ABSTRACT

FLOESS, EMILY MARIE. Quantifying Environmental Health Tradeoffs through Modeling and Measurements. (Under the direction of co-chairs Dr. Andrew Grieshop and Dr. Angela Harris).

Billions of the world's poorest households are faced with the lack of access to safe drinking water and clean cooking, and experience moderate to severe food insecurity. Due to the lack of clean cooking, nearly three billion people in low- and middle-income countries (LMICs) rely on polluting fuels, resulting in millions of avoidable deaths annually. Polluting fuels also emit short-lived climate forcers (SLCFs) and greenhouse gases (GHGs). Energy poverty has been identified as playing a key role in household decision-making and is closely linked with other environmental health risks. For example, one solution to microbiologically contaminated water is boiling, often promoted without acknowledging the additional risks incurred from indoor air degradation from using solid fuels or financial constraints. Another example is that properly heating and storing food can reduce contamination but requires energy. Liquefied petroleum gas (LPG) and grid-based electricity are scalable alternatives to polluting fuels for cooking, water heating, and heating food, but have raised climate and health concerns.

Few studies have looked at the trade-offs and co-benefits of different household energy interventions, and how they impact climate, health, and contamination. The goal of this research is to understand the connection between energy poverty and household health impacts, with a focus on microbiological contamination, health tradeoffs, and household energy interventions. The first objective is to investigate whether the health benefits of boiling drinking water with solid fuels outweigh the increased exposure to indoor air pollution. The second objective is to understand the impact of a household's food, water, and energy insecurity on food and water contamination. The third objective is to understand if there are net health and climate benefits to increased use of fossil fuels like LPG for cooking.

For the first objective, we calculated the total change in disability-adjusted life years (DALYs) from household air pollution (HAP) and diarrhea from fecal contamination of drinking water for scenarios of different source water quality, boiling effectiveness, and stove type. We found that for households with high baseline HAP from existing solid fuel use, adding water boiling to cooking on a given stove was associated with a limited increase in HAP DALYs due to the log-linear exposure–response curves.

For the second objective, we sampled 237 households in a peri-urban area outside Blantyre, Malawi. We collected survey data on WaSH, cooking, health, food, and energy, as well as drinking water and stored food samples. Food and energy insecurity were associated with increased contamination of drinking water and with behaviors such as heating water, using more than one stove, burning trash as fuel, having electricity, having a fridge, and having piped water in the yard or home.

For the third objective, we accounted for upstream and end-use emissions from gas and electric cooking and input the emissions into a reduced-complexity climate model to estimate radiative forcing and temperature changes. We found that full transitions to LPG and/or electricity decrease emissions from both well-mixed GHG and SLCFs, resulting in a roughly 5 millikelvin global temperature reduction by 2040. Transitions to LPG and/or electricity also reduce annual emissions of the health-relevant fine particulate matter ($PM_{2.5}$) by over 6 Mt (99%) by 2040.

This work explores the interlaced impacts of household energy on health, food, water, and climate. Therefore, it is important to evaluate the trade-offs and co-benefits of interventions. Our findings show that boiling water with solid fuels, despite increasing indoor air pollution, can provide net health gains. In our small sample in peri-urban Malawi, energy and food insecurity are related and impact drinking water contamination. LPG and cooking electricity interventions can decrease SLCFs, GHG emissions, and health-relevant pollutants. These solutions emphasize that multiple dimensions must be considered when exploring household energy interventions.

Quantifying Environmental Health Tradeoffs through Modelling and Measurements

By
Emily Marie Floess

A dissertation submitted to the Graduate Faculty of
North Carolina State University
in partial fulfillment of the
requirements for the degree of
Doctor of Philosophy

Civil Engineering

Raleigh, North Carolina
2025

APPROVED BY:

_____	_____
Dr. Andrew Grieshop Committee Co-Chair	Dr. Angela Harris Committee Co-Chair
_____	_____
Dr. Ayse Ercumen	Dr. Fernando Garcia Menendez

DEDICATION

To Ava and Tara.

BIOGRAPHY

Emily Floess was born in Illinois, USA. She received her bachelor's and master's degrees in chemical engineering and environmental engineering, respectively, from the University of Illinois Urbana-Champaign, where she measured stove and brick kiln emissions and household energy usage in Nepal, Colombia, and China. Emily spent five years in Liberia, first as a Peace Corps volunteer and then working for a water treatment nonprofit. She joined North Carolina State University in Fall 2019 to pursue her Ph.D. in Civil Engineering under the direction of Dr. Andrew Grieshop and Dr. Angela Harris. She was an Energy Poverty PIRE in Southern Africa (EPPSA) fellow and an NC State Global One Health Fellow. She was also awarded an NC State Global One Health Travel Award, which enabled her to travel to Malawi to collect field data for her dissertation.

ACKNOWLEDGMENTS

I would like to thank my advisors, Dr. Andrew Grieshop and Dr. Angela Harris, for their guidance and support throughout my Ph.D. I appreciate Dr. Grieshop for always ensuring that I was well-funded, for giving me the opportunity to collaborate on a wide variety of projects, and for always being available for feedback. I appreciate Dr. Harris for the opportunity to get involved in drinking water research and expand and learn in that space after many years working in air quality.

I would also like to thank my committee members, Dr. Ayse Ercumen and Dr. Fernando Garcia Menendez. I appreciated the opportunity to work with Dr. Ercumen on two of my Ph.D. projects and expand my skills in epidemiology and environmental health. I appreciated Dr. Mendenez's support as a committee member, and for being always available to meet and advise.

I am grateful to the EPPSA team for collaboration, opportunities to learn outside of my field, the opportunity to present at a conference in Zambia, and the ability to pursue flexible research directions. I enjoyed the opportunity to work with Dr. Elisa Puzzolo, Dr. Dan Pope, Dr. Annelise Gill-Wiehl, Katherine Landesman, and Dr. Rob Bailis on the LPG project and appreciate your support. Thank you to the Global One Health Academy for my fellowship, which gave me the opportunity to collaborate, network, and conduct my fieldwork in Malawi. I enjoyed working with the team in the US and in Malawi and appreciate the support while collecting field data in Malawi and working on this project. Thank you to Dr. Cassandra Workman for the opportunity to join the project and collect field data in a new area of research for me. Thank you to my Dissertation Completion Grant cohort and to Dr. Friedman for support in the final stages.

Thank you to my past and present GAEL research group members, as well as fellow air quality past and present students and postdocs at NC State, for your support. I also really appreciate the support of my friends in Civil Engineering and other departments across NC State. Thank you to the people of the Civil, Construction, and Environmental Engineering Department, and especially Jodie Gregoritsch and Morgan Lawson, for all of your support. I really appreciate Dr. Barlaz for hosting the annual whitewater rafting trips- these were a highlight of my time at NC State. I am very grateful to our "Foodies" and "Chill People" group, past and present members, for such fun camping trips, meals, and companionship. Especially, thank you to

Qoriatul Fitriyah for your support, and Christina Quaassdorff for all the fun camping trips we planned and had together.

Thank you to Dr. Tami Bond, my Master's advisor, for first bringing me into the air quality and household energy areas of research, and for the continued support of my former Illinois research group and air quality cohort even after starting at NC State University. I especially appreciate the continued support of Dr. Cheryl Weyant and Dr. Mariam Fawaz.

A very big thanks to my running and biking communities, both back in Illinois and in Raleigh. During COVID, they became my biggest support and closest friends. I really want to thank the Cool Kids Run Club for your endless support during my Ph.D.! They were constantly cheering me on, even when I didn't have time to run for months.

Finally, thank you to all of my friends and family here in Raleigh, across the USA, and around the world for your support and encouragement! I am grateful to have met so many amazing people who offer their support and encouragement. Thank you to my family for offering your support through this process, including my parents, brother, and sister. I especially thank Mohammad, Tara, and Ava for their support.

TABLE OF CONTENTS

Contents

LIST OF TABLES

LIST OF FIGURES

Chapter 1: Introduction

1.1 Background & Motivation

One of the many definitions (Faiella & Lavecchia, 2021) of energy poverty is "*an inability to realize essential capabilities as a direct or indirect result of insufficient access to affordable, reliable, and safe energy services, and taking into account available reasonable alternative means of realizing these capabilities"*(Day et al., 2016). There are multiple dimensions to energy poverty, including energy availability, energy affordability, and clean energy (Che et al., 2021). In evaluating energy poverty, there is both an engineering approach, which estimates the "minimum energy requirements for basic energy services demanded by the household" (Sy & Mokaddem, 2022), and an economic approach focusing on "the identification of the energy poverty line based on household income and expenditure" (Sy & Mokaddem, 2022).

One impact of energy poverty is the continued use of solid fuels, with 2.6 billion people estimated to be cooking with solid fuels (Stoner et al., 2021). In urban areas, gaseous fuels dominate, and in rural areas, high levels of biomass are still used (Stoner et al., 2021). In 2030, it is estimated that 31% globally will still use polluting fuels (Stoner et al., 2021). In China, solid fuel use is connected with income (Tang & Liao, 2014). In Sub-Saharan Africa, approximately 84% of the population uses solid fuels (Azanaw & Endalew, 2025; Stoner et al., 2021). Replacing these solid fuels, and clean cooking is necessary to achieve several of the Sustainable Development Goals (Rosenthal et al., 2018). Reliable and affordable energy is necessary for development (Kaygusuz, 2012; Sy & Mokaddem, 2022).

The use of solid fuels results in high exposures to fine particulate matter ($PM_{2.5}$) (Desai et al., 2004). Indoor air pollution (IAP) causes stroke, ischemic heart disease, chronic obstructive pulmonary disease, lung cancer (Dherani et al., 2008), and acute lower respiratory infections (Sonego et al., 2015). IAP was associated with 6.7 million premature deaths annually in 2019 (IHME, 2022a).

The incomplete combustion of solid fuels (Oluwoye et al., 2020), such as from burning wood for cooking, also impacts the climate through long-lived and short-lived climate forcers, including methane (CH_4), nitrous oxide (N_2O), black carbon (BC), carbon monoxide (CO) and non-methane volatile organic contaminants (NMVOCs) (Forster et al., 2007; Goldemberg et al.,

2018). It is estimated that approximately 3800 Gg of BC is emitted per year from residential combustion (Klimont et al., 2017), and biomass combustion is responsible for approximately 0.4 degrees kelvin warming over 20 years (Jacobson, 2014). BC emissions from cooking are a significant source of pollution in developing countries (Y. Wang et al., 2022) and is a contributor to climate change and has health impacts (Anenberg et al., 2012; Bond & Sun, 2005; Janssen et al., 2011). In addition to warming pollutants, other emitted pollutants such as organic carbon (OC) and sulfur oxides (SOx) are climate cooling (Forster et al., 2007).

Biomass combustion also emits CO_2 (Johnson et al., 2009). In 2020, the total emissions from the cooking sector were estimated at 1.69 gigatons of carbon dioxide equivalent (United Nations & UN Energy, 2023). Some of this biomass is renewable (can be regrown), but the use of it exceeds regrowth (Ghilardi et al., 2016). Though CO_2 from cooking is a small faction of the total 34.9 $GtCO_2$ emitted annually (Liu et al., 2022), it contributes to ambient air pollution and health impacts (Chafe, Brauer, Klimont, Dingenen, et al., 2014). Additionally, climate impacts disproportionately impact people in Low and Middle-Income Countries (LMICs) (Atwoli et al., 2022; Bianco et al., 2024). Both the climate and health impacts of solid fuels make it important to find cleaner, healthier alternatives for household tasks, including boiling water, cooking, and reheating food.

Another major challenge impacting people in LMICs is the lack of clean drinking water (Bain et al., 2021, pp. 2014–2020). Two billion people lacked safely managed drinking water in 2020 (WHO/UNICEF, 2020). In 2019, 1.53 million deaths were attributed to diarrheal diseases (IHME, 2022b). Diarrhea is the leading cause of death and illness globally among children under 5 years (Troeger et al., 2018). For households facing unsafe drinking water, one solution to contaminated water is boiling. Boiling is one of the more common household water treatment methods, with an estimated 10.81% boiling (Geremew & Damtew, 2020). However, boiling is often done with solid fuels, which contributes to the same health and climate challenges discussed above . The overlap and similar interventions make combined solutions for water treatment and indoor air pollution important (T. Clasen & Smith, 2019a).

In addition, energy and water treatment are connected beyond boiling. It has been shown that access to electricity is positively associated with the percentage of people using safely managed clean water and sanitation services, and that these services increase as electricity increases (Mbiankeu Nguea, 2024).

Energy is also very important for cooking (Hager & Morawicki, 2013). An additional cause of diarrhea among children under 5 is not practicing exclusive breastfeeding and providing leftover food to the child (Delelegn et al., 2020) Food weaning safety and hygiene programs have been shown to reduce diarrhea (Siu et al., 2021). Education about food safety can include handwashing, washing of pots and utensils, reheating of pre-made food after storage before feeding, and boiling and cooling of water for drinking for children (Manaseki-Holland et al., 2021). However, the reheating of premade food and boiling of water as suggested require access to cooking fuels, which households facing energy poverty may not have (Gautam & Curtis, 2021), and could potentially increase indoor air pollution, especially when they cannot afford cleaner fuels (Mguni et al., 2020).

Another important Sustainable Goal is Zero Hunger (Sporchia et al., 2024, p. 2). Food insecurity affects around 691-783 million people globally in 2024 and disproportionately impacts Africa and Asia (Iannotti et al., 2024) and LMICs (Popkin et al., 2020). In East Africa, urban food insecurity is estimated to be around 60%(Gebremichael et al., 2022). Food insecurity is a difficult challenge to address in that there is little correlation between national food availability and food insecurity (L. C. Smith et al., 2000; Webb et al., 2006), and there is the double burden of food insecure people facing undernutrition and overweight and obesity(Popkin et al., 2020). This also makes food insecurity difficult to measure (Webb et al., 2006). For example, even when food is readily available, a household might not have the means to purchase the food, or the food might not be their preference (Ma et al., 2016).

One challenge is comparing different diseases and health impacts due to different measurements, risk factors, and data quality. The Global Burden of Disease Study (GBD) is a way to quantify different diseases and health impacts (Lopez, 2005). According to (Vos et al., 2015), the GBD "is a systematic, scientific effort to quantify the magnitude of all major diseases, risk factors, and intermediate clinical outcomes in a highly standardized way, to allow for comparisons over time, across populations and between health problems" (Vos et al., 2015). The Global Burden of Disease Study (GBD) uses Disability Adjusted Life Years (DALYs). DALYs are used for comparative risk assessment, including environmental risks such as IAP and water contamination. DALYs allow for comparison across different risk categories, and are the common metric used in the global burden of disease estimates (C. J. L. Murray et al., 2012). However, assumptions and simplifications are required to calculate them, and the value choices

in the model can influence which of the risks are the greatest (Arnesen & Kapiriri, 2004; T. Clasen et al., 2014). For example, in a study where DALYs from malnutrition and major depression were compared, they found that alternative age weights, disability weights, and discounts (due to different value choices in the models) led to an inversion of the ranking of these two burdens (Arnesen & Kapiriri, 2004).

One major challenge is that many households experience multiple health risks. For example, globally, many households face the challenge of both poor drinking water quality and the lack of access to clean cooking fuels, as well as food insecurity. Challenges with accessing energy impact the storage and reheating of food (Gautam & Curtis, 2021).

There are some studies which looked at the combined risks of unsafe drinking water, unsafe food, and household air pollution, including an intervention package of improved solid fuel-stoves, kitchen sinks, solar disinfection of drinking water, and hygiene promotion (Hartinger Pena, 2014; Hartinger et al., 2016). A randomized controlled trial in Rwanda combining a cookstove and water filter intervention found that the intervention reduced the prevalence of reported child diarrhea by 29% and that the benefits of the program outweighed the financial costs (Barstow et al., 2019; Kirby et al., 2019). A study in China measured the reduction in thermotolerant coliforms from boiling using different methods and modeled air pollution from boiling water (Cohen et al., 2020). However, the health benefits from boiling drinking water and the corresponding adverse health effects from HAP have not been previously modeled.

Another way to address the overlapping risks is using the Food, Energy, Water (FEW) nexus framework. FEW nexus thinking "is based on the idea that food, energy, and water form a hub of connections that provides useful insight" (Albrecht et al., 2018; Huntington et al., 2021). A review of existing Food, Energy, and Water (FEW) nexus research (Itayi et al., 2021) found that only three articles referred to household food, energy and water issues, one of which was for a developed country, and two for developing countries (Itayi et al., 2021). In one study, a model was developed to evaluate the water-energy-food nexus at a household scale(Hussien et al., 2017). A component of this study was calculating the required energy for food preparation (Hussien et al., 2017). An additional paper looked at the seasonal variability of the household-level water, energy, and food nexus (Hussien et al., 2018).

Many of the proposed solutions involving food contamination and insecurity and unsafe drinking water involves household energy use (Duret et al., 2021; Grzegorzek et al., 2023). Households account for more than 30% of the total global energy consumption (T. Wang et al., 2024), making finding cleaner alternatives important. While the percentage of the population using polluting fuels is decreasing (from 53% in 1990 to 36% in 2020), the overall number of people using polluting fuels has remained uncharged (Stoner et al., 2021).

One alternative to traditional wood stoves is liquefied petroleum gas (LPG). A major reason for the progress towards cleaner fuels is the increasing access to liquefied petroleum gas (LPG) (Stoner et al., 2021). LPG is well-suited to near-term scale-up (Global LPG Partnership, 2018), cleaner than alternative fuels at the point of use, is relatively simple to use, and requires relatively minimal investment in infrastructure (Puzzolo et al., 2019). Use of gaseous fuels like LPG has risen from 5% in 1990 to 44% in 2020 (Stoner et al., 2021). Electricity accounts for most of the remaining increase in primary access to clean cooking between 2010 and 2020. Though access to electricity is increasing rapidly throughout the global south, cooking with electricity is not as common in many countries and regions (Stoner et al., 2021). However, fossil-derived LPG and electric stoves powered by electricity from fossil fuels also have upstream emissions and end-use emissions. (Islam et al., 2021; Weyant, Thompson, et al., 2019) of concern, which may have major climate impacts as well (Afrane & Ntiamoah, 2011).

There are many studies recently about the adoption and health impacts of LPG (T. Clasen et al., 2020). Analysis has looked at the climate implications of adopting cleaner stoves for individual countries (Kypridemos, 2020). However, a global study of the health and climate implications of widespread LPG and electricity adoption has not been conducted.

1.2 Knowledge Gaps

Based on my literature search, I identified three major knowledge gaps:

1. Water, sanitation, and hygiene (WASH) and household air pollution (HAP) interventions are widely promoted, but no study has modeled the connected health impacts of these interventions.
2. Despite the interconnectedness, no study has looked at the impact of food, water, and energy insecurity and their impact on stored food and drinking water microbial contamination, and their connection to behaviors and household access across domains.

3. Liquefied Petroleum Gas (LPG) is widely promoted as an alternative to biomass stoves; however, the emissions and climate impacts of a large-scale transition to LPG for cooking have not been quantified.

1.3 Research Objectives

Some of the major challenges faced by people in LMICs include drinking water quality, air pollution, food insecurity, and energy poverty. Fourteen of the seventeen UN sustainability goals can somehow be connected to these four challenges (United Nations Department of Economic and Social Affairs, 2025). Despite this, policymakers, nonprofits, and researchers often deal with these challenges one at a time. The overarching goal of my thesis is to understand the different tradeoffs and co-benefits of environmental risks and coping strategies/ interventions that people in LMICs face using modeling and measurements. While interventions for these environmental risks have been researched individually, the potential tradeoffs and co-benefits of the different tradeoffs often have not been considered together. The following tradeoffs and research objectives are explored in my thesis:

1) Tradeoff: Boiling drinking water with solid fuels to reduce the pathogens in drinking water, but also increases indoor air pollution and exposure to $PM_{2.5}$.

Research Question: Do the benefits of boiling the water outweigh the risks of increased indoor air pollution exposure from boiling water?

2) Tradeoff: Reheating food, proper food storage, and boiling and heating water require increased energy, a challenge in households that are energy insecure.

Research Question: What are the impacts of energy, food, and water insecurity on stored food and drinking water handling practices and microbiological contamination in a household?

3) Tradeoff: Promoting LPG and electricity as a cleaner and easier-to-use cooking fuels, and the increased reliance on fuels with high upstream emissions for cooking.

Research Question: What are the health and climate implications of a transition from solid fuels to LPG and electricity?

To address these gaps, my dissertation will focus on the following three tasks:

1) Model the health tradeoffs of boiling drinking water with solid fuels.
2) Analyze the overlap of water, food, and energy poverty, and its impact on food storage and reheating practices.

3) Calculate the climate and health-relevant emissions and corresponding global temperature increase from transitioning to modern cooking fuels, including LPG and electricity.

Figure 1.1 shows a schematic of the connections between food, water, and energy, and how they relate to my different chapters.

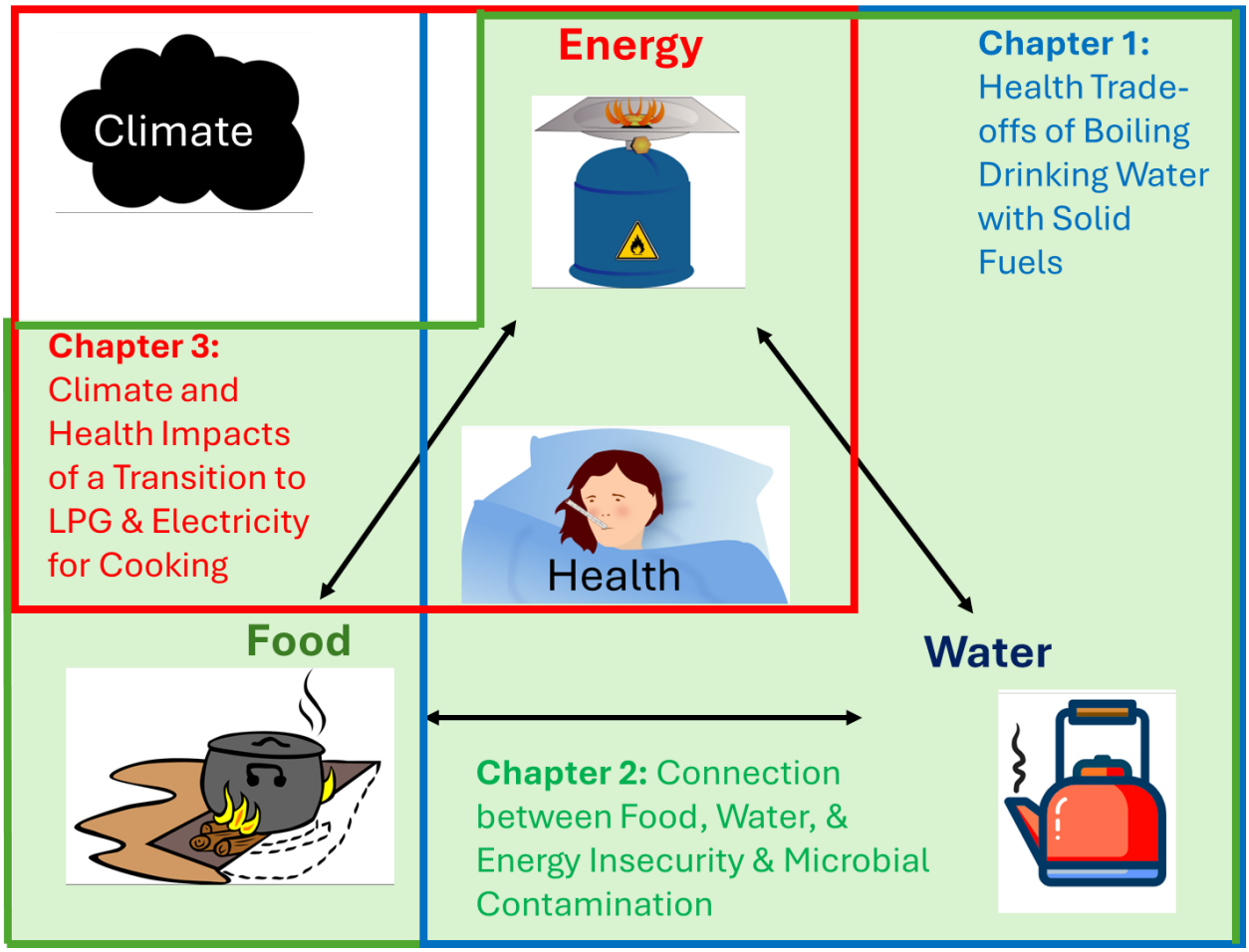


Figure 1.1 *Schematic of food, water, energy, health, and climate, and how they relate to my different chapters. Chapter 1 focuses on energy, water, and health. Chapter 2 focuses on food, water, energy, and health. Chapter 3 focuses on energy, health, and climate.*

1.4 Chapter Summaries

1.4.1 Chapter 2: Health Trade-Offs of Boiling Drinking Water with Solid Fuels: A Modeling Study

This chapter explores the trade-off of increased air pollution from boiling drinking water under multiple contamination and fuel use scenarios typical of low-income settings. We calculated the total change in disability-adjusted life years (DALYs) from household air pollution (HAP) and diarrhea from fecal contamination of drinking water for scenarios of

different source water quality, boiling effectiveness, and stove type for Uganda and Vietnam. Boiling drinking water reduced the diarrhea disease burden by a mean of 1,100 DALYs and 367 DALYs per 10,000 people for those under and over 5 years of age in Uganda, respectively, for high-risk water quality and the most efficient (lab-level) boiling scenario, with smaller reductions for less-contaminated water and ineffective boiling. In both countries, for households with high baseline HAP from existing solid fuel use, adding water boiling to cooking on a given stove was associated with a limited increase in HAP DALYs due to the log-linear exposure–response curves. Boiling, even at low effectiveness, was associated with net DALY reductions for medium- and high-risk water, even with unclean stoves/fuels. Use of clean stoves coupled with effective boiling significantly reduced total DALYs. Boiling water generally resulted in net decreases in DALYs. Future efforts should empirically measure health outcomes from HAP vs. diarrhea associated with boiling drinking water using field studies with different boiling methods and stove types.

1.4.2 Authors and Contributions:

Authors: Emily Floess (EF), Ayse Ercumen (AE), Angela Rose Harris (ARH), and Andrew Grieshop (AG)

All authors contributed to the research, concept design, and writing. EF conducted the literature review, wrote the code, and developed the model scenarios.

1.4.3 Chapter 3: Household Food, water, and energy insecurities and links to behaviors and environmental contamination in Peri-urban Malawi

In this chapter, we analyze the overlap of water, food, and energy insecurity and their interactions with water, food, and energy health-related behaviors and indicators. We sampled 237 households with a range of socioeconomic statuses in a peri-urban area outside Blantyre, Malawi. We collected survey data on household demographics and socioeconomics, water, sanitation, cooking, health, food, and energy. We collected drinking water and stored food samples. The survey included questions on household water, food, and energy insecurity. We examined relationships between the different insecurities, food and water contamination, and corresponding storage and heating practices. The majority of homes used charcoal and an improved, yet contaminated, drinking water source, but did not treat their water; of those who did, only one reported boiling. 52% of households responded that they experienced at least one experience of both food and energy insecurity, but no experiences of water insecurity. We found

an association between energy and food insecurities. Households which were food and energy insecure were associated with increased contamination of drinking water and with behaviors such as heating water, using more than one stove, burning trash as fuel, having electricity, having a fridge, and having piped water in the yard or home. However, water contamination was not associated with water insecurity, and food contamination was not associated with any of the three insecurities. The results from this study will help policymakers incorporate food, water, and energy insecurities holistically when considering household interventions to address microbial contamination.

1.4.4 Authors and Contributions

Authors: Emily Floess (EF), Ben Clark (BC), Cailtin G. Niven (CGN), Blessings Chirwa (BC), Monica Matekenya (MM), Emma Budden (EB), Stella Cadono (SC), John Chavula (JC), Victor Chisamanga (VC), Aubrey Dzinkambani (AD), Chisomo Kaponda (CK), Neema Ngondo (NN), Norah Patterson (NP), Sheena Symon (SS), Brighton Austin Chunga (BAC), Rochelle H Holm (RHH), Petros Chigwechokha (PC), Francis de Los Reyes (FR), Ayse Ercumen (AE), Cassandra L Workman (CLW), Andrew Grieshop (AG), Angela Rose Harris (ARH)

ARH and CLW developed the concept, designed the research, and secured the funding with the help of AG and AE. EF, BC, CGN, EB, and NP developed the survey instrument with the help of ARH, CLW, AG, and AE. BC and MM translated the survey instrument. BC, SC, JC, VC, AD, CK, NN, and SS collected the samples and survey data and helped with lab processing, with the help of EF, BC, CGN, EB, and SC. EF, CGN, and EB cleaned the data. EF wrote the code and conducted the analysis for this paper. EF wrote the paper with the help of AE, CLW, AG, ARH. BAC, RHH, PC, and FR advised on the research.

1.4.5 Chapter 4: Scaling up gas and electric cooking in low-and middle-income countries: climate threat or mitigation strategy with co-benefits?

In this chapter, we compare emissions and climate impacts of a business-as-usual (BAU) household cooking fuel trajectory to four large-scale transitions to gas and/or grid electricity in 77 LMICs. We account for upstream and end-use emissions from gas and electric cooking. We input the emissions into a reduced-complexity climate model to estimate radiative forcing and temperature changes associated with each scenario. We find full transitions to LPG and/or electricity decrease emissions from both well-mixed GHG and SLCFs, resulting in a roughly 5 millikelvin global temperature reduction by 2040 relative to BAU. Transitions to LPG and/or

electricity also reduce annual emissions of $PM_{2.5}$ by over 6 Mt (99%) by 2040, which would substantially lower health risks from household air pollution. Full transitions to LPG or grid electricity in LMICs improve climate impacts over BAU trajectories.

1.4.6 Authors and Contributions:

Authors: Emily Floess (EF), Andrew Grieshop (AG), Elisa Puzzolo (EP), Dan Pope (DP), Nicholas Leach (NL), Chris J. Smith (CJS), Annelise Gill-Wiehl (AGW), Katherine Landesman, (KL), & Rob Bailis (RB).

AG and RB developed the concept, designed the research, and secured funding. EP and DP advised on research design. NL and CJS developed the FaIR model and heavily supported its use in this application. EF, AG, and RB developed BAU and alternate scenarios with input from EP, DP. EF and KL developed tools to manage and analyze scenario data. RB, EF, and AG compiled life-cycle emissions data for each cooking option. EF developed code to integrate emission factors and transition scenarios into FaIR with support from KL. EF, AG, EP, DP, RB, AGW and KL coauthored an internal report that forms the basis for this manuscript. EF, AG, RB, EP, DP, and AGW wrote the manuscript. NL and CJS provided additional text about FaIR output and related discussions.

1.4.7 Chapter 5: Conclusions

This chapter includes conclusions, implications, and recommendations from each chapter in the context of the overarching research themes of this dissertation. Future areas of research and remaining questions are also explored.

Chapter 2: Health Trade-offs of Boiling Drinking Water with Solid Fuels: A Modeling Study

This chapter has been published as: Floess, E., Ercumen, A., Harris, A. R., & Grieshop, A. P. (2025). Health Trade-Offs of Boiling Drinking Water with Solid Fuels: A Modeling Study. Environmental Health Perspectives, 133(6), 067021. https://doi.org/10.1289/EHP15059

Abstract

Background Billions of the world's poorest households are faced with the lack of access to both safe drinking water and clean cooking. One solution to microbiologically contaminated water is boiling, often promoted without acknowledging the additional risks incurred from indoor air degradation from using solid fuels.

Objectives This modeling study explores the tradeoff of increased air pollution from boiling drinking water under multiple contamination and fuel use scenarios typical of low-income settings.

Methods We calculated the total change in disability-adjusted life years (DALYs) from household air pollution (HAP) and diarrhea from fecal contamination of drinking water for scenarios of different source water quality, boiling effectiveness, and stove type. We used Uganda and Vietnam, two countries with a high prevalence of water boiling and solid fuel use, as case studies.

Results Boiling drinking water reduced the diarrhea disease burden by a mean of 1100 DALYs and 367 DALYs per 10,000 people for those under and over 5 years of age in Uganda, respectively, for high-risk water quality and the most efficient (lab-level) boiling scenario, with smaller reductions for less contaminated water and ineffective boiling. Similar results were found in Vietnam, though with fewer avoided DALYs in children under 5 due to different demographics. In both countries, for households with high baseline HAP from existing solid fuel use, adding water boiling to cooking on a given stove was associated with a limited increase in HAP DALYs due to the log-linear exposure-response curves. Boiling, even at low effectiveness, was associated with *net* DALY reductions for medium- and high-risk water, even with unclean stoves/fuels. Use of clean stoves coupled with effective boiling significantly reduced total DALYs.

Discussion Boiling water generally resulted in net decreases in DALYs. Future efforts should empirically measure health outcomes from HAP vs. diarrhea associated with boiling drinking water using field studies with different boiling methods and stove types.

2.1 Introduction

Globally, many households face the challenges of both poor drinking water quality and unclean cooking fuels. Two billion people lack safely managed drinking water (WHO/UNICEF, 2020). In 2019, 1.53 million deaths were attributed to diarrheal diseases,(IHME, 2022b) and in 2016, 60% of all diarrheal deaths in low-and middle-income countries (LMICs) were attributed to improper water, sanitation, and hygiene (WASH) (Prüss-Ustün et al., 2019). Meanwhile, in 2020, 2.8 billion people cooked using polluting fuels (solid fuels and kerosene)(Stoner et al., 2021) resulting in high exposures to fine particulate matter ($PM_{2.5}$) (Desai et al., 2004). Household air pollution (HAP) is associated with various negative health outcomes including stroke (Lu et al., 2021), ischemic heart disease (IHD) (Fan, 2023), chronic obstructive pulmonary disease (COPD) (Siddharthan et al., 2018), lung cancer (LC) (Raspanti et al., 2016), and acute lower respiratory infections (ALRI) (Sonego et al., 2015), among others (Josyula et al., 2015). Air pollution was associated with 6.7 million premature deaths annually in 2019 (IHME, 2022a), with 2.3 million deaths attributed to HAP exposures (C. J. L. Murray et al., 2020; Roser, 2021). Both diarrheal diseases and lower respiratory infections are leading causes of death for children under 5 (Perin et al., 2022). Technologies providing safe water and clean household energy that are considered "low-cost" are often unaffordable to many households (Ray & Smith, 2021), making solutions out of reach.

A third of households in a study of 67 LMICs reported treating their drinking water at home (T. Clasen & Rosa, 2017). Boiling water is the most common household water treatment (Rosa & Clasen, 2010), with an estimated 1.2 billion users (70% of all household water treatment users) (Cohen & Colford, 2017). Based on household surveys, boiling for water treatment is most common in the Western Pacific region and least common in the Eastern Mediterranean and African regions. It is widespread in many Asian nations, including Indonesia (90.6% of households practicing water treatment reported boiling), Mongolia (95.2%), Uzbekistan (98.5%), and Vietnam (91.0%) (Rosa & Clasen, 2010). Though boiling on the African continent is comparatively less common, many countries in Africa have high rates of boiling (Geremew & Damtew, 2020; Rosa & Clasen, 2010), including Lesotho, Rwanda, Uganda (more than 80% of

households reported boiling), Burundi and Namibia (over 60% reported boiling) (Geremew & Damtew, 2020). Boiling for water treatment has been widely promoted for decades for low-income countries and emergency situations (CDC & USAID, 2009). A key limitation of boiling is the potential recontamination of stored boiled water by contact with hands and utensils because boiling does not provide residual protection. Improper boiling methods can also result in poor water quality (T. Clasen, Thao, et al., 2008; Psutka et al., 2011a; Rosa, Huaylinos, et al., 2014) and families often mix boiled and non-boiled water (Prihartono et al., 1994).

Other concerns raised by boiling water are the potential for increased air pollution exposures from fuel combustion (Cohen et al., 2020) and high fuel costs (World Health Organization, 2015). Solid fuel use is prevalent in low-income settings for both cooking and boiling water. Reducing the use of solid fuels reduces $PM_{2.5}$ concentrations (Zhao et al., 2018), yet transitions to clean fuels. such as liquified petroleum gas (LPG), have proven challenging (Mensah & Adu, 2015). Despite the perception that clean fuels are better and more convenient (Gould & Urpelainen, 2018), the associated financial burden (e.g., the cost relative to wood, which is often cheap or free) and other barriers often prevent their widespread adoption (Banerjee et al., 2016). One proposed solution is "improved cooking solutions" (ICS), or "*Cooking solutions that improve, however minimally, the adverse health, environmental, or economic outcomes from traditional solid fuel technologies"* (Global Alliance for Clean Cookstoves, 2015). ICS includes natural- or forced-draft biomass cookstoves with improved combustion efficiency. For example, pellet-fed gasifier stoves emit >90% less ($PM_{2.5}$) than conventional stoves (Champion & Grieshop, 2019a; Njenga et al., 2016; Pope et al., 2017a). However, despite their potential to provide health and other benefits relative to traditional stoves, behavioral, technical, and economic challenges have limited their adoption (Bailis et al., 2009; T. Clasen & Smith, 2019b). Electric stoves are an additional clean option but are not common in low-income countries due to their cost and the poor availability and reliability of electrical grid connections. In Uganda, for example, less than 1% of the population cooks with electricity (World Bank, 2022) due to the expense of electricity and lack of availability and/or subsidies (Price, 2017).

Those working to mitigate risks from HAP and unsafe drinking water face similar challenges in designing, implementing, and securing the sustained use of interventions such as clean fuel and household water treatment (T. Clasen & Smith, 2019b). However, few studies

have examined these linked risks together. A randomized controlled trial in Rwanda combining a "rocket-style" biomass burning natural draft cookstove and water filter found the intervention reduced the prevalence of reported child diarrhea by 29% and that the benefits of the program outweighed the financial costs (Barstow et al., 2019; Kirby et al., 2019). In a related cost-benefit analysis, the averted Disability-Adjusted Life Years (DALYs) from using the water filter and improved cookstove were found to be 239 and 556 per 10,000 people per year, respectively (Barstow et al., 2019). However, the study observed no significant reduction in 48-hour personal exposure to $PM_{2.5}$ (Kirby et al., 2019), consistent with challenges faced by stove replacement programs observed elsewhere (Pope et al., 2021a). A study in China measured the reduction in thermotolerant coliforms in water from boiling using different methods and modeled air pollution from boiling water. The modeled mean 24-hour $PM_{2.5}$ kitchen concentration from boiling water with biomass combustion was 79 $\mu g\ m^{-3}$ (Cohen et al., 2020), substantially above the World Health Organization (WHO) interm-1 target of 35 $\mu g\ m^{-3}$ (WHO, 2021). Boiling with electric kettles was associated with the largest reduction in thermotolerant coliforms. However, the study did not measure health outcomes. To date, no study has specifically investigated the tradeoffs associated with drinking water treatment by boiling using solid fuels and compared the health risks. The overarching goal of this study is to develop a modeling framework to quantify the net health impacts from boiling drinking water with solid fuels, accounting for a range of HAP-associated health outcomes and for diarrhea associated with water contaminated with fecal matter. We then apply this using available literature value for inputs for two countries, Uganda and Vietnam, selected as case studies.

2.2 Methods

2.2.1 Framework Definition and Test Population

DALYs are commonly used to quantify health burdens because they account for morbidity with differential disease severity (Gibney et al., 2013) and mortality. In our study, we used DALYs as the primary metric to compare multiple risks (Devleesschauwer et al., 2014). Quantitative Microbial Risk Assessment (QMRA) models are commonly used to determine the diarrhea risk associated with consuming water from a particular water source (J. Brown & Clasen, 2012; Havelaar & Melse, 2003). For HAP, the population attributable fractions based on exposure-response curves for individual diseases are used to calculate the burden of disease

(Asikainen et al., 2016; Pillarisetti et al., 2016b). We used the QMRA and exposure-response curves as opposed to direct epidemiological evidence in order to calculate the DALYs for a range of conditions, including different levels of water boiling effectiveness, source water qualities, and HAP levels. While epidemiological estimates exist for associations between boiling drinking water and child diarrheal outcomes, these provide an average over a range of conditions in the study population and do not allow estimating effects under specific scenarios and boiling efficiencies. Though the DALY calculation methods for these two risk factors are very different, they represent the best available, established methods to calculate the risks.

We adopted these two methods (Figure 2.1), creating two modules, and used literature-derived distributions of the relevant HAP, QMRA, and demographic parameters as inputs (Table A1 and Table 2.1 Household Demographics for Vietnam and Uganda). The *water risk module* uses a QMRA model to calculate the DALYs from drinking water contaminated by fecal matter before and after treatment by boiling. The *air risk module* uses an indoor box model to quantify the $PM_{2.5}$ concentrations for different stoves and a modified form of the Household Air Pollution Intervention Tool (HAPIT, Version 3.1.1) (Pillarisetti et al., 2015, 2016b) to quantify the DALYs associated with HAP under various scenarios. Both modules employ Monte Carlo simulations to capture the influence of variability and uncertainty in input parameters on model outputs.

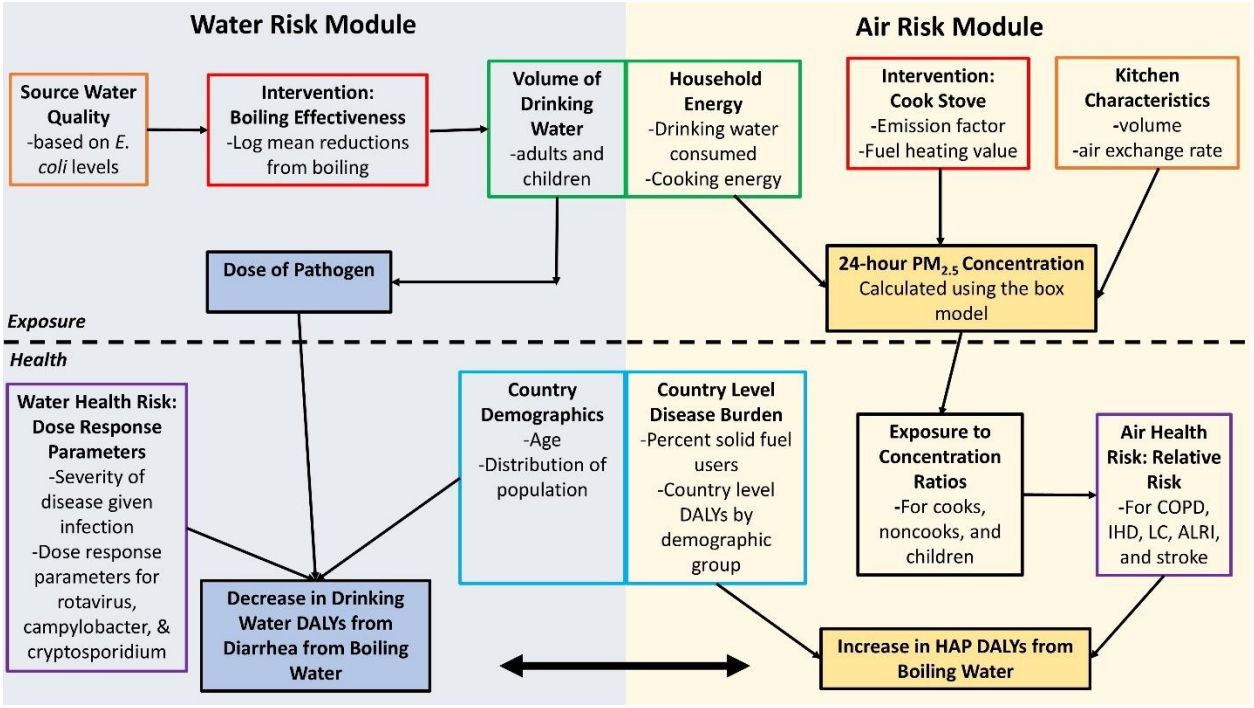


Figure 2.1 *Overview of methods to calculate and compare drinking water DALYs (Disability Adjusted Life Years) and Household Air Pollution (HAP) DALYs. PM2.5 is fine particulate matter. Air health risks are for Chronic Obstructive Pulmonary disease (COPD), Ischemic Heart Disease (IHD), Lung Cancer (LC), Acute Lower Respiratory Infection (ALRI), and Stroke.*

Table 2.1 *Household Demographics for Vietnam and Uganda*

	Vietnam	Uganda
Average Household Size	5[a]	5[a]
Life Expectancy Women	79.2[b]	69.2[b]
Life Expectancy Men	70[b]	62.3[b]
Adults Per Household	4.6[c]	4[c]
Children Under 5 Per household	0.4[c]	1[c]
Total Country Population	96362928[b]	41117856[b]
Cooks per household	1[c]	1[c]

Table 2.1 *(continued)*

Adults and children 5 and over 5 years of age (5-and-overs) (not including cooks)	3.6[c]	3[c]
Children under 5 years of age (Under-5s)	0.4[c]	1[c]
Percent Solid Fuel Use	49%[c]	95%[c]

Table Notes:

[a] United Nations. Household Size and Composition Around the World 2017 – Data Booklet. United Nations, Department of Economic and Social Affairs, Population Division; 2017. https://www.un.org/en/development/desa/population/publications/pdf/ageing/household_size_and_composition_around_the_world_2017_data_booklet.pdf(United Nations, 2017)

[b] Institute for Health Metrics and Evaluation. Global Burden of Disease Study 2019 (GBD 2019) Population Estimates 1950-2019. Institute for Health Metrics and Evaluation. January 28, 2021. http://ghdx.healthdata.org/sites/default/files/record-attached-files/IHME_GBD_2019_POP_1950_2019_INFO_SHEET_Y2021M01D28.PDF(Institute for Health Metrics and Evaluation, 2021)

[c] Pillarisetti A, Mehta S, Smith KR. Household Air Pollution Intervention Tool (HAPIT III). Clean Cooking Alliance. Published online 2015. https://www.cleancookingalliance.org/resources/450.html(Pillarisetti et al., 2015)

Globally, more than half of all deaths from HAP from solid fuel are from acute lower respiratory infection (ALRI) in children under 5 years of age (Bruce et al., 2006) and most diarrheal DALYs occur in children under 5 years of age (Karambizi et al., 2021). Therefore, we conducted analyses for two age groups: those under 5 years of age ("under-5s"), and all other age groups combined ("5-and-overs").

We designed the model to be used for any setting. However, we selected Uganda and Vietnam as case study countries as they are in distinct regions, have different population demographics, and high prevalences of boiling among household water treatment users (82% in Uganda (Geremew & Damtew, 2020), 91% in Vietnam(Rosa & Clasen, 2010)) and solid fuel use (96% in Uganda, 35% in Vietnam) (Stoner et al., 2021). To simplify the model for both countries, we assumed one cook for each household and a household size of 5 people per household, based on average household size and composition for LMICs (Pillarisetti et al., 2016b; United Nations, Department of Economic and Social Affairs, Population Division, 2019) and default values used in the HAPIT model (Pillarisetti et al., 2015). The number of adults and children under 5 varied by country, with 4.6 people over 5 and 0.4 children under 5 per household for Vietnam, and 4 people over 5 and 1 child under 5 for Uganda (Pillarisetti et al., 2015). In addition to the household demographics, we also varied the life expectancy, background disease data, deaths and DALYs for each country, while keeping the rest of the model inputs the same. The models were run for a sample population of 10,000 people.

2.2.2 Health Benefits from Boiling Drinking Water

The risk of illness from contaminated drinking water was characterized using a QMRA, focusing on selected reference pathogens (World Health Organization, 2016). Pathogens used in QMRAs are typically selected based on global public health relevance; because they are transmitted via environmental, waterborne, and foodborne routes (Kundu et al., 2018), the dominant pathogens may also depend on geographic region (Tian et al., 2017). Additionally, reference pathogens were selected to span different waterborne pathogen classes (viruses, bacteria, protozoa) (Bivins et al., 2017; World Health Organization, 2017). For this study, we selected pathogens identified as leading causes of diarrhea in multisite studies of diarrhea etiology in low-income countries (Kotloff et al., 2012; Lanata et al., 2013; Platts-Mills et al., 2015). Based on these studies, the locations selected for our modeling exercise, and previous QMRA studies (Bivins et al., 2017; Machdar et al., 2013; Uprety et al., 2020a), we selected a virus (rotavirus), a protozoan (*Cryptosporidium*), and a bacterium (*Campylobacter*) to quantify the risk from exposure to fecally contaminated water.

A QMRA for drinking water involves four steps (Bivins et al., 2017; J. Brown & Clasen, 2012; Burch et al., 2021; Haas et al., 1999; Murphy et al., 2016; Uprety et al., 2020a): 1) Hazard identification, 2) Exposure assessment, 3) Dose-response quantification, and 4) Risk assessment.

For the hazard identification, we used a uniform distribution of *E. coli* levels for each water quality category, using most probable number (MPN) ranges of: 0 MPN/100 mL for 'safe' water, 1-10 MPN/100 mL for 'low-risk' water, 11-100 MPN/100 mL for 'medium-risk' water, and 101-1000 MPN/100 mL for 'high-risk' water (Odonkor & Mahami, 2020). These untreated drinking water categories define baseline water qualities for the model. We used fecal indicator bacteria to pathogen ratios for the three pathogens (Table 2.2) from the literature to estimate the abundance of the selected pathogens in untreated water.

Table 2.2 *Ratio of E. coli to individual pathogens modeled and their dose-response relationships, illness probabilities, and percent susceptible, based on the literature*

Pathogen	Ratio of E. coli to Pathogen	Dose-Response Parameters & Model	Probability of Illness Given Infection, Percent Susceptible
Campylobacter	1:0.66(Kundu et al., 2018; Machdar et al., 2013)	β-Poisson α: mean=$1.51*10^{-1}$ std. dev.: $5.9*10^{-2}$, N_{50}: mean=$1.69*10^{-3}$, std. dev.:$2.78*10^{-3}$, P_{Di}=0.3 (Bivins et al., 2017; Black et al., 2022; Haas et al., 1999; Machdar et al., 2013; Medema et al., 1996; Westrell, 2004)	30%, 100%(Bivins et al., 2017; Machdar et al., 2013)
Rotavirus	$1:5*10^{-6}$ (Machdar et al., 2013)	β-Poisson α: mean=$2.48*10^{-1}$, std. dev.: $1.46*10^{-1}$, N_{50}: mean =8.16, std. dev.: 6.65, P_{Di}=0.51 (Bivins et al., 2017; Haas et al., 1999; Medema et al., 1996)	50%,13%(Bivins et al., 2017; Machdar et al., 2013)

Table 2.2 *(continued)*

Cryptosporidium	1:10^{-6} (Kundu et al., 2018; Machdar et al., 2013)	Exponential r: mean=$3.44*10^{-1}$ std. dev.: $1.46*10^{-1}$, P_{DI} = 0.7 (Bivins et al., 2017; Messner et al., 2001; Westrell, 2004)	70%, 100%(Bivins et al., 2017; Machdar et al., 2013)

We then estimated boiling effectiveness for the selected pathogens. The modeled intervention was boiling at different levels of microbiological effectiveness to account for different field conditions and household practices. The boiling effectiveness was quantified using log-reduction values (LRV), defined as the base-10 logarithm of the ratio of influent to effluent pathogen concentrations. The effectiveness of boiling drinking water was compiled from a literature review of field and lab studies; see Table A2 for full values used in literature review, and Table 2.3 for values used in model. This literature review included studies of boiling from 9 different countries from 3 continents, as well as laboratory studies. We chose a range of boiling effectiveness for use in the model, ranging from ineffective to laboratory level effectiveness. Water boiling studies reported LRVs for different fecal indicator organisms, including *E. coli,* thermotolerant coliforms (TTC), and fecal coliforms (FC). Since our modeled water quality was characterized using *E. coli,* we converted TTC and FC LRVs to *E. coli* LRVs (Hachich et al., 2012) based on assumed ratios. Although *E. coli* to FC ratios can vary in different seasons (Hathaway et al., 2014), the ratios were assumed to be constant throughout the year. LRV values in the literature (converted to *E. coli*) ranged from 6 for lab-level boiling to -0.26 for ineffective boiling. We multiplied *E. coli* LRVs by a pathogen-specific factor to quantify removal of the respective pathogens (C*ryptosporidium*, C*ampylobacter*, and rotavirus) (Table 2.4).

For the exposure assessment, we used Equation 1 to calculate the daily exposure to pathogens (E_d, in MPN) (Murphy et al., 2016),

$$E_d = C * \frac{1}{R} * I * 10^{-LRV} * V \quad [1]$$

where C is the concentration of pathogen in the source water (MPN per liter), R is the fractional mean analytical recovery (to account for success in microorganism counts) of the pathogen in the sample, I is the fraction of pathogens that are infectious (Bivins et al., 2017; Murphy et al.,

2016), LRV is the pathogen-specific log-reduction by boiling water, and V (liters) is the daily volume of water consumed per person. We assumed I and R to be 1.

Table 2.3 *Literature Sources of Log Reduction Values of E. coli and thermotolerant coliforms (TTC) used in our study*

Label used in this paper's results	Country, Water Source, and Reported Treatment	E. coli[a]	TTC[b]
Lab Level	Australia, Laboratory, Heated for1 minute, 75°C)	6.00(Sanciolo et al., 2015)	
Best Field	Cambodia, surface water, household reported boiling	2.00(Sobsey & Brown, 2012)	
Average Field	Cambodia, well, household reported boiling	1.50(Sobsey & Brown, 2012)	
Low Field	Peru, urban various sources, household reported boiling	*Converted to 0.56*	0.44(Rosa, Huaylinos, et al., 2014)
Ineffective Field	Peru, rural various sources, household reported boiling	*Converted to 0.0480*	0.06(Rosa, Huaylinos, et al., 2014)

[a] All values were converted to E. coli for comparison in the model if not reported as *e. coli LRV*

[b] TTC = Thermotolerant coliforms

Table 2.4 *Effect of Boiling on E. coli, Campylobacter, Cryptosporidium, and Rotavirus*

Organism (source)	Log Reduction value (LRV)[a]	Temperature	Contact Time (seconds)
E. coli (Sanciolo et al., 2015)	6	75ºC	60
Campylobacter (Sanciolo et al., 2015)	5	63ºC	300
Cryptosporidium (Sanciolo et al., 2015)	8	75ºC	60
Rotavirus (El-Senousy, 2020)	8	95ºC	60

[a] To convert to the pathogen specific LRV, the ratio of the LRV for the given pathogen to that for *E. coli* was used. These were not distributions but specific parameters.

We calculated the probability of illness from the daily exposure using dose-response relationships from the literature (Bivins et al., 2017; Haas et al., 1999; Machdar et al., 2013; Medema et al., 1996; Westrell, 2004). The dose-response parameters were assumed to be the same regardless of age (Table 2.2).

We calculated the probability of developing disease (diarrhea) per single exposure (P_D) as the product of the probability of disease given infection (P_{DI}) and the probability of infection (P_i) (Table 2.2). The probability of developing illness over period n, ($P_{D,n}$), was calculated using the probability of disease ($P_{D,n}=1-(1-P_D)^n$) and the annual symptomatic cases was calculated by multiplying the yearly probability of developing illness ($P_{D,yearly}$) times the exposed population (J. Brown & Clasen, 2012; Murphy et al., 2016; Uprety et al., 2020a).

For the risk assessment, DALYs from diarrhea (years lived with disability) were calculated by taking the disability weight times the duration of disease times the probability of

disease (Machdar et al., 2013; Murphy et al., 2016; Uprety et al., 2020a). Disability weights to quantify disease severity were obtained from the literature (Table 2.5). When calculating years of life lost, the disability weight is 1 and the duration was the life expectancy minus the age at death (Machdar et al., 2013). To make the life expectancy represent the demographics of the country of interest, we adjusted this method so that the remaining life expectancy at the time of death was selected using stratified random sampling, based on the population age distribution in that country, separated into two categories, children <5 years and all other ages. For disease burden, severity and duration varied by pathogen (*Cryptosporidium*, *Campylobacter*, or rotavirus) (Machdar et al., 2013).

