forestry moderate or higher livestock density", "Grasslands moderate livestock density", "Shrub cover moderate livestock density", " Crops and moderate livestock density", "Crops, large-scale irrigation, moderated or higher livestock density", "Sparse areas with moderate/high livestock density", "Bare areas with moderate livestock density"	
	Land use with high livestock density	*Livestock density* = "High livestock"	4
		Land cover and land use = "Grasslands high livestock density", "Shrub cover high livestock density", "Crops and high livestock density",	

Table A3.22. Emission-weighted national intake fraction ($\frac{kg_{inhaled}}{kg_{emitted}}$) and intake travel distances (ITD, in km) for the contiguous U.S. by sector. Sectors are defined based on the classification of the National Emission Inventory by the EPA. (U.S. Environmental Protection Agency 2018)

	Precursor	***Agriculture***	***Fuel Combustion***	***Industrial Processes***	***Mobile***	***All-sectors***
Intake fraction ($\frac{kg_{inhaled}}{kg_{emitted}}$)	$PM_{2.5}$	3.85E-07	1.14E-06	1.15E-06	1.81E-06	8E-07
	NH_3	3.44E-07	1.33E-06	9.93E-07	1.43E-06	3.68E-07
	SO_2		2.69E-07	2.58E-07	3.15E-07	2.66E-07
	NO_X		1.32E-07	1.14E-07	1.44E-07	1.34E-07
ITD25 (km)	$PM_{2.5}$	133	45	61	46	68
	NH_3	195	51	92	49	175
	SO_2		174	164	78	171
	NO_X		178	258	142	178
ITD50 (km)	$PM_{2.5}$	300	113	154	113	165
	NH_3	414	133	223	126	382
	SO_2		325	327	166	324
	NO_X		384	527	343	400
ITD95 (km)	$PM_{2.5}$	1394	689	895	693	1029
	NH_3	1528	797	1041	782	1496
	SO_2		1002	1144	792	1035
	NO_X		1297	1645	1413	1447

ITDx= Radial distance from the source in km to reach x% of the cumulative intake of an emission

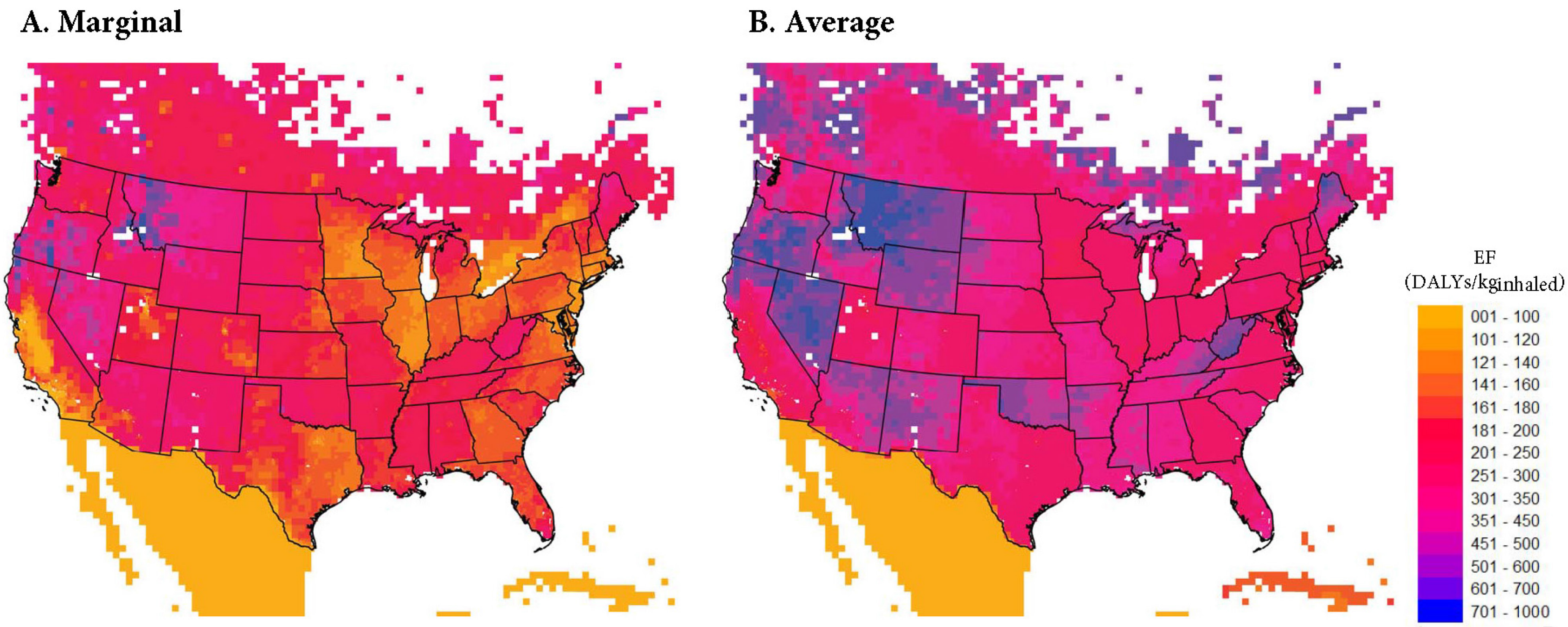


Figure A3.31. Effect factors (EF) for $PM_{2.5}$ in $\mu DALYs/kg_{precursor,inhaled}$ for two exposure-response slope: **A)** Marginal and **B)** Average using the approach by Fantke et al. (2018) Each point estimate represents the point-estimate based on the background $PM_{2.5}$ ambient levels from 2016.

Table A3.23. Pearson correlation coefficient between characterization factors (CFs) for $PM_{2.5}$ from primary $PM_{2.5}$, NH_3, SO_2, and NO_x ground emissions in the greater North American region and background ambient $PM_{2.5}$ concentrations in 2016 (WHO 2016) and precursor-specific intake fractions (iFs)

	Ambient PM2.5 concentration	$iF_{PM2.5}$	iF_{NH3}	iF_{SO2}	iF_{NOx}
$CF_{PM2.5}^{marginal}$	0.41****	0.91****	0.89****	0.62****	0.76****
$CF_{NH3}^{marginal}$	0.44****	0.93****	0.91****	0.64****	0.78****
$CF_{SO2}^{marginal}$	0.4****	0.84****	0.91****	0.61****	0.67****
$CF_{NOx}^{marginal}$	0.43****	0.85****	0.92****	0.63****	0.69****
$CF_{PM2.5}^{average}$	0.45****	0.57****	0.59****	0.91****	0.68****
$CF_{NH3}^{average}$	0.47****	0.59****	0.61****	0.92****	0.69****
$CF_{SO2}^{average}$	0.36****	0.52****	0.48****	0.48****	0.86****
$CF_{NOx}^{average}$	0.41****	0.55****	0.51****	0.52****	0.88****

p-value < .0001 '****'; p-value < .001 '***', p-value < .01 '**', p-value < .05 '*'

Table A3.24. Emission-weighted national characterization factors ($\frac{DALYs}{kg_{emitted}}$) and burden travel distances (BTD in km) for the contiguous U.S. by sector for exposure-response marginal and average defined by Fantke et al. (2018). Sectors are defined based on the classification of the National Emission Inventory by the EPA (2018).

	Precursor	***Agriculture***	***Fuel Combustion***	***Industrial Processes***	***Mobile***	***All-sectors***
$CF^{marginal}$ ($\frac{DALYs}{kg_{emitted}}$)	$PM_{2.5}$	5.56E-05	1.45E-04	1.34E-04	2.02E-04	1.03E-04
	NH_3	4.57E-05	1.41 E-04	9.79E-05	0.000152	4.84E-05
	SO_2		3.69E-05	3.52E-05	3.68E-05	3.63E-05
	NO_X		1.84E-05	1.69E-05	1.93E-05	1.85E-05
$CF^{average}$ ($\frac{DALYs}{kg_{emitted}}$)	$PM_{2.5}$	1.13E-04	2.98E-04	2.76E-04	4.19E-04	2.09E-04
	NH_3	9.37E-05	2.95E-04	2.07E-04	3.19E-04	9.91E-05
	SO_2		7.67E-05	7.26E-05	7.54E-05	7.52E-05
	NO_X		3.8E-05	3.45E-05	3.99E-05	3.8E-05
$BTD25^{marginal}$ (km)	$PM_{2.5}$	101	38	48	37	53
	NH_3	168	43	76	41	150
	SO_2		159	151	76	155
	NO_X		153	234	123	153
$BTD25^{average}$ (km)	$PM_{2.5}$	111	39	50	40	57
	NH_3	177	45	80	43	157
	SO_2		162	156	78	159
	NO_X		166	248	133	165
$BTD50^{marginal}$ (km)	$PM_{2.5}$	249	97	127	95	135
	NH_3	370	115	195	108	333
	SO_2		304	308	161	302
	NO_X		352	495	316	365
$BTD50^{average}$ (km)	$PM_{2.5}$	266	101	137	100	143
	NH_3	383	120	202	112	347
	SO_2		311	318	164	309
	NO_X		362	508	331	381
$BTD95^{marginal}$ (km)	$PM_{2.5}$	1301	646	848	657	914
	NH_3	1525	785	994	768	1475
	SO_2		963	1095	792	992
	NO_X		1262	1595	1403	1423
$BTD95^{average}$ (km)	$PM_{2.5}$	1328	654	868	668	950
	NH_3	1540	794	1000	777	1495
	SO_2		965	1100	804	996
	NO_X		1264	1599	1406	1426

BTDx= Radial distance from the source in km to reach x% of the cumulative health burden of an emission

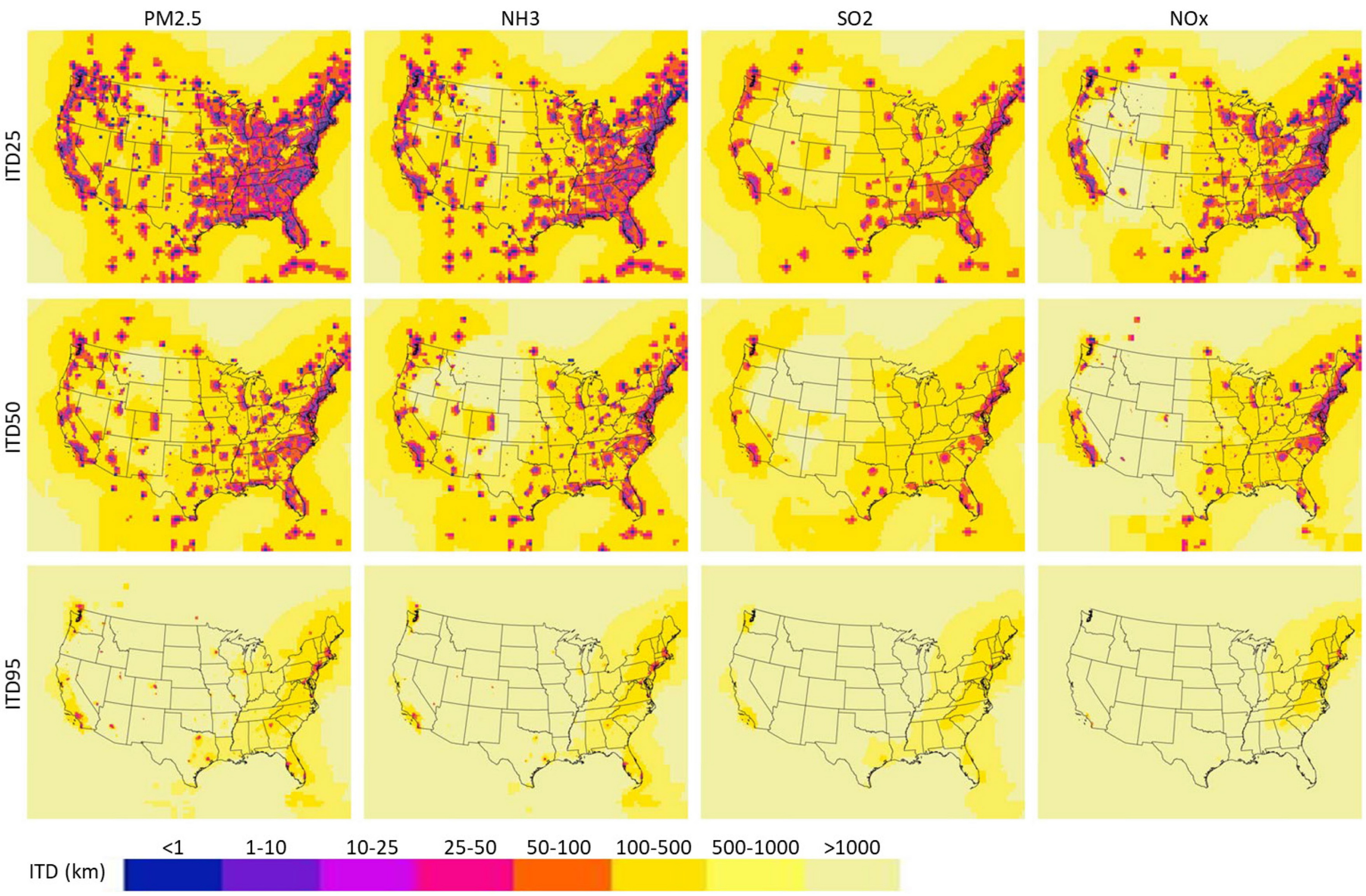
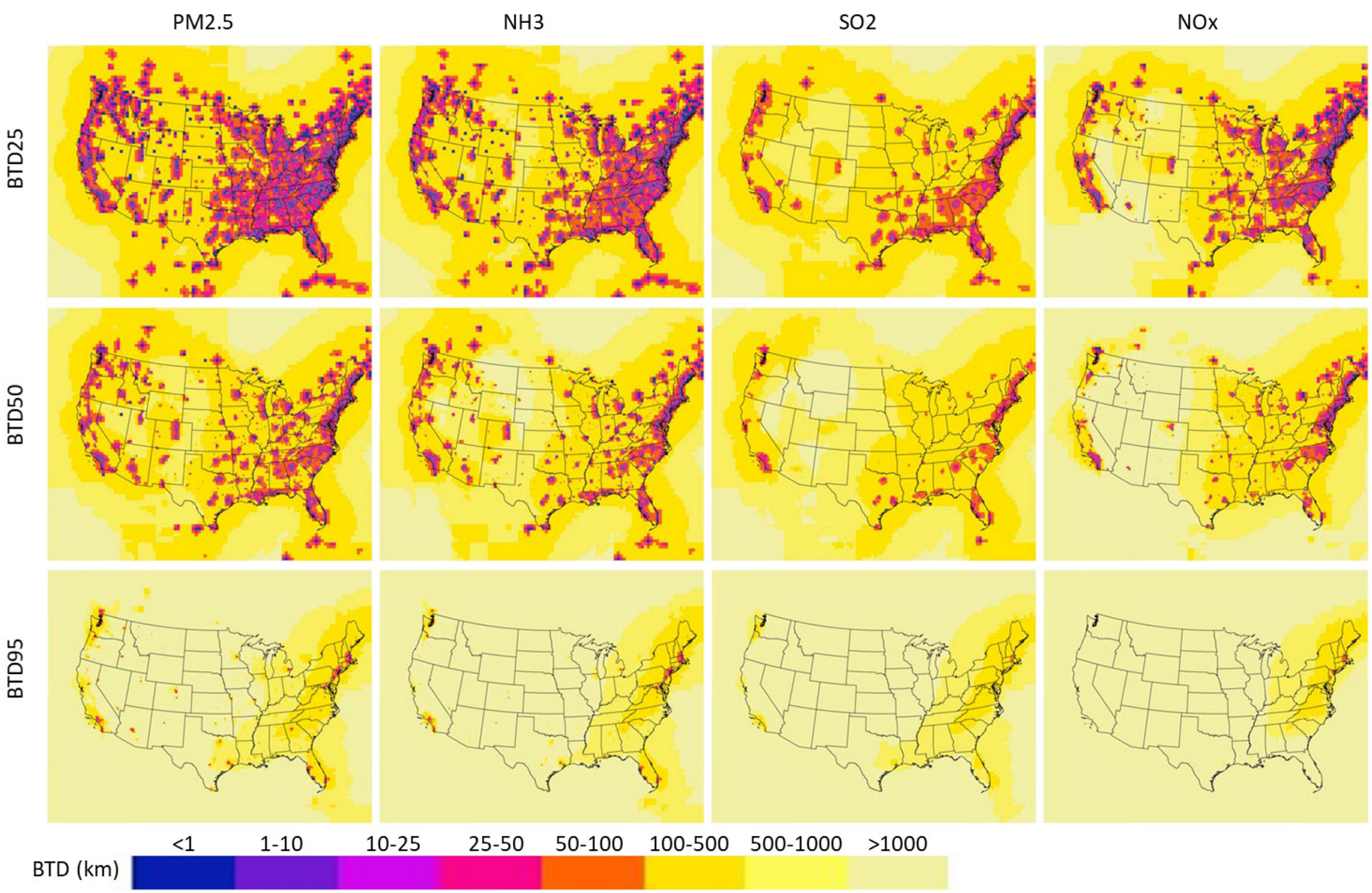


Figure A3.32. 25%, 50% and 75% intake travel distance (ITDx) in km. Each point estimate represents radial distance from the point to reach x% of the cumulative intake fraction for an emission released at the point.

A. Marginal slope



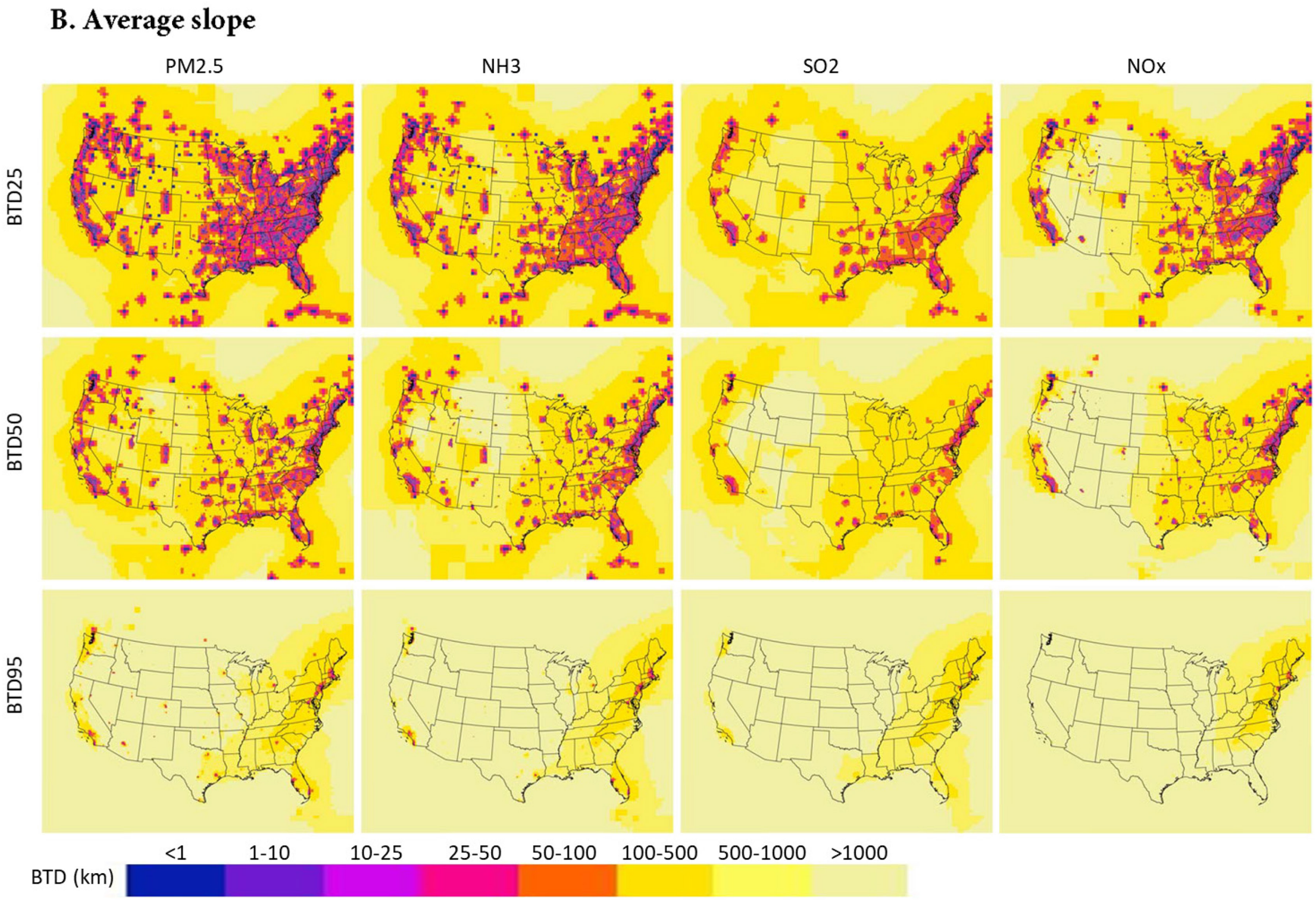


Figure A3.33. 25%, 50%, and 95% burden travel distance (BTDx) in km for exposure-response slopes: **A)** Marginal and **B)** Average. Each point estimate represents radial distance from the point to reach x% of the cumulative characterization factor for an emission released at the point.

Table A3.25. Distribution of 25%, 50%, and 95% intake (ITD) and burden (BTD) travel distance for rural* source locations in the contiguous U.S. (N=17,871).

			Min	*Q1*	*Median*	*Q3*	*Max*	*Mean*	*SD*
ITD25		$PM_{2.5}$	0.0	3.0	9.0	33.0	858.0	40.0	86.9
		NH_3	0.0	5.0	12.0	53.0	1105.0	63.1	135.1
		SO_2	0.0	30.0	81.0	188.0	1138.0	149.5	185.6
		NO_X	0.0	8.0	19.0	91.0	1505.0	131.0	275.9
ITD50		$PM_{2.5}$	0.0	11.0	26.0	102.0	1335.0	96.3	173.6
		NH_3	0.0	14.0	42.0	170.0	1848.0	158.7	278.2
		SO_2	7.0	69.0	177.0	372.0	1710.0	289.9	321.6
		NO_X	0.0	29.0	107.0	311.0	2320.0	312.4	485.3
ITD95		$PM_{2.5}$	10.0	149.0	409.0	823.0	3139.0	625.5	658.6
		NH_3	15.0	230.0	628.0	1316.0	3685.0	896.8	839.1
		SO_2	59.0	375.0	840.0	1486.0	3527.0	1061.2	856.4
		NO_X	25.0	515.0	1216.0	2153.0	3936.0	1405.2	1037.0
Marginal	**BTD25**	$PM_{2.5}$	0.0	3.0	8.0	30.0	576.0	32.3	64.9
		NH_3	0.0	5.0	11.0	46.0	782.0	50.6	101.3
		SO_2	0.0	30.0	78.0	174.0	942.0	135.0	158.3
		NO_X	0.0	8.0	19.0	82.0	1253.0	112.1	232.1
	BTD50	$PM_{2.5}$	0.0	11.0	24.0	88.0	981.0	80.6	138.7
		NH_3	0.0	13.0	36.0	147.0	1458.0	131.4	218.7
		SO_2	5.0	71.0	176.0	356.0	1483.0	270.5	281.2
		NO_X	0.0	28.0	101.0	284.5	2072.0	285.0	438.8
	BTD95	$PM_{2.5}$	8.0	156.0	399.0	788.0	2839.0	592.6	601.3
		NH_3	14.0	234.5	616.0	1305.0	3387.0	875.1	799.0
		SO_2	57.0	387.0	826.0	1493.0	3304.0	1059.9	828.3
		NO_X	19.0	549.5	1192.0	2246.0	3824.0	1428.5	1038.5
Average	**BTD25**	$PM_{2.5}$	0.0	3.0	8.0	30.0	605.0	34.4	71.7
		NH_3	0.0	5.0	11.0	47.0	899.0	54.5	114.0
		SO_2	0.0	30.0	78.0	175.0	1035.0	140.9	171.7
		NO_X	0.0	8.0	19.0	84.0	1417.0	123.8	261.3
	BTD50	$PM_{2.5}$	0.0	11.0	24.0	89.0	1149.0	85.4	152.5
		NH_3	0.0	13.0	37.0	151.0	1600.0	139.6	240.6
		SO_2	5.0	70.0	175.0	358.0	1569.0	281.7	308.1
		NO_X	0.0	29.0	101.0	288.0	2216.0	299.4	468.3
	BTD95	$PM_{2.5}$	10.0	154.5	398.0	791.0	3003.0	604.8	629.5
		NH_3	13.0	232.0	612.0	1321.5	3494.0	890.1	826.5
		SO_2	56.0	383.0	822.0	1492.0	3406.0	1067.1	849.9
		NO_X	18.0	544.0	1186.0	2258.5	3881.0	1433.1	1051.4

* Sources have been classified into urban/rural using the U.S. Census 2010 (2015). Urban grids are classified based on a population density of at least 386 people/km^2

Table A3.26. Distribution of 25%, 50%, and 95% intake (ITD) and burden (BTD) travel distance for urban* source locations in the contiguous U.S. (N=25,333).

