

A RECIPE FOR DISASTER

IMPACT OF EXTREME WEATHER ON NUTRITION AND METABOLIC HEALTH, WITH
A CASE STUDY OF ABORIGINAL AND TORRES STRAIT ISLANDER COMMUNITIES
IN NORTHERN AUSTRALIA

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Abstract

BACKGROUND

To date, the effects of extreme weather events (EWEs) on specific nutrients within the population's diet have not been quantified. With climate change projected to increase the severity of extreme weather across the globe, it is necessary to understand how the global nutrient supply has historically responded, and which subpopulations are most at risk. One particular subpopulation of importance is Aboriginal and Torres Strait Islander people, who are already more susceptible to nutritional insult and metabolic syndrome than their non-Indigenous counterparts. While extreme weather is not the primary driving force in poor health outcomes, I hypothesise that it further exacerbates cardiometabolic health burdens globally, and especially among vulnerable populations.

METHODS

In my first study, I conducted superposed epoch analysis to calculate the percentage change in nutrient supply during the year of an EWE relative to its five-year window. I composited the results globally and by United Nations designated low-income subgroups. I also reported changes in terms of Recommended Dietary Allowance (RDA) for children aged 1-3 years.

In my second study, I constructed a holistic model with data from 104 Aboriginal and Torres Strait Islander communities in the Northern Territory from 2010-2015. I used varimax-rotated Principal Component Analysis to extract and condense information from 218 variables for physical environment, census, and climate data. I then conducted MM-estimator regression to model the extreme heat impacts on cardiometabolic-related rates for emergency room, inpatient admission, primary healthcare, and mortality.

RESULTS

In the first study, most micronutrient supplies exhibited modest negative percentage change during the year of an EWE, including folate, magnesium, niacin, phosphorus, potassium, thiamin, vitamin B6, vitamin C, and zinc. Effects were magnified among Landlocked Developing Countries, which exhibited significant nutrient supply changes ranging from 1.6–8.0% of average supply. The observed nutrient supply deficits were found to be a large percentage (up to 41.5%) of what a healthy child's average sufficient dietary intake level should be.

The most compelling finding of the second study is that holding all else fixed, a unit increase in climate PC1 score is associated with a 77.8% change in emergency room rates, 6.7 percentage point increase in inpatient rates, and 9.3 percentage point increase in primary healthcare rates. Thus, a larger cardiometabolic health burden is strongly correlated with communities that experience relatively lower apparent temperature and humidity but greater maximum heatwave severity, e.g. Alice Springs area.

CONCLUSION

The EWE effects on nutrient supply are modest in isolation; however, in the context of nutrient needs for healthy child development, the effects observed are substantial. Children are a particularly vulnerable subpopulation of interest, given how certain nutritional deficiencies during gestation and the first five years of life can have irrecoverable consequences for health, growth, and development.

In the second study, I found that relative heat – or sudden rises in temperature above that of the recent past – poses the most significant threat to cardiometabolic health among Indigenous communities in northern Australia. Relative heat, rather than absolute heat, should therefore be the focus of public health preparation and response.

Both studies echo previous literature in stressing the urgency with which the international community must tackle the issue of nutritional and metabolic health among vulnerable populations, especially because this health landscape is poised to worsen with climate change.

Declaration

This is to certify that:

1. This thesis comprises only my original work towards the Master of Philosophy, except where indicated in the preface
2. Due acknowledgement has been made in the text to all other material used
3. This thesis is fewer than the maximum word limit in length, excluding tables, maps, bibliographies, and appendices

5 August 2019

Preface

COLLABORATIVE CONTRIBUTIONS

All work presented in this thesis is original, and all analysis was conducted independently. This thesis does not include any chapters presented in article format; however, material in [Chapter 3](#) come from a recent publication,¹ which has been rearranged in this thesis for ease of understanding. The publication has been appended ([Appendix A.1](#)). Material in [Chapter 4](#) is in the process of submission for publication. For these co-authored manuscripts, I designed the respective studies, conducted the analyses, interpreted the results, and wrote the manuscripts. My co-authors helped conceptualise aspects of the studies and provided feedback on the manuscripts. The only third-party copyright material included in the thesis is [Figure 2.1](#), and permission has been obtained from the authors to include this content in the open access version of the thesis.

PUBLICATIONS

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ETHICS

Ethics approval for the present study was obtained from the Human Research Ethics Committee (HREC) of University of South Australia [HREC Reference No. 31874], Central Australian Human Research Ethics Committee [HREC-13-182], and Human Research Ethics Committee of the Northern Territory Department of Health and Menzies School of Health

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“I WOULD MAINTAIN THAT THANKS ARE THE HIGHEST FORM OF THOUGHT, AND THAT GRATITUDE IS HAPPINESS DOUBLED BY WONDER.” – *GK CHESTERON*

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Jay– I’ve spent a lot of time on this thesis, but I’ve spent even more time just trying to write your “thanks.” It’s a work-in-progress, and I can’t wait to spend the rest of my life writing it.

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Abbreviations

AI	Adequate Intake
AT	Apparent Temperature
EHF	Excess Heat Factor
EM-DAT	International Disasters Database
EnRICH	Environments and Remote Indigenous Cardiometabolic Health study
EWE	Extreme weather events
FAO	Food and Agriculture Organisation
GENuS	Global Expanded Nutrient model
IPCC	Intergovernmental Panel on Climate Change
MetS	Metabolic syndrome
NT	Northern Territory, Australia
OLS	Ordinary Least Squares
PC	Principal components
PCA	Principal components analysis
RDA	Recommended Dietary Allowance
ROBPCA	Robust principal component analysis
SEA	Superposed epoch analysis
SREX	Special Report on Managing the Risks of Extreme Events and Disasters to Advance Climate Change Adaptation
UN	United Nations
WBGT	Wet Bulb Globe Temperature

Climate change is intrinsically linked to public health, food and water security, migration, peace, and security. It is a moral issue. It is an issue of social justice, human rights and fundamental ethics. We have a profound responsibility to the fragile web of life on this Earth, and to this generation and those that will follow.

Ban Ki-moon

1

Introduction

1.1 PLANETARY HEALTH

When it was first introduced in 1980, the term “planetary health” was used only by the odd environmentalist, conservationist, and health anthropologist. Yet in the last few years, it has exploded in usage among a much larger research community— a shift spearheaded by The Rockefeller Foundation’s partnership with *The Lancet* in 2014 to form the Commission on Planetary Health.² In their final report released in 2015, planetary health was formally defined as:

“the achievement of the highest attainable standard of health, wellbeing, and equity worldwide through judicious attention to the human systems—political, economic, and social—that shape the future of humanity and the Earth’s natural systems that define the safe environmental limits within which humanity can flourish. Put simply, planetary health is the health of human civilisation and the state of the natural systems on which it depends.”³

Planetary health differs from its predecessors “One Health”⁴ and “EcoHealth”⁵ in its contributing methodologies, core focus, and values. Most prominently, planetary health places a greater emphasis on human health, whereas the other two disciplines tend to equate hu-

man health with animal and plant health.⁶ Planetary health's more anthropocentric leanings make it the logical extension of "global health," or the study, research, and practice of improving health and achieving health equity for all people worldwide.⁷ Planetary health infuses the more established medical discipline of global health with new concepts of environmental stewardship, sustainability, and ecosystems-thinking; thus making planetary health uniquely fitted to be the lens through which we tackle today's intricate health challenges.⁸ The latest research in planetary health has identified how changes in the environment are affecting every dimension of our health and well-being,⁹ including nutritional outcomes,^{10,11} infectious disease,^{12–14} noncommunicable disease,^{15–17} displacement and conflict,^{18,19} and mental health outcomes.^{20,21}

The study of planetary health demands the formation of new coalitions across many different disciplines to meet the pervasive knowledge gaps in how our world impacts our health.²² But any kind of multidisciplinary work necessitates a nontrivial amount of translation, since crossing disciplinary boundaries often means speaking a new language. Now that I have briefly outlined the emerging field of planetary health within which I find my research localised, I will spend the rest of this chapter translating the two main concepts I have studied in my Masters project – extreme weather and malnutrition – before describing my study motivations, aims, and rationale.

1.2 EXTREME WEATHER

"Extreme events are generally easy to recognize but difficult to define."²³ Although extreme weather events affect us all universally, there is no singular universal understanding of what "extreme weather" actually means. The varying definitions for extreme weather largely stem from the fact that the concept of "extremeness" is entirely based upon relativity and context.²³ A 40°C day in Siberia is a much different flavour of extreme than a 40° day in the Sahara.

For this thesis, I resort to the authority of the Intergovernmental Panel on Climate Change (IPCC), which is the leading international body founded within the United Nations for the assessment of climate change. In their Special Report on Managing the Risks of Extreme Events and Disasters to Advance Climate Change Adaptation (SREX), an "extreme climate or weather event" is first broadly defined as the occurrence of a value of a weather or climate variable above (or below) a threshold value near the upper (or lower) ends of the range of observed values of the variable.²⁴ Beyond this somewhat vague and imprecise definition, the SREX chapter on "Changes in Climate Extremes and their Impacts on the Natural Physical Environment" further delineates three categories of extreme climate/weather events of

interest due to their consequential extreme *impacts* on ecosystems:

- 1) weather and climate variables (i.e. temperature, precipitation, winds)
- 2) phenomena related to weather and climate extremes (i.e. monsoons, El Niño and other modes of variability, tropical cyclones, and extratropical cyclones)
- 3) impacts on physical environment (i.e. droughts, floods, extreme sea level and coastal impacts, and other physical impacts)²⁵

Throughout this thesis, I will refer to extreme weather events (EWEs) as any selection or combination of events from within these three SREX categories. It is important to note that an EWE is distinct from a *natural disaster*, though they are often colloquially interchanged. The IPCC defines *disaster* as “severe alterations in the normal functioning of a community or a society due to hazardous physical events interacting with vulnerable social conditions, leading to widespread adverse human, material, economic, or environmental effects that require immediate emergency response to satisfy critical human needs and that may require external support for recovery.”²⁴

While there is significant overlap between EWEs and natural disasters, not all EWEs are natural disasters, and vice versa. The EWE is a physical environmental phenomenon, whereas the natural disaster is a combined enviro-social phenomenon, which encompasses both environmental stress and exposed, vulnerable populations or infrastructure. In this thesis, I opted to use EWEs and climatological variables because there exists better global data coverage of these climate/weather extremes. As one can imagine, natural disasters are even *more* subjectively defined than extreme weather, and as such are differentially analysed. That said, in line with the SREX categories, my focus on EWEs has been restricted to those that have been shown to have extreme impacts on ecosystems, particularly in terms of how they affect human systems.

Finally, there is the ever-so-sticky issue of addressing the potential influence of anthropogenic climate change on EWEs. Scientists are still debating whether (or how) to attribute EWEs to climate change, but the attributional science behind historical EWEs is rapidly improving.^{26,27} Meanwhile, the research body focused on future projections (rather than past events) is simultaneously growing. It is now projected with medium-to-high confidence that by the end of this century, we will have witnessed global increases in the frequency and/or magnitude of heat waves, heavy precipitation, tropical cyclones, and droughts, with effects varying depending on geography.^{28,29} Preparedness and response to EWEs have become increasingly salient priorities for countries worldwide, as we all adjust to living in a climate changed world.

1.3 NUTRITION AND METABOLIC SYNDROME

The nutrition transition first laid out by Barry Popkin in 1993,³⁰ describes the shifts in dietary patterns of populations in the modern age. Simplified into three steps, this transition follows a linear genealogy: first there are the periods of famine, then there are those of receding famine, and finally there is the era of metabolic syndrome and nutrition-related chronic diseases.³¹

Metabolic syndrome (or MetS) is loosely defined as the conglomeration of interrelated risk factors that directly promote the development of cardiovascular diseases and diabetes.³² These risk factors include abdominal obesity, atherogenic dyslipidemia, raised blood pressure, insulin resistance, glucose intolerance, and proinflammatory/prothrombotic states.³³

In the Western world, the progression to the third and final stage of the nutrition transition was largely mediated by the dramatic change in diet that occurred during the 20th century. By reducing fiber and whole grain intakes, while simultaneously increasing consumption of refined carbohydrates (primarily sugar), animal products, and hydrogenated fats, the West created a palate that was as delectable as it was deleterious to our health. This change in diet was made possible by the steep increases in wealth that accumulated during the Industrial Revolution.³⁰ Having moved from the cornfield to the cubicle – and from fresh foods to processed ones – our more sedentary economy has inevitably resulted in an increased prevalence of metabolic diseases.

What was once an exclusively Western phenomenon is now a global one— the developing world is rapidly transitioning, and the rise of metabolic diseases is occurring faster than ever.³⁴ The prevalence of obesity (defined as a body mass index greater or equal to 30 kg/m²) is currently growing much more rapidly in low and middle-income countries than in higher income countries, possibly reflecting a “catch-up effect” as the developed world starts to plateau.^{35,36} Yet at the same time, undernutrition and micronutrient deficiencies – afflictions that have plagued developing nations for centuries – continue to stubbornly persist. A vast majority of the world’s 821 million undernourished people, and 50.5 million children under five years old affected by wasting (low weight for height), reside in low-income countries.³⁷ Micronutrient malnutrition is responsible for a wide range of non-specific physiological impairments, reduced resistance to infections, increased susceptibility to metabolic disorders, and delayed or impaired physical and psychomotor development.^{38–40} Numerous studies have verified that stunted children have a significantly increased risk of developing obesity later on in life. In other words, children who grow up in conditions of undernutrition – or who experienced micronutrient deficiencies *in utero* –

are more predisposed to metabolic diseases as adults.^{41–44}

For developing nations, the nutrition transition no longer tracks along the same economic trajectory that the Western world once established. While the West's growth in waistline was coupled with a growth in the economy, for much of the developing world, the spread of metabolic syndrome has been facilitated by globalization, not necessarily a rapid rise in wealth.⁴⁵ The trend towards an obese profile is thus especially alarming, given that many developing nations do not have the healthcare capacity to care for these newly emerging chronic diseases in addition to their current endemic or infectious disease burden – also referred to as the “double burden of disease.” Cardiovascular diseases are the number one cause of death globally. In 2016, an estimated 17.9 million people died, representing 31% of all global deaths; more than three-quarters of these deaths took place in low and middle income countries.⁴⁶ The rapid rise of obesity and its associated metabolic diseases in the developing world may indeed be the most significant global health issue today.

1.4 STUDY AIMS AND RATIONALE

HYPOTHESES

With climate change projected to increase the frequency and intensity of EWEs globally, it is imperative that we investigate and understand the ways in which extreme weather impacts human health. While extreme weather is not the primary driving force in poor health outcomes, I hypothesise that it further exacerbates cardiometabolic health burdens globally, and especially among vulnerable populations. This has largely been proven only anecdotally; in this research project, I aim to objectively quantify the extreme weather impacts. In the first study, I take a global perspective to quantify the impact of EWEs on nutrient supply; and in the second study, I focus on the local context to explore links between climate indicators and healthcare outcomes for Indigenous communities in northern Australia.

STUDY 1: DO EXTREME WEATHER EVENTS AFFECT NUTRIENT SUPPLY ON A GLOBAL LEVEL?

Agricultural production has been shown to decline during and after an EWE.^{47–52} Some case studies have specifically linked EWEs to nutritional outcomes, such as risk of child stunting due to drought-related crop loss in Uganda⁵³ and persistent reduced growth among flood-exposed children in Bangladesh.⁵⁴ While many studies have referred to the well-observed trend of EWEs threatening food security, specifically in the developing world,^{55–57} no study has yet quantified the global impact of EWEs on total nutrient supply. The process

of detecting signals in either EWE or nutrition data on a population level is encumbered by limited data quality and scale; yet it is imperative that we investigate the possible link between EWEs and nutritional insults now, as our changing climate is threatening to further magnify their consequences.^{58,59}

Understanding the historical fluctuations in nutrient supply caused by EWEs will inform and support future estimates of nutritional impacts in the aftermath of such events. Sub-group analysis is of critical importance because the magnitude of the repercussions of EWEs are modulated by geography, economic development, and governance structures.^{60–65} Essentially, while two storms may look climatically identical, their repercussions can be vastly different. Recovery post-EWE is particularly formidable in low-income settings, where a task like infrastructure maintenance and equitable food distribution is a challenge even in fair weather. It is within these very contexts that nutrient supply fluctuations can have the severest consequences – and while EWEs are likely not the lone driving forces in the global burden of malnutrition, they may play an important role in exacerbating already existing issues.

STUDY 2: WHICH CLIMATE VARIABLES AFFECT CARDIOMETABOLIC HEALTH IN NORTHERN AUSTRALIA?

Extreme heat has been associated with negative cardiometabolic health outcomes in Australia, but our interpretation of this relationship has been largely limited to absolute temperature measurements in urban areas. We do not have a thorough understanding of how climate variables affect Indigenous health in northern Australia, yet this subgroup is one of the most impacted by cardiometabolic issues. Aboriginal and Torres Strait Islander Australians are three times more likely to have diabetes than non-Indigenous Australians, and nearly twice as likely to be obese.^{66,67} Beyond morbidity, Indigenous Australians have twice the rate of mortality from coronary heart disease and nearly five times the rate of mortality from diabetes compared to non-Indigenous Australians.⁶⁸ In the national effort to close the 10-year gap in life expectancy at birth between Indigenous and non-Indigenous Australians, MetS is a major target.⁶⁹

This study was conducted within an existing Australian National Health and Medical Research Council (NHMRC) Project Grant (NHMRC GNT1051824), titled “Environments and Remote Indigenous Cardiometabolic Health (EnRICH).” The EnRICH project collected built environment, census, climate, and health data from ~100 remote Indigenous communities in the Northern Territory of Australia from 2010-2015. The primary aim of this study is to explore the relationship between various climate variables and the following four health outcomes, which are specifically coded with cardiometabolic-related causes: age

and sex-standardised emergency room rates, inpatient admission rates, primary healthcare visit rates, and mortality rates. The built environment and census variables were included to provide a holistic model that accounts for various site-specific and socioeconomic confounders. Sifting through a large amount of raw and incomplete data required advanced machine learning techniques, and so a secondary aim of this study is to provide a robust, efficient methodology for large epidemiological studies that suffer from three main conditions: overspecification, multicollinearity, and outliers.

1.5 THESIS STRUCTURE

In this introductory chapter, I have provided context on the emerging field of Planetary Health, within which my research is uniquely situated. I defined my two areas of focus – extreme weather and MetS-related health outcomes. And to round out this chapter, I have detailed my hypothesis, study aims, and rationale. [Chapter 2](#) is the bibliographic network analysis I conducted for my literature review. [Chapter 3](#) is the SEA nutrient supply analysis, conducted globally with a specific focus on low-income settings. [Chapter 4](#) is the PCA regression analysis of Indigenous communities in northern Australia. To finish, [Chapter 5](#) is composed of my concluding remarks on this body of work, ultimately followed by references and appendix. If, by that point, you are not sick and tired of reading me, I have appended a short, creative memoir detailing my research journey to Australia and my future back in the United States ([Appendix A.14](#)).

Anything else you're interested in is not going to happen if you can't breathe the air and drink the water. Don't sit this one out. Do something. You are by accident of fate alive at an absolutely critical moment in the history of our planet.

Carl Sagan

2

Literature review

In the era of buzzwords like “big data,” the traditional literature review has received a much-needed facelift. Bibliometric network analysis is an evolved literature review – not only does it provide an accurate visualisation of the body of literature in a given field, but it also precipitates rapid in-depth analysis of the metadata, or the data about the data. In this case, the bibliometric metadata includes authors, their respective institutions, year of publication, the journals that published them, number of citations, etc. For the first time, we can finally see and explore a body of literature – not as an amorphous concept, but as a structured network of relationships.

2.1 BIBLIOGRAPHIC NETWORK ANALYSIS VS. SYSTEMATIC QUANTITATIVE REVIEW

The closest relative to the bibliometric network analysis is the systematic quantitative review.⁷⁰ Both types of literature review 1) use objective search criteria in a systematic query, 2) produce an overview of bibliometric characteristics (e.g. number of articles, geographic distribution of authors), and 3) can be used to identify gaps in the literature. Beyond these similarities, the systematic quantitative review proves to be the more demanding (and less

talented) sibling – it requires more grunt work and delivers less output. In conducting a quantitative systematic review, the final filter that determines whether a paper is gold or garbage in the field is the reader. She must read each and every publication that may be included in the review and ultimately determine where its weight lies in her database. This inherently narrows the scope of the literature review, as the human reader can only have so much time and patience on her hands – as well as objectivity in measuring relative importance. Quantitative systematic reviews are also designed to answer specified research questions (e.g. What methods have been used to detect X effects? Where was the research conducted?).⁷⁰

The bibliometric network analysis, on the other hand, asks just one primary question: what are the most influential papers in the field, and what do they say? It uses computers to do all the grunt work so that the reader is only needed at the very end – to read the most important papers, which are identified through the use of ranking algorithms. The scope of a bibliometric network analysis is quite generous – since the computer is crunching all the data, one can input as many documents as one likes, and as long as the computer does not crash, a bibliometric network analysis can be conducted. This type of literature review also puts heavy emphasis on the field itself – the ranking algorithms use number and *relevance* of citations. So a paper that includes all the right buzzwords and has 1,000,000 citations – none of which themselves contain the right buzzwords – will be weeded out of the final review. Instead of the naive reader determining what paper is important or influential, the experts of that field will be making that decision through the sum of their citation decisions.

If *climate change science* is a newborn field of investigation, then *planetary health* is a fetus. Due to its nascent status, the body of literature that composes planetary health is unsurprisingly scarce. Of this scarcity, two upsides exist: 1) there is great opportunity to make an impact on the field, and 2) performing a comprehensive literature review is much easier. Focusing specifically on the intersection between extreme weather events and nutrition, I was able to perform a bibliometric network analysis on the prominent papers in this area to date. To the best of my knowledge, this is the first systematic literature review conducted in this area.

2.2 METHODOLOGY

A bibliometric network analysis consists of 1) a systematic query of the existing literature, 2) tangible visualisation of the bibliometric network based on search results and their citations, and 3) identification of the most influential publications.⁷¹ An overview of the methodological approach is shown below (Figure 2.1). Since the methodology of the bib-

liometric network analysis has been scrupulously detailed elsewhere,⁷² let the following methodology provide merely a succinct summary of the procedure.

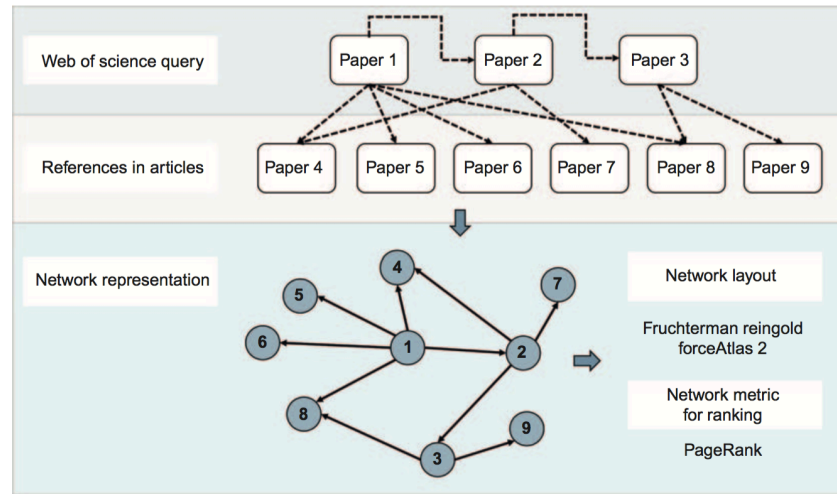


Figure 2.1: Bibliographic network analysis schematic of the three main stages.⁷²

SYSTEMATIC QUERY OF THE LITERATURE

The Web of Science literature database, created by Thomson Reuters,⁷³ was queried on 31 July 2019 to identify all relevant publications – peer-reviewed journal articles, conference papers, literature reviews, book chapters – that focus on the intersection between extreme weather events and nutrition. There was no filter on year of publication, so search results could return any publication from the dawn of time. The search scope was limited to include documents that focus, directly or indirectly, on extreme weather events and nutrition. To facilitate exact reproducibility, the search terms were as follows: .

- In **Title**: *health* OR well-being OR wellbeing OR welfare OR *nutrition* OR hospital* OR mortality OR morbidity
- In **Topic**: (“high-impact weather“ OR ”natural disaster“ OR ”natural hazard“ OR drought OR flood OR heatwave OR “cold spell” OR hail OR cyclone OR frost OR storm OR (extreme* AND (weather OR climate OR precipitation OR temperature OR dry OR wet OR cold OR hot OR heat))) AND (human OR public OR population)

Asterisks allow for the search results to have prefixes or suffixes (depending on asterisk location) in addition to the search term: e.g. * nutrition * allows for *malnutrition* and *nutritional deficiency* to pop up in the search result. Quotation marks require that the phrase within the marks is found verbatim in the search results.

In sum, the search yielded 2,490 results: 2,297 peer-reviewed articles, 86 books (or book chapters), and 107 books in series. The full record and cited references for each search result was downloaded from the Web of Science as standardised (UTF-8) text files. Next, the references of each publication were extracted as individual documents and added to the literature dataset (if they were not already there). Within the dataset, the original search results are categorised as “Literature” and any additional references added are categorised as “Reference.” This distinction comes in handy later in the visualisation of the network. Each document is identified by its DOI or a unique combination of first author name, year of publication, and journal. All data preparation of the Web of Science search results was conducted in R, using the “nails: Network Analysis Interface for Literature Studies.”⁷¹

VISUALISATION OF BIBLIOMETRIC NETWORK

In network theory, the entities of observation are *nodes*, and the interactions between these entities are *edges*.⁷⁴ Correspondingly, in a bibliometric network, every piece of literature – whether it is classified as “Literature” or “Reference” – is visualised as a unique node. The lines connecting these nodes, in this case referred to as *directed edges*, show the relationship between two documents. The direction of the edge (each line is curved in clockwise direction from referencing paper to cited paper) implies the citation relationship –e.g. an edge starting at “Bread not stone: The challenge of feminist biblical interpretation”⁷⁵ and curving clockwise towards the Bible means that the Bible was referenced in a feminist analysis, rather than the other way around.

To visualise the planetary health network of interest, node and edge tables were created from the literature dataset and then imported into Gephi, a network visualisation and analysis tool.⁷⁶ Once imported, the nodes and edges were filtered and spatially organised using the ForceAtlas 2 algorithm⁷⁷ to identify clusters of documents that are densely connected. Thus, the visualisation displays all the publications – and their references – from the original search, as arranged by common citations.

IDENTIFICATION OF THE MOST INFLUENTIAL PUBLICATIONS

“When in doubt, Google it out!” Today’s ubiquitous reliance on the Google web search engine to solve all of life’s big and little mysteries is well-known. What is lesser known is how exactly Google manages to pull off these miracles. One big chunk of that puzzle is the PageRank algorithm. Named after Larry Page, one of Google’s founders, the PageRank algorithm ranks the importance of websites not only by the number, but also the quality of links to a page.⁷⁸

For this analysis, the PageRank metric⁷⁹ was calculated for all nodes to identify the most influential publications in this network. The PageRank algorithm was used to rank the relevance of a given publication by taking into account the number of publications that reference it, weighted recursively by their own PageRank values. Thus, the PageRank metric reveals publications with particularly high relevance within a body of literature.

That said, the PageRank metric is fallible – it does not account for the impact factor of journals, nor the relevance of these journals to the intention of the original search query. Therefore, in addition to PageRank, identification of the most influential publications was supplemented by pure in-degree rank, or the number of times a publication was cited by another publication within the network.

2.3 RESULTS

BIBLIOMETRIC STATISTICS

In terms of number and frequency of publications from 1940-2019, there is a heavy skew to the right of the distribution, as the number of publications in this field more than quadrupled from 2000 to 2019 (Figure 2.2). This is congruent with the recent surge in interest and research prioritisation on climate change impacts. The multidisciplinary nature of this research topic means that there is a large diversity of fields that contribute to this growing body of literature (Figure 2.3). Among the top ten fields represented in this literature query, there is a relatively even balance between environmental sciences and health sciences. Other notable fields that registered in the top 20 for this literature query include: Marine Freshwater Biology, Toxicology, Physiology, Biodiversity Conservation, Biophysics, Environmental Engineering, and Health Care Sciences & Services. That research contributions come from a variety of expertise is incredibly important and integral to the work of planetary health.