Table 2.5 *Burden of Disease for Each Pathogen*

Pathogen	Outcomes	Severity [a]	Duration (Days)[b]	Duration (Years)- based on lifetime (56 here)[c]	DALYs per case[d]	Likelihood of Outcome[e]
Campylobacter	Gastroenteritis -population	0.067	5.1	0.014	0.0009	94%
Campylobacter	Gastroenteritis - when see doctor	0.39	8.4	0.023	0.009	6%
Campylobacter	Death from gastroenteritis	1		Life expectancy from population distribution	-	0.1%
rotavirus	Mild Diarrhea	0.1	7	0.02	0.0019	86%
rotavirus	Severe Diarrhea	0.23	7	0.02	0.0044	14%

Table 2.5 *(continued)*

rotavirus	Death from Diarrhea	1		Life expectancy from population distribution	-	0.7%
Cryptosporidium	Watery diarrhea	0.067	3.4	0.009	0.0024	100%
Cryptosporidium	Death	1		Life expectancy from population distribution	-	0.4%

[a,b,c,d,e] Reference #62(Machdar et al., 2013)

2.2.3 Health Impacts from Household Air Pollution

In the air risk module, first an air pollution box model was used to estimate the 24-hour $PM_{2.5}$ concentrations in the household (Johnson et al., 2011) and then DALYs were estimated using the framework of the HAPIT model (Pillarisetti et al., 2016b). We picked the HAPIT model as it is readily available and used in established studies. Most of the disease burden for children under 5 comes from ALRI, with a very small fraction of the disease burden from children under 5 (<1%) coming from COPD and Stroke, which are accounted for in the model. All 5 diseases in our model (ALRI, COPD, IHD, Stroke, and LC) affect the over 5 population. For the air risk module, we considered two baseline scenarios: one with a household 'already cooking' on a traditional woodstove with no water boiling, and one in which a household is 'not cooking, and also not boiling water'. We considered the following cookstoves as replacements for this baseline: 1) improved wood, 2) charcoal, 3) LPG, and 4) electric (Gould & Urpelainen, 2018; Lewis et al., 2015; Menghwani et al., 2019). In the model, we assumed 100% adoption (e.g., LPG completely replaces traditional wood for all household energy needs). Electric stoves were included to serve as an ideal counterfactual (i.e., completely clean cooking technology). We

considered three categories of stove use per day: 'cooking only' (no water boiling), 'water boiling only' (no cooking), and 'cooking and water boiling'.

Our model assumes stove energy is only used for cooking and water heating, and that all cooking takes place indoors. The required cooking energy (delivered to pot) for both the Ugandan and Vietnamese households was assumed to be lognormally distributed, with a mean (standard deviation) of 11 (5.5) MJ per day (Habib et al., 2004; Johnson et al., 2011). The daily energy for water heating (E_{WH}), (Equation 2), was calculated as the energy needed to heat the water from ambient temperature (T_a, assumed to be 15 °C) to boiling (100 °C), and then boiled for one minute. The volume of water heated (V, liters) was assumed to be normally distributed with mean (standard deviation) 3.12 (1.17) liters (Hossain et al., 2013). This was converted to mass using density (ρ, 1000 g/L). C_p is the heat capacity of water (4.186 J g^{-1} K^{-1}). Finally, the stove is assumed to boil the water for one minute, so the product of 60 seconds (t) and the power of the stove (P, in Watts) is added to get the total energy demand for heating water in a household.

$$E_{WH} = V * \rho * C_p * (100 - T_a) + P * t \quad [2]$$

Laboratory studies of boiling effectiveness have been conducted for numerous different temperatures and durations of boiling. Generally, heating water at higher temperatures for longer periods of time results in greater LRVs compared to lower temperatures and shorter periods (Sanciolo et al., 2015). The recommended boiling time in the literature ranges from 1 to 25 minutes (T. Clasen, Thao, et al., 2008). Though pathogens are deactivated at temperatures less than 100 ºC (World Health Organization, 2015), in field studies of water boiling, households typically heated water until they saw bubbles, and often longer (T. Clasen, Thao, et al., 2008). In this study, we assumed that once water reaches boiling temperature (calculated as described above), it is boiled at 100 ºC for 1 minute, based on CDC (CDC, 2020; CDC & USAID, 2009) and WHO (World Health Organization, 2015) recommendations, to reach the assumed LRV. The influence of elevation on boiling temperature was not considered in this analysis, but this would impact the temperature and thus the length of time needed for boiling for a given LRV.
Once the energy demand was estimated, an air pollution box model (Johnson et al., 2011) was used to calculate the indoor kitchen $PM_{2.5}$ concentration (μg m^{-3}) over 24 hours. The indoor air pollution model is based on a single-box model with variability captured using a Monte Carlo simulation, and calculates room concentrations assuming a well-mixed room and a single

emission source (Johnson et al., 2011). Model inputs included the daily cooking time, calculated from the daily energy demand and stove thermal efficiency, the emission rate (calculated using the stove emission factor and power, and fuel energy density), kitchen air exchange rate and volume, and concentration from proceeding time step (Johnson et al., 2011). The time for cooking and water heating was calculated using the energy demand divided by the assumed stove power (Watts) and thermal efficiency (Table 2.6). We assumed that cooking and water heating each occurred once per day to produce all daily energy for cooking and water heating. The emissions were calculated using the relevant emission factor (grams $PM_{2.5}$ per kilogram fuel) and heating value of fuel (Table 2.6).

Table 2.6 *Emission Factors (EF), Stove Power (SP), Thermal Efficiency (TE) of Stoves and Fuel Heating Value.*

Stove	Category	$PM_{2.5}$ EF Mean ± St. Dev. g/kg[a]	Stove Power (Watts)	Thermal Efficiency % ± St. Dev. [5]	Fuel Heating value (MJ/kg) mean, min, max, ± St. Dev.[b] (*Distribution)*
Traditional 3 stone wood (version 1)	Traditional Wood, Malawi	7.1 ± 1.3(McCracken & Smith, 1998; Wathore et al., 2017)	1958(McCracken & Smith, 1998; Wathore et al., 2017)	14.8 ± 1.8(McCracken & Smith, 1998; Wathore et al., 2017)	14.780, 13.500, 15.883(Brouwer et al., 1996) (*Triangular*)
Jiko	Charcoal	0.47(Obeng et al., 2017)	6056(Obeng et al., 2017)	23.30 ± 0.29(Obeng et al., 2017)	35.9(Atteridge et al., 2013) (*Point)*
MiniMoto(PP)	Gasifier	0.079(Champion et al., 2020)	3056(Champion et al., 2020)	37.9(Champion et al., 2020)	16.1 ± 0.18(Champion et al., 2020) (*Normal)*

Table 2.6 *(continued)*

Chitetezo Mbaula	Improved Wood	3.6(Jagger et al., 2017)	1116.7(Jagger et al., 2017)	20(Jagger et al., 2017)	14.780, 13.500, 15.883(Brouwer et al., 1996) (*Triangular*)
LPG	Clean	0.053 ± 0.04(Shen et al., 2018)	1529(Shen et al., 2018)	54.4 ± 1.5(Shen et al., 2018)	45.780 (Panigrahy et al., 2016) (*Point)*

[a] Distributions are lognormal

[b] Dry basis heating value is given for biomass, lower heating value is used for LPG

We selected a range of stoves and fuels ranging from basic, "unimproved" models (e.g. traditional wood stove) to modern, clean option (e.g. gasifiers, LPG, and electric stoves). To simplify the model, we also assumed an ambient concentration (Pillarisetti et al., 2015) to which the indoor concentration decays after the cooking event, and a second event (water heating) increases it again. Since the ambient concentration could vary drastically depending on the location (such as urban or rural) and also varies between Uganda and Vietnam (World Health Organization, 2022), for simplicity, we assumed a background concentration of 12 μg m^{-3},(US EPA, 2012) to represent a low ambient value with minimal health impacts. If a single stove did not provide sufficient power to heat the specified daily water and food allowing time for household concentrations to return to ambient levels between stove uses, a second stove was used in the model simultaneously, and in this scenario, we doubled emission rates. Although emission factors vary between stove operation stages (e.g., startup vs steady operation) (Cereceda-Balic et al., 2017; Deng et al., 2018; Roden et al., 2006, 2009), we assumed a constant average emission factor for the entire burning process. This approach may underestimate 24-hour emissions, since it doesn't reflect multiple starting events, which can produce high emissions (Thompson et al., 2019). For an example of the 24-hour $PM_{2.5}$ kitchen concentration for cooking and water heating, see *Figure A1*.

To calculate the health burden from HAP, we adapted the approach of the Household Air Pollution Intervention Tool (HAPIT) (Pillarisetti et al., 2015, 2016b). HAPIT (Version 3.1.1)

(Pillarisetti et al., 2016a) model inputs include 2010 background disease data, 2020 population data, 2010 solid fuel use data, and 2013 average household size (Pillarisetti et al., 2016b). We modified the inputs to use more recent 2019 background disease data (Institute for Health Metrics and Evaluation, 2021; Vos et al., 2015), in addition to our modeled pre-and post-intervention $PM_{2.5}$ exposures. The pre-intervention exposure is from the traditional wood stove, and the post-intervention exposure is from one of the four cleaner stoves (improved wood, gasifier, LPG, or electric). The relative risks were calculated for each exposure level, and this is used to calculate the population attributable fraction, the attributable burden and the averted burden associated with an intervention (e.g. switching from a baseline to cleaner stove) (Pillarisetti et al., 2015, 2016b). Personal exposure is estimated by multiplying the modeled 24-hour $PM_{2.5}$ kitchen concentration by an estimated ratio of personal exposures to kitchen concentrations (Bates et al., 2018; Bruce et al., 2006; Lim et al., 2012) with separate ratios applied for the cook, non-cook, and children under 5 of a household (Table 2.7).

Table 2.7 *Personal Exposure to Concentration Ratios*

Person	Women	Women to Children	Women to Men
Ratio[a]	0.742	0.85	0.61

[a] (Pillarisetti et al., 2015)

The burden of disease attributable to household $PM_{2.5}$ pollution was calculated for LC, IHD, stroke, ALRI, and COPD using 2019 background disease data, deaths & DALYs (Institute for Health Metrics and Evaluation, 2021; Vos et al., 2015) for Uganda and Vietnam, respectively, and the disease-specific integrated exposure response functions from Burnett et al., (Burnett et al., 2014) using data and code from the Institute for Health Metrics and Evaluation (IHME) website (IHME, 2010). Uncertainty was taken into account using results from Burnett et al., in which the integrated exposure response models were fit to 1,000 sets of source type-specific relative risk (RR) values, creating 1000 sets of parameter estimates (Burnett et al., 2014). In our modeling, we randomly drew from these 1000 sets of parameter estimates as part of the Monte Carlo simulation approach taken for the entire model. While there is no clear safe level of $PM_{2.5}$ exposure (Burnett et al., 2014), we used the distribution of 5.8-8.8 $\mu g\ m^{-3}$ as a counterfactual 'no effect' level for this model (Lim et al., 2012), which is the same level used by the HAPIT model (Pillarisetti et al., 2015, 2016b), though we used a distribution instead of the point estimate HAPIT uses (Pillarisetti et al., 2015, 2016b).

The relative risk and the existing fraction of each country's population exposed to solid fuels (i.e., fraction exposed equals the percent solid fuel users for each country) were used to calculate the attributable fraction (AF) (Equation 3) (Pillarisetti et al., 2015). In calculating the attributable fraction in the model, the fraction exposed is country-specific and fixed, but the relative risk varies with air pollution level.

$$AF = \frac{FractionExposed*(RR-1)}{FractionExposed*(RR-1)+1} \qquad [3]$$

The attributable fraction was multiplied by the DALYs or deaths from a given disease in the country or region of that specific population (given location and age group) to calculate the attributable burden associated with HAP (Pillarisetti et al., 2016b). To calculate the fraction of DALYs from children under 5, we used the fractions of children in that population and relevant under-5 DALYs for each disease.

2.2.4 Simulations, Analysis, Statistical Tests, & Sensitivity

When comparing HAP and drinking water DALYs, we define 'net DALYs' as the increase in HAP DALYs minus the decrease in drinking water DALYs resulting from boiling drinking water. Positive net DALYs means that the HAP DALYs increase is greater than the water DALY decrease, indicating a net increase in disease burden. Negative net DALYs means the water DALYs decrease is greater than the HAP increase, indicating a net health benefit.
We conducted Monte Carlo simulations to capture the influence of variability and uncertainty in the inputs. Each simulation draws from distributions for parameters of a stove and fuel type, and water boiling effectiveness and was run 10,000 times in R (R Core Team, 2021). The mean, standard deviation, and 95% confidence intervals of model output are reported. Additionally, to understand the variation in the outputs, the coefficient of variation (COV) (standard deviation over mean) was calculated. Environmental parameters are often log-normally distributed (Andersson, 2021), so we used the Shapiro-Wilk test to test the normality of our resulting distributions of drinking water and HAP DALYs before making statistical comparisons between different scenarios. If an output distribution was log-normal, it was log-transformed for hypothesis testing. We used the t-test to compare the risks across the different scenarios (i.e., different stove types or water boiling scenarios). P-values less than 0.05 were considered statistically significant.

A sensitivity analysis was conducted for the HAP and drinking water QMRA models to identify the specific impact of individual input variables on model output. Each input parameter was individually evaluated by varying the assigned value between a minimum and maximum value determined based on an assessment of the variability or uncertainty of the parameter from our literature review (Tables A3 and A4). Input parameters were then ranked in order of their influence on output values by taking the ratio of the output values for input at its minimum and maximum values (Mattioli et al., 2015).

2.3 Results

2.3.1 DALYs from Household Air Pollution

The simulations with the lowest to highest 24 h average $PM_{2.5}$ kitchen concentrations (for cooking and water heating scenarios) were electric, LPG, gasifier, charcoal, improved wood, and traditional wood, with values ranging from 12 μg m^{-3} (for the electric stove) to 5144 μg m^{-3} for cooking and water heating (data provided in Excel Table A11). The average 24-hour $PM_{2.5}$ concentration for the 'worst-case', traditional wood stove scenario was lower for water heating alone (1790 μg m^{-3}) than for cooking alone (3367 μg m^{-3}), while the concentration associated with both activities together was essentially the same as the sum of the two activities considered separately.

Figure 2.2 shows the DALYs calculated from these $PM_{2.5}$ values for the different stove and use scenarios for each country. Though the total DALYs per 10,000 people were similar between the two countries, the number of HAP DALYs associated with under-5s were higher in Uganda compared to Vietnam, with the under-5s DALYs in Uganda making up 22% to 50% (depending on scenario) of total, versus under-5s DALYs in Vietnam making up 1% to 2.4% of total DALYs. DALYs became significantly lower as stove type shifted from traditional wood to LPG stoves for cooking and water heating, with 96.8%, 97.1%, 97.3%, and 99.9% changes in DALYs for Uganda 5-and-overs, Uganda under-5s, Vietnam 5-and-overs, and Vietnam under-5s, respectively, eliminating almost all the DALYs associated with HAP. For the electric stove, since it was assumed that the electric stove contributes no additional $PM_{2.5}$, DALYs were 100% lower when the electric stove replaced other stoves. There were only small differences in DALYs when a traditional wood stove was replaced with an improved wood stove. For example, DALYs were 2.9% lower (for Uganda under-5s) and 11.0% lower (Vietnam 5-and-

overs) for water heating and cooking when switching from traditional wood stove to improved stove, suggesting the limited potential for health impacts from replacing traditional stoves with another basic wood stove.

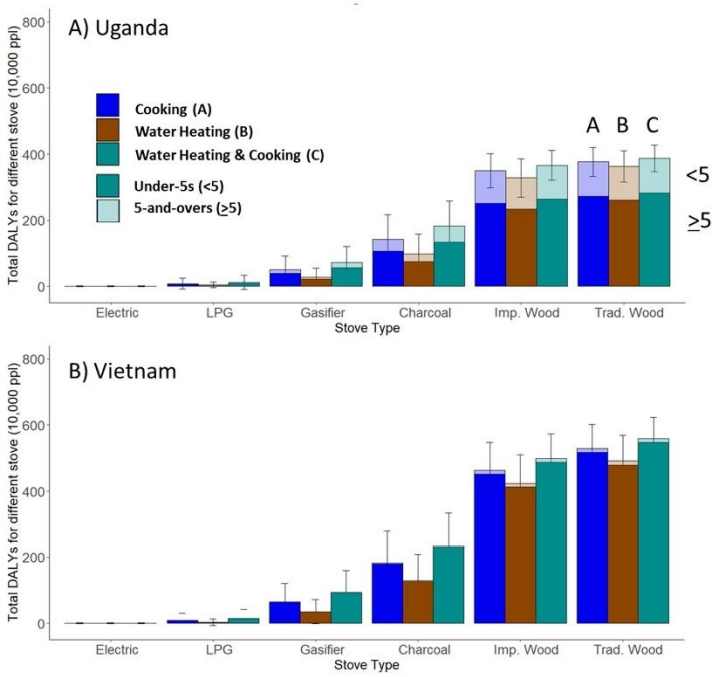


Figure 2.2 *Mean DALYs (Disability Adjusted Life Years) from indoor air pollution for different stove and use scenarios for Uganda (A) and Vietnam (B). Error bars show +/- one standard deviation. Baseline is no stove use. DALYs are calculated for scenarios of cooking only, water boiling, and water boiling plus cooking. Simulation was run for 10,000 iterations of our Monte Carlo Simulation, for a population of 10,000 people. Under-5s refers to children less than 5 years of age and 5-and-overs as all other age groups combined. The bars show Cooking (label "A"), Water Heating (label "B", and Water Heating & Cooking (label "C"), and Under-5s (label ("<5), and 5-and-overs ("≥5"). The stoves presented are electric, Liquified Petroleum Gas (LPG), Gasifier, Charcoal, Improved Wood (Imp. Wood), and Traditional Wood (Trad. Wood).*

In contrast to the additive nature of the $PM_{2.5}$ concentration when aggregating water heating and cooking, DALYs were not additive due to the log-linear nature of the exposure-response curves (Apte et al., 2015; Grieshop et al., 2011a). As a result, the DALYs associated with 'only cooking' and 'water heating and cooking' were similar (e.g., mean of 377 and 387 per 10,000 people, respectively, for traditional wood stove in Uganda for all ages), suggesting that the additional exposure from boiling adds a minimal increment to the HAP impact. However, results in Figure 2.2 show that the relative increment (fractional increase in DALYs from adding boiling) was slightly larger for cleaner cooking options.

2.3.2 DALYs from Water Contamination

The total DALYs from drinking water for Uganda and Vietnam were similar, but a larger share of the DALYs came from children under 5 in Uganda (23-27% compared to 11-14% in Vietnam, across different LRVs and source water values) because of the higher number of children per household in Uganda. DALYs from drinking water were a strong function of untreated water quality and boiling effectiveness. For example, for 5-and-overs in Uganda, and low-risk water, health impacts ranged from 51 DALYs per 10,000 people per year for lab-level boiling to 219 DALYs per 10,000 people per year from ineffective boiling, compared to 228 DALYs without boiling. For high-risk water for 5-and-overs, DALYs ranged from 59 per 10,000 people per year for lab-level boiling to 1128 per 10,000 people per year for ineffective boiling, compared with 1160 per 10,000 people per year without boiling. Using lab-level boiling compared to untreated water greatly reduced 5-and-over DALYs in both Uganda and Vietnam. For under-5s in Uganda, lab-level boiling compared to no boiling lowered DALYs by 94%, 89% and 74% for high-, medium-, and low-risk water, respectively, compared to ineffective boiling. The percent change in DALYs for under-5sin Vietnam were similar (94%, 78%, and 74% lower, respectively).

2.3.3 Comparison of water and air pollution DALYs

In most of our scenarios, the benefits of clean water outweighed the impacts of HAP from boiling that water. Figure 2.3 reports the changes in DALYs for water and HAP exposures under various boiling and stove scenarios. The higher fraction of DALYs for children under 5 years in Uganda for both water and air reflected their higher proportion in the population. Additionally, the relative contribution of the under-5s category was much greater for the HAP risk (driven by ALRI) than for water.

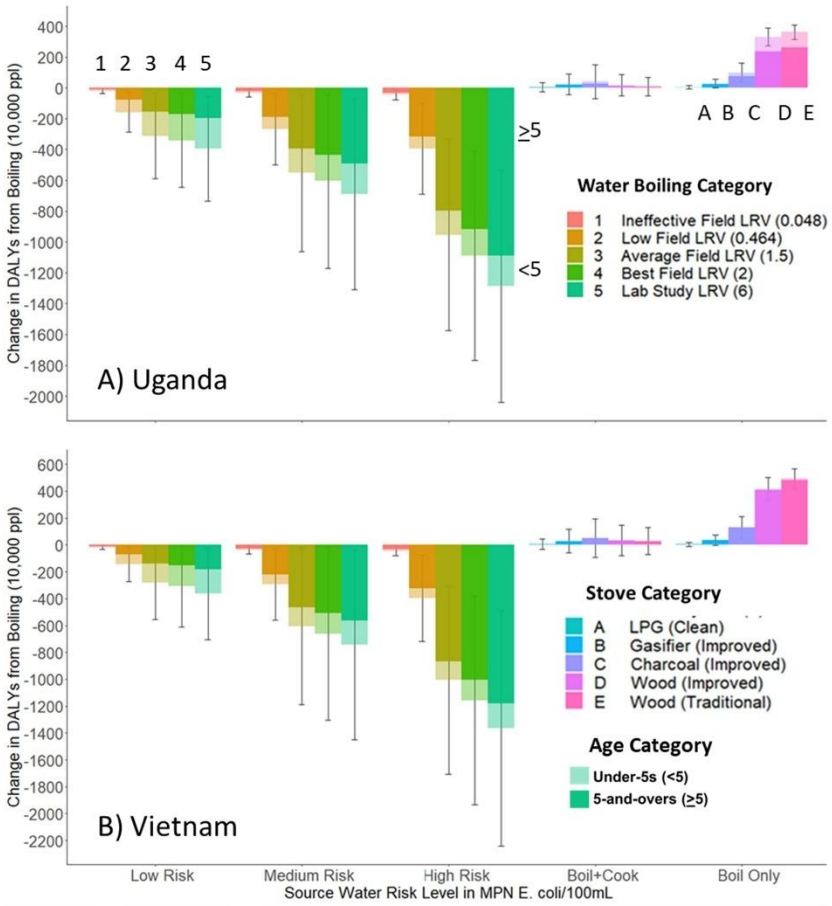


Figure 2.3 *Mean change in DALYs (Disability Adjusted Life Years) from boiling drinking water with different stove types for under-5s and 5-and-overs in Uganda (A) and Vietnam (B) for different stove types and use (assuming households either previously cooked and did not cook), and for different water source qualities and boiling effectiveness. The error bars show +/- one standard deviation from Monte Carlo simulations. Simulation was run for 10,000 iterations of our Monte Carlo Simulation, for a population of 10,000 people. LRV is Log Removal Value, and LPG is Liquefied Petroleum Gas. The first set of bars show different water boiling categories. The number in parenthesis is the respective log removal value (LRV), with ineffective Field LRV 0.048 (label "1"), Low field LRV 0.464 (label "2"), Average Field LRV 1.5 (label "3"), Best Field LRV 2 (label "4"), and Lab Study LRV 6 (label"5"). DALYs are separated into under-5s (label "<5"), and 5-and-overs (label ">5") showing the different age groups. The second group of bars show the stove category, including LPG (label "A"), Gasifier (label "B"), Charcoal (label "C"), Wood-improved (label "D"), Wood-traditional (label "E"). The keys with the corresponding letter labels are provided for the Water Boiling Categories, Stove Categories, and Age Categories.*

All source water categories boiled with lab-level effectiveness (LRV=6) reduced the waterborne DALYs more than HAP DALYs increased for all stove types and stove use scenarios (water heating without cooking, and water heating with cooking). For the scenario of a

household that already cooked with this type of stove and then also started using the stove to boil water, we found that if the source water was boiled with at least the "low field" effectiveness (LRV of 0.5 or greater), the decrease in drinking water DALYs from boiling was greater than the increase in HAP DALYs (for all scenarios of water quality, water boiling, and stove types). In other words, we observed a net benefit for all water risk categories and all stove types for a household that used the same stove for cooking and for boiling water with at least low field effectiveness. If a household only used the stove for boiling water, and did not cook, there was a net benefit if medium- or high- risk water was boiled with at least average field effectiveness for all stove types.

2.3.4 Log-removal rates needed for health benefits from water boiling

As another way to examine net benefits of boiling, the model was also used to determine 'break-even' points where increases in HAP DALYs were equal to the associated decrease in drinking water DALYs. Figure 2.4 shows the reduction in drinking water DALYs for 5-and-overs in Uganda plotted against LRVs for low-risk, medium-risk, and high-risk water qualities. The increase in HAP DALYs is also shown for two stoves, traditional and LPG, and for two different use scenarios, only water boiling and water boiling plus cooking. Where these two sets of curves cross can be considered the 'break-even' point, or the minimum LRV required to provide a net reduction in DALYs for a given stove scenario. High-risk water had a significant decrease in DALYs even with low LRVs. The large decrease in pathogen exposures even with low LRVs resulted in large health benefits. For the case of 5-and-overs in Uganda, the intersection of the curves and HAP lines show that, compared to only cooking in a home, boiling drinking water with an LRV of 0.18 or greater resulted in a net reduction in DALYs for all stove types and source water types; this was true even for the dirtiest stove (traditional wood stove) and low-risk water. In the case that a household was not cooking, but started boiling water, LRVs of 0.2, 0.3, and 1 were needed for high-, medium-, and low-risk water, respectively, to offset DALYs from HAP with a traditional wood stove. The LRV cutoff needed to achieve net health benefits increased as source water quality improved (for example, an LRV of 0.2 is needed for high-risk water compared to an LRV of 1 for low-risk water).

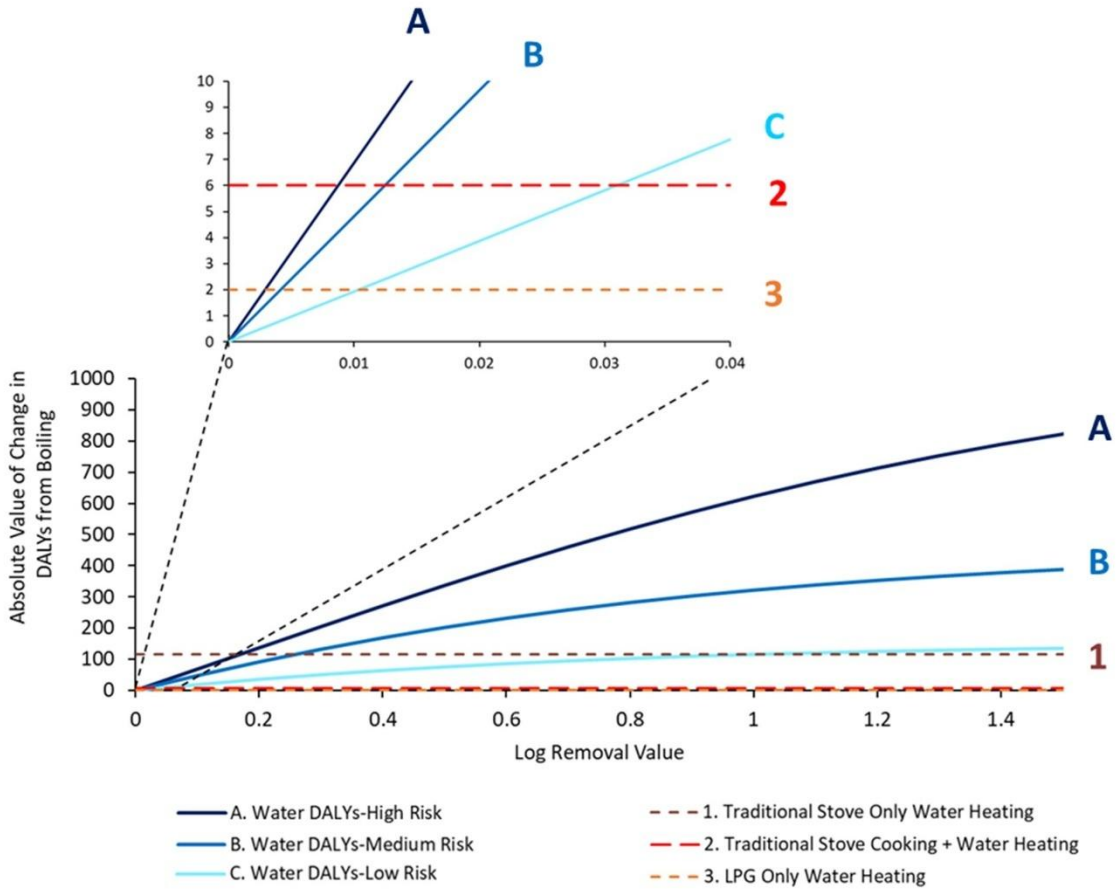


Figure 2.4 *The absolute value of net change in DALYs (Disability Adjusted Life Years) from boiling in water (reduction in Drinking Water DALYs and increase in HAP (Household Air Pollution) DALYs) versus boiling log removal value (LRV) for homes in Uganda, considering 5-and-overs (population 5 years old or older) only. The increase in DALYs, compared to baselines of both cooking and not cooking, are shown for LPG (Liquified Petroleum Gas) and traditional stoves. Water risk levels of low, medium, and high E. coli levels are shown. Inset shows a zoomed in version of the large panel with same axes labels to show tradeoffs at low LRVs. This plot presents the average value of the Monte Carlo Simulation for each log removal value. Water DALYs-High risk is labeled with "A", Water DALYs-Medium Risk is labeled with "B", Water DALYs-Low Risk is labeled with "C", Traditional Stove Only Water Heating is labeled with "1", Traditional Stove Cooking plus Water Heating is labeled with "2", and LPG Only Water Heating is labeled with "3".*

2.3.5 Sensitivity Analysis

Estimated reductions in DALYs from water boiling were most sensitive to the following parameters (listed from greatest to lowest sensitivity): source water *E. coli* levels, the assumed ratios of *Cryptosporidium*, rotavirus, and *Campylobacter* to *E. coli*, age at death, dose-response

parameters used in the QMRA, the LRVs, and the water volume ingested. For HAP DALYs, the input parameters with greatest influence (ranked from greatest to least) were: stove emission factor, household air exchange rate, fuel heating value, and room volume. For the sensitivity of the QMRA dose-response parameters, we varied the parameters for each of the three pathogens, and the level of risk per ingested dose. Of the three pathogens considered in the QMRA, rotavirus had the highest risk per dose of all the pathogens, and as a result, rotavirus exposure had the largest influence on QMRA DALYs (See *Figures A2, A3, A4, and A5*).

2.4 Discussion

In this study, we found that in most scenarios (even at low LRVs and with high-emitting cookstoves), boiling medium- and high-risk drinking water resulted in a net decrease in total DALYs. It was estimated that 1.1 billion people drink water that is of at least moderate risk (Bain, Cronk, Hossain, et al., 2014)**,** so boiling would likely benefit these 1.1 billion people. Additionally, though 89% of the world's population uses an improved drinking source, such as household connections, public standpipes, boreholes, protected wells, springs, and rainwater collection (World Health Organization & UNICEF, 2013)**,** and the odds of contamination are lower for so-called improved sources (Bain, Cronk, Wright, et al., 2014)**,** 10% of improved sources are still considered high risk (Bain, Cronk, Hossain, et al., 2014)**.** Thus, boiling could benefit even those using improved sources. However, in situations in which a high-emitting stove is used to boil water, and cooking is not already taking place in a home or cooking is done on a clean stove, boiling could have a net negative impact, showing the importance of considering risks from both water and air jointly.

Adoption of a new technology or practice is a major challenge for both water and stove interventions and will impact the generalizability of our model results. For example, in an intervention study in Rwanda, use of water filters and improved stoves was measured by self-report and spot-check observations, and though most household used the water filter, the majority continued to use traditional stoves (Rosa, Majorin, et al., 2014). In our model, switching from traditional wood and improved stoves to LPG or electric stoves resulted in 99% reductions of $PM_{2.5}$ and 96% reductions in the HAP DALYs, showing the huge potential for benefits from clean stoves, including for boiling. However, there are still many barriers to adopting LPG, including cost (Pye et al., 2020) and social and cultural perceptions (Bielecki & Wingenbach, 2014; Shankar et al., 2020a). Additionally, households often combine different stove and fuel

types, known as “stove stacking” (Ochieng et al., 2020; Piedrahita et al., 2016; Shankar et al., 2020a), limiting the health benefits of a stove intervention. Traditional stoves continue to be used due to their additional benefits, including heating the living space, lighting the home, heating water for bathing and washing, drying, smoking food, getting rid of waste, keeping insects and animals away, and social gatherings (Ruiz-Mercado & Masera, 2015). This can be especially relevant for water boiling, as previous studies have observed that households continued use of fuelwood to heat water after LPG and electricity are available (Martínez-Negrete et al., 2013; Ruiz-Mercado & Masera, 2015), possibly due to the cost (Ozoh et al., 2018) of such an energy intensive task. Despite these challenges, the use of polluting stoves such as biomass has continued to decrease, from 53% using polluting stoves in 1990 to 36% in 2020 (Stoner et al., 2021). However, there have been increases in charcoal use in many areas (Stoner et al., 2021), which our model suggests only moderately reduces $PM_{2.5}$ relative to traditional wood use.
Our model assumed that all cooking and boiling occurs indoors. However, in some areas, when using certain fuels, boiling outdoors is common (T. Clasen, McLaughlin, et al., 2008), which would reduce HAP exposure from boiling water. In addition, our model assumed that cooking and water boiling happened at two distinct times, while the same fire could be used for both cooking and water boiling, offsetting some emissions. However, emission rates are based on fuel consumed (Jetter & Kariher, 2009), which in either case is required to boil water and will result in PM emissions.

Boiling effectiveness, which varies widely, is key in determining whether boiling has a net health benefit. High adherence to a water treatment method has also been shown to be critical to realizing health benefits (J. Brown & Clasen, 2012). None of the field studies of boiling used for this study observed ‘lab-quality’ LRVs, and many field studies reported very low, even negative LRVs for boiling (Psutka et al., 2011a). Measured LRVs comparing post treatment to untreated water (from the source) are influenced by source water quality before it is boiled, post-boiling storage, dipping, and other sources of recontamination (T. Clasen, Thao, et al., 2008; Psutka et al., 2011a; Rosa, Huaylinos, et al., 2014). Thus, various factors can affect the end water quality despite treatment, limiting the potential benefits of boiling and resulting in a lower effective LRV. Our results showed that boiling is most beneficial in terms of a net reduction in scenarios with high-risk water; however, homes with high-risk drinking water may have the highest risk of recontamination due to poor sanitation practices (Rufener et al., 2010). Therefore,

it is important to maintain improvements in water quality post boiling if water is not immediately consumed (T. Clasen, Thao, et al., 2008; Heitzinger et al., 2016; Psutka et al., 2011a).

Benefits from increasing LRVs from different water treatment methods strongly depended on compliance of use (Enger et al., 2013) and full adoption of the intervention. It has been found that a few days of untreated water consumption after drinking treated water can completely negate the annual health benefits of drinking treated water (Hunter et al., 2009). The literature review conducted for this study on boiling LRVs suggested that societies and cultures with higher prevalence of boiling (e.g., Vietnam) have the highest LRVs (T. Clasen, Thao, et al., 2008). In countries like Zambia where boiling is not prevalent (Geremew & Damtew, 2020), and boiling is promoted as an intervention, the LRVs tend to be much lower (Psutka et al., 2011a). This suggests that introducing boiling as a water treatment method in a community that does not have a history of boiling presents additional challenges, and likely reduces the chances of effective boiling and a net decrease in DALYs (Psutka et al., 2011a).

One notable alternative to boiling is chlorination, which is cheap, effective, provides residual protection (Fagerli et al., 2017; Sobsey et al., 2003), and does not impact air quality. Chlorination has been shown to reduce the risk of child diarrhea and reduce risk of stored water contamination by *E. coli* (Arnold & Colford, 2007). Residual protection could result in higher real-world LRVs. Unlike boiling, chlorination can be applied in several different ways, such as at the source and before drinking (Sikder et al., 2020). However, there are several limitations related to chlorination, including challenges with the supply chain (Dössegger et al., 2021) and managing its use (including frequency and amount of added chlorine) (Nouiri, 2017). Both boiling and chlorination have tradeoffs; however, our study suggests that the minimal HAP impacts associated with boiling are likely not the central factor in deciding whether boiling or chlorination is the best option for a household.

The cost of stoves and fuels were not considered in this study. However, cost is a major factor in whether a household adopts drinking water treatment (Shrestha et al., 2018) or improved stoves (Levine & Cotterman, 2011; Seguin et al., 2018). A cost-benefit analysis comparing boiling with various stove/fuel options could expand on our findings and add another dimension to the tradeoffs we explore.

2.4.1 Strengths and Limitations

Our model is designed to give insights into possible tradeoffs when addressing multiple environmental health risks. Combining two very different models meant we had integrate data from a variety of sources and years. We tried to incorporate the default or previously used values for the HAPIT and QMRA models when possible, but in some instances used different or newer data, such as the background disease data. Because the focus of this study was to develop a model framework applicable to many countries and scenarios with a focus on exploring health tradeoffs rather than detailed contextual differences, this study used many of the same values (e.g., emission factors, fuel efficiency, water *E. coli* levels) for Uganda and Vietnam. Some inputs were country specific, such as demographic parameters. Use of context-specific data on parameters such as stove type, source water quality, and boiling effectiveness, would enable a more accurate evaluation of risks. Some such data are available for our case study countries, such as stove emission factors (S. C. Bhattacharya et al., 2002; Hankey et al., 2015) and source drinking water quality (Morgan et al., 2021; Pham et al., 2022) specific to Vietnam and Uganda, water boiling effectiveness in Vietnam (T. Clasen, Thao, et al., 2008), and studies of water boiling habits in Uganda (Maniragaba et al., 2023). Nonetheless, it is important to note that the focus of the modeling study was to compare risk trade-offs under different scenarios, rather than to provide accurate risk estimates for the specific countries we modeled.

An additional limitation is that the QMRA model did not cover all possible waterborne disease outcomes and their sequelae. Specifically, malnutrition was not included in our analysis, which was shown to significantly increase the health burden from diarrhea (Troeger et al., 2018). Given that our models indicated a net reduction in DALYs from boiling under most scenarios, including additional outcomes associated with consumption of microbiologically contaminated drinking water would have further strengthened our conclusions.

Additionally, some related past studies could be points of comparison, including of household air pollution levels in Vietnam (Vo et al., 2020) and Uganda (Wafula et al., 2023). Our study could be refined by using available data specific to Uganda and Vietnam. However, data for the same settings that covers the multiple dimensions in our analysis (e.g. boiling and air quality data for individual, or nationally representative, settings in a given country) is not currently available. Therefore, a targeted field study of water boiling, pathogen levels in pre- and

post-treated water, and household air pollution concentrations could be beneficial to evaluate boiling in a real-world setting.

Various assumptions used in our HAP modeling could be addressed with more specific input data or targeted measurements. For example, some of the stoves used in our model had poor efficiency, low stove power and low fuel heating values, and thus they are challenged to meet a household's water boiling needs. For these stoves, we assumed that the stove is used up to 24 hours for the household's cooking needs (as opposed to using multiple stoves for a shorter period). This simplifies the model and avoids assumptions about stove use timing, but is not realistic. The emission factors used for the stoves are averages even though emission factors change throughout the combustion process (Cereceda-Balic et al., 2017; Deng et al., 2018; Roden et al., 2009). However, limited data are available on phase-specific emission factors, which necessitated the use of averages. Emission rates were assumed to be the same for cooking and water heating for this study, but are likely different, since it has been shown that varying cooking styles (e.g., frying vs boiling) are associated with different emission rates (Buonanno et al., 2009). However, lacking cooking- and boiling-specific emissions for Uganda and Vietnam, we used average values as a reasonable assumption. Another important simplification is our assumption that a single stove was used for all household uses, ignoring stove stacking (Baiyegunhi & Hassan, 2014; Shankar et al., 2020a).

The box model used to calculate 24-hour $PM_{2.5}$ has been found to overestimate concentrations (Islam, 2020; Johnson et al., 2011, 2021), and so modeled exposures are likely biased high. Depending on where the actual $PM_{2.5}$ exposure falls on the exposure-response curve, this means we could be over- or under-estimating the net change in DALYs due to the added activity for boiling. For example, if the $PM_{2.5}$ with and without boiling falls above where the curves 'plateau', the difference in DALYs we estimated could be smaller than in reality. Our modeled values can be compared with past published field measurements. We estimated mean 24 h $PM_{2.5}$ concentrations ranging from 1797 μg m^{-3} to 5212 μg m^{-3}, 721 μg m^{-3} to 2068 μg m^{-3}, and 14 μg m^{-3} to 16 μg m^{-3} for traditional wood, improved wood and LPG stove use cases, respectively. In a cross-sectional study in India in four states, the measured mean 24-hour $PM_{2.5}$ concentrations were 590 μg m^{-3} in the kitchen for a traditional wood stove and 179 μg m^{-3} in the kitchen for (Balakrishnan et al., 2013). In another study in India of an improved stoves intervention, 24 h $PM_{2.5}$ for LPG stoves ranged from 70 to 103 μg m^{-3}, and was around 500 μg

m^{-3} for households using a traditional three stone fire (Islam et al., 2022a). Mean personal exposure concentrations measured in the HAPIN trial, where high LPG uptake was observed in intervention households, were 71.5 µg m^{-3} and 24.1 µg m^{-3} before and after the intervention, respectively (Johnson et al., 2022). A study in Nepal found 24 h $PM_{2.5}$ of 80 µg m^{-3} for electric stoves and 630 µg m^{-3} for traditional mud wood stoves (Pokhrel et al., 2015). These findings suggest that we both overestimate the impacts of traditional cooking and the benefits of 'realistic' clean stove adoption in many settings. For example, our model calculated substantially lower values for LPG-using households compared to most field studies, suggesting we may have overestimated the benefits of LPG use. Our modeled values for traditional wood stoves were higher than the field studies. Our estimated 24 h $PM_{2.5}$ concentrations for improved biomass stoves were similar to those observed for traditional wood stoves in several field studies, suggesting a bias in model parameters used as defaults. The is potentially at least partly due to stove stacking in the field studies, since many study households used multiple stoves (Pokhrel et al., 2015).

The observation that modeled $PM_{2.5}$ values for traditional stoves were much higher than typically observed in field studies suggests that assumptions in the HAP model (as used in global assessments) lead to estimates substantially higher than reality. However, in our application such a high bias in model results is likely conservative (overestimates HAP impacts while boiling with traditional biomass), and further emphasizes our finding that water boiling typically has a net benefit, even if using a very high-emitting stove. The relative differences we found between exposures associated with different stoves was fairly representative of real-world observations. For example, a 48% reduction in cooking area $PM_{2.5}$ was measured during an improved wood stove intervention study in Rwanda (Rosa, Majorin, et al., 2014), relative to our average modeled reductions of 62% for $PM_{2.5}$ concentrations for a similar scenario (3490 µg m^{-3} and 1334 µg m^{-3} for traditional and improved stoves, respectively). However, as acknowledged above, the non-linearity of the $PM_{2.5}$ exposure-response curves means that, depending on the pre-/post-boiling combination, the modeling could over- or underestimate the DALYs associated with the addition of boiling. Future work can explore this using a re-calibrated model or representative field observations.

Our results can also be compared with previous indoor air quality modeling studies. The study presenting the household air pollution box model used here estimated kitchen

concentrations during cooking, with 24-hr averages ranging from 15 μg m^{-3} for LPG to 1975 μg m^{-3} for traditional stoves (Johnson et al., 2011). The estimated $PM_{2.5}$ concentrations for wood stoves from our study using the model are higher, due to different emission factor, stove power, and thermal efficiency inputs for the traditional stoves. A study in China used this air pollution box model in a more sophisticated way with substantially more household data to refine assumptions. This study used inputs from past field studies in China, assigned a ventilation index based on observations of cooking area ventilation (presumably via a chimney or other active ventilation), and information on cooking and living area location to scale the model air exchange rate. This study reported average modeled kitchen $PM_{2.5}$ concentrations of 79 μg m^{-3} for households using biomass to boil water, with the three homes with poor ventilation having an average of 148 μg m^{-3} (Cohen et al., 2020). Our estimated $PM_{2.5}$ from water heating was significantly higher, likely due to the inclusion of a ventilation parameter and stove emission factors specific to China (Cohen et al., 2020; Shen, 2016), so a direct comparison is likely not warranted. However, this study provides an example of how HAP modeling can be refined for future studies of specific locations.

Our choice of IER is also a limitation. We used the Burnett et al. integrated exposure response functions (Burnett et al., 2014) as that is what the HAPIT model uses (Pillarisetti et al., 2016b). This is a limitation, as the updated meta-regression-Bayesian, regularized, trimmed (MR-BRT) curves were used in more recent assessments (C. J. L. Murray et al., 2020). Although these more recent exposure-response curves are available, we elected to use the IER curves for consistency with the HAPIT tool and the many existing studies using them, to allow more direct comparison with our findings.

Our results can also be compared with direct epidemiological studies. A systematic review of cooking with gas or electricity instead of solid fuels found that cooking with gas instead of polluting fuels lowered the risk of ALRI or pneumonia by 46%, while cooking with electricity instead of gas further decreased the ALRI risk by 26% (Puzzolo et al., 2024). We estimated a much higher reduction in DALYs in under-5s (over 95%) switching from the polluting wood stove to the gas stove or electric stoves or all three of our scenarios in Uganda (cooking only: 98% and 99%; cooking plus water boiling: 97% and 99% ; water boiling only: 98% and 99%). The ranges for adults were similar. Other modeling studies have estimated significant reductions in indoor air pollutants and correspondingly large health benefits

(Anenberg et al., 2017; Kypridemos et al., 2020). For example in Mozambique, a modeling study estimated that a rural natural draft stove reaching just 10% of households would avert 200 premature deaths and 14,000 DALYs (Anenberg et al., 2017). A modeling study of Cameroon included a scenario in which 58% of the households adopted LPG averted 28,000 DALYs (Kypridemos et al., 2020). Unfortunately, field studies studying health impacts from gas stoves and other HAP stove interventions have frequently observed limited improvements in health (Lai et al., 2024). For example, one study saw no improvement in severe childhood pneumonia with gas stove use, and the air pollution exposures remained above WHO health-based target values (Jack et al., 2021). Central limitations of our study are our assumption of full adoption (100% use) of the 'intervention' stove (improved biomass, gasifier, gas, and electric), thus no stove stacking, and not including exposures from other sources and high ambient air pollution levels. An additional limitation is that a significant portion of ambient $PM_{2.5}$ exposure can be attributed to emissions from household solid fuel uses (Chafe, Brauer, Klimont, Van Dingenen, et al., 2014; Chowdhury et al., 2023), which is not accounted for in our model; therefore, our estimated health impacts from burning solid fuels might be underestimated. Further modeling efforts could attempt to incorporate these factors into risk estimates.

We compared our drinking water estimates with results from two epidemiological studies. Cohen et al. found risk ratios of 0.61 (95% confidence interval (CI): 0.46-0.80) for boiling in an electric kettle, and 0.40 (95% CI: 0.08–2.14) for boiling in a pot (Cohen et al., 2015), corresponding to a 39% and 60% reduction in reported diarrhea, respectively. The source water in this study varied, with approximately half of those boiling water using an improved water source, though improved water sources may still be contaminated. In another study, Psutka et al. found (non-statistically significant) relative risks of 2.38 (95% CI: 0.75-7.54) and 1.26 (95% CI: 0.68-2.31) for a household *not* boiling water and a child having diarrhea sometime in the past 7 days and past month, respectively. These correspond to relative risks of 0.42 (95% CI: 0.13-1.33) and 0.79 (95% CI: 0.43-1.47), or a 58% and 21% reduction in the risk of diarrhea, for households reporting boiling water.(Psutka et al., 2011a) In the second study, nearly all of the source water was contaminated (Psutka et al., 2013). In our study, for under-5s in Uganda for moderately-effective boiling, we estimated mean reductions of 56% to 72% in DALYs depending on source water quality; for low-effectiveness boiling, we estimated reductions of 29% to 35%. Therefore, comparisons of DALY reductions from our study and reductions in

diarrhea risk in these epidemiologic studies suggest that our estimates based on moderate- and low-effectiveness boiling scenarios (the likely conditions for population-based epidemiological studies) are relatively consistent with empirically measured health benefits from boiling. Environmental factors outside the home may also have an important influence on HAP not addressed in our model. For example, although ambient air pollution levels in LMICs vary widely across countries and between urban and rural areas (Apte et al., 2015; Chafe, Brauer, Klimont, Dingenen, et al., 2014), for simplicity, we assumed a fixed background ambient $PM_{2.5}$ concentration; further analysis could vary this. If actual ambient air pollution levels are higher, $PM_{2.5}$ exposure levels will be shifted higher on the exposure-response curves, resulting in a smaller additional risk from the increment of $PM_{2.5}$ from boiling water. We also considered only cooking and water heating, and did not consider space heating, even though many countries in the world where boiling is common are located in cold regions (Geremew & Damtew, 2020; Rosa & Clasen, 2010). Additionally, it is assumed that boiling is only used for drinking water, not for making tea or bathing. However, if a household is burning fuel for space heating or other reasons, and boiling occurs simultaneously, no additional HAP DALYs would be incurred to boil water.

Several simplifying assumptions made in the water module also influence our results. For example, though we separated by population over and under the age of 5, we assumed a constant probability of death for all ages. However, this likely leads to an underestimation of the years of life lost due to death from diarrhea since children have the greatest risk of death and disease from diarrheal diseases (Fischer Walker et al., 2012). Children do not have a fully developed immunity so are more susceptible to diarrheal illnesses, which is not accounted for in the dose-response curves used in the modeling. Therefore, if child-specific dose-response curves were available and used, the benefits of boiling would likely be greater.

We estimated pathogen levels based on fecal indicator bacteria (i.e., *E. coli)* levels, which are imperfectly correlated with the selected pathogens (Wu et al., 2011). Further, pathogens present in drinking water vary widely by country and across seasons (Sadik et al., 2017). We expect that the results would vary widely based on the pathogens selected, as has been found in previous studies (Owens et al., 2020). Further, the risks associated with exposure to rotavirus would be dependent on the vaccination status of the population (Patel et al., 2011). However, even in a population fully vaccinated against rotavirus, the DALYs associated with rotavirus in

our model are intended to represent illness from a variety of enteric viruses. Further, rotavirus prevalence as high as 40% has been documented in untreated groundwater used for drinking (Ferguson et al., 2012). Our results were highly sensitive to parameters related to pathogen risk. Thus, pathogen-specific water quality data would be helpful to characterize risks associated with pre- and post-boiling water. Limited data exist, but new methods (with their own associated limitations) are expanding the potential for pathogen-specific data, such as the use of TaqMan array cards for environmental samples (Lappan et al., 2021). Additionally, water quality in LMICs can be highly temporally variable, with spikes in contamination, and intermittent exposure to contaminated drinking water can negate the benefits of improved water access.

DALYs are used for comparative risk assessment, including environmental risks such as HAP and water contamination. DALYs allow comparison across risk categories, and are the common metric used in the Global Burden of Disease estimates (C. J. L. Murray et al., 2012). Estimates for DALYs from air pollution and water are calculated using very different approaches, which we adopted for this study. Additionally, though DALYs account for the years of life lost and years lived with disability, they don't perfectly capture the acute versus chronic nature of disease, which is an important difference between HAP and water risks. Using these different methods to compare different risks and outcomes is an inherent limitation in the comparative risk assessment approach. However, we took this approach as it is the most widely used to compare diverse risk factors. Future work can examine other methods to calculate and compare the risks from drinking water and HAP, including field studies to provide context-specific findings to compare against the broad insights from this scoping analysis.

2.5 Conclusions

To our knowledge, this is the first study to compare water and air pollution DALYs for scenarios of household cooking and water boiling to determine if boiling water has a net benefit regardless of stove and fuel type. Our model identified certain scenarios that, when risks for water and air are considered separately, could suggest DALY reductions but that due to combined effects ultimately results in net positive DALYs. For example, if a household that does not cook their food is encouraged to boil water on a wood stove, they would experience increased air pollution exposure that may outweigh benefits of ineffectual water boiling. However, this scenario is likely an exception, and our modeling suggests that boiling even at low log-removal rates has net health benefits for medium- and high-risk source water, even if using a

relatively high-emitting stove. In contrast, when treating low-risk source water, boiling effectiveness and cookstove type influence whether net health benefits result from the practice. We recommend further field investigations to jointly assess health effects associated with contaminated drinking water and household air pollution and the development and evaluation of interventions to mitigate both exposures. Due to uncertainties and assumptions in the model, we recommend that country or context-specific inputs be used, and ideally studies of boiling and household air pollution with empirical measurements of water and air quality be conducted to improve understanding of the health risks and tradeoffs and evaluate our model. Specifically, more information on household-specific parameters, including pathogen contamination in water, stove types, cooking and boiling energy requirements, and parameters linking emissions to household air pollution and exposure could improve the model. Future efforts should empirically measure air pollution concentrations (to estimate health impacts) and diarrhea during field studies of different boiling methods and stove types, to both provide better input parameters and improve our ability to model risk tradeoffs.

2.5.1 Acknowledgments

This work was supported by the Energy Poverty PIRE in Southern Africa Project (National Science Foundation Award #1743741). EF acknowledges support from the NC State Global One Health Fellowship.

Data output from the project is available at the following link: https://doi.org/doi:10.5061/dryad.9zw3r22jz

Special thanks to Sean Daly for his suggestions and feedback on this project. Thank you to Cheryl Weyant for providing feedback on the writing. We would like to dedicate this paper to the memory of Haley Foard, a North Carolina State University undergraduate researcher who contributed to the literature review and research in the initial phase of the project during Summer 2020.

Chapter 3: Household Food, water, and energy insecurities and links to behaviors and environmental contamination in Peri-urban Malawi

This chapter is being prepared for submission as: Floess, E., Clark, B., Niven, C. G., Chirwa, B., Matekenya, M., Budden, E., Cadono, S., Chavula, J., Chisamanga, V., Dzinkambani, A., Kaponda, C., Ngondo, N., Patterson, N., Symons, S., Chunga, B. A., Holm, R.H., Chigwechokha, P., de Los Reyes, F., Ercumen, A., Workman, C. L., Grieshop, A., & Harris, A. R. (2025). Household Food, water, and energy insecurities and links to behaviors and environmental contamination in Peri-urban Malawi. Science of the Total Environment.

Abstract

Field studies quantifying the connection between household-level food, energy, and water insecurity are sparse, especially in low and middle-income countries in sub-Saharan Africa. However, energy shortages and poverty have been identified as playing key roles in household decision-making and are closely linked with other environmental health risks. Our objective was to analyze the overlap of water, food, and energy insecurity, and their interactions with water, food, and energy health-related behaviors and indicators. We sampled food and drinking water samples 237 households with a range of socioeconomic statuses in a peri-urban area outside Blantyre, Malawi. We also collected survey data on household demographics and socioeconomics, water use, sanitation, cooking, health, agricultural activities, fuel use, and validated scales of food, energy, and water insecurity. The majority of homes used charcoal and an improved, yet contaminated, drinking water source, but did not treat their water; of those who did, only one reported boiling. Eight percent of all households experienced all three insecurities, 82% had one or more, and 18% experienced none of the insecurities. The largest proportion of the population (52% of households) experienced at least one instance of both food and energy insecurity but no instances of water insecurity. We found that increased energy insecurity was associated with increased food insecurity. Food and energy insecurity were associated with increased contamination of drinking water and with behaviors such as heating water, using more than one stove, burning trash as fuel, having electricity, having a fridge, and having piped water in the yard or home. However, food and water contamination were not connected with water or food insecurity. The results from this study will help policymakers incorporate food, water, and

energy insecurities holistically when considering household interventions to address microbial contamination.

3.1 Introduction

3.1.1 Global burden of resource insecurity and its health impacts

Household-level food, water, and energy insecurity are critical global challenges that disproportionately affect low- and middle-income countries (LMICs) (FAO et al., 2024; Min et al., 2024; Mekonnen & Hoekstra, 2016) and are linked to the UN Sustainable Development Goals 2, 6, and 7 (United Nations, n.d.). Seventy-one percent of the global population experienced severe water scarcity at least one month per year in 2016 (Mekonnen & Hoekstra, 2016), and in 2020, 2 billion people lacked safely managed drinking water (WHO/UNICEF, 2020). In 2024, 1.18 billion people (14%) were energy poor (Min et al., 2024), and in 2023, 28.9% of the global population was moderately or severely food insecure (FAO et al., 2024). Additionally, food (Mekonnen et al., 2021), water (Gunda et al., 2025; Stoler, Brewis, et al., 2021), and energy (Ehsanullah et al., 2021) insecurities are expected to increase with climate change.