			Min	*Q1*	*Median*	*Q3*	*Max*	*Mean*	*SD*
	ITD25	$PM_{2.5}$	0.0	0.0	1.0	2.0	109.0	1.6	2.0
		NH_3	0.0	1.0	2.0	3.0	96.0	2.1	2.5
		SO_2	0.0	14.0	20.0	39.0	1088.0	52.0	88.6
		NO_X	0.0	2.0	3.0	5.0	1016.0	6.1	38.6
	ITD50	$PM_{2.5}$	0.0	3.0	4.0	7.0	127.0	5.8	6.0
		NH_3	0.0	3.0	5.0	9.0	312.0	8.3	13.6
		SO_2	3.0	28.0	45.0	175.0	1644.0	137.5	198.9
		NO_X	0.0	6.0	11.0	19.0	1943.0	49.6	184.2
	ITD95	$PM_{2.5}$	5.0	31.0	51.0	120.0	1430.0	107.3	137.2
		NH_3	11.0	44.0	94.0	323.0	2686.0	247.5	329.9
		SO_2	55.0	199.0	402.0	985.0	3479.0	736.3	738.3
		NO_X	14.0	151.0	774.0	1488.0	3631.0	977.4	921.5
Marginal	**BTD25**	$PM_{2.5}$	0.0	0.0	1.0	3.0	116.0	1.8	3.0
		NH_3	0.0	1.0	2.0	3.0	108.0	2.4	3.9
		SO_2	0.0	14.0	21.0	41.0	873.0	50.7	82.0
		NO_X	0.0	2.0	3.0	5.0	1053.0	13.2	83.7
	BTD50	$PM_{2.5}$	0.0	3.0	4.0	7.0	293.0	6.0	7.9
		NH_3	0.0	3.0	5.0	9.0	313.0	8.7	15.8
		SO_2	2.0	29.0	49.0	203.0	1411.0	145.3	198.0
		NO_X	0.0	6.0	12.0	22.0	1831.0	62.2	231.7
	BTD95	$PM_{2.5}$	3.0	31.0	55.0	134.0	1520.0	115.4	145.8
		NH_3	5.0	46.0	116.0	391.0	2501.0	283.0	364.0
		SO_2	54.0	249.0	523.0	1082.0	3260.0	788.4	736.9
		NO_X	7.0	192.0	1018.0	2037.0	3452.0	1180.8	978.1
Average	**BTD25**	$PM_{2.5}$	0.0	0.0	1.0	3.0	117.0	1.8	3.1
		NH_3	0.0	1.0	2.0	3.0	114.0	2.4	3.9
		SO_2	0.0	13.0	21.0	41.0	975.0	52.0	86.9
		NO_X	0.0	2.0	3.0	5.0	1230.0	14.4	91.1
	BTD50	$PM_{2.5}$	0.0	3.0	4.0	7.0	297.0	6.0	8.4
		NH_3	0.0	3.0	5.0	9.0	309.0	8.5	15.1
		SO_2	2.0	28.0	48.0	201.0	1537.0	148.3	212.2
		NO_X	0.0	6.0	11.0	22.0	1871.0	66.3	248.8
	BTD95	$PM_{2.5}$	3.0	31.0	54.0	130.0	1724.0	114.3	148.1
		NH_3	5.0	46.0	114.0	386.0	2535.0	284.7	376.5
		SO_2	52.0	237.0	489.0	1074.0	3359.0	783.0	753.0
		NO_X	7.0	178.0	1001.0	2048.0	3534.0	1175.2	990.9

* Sources have been classified into urban/rural using the U.S. Census 2010 (2015). Urban grids are classified based on a population density of at least 386 people/km^2

Table A3.27. Comparison of characterization factors in μDALYs/$kg_{emitted}$ by archetype from selected studies to the present study

Study	***Pollutant***	***Archetype***[a]			***National (emission-weighted)***	
		Urban	**Rural**	**Remote**	**Population (proxy)**	**All-sector emissions**
Van Zelm et al. (2016)[b]	$PM_{2.5}$				404	
	NH_3				135	
	SO_2				13	
	NO_X				48	
Gronlund et al. (2015)	$PM_{2.5}$	3055	273	7	1797	
	NH_3	117	117	7	117	
	SO_2	69	56	3.5	62	
	NO_X	14	117	0.7	13	
Present study[c]	Marginal					
	$PM_{2.5}$	624	87	66	469	103
	NH_3	344	62	43	276	48
	SO_2	47	34	21	49	36
	NO_X	34	18	12	29	19
	Average					
	$PM_{2.5}$	1303	179	127	982	209
	NH_3	716	126	81	581	99
	SO_2	98	69	41	101	75
	NO_X	72	36	24	59	38

[a] Archetypes defined according to Humbert et al. (2011) classification: Urban (>386 people/km^2), Rural (1<x<100 people/km^2), Remote (<1 people/km^2)
[b] Represent national estimates
[c] Archetype-specific estimates reflect median estimates
[*] All estimates have been adjusted for a breathing rate of 11.68 m^3/d for comparability with the present study

Table A3.28. Distribution of intake fractions ($\frac{kg_{inhaled}}{kg_{emitted}}$) of source locations and emission-weighted sector-specific estimates by state.

U.S. State	N	Intake fraction from $PM_{2.5}$ emissions											
		Descriptive statistics							Emission weighted by sector				
		Min	Q1	Median	Q3	Max	Mean	SD	Agriculture	Fuel Combustion	Industrial Processes	Mobile	All-sectors
Alabama	435	1.48E-07	5.11E-07	9.07E-07	1.74E-06	4.03E-06	1.24E-06	9.64E-07	4.40E-07	5.56E-07	6.94E-07	5.77E-07	4.91E-07
Arizona	997	1.45E-07	1.60E-06	5.94E-06	8.78E-06	1.29E-05	5.57E-06	3.82E-06	6.99E-07	1.79E-06	7.83E-07	2.70E-06	1.17E-06
Arkansas	222	1.76E-07	2.94E-07	5.31E-07	1.03E-06	2.95E-06	7.46E-07	5.65E-07	3.01E-07	3.96E-07	3.36E-07	4.04E-07	3.25E-07
California	8452	5.53E-08	3.67E-06	8.56E-06	1.38E-05	4.30E-05	9.84E-06	7.57E-06	9.18E-07	4.40E-06	5.78E-06	5.97E-06	1.74E-06
Colorado	778	1.07E-07	1.08E-06	3.47E-06	7.31E-06	1.25E-05	4.26E-06	3.41E-06	2.62E-07	1.58E-06	1.36E-06	1.90E-06	1.12E-06
Connecticut	618	3.74E-07	1.65E-06	2.40E-06	3.27E-06	7.12E-06	2.64E-06	1.40E-06	1.10E-06	1.21E-06	1.54E-06	1.41E-06	1.26E-06
Delaware	38	2.04E-07	4.17E-07	5.83E-07	8.59E-07	2.68E-06	7.32E-07	4.80E-07	3.74E-07	5.83E-07	6.19E-07	5.62E-07	5.45E-07
Florida	2296	1.07E-07	1.42E-06	2.73E-06	5.37E-06	1.55E-05	3.61E-06	2.86E-06	5.23E-07	1.88E-06	1.20E-06	1.85E-06	1.17E-06
Georgia	1008	2.33E-07	8.95E-07	2.24E-06	4.68E-06	9.30E-06	2.84E-06	2.22E-06	4.94E-07	1.14E-06	5.80E-07	1.69E-06	7.16E-07
Idaho	235	3.49E-08	8.93E-08	1.91E-07	1.00E-06	4.07E-06	6.44E-07	8.60E-07	1.56E-07	2.70E-07	1.34E-07	2.19E-07	1.50E-07
Illinois	1551	2.85E-07	1.68E-06	5.41E-06	8.41E-06	1.89E-05	5.84E-06	4.52E-06	6.56E-07	1.71E-06	2.26E-06	2.95E-06	1.27E-06
Indiana	610	4.00E-07	7.50E-07	1.43E-06	2.61E-06	5.21E-06	1.88E-06	1.31E-06	7.01E-07	7.63E-07	9.47E-07	1.04E-06	8.22E-07
Iowa	327	2.23E-07	4.36E-07	7.48E-07	1.39E-06	3.02E-06	9.77E-07	6.59E-07	3.68E-07	4.49E-07	5.12E-07	4.45E-07	4.02E-07
Kansas	302	1.09E-07	3.16E-07	6.98E-07	1.58E-06	4.14E-06	1.09E-06	1.04E-06	2.32E-07	4.95E-07	5.54E-07	5.43E-07	3.38E-07
Kentucky	356	2.74E-07	3.84E-07	6.13E-07	1.31E-06	4.21E-06	1.02E-06	8.71E-07	4.26E-07	6.46E-07	4.59E-07	5.78E-07	4.64E-07
Louisiana	368	1.05E-07	4.15E-07	7.62E-07	1.35E-06	3.45E-06	9.88E-07	7.08E-07	3.48E-07	4.72E-07	4.79E-07	4.94E-07	3.85E-07
Maine	154	2.96E-08	1.39E-07	3.74E-07	7.51E-07	1.94E-06	5.33E-07	4.86E-07	1.45E-07	1.85E-07	1.53E-07	1.91E-07	1.82E-07
Maryland	1636	1.55E-07	3.94E-06	6.33E-06	8.58E-06	1.78E-05	6.40E-06	3.15E-06	8.99E-07	2.20E-06	2.00E-06	2.68E-06	1.83E-06
Massachusetts	1163	7.13E-08	1.80E-06	3.31E-06	5.77E-06	1.72E-05	4.50E-06	3.60E-06	1.11E-06	1.70E-06	1.58E-06	1.85E-06	1.70E-06
Michigan	1110	7.45E-08	1.15E-06	2.31E-06	4.20E-06	7.43E-06	2.77E-06	1.90E-06	6.92E-07	1.09E-06	9.28E-07	1.50E-06	1.10E-06
Minnesota	627	3.80E-08	5.77E-07	2.16E-06	4.45E-06	9.92E-06	2.70E-06	2.33E-06	2.70E-07	5.67E-07	4.36E-07	9.91E-07	4.93E-07
Mississippi	246	1.94E-07	3.12E-07	4.29E-07	8.22E-07	2.43E-06	6.45E-07	4.96E-07	2.89E-07	3.37E-07	3.45E-07	3.68E-07	3.36E-07
Missouri	691	1.80E-07	3.85E-07	1.49E-06	3.30E-06	6.77E-06	2.02E-06	1.78E-06	3.41E-07	7.45E-07	5.94E-07	9.50E-07	4.76E-07
Montana	226	3.26E-08	5.48E-08	7.16E-08	9.96E-08	1.64E-06	1.68E-07	2.76E-07	6.73E-08	9.04E-08	9.22E-08	7.72E-08	7.38E-08
Nebraska	214	1.14E-07	1.59E-07	4.44E-07	2.59E-06	4.66E-06	1.32E-06	1.41E-06	1.91E-07	3.20E-07	3.27E-07	2.83E-07	2.33E-07
Nevada	641	7.78E-08	1.16E-06	5.59E-06	9.44E-06	1.23E-05	5.46E-06	4.01E-06	1.52E-07	1.91E-06	3.92E-07	2.05E-06	9.21E-07
New Hampshire	325	1.13E-07	1.48E-06	2.22E-06	3.52E-06	6.25E-06	2.49E-06	1.39E-06	6.38E-07	1.16E-06	1.03E-06	1.23E-06	1.19E-06
New Jersey	1676	2.78E-07	3.39E-06	9.10E-06	2.06E-05	5.84E-05	1.41E-05	1.32E-05	1.48E-06	5.49E-06	2.41E-06	6.07E-06	4.47E-06
New Mexico	379	1.11E-07	2.27E-07	7.62E-07	2.75E-06	5.26E-06	1.53E-06	1.54E-06	2.32E-07	5.25E-07	2.95E-07	5.22E-07	4.67E-07
New York	2289	1.40E-07	1.75E-06	4.35E-06	1.17E-05	5.80E-05	8.77E-06	1.05E-05	4.63E-07	2.69E-06	1.33E-06	4.40E-06	2.81E-06
North Carolina	888	6.75E-08	8.75E-07	1.46E-06	2.32E-06	5.24E-06	1.70E-06	1.10E-06	5.68E-07	1.02E-06	7.54E-07	1.01E-06	8.04E-07
North Dakota	118	5.45E-08	7.48E-08	8.98E-08	1.53E-07	1.58E-06	2.06E-07	2.71E-07	9.07E-08	9.18E-08	8.89E-08	9.84E-08	9.27E-08
Ohio	1139	3.13E-07	8.67E-07	1.62E-06	3.37E-06	7.29E-06	2.19E-06	1.58E-06	7.39E-07	8.71E-07	1.01E-06	1.18E-06	8.97E-07
Oklahoma	392	1.58E-07	3.92E-07	9.79E-07	2.26E-06	4.02E-06	1.35E-06	1.07E-06	3.27E-07	6.27E-07	4.30E-07	7.34E-07	4.55E-07
Oregon	436	4.30E-08	1.88E-07	9.36E-07	2.11E-06	6.56E-06	1.47E-06	1.57E-06	1.46E-07	6.28E-07	4.77E-07	7.45E-07	2.85E-07
Pennsylvania	2382	2.68E-07	1.46E-06	3.01E-06	5.83E-06	1.96E-05	4.46E-06	4.23E-06	1.06E-06	1.48E-06	1.54E-06	1.83E-06	1.52E-06
Rhode Island	68	1.76E-07	9.21E-07	2.56E-06	4.93E-06	8.21E-06	3.09E-06	2.38E-06	3.62E-07	8.38E-07	9.81E-07	8.72E-07	9.19E-07
South Carolina	465	2.01E-07	6.42E-07	1.23E-06	1.85E-06	3.42E-06	1.31E-06	7.73E-07	4.43E-07	6.98E-07	5.57E-07	6.08E-07	6.06E-07
South Dakota	124	9.24E-08	1.09E-07	1.25E-07	2.46E-07	1.85E-06	2.82E-07	3.61E-07	1.53E-07	1.74E-07	1.62E-07	1.72E-07	1.52E-07
Tennessee	632	2.79E-07	8.06E-07	1.52E-06	2.58E-06	4.79E-06	1.79E-06	1.20E-06	5.58E-07	8.33E-07	8.53E-07	1.05E-06	7.83E-07
Texas	3416	1.73E-07	1.81E-06	4.91E-06	7.16E-06	1.71E-05	4.82E-06	3.23E-06	5.37E-07	1.48E-06	1.53E-06	2.26E-06	1.34E-06
Utah	412	1.21E-07	3.83E-07	1.85E-06	3.72E-06	7.78E-06	2.32E-06	2.01E-06	2.81E-07	9.40E-07	1.45E-06	1.55E-06	8.26E-07
Vermont	69	1.47E-07	2.35E-07	4.22E-07	1.09E-06	1.61E-06	6.29E-07	4.85E-07	2.39E-07	2.85E-07	2.31E-07	2.88E-07	2.81E-07
Virginia	861	1.57E-07	8.20E-07	1.51E-06	3.13E-06	6.43E-06	2.05E-06	1.52E-06	7.27E-07	1.06E-06	6.83E-07	1.20E-06	8.96E-07
Washington	934	6.29E-08	1.22E-06	3.50E-06	5.16E-06	1.37E-05	3.71E-06	2.85E-06	2.03E-07	2.23E-06	9.90E-07	1.82E-06	5.92E-07
Washington D.C.	23	1.39E-06	2.26E-06	3.85E-06	4.59E-06	5.37E-06	3.57E-06	1.36E-06		2.36E-06	2.36E-06	2.36E-06	2.36E-06
West Virginia	142	2.80E-07	3.80E-07	5.30E-07	1.03E-06	2.25E-06	7.43E-07	4.88E-07	5.46E-07	4.68E-07	4.45E-07	5.66E-07	4.60E-07
Wisconsin	713	1.12E-07	7.41E-07	1.64E-06	3.02E-06	8.44E-06	2.25E-06	1.94E-06	5.76E-07	8.06E-07	7.30E-07	7.95E-07	6.97E-07
Wyoming	120	5.34E-08	1.14E-07	1.33E-07	1.74E-07	5.51E-07	1.55E-07	8.10E-08	1.43E-07	1.71E-07	1.92E-07	1.76E-07	1.60E-07
United States	43304	2.96E-08	1.16E-06	3.13E-06	7.04E-06	5.84E-05	5.33E-06	6.46E-06	3.85E-07	1.14E-06	1.15E-06	1.81E-06	8.00E-07

U.S. State	N	Intake fraction from NH_3 emissions											
		Descriptive statistics							Emission weighted by sector				
		Min	Q1	Median	Q3	Max	Mean	SD	Agriculture	Fuel Combustion	Industrial Processes	Mobile	All-sectors
Alabama	435	1.23E-07	4.07E-07	6.51E-07	1.19E-06	3.08E-06	9.15E-07	7.17E-07	3.60E-07	4.92E-07	3.51E-07	4.71E-07	3.55E-07
Arizona	997	1.18E-07	5.17E-07	1.30E-06	1.62E-06	2.75E-06	1.13E-06	6.30E-07	2.71E-07	5.38E-07	2.60E-07	6.65E-07	2.54E-07
Arkansas	222	2.00E-07	2.54E-07	3.67E-07	5.77E-07	1.57E-06	4.55E-07	2.67E-07	2.53E-07	3.03E-07	2.52E-07	3.15E-07	2.53E-07
California	8452	4.71E-08	1.44E-06	3.94E-06	7.25E-06	1.83E-05	4.77E-06	3.85E-06	4.99E-07	2.66E-06	4.93E-06	3.54E-06	5.27E-07
Colorado	778	1.03E-07	5.48E-07	1.56E-06	2.89E-06	4.28E-06	1.73E-06	1.24E-06	2.05E-07	9.61E-07	3.17E-07	1.03E-06	2.23E-07
Connecticut	618	3.28E-07	1.32E-06	1.88E-06	2.55E-06	5.16E-06	2.03E-06	9.86E-07	8.00E-07	1.13E-06	1.08E-06	1.11E-06	1.16E-06
Delaware	38	1.28E-07	2.52E-07	3.63E-07	6.36E-07	1.75E-06	4.86E-07	3.34E-07	2.41E-07	5.01E-07	2.48E-07	4.35E-07	2.55E-07
Florida	2296	9.51E-08	1.19E-06	2.29E-06	4.50E-06	1.43E-05	3.13E-06	2.59E-06	4.29E-07	1.52E-06	1.14E-06	1.75E-06	4.46E-07
Georgia	1008	2.00E-07	6.22E-07	1.38E-06	2.81E-06	5.42E-06	1.76E-06	1.31E-06	5.26E-07	1.33E-06	3.34E-07	1.12E-06	5.14E-07
Idaho	235	3.88E-08	7.14E-08	1.02E-07	2.46E-07	8.70E-07	1.84E-07	1.74E-07	9.38E-08	1.13E-07	1.01E-07	1.05E-07	8.87E-08
Illinois	1551	2.91E-07	1.03E-06	3.25E-06	5.02E-06	1.10E-05	3.53E-06	2.66E-06	5.34E-07	2.35E-06	7.20E-07	2.06E-06	6.25E-07
Indiana	610	3.78E-07	5.86E-07	9.53E-07	1.58E-06	3.01E-06	1.20E-06	7.22E-07	5.50E-07	7.50E-07	5.88E-07	7.80E-07	5.55E-07
Iowa	327	2.19E-07	3.54E-07	5.08E-07	7.23E-07	1.52E-06	5.77E-07	2.84E-07	3.08E-07	4.04E-07	3.31E-07	3.86E-07	3.10E-07
Kansas	302	1.37E-07	2.71E-07	4.47E-07	8.51E-07	2.08E-06	6.17E-07	4.91E-07	2.11E-07	4.83E-07	2.29E-07	4.62E-07	2.19E-07
Kentucky	356	2.54E-07	3.29E-07	4.75E-07	8.43E-07	2.56E-06	6.88E-07	4.89E-07	3.53E-07	4.42E-07	5.13E-07	4.69E-07	3.56E-07
Louisiana	368	8.42E-08	3.12E-07	4.87E-07	8.02E-07	1.95E-06	6.05E-07	3.71E-07	2.79E-07	3.14E-07	3.00E-07	3.70E-07	2.71E-07
Maine	154	2.70E-08	1.03E-07	2.70E-07	5.40E-07	1.25E-06	3.53E-07	3.01E-07	1.38E-07	1.37E-07	1.17E-07	1.58E-07	1.43E-07
Maryland	1636	1.14E-07	2.88E-06	4.56E-06	6.10E-06	1.23E-05	4.59E-06	2.22E-06	6.70E-07	2.32E-06	1.90E-06	2.03E-06	8.93E-07
Massachusetts	1163	6.31E-08	1.40E-06	2.36E-06	4.00E-06	1.02E-05	3.06E-06	2.17E-06	9.85E-07	1.35E-06	1.24E-06	1.47E-06	1.12E-06
Michigan	1110	6.02E-08	8.26E-07	1.57E-06	3.02E-06	5.19E-06	1.97E-06	1.35E-06	5.52E-07	1.31E-06	4.05E-07	1.24E-06	6.28E-07
Minnesota	627	3.44E-08	3.22E-07	9.32E-07	1.88E-06	3.93E-06	1.15E-06	9.34E-07	2.27E-07	4.57E-07	2.11E-07	5.63E-07	2.27E-07
Mississippi	246	2.00E-07	2.68E-07	3.40E-07	5.61E-07	1.36E-06	4.44E-07	2.56E-07	2.59E-07	2.66E-07	2.29E-07	2.99E-07	2.61E-07
Missouri	691	2.12E-07	3.40E-07	8.47E-07	1.67E-06	3.36E-06	1.12E-06	8.65E-07	3.05E-07	7.47E-07	4.43E-07	6.41E-07	3.10E-07
Montana	226	3.98E-08	5.84E-08	7.25E-08	9.91E-08	9.85E-07	1.19E-07	1.47E-07	7.28E-08	8.36E-08	9.34E-08	7.70E-08	7.18E-08
Nebraska	214	1.31E-07	1.76E-07	3.21E-07	1.25E-06	1.86E-06	6.49E-07	5.58E-07	1.96E-07	2.90E-07	3.67E-07	2.83E-07	1.99E-07
Nevada	641	6.08E-08	6.04E-07	2.28E-06	3.32E-06	4.69E-06	2.09E-06	1.43E-06	1.15E-07	1.02E-06	1.34E-07	9.23E-07	1.36E-07
New Hampshire	325	8.54E-08	1.14E-06	1.70E-06	2.43E-06	3.88E-06	1.76E-06	8.63E-07	5.95E-07	1.04E-06	1.53E-06	9.96E-07	7.32E-07
New Jersey	1676	2.29E-07	2.66E-06	6.68E-06	1.40E-05	3.64E-05	9.58E-06	8.41E-06	2.11E-06	4.10E-06	9.84E-06	4.25E-06	2.30E-06
New Mexico	379	1.12E-07	1.76E-07	4.04E-07	1.35E-06	2.61E-06	8.16E-07	7.74E-07	1.87E-07	3.61E-07	4.03E-07	3.67E-07	1.89E-07
New York	2289	1.19E-07	1.37E-06	3.09E-06	8.44E-06	3.69E-05	6.13E-06	6.94E-06	4.61E-07	3.53E-06	4.42E-07	3.00E-06	5.43E-07
North Carolina	888	5.36E-08	5.48E-07	9.06E-07	1.43E-06	3.05E-06	1.03E-06	6.33E-07	2.76E-07	7.02E-07	3.69E-07	6.52E-07	2.90E-07
North Dakota	118	5.53E-08	7.65E-08	9.40E-08	1.16E-07	6.08E-07	1.31E-07	1.04E-07	8.51E-08	9.96E-08	8.67E-08	9.28E-08	8.46E-08
Ohio	1139	3.04E-07	6.78E-07	1.11E-06	2.09E-06	4.60E-06	1.42E-06	9.05E-07	5.85E-07	7.88E-07	6.31E-07	8.45E-07	6.11E-07
Oklahoma	392	1.59E-07	2.97E-07	5.44E-07	1.11E-06	1.87E-06	7.10E-07	4.65E-07	2.42E-07	4.78E-07	3.28E-07	4.95E-07	2.51E-07
Oregon	436	4.39E-08	1.05E-07	3.24E-07	6.68E-07	2.34E-06	4.99E-07	5.22E-07	9.80E-08	3.28E-07	4.19E-07	2.93E-07	9.76E-08
Pennsylvania	2382	2.79E-07	1.22E-06	2.19E-06	4.18E-06	1.30E-05	3.21E-06	2.81E-06	9.75E-07	1.52E-06	1.29E-06	1.52E-06	1.02E-06
Rhode Island	68	1.51E-07	7.79E-07	1.96E-06	3.72E-06	6.08E-06	2.36E-06	1.74E-06	4.65E-07	8.55E-07	1.04E-06	8.38E-07	5.92E-07
South Carolina	465	1.72E-07	4.75E-07	7.86E-07	1.25E-06	2.41E-06	9.05E-07	5.17E-07	3.54E-07	5.97E-07	3.48E-07	4.56E-07	3.67E-07
South Dakota	124	1.02E-07	1.22E-07	1.34E-07	2.12E-07	6.80E-07	1.92E-07	1.23E-07	1.50E-07	1.84E-07	1.42E-07	1.69E-07	1.49E-07
Tennessee	632	2.73E-07	5.53E-07	9.56E-07	1.66E-06	2.81E-06	1.15E-06	7.04E-07	4.46E-07	7.62E-07	8.66E-07	7.14E-07	4.93E-07
Texas	3416	1.62E-07	1.05E-06	2.59E-06	3.67E-06	1.01E-05	2.66E-06	1.84E-06	3.45E-07	1.37E-06	9.98E-07	1.64E-06	3.83E-07
Utah	412	1.05E-07	2.17E-07	7.79E-07	1.51E-06	2.87E-06	9.60E-07	7.81E-07	1.75E-07	7.70E-07	7.91E-07	7.66E-07	2.32E-07
Vermont	69	1.21E-07	2.21E-07	3.20E-07	6.50E-07	9.30E-07	4.21E-07	2.55E-07	1.98E-07	2.46E-07	2.07E-07	2.50E-07	2.05E-07
Virginia	861	1.26E-07	5.21E-07	1.02E-06	2.22E-06	4.50E-06	1.42E-06	1.07E-06	4.46E-07	8.03E-07	4.12E-07	7.97E-07	4.46E-07
Washington	934	4.65E-08	4.75E-07	1.34E-06	2.21E-06	5.09E-06	1.49E-06	1.14E-06	1.29E-07	1.01E-06	3.29E-07	8.49E-07	1.17E-07
Washington D.C.	23	1.06E-06	1.67E-06	2.78E-06	3.30E-06	3.84E-06	2.59E-06	9.63E-07		1.73E-06	1.73E-06	1.73E-06	
West Virginia	142	2.48E-07	3.20E-07	4.35E-07	8.09E-07	1.72E-06	6.01E-07	3.64E-07	4.66E-07	4.38E-07	6.14E-07	4.57E-07	4.23E-07
Wisconsin	713	7.89E-08	4.68E-07	9.98E-07	1.80E-06	4.87E-06	1.35E-06	1.11E-06	4.15E-07	9.14E-07	5.03E-07	5.96E-07	4.47E-07
Wyoming	120	5.76E-08	1.05E-07	1.24E-07	1.43E-07	3.39E-07	1.29E-07	4.48E-08	1.24E-07	1.43E-07	1.93E-07	1.42E-07	1.24E-07
United States	43304	2.70E-08	7.04E-07	1.77E-06	3.90E-06	3.69E-05	3.08E-06	3.81E-06	3.44E-07	1.33E-06	9.93E-07	1.43E-06	3.68E-07