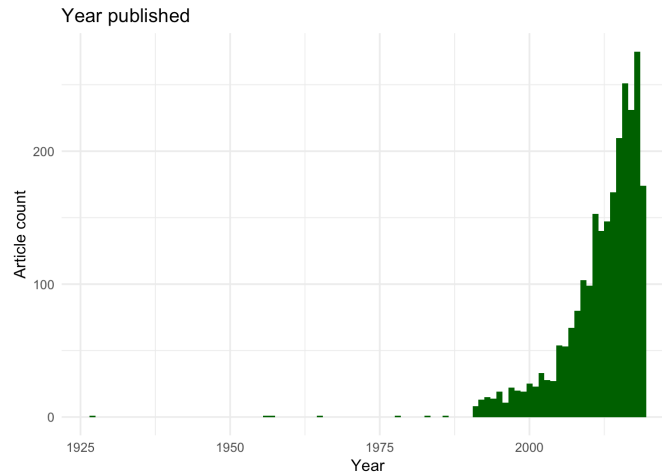


Figure 2.2: Number and frequency of publications from 1940-2019 at the intersection of extreme climate and nutrition.

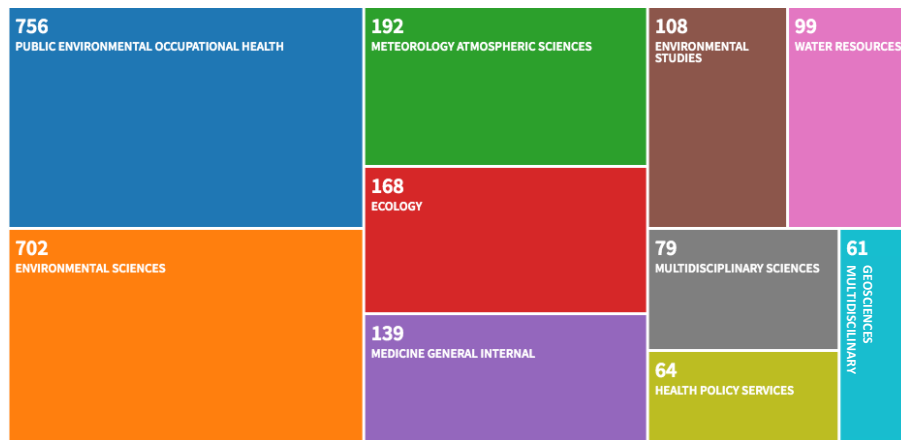


Figure 2.3: Treemap visualisation of the top 10 fields represented in the Web of Science search.

As for *who* is publishing and *where*, it appears that the most cited authors are clustered in research institutions in the USA, Europe, and Australia, which may reflect a bias in the research community (Figure 2.4). There is also significant representation from east Asia (i.e. China, Korea, and Japan). Among the most cited authors, there are many synergies among the researchers— several of them are co-authors on the same highly cited papers, which is likely why these clusters appear. As for the most cited publications, the traditional top-of-the-field journals feature prominently in this literature query (Figure 2.5. Journals such as *Environmental Health Perspectives*, *Environmental Health*, *American Journal of Epidemiology*, and *Annual Review of Public Health* are leaders in their respective research fields, so they are expected to comprise a large proportion of most cited publications in this literature query.

Both *The Lancet* and *Nature* appear in the top five most cited publications– with their historically high impact factors and heavy influence in both the academic and political worlds, it is unsurprising that both of these journals have something to say on the topic of extreme weather health impacts.

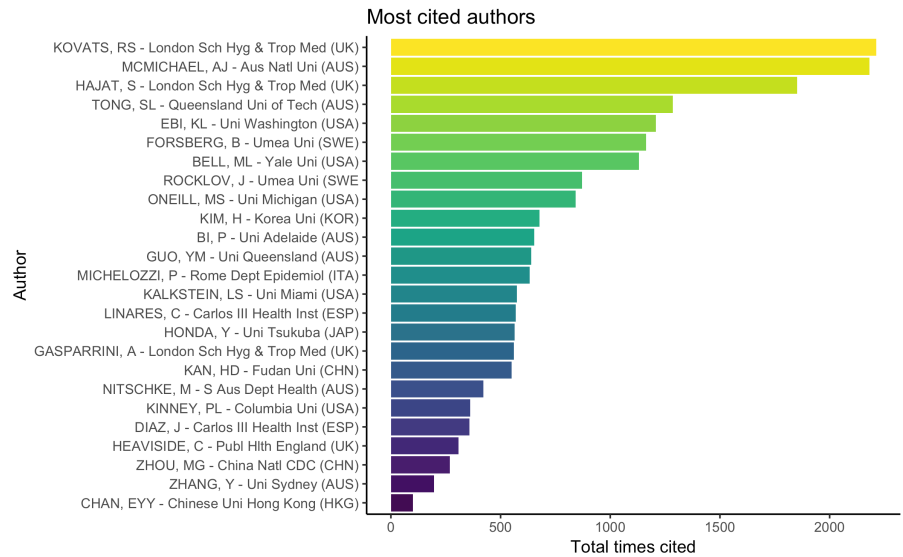


Figure 2.4: The top 25 most cited authors from the literature query for extreme climate and nutrition.

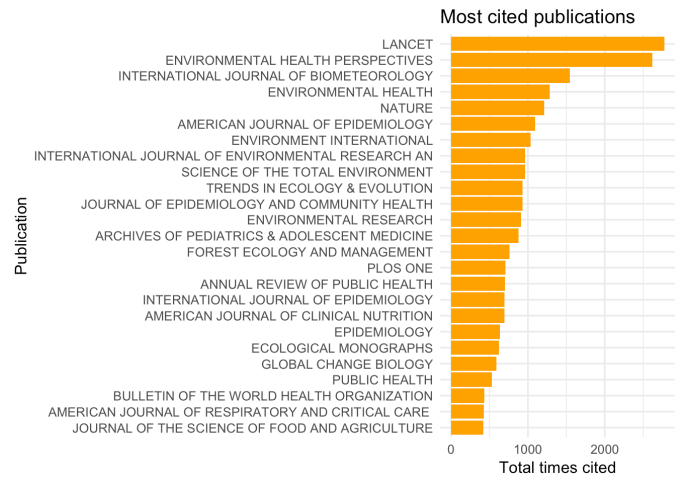


Figure 2.5: Most cited publications, sorted by number of published articles in the dataset and by the total number of citations.

In the wordcloud of all keywords found in this literature query (Figure 2.6), the size of the keyword is directly proportional to how many times it was cited. *Climate change* was the most cited word, with *mortality* and *public health* trailing close behind. Beyond those three

majority of the body of literature. However, given the high density of edges (even post-filtering), the mass of edges is too dense to ascertain the yearly distribution skew.

The bibliographic network analysis shows that there is one main body of literature on the topic of climate extremes and health outcomes, with two smaller subsidiary branches. These branches are far smaller than the main body, which clearly makes up the bulk of the relevant literature. The pear-shaped main body is tightly connected, with its affiliated studies interwoven in a dense net. All but five of the top 30 PageRanked studies are included in this main body; most are localised near the center. Interestingly, however, the top PageRanked paper, Norris et al., (2002)⁸⁰ is not centralised in the main body, instead lying on the outer edge. This one paper almost singlehandedly creates the pear-shaped figure. Other than this single divergence from the center, there are no other significant clusters within the main body.

According to the analysis, the bulk of the literature on this topic is well integrated in the field. Network integration does not necessarily imply consensus - for example, papers A, B, and C could cite paper Z as a misguided or flawed study that motivated their research. However, this type of citation is rare, and further manual analysis of the bibliographic network reveals a high level of consensus. The literature in this young and emerging field of planetary health is largely aligned in both research priorities and results. This makes intuitive sense, as this field was born out of a conscientious urgency, spurred into existence by many of the large international agencies that recognised climate change as a serious threat to human health.

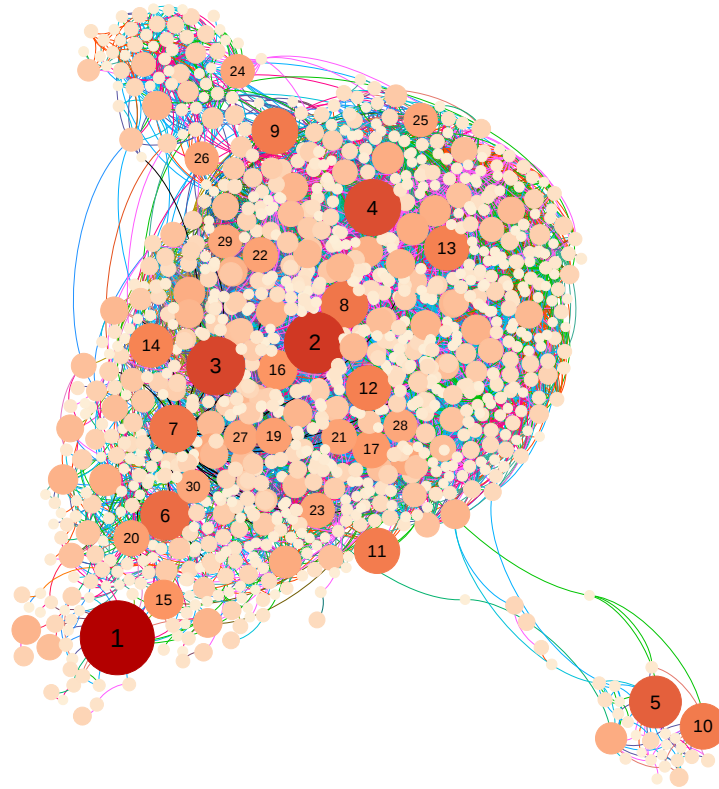


Figure 2.7: Bibliographic network of the scientific literature on climate extremes and nutrition. Dots represent publications, lines represent citations (each line is curved in clockwise direction from referencing paper to cited paper). The size and color of each dot represents its importance based on the PageRank metric – the larger and darker the dot, the higher the PageRank value. The top 30 PageRanked papers are marked.

MOST INFLUENTIAL PUBLICATIONS

The following [Table 2.1](#) briefly details and references the top 30 PageRanked studies, which are also indicated in the bibliographic network by number. Note that the study ranked 18th in the PageRank algorithm is not shown in the figure because it was pushed so far away from the center by the algorithm that it does not register on the diagram. This is the perfect example of why PageRank is a useful but fallible filtering tool — while healthcare utilisation and mortality among veterans in the Gulf War is both interesting and important, it is not even remotely related to the topic at hand.

Table 2.1: Top 30 PageRanked studies in the bibliographic network analysis

1	Norris, F. H., et al. (2002). 60,000 disaster victims speak: Part I. An empirical review of the empirical literature, 1981–2001. <i>Psychiatry</i> . ⁸⁰
2	Semenza, J. C., et al. (2002). Heat-related deaths during the July 1995 heat wave in Chicago. <i>N Engl J Med</i> . ⁸¹
3	McMichael, A. J., Woodruff, R. E., & Hales, S. (2006). Climate change and human health: present and future risks. <i>Lancet</i> . ⁵⁶
4	Curriero, F. C., et al. (2002). Temperature and mortality in 11 cities of the eastern United States. <i>Am J Epidemiol</i> . ⁸²
5	Allen, C. D., et al. (2010). A global overview of drought and heat-induced tree mortality reveals emerging climate change risks for forests. <i>For Ecol Manag</i> . ⁸³
6	Ahern, M., et al. (2005). Global health impacts of floods: epidemiologic evidence. <i>Epidemiol Rev</i> . ⁸⁴
7	Parry, M., et al. (2007). Climate change 2007–impacts, adaptation and vulnerability: Working group II contribution to the fourth assessment report of the IPCC (Vol. 4). ⁸⁵
8	Basu, R., & Samet, J. M. (2002). Relation between elevated ambient temperature and mortality: a review of the epidemiologic evidence. <i>Epidemiol Rev</i> . ⁸⁶
9	Kunst, A. E., Looman, C. W., & Mackenbach, J. P. (1993). Outdoor air temperature and mortality in the Netherlands: a time-series analysis. <i>Am J Epidemiol</i> . ⁸⁷
10	Breshears, D. D., et al. (2005). Regional vegetation die-off in response to global-change-type drought. <i>PNAS</i> . ⁸⁸
11	Watts, N., et al. (2015). Health and climate change: policy responses to protect public health. <i>Lancet</i> . ⁸⁹
12	Kovats, R. S., & Hajat, S. (2008). Heat stress and public health: a critical review. <i>Annu Rev Public Health</i> . ⁹⁰
13	Anderson, B. G., & Bell, M. L. (2009). Weather-related mortality: how heat, cold, and heat waves affect mortality in the United States. <i>Epidemiology</i> . ⁹¹
14	Patz, J. A., et al. (2005). Impact of regional climate change on human health. <i>Nature</i> . ⁵⁵
15	Neria, Y., Nandi, A., & Galea, S. (2008). Post-traumatic stress disorder following disasters: a systematic review. <i>Psychological Medicine</i> . ⁹²
16	Meehl, G. A., & Tebaldi, C. (2004). More intense, more frequent, and longer lasting heat waves in the 21st century. <i>Science</i> . ⁹³
17	Fouillet, A., et al. (2006). Excess mortality related to the August 2003 heat wave in France. <i>Int Arch Occup Environ Health</i> . ⁹⁴
18	Gray, G. C., & Kang, H. K. (2006). Healthcare utilization and mortality among veterans of the Gulf War. <i>Philos Trans Royal Soc B</i> . ⁹⁵
19	Easterling, D. R., et al. (2000). Climate extremes: observations, modeling, and impacts. <i>Science</i> . ⁹⁶
20	Alderman, K., Turner, L. R., & Tong, S. (2012). Floods and human health: a systematic review. <i>Environ Int</i> . ⁹⁷
21	Robine, J. M., et al. (2008). Death toll exceeded 70,000 in Europe during the summer of 2003. <i>C R Acad Sci</i> . ⁹⁸
22	McGeehin, M. A., & Mirabelli, M. (2001). The potential impacts of climate variability and change on temperature-related morbidity and mortality in the United States. <i>Environ Health Perspect</i> . ⁹⁹
23	Frumkin, H., et al. (2008). Climate change: the public health response. <i>Am J Public Health</i> . ¹⁰⁰
24	Pope III, C. A., et al. (2002). Lung cancer, cardiopulmonary mortality, and long-term exposure to fine particulate air pollution. <i>Jama</i> . ¹⁰¹
25	Group, T. E. (1997). Cold exposure and winter mortality from ischaemic heart disease, cerebrovascular disease, respiratory disease, and all causes in warm and cold regions of Europe. <i>Lancet</i> . ¹⁰²
26	Bell, M. L., et al. (2004). Ozone and short-term mortality in 95 US urban communities, 1987–2000. <i>Jama</i> . ¹⁰³
27	Luber, G., & McGeehin, M. (2008). Climate change and extreme heat events. <i>Am J Prev Med</i> . ¹⁰⁴
28	Semenza, J. C., et al. (1999). Excess hospital admissions during the July 1995 heat wave in Chicago. <i>Am J Prev Med</i> . ¹⁰⁵
29	Kalkstein, L. S., & Greene, J. S. (1997). An evaluation of climate/mortality relationships in large US cities and the possible impacts of a climate change. <i>Environ Health Perspect</i> . ¹⁰⁶
30	Keim, M. E. (2008). Building human resilience: the role of public health preparedness and response as an adaptation to climate change. <i>Am J Prev Med</i> . ¹⁰⁷

As mentioned above, Norris et al (2002)⁸⁰ is responsible for the pear shape of the main body (node 1). This top PageRanked study – powerfully titled “60,000 Disaster Victims Speak” – is the first empirical review of research published from 1981–2001 on the topic of health impacts from natural and man-made disasters. The aims of the review were to determine the potential range, magnitude, and duration of a disaster’s effects on the mental health of the stricken community; and the experiential, demographic, and psycho-social factors that influence those within that community who are most likely to be adversely affected.⁸⁰ The emphasis on mental health – rather than physical health or nutrition – is what makes node 1 jut out ever-so-slightly from the core of the main body of literature. Thus, the subgroup of nodes clustered around node 1 are focused on the mental health story. Accordingly, the closest node to node 1 is node 15, Neria & Galea (2008),⁹² which is a systematic review of post-traumatic stress disorder following disasters.

Some of the highest PageRanked publications are the earliest quantitative studies on the potential impact of climate change on human health: Kunst et al. (1993),⁸⁷ node 9, describes increased mortality in the Netherlands with increased outdoor air temperature; the Eurowinter Group (1997),¹⁰² node 25, look at mortality from cardiovascular and respiratory diseases in extreme cold conditions; Semenza et al (1999),¹⁰⁵ node 2, looks at excess hospital admissions during the Chicago 1995 heatwave; and Kalstein & Greene (1997),¹⁰⁶ node 29, explore climate and mortality relationships in large U.S. cities. These older studies have higher PageRank values because they are most frequently cited and referenced by more modern papers. While clearly foundational to this young field, many of these older studies are relatively outdated at this point, as climate projection models and statistical analyses have vastly improved over the past decade. As the field of planetary health grows, we will see younger papers rising in PageRank at much faster rates.

Nearly half of the top 30 PageRanked studies focused on the heat impacts on human morbidity and mortality (nodes 2, 4, 8, 9, 12, 13, 17, 21, 22, 26, 27, 28, 29). Only a handful of studies looked specifically at other types of extreme weather– Ahern et al (2005),⁸⁴ node 6, and Alderman et al (2012),⁹⁷ node 20, provide epidemiological evidence in review format of the human health impacts of floods; the Eurowinter Group (1997),¹⁰² node 25 mentioned above, examines extreme cold effects. A larger proportion of the top 30 PageRanked studies are general overviews of the broader health impacts of climate change (nodes 3, 7, 11, 14, 23, 30). Keim (2008),¹⁰⁷ Watts et al (2015),⁸⁹ and Frumkin et al (2008)¹⁰⁰ speak to the role of governance institutions in creating stronger public health policy that is prepared to respond to extreme weather. Parry et al (2007),⁸⁵ node 7, comes from the 2007 Intergovernmental Panel on Climate Change (IPCC) report, which was one of the first major international reports to emphasize the threat of food insecurity due to climate change. Given the prominent influence that IPCC reports have in the climate science sphere, it is not surprising to see its chapter on impacts, adaptation, and vulnerability represented among the highest ranked papers.

As for the slightly off-shooting PageRanked studies, Pope III et al (2002)¹⁰¹ and Bell et al (2004)¹⁰³ – nodes 24 and 26 – are the highest PageRanked studies in the larger of the two subsidiary branches, though they act more as a bridge between the branch and the body, than as central features of the branch itself. Pope III et al (2002) examines cardiopulmonary mortality in response to long-term exposure to air pollution– the remainder of the subsidiary branch deals explicitly with air pollution. Bell et al (2004) examines ozone and short-term mortality; the ozone link makes this study the perfect connecting node, as it links the larger main body of literature (which focuses primarily on extreme heat) and the subsidiary branch (which focuses on atmospheric air pollution).

Allen et al (2010)⁸³ and Breshears et al (2005)⁸⁸ – nodes 5 and 10 – are the highest PageR-ranked studies in the smaller of the two subsidiary branches. Not only is this branch structurally smaller than the other, but it is also pushed out further from the main body in the forcing algorithm; this indicates that it is either less connected to the main body of research or that its topics are slightly more tangential than those of other studies. Accordingly, both studies do not cover human health, but rather, arboreal health (specifically: tree mortality and regional vegetation die-off) in response to drought and extreme heat. Though these studies miss the mark on our human health target, they are still relevant due to the important human health benefits of ecological stability.¹⁰⁸

2.4 DISCUSSION

From the network presented, clearly there is budding interest in the intersection between extreme weather and human nutrition. Yet fundamental knowledge gaps exist due to the lack of quantitative and qualitative rigor in studies examining health consequences of EWEs around the world. In other words, while the current literature does a good job at pointing out the fact that extreme weather affects human health, it struggles to fill in those facts with colour, detail, and nuance. The most salient knowledge gaps exist within the literature's coverage of: 1) non-heat extreme events, 2) metabolic syndrome beyond mortality, 3) the role of nutrition, 4) geographic scope, and 5) identification of subpopulations at risk.

Broad-sweeping statements about global impacts of extreme weather are far more prevalent than specific direct health implications of any one type of EWE, barring extreme heat. Indeed, there is a glaring paucity of analysis done on any other type of EWE; of the top 30 PageRanked papers, only two spoke to extreme cold and floods as their main topics. This is not to disparage the role of extreme heat research in the planetary health field; indeed, it is an absolutely essential area with many pressing research priorities. However, this should not mean that other EWEs, such as cyclones and drought, should be entirely overlooked in a literature review that explicitly includes these terms in the Topic search of the literature query. While curious, it is important to remember that there may be coverage of these EWEs within the broader network, but these studies have not yet reached a large enough audience within the field to be highlighted among the top 30.

Also notably absent from the main body of literature is a deeper look at metabolic syndrome, and the role that nutrition plays. None of the top PageRanked papers specifically refer to metabolic syndrome or nutrition; in the former case, it is forgivable because “metabolic syndrome” was not an explicit search term. But “nutrition” most certainly was, and so its absence in the main body of literature is puzzling. It seems redundant to then point out that

there are also no studies among the top 30 that study fresh produce intake, or the maintenance of micronutrient health amidst crises. There are several studies that do study some aspect of metabolic syndrome, yet these are generally focused on mortality rates of cardiovascular diseases. Only one paper of the top 30 specifically speaks to morbidity; other than this, there is sparse discussion of how EWEs not only kill, but also injure and incapacitate their victims (beyond corporal damage), and often with long term consequences.

In terms of geographic coverage, nearly all of the top 30 PageRanked studies either focus solely on the United States and Europe, or they maintain a “global” perspective. Yet the latter approach often still favors the former foci– a common research challenge across disciplines being that there is a disproportionate amount of data collection and research scaffolding in the U.S. and Europe. It is difficult to draw discernibly insightful findings about a global snapshot when much of the globe still lacks the capacity for comprehensive, reliable data collection. Furthermore, there is a paucity of case studies identifying specific areas or subpopulations at risk. Even with studies that look at richer countries– rich in terms of both GDP and data– there are few that go beyond the national or regional scope to investigate the communities and peoples that are most vulnerable to the health effects of EWEs.

And so, although this burgeoning field has put together quite a number of important studies within a short period of time, there is still much work that needs to be done to connect changing climate and nutritional outcomes within populations. See **Strengths of study** in both [Section 3.5](#) and [Section 4.5](#) for continued in-depth analysis of how the previous literature specifically relates to my current studies, and how I went about addressing the relevant knowledge gaps.

As a final point, I remind the reader that the aim of this literature review was *not* to investigate climate change. It was to determine what studies have been conducted on the relationship between extreme weather and human health. Extreme weather events have occurred prior to anthropogenic climate change, and they will continue to occur regardless of the severity of future climate change. Therefore, viewed simplistically, the search query for extreme weather and health conducted here should not have resulted in so many climate change-specific studies. But our world today is far from simplistic: anthropogenic climate change fundamentally alters many of the climatic and atmospheric processes that underlie extreme weather, so climatologically speaking, the two will continue to be closely linked. This new reality, combined with a combination of socio-political factors – such as agendas of journals and their editors, personal motivations of environmentally-minded researchers, and the current eco-political status of the world – likely resulted in climate change featuring prominently in this literature review, ultimately mirroring its significance in the minds and hearts of those conducting planetary health research.

All across the world, in every kind of environment and region known to man, increasingly dangerous weather patterns and devastating storms are abruptly putting an end to the long-running debate over whether or not climate change is real. Not only is it real, it's here, and its effects are giving rise to a frighteningly new global phenomenon: the man-made natural disaster.

Barack Obama

3

The global effect of extreme weather events on nutrient supply

NOTE: *all material in this chapter comes from a recent publication,¹ which has been rearranged in this thesis for ease of understanding. See [Appendix A.1](#) for publication.*

3.1 ABSTRACT

Background To date, the effects of extreme weather events (EWEs) on specific nutrients within the population's diet have not been quantified. In this study, we investigated micronutrient, macronutrient, and fiber supply changes in the year that a major EWE occurred, with a targeted focus on low-income settings.

Methods Using data from the International Disasters Database and the Global Expanded Nutrient Supply model for the period 1961–2010, we applied superposed epoch analysis to calculate the percentage change in nutrient supply during the year of an EWE, relative to its historical context. We composited globally and by subgroup (European Union, Landlocked Developing Countries, Least Developed Countries, Low Income Food Deficit Countries, and Net Food Importing Developing Countries). Lastly, we reported nutrient supply

changes in terms of Recommended Dietary Allowance for children aged 1-3 years.

Findings For the global set, all micronutrient supplies exhibited modest negative percentage change during the year of an EWE; of these effects, those that reached a 0.05 significance level included calcium, folate, thiamin, vitamin B6, and vitamin C. The EWE effect was especially magnified among Landlocked Developing Countries and Low Income Food Deficit Countries. Observed year-of-event nutrient supply deficits were found to be a large percentage of what a healthy child's average sufficient dietary intake level should be.

Interpretation The global EWE effects on nutrient supply observed in this study are modest in isolation; however, in the context of nutrient needs for healthy child development in low-income settings, the effects observed are substantial.

Funding Australian-American Fulbright Commission

3.2 INTRODUCTION

BACKGROUND

Extreme weather events tend to disrupt food supply lines, especially in remote areas. To use Australia as an illustrative example, Cyclone Yasi wiped out 90% of Australia's banana supply in 2011, leading to a 400-500% price spike. One kilogram of bananas hovered at \$15 for the entire year following the cyclone.¹⁰⁹ The same banana shortage occurred in 2006 after Cyclone Larry. But production is only one side of the story; to get from the farm to the table, produce requires effective transportation and distribution. This is no small feat, given Australia's expansive breadth – for instance, the major city of Darwin lies 4,000 kilometers from the heart of the Murray-Darling Basin, which produces nearly 100% of Australia's rice and 90% of its almonds, grapes, and oranges.¹¹⁰

All around the world, agricultural production has been shown to decline during and after an EWE,⁴⁷⁻⁵² and some case studies have specifically linked EWEs to nutritional outcomes, such as risk of child stunting due to drought-related crop loss in Uganda⁵³ and persistent reduced growth among flood-exposed children in Bangladesh.⁵⁴ While many studies have referred to the well-observed trend of EWEs threatening food security, specifically in the developing world,⁵⁵⁻⁵⁷ no study has yet quantified the global impact of EWEs on total nutrient supply. The process of detecting signals in either EWE or nutrition data on a population level is encumbered by limited data quality and scale; yet it is imperative that we investigate the possible link between EWEs and nutritional insults now, as our changing climate is threatening to further magnify their consequences.^{58,59}

Climate change is projected to alter the frequency and intensity of EWEs– it is projected with medium-to-high confidence that by the end of this century, we will have witnessed global increases in the frequency and/or magnitude of heat waves, heavy precipitation, tropical cyclones, and droughts, though the level of likelihood varies by region.^{28,29} Understanding the historical fluctuations in nutrient supply caused by EWEs will inform and support future estimates of nutritional impacts in the aftermath of such events. To this end, it is necessary to acknowledge the socioeconomic factors– such as human geography, economic development, and governance structures– that transform extreme weather phenomena into full blown disasters.^{60–65} Recovery post-EWE is particularly formidable in low-income settings, where a task like infrastructure maintenance and equitable food distribution is a challenge even in fair weather. And it is within these very contexts that nutrient supply fluctuations can have the severest consequences – a vast majority of the world’s 821 million undernourished people, and 50.5 million children under five years old affected by wasting (low weight for height), reside in low-income countries.³⁷ While EWEs are likely not the lone driving forces in the global burden of malnutrition, they may play an important role in exacerbating already existing issues.

This study builds upon previous research conducted by Lesk and colleagues,¹¹¹ where national cereal production losses resulting from EWEs were estimated using superposed epoch analysis (SEA). The authors found that, from 1964–2007, droughts and extreme heat events significantly reduced national cereal production by 9–10%. In the current study, we utilised a modified SEA analysis method to test whether EWEs have a significant impact on micronutrient, macronutrient, and fiber supplies globally in the year that an EWE occurred (“year-of-event”). We aimed to identify which nutrient supplies were sensitive to EWEs. Acknowledging the socioeconomic gradient within which effects may vary, we aimed to conduct subgroup analysis with a focus on low-income groups. We adhered to the grouping conventions of the United Nations and the World Trade Organisation to study the following four subgroups: Landlocked Developing Countries, Least Developed Countries, Low Income Food Deficit Countries, and Net Food Importing Developing Countries. We used the European Union as a high-income comparison subgroup. Lastly, we aimed to contextualise our results by comparing the absolute change in the year-of-event nutrient supplies with the universally accepted Recommended Dietary Allowance (RDA) for children aged 1–3 years. The RDA is the average daily dietary intake level that is sufficient to meet the nutrient requirement of nearly all (97 to 98 percent) healthy individuals in a group.¹¹² Regarding environmental hazards, children are an especially vulnerable subpopulation due to the high nutritional needs of their developing physiology.^{113,114} As the evidence base grows for the long-term implications of early life (specifically 0–3 years) malnutrition on lifelong cognitive, social, and physical development,^{115–118} it is not only fitting, but critically important,

that we also take a child’s health perspective on the impacts of EWEs.