3.1.2 Challenges in Peri-urban areas

Peri-urban areas experience resource constraints and rapid population growth (Kombe, 2005), impacts from climate change (Manasi & Raju, 2020), and experience increased food (Haile Aboye et al., 2024), water (Leya et al., 2022), and energy (Cantoni et al., 2022) insecurities. Though energy insecurity has been linked with a lack of infrastructure (Caprotti et al., 2024), energy insecurity presents itself differently in urban areas compared to rural areas in Malawi (Mukwaya, 2016), with households needing to purchase fuel, such as charcoal, especially in urban areas (World Bank Group, 2022). Food is also a challenge in urban areas. For example, in urban Ghana, less than 3% produce their own food, and households rely on purchased food (Tuholske et al., 2020). Food insecurity is also high in urban slums (Ilori et al., 2024). Households in urban areas often have easier access to water; for example, they more often have water in their homes (Cortobius, 2017). However, water scarcity is still a challenge in many urban areas, including in Blantyre, Malawi (Chipeta, 2009). In Blantyre, Malawi, some of the challenges include lack of infrastructure to provide the necessary water across the city (Chipeta, 2009).

3.1.3 Connections between insecurities

Past studies have explored the interconnection between household insecurities. Water is a significant use of household energy (Howells et al., 2005; Kenway et al., 2013; Yu et al., 2018) and water and energy are interconnected (Eichelberger, 2010; Cook et al., 2008). Household water and food insecurity have been found to be strongly associated (Bethancourt et al., 2023; Brewis et al., 2020; Broyles et al., 2024; Mazenda & Nkwana, 2025; Rosinger & Young, 2024; Shamah-Levy et al., 2025), and water, sanitation, and energy access are determinants of food security (Mazenda & Nkwana, 2025). Water insecurity also impacts the ability to prepare food for infants (Schuster et al., 2020) and impacts what is being eaten (Brewis et al., 2020).

Energy and food insecurity are connected (Ningi et al., 2022). In Malawi, energy-insecure households reduced their food consumption by 2.3% for each 1% unit increase in the share of energy costs of their total household budget (Mkomba et al., 2021). Similar findings are found in Cambodia (Phoumin & Kimura, 2019). It is suggested that fuelwood scarcity could affect food security (Sola et al., 2016). In the United States children with moderate energy insecurity had greater odds of household food insecurity and child food insecurity (Cook et al., 2008). In cold weather, households struggled to afford heat and food (J. Bhattacharya et al., 2003). Low-income households and households with elderly people experience substantial seasonal differences in the incidence of food security in areas with high heating and cooling costs (Nord & Kantor, 2006).

Only three studies have examined household-level FEW nexus (Itayi et al., 2021). A study in Iraq developed a model for exploring household food, water, and energy consumption (Hussien et al., 2017, 2018). A study looked at food, water, and energy insecurity in Malawi (Nkiaka et al., 2021). Recently, a study explored the household food, energy, and water nexus as it connected to disaster preparedness (Painter et al., 2025).

3.1.4 Insecurities and Health Risks

Few studies explore the connection between household insecurities and microbial contamination. Studies with do often compare within their domain (for example, water insecurity and water contamination). In Canada, marginalized Indigenous communities experience water insecurity and contaminated water (Zambrano-Alvarado & Uyaguari-Diaz, 2024). Food spoilage from microbial contamination increases food insecurity (Elkhishin et al., 2017). Looking across different domains, children in households with very-high-risk drinking water contamination have

2.35 times the relative risk of being severely food insecure compared with food insecure (Miller et al., 2025). It is also hypothesized that energy insecurity leads to increased food and water contamination (Boateng, 2021). Indirectly connected to energy insecurity, there are also studies looking at microbial contamination related to boiling (Psutka et al., 2013). To our knowledge, no study has looked at all three of these insecurities at a household level together, along with microbiological contamination and behaviors. In addition, practices to reduce microbial contamination, such as boiling, are often recommended without considering energy insecurity.

Insecurities are directly connected with health risks. Food insecurity is linked to diarrhea (Chakraborty et al., 2024), anemia, stunting, and lower life expectancy (FAO et al., 2024; Beyene, 2023). Water insecurity is linked to respiratory illness (Chakraborty et al., 2024), emotional distress (Wutich & Ragsdale, 2008) and an increased risk of diarrhea (Jepson et al., 2021; Nounkeu et al., 2019). Households experiencing energy insecurity have higher odds of respiratory, mental health, and cardiovascular conditions (Siegel et al., 2024). Energy poverty contributes to poor mental health, limits health services, and impacts women's well-being (Byaro et al., 2024; Pradhan Shrestha et al., 2025).

By coping with insecurities, households often introduce health risks. Food-insecure households will reduce the number of meals eaten in a day and restrict adult consumption in favor of small children (Dunga & Dunga, 2017). Unsafe food practices (e.g., feeding leftovers) contribute to child diarrhea (Delelegn et al., 2020). Energy-insecure households will forgo necessities to maintain a healthy indoor temperature (Hernández & Laird, 2022). Water-insecure households consume contaminated water (Azupogo et al., 2023), use unsafe water (Collins et al., 2024), increase water storage capacity to ensure adequate water (Venkataramanan et al., 2020), and go further to find water (Achore et al., 2020). Joint impacts of insecurities impact a household's well-being (Asaki et al., 2024). (Foden et al., 2019; Shahbaz et al., 2022).

3.1.5 Study Objective

In this study, we evaluated the co-occurrence of FEW insecurities and their association with microbial contamination and household behaviors in peri-urban Malawi during the dry, winter season. We used validated experiential food, water, and energy insecurity scales to evaluate household-level insecurities and their connection between pathogen levels in drinking water and food samples and household behaviors and access to food, energy, and water.

3.2 Methods

3.2.1 Study Population and Location

This study took place in Bangwe, a peri-urban area of the city of Blantyre, in the southern part of Malawi. Bangwe has a population of 39,966 (UN-HABITAT, 2011), and the greater Blantyre metro area has a population 800,264 (National Planning Commission, n.d.) and is the second largest city in Malawi (World Population Review, 2025). Samples were collected from June to July 2024, during the period of the main harvest (FEWS NET, 2025) and the dry season, though there was some rain, as this part of Malawi receives higher annual precipitation than other parts of the country (Tadeyo et al., 2020, pp. 1979–2015). In June, in Blantyre, the temperature ranges from 53.4ºF to 70.9ºF, with average precipitation of 0.6 inches (Climate Data, 2025). In 2024, the southern part of Malawi experienced a crisis-level of food insecurity, with an early start to the lean season (FEWS NET, 2024). Characteristics of Malawi and the study population are provided in Table B1.

3.2.2 Research design

This was a cross-sectional field with all data collected during a one-month-long period from June-July 2024. This study consisted of validated experiential insecurity scales (Boateng et al., 2020a; Coates et al., 2007; Young et al., 2019a), survey questions on demographics, WaSH, energy, agricultural access, and food and water sample collection. Further details about the survey development and sample collection are provided below.

We recruited 237 households. Households were systematically selected using random central points in Bangwe. Every third household in all directions from the starting point was approached. Households were eligible for enrollment if they had at least one child under 5, and an adult over the age of 18 who was responsible for the children and was available and consented to participate. Enrolled households were visited once. Every household answered the insecurity questions, and 235 provided water samples, and 43 provided food samples.

3.2.3 Ethics Approval

Trained enumerators from Mzuzu University and Malawi University of Science and Technology administered the survey and collected the samples. The research protocol was approved by the Research Ethics Committee (MZUNIREC) at Mzuzu University (MZUNIREC/DOR/24/38) and the University of North Carolina, Greensboro (UNC-Greensboro IRB #:20-0245), with additional ethical oversight from North Carolina State University via the

Inter-Institutional Agreement. Participants provided written informed consent in the local language (Chichewa).

3.2.4 Insecurity Questions

The household survey instrument included validated experiential insecurity scales with five-point Likert scale questions (Boateng et al., 2020a; Coates et al., 2007; Young et al., 2019a). The Household Food Insecurity Access (HFIAS) scale assesses the frequencies of nine experiences of food insecurity within the last four weeks, including: not eating preferred foods, eating foods you don't want, worrying that you don't have enough food, eating a limited variety of foods, eating a smaller meal, eating fewer meals in a day, not having food to eat, going to sleep hungry, and going a whole day and night without eating (Coates et al., 2007; International Dietary Data Expansion Project, 2023).

The Household Energy Insecurity (HEINS) scale assesses the frequency of eight experiences of energy insecurity within the last four weeks (Boateng et al., 2020a), including: lacking money to buy fuel, reducing expenses, worry that stored fuel will be used up, reducing fuel consumption to an uncomfortable level, using fire for lighting, using up household fuel, and switching to a cheaper fuel source (Boateng et al., 2020). The wording of one question was updated to better fit Malawi. We changed "In the last four weeks, how frequently did your household energy (electricity, gas, charcoal, wood, etc.) get used up and you didn't have money to pay for it without somebody's help?" to "In the last four weeks, how frequently did your household fuel (electricity, gas, charcoal, wood, etc.) get used up so you didn't have anymore?"

The Household Water Insecurity Experiences (HWISE) scale (Young et al., 2019) assesses the frequencies of 12 experiences of water insecurity in the last four weeks, including: worrying about not having enough water, not being able to wash hands, having to change schedules/plans, not having as much water to drink as preferred, water source being interrupted or limited, not having enough water to wash clothes, having to change what was being eaten, not having enough water to bathe, feeling angry about the water situation, going to sleep thirst, have no usable or drinkable water, and feeing ashamed (Young et al., 2019).

3.2.5 General Survey Questions

The household covered multiple household domains relevant to food, water, and energy use, including demographics, WaSH, food access, energy use, health, and hygiene. WaSH questions came from the WHO joint monitoring program core questions on WaSH (World Health Organization & UNICEF, 2018). Energy questions came from the WHO core questions on household energy use (World Health Organization, 2019), which includes the Harmonized survey questions for monitoring household energy use and SDG indicators 7.1.1 and 7.1.2 (World Health Organization et al., 2019), and guidelines for questionnaire development (O'Sullivan & Barnes, 2006). We also added additional questions based on feedback from students in Malawi and pilot data collection, such as questions on how a home is warmed. Questions were translated and back-translated to ensure the questions have the correct meaning. Enumerators were trained over several weeks on survey and environmental data collection, as well as ethical data collection. Surveys were conducted in Chichewa by Malawian students in respondents' homes.

3.2.6 Environmental Sampling

Enumerators asked participants for a glass of water as they would give to a child under 5. At least 400 mL of water were collected in 500 mL capacity sterile Whirl-Pak bags (Whirl-Pak Filtration Group, 2025). 235 drinking water samples were collected. It was noted if the water sample came from a storage container, when it was collected, if it was covered, the source of the water, if the water was treated, and how.

Enumerators asked households if they have food stored for children under 5, and if not, if they have stored food available for any household member. The food type was recorded, in addition to how long ago the food had been prepared, if and when the food had been reheated, and the storage container for the food, and a small sample of food was placed into a sterile tube (Fisher Scientific, 2025). 43 food samples were collected. All samples were stored and transported on ice and analyzed within 6 hours of collection at the Malawi University of Science and Technology.

3.2.7 Microbiological Analysis

E. coli concentration was enumerated in the food and water samples using IDEXX selective media Colilert-18 and Quanti tray 2000s. For the water samples, 100 mL of water was used. For the food samples, 8 grams of food was placed in 40 mL of sterile water in a 13 oz whirl Pak bag, and vigorously mixed for 30 seconds (Harris et al., 2018). Then, 10mL of the food elution was added to 90mL of sterile water and processed using the IDEXX protocol. The samples were sealed with the Quanti-Tray sealer model 2X) and incubated for 18 to 22 hours at 35 °C. The Quanti-Tray/2000 system can quantify the number of *E. coli* in 100 mL water samples over a range of 1-2419.6 MPN per 100 mL. Data below 1 was considered nondetect, and over 2419.6 was considered the maximum limit of detection (Daly et al., 2024; Genter et al., 2022).

After incubation, wells that fluoresced under UV light were positive for *E. coli,* and the most probable number (MPN) was determined. The most probable number estimates quantitative values by culturing replicate portions of the organism sample, and then the presence or absence of the microorganism is determined (Chandrapati & Williams, 2014). One field blank and one laboratory blank using 100 mL sterilized water, but quantified using the same protocol, were analyzed on each day of sampling (Harris et al., 2018).

3.2.8 Data Processing

Analysis of the insecurity scales was done using existing methods, with the often and always categories both scored as a three (Boateng et al., 2020a; Coates et al., 2007; Young et al., 2019a). We used existing insecurity cutoffs or developed new ones. For the HWISE scale, we used scores of 0-2 as non-to marginal, 3-11 as low, 12-23 as moderate, and 24-36 as high (Frongillo et al., 2024; Young et al., 2019a). For food insecurity, we used ordinal categories of mild, moderate, and severe food insecurity (Coates et al., 2007). In the absence of a literature-defined value for energy, we used a threshold similar to HWISE for HEINs (greater than 2 is considered mild or greater energy insecurity, greater than 8 is considered moderate/severe energy insecurity, with a maximum score of 24). We use the moderate/severe cutoffs to report insecurity in the main results.

Using the household survey data, we developed binary indicators of household behavior and infrastructure (e.g., fridge use, reheating food, water storage). For contamination variables, we looked at the presence/ absence of *E. coli* in food/water and log-transformed values.

3.2.9 Statistical Analysis

Analysis was conducted in R (R Core Team, 2025). Bivariate statistics, including t-tests, Chi-squared or Fisher's exact (for sample sizes less than five), and Pearson's correlation, were used to assess differences in contamination for secure/insecure households, significance for behaviors, and household access given insecurity status, and the relationship between insecurity scores. For the food contamination samples, we only used bivariate tests due to the small sample size. For water contamination, we also used a Generalized Estimating Equation (GEE) (Halekoh et al., 2006) model to look at the relationship between water contamination and water and energy insecurity, source type, and treatment, with household income as a confounder. All data was tested for normality using the Shapiro-Wilk test and visually using a histogram and quantile-quantile plot. P values less than 0.05 were considered significant.

A Principal Component Analysis (PCA) was used to analyze the individual insecurity data (Lê et al., 2008), with a scree plot being used to identify the number of components(J. D. Brown, 2009).

3.3 Results

3.3.1 Study Population

Table 3.1 gives an overview of the study population. Households in Bangwe exhibited WaSH, energy, and demographic characteristics typical of urban Malawi (a comparison of this study population to other studies in Malawi is provided in Table B1), with widespread charcoal and improved water sources. Over half (58%) of households used more than one fuel source (also indicated by the percentages summing to over 100% of different fuels used- for example, 95% of households used charcoal and 48% wood). 97% of households used improved water sources for drinking (defined as piped water, boreholes, protected wells, rainwater, packaged, and delivered water (WHO et al., 2025)). Most well users had a protected well (14/16) for drinking. Nine percent of the samples taken directly from the tap at the time of collection. On average, water was stored for at least one day. For water used other than drinking, 71% used an

improved water source, and 64% of the well water users used a protected well. Only 15% treated their water, and those who did mostly used bleach or chlorine (13%).

All but four households (99%) owned a latrine. Sixty-six percent of households had a grid electricity connection. Electricity, candles, and phones/flashlights were the main light sources. Charcoal was the dominant energy source for all energy needs (95% used it for some purpose), followed by wood (48% of households used it). There were no LPG users, but there was one biogas user. Many households also used leftover warm charcoal as an energy source. Two households used crop residue for cooking, and one used solar for water heating only. Households that used clean sources used them in addition to other fuel sources. For example, 16 households used electricity for water heating, but all of them also used charcoal, leftover warm charcoal, and wood for water heating. Though few households boiled drinking water, 86% of households warmed water and 82% warmed their home.

Table 3.1 *Characteristics of households in our study population. This table summarizes key WaSH, energy, and sociodemographic characteristics. The number of households is provided, followed by the percentage. Values summing to over 100 indicate multiple source use (stacking).*

	Number of Households (%)	
	WaSH	
Primary Water Source	**Drinking**	**Non-Drinking**
Tubewell/borehole	51 (22)	31 (13)
Well	16 (7)	81 (35)
Surface Water	2 (1)	34 (14)
Piped	132 (56)	71 (30)
Vendor	30 (13)	13 (6)
Other	4(1)	5(2)
Treat Drinking Water		
Boil	5 (2)	
Bleach/Chlorine	31 (13)	
Other/Don't know/Don't Treat	199 (85)	

Table 3.1 *(continued)*

Water sample collected from the tap	214 (91)			
Spend time to collect water	73 (31)			
	Too expensive	**No water from source**	**Source not accessible**	**Other**
Reason water isn't accessible	12 (5)	18 (8)	4 (2)	4 (2)
Average time water is stored (days)	1.318			
Owns Latrine	233 (99)			
Designated Hand Washing Station	24 (10)			
	Electricity			
No Electrical Connection	70 (30)			
Off grid connection (such as solar or generator)	12 (5)			
Grid	155 (66)			
	Lighting Source			
Electricity (Grid/Solar)	162 (69)			
Candles/Other	181 (77)			
Battery lamp/flashlight/phone light	230 (98)			
	Energy			
Proportion Fuels Used	**Electricity/ Solar/Gas**	**Charcoal**	**Leftover Warm Charcoal**	**Wood/ Briquettes/ Other**

Table 3.1 *(continued)*

Primary Cooking Fuel	6 (3)	195 (82)	0 (0)	30 (13)
Water Heating (All)	18 (8)	181 (76)	44 (19)	65 (27)
Heating (All)	0 (0)	123 (52)	98 (41)	8 (3)
Reheating Food (All)	6 (3)	50 (21)	12 (5)	15 (6)
All Fuels Used	22 (9)	225 (95)	109 (46)	114 (48)
Stove Stacking	**1 fuel only**	**2 fuels only**	**3 fuels**	**4 fuels**
Multiple fuel use	99 (42)	90 (40)	34 (14)	4 (2)
	Don't purchase (collect)	**Purchase daily**	**Every other day**	**Purchase less than daily**
Purchase fuel	7 (3)	41 (17)	117 (49)	65 (27)
	Completely outside	**Separate structure/porch**	**Kitchen in living space**	**Inside living space**
Cooking Location	67 (29)	128 (54)	54 (23)	73 (31)
	Plastic bags	**Paper**	**Twigs**	**Bottles/synthetic hair/other**
Lighting Fire	215 (91)	85 (36)	59 (25)	29 (12)
	Owns Fridge	**Always working Fridge**	**Sometimes/ Rarely/ Never Working**	**Food Sample in Fridge**
Fridge	56 (24)	29 (12)	18 (8)	0 (0)
	In past 7 days, houses which			
Stored food in fridge for a child under 5	9 (4)			
Reheated Stored Food	67 (29)			
Boiled drinking water	1 (0.4)			
Heated the home	193 (82)			
Had electricity	165 (70)			

Table 3.1 *(continued)*

Heated water for any purpose	203 (86)			
	Heated Water For			
Bathing	199 (85)			
Drinking/Tea	206 (88)			
Laundry/Other	8 (3)			
Hand Washing	42 (18)			
	Water Heating	**Cooking**	**Reheating Food**	**Heating Drinking Water**
Reduce Fuel For:	116 (50)	72 (30)	46 (19)	14 (6)
Insecurity	**None**	**Mild**	**Moderate**	**Severe**
Food	35 (18)	15 (6)	55 (23)	132 (56)
Energy	37 (16)	50 (21)	110 (46)	40 (17)
Water	138 (58)	76 (32)	21 (9)	2 (1)
	Sociodemographic			
Own Home	82 (35)			
Primary Education & Higher	166 (71)			
Involved in agriculture	79 (35)			
Own Animals	57 (24)			
Received food aid	5 (2)			
	Mean Weekly Expenditure Malawian Kwacha (USD)		**Percent below global poverty line (<$3.00 a day)**	
Household Expenditure	29435 ($17.05)		187 (79)	
	Household Size			
Average Number of Adults	2.74			

Table 3.1 *(continued)*

Average Number of Children ≥ 5	1.37
Average Number of Children <5	1.21

3.4 Food, Water, and Energy Insecurity and their overlap

Households exhibited overlap in their experiences between food, energy, and water insecurity (results shown in the Venn diagram in Figure 3.1 using the moderate/severe insecurity cutoff, with values provided in Table B2). As shown, a significant number of households experienced both food and energy insecurity (60%). Food insecurity was the largest category for which households experienced that insecurity alone (18%). Eight percent of households experienced moderate/severe levels of all three insecurities concurrently. Only a few households experienced water insecurity alone (0.4%), water and food insecurity, but not energy insecurity (1%), water and energy insecurity, but not food insecurity (0.4%), and energy insecurity only, with no water or food insecurity (3%). The analysis using the mild cut-off for secure/insecure can be found in Figure B1 and Table B2. We also calculated the mean and maximum insecurity scores for the 237 households in our sample size. For food insecurity, there was a mean of 10.42, and a maximum insecurity score of 27 (out of a maximum possible score of 27). For energy insecurity, there was a mean of 9.61, and a maximum insecurity score of 24 (out of a maximum possible score of 24). For water insecurity, there was a mean of 3.89, and a maximum insecurity score of 31 (out of a maximum possible score of 36). Only 42 (18%) households experienced no insecurities using the moderate/severe cutoff and 21(9%) experienced no insecurities using the mild cutoff.

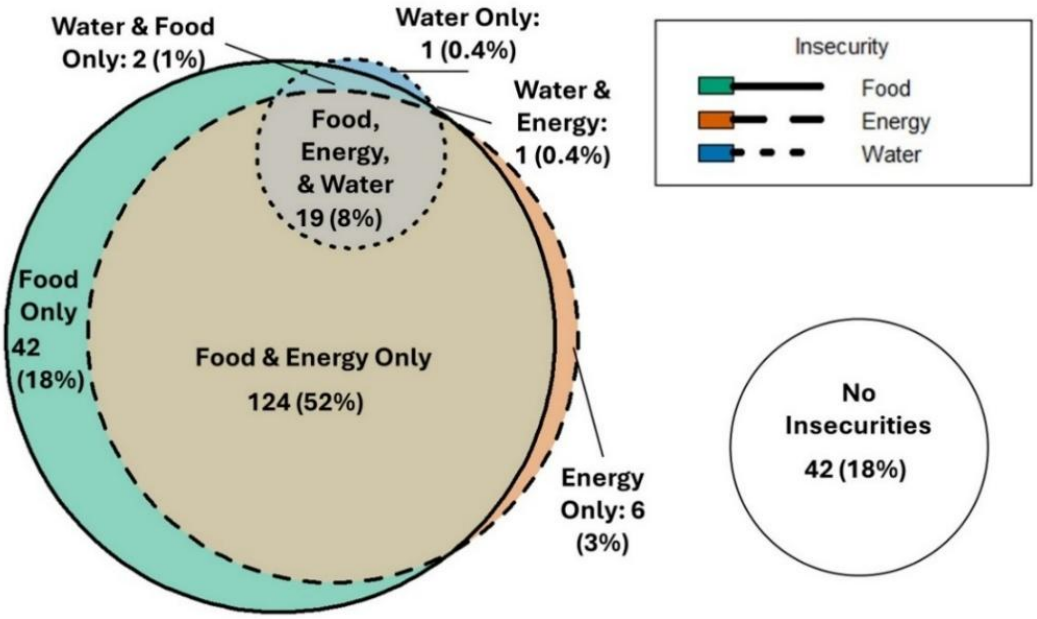


Figure 3.1 *Venn diagram showing the proportion of households experiencing each category of insecurity using the moderate/severe cutoffs, with energy insecurity red (large, dashed lines), food insecurity green (solid dashed lines), and water insecurity blue (small, dashed lines). The size of the ovals represents the relative size of each category. A Venn diagram showing the overlap using mild insecurity cutoffs, and a table showing the specific values for each category, is provided in Figure B1 and Table B2 provide the values for the mild and moderate/severe cases.*

We explored correlations between the individual scores for food, water, and energy insecurity (Figure 3.2). We found that food and energy insecurity were positively correlated ($r=0.71$, CI:0.64-0.76, Pearson's Correlation, $p<0.001$). Energy and water ($r=0.33$, 95% CI: 0.21-0.444, Pearson's Correlation, $p<0.001$) and food and water ($r=0.43$, 95% CI: 0.21-0.44, Pearson's Correlation, $p<0.001$) insecurities were also positively correlated. A comparison of the insecurities in our study with other studies is provided in Table B3.

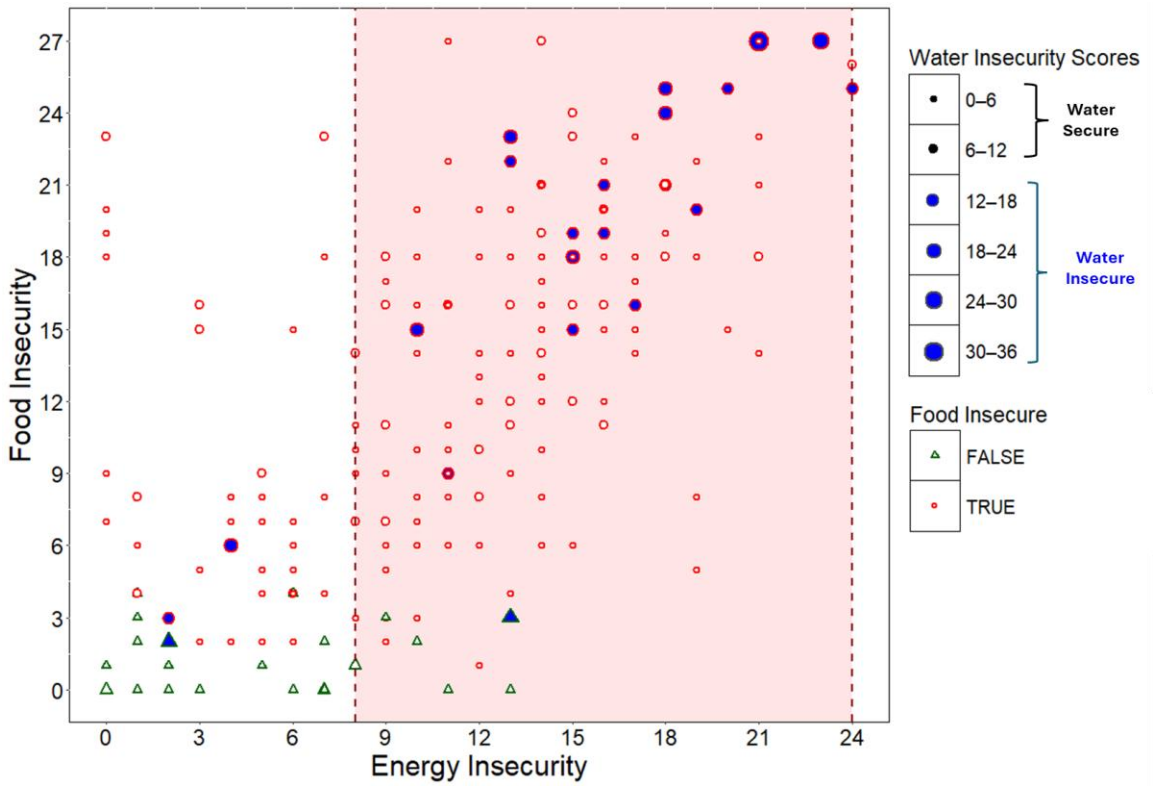


Figure 3.2 *Distribution of household food, energy, and water insecurity scores. Each point represents a household, with the energy insecurity score on the x-axis and the food insecurity score on the y-axis. The point color and shape indicate the food insecurity status, with a green triangle indicating food secure, and a red circle indicating food insecure. The point size indicates water insecurity, with larger sizes indicating a higher water insecurity score. Households that are water insecure (defined as greater than or equal to 12) are shaded blue. The vertical lines indicate the thresholds for energy insecurity.*

3.4.1 Individual Insecurity Items and Principal Component Analysis

We explored the most frequently affirmed individual insecurity questions along with their highest mean scores. Table B4 shows the individual insecurity questions, their mean scores, the percent of households having a score of 0, 1, 2, or 3 for each question, and the overall occurrence of that experience. For example, 77% of households reported not eating their preferred foods (mean score = 1.52), while 78% worried that their stored fuel would run out (mean score = 1.47). For the latter, scores of 1 occurred more frequently than scores of 2 or 3, resulting in a lower mean.

Individual energy and food insecurity questions yielded the highest mean scores and were most frequently affirmed. In contrast, water insecurity items generally showed lower mean scores and were affirmed less often than food and energy insecurity items. The exceptions were

questions related to leaving home due to lack of fuel (six water insecurity items had higher mean scores, and four were more frequently affirmed), as well as going to bed hungry or going an entire day and night without eating. Notably, the question about worrying that water would not be sufficient had a relatively higher mean score (0.78) and was affirmed by 45% of households.

The most frequently affirmed insecurity experiences and the higher-scoring individual insecurity questions were all food and energy-related. The most frequently affirmed insecurity item was worrying that your stored fuel will run out before you have money to refill (78% of households, with a mean score of 1.47). The question with the highest mean score was eating preferred foods (77% of households, with a mean score of 1.52). Other frequently affirmed individual insecurity questions and top mean scores including lacking money to buy fuel (74% of households, mean score of 1.51), reducing expenses for basic necessities because there was not enough money to pay for fuel (74% of households, mean score of 1.49), and eating foods you didn't really want because of a lack of resources to obtain other types of food (77%, mean score of 1.45). The least affirmed experiences for water were tied between going to sleep thirsty (5%, with a mean score of 0.08) and feeling ashamed because of problems with water (5% of households, with a mean score of 0.10). The least affirmed experience for energy was leaving home because there was no fuel (22% of households, mean of 0.34). The least affirmed experience for food was going a whole day and a whole night without eating because there was not enough food (34% of households, with a mean of 0.59).

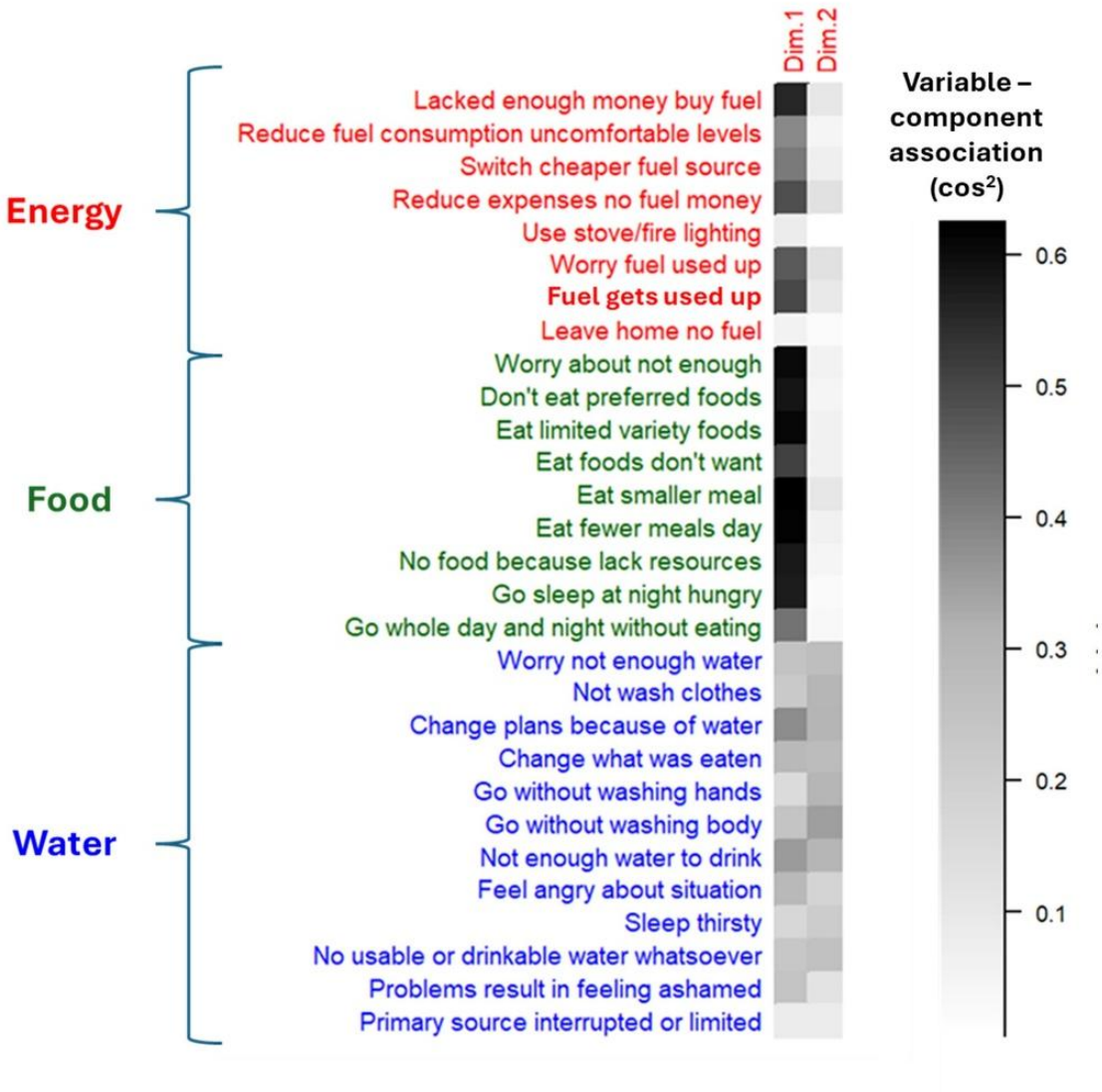


Figure 3.3 *Variable-component associations for food, energy, and water insecurity indicators. Insecurity indicators are grouped by their domain (energy in red, food in green, and water in blue). The full question and corresponding variables are provided in Table B5. The first two dimensions of the Principal Component Analysis are shown (Scree plot shown in Figure B2). Darker shading indicates stronger contributions to principal components 1 and 2, and lighter shading indicates a smaller contribution.*

The Principal Component Analysis (PCA) identified that the variability in our study sample for the insecurity items is best represented by two dimensions, which collectively explained the majority of the variance (51%, scree plot, *Figure B2*). The first principal component is strongly dominated by the food and energy insecurity items (Figure 3.3), suggesting a shared trend between these two resource domains. The second principal component is primarily defined by the water insecurity items (Figure 3.3), indicating a distinct, independent

pattern for water access. Several water insecurity items are moderately represented, with interrupted (water) and leave (energy) weakly represented. All of the food insecurity items are strongly represented. All but two of the energy uses (stove/fire for lighting, and leaving home due to no fuel) are strongly represented.

3.4.2 Characteristics of households experiencing all three insecurities

Table 3.2 shows the socio-economic, access, and behavior-related indicators among households experiencing concurrent food, water, and energy insecurity, compared with households not facing all three insecurities simultaneously, and the *p*-values from Fisher's exact or Chi-squared tests (selected from sample size). Nineteen households were food, energy, and water insecure, and 218 did not experience all three insecurities concurrently.

Households with all three insecurities were less likely to be in the upper two wealth quintiles (21% vs. 44%, chi-squared test, p=0.039). Households experiencing all three insecurities were more likely to use an unimproved latrine without a slab (53% versus 24%, chi-square test, p = 0.002). Items with lower but not significant p-values (p-values less than 0.1) included incomplete primary education or less (26% of households experiencing all three insecurities versus 11%, p = 0.060) and receiving food aid (11% for households experiencing triple insecurities versus 2%, p = 0.083). The other items did not show significant associations with concurrent insecurities.

Table 3.2 *Comparison of household food-related behaviors and access characteristics by triple (food, energy, & water) insecurity status. Values show the percentage and number (in parentheses) of households classified as insecure or secure with that behavior or access characteristic. P-values are shown for group comparisons (a =Fisher's exact test, all others are Chi-squared). Items in bold are significant (p-value <0.05).*

Indicator	Label	**Food, Energy, and Water Insecure (n = 19)**	**Food, Energy, Water Secure (n = 218)**	P value
Socioeconomic Status	Incomplete primary or less	26% (5)	11% (23)	0.060[a]
	Upper 2 wealth quintiles	**21% (4)**	**44% (95)**	**0.039**
Access	**Latrine w/o Slab**	**53% (10)**	**24% (52)**	**0.022**
	Piped in dwelling	5% (1)	9 % (19)	1.000[a]
	Receives food aid	11% (2)	2% (4)	0.083[a]
	Has grazing land	0% (0)	1% (2)	1.000[a]
	Has agricultural land	42% (8)	33% (72)	0.537[a]
	Own animals	26% (5)	24% (52)	1.000[a]
	Owns fridge	16% (3)	24% (53)	0.422[a]
	Fridge working	5% (1)	13% (28)	1.000[a]
	Clean Stove	5% (1)	12% (27)	0.481[a]
Behavior	Handwashing station present	5% (1)	11% (23)	0.702[a]
	Cooks potatoes	11% (2)	3% (7)	0.312[a]
	Animals enter home	32% (6)	32% (69)	0.869
	Uses fridge	0% (0)	4% (9)	0.529[a]
	Heated/reheated ≥1hr ago	5% (1)	3% (7)	1.000[a]
	Stores cooked food	58% (11)	46% (100)	0.444
	Stores drinking water	100% (19)	89% (195)	1.000[a]
	Treats drinking water	5% (1)	5% (10)	1.000[a]

[a] =Fisher's Exact, all others Chi-Squared

3.4.3 Microbial Contamination of Water and Food

E. coli contamination was detected in 65.7% of drinking water samples and many food samples. Figure 3.4 shows the contamination levels alongside the corresponding insecurity status. For drinking water, contamination was significantly higher in energy-insecure households (mean 7.0 MPN *E. coli* per 100 mL) compared to energy-secure households (mean 3.76 MPN *E. coli* per 100 mL, T-test, $p = 0.038$), and in food-insecure households (mean 7.00 MPN *E. coli* per 100 mL) compared to food-secure households (mean 3.58 MPN *E. coli per 100* m, T-test, $p= 0.0316$). However, contamination levels did not differ significantly between water-insecure and water-secure households. For food samples, there was no association between contamination and household insecurity status for food, water, or energy.

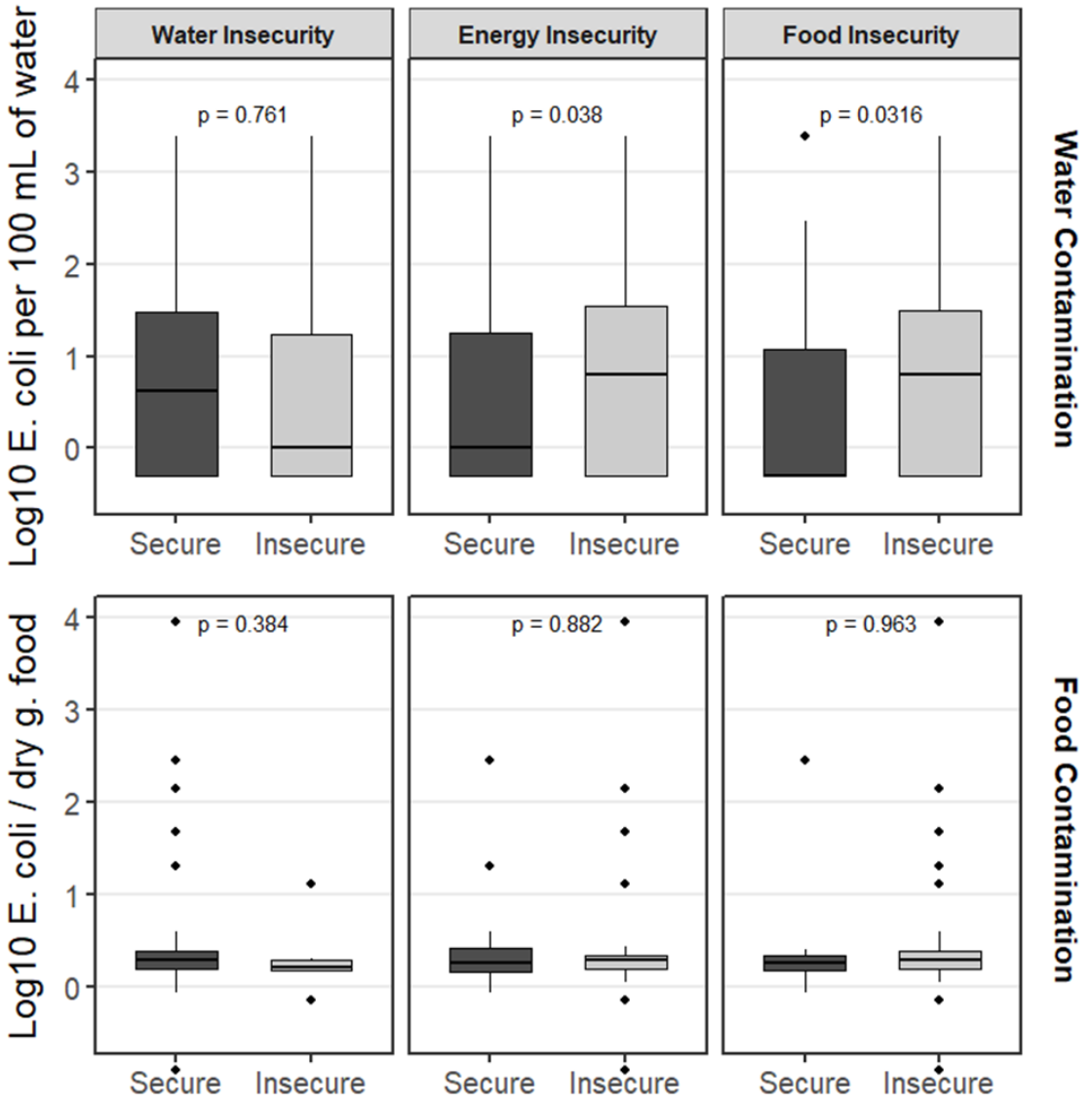


Figure 3.4 *Household insecurity status and E. coli contamination of water and food. Boxplots show E. coli concentrations (log_{10} MPN per 100 mL water in the top row, and log_{10} CFU per dry gram of food in the bottom row), for water, energy, and food secure and insecure households. P-values for each group are displayed.*

Table 3.3 shows the *E. coli* contamination level in household drinking water and the corresponding insecure and secure status. In all categories, the higher percentage was non-detect.

Table 3.3 *Distribution of E. coli water contamination levels (MPN/100 mL) in household drinking water samples, shown overall and by water, food, and energy insecurity status. Values shown are the percent of households with drinking water within that level of contamination for each secure and insecure category. The last row shows the total number of households in each insecurity category. The percentage is followed by the number of households in parentheses. Non-detect is ≤ 0.5 MPN/100 mL, and Low (>0.5-10), Medium (10-100), High (100-1000), and very high (>1000 MPN/100 mL) are shown (Odonkor & Mahami, 2020).*

E. coli Level (MPN/100 mL)	**Fraction in each WHO category**	**Water**		**Energy**		**Food**	
		Insecure	**Secure**	**Insecure**	**Secure**	**Insecure**	**Secure**
Non-detect (≤0.5)	34.3% (81)	47.8% (11)	32.9% (70)	26.7% (40)	47.7% (41)	29.4% (55)	53.1% (26)
Low (>0.5–10)	26.3% (62)	8.7% (2)	28.2% (60)	31.3% (47)	17.4% (15)	28.3% (53)	18.4% (9)
Medium (10–100)	25% (59)	30.4% (7)	24.4% (52)	27.3% (41)	20.9% (18)	27.3% (51)	16.3% (8)
High (100–1000)	12.3% (29)	8.7% (2)	12.7% (27)	12.7% (19)	11.6% (10)	13.4% (25)	8.2% (4)
Very High (>1000)	2.1% (5)	4.3% (1)	1.9% (4)	2% (3)	2.3% (2)	1.6% (3)	4.1% (2)
Total (n)	100% (237)	9.7% (23)	90.3% (214)	63.3% (150)	36.7% (87)	78.9% (187)	21.1% (50)

Households that stored their drinking water had higher levels of *E. coli* compared with those who did not (mean *E. coli* when stored: 0.90 MPN *E. coli*/100mL versus 6.63 MPN *E. coli*/100 mL when not stored, not storing 7.4 times more *E. coli*, T-test, $p<0.001$). Water collected from a piped source or vendor had significantly lower contamination than water collected from boreholes, wells, or surface source water (piped or vendor: mean of 3.30 MPN *E.*

coli per 100 mL; boreholes, wells, and surface water: mean of 18.83 MPN *E. coli* per 100 mL, T-test, p<0.001). Of the households using piped water, 112 (84%) stored the water, while 20 (15%) did not. Households that did not use a piped or vendor source all stored their water. For piped water not stored, the mean *E. coli* was 4.84 MPN per 100 mL, with 16 samples (80%) non-detect. Piped water that was stored had a mean *E. coli* of 84.8 MPN per 100 mL, with 42 samples (37.5% non-detect) non-detect (see SI, Figure B3, Figure B4, Table B7). Further comparisons are in Table B7.

In a GEE model adjusting for confounders, water storage was significantly associated with contamination. Households that stored water had 268.4% higher odds of *E. coli* detection (OR=3.68, 95% CI [1.38, 9.81], p=0.0091). Households that used piped or vendor water had -77.7% (OR=0.22, 95% CI [0.09, 0.54], p=0.000856) increased odds of *E. coli* detection, compared with households that did not store and did not use piped/vendor water. No other significant associations were identified (Table S8).

Forty-three stored food samples were collected. Figure 3.4 shows food contamination as it compares with the insecurity status. The mean *E. coli* level of these samples was 226 MPN *E. coli*/ dry gram food, and the median was 1.9 MPN *E. coli*/ dry gram food. Twenty-four samples (56%) were below 2 MPN *E. coli*/ dry gram food. Potato samples exhibited lower levels of *E. coli* contamination compared to other sample types (mean: 270 MPN *E. coli*/dry gram if it is not potato, 1.5 MPN *E. coli*/dry gram if it is potato, Fisher's exact (P=0.03)). We found no significant correlation between *E. coli* contamination in food and household food, water, and energy security or management behaviors, including reheating, refrigeration use. Tables B9 and B10 show the different food attributes and whether they had detect or non-detect *E. coli* and the corresponding P values.

3.4.4 Insecurities and Related Behaviors

Food, energy, and water insecurity were associated with specific household behaviors and access metrics, as shown in Table 3.4 (Food), Table 3.5 (Energy), and Table 3.6 (Water). Surprisingly, food insecure households were more likely to own a fridge (27% versus 19%, Chi-Squared Test, p<0.001), and have piped water access (75% versus 35%, Chi-Squared Test, p=0.002). None of the other food related behaviors were significant.

Energy insecure households are more likely to: use multiple stoves (61% vs 46%, Chi-Squared Test, P=0.017) and burn trash as a fuel (34% vs 9%, Chi-Squared Test, P<0.001). Energy secure households more likely to heat water daily (86% versus 72%, Chi-Squared Test, p=0.019), heat water with clean fuels (14% versus 3%, Chi-Squared Test, p =0.003), have electricity at least 5 days (76% versus 45%, Chi-Squared Test, p<0.001), have piped water (70% versus 49%, Chi-Squared Test, p=0.001), and own a refrigerator (40% versus 14%, Chi-Squared Test, p=0.001). Storing cooked food, reheating food, clean stoves, and daily fuel purchasing was not different between energy secure and insecure households.

Water insecure households are more likely to use secondary sources (48% vs 25%, Fisher's Exact Test, P=0.034), report water supply interruptions (61% versus 28%, Chi-Squared Test, p =0.001), and lack sufficient water (74% vs 8%, Chi-Squared Test, P<0.001). Water secure households are more likely to be satisfied with their water source (65% vs 90%, Fisher's Exact Test, P=0.002) and have water supplied continuously (61% versus 86%, Fisher's Exact Test, p =0.005 for 24 hours a day, and 65% versus 89%, Fisher's Exact Test, p=0.005 for 7 days a week). Treating water and having piped water in the home/yard were not associated with water insecurity.

Table 3.4 *Comparison of household food-related behaviors and access characteristics by food insecurity status. Values show the percentage and number (in parentheses) of households classified as insecure or secure with that behavior or access characteristic. P-values are shown for group comparisons (a =Fisher's exact test, all others are Chi-squared). Items in bold are significant (p-value <0.05).*

Indicator	Label	Food Insecure (n=128)	Food Secure (n=109)	P-value[a]
Behavior	Reheat Food	29% (37)	28% (30)	1.000
	Use fridge	2% (3)	6% (6)	0.429[a]
	Store cooked food	48% (62)	45% (49)	0.685
	Stored cooked food available	20% (26)	20% (22)	0.811
Access	**Own Fridge**	**27% (35)**	**19% (21)**	**<0.001**
	Piped water	**75% (96)**	**35% (38)**	**0.002**
	Own Animals	34% (43)	13% (14)	0.462
	Receives Food Aid	4.7% (6)	0% (0)	0.347[a]
	Access to land for grazing	47% (60)	18% (20)	1[a]
	Access to agricultural land	1.6% (2)	0% (0)	0.293

[a] =Fisher's Exact, all others Chi-Squared

Table 3.5 *Comparison of household energy-related behaviors and access characteristics by energy insecurity status. Values show the percentage and number (in parentheses) of households classified as insecure or secure with that behavior or access characteristic. P-values are shown for group comparisons (a =Fisher's exact test, all others are Chi-squared). Items in bold are significant (p-value <0.05).*

Indicator	Label	Energy Insecure (n=150)	Energy Secure (n=87)	P-value[a]
Behavior	**Use at least two stoves**	**61% (92)**	46% (40)	**0.017**
	Store cooked food in fridge at least one day	1% (2)	8% (7)	0.399[a]
	Store cooked food at least one day	45% (68)	49% (43)	0.636
	Reheat food at least one day	25% (38)	33% (29)	0.311
	Heat water for any purpose every day	72% (108)	**86% (75)**	**0.019**
	Heat water with Solar, gas, or electric	3% (5)	**14% (12)**	**0.00263**
	Heat home for 6 or 7 days	37% (56)	49% (43)	0.092
	Use clean stove	11% (17)	20% (17)	0.122

Table 3.5 *(continued)*

	Burn Trash as fuel at least one day	**34% (51)**	9% (8)	**<.001**
	Buy Fuel Daily	20% (30)	13% (11)	0.129
	Collect fuel	2% (3)	6% (5)	0.152[a]
Access	**Have electricity at least 5 days**	45% (68)	**76% (66)**	**<.001**
	Have piped water	49% (73)	**70% (61)**	**0.001**
	Own Fridge	14% (21)	**40% (35)**	**<.001**

[a] =Fisher's Exact, all others Chi-Squared

Table 3.6 *Comparison of household water-related behaviors and access characteristics by water insecurity status. Values show the percentage and number (in parentheses) of households classified as insecure or secure with that behavior or access characteristic. P-values are shown for group comparisons (a =Fisher's exact test, all others are Chi-squared). Items in bold are significant (p-value <0.05).*

Indicator	**Label**	**Water Insecure (n=23)**	**Water Secure (n=214)**	**P-value [a]**
Behavior	Treat water	22% (5)	18% (39)	0.897[a]
	Water stored	96% (22)	90% (192)	0.703[a]
	Use secondary water source	48% (11)	25% (53)	**0.034[a]**
	Vendor Water	4.3% (1)	16% (29)	0.325[a]
Access	Have piped water in home/dwelling	9% (2)	8% (18)	1[a]
	Have piped water in yard	70% (16)	14% (29)	0.347
	Spend time (more than 0 minutes) collecting water	43% (10)	29% (63)	0.17
	Water supply interrupted	61% (14)	28% (59)	**0.001**
	Water supplied 24 hours a day	61% (14)	86% (184)	**0.005[a]**
	Water supplied 7 days a week	65% (15)	89% (190)	**0.005[a]**
	Satisfied with water source	65% (15)	90% (193)	**0.002[a]**

Table 3.6 *(continued)*

Household did not have sufficient water	74% (17)	8% (17)	**<.001**
Knew when water is interrupted	13% (3)	4.2% (9)	0.708[a]

[a] =Fisher's Exact, all others Chi-Squared

3.5 Discussion

Our findings suggest that resource security in our peri-urban setting in Malawi occurs along a continuum and was achieved more for water prior to achieving food and energy security. Significant progress has been made for drinking water infrastructure in the urban areas and the Southern part of Malawi (Cassivi et al., 2020), likely decreasing water insecurity (Miller et al., 2025). Additionally, the study location experiences higher precipitation than other parts of Malawi (Tadeyo et al., 2020, pp. 1979–2015), which may influence the lower prevalence of water insecurity (Stoler, Miller, et al., 2021). However, in urban areas, fuels are becoming more expensive and more difficult to collect (Jagger & Perez-Heydrich, 2016), and urban areas experience extremely high levels of food insecurity (Crush et al., 2012). In addition, energy insecurity is more prevalent in Southern Malawi (Mkomba et al., 2021), and in 2024, the southern part of Malawi experienced a Crisis level of food insecurity, with an early start to the lean season (FEWS NET, 2024). As evidenced by responses to survey items and supported in the literature, households living in a peri-urban context typically rely on purchasing of fuel and food rather than self-supply (Chilanga et al., 2017; Jagger & Perez-Heydrich, 2016). Additionally, expenditures for these items on a weekly basis tend to be highest for food, and lowest for water (price comparison provided in Table S11) (Blantyre Water Board, 2024; Jagger & Perez-Heydrich, 2016; Kalumbi et al., 2020; Mercy Bwanaisa, 2023; Schneider, 2022). Purchases for fuel and food tend to be co-dependent, as fuel is needed to cook the food (Sola et al., 2016). We observed strong correlations between food and energy scale items, but water scale items had a weaker correlation. During our study period, a significant fraction of our population expressed concerns over food and fuel shortages (77 and 74% respectively), but water supply shortages were a less common concern (32% reported primary water sources being interrupted or limited). Other studies in areas with decent water supply and infrastructure also find strong correlations

between food and water energy insecurity, such as in the United States and Cambodia (Cook et al., 2008; Phoumin & Kimura, 2019; UN-Water, 2024, 2025), with even more food and water insecurity occurring during colder seasons (J. Bhattacharya et al., 2003; Nord & Kantor, 2006), like the study period of our study. Additionally, income and finances play a significant role in a household's food (Loopstra & Tarasuk, 2013), and energy (A. G. Murray & Mills, 2014) insecurity. With 79% of our population below the poverty line, income likely plays a role. This suggests that the pathways by which resource insecurity manifests are influenced by a combination of contextual features such as the mechanism of provision, costs of each resource, household income, and availability of resources, which can vary by urbanization level and city-wide resource security.

Our study explored the relationship between microbial contamination in food and water and water and food insecurity. Correlations were not observed between water insecurity and contamination, and food insecurity and contamination, but were found for water contamination and food and energy insecurities. This suggests these outcomes exist through different mechanisms in our setting. As observed in our study and many other water contamination studies (T. F. Clasen & Bastable, 2003; Levy et al., 2008), water storage can introduce contamination in drinking water prior to consumption. Consistent with past studies (Kumpel & Nelson, 2013; Majuru et al., 2016), we observed that even households with piped water supply were practicing water storage. In our study, and past studies, both water insecure and secure households were storing water (Jepson et al., 2021), and in some cases, households with larger storage capacity considered more secure (Wutich & Ragsdale, 2008). Therefore, both water secure and insecure households would be expected to experience contaminated water. In contrast to past studies (Collins et al., 2024), in our study, water treatment practices were not related to water security.

To our knowledge, no studies have directly evaluated household behaviors to reduce or prevent contamination in water and food as it relates energy insecurity. One behavior to reduce water contamination at the household level is water treatment, which could theoretically relate to energy security if the treatment approach requires fuels, such as boiling, which is used and promoted in some locations (Cohen et al., 2020; Floess et al., 2025). Boiling drinking water is a fuel intensive practice that is often promoted to improve water quality in resource limited settings (Garcia-Suarez et al., 2019; Gilman' & Skillicorn, n.d.; Zhu et al., 2023). The prevalence of boiling in our study was much lower than in other studies in Malawi (2 households (1 %)

versus 25% reporting boiling in a prior study) (Mkwate et al., 2017). However, 85% reported heating water for bathing and 88% for drinking and tea. Although we did observe energy secure households having significantly higher quality water than insecure households, few households in our study reported boiling, so energy demand of treatment does not appear to be the driver of the differences in water quality. Not having fuels has been shown to be a barrier to boiling water (Workman, 2019). Given the large proportion of households reporting energy insecurity and the poor quality of water exhibited in energy insecure households, there may be a concern that the energy demand for boiling water could be a barrier to water quality improvements.