U.S. State	N	Intake fraction from SO_2 emissions										
		Descriptive statistics							Emission weighted by sector			
		Min	Q1	Median	Q3	Max	Mean	SD	Fuel Combustion	Industrial Processes	Mobile	All-sectors
Alabama	435	9.01E-08	2.12E-07	2.75E-07	3.52E-07	4.03E-07	2.78E-07	7.68E-08	2.32E-07	2.17E-07	2.13E-07	2.28E-07
Arizona	997	8.64E-08	1.42E-07	1.62E-07	1.76E-07	1.99E-07	1.56E-07	2.75E-08	1.13E-07	1.33E-07	1.55E-07	1.25E-07
Arkansas	222	1.47E-07	1.72E-07	1.88E-07	2.10E-07	2.64E-07	1.93E-07	2.75E-08	1.74E-07	1.77E-07	1.88E-07	1.74E-07
California	8452	4.75E-08	4.02E-07	8.12E-07	1.26E-06	2.71E-06	8.92E-07	5.68E-07	7.05E-07	7.22E-07	1.06E-06	4.74E-07
Colorado	778	9.36E-08	1.17E-07	1.33E-07	1.40E-07	1.85E-07	1.29E-07	1.76E-08	1.18E-07	1.22E-07	1.27E-07	1.19E-07
Connecticut	618	1.21E-07	2.92E-07	3.17E-07	3.91E-07	7.29E-07	3.40E-07	8.81E-08	3.01E-07	2.97E-07	2.86E-07	3.01E-07
Delaware	38	7.59E-08	1.03E-07	1.24E-07	2.59E-07	3.01E-07	1.70E-07	7.79E-08	1.71E-07	2.30E-07	1.70E-07	1.74E-07
Florida	2296	7.12E-08	2.34E-07	3.65E-07	4.77E-07	7.37E-07	3.66E-07	1.55E-07	2.70E-07	2.74E-07	2.82E-07	2.70E-07
Georgia	1008	1.32E-07	2.63E-07	6.36E-07	9.59E-07	1.21E-06	6.31E-07	3.43E-07	3.27E-07	2.25E-07	3.94E-07	3.14E-07
Idaho	235	3.40E-08	4.94E-08	5.62E-08	5.94E-08	8.12E-08	5.47E-08	1.02E-08	5.98E-08	7.27E-08	5.59E-08	5.41E-08
Illinois	1551	2.10E-07	3.24E-07	4.89E-07	5.67E-07	9.24E-07	4.63E-07	1.35E-07	2.96E-07	3.13E-07	3.95E-07	3.01E-07
Indiana	610	2.42E-07	2.96E-07	3.08E-07	3.32E-07	3.75E-07	3.13E-07	2.66E-08	2.85E-07	3.01E-07	3.14E-07	2.86E-07
Iowa	327	1.50E-07	2.11E-07	2.28E-07	2.85E-07	3.60E-07	2.39E-07	5.08E-08	2.45E-07	2.98E-07	2.32E-07	2.47E-07
Kansas	302	9.70E-08	1.70E-07	1.92E-07	2.09E-07	2.50E-07	1.87E-07	3.76E-08	2.07E-07	1.61E-07	1.89E-07	2.00E-07
Kentucky	356	1.94E-07	2.38E-07	2.50E-07	2.63E-07	3.14E-07	2.52E-07	2.01E-08	2.50E-07	2.46E-07	2.67E-07	2.50E-07
Louisiana	368	8.04E-08	2.00E-07	2.39E-07	2.72E-07	3.37E-07	2.34E-07	5.26E-08	2.22E-07	1.88E-07	1.57E-07	2.05E-07
Maine	154	1.35E-08	4.62E-08	7.60E-08	8.71E-08	1.33E-07	6.96E-08	2.80E-08	5.76E-08	5.28E-08	5.14E-08	5.61E-08
Maryland	1636	7.43E-08	3.10E-07	3.72E-07	4.52E-07	6.45E-07	3.90E-07	1.10E-07	3.36E-07	5.30E-07	2.49E-07	3.37E-07
Massachusetts	1163	3.53E-08	2.66E-07	3.19E-07	3.83E-07	5.47E-07	3.20E-07	8.97E-08	2.57E-07	3.33E-07	2.48E-07	2.59E-07
Michigan	1110	4.20E-08	2.55E-07	2.81E-07	2.94E-07	3.48E-07	2.67E-07	5.07E-08	2.36E-07	1.98E-07	2.56E-07	2.34E-07
Minnesota	627	2.83E-08	1.36E-07	1.63E-07	1.84E-07	2.20E-07	1.50E-07	4.77E-08	1.17E-07	1.05E-07	1.54E-07	1.14E-07
Mississippi	246	1.46E-07	1.88E-07	2.08E-07	2.31E-07	2.98E-07	2.09E-07	2.90E-08	1.54E-07	1.99E-07	1.77E-07	1.59E-07
Missouri	691	1.53E-07	1.95E-07	2.24E-07	2.82E-07	3.65E-07	2.37E-07	4.94E-08	2.43E-07	2.20E-07	2.36E-07	2.40E-07
Montana	226	3.22E-08	4.32E-08	4.97E-08	5.88E-08	7.41E-08	5.09E-08	1.09E-08	6.47E-08	6.39E-08	5.12E-08	6.29E-08
Nebraska	214	8.93E-08	1.23E-07	1.70E-07	1.84E-07	1.93E-07	1.53E-07	3.43E-08	1.45E-07	1.68E-07	1.52E-07	1.45E-07
Nevada	641	5.28E-08	7.98E-08	1.41E-07	1.61E-07	2.10E-07	1.29E-07	4.14E-08	1.01E-07	1.03E-07	1.35E-07	1.03E-07
New Hampshire	325	6.53E-08	2.84E-07	3.29E-07	4.30E-07	5.47E-07	3.54E-07	1.15E-07	2.96E-07	3.10E-07	2.92E-07	2.95E-07
New Jersey	1676	9.97E-08	5.39E-07	1.20E-06	1.65E-06	1.90E-06	1.11E-06	5.70E-07	5.94E-07	3.16E-07	7.55E-07	6.13E-07
New Mexico	379	9.71E-08	1.12E-07	1.20E-07	1.26E-07	1.47E-07	1.19E-07	9.21E-09	1.03E-07	1.41E-07	1.18E-07	1.22E-07
New York	2289	7.41E-08	2.94E-07	7.00E-07	1.10E-06	1.83E-06	7.46E-07	4.53E-07	3.50E-07	2.90E-07	5.10E-07	3.50E-07
North Carolina	888	3.57E-08	2.46E-07	3.71E-07	4.15E-07	5.46E-07	3.36E-07	1.27E-07	3.41E-07	2.05E-07	1.72E-07	3.11E-07
North Dakota	118	3.85E-08	4.91E-08	5.99E-08	6.63E-08	9.16E-08	5.90E-08	1.08E-08	5.90E-08	5.66E-08	5.92E-08	5.87E-08
Ohio	1139	2.46E-07	2.90E-07	3.18E-07	3.34E-07	3.99E-07	3.13E-07	2.70E-08	2.93E-07	2.95E-07	3.03E-07	2.93E-07
Oklahoma	392	1.12E-07	1.96E-07	2.21E-07	2.45E-07	2.98E-07	2.21E-07	3.58E-08	1.95E-07	1.90E-07	2.18E-07	1.94E-07
Oregon	436	3.80E-08	6.15E-08	1.49E-07	2.02E-07	2.60E-07	1.41E-07	7.17E-08	6.92E-08	1.53E-07	1.57E-07	7.59E-08
Pennsylvania	2382	2.51E-07	4.17E-07	5.50E-07	7.61E-07	1.51E-06	5.87E-07	1.90E-07	4.45E-07	5.34E-07	4.81E-07	4.51E-07
Rhode Island	68	8.51E-08	2.12E-07	2.71E-07	2.84E-07	3.08E-07	2.43E-07	5.90E-08	1.79E-07	2.12E-07	1.54E-07	1.79E-07
South Carolina	465	1.02E-07	2.22E-07	2.56E-07	3.26E-07	4.35E-07	2.73E-07	7.30E-08	2.28E-07	2.43E-07	1.79E-07	2.28E-07
South Dakota	124	7.19E-08	8.36E-08	9.29E-08	1.35E-07	1.51E-07	1.05E-07	2.57E-08	1.15E-07	8.87E-08	1.12E-07	1.12E-07
Tennessee	632	2.01E-07	2.92E-07	3.24E-07	3.48E-07	4.65E-07	3.21E-07	4.96E-08	2.96E-07	3.12E-07	3.21E-07	2.98E-07
Texas	3416	1.16E-07	3.95E-07	5.74E-07	7.66E-07	1.48E-06	6.35E-07	3.57E-07	3.47E-07	3.63E-07	5.91E-07	3.55E-07
Utah	412	7.60E-08	9.76E-08	1.05E-07	1.17E-07	1.36E-07	1.07E-07	1.36E-08	1.07E-07	1.18E-07	1.16E-07	1.08E-07
Vermont	69	8.11E-08	1.01E-07	1.05E-07	1.78E-07	3.79E-07	1.51E-07	8.04E-08	1.81E-07		1.69E-07	1.79E-07
Virginia	861	8.68E-08	2.27E-07	2.66E-07	3.14E-07	6.33E-07	2.83E-07	8.92E-08	2.52E-07	2.62E-07	2.21E-07	2.53E-07
Washington	934	3.58E-08	7.85E-08	1.47E-07	1.94E-07	2.87E-07	1.40E-07	6.89E-08	1.67E-07	6.82E-08	1.33E-07	1.01E-07
Washington D.C.	23	2.21E-07	2.65E-07	2.97E-07	3.04E-07	3.13E-07	2.83E-07	2.82E-08	2.59E-07	2.59E-07	2.59E-07	2.59E-07
West Virginia	142	2.44E-07	2.66E-07	2.91E-07	3.76E-07	6.21E-07	3.35E-07	9.80E-08	3.26E-07	3.78E-07	3.44E-07	3.27E-07
Wisconsin	713	5.15E-08	1.81E-07	2.96E-07	3.26E-07	4.67E-07	2.65E-07	9.01E-08	1.91E-07	1.96E-07	2.42E-07	1.92E-07
Wyoming	120	5.89E-08	7.60E-08	8.38E-08	9.48E-08	1.18E-07	8.56E-08	1.30E-08	9.00E-08	8.33E-08	9.05E-08	8.87E-08
United States	43304	1.35E-08	2.14E-07	3.35E-07	6.18E-07	2.71E-06	5.03E-07	4.37E-07	2.69E-07	2.58E-07	3.15E-07	2.66E-07

U.S. State	N	Intake fraction from NO_x emissions										
		Descriptive statistics							Emission weighted by sector			
		Min	Q1	Median	Q3	Max	Mean	SD	Fuel Combustion	Industrial Processes	Mobile	All-sectors
Alabama	435	2.96E-08	9.85E-08	1.39E-07	1.78E-07	3.23E-07	1.41E-07	5.48E-08	1.06E-07	9.88E-08	1.05E-07	1.04E-07
Arizona	997	3.54E-08	7.54E-08	1.34E-07	1.71E-07	2.38E-07	1.28E-07	5.04E-08	7.96E-08	7.07E-08	9.48E-08	8.99E-08
Arkansas	222	9.86E-08	1.22E-07	1.57E-07	2.16E-07	4.96E-07	1.83E-07	8.28E-08	1.36E-07	1.26E-07	1.40E-07	1.36E-07
California	8452	2.79E-08	2.50E-07	3.89E-07	5.06E-07	1.18E-06	4.01E-07	2.11E-07	2.37E-07	2.38E-07	2.65E-07	2.43E-07
Colorado	778	7.45E-08	1.20E-07	2.20E-07	2.91E-07	4.04E-07	2.08E-07	9.00E-08	1.24E-07	1.15E-07	1.33E-07	1.23E-07
Connecticut	618	2.80E-08	9.48E-08	1.18E-07	1.45E-07	2.38E-07	1.20E-07	3.99E-08	7.20E-08	7.53E-08	7.18E-08	7.19E-08
Delaware	38	3.06E-08	7.51E-08	8.46E-08	1.01E-07	2.14E-07	9.30E-08	3.29E-08	7.97E-08	7.92E-08	7.36E-08	7.50E-08
Florida	2296	1.14E-08	4.81E-08	6.24E-08	8.14E-08	1.67E-07	6.62E-08	2.52E-08	5.67E-08	5.05E-08	4.86E-08	4.97E-08
Georgia	1008	3.91E-08	1.19E-07	2.47E-07	4.29E-07	6.14E-07	2.77E-07	1.69E-07	1.41E-07	7.77E-08	1.70E-07	1.50E-07
Idaho	235	3.34E-08	5.09E-08	6.47E-08	9.55E-08	2.08E-07	7.84E-08	3.72E-08	6.22E-08	5.55E-08	6.05E-08	5.92E-08
Illinois	1551	1.18E-07	2.34E-07	3.74E-07	4.66E-07	6.91E-07	3.63E-07	1.40E-07	2.19E-07	1.77E-07	2.44E-07	2.28E-07
Indiana	610	1.21E-07	1.83E-07	2.31E-07	3.17E-07	4.63E-07	2.56E-07	8.80E-08	1.67E-07	1.80E-07	2.00E-07	1.86E-07
Iowa	327	1.08E-07	1.47E-07	1.88E-07	2.80E-07	4.29E-07	2.13E-07	7.96E-08	1.45E-07	1.57E-07	1.45E-07	1.44E-07
Kansas	302	7.69E-08	1.25E-07	1.73E-07	2.71E-07	4.32E-07	2.02E-07	9.81E-08	1.44E-07	1.19E-07	1.47E-07	1.34E-07
Kentucky	356	7.76E-08	1.12E-07	1.32E-07	1.87E-07	3.10E-07	1.51E-07	5.52E-08	1.26E-07	1.03E-07	1.21E-07	1.21E-07
Louisiana	368	3.24E-08	1.00E-07	1.23E-07	1.74E-07	3.66E-07	1.41E-07	6.26E-08	9.00E-08	1.02E-07	9.03E-08	9.30E-08
Maine	154	3.57E-09	1.43E-08	2.77E-08	3.94E-08	1.31E-07	3.39E-08	2.88E-08	1.67E-08	1.56E-08	1.54E-08	1.56E-08
Maryland	1636	2.15E-08	2.03E-07	2.82E-07	3.57E-07	5.24E-07	2.78E-07	9.80E-08	1.38E-07	1.87E-07	1.41E-07	1.41E-07
Massachusetts	1163	5.39E-09	9.07E-08	1.29E-07	1.97E-07	4.41E-07	1.55E-07	8.93E-08	8.15E-08	8.00E-08	7.82E-08	7.91E-08
Michigan	1110	2.04E-08	1.80E-07	2.60E-07	3.12E-07	4.22E-07	2.46E-07	8.48E-08	1.57E-07	7.56E-08	1.68E-07	1.55E-07
Minnesota	627	1.46E-08	1.25E-07	2.24E-07	3.04E-07	4.27E-07	2.13E-07	1.05E-07	1.34E-07	4.72E-08	1.37E-07	1.23E-07
Mississippi	246	4.89E-08	9.87E-08	1.10E-07	1.43E-07	2.23E-07	1.22E-07	3.82E-08	8.07E-08	8.26E-08	1.02E-07	9.65E-08
Missouri	691	1.07E-07	1.42E-07	2.35E-07	3.23E-07	4.71E-07	2.39E-07	9.48E-08	1.68E-07	1.41E-07	1.69E-07	1.64E-07
Montana	226	3.27E-08	4.43E-08	4.98E-08	5.83E-08	1.07E-07	5.22E-08	1.26E-08	5.67E-08	5.10E-08	4.84E-08	5.00E-08
Nebraska	214	7.42E-08	9.40E-08	1.40E-07	3.10E-07	4.96E-07	2.07E-07	1.32E-07	1.24E-07	1.27E-07	1.08E-07	1.09E-07
Nevada	641	4.81E-08	6.82E-08	8.89E-08	1.03E-07	1.47E-07	8.80E-08	2.20E-08	6.61E-08	6.48E-08	6.94E-08	6.79E-08
New Hampshire	325	1.87E-08	6.81E-08	9.47E-08	1.14E-07	1.75E-07	9.28E-08	3.44E-08	6.03E-08	6.95E-08	5.83E-08	5.88E-08
New Jersey	1676	2.91E-08	1.66E-07	3.14E-07	5.67E-07	1.19E-06	3.88E-07	2.68E-07	2.08E-07	1.15E-07	1.91E-07	1.93E-07
New Mexico	379	6.75E-08	8.28E-08	9.20E-08	1.15E-07	1.59E-07	9.86E-08	2.03E-08	8.29E-08	8.29E-08	8.60E-08	8.47E-08
New York	2289	1.03E-08	1.31E-07	2.08E-07	3.90E-07	1.22E-06	2.87E-07	2.18E-07	2.07E-07	1.00E-07	1.53E-07	1.64E-07
North Carolina	888	1.43E-08	1.30E-07	1.95E-07	2.64E-07	4.69E-07	2.04E-07	9.70E-08	1.48E-07	1.01E-07	1.42E-07	1.40E-07
North Dakota	118	3.08E-08	4.54E-08	5.35E-08	5.93E-08	2.08E-07	5.91E-08	2.67E-08	5.16E-08	4.76E-08	5.04E-08	5.01E-08
Ohio	1139	8.50E-08	1.79E-07	2.44E-07	3.40E-07	5.00E-07	2.58E-07	9.68E-08	1.57E-07	1.66E-07	1.93E-07	1.79E-07
Oklahoma	392	8.54E-08	1.40E-07	1.95E-07	2.92E-07	4.16E-07	2.20E-07	9.31E-08	1.40E-07	1.27E-07	1.64E-07	1.44E-07
Oregon	436	3.24E-08	5.09E-08	9.95E-08	1.67E-07	3.09E-07	1.18E-07	7.21E-08	7.19E-08	6.71E-08	7.65E-08	7.08E-08
Pennsylvania	2382	6.52E-08	1.88E-07	2.53E-07	3.36E-07	7.75E-07	2.82E-07	1.25E-07	1.68E-07	1.59E-07	1.82E-07	1.74E-07
Rhode Island	68	1.33E-08	5.25E-08	1.03E-07	1.65E-07	2.48E-07	1.13E-07	6.68E-08	5.14E-08	5.03E-08	4.27E-08	4.45E-08
South Carolina	465	2.98E-08	8.35E-08	1.16E-07	1.70E-07	2.70E-07	1.26E-07	5.39E-08	8.58E-08	7.38E-08	8.94E-08	8.72E-08
South Dakota	124	6.14E-08	6.85E-08	7.50E-08	1.03E-07	4.13E-07	1.06E-07	7.44E-08	8.13E-08	7.61E-08	8.76E-08	8.23E-08
Tennessee	632	8.01E-08	1.32E-07	1.79E-07	2.28E-07	3.82E-07	1.89E-07	7.20E-08	1.49E-07	1.34E-07	1.46E-07	1.45E-07
Texas	3416	6.44E-08	1.90E-07	3.67E-07	4.92E-07	8.01E-07	3.53E-07	1.71E-07	1.65E-07	1.28E-07	2.21E-07	1.81E-07
Utah	412	6.16E-08	7.88E-08	1.04E-07	1.27E-07	2.00E-07	1.07E-07	3.27E-08	8.27E-08	8.33E-08	9.52E-08	8.88E-08
Vermont	69	1.94E-08	4.15E-08	5.87E-08	1.33E-07	1.84E-07	8.23E-08	5.21E-08	4.47E-08	5.25E-08	4.46E-08	4.45E-08
Virginia	861	1.84E-08	7.08E-08	1.03E-07	1.52E-07	3.14E-07	1.17E-07	6.28E-08	7.42E-08	6.55E-08	7.45E-08	7.32E-08
Washington	934	2.15E-08	8.50E-08	1.34E-07	1.65E-07	3.05E-07	1.33E-07	6.11E-08	7.93E-08	8.47E-08	8.67E-08	8.11E-08
Washington D.C.	23	7.72E-08	1.08E-07	1.70E-07	1.85E-07	2.09E-07	1.52E-07	4.67E-08	1.10E-07	1.10E-07	1.10E-07	1.10E-07
West Virginia	142	5.54E-08	7.88E-08	9.11E-08	1.20E-07	1.82E-07	1.03E-07	3.32E-08	9.87E-08	8.95E-08	9.47E-08	9.56E-08
Wisconsin	713	2.65E-08	1.60E-07	2.32E-07	3.23E-07	5.71E-07	2.46E-07	1.15E-07	1.51E-07	1.27E-07	1.48E-07	1.47E-07
Wyoming	120	5.22E-08	6.68E-08	7.16E-08	7.78E-08	1.12E-07	7.28E-08	1.02E-08	7.44E-08	7.38E-08	7.65E-08	7.49E-08
United States	43304	3.57E-09	1.15E-07	2.08E-07	3.61E-07	1.22E-06	2.58E-07	1.85E-07	1.32E-07	1.14E-07	1.44E-07	1.34E-07

Table A3.29. Distribution of marginal characterization factors ($\frac{DALYs}{kg_{emitted}}$) of source locations and emission-weighted sector-specific estimates by state.