3.3 METHODS

DATA

We used the Global Expanded Nutrient model (GENuS, <https://dataverse.harvard.edu/dataverse/GENuS>) and the International Disasters Database (EM-DAT, <https://www.emdat.be/database>) as the basis for the analysis of EWEs on nutrition supply. The GENuS model provides historical time series of 23 individual nutrient supplies at the national level of 152 countries from 1961-2011. The model’s raw inputs - Food and Agriculture Organisation (FAO) production and trade data (obtained from the FAOSTAT database) - are used to calculate national supplies of edible food. These food supplies are then matched with nutrient density charts from regional food composition tables to estimate national nutrient supplies.¹⁰

The EM-DAT database is the world’s most comprehensive collection of natural and technological disasters from 1900 to present day. Using EM-DAT, the following EWEs were extracted for the period 1964–2010: floods, droughts, extreme heat events, extreme cold events, and storms (see [Appendix A.2](#) for complete definitions). The EWEs were separated into single-year events or multi-year events. Multi-year EWEs were identified as a country experiencing the same EWE for two or more years. For the purposes of this study, these multi-year events did not necessarily have to be uninterrupted; for example, if Malaysia experienced a flood in January 1993 and then again in January 1994, the flood was demarcated as a multi-year event. We decided on a multi-year event classification in these cases, as the EM-DAT database contains EWE data by year, not by month or season.

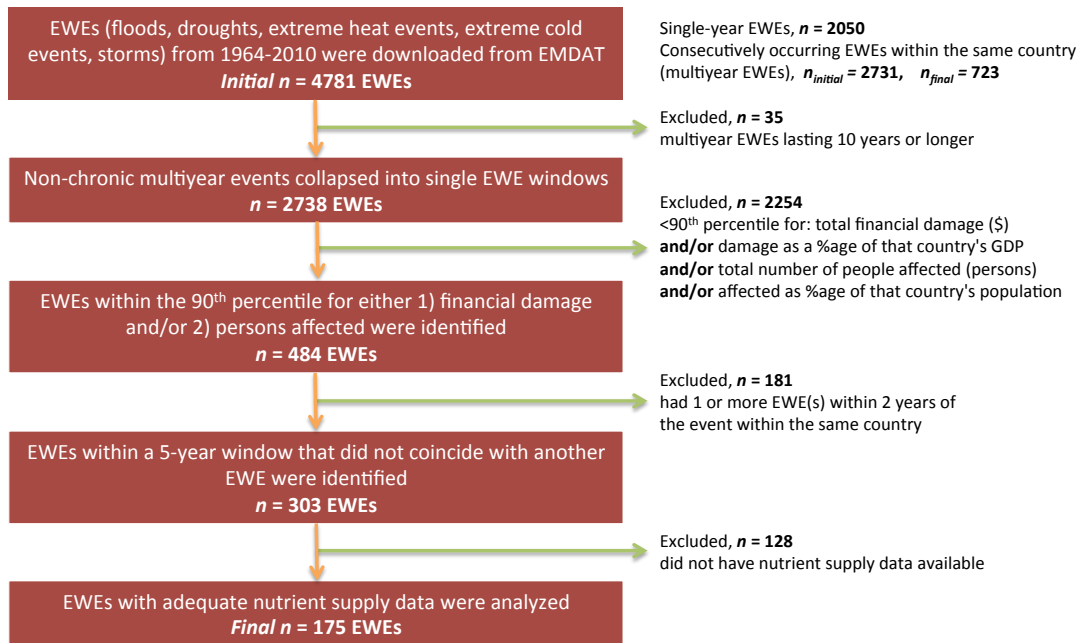
Any EWE effects on nutrition captured by this study must be significant enough to overcome the limited spatial and temporal resolution of the GENuS and EM-DAT databases. In other words, because each event is identified by country and year, rather than specific geographic coordinates and dates, we can only determine if one solitary event somewhere in the country at some point in the year ultimately affected the entire country’s yearly nutrient supply. Clearly, this requires a very significant event; for example, the effect of a severely damaging flood in one province of southeastern China in early January will likely not be captured by the year’s nutrient supply data due to the dilution effect of the rest of flood-free China. Therefore, in this study, we chose to isolate and analyse what we considered the most severe EWEs in order to address the challenge of overcoming poor data resolution in both time and space. To be included in this study, an EWE had to meet or exceed the 90th

percentile of all recorded EWEs for at least one of the following conditions:

- Total financial damage, in absolute terms OR as a percentage of that country's Gross Domestic Product (GDP) at the time of the EWE
- Total number of people affected, in absolute terms OR as a percentage of that country's population at the time of the EWE

Those that fulfilled the criteria are referred to as “major EWEs” in this paper. Population and GDP data was obtained from World Bank Open Data (<https://data.worldbank.org/>). Lastly, if a major EWE coincided with at least one other major EWE within two years of occurrence, then both EWEs were excluded to avoid conflating effects of multiple events (Figure 3.1). This study is focused exclusively on the effect of one isolated EWE, rather than a combination of EWEs. See Appendix A.3 for sensitivity analysis conducted on the inclusion criteria.

Figure 3.1: Flowchart chronicling inclusion criteria for the study, with respective sample sizes noted at each step. Arrows to the right explain which observations were excluded and why.



One final technical note regarding the selection and definition of EWEs for this study is the acknowledgment that these EWEs represent a lumping together of very heterogeneous climate and/or weather phenomena. While all EWEs studied here are embedded within the aforementioned three categories of extreme climate/weather events delineated by the IPCC

SREX (see [Section 1.2](#)), these EWEs are not necessarily directly comparable to one other on temporal, spatial, or climatological scales. By incorporating weather extremes (i.e. extreme heat) and climate extremes (i.e. drought), I am operating on a dynamic time scale. In the case of floods and droughts, I am also introducing non-weather-related aspects such as land use and water management. Indeed, many of the EWEs studied here would likely be better viewed as compound events, in the sense that they are not not caused by variations in a single atmospheric weather or climate variable, but are generally the result of specific conditions in several variables, as well as of some surface properties or states.²⁵ Akin to the IPCC SREX, I chose to study this particular combination of EWEs not for any kind of strict technical harmonisation of climatological variables, but because these EWEs resulted in extreme impacts on human systems. However, it should be noted that by clumping these EWEs together, there may be issues with interpretation, particularly at the level of individualised EWE types.

DATA ANALYSIS

SUPERPOSED EPOCH ANALYSIS (SEA)

Superposed epoch analysis (SEA) is a compositing approach that overlays multiple time series to identify a common signal in the data. SEA analysis is preferred in cases where the response to particular events (e.g. folate supply in response to EWEs) may be obfuscated by noise from other competing influences that operate at similar time scales (e.g. seasonal variation of folate-rich produce).¹¹⁹ SEA sorts data into categories dependent on a key date for synchronization, then compares the means of those categories. The SEA method as applied here functions under the assumption that if the number of time series composited is sufficiently large, a common underlying response to the event should theoretically emerge in the composite, while the noise caused by other variables in the data (e.g. intranational policy changes or economic shocks) should be distributed evenly – positively and negatively – and therefore disappear after averaging.¹¹⁹

Here, we applied the SEA method to nutrition supply data in order to analyse the average response during the years of a major EWE. For all non-overlapping major EWEs, five-year windows were produced by isolating the GENUS model's nutrient supply data from two years before the event, the year-of-event, and two years after the event. Multi-year events were coerced into one "year-of-event" value by averaging the values for each year of the event; i.e. for the 3-year drought in Ethiopia from 1990-1992, the Vitamin A levels for 1990, 1991, and 1992 were averaged to produce one year-of-event value. The window was then centered around the event — Vitamin A levels for 1988 and 1989 were used as the two years leading up to the event; and 1994 and 1995 were used as the two years following.

For each of these five-year time series, the percentage change relative to the non-EWE-year average was calculated.⁽¹⁾ The non-EWE year average is comprised of nutrient values from two years before and after the event, and is used here as a rough proxy of what nutrient supply *should* look like in a non-disaster year in the country of interest. All percentage changes were then composited to produce a single time series analysis of the nutrients before, during, and after an EWE, in order to isolate the EWE effect on nutrients in the year-of-event. For these composites, 95% confidence intervals of the percentage changes in the year-of-event were generated by bootstrapping the composite's individual components 1,000 times and subsequently estimating the bias-corrected and accelerated (BCa) confidence interval. Among statisticians, this confidence interval estimation has gained favor due to its ability to correct for both bias and skewness in the distribution of bootstrap estimates.¹²⁰

$$\text{EWE effect as percentage change} = \left[\sum_{i=1}^n \frac{(x_{it} - \mu_{iz})}{\mu_{iz}} \right]_{\text{nutrient}} * 100\% \quad (1)$$

$i = \text{unique EWE}, t = \text{year of EWE}, z = 5\text{-year window excluding } t$

GRAPHICAL REPRESENTATION OF SEA PROCESS

Figure 3.2: This schematic shows the data processing part of SEA. Three real extreme weather events are used here as an example – a storm in Honduras 2005, a drought in Vietnam 1998, and a flood in Tunisia 1969. Seven-year windows are isolated for each observation by taking three years before the event, the year-of-event, and three years after the event. For each of those years, observation-specific aggregated iron nutrient supply data is extracted– which is represented in the diagram by the green numerals at the very bottom of the figure (units: kg/capita/year).

NOTE: Due to the gradual increase in food availability over time, standard deviations may increase with larger windows. Therefore in the current study, I opted to use five-year windows instead.

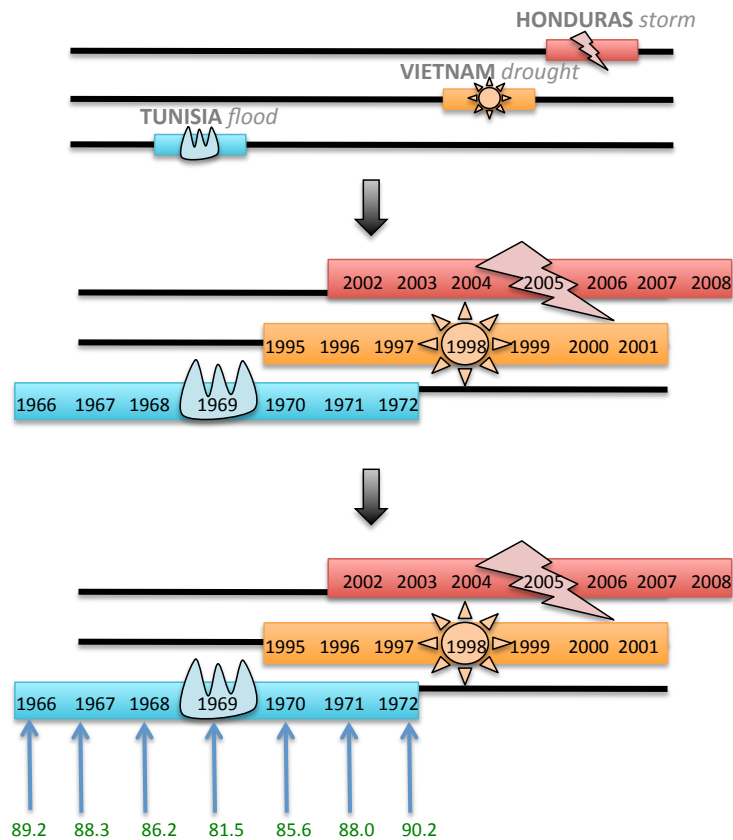
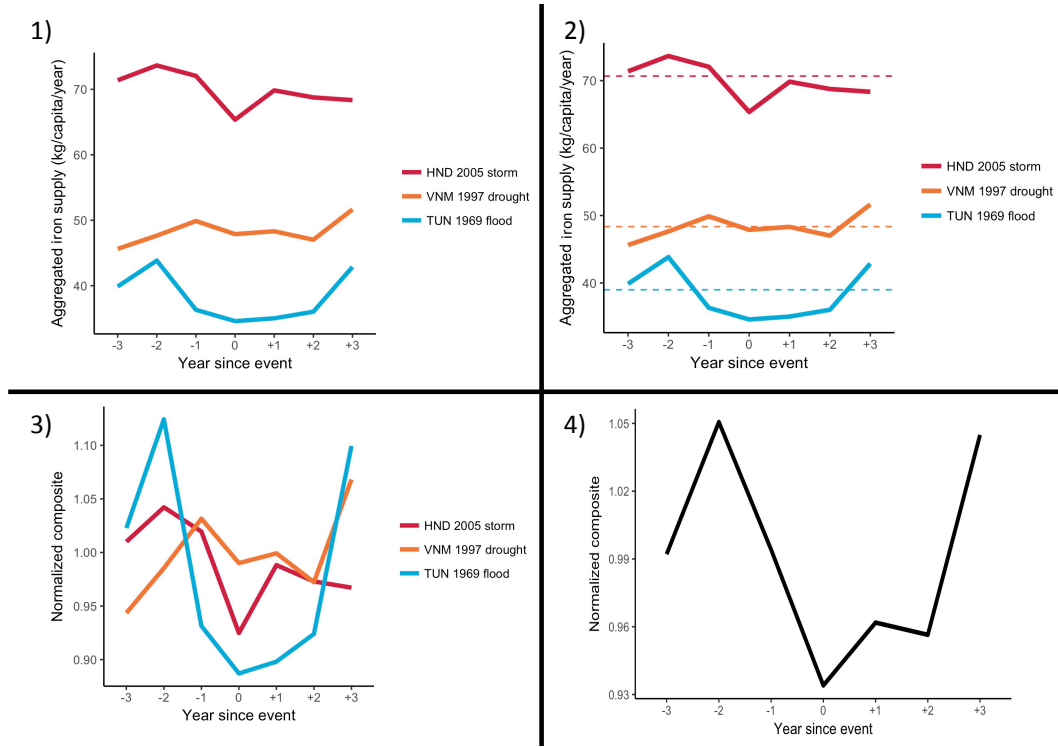


Figure 3.3: This schematic shows the data analysis part of SEA. 1) The aggregated iron nutrient supply is graphed for each observation, 2) the average of the seven-year window, excluding the year-of-event, is calculated (i.e. the dotted line represents the average of nutrient supply from three years before and after the event), 3) each observation is normalised by subtracting the average from the observed measurement, and dividing by the average of the non-disaster years, and 4) the normalised curves are composited into one.



GLOBAL COMPARISON GROUP VISUALISATION

For visualisation of the global EWE dataset, a comparison group was generated by bootstrap to compare our global composited results to a “business-as-usual” group. The comparison group consisted of 1,000 sets of fictitious EWEs (on average, 150 EWEs per set) generated by randomly resampling years and countries of occurrence within the same exact event distribution as the global EWE set (Figure 3.4). If a randomly generated fictitious EWE happened to actually be a real event, it was still included in the comparison group. Thus, the comparison group represents the overall true distribution of nutrient supply, not just the distribution of supply for years without any EWEs. Neither the real EWE time series nor comparison time series were de-trended to account for positive, technology-induced food production growth over time, which has persistently increased food supply and thus the accessible nutrient supply. Instead, nutrient supply fluctuations due to EWEs are visualised by noting the difference between experimental and comparison composites.

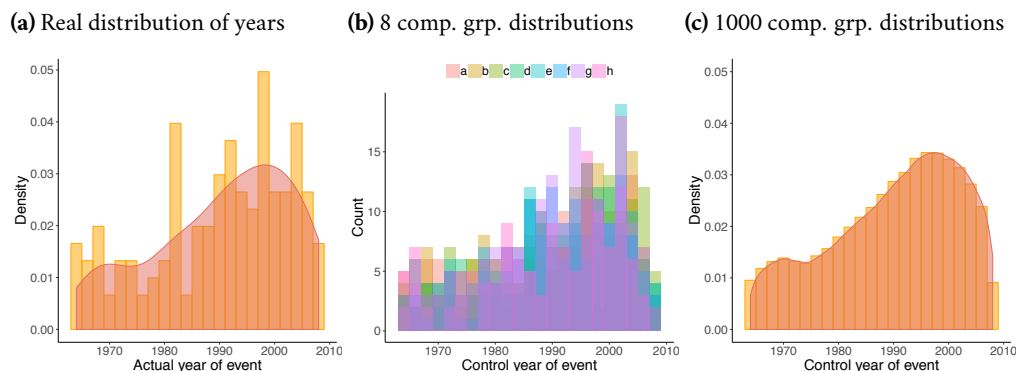


Figure 3.4: A graphical representation of the bootstrapped kernel density estimator calculated so that the false-EWE comparison groups had the same distribution of years as the global dataset. In (a), the real distribution of years from the global dataset is visualised, with its kernel density distribution overlaid. In (b), years of occurrence have randomly been resampled for 8 comparisons sets, using the kernel density estimator; (c) shows the distribution of years for 1,000 comparisons sets, averaged.

SUBGROUP ANALYSIS

To test which low-income groups within our global set were most sensitive to EWE effects, we then conducted subgroup analysis. Using the exact same SEA procedure from the global set analysis, we tested for significant nutrient supply changes within the four of the five low-income subgroups that the FAO recognises in its FAOSTAT database: Landlocked Developing Countries, Least Developed Countries, Low Income Food Deficit Countries, and Net Food-Importing Developing Countries. We did not separately analyse the Small Island Developing States group because these nations collectively lacked sufficient nutrient supply data coverage for SEA analysis; the few observations that we did have, however, were included in the global analysis. [Table 3.1](#) details the inclusion criteria for group membership, as well as the primary authority that establishes and maintains each group. We included the European Union in the subgroup analysis to provide a high-income comparison. See [Appendix A.10](#) for the complete and detailed list of all EWEs analysed in this study, as well as their accompanying group code, if applicable. Note that not all countries included in this study were part of a subgroup; and some countries had multiple subgroup memberships.

Table 3.1: Description of the subgroups of Developing Countries included in present study

Group	# of countries*	Inclusion criteria	Authority
Landlocked Developing Countries	32	1) No territorial access to sea; and 2) classified as a “developing country” by United Nations Department of Economic and Social Affairs ^{121,122}	UN Office of the High Representative for the Least Developed Countries, Landlocked Developing Countries and the Small Island Developing States
Least Developed Countries	47	1) Gross national income per capita; 2) human assets – indicators of nutrition, health, school enrollment and literacy; and 3) economic vulnerability – indicators of natural and trade-related shocks, physical and economic exposure to shocks, smallness, and remoteness ¹²³	UN Economic and Social Council
Low Income Food Deficit Countries	51	1) Gross national income per capita; 2) net food trade position (i.e. gross imports less gross exports) averaged over the relevant years; 3) self-exclusion criterion (i.e. UN members opt out of group classification); and 4) persistence of position ¹²⁴	Food and Agriculture Organisation
Net Food Importing Developing Countries	78	1) Classified as a Least Developed Country; and 2) self-inclusion criterion (i.e. WTO members who submit a claim to group classification) ¹²⁵	World Trade Organisation (WTO) Committee on Agriculture

* = as of publication; note that country grouping may change every few years depending on the authority

Lastly, to interpret this study’s results in a relevant public health context, the absolute change of each nutrient supply during the year-of-event was compared to that nutrient’s Recommended Dietary Allowance (RDA), which is the universally accepted reference value for nutrition. To calculate the effect of EWEs on each nutrient as a percentage of its RDA, the original equation was modified to include RDA values.⁽²⁾ As before, the 95% confidence intervals of the absolute changes in nutrient supply were generated by bootstrapping the composite’s individual components 1,000 times and subsequently estimating the BCa confidence interval.¹²⁰

$$\text{EWE effect as percentage of RDA} = \left[\sum_{i=1}^n \frac{(x_{it} - \mu_{iz})}{RDA} \right]_{\text{nutrient}} * 100\% \quad (2)$$

i =unique EWE, t =year of EWE, z = 5-year window excluding t

All data processing, SEA analysis, figures, and tables were generated using R Version 1.1.383. The code is available upon request.

3.4 RESULTS

LOCATION AND TYPES OF EWEs OVER TIME

Using both absolute and relative thresholds of financial damage (i.e. absolute dollar amount and amount as a percentage of GDP), we could include countries from all socioeconomic backgrounds in the analysis (Figure 3.5). Countries are represented in varying shades that indicate to what extent they satisfy both or either thresholds of financial damage and of persons affected. EWEs in high-income countries (e.g. Sweden, USA) tend to cause greater financial damage while affecting fewer people, whereas EWEs in low-income countries (e.g. Sudan, Philippines, Peru) cause less financial damage, but affect a greater number of people. Of the major EWEs included in the study, the majority were droughts, floods, and storms, suggesting that these EWEs are the most damaging to human health and wealth (Figure 3.6). Note that in Figure 3.6, the total number of observations is $n=227$; we disaggregated multi-year events to show the incidence of EWEs more accurately. Henceforth, for the purposes of the SEA analysis, we will refer to the total number of observations as $n=175$, as this reflects multiyear EWEs collapsed into a single observation.

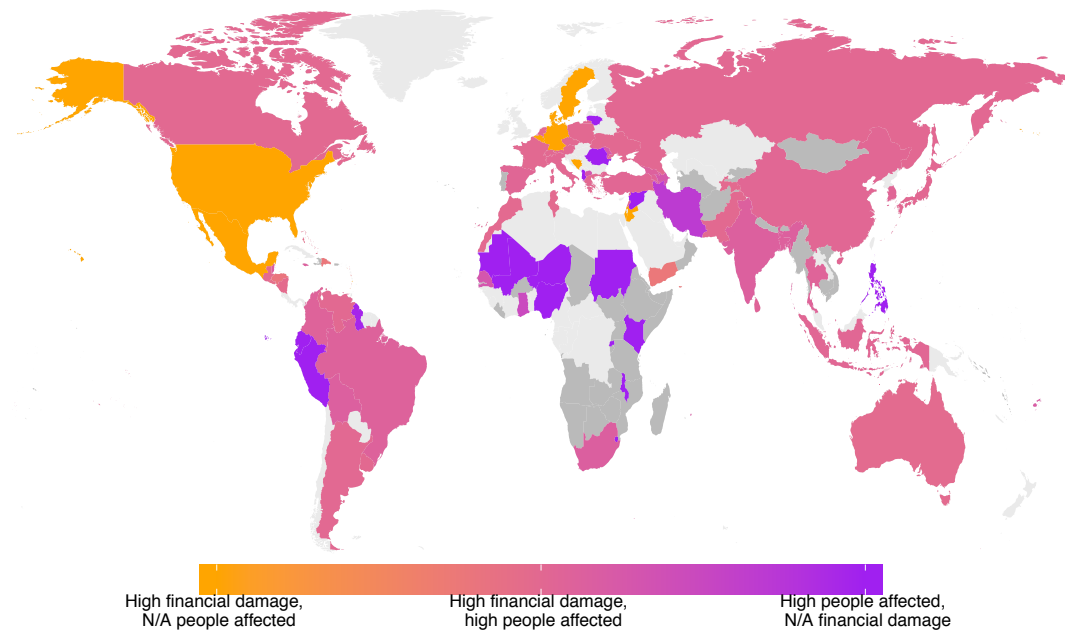


Figure 3.5: Countries in dark grey were included in the preliminary analysis but excluded from the final analysis due to insufficient nutrient data. Countries in light grey were not included at all, due to dense overlapping time series of EWEs. Among the countries included in this study, those that trend towards orange experienced EWEs with greater financial damage than people affected, proportional to the event year's GDP and population respectively. On the other side of the spectrum, countries that trend toward purple experienced EWEs with more people affected than financial damage incurred. Countries that are pure orange or pure purple did not indicate any people affected or financial damage, respectively, hence the N/A descriptors on the legend. Tick marks near the ends of the legend indicate when values become non-NA for the relevant variable.

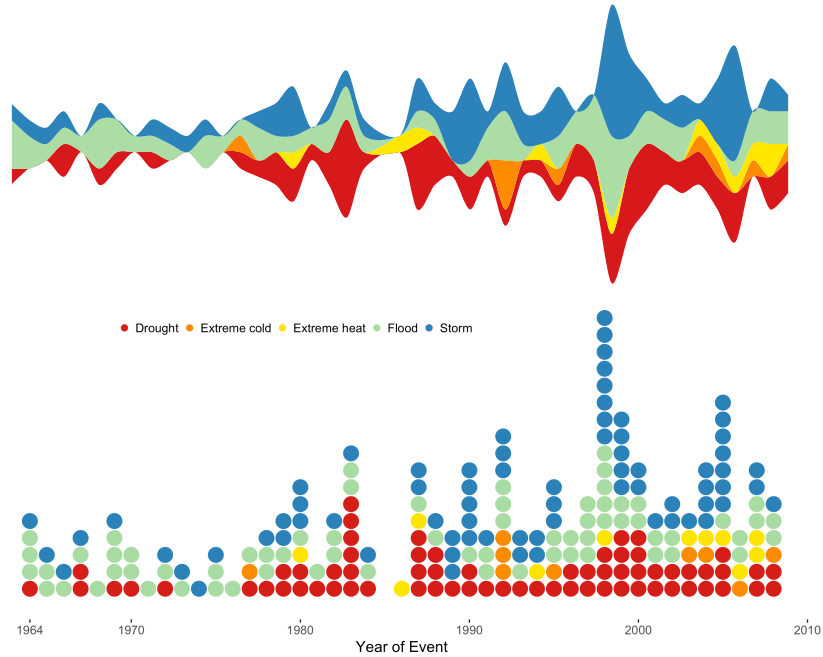


Figure 3.6: Stream-graph and dot plot representations of all major EWEs from 1964–2010 included in this study (total $n=227$: drought $n=67$, extreme cold $n=9$, extreme heat $n=11$, flood $n=67$, storm $n=73$). The latter half of this year range is modestly over-represented, due to a combination of better data collection methods, increasing impacts of climate change, and a growing population and global economy.

EFFECT ON MICRONUTRIENTS: CONSISTENT DIP IN YEAR-OF-EVENT

For the global dataset (i.e. all countries included in the study), all micronutrient supplies exhibited modest negative percentage change during the year of an EWE; these effects were statistically significant (at the 0.05 significance level) for calcium, copper, folate, iron, magnesium, niacin, phosphorus, potassium, riboflavin, thiamin, vitamin B6, vitamin C, and zinc. The comparison group plot (Figure 3.7) visualises these global percentage changes compared to the reference without a major EWE (i.e. “business-as-usual”), whereas Figure 3.8 shows the percentage changes of the global dataset overlaid by the percentage changes of the five subgroups. Figure 3.9 addresses the potential source of bias arising from varying sample sizes.