However, we observed that energy insecure households still reported use of fuel for warming water, primarily for bathing. Further, clean fuels were often used for water warming (6 households used clean fuels for cooking, while 18 used clean fuels for water heating), which has been observed in other settings as well (Psutka et al., 2011b; Zhu et al., 2023), with solar promoted for water heating (Batidzirai et al., 2009). Interestingly, no one in our study used LPG or Pellets despite promotion and benefits in Malawi and other regions (Champion & Grieshop, 2019b; Floess et al., 2023; Grieshop et al., 2011b). Our study households were willing to use fuel, including clean fuels, even if they were insecure in the energy domain, for water heating; however, the priority was for comfort in bathing over ensuring microbiologically safe water. Other studies in the Southern Africa region have shown bathing to be a common occurrence (Mujuru et al., 2020) and the importance of bathing to households (Rusca et al., 2017), with a significant fraction of household energy used on water heating (23%) (Kalua, 2020). However, warming water, but not boiling, can potentially increase pathogen risk (Van Der Wielen et al., 2023)

Energy insecurity alone did not explain water treatment, boiling, and food storage/reheating behavior, and alternative aspects of behavior, such as knowledge, norms, and priorities, seem to play a larger role in our study households and should be targeted if considering a behavior change intervention for improving water quality. Energy insecurity also relates to safe water quality from centralized treatment facilities, in that water treatment requires energy, and in Blantyre, booster pumping stations are necessary due to the hilly terrain (J. L. Taulo et al., 2017). The lack of and expense of electricity can make water expensive and make operating central treatment systems difficult (Schäfer et al., 2014). In addition to water contamination, energy security could theoretically relate to food contamination through food

reheating and fridge storage (Bjurselius & Ernow, 2009), though we did not see a connection in our study.

We observed some notable similarities in household approaches to coping with resource insecurities in energy and water. Households that were water and energy insecure would rely on a combination of water and fuel sources to meet their resource needs. Stove stacking, or the use of multiple stove/fuel types, is a way households cope with variations in fuel prices, access, and reliability of fuel sources, even when clean sources are available (Jewitt et al., 2020; Tsoeu-Ntokoane et al., 2025). Similarly, using alternative water sources such as buying water, using unsafe water, or non-primary water sources is a coping strategy against water insecurity (Collins et al., 2024) and even as a way to build resilience (Elliott et al., 2019). In our study population, we saw water-insecure households more likely to use multiple water sources and use unimproved sources for non-drinking water. However, the use of multiple stoves and multiple water sources can introduce health risks (Snider et al., 2018; Steyn et al., 2004; Uprety et al., 2020b). Although having alternatives to a primary stove/fuel and water source may serve as a coping strategy for insecure households to have access to these basic resources, it also poses potential health hazards, as households may rely on unsafe resources to meet their needs. This underscores that for assessment of energy, food, and water access, it is important to capture all the sources and fuels households rely on, and that when addressing these insecurities, interventions should focus on providing coping strategies that do not put the household at greater risk. For instance, strategies could include a clean stack (Medina et al., 2019; Shankar et al., 2020b) or predictions of water disruptions (Thomson et al., 2024), rather than alternative water sources.

3.5.1 Limitations

This was a cross-sectional study, so we cannot infer causality, and we relied on self-reported behavior and stove and water usage, which may be underreported (Norwood et al., 2016) and have potential recall and desirability bias. Our sample size was relatively small, and in a single location and time, not taking into account seasonality, which can have an important impact on energy usage (Lam et al., 2017), contamination (Kostyla et al., 2015) and food consumption (Stelmach-Mardas et al., 2016). Additionally, microbiological sampling was limited to *E. coli,* which might not accurately represent health impacts (Gruber et al., 2014). We may not have included all cofounders in the model.

3.6 Conclusions

The well-being outcomes of resource insecurity manifest in unique pathways depending on context and the type of resource that is limiting (Asaki et al., 2024). We were particularly interested in exploring how resource insecurities relate to microbial contamination in food and water, as well as other health-related behaviors. Overall, in our study, households experienced overlapping insecurities, with the majority being both energy and food insecure (52%). We observed that a few behaviors, mostly unconnected with health or contamination risks, were correlated with resource insecurities, and water and food contamination were not associated with resource insecurities in clear mechanistic ways. Although resource insecurities have the potential to interact in complex ways to drive certain behaviors and health outcomes, we did not find microbial contamination in food and water, and the behaviors to manage contamination were strongly influenced by their respective insecurity. Though there was a connection between water contamination and food and energy insecurity, there was not a clear explanation. The link between insecurities and contamination should be further explored, including further measurements on other contamination sources, health outcomes, and household practices.

3.7 Acknowledgements

3.7.1 Funding

This work was supported by the NSF grants #1951006 (Workman) and #1950212 (Harris), NC State Global One Health Fellowship, NC State Global One Health Travel Grant, Energy Poverty PIRE in Southern Africa Project (National Science Foundation Award No. 1743741), and the NC State Graduate School Doctoral Dissertation Completion Grant.

3.7.2 Authors and Contributors:

Authors: Emily Floess (EF), Ben Clark (BC), Cailtin G. Niven (CGN), Blessings Chirwa (BC), Monica Matekenya (MM), Emma Budden (EB), Stella Cadono (SC), John Chavula (JC), Victor Chisamanga (VC), Aubrey Dzinkambani (AD), Chisomo Kaponda (CK), Neema Ngondo (NN), Norah Patterson (NP), Sheena Symon (SS), Brighton Austin Chunga (BAC), Rochelle H Holm (RHH), Petros Chigwechokha (PC), Francis de Los Reyes (FR), Ayse Ercumen (AE), Cassandra L Workman (CLW), Andrew Grieshop (AG), Angela Rose Harris (ARH)

ARH and CLW developed the concept, designed the research, and secured the funding with the help of AG and AE. EF, BC, CGN, EB, and NP developed the survey instrument with

the help of ARH, CLW, AG, and AE. BC and MM translated the survey instrument. BC, SC, JC, VC, AD, CK, NN, and SS collected the samples and survey data and helped with lab processing, with the help of EF, BC, CGN, EB, and SC. EF, CGN, and EB cleaned the data. EF wrote the code and conducted the analysis. EF wrote the paper with the help of AE, CLW, AG, ARH. BAC, RHH, PC, and FR advised on the research.

3.7.3 Data availability

The data is available on request.

Chapter 4: Scaling up gas and electric cooking in low- and middle-income countries: climate threat or mitigation strategy with co-benefits?

This chapter has been published as: Floess, E., Grieshop, A., Puzzolo, E., Pope, D., Leach, N., Smith, C. J., Gill-Wiehl, A., Landesman, K., & Bailis, R. (2023). Scaling up gas and electric cooking in low-and middle-income countries: climate threat or mitigation strategy with co-benefits?. Environmental Research Letters, 18(3), 034010. 10.1088/1748-9326/acb501

Abstract

Nearly three billion people in low- and middle-income countries (LMICs) rely on polluting fuels, resulting in millions of avoidable deaths annually. Polluting fuels also emit short-lived climate forcers and greenhouse gases (GHGs). Liquefied petroleum gas (LPG) and grid-based electricity are scalable alternatives to polluting fuels but have raised climate and health concerns. Here, we compare emissions and climate impacts of a business-as-usual household cooking fuel trajectory to four large-scale transitions to gas and/or grid electricity in 77 LMICs. We account for upstream and end-use emissions from gas and electric cooking, assuming electrical grids evolve according to the 2022 World Energy Outlook's "Stated Policies" Scenario. We input the emissions into a reduced-complexity climate model to estimate radiative forcing and temperature changes associated with each scenario. We find full transitions to LPG and/or electricity decrease emissions from both well-mixed GHG and short-lived climate forcers, resulting in a roughly 5 millikelvin global temperature reduction by 2040. Transitions to LPG and/or electricity also reduce annual emissions of $PM_{2.5}$ by over 6 Mt (99%) by 2040, which would substantially lower health risks from Household Air Pollution.

4.1 Introduction

Nearly 3 billion people, 40% of the world's population, lack access to clean cooking fuels and technologies (ESMAP, 2021). Instead, they rely on polluting fuels like wood, charcoal, other solid biomass, kerosene, and coal (World Health Organization, 2021). Commonly-used household stoves cannot burn these fuels efficiently and cleanly, resulting in exposure to products of incomplete combustion or "household air pollution" (HAP) that contributes to nearly 4 million premature deaths each year (World Health Organization, n.d.). Polluting fuels also

contribute to ambient air pollution (Lacey et al., 2017) and emit well-mixed greenhouse gases (GHGs) and short-lived climate forcers (SLCFs) that cause climate change (Grieshop et al., 2011c; Haines et al., 2017). Unsustainable harvesting of biomass fuels contributes to local environmental degradation (Bailis et al., 2015). Impacts of polluting fuel use fall disproportionately on women, adding to preexisting gender inequalities (Jagoe et al., 2020). These challenges have persisted for decades despite thousands of programs and policies designed to facilitate a transition to cleaner cooking.

The global prioritization of clean cooking is reflected in the seventh Sustainable Development Goal (SDG7), which aims to achieve universal "access to affordable, reliable, sustainable and modern energy" by 2030 (UNDP, 2020). 600 million people gained *primary access* to clean cooking fuels or technologies between 2010 and 2020 (ESMAP, 2021). Following WHO and others, we use the term *primary access* to refer to populations that use a clean fuel for most or all their cooking needs (Stoner et al., 2021). There is some ambiguity in this indicator because the household surveys that provide this data only collect information about the most frequently used cooking fuel in each household (IEA et al., 2019).

Despite these increases in access to clean cooking options, progress is uneven and some regions lag (Appendix C Section 1). Over 75% of the population that gained primary access to clean cooking between 2010 and 2020 did so by adopting liquefied petroleum gas (LPG) (Stoner et al., 2021). LPG is well-suited to near-term scale-up (Global LPG Partnership, 2018), and many LMIC governments have set ambitious targets promoting adoption (Puzzolo et al., 2020). Unlike electricity and piped natural gas, LPG does not require major investment in infrastructure to scale. It is clean-burning and simple to use (Islam et al., 2022b; Puzzolo et al., 2019). Electricity accounts for most of the remaining increase in primary access to clean cooking. While access to electricity is increasing rapidly in LMICs, cooking with electricity is less common (Stoner et al., 2021). Other clean cooking options like biogas, ethanol, solar thermal cookers, and biomass pellets burned in advanced stoves have gained traction in some markets, but globally they are much less prevalent than LPG and electric cooking.

Transitions from polluting to clean fuels and technologies results in large reductions in HAP exposure (Liao et al., 2021; Pope et al., 2017b, 2021b). However, the past growth and planned scale-up of LPG raises questions about trade-offs between mitigating the health impacts of polluting fuels and the potential climate impacts of large-scale increases in fossil fuel

consumption. Conventional LPG is a by-product of the petroleum and natural gas industries, with emissions arising from extraction, processing, and transport (US EPA, 2016a). Grid-based electricity, completely clean at point of use, is derived primarily from fossil fuels in LMICs, and has similar issues (Global LPG Partnership, 2018; World Bank, 2024).

Fuelwood, charcoal, and other biomass fuels are *potentially* renewable. However, a substantial fraction of current woodfuel consumption is unsustainable and causes declines in standing stocks of biomass (Bailis et al., 2015). In addition, biomass fuels emit more SLCFs than LPG or grid-based power (Appendix C Section 7) and are detrimental for health due to the formation of products of incomplete combustion. Thus, a transition from polluting fuels to LPG or grid-based power could mitigate climate change through two mechanisms: lower consumption of unsustainable biomass and reduced SLCF emissions.

Previous work has quantified the global carbon footprint of biomass dependence at one point in time (Bailis et al., 2015), examined climate impacts of individual cooking choices (Grieshop et al., 2011c), and modeled the climate impacts of "shutting off" biomass demand (Kodros et al., 2015a; Huang et al., 2018). One analysis estimated that a transition to LPG in Cameroon resulted in net global cooling of 0.3-1.3 millikelvin by 2100, depending on the levels of LPG adoption and biomass sustainability (Kypridemos Chris et al., 2020). We build on these previous studies with the first global analysis of health and climate implications of transitions to both LPG and electricity.

4.2 Methods

4.2.1 Fuel Transition Scenarios

The analysis included LMIC countries with a population of at least 1 million households using polluting solid fuels and/or kerosene in 2018 (the baseline year) based on the WHO global database of primary fuels/ energy used for cooking (Stoner et al., 2021). The analysis includes over 2.6 billion polluting fuel users from 77 countries. The scenarios are described below and summarized in Table 4.1.

The Business as Usual (BAU) scenario assumes that past rates of change in primary household fuel choice are extended into the future. Past household cooking fuel choices were calculated for rural and urban areas of each country using WHO's household cooking fuel choice database, which includes six fuel categories: Biomass (consists mainly of unprocessed firewood,

but also includes crop residues and dung), Charcoal, Coal, Kerosene, Gas (includes LPG, natural gas, and biogas), and Electricity (Stoner et al., 2021). Average rates of change for each fuel and other key assumptions are described in Appendix C Section 3.

The Full Transition-LPG (FT-LPG) scenario makes two key assumptions: 1) households using polluting fuels (Kerosene, Coal, Charcoal and Biomass) transition steadily to LPG such that use of polluting fuels falls to zero by 2040 and 2) any electricity use at baseline evolves as in the BAU scenario. Therefore, by 2040, all cooking is done with either LPG or a mix of LPG and electricity.

The Full Transition to LPG and Electricity (FT-LE) scenario follows the same pattern as the FT-LPG scenario, but uses electricity as the main transition, while allowing BAU rates of LPG to continue. The Full Transition to Electricity (FTE) examines a hypothetical transition to 100% cooking with electricity (including LPG-using households transitioning to exclusive use of electricity by 2040). The Intermediate (IT) scenario assumes BAU rates for each clean option increase by 50%.

Table 4.1*: Descriptions of the scenarios developed for this analysis*

Scenario name (abbreviation)	**Description**
Business as usual (BAU)	Future primary cooking fuels adoption rates follow recent country-specific trends as defined by WHO disaggregated by rural and urban populations(Stoner et al., 2021).
Intermediate transition (IT)	Adoption rates of LPG and electricity increase by 50% by 2040, displacing more polluting fuels than in BAU
Full transition to LPG (FT-LPG)	All polluting cooking fuels are displaced with LPG by 2040 but rate of electricity adoption proceeds as in BAU, resulting in an LPG dominant future.
Full transition to LPG and Electricity (FT-LE)	All polluting cooking fuels are displaced with grid-based electricity by 2040, but the rate of LPG adoption proceeds as in BAU, resulting in a balanced mix of LPG and electricity in the future.
Full transition to Electricity (FT-Elec)	All polluting cooking fuels and LPG are displaced with grid-based electricity by 2040, resulting in electricity dominant future.

4.2.2 Emissions

Household fuels emit a wide variety of pollutants including well-mixed GHGs like carbon dioxide (CO_2), methane (CH_4), and nitrous oxide (N_2O) as well as SLCFs like black and organic carbon (BC and OC), non-methane volatile organic carbon (NMVOC), sulfur and nitrogen oxides (SO_x and NO_x) and carbon monoxide (CO) (Masera et al., 2015). BC and OC are constituents of fine particulate matter ($PM_{2.5}$), exposure to which is associated with numerous health risks (Health Effects Institute, 2020). Exposure to SO_x, NO_x, and CO can also damage health.

Emissions from "upstream" processes like extraction, refining, and transportation of fossil-based cooking fuels (kerosene, LPG, and coal) were derived from GREET, a life cycle model developed by Argonne National Labs primarily for analyzing transportation fuels (Argonne National Laboratory, 2021). GREET was also used to estimate transportation emissions associated with charcoal. GREET's default parameters reflect current US conditions, but the model allows users to adjust inputs to reflect other regions. For the global analysis, we determined the dominant consumers of each fuel from our sample of 77 countries, as well as the major exporters supplying these countries and adjusted GREET accordingly. We describe specific approaches for each fuel in Appendix C Section 4.

For upstream emissions from charcoal production, the average emission factors for CO, NO_x, $PM_{2.5}$, SO_x, BC, OC, CH_4, N_2O, CO_2, and NMVOC were compiled from previous collections of field emission factors (Akagi et al., 2011; Pennise et al., 2001; US EPA, 2016a) and converted to a delivered energy basis using an assumed stove efficiency (US EPA, 2016a) (Table C9). For biomass, we assumed that wood is locally collected and has no upstream emissions. The end use emission factors for biomass, charcoal, kerosene, coal and LPG were taken from previous compilations of lab and field data (Akagi et al., 2011; Grieshop et al., 2011c; Pennise et al., 2001; US EPA, 2016a).

Shares of electricity production and total production for different years were taken from the World Bank Development indicators (World Bank, 2017) with missing data supplemented by International Energy Agency (IEA) statistics (IEA, 2019). Future grid mixes were simulated using projections from the IEA's World Energy Outlook (WEO) "Stated Policies" scenario through 2040 (IEA, 2020). Lifecycle grid emissions per kWh of electricity produced from each type of power generation were estimated using GREET (Argonne National Laboratory, 2021).

Plant-specific emissions are included in GREET's database with some tunable parameters. GREET's default values assume a US-based grid and power plant feedstock. We changed some parameters for coal, as mentioned above. Parameters for other feedstocks were left at their default values. We describe grid projections, emission factors, and additional assumptions in Appendix C Section 5.

When woody biomass is harvested and burned as fuelwood or charcoal, much of the carbon in the wood is converted to CO_2, contributing to climate change. However, depending on the rate of harvest and land management practices, some, or all the woody biomass regenerates, reducing the impact of the CO_2 emitted during combustion. When there are imbalances between woody biomass harvest and regrowth, CO_2 emitted during combustion is not fully sequestered by regenerating trees. This is called "non-renewable biomass" (NRB). The ratio of NRB to woody biomass consumption is the "fraction of non-renewable biomass" (fNRB). We use country-specific pan-tropical estimates of fNRB from a previous study (Bailis et al., 2015) to account for net CO_2 emissions from wood and charcoal (see Appendix C Section 6 for more detail).

For the global health impact assessment, we did not estimate contributions of emissions to specific health outcomes. Instead, we estimated changes in emissions of (and assumed exposure to) the following health-damaging pollutants: $PM_{2.5}$, CO, NO_x, and SO_x (US EPA, n.d.). This research group carried out a parallel study of national-level assessments in five priority countries using the ABODE model to estimate health impacts associated with changes in exposure (Pillarisetti, 2019, p. 0). The results of these health models are discussed in a separate paper.

4.2.3 Climate Impacts

We estimate climate impacts of the different scenarios using the FaIR v1.6.2 climate model, which is a simple emissions-based model that accounts for non-linearities in the carbon cycle and includes simplified processes representing greenhouse gas, aerosol, ozone, and other forcings from precursor emissions (Leach et al., 2021; C. J. Smith et al., 2018; Thomson et al., 2011). We use the multi-species configuration, with the RCP4.5 scenario as a baseline for the BAU scenario (C. Smith, 2021; Thomson et al., 2011). RCP4.5 is a pathway for stabilization of radiative forcing by 2100, projecting somewhere in the region of 2.5-3^{o}C global mean temperature increase above pre-industrial by the end of this century, and is the closest RCP scenario to current global climate policy (Hausfather & Peters, 2020). Uncertainty was calculated

based on runs using parameters derived from a 2237 member ensemble developed for analysis in IPCC's Sixth Assessment Report (C. Smith, 2021). This ensemble is observationally constrained in order to span the assessed range in climate system uncertainty, including global temperature change (1850-2019), atmospheric CO_2 concentrations (1750-2014), change in ocean heat content (1971-2018), and assessments of equilibrium climate sensitivity, transient climate response and airborne fraction of CO_2 emissions (C. Smith, 2021; C. Smith et al., 2021). Differences in emissions between the BAU and other scenarios were calculated for CO_2, CH_4, N_2O, SO_x, CO, NMVOC, NO_x, BC, and OC, and added to the RCP4.5 baseline emissions trajectory. The resulting emissions trajectories were run in the FaIR climate model to obtain annual changes in GHG concentrations, climate forcing, and temperature projected to 2040. To estimate uncertainties, we report the median and 5^{th}, 25^{th}, 75^{th} and 95^{th} percentile values of the ensemble simulations, with emissions held constant. Therefore, uncertainty estimates do not represent uncertainties in scenarios, only in climate system response.

4.3 Results

4.3.1 Future Household Energy Transitions

Figure 4.1 compares energy consumption, number of fuel users and energy consumed under BAU and a full transition to LPG (FT-LPG). Under BAU, demand for biomass, coal, and kerosene decrease by 25%, 96%, and 25%, respectively, between 2018 and 2040. However, these patterns are not consistent across all regions. For example, BAU biomass demand decreases steeply in Asia/Pacific regions but increases in Africa. In addition, BAU charcoal consumption increases globally over this period by over 125%, driven mainly by growth in urban consumption in Africa. Clean fuel use also increases under BAU: LPG consumption increases by 50% and electricity demand for cooking doubles.

4.3.2 Changes in Emissions of Health-Damaging Pollutants

To gauge health impacts, we report changes in emissions of health-damaging pollutants including fine particulate matter ($PM_{2.5}$), carbon monoxide (CO), nitrogen oxides (NO_x) and sulfur oxides (SO_x). Here, and below, we refer to emissions from cooking fuels in the 77 countries included in our analysis. In 2018, approximately 7.6 Mt of $PM_{2.5}$ were emitted from cooking fuels (Figure 4.2A). Under the BAU scenario, this is projected to decline by 24%, driven by transitions from polluting fuels to LPG and electricity described above. Under the

Intermediate scenario, a modest increase in clean fuel adoption results in a 12% reduction of $PM_{2.5}$ emissions relative to BAU. Under full transitions to either LPG or electricity, $PM_{2.5}$ emissions from residential cooking are nearly eliminated.

CO emissions follow a similar pattern as $PM_{2.5}$ (Figure 4.2B). In 2018, we estimate that 71 Mt of CO was emitted from cooking fuels. Under the BAU scenario, CO emissions decrease 5% to 67 Mt by 2040 (CO declines less than $PM_{2.5}$ due to growth in charcoal consumption). In the Intermediate scenario, 2040 CO emissions are ~10% lower than BAU, and in the full transitions to either LPG or electricity, CO emissions decrease by over 95%.

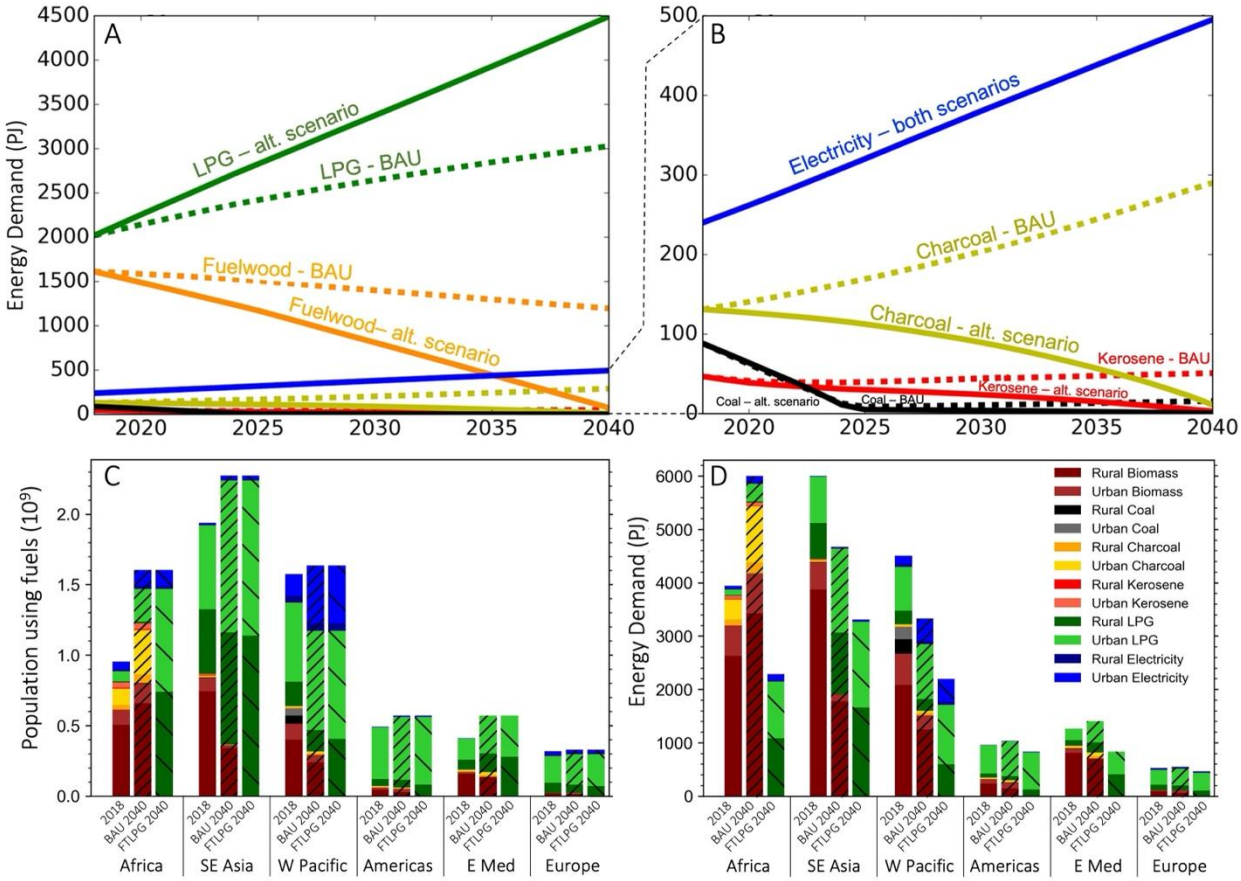


Figure 4.1*: Energy demand in BAU (dashed) and FT-LPG (solid) scenarios (A) and the same graph zoomed in to show the less common fuels in more detail (B). The number of fuel users in 2018 and 2040 (C) and rural/urban energy demand by fuel (D) in 2018 and 2040 for all scenarios. C and D are disaggregated by WHO regions.*

NO_x emissions result primarily from atmospheric nitrogen and increase with higher combustion temperatures. LPG, coal, and thermal power generation occur at higher temperatures

than biomass combustion in household stoves; therefore life-cycle NO_x emissions are higher from LPG, gas and electric cooking (US EPA, 1999). SO_x emissions primarily occur because of fuel-bound sulfur (US EPA, 2016b), which occurs in trace amounts in biomass but can be several percent by weight in coal (Hussain & Luo, 2019). Under the BAU scenario, NO_x emissions increase by ~20% between 2018 and 2040 and SO_x emissions decrease by a similar magnitude (Figure 4.2C and D). Under Intermediate and FT-LPG scenarios NO_x emissions increase further because of increased LPG consumption. In contrast, SO_x emissions are lower in all scenarios relative to BAU except for FT-Elec. In that scenario, SO_x emissions are nearly 30% higher than BAU due to increased coal-based electricity consumption (see Appendix C Section 10 for a discussion of regional variation in health-relevant emissions).

4.3.3 Emissions of Well-Mixed GHGs and SLCFs

Figure 4.3 shows fuel-specific emissions of well-mixed GHGs and BC in 2018 and in 2040 for each scenario. CO_2-equivalent units (CO_2e) represent the climate impacts of well-mixed GHGs (CO_2, CH_4, and N_2O) weighted by their 100-year Global Warming Potentials . In 2018, total emissions of well-mixed GHGs from residential cooking was 1.14 Gt-CO2e. Under BAU, we project these to increase by 14%, to 1.30 Gt- CO_2e by 2040. Under the Intermediate scenario, emissions decrease 1.2% relative to BAU (to 1.28 Gt- CO_2e) by 2040. More substantial reductions relative to BAU occur under the full-transition scenarios: 17%, 31%, and 47% for the FT-LPG, FT-LE, and FT-Elec scenarios, respectively.

In 2018, household cooking emitted ~1.2 Mt of BC. Emissions decrease to 1.0 Mt by 2040 in the BAU scenario, decline by ~12% under the Intermediate scenario and are nearly eliminated under full transitions to LPG and/or electricity. OC and NMVOC emissions follow similar patterns (see Appendix C Section 10).

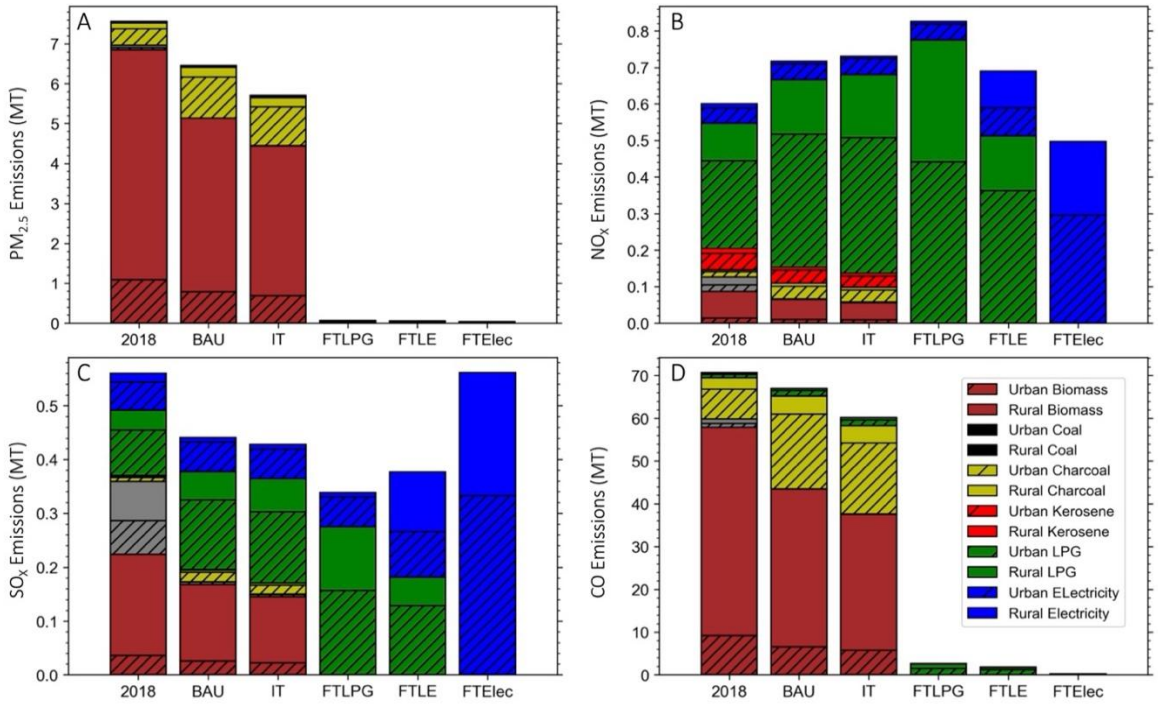


Figure 4.2 *Fuel-specific emissions of health-damaging pollutants in 2018 and 2040 for each scenario: $PM_{2.5}$ (A), NO_x (B), SO_x (C), and CO (D)*

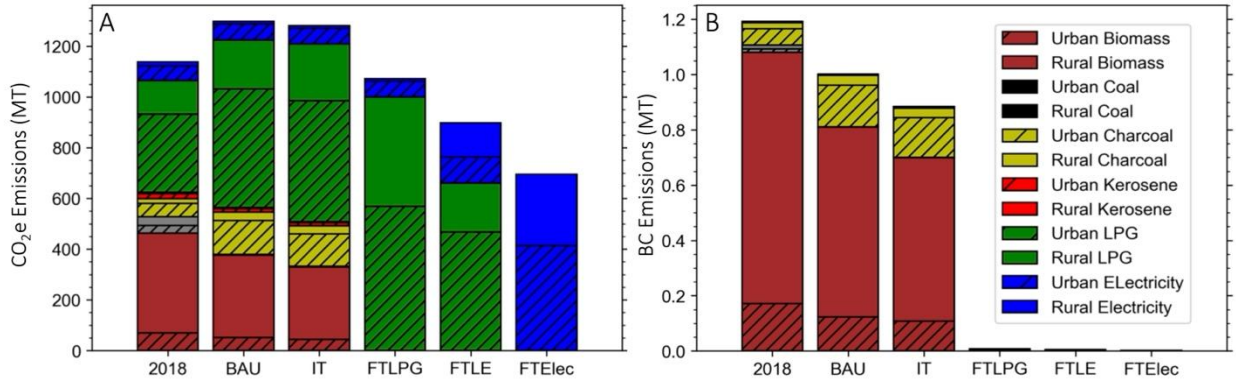


Figure 4.3 *Fuel-specific emissions of well-mixed GHGs (A) and BC (B) in 2018 and in 2040 for all scenarios*

4.3.4 Impacts on Radiative Forcing and Temperature

Under BAU, compared to a scenario of zero emissions from cooking, household cooking emissions contribute to an increase in effective radiative forcing of roughly 39 mW/m^2 (-97 to 42 mW/m^2; 95% CI) and 15 millikelvin (-41 to 26 millikelvin; 95% CI) of warming by 2040. Our alternate intervention scenarios result in both reduced forcing and lower temperature (Figure 4.4). By 2040, median temperature is 0.3 millikelvin lower in the Intermediate scenario and 4.7

to 5.1 millikelvin lower in the full transition scenarios (Figure 4.4A). However, the confidence intervals for each scenario significantly overlap with zero (FT-E: -0.0238 to 0.0245, FT-LE: -0.0247 to 0.0267, FT-LPG: -0.0244 to 0.0271, Intermediate: -0.0027 to 0.0035) so that we cannot state with certainty that the transitions would result in net cooling. Nevertheless, full transitions to LPG and/or electricity cause sustained reductions in annual emissions, resulting in median temperature pathways that will continue to diverge from BAU well into the future. Moreover, relative uncertainty in the temperature response should decrease in the future, due to the longer lifetimes of well-mixed GHGs and higher certainty associated with their effects.

Short-term climate forcing is dominated by aerosols, with reductions in OC and BC resulting in net warming and cooling, respectively (Figure 4.5). Reductions in well-mixed climate GHGs like CO_2 have minimal impact on temperature during the timeframe of our analysis. We note that cumulative CO_2e emissions do not necessarily correspond well with their associated climate response for mixtures of long- and short-lived GHGs as in our transition scenarios (Allen et al., 2018, 2022). However, changes in CO_2e (Figure 4.3***Figure 4.4***) provide some indication of the long-term impacts of each scenario. For example, under the BAU scenario, cumulative CO_2e emissions are 27.7 Gt between 2018 and 2040. The three full transition scenarios reduce cumulative emissions of well-mixed GHGs by 2.3-4.3 Gt CO_2e over the simulation period (see Appendix C Section 11 for more detailed discussion of GHG and SLCF emissions).

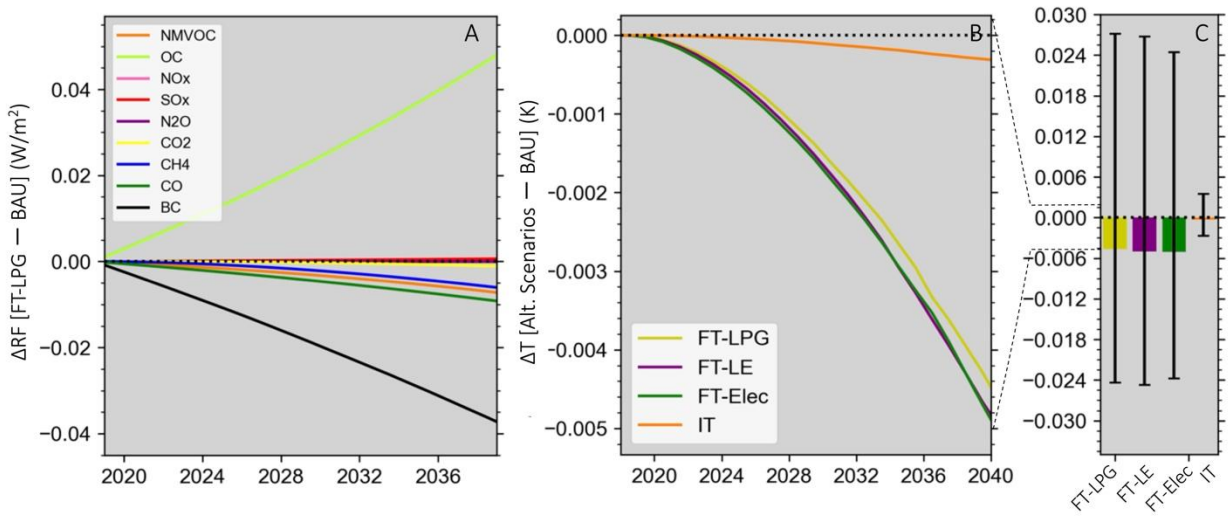


Figure 4.4*: Pollutant-specific changes in radiative forcing between BAU and FT-LPG (A) and change in temperature between BAU and all scenarios (B), with 95% confidence intervals for temperature in 2040 shown by expanding the y-axis from B (C). Error bars show the 95% confidence intervals from runs using a 2237-member ensemble of model parameters (see methods).*

SLCFs dominate the projected climate impacts and associated uncertainty through 2040. Figure 4.5A shows the net temperature change and uncertainty (shown as the 5-95% confidence interval of an observationally constrained, perturbed parameter ensemble) between FT-LPG and BAU scenarios attributed to each pollutant. Figure 4.5C summarizes this for each scenario. BC and OC have the largest impacts as well as the widest confidence intervals due to uncertainties in climate response to aerosol emissions; CH_4, NMVOC, and CO also have substantial impacts, largely due to their roles in tropospheric ozone formation. The net effect could be positive or negative based on overall uncertainty; however, the median response of the ensemble for all scenarios shows that cooling due to decreases in emissions warming agents (BC, CO, CH_4, and NMVOCs) overcomes warming arising from OC reductions. Figure 4.5B shows how regional emission reductions contribute to overall temperature changes by 2040. The African region has the largest impact, driven by reductions in BC, CH_4, NMVOC, and CO from decreased demand for fuelwood and charcoal. Under BAU, the African region has substantial increases in charcoal and fuelwood consumption (Figure 4.1). Under the FT-LPG and other full transition scenarios, which phase out demand for charcoal and fuelwood, SLCF emissions are nearly eliminated.

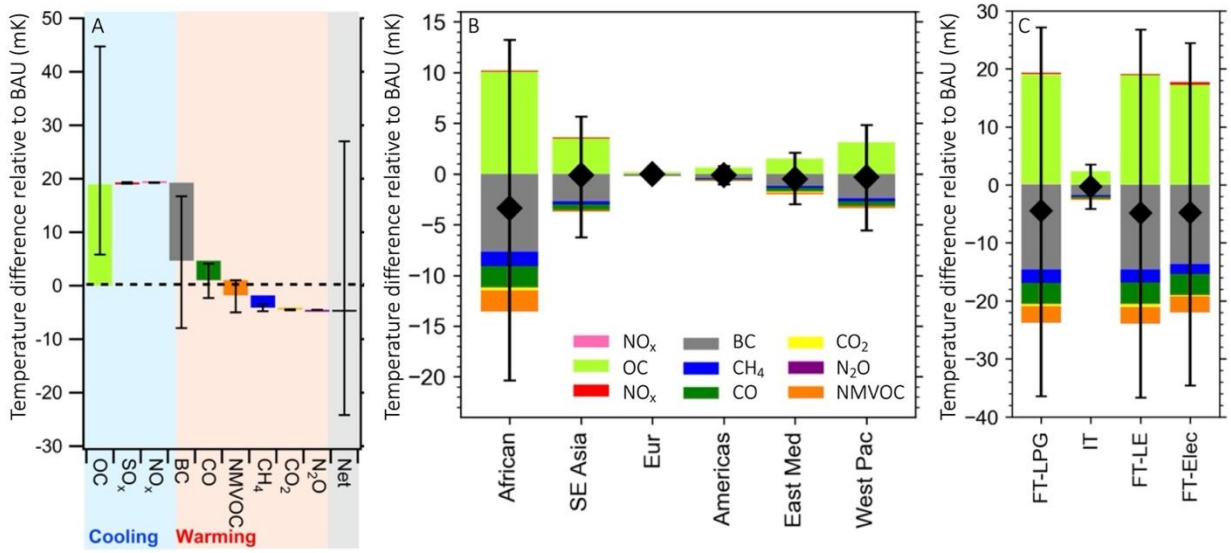


***Figure 4.5**: pollutant-specific contributions to temperature difference between BAU and FT-LPG scenarios (A) and disaggregated by contributions from each WHO region (B). Pollution-specific temperature changes for all scenarios are shown in C. Error bars show the 95% confidence intervals as defined in Figure 4.4.*

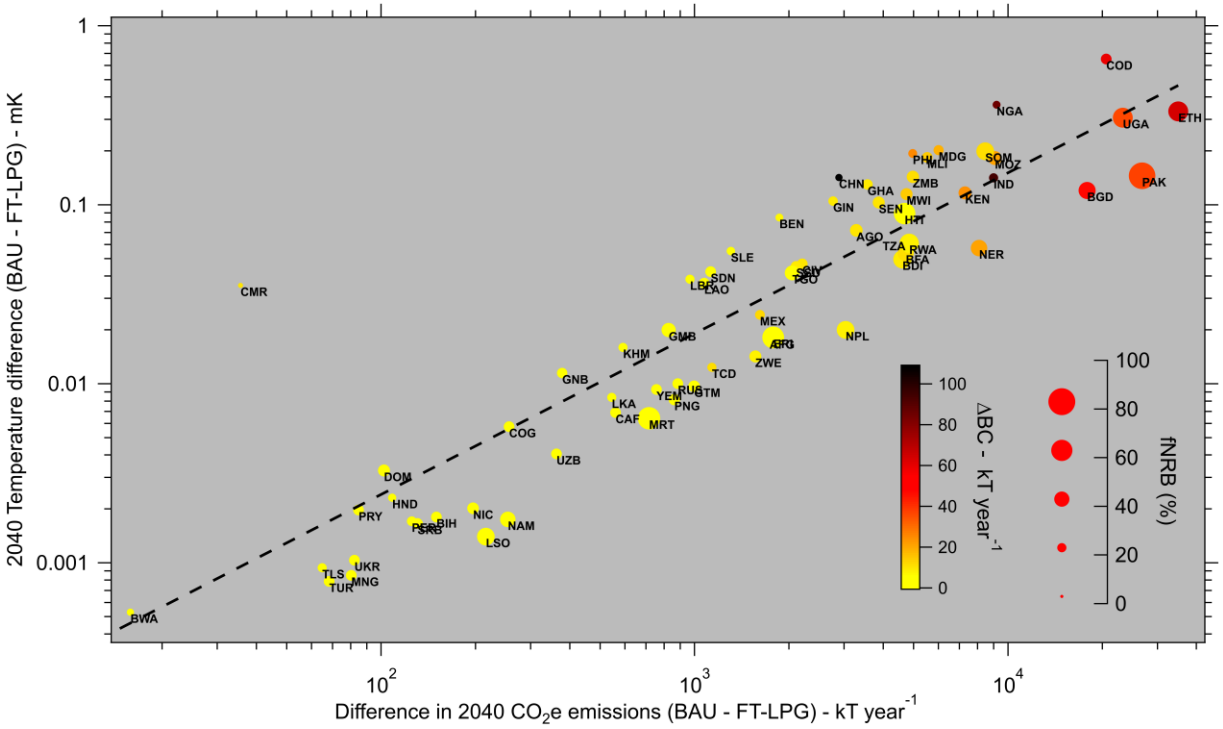


***Figure 4.6**: A scatter plot of the country-attributed differences between BAU and FT-LPG scenarios; x-axis indicates differences in modeled temperature in 2040, y-axis shows differences in CO_2e emissions in that year. The color indicates changes in BC emissions and size indicates national level fNRB. Three letter country codes are defined in Table S1. The dashed black line is a log-transformed linear fit and is included to guide the eye. Note that temperature differences*

shown (BAU – FT-LPG) are the additive inverse of Figures 4C and 5, to enable the use of log axes.

Changes in $PM_{2.5}$, BC, and temperature are well-correlated because BC is a constituent of $PM_{2.5}$ and a key driver of short-term temperature change. Figure 4.6 shows that the modeled short-term temperature changes, though mostly driven by SLCF reductions, also scale with changes in CO_2e. These are reductions for all counties except Thailand and Myanmar (not shown). CO_2e is a more robust indicator of long-term temperature impacts. The generally linear relationship between ΔCO_2e and ΔT is moderated by several factors. For example, variation in the fraction of non-renewable biomass (fNRB), a geographically-specific parameter characterizing the sustainability of woodfuel demand (see Appendix C Section 6), has a strong influence on ΔCO_2e. Further, the varying relative contributions of CH_4 and CO_2 to total CO_2e reductions (Table C10) affects this relationship, as warming from CH_4 is more strongly associated with annual emission changes than warming from CO_2, which is well-understood to be a function of cumulative emissions.

4.4 Discussion

We have analyzed emissions and climate impacts of global transitions from BAU to clean residential cooking fuels in 77 countries. Over half of the population in our sample used either LPG (48%) or electricity (6%) as a primary cooking fuel in 2018. Our BAU scenario projects increases in the primary use of LPG (58%) and electricity (10%) by 2040, with polluting fuels decreasing in the same proportion. However, the rate of charcoal use doubles from 3% to 6% of the population, driven by expansion in Africa, where the number of people using charcoal as a primary fuel increases by nearly 220 million. Similarly, while global dependence on biomass decreases, in Africa the population using it increases by nearly 190 million.

Under BAU, overall emissions of most health-damaging pollutants decrease, though the reductions are modest. Health and environmental impacts decline by 2040, particularly in Asia, but we estimate over 700 million people across the region would still use polluting fuels. In addition, negative health and climate impacts will increase substantially in Africa as the use of polluting fuels expands. Increasing the pace of LPG/electricity cooking transitions will lead to large global benefits. However, in the absence of major investments and shifts in policy, full transitions to such clean fuels by 2040 is only likely to occur in a handful of countries included in this analysis (Stoner et al., 2021). Achieving universal adoption of LPG and/or electricity for

cooking would entail meeting multiple challenges (Banerjee et al., 2016; Kimemia & Annegarn, 2016) and require substantial investment (SEforAll, 2021). To date, investment has been slow, in part because of donor fears that financing expanded access to fossil-derived LPG sends the "wrong message" or will harm the climate. This analysis demonstrates that continuing along a BAU trajectory results in larger emissions of both SLCFs and well-mixed GHGs than a shift to LPG and/or grid-based (also largely fossil-derived) electricity. Moreover, despite large uncertainties in near-term temperature change (Figure 4.5), if we extend median trends into the future, the transitions from BAU pathways to LPG (and/or electricity) will likely result in net cooling while also essentially eliminating the sector's HAP emissions and associated health risks.

Incremental changes, illustrated by our Intermediate scenario, result in modest reductions in climate forcers and negligible short-term temperature impact relative to BAU. In contrast, full transitions to LPG and/or electricity result in near elimination of the strongest SLCFs resulting in 4.7-5.2 millikelvins near-term cooling compared to BAU as well as substantial reductions of well-mixed GHGs that would contribute to long-term cooling. The same transitions result in near elimination of $PM_{2.5}$. Under some scenarios, emissions of NO_x or SO_x increase, but the health benefits of zeroing out $PM_{2.5}$ emissions from household sources would far outweigh the impacts of additional NO_x and SO_x. This is a rare example in which a fossil fuel-based energy transition can mitigate short- and long-term climate change while bringing large co-benefits: reduced health risks, time savings, and other social benefits associated with access to clean cooking options.

As with any complex modeling effort, our study has several limitations. Upstream emissions for most fuel pathways were taken from GREET, which is a life cycle model parameterized for fuels used in the US (Argonne National Laboratory, 2021). We made changes to reflect global conditions (Appendix C Section 5), but the resulting emission factors may be inaccurate. The same applies to end-use emissions. In addition, we use total life cycle emissions as a proxy for health risk, but this does not consider that upstream emissions result in different exposures than end use emissions.

The fNRB data used in this analysis is the only available global estimate of woody biomass renewability. There are numerous sources of uncertainty in the models used to derive fNRB, which may over- or underestimate net CO_2 emissions from woodfuels (Bailis et al.,

2015). In addition, fNRB is held constant in these scenarios; however, it is a function of woodfuel demand among other factors. In the full transition scenarios, as woodfuel demand decreases, fNRB should also decrease, leading to higher rates of regeneration and larger climate benefits from those transitions.

The FaIR model is a reduced-complexity climate model calibrated to an ensemble of observationally-constrained climate model simulations to estimate the range of plausible climate response (C. J. Smith et al., 2018). However, impacts of SLCFs vary depending on source location (Kodros et al., 2015b) and the radiative forcing response to emissions of aerosol species is highly uncertain.

There is increasing interest in cooking with electricity from decentralized sources (ESMAP, 2020b), which was not explored in this analysis. Off-grid options have become more feasible as the costs of renewable energy generation and storage have decreased and more efficient and inexpensive appliances like induction stoves and electric pressure cookers have become accessible (ESMAP, 2020a).

4.5 Conclusion

To our knowledge, this is the first study to examine emissions reductions and climate impacts of global clean cooking transitions in LMICs from polluting fuels to LPG and electricity. Under BAU conditions, HAP emissions decline modestly between 2018 and 2040, driven by a transition already underway in parts of Asia. However, in Africa, the population relying on polluting fuels will grow in the absence of substantial interventions. A full transition to LPG will lead to drastic reductions in emissions of nearly all climate-forcing and health-damaging pollutants, and possibly contribute to a small reduction in global temperature relative to the BAU scenario. A transition to grid electricity would require larger investment but have a similar result. Thus, a rapid transition to LPG and/or electricity will reduce health risks for over 2 billion people, by reducing household exposures and addressing a major contributor to ambient air pollution. Transitions are also likely to result in both near- and long-term cooling. Larger climate benefits would result from transitioning to clean fuels with lower life-cycle carbon emissions than conventional LPG and grid-based electricity such as bio-LPG, bioethanol, or 100% renewable electricity. However, it is unclear if these options can be scaled-up at the same rate as fossil-based LPG or grid expansion.

4.6 Acknowledgements

The authors gratefully acknowledge funding from the Clean Cooking Alliance (grant no. C-12881-1). Additionally, we would like to acknowledge the NCSU undergraduate students who helped with the project (Grace Gould, Jasmine Hayden-Lowe, Silas Huckins) as well as National Science Foundation (award no. 1743741).

4.7 Author contributions

AG and RB developed the concept, designed the research, and secured funding. EP and DP advised on research design. NL and CJS developed the FaIR model and heavily supported its use in this application. EF, AG, and RB developed BAU and alternate scenarios with input from EP, DP. EF and KL developed tools to manage and analyze scenario data. RB, EF, and AG compiled life-cycle emissions data for each cooking option. EF developed code to integrate emission factors and transition scenarios into FaIR with support from KL. EF, AG, EP, DP, RB, AGW and KL coauthored an internal report that forms the basis for this manuscript. EF, AG, RB, EP, DP, and AGW wrote the manuscript. NL and CJS provided additional text about FaIR output and related discussions.

4.8 Ethical Compliance

This study involved no human subjects. The authors declare no conflicts of interest.

4.9 Data Availability

All input, intermediate, and final output datasets are available for download from this link: https://datadryad.org/dataset/doi:10.5061/dryad.jq2bvq8d9.

Chapter 5: Conclusions

5.1 Findings and implications

This chapter provides high-level overviews and summarizes key findings from my dissertation

5.2 Chapter 2

5.2.1 Summary:

In this chapter, we used a Quantitative Microbial Risk assessment (QMRA) and exposure-response curves to calculate the DALYs for a range of conditions, including different levels of water boiling effectiveness, source water qualities, and Household Air Pollution levels. We used literature-derived distributions of the relevant Household Air Pollution, Quantitative Microbial Risk Assessment, and demographic parameters as inputs. The QMRA calculates the DALYs from drinking water contaminated by fecal matter before and after treatment by boiling. The air risk module uses an indoor box model to quantify the $PM_{2.5}$ concentrations for different stoves and a modified form of the Household Air Pollution intervention Tool to quantify the DALYs associated with Household Air Pollution under various scenarios. We selected Uganda and Vietnam as case study countries.

5.2.2 Key Findings:

1. In most of the scenarios, the benefits of clean water outweigh the impacts of household air pollution from boiling that water.
2. A larger share of the DALYs come from children under 5 years in Uganda compared to Vietnam, because of the higher number of children per household in Uganda
3. For the scenario of a household that is already cooking on a stove, and boils water as well, if the water was boiled with at least the “low field” effectiveness, the decrease in drinking water DALYs from boiling was greater than the increase in household air pollution DALYs
4. In the case that a household was not cooking, but started boiling water, higher log removal values are needed to offset DALYs from HAP from a traditional wood stove.

5.2.3 Implications

1. Our results suggest that boiling medium- and high-risk drinking water typically yields a net health benefit, implying that interventions that promote boiling have a net health benefit. However, it is important to consider the stove type and if cooking occurs in the home to understand if it provides a net benefit.
2. When high polluting stoves and no cooking activities take place in a home, there can be a net negative impact from boiling. This shows the importance of assessments which jointly consider the health impacts of drinking water and air quality.
3. Our results show a significant reduction in HAP DALYs from a transition to clean fuels. This shows the importance of policies promoting clean stoves, which can improve air quality and reduce the health impacts of boiling drinking water.
4. Boiling effectiveness, which varies widely, is key in determining whether boiling has a net health benefit. Future research should focus on how to improve boiling effectiveness in real-world settings.

5.3 Chapter 3

5.3.1 Summary:

In this chapter, we evaluated data from a cross-sectional field study that took place in Bangwe, peri-urban Blantyre, Malawi, during the Winter and dry season from June to July 2024. The household survey included validated insecurity scales related to food, water, and energy use. We also asked questions on demographics, WaSH, food access, energy use, health, and hygiene. We collected samples of drinking water for children under 5 and stored food samples for children (or adults if not available). We enumerated *E. coli* concentrations in the food and water samples using IDEXX. We calculated the number of households experiencing mild and moderate/severe food insecurity. For water, we ran a Generalized Estimating Equation, and used a chi-squared, Fisher's exact, t-test, and Pearson correlation to determine significance, and a p-value <0.05 was considered significant.

5.3.2 Key Findings:

1. Households primarily used charcoal and improved water sources. However, few households treated or boiled their water, but many warmed water.

2. Most households experienced both food and energy insecurity, and a small fraction experienced all three.
3. Energy and food-insecure households were more likely to have contaminated drinking water.
4. Water insecure households are more likely to use secondary sources, report water supply interruption, and lack sufficient water
5. Energy secure households are more likely to heat water daily, heat water with clean fuels, have electricity at least 5 days a week, have piped water, and own a refrigerator

5.3.3 Implications:

1. Though our study location was relatively water secure, households still experienced high food and energy insecurity, showing that different resource securities don't occur simultaneously, but sometimes correlate. This shows the importance of interventions that consider all three insecurities together, rather than individually.
2. Energy and food insecurity were associated with decreased water contamination, showing the importance of considering insecurities across different domains. Future research should consider how insecurities impact different contamination levels.
3. Water contamination was not associated with water insecurity, showing that addressing water security alone may not decrease the contamination of the water. Safer buffers to water insecurity, which don't increase contamination, should be researched.
4. Many households heated water for bathing and tea, frequently using clean fuels to do this, but did not boil water, showing the potential for promoting clean fuels for water heating, and that comfort took priority over safety.
5. There are similar coping mechanisms for different behaviors, for example, water-insecure households use multiple water sources while energy-insecure households use multiple stoves, suggesting opportunities to address these in parallel

5.4 Chapter 4

5.4.1 Summary:

In this chapter, we looked at several fuel transition scenarios for replacing solid fuels with clean fuels. The Business as Usual scenario assumed that past rates of change in primary household cooking fuel choices are extended into the future. The Full transition to LPG scenario assumes that households using polluting fuels transition steadily to LPG such that use of

polluting fuels falls to zero by 2040 and that any electricity use at baseline evolves as in the BAU scenario. The full transition to LPG and electricity uses electricity as the main transition, while allowing BAU rates of LPG to continue. The full transition to electricity assumed 100% cooking with electricity. The intermediate scenario assumes BAU rates for each clean option increase by 50%. Emissions from upstream processes were derived from the Greenhouse Gas Regulated Emissions and Energy Use in Transportation (GREET) model. Electricity production data were taken from World Bank Indicators and International Energy Agency statistics. Other emissions were taken from emission inventories. Climate impacts were estimated using the Finite Amplitude Impulse Response (FaIR) simple climate model, with RCP4.5 as the baseline scenario.

5.4.2 Key Findings:

1. PM2.5 emissions decline under a BAU scenario, but under full transitions to either LPG or electricity, PM2.5 emissions from residential cooking are nearly eliminated.
2. NO_x emissions increase under a BAU scenario while SO_x decrease. Under the intermediate transitions and full transition scenarios, NOx emissions increase because of increased LPG consumption.
3. Well-mixed greenhouse gases decrease under the full transition scenarios relative to the BAU scenarios.
4. The intervention scenarios result in reduced climate forcing.