U.S. State	N	Marginal characterization factor from $PM_{2.5}$ emissions											
		Descriptive statistics							Emission weighted by sector				
		Min	Q1	Median	Q3	Max	Mean	SD	Agriculture	Fuel Combustion	Industrial Processes	Mobile	All-sectors
Alabama	435	2.42E-05	9.45E-05	1.75E-04	3.29E-04	7.21E-04	2.32E-04	1.76E-04	8.17E-05	1.02E-04	1.26E-04	1.06E-04	8.95E-05
Arizona	997	2.47E-05	2.60E-04	9.11E-04	1.23E-03	1.62E-03	7.81E-04	5.00E-04	1.08E-04	2.65E-04	1.30E-04	3.80E-04	1.76E-04
Arkansas	222	3.25E-05	5.75E-05	1.02E-04	1.98E-04	4.27E-04	1.39E-04	9.89E-05	5.50E-05	7.63E-05	6.31E-05	7.61E-05	6.15E-05
California	8452	1.22E-05	3.09E-04	6.31E-04	9.79E-04	2.85E-03	7.13E-04	5.06E-04	8.77E-05	3.30E-04	4.31E-04	4.31E-04	1.47E-04
Colorado	778	1.88E-05	1.59E-04	5.38E-04	8.67E-04	1.42E-03	5.36E-04	3.77E-04	4.26E-05	2.07E-04	1.83E-04	2.41E-04	1.49E-04
Connecticut	618	3.54E-05	1.68E-04	2.49E-04	3.51E-04	7.79E-04	2.77E-04	1.52E-04	1.21E-04	1.11E-04	1.32E-04	1.19E-04	1.13E-04
Delaware	38	2.19E-05	4.76E-05	6.58E-05	9.72E-05	3.38E-04	8.58E-05	6.07E-05	4.03E-05	6.38E-05	6.81E-05	6.12E-05	5.93E-05
Florida	2296	1.60E-05	1.97E-04	3.93E-04	8.72E-04	2.62E-03	5.84E-04	5.11E-04	7.71E-05	2.93E-04	1.87E-04	2.91E-04	1.80E-04
Georgia	1008	3.54E-05	1.30E-04	3.05E-04	6.19E-04	1.20E-03	3.85E-04	2.92E-04	7.35E-05	1.61E-04	8.32E-05	2.31E-04	1.03E-04
Idaho	235	8.64E-06	2.03E-05	4.59E-05	2.55E-04	1.01E-03	1.54E-04	2.05E-04	3.52E-05	6.03E-05	2.99E-05	4.97E-05	3.52E-05
Illinois	1551	4.37E-05	2.02E-04	5.09E-04	7.08E-04	1.48E-03	5.15E-04	3.42E-04	7.87E-05	1.70E-04	2.16E-04	2.73E-04	1.32E-04
Indiana	610	6.20E-05	1.02E-04	2.02E-04	3.74E-04	7.31E-04	2.64E-04	1.86E-04	9.68E-05	1.05E-04	1.12E-04	1.39E-04	1.11E-04
Iowa	327	2.88E-05	5.73E-05	1.00E-04	2.05E-04	4.50E-04	1.36E-04	9.57E-05	4.81E-05	5.81E-05	6.49E-05	5.86E-05	5.25E-05
Kansas	302	1.77E-05	5.22E-05	1.22E-04	2.61E-04	6.27E-04	1.76E-04	1.61E-04	3.83E-05	8.01E-05	8.90E-05	8.74E-05	5.52E-05
Kentucky	356	4.87E-05	7.12E-05	1.14E-04	2.45E-04	7.22E-04	1.93E-04	1.66E-04	7.82E-05	1.10E-04	8.06E-05	1.02E-04	8.41E-05
Louisiana	368	1.38E-05	6.54E-05	1.16E-04	2.19E-04	5.73E-04	1.60E-04	1.20E-04	5.65E-05	7.27E-05	7.51E-05	7.37E-05	5.84E-05
Maine	154	6.47E-06	2.92E-05	7.16E-05	1.35E-04	3.67E-04	1.02E-04	9.46E-05	2.92E-05	3.46E-05	3.12E-05	3.55E-05	3.44E-05
Maryland	1636	1.52E-05	4.11E-04	6.79E-04	9.10E-04	1.89E-03	6.79E-04	3.40E-04	9.67E-05	2.27E-04	2.05E-04	2.75E-04	1.89E-04
Massachusetts	1163	3.52E-06	2.12E-04	3.78E-04	6.60E-04	1.82E-03	5.03E-04	3.83E-04	1.33E-04	1.90E-04	1.75E-04	2.02E-04	1.89E-04
Michigan	1110	1.12E-05	1.62E-04	3.27E-04	5.59E-04	9.69E-04	3.74E-04	2.46E-04	9.44E-05	1.45E-04	1.21E-04	1.95E-04	1.46E-04
Minnesota	627	5.88E-06	6.67E-05	2.32E-04	4.71E-04	1.05E-03	2.89E-04	2.43E-04	3.25E-05	6.32E-05	5.13E-05	1.06E-04	5.55E-05
Mississippi	246	3.50E-05	5.75E-05	7.67E-05	1.63E-04	4.84E-04	1.24E-04	1.01E-04	5.33E-05	6.01E-05	6.29E-05	6.64E-05	6.12E-05
Missouri	691	3.03E-05	6.22E-05	2.54E-04	5.24E-04	1.03E-03	3.25E-04	2.74E-04	5.53E-05	1.21E-04	9.35E-05	1.51E-04	7.78E-05
Montana	226	7.50E-06	1.24E-05	1.61E-05	2.87E-05	5.94E-04	5.61E-05	1.08E-04	1.50E-05	2.13E-05	2.19E-05	1.96E-05	1.80E-05
Nebraska	214	1.75E-05	2.49E-05	6.57E-05	3.65E-04	6.12E-04	1.79E-04	1.85E-04	2.85E-05	4.49E-05	4.59E-05	4.04E-05	3.39E-05
Nevada	641	1.56E-05	1.53E-04	3.95E-04	8.42E-04	1.65E-03	5.01E-04	4.19E-04	2.59E-05	2.99E-04	5.90E-05	3.11E-04	1.45E-04
New Hampshire	325	2.01E-05	1.95E-04	3.08E-04	4.55E-04	8.33E-04	3.39E-04	1.89E-04	8.89E-05	1.55E-04	1.38E-04	1.64E-04	1.59E-04
New Jersey	1676	2.73E-05	3.15E-04	7.61E-04	1.66E-03	4.69E-03	1.11E-03	9.63E-04	1.46E-04	4.53E-04	2.04E-04	4.96E-04	3.72E-04
New Mexico	379	2.07E-05	4.10E-05	1.24E-04	4.49E-04	1.31E-03	2.94E-04	3.34E-04	4.15E-05	1.08E-04	5.75E-05	1.06E-04	9.53E-05
New York	2289	1.17E-05	1.90E-04	4.15E-04	8.83E-04	4.96E-03	6.74E-04	7.35E-04	5.26E-05	2.09E-04	1.18E-04	3.19E-04	2.15E-04
North Carolina	888	8.33E-06	1.41E-04	2.43E-04	3.63E-04	7.84E-04	2.68E-04	1.67E-04	9.06E-05	1.64E-04	1.21E-04	1.58E-04	1.28E-04
North Dakota	118	9.39E-06	1.22E-05	1.47E-05	2.95E-05	2.83E-04	3.79E-05	5.34E-05	1.43E-05	1.54E-05	1.49E-05	1.58E-05	1.48E-05
Ohio	1139	3.59E-05	1.17E-04	2.20E-04	4.64E-04	9.97E-04	2.98E-04	2.18E-04	9.61E-05	1.16E-04	1.27E-04	1.50E-04	1.17E-04
Oklahoma	392	2.71E-05	7.66E-05	2.04E-04	4.69E-04	8.25E-04	2.77E-04	2.19E-04	6.31E-05	1.24E-04	8.35E-05	1.47E-04	8.95E-05
Oregon	436	1.08E-05	5.42E-05	2.44E-04	5.44E-04	1.53E-03	3.72E-04	3.84E-04	3.60E-05	1.37E-04	1.07E-04	1.56E-04	6.94E-05
Pennsylvania	2382	3.22E-05	1.89E-04	3.93E-04	7.56E-04	2.54E-03	5.75E-04	5.45E-04	1.32E-04	1.84E-04	1.90E-04	2.27E-04	1.88E-04
Rhode Island	68	1.83E-05	9.55E-05	3.39E-04	6.41E-04	1.08E-03	4.00E-04	3.22E-04	4.31E-05	1.00E-04	1.20E-04	1.04E-04	1.11E-04
South Carolina	465	3.25E-05	1.05E-04	2.07E-04	3.20E-04	5.86E-04	2.24E-04	1.34E-04	7.50E-05	1.18E-04	9.24E-05	1.01E-04	1.01E-04
South Dakota	124	1.41E-05	1.63E-05	1.98E-05	3.51E-05	2.93E-04	4.51E-05	5.84E-05	2.22E-05	2.62E-05	2.65E-05	2.59E-05	2.32E-05
Tennessee	632	5.27E-05	1.52E-04	2.80E-04	4.88E-04	8.18E-04	3.30E-04	2.12E-04	1.04E-04	1.55E-04	1.58E-04	1.91E-04	1.45E-04
Texas	3416	2.58E-05	2.17E-04	5.84E-04	8.53E-04	2.28E-03	5.86E-04	4.03E-04	7.48E-05	1.88E-04	1.92E-04	2.78E-04	1.70E-04
Utah	412	2.18E-05	5.07E-05	1.91E-04	3.41E-04	7.32E-04	2.18E-04	1.69E-04	3.82E-05	9.29E-05	1.33E-04	1.47E-04	8.70E-05
Vermont	69	2.27E-05	3.61E-05	5.97E-05	1.77E-04	2.67E-04	1.01E-04	8.16E-05	3.64E-05	4.24E-05	3.54E-05	4.31E-05	4.19E-05
Virginia	861	1.27E-05	1.07E-04	1.79E-04	3.50E-04	7.56E-04	2.40E-04	1.66E-04	1.00E-04	1.25E-04	9.57E-05	1.35E-04	1.13E-04
Washington	934	1.23E-05	2.40E-04	5.39E-04	8.05E-04	1.89E-03	5.78E-04	4.12E-04	3.99E-05	3.36E-04	1.57E-04	2.71E-04	9.60E-05
Washington D.C.	23	1.41E-04	2.24E-04	3.91E-04	4.63E-04	5.40E-04	3.57E-04	1.37E-04		2.34E-04	2.34E-04	2.34E-04	2.34E-04
West Virginia	142	4.53E-05	6.68E-05	9.29E-05	1.78E-04	3.83E-04	1.31E-04	8.58E-05	8.06E-05	7.18E-05	7.61E-05	8.79E-05	7.43E-05
Wisconsin	713	1.74E-05	9.54E-05	1.93E-04	3.39E-04	9.06E-04	2.53E-04	2.07E-04	7.10E-05	9.52E-05	8.72E-05	9.35E-05	8.38E-05
Wyoming	120	1.16E-05	2.15E-05	2.55E-05	3.13E-05	1.39E-04	3.10E-05	2.01E-05	2.74E-05	3.48E-05	3.87E-05	3.42E-05	3.17E-05
United States	43304	3.52E-06	1.56E-04	3.78E-04	7.37E-04	4.96E-03	5.23E-04	5.01E-04	5.56E-05	1.45E-04	1.34E-04	2.02E-04	1.03E-04

U.S. State	N	Marginal characterization factor from NH_3 emissions												
		Descriptive statistics							Emission weighted by sector					
		Min	Q1	Median	Q3	Max	Mean	SD	Agriculture	Fuel Combustion	Industrial Processes	Mobile	All-sectors
Alabama	435	1.99E-05	7.45E-05	1.21E-04	2.21E-04	5.51E-04	1.69E-04	1.31E-04	6.45E-05	8.89E-05	6.28E-05	8.51E-05	6.35E-05
Arizona	997	1.56E-05	8.78E-05	1.90E-04	2.35E-04	4.73E-04	1.69E-04	9.11E-05	4.45E-05	8.55E-05	4.44E-05	9.95E-05	4.22E-05
Arkansas	222	3.51E-05	4.54E-05	6.76E-05	1.08E-04	2.24E-04	8.14E-05	4.32E-05	4.49E-05	5.42E-05	4.51E-05	5.67E-05	4.49E-05
California	8452	1.00E-05	1.28E-04	2.95E-04	5.08E-04	1.22E-03	3.45E-04	2.57E-04	4.85E-05	1.97E-04	3.49E-04	2.54E-04	5.12E-05
Colorado	778	1.80E-05	8.56E-05	2.14E-04	3.65E-04	4.87E-04	2.22E-04	1.41E-04	3.25E-05	1.27E-04	5.14E-05	1.34E-04	3.52E-05
Connecticut	618	3.06E-05	1.38E-04	1.96E-04	2.65E-04	5.65E-04	2.10E-04	1.07E-04	8.83E-05	9.64E-05	1.16E-04	9.54E-05	1.22E-04
Delaware	38	1.30E-05	2.85E-05	4.07E-05	7.11E-05	2.18E-04	5.54E-05	4.15E-05	2.49E-05	5.44E-05	2.52E-05	4.68E-05	2.65E-05
Florida	2296	1.40E-05	1.68E-04	3.23E-04	7.42E-04	2.43E-03	5.08E-04	4.65E-04	6.15E-05	2.35E-04	1.34E-04	2.76E-04	6.47E-05
Georgia	1008	2.99E-05	9.20E-05	1.87E-04	3.80E-04	7.02E-04	2.40E-04	1.72E-04	7.83E-05	1.83E-04	4.91E-05	1.54E-04	7.59E-05
Idaho	235	8.51E-06	1.41E-05	1.98E-05	5.76E-05	2.04E-04	4.20E-05	4.20E-05	1.85E-05	2.34E-05	1.93E-05	2.17E-05	1.77E-05
Illinois	1551	4.48E-05	1.23E-04	3.01E-04	4.23E-04	8.47E-04	3.07E-04	1.96E-04	6.43E-05	2.11E-04	7.98E-05	1.89E-04	7.28E-05
Indiana	610	5.80E-05	7.80E-05	1.29E-04	2.25E-04	4.21E-04	1.67E-04	1.04E-04	7.42E-05	9.81E-05	7.31E-05	1.04E-04	7.49E-05
Iowa	327	2.75E-05	4.46E-05	6.38E-05	9.88E-05	2.02E-04	7.66E-05	3.99E-05	3.87E-05	5.06E-05	4.21E-05	4.89E-05	3.89E-05
Kansas	302	2.10E-05	4.17E-05	7.23E-05	1.37E-04	3.18E-04	9.77E-05	7.60E-05	3.26E-05	7.56E-05	3.60E-05	7.23E-05	3.39E-05
Kentucky	356	4.64E-05	5.99E-05	8.43E-05	1.60E-04	4.27E-04	1.27E-04	9.18E-05	6.23E-05	7.44E-05	8.47E-05	8.11E-05	6.32E-05
Louisiana	368	1.09E-05	4.85E-05	7.40E-05	1.27E-04	3.15E-04	9.57E-05	6.23E-05	4.43E-05	4.80E-05	4.62E-05	5.45E-05	4.16E-05
Maine	154	5.84E-06	2.25E-05	4.92E-05	9.89E-05	2.35E-04	6.67E-05	5.67E-05	2.68E-05	2.56E-05	2.37E-05	2.88E-05	2.74E-05
Maryland	1636	1.09E-05	3.02E-04	4.86E-04	6.50E-04	1.30E-03	4.86E-04	2.39E-04	7.20E-05	2.36E-04	1.79E-04	2.07E-04	9.58E-05
Massachusetts	1163	2.92E-06	1.60E-04	2.77E-04	4.59E-04	1.08E-03	3.42E-04	2.32E-04	1.16E-04	1.47E-04	1.40E-04	1.59E-04	1.30E-04
Michigan	1110	9.19E-06	1.13E-04	2.24E-04	3.93E-04	6.77E-04	2.63E-04	1.75E-04	7.54E-05	1.70E-04	5.59E-05	1.62E-04	8.53E-05
Minnesota	627	5.18E-06	3.89E-05	1.02E-04	2.01E-04	4.17E-04	1.25E-04	9.75E-05	2.75E-05	5.10E-05	2.56E-05	6.20E-05	2.75E-05
Mississippi	246	2.91E-05	4.78E-05	5.80E-05	1.04E-04	2.69E-04	8.27E-05	5.23E-05	4.58E-05	4.75E-05	3.90E-05	5.24E-05	4.63E-05
Missouri	691	3.47E-05	5.15E-05	1.42E-04	2.74E-04	5.07E-04	1.76E-04	1.31E-04	4.66E-05	1.16E-04	6.46E-05	9.98E-05	4.76E-05
Montana	226	8.29E-06	1.15E-05	1.42E-05	1.98E-05	3.61E-04	3.34E-05	5.62E-05	1.38E-05	1.89E-05	2.02E-05	1.73E-05	1.38E-05
Nebraska	214	1.95E-05	2.46E-05	4.47E-05	1.66E-04	2.45E-04	8.78E-05	7.37E-05	2.76E-05	3.96E-05	5.00E-05	3.87E-05	2.79E-05
Nevada	641	1.14E-05	7.07E-05	1.68E-04	3.31E-04	7.59E-04	2.17E-04	1.81E-04	2.01E-05	1.59E-04	2.34E-05	1.46E-04	2.28E-05
New Hampshire	325	1.54E-05	1.50E-04	2.28E-04	3.33E-04	5.21E-04	2.38E-04	1.19E-04	8.16E-05	1.36E-04	1.95E-04	1.32E-04	9.90E-05
New Jersey	1676	2.25E-05	2.44E-04	5.64E-04	1.12E-03	2.87E-03	7.50E-04	6.03E-04	1.96E-04	3.35E-04	7.53E-04	3.47E-04	2.12E-04
New Mexico	379	1.99E-05	3.01E-05	7.04E-05	2.25E-04	6.13E-04	1.59E-04	1.72E-04	3.15E-05	7.12E-05	8.51E-05	7.40E-05	3.24E-05
New York	2289	9.94E-06	1.49E-04	3.01E-04	6.42E-04	3.14E-03	4.74E-04	4.83E-04	5.12E-05	2.57E-04	5.66E-05	2.22E-04	5.62E-05
North Carolina	888	6.39E-06	8.63E-05	1.50E-04	2.25E-04	4.59E-04	1.64E-04	9.80E-05	4.33E-05	1.10E-04	5.68E-05	1.03E-04	4.55E-05
North Dakota	118	8.32E-06	1.16E-05	1.36E-05	1.83E-05	1.13E-04	2.19E-05	2.10E-05	1.24E-05	1.45E-05	1.33E-05	1.38E-05	1.24E-05
Ohio	1139	3.47E-05	8.83E-05	1.52E-04	2.81E-04	6.27E-04	1.92E-04	1.25E-04	7.50E-05	9.98E-05	8.00E-05	1.08E-04	7.86E-05
Oklahoma	392	2.55E-05	5.38E-05	1.09E-04	2.25E-04	4.03E-04	1.40E-04	9.66E-05	4.26E-05	9.09E-05	5.82E-05	9.50E-05	4.42E-05
Oregon	436	9.78E-06	2.89E-05	8.44E-05	1.60E-04	5.40E-04	1.22E-04	1.24E-04	2.32E-05	6.78E-05	9.71E-05	6.15E-05	2.36E-05
Pennsylvania	2382	3.24E-05	1.52E-04	2.77E-04	5.32E-04	1.68E-03	4.11E-04	3.62E-04	1.19E-04	1.86E-04	1.61E-04	1.85E-04	1.24E-04
Rhode Island	68	1.54E-05	8.17E-05	2.61E-04	4.83E-04	7.95E-04	3.03E-04	2.36E-04	5.79E-05	1.03E-04	1.29E-04	1.01E-04	7.52E-05
South Carolina	465	2.74E-05	7.69E-05	1.40E-04	2.13E-04	4.03E-04	1.54E-04	8.92E-05	5.86E-05	9.87E-05	5.70E-05	7.55E-05	6.08E-05
South Dakota	124	1.49E-05	1.72E-05	1.96E-05	2.93E-05	1.04E-04	2.85E-05	2.06E-05	2.03E-05	2.58E-05	1.91E-05	2.41E-05	2.04E-05
Tennessee	632	5.02E-05	1.03E-04	1.80E-04	3.06E-04	5.10E-04	2.11E-04	1.26E-04	8.18E-05	1.37E-04	1.53E-04	1.30E-04	9.04E-05
Texas	3416	2.01E-05	1.27E-04	3.06E-04	4.42E-04	1.34E-03	3.26E-04	2.33E-04	4.88E-05	1.72E-04	1.29E-04	2.03E-04	5.34E-05
Utah	412	1.69E-05	3.16E-05	8.12E-05	1.40E-04	2.73E-04	9.46E-05	6.49E-05	2.55E-05	7.56E-05	7.80E-05	7.57E-05	2.98E-05
Vermont	69	1.93E-05	3.39E-05	5.03E-05	1.05E-04	1.54E-04	6.67E-05	4.29E-05	3.03E-05	3.64E-05	3.25E-05	3.71E-05	3.12E-05
Virginia	861	9.94E-06	6.87E-05	1.19E-04	2.42E-04	4.91E-04	1.63E-04	1.15E-04	5.84E-05	9.06E-05	4.43E-05	8.76E-05	5.79E-05
Washington	934	9.03E-06	9.23E-05	2.13E-04	3.34E-04	7.00E-04	2.31E-04	1.63E-04	2.40E-05	1.50E-04	5.83E-05	1.27E-04	2.24E-05
Washington D.C.	23	1.06E-04	1.65E-04	2.82E-04	3.32E-04	3.87E-04	2.58E-04	9.71E-05		1.71E-04	1.71E-04	1.71E-04	
West Virginia	142	3.56E-05	5.74E-05	7.71E-05	1.45E-04	2.53E-04	1.04E-04	5.94E-05	6.45E-05	6.81E-05	8.97E-05	7.10E-05	6.34E-05
Wisconsin	713	1.20E-05	6.08E-05	1.18E-04	2.01E-04	5.23E-04	1.52E-04	1.18E-04	5.08E-05	1.02E-04	5.99E-05	6.94E-05	5.42E-05
Wyoming	120	1.10E-05	1.95E-05	2.13E-05	2.45E-05	9.42E-05	2.37E-05	1.11E-05	2.16E-05	2.54E-05	3.35E-05	2.59E-05	2.17E-05
United States	43304	2.92E-06	9.45E-05	2.16E-04	4.09E-04	3.14E-03	3.07E-04	3.11E-04	4.57E-05	1.41 E-04	9.79E-05	1.52E-04	4.84E-05