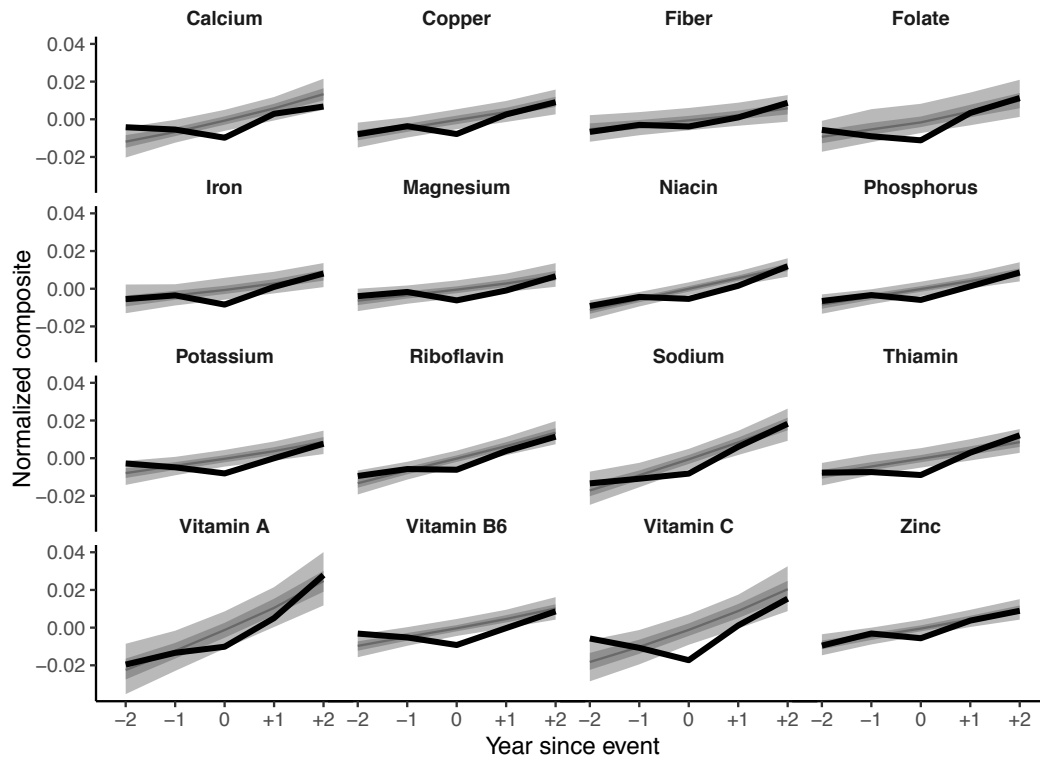


Figure 3.7: Percentage change of micronutrient and fiber supply for each five-year window in the global set ($n=175$), composited and centered around the year-of-event. Grey ribbons represent the 1,000 false-EWE comparison composites; the darker shaded region is the interquartile range, and the lighter shaded region is the 95th percentile range. Note that the upward trend is due to the positive growth in food production over the years.

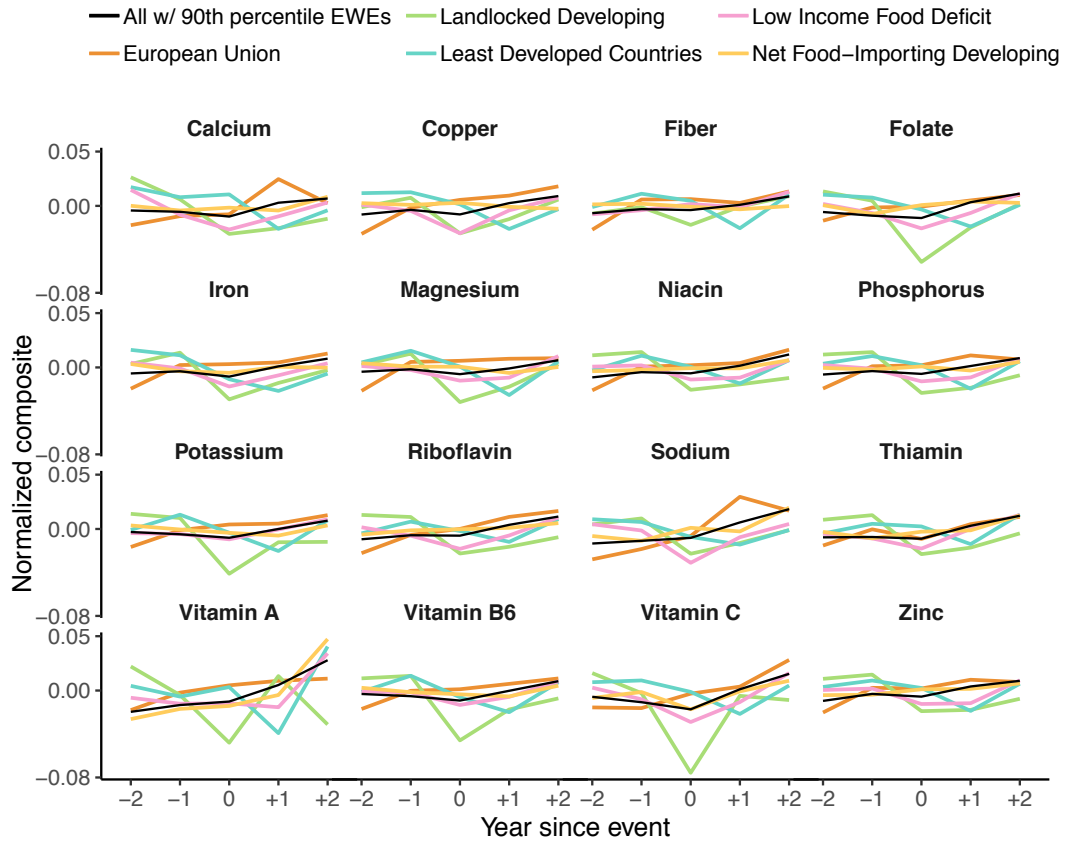


Figure 3.8: Percentage change of micronutrient and fiber supply for each five-year window (global $n=175$, European Union $n=29$, Landlocked Developing $n=19$, Least Developed Countries $n=15$, Low Income Food Deficit $n=32$, and Net Food-Importing Developing $n=64$), composited and centered around the year-of-event.

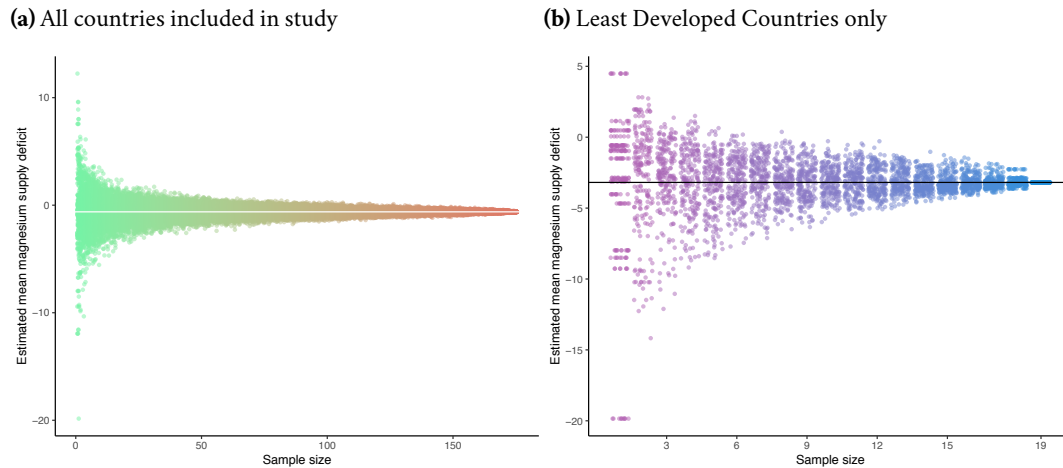


Figure 3.9: To demonstrate that sample size does not have a meaningful influence on estimated EWE effects, we selected magnesium for a sample size illustration. We calculated magnesium effect sizes with random sub-samples of (1, 2, ..., n) points, bootstrapped 200 times each. In **(a)**, the white line shows the final composited change in magnesium during the year-of-event for all countries included in this study (-0.00620, or -0.62%). There is initial variability at lower sample sizes; however, the estimates quickly converge into the final estimated mean well before the actual sample size is reached ($n=175$). In **(b)**, the black line shows the final composited change in magnesium during the year-of-event for the Landlocked Developing Countries included in this study (-0.0319, or -3.19%). This subgroup has a much smaller sample size ($n=19$), therefore the discrete sample size bins show greater variability, which is then reflected in larger confidence intervals. Sample size testing method adapted from Lesk et al (2016).¹¹¹

The subgroup analysis found that the EWE effect on nutrient supplies was especially magnified among Landlocked Developing Countries, though Low Income Food Deficit Countries also exhibited large and significant percentage changes of certain nutrient supplies (Table 3.2). Landlocked Developing Countries appeared to have the most sensitive nutrient supplies; this subgroup had the greatest nutrient supply changes of the entire study with vitamin C, folate, and vitamin A at -7.57%, -5.16%, and -4.80% respectively. The nutrient supplies for the European Union, Least Developed Countries, and Net Food-Importing Developing Countries did not show any significant percentage changes during the year-of-event.

Table 3.2: Percentage change of micronutrient and fiber supplies during year-of-event, relative to non-EWE-year averages, with 95% confidence intervals

Nutrient	All countries incl. in study	European Union	Landlocked Developing Countries	Least Developed Countries	Low Income Food Deficit Countries	Net Food-Import Developing Countries
Calcium	-0.98* (-1.99, -0.06)	-0.77 (-4.74, 1.95)	-2.58* (-5.87, -0.22)	1.06 (-0.13, 3.66)	-2.17* (-4.72, -0.04)	-0.16 (-1.67, 1.09)
Copper	-0.78* (-1.74, -0.14)	0.55 (-0.44, 1.98)	-2.53* (-6.66, -0.91)	0.15 (-1.31, 1.47)	-2.52* (-5.68, -0.42)	0.28 (-0.76, 1.25)
Fiber	-0.38 (-1.09, 0.35)	0.62 (-0.85, 2.24)	-1.75 (-5.33, 1.5)	0.46 (-1.85, 2.25)	0.17 (-1.38, 2.21)	-0.08 (-1.28, 1.07)
Folate	-1.12* (-1.99, -0.37)	-0.06 (-1.11, 0.95)	-5.16* (-9.47, -2.48)	-0.33 (-1.71, 1.02)	-2.07* (-4.49, -0.58)	0.07 (-1.32, 1.37)
Iron	-0.84* (-1.53, -0.25)	0.30 (-0.46, 1.44)	-2.94* (-5.46, -1.37)	-1.09 (-2.89, 0.73)	-1.75 (-3.24, 0.06)	-0.49 (-1.93, 0.6)
Magnesium	-0.62* (-1.35, -0.02)	0.61 (-0.5, 2.04)	-3.19* (-6.57, -1.31)	0.08 (-2.41, 1.83)	-1.22 (-2.77, 0.3)	0.06 (-1.03, 1.03)
Niacin	-0.54* (-1.11, -0.05)	0.20 (-0.85, 1.06)	-2.06* (-4.86, -0.12)	0.06 (-1.10, 1.71)	-1.11 (-2.73, 0.04)	-0.07 (-1.17, 0.70)
Phosphorus	-0.59* (-1.18, -0.03)	0.20 (-1.08, 1.77)	-2.35* (-5.58, -0.79)	0.21 (-1.11, 1.73)	-1.28* (-3.24, -0.07)	0.09 (-0.98, 0.87)
Potassium	-0.81* (-1.59, -0.19)	0.41 (-0.61, 1.53)	-4.12* (-7.34, -1.61)	-0.35 (-1.81, 1.19)	-0.95 (-2.89, 0.28)	-0.35 (-1.63, 0.59)
Riboflavin	-0.61* (-1.26, -0.06)	0.01 (-1.19, 1.25)	-2.26* (-5.26, -0.42)	-0.19 (-1.56, 1.51)	-1.83* (-3.92, -0.37)	-0.03 (-1.20, 0.81)
Sodium	-0.82 (-1.78, 0.04)	-0.65 (-2.69, 1.47)	-2.28 (-8.79, 1.17)	-0.73 (-2.18, 1.06)	-3.11* (-6.96, -1.31)	0.11 (-1.13, 1.82)
Thiamin	-0.90* (-1.60, -0.29)	-0.92 (-2.69, 0.44)	-2.32* (-5.70, -0.70)	0.23 (-1.76, 1.45)	-1.80* (-4.05, -0.02)	-0.25 (-1.46, 0.62)
Vitamin A	-1.01 (-2.31, 0.09)	0.48 (-0.95, 2.22)	-4.80* (-8.99, -1.81)	0.32 (-2.12, 3.86)	-1.18 (-4.21, 0.68)	-1.42 (-4.08, 1.22)
Vitamin B6	-0.92* (-1.73, -0.35)	0.12 (-0.64, 1.09)	-4.59* (-8.97, -1.95)	-0.61 (-2.07, 0.74)	-1.33* (-3.85, -0.11)	-0.35 (-1.63, 0.71)
Vitamin C	-1.73* (-3.11, -0.35)	-0.29 (-2.27, 1.76)	-7.57* (-13.72, -2.55)	-0.13 (-2.15, 2.51)	-2.90* (-6.43, -0.61)	-1.73 (-3.46, 0.28)
Zinc	-0.56* (-1.12, -0.03)	0.19 (-0.96, 1.94)	-1.90* (-4.32, -0.49)	0.23 (-1.4, 1.54)	-1.24 (-2.76, 0.11)	0.11 (-0.82, 1.09)

* = Bold denotes significance at the 0.05 level

EFFECT ON MACRONUTRIENTS: LESS SIGNIFICANT

When macronutrients and calories were analysed, the subgroup analysis showed a similar pattern in that significant effects were found among the global dataset, among Landlocked Developing Countries, and among Low Income Food Deficit Countries, but not among the other subgroups (Table 3.3). Compared to micronutrient supply, we did not find as large or comprehensive of a supply reduction during the year-of-event for any subgroup. Indeed, compared to its micronutrient counterpart (Figure 3.7), the macronutrient comparison plot

(Figure 3.10) shows a far more erratic picture. For clarity purposes, only the global group, Landlocked Developing Countries, and Low Income Food Deficit Countries are shown in the macronutrient comparison plot (see Appendix A.7 for the complete comparison plot with all 5 subgroups). The most notable result from the macronutrient supply analysis is that both Landlocked Developing Countries and Low Income Food Deficit Countries exhibited an approximately –2 percentage change in protein supply during the year-of-event.

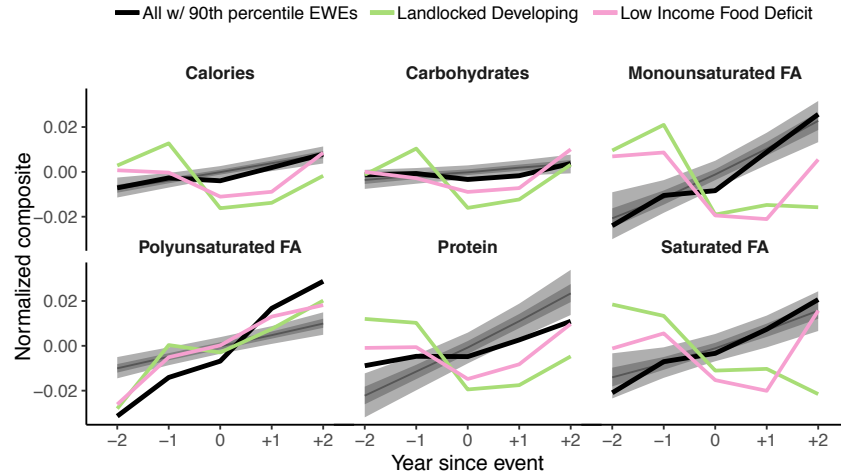


Figure 3.10: Percentage change of macronutrient supply for each five-year window (global $n=175$, Landlocked Developing $n=19$, Low Income Food Deficit $n=32$), composited and centered around the year-of-event. Grey ribbons represent the 1,000 false-EWE comparison composites; the darker shaded region is the interquartile range, and the lighter shaded region is the 95th percentile range.

Table 3.3: Percentage change of macronutrient supplies during year-of-event, relative to non-EWE-year averages, with 95% confidence intervals

Nutrient	All countries incl. in study	European Union	Landlocked Developing Countries	Least Developed Countries	Low Income Food Deficit Countries	Net Food-Import Developing Countries
Calories	-0.40* (-0.92, -0.01)	-0.34 (-1.57, 0.54)	-1.62* (-5.79, -0.16)	0.44 (-0.31, 1.53)	-1.11 (-3.50, 0.03)	0.22 (-0.33, 0.73)
Carbohydrates	-0.34 (-0.76, 0.08)	-0.18 (-1.01, 0.87)	-1.61* (-4.11, -0.41)	0.20 (-0.46, 1.18)	-0.89 (-2.51, 0.18)	0.13 (-0.57, 0.70)
Monounsaturated FA	-0.84 (-2.00, 0.03)	-0.97 (-2.82, 0.62)	-1.90 (-13.06, 2.11)	1.57 (-0.83, 4.28)	-1.94 (-8.16, 0.39)	0.20 (-1.02, 1.57)
Polyunsaturated FA	-0.68 (-1.57, 0.33)	-0.58 (-2.02, 0.95)	-0.30 (-4.36, 2.87)	3.44 (0.24, 8.93)	0.02 (-2.64, 3.01)	0.07 (-1.40, 2.12)
Protein	-0.48 (-1.03, 0.07)	-0.24 (-1.64, 1.31)	-1.95* (-5.53, -0.43)	0.13 (-0.92, 1.12)	-1.48* (-3.56, -0.22)	0.32 (-0.57, 1.07)
Saturated FA	-0.34 (-1.35, 0.40)	-0.02 (-2.34, 2.17)	-1.10 (-8.25, 2.16)	0.83 (-1.56, 3.24)	-1.53 (-5.71, 0.48)	0.84 (-0.18, 1.96)

* = Bold denotes significance at the 0.05 level

LANDLOCKED DEVELOPING COUNTRIES MOST IMPACTED

Given that Landlocked Developing Countries showed the largest EWE effects, this subgroup was isolated for further analysis (see [Appendix A.9](#) for countries and EWEs included in this subgroup). Comparing the global set and the Landlocked Developing Countries set, [Figure 3.11](#) most clearly depicts the percentage changes of all micronutrients, macronutrients, and fiber. Vitamin C, folate, and vitamin A score the highest in percentage change for both sets. For all nutrients studied (except for polyunsaturated fatty acids), Landlocked Developing Countries exhibit both larger percentage changes and wider confidence intervals than the global set exhibits.

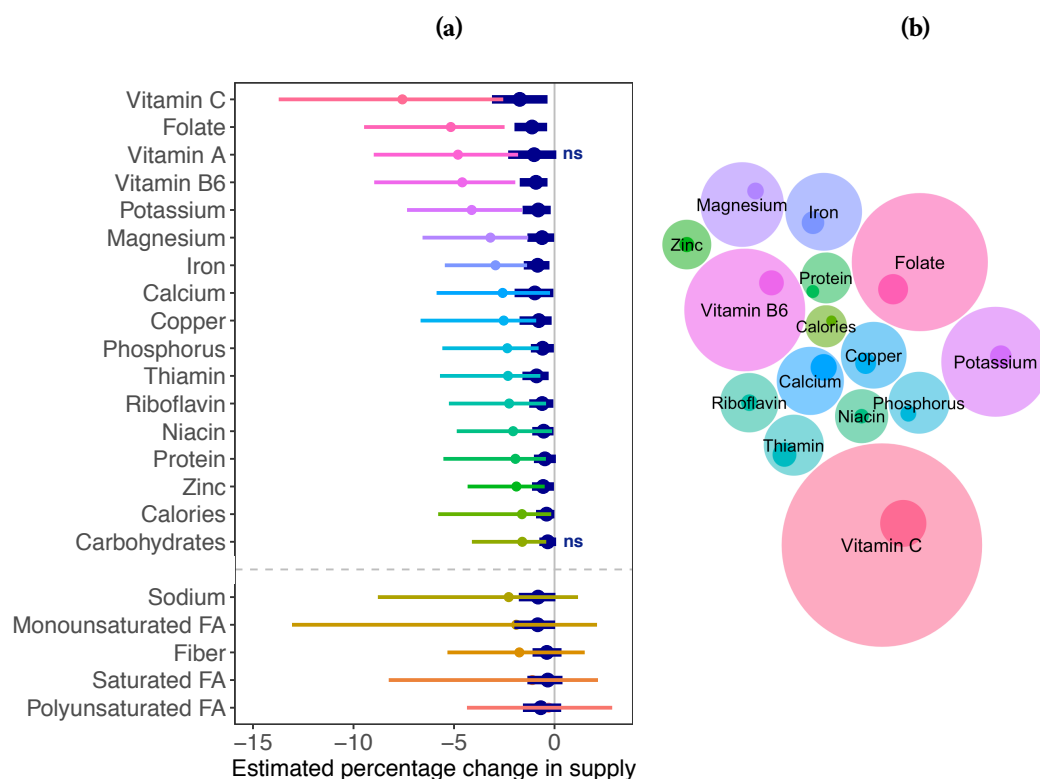


Figure 3.11: In (a), the percentage change of all nutrients and fiber in the year-of-event are plotted in rainbow colors for the Landlocked Developing Countries set, and in dark blue for the global set. The plot is organised vertically by decreasing size of nutrient supply percentage changes in Landlocked Developing Countries. Confidence intervals are drawn through the points. All nutrient supply changes above the dotted horizontal line reached significance at the 0.05 level for Landlocked Developing Countries, and for the global set except where indicated by "ns." In (b), percentage changes for the Landlocked Developing Countries set and the global set are visualised; only the nutrients that experience significant changes in both sets are shown here. For all circles, the radius is proportional to the size of the percentage change in nutrient supply. The larger circles represent the nutrient supply deficits for the Landlocked Developing Countries set, and the smaller circles represent the nutrient supply deficits for the global set.

The considerable difference in magnitude of effect between the two sets is best visualised in [Figure 3.11\(b\)](#), where both percentage changes (significant at 0.05) are overlaid. Notably, the smallest effect for Landlocked Developing Countries (carbohydrates, -1.61%) is on par with the largest effects found within the global set.

Accordingly, Landlocked Developing Countries appear to be a driving factor in the overall effect found in the global set. When the SEA analysis was conducted on the global set excluding Landlocked Developing Countries, the sign of effects did not change – i.e. all micronutrients, macronutrients (except saturated fatty acids), and fiber showed negative percentage changes. However, the magnitude of effect decreased, as well as the significance. Without Landlocked Developing Countries included in the global set, only thiamin showed negative supply changes that were significant at the 0.05 level ([Appendix A.4](#)).

EWE DEFICITS ARE LARGE PERCENTAGE OF A HEALTHY CHILD'S NUTRITIONAL NEEDS

For the global set and the Landlocked Developing Countries set, we calculated the absolute change in nutrient supplies during year-of-event. These deficits were then framed as a percentage of the Recommended Dietary Allowance (RDA) for children aged 1-3 years ([Table 3.4](#) for the most substantial EWE effects; see [Appendix A.6](#) for the complete table). The EWE impact on potassium supply in Landlocked Developing Countries is nearly 40% of what a healthy child's average sufficient dietary intake level of potassium should be. This makes up the largest EWE effect on nutrient supplies; note, however, that potassium is also the only micronutrient studied here that does not have a clear RDA. The EWE effects on vitamin C, protein, and vitamin B6 supplies are also substantial, making up 34.44%, 17.03%, and 15.24% of their respective RDAs. [Appendix A.8](#) shows the percentage change of nutrient supply during year-of-event as a percentage of Adequate Intake for infants aged 0-12 months, and similar substantial effects are observed.

Table 3.4: Change in nutrient supply during year-of-event, as a percentage of Recommended Dietary Allowance for children aged 1-3 years, with 95% confidence intervals

Nutrient	Child RDA, mg/person/day*	Change during year-of-event, all countries incl. in study		Change during year-of-event, Landlocked Developing Countries	
		in mg/person/day [†]	as percentage of RDA	in mg/person/day [†]	as percentage of RDA
Calcium	700	-4.87 (-13.64, 3.67)	-0.70 (-1.95, 0.52)	-13.67* (-35.4, -3.24)	-1.95* (-5.06, -0.46)
Folate	150	-3.69* (-6.89, -1.69)	-2.46* (-4.59, -1.13)	-13.92* (-25.91, -6.11)	-9.28* (-17.28, -4.08)
Iron	7	-0.14* (-0.26, -0.04)	-2.05* (-3.76, -0.57)	-0.48* (-0.94, -0.24)	-6.90* (-13.43, -3.39)
Magnesium	80	-2.69* (-5.04, -0.44)	-3.36* (-6.30, -0.55)	-10.9* (-19.98, -5.27)	-13.63* (-24.97, -6.58)
Niacin	6	-0.09* (-0.18, -0.01)	-1.53* (-3.03, -0.13)	-0.33* (-0.75, -0.01)	-5.42* (-12.52, -0.20)
Phosphorus	460	-7.36 (-15.05, 0.15)	-1.60 (-3.27, 0.03)	-28.4* (-63.79, -11.44)	-6.17* (-13.87, -2.49)
Potassium [‡]	300	-21.9* (-43.94, -3.27)	-7.30* (-14.65, -1.09)	-117.56* (-220.03, -47.02)	-39.19* (-73.34, -15.67)
Riboflavin	0.5	-0.005 (-0.01, 0.003)	-0.99 (-2.74, 0.67)	-0.03* (-0.06, -0.004)	-5.31* (-12.46, -0.73)
Thiamin	0.5	-0.01* (-0.02, -0.003)	-2.21* (-4.02, -0.61)	-0.03* (-0.07, -0.01)	-6.11* (-13.53, -1.81)
Vitamin A	300	-5.88 (-13.65, 0.69)	-1.96 (-4.55, 0.23)	-25.12* (-56.1, -9.75)	-8.37* (-18.70, -3.25)
Vitamin B6	0.5	-0.02* (-0.03, -0.003)	-3.56* (-6.80, -0.69)	-0.08* (-0.14, -0.03)	-15.24* (-27.34, -6.53)
Vitamin C	15	-1.21 (-2.9, 0.94)	-8.08 (-19.33, 6.24)	-5.17* (-10.58, -0.12)	-34.44* (-70.54, -0.80)
Zinc	3	-0.06* (-0.12, -0.005)	-2.12* (-4.03, -0.15)	-0.18* (-0.41, -0.05)	-6.10* (-13.62, -1.64)
Calories [‡]	950	-10.24* (-23.69, -0.41)	-1.08* (-2.49, -0.04)	-40.41* (-150.36, -3.15)	-4.25* (-15.83, -0.33)
Carbohydrates	130	-1.46 (-3.28, 0.32)	-1.12 (-2.52, 0.25)	-6.23* (-15.22, -1.82)	-4.79* (-11.71, -1.4)
Protein	7.70	-0.36 (-0.77, 0.07)	-4.73 (-9.95, 0.92)	-1.31* (-4.30, -0.31)	-17.03* (-55.79, -4.06)

* = Bold denotes significance at the 0.05 level

[†] = All vitamins measured in mg/person/day except vitamin A (μg RAE/person/day) and folate (μg/person/day); fiber measured in g/person/day; calories measured in kcal/person/day

[‡] = There is no official RDA for potassium, so Adequate Intake (AI) indicator is used instead. AI is the recommended average daily intake level of a nutrient based on observed or experimentally determined approximations of intakes that are assumed to be adequate for a group of healthy people. For recommended daily estimated calories, see Gidding et al (2006).¹²⁶

Between the absolute change (mg/person/day) values in [Table 3.4](#) and the percentage change (%) values in [Table 3.2](#), the level of significance may change for the same nutrients. In calcu-

lating absolute and percentage change, the exact same data was used; however, the bootstrapped BCa confidence intervals vary by how the nutrient supply changes are calculated, thus resulting in possible differences with significance testing (See [Appendix A.5](#) for the absolute change of micronutrient, macronutrient, and fiber supplies during year-of-event).

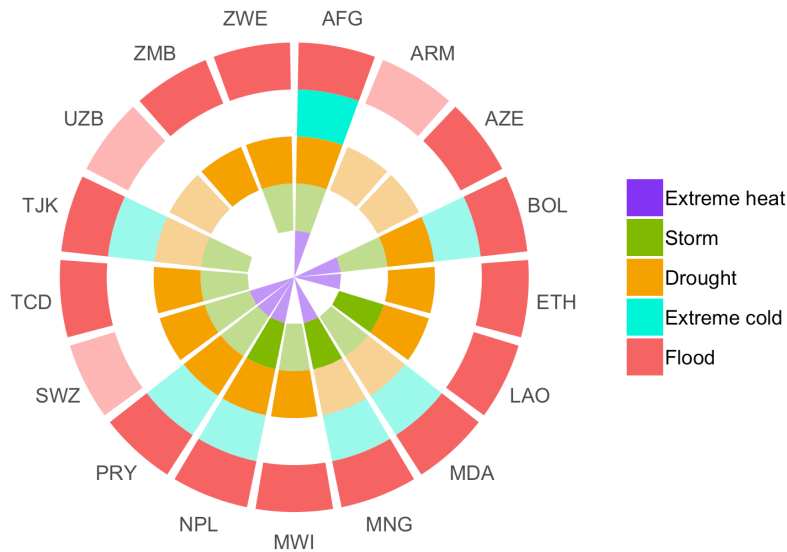
3.5 DISCUSSION

All micronutrient supplies in this study exhibited negative percentage change during the year of a major EWE. Macronutrient supplies showed milder and more erratic responses, likely due to their being derived from a more diverse range of data sources. In other words, because macronutrients come from nearly all food groups – whereas micronutrients are derived primarily from fruits and vegetables – the acquisition of macronutrients may be notably easier when food options are limited, such as in the immediate aftermath of an extreme event. While the scope of this study was focused on nutrient supply, future research should further investigate the stability of fresh produce in response to EWEs, and how vulnerable populations may substitute away from micronutrient-rich foods during EWEs in order to reach adequate caloric consumption. (Note that prior to conducting the present study, I mimicked the protocol of Lesk et al. (2016)¹¹¹ and was able to replicate their results regarding cereal production. I further modeled fruit, vegetable, and cereal supply. Due to space constraints, I have not included that data in this thesis.)