5.4.3 Implications:

1. Despite the upstream emissions, full transitions to LPG and electricity for cooking will lead to climate and health benefits, suggesting that transitions to these fuels should be encouraged.
2. The intermediate transition scenarios result in modest reductions in climate forcers and negligible short-term temperature impacts relative to BAU, while full transitions to LPG and /or electricity result in the near elimination of the strongest SLCFs and GHGs, indicating the importance of full transition scenarios.
3. For the scenarios in which emissions of NO_x and SO_x increase, the health benefits of removing $PM_{2.5}$ far outweigh the impacts of additional NO_x and SO_x, highlighting the importance of considering tradeoffs of different pollutant reductions and increases with stove interventions.

4. A rapid transition to LPG and/or electricity will reduce the health risks for over 2 billion people, implying that a rapid transition to LPG/electricity should be encouraged.

5.5 Overarching Conclusions

My dissertation research highlights the need to understand the intersections and trade-offs of different household energy interventions across different domains. For my two modeling studies, we found that boiling drinking water and transitioning to LPG and/or electricity for cooking led to next benefits in most scenarios. For boiling water, there were net health benefits for medium- and high-risk water even when using a higher-emitting stove. Transitioning to LPG and electricity for cooking showed a significant reduction in health and climate-relevant pollutants.

However, when we conducted a field study looking at food, energy, and water insecurity, and its connection with stored food and drinking water microbial contamination and household behaviors and access, we found that only one household used biogas, no households used LPG, and only 6 used electricity for cooking, and 18 for water heating. Only two households reported boiling drinking water. In addition, clean cooking and boiling drinking water were not associated with energy security. This shows that interventions of clean cooking and boiling water might be more complicated, even beyond energy access.

Additionally, we found that energy insecurity impacts water and food contamination, showing that energy insecurity impacts a household's well-being beyond the domain of energy. In our study, households experienced overlapping insecurities, with the majority being both energy and food-insecure (52%). However, there was no clear explanation of this connection between water contamination and food and energy insecurity.

5.6 Future research

Future research should focus on clarifying the connection between water contamination and food and energy insecurity. Further measurements of the contamination of various household water sources and food practices could help explain the connection. For example, it's possible that heating water (though not fully boiling it) reduced some microbial contamination. Additionally, the low prevalence of boiling in our study site in Malawi shows the challenges of promoting this as a practice, even when there is a net health benefit. Further research on boiling should take place where boiling occurs and should focus on measuring air pollution

concentrations and diarrhea incidence, and researching barriers to water boiling. For the clean fuel transition for cooking, although we showed that transitioning to electricity or LPG for cooking can yield significant health and climate impacts, it is unclear if this is feasible on a large scale. Though some countries are implementing plans to increase LPG use (Asante et al., 2018; Gaikwad et al., 2024; Gould et al., 2024; Thoday et al., 2018; Yetano Roche et al., 2024), further research could focus on the cost and feasibility of scaling this up globally, especially in countries with high biomass use, and no government plan or subsidies for increasing the use of LPG for cooking. For example, in our field study in Malawi, none of the households used LPG, showing the challenges of widespread adoption of this cooking fuel. Additionally, the connections introduced in this thesis could be explored further. For example, the feasibility of using LPG for boiling drinking water and heating food could be explored, or the climate impacts of a widespread intervention to boil drinking water with solid fuels.

REFERENCES

1. Afrane, G., & Ntiamoah, A. (2011). Comparative Life Cycle Assessment of Charcoal, Biogas, and Liquefied Petroleum Gas as Cooking Fuels in Ghana. *Journal of Industrial Ecology*, *15*(4), 539–549. https://doi.org/10.1111/j.1530-9290.2011.00350.x
2. Akagi, S. K., Yokelson, R. J., Wiedinmyer, C., Alvarado, M. J., Reid, J. S., Karl, T., Crounse, J. D., & Wennberg, P. O. (2011). Emission factors for open and domestic biomass burning for use in atmospheric models. *Atmospheric Chemistry and Physics*, *11*(9), 4039–4072. https://doi.org/10.5194/acp-11-4039-2011
3. Allen, M. R., Peters, G. P., Shine, K. P., Azar, C., Balcombe, P., Boucher, O., Cain, M., Ciais, P., Collins, W., Forster, P. M., Frame, D. J., Friedlingstein, P., Fyson, C., Gasser, T., Hare, B., Jenkins, S., Hamburg, S. P., Johansson, D. J. A., Lynch, J., … Tanaka, K. (2022). Indicate separate contributions of long-lived and short-lived greenhouse gases in emission targets. *Npj Climate and Atmospheric Science*, *5*(1), 5. https://doi.org/10.1038/s41612-021-00226-2
4. Allen, M. R., Shine, K. P., Fuglestvedt, J. S., Millar, R. J., Cain, M., Frame, D. J., & Macey, A. H. (2018). A solution to the misrepresentations of CO2-equivalent emissions of short-lived climate pollutants under ambitious mitigation. *Npj Climate and Atmospheric Science*, *1*(1), 16. https://doi.org/10.1038/s41612-018-0026-8
5. Andersson, A. (2021). Mechanisms for log normal concentration distributions in the environment. *Scientific Reports*, *11*(1), 16418. https://doi.org/10.1038/s41598-021-96010-6
6. Anenberg, S. C., Henze, D. K., Lacey, F., Irfan, A., Kinney, P., Kleiman, G., & Pillarisetti, A. (2017). Air pollution-related health and climate benefits of clean cookstove programs in Mozambique. *Environmental Research Letters*, *12*(2), 025006. https://doi.org/10.1088/1748-9326/aa5557
7. Apte, J. S., Marshall, J. D., Cohen, A. J., & Brauer, M. (2015). Addressing Global Mortality from Ambient PM2.5. *Environ. Sci. Technol.*, 10.
8. Argonne National Laboratory. (2021). *The Greenhouse Gases, Regulated Emissions, and Energy Use in Transportation (GREET) Model* (Version 2021) [Computer software]. Center for Transportation Research. https://greet.es.anl.gov/index.php

9. Arnesen, T., & Kapiriri, L. (2004). Can the value choices in DALYs influence global priority-setting? *Health Policy*, *70*(2), 137–149. https://doi.org/10.1016/j.healthpol.2003.08.004
10. Arnold, B. F., & Colford, J. M. (2007). TREATING WATER WITH CHLORINE AT POINT-OF-USE TO IMPROVE WATER QUALITY AND REDUCE CHILD DIARRHEA IN DEVELOPING COUNTRIES: A SYSTEMATIC REVIEW AND META-ANALYSIS. *The American Journal of Tropical Medicine and Hygiene*, *76*(2), 354–364. https://doi.org/10.4269/ajtmh.2007.76.354
11. Asikainen, A., Carrer, P., Kephalopoulos, S., Fernandes, E. de O., Wargocki, P., & Hänninen, O. (2016). Reducing burden of disease from residential indoor air exposures in Europe (HEALTHVENT project). *Environmental Health*, *15*(S1), S35. https://doi.org/10.1186/s12940-016-0101-8
12. Atwoli, L., Erhabor, G. E., Gbakima, A. A., Haileamlak, A., Ntumba, J.-M. K., Kigera, J., Laybourn-Langton, L., Mash, R., Muhia, J., Mulaudzi, F. M., Ofori-Adjei, D., Okonofua, F., Rashidian, A., El-Adawy, M., Sidibé, S., Snouber, A., Tumwine, J., Yassien, M. S., Yonga, P., … Zielinski, C. (2022). COP27 Climate Change Conference: Urgent action needed for Africa and the world. *The Lancet Oncology*, *23*(12), 1486–1488. https://doi.org/10.1016/S1470-2045(22)00645-3
13. Azanaw, J., & Endalew, M. (2025). Determinants of solid fuel use in Sub-Saharan Africa: A multilevel analysis using DHS data. *PLOS One*, *20*(4), e0321721. https://doi.org/10.1371/journal.pone.0321721
14. Bailis, R., Cowan, A., Berrueta, V., & Masera, O. (2009). Arresting the Killer in the Kitchen: The Promises and Pitfalls of Commercializing Improved Cookstoves. *World Development*, *37*(10), 1694–1705. https://doi.org/10.1016/j.worlddev.2009.03.004
15. Bailis, R., Drigo, R., Ghilardi, A., & Masera, O. (2015). The Carbon Footprint of Traditional Woodfuels. *Nature Climate Change*, *5*, 266–272.
16. Bain, R., Cronk, R., Hossain, R., Bonjour, S., Onda, K., Wright, J., Yang, H., Slaymaker, T., Hunter, P., Prüss-Ustün, A., & Bartram, J. (2014). Global assessment of exposure to faecal contamination through drinking water based on a systematic review. *Tropical Medicine & International Health*, *19*(8), 917–927. https://doi.org/10.1111/tmi.12334

17. Bain, R., Cronk, R., Wright, J., Yang, H., Slaymaker, T., & Bartram, J. (2014). Fecal Contamination of Drinking-Water in Low- and Middle-Income Countries: A Systematic Review and Meta-Analysis. *PLoS Medicine*, *11*(5), e1001644. https://doi.org/10.1371/journal.pmed.1001644
18. Baiyegunhi, L. J. S., & Hassan, M. B. (2014). Rural household fuel energy transition: Evidence from Giwa LGA Kaduna State, Nigeria. *Energy for Sustainable Development*, *20*, 30–35. https://doi.org/10.1016/j.esd.2014.02.003
19. Balakrishnan, K., Ghosh, S., Ganguli, B., Sambandam, S., Bruce, N., Barnes, D. F., & Smith, K. R. (2013). State and national household concentrations of PM2.5 from solid cookfuel use: Results from measurements and modeling in India for estimation of the global burden of disease. *Environmental Health*, *12*(1), 77. https://doi.org/10.1186/1476-069X-12-77
20. Banerjee, M., Prasad, R., Rehman, I. H., & Gill, B. (2016). Induction stoves as an option for clean cooking in rural India. *Energy Policy*, *88*, 159–167. https://doi.org/10.1016/j.enpol.2015.10.021
21. Barstow, C., Bluffstone, R., Silon, K., Linden, K., & Thomas, E. (2019). A cost-benefit analysis of livelihood, environmental and health benefits of a large scale water filter and cookstove distribution in Rwanda. *Development Engineering*, *4*, 100043. https://doi.org/10.1016/j.deveng.2019.100043
22. Bates, M. N., Pokhrel, A. K., Chandyo, R. K., Valentiner-Branth, P., Mathisen, M., Basnet, S., Strand, T. A., Burnett, R. T., & Smith, K. R. (2018). Kitchen PM2.5 concentrations and child acute lower respiratory infection in Bhaktapur, Nepal: The importance of fuel type. *Environmental Research*, *161*, 546–553. https://doi.org/10.1016/j.envres.2017.11.056
23. Bhattacharya, S. C., Albina, D. O., & Salam, P. A. (2002). Emission factors of wood and charcoal-fired cookstoves. *Biomass and Bioenergy*.
24. Bianco, G., Espinoza-Chávez, R. M., Ashigbie, P. G., Junio, H., Borhani, C., Miles-Richardson, S., & Spector, J. (2024). Projected impact of climate change on human health in low- and middle-income countries: A systematic review. *BMJ Global Health*, *8*(Suppl 3), e015550. https://doi.org/10.1136/bmjgh-2024-015550

25. Bielecki, C., & Wingenbach, G. (2014). Rethinking improved cookstove diffusion programs: A case study of social perceptions and cooking choices in rural Guatemala. *Energy Policy*, *66*, 350–358. https://doi.org/10.1016/j.enpol.2013.10.082
26. Bivins, A. W., Sumner, T., Kumpel, E., Howard, G., Cumming, O., Ross, I., Nelson, K., & Brown, J. (2017). Estimating Infection Risks and the Global Burden of Diarrheal Disease Attributable to Intermittent Water Supply Using QMRA. *Environmental Science & Technology*, *51*(13), 7542–7551. https://doi.org/10.1021/acs.est.7b01014
27. Bond, T. C., & Sun, H. (2005). Can Reducing Black Carbon Emissions Counteract Global Warming? *Environmental Science & Technology*, *39*(16), 5921–5926. https://doi.org/10.1021/es0480421
28. Brown, J., & Clasen, T. (2012). High Adherence Is Necessary to Realize Health Gains from Water Quality Interventions. *PLoS ONE*, *7*(5), e36735. https://doi.org/10.1371/journal.pone.0036735
29. Bruce, N., Rehfuess, E., Mehta, S., Hutton, G., & Smith, K. R. (2006). Indoor Air Pollution. In *Disease Control Priorities in Developing Countries* (2nd ed.). The International Bank for Reconstruction and Development/ The World Bank.
30. Buonanno, G., Morawska, L., & Stabile, L. (2009). Particle emission factors during cooking activities. *Atmospheric Environment*, *43*(20), 3235–3242. https://doi.org/10.1016/j.atmosenv.2009.03.044
31. Burch, T. R., Stokdyk, J. P., Spencer, S. K., Kieke, B. A., Firnstahl, A. D., Muldoon, M. A., & Borchardt, M. A. (2021). Quantitative Microbial Risk Assessment for Contaminated Private Wells in the Fractured Dolomite Aquifer of Kewaunee County, Wisconsin. *Environmental Health Perspectives*, *129*(6), 067003. https://doi.org/10.1289/EHP7815
32. Burnett, R. T., Pope, C. A., Ezzati, M., Olives, C., Lim, S. S., Mehta, S., Shin, H. H., Singh, G., Hubbell, B., Brauer, M., Anderson, H. R., Smith, K. R., Balmes, J. R., Bruce, N. G., Kan, H., Laden, F., Prüss-Ustün, A., Turner, M. C., Gapstur, S. M., … Cohen, A. (2014). An Integrated Risk Function for Estimating the Global Burden of Disease Attributable to Ambient Fine Particulate Matter Exposure. *Environmental Health Perspectives*, *122*(4), 397–403. https://doi.org/10.1289/ehp.1307049

33. CDC. (2020). *Making Water Safe in an Emergency*. Water, Sanitation, & Hygiene (WASH)-Related Emergencies & Outbreaks. https://www.cdc.gov/healthywater/emergency/making-water-safe.html#:~:text=If%20the%20water%20is%20clear,sanitized%20containers%20with%20tight%20covers.
34. CDC, & USAID. (2009, January). *Household Water Treatment Options in Developing Countries: Boiling*. https://omiusajpic.org/wp-content/uploads/2009/12/boiling20091.pdf
35. Cereceda-Balic, F., Toledo, M., Vidal, V., Guerrero, F., Diaz-Robles, L. A., Petit-Breuilh, X., & Lapuerta, M. (2017). Emission factors for PM2.5, CO, CO2, NOx, SO2 and particle size distributions from the combustion of wood species using a new controlled combustion chamber 3CE. *Science of The Total Environment*, *584–585*, 901–910. https://doi.org/10.1016/j.scitotenv.2017.01.136
36. Chafe, Z. A., Brauer, M., Klimont, Z., Dingenen, R. V., Mehta, S., Rao, S., Riahi, K., Dentener, F., & Smith, K. R. (2014). Household Cooking with Solid Fuels Contributes to Ambient PM2.5 Air Pollution and the Burden of Disease. *Environmental Health Perspectives*, *122*(12), 7.
37. Chafe, Z. A., Brauer, M., Klimont, Z., Van Dingenen, R., Mehta, S., Rao, S., Riahi, K., Dentener, F., & Smith, K. R. (2014). Household Cooking with Solid Fuels Contributes to Ambient $PM_{2.5}$ Air Pollution and the Burden of Disease. *Environmental Health Perspectives*, *122*(12), 1314–1320. https://doi.org/10.1289/ehp.1206340
38. Champion, W. M., & Grieshop, A. P. (2019). Pellet-Fed Gasifier Stoves Approach Gas-Stove Like Performance during in-Home Use in Rwanda. *Environmental Science & Technology*, *53*(11), 6570–6579. https://doi.org/10.1021/acs.est.9b00009
39. Che, X., Zhu, B., & Wang, P. (2021). Assessing global energy poverty: An integrated approach. *Energy Policy*, *149*, 112099. https://doi.org/10.1016/j.enpol.2020.112099
40. Chowdhury, S., Pillarisetti, A., Oberholzer, A., Jetter, J., Mitchell, J., Cappuccilli, E., Aamaas, B., Aunan, K., Pozzer, A., & Alexander, D. (2023). A global review of the state of the evidence of household air pollution's contribution to ambient fine particulate matter and their related health impacts. *Environment International*, *173*, 107835. https://doi.org/10.1016/j.envint.2023.107835

41. Clasen, T., Checkley, W., Peel, J. L., Balakrishnan, K., McCracken, J. P., Rosa, G., Thompson, L. M., Barr, D. B., Clark, M. L., Johnson, M. A., Waller, L. A., Jaacks, L. M., Steenland, K., Miranda, J. J., Chang, H. H., Kim, D.-Y., McCollum, E. D., Davila-Roman, V. G., Papageorghiou, A., … HAPIN Investigators. (2020). Design and Rationale of the HAPIN Study: A Multicountry Randomized Controlled Trial to Assess the Effect of Liquefied Petroleum Gas Stove and Continuous Fuel Distribution. *Environmental Health Perspectives*, *128*(4), 047008. https://doi.org/10.1289/EHP6407
42. Clasen, T., McLaughlin, C., Nayaar, N., Boisson, S., Gupta, R., Desai, D., & Shah, N. (2008). Microbiological Effectiveness and Cost of Disinfecting Water by Boiling in Semi-urban India. *The American Journal of Tropical Medicine and Hygiene*, *79*(3), 407–413. https://doi.org/10.4269/ajtmh.2008.79.407
43. Clasen, T., Pruss-Ustun, A., Mathers, C. D., Cumming, O., Cairncross, S., & Colford, J. M. (2014). Estimating the impact of unsafe water, sanitation and hygiene on the global burden of disease: Evolving and alternative methods. *Tropical Medicine & International Health*, *19*(8), 884–893. https://doi.org/10.1111/tmi.12330
44. Clasen, T., & Rosa, G. (2017). Consistency of Use and Effectiveness of Household Water Treatment among Indian Households Claiming to Treat Their Water. *The American Journal of Tropical Medicine and Hygiene*, *97*(1), 259–270. https://doi.org/10.4269/ajtmh.16-0428
45. Clasen, T., & Smith, K. R. (2019a). Let the “A” in WASH Stand for Air: Integrating Research and Interventions to Improve Household Air Pollution (HAP) and Water, Sanitation and Hygiene (WaSH) in Low-Income Settings. *Environmental Health Perspectives*, *127*(2), 025001. https://doi.org/10.1289/EHP4752
46. Clasen, T., & Smith, K. R. (2019b). Let the “A” in WASH Stand for Air: Integrating Research and Interventions to Improve Household Air Pollution (HAP) and Water, Sanitation and Hygiene (WaSH) in Low-Income Settings. *Environmental Health Perspectives*, *127*(2), 025001. https://doi.org/10.1289/EHP4752
47. Clasen, T., Thao, D. H., Boisson, S., & Shipin, O. (2008). Microbiological Effectiveness and Cost of Boiling to Disinfect Drinking Water in Rural Vietnam. *Environmental Science & Technology*, *42*(12), 4255–4260. https://doi.org/10.1021/es7024802

48. Cohen, A., & Colford, J. M. (2017). Effects of Boiling Drinking Water on Diarrhea and Pathogen-Specific Infections in Low- and Middle-Income Countries: A Systematic Review and Meta-Analysis. *The American Journal of Tropical Medicine and Hygiene*, *97*(5), 1362–1377. https://doi.org/10.4269/ajtmh.17-0190
49. Cohen, A., Pillarisetti, A., Luo, Q., Zhang, Q., Li, H., Zhong, G., Zhu, G., Colford, J. M., Smith, K. R., Ray, I., & Tao, Y. (2020). Boiled or Bottled: Regional and Seasonal Exposures to Drinking Water Contamination and Household Air Pollution in Rural China. *Environmental Health Perspectives*, *128*(12), 127002. https://doi.org/10.1289/EHP7124
50. Cohen, A., Tao, Y., Luo, Q., Zhong, G., Romm, J., Colford, J. M., & Ray, I. (2015). Microbiological Evaluation of Household Drinking Water Treatment in Rural China Shows Benefits of Electric Kettles: A Cross-Sectional Study. *PLOS ONE*, *10*(9), e0138451. https://doi.org/10.1371/journal.pone.0138451
51. Day, R., Walker, G., & Simcock, N. (2016). Conceptualising energy use and energy poverty using a capabilities framework. *Energy Policy*, *93*, 255–264. https://doi.org/10.1016/j.enpol.2016.03.019
52. Delelegn, M. W., Endalamaw, A., & Belay, G. M. (2020). Determinants of Acute Diarrhea Among Children Under-Five in Northeast Ethiopia: Unmatched Case–Control Study. *Pediatric Health, Medicine and Therapeutics*, *Volume 11*, 323–333. https://doi.org/10.2147/PHMT.S256309
53. Deng, M., Zhang, S., Shan, M., Li, J., Baumgartner, J., Carter, E., & Yang, X. (2018). The impact of cookstove operation on PM2.5 and CO emissions: A comparison of laboratory and field measurements. *Environmental Pollution*, *243*, 1087–1095. https://doi.org/10.1016/j.envpol.2018.09.064
54. Desai, M. A., Mehta, S., Smith, K. R., World Health Organization, & Protection of the Human Environment. (2004). *Indoor smoke from solid fuels: Assessing the environmental burden of disease at national and local levels*. Protection of the Human Environment, World Health Organization.
55. Devleesschauwer, B., Havelaar, A. H., Maertens de Noordhout, C., Haagsma, J. A., Praet, N., Dorny, P., Duchateau, L., Torgerson, P. R., Van Oyen, H., & Speybroeck, N. (2014). Calculating disability-adjusted life years to quantify burden of disease.

International Journal of Public Health, *59*(3), 565–569. https://doi.org/10.1007/s00038-014-0552-z

56. Dherani, M., Pope, D., Mascarenhas, M., Smith, K. R., Weber, M., & Bruce, N. (2008). Indoor air pollution from unprocessed solid fuel use and pneumonia risk in children aged under five years: A systematic review and meta-analysis. *Bulletin of the World Health Organization*, *86*(5), 390–398. https://doi.org/10.2471/BLT.07.044529
57. Dössegger, L., Tournefier, A., Germann, L., Gärtner, N., Huonder, T., Etenu, C., Wanyama, K., Ouma, H., & Meierhofer, R. (2021). Assessment of low-cost, non-electrically powered chlorination devices for gravity-driven membrane water kiosks in eastern Uganda. *Waterlines*, *40*(2), 92–106. https://doi.org/10.3362/1756-3488.20-00014
58. Enger, K. S., Nelson, K. L., Rose, J. B., & Eisenberg, J. N. S. (2013). The joint effects of efficacy and compliance: A study of household water treatment effectiveness against childhood diarrhea. *Water Research*, *47*(3), 1181–1190. https://doi.org/10.1016/j.watres.2012.11.034
59. ESMAP. (2020a). *Cooking with Electricity: A Cost Perspective*. World Bank. https://doi.org/10.1596/34566
60. ESMAP. (2020b). *The State of Access to Modern Energy Cooking Services*. World Bank. https://doi.org/10.1596/34565
61. ESMAP. (2021). *Tracking SDG 7: The Energy Progress Report*. The World Bank. https://trackingsdg7.esmap.org/time?c=World&p=Access_to_Clean_Cooking&i=Clean_cooking_access_rate_for_Total_area
62. Fagerli, K., Trivedi, K. K., Sodha, S. V., Blanton, E., Ati, A., Nguyen, T., Delea, K. C., Ainslie, R., Figueroa, M. E., Kim, S., & Quick, R. (2017). Comparison of boiling and chlorination on the quality of stored drinking water and childhood diarrhoea in Indonesian households. *Epidemiology and Infection*, *145*(15), 3294–3302. https://doi.org/10.1017/S0950268817002217
63. Faiella, I., & Lavecchia, L. (2021). Energy poverty. How can you fight it, if you can't measure it? *Energy and Buildings*, *233*, 110692. https://doi.org/10.1016/j.enbuild.2020.110692
64. Fan, J. (2023). The burden of ischemic heart disease attributable to ambient and household particulate matter pollution, 1990–2019: A global analysis. *Environmental*

Science and Pollution Research, *30*(53), 114514–114524. https://doi.org/10.1007/s11356-023-30336-8

65. Ferguson, A. S., Layton, A. C., Mailloux, B. J., Culligan, P. J., Williams, D. E., Smartt, A. E., Sayler, G. S., Feighery, J., McKay, L. D., Knappett, P. S. K., Alexandrova, E., Arbit, T., Emch, M., Escamilla, V., Ahmed, K. M., Alam, Md. J., Streatfield, P. K., Yunus, M., & Van Geen, A. (2012). Comparison of fecal indicators with pathogenic bacteria and rotavirus in groundwater. *Science of The Total Environment*, *431*, 314–322. https://doi.org/10.1016/j.scitotenv.2012.05.060
66. Fischer Walker, C. L., Perin, J., Aryee, M. J., Boschi-Pinto, C., & Black, R. E. (2012). Diarrhea incidence in low- and middle-income countries in 1990 and 2010: A systematic review. *BMC Public Health*, *12*(1), 220. https://doi.org/10.1186/1471-2458-12-220
67. Foden, M., Browne, A. L., Evans, D. M., Sharp, L., & Watson, M. (2019). The water–energy–food nexus at home: New opportunities for policy interventions in household sustainability. *The Geographical Journal*, *185*(4), 406–418. https://doi.org/10.1111/geoj.12257
68. Forster, P., Ramaswamy, V., Artaxo, P., Berntsen, T., Betts, R., Fahey, D. W., Haywood, J., Lean, J., Lowe, D. C., Raga, G., Schulz, M., Dorland, R. V., Bodeker, G., Etheridge, D., Foukal, P., Fraser, P., Geller, M., Joos, F., Keeling, C. D., … Dorland, R. V. (2007). *Changes in Atmospheric Constituents and in Radiative Forcing*. 106.
69. Gautam, O. P., & Curtis, V. (2021). Food Hygiene Practices of Rural Women and Microbial Risk for Children: Formative Research in Nepal. *The American Journal of Tropical Medicine and Hygiene*, *105*(5), 1383–1395. https://doi.org/10.4269/ajtmh.20-0574
70. Gebremichael, B., Beletew, B., Bimerew, M., Haile, D., Biadgilign, S., & Baye, K. (2022). Magnitude of urban household food insecurity in East Africa: A systematic review and meta-analysis. *Public Health Nutrition*, *25*(4), 994–1004. https://doi.org/10.1017/S1368980021003529
71. Geremew, A., & Damtew, Y. T. (2020). Household water treatment using adequate methods in sub-Saharan countries: Evidence from 2013–2016 Demographic and Health Surveys. *Journal of Water, Sanitation and Hygiene for Development*, *10*(1), 66–75. https://doi.org/10.2166/washdev.2019.107

72. Gibney, K., Sinclair, M., O'Toole, J., & Leder, K. (2013). Using disability-adjusted life years to set health-based targets: A novel use of an established burden of disease metric. *Journal of Public Health Policy*, *34*(3), 439–446. https://doi.org/10.1057/jphp.2013.22
73. Global Alliance for Clean Cookstoves. (2015). *The State of the Global Clean and Improved Cooking Sector* (Technical Report 96499). World Bank. https://openknowledge.worldbank.org/bitstream/handle/10986/21878/96499.pdf
74. Global LPG Partnership. (2018). *The Global LPG Partnership—Fact Sheet* (p. 6). Global LPG Partnership. https://static1.squarespace.com/static/5633c4c2e4b05a5c7831fbb5/t/5b2bae2288251ba7a0589660/1529589286458/The+Global+LPG+Partnership+-+Executive+Summary+-+website+20+Jun+2018.pdf
75. Goldemberg, J., Martinez-Gomez, J., Sagar, A., & Smith, K. R. (2018). Household air pollution, health, and climate change: Cleaning the air. *Environmental Research Letters*, *13*(3), 030201. https://doi.org/10.1088/1748-9326/aaa49d
76. Gould, C. F., & Urpelainen, J. (2018). LPG as a clean cooking fuel: Adoption, use, and impact in rural India. *Energy Policy*, *122*, 395–408. https://doi.org/10.1016/j.enpol.2018.07.042
77. Grieshop, A. P., Marshall, J. D., & Kandlikar, M. (2011a). Health and climate benefits of cookstove replacement options. *Energy Policy*, *39*(12), 7530–7542. https://doi.org/10.1016/j.enpol.2011.03.024
78. Grieshop, A. P., Marshall, J. D., & Kandlikar, M. (2011b). Health and climate benefits of cookstove replacement options. *Energy Policy*, *39*(12), 7530–7542. https://doi.org/10.1016/j.enpol.2011.03.024
79. Haas, C. N., Rose, J., & Gerba, C. (1999). *Quantitative Microbial Risk Assessment*. Wiley & sons.
80. Habib, G., Venkataraman, C., Shrivastava, M., Banerjee, R., Stehr, J. W., & Dickerson, R. R. (2004). New methodology for estimating biofuel consumption for cooking: Atmospheric emissions of black carbon and sulfur dioxide from India: BIOFUEL COMBUSTION AND ATMOSPHERIC EMISSIONS. *Global Biogeochemical Cycles*, *18*(3), n/a-n/a. https://doi.org/10.1029/2003GB002157

81. Hachich, E. M., Di Bari, M., Christ, A. P. G., Lamparelli, C. C., Ramos, S. S., & Sato, M. I. Z. (2012). Comparison of thermotolerant coliforms and Escherichia coli densities in freshwater bodies. *Brazilian Journal of Microbiology*, *43*(2), 675–681. https://doi.org/10.1590/S1517-83822012000200032
82. Haines, A., Amann, M., Borgford-Parnell, N., Leonard, S., Kuylenstierna, J., & Shindell, D. (2017). Short-lived climate pollutant mitigation and the Sustainable Development Goals. *Nature Climate Change*, *7*(12), Article 12. https://doi.org/10.1038/s41558-017-0012-x
83. Hankey, S., Sullivan, K., Kinnick, A., Koskey, A., Grande, K., Davidson, J. H., & Marshall, J. D. (2015). Using objective measures of stove use and indoor air quality to evaluate a cookstove intervention in rural Uganda. *Energy for Sustainable Development*, *25*, 67–74. https://doi.org/10.1016/j.esd.2014.12.007
84. Hartinger Pena, S. M. (2014). *Reducing childhood illness – Fostering growth An integrated home-based intervention package (IHIP) to improve indoor-air pollution, drinking water quality and child nutrition* [University of Basel]. https://edoc.unibas.ch/34762/1/Thesis-SH-Final%20for%20CD.pdf
85. Hartinger, S. M., Lanata, C., Hattendorf, J., Verastegui, H., Gil, A., Wolf, J., & Mäusezahl, D. (2016). Improving household air, drinking water and hygiene in rural Peru: A community-randomized–controlled trial of an integrated environmental home-based intervention package to improve child health. *International Journal of Epidemiology*, dyw242. https://doi.org/10.1093/ije/dyw242
86. Hathaway, J. M., Krometis, L. H., & Hunt, W. F. (2014). Exploring Seasonality in *Escherichia coli* and Fecal Coliform Ratios in Urban Watersheds. *Journal of Irrigation and Drainage Engineering*, *140*(4), 04014003. https://doi.org/10.1061/(ASCE)IR.1943-4774.0000700
87. Hausfather, Z., & Peters, G. P. (2020). Emissions – the 'business as usual' story is misleading. *Nature*, *577*(7792), 618–620. https://doi.org/10.1038/d41586-020-00177-3
88. Havelaar, A. H., & Melse, J. M. (2003). *Quantifying public health risk in the WHO Guidelines for Drinking-Water Quality: A burden of disease approach* (RIVM 734301022/2003; WHO Guidelines for Drinking-Water Quality). World Health

Organization. https://www.who.int/water_sanitation_health/publications/rivmrep.pdf?ua=1

89. Health Effects Institute. (2020). *State of Global Air 2020* (p. 28) [Special Report]. Health Effects Institute. https://www.stateofglobalair.org/sites/default/files/documents/2022-09/soga-2020-report.pdf
90. Heitzinger, K., Rocha, C. A., Quick, R. E., Montano, S. M., Tilley, D. H., Mock, C. N., Carrasco, A. J., Cabrera, R. M., & Hawes, S. E. (2016). The challenge of improving boiling: Lessons learned from a randomized controlled trial of water pasteurization and safe storage in Peru. *Epidemiology and Infection*, *144*(10), 2230–2240. https://doi.org/10.1017/S0950268816000236
91. Hossain, M. A., Rahman, M. M., Murrill, M., Das, B., Roy, B., Dey, S., Maity, D., & Chakraborti, D. (2013). Water consumption patterns and factors contributing to water consumption in arsenic affected population of rural West Bengal, India. *Science of The Total Environment*, *463–464*, 1217–1224. https://doi.org/10.1016/j.scitotenv.2012.06.057
92. Huang, Y., Unger, N., Storelvmo, T., Harper, K., Zheng, Y., & Heyes, C. (2018). Global radiative effects of solid fuel cookstove aerosol emissions. *Atmospheric Chemistry and Physics*, *18*(8), 5219–5233. https://doi.org/10.5194/acp-18-5219-2018
93. Hunter, P. R., Zmirou-Navier, D., & Hartemann, P. (2009). Estimating the impact on health of poor reliability of drinking water interventions in developing countries. *Science of The Total Environment*, *407*(8), 2621–2624. https://doi.org/10.1016/j.scitotenv.2009.01.018
94. Hussain, R., & Luo, K. (2019). The Geological Availability and Emissions of Sulfur and SO2 from the Typical Coal of China. *Aerosol and Air Quality Research*, *19*(3), 559–570. https://doi.org/10.4209/aaqr.2018.08.0281
95. Hussien, W. A., Memon, F. A., & Savic, D. A. (2017). An integrated model to evaluate water-energy-food nexus at a household scale. *Environmental Modelling & Software*, *93*, 366–380. https://doi.org/10.1016/j.envsoft.2017.03.034
96. Hussien, W. A., Memon, F. A., & Savic, D. A. (2018). A risk-based assessment of the household water-energy-food nexus under the impact of seasonal variability. *Journal of Cleaner Production*, *171*, 1275–1289. https://doi.org/10.1016/j.jclepro.2017.10.094

97. Iannotti, L., Kleban, E., Fracassi, P., Oenema, S., & Lutter, C. (2024). Evidence for Policies and Practices to Address Global Food Insecurity. *Annual Review of Public Health*, *45*(1), 375–400. https://doi.org/10.1146/annurev-publhealth-060922-041451
98. IEA. (2019). *World Energy Statistics 2019* (World Energy Statistics, p. 891). International Energy Agency. https://doi.org/10.1787/2e828dea-en
99. IEA. (2020). *World Energy Outlook 2020 – Analysis* (World Energy Outlook). INTERNATIONAL ENERGY AGENCY. https://www.iea.org/reports/world-energy-outlook-2020
100. IEA, IRENA, UNSD, World Bank, & WHO. (2019). *Tracking SDG 7: The energy progress report* (p. 263) [Energy Progress Report]. World Bank. https://trackingsdg7.esmap.org/data/files/download-documents/sdg7-report2022-full_report.pdf
101. IHME. (2010). *Global Burden of Disease Study 2010 (GBD 2010)—Ambient Air Pollution Risk Model 1990—2010*. Global Health Data Exchange. https://ghdx.healthdata.org/record/ihme-data/gbd-2010-ambient-air-pollution-risk-model-1990-2010
102. IHME. (2022a). *Air pollution—Level 2 risk*. https://www.healthdata.org/results/gbd_summaries/2019/air-pollution-level-2-risk#:~:text=Summary%20In%202019%2C%20air%20pollution,%C2%B749)%20deaths%20in%202019.
103. IHME. (2022b). *Diarrheal diseases—Level 3 cause*. https://www.healthdata.org/results/gbd_summaries/2019/diarrheal-diseases-level-3-cause
104. Institute for Health Metrics and Evaluation. (2021, January 28). *Global Burden of Disease Study 2019 (GBD 2019) Population Estimates 1950-2019*. Institute for Health Metrics and Evaluation. http://ghdx.healthdata.org/sites/default/files/record-attached-files/IHME_GBD_2019_POP_1950_2019_INFO_SHEET_Y2021M01D28.PDF
105. Islam, M. M. (2020, December 14). *Evaluation of Cookstove Technologies in a Field Intervention Trial in Rural India: Quantifying Indoor Air Quality and Emissions Performance.* https://repository.lib.ncsu.edu/handle/1840.20/38493
106. Islam, M. M., Wathore, R., Zerriffi, H., Marshall, J. D., Bailis, R., & Grieshop, A. P. (2021). In-use emissions from biomass and LPG stoves measured during a large, multi-

year cookstove intervention study in rural India. *Science of The Total Environment*, *758*, 143698. https://doi.org/10.1016/j.scitotenv.2020.143698

107. Islam, M. M., Wathore, R., Zerriffi, H., Marshall, J. D., Bailis, R., & Grieshop, A. P. (2022a). Assessing the Effects of Stove Use Patterns and Kitchen Chimneys on Indoor Air Quality during a Multiyear Cookstove Randomized Control Trial in Rural India. *Environmental Science & Technology*, *56*(12), 8326–8337. https://doi.org/10.1021/acs.est.1c07571

108. Islam, M. M., Wathore, R., Zerriffi, H., Marshall, J. D., Bailis, R., & Grieshop, A. P. (2022b). Assessing the Effects of Stove Use Patterns and Kitchen Chimneys on Indoor Air Quality during a Multiyear Cookstove Randomized Control Trial in Rural India. *Environmental Science & Technology*. https://doi.org/10.1021/acs.est.1c07571

109. Itayi, C. L., Mohan, G., & Saito, O. (2021). Understanding the conceptual frameworks and methods of the food–energy–water nexus at the household level for development-oriented policy support: A systematic review. *Environmental Research Letters*, *16*(3), 033006. https://doi.org/10.1088/1748-9326/abd660

110. Jack, D. W., Ae-Ngibise, K. A., Gould, C. F., Boamah-Kaali, E., Lee, A. G., Mujtaba, M. N., Chillrud, S., Kaali, S., Quinn, A. K., Gyaase, S., Oppong, F. B., Carrión, D., Agyei, O., Burkhart, K., Ana-aro, J. A., Liu, X., Berko, Y. A., Wylie, B. J., Etego, S. A., … Asante, K. P. (2021). A cluster randomised trial of cookstove interventions to improve infant health in Ghana. *BMJ Global Health*, *6*(8), e005599. https://doi.org/10.1136/bmjgh-2021-005599

111. Jacobson, M. Z. (2014). Effects of biomass burning on climate, accounting for heat and moisture fluxes, black and brown carbon, and cloud absorption effects: Effects of biomass burning on climate. *Journal of Geophysical Research: Atmospheres*, *119*(14), 8980–9002. https://doi.org/10.1002/2014JD021861

112. Jagoe, K., Rossanese, M., Charron, D., Rouse, J., Waweru, F., Waruguru, M., Delapena, S., Piedrahita, R., Livingston, K., & Ipe, J. (2020). Sharing the burden: Shifts in family time use, agency and gender dynamics after introduction of new cookstoves in rural Kenya. *Energy Research & Social Science*, *64*, 101413.

113. Janssen, N. A. H., Hoek, G., Simic-Lawson, M., Fischer, P., van Bree, L., Keuken, M., Atkinson, R. W., Anderson, H. R., Brunekreef, B., & Cassee, F. R. (2011). Black Carbon

as an Additional Indicator of the Adverse Health Effects of Airborne Particles Compared with PM10 and PM2.5. *Environmental Health Perspectives*, *119*(12).

114. Jetter, J. J., & Kariher, P. (2009). Solid-fuel household cook stoves: Characterization of performance and emissions. *Biomass and Bioenergy*, *33*(2), 294–305. https://doi.org/10.1016/j.biombioe.2008.05.014

115. Johnson, M., Edwards, R., Ghilardi, A., Berrueta, V., Gillen, D., Frenk, C. A., & Masera, O. (2009). Quantification of Carbon Savings from Improved Biomass Cookstove Projects. *Environmental Science & Technology*, *43*(7), 2456–2462. https://doi.org/10.1021/es801564u

116. Johnson, M., Lam, N., Brant, S., Gray, C., & Pennise, D. (2011). Modeling indoor air pollution from cookstove emissions in developing countries using a Monte Carlo single-box model. *Atmospheric Environment*, *45*(19), 3237–3243. https://doi.org/10.1016/j.atmosenv.2011.03.044

117. Johnson, M., Piedrahita, R., Pillarisetti, A., Shupler, M., Menya, D., Rossanese, M., Delapeña, S., Penumetcha, N., Chartier, R., Puzzolo, E., & Pope, D. (2021). Modeling approaches and performance for estimating personal exposure to household air pollution: A case study in Kenya. *Indoor Air*, *31*(5), 1441–1457. https://doi.org/10.1111/ina.12790

118. Johnson, M., Pillarisetti, A., Piedrahita, R., Balakrishnan, K., Peel, J. L., Steenland, K., Underhill, L. J., Rosa, G., Kirby, M. A., Díaz-Artiga, A., McCracken, J., Clark, M. L., Waller, L., Chang, H. H., Wang, J., Dusabimana, E., Ndagijimana, F., Sambandam, S., Mukhopadhyay, K., … and the Household Air Pollution Intervention Network (HAPIN) Trial Investigators. (2022). Exposure Contrasts of Pregnant Women during the Household Air Pollution Intervention Network Randomized Controlled Trial. *Environmental Health Perspectives*, *130*(9), 097005. https://doi.org/10.1289/EHP10295

119. Josyula, S., Lin, J., Xue, X., Rothman, N., Lan, Q., Rohan, T. E., & Hosgood, H. D. (2015). Household air pollution and cancers other than lung: A meta-analysis. *Environmental Health*, *14*(1), 24. https://doi.org/10.1186/s12940-015-0001-3

120. Karambizi, N. U., McMahan, C. S., Blue, C. N., & Temesvari, L. A. (2021). Global estimated Disability-Adjusted Life-Years (DALYs) of diarrheal diseases: A systematic analysis of data from 28 years of the global burden of disease study. *PLOS ONE*, *16*(10), e0259077. https://doi.org/10.1371/journal.pone.0259077

121. Kimemia, D., & Annegarn, H. (2016). Domestic LPG interventions in South Africa: Challenges and lessons. *Energy Policy*, *93*, 150–156. https://doi.org/10.1016/j.enpol.2016.03.005

122. Kirby, M. A., Nagel, C. L., Rosa, G., Zambrano, L. D., Musafiri, S., Ngirabega, J. de D., Thomas, E. A., & Clasen, T. (2019). Effects of a large-scale distribution of water filters and natural draft rocket-style cookstoves on diarrhea and acute respiratory infection: A cluster-randomized controlled trial in Western Province, Rwanda. *PLOS Medicine*, *16*(6), e1002812. https://doi.org/10.1371/journal.pmed.1002812

123. Klimont, Z., Kupiainen, K., Heyes, C., Purohit, P., Cofala, J., Rafaj, P., Borken-Kleefeld, J., & Schöpp, W. (2017). Global anthropogenic emissions of particulate matter including black carbon. *Atmospheric Chemistry and Physics*, *17*(14), 8681–8723. https://doi.org/10.5194/acp-17-8681-2017

124. Kodros, J. K., Scott, C. E., Farina, S. C., Lee, Y. H., L'Orange, C., Volckens, J., & Pierce, J. R. (2015a). Uncertainties in global aerosols and climate effects due to biofuel emissions. *Atmos. Chem. Phys.*, *15*(15), 8577–8596. https://doi.org/10.5194/acp-15-8577-2015

125. Kodros, J. K., Scott, C. E., Farina, S. C., Lee, Y. H., L'Orange, C., Volckens, J., & Pierce, J. R. (2015b). Uncertainties in global aerosols and climate effects due to biofuel emissions. *Atmos. Chem. Phys.*, *15*(15), 8577–8596. https://doi.org/10.5194/acp-15-8577-2015

126. Kotloff, K. L., Blackwelder, W. C., Nasrin, D., Nataro, J. P., Farag, T. H., van Eijk, A., Adegbola, R. A., Alonso, P. L., Breiman, R. F., Golam Faruque, A. S., Saha, D., Sow, S. O., Sur, D., Zaidi, A. K. M., Biswas, K., Panchalingam, S., Clemens, J. D., Cohen, D., Glass, R. I., … Levine, M. M. (2012). The Global Enteric Multicenter Study (GEMS) of Diarrheal Disease in Infants and Young Children in Developing Countries: Epidemiologic and Clinical Methods of the Case/Control Study. *Clinical Infectious Diseases*, *55*(suppl_4), S232–S245. https://doi.org/10.1093/cid/cis753

127. Kundu, A., Wuertz, S., & Smith, W. A. (2018). Quantitative microbial risk assessment to estimate the risk of diarrheal diseases from fresh produce consumption in India. *Food Microbiology*, *75*, 95–102. https://doi.org/10.1016/j.fm.2018.01.017

128. Kypridemos, C. (2020). Health and Climate Impacts of Scaling Adoption of Liquefied Petroleum Gas (LPG) for Clean Household Cooking in Cameroon: A Modeling Study. *Environmental Health Perspectives*, 12.

129. Kypridemos, C., Puzzolo, E., Aamaas, B., Hyseni, L., Shupler, M., Aunan, K., & Pope, D. (2020). Health and Climate Impacts of Scaling Adoption of Liquefied Petroleum Gas (LPG) for Clean Household Cooking in Cameroon: A Modeling Study. *Environmental Health Perspectives*, *128*(4), 047001. https://doi.org/10.1289/EHP4899

130. Kypridemos Chris, Puzzolo Elisa, Aamaas Borgar, Hyseni Lirije, Shupler Matthew, Aunan Kristin, & Pope Daniel. (2020). Health and Climate Impacts of Scaling Adoption of Liquefied Petroleum Gas (LPG) for Clean Household Cooking in Cameroon: A Modeling Study. *Environmental Health Perspectives*, *128*(4), 047001. https://doi.org/10.1289/EHP4899

131. Lacey, F. G., Henze, D. K., Lee, C. J., Donkelaar, A. van, & Martin, R. V. (2017). Transient climate and ambient health impacts due to national solid fuel cookstove emissions. *Proceedings of the National Academy of Sciences*, *114*(6), 1269–1274. https://doi.org/10.1073/pnas.1612430114

132. Lai, P. S., Lam, N. L., Gallery, B., Lee, A. G., Adair-Rohani, H., Alexander, D., Balakrishnan, K., Bisaga, I., Chafe, Z. A., Clasen, T., Díaz-Artiga, A., Grieshop, A., Harrison, K., Hartinger, S. M., Jack, D., Kaali, S., Lydston, M., Mortimer, K. M., Nicolaou, L., … Ozoh, O. B. (2024). Household Air Pollution Interventions to Improve Health in Low- and Middle-Income Countries: An Official American Thoracic Society Research Statement. *American Journal of Respiratory and Critical Care Medicine*, *209*(8), 909–927. https://doi.org/10.1164/rccm.202402-0398ST

133. Lanata, C. F., Fischer-Walker, C. L., Olascoaga, A. C., Torres, C. X., Aryee, M. J., Black, R. E., & for the Child Health Epidemiology Reference Group of the World Health Organization and UNICEF. (2013). Global Causes of Diarrheal Disease Mortality in Children <5 Years of Age: A Systematic Review. *PLoS ONE*, *8*(9), e72788. https://doi.org/10.1371/journal.pone.0072788

134. Lappan, R., Henry, R., Chown, S. L., Luby, S. P., Higginson, E. E., Bata, L., Jirapanjawat, T., Schang, C., Openshaw, J. J., O'Toole, J., Lin, A., Tela, A., Turagabeci, A., Wong, T. H. F., French, M. A., Brown, R. R., Leder, K., Greening, C., & McCarthy,

D. (2021). Monitoring of diverse enteric pathogens across environmental and host reservoirs with TaqMan array cards and standard qPCR: A methodological comparison study. *The Lancet Planetary Health*, *5*(5), e297–e308. https://doi.org/10.1016/S2542-5196(21)00051-6

135. Leach, N. J., Jenkins, S., Nicholls, Z., Smith, C. J., Lynch, J., Cain, M., Walsh, T., Wu, B., Tsutsui, J., & Allen, M. R. (2021). FaIRv2.0.0: A generalized impulse response model for climate uncertainty and future scenario exploration. *Geoscientific Model Development*, *14*(5), 3007–3036. https://doi.org/10.5194/gmd-14-3007-2021

136. Levine, D. I., & Cotterman, C. (2011). *What Impedes Efficient Adoption of Products? Evidence from Randomized Variation in Sales Offers for Improved Cookstoves in Uganda*. 30.

137. Lewis, J. J., Bhojvaid, V., Brooks, N., Das, I., Jeuland, M. A., Patange, O., & Pattanayak, S. K. (2015). Piloting Improved Cookstoves in India. *Journal of Health Communication*, *20*(sup1), 28–42. https://doi.org/10.1080/10810730.2014.994243

138. Liao, J., Kirby, M. A., Pillarisetti, A., Piedrahita, R., Balakrishnan, K., Sambandam, S., Mukhopadhyay, K., Ye, W., Rosa, G., Majorin, F., Dusabimana, E., Ndagijimana, F., McCracken, J. P., Mollinedo, E., de Leon, O., Díaz-Artiga, A., Thompson, L. M., Kearns, K. A., Naeher, L., … Young, B. N. (2021). LPG stove and fuel intervention among pregnant women reduce fine particle air pollution exposures in three countries: Pilot results from the HAPIN trial. *Environmental Pollution*, *291*, 118198. https://doi.org/10.1016/j.envpol.2021.118198

139. Lim, S. S., Vos, T., Flaxman, A. D., Danaei, G., Shibuya, K., Adair-Rohani, H., AlMazroa, M. A., Amann, M., Anderson, H. R., Andrews, K. G., Aryee, M., Atkinson, C., Bacchus, L. J., Bahalim, A. N., Balakrishnan, K., Balmes, J., Barker-Collo, S., Baxter, A., Bell, M. L., … Ezzati, M. (2012). A comparative risk assessment of burden of disease and injury attributable to 67 risk factors and risk factor clusters in 21 regions, 1990–2010: A systematic analysis for the Global Burden of Disease Study 2010. *The Lancet*, *380*(9859), 2224–2260. https://doi.org/10.1016/S0140-6736(12)61766-8

140. Lu, H., Tan, Z., Liu, Z., Wang, L., Wang, Y., Suo, C., Zhang, T., Jin, L., Dong, Q., Cui, M., Jiang, Y., & Chen, X. (2021). Spatiotemporal trends in stroke burden and mortality attributable to household air pollution from solid fuels in 204 countries and territories

from 1990 to 2019. *Science of The Total Environment*, *775*, 145839. https://doi.org/10.1016/j.scitotenv.2021.145839

141. Machdar, E., van der Steen, N. P., Raschid-Sally, L., & Lens, P. N. L. (2013). Application of Quantitative Microbial Risk Assessment to analyze the public health risk from poor drinking water quality in a low income area in Accra, Ghana. *Science of The Total Environment*, *449*, 134–142. https://doi.org/10.1016/j.scitotenv.2013.01.048

142. Manaseki-Holland, S., Manjang, B., Hemming, K., Martin, J. T., Bradley, C., Jackson, L., Taal, M., Gautam, O. P., Crowe, F., Sanneh, B., Ensink, J., Stokes, T., & Cairncross, S. (2021). Effects on childhood infections of promoting safe and hygienic complementary-food handling practices through a community-based programme: A cluster randomised controlled trial in a rural area of The Gambia. *PLOS Medicine*, *18*(1), e1003260. https://doi.org/10.1371/journal.pmed.1003260

143. Maniragaba, F., Nzabona, A., Lwanga, C., Ariho, P., & Kwagala, B. (2023). Factors that influence safe water drinking practices among older persons in slums of Kampala: Analyzing disparities in boiling water. *PLOS ONE*, *18*(9), e0291980. https://doi.org/10.1371/journal.pone.0291980

144. Martínez-Negrete, M., Martínez, R., Joaquín, R., Sheinbaum, C., & Masera, O. R. (2013). Is modernization making villages more energy efficient? A long-term comparative end-use analysis for Cheranatzicurin village, Mexico. *Energy for Sustainable Development*, *17*(5), 463–470. https://doi.org/10.1016/j.esd.2013.05.004

145. Masera, O. R., Rob Bailis, Rudi Drigo, Adrian Ghilardi, & Ilse Ruiz-Mercado. (2015). Environmental Burden of Traditional Bioenergy Use. *Annual Review of Environment and Resources*, *40*, 121–150. https://doi.org/doi:10.1146/annurev-environ-102014-021318

146. Mattioli, M. C. M., Davis, J., & Boehm, A. B. (2015). Hand-to-Mouth Contacts Result in Greater Ingestion of Feces than Dietary Water Consumption in Tanzania: A Quantitative Fecal Exposure Assessment Model. *Environmental Science & Technology*, *49*(3), 1912–1920. https://doi.org/10.1021/es505555f

147. Mbiankeu Nguea, S. (2024). Uncovering the linkage between sustainable development goals for access to electricity and access to safely managed drinking water and sanitation services. *Social Science & Medicine*, *345*, 116687. https://doi.org/10.1016/j.socscimed.2024.116687

148. Medema, G. J., Teunis, P. F. M., Havelaar, A. H., & Haas, C. N. (1996). Assessment of the dose-response relationship of Campylobacter jejuni. *International Journal of Food Microbiology*, *30*(1–2), 101–111. https://doi.org/10.1016/0168-1605(96)00994-4

149. Menghwani, V., Zerriffi, H., Dwivedi, P., Marshall, J. D., Grieshop, A., & Bailis, R. (2019). Determinants of Cookstoves and Fuel Choice Among Rural Households in India. *EcoHealth*, *16*(1), 21–60. https://doi.org/10.1007/s10393-018-1389-3

150. Mensah, J. T., & Adu, G. (2015). An empirical analysis of household energy choice in Ghana. *Renewable and Sustainable Energy Reviews*, *51*, 1402–1411. https://doi.org/10.1016/j.rser.2015.07.050

151. Mguni, P., Van Vliet, B., Spaargaren, G., Nakirya, D., Osuret, J., Isunju, J. B., Ssekamatte, T., & Mugambe, R. (2020). What could go wrong with cooking? Exploring vulnerability at the water, energy and food Nexus in Kampala through a social practices lens. *Global Environmental Change*, *63*, 102086. https://doi.org/10.1016/j.gloenvcha.2020.102086

152. Morgan, C. E., Bowling, J. M., Bartram, J., & Kayser, G. L. (2021). Attributes of drinking water, sanitation, and hygiene associated with microbiological water quality of stored drinking water in rural schools in Mozambique and Uganda. *International Journal of Hygiene and Environmental Health*, *236*, 113804. https://doi.org/10.1016/j.ijheh.2021.113804

153. Murphy, H. M., Thomas, M. K., Schmidt, P. J., Medeiros, D. T., McFADYEN, S., & Pintar, K. D. M. (2016). Estimating the burden of acute gastrointestinal illness due to *Giardia, Cryptosporidium, Campylobacter, E. coli* O157 and norovirus associated with private wells and small water systems in Canada. *Epidemiology and Infection*, *144*(7), 1355–1370. https://doi.org/10.1017/S0950268815002071

154. Murray, C. J. L., Aravkin, A. Y., Zheng, P., Abbafati, C., Abbas, K. M., Abbasi-Kangevari, M., Abd-Allah, F., Abdelalim, A., Abdollahi, M., Abdollahpour, I., Abegaz, K. H., Abolhassani, H., Aboyans, V., Abreu, L. G., Abrigo, M. R. M., Abualhasan, A., Abu-Raddad, L. J., Abushouk, A. I., Adabi, M., … Lim, S. S. (2020). Global burden of 87 risk factors in 204 countries and territories, 1990–2019: A systematic analysis for the Global Burden of Disease Study 2019. *The Lancet*, *396*(10258), 1223–1249. https://doi.org/10.1016/S0140-6736(20)30752-2

155. Murray, C. J. L., Vos, T., Lozano, R., Naghavi, M., Flaxman, A. D., Michaud, C., Ezzati, M., Shibuya, K., Salomon, J. A., Abdalla, S., Aboyans, V., Abraham, J., Ackerman, I., Aggarwal, R., Ahn, S. Y., Ali, M. K., AlMazroa, M. A., Alvarado, M., Anderson, H. R., … Lopez, A. D. (2012). Disability-adjusted life years (DALYs) for 291 diseases and injuries in 21 regions, 1990–2010: A systematic analysis for the Global Burden of Disease Study 2010. *The Lancet*, *380*(9859), 2197–2223. https://doi.org/10.1016/S0140-6736(12)61689-4

156. Njenga, M., Iiyama, M., Jamnadass, R., Helander, H., Larsson, L., de Leeuw, J., Neufeldt, H., Röing de Nowina, K., & Sundberg, C. (2016). Gasifier as a cleaner cooking system in rural Kenya. *Journal of Cleaner Production*, *121*, 208–217. https://doi.org/10.1016/j.jclepro.2016.01.039

157. Nouiri, I. (2017). Optimal design and management of chlorination in drinking water networks: A multi-objective approach using Genetic Algorithms and the Pareto optimality concept. *Applied Water Science*, *7*(7), 3527–3538. https://doi.org/10.1007/s13201-017-0620-7

158. Ochieng, C. A., Zhang, Y., Nyabwa, J. K., Otieno, D. I., & Spillane, C. (2020). Household perspectives on cookstove and fuel stacking: A qualitative study in urban and rural Kenya. *Energy for Sustainable Development*, *59*, 151–159. https://doi.org/10.1016/j.esd.2020.10.002

159. Odonkor, S. T., & Mahami, T. (2020). *Escherichia coli* as a Tool for Disease Risk Assessment of Drinking Water Sources. *International Journal of Microbiology*, *2020*, 1–7. https://doi.org/10.1155/2020/2534130

160. Oluwoye, I., Altarawneh, M., Gore, J., & Dlugogorski, B. Z. (2020). Products of incomplete combustion from biomass reburning. *Fuel*, *274*, 117805. https://doi.org/10.1016/j.fuel.2020.117805

161. Owens, C. E. L., Angles, M. L., Cox, P. T., Byleveld, P. M., Osborne, N. J., & Rahman, M. B. (2020). Implementation of quantitative microbial risk assessment (QMRA) for public drinking water supplies: Systematic review. *Water Research*, *174*, 115614. https://doi.org/10.1016/j.watres.2020.115614

162. Ozoh, O., Okwor, T., Adetona, O., Akinkugbe, A., Amadi, C., Esezobor, C., Adeyeye, O., Ojo, O., Nwude, V., & Mortimer, K. (2018). Cooking Fuels in Lagos, Nigeria:

Factors Associated with Household Choice of Kerosene or Liquefied Petroleum Gas (LPG). *International Journal of Environmental Research and Public Health*, *15*(4), 641. https://doi.org/10.3390/ijerph15040641

163. Patel, M. M., Steele, D., Gentsch, J. R., Wecker, J., Glass, R. I., & Parashar, U. D. (2011). Real-world Impact of Rotavirus Vaccination. *Pediatric Infectious Disease Journal*, *30*(1), S1–S5. https://doi.org/10.1097/INF.0b013e3181fefa1f

164. Pennise, D. M., Smith, K. R., Kithinji, J. P., Rezende, M. E., Raad, T. J., Zhang, J., & Fan, C. (2001). Emissions of greenhouse gases and other airborne pollutants from charcoal making in Kenya and Brazil. *Journal of Geophysical Research: Atmospheres*, *106*(D20), 24143–24155. https://doi.org/10.1029/2000JD000041

165. Perin, J., Mulick, A., Yeung, D., Villavicencio, F., Lopez, G., Strong, K. L., Prieto-Merino, D., Prieto-Merino, D., Cousens, S., Black, R. E., & Liu, L. (2022). Global, regional, and national causes of under-5 mortality in 2000–19: An updated systematic analysis with implications for the Sustainable Development Goals. *The Lancet Child & Adolescent Health*, *6*(2), 106–115.