U.S. State	N	Marginal characterization factor from SO_2 emissions										
		Descriptive statistics							Emission weighted by sector			
		Min	Q1	Median	Q3	Max	Mean	SD	Fuel Combustion	Industrial Processes	Mobile	All-sectors
Alabama	435	1.38E-05	3.77E-05	4.88E-05	6.37E-05	7.29E-05	4.97E-05	1.44E-05	4.15E-05	3.80E-05	3.71E-05	4.06E-05
Arizona	997	1.05E-05	2.23E-05	2.48E-05	2.67E-05	3.00E-05	2.40E-05	3.87E-06	1.85E-05	2.20E-05	2.34E-05	2.05E-05
Arkansas	222	2.60E-05	3.11E-05	3.38E-05	3.79E-05	4.59E-05	3.46E-05	4.73E-06	3.07E-05	3.14E-05	3.37E-05	3.07E-05
California	8452	9.53E-06	3.72E-05	6.93E-05	9.58E-05	2.05E-04	7.05E-05	3.85E-05	5.74E-05	5.96E-05	7.94E-05	4.15E-05
Colorado	778	1.46E-05	1.85E-05	2.00E-05	2.07E-05	2.87E-05	1.98E-05	2.32E-06	1.87E-05	1.90E-05	1.96E-05	1.87E-05
Connecticut	618	1.25E-05	2.68E-05	3.14E-05	3.58E-05	4.92E-05	3.17E-05	6.93E-06	2.56E-05	2.65E-05	2.48E-05	2.56E-05
Delaware	38	7.14E-06	1.01E-05	1.20E-05	2.70E-05	3.25E-05	1.72E-05	8.68E-06	1.72E-05	2.37E-05	1.70E-05	1.75E-05
Florida	2296	1.02E-05	3.15E-05	5.19E-05	7.15E-05	1.12E-04	5.37E-05	2.60E-05	3.73E-05	3.56E-05	4.07E-05	3.72E-05
Georgia	1008	2.05E-05	3.99E-05	9.03E-05	1.33E-04	1.67E-04	8.94E-05	4.64E-05	4.86E-05	3.30E-05	5.66E-05	4.65E-05
Idaho	235	6.50E-06	9.17E-06	1.02E-05	1.10E-05	1.35E-05	1.00E-05	1.35E-06	1.06E-05	1.23E-05	1.01E-05	9.92E-06
Illinois	1551	3.05E-05	3.86E-05	4.49E-05	4.85E-05	6.01E-05	4.46E-05	6.88E-06	3.72E-05	3.83E-05	4.12E-05	3.75E-05
Indiana	610	3.33E-05	3.89E-05	4.37E-05	4.61E-05	5.11E-05	4.24E-05	4.44E-06	4.08E-05	3.78E-05	4.14E-05	4.05E-05
Iowa	327	1.91E-05	2.63E-05	2.83E-05	3.36E-05	4.05E-05	2.91E-05	4.94E-06	2.98E-05	3.49E-05	2.85E-05	3.00E-05
Kansas	302	1.53E-05	2.60E-05	3.02E-05	3.21E-05	3.85E-05	2.90E-05	5.74E-06	3.21E-05	2.58E-05	2.97E-05	3.12E-05
Kentucky	356	3.25E-05	3.93E-05	4.20E-05	4.42E-05	5.11E-05	4.18E-05	3.32E-06	4.05E-05	3.94E-05	4.26E-05	4.05E-05
Louisiana	368	1.04E-05	3.06E-05	3.58E-05	4.14E-05	5.38E-05	3.52E-05	8.55E-06	3.33E-05	2.75E-05	2.11E-05	3.02E-05
Maine	154	2.61E-06	8.66E-06	1.31E-05	1.46E-05	1.94E-05	1.18E-05	4.08E-06	9.86E-06	9.82E-06	8.53E-06	9.66E-06
Maryland	1636	6.67E-06	3.11E-05	3.77E-05	4.65E-05	6.96E-05	4.00E-05	1.22E-05	3.66E-05	5.94E-05	2.47E-05	3.67E-05
Massachusetts	1163	2.24E-06	2.61E-05	3.34E-05	4.24E-05	6.28E-05	3.40E-05	1.08E-05	2.67E-05	3.74E-05	2.48E-05	2.69E-05
Michigan	1110	6.57E-06	2.93E-05	3.22E-05	3.57E-05	4.17E-05	3.14E-05	5.91E-06	2.72E-05	2.24E-05	2.96E-05	2.70E-05
Minnesota	627	4.05E-06	1.68E-05	1.97E-05	2.20E-05	2.65E-05	1.82E-05	5.28E-06	1.45E-05	1.35E-05	1.86E-05	1.43E-05
Mississippi	246	2.10E-05	3.31E-05	3.63E-05	3.92E-05	4.80E-05	3.64E-05	5.30E-06	2.20E-05	3.48E-05	2.96E-05	2.34E-05
Missouri	691	2.49E-05	3.07E-05	3.35E-05	3.89E-05	5.19E-05	3.50E-05	5.74E-06	3.63E-05	3.41E-05	3.51E-05	3.59E-05
Montana	226	5.78E-06	7.25E-06	8.49E-06	9.76E-06	1.15E-05	8.48E-06	1.51E-06	1.02E-05	1.03E-05	8.71E-06	1.00E-05
Nebraska	214	1.35E-05	1.75E-05	2.33E-05	2.45E-05	2.58E-05	2.10E-05	4.06E-06	2.04E-05	2.30E-05	2.11E-05	2.05E-05
Nevada	641	9.63E-06	1.35E-05	1.80E-05	2.00E-05	2.59E-05	1.73E-05	3.86E-06	1.47E-05	1.51E-05	1.86E-05	1.49E-05
New Hampshire	325	1.11E-05	3.39E-05	4.08E-05	5.15E-05	6.37E-05	4.22E-05	1.30E-05	3.63E-05	3.62E-05	3.47E-05	3.62E-05
New Jersey	1676	8.96E-06	4.71E-05	8.94E-05	1.17E-04	1.49E-04	8.25E-05	3.88E-05	4.81E-05	2.71E-05	5.79E-05	4.90E-05
New Mexico	379	1.62E-05	1.88E-05	2.01E-05	2.09E-05	2.46E-05	1.99E-05	1.46E-06	1.74E-05	2.34E-05	1.97E-05	2.04E-05
New York	2289	6.41E-06	3.42E-05	5.24E-05	7.85E-05	1.45E-04	5.78E-05	2.88E-05	3.26E-05	3.27E-05	4.08E-05	3.32E-05
North Carolina	888	4.89E-06	3.81E-05	5.91E-05	6.83E-05	8.60E-05	5.32E-05	2.09E-05	5.45E-05	3.23E-05	2.67E-05	4.96E-05
North Dakota	118	5.43E-06	7.10E-06	8.47E-06	9.26E-06	1.16E-05	8.25E-06	1.32E-06	8.44E-06	8.19E-06	8.20E-06	8.40E-06
Ohio	1139	2.71E-05	3.57E-05	4.06E-05	4.33E-05	5.13E-05	3.94E-05	5.17E-06	3.76E-05	3.51E-05	3.70E-05	3.75E-05
Oklahoma	392	1.86E-05	3.45E-05	4.02E-05	4.48E-05	5.74E-05	4.01E-05	7.61E-06	3.45E-05	3.33E-05	3.96E-05	3.43E-05
Oregon	436	7.62E-06	1.60E-05	3.45E-05	4.16E-05	5.31E-05	3.06E-05	1.45E-05	1.43E-05	3.10E-05	3.23E-05	1.62E-05
Pennsylvania	2382	2.68E-05	4.78E-05	6.13E-05	8.18E-05	1.28E-04	6.45E-05	1.86E-05	5.19E-05	5.83E-05	5.26E-05	5.23E-05
Rhode Island	68	8.49E-06	2.32E-05	3.13E-05	3.34E-05	3.65E-05	2.77E-05	7.84E-06	1.93E-05	2.34E-05	1.64E-05	1.93E-05
South Carolina	465	1.60E-05	3.48E-05	4.18E-05	5.36E-05	7.34E-05	4.45E-05	1.28E-05	3.72E-05	3.95E-05	2.80E-05	3.71E-05
South Dakota	124	1.05E-05	1.19E-05	1.29E-05	1.70E-05	1.98E-05	1.41E-05	2.80E-06	1.43E-05	1.28E-05	1.49E-05	1.42E-05
Tennessee	632	3.41E-05	5.25E-05	5.77E-05	6.19E-05	7.68E-05	5.68E-05	8.37E-06	5.23E-05	5.50E-05	5.67E-05	5.26E-05
Texas	3416	1.58E-05	5.00E-05	7.79E-05	1.01E-04	1.87E-04	8.35E-05	4.54E-05	4.77E-05	4.83E-05	7.59E-05	4.84E-05
Utah	412	1.21E-05	1.51E-05	1.61E-05	1.74E-05	1.99E-05	1.61E-05	1.41E-06	1.67E-05	1.72E-05	1.69E-05	1.68E-05
Vermont	69	1.34E-05	1.50E-05	1.54E-05	2.56E-05	4.57E-05	2.11E-05	9.36E-06	2.48E-05		2.35E-05	2.46E-05
Virginia	861	6.83E-06	2.30E-05	2.98E-05	4.45E-05	6.77E-05	3.28E-05	1.29E-05	2.98E-05	3.91E-05	2.09E-05	3.21E-05
Washington	934	6.71E-06	1.34E-05	2.29E-05	3.37E-05	5.19E-05	2.40E-05	1.25E-05	2.74E-05	1.11E-05	1.94E-05	1.60E-05
Washington D.C.	23	2.19E-05	2.64E-05	2.99E-05	3.05E-05	3.13E-05	2.83E-05	2.94E-06	2.58E-05	2.58E-05	2.58E-05	2.58E-05
West Virginia	142	3.51E-05	3.81E-05	4.50E-05	4.79E-05	6.79E-05	4.52E-05	8.20E-06	4.24E-05	4.85E-05	4.54E-05	4.26E-05
Wisconsin	713	7.63E-06	2.32E-05	3.50E-05	3.79E-05	5.08E-05	3.15E-05	9.25E-06	2.40E-05	2.44E-05	2.90E-05	2.41E-05
Wyoming	120	9.95E-06	1.21E-05	1.34E-05	1.50E-05	1.90E-05	1.37E-05	2.03E-06	1.44E-05	1.34E-05	1.44E-05	1.42E-05
United States	43304	2.24E-06	2.76E-05	4.16E-05	6.83E-05	2.05E-04	5.19E-05	3.41E-05	3.69E-05	3.52E-05	3.68E-05	3.63E-05

U.S. State	N	Marginal characterization factor from NO_x emissions										
		Descriptive statistics							Emission weighted by sector			
		Min	Q1	Median	Q3	Max	Mean	SD	Fuel Combustion	Industrial Processes	Mobile	All-sectors
Alabama	435	4.68E-06	1.73E-05	2.51E-05	3.25E-05	6.28E-05	2.56E-05	1.06E-05	1.88E-05	1.74E-05	1.87E-05	1.84E-05
Arizona	997	5.07E-06	1.24E-05	2.04E-05	2.44E-05	3.53E-05	1.92E-05	6.59E-06	1.28E-05	1.16E-05	1.44E-05	1.39E-05
Arkansas	222	1.72E-05	2.17E-05	2.91E-05	3.96E-05	1.08E-04	3.42E-05	1.77E-05	2.49E-05	2.30E-05	2.57E-05	2.49E-05
California	8452	2.71E-06	2.33E-05	3.19E-05	4.09E-05	1.25E-04	3.34E-05	1.53E-05	2.12E-05	2.15E-05	2.30E-05	2.16E-05
Colorado	778	1.20E-05	1.89E-05	3.03E-05	3.81E-05	7.80E-05	3.00E-05	1.24E-05	1.89E-05	1.82E-05	1.97E-05	1.87E-05
Connecticut	618	2.42E-06	9.68E-06	1.23E-05	1.58E-05	2.62E-05	1.27E-05	4.73E-06	6.79E-06	7.44E-06	6.83E-06	6.81E-06
Delaware	38	3.55E-06	8.17E-06	9.85E-06	1.23E-05	2.64E-05	1.09E-05	4.35E-06	8.70E-06	8.68E-06	7.97E-06	8.14E-06
Florida	2296	1.58E-06	7.01E-06	9.80E-06	1.27E-05	2.83E-05	1.02E-05	4.20E-06	8.58E-06	7.81E-06	7.35E-06	7.53E-06
Georgia	1008	5.85E-06	1.80E-05	3.58E-05	6.05E-05	8.39E-05	3.94E-05	2.30E-05	2.11E-05	1.20E-05	2.49E-05	2.22E-05
Idaho	235	5.95E-06	9.09E-06	1.15E-05	2.08E-05	5.15E-05	1.57E-05	9.10E-06	1.11E-05	9.83E-06	1.11E-05	1.08E-05
Illinois	1551	1.74E-05	2.83E-05	3.74E-05	4.46E-05	6.89E-05	3.67E-05	1.04E-05	2.54E-05	2.24E-05	2.72E-05	2.60E-05
Indiana	610	1.77E-05	2.48E-05	3.21E-05	4.51E-05	6.31E-05	3.55E-05	1.23E-05	2.35E-05	2.33E-05	2.70E-05	2.54E-05
Iowa	327	1.44E-05	1.97E-05	2.50E-05	3.94E-05	6.33E-05	2.95E-05	1.16E-05	1.94E-05	2.03E-05	1.96E-05	1.94E-05
Kansas	302	1.22E-05	1.96E-05	2.78E-05	4.49E-05	6.69E-05	3.22E-05	1.56E-05	2.27E-05	1.90E-05	2.32E-05	2.12E-05
Kentucky	356	1.24E-05	1.89E-05	2.22E-05	3.38E-05	5.38E-05	2.65E-05	1.05E-05	2.03E-05	1.70E-05	2.00E-05	1.98E-05
Louisiana	368	4.63E-06	1.60E-05	2.02E-05	2.84E-05	5.86E-05	2.29E-05	1.07E-05	1.42E-05	1.67E-05	1.43E-05	1.48E-05
Maine	154	7.39E-07	2.91E-06	5.04E-06	7.26E-06	2.93E-05	6.65E-06	6.22E-06	3.22E-06	3.12E-06	2.88E-06	2.97E-06
Maryland	1636	2.40E-06	2.12E-05	3.01E-05	3.85E-05	5.55E-05	2.95E-05	1.08E-05	1.44E-05	2.07E-05	1.47E-05	1.48E-05
Massachusetts	1163	3.24E-07	1.01E-05	1.46E-05	2.30E-05	4.67E-05	1.74E-05	9.56E-06	8.91E-06	9.37E-06	8.52E-06	8.64E-06
Michigan	1110	2.83E-06	2.38E-05	3.39E-05	4.09E-05	6.22E-05	3.22E-05	1.13E-05	1.97E-05	9.57E-06	2.13E-05	1.96E-05
Minnesota	627	2.11E-06	1.55E-05	2.59E-05	3.32E-05	4.68E-05	2.44E-05	1.09E-05	1.58E-05	6.28E-06	1.62E-05	1.46E-05
Mississippi	246	7.61E-06	1.71E-05	1.97E-05	2.61E-05	4.22E-05	2.21E-05	7.65E-06	1.39E-05	1.44E-05	1.80E-05	1.70E-05
Missouri	691	1.70E-05	2.26E-05	3.68E-05	4.95E-05	9.28E-05	3.77E-05	1.51E-05	2.62E-05	2.13E-05	2.64E-05	2.56E-05
Montana	226	5.73E-06	7.33E-06	8.59E-06	9.71E-06	4.18E-05	9.87E-06	4.99E-06	9.13E-06	8.35E-06	8.36E-06	8.37E-06
Nebraska	214	1.14E-05	1.43E-05	2.00E-05	4.19E-05	6.63E-05	2.88E-05	1.72E-05	1.78E-05	1.80E-05	1.58E-05	1.58E-05
Nevada	641	8.24E-06	1.00E-05	1.14E-05	1.37E-05	3.13E-05	1.28E-05	4.41E-06	1.05E-05	1.05E-05	1.14E-05	1.11E-05
New Hampshire	325	2.50E-06	9.12E-06	1.24E-05	1.49E-05	2.45E-05	1.24E-05	4.65E-06	7.95E-06	8.90E-06	7.72E-06	7.78E-06
New Jersey	1676	2.93E-06	1.57E-05	2.74E-05	4.46E-05	9.96E-05	3.14E-05	1.94E-05	1.75E-05	1.01E-05	1.63E-05	1.64E-05
New Mexico	379	1.10E-05	1.38E-05	1.52E-05	2.02E-05	3.33E-05	1.71E-05	4.67E-06	1.39E-05	1.40E-05	1.47E-05	1.43E-05
New York	2289	9.58E-07	1.37E-05	1.96E-05	3.28E-05	1.03E-04	2.48E-05	1.56E-05	1.75E-05	1.20E-05	1.37E-05	1.46E-05
North Carolina	888	1.99E-06	2.13E-05	3.10E-05	4.16E-05	7.09E-05	3.21E-05	1.48E-05	2.38E-05	1.61E-05	2.24E-05	2.22E-05
North Dakota	118	4.67E-06	6.80E-06	7.87E-06	8.83E-06	3.58E-05	9.17E-06	4.79E-06	7.71E-06	7.23E-06	7.45E-06	7.46E-06
Ohio	1139	1.30E-05	2.33E-05	3.21E-05	4.55E-05	6.76E-05	3.44E-05	1.33E-05	2.07E-05	2.06E-05	2.45E-05	2.29E-05
Oklahoma	392	1.40E-05	2.52E-05	3.76E-05	5.73E-05	8.16E-05	4.18E-05	1.87E-05	2.52E-05	2.26E-05	3.02E-05	2.61E-05
Oregon	436	6.81E-06	1.07E-05	2.33E-05	4.10E-05	8.31E-05	2.81E-05	1.88E-05	1.47E-05	1.37E-05	1.57E-05	1.45E-05
Pennsylvania	2382	6.85E-06	2.38E-05	3.22E-05	4.38E-05	1.02E-04	3.60E-05	1.63E-05	2.13E-05	1.99E-05	2.26E-05	2.18E-05
Rhode Island	68	1.39E-06	5.29E-06	1.34E-05	2.13E-05	3.20E-05	1.41E-05	9.13E-06	5.97E-06	5.87E-06	4.86E-06	5.09E-06
South Carolina	465	4.71E-06	1.35E-05	1.90E-05	2.87E-05	4.84E-05	2.12E-05	9.49E-06	1.41E-05	1.20E-05	1.46E-05	1.43E-05
South Dakota	124	9.06E-06	1.01E-05	1.12E-05	1.53E-05	6.41E-05	1.58E-05	1.15E-05	1.12E-05	1.14E-05	1.27E-05	1.19E-05
Tennessee	632	1.43E-05	2.36E-05	3.24E-05	4.06E-05	6.54E-05	3.38E-05	1.22E-05	2.64E-05	2.39E-05	2.60E-05	2.58E-05
Texas	3416	8.18E-06	2.64E-05	4.94E-05	6.44E-05	1.08E-04	4.74E-05	2.20E-05	2.42E-05	1.88E-05	3.08E-05	2.58E-05
Utah	412	9.80E-06	1.25E-05	1.45E-05	1.65E-05	3.24E-05	1.50E-05	3.66E-06	1.26E-05	1.34E-05	1.37E-05	1.32E-05
Vermont	69	3.47E-06	6.30E-06	8.31E-06	2.13E-05	3.03E-05	1.30E-05	8.73E-06	6.75E-06	7.88E-06	6.70E-06	6.70E-06
Virginia	861	1.92E-06	8.43E-06	1.39E-05	1.94E-05	3.45E-05	1.45E-05	7.27E-06	9.84E-06	1.02E-05	9.36E-06	9.57E-06
Washington	934	3.27E-06	1.55E-05	2.08E-05	2.72E-05	5.05E-05	2.25E-05	1.07E-05	1.33E-05	1.42E-05	1.43E-05	1.35E-05
Washington D.C.	23	7.91E-06	1.09E-05	1.75E-05	1.88E-05	2.12E-05	1.55E-05	4.73E-06	1.12E-05	1.12E-05	1.12E-05	1.12E-05
West Virginia	142	8.65E-06	1.28E-05	1.49E-05	1.84E-05	2.96E-05	1.62E-05	4.58E-06	1.41E-05	1.34E-05	1.41E-05	1.40E-05
Wisconsin	713	3.90E-06	2.04E-05	2.78E-05	3.76E-05	7.33E-05	2.96E-05	1.28E-05	1.89E-05	1.64E-05	1.86E-05	1.85E-05
Wyoming	120	8.60E-06	1.07E-05	1.15E-05	1.26E-05	2.20E-05	1.19E-05	2.04E-06	1.21E-05	1.20E-05	1.25E-05	1.22E-05
United States	43304	3.24E-07	1.58E-05	2.60E-05	3.92E-05	1.25E-04	2.93E-05	1.73E-05	1.84E-05	1.69E-05	1.93E-05	1.85E-05

Table A3.30. Distribution of average characterization factors ($\frac{DALYs}{kg_{emitted}}$) of source locations and emission-weighted sector-specific estimates by state.