In our study, subgroup analysis determined that Landlocked Developing Countries and Low Income Food Deficit Countries are especially sensitive to EWEs, exhibiting significant nutrient supply changes ranging from $-1.28-7.57\%$ of the average supply. These results were accompanied by wider confidence intervals than those of the global results; the wider confidence intervals are an inevitable consequence of a small and relatively volatile sample pool, as penalised by the BCa method. These wider confidence intervals indicate that the micronutrient supplies of Landlocked Developing Countries could experience deficits as large as 13.7% of Vitamin C and 9.47% of folate during the year-of-event. It is surprising that of the subgroups, Least Developed Countries and Net Food-Importing Developing Countries did not exhibit significant nutrient supply changes during the year-of-event, though they did trend towards negative effects. This finding could be explained by better access to humanitarian response and food aid within these subgroups.

Of the UN-designated developing countries, the Landlocked Developing Countries are those that are surrounded by land on all sides of the border, thus having no direct access to water ports. This has explicit implications for food security – domestic food prices in Landlocked Developing Countries are up to three times more volatile than in their coastal

counterparts, as Landlocked Developing Countries are often locked out of the global food market through high tariffs, overly bureaucratic border crossings, “rent-seeking” behavior by authorities and transport sectors, and poor infrastructure.^{127,128} The volume of international trade of a landlocked developing country is, on average, just 60% of the trade volume of a comparable coastal country.¹²⁹ Current domestic food production, however, is not sufficient to compensate for the lack of trade in many of these areas; Landlocked Developing Countries typically have less arable land and less agricultural land under irrigation, leaving them particularly vulnerable to the effects of climate change and EWEs.¹²⁷ Figure 3.12 breaks down the frequency and type of all EWEs that Landlocked Developing Countries have experienced from 1964-2010 – floods and droughts appear to be the most common EWEs both historically and in our analysis of major EWEs.



AFG = Afghanistan, ARM = Armenia, AZE = Azerbaijan, BOL = Bolivia, ETH = Ethiopia, LAO = Laos, MDA = Moldova, MNG = Mongolia, MWI = Malawi, NPL = Nepal, PRY = Paraguay, SWZ = Swaziland, TCD = Chad, TJK = Tajikistan, UZB = Uzbekistan, ZMB = Zambia, ZWE = Zimbabwe

Figure 3.12: Prevalence and frequency of EWEs in Landlocked Developing Countries. The countries represented in this figure have recorded an EWE from 1964-2010. The darker shade indicates that five or more of such events were recorded during this time period; the lighter shade indicates that less than five such events were recorded during this time period; and white indicates there have been no *recorded* events of that type during this time period. Note that it is quite possible that such events did occur but that they were not recorded in the EM-DAT database (see Section 3.5 below). Also note that none of these countries have recorded five or more extreme heat events during this time period; however, extreme heat events are projected to increase in the near future with severe implications for food security.¹³⁰

The implications of this study are concerning, especially for vulnerable populations in resource-constrained countries that are already at risk of micronutrient deficiencies. Preg-

nant women and children under five years of age are among the most vulnerable; it is estimated that chronic and acute child malnutrition, low birthweights, and suboptimal breastfeeding cause the deaths of 3.5 million mothers and young children every year.¹³¹ Various micro- and macro-nutrients (i.e. protein, fatty acids, iron, copper, zinc, B-vitamins) are necessary for the neurodevelopmental processes that occur rapidly during pregnancy and infancy, such as neuron proliferation and myelination.¹³² Maternal micronutrient deficiencies during lactation can also cause a reduction in the concentration of nutrients in breast milk (especially thiamin, riboflavin, vitamins B6, vitamin A, and iodine), with subsequent infant depletion.^{133,134} Repercussions of these nutritional insults are long-lasting; under-nutrition during pregnancy and the first two years of life is a major determinant of stunting and poor development, with potential long-term consequences for adult health and work productivity.¹¹⁶

While agricultural yields have been consistently increasing since the Industrial Revolution, the world has also witnessed an increase in the absolute number of people *and* the percentage of people in the world having insufficient dietary energy consumption in 2017.³⁷ Current estimates indicate that 250 million children younger than five years in low-income and middle-income countries are at risk of not reaching their developmental potential.¹³⁵ The EWE effects found in this study could significantly exacerbate current malnutrition burdens, as well as endanger those children barely scraping by on the edge of adequate nutrition. While there is a clear need to provide nutrient supplementation during and after an EWE, it is also imperative that nations are better equipped to prepare for EWEs and their potential consequences on nutritional health. Anticipatory humanitarian aid (such as the World Food Programme's Forecast-based Financing approach) must include comprehensive nutrient accessibility prior to an event, to prevent or mitigate shocks on the nutrient supply. Strengthening domestic infrastructure of food supply and healthcare will also ensure that when an EWE occurs, a nation will be self-equipped to establish nutrient security.

STRENGTHS OF STUDY

Previously, agricultural production has been shown to decline during and after an EWE. Specifically, Cottrell et al. (2019) identified “shocks,” or sudden losses to food production, as a result of complex social-ecological stressors that include EWEs; they found that shock frequencies were highest in South Asia for crops, the Caribbean for livestock, Eastern Europe for fisheries, and South America for aquaculture sectors.⁵¹ Beyond this model of production shocks, the most extensively studied topic is the effect of EWEs on cereal production. There is broad consensus that globally, droughts have the most significant negative consequences for food production, specifically in how they reduce cereal yield.^{49,50,52} Evi-

dence for the effect of other EWEs (i.e. floods, storms, extreme heat, extreme cold) on food production is more sparse and generally focused on economic consequences.^{136,137}

Also absent from the literature is the quantification of EWE impacts on nutrition. In the FAO's "Climate change and food security: risks and responses" released in 2016, the word "*micronutrient*" is mentioned only twice in the lengthy 110-page report: once in the introduction, to cite the statistic that 2 billion people in the world lack the essential micronutrients they need to lead healthy lives; and once in the discussion, to explain how "famine foods" such as bushmeat and forest plants are high in micronutrients.⁴⁷ Macronutrients have no mention in this report. Two large and well-cited reviews that address climate change impacts on human health (McMichael et al., 2006 and Patz et al., 2005) both touch upon general EWE impacts on nutrition as a crucial pathway to study, yet neither indicate or reference a comprehensive, quantitative evidence base of such impacts.^{55,56} Only a few case studies have specifically linked EWEs to nutritional outcomes, such as risk of child stunting due to drought-related crop loss in Uganda⁵³ and persistent reduced growth among flood-exposed children in Bangladesh.⁵⁴ These studies are limited in geographical scope and applicability to a global context.

Food production analysis can only at best imply a link to food consumption. In the current study, by shifting the focus onto nutrient supply, I measured the *outcome* (nutrition, proxied by nutrient supply) rather than the *input* (consumption, proxied by food production). To date, this is the first quantification of the nutrient supply reductions experienced during EWEs globally and compared to various low-income subgroups. By further framing the nutrient supply reductions in terms of child Recommended Dietary Allowances, I also provided a practical, relevant, and important context for interpreting the results of an EWE superposed epoch analysis.

LIMITATIONS

With the GENUS Model, using total aggregated supply per capita per country as a proxy for national nutrient consumption has several limitations: 1) it does not directly measure consumption, 2) it is based on FAO food production data, and the FAO interpolates some of its data instead of directly measuring it, due to gaps in data collection for certain countries,¹³⁸ 3) for other countries, there is absolutely no available food production or supply data, thus rendering interpolation impossible, and 4) the per capita data does not discriminate between age, gender, or socioeconomic status (except for the year 2011). Certain subpopulations within a country may be more disadvantaged than others, with less access to food, and thus more exposed to the effects of food disruptions.^{139,140} That our analysis does not cover Small Island Developing States (SIDS) as a separate subgroup is also a major

limitation– SIDS are known to be extremely vulnerable to EWEs and limited in their ability to import fresh foods in the case of an emergency.¹⁴¹ One caveat with using EM-DAT data is that the database is a compilation of field reports and post-disaster assessments, often carried out by a constellation of government ministries, NGOs, and international governance agencies such as the UN. While units have been standardised throughout the database, the method of collecting and analysing data in the aftermath of an EWE is not standardised. Additionally, because EM-DAT is not based upon observed weather data or climate reanalysis, this database likely misses events that climatologically qualify as EWEs but may not have had significant enough human impacts to warrant a post-disaster assessment. Lastly, while measuring supply fluctuations is important (as we did in the current study), measuring actual nutrient consumption would more closely align with health consequences. Future studies that focus on the link between supply and consumption should identify breakdowns in the supply chain, precisely when they occur post-EWE, and who is most affected.

CONCLUSION

An early pioneer in the sphere of planetary health, Amartya Sen wisely noted in 1981:

“I expect some day one might indeed grow rice or catch fish in the Sahara. But while science marches on slowly, some means have to be found for freeing the Sahelian population from vulnerability to droughts and the prospect of famines.”¹⁴²

Previous studies have established the negative effect of EWEs on food production, but few have made the final link between this food disruption to human nutrition. In this study, we aimed to bridge EWEs and nutritional supply, through the quantification of micronutrient, macronutrient, and fiber supply fluctuations during the year of major EWEs. We found modest – but significant – micronutrient and macronutrient supply declines in the year-of-event globally and among UN-designated low-income groups. We identified Landlocked Developing Countries as an especially vulnerable subpopulation, and further contextualised the magnitude of deficits in nutrient supplies by comparing them to the Recommended Dietary Allowances for children aged 1-3 years. Due to socioeconomic factors and the physiology of human development, children in low-income settings not only face the greatest exposure to environmental risk, but they also stand to bear the most severe long-term health consequences. As climate change increases the volatility of EWEs worldwide, it is imperative that the international community better prepares for and addresses the nutritional impacts of EWEs, especially within low-income settings.

The rich will find their world to be more expensive, inconvenient, uncomfortable, disrupted and colourless; in general, more unpleasant and unpredictable, perhaps greatly so. The poor will die.

Kirk R. Smith

4

Climate impacts on Indigenous communities in northern Australia

In the previous chapter, I explored the effect of EWEs on global nutrient supply, and theorised the human health consequences. In this chapter, I directly measure and analyse cardiometabolic health outcomes in response to one specific type of EWE (extreme heat) in one specific geographical context (northern Australia).

4.1 ABSTRACT

Extreme heat has been associated with negative health outcomes in Australia, but documentation of this relationship has been largely limited to absolute temperature conditions in urban areas. This study analysed a comprehensive dataset of 104 Aboriginal and Torres Strait Islander communities dispersed throughout the Northern Territory from 2010-2015. Using Principal Component Analysis and MM-estimator robust regression, I built a holistic model that accounts for built, environmental, and socioeconomic disparities. I found that cardiometabolic-related emergency room rates, inpatient admission rates, and primary healthcare rates are significantly correlated with heat stress indicators. Increased emergency room rates occur mostly in communities that experience relatively lower apparent

temperature and humidity, but greater maximum heatwave severity (particularly in the spring and summer). Results of this study find that health is most negatively harmed by relative heat, rather than absolute heat or humidity - thus providing a more nuanced picture of the health threats posed by impending climate change in northern Australia.

4.2 INTRODUCTION

By the end of 2007, the life expectancy at birth for Indigenous males was 67.5 years, and for females, 73.1 years – these figures were 11.4 and 9.6 years lower than life expectancy for non-Indigenous males and females respectively. In 2008, the Council of Australian Governments (COAG) launched the “Closing the Gap Strategy,” with its target to achieve by 2030 life expectancy equality for all Australians. Today, the gap in life expectancy between Aboriginal and Torres Strait Islander people and non-Indigenous people in Australia still hovers around 10 years; there has been no significant change in the Indigenous mortality rate between 2006 – the baseline – and 2017, the last measured year.¹⁴³

A prominent contributing factor to the discrepancy in life expectancy is metabolic syndrome (MetS), which is a conglomeration of interrelated risk factors that directly promote the development of cardiovascular disease and diabetes.³² These risk factors include: abdominal obesity, atherogenic dyslipidemia, raised blood pressure, insulin resistance, glucose intolerance, and proinflammatory/prothrombotic states.³² Due to socioeconomic and physiological factors, Indigenous Australians are more susceptible to MetS than their non-Indigenous counterparts – Aboriginal and Torres Strait Islander Australians are three times more likely to have diabetes than non-Indigenous Australians, and nearly twice as likely to be obese.^{66,144} Beyond morbidity, Indigenous Australians have two times the rate of mortality from coronary heart disease and nearly five times the rate of mortality from diabetes compared to non-Indigenous Australians.^{68,145} The most recent hospitalisation data mirrors this unequal health burden: the age-standardised hospitalisation rate for Indigenous Australians is 2.3 times that for non-Indigenous Australians; and in 2013-2014, there were 392,142 public hospital emergency department presentations by Indigenous people for all causes, thereby composing 5.4% of all such presentations.¹⁴⁶ As a comparison, Indigenous people represented 2.5% of the total population in 2011, and 2.8% in 2016.¹⁴⁷

Disproportionately greater morbidity among Indigenous Australians is most prominent in the Northern Territory of Australia. Across the entire country, Aboriginal and Torres Strait Islander Australians compose 3.3% of the population; within the Northern Territory, they compose a disproportionate 30% of the population, the highest proportion of any state or territory in Australia.¹⁴⁸ Compared to the rest of the country, age-standardised DALY

(disability-adjusted life years) rates for Indigenous Australians were highest in the Northern Territory (499 per 1,000 people), primarily owing to injuries, cardiovascular diseases, kidney/urinary diseases, endocrine disorders, infectious diseases, and gastrointestinal disorders.¹⁴⁵ The backdrop of this health burden is a scorching landscape that few would describe as hospitable – the Northern Territory has historically experienced extreme social and climatic vulnerability.¹⁴⁹ Within the next 50 years, the Northern Territory is projected to experience (with high confidence): higher average temperatures, higher sea surface temperatures, rising sea levels, more extreme hot days, and more intense cyclones.¹⁵⁰ The federally commissioned Garnaut Review has modelled the impacts of temperature-related deaths and hospitalizations under different climate scenarios to 2100 and found that the greatest negative impacts will occur in Queensland, the Northern Territory, and Western Australia.¹⁵¹ Within these regions, remote Indigenous communities are poised to be among the most adversely affected by climate change, primarily due to 1) increased physical exposure to climate hazards, 2) high reliance on natural systems to sustain cultural practices and a traditional sense of holistic well-being, and 3) reduced adaptive capacity as a result of historic marginalisation and institutional paternalism.^{152–154} At the same time, it must also be acknowledged that despite these many historical and ongoing injustices, Indigenous communities have repeatedly shown their inherent strength, adaptability, and resilience.¹⁵²

The current study was conducted within an existing Australian National Health and Medical Research Council (NHMRC) Project Grant (NHMRC GNT1051824), titled “Environments and Remote Indigenous Cardiometabolic Health (EnRICH).” The EnRICH project collected built environment, census, and climate data from ~100 remote Indigenous communities in the Northern Territory of Australia from 2010-2015. The primary aim of this study was to explore the relationship between various climate variables and four cardiometabolic-related health outcomes: age and sex-standardised emergency room rates, inpatient admission rates, primary healthcare visit rates, and mortality rates. The built environment and census variables were included to provide a holistic model that allows me to control for various site-specific and socioeconomic confounders. A secondary aim of this study was to build a robust, efficient methodology to compile a complete dataset for large epidemiological studies that may otherwise suffer from three main statistical challenges: overspecification, multicollinearity, and outliers.

METHODOLOGICAL RATIONALE

The EnRICH database contains 218 potentially significant variables which I categorised into three groups: built environment, census, and climate. Conducting an ordinary regression approach on these variables would result in an inefficient model that suffers from

overspecification, the condition that arises when there are many more variables than there are observations. In order to avoid this condition, I chose Principal Component Analysis (PCA), which works by reducing the dimensionality of the data rather than reducing the number of variables. Using PCA, my multivariate dataset is projected on a high-dimensional data space, in which each variable has its own axis. Principal Component Analysis is then conducted to determine a lower-dimensional picture – a projection of the data from its most informative viewpoint.

In this study, I used robust PCA (ROBPCA) rather than classical PCA; the latter becomes unreliable when outliers are present because both the classical variance (which is being maximised) and the classical covariance matrix (which is being decomposed) are very sensitive to anomalous observations.¹⁵⁵ Robust PCA replaces the classical covariance matrix with a robust covariance estimator. Robust analysis produces more consistent and efficient estimators and test statistics when the model is slightly misspecified.^{156,157} Using my ROBPCA output, I then conducted varimax rotation and manually adjusted the principal component scores. Varimax rotation reduces the data sub-space by maximising the sum of the variance of the squared loadings.¹⁵⁸ This results in high factor loadings for a smaller number of variables, thus rendering principal component analysis easier to interpret.

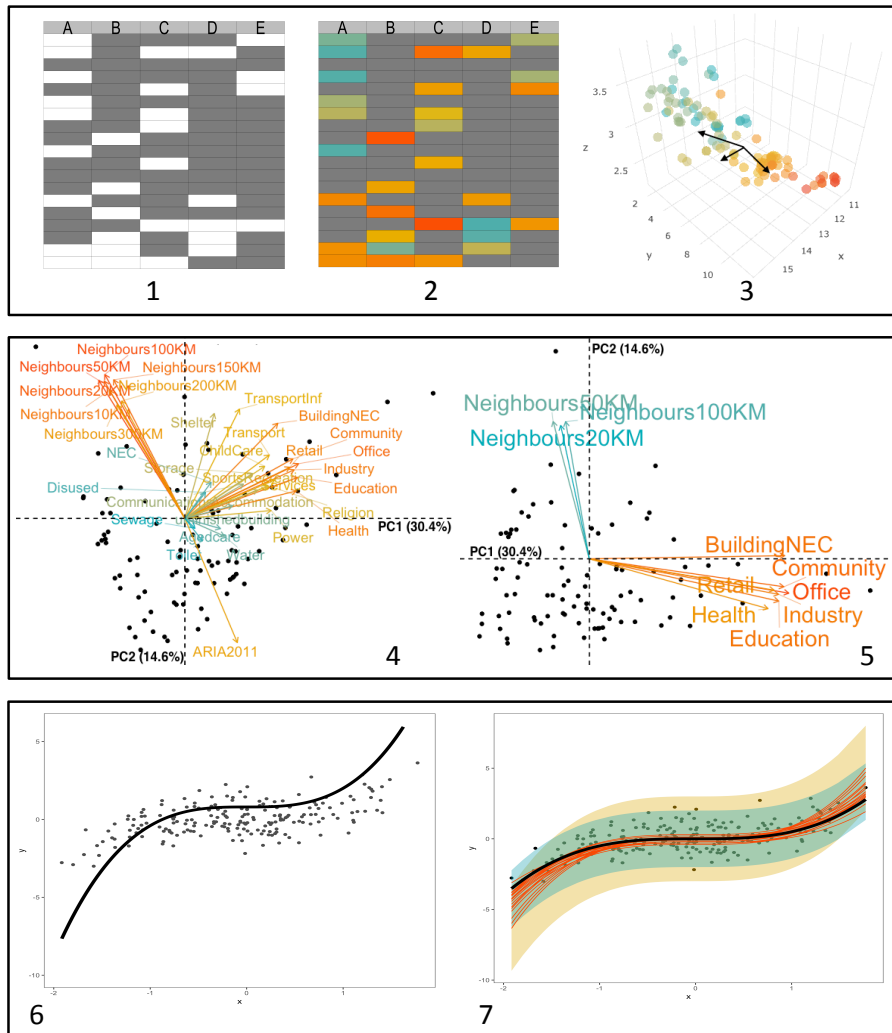
The results of the varimax-rotated PCA (which are obtained as “scores”) are then used as explanatory variables for the health outcome regressions. Since I isolated two principal components for each of the three categories, I ended up with six explanatory variables: built environment PC1/PC2, census PC1/PC2, and climate PC1/PC2. In this study, I preferred the MM-estimator models over the simple Ordinary Least Squares regression models. The MM-estimator, proposed by VJ Yohai (1987), retains the outlier-resistance of the S-estimator methods related to trimmed least squares, and the greater efficiency of M-estimators.^{159,160} The combined high breakdown-point and high efficiency means that this method is applicable to smaller batches of samples, which is ideal for this study.

4.3 METHOD

STUDY DESIGN DIAGRAM

On the following page, [Figure 4.1](#) presents a simplified schematic consisting of seven panels that consecutively describe the various methods utilised in this paper. The “built environment” category is used here as an example.

Figure 4.1: Schematic of methods utilised in this paper. In step 1) raw data (with variables A–E) are extracted from database for every single community; each variable has at least one missing value. 2) Using Multivariate Imputation by Chained Equations (MICE), the missing data are replaced with iteratively predicted values. 3) The multivariate dataset is projected on a high-dimensional data space. 4) Principal Component Analysis is conducted to determine a lower-dimensional projection. The biplot shows the magnitude and direction of loadings, plotted over PC1 and PC2 scores. 5) The loadings are varimax-rotated to create greater discrimination among loading values. The most influential loadings are now highlighted. 6) After adjusting scores with varimax-rotated loadings, an Ordinary Least Squares model is run by regressing the outcome variable (i.e. Emergency room rates) on the PC1 and PC2 scores. 7) MM-estimator regression - a robust, iterative, machine learning method – is conducted to minimise influence of outliers and increase the model’s explanatory power. The yellow band represents the first few iterations of estimated regression curves, which are biased due to outliers. The blue band, and subsequently the red curves, represent further iterations that get closer and closer to the final MM-estimator, shown in black. Note: colour scheme does not reflect loadings in this final panel.



STUDY POPULATION

Communities were selected for the EnRICH study based on eligibility assessment criteria, specifically: (1) community located within the NT; (2) estimated total resident population size greater than or equal to 50 persons; (3) proportion of Aboriginal and Torres Strait Islander residents greater than or equal to 70% of total community population; and (4) community attributed to a relevant geographic unit of Indigenous Location (ILOC), as defined by the Australian Bureau of Statistics (ABS) Population and Housing Census 2011.¹⁶¹

MEASURES

PREDICTORS

The built environment variables of the EnRICH database were obtained from three primary data sources: 1) ABS Census of Population and Housing 2011 conducted on 9 August 2011, 2) Serviced Land Availability Programme Map from minimum 01 July 2000 – maximum 22 July 2018, and 3) Australian Government Indigenous Programmes and Policy Location 2013.¹⁶² The built environment variables were largely focused on community remoteness, existing infrastructure, and count of facilities related to healthcare, education, accommodation, and industry. For the census variables used in this study, relevant community-level indicators were obtained from the ABS 2011 Population and Housing Census and expressed at the spatial ILOC unit. These variables focused on levels of employment, various forms of household composition, demographics, and education levels.

Lastly, the climate variables were created with the assistance of weather exposure data resources from the Centre for Air Pollution, Energy and Health Research (CAR) data platform (<https://cardat.github.io>) and the Collaborative Environment for Scholarly Analysis and Synthesis (CoESRA; <https://coesra.tern.org.au>). Temperature exposure estimates, as well as precipitation and wet bulb globe temperature estimates, were created using the gridded meteorological datasets from the Australian Water Availability Project (AWAP)¹⁶³ and the Bureau of Meteorology (BOM).¹⁶⁴ For all climate variables in this study, the pooled estimates for each ILOC community are averaged from the annual averages across 2000-2015, thus representing long-term climate aggregations.¹⁶⁵

See [Appendix A.11](#) for the full list of predictor variables used in this study.

OUTCOMES

Individual de-identified comprehensive cardiometabolic disease and risk profile data from the Northern Territory (NT) Department of Health for the period 1 January 2010 to 31 De-

cember 2015 include: 1) inpatient activity (diagnosis and procedures at a hospital), 2) Emergency Department data collection (presentation at a hospital emergency department), and 3) primary health care collection (diagnosis/clinical assessment at primary health care centre). De-identified cardiovascular-specific mortality data from the Births, Deaths, and Marriages Office (NT Department of the Attorney-General and Justice) for the period 1 January 2010 to 31 December 2015 was also obtained. See [Appendix A.12](#) for the full list of ICD-10 codes used to identify the cardiometabolic-related diagnoses, procedures, assessments, and presentations that compose the four health outcome variables used in the present study.

Note that a study design and methodology paper for the whole EnRICH database is currently in-progress.

MISSING DATA IMPUTATION

I selected and separated 218 variables into three broad categories: built environment ($n=33$), census ($n=118$), and climate ($n=67$). Most observations (total $n=104$) had at least one missing value within each of these categories, but Principal Component Analysis (PCA) requires each observation to have complete or close to complete data. Therefore, I conducted Multivariate Imputation by Chained Equations (MICE) to impute missing values in the observations, using the R package *mice*.¹⁶⁶ Broadly outlined, the *mice* package 1) inspects the missing data pattern, 2) imputes the missing data m times, resulting in m completed data sets, 3) diagnoses the quality of the imputed values, 4) analyses each completed data set, and 5) pools the results of the repeated analyses. I coded the algorithm to create 5 imputed datasets through predictive mean matching (PMM), where an incomplete column (the target column) is “filled in” by generating plausible synthetic values given a specific set of predictors, which are drawn from other columns in the data. I chose MICE as my imputation method over other methods (i.e. complete case analysis, linear interpolation, maximum likelihood methods) because MICE is more flexible and responsive, specifically in how it leverages both observed values and patterned relations between variables.¹⁶⁷ Additionally, since MICE analyses multiple predictions for each missing value, it properly takes into account the uncertainty in the imputations and thus yields accurate standard errors.¹⁶⁸

ROBUST PRINCIPAL COMPONENT ANALYSIS OF SEPARATED CATEGORIES

I conducted robust Principal Component Analysis (ROBPCA) on the three separate imputed datasets of built environment, census, and climate variables. I used the R package *PcaHubert*, which employs the ROBPCA method of Hubert et al (2005).^{155,169} In the first step, the data are scaled to unit variance and preprocessed by singular value decomposition of the input data matrix. Next, a measure of outlyingness is computed for each data point

using the Minimum Covariance Determinant (MCD) method.¹⁷⁰ As the high-dimensional data points are projected on many univariate directions, the univariate MCD estimator of location and scale is computed and the standardised distance to the center is measured. The largest of these distances (over all considered directions) is the outlyingness measure of the data point. The h data points with smallest outlyingness measure are used to compute the covariance matrix. Finally, the appropriate number k of principal components is determined, and the data points are projected on the k -dimensional subspace spanned by the k eigenvectors corresponding to the largest k eigenvalues of the covariance matrix. The location and scatter of the projected data are computed using the reweighted MCD estimator and the eigenvectors of this scatter matrix, thus yielding the robust principal components.¹⁶⁹

VARIMAX ROTATION, THEN PRINCIPAL COMPONENT SCORE DETERMINATION

With my ROBPCA output, I then conducted varimax rotation and manually adjusted the principal component scores. To utilise varimax rotation, I first had to calculate raw loadings from my ROBPCA output; this was calculated by multiplying the ROBPCA eigenvectors by the diagonalised square root of the ROBPCA eigenvalues. I then applied the R package *varimax* function to create varimax-rotated loadings.¹⁷¹ Because these varimax-rotated loadings are no longer orthogonal (a necessary precondition to calculate principal component scores), I used single value decomposition to create transposed pseudo-inverses of the varimax-rotated loadings, and then multiplied by the scaled values of the original raw data in order to obtain the final standardised principal component scores for each observation.^{172,173}

RPCR: ROBUST PRINCIPAL COMPONENT REGRESSION

In the final leg of my analysis, I regressed various health indicators on the principal component scores for each category. Since I had two principal components per category, this resulted in six explanatory variables, referred to here as *built1*, *built2*, *census1*, *census2*, *climate1*, and *climate2*. The health indicators analysed were age- and sex-standardised emergency room rates, inpatient admission rates, primary healthcare visit rates, and cardiometabolic-related mortality rates. I log-transformed the emergency room rate variable and the mortality rate variable to adjust for skew, and then conducted an Ordinary Least Square (OLS) linear regression for all health indicators. Because all of the dependent variables have important outliers, I followed with a suite of robust regression models. I compared Least Trimmed Squares, S-estimator, M-estimator, and MM-estimator robust regressions, and determined that the MM-estimator model was the best fit for my data. I used R package *ro-*

bust to conduct MM-estimator robust regressions.¹⁷⁴ The MM-estimator procedure is as follows: 1) initial estimates of the coefficients and corresponding residuals are taken from a high resistant regression (i.e. S-estimation with Huber or bisquare weights), 2) the residuals are used to compute an M-estimation of the scale of the final residuals, 3) the initial residual estimates and the new residual scale are used in the first iteration of weighted least squares to determine the M-estimates of the regression coefficients, 4) new weights are calculated, and 5) keeping constant the measure of the scale of residuals, steps 3 and 4 are continually reiterated until convergence.¹⁷⁵

ETHICS APPROVAL

Ethics approval for the present study was obtained from the Human Research Ethics Committee (HREC) of University of South Australia [HREC Reference No. 31874], Central Australian Human Research Ethics Committee [HREC-13-182], and Human Research Ethics Committee of the Northern Territory Department of Health and Menzies School of Health Research [HREC 2013-2083]. All ethics clearances were also registered with the University of Melbourne Medicine and Dentistry Human Ethics Sub-Committee [ID 1852871].