166. Pham, T. L., Tran, T. H. Y., Tran, T. T., Ngo, X. Q., & Nguyen, X. D. (2022). Assessment of surface water quality in a drinking water supply reservoir in Vietnam: A combination of different indicators. *Rendiconti Lincei. Scienze Fisiche e Naturali*, *33*(3), 653–662. https://doi.org/10.1007/s12210-022-01086-5

167. Piedrahita, R., Dickinson, K. L., Kanyomse, E., Coffey, E., Alirigia, R., Hagar, Y., Rivera, I., Oduro, A., Dukic, V., Wiedinmyer, C., & Hannigan, M. (2016). Assessment of cookstove stacking in Northern Ghana using surveys and stove use monitors. *Energy for Sustainable Development*, *34*, 67–76. https://doi.org/10.1016/j.esd.2016.07.007

168. Pillarisetti, A. (2019). *Air Pollution Burden of Disease Explorer (ABODE), https://householdenergy.shinyapps.io/abode/* [Computer software]. Emory University and UC Berkeley. https://householdenergy.shinyapps.io/abode/

169. Pillarisetti, A., Mehta, S., & Smith, K. R. (2015). Household Air Pollution Intervention Tool (HAPIT III). In *Clean Cooking Alliance*. https://www.cleancookingalliance.org/resources/450.html

170. Pillarisetti, A., Mehta, S., & Smith, K. R. (2016a). *HAPIT 3.1.1*. https://householdenergy.shinyapps.io/hapit3/

171. Pillarisetti, A., Mehta, S., & Smith, K. R. (2016b). HAPIT, the Household Air Pollution Intervention Tool, to evaluate the health benefits and cost-effectiveness of clean cooking interventions. In E. A. Thomas (Ed.), *Broken Pumps and Promises: Incentivizing Impact in Environmental Health* (pp. 147–169). Springer International Press.

172. Platts-Mills, J. A., Babji, S., Bodhidatta, L., Gratz, J., Haque, R., Havt, A., McCormick, B. J., McGrath, M., Olortegui, M. P., Samie, A., Shakoor, S., Mondal, D., Lima, I. F., Hariraju, D., Rayamajhi, B. B., Qureshi, S., Kabir, F., Yori, P. P., Mufamadi, B., … Houpt, E. R. (2015). Pathogen-specific burdens of community diarrhoea in developing countries: A multisite birth cohort study (MAL-ED). *The Lancet Global Health*, *3*(9), e564–e575. https://doi.org/10.1016/S2214-109X(15)00151-5

173. Pokhrel, A. K., Bates, M. N., Acharya, J., Valentiner-Branth, P., Chandyo, R. K., Shrestha, P. S., Raut, A. K., & Smith, K. R. (2015). PM 2.5 in household kitchens of Bhaktapur, Nepal, using four different cooking fuels. *Atmospheric Environment*, *113*, 159–168. https://doi.org/10.1016/j.atmosenv.2015.04.060

174. Pope, D., Bruce, N., Dherani, M., Jagoe, K., & Rehfuess, E. (2017a). Real-life effectiveness of 'improved' stoves and clean fuels in reducing PM 2.5 and CO: Systematic review and meta-analysis. *Environment International*, *101*, 7–18. https://doi.org/10.1016/j.envint.2017.01.012

175. Pope, D., Bruce, N., Dherani, M., Jagoe, K., & Rehfuess, E. (2017b). Real-life effectiveness of 'improved' stoves and clean fuels in reducing PM 2.5 and CO: Systematic review and meta-analysis. *Environment International*, *101*, 7–18. https://doi.org/10.1016/j.envint.2017.01.012

176. Pope, D., Johnson, M., Fleeman, N., Jagoe, K., Duarte, R., Maden, M., Ludolph, R., Bruce, N., Shupler, M., Adair-Rohani, H., & Lewis, J. (2021a). Are cleaner cooking solutions clean enough? A systematic review and meta-analysis of particulate and carbon monoxide concentrations and exposures. *Environmental Research Letters*, *16*(8), 083002. https://doi.org/10.1088/1748-9326/ac13ec

177. Pope, D., Johnson, M., Fleeman, N., Jagoe, K., Duarte, R., Maden, M., Ludolph, R., Bruce, N., Shupler, M., Adair-Rohani, H., & Lewis, J. (2021b). Are cleaner cooking solutions clean enough? A systematic review and meta-analysis of particulate and carbon

monoxide concentrations and exposures. *Environmental Research Letters*, *16*(8), 083002. https://doi.org/10.1088/1748-9326/ac13ec

178. Price, R. (2017). *"Clean" Cooking Energy in Uganda – technologies, impacts, and key barriers and enablers to market acceleration*. 23.

179. Prihartono, N., Adisasmita, A., Costello, C., Damayanti, R., Prasetyo, S., & Syarif, S. (1994). Water Preparation Practices in South Kalimantan, Indonesia. *Journal of Diarrhoeal Diseases Research*, *12*(4), 279–286.

180. Prüss-Ustün, A., Wolf, J., Bartram, J., Clasen, T., Cumming, O., Freeman, M. C., Gordon, B., Hunter, P. R., Medlicott, K., & Johnston, R. (2019). Burden of disease from inadequate water, sanitation and hygiene for selected adverse health outcomes: An updated analysis with a focus on low- and middle-income countries. *International Journal of Hygiene and Environmental Health*, *222*(5), 765–777. https://doi.org/10.1016/j.ijheh.2019.05.004

181. Psutka, R., Peletz, R., Michelo, S., Kelly, P., & Clasen, T. (2011). Assessing the Microbiological Performance and Potential Cost of Boiling Drinking Water in Urban Zambia. *Environmental Science & Technology*, *45*(14), 6095–6101. https://doi.org/10.1021/es2004045

182. Psutka, R., Priest, P., Davies, T., Rakunuea, T., Iddings, S., & Reiffer, A. (2013). Assessing the demographic, behavioural and environmental characteristics and the potential effectiveness of a household water filter in the Republic of Kiribati. *Journal of Water, Sanitation and Hygiene for Development*, *3*(4), 530–540. https://doi.org/10.2166/washdev.2013.139

183. Puzzolo, E., Cloke, J., Parikh, J., Evans, A., & Pope, D. (2020). *NATIONAL SCALING UP OF LPG TO ACHIEVE SDG 7: Implications for Policy, Implementation, Public Health and Environment* (p. 15). UK Aid. https://mecs.org.uk/wp-content/uploads/2020/02/MECS-LPG-Briefing-Paper_Jan-2020.pdf

184. Puzzolo, E., Fleeman, N., Lorenzetti, F., Rubinstein, F., Li, Y., Xing, R., Shen, G., Nix, E., Maden, M., Bresnahan, R., Duarte, R., Abebe, L., Lewis, J., Williams, K. N., Adahir-Rohani, H., & Pope, D. (2024). Estimated health effects from domestic use of gaseous fuels for cooking and heating in high-income, middle-income, and low-income countries:

A systematic review and meta-analyses. *The Lancet Respiratory Medicine*, *12*(4), 281–293. https://doi.org/10.1016/S2213-2600(23)00427-7

185. Puzzolo, E., Zerriffi, H., Carter, E., Clemens, H., Stokes, H., Jagger, P., Rosenthal, J., & Petach, H. (2019). Supply Considerations for Scaling Up Clean Cooking Fuels for Household Energy in Low- and Middle-Income Countries. *GeoHealth*, *3*(12), 370–390. https://doi.org/10.1029/2019GH000208

186. Pye, A., Ronzi, S., Mbatchou Ngahane, B. H., Puzzolo, E., Ashu, A. H., & Pope, D. (2020). Drivers of the Adoption and Exclusive Use of Clean Fuel for Cooking in Sub-Saharan Africa: Learnings and Policy Considerations from Cameroon. *International Journal of Environmental Research and Public Health*, *17*(16), 5874. https://doi.org/10.3390/ijerph17165874

187. R Core Team. (2021). *A language and environment for statistical computing.* [Computer software]. R Foundation for Statistical Computing. https://www.R-project.org/

188. Raspanti, G. A., Hashibe, M., Siwakoti, B., Wei, M., Thakur, B. K., Pun, C. B., Al-Temimi, M., Lee, Y.-C. A., & Sapkota, A. (2016). Household air pollution and lung cancer risk among never-smokers in Nepal. *Environmental Research*, *147*, 141–145. https://doi.org/10.1016/j.envres.2016.02.008

189. Ray, I., & Smith, K. R. (2021). Towards safe drinking water and clean cooking for all. *The Lancet Global Health*, S2214109X20304769. https://doi.org/10.1016/S2214-109X(20)30476-9

190. Roden, C. A., Bond, T. C., Conway, S., Osorto Pinel, A. B., MacCarty, N., & Still, D. (2009). Laboratory and field investigations of particulate and carbon monoxide emissions from traditional and improved cookstoves. *Atmospheric Environment*, *43*(6), 1170–1181. https://doi.org/10.1016/j.atmosenv.2008.05.041

191. Roden, C. A., Bond, T. C., Conway, S., & Pinel, A. B. O. (2006). Emission Factors and Real-Time Optical Properties of Particles Emitted from Traditional Wood Burning Cookstoves. *Environmental Science & Technology*, *40*(21), 6750–6757. https://doi.org/10.1021/es052080i

192. Rosa, G., & Clasen, T. (2010). Estimating the Scope of Household Water Treatment in Low- and Medium-Income Countries. *The American Journal of Tropical Medicine and Hygiene*, *82*(2), 289–300. https://doi.org/10.4269/ajtmh.2010.09-0382

193. Rosa, G., Huaylinos, M. L., Gil, A., Lanata, C., & Clasen, T. (2014). Assessing the Consistency and Microbiological Effectiveness of Household Water Treatment Practices by Urban and Rural Populations Claiming to Treat Their Water at Home: A Case Study in Peru. *PLoS ONE*, *9*(12), e114997. https://doi.org/10.1371/journal.pone.0114997

194. Rosa, G., Majorin, F., Boisson, S., Barstow, C., Johnson, M., Kirby, M., Ngabo, F., Thomas, E., & Clasen, T. (2014). Assessing the Impact of Water Filters and Improved Cook Stoves on Drinking Water Quality and Household Air Pollution: A Randomised Controlled Trial in Rwanda. *PLoS ONE*, *9*(3), e91011. https://doi.org/10.1371/journal.pone.0091011

195. Roser, M. (2021). *Data review: How many people die from air pollution?* https://ourworldindata.org/data-review-air-pollution-deaths

196. Rufener, S., Mäusezahl, D., Mosler, H.-J., & Weingartner, R. (2010). Quality of Drinking-water at Source and Point-of-consumption - Drinking Cup As a High Potential Recontamination Risk: A Field Study in Bolivia. *Journal of Health, Population and Nutrition*, *28*(1), 34–41. https://doi.org/10.3329/jhpn.v28i1.4521

197. Ruiz-Mercado, I., & Masera, O. (2015). Patterns of Stove Use in the Context of Fuel–Device Stacking: Rationale and Implications. *EcoHealth*, *12*(1), 42–56. https://doi.org/10.1007/s10393-015-1009-4

198. Sadik, N. J., Uprety, S., Nalweyiso, A., Kiggundu, N., Banadda, N. E., Shisler, J. L., & Nguyen, T. H. (2017). Quantification of multiple waterborne pathogens in drinking water, drainage channels, and surface water in Kampala, Uganda, during seasonal variation. *GeoHealth*, *1*(6), 258–269. https://doi.org/10.1002/2017GH000081

199. Sanciolo, P., Monis, P., Blackbeard, J., Salveson, A., Ryan, G., & Gray, S. (2015). *Pasteurisation for the Production of Class A Water*.

200. SEforAll. (2021). *Energizing Finance: Understanding the Landscape 2021* (Energizing Finance Research Series, p. 106). SEforAll, Climate Policy Institute. https://www.seforall.org/publications/energizing-finance-understanding-the-landscape-2021

201. Seguin, R., Flax, V. L., & Jagger, P. (2018). Barriers and facilitators to adoption and use of fuel pellets and improved cookstoves in urban Rwanda. *PLOS ONE*, *13*(10), e0203775. https://doi.org/10.1371/journal.pone.0203775

202. Shankar, A. V., Quinn, A. K., Dickinson, K. L., Williams, K. N., Masera, O., Charron, D., Jack, D., Hyman, J., Pillarisetti, A., Bailis, R., Kumar, P., Ruiz-Mercado, I., & Rosenthal, J. P. (2020). Everybody stacks: Lessons from household energy case studies to inform design principles for clean energy transitions. *Energy Policy*, *141*, 111468. https://doi.org/10.1016/j.enpol.2020.111468

203. Shen, G. (2016). Changes from traditional solid fuels to clean household energies – Opportunities in emission reduction of primary PM2.5 from residential cookstoves in China. *Biomass and Bioenergy*, *86*, 28–35. https://doi.org/10.1016/j.biombioe.2016.01.004

204. Shrestha, K., Thapa, B., Aihara, Y., Shrestha, S., Bhattarai, A., Bista, N., Kazama, F., & Shindo, J. (2018). Hidden Cost of Drinking Water Treatment and Its Relation with Socioeconomic Status in Nepalese Urban Context. *Water*, *10*(5), 607. https://doi.org/10.3390/w10050607

205. Siddharthan, T., Grigsby, M. R., Goodman, D., Chowdhury, M., Rubinstein, A., Irazola, V., Gutierrez, L., Miranda, J. J., Bernabe-Ortiz, A., Alam, D., Kirenga, B., Jones, R., Van Gemert, F., Wise, R. A., & Checkley, W. (2018). Association between Household Air Pollution Exposure and Chronic Obstructive Pulmonary Disease Outcomes in 13 Low- and Middle-Income Country Settings. *American Journal of Respiratory and Critical Care Medicine*, *197*(5), 611–620. https://doi.org/10.1164/rccm.201709-1861OC

206. Sikder, M., String, G., Kamal, Y., Farrington, M., Rahman, A. S., & Lantagne, D. (2020). Effectiveness of water chlorination programs along the emergency-transition-post-emergency continuum: Evaluations of bucket, in-line, and piped water chlorination programs in Cox's Bazar. *Water Research*, *178*, 115854. https://doi.org/10.1016/j.watres.2020.115854

207. Siu, J., Jackson, L. J., Bensassi, S., Manjang, B., & Manaseki-Holland, S. (2021). Cost-effectiveness of a weaning food safety and hygiene programme in rural Gambia. *Tropical Medicine & International Health*, *26*(12), 1624–1633.

208. Smith, C. (2021, September 16). *FaIR v1.6.2 calibrated and constrained parameter set*. https://zenodo.org/record/5513022#.Yt_jfHbMLb0

209. Smith, C. J., Forster, P. M., Allen, M., Leach, N., Millar, R. J., Passerello, G. A., & Regayre, L. A. (2018). *FAIR v1.3: A simple emissions-based impulse response and carbon cycle model*. https://doi.org/10.5194/gmd-11-2273-2018

210. Smith, C., Nicholls, Z. R. J., Armour, K., Collins, W., Forster, P., Meinshausen, M., Palmer, M. D., & Watanabe, M. (2021). The Earth's Energy Budget, Climate Feedbacks, and Climate Sensitivity Supplementary Material. In V. Masson-Delmotte, P. Zhai, A. Pirani, S. L. Connors, C. Péan, S. Berger, N. Caud, Y. Chen, L. Goldfarb, M. I. Gomis, M. Huang, K. Leitzell, E. Lonnoy, J. B. R. Matthews, T. K. Maycock, T. Waterfield, O. Yelekçi, R. Yu, & B. Zhou (Eds.), *Climate Change 2021: The Physical Science Basis. Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change*. Available from https://www.ipcc.ch/

211. Smith, L. C., El Obeid, A. E., & Jensen, H. H. (2000). The geography and causes of food insecurity in developing countries. *Agricultural Economics*, *22*(2), 199–215. https://doi.org/10.1111/j.1574-0862.2000.tb00018.x

212. Sobsey, M. D., Handzel, T., & Venczel, L. (2003). Chlorination and safe storage of household drinking water in developing countries to reduce waterborne disease. *Water Science and Technology*, *47*(3), 221–228. https://doi.org/10.2166/wst.2003.0199

213. Sonego, M., Pellegrin, M. C., Becker, G., & Lazzerini, M. (2015). Risk Factors for Mortality from Acute Lower Respiratory Infections (ALRI) in Children under Five Years of Age in Low and Middle-Income Countries: A Systematic Review and Meta-Analysis of Observational Studies. *PLOS ONE*, *10*(1), e0116380. https://doi.org/10.1371/journal.pone.0116380

214. Stoner, O., Lewis, J., Martínez, I. L., Gumy, S., Economou, T., & Adair-Rohani, H. (2021a). Household cooking fuel estimates at global and country level for 1990 to 2030. *Nature Communications*, *12*(1), 5793. https://doi.org/10.1038/s41467-021-26036-x

215. Stoner, O., Lewis, J., Martínez, I. L., Gumy, S., Economou, T., & Adair-Rohani, H. (2021b). Household cooking fuel estimates at global and country level for 1990 to 2030. *Nature Communications*, *12*(1), 5793. https://doi.org/10.1038/s41467-021-26036-x

216. Stoner, O., Lewis, J., Martínez, I. L., Gumy, S., Economou, T., & Adair-Rohani, H. (2021c). Household cooking fuel estimates at global and country level for 1990 to 2030. *Nature Communications*, *12*(1), 5793. https://doi.org/10.1038/s41467-021-26036-x

217. Stoner, O., Lewis, J., Martínez, I. L., Gumy, S., Economou, T., & Adair-Rohani, H. (2021d). Household cooking fuel estimates at global and country level for 1990 to 2030—Supplemental Data. *Nature Communications*, *12*(1), 5793. https://doi.org/10.1038/s41467-021-26036-x

218. Sy, S. A., & Mokaddem, L. (2022). Energy poverty in developing countries: A review of the concept and its measurements. *Energy Research & Social Science*, *89*, 102562. https://doi.org/10.1016/j.erss.2022.102562

219. Tang, X., & Liao, H. (2014). Energy poverty and solid fuels use in rural China: Analysis based on national population census. *Energy for Sustainable Development*, *23*, 122–129. https://doi.org/10.1016/j.esd.2014.08.006

220. Thompson, R. J., Li, J., Weyant, C. L., Edwards, R., Lan, Q., Rothman, N., Hu, W., Dang, J., Dang, A., Smith, K. R., & Bond, T. C. (2019). Field Emission Measurements of Solid Fuel Stoves in Yunnan, China Demonstrate Dominant Causes of Uncertainty in Household Emission Inventories. *Environmental Science & Technology*, *53*(6), 3323–3330. https://doi.org/10.1021/acs.est.8b07040

221. Thomson, A. M., Calvin, K. V., Smith, S. J., Kyle, G. P., Volke, A., Patel, P., Delgado-Arias, S., Bond-Lamberty, B., Wise, M. A., Clarke, L. E., & Edmonds, J. A. (2011). RCP4.5: A pathway for stabilization of radiative forcing by 2100. *Climatic Change*, *109*(1), 77. https://doi.org/10.1007/s10584-011-0151-4

222. Tian, P., Yang, D., Shan, L., Wang, D., Li, Q., Gorski, L., Lee, B. G., Quiñones, B., & Cooley, M. B. (2017). Concurrent Detection of Human Norovirus and Bacterial Pathogens in Water Samples from an Agricultural Region in Central California Coast. *Frontiers in Microbiology*, *8*, 1560. https://doi.org/10.3389/fmicb.2017.01560

223. Troeger, C., Colombara, D. V., Rao, P. C., Khalil, I. A., Brown, A., Brewer, T. G., Guerrant, R. L., Houpt, E. R., Kotloff, K. L., Misra, K., Petri, W. A., Platts-Mills, J., Riddle, M. S., Swartz, S. J., Forouzanfar, M. H., Reiner, R. C., Hay, S. I., & Mokdad, A. H. (2018). Global disability-adjusted life-year estimates of long-term health burden and

undernutrition attributable to diarrhoeal diseases in children younger than 5 years. *The Lancet Global Health*, *6*(3), e255–e269. https://doi.org/10.1016/S2214-109X(18)30045-7

224. UNDP. (2020). *SUSTAINABLE DEVELOPMENT GOAL 7*. Sustainable Development Knowledge Platform. https://sustainabledevelopment.un.org/sdg7

225. United Nations, Department of Economic and Social Affairs, Population Division. (2019). *Patterns and trends in household size and composition: Evidence from a United Nations dataset* (ST/ESA/SER.A/433). United Nations. https://www.un.org/en/development/desa/population/publications/pdf/ageing/household_size_and_composition_technical_report.pdf

226. Uprety, S., Dangol, B., Nakarmi, P., Dhakal, I., Sherchan, S. P., Shisler, J. L., Jutla, A., Amarasiri, M., Sano, D., & Nguyen, T. H. (2020). Assessment of microbial risks by characterization of Escherichia coli presence to analyze the public health risks from poor water quality in Nepal. *International Journal of Hygiene and Environmental Health*, *226*, 113484. https://doi.org/10.1016/j.ijheh.2020.113484

227. US EPA. (n.d.). *Criteria Air Pollutants*. United States Environmental Protection Agency. https://www.epa.gov/criteria-air-pollutants

228. US EPA. (1999). *Nitrogen oxides (NOx) why and how they are controlled*. Office of Air Quality Planning and Standards - US EPA. https://www3.epa.gov/ttncatc1/dir1/fnoxdoc.pdf

229. US EPA. (2012). *REVISED AIR QUALITY STANDARDS FOR PARTICLE POLLUTION AND UPDATES TO THE AIR QUALITY INDEX (AQI)*. US EPA. https://www.epa.gov/sites/production/files/2016-04/documents/2012_aqi_factsheet.pdf

230. US EPA. (2016a). *Life Cycle Assessment of Cooking Fuel Systems in India, China, Kenya, and Ghana* (Office of Research and Development National Risk Management Research Laboratory EP-D-11-006). U.S. Environmental Protection Agency. https://cfpub.epa.gov/si/si_public_record_report.cfm?dirEntryId=339679&Lab=NRMRL&simplesearch=0&showcriteria=2&sortby=pubDate&timstype=Published+Report&datebeginpublishedpresented

231. US EPA. (2016b, June 2). *Sulfur Dioxide Basics* [Overviews and Factsheets]. Office of Atmospheric Research (OAR), Https://Www.Epa.Gov/So2-Pollution/Sulfur-Dioxide-Basics. https://www.epa.gov/so2-pollution/sulfur-dioxide-basics

232. Vo, T. L. H., Shimada, Y., & Yoneda, M. (2020). INDOOR CONCENTRATION AND PERSONAL EXPOSURE TO PARTICULATE MATTER IN VIETNAM: A COUNTRY REPORT. *Journal of Japan Society of Civil Engineers, Ser. G (Environmental Research)*, *76*(5), I_415-I_431. https://doi.org/10.2208/jscejer.76.5_I_415

233. Vos, T., Barber, R. M., Bell, B., Bertozzi-Villa, A., Biryukov, S., Bolliger, I., Charlson, F., Davis, A., Degenhardt, L., Dicker, D., Duan, L., Erskine, H., Feigin, V. L., Ferrari, A. J., Fitzmaurice, C., Fleming, T., Graetz, N., Guinovart, C., Haagsma, J., … Murray, C. J. L. (2015). Global, regional, and national incidence, prevalence, and years lived with disability for 301 acute and chronic diseases and injuries in 188 countries, 1990-2013: A systematic analysis for the Global Burden of Disease Study 2013. *The Lancet*, *386*(9995), 743–800. https://doi.org/10.1016/S0140-6736(15)60692-4

234. Wafula, S. T., Nalugya, A., Mendoza, H., Kansiime, W. K., Ssekamatte, T., Walekhwa, A. W., Mugambe, R. K., Walter, F., Ssempebwa, J. C., & Musoke, D. (2023). Indoor air pollutants and respiratory symptoms among residents of an informal urban settlement in Uganda: A cross-sectional study. *PLOS ONE*, *18*(8), e0290170. https://doi.org/10.1371/journal.pone.0290170

235. Wang, Y., Shupler, M., Birch, A., Chu, Y. L., Jeronimo, M., Rangarajan, S., Mustaha, M., Heenan, L., Seron, P., Lanas, F., Salazar, L., Saavedra, N., Oliveros, M. J., Lopez-Jaramillo, P., Camacho, P. A., Otero, J., Perez-Mayorga, M., Yeates, K., West, N., … Hystad, P. (2022). Measuring and predicting personal and household Black Carbon levels from 88 communities in eight countries. *Science of The Total Environment*, *818*, 151849. https://doi.org/10.1016/j.scitotenv.2021.151849

236. Webb, P., Coates, J., Frongillo, E. A., Rogers, B. L., Swindale, A., & Bilinsky, P. (2006). Measuring Household Food Insecurity: Why It's So Important and Yet So Difficult to Do. *The Journal of Nutrition*, *136*(5), 1404S-1408S. https://doi.org/10.1093/jn/136.5.1404S

237. Westrell, T. (2004). *Microbial risk assessment and its implications for risk management in urban water systems*.

238. Weyant, C. L., Thompson, R., Lam, N. L., Upadhyay, B., Shrestha, P., Maharjan, S., Rai, K., Adhikari, C., Fox, M. C., & Pokhrel, A. K. (2019). In-Field Emission

Measurements from Biogas and Liquified Petroleum Gas (LPG) Stoves. *Atmosphere*, *10*(12), 729. https://doi.org/10.3390/atmos10120729

239. WHO. (2021). *WHO global air quality guidelines: Particulate matter (PM2.5 and PM10), ozone, nitrogen dioxide, sulfur dioxide and carbon monoxide*. https://www.who.int/publications-detail-redirect/9789240034228

240. WHO/UNICEF. (2020). *Progress on Household Drinking Water, Sanitation and Hygiene*. WHO/UNICEF Joint. https://www.who.int/news/item/01-07-2021-billions-of-people-will-lack-access-to-safe-water-sanitation-and-hygiene-in-2030-unless-progress-quadruples-warn-who-unicef

241. World Bank. (2017). *World Development Indicators: Electricity production, sources, and access*. http://wdi.worldbank.org/table/3.7

242. World Bank. (2022). *Access to clean fuels and technologies for cooking (% of population)—Uganda*. https://data.worldbank.org/indicator/EG.CFT.ACCS.ZS?locations=UG

243. World Bank. (2024). *Urban population (% of total population)*. The World Bank - Data. https://data.worldbank.org/indicator/SP.URB.TOTL.IN.ZS?locations=UG

244. World Health Organization. (n.d.). *Household air pollution and health*. Home/Newsroom/Fact Sheets/Detail/Household Air Pollution and Health. Retrieved March 29, 2022, from https://www.who.int/news-room/fact-sheets/detail/household-air-pollution-and-health

245. World Health Organization. (2015, January). *Technical Brief: Boil Water*. World Health Organization. https://apps.who.int/iris/bitstream/handle/10665/155821/WHO_FWC_WSH_15.02_eng.pdf?sequence=1

246. World Health Organization. (2016). *Quantitative Microbial Risk Assessment: Application for Water Safety Management*. World Health Organization. https://apps.who.int/iris/bitstream/handle/10665/246195/9789241565370-eng.pdf?sequence=1

247. World Health Organization. (2017). *Guidelines for drinking-water quality: Fourth edition incorporating the first addendum.* (4th ed.). https://iris.who.int/bitstream/handle/10665/254637/9789241549950-eng.pdf?sequence=1

248. World Health Organization. (2021). *Defining clean fuels and technologies*. Clean Household Energy Solutions Toolkit. https://www.who.int/tools/clean-household-energy-solutions-toolkit/module-7-defining-clean

249. World Health Organization. (2022). *Air quality database: Update 2022*. https://www.who.int/data/gho/data/themes/air-pollution/who-air-quality-database/2022

250. World Health Organization & UNICEF. (2013). *Progress on Sanitation and Drinking Water 2013 Update*. https://www.unwater.org/app/uploads/2020/04/WHOUNICEF-Joint-Monitoring-Programme-for-Water-Supply-and-Sanitation-JMP-%E2%80%93-2013-Update.pdf

251. Wu, J., Long, S. C., Das, D., & Dorner, S. M. (2011). Are microbial indicators and pathogens correlated? A statistical analysis of 40 years of research. *Journal of Water and Health*, *9*(2), 265–278. https://doi.org/10.2166/wh.2011.117

252. Zhao, B., Zheng, H., Wang, S., Smith, K. R., Lu, X., Aunan, K., Gu, Y., Wang, Y., Ding, D., Xing, J., Fu, X., Yang, X., Liou, K. N., & Hao, J. (2018). Change in household fuels dominates the decrease in PM2.5 exposure and premature mortality in China in 2005–2015. *Proceedings of the National Academy of Sciences of the United States of America*, *115*(49), 12401–12406. https://doi.org/10.1073/pnas.1812955115

APPENDICES

Appendix A: Supplementary material for Chapter 2

A.1. Tables

Table A 1 *Parameters Needed for Models*

IAP Model	QMRA Model	Demographics
Drinking water consumed Fuel emission factor Fuel Heating value Stove power Thermal Efficiency	*E. coli* level in drinking water Dose response parameters of pathogens Burden of disease for each pathogen probability of illness percent susceptible boiling effectiveness	Number of people in household Number of cooks, noncooks, and children per household Fraction of population which is under 5 Life Expectancy men Life Expectancy women Percent solid fuel users

Table A 2 *Literature Review of Log Reduction Values of E. coli, TTC, and FC*

Country[Citation]	E. coli[a]	TTC	FC	Value used in presented results
Laboratory (1 minute, 75°C)(Sanciolo et al., 2015)	6.00			Yes
Tanzania 1(Mohamed et al., 2016)		2.50		No
Tanzania 2(Mohamed et al., 2016)		2.19		No
India(T. Clasen & Rosa, 2017)			2.02	No
Cambodia surface water(Sobsey & Brown, 2012)	2.00			Yes
Vietnam <2 hr(T. Clasen, Thao, et al., 2008)		1.95		No
Cambodia rain(Sobsey & Brown, 2012)	1.90			No
Cambodia uncovered(Sobsey & Brown, 2012)	1.90			No
Cambodia pour(Sobsey & Brown, 2012)	1.90			No

Table A2 *(continued)*

Vietnam flask(T. Clasen, Thao, et al., 2008)		1.89		No
Indonesia(Sodha et al., 2011)		1.88		No
Vietnam 2-4hr(T. Clasen, Thao, et al., 2008)		1.81		No
Cambodia Covered(Sobsey & Brown, 2012)	1.80			No
Cambodia Dipping(Sobsey & Brown, 2012)	1.80			Yes
Tanzania 3(Mohamed et al., 2016)		1.50		No
Cambodia Well(Sobsey & Brown, 2012)	1.50			Yes
Vietnam 4-8 hr(T. Clasen, Thao, et al., 2008)		1.45		No
Vietnam 8-16 hr(T. Clasen, Thao, et al., 2008)		1.29		No
Vietnam Jug(T. Clasen, Thao, et al., 2008)		1.27		No

Table A2 *(continued)*

Vietnam Alum. vessel(T. Clasen, Thao, et al., 2008)		1.24		No
Vietnam 16-24 hr(T. Clasen, Thao, et al., 2008)		1.10		No
Guatemala(Rosa et al., 2010)		0.88		No
Vietnam >24 hr(T. Clasen, Thao, et al., 2008)		0.83		No
China Electric kettle(Cohen & Colford, 2017)		0.56		Yes
Peru Urban Visit 2(Rosa, Huaylinos, et al., 2014)		0.44		No
China Pot(Cohen & Colford, 2017)		0.37		No
Peru Urban 3(Rosa, Huaylinos, et al., 2014)		0.36		No
Peru Urban 1(Rosa, Huaylinos, et al., 2014)		0.14		No

Table A2 *(continued)*

Peru Rural 2(Rosa, Huaylinos, et al., 2014)		0.09		No
Peru Rural 3(Rosa, Huaylinos, et al., 2014)		0.07		No
Peru Rural 1(Rosa, Huaylinos, et al., 2014)		0.06		Yes
Zambia same day(Psutka et al., 2011a)		-0.17		No
Zambia(Psutka et al., 2011a)		-0.26		Yes

[a] All values were converted to E. coli for comparison in the model. The righthand column shows the selected values presented in the results. Table continues over 3 pages.

Table A 3 *Parameters Varied in the Sensitivity Analysis for Household Air Pollution*

Parameter[Citation]	Unit	Minimum	Mean	Maximum
Air Exchange Rate(McCracken & Smith, 1998; Parajuli et al., 2016; Park & Lee, 2003)	Hour^-1	1.39	10.4	24.9
Volume(Huboyo et al., 2018; Jagger et al., 2017; Johnson et al., 2011)	Meter^3	3	30	100
Daily Cooking Energy(Johnson et al., 2011)	MJ	1.87	10.84	45.85
Daily water consumed and boiled(Del Razo et al., 2002; Hossain et al., 2013; Kile et al., 2007)	Liters	0.67	2.55	6.10
Stove Efficiency(Obeng et al., 2017; Shen et al., 2018; Wathore et al., 2017)	Percent	10	14	19
Fuel Emission Factor(Champion et al., 2020; Shen et al., 2018; Weyant, Chen, et al., 2019)	g/kg	3.98	7.00	11.76
Stove Power(Champion et al., 2020; Obeng et al., 2017; Shen et al., 2018)	MJ/hour	0.64	4.9	34

Table A3 *(continued)*

Fuel Heating Value(Brouwer et al., 1996; Champion et al., 2020; Panigrahy et al., 2016)	MJ/kg	13.5	19.49	45.780
Exposure to concentration ratios (Pillarisetti et al., 2015; Shupler et al., 2018) [a]	Fraction	0.33	0.35	0.74

[a] The uncertainty values for the exposure to concentration ratios are based on the uncertainty range for $PM_{2.5}$ exposure to women. The uncertainty ranges for children and men also fall within this range, so this range is representative of all household members in the sensitivity analysis

Table A 4 *Parameters Used in the Sensitivity Analysis of the Water Risk Module*

Parameter[CItation]	Unit	Minimum	Mean	Maximum
Age at Death(World Health Organization, 2023)	#	1	66.7	90
E. coli level (literature based)(Bivins et al., 2017)	MPN	$9.02*10^{-7}$	$1.66*10^{-1}$	116
Log Reduction(Sobsey & Brown, 2012)	Unitless	-0.208	2	6
K value (*Cryptosporidium*)(Bivins et al., 2017)	Unitless	$7.89*10^{-5}$	$2.77*10^{-1}$	8.10
Ratio *Cryptosporidium* to *e. coli*(Bivins et al., 2017)	Unitless	$2.28*10^{-10}$	$1.126*10^{-6}$	$6.28*10^{-5}$
Alpha value (rotavirus)(Bivins et al., 2017)	Unitless	0.0382	0.25	1.7
N fifty value (rotavirus)(Bivins et al., 2017)	Unitless	0.653	8.24	58.16
Ratio rotavirus to *E. coli*(Bivins et al., 2017)	Unitless	$6.055*10^{-9}$	$9.533*10^{-7}$	$2.5*10^{-5}$
Alpha Value (*Campylobacter*)(Bivins et al., 2017)	Unitless	0.00022	0.155	6.96

Table A4 *(continued)*

Nfifty value (*Campylobacter*)(Bivins et al., 2017)	Unitless	41.30	1673	35554
Ratio *Campylobacter* to *E. coli*(Bivins et al., 2017)	Unitless	$6.054*10^{-9}$	$6.59*10^{-3}$	1.63

A.2. Figures

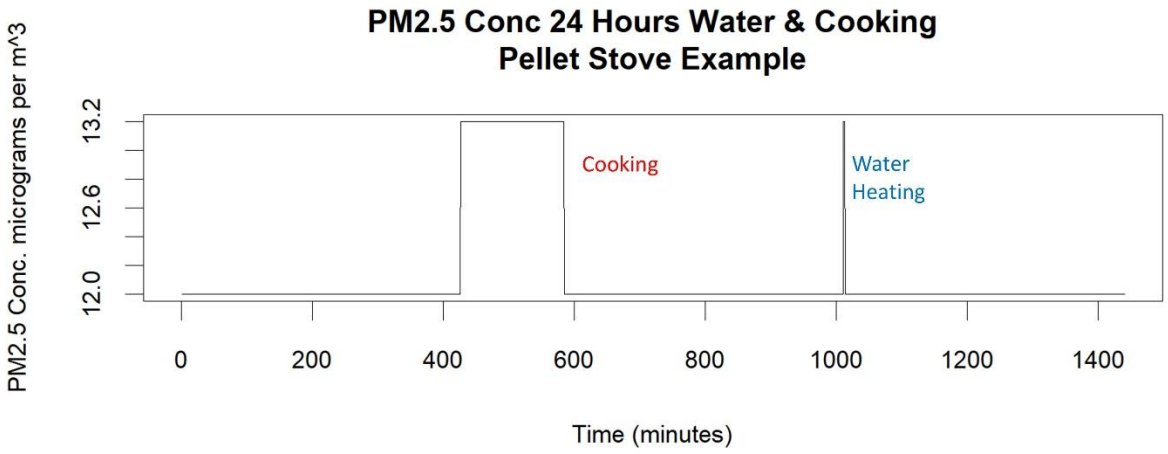


Figure A 1 *Example Air Pollution Box Model Run of 24 hour Fine Particulate Matter ($PM_{2.5}$) Concentration.*

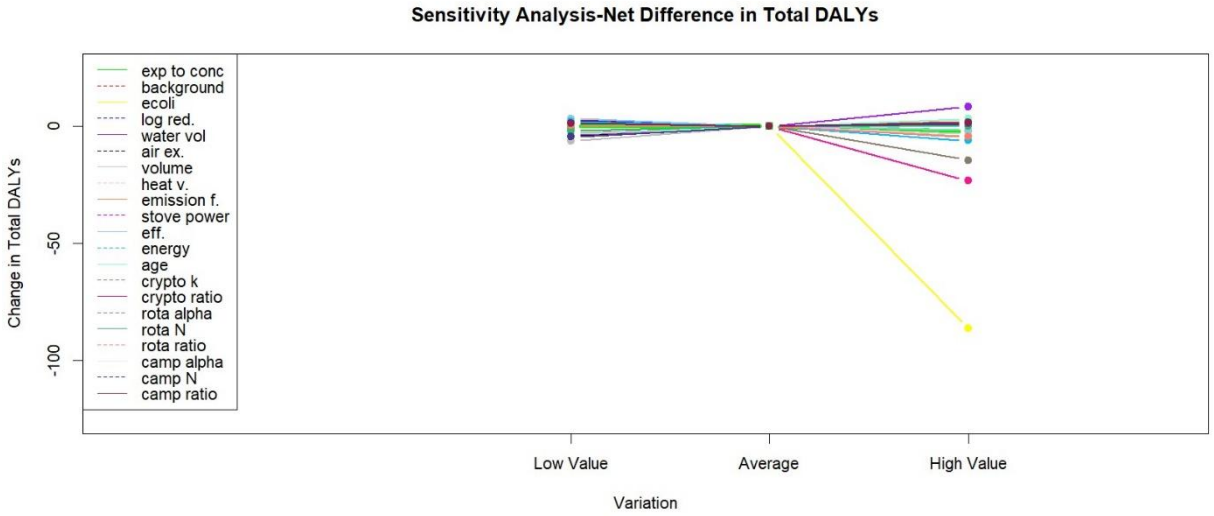


Figure A 2 *Sensitivity Analysis Showing the Net Difference in Total Disability Adjusted Life Years (DALYs) – Total DALYs (defined as the increase in air pollution DALYs from boiling water minus the decrease in DALYs from) using the lowest, average, and highest values from the parameter distributions, with the average values as a baseline. Exp to conc = Exposure to concentration ratio. Log red. = Log reduction value. Water vol = Water volume. Air ex. = Air exchange rate. Heat v. = Heat value. Emission f. = Emission factor. Eff. = Efficiency. Crypto=Cryptosporidium. Rota= Rotavirus. Camp = Campylobacter.*

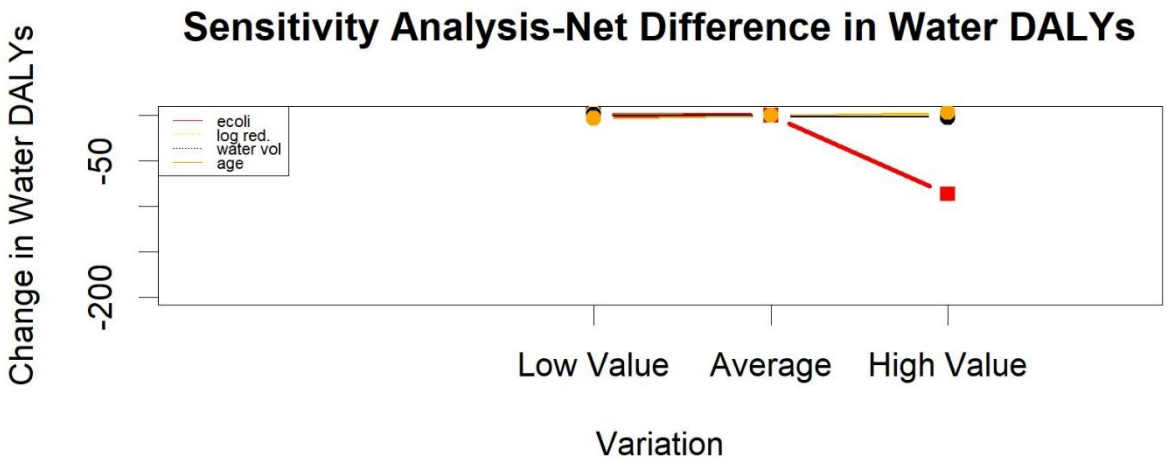


Figure A 3 *Sensitivity Analysis For Water Disability Adjusted Life Years (DALYs) - Showing the Water DALYs (drinking water DALYs after boiling water compared to before boiling) using the lowest, average, and highest values from the parameter distributions, with the average values as a baseline. Log red. = Log Reduction Value. Water vol. = water volume.*

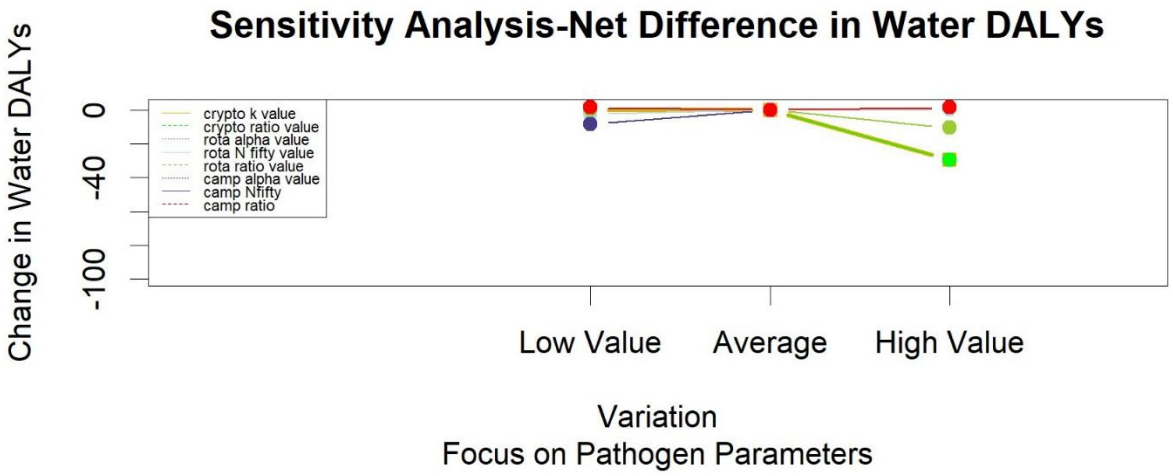


Figure A 4 *Sensitivity Analysis for Water Disability Adjusted Life Years (DALYs): Pathogen Specific Parameters – Showing the Water DALYs (drinking water DALYs after boiling water compared to before boiling) using the lowest, average, and highest values from the parameter distributions, with the average values as a baseline. Crypto = Cryptosporidium. Rota= Rotavirus. Camp = Campylobacter.*

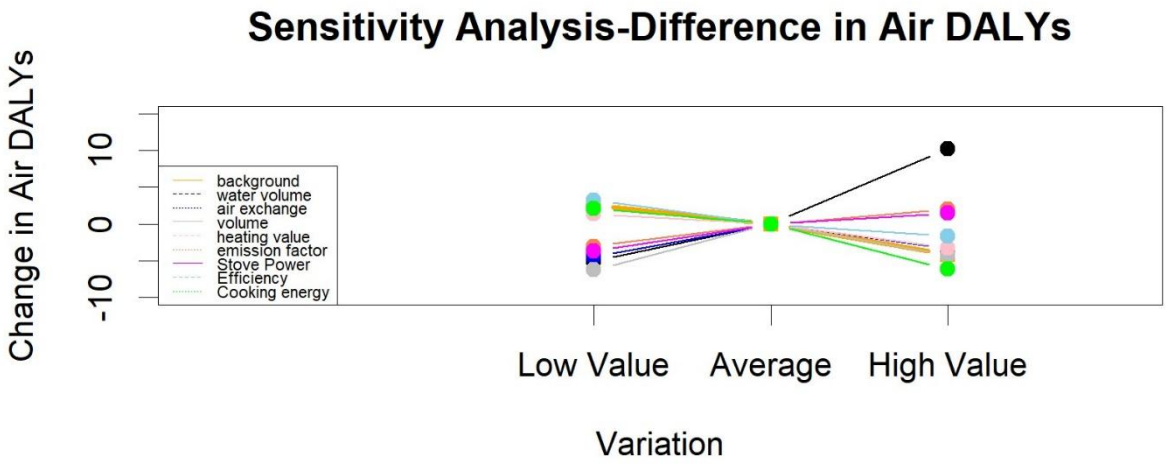


Figure A 5 *Sensitivity Analysis Showing in Air Disability Adjusted Life Years (DALYs) (DALYs from boiling water and cooking compared to just cooking) using the lowest, average, and highest values from the parameter distributions, with the average values as a baseline.*

A.3. References

1. Sanciolo P, Monis P, Blackbeard J, Salveson A, Ryan G, Gray S. Pasteurisation for the Production of Class A Water. Published online 2015.

2. Mohamed H, Clasen T, Njee RM, Malebo HM, Mbuligwe S, Brown J. Microbiological effectiveness of household water treatment technologies under field use conditions in rural Tanzania. *Trop Med Int Health*. 2016;21(1):33-40. doi:10.1111/tmi.12628

3. Clasen T, Rosa G. Consistency of Use and Effectiveness of Household Water Treatment among Indian Households Claiming to Treat Their Water. *The American Journal of Tropical Medicine and Hygiene*. 2017;97(1):259-270. doi:10.4269/ajtmh.16-0428

4. Sobsey MD, Brown J. Boiling as Household Water Treatment in Cambodia: A Longitudinal Study of Boiling Practice and Microbiological Effectiveness. *The American Journal of Tropical Medicine and Hygiene*. 2012;87(3):394-398. doi:10.4269/ajtmh.2012.11-0715

5. Clasen T, Thao DH, Boisson S, Shipin O. Microbiological Effectiveness and Cost of Boiling to Disinfect Drinking Water in Rural Vietnam. *Environ Sci Technol*. 2008;42(12):4255-4260. doi:10.1021/es7024802

6. Sodha SV, Menon M, Trivedi K, et al. Microbiologic effectiveness of boiling and safe water storage in South Sulawesi, Indonesia. *Journal of Water and Health*. 2011;9(3):577-585. doi:10.2166/wh.2011.255

7. Rosa G, Clasen T, Miller L. Microbiological Effectiveness of Disinfecting Water by Boiling in Rural Guatemala. *The American Journal of Tropical Medicine and Hygiene*. 2010;82(3):473-477. doi:10.4269/ajtmh.2010.09-0320

8. Cohen A, Colford JM. Effects of Boiling Drinking Water on Diarrhea and Pathogen-Specific Infections in Low- and Middle-Income Countries: A Systematic Review and Meta-Analysis. *The American Journal of Tropical Medicine and Hygiene*. 2017;97(5):1362-1377. doi:10.4269/ajtmh.17-0190

9. Rosa G, Huaylinos ML, Gil A, Lanata C, Clasen T. Assessing the Consistency and Microbiological Effectiveness of Household Water Treatment Practices by Urban and Rural Populations Claiming to Treat Their Water at Home: A Case Study in Peru. Ibekwe AM, ed. *PLoS ONE*. 2014;9(12):e114997. doi:10.1371/journal.pone.0114997

10. Psutka R, Peletz R, Michelo S, Kelly P, Clasen T. Assessing the Microbiological Performance and Potential Cost of Boiling Drinking Water in Urban Zambia. *Environ Sci Technol*. 2011;45(14):6095-6101. doi:10.1021/es2004045

11. McCracken JP, Smith KR. EMISSIONS AND EFFICIENCY OF IMPROVED WOODBURNING COOKSTOVES IN HIGHLAND GUATEMALA. Published online 1998:9.

12. Parajuli I, Lee H, Shrestha KR. Indoor Air Quality and ventilation assessment of rural mountainous households of Nepal. *International Journal of Sustainable Built Environment*. 2016;5(2):301-311. doi:10.1016/j.ijsbe.2016.08.003

13. Park E, Lee K. Particulate exposure and size distribution from wood burning stoves in Costa Rica. Published online 2003:7.