U.S. State	N	Average characterization factor from $PM_{2.5}$ emissions											
		Descriptive statistics							Emission weighted by sector				
		Min	Q1	Median	Q3	Max	Mean	SD	Agriculture	Fuel Combustion	Industrial Processes	Mobile	All-sectors
Alabama	435	5.03E-05	1.96E-04	3.62E-04	6.91E-04	1.52E-03	4.86E-04	3.72E-04	1.69E-04	2.13E-04	2.65E-04	2.21E-04	1.87E-04
Arizona	997	4.38E-05	4.56E-04	1.78E-03	2.45E-03	3.32E-03	1.54E-03	1.02E-03	2.04E-04	5.14E-04	2.41E-04	7.52E-04	3.39E-04
Arkansas	222	6.80E-05	1.20E-04	2.14E-04	4.13E-04	8.82E-04	2.90E-04	2.05E-04	1.15E-04	1.58E-04	1.32E-04	1.58E-04	1.28E-04
California	8452	2.02E-05	6.50E-04	1.35E-03	2.11E-03	6.46E-03	1.54E-03	1.11E-03	1.81E-04	7.08E-04	9.26E-04	9.29E-04	3.04E-04
Colorado	778	3.54E-05	2.77E-04	9.45E-04	1.67E-03	2.76E-03	1.00E-03	7.40E-04	7.74E-05	3.88E-04	3.38E-04	4.55E-04	2.78E-04
Connecticut	618	7.49E-05	3.50E-04	5.19E-04	7.35E-04	1.61E-03	5.75E-04	3.16E-04	2.49E-04	2.31E-04	2.77E-04	2.49E-04	2.36E-04
Delaware	38	4.61E-05	1.01E-04	1.40E-04	2.08E-04	7.10E-04	1.83E-04	1.28E-04	8.59E-05	1.36E-04	1.45E-04	1.31E-04	1.27E-04
Florida	2296	3.30E-05	4.01E-04	7.99E-04	1.72E-03	5.22E-03	1.16E-03	1.01E-03	1.56E-04	5.90E-04	3.75E-04	5.84E-04	3.63E-04
Georgia	1008	7.32E-05	2.73E-04	6.47E-04	1.32E-03	2.55E-03	8.19E-04	6.27E-04	1.53E-04	3.39E-04	1.74E-04	4.90E-04	2.15E-04
Idaho	235	1.42E-05	3.35E-05	7.24E-05	4.07E-04	1.63E-03	2.50E-04	3.34E-04	5.71E-05	9.93E-05	4.87E-05	8.13E-05	5.70E-05
Illinois	1551	9.08E-05	4.29E-04	1.09E-03	1.52E-03	3.16E-03	1.11E-03	7.40E-04	1.67E-04	3.63E-04	4.63E-04	5.87E-04	2.81E-04
Indiana	610	1.29E-04	2.16E-04	4.22E-04	7.93E-04	1.55E-03	5.58E-04	3.95E-04	2.04E-04	2.21E-04	2.38E-04	2.96E-04	2.34E-04
Iowa	327	5.92E-05	1.19E-04	2.09E-04	4.23E-04	9.23E-04	2.81E-04	1.96E-04	9.98E-05	1.21E-04	1.36E-04	1.22E-04	1.09E-04
Kansas	302	3.49E-05	1.06E-04	2.35E-04	5.30E-04	1.29E-03	3.55E-04	3.28E-04	7.70E-05	1.63E-04	1.81E-04	1.78E-04	1.12E-04
Kentucky	356	9.95E-05	1.44E-04	2.29E-04	5.06E-04	1.47E-03	3.95E-04	3.40E-04	1.59E-04	2.28E-04	1.65E-04	2.09E-04	1.71E-04
Louisiana	368	2.87E-05	1.38E-04	2.45E-04	4.63E-04	1.22E-03	3.38E-04	2.56E-04	1.18E-04	1.53E-04	1.59E-04	1.55E-04	1.23E-04
Maine	154	1.08E-05	5.49E-05	1.37E-04	2.64E-04	7.12E-04	1.94E-04	1.80E-04	5.31E-05	6.52E-05	5.77E-05	6.71E-05	6.47E-05
Maryland	1636	3.20E-05	8.90E-04	1.47E-03	1.98E-03	4.06E-03	1.47E-03	7.30E-04	2.08E-04	4.90E-04	4.44E-04	5.95E-04	4.08E-04
Massachusetts	1163	7.08E-06	4.30E-04	7.66E-04	1.37E-03	3.85E-03	1.04E-03	8.12E-04	2.71E-04	3.88E-04	3.58E-04	4.13E-04	3.87E-04
Michigan	1110	2.19E-05	3.45E-04	7.10E-04	1.22E-03	2.13E-03	8.09E-04	5.38E-04	2.00E-04	3.12E-04	2.60E-04	4.23E-04	3.14E-04
Minnesota	627	1.07E-05	1.34E-04	4.68E-04	9.42E-04	2.10E-03	5.78E-04	4.86E-04	6.51E-05	1.27E-04	1.02E-04	2.14E-04	1.11E-04
Mississippi	246	7.38E-05	1.20E-04	1.61E-04	3.38E-04	1.01E-03	2.59E-04	2.10E-04	1.12E-04	1.26E-04	1.32E-04	1.40E-04	1.29E-04
Missouri	691	6.30E-05	1.29E-04	5.26E-04	1.10E-03	2.19E-03	6.81E-04	5.78E-04	1.15E-04	2.53E-04	1.96E-04	3.17E-04	1.62E-04
Montana	226	1.35E-05	2.14E-05	2.78E-05	4.60E-05	9.45E-04	8.80E-05	1.66E-04	2.56E-05	3.59E-05	3.68E-05	3.25E-05	3.01E-05
Nebraska	214	3.47E-05	4.85E-05	1.31E-04	7.31E-04	1.25E-03	3.63E-04	3.78E-04	5.63E-05	9.04E-05	9.26E-05	8.08E-05	6.76E-05
Nevada	641	2.63E-05	2.78E-04	7.12E-04	1.56E-03	2.94E-03	9.13E-04	7.73E-04	4.45E-05	5.61E-04	1.06E-04	5.88E-04	2.68E-04
New Hampshire	325	3.67E-05	3.91E-04	5.99E-04	9.04E-04	1.67E-03	6.72E-04	3.75E-04	1.76E-04	3.08E-04	2.73E-04	3.26E-04	3.17E-04
New Jersey	1676	5.94E-05	6.89E-04	1.69E-03	3.69E-03	1.04E-02	2.45E-03	2.14E-03	3.17E-04	1.00E-03	4.49E-04	1.10E-03	8.20E-04
New Mexico	379	3.81E-05	7.62E-05	2.09E-04	8.01E-04	2.11E-03	4.98E-04	5.52E-04	7.72E-05	1.87E-04	1.03E-04	1.84E-04	1.65E-04
New York	2289	2.44E-05	4.08E-04	9.05E-04	1.96E-03	1.08E-02	1.49E-03	1.63E-03	1.11E-04	4.59E-04	2.55E-04	7.03E-04	4.72E-04
North Carolina	888	1.69E-05	2.86E-04	4.91E-04	7.42E-04	1.60E-03	5.43E-04	3.42E-04	1.83E-04	3.32E-04	2.45E-04	3.22E-04	2.60E-04
North Dakota	118	1.69E-05	2.25E-05	2.68E-05	5.19E-05	5.14E-04	6.71E-05	9.24E-05	2.65E-05	2.81E-05	2.71E-05	2.91E-05	2.73E-05
Ohio	1139	7.58E-05	2.49E-04	4.62E-04	9.85E-04	2.09E-03	6.31E-04	4.62E-04	2.04E-04	2.45E-04	2.68E-04	3.17E-04	2.48E-04
Oklahoma	392	5.35E-05	1.57E-04	4.20E-04	9.81E-04	1.73E-03	5.74E-04	4.58E-04	1.29E-04	2.57E-04	1.72E-04	3.05E-04	1.84E-04
Oregon	436	1.77E-05	8.55E-05	3.90E-04	8.38E-04	2.46E-03	5.87E-04	6.07E-04	5.73E-05	2.28E-04	1.76E-04	2.64E-04	1.12E-04
Pennsylvania	2382	6.80E-05	4.00E-04	8.31E-04	1.60E-03	5.35E-03	1.22E-03	1.16E-03	2.81E-04	3.91E-04	4.05E-04	4.84E-04	4.01E-04
Rhode Island	68	3.73E-05	1.94E-04	6.94E-04	1.33E-03	2.26E-03	8.30E-04	6.74E-04	8.73E-05	2.04E-04	2.46E-04	2.13E-04	2.27E-04
South Carolina	465	6.68E-05	2.18E-04	4.31E-04	6.62E-04	1.22E-03	4.64E-04	2.78E-04	1.54E-04	2.44E-04	1.91E-04	2.09E-04	2.09E-04
South Dakota	124	2.67E-05	3.16E-05	3.80E-05	7.15E-05	5.95E-04	8.78E-05	1.17E-04	4.39E-05	5.07E-05	4.93E-05	5.04E-05	4.45E-05
Tennessee	632	1.08E-04	3.11E-04	5.83E-04	1.03E-03	1.74E-03	6.90E-04	4.50E-04	2.14E-04	3.19E-04	3.24E-04	3.98E-04	2.99E-04
Texas	3416	5.14E-05	4.49E-04	1.22E-03	1.79E-03	4.56E-03	1.22E-03	8.35E-04	1.53E-04	3.89E-04	3.96E-04	5.79E-04	3.51E-04
Utah	412	3.78E-05	9.02E-05	3.58E-04	6.12E-04	1.42E-03	4.05E-04	3.26E-04	6.72E-05	1.76E-04	2.55E-04	2.82E-04	1.61E-04
Vermont	69	4.30E-05	6.95E-05	1.17E-04	3.45E-04	5.17E-04	1.95E-04	1.58E-04	7.02E-05	8.24E-05	6.82E-05	8.37E-05	8.14E-05
Virginia	861	2.69E-05	2.19E-04	3.68E-04	7.30E-04	1.57E-03	4.97E-04	3.53E-04	2.03E-04	2.57E-04	1.92E-04	2.81E-04	2.32E-04
Washington	934	2.08E-05	3.95E-04	9.48E-04	1.43E-03	3.50E-03	1.01E-03	7.41E-04	6.68E-05	5.99E-04	2.75E-04	4.85E-04	1.67E-04
Washington D.C.	23	3.06E-04	4.87E-04	8.45E-04	1.00E-03	1.18E-03	7.74E-04	2.96E-04		5.10E-04	5.10E-04	5.10E-04	5.10E-04
West Virginia	142	9.24E-05	1.32E-04	1.87E-04	3.66E-04	7.04E-04	2.63E-04	1.67E-04	1.65E-04	1.47E-04	1.54E-04	1.80E-04	1.51E-04
Wisconsin	713	3.40E-05	1.97E-04	4.06E-04	7.20E-04	1.92E-03	5.31E-04	4.39E-04	1.48E-04	1.99E-04	1.82E-04	1.96E-04	1.75E-04
Wyoming	120	2.00E-05	3.87E-05	4.48E-05	5.53E-05	2.26E-04	5.32E-05	3.19E-05	4.79E-05	5.74E-05	6.41E-05	5.84E-05	5.40E-05
United States	43304	7.08E-06	3.18E-04	7.78E-04	1.54E-03	1.08E-02	1.10E-03	1.08E-03	1.13E-04	2.98E-04	2.76E-04	4.19E-04	2.09E-04

U.S. State	N	Average characterization factor from NH_3 emissions											
		Descriptive statistics							Emission weighted by sector				
		Min	Q1	Median	Q3	Max	Mean	SD	Agriculture	Fuel Combustion	Industrial Processes	Mobile	All-sectors
Alabama	435	4.12E-05	1.55E-04	2.54E-04	4.64E-04	1.16E-03	3.53E-04	2.76E-04	1.34E-04	1.86E-04	1.30E-04	1.77E-04	1.32E-04
Arizona	997	3.00E-05	1.55E-04	3.66E-04	4.61E-04	8.80E-04	3.26E-04	1.78E-04	8.18E-05	1.61E-04	7.95E-05	1.91E-04	7.74E-05
Arkansas	222	7.34E-05	9.50E-05	1.41E-04	2.27E-04	4.69E-04	1.70E-04	9.07E-05	9.34E-05	1.13E-04	9.37E-05	1.18E-04	9.34E-05
California	8452	1.72E-05	2.65E-04	6.34E-04	1.09E-03	2.74E-03	7.42E-04	5.62E-04	9.81E-05	4.20E-04	7.53E-04	5.47E-04	1.03E-04
Colorado	778	3.35E-05	1.50E-04	4.01E-04	6.77E-04	9.49E-04	4.15E-04	2.74E-04	6.10E-05	2.39E-04	9.36E-05	2.53E-04	6.57E-05
Connecticut	618	6.48E-05	2.87E-04	4.07E-04	5.53E-04	1.17E-03	4.37E-04	2.21E-04	1.82E-04	2.01E-04	2.42E-04	1.99E-04	2.53E-04
Delaware	38	2.75E-05	6.05E-05	8.70E-05	1.52E-04	4.59E-04	1.18E-04	8.76E-05	5.30E-05	1.16E-04	5.38E-05	9.99E-05	5.64E-05
Florida	2296	2.88E-05	3.39E-04	6.58E-04	1.46E-03	4.82E-03	1.01E-03	9.16E-04	1.25E-04	4.73E-04	2.77E-04	5.53E-04	1.31E-04
Georgia	1008	6.18E-05	1.91E-04	3.98E-04	8.11E-04	1.49E-03	5.10E-04	3.69E-04	1.63E-04	3.88E-04	1.02E-04	3.27E-04	1.59E-04
Idaho	235	1.46E-05	2.46E-05	3.35E-05	9.31E-05	3.32E-04	6.93E-05	6.81E-05	3.17E-05	3.97E-05	3.32E-05	3.67E-05	3.04E-05
Illinois	1551	9.29E-05	2.61E-04	6.44E-04	9.03E-04	1.81E-03	6.59E-04	4.24E-04	1.36E-04	4.53E-04	1.70E-04	4.05E-04	1.54E-04
Indiana	610	1.21E-04	1.65E-04	2.74E-04	4.77E-04	8.96E-04	3.53E-04	2.20E-04	1.57E-04	2.08E-04	1.54E-04	2.20E-04	1.58E-04
Iowa	327	5.69E-05	9.28E-05	1.34E-04	2.05E-04	4.20E-04	1.59E-04	8.22E-05	8.07E-05	1.06E-04	8.83E-05	1.02E-04	8.11E-05
Kansas	302	4.21E-05	8.53E-05	1.46E-04	2.77E-04	6.55E-04	1.98E-04	1.55E-04	6.65E-05	1.55E-04	7.35E-05	1.48E-04	6.91E-05
Kentucky	356	9.28E-05	1.21E-04	1.71E-04	3.30E-04	8.89E-04	2.60E-04	1.89E-04	1.27E-04	1.53E-04	1.76E-04	1.66E-04	1.29E-04
Louisiana	368	2.28E-05	1.01E-04	1.57E-04	2.68E-04	6.81E-04	2.02E-04	1.32E-04	9.26E-05	1.01E-04	9.74E-05	1.14E-04	8.71E-05
Maine	154	9.79E-06	4.13E-05	9.45E-05	1.90E-04	4.56E-04	1.27E-04	1.09E-04	5.00E-05	4.80E-05	4.38E-05	5.46E-05	5.12E-05
Maryland	1636	2.29E-05	6.56E-04	1.05E-03	1.41E-03	2.79E-03	1.05E-03	5.15E-04	1.55E-04	5.10E-04	3.90E-04	4.47E-04	2.07E-04
Massachusetts	1163	5.88E-06	3.26E-04	5.61E-04	9.46E-04	2.28E-03	7.06E-04	4.91E-04	2.36E-04	3.00E-04	2.85E-04	3.26E-04	2.65E-04
Michigan	1110	1.79E-05	2.42E-04	4.81E-04	8.49E-04	1.49E-03	5.69E-04	3.82E-04	1.60E-04	3.68E-04	1.18E-04	3.50E-04	1.81E-04
Minnesota	627	9.63E-06	7.83E-05	2.01E-04	4.03E-04	8.38E-04	2.51E-04	1.95E-04	5.60E-05	1.03E-04	5.12E-05	1.25E-04	5.60E-05
Mississippi	246	6.08E-05	9.98E-05	1.21E-04	2.15E-04	5.62E-04	1.72E-04	1.09E-04	9.60E-05	9.94E-05	8.17E-05	1.10E-04	9.69E-05
Missouri	691	7.23E-05	1.07E-04	2.94E-04	5.67E-04	1.08E-03	3.68E-04	2.78E-04	9.69E-05	2.43E-04	1.35E-04	2.09E-04	9.90E-05
Montana	226	1.43E-05	2.05E-05	2.55E-05	3.33E-05	5.74E-04	5.46E-05	8.72E-05	2.47E-05	3.23E-05	3.49E-05	2.97E-05	2.47E-05
Nebraska	214	3.89E-05	4.98E-05	9.04E-05	3.34E-04	5.01E-04	1.78E-04	1.50E-04	5.60E-05	8.13E-05	1.02E-04	7.89E-05	5.67E-05
Nevada	641	1.99E-05	1.28E-04	3.03E-04	6.20E-04	1.34E-03	3.89E-04	3.22E-04	3.50E-05	3.00E-04	4.10E-05	2.73E-04	3.98E-05
New Hampshire	325	2.82E-05	2.99E-04	4.55E-04	6.59E-04	1.05E-03	4.72E-04	2.36E-04	1.61E-04	2.71E-04	3.91E-04	2.62E-04	1.96E-04
New Jersey	1676	4.89E-05	5.33E-04	1.24E-03	2.48E-03	6.37E-03	1.66E-03	1.34E-03	4.28E-04	7.40E-04	1.67E-03	7.66E-04	4.65E-04
New Mexico	379	3.73E-05	5.70E-05	1.24E-04	3.87E-04	9.91E-04	2.70E-04	2.83E-04	6.06E-05	1.25E-04	1.47E-04	1.29E-04	6.17E-05
New York	2289	2.07E-05	3.20E-04	6.56E-04	1.43E-03	6.85E-03	1.04E-03	1.07E-03	1.08E-04	5.66E-04	1.17E-04	4.88E-04	1.19E-04
North Carolina	888	1.30E-05	1.77E-04	3.04E-04	4.59E-04	9.36E-04	3.32E-04	2.00E-04	8.75E-05	2.25E-04	1.15E-04	2.09E-04	9.20E-05
North Dakota	118	1.54E-05	2.20E-05	2.64E-05	3.38E-05	1.94E-04	4.02E-05	3.60E-05	2.40E-05	2.80E-05	2.52E-05	2.63E-05	2.38E-05
Ohio	1139	7.34E-05	1.87E-04	3.22E-04	5.97E-04	1.32E-03	4.06E-04	2.65E-04	1.59E-04	2.11E-04	1.70E-04	2.29E-04	1.66E-04
Oklahoma	392	5.12E-05	1.11E-04	2.26E-04	4.66E-04	8.11E-04	2.90E-04	2.01E-04	8.71E-05	1.88E-04	1.21E-04	1.97E-04	9.06E-05
Oregon	436	1.66E-05	4.48E-05	1.35E-04	2.58E-04	8.71E-04	1.95E-04	1.97E-04	3.75E-05	1.15E-04	1.55E-04	1.03E-04	3.80E-05
Pennsylvania	2382	6.86E-05	3.24E-04	5.86E-04	1.14E-03	3.54E-03	8.73E-04	7.69E-04	2.53E-04	3.96E-04	3.43E-04	3.95E-04	2.65E-04
Rhode Island	68	3.14E-05	1.66E-04	5.35E-04	1.00E-03	1.66E-03	6.28E-04	4.94E-04	1.18E-04	2.10E-04	2.64E-04	2.05E-04	1.53E-04
South Carolina	465	5.63E-05	1.59E-04	2.83E-04	4.39E-04	8.34E-04	3.17E-04	1.84E-04	1.21E-04	2.05E-04	1.18E-04	1.56E-04	1.25E-04
South Dakota	124	2.94E-05	3.43E-05	3.89E-05	5.94E-05	2.10E-04	5.61E-05	3.95E-05	4.10E-05	5.13E-05	3.83E-05	4.76E-05	4.10E-05
Tennessee	632	1.03E-04	2.11E-04	3.69E-04	6.34E-04	1.07E-03	4.41E-04	2.66E-04	1.68E-04	2.85E-04	3.20E-04	2.69E-04	1.86E-04
Texas	3416	4.02E-05	2.60E-04	6.41E-04	9.25E-04	2.69E-03	6.76E-04	4.81E-04	1.00E-04	3.56E-04	2.66E-04	4.22E-04	1.09E-04
Utah	412	3.03E-05	5.61E-05	1.53E-04	2.57E-04	5.29E-04	1.75E-04	1.26E-04	4.54E-05	1.45E-04	1.50E-04	1.45E-04	5.38E-05
Vermont	69	3.62E-05	6.57E-05	9.75E-05	2.05E-04	2.98E-04	1.29E-04	8.30E-05	5.82E-05	7.08E-05	6.27E-05	7.21E-05	6.00E-05
Virginia	861	2.10E-05	1.40E-04	2.49E-04	5.09E-04	1.05E-03	3.38E-04	2.45E-04	1.19E-04	1.88E-04	9.16E-05	1.83E-04	1.18E-04
Washington	934	1.53E-05	1.51E-04	3.75E-04	5.95E-04	1.29E-03	4.04E-04	2.92E-04	4.03E-05	2.67E-04	9.82E-05	2.26E-04	3.73E-05
Washington D.C.	23	2.31E-04	3.60E-04	6.10E-04	7.21E-04	8.43E-04	5.61E-04	2.10E-04		3.73E-04	3.73E-04	3.73E-04	
West Virginia	142	7.25E-05	1.13E-04	1.54E-04	2.89E-04	5.03E-04	2.08E-04	1.18E-04	1.33E-04	1.40E-04	1.86E-04	1.45E-04	1.30E-04
Wisconsin	713	2.36E-05	1.24E-04	2.48E-04	4.25E-04	1.11E-03	3.20E-04	2.50E-04	1.06E-04	2.16E-04	1.25E-04	1.46E-04	1.13E-04
Wyoming	120	1.98E-05	3.47E-05	3.90E-05	4.52E-05	1.47E-04	4.25E-05	1.77E-05	3.96E-05	4.59E-05	6.04E-05	4.60E-05	3.98E-05
United States	43304	2.92E-06	9.45E-05	2.16E-04	4.09E-04	3.14E-03	3.07E-04	3.11E-04	4.57E-05	1.41 E-04	9.79E-05	1.52E-04	4.84E-05

U.S. State	N	Average characterization factor from SO_2 emissions										
		Descriptive statistics							Emission weighted by sector			
		Min	Q1	Median	Q3	Max	Mean	SD	Fuel Combustion	Industrial Processes	Mobile	All-sectors
Alabama	435	2.87E-05	7.84E-05	1.02E-04	1.32E-04	1.52E-04	1.03E-04	3.01E-05	8.64E-05	7.91E-05	7.70E-05	8.45E-05
Arizona	997	2.04E-05	4.23E-05	4.72E-05	5.11E-05	5.80E-05	4.57E-05	7.69E-06	3.51E-05	4.12E-05	4.48E-05	3.86E-05
Arkansas	222	5.44E-05	6.45E-05	6.98E-05	7.92E-05	9.67E-05	7.21E-05	1.01E-05	6.41E-05	6.53E-05	7.01E-05	6.41E-05
California	8452	1.64E-05	7.70E-05	1.46E-04	2.04E-04	4.52E-04	1.49E-04	8.43E-05	1.20E-04	1.25E-04	1.69E-04	8.49E-05
Colorado	778	2.91E-05	3.57E-05	3.89E-05	4.02E-05	5.36E-05	3.83E-05	4.13E-06	3.60E-05	3.66E-05	3.80E-05	3.61E-05
Connecticut	618	2.55E-05	5.57E-05	6.53E-05	7.42E-05	1.05E-04	6.58E-05	1.45E-05	5.34E-05	5.52E-05	5.17E-05	5.33E-05
Delaware	38	1.52E-05	2.15E-05	2.56E-05	5.80E-05	6.96E-05	3.69E-05	1.87E-05	3.68E-05	5.09E-05	3.64E-05	3.76E-05
Florida	2296	2.10E-05	6.41E-05	1.05E-04	1.43E-04	2.27E-04	1.07E-04	5.13E-05	7.57E-05	7.28E-05	8.15E-05	7.55E-05
Georgia	1008	4.24E-05	8.33E-05	1.90E-04	2.82E-04	3.55E-04	1.88E-04	9.89E-05	1.01E-04	6.83E-05	1.19E-04	9.71E-05
Idaho	235	1.14E-05	1.64E-05	1.85E-05	1.95E-05	2.50E-05	1.80E-05	2.67E-06	1.90E-05	2.26E-05	1.81E-05	1.77E-05
Illinois	1551	6.43E-05	8.19E-05	9.56E-05	1.04E-04	1.28E-04	9.48E-05	1.50E-05	7.84E-05	8.08E-05	8.73E-05	7.90E-05
Indiana	610	7.07E-05	8.20E-05	9.16E-05	9.66E-05	1.08E-04	8.91E-05	8.99E-06	8.51E-05	7.98E-05	8.72E-05	8.47E-05
Iowa	327	3.94E-05	5.49E-05	5.92E-05	7.08E-05	8.58E-05	6.11E-05	1.07E-05	6.26E-05	7.37E-05	5.97E-05	6.30E-05
Kansas	302	3.06E-05	5.32E-05	6.19E-05	6.59E-05	7.96E-05	5.95E-05	1.21E-05	6.62E-05	5.28E-05	6.10E-05	6.42E-05
Kentucky	356	6.76E-05	8.06E-05	8.52E-05	9.05E-05	1.02E-04	8.54E-05	6.86E-06	8.32E-05	8.11E-05	8.74E-05	8.31E-05
Louisiana	368	2.16E-05	6.40E-05	7.50E-05	8.60E-05	1.14E-04	7.38E-05	1.81E-05	6.95E-05	5.75E-05	4.42E-05	6.32E-05
Maine	154	4.57E-06	1.61E-05	2.52E-05	2.79E-05	3.70E-05	2.24E-05	8.16E-06	1.87E-05	1.82E-05	1.62E-05	1.83E-05
Maryland	1636	1.41E-05	6.70E-05	8.11E-05	1.00E-04	1.50E-04	8.60E-05	2.62E-05	7.79E-05	1.27E-04	5.29E-05	7.81E-05
Massachusetts	1163	4.52E-06	5.26E-05	6.80E-05	8.66E-05	1.28E-04	6.92E-05	2.23E-05	5.42E-05	7.59E-05	5.02E-05	5.47E-05
Michigan	1110	1.28E-05	6.20E-05	6.83E-05	7.57E-05	8.90E-05	6.65E-05	1.29E-05	5.73E-05	4.69E-05	6.25E-05	5.67E-05
Minnesota	627	7.71E-06	3.39E-05	4.01E-05	4.45E-05	5.54E-05	3.69E-05	1.10E-05	2.92E-05	2.72E-05	3.78E-05	2.88E-05
Mississippi	246	4.39E-05	6.89E-05	7.56E-05	8.22E-05	1.01E-04	7.62E-05	1.12E-05	4.59E-05	7.30E-05	6.20E-05	4.88E-05
Missouri	691	5.18E-05	6.37E-05	6.94E-05	8.19E-05	1.10E-04	7.30E-05	1.24E-05	7.59E-05	7.12E-05	7.32E-05	7.51E-05
Montana	226	1.06E-05	1.35E-05	1.56E-05	1.83E-05	2.21E-05	1.58E-05	3.01E-06	1.95E-05	1.95E-05	1.62E-05	1.91E-05
Nebraska	214	2.67E-05	3.56E-05	4.81E-05	5.08E-05	5.33E-05	4.31E-05	8.75E-06	4.18E-05	4.75E-05	4.34E-05	4.20E-05
Nevada	641	1.68E-05	2.41E-05	3.38E-05	3.76E-05	4.80E-05	3.21E-05	7.66E-06	2.72E-05	2.78E-05	3.48E-05	2.76E-05
New Hampshire	325	2.08E-05	6.79E-05	8.13E-05	1.04E-04	1.29E-04	8.49E-05	2.68E-05	7.28E-05	7.30E-05	6.97E-05	7.26E-05
New Jersey	1676	1.93E-05	1.03E-04	1.98E-04	2.60E-04	3.29E-04	1.82E-04	8.62E-05	1.06E-04	5.90E-05	1.28E-04	1.08E-04
New Mexico	379	3.19E-05	3.68E-05	3.91E-05	4.04E-05	4.91E-05	3.86E-05	2.77E-06	3.35E-05	4.64E-05	3.84E-05	3.99E-05
New York	2289	1.33E-05	7.06E-05	1.13E-04	1.72E-04	3.18E-04	1.25E-04	6.47E-05	6.93E-05	6.73E-05	8.83E-05	7.03E-05
North Carolina	888	9.92E-06	7.75E-05	1.20E-04	1.39E-04	1.76E-04	1.08E-04	4.26E-05	1.10E-04	6.55E-05	5.43E-05	1.00E-04
North Dakota	118	1.04E-05	1.37E-05	1.66E-05	1.82E-05	2.33E-05	1.61E-05	2.74E-06	1.65E-05	1.59E-05	1.60E-05	1.64E-05
Ohio	1139	5.72E-05	7.48E-05	8.56E-05	9.13E-05	1.08E-04	8.31E-05	1.08E-05	7.87E-05	7.39E-05	7.80E-05	7.84E-05
Oklahoma	392	3.73E-05	7.09E-05	8.27E-05	9.25E-05	1.18E-04	8.26E-05	1.58E-05	7.11E-05	6.84E-05	8.15E-05	7.07E-05
Oregon	436	1.33E-05	2.52E-05	5.54E-05	6.88E-05	8.77E-05	4.99E-05	2.37E-05	2.40E-05	5.06E-05	5.32E-05	2.67E-05
Pennsylvania	2382	5.64E-05	1.02E-04	1.32E-04	1.76E-04	2.80E-04	1.38E-04	4.04E-05	1.10E-04	1.25E-04	1.13E-04	1.11E-04
Rhode Island	68	1.73E-05	4.68E-05	6.33E-05	6.77E-05	7.42E-05	5.61E-05	1.59E-05	3.91E-05	4.73E-05	3.32E-05	3.91E-05
South Carolina	465	3.25E-05	7.20E-05	8.61E-05	1.11E-04	1.50E-04	9.18E-05	2.63E-05	7.68E-05	8.15E-05	5.77E-05	7.65E-05
South Dakota	124	2.06E-05	2.37E-05	2.60E-05	3.48E-05	4.09E-05	2.85E-05	6.06E-06	2.89E-05	2.53E-05	3.02E-05	2.86E-05
Tennessee	632	7.07E-05	1.08E-04	1.19E-04	1.27E-04	1.59E-04	1.17E-04	1.69E-05	1.07E-04	1.13E-04	1.17E-04	1.08E-04
Texas	3416	3.15E-05	1.03E-04	1.62E-04	2.09E-04	3.88E-04	1.73E-04	9.38E-05	9.86E-05	9.93E-05	1.57E-04	9.99E-05
Utah	412	2.22E-05	2.77E-05	3.00E-05	3.24E-05	3.70E-05	3.00E-05	2.77E-06	3.13E-05	3.22E-05	3.14E-05	3.13E-05
Vermont	69	2.55E-05	2.87E-05	2.94E-05	5.01E-05	9.22E-05	4.13E-05	1.93E-05	4.88E-05		4.60E-05	4.84E-05
Virginia	861	1.44E-05	4.79E-05	6.23E-05	9.02E-05	1.45E-04	6.78E-05	2.66E-05	6.03E-05	7.83E-05	4.35E-05	6.48E-05
Washington	934	1.17E-05	2.27E-05	3.94E-05	5.64E-05	8.60E-05	4.06E-05	2.05E-05	4.63E-05	1.95E-05	3.34E-05	2.75E-05
Washington D.C.	23	4.68E-05	5.66E-05	6.41E-05	6.55E-05	6.73E-05	6.07E-05	6.38E-06	5.52E-05	5.52E-05	5.52E-05	5.52E-05
West Virginia	142	7.14E-05	7.80E-05	9.02E-05	1.01E-04	1.46E-04	9.33E-05	1.83E-05	8.86E-05	1.01E-04	9.41E-05	8.90E-05
Wisconsin	713	1.50E-05	4.81E-05	7.39E-05	8.00E-05	1.08E-04	6.63E-05	2.00E-05	4.99E-05	5.07E-05	6.08E-05	5.01E-05
Wyoming	120	1.86E-05	2.32E-05	2.55E-05	2.89E-05	3.58E-05	2.61E-05	3.90E-06	2.74E-05	2.55E-05	2.76E-05	2.70E-05
United States	43304	4.52E-06	5.57E-05	8.65E-05	1.43E-04	4.52E-04	1.09E-04	7.35E-05	7.67E-05	7.26E-05	7.54E-05	7.52E-05