4.4 RESULTS

RAW DATA GROUPED INTO BUILT ENVIRONMENT, CENSUS, AND CLIMATE CATEGORIES.

In order to ultimately create categorical PCs, the raw data from the EnRICH dataset were grouped into three categories: built environment, census, and climate. [Figure 4.2](#) shows how all 218 variables were further grouped within each category. The size and shade of each variable group indicates its relative contribution to the total EnRICH dataset. Built environment has the fewest absolute number of variables and census has the most variables. Of the variables within the climate category, most fell under one of three heat stress indicators: Apparent Temperature, Excess Heat Factor, and Wet Bulb Globe Temperature ([Table 4.1](#)).

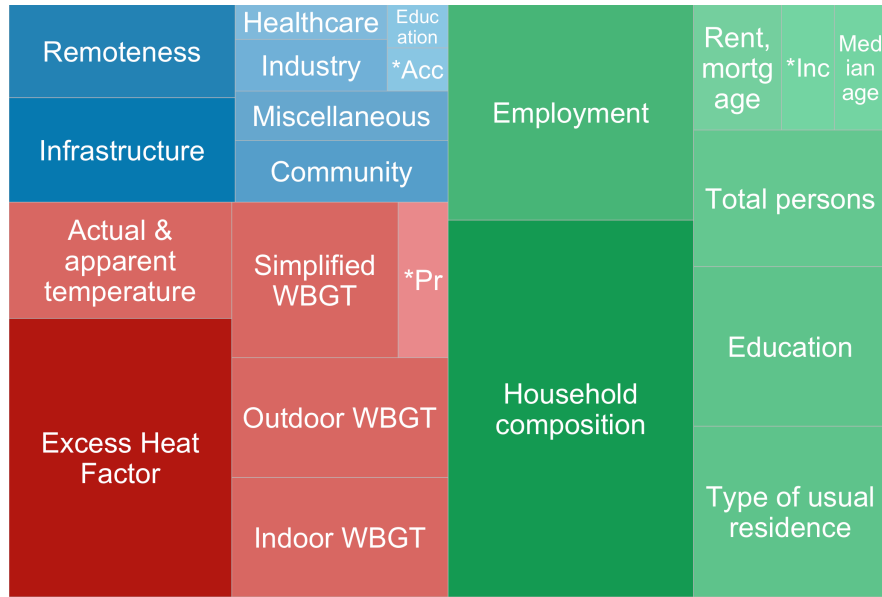


Figure 4.2: Treemap of the contributing variable groups within each category. Blue squares compose the built environment category ($n=33$ variables), red squares compose the climate category ($n=67$), and green squares compose the census category ($n=118$). The size and shading of squares are proportional to how many variables are found within each group.

Table 4.1: Summary description of the heat stress indicators used in this study.^{176–178}

Heat stress indicator	Description
Apparent Temperature (AT)	Adjustment to the ambient temperature (T) based on the level of humidity and wind speed
Excess Heat Factor (EHF)	Heatwave intensity indicator that incorporates how hot a three-day period is with respect to 1) an annual temperature threshold and 2) the recent past, specifically the previous 30 days
Wet Bulb Globe Temperature (WBGT)	Combined temperature/humidity stress indicator that incorporates measurements from: 1) the wet-bulb thermometer, 2) the black globe thermometer and 3) the shade air temperature

VARIMAX-ROTATED PCA SCORES ARE GENERATED FOR THE THREE CATEGORIES.

The categories of built environment, census, and climate exhibit variation among the data, especially when stratified by latitude (Figure 4.3). Each composited bar represents an individual community in the study, decomposed into the varimax-rotated scores of the six PCs. Scores within categories (i.e. census PC1 and census PC2) are negatively correlated, which is consistent with the PCA method, since the first two PCs should explain different aspects of variation in the data. Scores between categories (i.e. census PC1 and climate

PC1) are not necessarily correlated in any direction. [Table 4.2](#) provides a *simplified* interpretation of the six PC scores through loading analysis. Every original variable that is input into the PCA is assigned a loading factor, which determines its relevance (or weight) in the PC score. For each PC, the loading factors with the highest magnitudes are the most important; they were extracted and analysed based on the direction of their correlation with the PC score. Negative loading factors are negatively correlated with the PC, while positive factors are positively correlated.

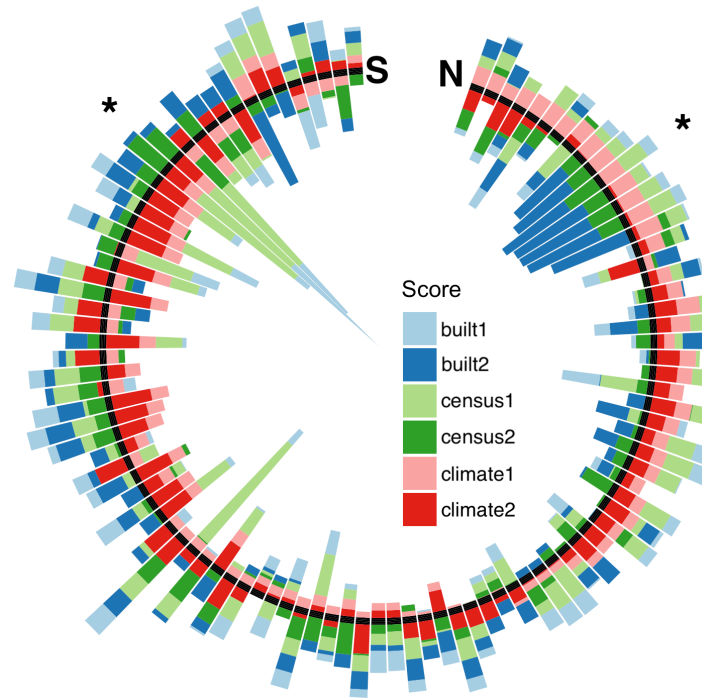


Figure 4.3: PC scores of all three categories (built environment, census, and climate) for each community observation (total $n=104$), oriented by polar coordinates. Bars below the black line (i.e. within the circle) are negative scores, whereas bars above the black line (i.e. outside the circle) are positive scores. The two asterisks denote two clusters of observations with large correlated scores. The left asterisk cluster is located in the southern-most latitudes of this study; communities in this cluster share large negative scores for census PC1 and built environment PC1. The right asterisk cluster is located in the northern-most latitudes; communities in this cluster share large negative values for built environment PC2.

Table 4.2: Simplified interpretation of the six PC scores, through loadings analysis.

Principal component	Most significant loadings, with direction of correlation	Simplified interpretation
built1	– Count of buildings, religion – Count of buildings, sport and recreation – Count of buildings, office – Count of buildings, community – Count of buildings, health	A community with a large positive built1 score is either less developed in terms of the built environment, or smaller in size relative to other communities.
built2	– Other AGIL* communities w/in 100km – Other AGIL communities w/in 150km – Other AGIL communities w/in 50km – Other AGIL communities w/in 200km	A community with a large positive built2 score is more isolated and will have fewer neighboring communities within 50-200 km.
census1	– Internet connection in household – Year 9 or less as highest level of schooling – Households with 1 usual resident – Households with 5 usual residents – Total number of households	A community with a large positive census1 score is has fewer households relative to other communities and exhibits a mix of socioeconomic conditions .
census2	+ Average household size + Percent dwelling needing extra bedroom + Average number of persons per bedroom + Percent labour force participation + Median weekly household income	A community with a large positive census2 score has more household overcrowding and higher employment rates .
climate1	– Annual avg of max AT – Avg of AT 1500, spring – Avg of outdoors WBGT 1500, spring – Avg of indoor WBGT 1500, spring + Annual avg of max EHF values, summer	A community with a large positive climate1 score experiences lower apparent temperature and humidity, but greater maximum heatwave severity .
climate2	– Avg of max duration of heatwaves, summer – Avg duration of consecutive heatwaves, summer – Annual avg of heatwave days, summer – Avg of max duration of heatwaves, autumn – Annual avg of EHF duration	A community with a large positive climate2 score experiences shorter heatwaves compared to other communities.

* AGIL = Australian Government Indigenous Programmes and Policy Locations

HEALTH OUTCOMES ARE REGRESSED ON THE PC SCORE VARIABLES.

When I regressed the health outcomes on the six PC score variables, all health outcomes were better explained by the MM-estimator than Ordinary Least Squares, as evidenced by universally higher adjusted R-squared values and lower residual standard errors (Table 4.3). The better model fit also changed the significance levels and distributions of the explanatory variables for both the inpatient and primary healthcare models (Figure 4.5). Of the four regression models, mortality had the lowest explanatory power. Residual analysis of the emergency room and inpatient MM-estimator models shows that even though the MM-estimator specialises in limiting the influence of outliers, it cannot completely eliminate all outlier influences on model behavior (Figure 4.4).

Table 4.3: Results of the Ordinary Least Squares and MM-estimator models; standard errors in parentheses below estimates.

	Emergency room [†]		Inpatient		Primary healthcare		Mortality [†]	
	OLS	MM-est	OLS	MM-est	OLS	MM-est	OLS	MM-est
Intercept	1.57*** (0.121)	1.78*** (0.141)	22.1*** (1.42)	20.1*** (1.75)	24.3*** (2.28)	24.0*** (3.00)	1.22*** (0.068)	1.24*** (0.079)
Built1	-0.192 · (0.115)	-0.126 (0.131)	-4.040* (1.960)	-8.26** (2.83)	1.640 (2.35)	1.430 (3.25)	-0.155 · (0.082)	-0.128 (0.118)
Built2	0.089 (0.159)	-0.190 (0.172)	3.320* (1.410)	5.57*** (1.58)	6.300** (2.28)	7.00* (3.32)	-0.157** (0.059)	-0.147* (0.069)
Census1	0.069 (0.060)	0.050 (0.082)	1.200 (0.943)	1.330 (1.48)	-3.090 · (1.81)	-2.970 (2.26)	0.021 (0.052)	0.001 (0.068)
Census2	-0.023 (0.112)	-0.059 (0.130)	-0.526 (1.800)	2.250 (2.35)	-5.320* (2.24)	-6.020 · (3.33)	-0.088 (0.089)	-0.088 (0.105)
Climate1	0.750*** (0.184)	0.78*** (0.17)	6.720* (2.890)	12.7*** (3.24)	8.720** (3.08)	9.250* (4.34)	-0.210 · (0.120)	-0.197 (0.145)
Climate2	-0.123 (0.100)	-0.174 (0.107)	-0.104 (1.200)	-1.800 (1.61)	3.860* (1.84)	4.720 · (2.46)	0.114 · (0.0652)	0.125 · (0.074)
Adj R²	0.242	0.413	0.138	0.261	0.199	0.272	0.118	0.134
RSE	0.922 on 71 df	0.774 on 71 df	12.90 on 84 df	10.20 on 84.00 df	17.20 on 62 df	17.10 on 62 df	0.663 on 89 df	0.699 on 89 df

Significance codes: $p < 0.001$ '***' 0.01 '**' 0.05 '*' 0.1 '.'

[†] = outcome variables were log-transformed

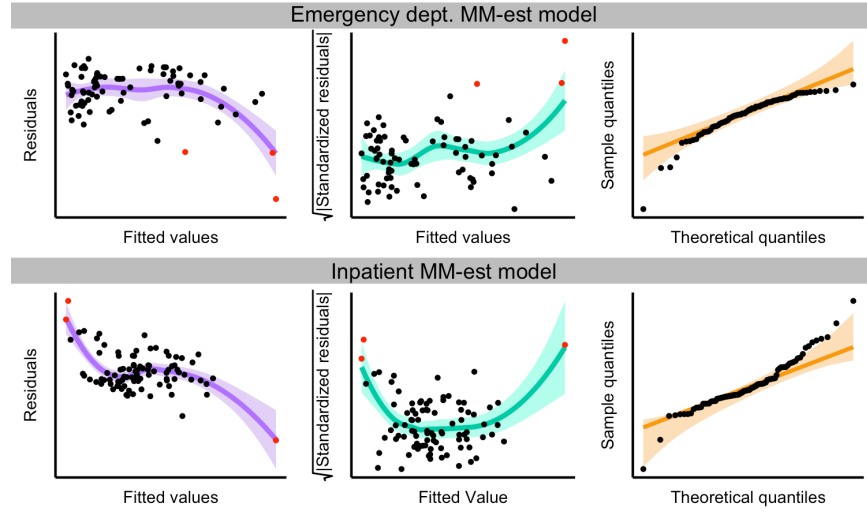


Figure 4.4: Residual analysis for emergency room and inpatient MM-estimator models. The left plots show residuals versus the fitted values. The center plots show the standardised residuals (mean of zero and variance of one) versus the fitted values. The right plots show the Quantile-Quantile (QQ) plot; this plot evaluates the assumption that the errors are normally distributed. Both models show slight deviation at the ends. All residual plots show a colored trend line with its respective LOESS (locally estimated scatterplot smoothing) ribbon. Outliers are colored in red.

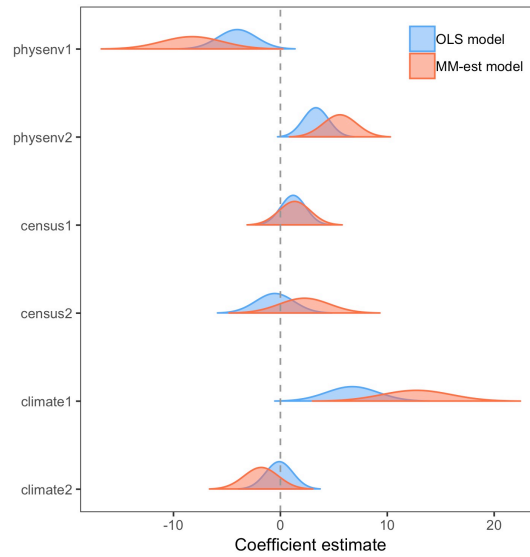


Figure 4.5: Normally distributed coefficients for the OLS and MM-estimator models of inpatient rates. The dotted line centered at zero is drawn to imply significance of the explanatory variables; the further away from zero the coefficient distribution lies, the more significant. In the MM-estimator model, the built environment PC1 score is significant at the 0.01 level; the built environment PC2 score and climate PC1 score are significant at the 0.001 level, and correspondingly, neither tail touches the dotted line.

All health outcomes were better explained by the MM-estimator than Ordinary Least Squares, as evidenced by universally higher adjusted R-squared values and lower residual standard errors (Table 4.3). The better model fit also changed the significance levels and distributions of the explanatory variables for both the inpatient and primary healthcare models (Figure 4.5). Of the four regression models, mortality had the lowest explanatory power. Residual analysis of the emergency room and inpatient MM-estimator models shows that even though the MM-estimator specialises in limiting the influence of outliers, it cannot completely eliminate all outlier influences on model behavior (Figure 4.4).

CLIMATE PC1 SCORE IS DECOMPOSED FOR FURTHER ANALYSIS.

The climate PC1 score is the most important variable in my dataset because it explains large changes in emergency room, inpatient admission, and primary healthcare rates at a statistically significant level. The strongest association is between climate PC1 score and emergency room rates. Graphically plotted onto a map of the Northern Territory, it is clear there is a strong positive association between climate PC1 score and emergency room rates (Figure 4.6).

(a) Emergency room rates

(b) Climate PC1 scores

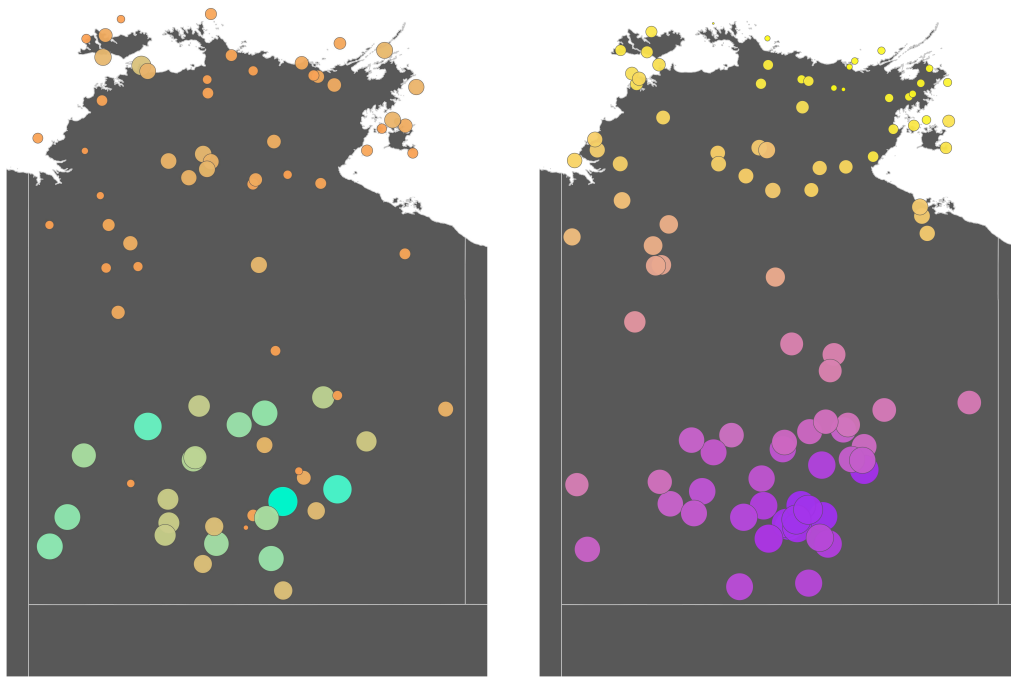


Figure 4.6: Emergency room rates and climate PC1 scores mapped onto community coordinates in the Northern Territory. On the left side, the larger, bluer dots represent higher emergency room rates; as the dots get smaller and more orange, the rate decreases. On the right side, the larger, purple dots represent higher climate PC1 scores; as the dots get smaller and more yellow, the score decreases.

To address one of the most salient possibilities for confounding in the relationship between climate PC1 score and health outcomes, I also undertook an analysis of healthcare centers. Given the North-South gradient of emergency room rates, one plausible argument could be that rather than a causal climate effect, there are simply more emergency departments in the south compared to the north. Another plausible argument is that there are fewer primary healthcare centers in the south, which means that routine illnesses are not being addressed at the point of care, and so patients worsen until critical emergency measures are required. To test these hypotheses, I mapped healthcare centers and hospitals, as well as the built environment PC1 score (Figure 4.7). Healthcare centers are evenly spread throughout the NT; and for those communities without healthcare centers, it appears they are located relatively close to one of the six NT hospitals. This finding corresponds perfectly with the built environment PC1 score, which also shows an even spread throughout the NT. Health centers are one of the top loading variables in the decomposition of the built environment PC1 score, so it is a strong vote of confidence that the two plots match up.

(a) Emergency room rates

(b) Built environment PC1 scores

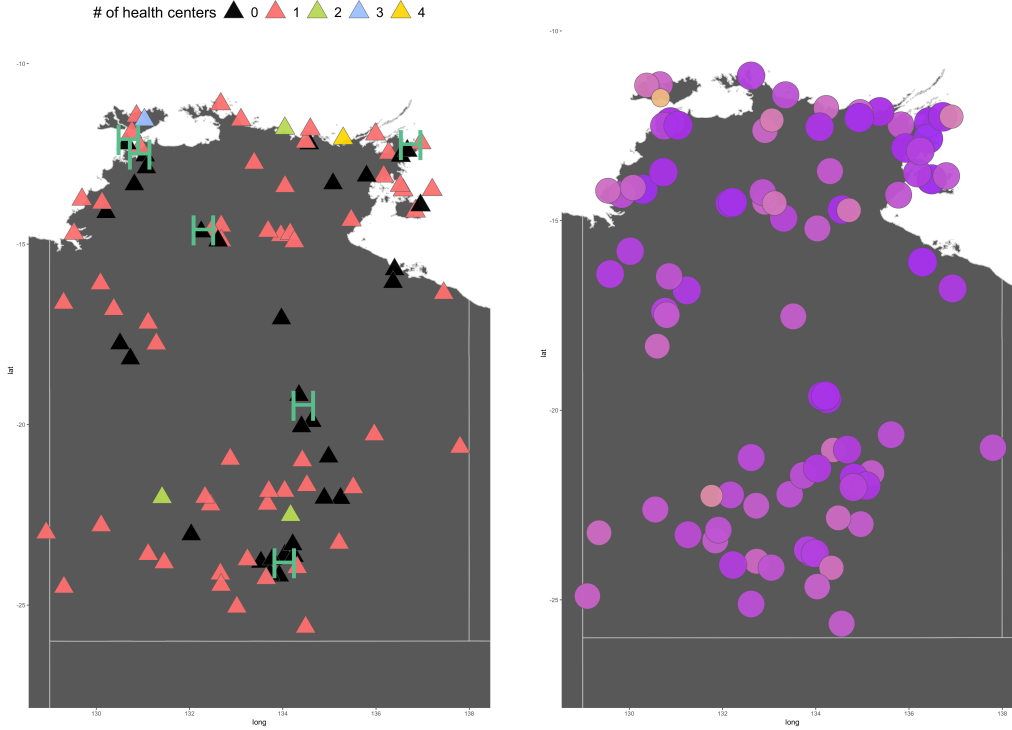


Figure 4.7: In (a), each triangle represents a community. The color of the triangle corresponds with how many healthcare centers are located in that community. Green “H” symbols represent the six hospitals located in the NT. In (b), built environment PC1 scores are mapped onto community coordinates, using the same exact size and color gradient as that of Figure 4.6b. The homogeneity of size and color in this plot shows that built environment PC1 scores are relatively similar between communities.

According to the MM-estimator, a unit increase in the climate PC1 score is significantly associated with a 78% increase in emergency room rates, 6.7 percentage point increase in inpatient rates, and 9.3 percentage point increase in primary healthcare rates. In order to interpret the relationship between climate PC1 score and health outcomes, the climate PC1 score is decomposed into its constituent parts: i.e. its 67 individual variables and their respective loadings. The heatmap portion of Figure 4.8 shows how 42 variables (of the 67 climate variables) map onto communities. Each row of the heatmap represents a community, arranged by decreasing latitude to match the maps in Figure 4.6 and Figure 4.7. Each column of the heatmap represents a climate variable, grouped by atmospheric moisture, Excess Heat Factor, Apparent Temperature, and Wet Bulb Globe Temperature. The bar graph on top of the heatmap shows the magnitude and direction of the varimax-rotated loading factors affiliated with each variable for climate PC1.

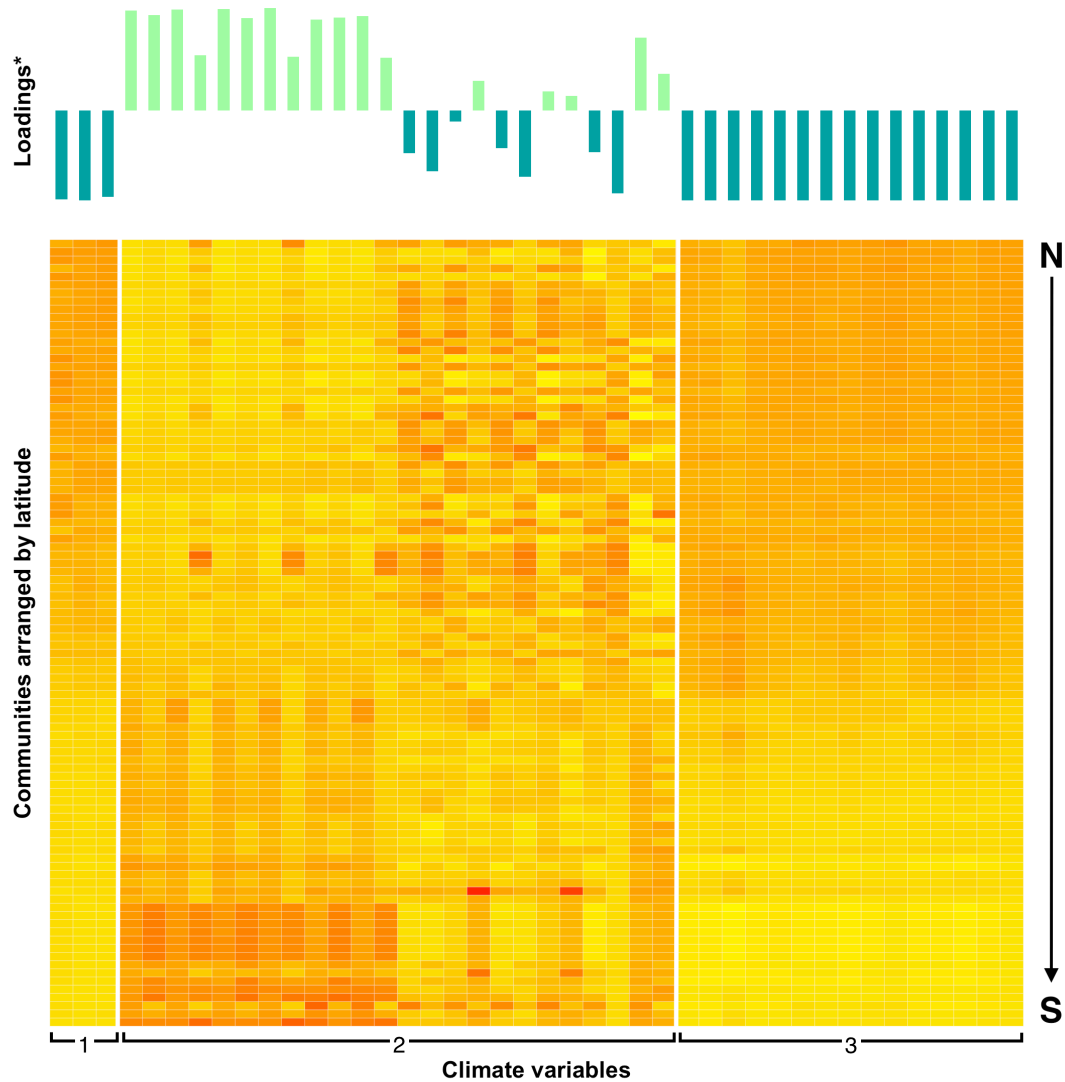


Figure 4.8: Selected climate variables heatmapped onto communities, with their respective varimax-rotated loading factors indicating magnitude and direction in the bar graph above. Section 1 consists of atmospheric moisture variables, section 2 consists of Excess Heat Factor variables, and section 3 consists of apparent temperature and wet bulb globe temperatures.

Atmospheric moisture, apparent temperature, and wet bulb globe temperature (sections 1 and 3 of the heatmap, [Figure 4.8](#)) show a consistent gradient pattern from north to south, with the northernmost communities experiencing wetter, hotter, and more humid weather than the southernmost communities. In terms of how they load onto the climate PC1 score, all of these variables have a large negative loading factor. In section 2 of the heatmap, the variables describing Excess Heat Factor – such as duration, load, and maximum values – show a more varied pattern. Variables for EHF values and load are on the left side of section 2; they appear to follow a seasonal pattern, as every column represents the average for

either the year or for each season individually (i.e. spring, summer, and autumn; winter is excluded due to null values). On the right side of section 2, the EHF variables include count and duration of heatwave days. These variables are also segregated by season, but the pattern appears to be consistent throughout the year; all together, these EHF variables have the only positively correlated loading factors, and they create a gradient pattern opposite to that of the non-EHF variables. See [Table 4.4](#) for the full descriptions of the variables in each section, as well as the measuring period, rotated loading value, and direction of gradient.