14. Huboyo HS, Lestari P, Tohno S. Modeling Indoor PM2.5 Air Pollution, Estimating Exposure, and Problems Associated with Rural Indonesian Households Using Wood Fuel. In: McLellan B, ed. *Sustainable Future for Human Security*. Springer Singapore; 2018:287-300. doi:10.1007/978-981-10-5433-4_20

15. Jagger P, Pedit J, Bittner A, Hamrick L, Phwandapwhanda T, Jumbe C. Fuel efficiency and air pollutant concentrations of wood-burning improved cookstoves in Malawi: Implications

for scaling-up cookstove programs. *Energy for Sustainable Development*. 2017;41:112-120. doi:10.1016/j.esd.2017.08.007

16. Johnson M, Lam N, Brant S, Gray C, Pennise D. Modeling indoor air pollution from cookstove emissions in developing countries using a Monte Carlo single-box model. *Atmospheric Environment*. 2011;45(19):3237-3243. doi:10.1016/j.atmosenv.2011.03.044

17. Del Razo LM, Garcia-Vargas GG, Garcia-Salcedo J, et al. Arsenic levels in cooked food and assessment of adult dietary intake of arsenic in the Region Lagunera, Mexico. *Food and Chemical Toxicology*. 2002;40(10):1423-1431. doi:10.1016/S0278-6915(02)00074-1

18. Hossain MA, Rahman MM, Murrill M, et al. Water consumption patterns and factors contributing to water consumption in arsenic affected population of rural West Bengal, India. *Science of The Total Environment*. 2013;463-464:1217-1224. doi:10.1016/j.scitotenv.2012.06.057

19. Kile ML, Houseman EA, Breton CV, et al. Association between total ingested arsenic and toenail arsenic concentrations. *Journal of Environmental Science and Health, Part A*. 2007;42(12):1827-1834. doi:10.1080/10934520701566819

20. Obeng G, Mensah E, Ashiagbor G, Boahen O, Sweeney D. Watching the Smoke Rise Up: Thermal Efficiency, Pollutant Emissions and Global Warming Impact of Three Biomass Cookstoves in Ghana. *Energies*. 2017;10(5):641. doi:10.3390/en10050641

21. Shen G, Hays MD, Smith KR, Williams C, Faircloth JW, Jetter JJ. Evaluating the Performance of Household Liquefied Petroleum Gas Cookstoves. *Environ Sci Technol*. 2018;52(2):904-915. doi:10.1021/acs.est.7b05155

22. Wathore R, Mortimer K, Grieshop AP. In-Use Emissions and Estimated Impacts of Traditional, Natural- and Forced-Draft Cookstoves in Rural Malawi. *Environ Sci Technol*. 2017;51(3):1929-1938. doi:10.1021/acs.est.6b05557

23. Champion WM, Warren SH, Kooter IM, et al. Mutagenicity- and pollutant-emission factors of pellet-fueled gasifier cookstoves: Comparison with other combustion sources. *Science of The Total Environment*. 2020;739:139488. doi:10.1016/j.scitotenv.2020.139488

24. Weyant CL, Chen P, Vaidya A, et al. Emission Measurements from Traditional Biomass Cookstoves in South Asia and Tibet. *Environ Sci Technol*. 2019;53(6):3306-3314. doi:10.1021/acs.est.8b05199

25. Brouwer I, Hartog AP den, Kamwendo M, Heldens M. Wood quality and wood preferences in relation to food preparation and diet composition in Central Malawi. *Ecol of Food & Nutrition*. 1996;35(1):1-13. doi:10.1080/03670244.1996.9991471

26. Panigrahy S, Mishra NK, Mishra SC, Muthukumar P. Numerical and experimental analyses of LPG (liquefied petroleum gas) combustion in a domestic cooking stove with a porous radiant burner. *Energy*. 2016;95:404-414. doi:10.1016/j.energy.2015.12.015

27. Pillarisetti A, Mehta S, Smith KR. Household Air Pollution Intervention Tool (HAPIT III). *Clean Cooking Alliance*. Published online 2015. https://www.cleancookingalliance.org/resources/450.html

28. Shupler M, Godwin W, Frostad J, Gustafson P, Arku RE, Brauer M. Global estimation of exposure to fine particulate matter (PM2.5) from household air pollution. *Environment International*. 2018;120:354-363. doi:10.1016/j.envint.2018.08.026

29. World Health Organization. Uganda [Country overview]. WHO Data. 2023. Accessed January 31, 2024. https://data.who.int

30. Bivins AW, Sumner T, Kumpel E, et al. Estimating Infection Risks and the Global Burden of Diarrheal Disease Attributable to Intermittent Water Supply Using QMRA. *Environ Sci Technol*. 2017;51(13):7542-7551. doi:10.1021/acs.est.7b01014

Appendix B: Supplementary material for Chapter 3

B.1. Tables & Figures

Table B 1 *Household socioeconomic, water, sanitation, energy, and food insecurity indicators from the present study compared with data for Malawi from past studies or reports.*

Item	Our study	Comparison
Daily income	$17.05 USD weekly per capita expenditure ($2.45/day)	· above $1.90/day poverty line, below $3.20/day lower-middle-income threshold (World Bank Group, 2021).
Fuel	97% charcoal use	75% use charcoal in urban areas of Malawi (World Bank Group, 2022).
Water	83% improved water sources	52.4% urban Malawi (UNICEF & WHO, 2024).
Electricity	69% had grid access	15% nationally (Jagger et al., 2022).
Water Treatment	13% used bleach/chlorine 2% boiled 85% did not treat or accounted for unsure.	30.67% reportedly treat, 23.2% use adequate methods for improved sources, 34.38% reportedly treat for unimproved water sources, and 26.82% reportedly use adequate methods (Geremew & Damtew, 2020)
Latrine ownership	99% owned latrines	85.3% in Malawi (National Statistics Office, 2019)
Education	71% completed primary or higher; 13.5% illiterate despite some schooling.	90% literacy in Blantyre City, 75% in Blantyre District (National Statistics Office, 2019)
Household composition	2.7 adults, 1.4 children, and 1.2 children under age 5.	Average household size of 4.4 in Malawi (National Statistics Office, 2019)

Table B1 *(continued)*

Urban versus Rural	Study location is peri-urban, but sometimes defined as urban and exhibited urban characteristics(Kaonga et al., n.d.; National Planning Commision, n.d.; National Statistical Office, 2019; United Nations Human Settlements Programme (-, 2011)	19% of Malawi's population is urban (World Bank Group, 2024)
Drinking water contamination	60.6% of water had low or very low risk levels of *E. coli*	Water collected in the dry season at the point of consumption was low or very low risk (71%). Water at the source was less contaminated than point of consumption (Cassivi et al., 2021).
Stored food contamination	44% of samples had *E. coli* over 2 MPN per dry gram food.	48% of food samples have *E. coli* (S. Taulo et al., 2008)

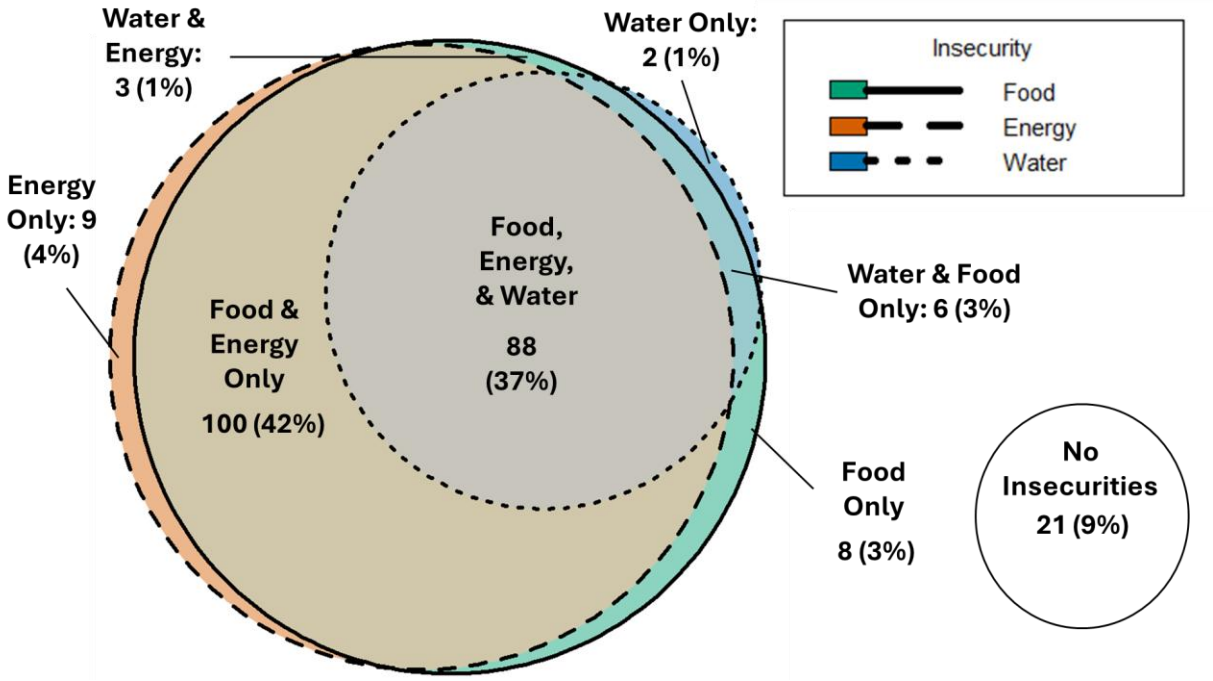


Figure B 1 *Venn diagram showing the proportion of households experiencing each category of insecurity using the mild cutoffs, with energy insecurity red (large dashed lines), food insecurity green (solid dashed lines), and water insecurity blue (small dashed lines). The size of the ovals represents the relative size of each category.*

Table B 2 *Overlap of food, energy, and water insecurity among households, using a mild and moderate/severe cutoff. Values shown are the number of households, followed by the percent. The categories show the co-occurrence of insecurities, followed by households only experiencing one type of insecurity, and the total number of households experiencing each type of insecurity.*

Insecurity Group	Mild	Moderate/Severe
Food-Energy-Water	88 (37%)	19 (8%)
Food-Water	6 (3%)	2 (1%)
Food-Energy	100 (42%)	124 (52%)
Energy-Water	3 (1%)	1 (4%)
Food only	8 (3%)	42 (18%)
Water only	2 (1%)	1 (0.4%)
Energy only	9 (4%)	6 (3%)
Food total	202 (85.2%)	187 (78.9%)
Water total	99 (41.8%)	23 (9.7%)
Energy total	200 (84.4%)	150 (63.3%)
None	21 (9%)	42 (18%)

Table B3 *Comparison of food, energy, and water insecurity in this study and other studies*

Item	Comparison	Reference
Food Insecurity	Southern region mean 15.96, Central 12.50, North mean 8.91	(Banda et al., 2025)
Energy Insecurity	Different methodology, but 42.5% of households were energy insecure	(Mkomba et al., 2021)
Water Insecurity	Mean HWISE scores of 4.0 and 5.83 in Lilongwe	(Shah et al., 2023; Stoler et al., 2021)
Food & Energy Insecurity	A study in Malawi showed that energy insecure households reduced their food consumption by 2.3% for each 1% unit increase in the share of energy costs of their total household budget	(Mkomba et al., 2021)
Food & Energy Insecurity	A study in South Africa also found that energy insecurity and food insecurity were connected	(Ningi et al., 2022)
Food & Energy Insecurity	In Cambodia, a study found that a household will likely reduce its food consumption by about 4.1% for every 1% increase in the share of energy expenditure	(Phoumin & Kimura, 2019)
Food & Energy Insecurity	in the United States found that compared to children with energy security, children with moderate energy insecurity had greater odds of household food insecurity and child food insecurity	(Cook et al., 2008)

Table B3 *(continued)*

Food & Energy Insecurity	in the US found that in cold weather, there was a significant reduction in caloric intake among both children and adults and poor families, and poor families spent less on household fuel than wealthy families, and households struggled to afford heat and food	(J. Bhattacharya et al., 2003)
Food & Energy Insecurity	Low-income households and households with elderly people, experiencing substantial seasonal differences in the incidence of very low food security in areas with high heating costs and high summer cool costs, showing the importance of understanding the tradeoffs households make between heating and cooling costs and other basic needs impacting food security	(Nord & Kantor, 2006)
Water and food	. Household water insecurity has been found to be strongly associated with food insecurity	(Brewis et al., 2020; Broyles et al., 2024) Unlike
Water and food insecurity	Unlike a Kenya pastoralist study which focused on a self-sufficient population, fewer in this sample experienced food and water insecurity simultaneously.	(Bethancourt et al., 2023)
Water and food insecurity	Food and water insecurity found to occur concurrently in the United States	(Rosinger & Young, 2024)
Water & Energy Insecurity	Water and energy insecurity correlation has not been previously studied in SSA, but parallels exist in Alaska and the U.S.	(Eichelberger, 2010; Cook et al., 2008)

Table B3 *(continued)*

Water, Food, and Energy Insecurity	PR-FEW Index for Malawi: food = 0.37, energy = 0.18, water = 0.24 (Nkiaka et al., 2021).A study which looked at food, water, and energy insecurity using a different scale found Malawi had the highest energy and water insecurity, but was not among the highest for food insecurity	(Nkiaka et al., 2021)

Table B4 *Frequency of food, energy, and water insecurity experiences in the past four weeks. Items are shaded and labeled by insecurity domain (Food, energy, or water), and the label and full question are provided. Response categories are reported as the percentage of households selecting 0 (never), 1 (rarely), 2 (sometimes), or 3 (often), followed by mean scores for each item.*

Security	Label	Question	**0**	**1**	**2**	**3**	**Mean**
Food	Pref	In the last 4 weeks, how frequently were you or any household member not able to eat the kinds of foods you preferred because of a lack of resources?	23%	24%	31%	22%	1.52
Energy	Lack	In the last four weeks, how frequently have you or anyone in your household lacked enough money to buy fuel (including electricity, gas, charcoal, wood, etc.)?	26%	21%	29%	24%	1.51
Energy	Expense	In the last 4 weeks, how frequently did you reduce your expenses for what you consider to be basic household necessities because there was not enough money to pay for these and to pay for your home fuel?	26%	21%	32%	21%	1.49
Energy	Worry	In the last four weeks, how frequently did you worry that your stored fuel (electric power or LPG, charcoal or wood) will be used up before you get money to refill?	22%	29%	30%	19%	1.47
Food	Not Want	In the last 4 weeks, how frequently did you or any household member have to eat some foods that you really did not want to eat because of a lack of resources to obtain other types of food?	23%	28%	30%	19%	1.45
Food	Worry	In the last 4 weeks, how frequently did you worry that your household would not have enough food?	29%	22%	30%	19%	1.39
Food	Variety	In the last 4 weeks, how frequently did you or any household member have to eat a limited variety of foods due to a lack of resources?	28%	30%	25%	18%	1.32
Energy	Reduce	In the last four weeks, how frequently did you or anyone in your household reduce fuel consumption to uncomfortable or inconvenient levels because you were running out of money to buy fuel?	36%	19%	27%	18%	1.27
Food	Smaller	In the last 4 weeks, how frequently did you or any household member have to eat a smaller meal than you felt you needed because there was not enough food?	30%	29%	27%	14%	1.26
Energy	Lighting	In the last four weeks, how frequently did you use your stove, open fire, or candle for lighting at home?	37%	22%	23%	19%	1.23
Food	Fewer	In the last 4 weeks, how frequently did you or any household member have to eat fewer meals in a day because there was not enough food?	36%	23%	24%	17%	1.22
Energy	Used Up	In the last four weeks, how frequently did your household fuel (electricity, gas, charcoal, wood, etc.) get used up so you didn't have anymore?	33%	28%	27%	12%	1.19
Energy	Switch	In the last four weeks, how frequently did you or anyone in your household switch to a cheaper fuel source because you were running out of money to buy fuel?	39%	21%	27%	12%	1.13

Table B4 *(continued)*

Food	None	In the last four weeks, how frequently was there ever no food to eat of any kind in your household because of lack of resources to get food?	50%	19%	21%	9%	0.89
Water	Worry	In the last 4 weeks, how frequently did you or anyone in your household worry you would not have enough water for all of your household needs?	55%	18%	20%	7%	0.78
Food	Bed	In the last 4 weeks, how frequently did you or any household member go to sleep at night hungry because there was not enough food?	57%	17%	18%	8%	0.76
Food	Day	In the last 4 weeks, how frequently did you or any household member go a whole day and night without eating anything because there was not enough food?	66%	14%	16%	4%	0.59
Water	Inter	In the last 4 weeks, how frequently has your primary water source been interrupted or limited (e.g. water pressure, less water than expected, river dried up)?	68%	15%	12%	5%	0.55
Water	Clothes	In the last 4 weeks, how frequently have problems with water meant that clothes could not be washed?	72%	10%	14%	5%	0.51
Water	Plans	In the last 4 weeks, how frequently have you or anyone in your household had to change schedules or plans due to problems with your water situation?	72%	16%	10%	3%	0.44
Water	Angry	In the last 4 weeks, how frequently did you or anyone in your household feel angry about your water situation?	78%	11%	6%	5%	0.38
Water	Drink	In the last 4 weeks, how frequently has there not been as much water to drink as you would like for you or anyone in your household?	78%	12%	7%	3%	0.34
Energy	Leave	In the last four weeks, how frequently did you or anyone in your household leave your home for all or part of the day because there was no fuel at home for cooking, ironing, lighting, heating, or entertainment?	78%	12%	7%	3%	0.34
Water	Food	In the last 4 weeks, how frequently have you or anyone in your household had to change what was being eaten because there were problems with water (e.g., for washing foods, cooking, etc.)?	84%	10%	5%	2%	0.25
Water	None	In the last 4 weeks, how frequently has there been no usable or drinkable water whatsoever in your household?	87%	10%	2%	1%	0.18
Water	Body	In the last 4 weeks, how frequently have you or anyone in your household had to go without washing their body because of problems with water (e.g., not enough water, dirty, unsafe)?	88%	8%	3%	1%	0.17
Water	Hands	In the last 4 weeks, how frequently have you or anyone in your household had to go without washing hands after dirty activities (e.g., defecating or changing diapers, cleaning animal dung) because of problems with water?	91%	5%	3%	0%	0.13

Table B4 *(continued)*

Water	Shame	In the last 4 weeks, how frequently have problems with water caused you or anyone in your household to feel ashamed/excluded/stigmatized?	95%	3%	2%	1%	0.10
Water	Sleep	In the last 4 weeks, how frequently have you or anyone in your household gone to sleep thirsty because there wasn't any water to drink?	95%	4%	0%	1%	0.08

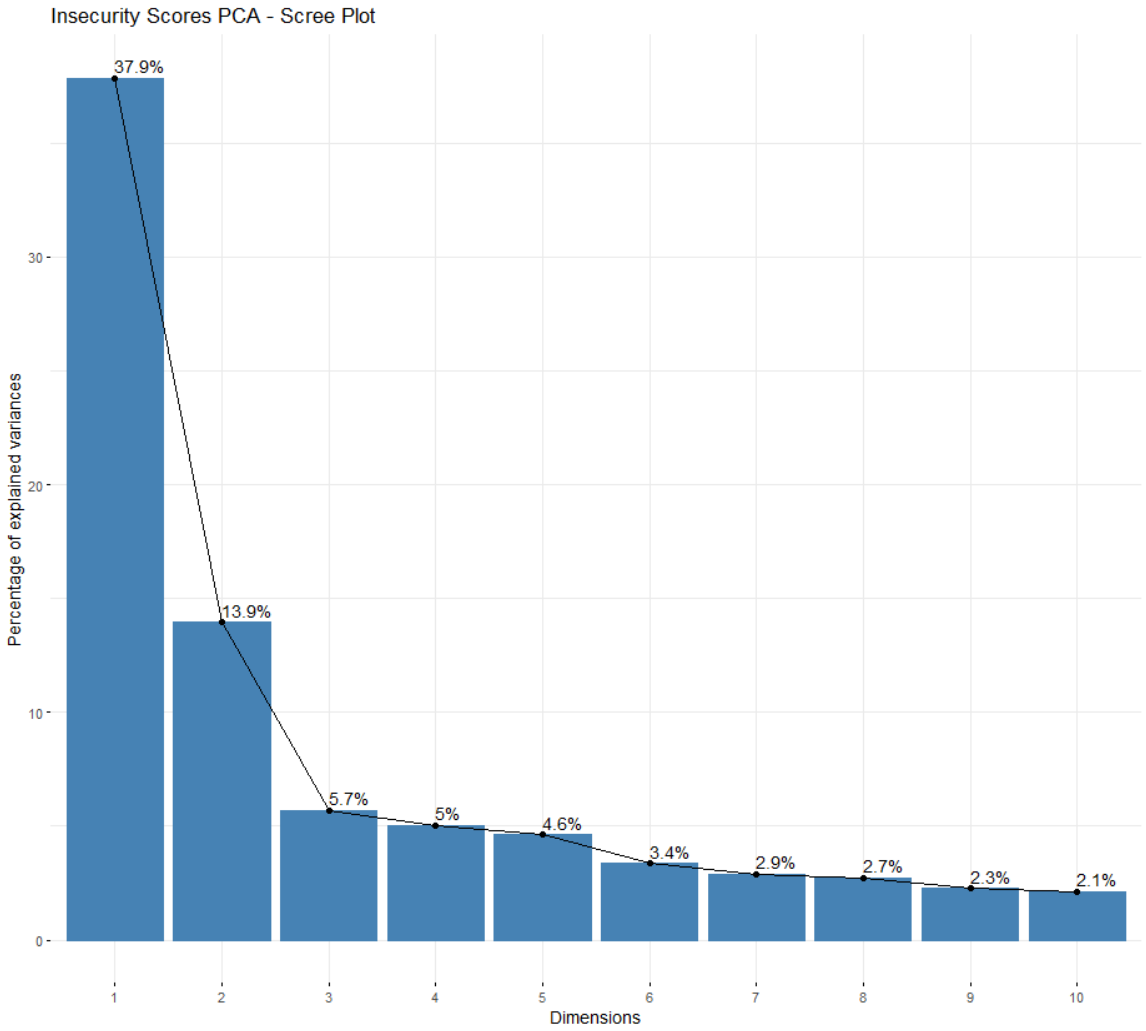


Figure B 2 *Scree plot from the principal component analysis (PCA) of insecurity scares. The bars show the percentage of variance explained by each dimension. Using the scree plot, we used the first two dimensions in our principal component analysis.*

Table B5 *Survey items used to assess household food, water, and energy insecurity. Each row lists the domain, variable name, a simplified label, and a full survey question. Food insecurity questions are from the Household Food Insecurity Access Scale (Coates et al., 2007), Energy insecurity questions are from the Household Energy Insecurity Scale (Boateng et al., 2020b), and water insecurity from the Household Water Insecurity Experiences scale (Young et al., 2019b).*

Item	Variable	Simple Description	Full Question
Water	hwise_worry	Worry not enough water	[HWISE Scale] In the last 4 weeks, how frequently did you or anyone in your household worry you would not have enough water for all of your household needs?
Water	hwise_clothes	Not Wash Clothes	[HWISE Scale] In the last 4 weeks, how frequently have problems with water meant that clothes could not be washed?
Water	hwise_plans	change plans because of water	[HWISE Scale] In the last 4 weeks, how frequently have you or anyone in your household had to change schedules or plans due to problems with your water situation? (Activities that may have been interrupted include caring for others, doing household chores, agricultural work, income-generating activities, sleeping, etc.)
Water	hwise_food	change what was eaten	[HWISE Scale] In the last 4 weeks, how frequently have you or anyone in your household had to change what was being eaten because there were problems with water (e.g., for washing foods, cooking, etc.)?
Water	hwise_hands	go without washing hands	[HWISE Scale] In the last 4 weeks, how frequently have you or anyone in your household had to go without washing hands after dirty activities (e.g., defecating or changing diapers, cleaning animal dung) because of problems with water?

Table B5 *(continued)*

Water	hwise_body	go without washing body	[HWISE Scale] In the last 4 weeks, how frequently have you or anyone in your household had to go without washing their body because of problems with water (e.g., not enough water, dirty, unsafe)?
Water	hwise_drink	Not enough water to drink	[HWISE Scale] In the last 4 weeks, how frequently has there not been as much water to drink as you would like for you or anyone in your household?
Water	hwise_angry	feel angry about situation	[HWISE Scale] In the last 4 weeks, how frequently did you or anyone in your household feel angry about your water situation?
Water	hwise_sleep	Sleep thirsty	[HWISE Scale] In the last 4 weeks, how frequently have you or anyone in your household gone to sleep thirsty because there wasn't any water to drink?
Water	hwise_none	no usable or drinkable water whatsoever	[HWISE Scale] In the last 4 weeks, how frequently has there been no usable or drinkable water whatsoever in your household?
Water	hwise_shame	problems result in feeling ashamed	[HWISE Scale] In the last 4 weeks, how frequently have problems with water caused you or anyone in your household to feel ashamed/excluded/stigmatized?
Water	hwise_inter	primary source interrupted or limited	[HWISE Scale] In the last 4 weeks, how frequently has your primary water source been interrupted or limited (e.g. water pressure, less water than expected, river dried up)?

Table B5 *(continued)*

Food	hfias_worry	worry about not enough	[HFIAS] In the last 4 weeks, how frequently did you worry that your household would not have enough food?
Food	hfias_pref	don't eat preferred foods	[HFIAS] In the last 4 weeks, how frequently were you or any household member not able to eat the kinds of foods you preferred because of a lack of resources?
Food	hfias_variety	eat limited variety foods	[HFIAS] In the last 4 weeks, how frequently did you or any household member have to eat a limited variety of foods due to a lack of resources?
Food	hfias_not_want	eat foods don't want	[HFIAS] In the last 4 weeks, how frequently did you or any household member have to eat some foods that you really did not want to eat because of a lack of resources to obtain other types of food?
Food	hfias_smaller	eat smaller meal	[HFIAS] In the last 4 weeks, how frequently did you or any household member have to eat a smaller meal than you felt you needed because there was not enough food?
Food	hfias_fewer	eat fewer meals day	[HFIAS] In the last 4 weeks, how frequently did you or any household member have to eat fewer meals in a day because there was not enough food?
Food	hfias_none	no food because lack resources	[HFIAS] In the last four weeks, how frequently was there ever no food to eat of any kind in your household because of lack of resources to get food?

Table B5 *(continued)*

Food	hfias_bed	go sleep at night hungry	[HFIAS] In the last 4 weeks, how frequently did you or any household member go to sleep at night hungry because there was not enough food?
Food	hfias_day	go whole day and night without eating	[HFIAS] In the last 4 weeks, how frequently did you or any household member go a whole day and night without eating anything because there was not enough food?
Energy	energy_lack	lacked enough money buy fuel	[Energy scale] In the last four weeks, how frequently have you or anyone in your household lacked enough money to buy fuel (including electricity, gas, charcoal, wood, etc.)?
Energy	energy_reduce	reduce fuel consumption uncomfortable levels	[Energy scale] In the last four weeks, how frequently did you or anyone in your household reduce fuel consumption to uncomfortable or inconvenient levels because you were running out of money to buy fuel?
Energy	energy_switch	switch cheaper fuel source	[Energy scale] In the last four weeks, how frequently did you or anyone in your household switch to a cheaper fuel source because you were running out of money to buy fuel?
Energy	energy_expense	reduce expenses no fuel money	[Energy scale] In the last 4 weeks, how frequently did you reduce your expenses for what you consider to be basic household necessities because there was not enough money to pay for these and to pay for your home fuel?
Energy	energy_lighting	Use stove/fire lighting	[Energy scale] In the last four weeks, how frequently did you use your stove, open fire, or candle for lighting at home?

Table B5 *(continued)*

Energy	energy_worry	Worry fuel used up	[Energy scale] In the last four weeks, how frequently did you worry that your stored fuel (electric power or LPG, charcoal or wood) will be used up before you get money to refill?
Energy	energy_usedup	fuel get used up	[Energy scale] In the last four weeks, how frequently did your household fuel (electricity, gas, charcoal, wood, etc.) get used up so you didn't have anymore?
Energy	energy_leave	leave home no fuel	[Energy scale] In the last four weeks, how frequently did you or anyone in your household leave your home for all or part of the day because there was no fuel at home for cooking, ironing, lighting, heating, or entertainment?

Table B6 *Top ten variables for principal components 1 & 2, and their loading and absolute loadings*

Principal Component	Rank	Variable	Loading	Absolute Loading
PC1	1	hfias_smaller	0.238752	0.238752
PC1	2	hfias_fewer	0.23731	0.23731
PC1	3	hfias_variety	0.235729	0.235729
PC1	4	hfias_worry	0.234408	0.234408
PC1	5	hfias_pref	0.230781	0.230781
PC1	6	hfias_none	0.229191	0.229191
PC1	7	hfias_bed	0.228368	0.228368
PC1	8	energy_lack	0.224568	0.224568
PC1	9	hfias_not_want	0.21556	0.21556
PC1	10	energy_usedup_improved	0.212905	0.212905
PC2	1	hwise_body	-0.29483	0.294828
PC2	2	hwise_plans	-0.27389	0.273892
PC2	3	hwise_hands	-0.27347	0.273472
PC2	4	hwise_clothes	-0.2724	0.272396
PC2	5	hwise_drink	-0.27181	0.271805
PC2	6	hwise_food	-0.26146	0.261463
PC2	7	hwise_worry	-0.25821	0.258207
PC2	8	hwise_none	-0.25193	0.251928
PC2	9	hwise_sleep	-0.22906	0.229055
PC2	10	hwise_angry	-0.21208	0.212081

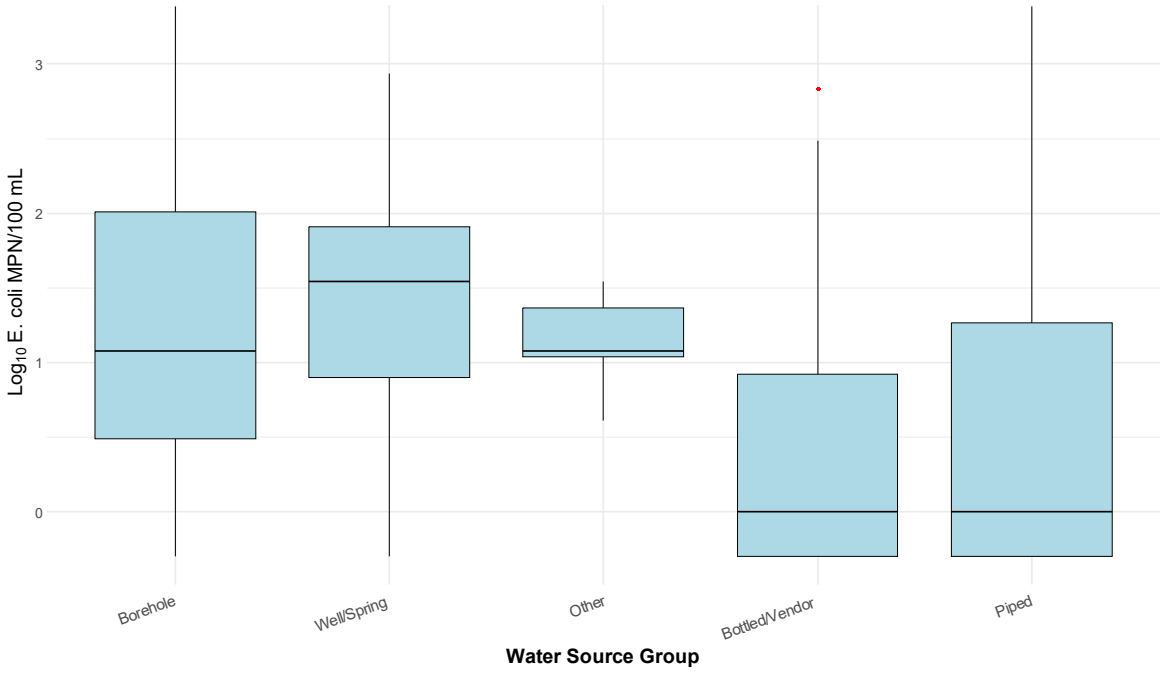


Figure B 3 *Distribution of E. coli contamination (log$_{10}$ MPN/100 mL drinking water) in household drinking water by primary water source type, showing borehole, well/spring, other, bottled/vendor, and piped.*

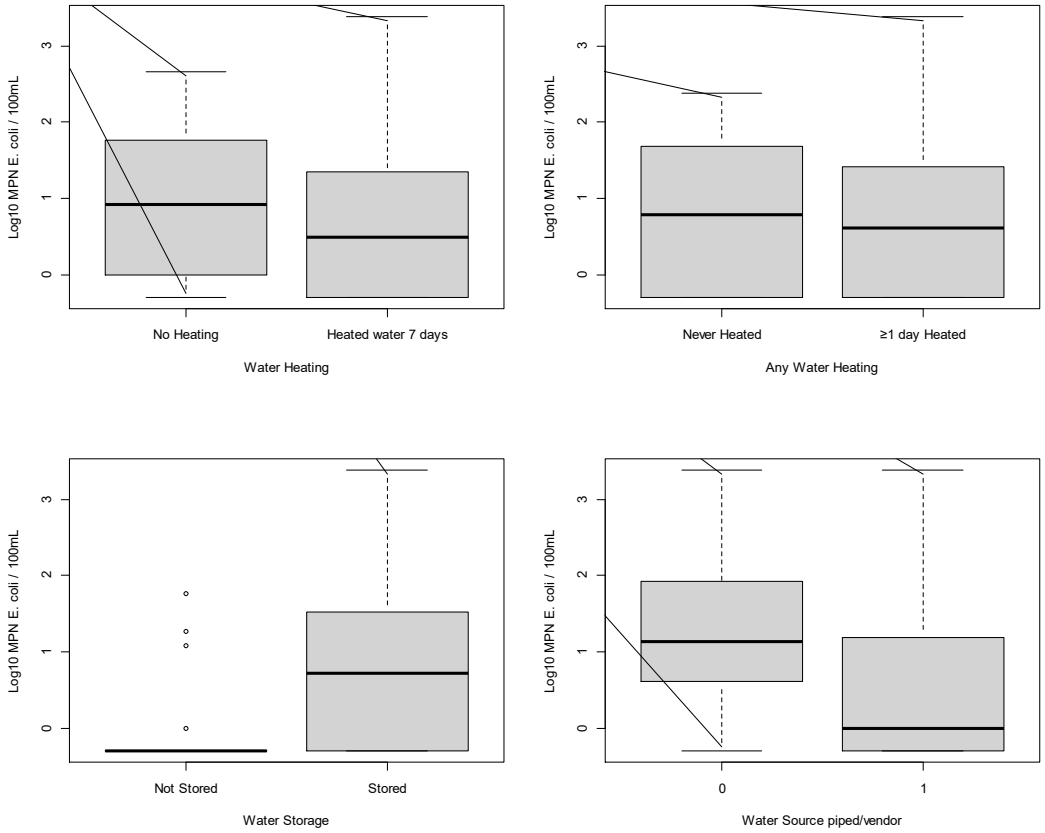


Figure B 4 *Boxplots of household drinking water contamination (log$_{10}$ E. coli MPN/100 mL drinking water), by water handling and source characteristics, including if the water was heated 1 or 7 days, if the water was stored or not, and if the water came from a pipe or vendor.*

Table B7 *Mean E. coli concentration (MPN/100 mL drinking water) in household drinking water by water handling and source characteristics. The P-value from a T-test comparing two means is shown, with a p-value less than 0.05, which is significant.*

	Mean Log 10 MPN E. coli/100 mL		**Mean MPN *E. coli*/100 mL**		
Variable	**Not Observed**	**Observed**	**Not Observed**	**Observed**	**P-value**
Water Heating 7 days	0.693	0.919	4.93	8.31	0.132
Any Water Heating (≥1 day)	0.737	0.782	5.46	6.05	0.797
Water Storage	-0.0482	0.8215	0.895	6.63	1.78E-06
Water Source (Piped/Vendor)	0.519	1.275	3.30	18.83	1.48E-07
Treating Water	0.957	0.733	9.06	5.41	0.505

Table B8 *Generalized Estimating Equation (GEE) model results for drinking water characteristics and microbial contamination. The table shows the estimated coefficients, the standard errors, the confidence intervals, and p-values, with a p-value less than 0.05 considered significant.*

Term	B	SE	Z	P value	CI B low	CI B high	OR	OR low	OR high
(Intercept)	0.72	0.75	0.91	3.40E-01	-0.76	2.19	2.05	0.47	8.93
Storing water	1.30	0.50	6.80	9.10E-03	0.32	2.28	3.68	1.38	9.81
Treating Water	-0.47	0.79	0.35	5.53E-01	-2.02	1.08	0.63	0.13	2.95
Water source (piped/vendor)	-1.50	0.45	11.12	8.56E-04	-2.38	-0.62	0.22	0.09	0.54
Energy Insecurity	-0.01	0.03	0.08	7.83E-01	-0.07	0.05	0.99	0.94	1.05
Household Wealth	-0.18	0.10	3.55	5.97E-02	-0.37	0.01	0.83	0.69	1.01

Table B9 *Results of Fisher's exact tests evaluating associations between food sample characteristics and E. coli detection. For each item, the sample was grouped based on whether the characteristics were observed or not, and the number of samples with detectable versus nondetectable E. coli is shown. The reported values are the number of detects and non-detects across groups, along with corresponding p-values. P-values less than 0.05 are significant.*

Variable	Observed		Not Observed		P value (Fisher's Exact)
	Nondetect	Detect	Nondetect	Detect	
Reheated	4	5	22	12	0.445
Food Secure	5	3	21	14	1
Energy Secure	9	7	17	10	0.752
Water Secure	21	16	5	1	0.377
Own Fridge	2	1	24	16	1
Potato	7	0	19	17	0.031
Cassava	2	0	24	17	0.511
Nsima	5	8	21	9	0.0887
Rice	4	4	22	13	0.692
Beans	4	0	22	17	0.14
Porridge	2	1	24	16	1
Pumpkin	0	1	26	16	0.395

Table B10 Associations between food handling practices and E. coli contamination. We compared if food was reheated or not by using a T-test, and we compared storage times and contamination using a Pearson correlation

Item	Test	P-value	Correlation	Means
Reheating	T-test	0.6354		Not reheated: 0.502/ Reheated 0.412
Storage Time	Pearson Correlation	0.4794	0.1108	

Table B11 *Comparison of estimated costs and consumption of fuel, food, and water in Malawi and Blantyre*

Item	**Cost**	**Consumption**	**Estimated Cost**	**Estimated Cost per week for HH of 4**	**Reference**
Water	In Blantyre, the 5000 liters costs MK 1.75 per liter in 2024	Consumption in Burkina Faso was estimated to be 3.83 +/- 3.43 L/per person/day	6.7 MK per person per day	187.6 MK (0.11 USD)	Cost: (Blantyre Water Board, 2024) Consumption: (Mounirou et al., 2023)
Water			$0.28 a month for water in Malawi	121.40 MK (.07USD)	(Kalumbi et al., 2020)
Fuel			463 MK per week in 2010	463 MK (0.27 USD)	(Jagger & Perez-Heydrich, 2016)
Food			A basic plate of food in Malawi estimated to cost USD $0.62 in (2021)	90,316.55 MK ($52.08 USD)	(Mercy Bwanaisa, 2023)
Food			A nutritious diet in Malawi:$2.32 USD / person /day	112,652.90 MK ($64.96 USD)	(Schneider, 2022)

B.2. References

1. Banda, L. O. L., Banda, C. V., Banda, J. T., & Chidimbah Munthali, G. N. (2025). Food insecurity in Malawi: Regional disparities, sociocultural determinants, and the role of mobile advisory services. *Food and Humanity*, *5*, 100695. https://doi.org/10.1016/j.foohum.2025.100695
2. Bhattacharya, J., DeLeire, T., Haider, S., & Currie, J. (2003). Heat or Eat? Cold-Weather Shocks and Nutrition in Poor American Families. *American Journal of Public Health*, *93*(7).
3. Blantyre Water Board. (2024, March 31). *Adjustment of Water Tariffs*. Blantyre Water Board. https://www.bwb.mw/Tariffs.php
4. Boateng, G. O., Balogun, M. R., Dada, F. O., & Armah, F. A. (2020). Household energy insecurity: Dimensions and consequences for women, infants and children in low- and middle-income countries. *Social Science & Medicine*, *258*, 113068. https://doi.org/10.1016/j.socscimed.2020.113068
5. Brewis, A., Workman, C., Wutich, A., Jepson, W., Young, S., & Household Water Insecurity Experiences – Research Coordination Network (HWISE-RCN). (2020). Household water insecurity is strongly associated with food insecurity: Evidence from 27 sites in low- and middle-income countries. *American Journal of Human Biology*, *32*(1). https://doi.org/10.1002/ajhb.23309
6. Broyles, L. M. T., Huanca, T., Conde, E., & Rosinger, A. Y. (2024). Water insecurity may exacerbate food insecurity even in water-rich environments: Evidence from the Bolivian Amazon. *Science of The Total Environment*, *954*, 176705. https://doi.org/10.1016/j.scitotenv.2024.176705
7. Cassivi, A., Tilley, E., Waygood, E. O. D., & Dorea, C. (2021). Household practices in accessing drinking water and post collection contamination: A seasonal cohort study in Malawi. *Water Research*, *189*, 116607. https://doi.org/10.1016/j.watres.2020.116607
8. Coates, J., Swindale, A., & Bilinsky, P. (2007). *Household Food Insecurity Access Scale (HFIAS) for Measurement of Food Access: Indicator Guide: Version 3: (576842013-001)* [Dataset]. https://doi.org/10.1037/e576842013-001
9. Cook, J. T., Frank, D. A., Casey, P. H., Rose-Jacobs, R., Black, M. M., Chilton, M., deCuba, S. E., Appugliese, D., Coleman, S., Heeren, T., Berkowitz, C., & Cutts, D. B.

(2008). A Brief Indicator of Household Energy Security: Associations With Food Security, Child Health, and Child Development in US Infants and Toddlers. *Pediatrics*, *122*(4), e867–e875. https://doi.org/10.1542/peds.2008-0286

10. Geremew, A., & Damtew, Y. T. (2020). Household water treatment using adequate methods in sub-Saharan countries: Evidence from 2013–2016 Demographic and Health Surveys. *Journal of Water, Sanitation and Hygiene for Development*, *10*(1), 66–75. https://doi.org/10.2166/washdev.2019.107
11. Jagger, P., & Perez-Heydrich, C. (2016). Land use and household energy dynamics in Malawi. *Environmental Research Letters*, *11*(12), 125004. https://doi.org/10.1088/1748-9326/11/12/125004
12. Kalumbi, L. R., Thaulo, C., MacPherson, E. E., & Morse, T. (2020). Perspectives and Practices on Water, Sanitation, and Hygiene from a Fishing Community along Lake Malombe, Southern Malawi. *International Journal of Environmental Research and Public Health*, *17*(18), 6703. https://doi.org/10.3390/ijerph17186703
13. Kaonga, C. C., Kambala, C., Mwendera, C., & Mkandawire, T. (n.d.). Water quality assessment in Bangwe Township, Blantyre City, Malawi. *Afr. J. Environ. Sci. Technol.*
14. Mercy Bwanaisa, S. L. H. (2023). Recalibration of benchmarks is necessary: Even the most basic meal was not affordable for Malawi's poor between 2017 and 2021. *Frontiers in Sustainable Food Systems*, *7*(1155661). https://doi.org/10.3389/fsufs.2023.1155661
15. Mkomba, F. K., Saha, A. K., & Wali, U. G. (2021). Household-Level Effects of Energy Insecurity on Welfare in Southern Africa: A Malawian Case Study. *International Journal of Renewable Energy Development*, *10*(1), 105–118. https://doi.org/10.14710/ijred.2021.33234
16. Mounirou, L. A., Sawadogo, B., Yanogo, H., Yonaba, R., Zorom, M., Faye, M. D., Kafando, M. B., Biaou, A. C., Koïta, M., & Karambiri, H. (2023). Estimation of the Actual Specific Consumption in Drinking Water Supply Systems in Burkina Faso (West Africa): Potential Implications for Infrastructure Sizing. *Water*, *15*(19), 3423. https://doi.org/10.3390/w15193423
17. National Planning Commision. (n.d.). *Facts about Blantyre*. https://npc.mw/blantyre-2/
18. National Statistical Office. (2019). *2018 Malawi Population and Housing Census Main Report* (p. 88). Government of Malawi.

https://malawi.unfpa.org/sites/default/files/resource-pdf/2018%20Malawi%20Population%20and%20Housing%20Census%20Main%20Report%20%281%29.pdf

19. National Statistics Office. (2019). *2018 Malawi Poplation and Housing Census Main Report*. https://malawi.unfpa.org/sites/default/files/resource-pdf/2018%20Malawi%20Population%20and%20Housing%20Census%20Main%20Report%20%281%29.pdf
20. Nord, M., & Kantor, L. S. (2006). Seasonal Variation in Food Insecurity Is Associated with Heating and Cooling Costs among Low-Income Elderly Americans. *The Journal of Nutrition*, *136*(11), 2939–2944. https://doi.org/10.1093/jn/136.11.2939
21. Phoumin, H., & Kimura, F. (2019). The impacts of energy insecurity on household welfare in Cambodia: Empirical evidence and policy implications. *Economic Modelling*, *82*, 35–41. https://doi.org/10.1016/j.econmod.2019.09.024
22. Rosinger, A. Y., & Young, S. L. (2024). Trends and disparities in concurrent tap water avoidance and household food insecurity among US children. *Nature Water*, *2*(7), 638–648. https://doi.org/10.1038/s44221-024-00261-2
23. Schneider, K. R. (2022). Nationally representative estimates of the cost of adequate diets, nutrient level drivers, and policy options for households in rural Malawi. *Food Policy*, *113*, 102275. https://doi.org/10.1016/j.foodpol.2022.102275
24. Taulo, S., Wetlesen, A., Abrahamsen, R., Kululanga, G., Mkakosya, R., & Grimason, A. (2008). Microbiological hazard identification and exposure assessment of food prepared and served in rural households of Lungwena, Malawi. *International Journal of Food Microbiology*, *125*(2), 111–116. https://doi.org/10.1016/j.ijfoodmicro.2008.02.025
25. United Nations Human Settlements Programme (-. (2011). *Malawi: Blantyre Urban Profile* (978-92-1-132377–1). UN-HABITAT Regional and nformation Offices or direc. https://unhabitat.org/sites/default/files/download-manager-files/Malawi%20Blantyre%20Urban%20Profile.pdf
26. World Bank Group, U. P. D. (2024). *Urban population (% of total population)*. World Urbanization Prospects, United Nations. https://data.worldbank.org/indicator/SP.URB.TOTL.IN.ZS

27. Young, S. L., Boateng, G. O., Jamaluddine, Z., Miller, J. D., Frongillo, E. A., Neilands, T. B., Collins, S. M., Wutich, A., Jepson, W. E., & Stoler, J. (2019). The Household Water InSecurity Experiences (HWISE) Scale: Development and validation of a household water insecurity measure for low-income and middle-income countries. *BMJ Global Health*, *4*(5), e001750. https://doi.org/10.1136/bmjgh-2019-001750

Appendix C: Supplementary material for Chapter 4

C.1. Recent evolution of clean cooking access

The global prioritization of clean cooking is reflected in the seventh Sustainable Development Goal (SDG7), which aims to achieve universal "access to affordable, reliable, sustainable and modern energy" by 2030[1]. SGD7 is divided between access to electricity and clean cooking technologies. At a country level, the latter is tracked by measuring the proportion of the population with "primary reliance on clean fuels and technologies". For this analysis, we follow the World Health Organization (WHO) definition of "clean" cooking fuels and technologies, which is based on the ability of the fuel and technology to attain levels of fine particulate matter ($PM_{2.5}$) and carbon monoxide (CO) recommended in the 2021 WHO Air Quality Guidelines[2]. This includes solar, electric, biogas, natural gas, liquefied petroleum gas (LPG), and alcohol fuels including ethanol as well as pellet fuels burned in some types of advanced gasifier stoves[3].

In the past decade, some regions have made considerable progress toward this objective, but in other regions progress is slow. For example, between 2010 and 2020, one analysis estimates that primary reliance on clean fuels in Central and Southern Asia increased by over 550 million people, shifting the SDG7 indicator from 38 to 61% of the population[4]. Similarly, in East and Southeast Asia, nearly 370 million people gained access between 2010 and 2020, which moved the SDG7 indicator from 51% to 65%[4]. However, in sub-Saharan Africa, during the same time period, primary reliance on clean fuels increased by fewer than 80 million, a shift from just 12 to 16% of the population, leaving 84% still reliant on wood, charcoal and other polluting fuels [4].

There are many clean cooking options that can contribute to achieving SDG7. However, much of the progress observed to date is a result of expanding access to liquefied petroleum gas (LPG). Indeed, over three quarters of the population that gained primary access to clean cooking between 2010 and 2020 in our sample countries did so by adopting LPG[4]. LPG advocates note that it is well-suited to near-term scale-up[5], and many LMIC governments are prioritizing LPG as a clean fuel (including setting ambitious targets for scale)[6]. In addition to being very clean at the point of use, LPG is relatively simple to use. It requires minimal investment in infrastructure in comparison to grid-based electricity or piped gas, and petroleum companies already have a global presence with retail distribution centers scattered throughout urban and peri-urban areas

worldwide[7]. These factors have all contributed to the rapid uptake of LPG throughout the Global South[8].

Electricity accounts for most of the remaining increase in primary access to clean cooking between 2010 and 2020. However, though access to electricity is increasing rapidly throughout the global south, cooking with electricity is not common. Indeed, there are just 10 countries in which a majority of households in our sample use electricity as a primary cooking option[4]. Other clean cooking options like biogas, ethanol and solar thermal cookers, and cleaner fuels such as pellet biomass fuels burned in advanced stoves have been adopted in certain localities but have not achieved sufficient primary usage nor scale to appear explicitly in global datasets used for this analysis1.

C.2. Derivation of useful energy delivered

There are numerous household surveys that collect information concerning choice of primary cooking fuel and stoves [e.g. 15]. However, few quantify the amount of fuel consumption, which is challenging to measure through self-reporting or during a brief household visit. For the current analysis, we used data from three recent nationally representative household surveys that attempted to quantify fuel consumption from Haiti, Rwanda, and Kenya[16–18]. These surveys quantify use of each fuel by asking specifically about quantity and frequency of fuel purchased and/or collected. Fuel quantities were converted to 'useful' energy using the same calorific values and stove efficiencies used elsewhere in this analysis (Table C9). Overall, the median useful energy per capita in the three-country sample is 2.6 MJ/day (Figure C1-Left). However, there is some evidence that useful energy per capita is higher among solid fuel users than in households that rely primarily or exclusively on LPG. Indeed, this appears to be the case in the

1 For example, the African Biogas Partnership Program disseminated ~70,000 biogas digesters in 5 African countries between 2007 and 2019 [9]. Similarly several million household-scale biogas digesters have been installed in South and Southeast Asia [10–13] . However, household survey data often combines biogas with LPG, so biogas does not appear explicitly. In addition, between late 2019 and early 2022, an ethanol fuel company claims to have reached ~400,000 users in Nairobi and adjacent counties in Kenya but data on ethanol uptake are not yet reflected in current household fuel datasets [14].

selected household surveys, where the median per capita useful energy among exclusive LPG users is 1.5 MJ/day (Figure C1-Right)2. Many other countries in our sample have higher rates of LPG use than the three countries for which we have detailed energy consumption data. Thus, we use 2 MJ/day, which is closer to per capita useful energy consumption among exclusive LPG users than the all-fuel median.

C.3. Figures

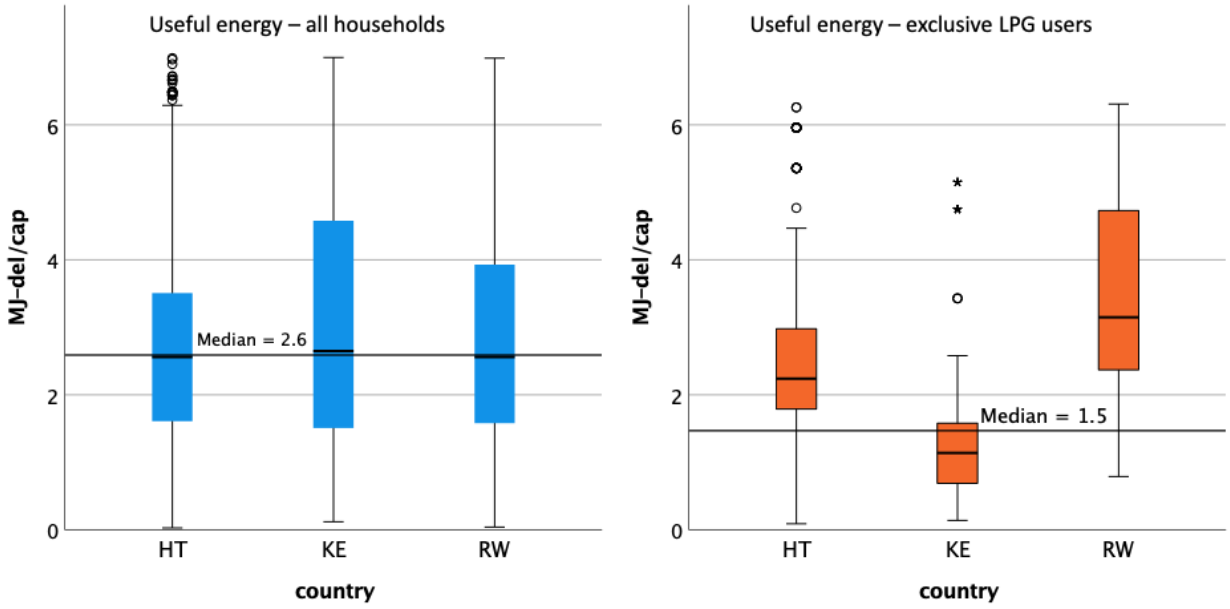


Figure C 1 *Daily useful energy per capita from three nationally representative surveys from all sources (left) and exclusive LPG users (right)*

2 Higher useful energy among solid fuel users may be because solid fuel-burning stoves are not easily shut off; after the meal is cooked, the remaining fuel continues to burn. In contrast, stoves using LPG and other commercial fuels are easily shut off after cooking is complete, thus the same cooking task utilizes less "useful" energy.

Key assumptions about Primary Fuel Choice in the BAU scenario

C.3.1. Historical rates of change

To project future fuel use in the BAU scenario, we used past patterns of shifts in primary fuel use and extended them into the future. Average annual rates of change in household fuel choices among rural and urban populations of each country in our sample are shown in Table C1.