U.S. State	N	Average characterization factor from NO_x emissions										
		Descriptive statistics							Emission weighted by sector			
		Min	**Q1**	**Median**	**Q3**	**Max**	**Mean**	**SD**	**Fuel Combustion**	**Industrial Processes**	**Mobile**	**All-sectors**
Alabama	435	9.70E-06	3.59E-05	5.19E-05	6.75E-05	1.30E-04	5.32E-05	2.19E-05	3.89E-05	3.61E-05	3.88E-05	3.82E-05
Arizona	997	1.01E-05	2.44E-05	4.00E-05	4.88E-05	7.02E-05	3.80E-05	1.34E-05	2.53E-05	2.27E-05	2.86E-05	2.75E-05
Arkansas	222	3.59E-05	4.50E-05	6.01E-05	8.33E-05	2.14E-04	7.08E-05	3.58E-05	5.16E-05	4.77E-05	5.32E-05	5.15E-05
California	8452	5.63E-06	4.86E-05	6.77E-05	8.71E-05	2.59E-04	7.08E-05	3.32E-05	4.43E-05	4.50E-05	4.83E-05	4.52E-05
Colorado	778	2.40E-05	3.58E-05	5.73E-05	7.39E-05	1.30E-04	5.66E-05	2.19E-05	3.63E-05	3.48E-05	3.82E-05	3.61E-05
Connecticut	618	5.09E-06	2.01E-05	2.54E-05	3.29E-05	5.39E-05	2.64E-05	9.77E-06	1.41E-05	1.55E-05	1.42E-05	1.42E-05
Delaware	38	7.43E-06	1.74E-05	2.10E-05	2.63E-05	5.56E-05	2.31E-05	9.20E-06	1.85E-05	1.85E-05	1.70E-05	1.73E-05
Florida	2296	3.23E-06	1.40E-05	1.97E-05	2.57E-05	5.58E-05	2.05E-05	8.52E-06	1.75E-05	1.59E-05	1.49E-05	1.53E-05
Georgia	1008	1.20E-05	3.74E-05	7.51E-05	1.27E-04	1.79E-04	8.31E-05	4.89E-05	4.40E-05	2.48E-05	5.21E-05	4.65E-05
Idaho	235	1.08E-05	1.65E-05	2.11E-05	3.43E-05	8.28E-05	2.74E-05	1.46E-05	2.04E-05	1.81E-05	2.01E-05	1.97E-05
Illinois	1551	3.65E-05	6.00E-05	7.97E-05	9.49E-05	1.47E-04	7.81E-05	2.24E-05	5.36E-05	4.72E-05	5.77E-05	5.50E-05
Indiana	610	3.67E-05	5.24E-05	6.72E-05	9.48E-05	1.35E-04	7.49E-05	2.62E-05	4.93E-05	4.90E-05	5.69E-05	5.34E-05
Iowa	327	2.97E-05	4.08E-05	5.19E-05	8.15E-05	1.30E-04	6.10E-05	2.39E-05	4.03E-05	4.24E-05	4.06E-05	4.02E-05
Kansas	302	2.45E-05	4.00E-05	5.61E-05	9.09E-05	1.38E-04	6.52E-05	3.16E-05	4.63E-05	3.89E-05	4.74E-05	4.34E-05
Kentucky	356	2.51E-05	3.85E-05	4.54E-05	6.93E-05	1.10E-04	5.42E-05	2.17E-05	4.17E-05	3.45E-05	4.10E-05	4.05E-05
Louisiana	368	9.58E-06	3.34E-05	4.21E-05	6.02E-05	1.27E-04	4.82E-05	2.29E-05	2.96E-05	3.47E-05	2.98E-05	3.09E-05
Maine	154	1.23E-06	5.25E-06	9.65E-06	1.41E-05	5.15E-05	1.24E-05	1.12E-05	6.02E-06	5.80E-06	5.40E-06	5.55E-06
Maryland	1636	5.02E-06	4.58E-05	6.53E-05	8.30E-05	1.19E-04	6.37E-05	2.32E-05	3.10E-05	4.46E-05	3.16E-05	3.18E-05
Massachusetts	1163	6.48E-07	2.05E-05	2.98E-05	4.68E-05	9.85E-05	3.57E-05	2.02E-05	1.81E-05	1.90E-05	1.74E-05	1.76E-05
Michigan	1110	5.61E-06	5.04E-05	7.23E-05	8.75E-05	1.32E-04	6.85E-05	2.43E-05	4.16E-05	1.99E-05	4.52E-05	4.15E-05
Minnesota	627	4.06E-06	3.15E-05	5.14E-05	6.72E-05	9.42E-05	4.90E-05	2.20E-05	3.19E-05	1.24E-05	3.27E-05	2.96E-05
Mississippi	246	1.59E-05	3.57E-05	4.11E-05	5.45E-05	8.88E-05	4.61E-05	1.61E-05	2.91E-05	2.99E-05	3.76E-05	3.54E-05
Missouri	691	3.56E-05	4.66E-05	7.70E-05	1.03E-04	1.87E-04	7.85E-05	3.15E-05	5.45E-05	4.43E-05	5.50E-05	5.32E-05
Montana	226	1.07E-05	1.37E-05	1.61E-05	1.84E-05	6.17E-05	1.80E-05	7.39E-06	1.76E-05	1.59E-05	1.57E-05	1.59E-05
Nebraska	214	2.27E-05	2.85E-05	4.08E-05	8.46E-05	1.35E-04	5.85E-05	3.52E-05	3.62E-05	3.68E-05	3.20E-05	3.20E-05
Nevada	641	1.54E-05	1.95E-05	2.19E-05	2.67E-05	5.21E-05	2.40E-05	6.81E-06	2.03E-05	2.01E-05	2.17E-05	2.11E-05
New Hampshire	325	4.92E-06	1.80E-05	2.48E-05	2.97E-05	4.72E-05	2.45E-05	9.18E-06	1.58E-05	1.77E-05	1.53E-05	1.54E-05
New Jersey	1676	6.26E-06	3.41E-05	6.04E-05	9.90E-05	2.20E-04	6.94E-05	4.32E-05	3.85E-05	2.21E-05	3.57E-05	3.60E-05
New Mexico	379	2.18E-05	2.74E-05	2.99E-05	3.78E-05	5.87E-05	3.28E-05	7.69E-06	2.75E-05	2.76E-05	2.88E-05	2.83E-05
New York	2289	1.98E-06	2.93E-05	4.19E-05	7.11E-05	2.25E-04	5.39E-05	3.47E-05	3.80E-05	2.50E-05	2.95E-05	3.14E-05
North Carolina	888	4.04E-06	4.34E-05	6.30E-05	8.44E-05	1.45E-04	6.53E-05	3.03E-05	4.82E-05	3.27E-05	4.57E-05	4.52E-05
North Dakota	118	8.67E-06	1.30E-05	1.54E-05	1.72E-05	6.65E-05	1.75E-05	8.63E-06	1.50E-05	1.40E-05	1.45E-05	1.45E-05
Ohio	1139	2.68E-05	4.94E-05	6.78E-05	9.65E-05	1.42E-04	7.26E-05	2.82E-05	4.35E-05	4.34E-05	5.17E-05	4.82E-05
Oklahoma	392	2.83E-05	5.21E-05	7.68E-05	1.19E-04	1.70E-04	8.64E-05	3.91E-05	5.19E-05	4.63E-05	6.22E-05	5.37E-05
Oregon	436	1.16E-05	1.85E-05	3.80E-05	6.58E-05	1.26E-04	4.55E-05	2.90E-05	2.52E-05	2.35E-05	2.69E-05	2.49E-05
Pennsylvania	2382	1.49E-05	5.05E-05	6.87E-05	9.28E-05	2.17E-04	7.64E-05	3.47E-05	4.50E-05	4.22E-05	4.81E-05	4.63E-05
Rhode Island	68	2.83E-06	1.08E-05	2.72E-05	4.40E-05	6.66E-05	2.90E-05	1.91E-05	1.21E-05	1.19E-05	9.87E-06	1.03E-05
South Carolina	465	9.66E-06	2.79E-05	3.92E-05	5.87E-05	9.82E-05	4.37E-05	1.95E-05	2.90E-05	2.48E-05	3.02E-05	2.94E-05
South Dakota	124	1.78E-05	2.02E-05	2.22E-05	2.96E-05	1.30E-04	3.17E-05	2.35E-05	2.24E-05	2.25E-05	2.54E-05	2.38E-05
Tennessee	632	2.88E-05	4.81E-05	6.70E-05	8.47E-05	1.38E-04	7.00E-05	2.62E-05	5.45E-05	4.90E-05	5.36E-05	5.31E-05
Texas	3416	1.68E-05	5.41E-05	1.03E-04	1.34E-04	2.18E-04	9.80E-05	4.57E-05	4.97E-05	3.84E-05	6.36E-05	5.30E-05
Utah	412	1.90E-05	2.40E-05	2.76E-05	3.17E-05	5.05E-05	2.84E-05	5.99E-06	2.44E-05	2.55E-05	2.62E-05	2.54E-05
Vermont	69	6.48E-06	1.22E-05	1.62E-05	4.14E-05	5.86E-05	2.52E-05	1.69E-05	1.30E-05	1.52E-05	1.30E-05	1.30E-05
Virginia	861	4.04E-06	1.75E-05	2.83E-05	3.97E-05	7.36E-05	2.99E-05	1.52E-05	2.01E-05	2.03E-05	1.93E-05	1.96E-05
Washington	934	5.94E-06	2.63E-05	3.71E-05	4.77E-05	9.12E-05	3.92E-05	1.86E-05	2.33E-05	2.50E-05	2.53E-05	2.39E-05
Washington D.C.	23	1.70E-05	2.35E-05	3.77E-05	4.07E-05	4.58E-05	3.35E-05	1.02E-05	2.42E-05	2.42E-05	2.42E-05	2.42E-05
West Virginia	142	1.75E-05	2.60E-05	3.01E-05	3.83E-05	5.97E-05	3.28E-05	9.35E-06	2.92E-05	2.74E-05	2.89E-05	2.87E-05
Wisconsin	713	7.75E-06	4.21E-05	5.83E-05	7.85E-05	1.54E-04	6.18E-05	2.72E-05	3.92E-05	3.39E-05	3.87E-05	3.84E-05
Wyoming	120	1.66E-05	2.08E-05	2.23E-05	2.43E-05	3.95E-05	2.29E-05	3.58E-06	2.33E-05	2.31E-05	2.40E-05	2.35E-05
United States	43304	6.48E-07	3.18E-05	5.38E-05	8.22E-05	2.59E-04	6.10E-05	3.68E-05	3.80E-05	3.45E-05	3.99E-05	3.80E-05

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APPENDIX 4
Bridging the gap between environmental and nutritional sciences towards more sustainable foods: A case study on pizza

Table A4.31. Pizzas in the What We Eat in America/National Health and Nutrition Examination Survey (WWEIA/NHANES) 2007-2014 database and their pizza types classes

#	*Pizza description*	*Pizza type class*
1	Pizza, cheese, from school lunch, thin crust	Cheese Pizza
2	Pizza, cheese, prepared from frozen, thin crust	Cheese Pizza
3	Pizza, cheese, from restaurant or fast food, thick crust	Cheese Pizza
4	Pizza, cheese, prepared from frozen, thick crust	Cheese Pizza
5	Pizza, cheese, from restaurant or fast food, NS as to type of crust	Cheese Pizza
6	Pizza, cheese, from restaurant or fast food, regular crust	Cheese Pizza
7	Pizza, extra cheese, thick crust	Cheese Pizza
8	Pizza, extra cheese, NS as to type of crust	Cheese Pizza
9	Pizza, extra cheese, regular crust	Cheese Pizza
10	Pizza, cheese, from school lunch, thick crust	Cheese Pizza
11	Pizza, extra cheese, thin crust	Cheese Pizza
12	Pizza, cheese, stuffed crust	Cheese Pizza
13	Pizza, cheese, from restaurant or fast food, thin crust	Cheese Pizza
14	Pizza, with meat other than pepperoni, from school lunch, thin crust	Red Meat Pizza
15	Pizza with chicken and fruit, regular crust	Chicken Pizza
16	Pizza with chicken and vegetables, thick crust	Chicken Pizza
17	Pizza with chicken and vegetables, regular crust	Chicken Pizza
18	Pizza with chicken, thick crust	Chicken Pizza
19	Pizza with chicken, regular crust	Chicken Pizza
20	Pizza with chicken and vegetables, thin crust	Chicken Pizza
21	Pizza with chicken, thin crust	Chicken Pizza
22	Pizza with pepperoni, from school lunch, thin crust	Red Meat Pizza
23	Pizza with pepperoni, from restaurant or fast food, thick crust	Red Meat Pizza
24	Pizza with pepperoni, from restaurant or fast food, NS as to type of crust	Red Meat Pizza
25	Pizza with pepperoni, from restaurant or fast food, regular crust	Red Meat Pizza
26	Pizza with meat, prepared from frozen, thick crust	Red Meat Pizza
27	Pizza with meat, prepared from frozen, thin crust	Red Meat Pizza
28	Pizza with extra meat and extra vegetables, prepared from frozen, thin crust	Red Meat Pizza
29	Pizza with meat and vegetables, prepared from frozen, thick crust	Red Meat Pizza
30	Pizza with pepperoni, from school lunch, thick crust	Red Meat Pizza
31	Pizza with meat and vegetables, prepared from frozen, thin crust	Red Meat Pizza
32	Pizza with extra meat and extra vegetables, prepared from frozen, thick crust	Red Meat Pizza

#	*Pizza description*	*Pizza type class*
33	Pizza with meat and vegetables, thick crust	Red Meat Pizza
34	Pizza with meat and vegetables, NS as to type of crust	Red Meat Pizza
35	Pizza with meat and vegetables, thin crust	Red Meat Pizza
36	Pizza with meat other than pepperoni, from restaurant or fast food, NS as to type of crust	Red Meat Pizza
37	Pizza with meat other than pepperoni, from restaurant or fast food, regular crust	Red Meat Pizza
38	Pizza, with meat other than pepperoni, from school lunch, thick crust	Red Meat Pizza
39	Pizza with meat and vegetables, regular crust	Red Meat Pizza
40	Pizza with meat other than pepperoni, from restaurant or fast food, thick crust	Red Meat Pizza
41	Pizza with pepperoni, stuffed crust	Red Meat Pizza
42	Pizza, with meat other than pepperoni, stuffed crust	Red Meat Pizza
43	Pizza with meat and fruit, regular crust	Red Meat Pizza
44	Pizza with extra meat and extra vegetables, regular crust	Red Meat Pizza
45	Pizza with meat and fruit, thick crust	Red Meat Pizza
46	Pizza with meat and fruit, thin crust	Red Meat Pizza
47	Pizza with extra meat and extra vegetables, NS as to type of crust	Red Meat Pizza
48	Pizza with extra meat and extra vegetables, thin crust	Red Meat Pizza
49	Pizza with extra meat and extra vegetables, thick crust	Red Meat Pizza
50	Pizza with meat other than pepperoni, from restaurant or fast food, thin crust	Red Meat Pizza
51	Pizza with pepperoni, from restaurant or fast food, thin crust	Red Meat Pizza
52	Pizza with extra meat, regular crust	Red Meat Pizza
53	Pizza with extra meat, NS as to type of crust	Red Meat Pizza
54	Pizza with extra meat, thick crust	Red Meat Pizza
55	Pizza with extra meat, thin crust	Red Meat Pizza
56	Pizza, no cheese, thin crust	Other Pizza
57	Pizza, cheese, with fruit, thick crust	Other Pizza
58	Pizza, cheese, with fruit, regular crust	Other Pizza
59	Pizza, no cheese, regular crust	Other Pizza
60	Pizza, no cheese, NS as to type of crust	Other Pizza
61	Pizza, cheese, with fruit, thin crust	Other Pizza
62	Pizza, no cheese, thick crust	Other Pizza
63	Pizza with seafood, thin crust	Seafood Pizza
64	Pizza with seafood, regular crust	Seafood Pizza
65	White pizza, thin crust	Other Pizza
66	White pizza, thick crust	Other Pizza
67	White pizza, regular crust	Other Pizza
68	Pizza with beans and vegetables, thick crust	Vegetable Pizza
69	Pizza with beans and vegetables, thin crust	Vegetable Pizza
70	Pizza with cheese and extra vegetables, regular crust	Vegetable Pizza
71	Pizza with cheese and extra vegetables, thick crust	Vegetable Pizza
72	Pizza, cheese, with vegetables, prepared from frozen, thin crust	Vegetable Pizza
73	Pizza, cheese, with vegetables, regular crust	Vegetable Pizza
74	Pizza, cheese, with vegetables, thick crust	Vegetable Pizza
75	Pizza with cheese and extra vegetables, thin crust	Vegetable Pizza

#	*Pizza description*	*Pizza type class*
76	Pizza, cheese with vegetables, prepared from frozen, thick crust	Vegetable Pizza
77	Pizza, cheese, with vegetables, NS as to type of crust	Vegetable Pizza
78	Pizza, cheese, with vegetables, thin crust	Vegetable Pizza

Table A4.32. Nutritional characterizations factors (CF) in DALYs/kg and nutritional profile in kg/serving by dietary risks in select types of pizzas in the U.S. diet

Dietary risk	CF (DALY/kg)	Pizza composition by dietary factor in kg/FU (FU=140g=serving)						
		Pizza, extra meat	Pizza, extra meat and vegetables	Pizza, extra cheese	Pizza, extra vegetables	Pizza with beans and vegetables	Pizza, no cheese	Pizza, cheese with fruit
Seafood (omega-3)	-1.00E-07							
Calcium	-6.00E-09	2.83E-04	2.83E-04	3.88E-04	3.01E-04	2.27E-04	2.13E-05	2.20E-04
Nuts and seeds	-1.80E-09							
Fiber$_{other}$	-1.10E-09	4.08E-04	5.59E-04	4.65E-04	7.56E-04	1.41E-03	6.68E-04	8.15E-04
Polyunsaturated fatty acids	-6.70E-10	3.86E-03	3.61E-03	3.51E-03	3.28E-03	3.07E-03	2.82E-03	1.94E-03
Whole grains	-4.70E-10							
Legumes	-2.70E-10					1.43E-02		
Fruits	-2.20E-10							2.52E-02
Fiber$_{f,v,l,w}$	-2.00E-10	1.59E-03	1.59E-03	1.81E-03	1.70E-03	1.42E-03	1.49E-03	2.15E-03
Vegetables	-9.80E-11	3.36E-02	4.21E-02	3.83E-02	5.40E-02	4.11E-02	4.26E-02	3.37E-02
Milk	-8.90E-12							
Sugar-sweetened beverages	6.50E-11							
Red meat	1.00E-10	3.48E-03	2.32E-03					
Saturated fatty acids	7.00E-10	9.95E-03	8.87E-03	8.62E-03	7.12E-03	5.77E-03	1.23E-03	5.13E-03
Processed meat	1.10E-09	1.44E-02	9.63E-03					
Trans fatty acids	4.90E-09	6.65E-04	6.83E-04	3.83E-04	3.02E-04	2.84E-04	5.87E-04	2.93E-04
Sodium	1.20E-08	9.09E-04	8.46E-04	7.77E-04	7.37E-04	6.91E-04	3.49E-04	6.86E-04

Fiber$_{other}$= fiber from sources other than fruits, vegetables, legumes, and whole grains
Fiber$_{f,v,l,w}$=fiber from fruit, vegetables, legumes, and whole grains

Table A4.33. Average mass in grams per serving equivalents for components in the Food Patterns Equivalents Database (FPED)

FPED component	*Serving equivalent unit*	*Grams*
Intact fruits (whole or cut) of citrus, melons, and berries	cup eq	162.7
Intact fruits (whole or cut); excluding citrus, melons, and berries	cup eq	127.3
Fruit juices, citrus and non citrus	cup eq	214.0
Dark green vegetables	cup eq	112.6
Tomatoes and tomato products	cup eq	176.3
Other red and orange vegetables, excluding tomatoes and tomato products	cup eq	166.4
White potatoes	cup eq	122.1
Other starchy vegetables, excluding white potatoes	cup eq	142.8
Other vegetables not in the vegetable components listed above	cup eq	130.2
Legumes computed as vegetables	cup eq	120.5
Whole grains	oz eq	22.2
Refined or non-whole grains	oz eq	22.2
Beef, veal, pork, lamb, game meat; excludes organ meats and cured meat	oz eq	28.4
Cured/luncheon meat made from beef, pork, or poultry	oz eq	28.4
Organ meat from beef, veal, pork, lamb, game, and poultry	oz eq	28.4
Chicken, turkey, Cornish hens, and game birds; excludes organ meats and cured meat	oz eq	28.4
Seafood (finfish, shellfish and other seafood) high in n-3 fatty acids	oz eq	28.4
Seafood (finfish, shellfish and other seafood) low in n-3 fatty acids	oz eq	28.4
Eggs (chicken, duck, goose, quail) and egg substitutes	oz eq	50.0
Soy products, excluding calcium fortified soy milk and immature soybeans	oz eq	35.0
Peanuts, tree nuts, and seeds, excludes coconut	oz eq	15.1
Legumes computed as protein foods	oz eq	482.1
Fluid milk and calcium fortified soy milk	cup eq	245.0
Yogurt	cup eq	245.0
Cheese	cup eq	54.3
Total milk, yogurt, cheese, and whey	cup eq	69.2
Oils	Grams	1.0
Solid fats	Grams	1.0
Foods defined as added sugars	tsp. eq	4.2
Alcoholic beverages	number of drinks	14.0

Table A4.34. Characterization factors for particulate matter precursors using a marginal slope of a non-linear exposure response function.