Table 4.4: Variables included in heatmap, with their corresponding descriptions and loading factors. All variables are averaged across the period 2000-2015.

Col.	Variable	Description	Measuring pd	Rotated loading	Gradient
Section 1: Atmospheric moisture					
1	Rainfall total	Measured in mm	Year	-1.087	N - S
2-3	Vapour pressure	Measured in hPa at 0900 and 1500	Year	-1.161 [†]	N - S
Section 2: Extreme Heat Factor (EHF)					
4-7	Values	Average EHF values over all heatwave days (i.e. days with EHF>0)	Year & season*	1.08 [†]	S - N
8-11	Values maximum	Maximum EHF value of all heatwave days	Year & season*	1.074 [†]	S - N
12-15	Load	Cumulative total of EHF values during periods of consecutive heatwave days	Year & season*	1.017 [†]	S - N
16-19	Duration	Average length of days for each period with consecutive heatwave days	Year	-0.521	N - S
			Spring	-0.744	N - S
			Summer	-0.133	N - S
			Autumn	0.364	-
20-23	Duration maximum	Maximum length of days of all periods with consecutive heatwave days	Year	-0.458	N - S
			Spring	-0.808	N - S
			Summer	0.237	N - S
			Autumn	0.180	-
24-27	Count	Number of heatwave days	Year	-0.507	N - S
			Spring	-1.011	N - S
			Summer	0.897	-
			Autumn	0.449	-
Section 3: Apparent Temperature (AT) and Wet Bulb Globe Temperature (WBGT)					
28-32	AT maximum	Heat index calculated for the hottest part of each day, derived using maximum temperature and vapour pressure at 1500	Year & season	-1.226 [†]	N - S
33-37	AT minimum	Heat index calculated for the coolest part of each day, derived using minimum temperature and vapour pressure at 0900	Year & season	-1.208 [†]	N - S
38-42	Simplified WBGT maximum	Maximum value of all SWBGT values	Year & season	-1.23 [†]	N -S

* EHF seasons exclude winter

† For variables with multiple measurements (i.e. vapour pressure measured at 0900 and 1500; EHF values measured for the year and seasons separately), the rotated loadings were grouped by variable and then averaged if all rotated loadings had the same sign.

To further clarify the N-S gradient described here, [Figure 4.9](#) shows plots of the three different types of heat stress variables, mapped onto the NT coordinates. Note that the EHF variable has the opposite gradient as the apparent temperature and wet bulb globe temperature variables.

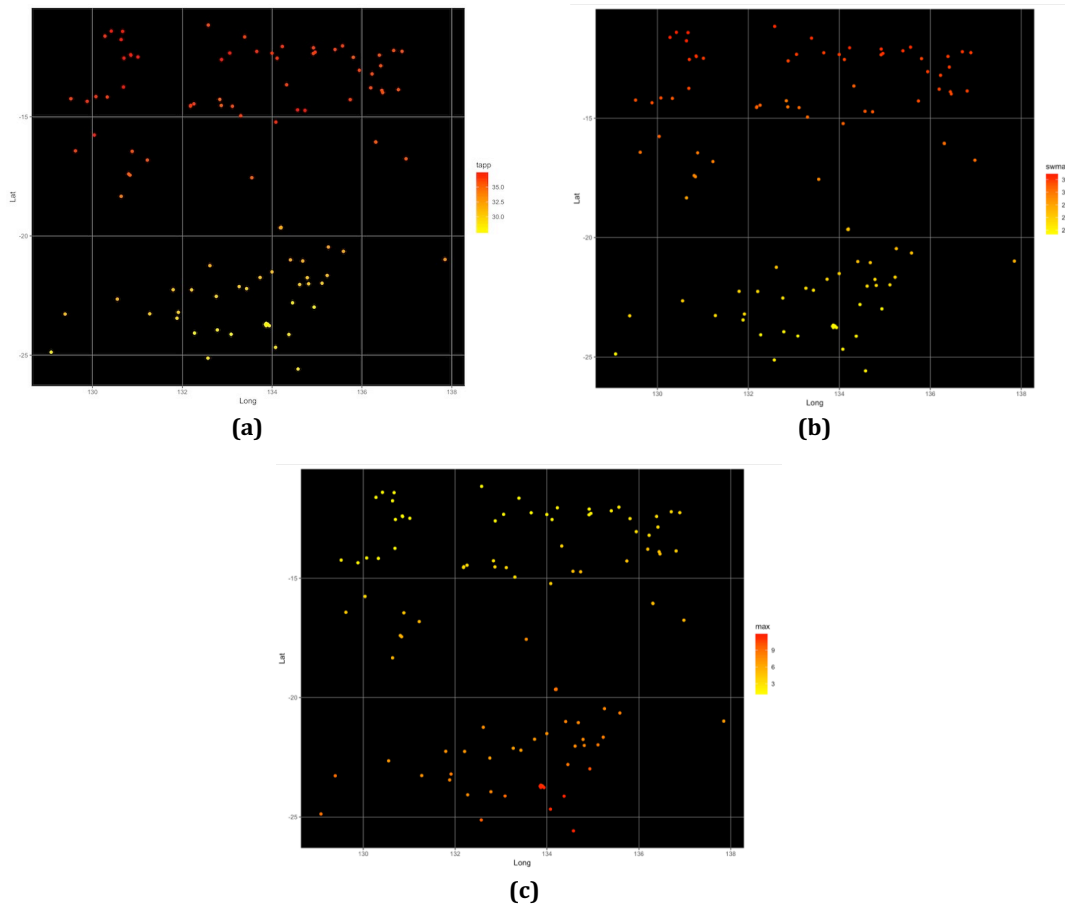


Figure 4.9: Variables from the three heat stress categories, mapped onto the coordinates of the NT: **(a)** Apparent Temperature maximum; **(b)** Simplified Wet Bulb Globe Temperature Maximum; and **(c)** Excess Health Value maximum

4.5 DISCUSSION

The most important regressor in all the cardiometabolic-related models was the climate PC1 score. According to the MM-estimator, a unit increase in the climate PC1 score is significantly associated with a 78% increase in emergency room rates, 6.7 percentage point increase in inpatient rates, and 9.3 percentage point increase in primary healthcare rates. When decomposing the climate PC1 score, I found that a community with a large positive climate PC1 score experiences lower apparent temperature and humidity but greater maximum heatwave severity, particularly in the spring and summer. My results agree with recent previous findings on the importance of relative heat over absolute temperature or humidity,^{86,179,180} but provide the first detailed analysis of this phenomenon among Indigenous communities in Australia. EHF is a site-specific indicator of relative heat, so the

community with the highest absolute temperature year-round does not necessarily have the highest EHF value, as is the case in my study (Figure 4.8). EHF values take into account the idea that people will, to some extent, acclimatise to their local climate and temperature variation throughout the year, adapting through their physiology, culture, and engineered supporting infrastructure;¹⁸¹ and so, it is the sudden rises in temperature above that of the recent past that people are least equipped to handle.¹⁷⁸ My results indicate that EHF heat-wave duration and count are not as important as the actual EHF values and load for the population studied here.

In terms of the other variables in the regression models, the census PC scores do not appear to have any large effect, excepting a modestly significant coefficient on census PC2 score in the primary healthcare model. This may imply that the positive effect of employment outweighs the negative effect of household overcrowding. Alternatively, it may imply that in larger households, there are more family members to look after the sick, thus reducing the number of people seeking primary healthcare attention. A positive effect of built environment PC2 score is statistically significant in both inpatient and primary healthcare rates, which is interpreted as the more isolated a community is, the higher the rates of those seeking medical attention. Contrary to this, the inpatient model has a statistically significant negative coefficient on built environment PC1 score, which implies that inpatient rates decrease as the community scores lower in development. While this relationship seems counterintuitive, it can be interpreted from a purely logistical point of view: community A may have the same health burden as community B, but if community A is less developed than B, they may not have the proper inpatient facilities to send their sick to. This would result in an association between lower development in terms of the built environment and lower inpatient rates. The climate PC2 score is only modestly significant in the primary healthcare model, which may imply that shorter heatwaves are associated with higher primary healthcare rates. However, it is important to note that the climate PC2 score provides no information about the frequency or intensity of heatwaves, only the duration.

Increased hospital admissions due to “heatwaves” (variably defined) have been reported in Adelaide,^{182,183} Melbourne,¹⁸⁴ Sydney,¹⁸⁵ metropolitan New South Wales,¹⁸⁶ and Darwin.¹⁸⁷ This study is a natural extension of previous work done in the Northern Territory that found differential effects of temperature extremes on hospital admission rates for respiratory and cardiovascular diseases between Indigenous and non-Indigenous Australians in the Northern Territory.^{188,189} These are the only two studies conducted in Australia that study the specific effects of climate extremes on the health of Indigenous peoples; all other Australian studies largely neglect this subpopulation. Both Webb et al. (2014) and Green et al. (2015) used daily maximum and minimum temperatures in each designated geographi-

cal region to calculate the relative lowest percentile “very cold” and highest percentile “very hot” daily extremes. Both studies then used Poisson log-linear models to study the effect of these weather variables on hospital admissions from five Northern Territory hospitals.

Both Webb et al. (2014) and Green et al. (2015) concluded that Indigenous Australians in the Northern Territory are more sensitive to extreme ambient temperature conditions than the non-Indigenous population, based on two categories of cardiac diseases and two categories of respiratory diseases, respectively. This is important to determine, especially as it confirms that health disparities between Indigenous and non-Indigenous may be exacerbated by climate change – however, what is lacking from these analyses is the inherent heterogeneity *among* Indigenous populations in the Northern Territory, as well as the many potential confounding variables that exist within the built and social environments. Additionally, using the 95th percentile of ambient temperatures is an efficient but crude method to study extreme heat. This method does not take into account the extent to which heat is dissipated overnight following a very hot day, which ultimately dictates the accumulating thermal load – or “excess heat” – impacting vulnerable people and systems.¹⁷⁸ Lastly, the Poisson log-linear model was calculated using separate estimates for Indigenous and non-Indigenous populations. This potentially discards a lot of shared information in unobserved error terms; whereas spatially dependent random effects in disease mapping is considered as a way of adjusting for unknown confounders.^{190,191}

STRENGTHS OF STUDY

In the current study, I have extended the health outcomes beyond cause-specific admission rates; I was able to comment on primary healthcare, emergency department, and mortality rates in addition. My cardiometabolic criteria for hospital admissions meant I could include conditions such as Type 2 diabetes mellitus, obesity, stroke, nephritic syndrome, and renal failure – in addition to the cardiac disease hospital admissions that Webb et al. (2014) examined. This study extends previous work by broadening the spatial area of research and deepening the descriptive scope. Previous studies linking extreme heat and health in Australia have focused on singular prescribed areas, where wholly contiguous metropolitan areas have been divided up by administrative boundaries. My present study is especially equipped to measure spatial variation between places, not just within on circumscribed place, because I analyse wholly discrete community points across a dispersed geographical area. In terms of sheer geographical area, my study covers immense ground — the Northern Territory spans 1.348 million square kilometers.¹⁹²

My PCA regression also allowed a much more comprehensive girth of analysis: I was ultimately able to include information from 33 built environment variables, 118 socioeco-

nomic census variables, and 67 climate variables. PCA is the most suitable tool for my study because it tackles both overspecification and multicollinearity without losing any important information. While variable selection methods such as LASSO (Least Absolute Shrinkage and Selection Operator) and Ridge regression analyses do select features that aim to minimise the model size and maximise the model fit, these methods do not directly address the issue of multicollinearity, which arises when there are significant correlations within the data. These methods also struggle to account for relationships between explanatory variables and can discard important information contained in certain variables due to a surface-level lack of significance. In the current study, the huge swath of data analysed serves the double function of addressing potential confounders, as well as allowing for nuanced interpretation – i.e. I was able to investigate precisely which aspect of extreme temperature (i.e. absolute value, relative value, duration) is most strongly related with negative health outcomes.

LIMITATIONS

That the census scores are not generally significant in these models may be an indicator of measurement bias rather than a lack of actual effect – retrieving census data from these isolated, remote communities may be unreliable. The cardiometabolic health outcomes do not capture the entire health burden associated with this health condition, since hospital admission rates are typically only seen when the disease has progressed to a very severe degree. The inclusion of primary healthcare rates should negate this limitation, but here too there may be selection bias (i.e. only certain types of people seek out formal Westernised healthcare, which is what is modelled here). Additionally, a focus on cardiometabolic health does not represent the total health burden experienced by a given community. Another limitation of the study is that although I used health, census, and built environment data from 2010-2015, the small sample size of my observations meant that I could not perform any longitudinal analyses. The cross-sectional, pooled nature of this study therefore limits inference on the temporal direction of associations, as noted in Carroll et al. (2019).¹⁹³ Lastly, note that the composition of the raw EnRICH dataset is meaningful only in terms of contextualising the final principal component (PC) scores (Figure 4.2) – in other words, since built environment has fewer variables initially, the two built environment PCs have fewer “moving parts” contributing to their scores. The census and climate PCs are thus inherently more difficult to interpret because they have more variables contributing to the scores.

CONCLUSION

In this study, accounting as best I could for built environment and socio-demographic variations, I explored the link between climate and health among Aboriginal and Torres Strait Islander communities in northern Australia. Rather than handpicking several climate variables, I processed and analysed 67 climate variables and their relationships to four different types of health outcomes (emergency room rates, inpatient admission rates, primary health-care rates, and cardiometabolic-related mortality rates) to see if I could detect a significant climate effect. Using this methodology, I am able to extract and condense information from 218 variables into six meaningful indicators (i.e. the six principal components that ultimately form my final models). Because these six indicators are composed of many adjustment variables, I was able to capture the nuances of built environment, census, and climate data for my population. This type of comprehensive, holistic model building is crucially important in today's age of complex interacting factors.

Climate change is a big scam for a lot of people to make a lot of money.

Donald Trump

5

Conclusion

[Chapter 1](#) of this thesis introduced the budding field of planetary health, detailed an overview of extreme weather and cardiometabolic health outcomes, and laid out the motivations, aims, and rationales for the two studies conducted within this Masters project. [Chapter 2](#) queried the available literature on the nexus between extreme weather and health, and displayed the results in the accessible (and rather colorful) format of bibliographic network analysis. [Chapter 3](#) and [Chapter 4](#) dove into the intricacies of the two studies conducted, with the specific conclusions outlined below.

5.1 STUDY 1: SEA NUTRIENT SUPPLY GLOBALLY

Previous studies have established the negative effect of EWEs on food production, but few have made the final link between food disruption and human nutrition. In this study, I aimed to bridge EWEs and nutritional supply, through the quantification of micronutrient, macronutrient, and fiber supply fluctuations during the year of major EWEs. I found modest – but significant – micronutrient and macronutrient supply declines in the year-of-event globally and among UN-designated low-income groups. I identified Landlocked Developing Countries as an especially vulnerable subpopulation, and further contextualised the magnitude of deficits in nutrient supplies by comparing them to the Recommended Di-

etary Allowances for children aged 1-3 years. Due to socioeconomic factors and the physiology of human development, children in low-income settings not only face the greatest exposure to environmental risk, but they also stand to bear the most severe long-term health consequences. As climate change increases the volatility of EWEs worldwide, it is imperative that the international community addresses the nutritional impacts of EWEs, especially within low-income settings.

While agricultural yields have been consistently increasing since the Industrial Revolution, the world has also witnessed an increase in the absolute number of people *and* the percentage of people in the world with insufficient dietary energy consumption in 2017³⁷ Current estimates indicate that 250 million children younger than five years in low-income and middle-income countries are at risk of not reaching their developmental potential.¹³⁵ The EWE effects found in this study could significantly exacerbate current malnutrition burdens, as well as endanger those children barely scraping by on the edge of adequate nutrition. With climate change projected to increase the frequency and intensity of EWEs globally, it is expected that the resulting effects on health will further increase inequities between rich and poor nations, and moreover, within nations.^{194,195} Given that Landlocked Developing Countries have historically struggled in response to EWEs, the international community must not neglect this highly vulnerable subgroup, and should instead make concerted efforts to work with these countries to develop appropriate nutritional and agricultural interventions.

5.2 STUDY 2: PCA REGRESSION IN NORTHERN AUSTRALIA

Using my robust PCA regression methodology, I was able to extract and condense information from 218 variables into six meaningful indicators (i.e. the six principal components that ultimately form my final models). Because these six indicators are composed of many adjustment variables, I was able to capture the nuances of physical environment, census, and climate data for my population. This type of comprehensive, holistic model building is crucially important in today's age of complex interacting factors.

My results agree with recent previous research that it is not absolute temperature or humidity that most negatively harms health, but rather relative heat. EHF is a site-specific indicator of relative heat, so the community with the highest absolute temperature year-round does not necessarily have the highest EHF value, as is the case in the present study (Figure 4.8). EHF values account for the likelihood that people will, to some extent, acclimatise to their local climate and temperature variation throughout the year, adapting through their physiology, culture, and engineered supporting infrastructure;¹⁸¹ and so, it is

the sudden rises in temperature above that of the recent past that people are least equipped to handle.¹⁷⁸ My results also indicate that EHF heatwave duration and count are not as important as the actual EHF values and load.

The federal government's latest Closing the Gap report has confirmed that their target of halving the gap in Indigenous and non-Indigenous child mortality rates by 2018 was not met, and their target to close the gap in life expectancy by 2031 is not on track.¹⁴³ These projections did not take into consideration the additional effect of extreme heat on health outcomes; nor the fact that northern Australia is expected to experience more frequent extreme heat events with each passing year.¹⁹⁶ Collective action on addressing the health inequities between Indigenous and non-Indigenous Australians will have to include a fuller understanding and appreciation of how climate variables further exacerbate existing health conditions.

5.3 WHERE TO FROM HERE?

The extreme weather impact on human health is an urgently important area to research right now— I have only covered a modicum of ground with my two studies, and there are many ways forward to advance this research area. For example, while measuring supply fluctuations is important (as I did in my first study), measuring actual nutrient consumption would more closely align with health consequences. A person's nutritional health is not necessarily dependent on what nutrients are physically available, but rather, what nutrients one has *access* to and consumes. Future studies that focus on the link between supply and consumption should identify breakdowns in the supply chain, precisely when they occur post-EWE, and who is most affected. As for the second study, now that we have identified extreme relative heat as a specific environmental trigger that exacerbates cardiometabolic outcomes for Indigenous communities in northern Australia, future research should go into how best to alleviate the health impacts of these sudden onset extreme heat episodes. Having a targeted focus on relative heat means stepping away from the current shotgun approach of battling high absolute heat.

If we are to make a serious attempt at closing the gap in health inequality between Indigenous and non-Indigenous Australians – and more broadly, peoples of rich and poor nations around the world – then we must take a planetary health perspective. We have seen time and time again that climate change is a justice issue: that those who stand to be most affected by climate change will not be those who caused it.¹⁹⁷ Minorities and Indigenous peoples all around the world are especially vulnerable to a changing climate, largely due to a complex mix of socioeconomic marginalisation, historical legacies of discrimination, physi-

cal exposure to climate hazards, and close cultural relationships to the natural world.^{198,199} Yet while the poor stand to lose the most, the health effects of climate change will touch us all in one way or another— whether it is through re-emerging infectious diseases from deforested areas, asthma and respiratory illnesses from air pollution, reduced nutrient content in agricultural output, or mental illness from environmental damage and resettlement.⁹ Wendell Berry, American novelist, poet, essayist, environmental activist, cultural critic, and farmer, wrote in *The Long-Legged House* in 1969:

“We have lived our lives by the assumption that what was good for us would be good for the world. We have been wrong. We must change our lives so that it will be possible to live by the contrary assumption, what is good for the world will be good for us. And that requires that we make the effort to know the world and learn what is good for it.”²²

The most important research questions in human health are far too complex and urgent to ignore the need for interdisciplinary answers. Just as we shape our environment, it too shapes us; and to solve the health crises of today, we must expand our conception of health to beyond the human body. It is a way of thinking that Indigenous Australians have been promoting for far longer than the international community has been listening, and it is high time that the research responds.^{200–203}

And as long as there are people in power denying the reality of changing climate and its effect on humanity, researchers have a moral obligation to prove them wrong. This thesis, looking at the nutritional impact of extreme weather events as well as the extreme heat effect on cardiometabolic health outcomes, contributes to just one tiny piece of the enormously complex climate and health puzzle we face today. My primary goal as a researcher is to continue contributing to this rapidly growing field of interdisciplinary change-makers and do what little I can towards crafting a better, brighter, kinder future.

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Appendix: List of Materials

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The global effect of extreme weather events on nutrient supply: a superposed epoch analysis



Caro S Park, Elisabeth Vogel, Leila M Larson, Samuel S Myers, Mark Daniel, Beverley-Ann Biggs

Summary

Background To date, the effects of extreme weather events on nutrient supply within the population have not been quantified. In this study, we investigated micronutrient, macronutrient, and fibre supply changes during 175 extreme weather events within 87 countries in the year that a major extreme weather event occurred, with a targeted focus on low-income settings.

Methods We collected data from the International Disasters Database and the Global Expanded Nutrient Supply model for the period 1961–2010, and applied superposed epoch analysis to calculate the percentage change in nutrient supply during the year of an extreme weather event relative to its historical context. We composited globally and by subgroup (EU, landlocked developing countries, least developed countries, low-income food deficit countries, and net food-importing developing countries). Lastly, we reported nutrient supply changes in terms of recommended dietary allowance for children aged 1–3 years.

Findings Globally, all micronutrient supplies had a modest negative percentage change during the year of an extreme weather event; of these effects, those that reached an $\alpha=0.05$ significance level included calcium, folate, thiamin, vitamin B6, and vitamin C, with nutrient supply changes ranging from -0.40 to -1.73% of the average supply. The effect of an extreme weather event was especially magnified among landlocked developing countries and low-income food deficit countries, with significant nutrient supply changes ranging from -1.61 to -7.57% of the average supply. Furthermore, the observed nutrient supply deficits in landlocked developing countries constituted a large percentage (ranging from 1.95 to 39.19%) of what a healthy child's sufficient average dietary intake should be.

Interpretation The global effects of extreme weather events on nutrient supply found in this study are modest in isolation; however, in the context of nutrient needs for healthy child development in low-income settings, the effects observed are substantial.

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Introduction

Extreme weather events are defined as especially severe or unseasonal weather phenomena at the extremes of the historical distribution and rare for a particular place or time.¹ Agricultural production has been shown to decline during and after an extreme weather event,^{2–7} and some case studies have specifically linked extreme weather events to nutritional outcomes, such as risk of child stunting due to drought-related crop loss in Uganda⁸ and persistent reduced growth among flood-exposed children in Bangladesh.⁹ Although many studies have referred to extreme weather events threatening food security, specifically in developing countries,^{10–12} no study has yet quantified the global impact of extreme weather events on total nutrient supply. Yet it is imperative that we investigate this relationship now, as it is projected with high confidence that by the end of this century, we will have witnessed global increases in the frequency and magnitude of heatwaves, heavy precipitation, tropical cyclones, and droughts.^{13–16}

Understanding historical nutrient supply fluctuations caused by extreme weather events will inform future

estimates of nutritional impacts in the aftermath of such events. To this end, it is necessary to acknowledge the socioeconomic factors—such as human geography, economic development, and governance structure—that modulate a nation's response to extreme weather events.^{17–22} Recovery is particularly difficult in low-income settings, where infrastructure maintenance and equitable food distribution are challenges even in fair weather. A vast majority of the world's 821 million undernourished people and 50.5 million children under 5 affected by wasting (low weight for height) reside in low-income countries, and they stand to lose the most from further nutrient supply fluctuations.²³

This study builds on previous research by Lesk and colleagues,²⁴ where national cereal production losses resulting from extreme weather events were estimated using superposed epoch analysis. We used a modified superposed epoch analysis method to test whether extreme weather events have a significant impact on micronutrient, macronutrient, and fibre supplies in the year that an extreme weather event occurred (so-called year-of-event). Acknowledging the socioeconomic gradient of exposure,

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Research in context

Evidence before this study

A bibliometric network analysis was done for the systematic query of literature in Web of Science. The following search terms were used in the title: *health* OR well-being OR wellbeing OR welfare OR *nutrition* OR *hospital* OR mortality OR morbidity. The following search terms were used in the topic: ("high-impact weather" OR "natural disaster" OR "natural hazard" OR drought OR flood OR heatwave OR "cold spell" OR hail OR cyclone OR frost OR storm OR (extreme* AND (weather OR climate OR precipitation OR temperature OR dry OR wet OR cold OR hot OR heat))) AND (human OR public OR population)". In the space of extreme weather events and nutrition, the most extensively studied topic was the effect of extreme weather events on cereal production. There is broad consensus that globally, droughts reduce cereal yield. Evidence for the effect of other extreme weather events (eg, floods, storms, extreme heat, extreme cold) was found largely in local case studies. Few studies have determined the nutritional consequences of these weather-related shocks, and those that have are limited in geographical scope.

Added value of this study

At best, food production analysis can only imply a link to food consumption. By shifting the focus onto nutrient supply,

we attempted to measure the outcome (nutrition, proxied by nutrient supply) rather than the input (consumption, proxied by food production). To date, this is the first quantification of the nutrient supply reductions during extreme weather events, globally and within various low-income subgroups. By further framing the nutrient supply reductions in terms of child recommended dietary allowances, we also provided a practical, relevant, and important context for interpreting the results of this superposed epoch analysis.

Implications of all the available evidence

This study echoes previous literature which urges the international community to tackle the issue of malnutrition among vulnerable populations, especially because the nutritional landscape is poised to worsen with climate change. Our results show a significant reduction of micronutrients and macronutrients during an extreme weather event globally; this effect is further magnified within landlocked developing countries. These results point to a clear need to provide supplementation before, during, and in the immediate aftermath of an event. Children are a particularly susceptible subpopulation of interest, given how certain nutritional deficiencies can have irrecoverable consequences for health, growth, and development.

we adhered to the grouping conventions of the UN and the World Trade Organization for our subgroup analyses. Lastly, we contextualised our results by comparing the year-of-event nutrient supply changes with the universally accepted recommended dietary allowance (RDA) for children aged 1–3 years. The RDA is the average daily dietary intake that is sufficient to meet the nutrient requirements of nearly all healthy individuals in a group.²⁵ Regarding environmental hazards, children are an especially susceptible subpopulation because of the high nutritional needs of their developing physiology.^{26,27} As the evidence base grows for the long-term implications of early life malnutrition on lifelong cognitive, social, and physical development,^{28–31} it is not only fitting, but crucially important, that we also take a child's health perspective on the impacts of extreme weather events.

Methods

Data collection

We used the Global Expanded Nutrient Supply model (GENuS) and the International Disasters Database (EM-DAT) as the basis of our analysis. The GENuS model provides historical time series of 23 individual nutrient supplies at the national level for 152 countries from 1961–2011. The model's raw inputs—UN Food and Agriculture Organization (FAO) production and trade data—are used to calculate national supplies of edible food, which are then matched with nutrient density charts from regional food composition tables to estimate national nutrient supplies.¹² The EM-DAT database is the

world's most comprehensive collection of natural and technological disasters from 1900 to the present day. Using EM-DAT, the following extreme weather events were extracted for the period 1964–2010: floods, droughts, extreme heat events, extreme cold events, and storms (see appendix p 16 for definitions). The extreme weather events were separated into single-year events or multi-year events. Extreme weather events were defined as multi-year if a country had the same type of extreme weather event for at least 2 years in a row. For this study, multi-year events did not have to be uninterrupted.

Any effects of extreme weather events on nutrition captured by this study must be substantial enough to overcome the limited spatial and temporal resolution of the GENuS and EM-DAT databases. In other words, because each event is identified by country and year, rather than by specific geographical coordinates and dates, we could only determine if one solitary event somewhere in the country at some point in the year ultimately affected the entire country's yearly nutrient supply. To overcome the challenges of poor data resolution in both time and space, we chose to isolate what we considered were the most severe extreme weather events. To be included in this study, an extreme weather event had to meet or exceed the 90th percentile of all recorded extreme weather events, across all countries with available data from 1964–2010 for at least one of the following conditions: total financial damage, in absolute terms or as a percentage of that country's gross domestic product (GDP) at the time of the extreme weather event; or total number of people affected,

See Online for appendix

For GENuS see <https://dataverse.harvard.edu/dataverse/GENuS>

For EM-DAT see <https://www.emdat.be/database>

in absolute terms or as a percentage of that country's population at the time of the extreme weather event.