***Table C1**: Annual rates of change in primary fuel from 2000 to 2020 from the WHO household fuel database (data are derived from fuel use percentages estimated by Stoner and colleagues[4], published as CC by 4.0)*

		LPG		Biomass		Charcoal		Kerosene		Coal		Electricity	
ISO3	**Country name**	**Rural**	**Urban**	**Rural**	**Urban**	**Rural**	**Urban**	**Rural**	**Urban**	**Rural**	**Urban**	**Rural**	**Urban**
AFG	Afghanistan	0.74%	2.97%	-0.74%	-2.25%	-0.02%	-0.34%	0.00%	0.00%	0.00%	-0.02%	0.00%	-0.17%
AGO	Angola	0.02%	-0.26%	1.47%	0.05%	-1.41%	0.01%	0.01%	0.01%	0.00%	0.00%	0.00%	0.10%
BGD	Bangladesh	0.28%	1.21%	-0.28%	-1.08%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.01%	-0.01%
BEN	Benin	0.02%	0.36%	-0.43%	-1.39%	0.44%	1.61%	-0.05%	-0.05%	0.01%	0.04%	0.00%	0.01%
BOL	Bolivia (Plurinational State of)	2.14%	0.42%	-2.12%	-0.32%	0.00%	0.00%	-0.02%	-0.02%	0.00%	0.00%	0.00%	-0.05%
BIH	Bosnia and Herzegovina	0.08%	-0.24%	0.64%	0.78%	0.01%	-0.01%	0.00%	0.00%	0.00%	-0.18%	-0.73%	-0.32%
BWA	Botswana	-0.01%	-1.29%	-0.21%	0.15%	0.00%	0.00%	-0.11%	-0.11%	0.00%	0.01%	0.19%	1.36%
BRA	Brazil	1.32%	0.14%	-1.45%	-0.12%	0.12%	-0.01%	0.00%	0.00%	0.00%	0.00%	0.00%	-0.01%
BFA	Burkina Faso	0.01%	1.07%	0.01%	-1.48%	-0.02%	0.44%	-0.01%	-0.01%	0.00%	-0.01%	0.00%	-0.01%
BDI	Burundi	0.00%	-0.02%	0.26%	-0.38%	-0.25%	0.47%	0.00%	0.00%	0.00%	-0.02%	0.00%	-0.02%
CIV	Côte d'Ivoire	-0.06%	0.86%	0.51%	-0.57%	-0.35%	-0.31%	0.00%	0.00%	-0.02%	-0.02%	0.00%	0.04%
KHM	Cambodia	0.58%	2.58%	-0.78%	-2.16%	0.14%	-0.66%	-0.01%	-0.01%	0.00%	0.00%	0.07%	0.26%
CMR	Cameroon	0.07%	1.03%	-0.05%	-0.97%	0.05%	0.32%	-0.09%	-0.09%	0.00%	0.02%	0.00%	0.02%
CAF	Central African Republic	0.00%	0.00%	0.04%	-0.05%	-0.02%	0.03%	0.00%	0.00%	0.01%	0.01%	0.00%	-0.01%
TCD	Chad	-0.04%	0.48%	0.52%	1.88%	-0.33%	-1.61%	-0.01%	-0.01%	-0.04%	-0.50%	-0.02%	-0.05%
CHN	China	0.04%	-0.26%	1.07%	0.17%	0.00%	0.00%	0.00%	0.00%	-1.55%	-0.91%	0.34%	0.86%
COL	Colombia	1.85%	1.25%	-1.53%	-0.16%	0.00%	0.00%	-0.06%	-0.06%	-0.02%	-0.02%	-0.23%	-0.91%
COG	Congo	0.08%	1.67%	0.04%	-0.77%	-0.13%	-1.04%	0.02%	0.02%	0.00%	-0.01%	0.01%	-0.19%
COD	Dem Rep of the Congo	0.01%	0.01%	0.22%	-1.05%	-0.22%	0.67%	0.00%	0.00%	0.00%	0.01%	0.00%	0.31%
DOM	Dominican Republic	0.37%	0.02%	-0.28%	0.01%	0.17%	0.08%	0.00%	0.00%	-0.22%	-0.11%	0.00%	0.01%
ERI	Eritrea	0.02%	0.65%	-0.11%	0.28%	0.07%	0.58%	-0.04%	-0.04%	0.00%	0.01%	0.00%	-0.05%
ETH	Ethiopia	0.00%	0.00%	-0.03%	-1.06%	0.03%	1.05%	-0.01%	-0.01%	0.00%	0.01%	0.00%	1.02%
GMB	Gambia	-0.03%	-0.19%	0.02%	-1.57%	0.05%	1.79%	0.00%	0.00%	0.00%	0.01%	0.00%	0.00%
GHA	Ghana	0.35%	1.30%	-0.89%	-0.59%	0.55%	-0.59%	-0.02%	-0.02%	0.00%	0.00%	0.00%	-0.02%
GTM	Guatemala	-0.24%	-0.30%	0.20%	-0.26%	0.00%	0.00%	0.01%	0.01%	0.00%	0.00%	0.01%	0.45%
GIN	Guinea	0.01%	0.01%	-0.45%	-0.92%	0.46%	0.84%	-0.02%	-0.02%	0.01%	0.00%	0.00%	0.08%
GNB	Guinea-Bissau	0.00%	-0.09%	-0.08%	-0.14%	0.06%	0.22%	0.01%	0.01%	0.00%	0.00%	0.00%	0.00%
HTI	Haiti	0.02%	0.04%	0.05%	-0.14%	-0.07%	0.39%	-0.02%	-0.02%	0.00%	0.01%	0.00%	0.01%
HND	Honduras	0.37%	0.96%	-0.33%	0.18%	0.00%	0.00%	-0.08%	-0.08%	0.00%	0.00%	0.05%	-0.19%
IND	India	1.67%	2.10%	-1.53%	-0.87%	0.00%	0.00%	-0.09%	-0.09%	-0.06%	-0.23%	0.01%	0.00%
IDN	Indonesia	3.33%	4.41%	-2.48%	-0.64%	-0.02%	-0.01%	-0.87%	-0.87%	-0.01%	-0.01%	0.00%	-0.03%
IRN	Iran (Islamic Republic of)	0.18%	0.03%	-0.05%	0.00%	0.00%	0.00%	-0.13%	-0.13%	0.00%	0.00%	0.00%	0.00%
KEN	Kenya	0.16%	1.54%	-0.41%	0.64%	0.16%	0.10%	-0.05%	-0.05%	0.12%	0.01%	0.00%	0.01%
KGZ	Kyrgyzstan	-0.18%	-0.79%	0.48%	0.04%	-0.31%	-0.06%	0.01%	0.01%	-1.71%	-0.21%	1.96%	1.23%
LAO	Lao People's Dem Rep	0.04%	0.50%	-0.89%	-1.15%	0.82%	0.39%	0.00%	0.00%	0.01%	-0.01%	0.03%	0.22%
LSO	Lesotho	0.41%	0.14%	0.06%	-0.02%	0.00%	0.00%	-0.68%	-0.68%	0.00%	-0.01%	0.19%	1.67%
LBR	Liberia	-0.01%	-0.02%	-0.25%	0.21%	0.30%	-0.10%	-0.01%	-0.01%	0.00%	0.00%	0.00%	-0.01%
MDG	Madagascar	-0.01%	-0.05%	-0.33%	-0.54%	0.34%	0.55%	0.00%	0.00%	0.01%	0.04%	0.00%	0.01%
MWI	Malawi	0.00%	0.01%	-0.38%	-2.20%	0.38%	2.42%	0.00%	0.00%	0.00%	0.00%	0.01%	-0.13%
MLI	Mali	-0.01%	-0.01%	-0.23%	-2.34%	0.27%	2.32%	-0.02%	-0.02%	0.01%	0.02%	0.01%	0.01%

		LPG		Biomass		Charcoal		Kerosene		Coal		Electricity	
ISO3	**Country name**	**Rural**	**Urban**	**Rural**	**Urban**	**Rural**	**Urban**	**Rural**	**Urban**	**Rural**	**Urban**	**Rural**	**Urban**
MRT	Mauritania	0.29%	0.75%	-0.01%	0.01%	-0.27%	-0.88%	0.00%	0.00%	0.00%	0.00%	-0.02%	0.09%
MEX	Mexico	0.43%	-0.33%	-0.44%	0.28%	0.01%	0.01%	0.00%	0.00%	0.00%	0.00%	0.01%	0.05%
MNG	Mongolia	0.02%	0.15%	-0.74%	-1.38%	0.00%	0.00%	0.00%	0.00%	0.16%	-0.06%	0.53%	1.29%
MOZ	Mozambique	0.00%	0.28%	-0.25%	-0.96%	0.27%	0.46%	0.00%	0.00%	0.02%	0.14%	-0.02%	0.11%
MMR	Myanmar	0.00%	0.09%	0.42%	-0.72%	-0.74%	-2.41%	0.00%	0.00%	-0.01%	-0.01%	0.29%	2.91%
NAM	Namibia	-0.01%	0.18%	0.05%	0.21%	-0.04%	-0.02%	-0.02%	-0.02%	-0.01%	-0.01%	0.06%	-0.31%
NPL	Nepal	0.74%	2.41%	-0.60%	-0.31%	0.00%	0.00%	-0.12%	-0.12%	0.00%	0.00%	0.01%	0.01%
NIC	Nicaragua	0.10%	1.56%	-0.06%	-1.35%	-0.01%	-0.04%	-0.01%	-0.01%	0.00%	0.00%	-0.01%	-0.09%
NER	Niger	-0.01%	0.34%	0.01%	-0.66%	0.02%	0.33%	-0.01%	-0.01%	0.00%	0.01%	0.00%	-0.03%
NGA	Nigeria	0.11%	0.85%	-0.15%	-0.51%	0.03%	0.14%	-0.03%	-0.03%	0.01%	0.16%	0.02%	0.06%
PAK	Pakistan	1.00%	1.21%	-0.98%	-1.17%	0.01%	0.00%	-0.05%	-0.05%	0.00%	0.00%	0.00%	0.01%
PNG	Papua New Guinea	0.04%	-0.28%	-0.11%	1.01%	0.01%	0.01%	-0.06%	-0.06%	0.00%	0.00%	0.12%	0.41%
PRY	Paraguay	0.74%	-0.09%	-1.30%	-0.42%	0.04%	-0.32%	0.00%	0.00%	-0.01%	0.00%	0.51%	0.82%
PER	Peru	1.54%	1.92%	-1.41%	-0.36%	-0.01%	0.01%	-0.11%	-0.11%	0.00%	-0.04%	0.00%	-0.05%
PHL	Philippines	0.32%	0.47%	-0.44%	-0.19%	0.29%	0.29%	-0.15%	-0.15%	0.00%	0.01%	-0.01%	0.06%
RUS	Russian Federation	0.06%	0.19%	0.18%	0.10%	0.00%	0.00%	0.00%	0.00%	0.00%	0.01%	-0.45%	-0.45%
RWA	Rwanda	0.00%	0.15%	-0.22%	-0.74%	0.22%	0.61%	0.00%	0.00%	0.00%	-0.01%	0.00%	-0.01%
SEN	Senegal	-0.18%	-1.24%	-0.14%	0.23%	0.28%	0.95%	0.00%	0.00%	0.00%	0.00%	0.04%	0.06%
SRB	Serbia	0.43%	0.22%	-0.54%	-0.01%	0.01%	0.00%	0.00%	0.00%	-0.08%	-0.03%	0.21%	-0.09%
SLE	Sierra Leone	0.00%	0.03%	0.02%	-2.65%	0.12%	2.73%	-0.08%	-0.08%	0.00%	0.01%	0.00%	0.01%
SOM	Somalia	0.00%	0.12%	-1.21%	-0.75%	1.24%	0.54%	-0.02%	-0.02%	0.00%	0.00%	0.01%	0.04%
ZAF	South Africa	0.00%	0.06%	-1.01%	-0.04%	0.00%	0.00%	-0.91%	-0.91%	-0.16%	-0.14%	2.05%	0.95%
SSD	South Sudan	0.00%	0.00%	0.11%	0.27%	-0.04%	-0.16%	0.00%	0.00%	0.00%	-0.01%	0.00%	0.00%
LKA	Sri Lanka	0.51%	0.88%	-0.40%	-0.42%	0.00%	0.00%	-0.08%	-0.08%	0.00%	0.00%	-0.01%	-0.04%
SDN	Sudan	1.83%	2.68%	-2.24%	-3.16%	0.27%	0.38%	0.00%	0.00%	0.01%	0.00%	0.01%	0.01%
TJK	Tajikistan	1.71%	-0.28%	-2.98%	-0.95%	-0.01%	-0.02%	0.00%	0.00%	-0.01%	-0.01%	1.25%	1.25%
THA	Thailand	1.61%	0.12%	-0.75%	0.09%	-0.84%	-0.15%	0.00%	0.00%	0.00%	0.00%	-0.02%	-0.05%
TLS	Timor-Leste	0.01%	0.13%	-0.06%	-1.44%	0.00%	-0.01%	-0.02%	-0.02%	0.00%	0.00%	0.10%	0.94%
TGO	Togo	0.02%	0.88%	0.22%	-0.18%	-0.17%	-0.68%	-0.04%	-0.04%	0.00%	0.00%	0.00%	0.03%
TUR	Turkey	0.48%	0.09%	-0.38%	-0.01%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	-0.02%
TZA	Tanzania	0.50%	0.41%	-0.57%	-0.56%	0.12%	0.22%	-0.05%	-0.05%	-0.04%	-0.01%	0.02%	0.14%
UGA	Uganda	0.00%	0.03%	-0.37%	0.69%	0.41%	-0.26%	-0.02%	-0.02%	0.00%	0.01%	0.00%	-0.16%
UKR	Ukraine	0.02%	-0.21%	0.05%	-0.02%	-0.01%	0.00%	0.00%	0.00%	-0.11%	-0.12%	0.02%	0.37%
UZB	Uzbekistan	0.02%	-0.04%	-0.08%	-0.01%	0.00%	0.00%	0.00%	0.00%	0.00%	-0.01%	-0.03%	-0.01%
VNM	Viet Nam	2.60%	2.58%	-2.16%	-0.84%	-0.20%	-0.51%	-0.09%	-0.09%	-0.16%	-0.41%	0.01%	-0.14%
YEM	Yemen	0.08%	0.03%	-0.13%	-0.01%	0.01%	0.00%	0.05%	0.05%	0.00%	0.00%	0.00%	-0.01%
ZMB	Zambia	0.00%	0.01%	-0.29%	-0.28%	0.24%	0.59%	0.00%	0.00%	0.00%	-0.01%	0.05%	-0.31%
ZWE	Zimbabwe	0.03%	0.42%	-0.02%	0.38%	0.00%	0.01%	0.02%	0.02%	0.00%	0.00%	-0.04%	-0.91%

C.3.2. Fuels used in the scenarios and fuel choice hierarchy

Simply applying past rates of change could result in the percentage of fuels used in a country exceeding 100%. To avoid this, we developed a "fuel hierarchy" based on the assumption that when households change primary cooking fuels, they are more likely to adopt cleaner fuels rather than more traditional/more polluting fuels [19]. Accordingly, to simulate this, we applied growth rates in the following order: LPG; Electricity; Kerosene; Charcoal; Biomass; and Coal (assumptions used for the fuel hierarchy are provided in SI Section 3). We use the same fuel grouping used by WHO in their analyses of current and future household fuel choice. WHO defines the following categories:

WHO fuel groups[3,4]		Comment
Polluting	Biomass	This category includes fuelwood and other minimally processed solid organic material like crop residues and dung. Fuelwood is the dominant form of biomass used for cooking in LMICs, and for this assessment, we use emission factors for fuelwood to estimate climate impacts of biomass.
	Charcoal	Charcoal is made from wood or other organic matter that is pyrolyzed (heated in an oxygen-poor environment so that volatile materials are driven off, leaving behind mainly elemental carbon). Charcoal is a common fuel in urban and peri-urban areas in some LMICs.
	Coal	Fossil-based solid fuel commonly used for industrial heat and electricity production but also used as residential fuel in China, Mongolia, and few other LMICs.
	Kerosene	Kerosene (also called paraffin) is a petroleum distillate used for cooking and lighting in many LMICs.
Clean	Gas	Gas includes LPG, piped natural gas, and biogas. Of these, LPG, a mix of butane and propane, is by far the most common residential cooking fuel in LMICs.
	Electricity	Electricity is a popular source of primary cooking energy in a small number of LMICs. In this assessment, we assume that when electricity is used for cooking, it originates from the country's national grid, and we

estimate emissions based on each country's current and projected future grid mixes.

We define a fuel choice hierarchy in the BAU scenario to ensure the total percentage of primary fuel choice does not exceed 100%. To address this, we assigned fuels using a hierarchical set of assumptions:

- When changing fuels, households prefer clean fuels over polluting so gas or electricity would be selected before kerosene, biomass or charcoal
- Fuels are prioritized in the following order: electricity, gas, kerosene, charcoal, coal (only in locations coal was in use at baseline), and biomass
- All fuel use adds to 100%
- If biomass drops to zero, so that gas, electricity, kerosene and/or charcoal reach 100% electricity and gas continue to grow and the other fuels decline
- If populations are saturated with 100% gas and electricity users before 2040, we assume electricity usage continues to grow, but gas usage decline

In the full transition scenarios, there were some instances in which the rate of decline of polluting fuels was higher under BAU than would have occurred by a 20-year shift to LPG (for example, cooking with coal in China, which is rapidly declining). In these cases, we use the BAU rate instead.

C.4. GREET Emission Factors

C.4.1. Crude oil

Crude oil is a major input in the production of fossil-derived cooking fuels such as LPG and kerosene and a key input in the transportation of all commercial cooking fuels. Rather than try to estimate the emissions from crude oil demand in every country in our model, we simulated a global mix by identifying the sources of global crude oil exports worldwide and assuming each country in the sample obtains either crude oil or refined products from this global mix. GREET includes life-cycle data from 7 potential sources of crude oil: the Middle East, Africa, Latin America, Canada, the US, and Mexico. To simulate a global export market in GREET, we used UN energy statistics to estimate each region's share of global exports in 2018 [20]. This allocation is shown in *Figure C2.* :

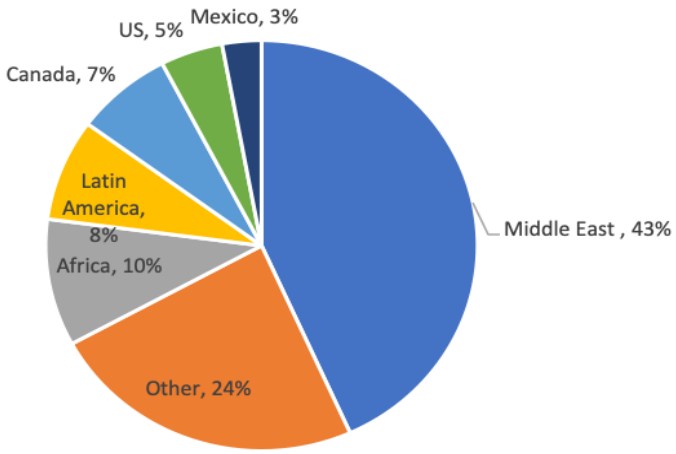


Figure C 2 *Percent of global exports of crude oil in 2018* [20]

To estimate transportation distances of crude oil from producing countries to countries in our sample, we limited the analysis to the five top crude oil importers: China, India, Thailand, Turkey, and South Africa, which represent over 90% of the total crude oil imported by countries included in the analysis. We then calculated the average import distance based on a volume-weighted average of distances from each major exporter to these top-5 importers (*Table C2)*.

Table C2 *Export fractions and transport distance between crude oil producers and selected countries*

Country/Region	% of global exports	Weighted average distance from 5 largest importers (km) [b]
Middle East	43%	9309
Africa	10%	8941
Latin America	8%	9349
Canada	7%	10621
US	5%	11734
Mexico	3%	11718
Other [a]	24%	2244

[a] Assumptions about distances for "other" exporters depended on the importing region. For China, we assumed the distance traveled was 3,200 km, which is the length of a pipeline between Taishet, Russia and Daqing, China, that transports roughly 50% of the oil traded between Russia and China [21]. India imports nearly all its oil from the US, Africa and the Middle East so "other" countries were not considered relevant [22]. Thailand imports significant quantities from neighboring countries in SE Asia [23]. For Turkey, we assumed "other" originated from Russia based on [24], and for South Africa, we assumed "other" originated from India based on World Bank trade data [25].

[b] In all cases except the China-Russia pipeline, distances were estimated using an online shipping distance calculator [26].

C.4.2. LPG and kerosene

For LPG and kerosene, the team assumed upstream emissions also result from fuel available on the global market. LPG is produced from both crude oil and natural gas; GREET allows users to set the proportion of LPG produced from each feedstock. We used the global average of 63% from natural gas and 37% from crude oil based on data from the WLPGA [27]. Kerosene is produced entirely from crude oil. For kerosene and the portion of LPG derived from crude oil, we used the same mix of global crude oil described in Figure C2. To estimate the emissions from the global LPG trade, we identified the largest LPG importers in the sample (Figure C2). Russia is self-sufficient in LPG supply, but the other major consumers import between 34 and 74% of LPG to meet total demand. As with crude oil, we estimate distances between major LPG exporters (*Table C4)*. For kerosene, UN data indicated that nearly all the largest consumers are self-sufficient, so no estimates of long-distance transportation were necessary.

Table C3 *Largest LPG consuming countries in the global sample* [20]

Country	Production (kton)	Imports (kton)	Exports (kton)	Consumption (kton)	% of cons in sample (%)	pct imported
China	40,615	20,521	1,407	59,729	39%	34%
India	12,768	14,521	455	27,046	18%	54%
Russian Federation	17,030	0	6,115	11,015	7%	0%
Indonesia	1,991	5,762	0	7,753	5%	74%
Mexico	3,372	4,313	21	7,665	5%	56%
Total	75,776	45,117	7,998	113,208	73%	40%

Table C4 Major LPG exporting countries/regions [20]

Country/Region	% of global exports	Weighted average distance from 5 largest importers (km) [b]
Middle East	35%	9394
US	32%	10781
Other [a]	22%	1583
Canada	6%	9628
Africa	2%	8394
Latin America	2%	8664

[a] includes Russia, Australia, EU, and several Asian countries

[b] In all cases except the China-Russia pipeline, distances were estimated using an online shipping distance calculator [26].

C.4.3. Coal

GREET also includes upstream emissions data from coal extraction and processing. To simulate global rather than US-based coal, we changed the ratio of underground to surface mining from 30:70 to 60:40 based on data from the World Coal Institute [28]. We also altered the sulfur content of coal to match the average of Chinese coal, which is ~2% [29].3

3 We justify using a value for China because cooking electricity consumption in China represents over 60% of all electricity used for cooking in sample countries in 2018 and its share will increase under most scenarios.

C.4.4. Diesel used for ground transport

We also used GREET to estimate the emissions from road-based transportation of fossil fuels as well as charcoal. The sulfur content of diesel fuel is regulated and does not exceed 15 ppm in the US [30], but varies widely in other countries. To reflect diesel fuel used in countries included in the sample, we used 540 ppm, which is the consumption-weighted average of sulfur in diesel fuel in sample countries based on 2019 data compiled by the International Council on Clean Transportation [31].

C.5. Grid projections and emission factors

Future grid mixes were simulated using projections from the IEA's World Energy Outlook (WEO) "Stated Policies" scenario through 2040, which include all world regions and major economies like Brazil, Russia, India, China, and South Africa (*Table C5)*. Countries that were not explicitly included in WEO projections were assumed to follow the regional projection if it resulted in a cleaner grid over time. If the future regional mix was more polluting than the country's own mix in 2020, we assumed that the country's grid mix remained constant. Grid losses were accounted for using World Bank indicator data [32]**.** Plant-specific emissions are included in GREET's database with some tunable parameters. GREET's default values assume a US-based grid and power plant feedstock. We changed some parameters for coal, as mentioned above. Parameters for other feedstocks were left at their default values.

Table C5 *Grid mix projections from WEO 2020 "Stated Policy" Scenario [33] (published as CC by 4.0)*

Country/Region	Total (TWh)	Solar PV	Wind	Hydro	Biomass	Coal	Gas	Oil	Nuclear	Fossil fuels w/CCS
					2020					
Brazil	605	1.3%	9.4%	65.7%	8.6%	2.8%	9.1%	0.7%	2.3%	0.0%
Russia	1057	0.1%	0.1%	17.9%	0.3%	15.8%	44.5%	0.7%	20.4%	0.0%
China	7787	3.5%	6.1%	17.1%	1.9%	63.7%	2.9%	0.1%	4.7%	0.0%
India	1609	4.0%	4.2%	10.8%	3.4%	70.0%	4.3%	0.5%	2.9%	0.0%
SE Asia	1111	1.6%	0.7%	14.8%	3.5%	43.1%	32.4%	1.5%	0.0%	0.0%
S Africa	251	1.8%	3.9%	0.4%	0.3%	87.7%	0.0%	0.0%	4.9%	0.0%
Africa w/o S Africa	576	1.0%	1.2%	23.4%	0.2%	3.6%	0.0%	11.9%	0.2%	0.0%
Eurasia w/o Russia	278	0.8%	0.5%	23.3%	0.1%	28.5%	45.7%	0.3%	0.8%	0.0%

Lat Am w/o Brazil	672	2.1%	3.1%	44.1%	2.8%	7.4%	27.8%	10.3%	1.6%	0.0%
Asia w/o China and India	3565	4.0%	1.4%	10.6%	3.2%	37.1%	32.1%	3.1%	6.9%	0.0%
Europe	3952	4.5%	13.1%	16.7%	6.0%	15.0%	21.4%	1.3%	21.2%	0.0%
Middle East	1188	0.9%	0.2%	1.0%	0.0%	0.2%	71.0%	25.9%	0.6%	0.0%
2030										
Brazil	752	9.4%	15.7%	56.5%	9.0%	1.5%	4.2%	0.3%	3.2%	0.0%
Russia	1253	0.5%	1.6%	15.6%	0.6%	11.5%	52.1%	0.3%	17.5%	0.0%
China	10232	12.7%	13.8%	14.0%	3.7%	45.9%	3.0%	0.1%	6.6%	0.1%
India	2545	16.3%	7.9%	8.9%	3.1%	54.6%	4.7%	0.2%	4.3%	0.0%
SE Asia	1682	5.4%	3.0%	12.2%	3.6%	39.7%	31.9%	0.9%	0.0%	0.0%
S Africa	278	7.2%	13.7%	0.7%	2.5%	68.3%	2.2%	0.0%	5.0%	0.0%
Africa w/o S Africa	937	6.6%	4.3%	24.6%	1.1%	6.5%	45.4%	6.9%	1.5%	0.0%
Eurasia w/o Russia	364	2.1%	2.2%	20.1%	0.1%	25.0%	49.9%	0.0%	0.5%	0.0%
Lat Am w/o Brazil	864	7.3%	8.4%	48.6%	3.5%	2.6%	23.0%	4.4%	1.1%	0.0%
Asia w/o China and India	4515	9.5%	5.1%	11.0%	3.4%	30.9%	26.6%	2.0%	9.1%	0.1%
Europe	4601	10.9%	24.9%	16.4%	6.4%	5.5%	17.3%	0.5%	16.9%	0.2%
Middle East	1616	4.9%	1.6%	1.8%	0.4%	1.1%	71.1%	15.2%	3.2%	0.0%
2040										
Brazil	925	12.4%	17.4%	50.7%	8.4%	1.1%	4.6%	0.3%	4.8%	0.0%
Russia	1377	0.9%	3.8%	15.4%	2.3%	9.5%	48.4%	0.1%	18.3%	0.0%
China	11995	19.7%	17.3%	13.1%	4.1%	33.0%	3.6%	0.0%	8.6%	0.3%
India	3853	32.7%	13.3%	8.0%	2.8%	32.8%	4.1%	0.1%	5.8%	0.0%
SE Asia	2269	8.6%	5.6%	13.2%	4.1%	35.1%	28.8%	0.6%	0.5%	0.0%
S Africa	328	12.5%	24.7%	1.2%	4.9%	40.9%	5.5%	0.0%	7.6%	0.0%
Africa w/o S Africa	1380	13.7%	7.8%	23.6%	1.7%	4.0%	36.8%	4.5%	1.4%	0.0%
Eurasia w/o Russia	465	2.8%	3.2%	18.6%	0.3%	21.0%	52.2%	0.0%	1.7%	0.0%
Lat Am w/o Brazil	1087	11.2%	10.9%	46.5%	3.9%	1.2%	19.9%	2.1%	2.5%	0.0%
Asia w/o China and India	5556	12.6%	9.4%	11.9%	4.0%	24.9%	24.9%	1.0%	7.5%	0.6%
Europe	5191	12.5%	33.3%	16.0%	6.4%	3.3%	13.3%	0.2%	13.4%	0.1%
Middle East	2230	10.9%	5.1%	1.7%	1.1%	1.0%	64.9%	10.0%	3.6%	0.0%

Table C5 shows emissions factors derived from GREET as described in the methods section of the main text.

Table C6 Life cycle grid emissions in grams per kWh of electricity produced from each type of power generation were estimated using modified inputs from the 2021 version of Argonne National Lab's GREET model [34]

Fuel cycle	VOC	CO	NO_x	PM_{10}	$PM_{2.5}$	SO_x	BC	OC	CH_4	N_2O	CO_2
Oil Boiler	0.07	0.13	0.38	0.03	0.03	0.19	0.00	0.01	1.14	0.00	115.59
NG CC Turbine	0.06	0.16	0.18	0.00	0.00	0.08	0.00	0.00	1.28	0.01	37.15
Coal Boiler	0.08	0.02	0.06	0.05	0.01	0.07	0.00	0.00	2.47	0.00	16.75
Nuclear-PWR	0.00	0.01	0.01	0.00	0.00	0.00	0.00	0.00	0.02	0.00	5.76
Hydro	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Plant infrastructure											
Oil Boiler	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.77
NG CC Turbine	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.41
Coal Boiler	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.77
Nuclear-PWR	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.43
Hydro	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	2.16
Power production											
Oil Boiler	0.01	0.08	2.25	0.16	0.13	2.74	0.01	0.01	0.03	0.01	889
NG CC Turbine	0.00	0.03	0.05	0.02	0.02	0.01	0.00	0.01	0.01	0.00	393
Coal Boiler	0.01	0.30	0.71	0.08	0.06	0.94	0.00	0.00	0.16	0.02	987
Nuclear-PWR	--	--	--	--	--	--	--	--	--	--	--
Hydro	--	--	--	--	--	--	--	--	--	--	--
Total											
Oil Boiler	0.09	0.22	2.63	0.19	0.16	2.93	0.01	0.02	1.17	0.01	1,006
NG CC Turbine	0.06	0.19	0.23	0.02	0.02	0.09	0.00	0.01	1.29	0.01	430
Coal Boiler	0.09	0.32	0.77	0.13	0.07	1.02	0.00	0.01	2.63	0.02	1,005
Nuclear-PWR	0.00	0.01	0.01	0.00	0.00	0.00	0.00	0.00	0.02	0.00	6
Hydro	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	2

Table C6 shows life cycle emissions though generation of electricity at the power plant. However, grid losses can be substantial, particularly in LMICs. We account for grid losses using data from the World Bank, which has information from 56 of the 77 countries in our sample. Losses range from ~6% in China and Thailand to 60% or more in Togo and Haiti. Available data are shown in Table C7. For countries lacking data, we used the average of losses weighted by electricity demand for cooking, which is ~8%.

Table C7 *Grid losses in percent based on World Bank data [35] (published as CC by 4.0)*

Country Code	% losses	Country Code	% losses
AGO	11.3	MNG	14.8
BGD	11.4	MOZ	14.7
BIH	8.2	NAM	36.2
BOL	9.2	NER	41.8
BRA	15.8	NGA	16.1
BWA	11.0	NIC	20.8
CHN	5.5	NPL	32.2
CIV	14.3	PAK	17.1
CMR	11.1	PER	11.0
COD	21.4	PHL	9.4
COG	44.5	PRY	6.6
COL	10.7	RUS	10.0
DOM	12.2	SDN	14.3
ERI	12.9	SEN	12.9
ETH	18.7	SRB	15.4
GHA	22.6	SSD	5.7
GTM	9.5	TGO	71.0
HND	34.9	THA	6.1
HTI	60.1	TJK	17.0
IDN	9.4	TUR	14.8
IND	19.3	TZA	17.7
IRN	12.6	UKR	10.8
KEN	17.6	UZB	8.8
KGZ	23.7	VNM	9.3
KHM	23.4	YEM	25.8
LKA	11.4	ZAF	8.4
MEX	13.7	ZMB	15.0
MMR	20.5	ZWE	16.4

Applying the emission factors from Table C6 and loss factors from Table C7 to the grid mix described in Table C5 results in country-specific emission factors. In the base year 2018 emission factors ranged from over 1000 gCO_2e per kWh in countries that are heavily dependent on coal and/or have high grid losses to < 10 gCO_2e per kWh in countries that are heavily dependent on hydroelectric power. Emission factors per kWh consumed are shown in Figure C3.

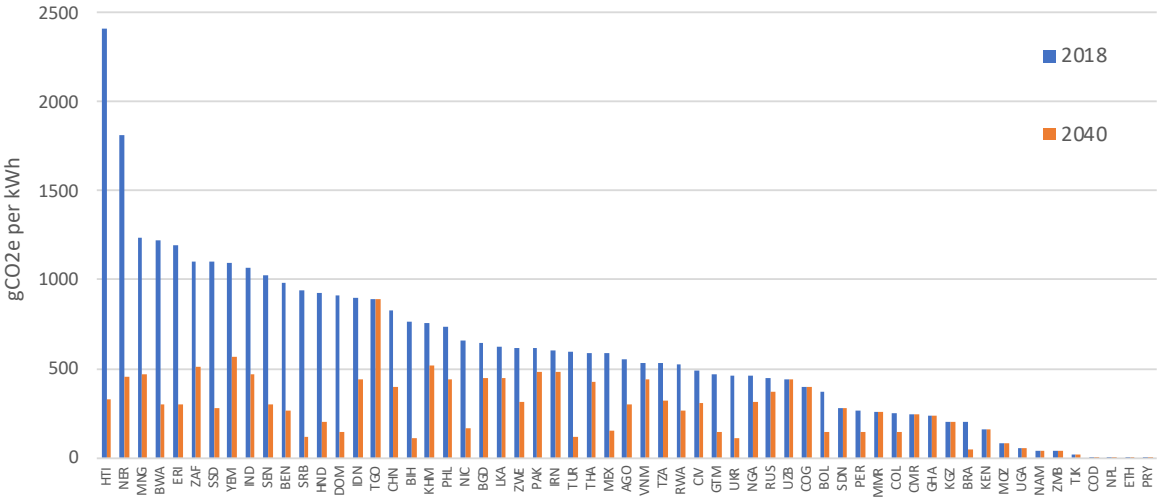


Figure C3 *Grid emission factors per kWh consumed based on the national mix in 2018 and projected mix in 2040*

C.6. Accounting for non-renewable biomass

While these estimates cover most LMICs, some countries included in our sample were not included. For these countries, a LMIC-wide average of 28.8% fNRB was used. Country-level fNRB values are shown in Table C8.

Table C8: Country-level fNRB values [from 36]

Country	ISO3	fNRB (%)	Country	ISO3	fNRB (%)
Afghanistan	AFG	25.7	Mali	MLI	28.5
Angola	AGO	34.9	Myanmar	MMR	4.4
Burundi	BDI	55.5	Mongolia	MNG	25.7
Benin	BEN	19.3	Mozambique	MOZ	39.6
Burkina Faso	BFA	47.1	Mauritania	MRT	69.1
Bangladesh	BGD	50.9	Malawi	MWI	32.8
Bosnia and Herzegovina	BIH	28.8	Namibia	NAM	45.3
Bolivia (Plurinational State of)	BOL	22.2	Niger	NER	49.0
Brazil	BRA	17.4	Nigeria	NGA	18.8
Botswana	BWA	17.0	Nicaragua	NIC	31.9
Central African Republic	CAF	35.2	Nepal	NPL	52.4
China	CHN	16.5	Pakistan	PAK	83.3
Côte d'Ivoire	CIV	35.2	Peru	PER	26.1
Cameroon	CMR	9.0	Philippines	PHL	21.8
DR of the Congo	COD	35.2	Papua New Guinea	PNG	31.2
Congo	COG	35.2	Paraguay	PRY	29.1
Colombia	COL	29.7	Russian Federation	RUS	28.8
Dominican Republic	DOM	33.0	Rwanda	RWA	58.9
Eritrea	ERI	67.6	Sudan	SDN	25.7
Ethiopia	ETH	60.9	Senegal	SEN	33.3
Ghana	GHA	27.7	Sierra Leone	SLE	21.7
Guinea	GIN	24.1	Somalia	SOM	52.4
Gambia	GMB	41.4	Serbia	SRB	28.8
Guinea-Bissau	GNB	27.8	South Sudan	SSD	35.2
Guatemala	GTM	31.7	Chad	TCD	23.7
Honduras	HND	19.9	Togo	TGO	43.1
Haiti	HTI	66.3	Thailand	THA	3.0
Indonesia	IDN	41.1	Tajikistan	TJK	25.7
India	IND	23.2	Timor-Leste	TLS	23.7

Iran (Islamic Republic of)	IRN	25.7	Turkey	TUR	25.7
Kenya	KEN	36.7	Tanzania	TZA	17.6
Kyrgyzstan	KGZ	25.7	Uganda	UGA	61.1
Cambodia	KHM	23.1	Ukraine	UKR	28.8
Lao PDR	LAO	25.7	Uzbekistan	UZB	25.7
Liberia	LBR	23.0	Viet Nam	VNM	11.7
Sri Lanka	LKA	23.6	Yemen	YEM	25.7
Lesotho	LSO	52.4	South Africa	ZAF	23.8
Madagascar	MDG	26.6	Zambia	ZMB	33.8
Mexico	MEX	25.9	Zimbabwe	ZWE	33.1

C.7. Cooking Upstream and End-Use Emission Factors

Table C9 *Life-cycle emission factors for each fuel pathway (grams pollutant per MJ-delivered). Dashes indicate that emissions are negligible. Numerical superscripts refer to references used for each pollutant.*

Production and processing	**Biomass** [a]	**Charcoal** [a]	**Coal**	**Kerosene**	**LPG**
CO	--	34.5 [37]	0.0100 [34]	0.0200 [34]	0.0300 [34]
NO_x	--	0.060 [38]	--	0.0700 [34]	0.0300 [34]
$PM_{2.5}$	--	3.42 [37]	--	--	--
SO_x	--	--	--	0.0300 [34]	0.0400 [34]
BC	--	0.420 [37]	0.0130 [34]	0.00100 [34]	0.000300 [34]
OC	--	1.50 [37]	--	--	--
CH_4	--	8.25 [37]	0.480 [34]	0.210 [34]	0.210 [34]
N_2O	--	0.030 [38]	--	0.000300 [34]	0.000300 [34]
NMVOC	--	61.7 [39]	--	0.0100 [34]	0.0200 [34]--
CO_2	--	349 [37]	1.41 [34]	19.0 [34]	22.5 [34]
Transportation					
CO	--	--	--	--	0.0100 [34]
NO_x	--	0.0100 [34]	0.0100 [34]	0.0100 [34]	0.0600 [34]
$PM_{2.5}$	--	--	--	--	--
SO_x	--	--	--	--	0.0200 [34]
BC	--	--	--	--	0.00110 [34]
OC	--	--	--	--	--
CH_4	--	--	--	--	0.0100 [34]
N_2O	--	--	--	--	0.000100 [34]
NMVOC	--	--	--	--	--
CO_2	--	1.87 [34]	1.84 [34]	0.610 [34]	6.41 [34]
End-use					
CO	35.9 [37]	36.4 [39]	23.1 [38]	1.20 [38]	0.525 [38]
NO_x	0.0500 [38]	0.060 [38]	0.475 [38]	1.20 [38]	0.0792 [38]
$PM_{2.5}$	4.25 [37]	0.320 [40]	1.40 [38]	0.00300 [38]	0.0133 [38]
SO_x	0.140 [38]	0.070 [38]	1.61 [38]	0.00116 [38]	1.00E-05 [38]
BC	0.670 [37]	0.190 [39]	0.300 [37]	--	--
OC	1.970 [37]	0.250 [39]	0.210 [37]	--	--
CH_4	3.87 [37]	1.02 [39]	1.88 [38]	0.0170 [38]	0.0140 [38]
N_2O	--	--	--	--	--
NMVOC	3.90 [38]	1.60 [38]	5.76 [38]	0.0260 [38]	2.11 [38]--

CO_2	634 [37]	459 [39]	572 [38]	151 [38]	137 [38]
Total [b]					
CO	35.9	70.8	23.1	1.22	0.565
NO_x	0.0500	0.130	0.49	1.27	0.169
$PM_{2.5}$	4.25	4.15	1.40	0.00300	0.0132
SO_x	0.140	0.0700	1.61	0.0312	0.0600
BC	0.670	0.610	0.31	0.000800	0.00140
OC	1.79	1.75	0.21	--	--
CH_4	3.87	9.27	2.36	0.227	0.234
N_2O	0.00	0.0300	0.00	0.000300	0.000400
NMVOC	3.90	63.3	5.76	0.0360	2.14
CO_2	633.7	809.9	574.8	170	166

[a] End-use CO_2 emissions from biomass and charcoal should be adjusted by the country-specific fNRB factor listed in SI Section 1.

[b] Totals are the simple sum of Production and processing, Transportation, and End-use, rounded to three significant figures.

C.8. Energy Demand by Scenario Type

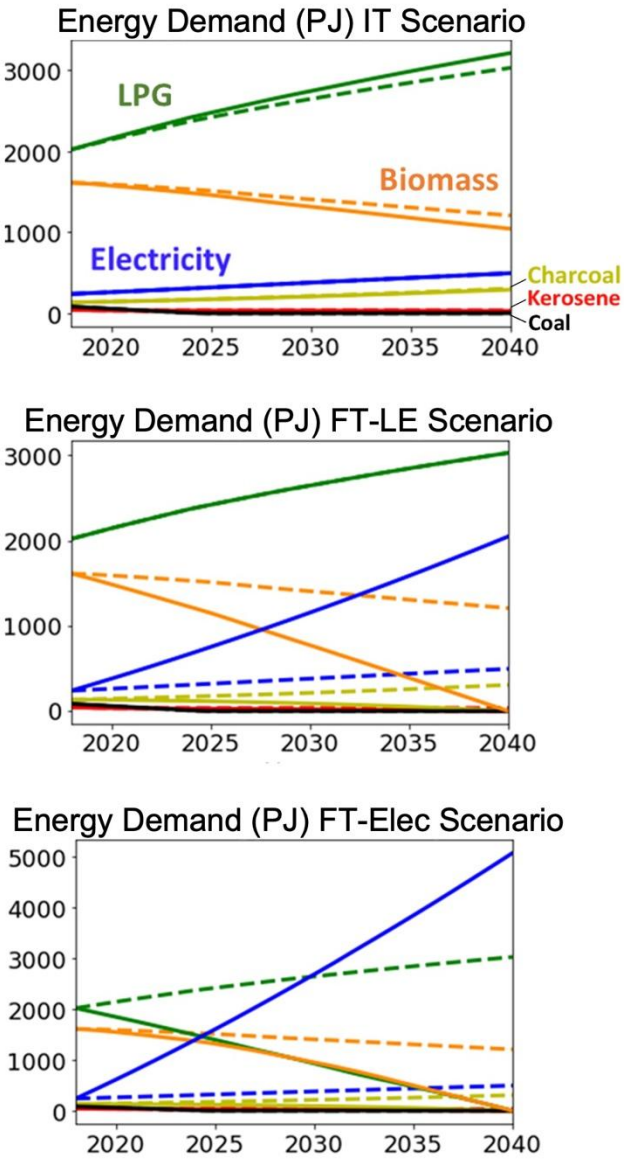


Figure C4 *Comparison of energy demand by households in the BAU scenario (dashed lines) and IT (top), FT-LE (middle) and FT-Elec (bottom) scenarios. In each plot the data from alternative scenarios are shown with solid lines.*

C.9. Emissions of health-damaging and climate forcing pollutants

C.9.1. Short-lived forcers

In the main text, we compare BC emissions at baseline and in 2040 across scenarios. In Figure C5, we show that NMVOCs and OC emissions follow similar patterns though NMVOCs are higher in 2040 than 2018 in both BAU and IT scenarios, while OC, like BC, is lower. Under full transitions to LPG and/or electricity, NMVOC and OC emissions are nearly eliminated.

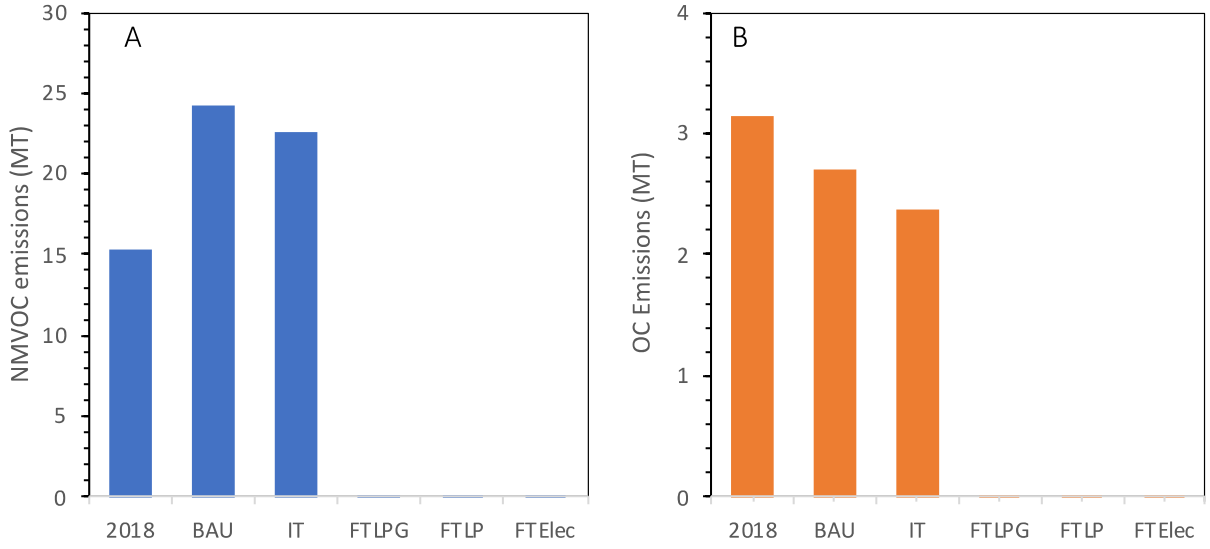
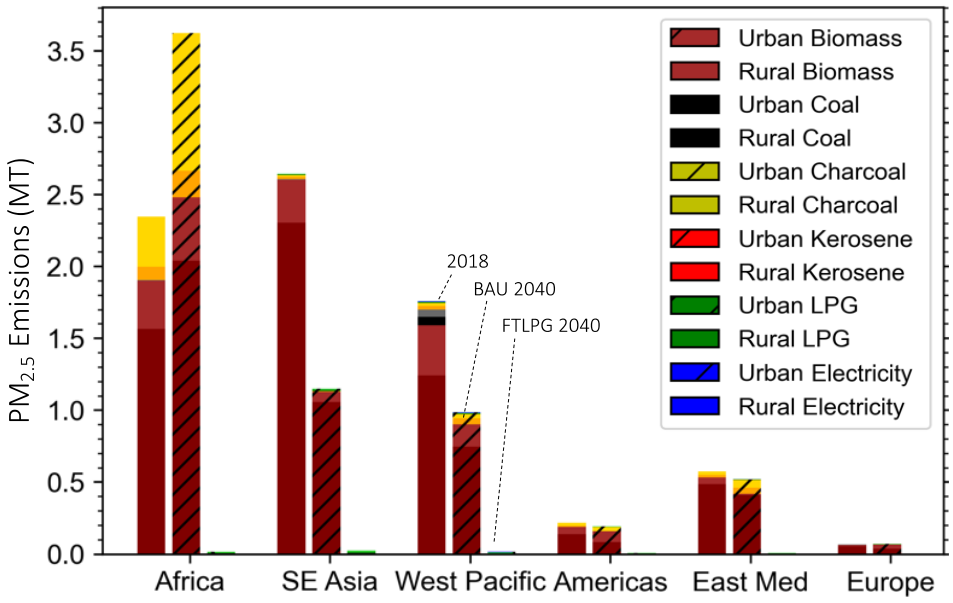


Figure C5 *Emissions of well-mixed NMHCs (A) and OC (B) at baseline and in 2040 for all scenarios*

C.9.2. Regional breakdown

Emissions of health-damaging pollutants vary by region (Figure C6). In 2018, $PM_{2.5}$ emissions were highest in the African and SE Asian regions. Under BAU, $PM_{2.5}$ emissions decrease in every region by 2040 except Africa, where our projections show that they increase by >50% due to increased (mostly rural) biomass and (mostly urban) charcoal consumption. By 2040, a FT-LPG scenario results in large reductions in all regions including nearly 95% reduction in Africa.



:

Figure C6 *Fuel-specific urban and rural emissions of $PM_{2.5}$ by WHO region in the BAU and FT-LPG scenarios*

C.10. More detailed breakdown of GHG emissions

C.10.1. Country-level changes

The largest reductions in emissions between BAU and the three FT scenarios occur in countries with large populations of polluting fuel users that are projected to remain high under BAU, as well as countries with clean electricity production. These include Ethiopia, with reductions of 32-55 Mt CO_2e/yr by 2040 under the full transitions, Democratic Republic of the Congo (18-40 Mt CO_2e), Uganda (22-34 MtCO2e) and Pakistan (24-25 MT CO_2e). All these countries have large contributions from hydro-electric power in 2018: Democratic Republic of the Congo (99.7%), Ethiopia (92.7%), Uganda (89.1%) and Pakistan (30.7%), contributing to the large decline in GHGs.

C.10.2. Specific pollutants

Changes in emissions of specific GHGs vary. CO_2 and CH_4 emissions closely mirror CO_2e emissions described above. However, N_2O, behaves differently because N_2O emissions from electricity are higher N_2O increases 90% between 2018 and 2040 under the BAU scenario. N_2O emissions are ~70% lower in the FT-LPG scenario, but only 50% lower in the FT-E scenario and 10% higher in the FT-EO scenario.

SLCFs follow similar patterns: as explained in the main text, BC emissions decrease by ~17% between 2018 and 2040 in the BAU scenario and decline by ~12% under the IT scenario and are

nearly eliminated under full transitions to LPG and/or electricity. OC and NMVOC emissions follow similar patterns. Both decrease slightly between 2018 and 2040 under BAU. In the IT scenario, OC emissions increase by roughly 12% relative to BAU, and are nearly eliminated in full transitions. NMVOCs decrease ~6% under IT and are also nearly eliminated under the full transitions. Other SLCFs, SO_x, NO_x, and CO, were discussed in the section on health damaging pollutants.

***Table C10**: Changes in Emissions*

	2018	2040				
	(all)	BAU	IT	FT-LPG	FT-LE	FT-Elec
CO_2	836.4297	948.0805	940.3771	825.8725	722.2453	645.9218
NMVOC	15.31756	24.16058	22.61973	0.006155	0.022334	0.065279
CO	70.64852	66.98022	60.1796	2.610679	1.784506	0.215057
NO_x	0.600458	0.716758	0.730784	0.825862	0.690274	0.497227
PM_{10}	28.58372	21.72236	18.81904	0.007672	0.023125	0.06925
$PM_{2.5}$	7.560072	6.454984	5.702069	0.064781	0.0542	0.040127
SO_x	0.559818	0.441057	0.427742	0.338491	0.37649	0.561177
BC	1.191671	1.001679	0.883463	0.006461	0.004674	0.001475
OC	3.139732	2.699641	2.381576	0.000203	0.002149	0.006116
CH_4	6.609108	7.114238	6.566668	1.24873	1.265119	1.636891
N_2O	0.006448	0.012221	0.011867	0.00363	0.005902	0.013497
CO_2e	1138.421	1297.164	1281.208	1072.004	897.8612	694.3095

Figure C 3 Pollutant-specific emissions in 2018 (all scenarios) and 2040 in each Scenario

C.11 Temperature and Uncertainty Results

***Table C11** Temperature differences in 2040 relative to BAU for Different Scenarios (used for Figure 4C)*

	5th percentile (K)	50th percentile (K)	95th percentile(K)
Full Electricity	-2.38E-02	-5.08E-03	2.44E-02
FT-Elec	-2.47E-02	-4.99E-03	2.67E-02
FT-LPG	-2.44E-02	-4.67E-03	2.71E-02
IT	-2.67E-03	-3.23E-04	3.51E-03

Table C12 *Pollution-specific temperature differences in 2040 between FT-LPG and BAU, used for Figure 5A*

Pollutant	5th Percentile (K)	50th Percentile (K)	95th Percentile (K)
NMVOC	-6.00E-03	-2.82E-03	-5.70E-06
OC	5.81E-03	1.89E-02	4.47E-02
NOx	3.37E-05	7.50E-05	1.23E-04
Sox	1.27E-04	2.55E-04	4.22E-04
N2O	-1.38E-05	-1.06E-05	-8.06E-06
CO2	-5.01E-04	-4.01E-04	-3.20E-04
CH4	-2.98E-03	-2.31E-03	-1.73E-03
CO	-6.99E-03	-3.65E-03	-5.67E-04
BC	-2.72E-02	-1.46E-02	-2.55E-03
Total	-2.44E-02	-4.71E-03	2.68E-02

Table C13 *Region- & pollution-specific temperature differences in 2040 between FT-LPG and BAU, used for Figure 5C*

Region	NMVOC	OC	NOx	SOx	N2O	CO2	CH4	CO	BC
Africa	-2.10E-03	1.01E-02	0.00E+00	1.00E-04	0.00E+00	-3.00E-04	-1.40E-03	-2.10E-03	-7.70E-03
SE Asia	-1.00E-04	3.50E-03	0.00E+00	1.00E-04	0.00E+00	0.00E+00	-3.00E-04	-6.00E-04	-2.70E-03
Europe	0.00E+00	2.00E-04	0.00E+00	0.00E+00	0.00E+00	0.00E+00	0.00E+00	0.00E+00	-2.00E-04
Americas	-1.00E-04	6.00E-04	0.00E+00	0.00E+00	0.00E+00	0.00E+00	-1.00E-04	-1.00E-04	-4.00E-04
East Med	-2.00E-04	1.50E-03	0.00E+00	0.00E+00	0.00E+00	-1.00E-04	-2.00E-04	-3.00E-04	-1.20E-03
Western Pacific	-2.00E-04	3.10E-03	0.00E+00	0.00E+00	0.00E+00	0.00E+00	-3.00E-04	-5.00E-04	-2.40E-03

C.11. References

1. UNDP. SUSTAINABLE DEVELOPMENT GOAL 7. *Sustainable Development Knowledge Platform* https://sustainabledevelopment.un.org/sdg7 (2020).

2. World Health Organization. *WHO global air quality guidelines: particulate matter (PM2.5 and PM10), ozone, nitrogen dioxide, sulfur dioxide and carbon monoxide*. https://apps.who.int/iris/handle/10665/345329.

3. World Health Organization. Defining clean fuels and technologies. *Clean Household Energy Solutions Toolkit* https://www.who.int/tools/clean-household-energy-solutions-toolkit/module-7-defining-clean (2021).
4. Stoner, O. *et al.* Household cooking fuel estimates at global and country level for 1990 to 2030 - Supplemental Data. *Nat Commun* **12**, 5793 (2021).
5. Global LPG Partnership. *The Global LPG Partnership - Fact Sheet*. 6 https://static1.squarespace.com/static/5633c4c2e4b05a5c7831fbb5/t/5b2bae2288251ba7a0589660/1529589286458/The+Global+LPG+Partnership+-+Executive+Summary+-+website+20+Jun+2018.pdf (2018).
6. Kypridemos Chris *et al.* Health and Climate Impacts of Scaling Adoption of Liquefied Petroleum Gas (LPG) for Clean Household Cooking in Cameroon: A Modeling Study. *Environmental Health Perspectives* **128**, 047001 (2020).
7. Puzzolo, E. *et al.* Supply Considerations for Scaling Up Clean Cooking Fuels for Household Energy in Low- and Middle-Income Countries. *GeoHealth* **3**, 370–390 (2019).
8. IEA. *World Energy Outlook 2021*. www.iea.org/weo.
9. Sika, J. M. From Nairobi in 2007 to Dakar in 2020. *Africa Biogas Partnership Programme* https://www.africabiogas.org/blog/from-nairobi-in-2007-to-dakar-in-2020/ (2019).
10. Meeks, R., Sims, K. R. E. & Thompson, H. Waste Not: Can Household Biogas Deliver Sustainable Development? *Environ Resource Econ* **72**, 763–794 (2019).
11. Hyman, J. & Bailis, R. Assessment of the Cambodian National Biodigester Program. *Energy for Sustainable Development* **46**, 11–22 (2018).
12. Mittal, S., Ahlgren, E. O. & Shukla, P. R. Barriers to biogas dissemination in India: A review. *Energy Policy* **112**, 361–370 (2018).
13. Bond, T. & Templeton, M. R. History and future of domestic biogas plants in the developing world. *Energy for Sustainable Development* **15**, 347–354 (2011).
14. KOKO Networks. 400,000 Kenyan Household Subscribers On KOKO's Clean Fuel Platform. *Koko News* https://kokonetworks.com/news/400000-kenyan-household-subscribers-on-kokos-clean-fuel-platform/ (2022).
15. ICF. The DHS Program STATcompiler. http://www.statcompiler.com (2022).

16. EED & SEI. *Kenya Cooking Sector Study: Assessment of the Supply and Demand of Cooking Solutions at the Household Level*. 163 https://www.eedadvisory.com/resources/resources/ (2019).
17. Clean Cooking Alliance. *Haiti Urban Household Energy Baseline Dataset*. (2019).
18. MININFRA. *National Survey on Cooking Fuel Energy and Technologies in Households, Commercial and Public Institutions in Rwanda*. 113 (2020).
19. Jagger, P. & Jumbe, C. Stoves or sugar? Willingness to adopt improved cookstoves in Malawi. *Energy Policy* **92**, 409–419 (2016).
20. United Nations Statistics Division. UNdata | explorer. http://data.un.org/Explorer.aspx?d=EDATA (2021).
21. Wikipedia. Eastern Siberia–Pacific Ocean oil pipeline - Wikipedia. https://en.wikipedia.org/wiki/Eastern_Siberia%E2%80%93Pacific_Ocean_oil_pipeline#cite_note-upstream2-18 (2022).
22. Verma, N. U.S. becomes India's second biggest oil supplier, Saudi plunges to No. 4. *Reuters* (2021).
23. International Trade Administration. Energy Resource Guide - Thailand - Oil and Gas. https://www.trade.gov/energy-resource-guide-thailand-oil-and-gas.
24. Energy Information Administration (EIA). TURKEY - Analysis. https://www.eia.gov/international/analysis/country/TUR (2017).
25. World Bank. South Africa Fuel Imports by country & region 2019. *World Integrated Trade Solution (WITS)* https://wits.worldbank.org/CountryProfile/en/Country/ZAF/Year/2019/TradeFlow/Import/Partner/all/Product/Fuels/Show/Partner%20Name;MPRT-TRD-VL;MPRT-PRDCT-SHR;AHS-WGHTD-AVRG;MFN-WGHTD-AVRG;/Sort/MPRT-TRD-VL/Chart/top10 (2022).
26. sea-distances.org. Shipping Distance Calculator. https://sea-distances.org/ (2022).
27. WLPGA. *Statistical Review of Global LPG 2020*. https://www.wlpga.org/publication/statistical-review-of-global-lpg-2021/.
28. World Coal Institute. *The Coal Resource, A Comprehensive Overview of Coal*. 44 https://www.scribd.com/document/18825349/The-Coal-Resource-A-Comprehensive-Overview-of-Coal-World-Coal-Institute (2005).

29. Hussain, R. & Luo, K. The Geological Availability and Emissions of Sulfur and SO2 from the Typical Coal of China. *Aerosol and Air Quality Research* **19**, 559–570 (2019).
30. US EPA, O. Diesel Fuel Standards and Rulemakings. https://www.epa.gov/diesel-fuel-standards/diesel-fuel-standards-and-rulemakings (2015).
31. Miller, J. & Jin, L. *GLOBAL PROGRESS TOWARD SOOT-FREE DIESEL VEHICLES IN 2019*. Supplemental Table S2 https://theicct.org/sites/default/files/publications/Global_progress_sootfree_diesel_2019_20190920.pdf (2019).
32. World Bank. World Development Indicators: Electricity production, sources, and access. http://wdi.worldbank.org/table/3.7 (2017).
33. IEA. *World Energy Outlook 2020 – Analysis*. https://www.iea.org/reports/world-energy-outlook-2020 (2020).
34. Argonne National Laboratory. The Greenhouse Gases, Regulated Emissions, and Energy Use in Transportation (GREET) Model. (2021).
35. World Bank. World Bank Open Data. *DataBank* https://data.worldbank.org (2021).
36. Bailis, R., Drigo, R., Ghilardi, A. & Masera, O. The Carbon Footprint of Traditional Woodfuels. *Nature Climate Change* **5**, 266–272 (2015).
37. Grieshop, A. P., Marshall, J. D. & Kandlikar, M. Health and climate benefits of cookstove replacement options. *Energy Policy* **39**, 7530–7542 (2011).
38. US EPA. Life Cycle Assessment of Cooking Fuel Systems in India, China, Kenya, and Ghana. https://cfpub.epa.gov/si/si_public_record_report.cfm?dirEntryId=339679&Lab=NRMRL&simplesearch=0&showcriteria=2&sortby=pubDate&timstype=Published+Report&datebeginpublished presented.
39. Akagi, S. K. *et al.* Emission factors for open and domestic biomass burning for use in atmospheric models. *Atmospheric Chemistry and Physics* **11**, 4039–4072 (2011).
40. Singh, P., Gundimeda, H. & Stucki, M. Environmental footprint of cooking fuels: a life cycle assessment of ten fuel sources used in Indian households. *Int J Life Cycle Assess* **19**, 1036–1048 (2014).