	PM2.5	*SO2*	*NOx*	*NH3*
Characterization factors				
(kgPM2.5-eq/kg emitted) *	1.20E-03	5.20E-02	1.10E-02	1.10E-01
(DALYs/kg emitted) †	5.56E-05	3.63E-05	1.85E-05	4.57E-05

* Obtained from Stylianou et al. (2016)
† Obtained from Stylianou et al. (2018)

Table A4.35. List of pizza items reported to be consumed in the WWEIA/NHANES 2005-2008 by adults above the age of 19 years old, excluding pregnant women

Description	*Average intake (g/d)*	*Average energy intake (kcal/d)*
Topping from cheese pizza	0.014	0.031
Topping from vegetable pizza	0.010	0.016
Topping from meat pizza	0.038	0.115
Pizza, cheese, prepared from frozen, thin crust	0.438	1.174
Pizza, cheese, prepared from frozen, thick crust	0.042	0.108
Pizza, cheese, from restaurant or fast food, NS as to type of crust	0.045	0.128
Pizza, cheese, from restaurant or fast food, thin crust	2.787	8.105
Pizza, cheese, from restaurant or fast food, regular crust	0.475	1.255
Pizza, cheese, from restaurant or fast food, thick crust	2.314	6.255
Pizza, extra cheese, thin crust	0.025	0.077
Pizza, extra cheese, thick crust	0.011	0.031
Pizza, cheese, w/ vegetables, prepared from frozen, thin crust	0.119	0.293
Pizza, cheese w/ vegetables, prepared from frozen, thick crust	0.245	0.589
Pizza, cheese, w/ vegetables, thin crust	0.839	1.927
Pizza, cheese, w/ vegetables, regular crust	0.117	0.276
Pizza, cheese, w/ vegetables, thick crust	0.789	1.934
Pizza w/ cheese and extra vegetables, thin crust	0.023	0.059
Pizza w/ cheese and extra vegetables, thick crust	0.018	0.041
Pizza, cheese, w/ fruit, thick crust	0.517	1.216
Pizza w/ meat, prepared from frozen, thin crust	1.007	2.861
Pizza w/ meat, prepared from frozen, thick crust	0.257	0.712
Pizza w/ meat, NS as to type of crust	0.116	0.351
Pizza w/ meat, thin crust	3.360	9.873
Pizza w/ meat, thick crust	4.956	15.304
Pizza w/ pepperoni, from restaurant or fast food, NS as to type of crust	0.017	0.048
Pizza w/ pepperoni, from restaurant or fast food, thin crust	0.935	3.005
Pizza w/ pepperoni, from restaurant or fast food, regular crust	1.287	3.551
Pizza w/ pepperoni, from restaurant or fast food, thick crust	1.438	4.084
Pizza w/ meat other than pepperoni, from restaurant or fast food, thin crust	0.405	1.247
Pizza w/ meat other than pepperoni, from restaurant or fast food, regular crust	0.343	0.938
Pizza w/ meat other than pepperoni, from restaurant or fast food, thick crust	0.396	1.110
Pizza w/ extra meat, NS as to type of crust	0.002	0.007
Pizza w/ extra meat, thin crust	0.150	0.488
Pizza w/ extra meat, regular crust	0.325	0.951
Pizza w/ extra meat, thick crust	0.137	0.411
Pizza w/ meat and vegetables, prepared from frozen, thin crust	0.298	0.822
Pizza w/ meat and vegetables, prepared from frozen, thick crust	0.096	0.261
Pizza w/ meat and vegetables, NS as to type of crust	0.046	0.118
Pizza w/ meat and vegetables, thin crust	2.468	6.508

Description	*Average intake (g/d)*	*Average energy intake (kcal/d)*
Pizza w/ meat and vegetables, regular crust	0.291	0.711
Pizza w/ meat and vegetables, thick crust	2.010	5.424
Pizza w/ extra meat and extra vegetables, NS as to type of crust	0.006	0.015
Pizza w/ extra meat and extra vegetables, thin crust	0.380	1.033
Pizza w/ extra meat and extra vegetables, thick crust	0.343	0.953
Pizza w/ extra meat and extra vegetables, regular crust	0.053	0.145
Pizza w/ meat and fruit, thin crust	0.227	0.537
Pizza w/ meat and fruit, regular crust	0.183	0.428
Pizza w/ meat and fruit, thick crust	0.548	1.341
Pizza w/ beans and vegetables, thin crust	0.039	0.094
Pizza w/ beans and vegetables, thick crust	0.088	0.219
Pizza, no cheese, NS as to type of crust	0.001	0.003
Pizza, no cheese, thin crust	0.033	0.071
Pizza, no cheese, thick crust	0.047	0.123
White pizza, thin crust	0.112	0.414
White pizza, regular crust	0.024	0.089
White pizza, thick crust	0.196	0.716
Pizza rolls	0.327	0.986

Table A4.36. Metadata for mapping life cycle assessments to Standard Reference (SR) commodities. LCIs in blue indicate a "new" average group LCIs

#	*Ingredients*	*LCI*	*Database*	*Proxy*	*Food group*	*Retail-to-intake factor**
1	beef,ground,75% ln meat / 25% fat,crumbles,ckd,pan-browned	75% beef,25% fat		Yes	Meat	1.05
2	bns,pinto,mature,bld	beans, IP, at farm/kg/CH S	ESU	No	Vegetables	0.42
3	cheese substitute, mozzarella	mozzarella, at dairy/kg/CH S	ESU	No	Dairy	1
4	cheese, cheddar	mozzarella, at dairy/kg/CH S	ESU	No	Dairy	1
5	cheese,mozzarella,part skim,lo moist	mozzarella, at dairy/kg/CH S	ESU	No	Dairy	1
6	cheese,parmesan,grated	mozzarella, at dairy/kg/CH S	ESU	No	Dairy	1
7	cheese,romano	mozzarella, at dairy/kg/CH S	ESU	No	Dairy	1
8	cornmeal, degermed, unenriched, yellow	Maize starch {GLO}| market for | Cut-off, U	Ecoinvent	Yes	Grains	1
9	fat used in pizza recipe	Fats (food group average)		Yes	Fats	1
10	fat,lard	animal fat, at plant/kg/CH S	ESU	Yes	Fats	1
11	garlic,raw				Vegetables	1.15
12	leavening agents, yeast, baker's, active dry	yeast, at plant/kg/RER S	ESU	No	Dairy	
13	lettuce,iceberg,raw	Iceberg lettuce {GLO}| production | Cut-off, U	Ecoinvent	No	Vegetables	1.05
14	mushrooms, white, cooked, boiled, drained, without salt	white mushrooms, at farm/kg/CH S	ESU	No	Vegetables	1.03
15	mushrooms,raw	white mushrooms, at farm/kg/CH S	ESU	No	Vegetables	1.03
16	oil, canola	Oils (food group average)		Yes	Oils	1
17	oil, corn, industrial and retail, all purpose salad or cooking	Maize oil, at oil mill (WFLDB 3.1)/GLO S	WFLDB	No	Oils	1
18	oil, olive, salad or cooking	Olive oil, at oil mill (WFLDB 3.1)/GLO S	WFLDB	No	Oils	1

* Obtained from the Food Intakes Converted to Retail Commodities Database (FICRCD) (USDA 2017)

#	Ingredients	LCI	Database	Proxy	Food group	Retail-to-intake factor*
19	oil, peanut, salad or cooking	Peanut oil, at oil mill (WFLDB 3.1)/GLO S	WFLDB	No	Oils	1
20	oil,soybn	Soybean oil, refined {US}| soybean oil refinery operation | Cut-off, U	Ecoinvent	No	Oils	1
21	olives,ripe,cnd(sml-ex lrg)	Olive {GLO}| market for olive | Cut-off, U	Ecoinvent	No	Vegetables	0.89
22	onions, cooked, boiled, drained, without salt	Onion, at farm (WFLDB 3.1)/GLO S	WFLDB	No	Vegetables	1.18
23	onions,raw	Onion, at farm (WFLDB 3.1)/GLO S	WFLDB	No	Vegetables	1.11
24	pepper jack cheese	Hard cheese, Emmental-style, at dairy (WFLDB 3.1)/GLO S	WFLDB	yes	Dairy	1
25	pepperoni,pork,bf	saucisson, at plant/kg/CH S	ESU	Yes	Meat	1.38
26	peppers, hot chili, green, raw	Green bell pepper {GLO}| production | Cut-off, U	Ecoinvent	No	Vegetables	1.37
27	peppers, sweet, green, cooked, boiled, drained, without salt	Green bell pepper {GLO}| production | Cut-off, U	Ecoinvent	No	Vegetables	1.22
28	pineapple, canned, juice pack, drained	Pineapple {GLO}| production | Cut-off, U	Ecoinvent	No	Fruits	1.96
29	pnappl,raw	Pineapple {GLO}| production | Cut-off, U	Ecoinvent	No	Fruits	1.96
30	pork,cured,ham,bnless,unhtd	Pork, fresh meat, at slaughterhouse (WFLDB 3.1)/CA S	WFLDB	No	Meat	1.07
31	refried beans,canned (incl usda commodity)	beans, IP, at farm/kg/CH S	ESU	No	Vegetables	
32	sauce, pasta, spaghetti/marinara, ready-to-serve	sauce, tomato, vegetarian, at plant/kg/CH S	ESU	Yes	Vegetables	2.42
33	sausage,pork&bf,fresh,ckd	saucisson, at plant/kg/CH S	ESU	No	Meat	1
34	shortening, vegetable, household, composite	animal fat, at plant/kg/CH S	ESU	Yes	Fats	1
35	shortening,institutional,comp	animal fat, at plant/kg/CH S	ESU	Yes	Fats	1
36	sodium	Sodium chloride, powder {GLO}| market for | Cut-off, U	Ecoinvent	No	Other	

#	Ingredients	LCI	Database	Proxy	Food group	Retail-to-intake factor*
37	soy protein isolate				Other	
38	sugars,granulated	Sugar, from sugarcane {GLO}| market for | Cut-off, U	Ecoinvent	No	Sugars	1
39	sweet dwarf pepper	Green bell pepper {GLO}| production | Cut-off, U	Ecoinvent	No	Vegetables	1.22
40	tomato puree,cnd	Tomato pulp, 5° Brix, at plant (WFLDB 3.1)/GLO S	WFLDB	Yes	Vegetables	2.42
41	tomatoes,red,cnd,whl,reg pk	Tomato, fresh grade {MX}| tomato production, fresh grade, open field | Cut-off, U	Ecoinvent	No	Vegetables	1.27
42	tomatoes,red,ripe,raw	Tomato, fresh grade {MX}| tomato production, fresh grade, open field | Cut-off, U	Ecoinvent	No	Vegetables	1.1
43	water,municipal	Tap water {GLO}| market group for | Cut-off, U	WFLDB	No	Other	
44	wheat flour, whole-grain	Wheat flour, at industrial mill (WFLDB 3.1)/GLO S	WFLDB	No	Grains	1
45	wheat flr,white,allpurp,enr,bleach	Wheat flour, at industrial mill (WFLDB 3.1)/GLO S	WFLDB	No	Grains	1
46	yeast,baker's,compressed	yeast, at plant/kg/RER S	ESU	No	Dairy	
47	yellow bean flour	Refined grains (food group average)		Yes	Grains	1

Table A4.37. Metadata for mapping life cycle assessments to Food Pattern Equivalent Database (FPED) food groups. LCIs in blue indicate a "new" average group LCIs

#	*Food Group*	*LCI*	*Database*	*Proxy*	*Food group*	*Retail-to-intake factor*[*]
1	Added sugars (tsp eq.)	Sugars (food group average)		Yes	Sugars	1
2	Cheeses (cup eq.)	mozzarella, at dairy/kg/CH S	ESU	Yes	Dairy	1
3	Cured meat (oz eq)	Cured meat (food group average)		Yes	Meat	1.210403
4	Eggs and substitutes (oz eq)	Chicken egg, in barn single tiered, at farm (WFLDB 3.1)/GLO S	WFLDB	No	Meat	1.14
5	Legumes (cup eq)	Legumes (food group average)		Yes	Vegetables	0.42
6	Legumes (oz eq)	Legumes (food group average)		Yes	Vegetables	0.42
7	Meat (oz eq)	Red meat (food group average)		Yes	Meat	1.05
8	Oils (g)	Oils (food group average)		Yes	Oils	1
9	Other vegetables (cup eq)	Vegetables (food group average)		Yes	Vegetables	1.135524
10	Poultry (oz eq)	Chicken, fresh meat, at slaughterhouse (WFLDB 3.1)/US S	WFLDB	No	Meat	1.25
11	Refined grain (oz eq)	Refined grains (food group average)		Yes	Grains	1
12	Solid fats (g)	Fats (food group average)		Yes	Fats	1
13	Tomatoes (cup eq)	Tomatoes (food group average)		Yes	Vegetables	1.883282
14	Whole fruits excluding citrus, melons and berries (cup eq)	Fruits (food group average)		Yes	Fruits	1.96

[*] Obtained from the Food Intakes Converted to Retail Commodities Database (FICRCD) (USDA 2017)

Table A4.38. Metadata for mapping life cycle assessments to Food Commodity Intake Database (FCID) components

#	Components	LCI	Database	Proxy	Food group	Retail-to-intake factor*
1	Basil, dried leaves	basil, dried, conventional, at plant/kg/CH S	ESU	No	Other	
2	Bean, pinto, seed	beans, greenhouse, at farm/kg/CH S	ESU	No	Vegetables	
3	Beef, fat	Beef, food grade fat, at slaughterhouse (WFLDB 3.1)/US s	WFLDB	No	Fats	1
4	Beef, meat	Beef, fresh meat, at slaughterhouse (WFLDB 3.1)/US S	WFLDB	No	Meat	1.2
5	Beef, meat byproducts	Beef, cat. 3 slaughter by-products, at slaughterhouse (WFLDB 3.1)/US S	WFLDB	No	Meat	1.2
6	Beet, sugar	Sugar, from sugar beet, at sugar refinery (WFLDB 3.1)/GLO S	WFLDB	No	Sugars	1
7	Cassava				Vegetables	1.67
8	Celery	celery, storage, ÖLN, at farm/kg/CH S	ESU	No	Vegetables	1.12
9	Chicken, fat	Chicken, food grade offal, at slaughterhouse (WFLDB 3.1)/US S	WFLDB	No	Fats	1
10	Chicken, meat	Chicken, fresh meat, at slaughterhouse (WFLDB 3.1)/US S	WFLDB	No	Meat	1.23
11	Chicken, meat byproducts	Chicken, cat. 3 slaughter by-products, at slaughterhouse (WFLDB 3.1)/US S	WFLDB	No	Meat	1.23
12	Chicken, skin	Chicken, food grade offal, at slaughterhouse (WFLDB 3.1)/US S	WFLDB	No	Meat	1.23
13	Cilantro, leaves				Vegetables	
14	Coriander, seed				Other	
15	Corn, field, oil	Maize oil, at oil mill (WFLDB 3.1)/GLO S	WFLDB	No	Oils	1
16	Corn, field, starch	Maize starch {GLO}| market for | Cut-off, U	Ecoinvent	No	Grains	
17	Corn, field, syrup	Molasses, from sugar beet {RoW}| beet sugar production | Cut-off, U	Ecoinvent	Yes	Sugars	1
18	Cottonseed, oil	Cottonseed oil, refined {US}| cottonseed oil refinery operation | Cut-off, U	Ecoinvent	No	Oils	
19	Egg, white	Chicken egg, in barn single tiered, at farm (WFLDB 3.1)/GLO S	WFLDB	No	Other	1.14
20	Egg, whole	Chicken egg, in barn single tiered, at farm (WFLDB 3.1)/GLO S	WFLDB	No	Other	1.14
21	Garlic, bulb				Vegetables	1.15
22	Ginger, dried				Other	
23	Guar, seed				Other	
24	Herbs, other				Other	
25	Honey	honey, at farm/CH S	ESU	No	Sugars	1
26	Lettuce, head	Iceberg lettuce {GLO}| production | Cut-off, U	Ecoinvent	No	Vegetables	1.35

* Obtained from the Food Intakes Converted to Retail Commodities Database (FICRCD) (USDA 2017)

#	*Components*	*LCI*	*Database*	*Proxy*	*Food group*	*Retail-to-intake factor* *
27	Marjoram				Vegetables	
28	Milk, fat	mozzarella, at dairy/kg/CH S	ESU	Yes	Dairy	1
29	Milk, nonfat solids	mozzarella, at dairy/kg/CH S	ESU	Yes	Dairy	1
30	Milk, water	mozzarella, at dairy/kg/CH S	ESU	Yes	Dairy	1
31	Mushroom	white mushrooms, at farm/kg/CH S	ESU	No	Vegetables	1.03
32	Olive	Olive {GLO}| market for olive | Cut-off, U	Ecoinvent	No	Vegetables	0.89
33	Olive, oil	Olive oil, at oil mill (WFLDB 3.1)/GLO S	WFLDB	No	Oils	1
34	Onion, bulb	Onion, at farm (WFLDB 3.1)/GLO S	WFLDB	No	Vegetables	1.11
35	Onion, bulb, dried	Onion, at farm (WFLDB 3.1)/GLO S	WFLDB	No	Vegetables	1.18
36	Peanut, oil	Peanut oil, at oil mill (WFLDB 3.1)/GLO S	WFLDB	No	Oils	1
37	Pepper, bell	Green bell pepper {GLO}| production | Cut-off U	Ecoinvent	No	Vegetables	1.22
38	Pepper, black and white	Green bell pepper {GLO}| production | Cut-off, U	Ecoinvent	No	Vegetables	
39	Pepper, nonbell	Green bell pepper {GLO}| production | Cut-off, U	Ecoinvent	Yes	Vegetables	1.22
40	Pineapple	Pineapple {GLO}| production | Cut-off, U	Ecoinvent	No	Fruits	1.96
41	Pork, fat	Pork, food grade fat, at slaughterhouse (WFLDB 3.1)/CA S	WFLDB	No	Fats	1
42	Pork, meat	Pork, fresh meat, at slaughterhouse (WFLDB 3.1)/CA S	WFLDB	No	Meat	1.47
43	Pork, meat byproducts	Pork, cat. 3 slaughter by-products, at slaughterhouse (WFLDB 3.1)/CA S	WFLDB	No	Meat	1.47
44	Pork, skin	Pork, food grade rind, at slaughterhouse (WFLDB 3.1)/CA S	WFLDB	No	Meat	
45	Potato, flour	Potato {US}| production | Cut-off, U	Ecoinvent	No	Grains	1
46	Rapeseed, oil	Rapeseed oil, at oil mill (WFLDB 3.1)/GLO S	WFLDB	No	Oils	
47	Rice, flour	rice flour, at regional storage/kg/US S	ESU	No	Grains	1
48	Safflower, oil				Oils	1
49	Savory				Vegetables	
50	Seaweed				Vegetables	
51	Sesame, oil				Oils	1
52	Sheep, fat	animal fat, at plant/kg/CH S	ESU	Yes	Fats	1
53	Sheep, meat	Sheep for slaughtering, live weight {US}| sheep production, for meat | Cut-off, U	Ecoinvent	No	Meat	1.11
54	Soybean, oil	Soybean oil, refined {US}| soybean oil refinery operation | Cut-off, U	Ecoinvent	No	Oils	1
55	Spices, other	spices, at plant/kg/CH S	ESU	No	Other	

#	Components	LCI	Database	Proxy	Food group	Retail-to-intake factor *
56	Sugarcane, sugar	Sugar, from sugarcane {GLO}| market for | Cut-off, U	Ecoinvent	No	Sugars	1
57	Sunflower, oil	Sunflower oil, at oil mill (WFLDB 3.1)/GLO S	WFLDB	No	Oils	1
58	Tomato	Tomato, fresh grade {MX}| tomato production, fresh grade, open field | Cut-off, U	Ecoinvent	No	Vegetables	1.13
59	Tomato, puree	Tomato pulp, 5° Brix, at plant (WFLDB 3.1)/GLO S	WFLDB	Yes	Vegetables	2.42
60	Water, indirect, all sources	Tap water {CA-QC}| market for | Alloc Rec, U	Ecoinvent	No	Other	
61	Wheat, flour	Wheat flour, at industrial mill (WFLDB 3.1)/GLO S	WFLDB	No	Grains	1

Table A4.39. Metadata for mapping life cycle assessments to Food Intakes Converted to Retail Commodities Database (FICRCD) commodities. LCIs in blue indicate a "new" average group LCIs

#	*Commodities*	*LCI*	*Database*	*Proxy*	*Food group*
1	Beef	Beef, fresh meat, at slaughterhouse (WFLDB 3.1)/US S	WFLDB	No	Meat
2	Cheese	mozzarella, at dairy/kg/CH S	ESU	Yes	Dairy
3	Chicken	Chicken, fresh meat, at slaughterhouse (WFLDB 3.1)/US S	WFLDB	No	Meat
4	Corn Flour & Meal	Maize starch {GLO}| market for | Cut-off, U	Ecoinvent	yes	Grains
5	Eggs, without shell (liquid eggs)	Chicken egg, in barn single tiered, at farm (WFLDB 3.1)/GLO S	WFLDB	No	Other
6	Eggs, with shell (shell eggs)	Chicken egg, in barn single tiered, at farm (WFLDB 3.1)/GLO S	WFLDB	No	Other
7	Total Fluid Milk	Milk (food group average)		Yes	Dairy
8	Legumes (dry beans & peas)	Legumes (food group average)		Yes	Vegetables
9	Lettuce (head & leaf)	Iceberg lettuce {GLO}| production | Cut-off, U	Ecoinvent	No	Vegetables
10	Margarine	Margarine (food group average)		Yes	Fats
11	Onions	Onion, at farm (WFLDB 3.1)/GLO S	WFLDB	No	Vegetables
12	Peppers	Green bell pepper {GLO}| production | Cut-off U	Ecoinvent	No	Vegetables
13	Pork	Pork, fresh meat, at slaughterhouse (WFLDB 3.1)/CA S	WFLDB	No	Meat
14	Salad and Cooking Oils	Oils (food group average)		Yes	Oils
15	Shortening	animal fat, at plant/kg/CH S	ESU	Yes	Fats
16	Tomatoes	Tomatoes (food group average)		Yes	Vegetables
17	Total Caloric Sweeteners	Sugars (food group average)		Yes	Sugars
18	Tropical Fruits	Tropical fruits (food group average)		Yes	Fruits
19	Wheat flour	Wheat flour, at industrial mill (WFLDB 3.1)/GLO S	WFLDB	No	Grains
20	Total Vegetables	Vegetables (food group average)		Yes	Vegetables

Table A4.40. Estimated greenhouse gas emissions for new LCIs used in study. Food group averages represent the Estimates average of all LCIs identified to belong in the respective food group.

New LCI description	*kg CO2 eq/kg*
75% beef,25% fat[*]	21.09
Cured meat (food group average)	3.69
Red meat (food group average)	13.26
Refined grains (food group average)	0.85
Fats (food group average)	1.95
Beef (food group average)	27.59
Chicken (food group average)	5.00
Citrus fruits (food group average)	0.21
Eggs (food group average)	3.98
Fruits (food group average)	0.77
Grains (food group average)	1.56
Legumes (food group average)	0.91
Margarine (food group average)	2.31
Milk (food group average)	1.64
Oils (food group average)	3.54
Pig (food group average)	5.23
Pork (food group average)	10.25
Sugars (food group average)	0.29
Tomatoes (food group average)	0.65
Tropical fruits (food group average)	0.24
Vegetables (food group average)	1.04

[*] Calculated as the weighted average of two LCIs. For the *fat* part we used 'animal fat, at plant/kg/CH S' and for the *beef* part 'Beef, fresh meat, at slaughterhouse (WFLDB 3.1)/US S'

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