Extreme weather events that fulfilled the criteria for inclusion in this study were referred to as major extreme weather events (see appendix pp 3–4 for sensitivity analysis of threshold criteria). Population and GDP data were obtained from World Bank Open Data. Lastly, if a major extreme weather event coincided with at least one other major extreme weather event within 2 years of occurrence, then both extreme weather events were excluded to avoid conflating effects of multiple events (see appendix p 2 for complete exclusion flowchart). No ethical approval was necessary for this study; all data used are openly available online.

Data analysis

Superposed epoch analysis is a compositing approach that overlays multiple time series to identify a common signal in the data. It is preferred in cases where the response to particular events (eg, folate supply in response to extreme weather events) may be obfuscated by noise from other competing influences that operate at similar timescales (eg, seasonal variation of folate-rich produce). Superposed epoch analysis sorts data into categories dependent on a key synchronisation date, then compares the means of those categories. The superposed

epoch analysis method as applied here functions under the assumption that if the number of time series composited is sufficiently large, a common underlying response to the event should theoretically emerge in the composite, while the noise caused by other variables in the data (eg, intranational policy changes or economic shocks) should be distributed evenly—positively and negatively—and therefore disappear after averaging.³³

We applied the superposed epoch analysis method to nutrient supply data in the following manner. First, for all non-overlapping major extreme weather events, we produced 5-year windows by isolating the GENU model's nutrient supply data from 2 years before the event, the year-of-event, and 2 years after the event. For multi-year events, one year-of-event value was generated by averaging the values for each year of the event. Next, for each of these 5-year time series, the percentage change relative to the non-extreme weather event year average was calculated as follows:

$$\text{Effect of extreme weather event as percentage change} = \left[\frac{\sum_{i=1}^n (x_{it} - \mu_{iz})}{\mu_{iz}} \right]_{\text{nutrient}} \times 100\%$$

where i is the unique extreme weather event, t is the year of the event, and z is the 5-year window excluding t .

For World Bank Open Data see <https://data.worldbank.org/>

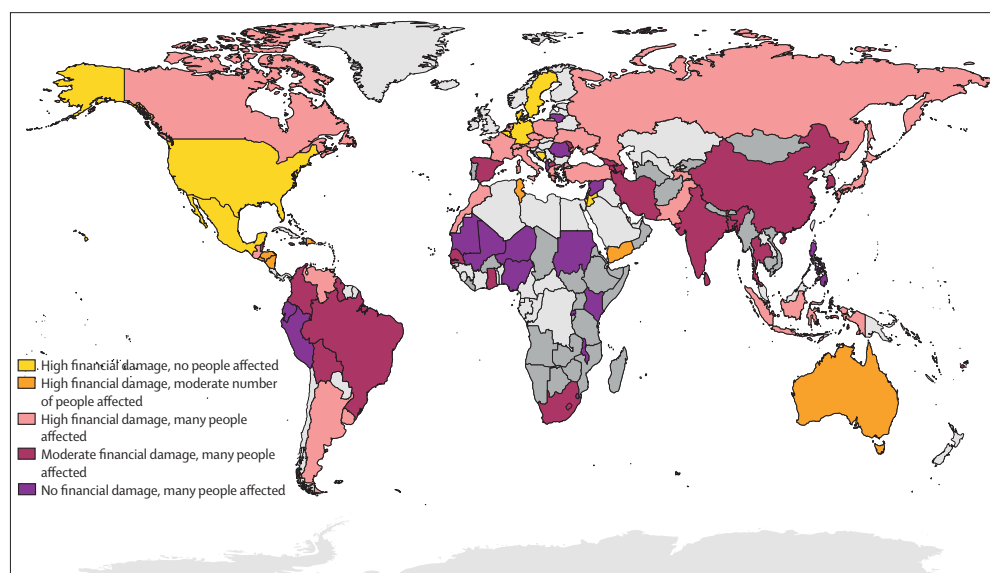


Figure 1: Map of countries with major extreme weather events included in this study, 1964–2008

Countries are represented in varying shades that indicate to what extent they satisfy both or either thresholds of financial damage and of people affected. 50 countries in dark grey were included in the preliminary analysis but excluded from the final analysis because of insufficient nutrient data. Countries in light grey were not included at all, because of dense overlapping time series of extreme weather events (see appendix p 2 for exclusion flowchart). Among the 87 countries included in this study, orange countries had extreme weather events with greater financial damage than people affected, and maroon countries had extreme weather events with more people affected than financial damage incurred. Yellow countries did not have any people affected by the extreme weather event and purple countries did not have any financial damage caused by an extreme weather event, as indicated by the International Disasters Database. Pink countries had extreme weather events with both high financial damage and many people affected.

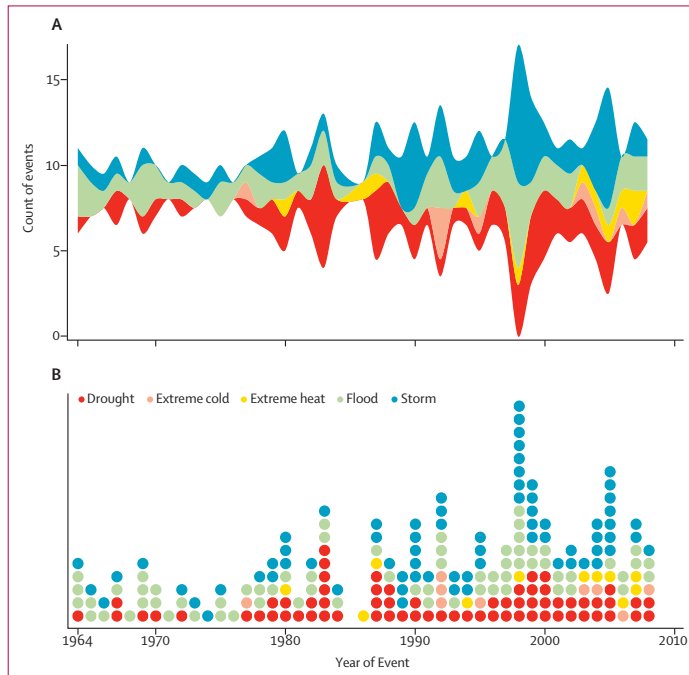


Figure 2: Stream-graph and dot-plot representations of all major extreme weather events from 1964–2008 included in this study

The total number of observations here is 227 extreme weather events. 67 were caused by droughts, nine by extreme cold, 11 by extreme heat, 67 by floods, and 73 by storms. The years 1985–2008 are modestly over-represented, because of a combination of better data collection methods, increasing effects of climate change, and a growing population and global economy. We disaggregated multi-year events to show the incidence of extreme weather events more accurately. Note that although we collected International Disasters Database data through 2010, extreme weather events from 2009 and 2010 were excluded from the final analysis due to dense overlapping events (appendix p 2).

For the FAOSTAT database see
<http://www.fao.org/faostat>

The non-extreme weather event year average is comprised of nutrient values from 2 years before and after the event and is used here as a rough proxy of what nutrient supply should look like in a non-disaster year in the country of interest. All percentage changes were then composited to produce a single time series analysis of the nutrients before, during, and after an extreme weather event. For these composites, 95% CIs were generated by bootstrapping the composite's individual components 1000 times and subsequently estimating the bias-corrected and accelerated CI; these 95% CIs correspond with a significance level of $\alpha=0.05$. See appendix (pp 1–2) for a graphical illustration of the superposed epoch analysis process.³⁴

To visualise the global extreme weather event dataset, a comparison group was generated by bootstrap to compare our global composited results to a business-as-usual group. The comparison group consisted of 1000 sets of fictitious extreme weather events (on average, around 150 extreme weather events per set), generated by randomly resampling years and countries

of occurrence within the same event distribution as the global extreme weather event dataset (see appendix p 4 for distributions). If a randomly generated fictitious extreme weather event happened to be a real event, it was still included in the comparison group. Thus, the comparison group represents the overall true distribution of nutrient supply, not just the distribution of supply for years without extreme weather events. Neither the real extreme weather event time series nor the comparison time series were de-trended to take into account positive, technology-induced food production growth over time, which has persistently increased food supply and thus the accessible nutrient supply. Instead, nutrient supply fluctuations due to extreme weather events are visualised by noting the difference between experimental and comparison composites.

To test which low-income countries within our global dataset were most sensitive to extreme weather event effects, we did a subgroup analysis. Using the same superposed epoch analysis procedure, we tested for significant nutrient supply changes within four of the five low-income subgroups that the FAO recognises in its FAOSTAT database: landlocked developing countries, least developed countries, low-income food deficit countries, and net food-importing developing countries. We did not separately analyse the small island developing states subgroup because these nations collectively lacked sufficient data; the few observations we did have were included in the global analysis. Details of the inclusion criteria for group membership, as well as the primary authority that establishes and maintains each group are shown in the appendix (p 13). We included the EU in the subgroup analysis to provide a high-income comparison. See appendix (pp 14–16) for the detailed list of all extreme weather events analysed in this study. Note that not all countries included in this study were part of a subgroup, and some countries were members of multiple subgroups.

Finally, to interpret our results in a relevant public health context, we compared the absolute change of each nutrient supply during the year-of-event to that nutrient's RDA for children aged 1–3 years as follows:

$$\text{Effect of extreme weather event as percentage of RDA} = \left[\frac{\sum_{i=1}^n (x_{it} - \mu_{iz})}{\text{RDA}} \right]_{\text{nutrient}} \times 100\%$$

where i is the unique extreme weather event, t is the year of the event, and z is the 5-year window excluding t .

As before, the 95% CIs were generated by bootstrapping the composite's individual components 1000 times and subsequently estimating the bias-corrected and accelerated CI, which corresponds with an $\alpha=0.05$ significance level.³⁴ All data processing, superposed epoch analysis, figures, and tables were

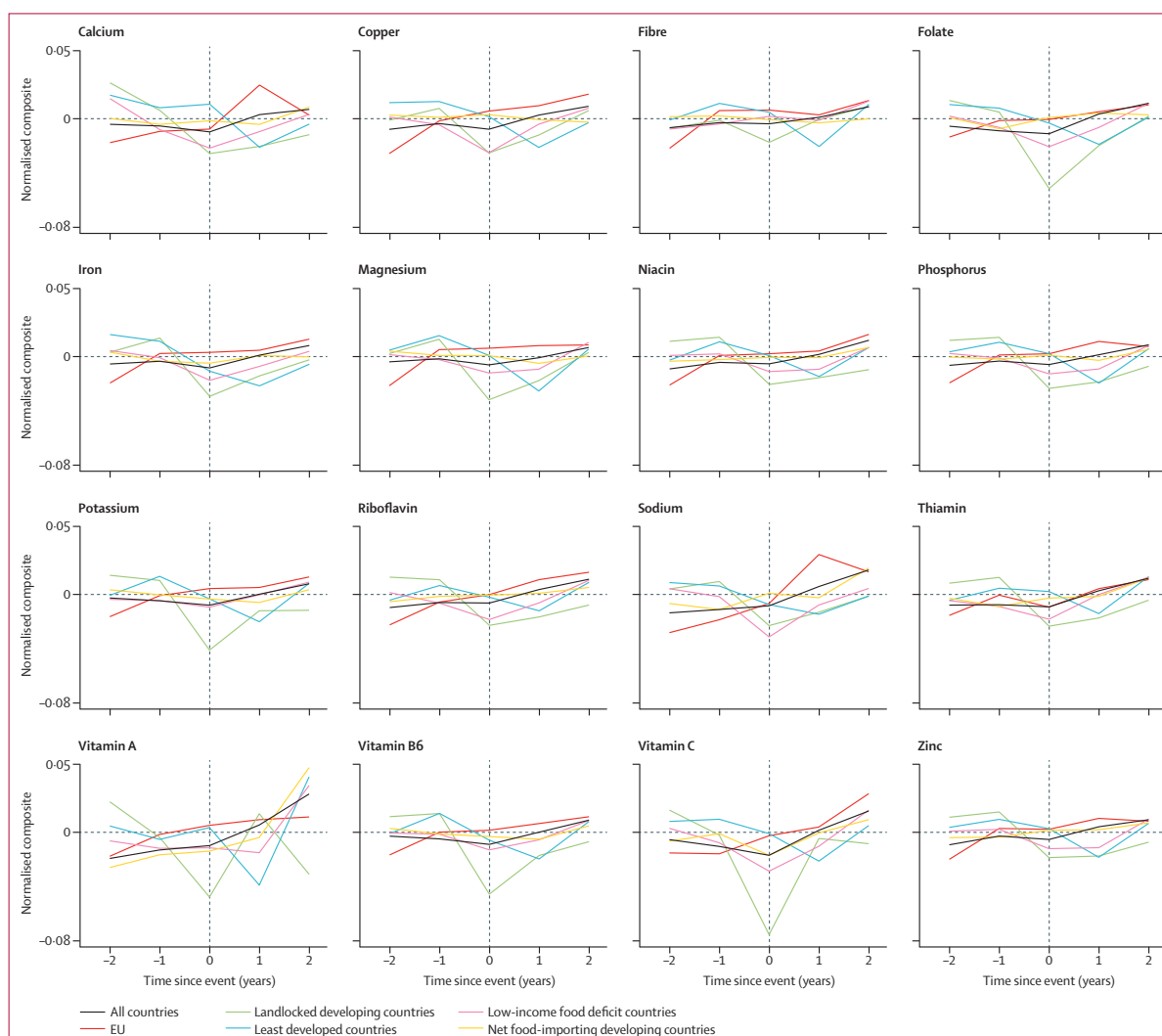


Figure 3: Subgroup analysis of the percentage change in micronutrient and fibre supply for each 5-year window, composited and centred around the year-of-event

The global dataset (all countries) has 175 extreme weather events. The EU subgroup has 29 extreme weather events, landlocked developing countries have 19, least developed countries have 15, low-income food deficit countries have 32, and net food-importing developing countries have 64 (see appendix p 4 for the potential sources of bias arising from varying sample sizes).

generated using R (version 1.1.383). The code is available upon request.

Role of the funding source

The Australian-American Fulbright Commission had no role in data collection, data analysis, data interpretation, writing of the manuscript, or the decision to submit for publication. The corresponding author had full access to all the data in the study and had final responsibility for the decision to submit for publication.

Results

Using both absolute and relative thresholds for inclusion criteria, we included 87 countries from all socioeconomic backgrounds in the superposed epoch analysis of the global effect of extreme weather events on nutrient supply (figure 1) from 1964–2008. Extreme weather events in high-income countries (eg, Sweden, USA) tended to cause greater financial damage while affecting fewer people, whereas extreme weather events in low-income countries (eg, Sudan, Philippines, Peru)

	All countries	EU	Landlocked developing countries	Least developed countries	Low-income food deficit countries	Net food-importing developing countries
Calories	-0.40%* (-0.92 to -0.01)	-0.34% (-1.57 to 0.54)	-1.62%* (-5.79 to -0.16)	0.44% (-0.31 to 1.53)	-1.11% (-3.50 to 0.03)	0.22% (-0.33 to 0.73)
Carbohydrates	-0.34% (-0.76 to 0.08)	-0.18% (-1.01 to 0.87)	-1.61%* (-4.11 to -0.41)	0.2% (-0.46 to 1.18)	-0.89% (-2.51 to 0.18)	0.13% (-0.57 to 0.70)
Monounsaturated fatty acids	-0.84% (-2.00 to 0.03)	-0.97% (-2.82 to 0.62)	-1.9% (-13.06 to 2.11)	1.57% (-0.83 to 4.28)	-1.94% (-8.16 to 0.39)	0.2% (-1.02 to 1.57)
Polyunsaturated fatty acids	-0.68% (-1.57 to 0.33)	-0.58% (-2.02 to 0.95)	-0.3% (-4.36 to 2.87)	3.44% (0.24 to 8.93)	0.02% (-2.64 to 3.01)	0.07% (-1.40 to 2.12)
Protein	-0.48% (-1.03 to 0.07)	-0.24% (-1.64 to 1.31)	-1.95%* (-5.53 to -0.43)	0.13% (-0.92 to 1.12)	-1.48%* (-3.56 to 0.22)	0.32% (-0.57 to 1.07)
Saturated fatty acids	-0.34% (-1.35 to 0.40)	-0.02% (-2.34 to 2.17)	-1.1% (-8.25 to 2.16)	0.83% (-1.56 to 3.24)	-1.53% (-5.71 to 0.48)	0.84% (-0.18 to 1.96)

Data are % (95% CI). *Significant at the $\alpha=0.05$ significance level.

Table 1: Percentage change in macronutrient supplies during the year-of-event relative to non-extreme weather event year averages

tended to cause less financial damage while affecting a greater number of people. A total of 227 extreme weather events were included in the study; 67 were caused by droughts, nine by extreme cold, 11 by extreme heat, 67 by floods, and 73 by storms (figure 2). However, when we aggregated multi-year events, the number of extreme weather events fell to 175, as this reflects multi-year extreme weather events collapsed into singular observations.

For the global dataset (ie, all countries included in this study), all micronutrient supplies exhibited modest negative percentage change during the year of an extreme weather event. These effects were significant (at the $\alpha=0.05$ significance level) for calcium, copper, folate, iron, magnesium, niacin, phosphorus, potassium, riboflavin, thiamin, vitamin B6, vitamin C, and zinc; these significant effects ranged from -0.54% for niacin to -1.73% for vitamin C (appendix p 6). The comparison group plot (appendix p 7) visualises these global percentage changes compared with the business-as-usual group, whereas figure 3 shows the percentage changes of the global dataset overlaid by the percentage changes of the five subgroups.

The extreme weather event effect was especially magnified among landlocked developing countries and low-income food deficit countries (appendix p 6). Landlocked developing countries had the greatest nutrient supply changes of the entire study with vitamin C at -7.57%, folate at -5.16%, and vitamin A at -4.80%. The nutrient supplies for the EU, least developed countries, and net food-importing developing countries did not show any significant percentage changes during the year-of-event (see appendix p 10 for the absolute changes in nutrient supply).

Compared with micronutrient supply, we did not find as large or comprehensive of a reduction in macronutrient supply during the year-of-event for any subgroup (table 1). The macronutrient comparison plot (appendix pp 7–8)

shows a far more erratic picture. Macronutrients had highly variable values for all years of the 5-year windows, not just in the year-of-event. The most notable result from the macronutrient supply analysis is that landlocked developing countries and low-income food deficit countries had a significant -1.95% and -1.48% change in protein supply during the year-of-event.

We further compared effect sizes between the global dataset and the landlocked developing countries (figure 4). Vitamin C, folate, and vitamin A had the greatest magnitudes of percentage change in both sets. For all nutrients studied (except polyunsaturated fatty acids), landlocked developing countries had both larger percentage changes and wider CIs than those of the global dataset. The considerable difference in the magnitude of effect between the two sets is best visualised in figure 4, where both percentage changes (significant at the $\alpha=0.05$ significance level) are overlaid. Notably, the smallest effect for landlocked developing countries (carbohydrates at -1.61%) is on par with the largest effects found within the global dataset.

Accordingly, landlocked developing countries appear to be a driving factor in the overall global effect (see appendix p 13 for the list of landlocked developing countries). Superposed epoch analysis of the global dataset excluding landlocked developing countries did not change the direction of the effects; however, the magnitude decreased, as well as the significance. Without landlocked developing countries included in the global dataset, only thiamin showed supply changes that were significant at the $\alpha=0.05$ significance level (appendix p 9).

The absolute nutrient supply deficits of the global dataset and landlocked developing countries were then framed as percentages of the respective RDAs for children aged 1–3 years (see table 2 for the most substantial effects; see appendix p 11 for the complete table). The effect of extreme weather events on potassium supply in landlocked developing countries was nearly 40% of what a healthy

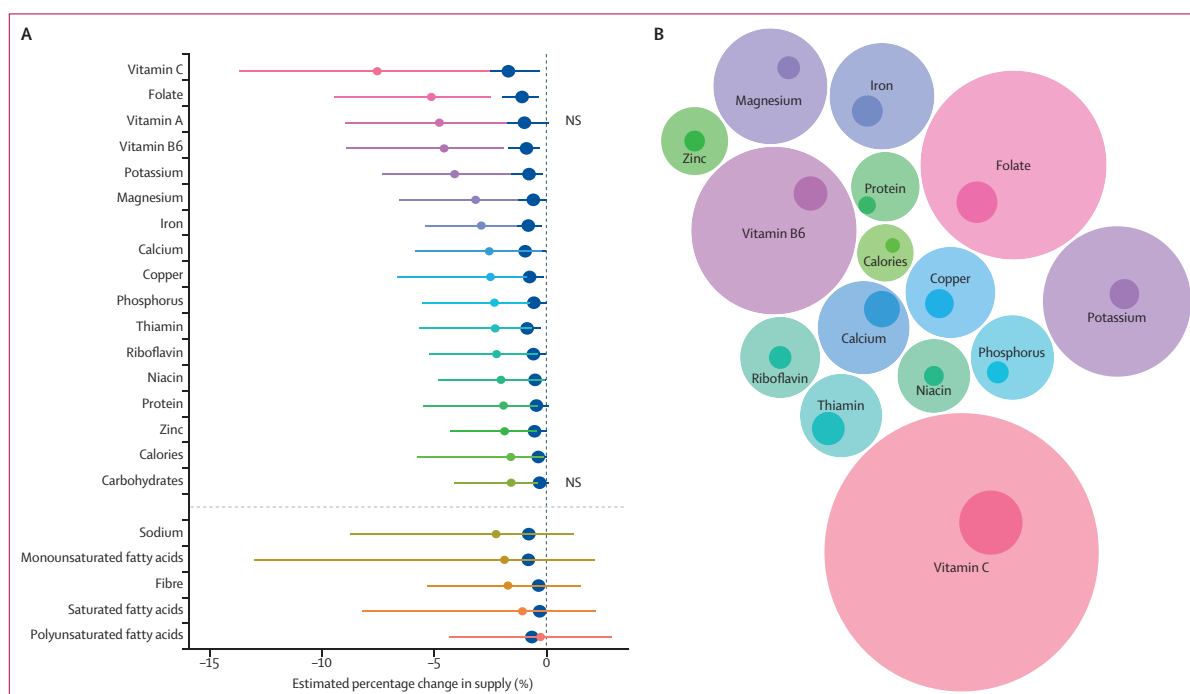


Figure 4: Comparison of effect sizes between the global dataset and the landlocked developing countries

(A) The percentage change of all nutrients in the year-of-event are plotted in rainbow colours for the landlocked developing countries, and in dark blue for the global dataset. The plot is organised vertically by decreasing magnitude of percentage changes in landlocked developing countries. CIs are drawn through the points. All nutrient supply changes above the dotted horizontal line reached significance at the $\alpha=0.05$ significance level for landlocked developing countries, and also for the global dataset except where indicated. (B) Percentage changes for the landlocked developing countries and the global dataset are visualised; only the nutrients that had significant changes in both sets are shown here. For all circles, the radius is proportional to the size of the percentage change in nutrient supply. The larger circles represent the nutrient supply deficits for the landlocked developing countries, and the smaller circles represent the nutrient supply deficits for the global dataset. NS=not significant.

child's sufficient average dietary intake level of potassium should be. This makes up the largest effect of extreme weather events on nutrient supplies; however, potassium is also the only micronutrient studied here that does not have a clear RDA. Instead, the adequate intake indicator is used. Adequate intake is the recommended average daily intake of a nutrient based on observed or experimentally determined approximations of intakes that are assumed to be adequate for a group of healthy people. The effects of extreme weather events on vitamin C, protein, and vitamin B6 supplies are also substantial, making up 34.44%, 17.03%, and 15.24% of their respective RDAs. Appendix p 12 shows the percentage change of nutrient supply during year-of-event as a percentage of adequate intake for infants aged 0–12 months, and similar substantial effects are observed.

Discussion

All micronutrient supplies in this study exhibited negative percentage change during the year of a major extreme weather event. Macronutrient supplies showed more varied responses, probably because they are derived

from a more diverse range of sources. Macronutrients come from nearly all food groups whereas micronutrients are derived primarily from fruits and vegetables, so the acquisition of macronutrients would be notably easier when food options are limited, such as in the immediate aftermath of an extreme weather event. Although outside the scope of the current study, future research should investigate the stability of fresh produce in response to extreme weather events, and how susceptible populations might substitute away from micronutrient-rich foods during extreme weather events in order to reach adequate caloric consumption.

In our study, landlocked developing countries and low-income food deficit countries were especially sensitive to extreme weather events, showing significant nutrient supply changes ranging from -1.28 to -7.57% of the average supply. These results were accompanied by wider CIs than those of the global results, which is an inevitable consequence of smaller and relatively volatile sample pools, as penalised by the bias-corrected and accelerated method. It is surprising that least developed countries and net food-importing developing countries did not

	Child RDA (mg/person per day)	All countries		Landlocked developing countries	
		In mg/person per day (95% CI)	As percentage of child RDA (95% CI)	In mg/person per day (95% CI)	As percentage of child RDA (95% CI)
Calcium	700	-4.87 (-13.64 to 3.67)	-0.7% (-1.95 to 0.52)	-13.67* (-35.4 to -3.24)	-1.95%* (-5.06 to -0.46)
Folate	150	-3.69* (-6.89 to -1.69)	-2.46%* (-4.59 to -1.13)	-13.92* (-25.91 to -6.11)	-9.28%* (-17.28 to -4.08)
Iron	7	-0.14* (-0.26 to -0.04)	-2.05%* (-3.76 to -0.57)	-0.48* (-0.94 to -0.24)	-6.90%* (-13.43 to -3.39)
Magnesium	80	-2.69* (-5.04 to -0.44)	-3.36%* (-6.30 to -0.55)	-10.9* (-19.98 to -5.27)	-13.63%* (-24.97 to -6.58)
Niacin	6	-0.09* (-0.18 to -0.01)	-1.53%* (-3.03 to -0.13)	-0.33* (-0.75 to -0.01)	-5.42%* (-12.52 to -0.20)
Phosphorus	460	-7.36 (-15.05 to 0.15)	-1.6% (-3.27 to 0.03)	-28.4* (-63.79 to -11.44)	-6.17%* (-13.87 to -2.49)
Potassium	300	-21.9* (-43.94 to -3.27)	-7.30%* (-14.65 to -1.09)	-117.56* (-220.03 to -47.02)	-39.19%* (-73.34 to -15.67)
Riboflavin	0.5	-0.005 (-0.01 to 0.003)	-0.99% (-2.74 to 0.67)	-0.03* (-0.06 to -0.004)	-5.31%* (-12.46 to -0.73)
Thiamin	0.5	-0.01* (-0.02 to -0.003)	-2.21%* (-4.02 to -0.61)	-0.03* (-0.07 to -0.01)	-6.11%* (-13.53 to -1.81)
Vitamin A	300	-5.88 (-13.65 to 0.69)	-1.96% (-4.55 to 0.23)	-25.12* (-56.1 to -9.75)	-8.37%* (-18.70 to -3.25)
Vitamin B6	0.5	-0.02* (-0.03 to -0.003)	-3.56%* (-6.80 to -0.69)	-0.08* (-0.14 to -0.03)	-15.24%* (-27.34 to -6.53)
Vitamin C	15	-1.21 (-2.9 to 0.94)	-8.08% (-19.33 to 6.24)	-5.17* (-10.58 to -0.12)	-34.44%* (-70.54 to -0.80)
Zinc	3	-0.06* (-0.12 to -0.005)	-2.12%* (-4.03 to -0.15)	-0.18* (-0.41 to -0.05)	-6.10%* (-13.62 to -1.64)
Calories	950	-10.24* (-23.69 to -0.41)	-1.08%* (-2.49 to -0.04)	-40.41* (-150.36 to -3.15)	-4.25%* (-15.83 to -0.33)
Carbohydrates	130	-1.46 (-3.28 to 0.32)	-1.12% (-2.52 to 0.25)	-6.23* (-15.22 to -1.82)	-4.79%* (-11.71 to -1.4)
Protein	7.7	-0.36 (-0.77 to 0.07)	-4.73% (-9.95 to 0.92)	-1.31* (-4.30 to -0.31)	-17.03%* (-55.79 to -4.06)

The table is organised by micronutrients first and then by macronutrients. All vitamins were measured in mg/person per day except vitamin A (µg retinol activity equivalents per person per day) and folate (µg/person per day). Fibre was measured in g/person per day. Calories were measured in kcal/person per day. There is no official RDA for potassium, so the adequate intake indicator is used instead. RDA=recommended dietary allowance. *Significant at the α=0.05 significance level.

Table 2: Change in nutrient supply during the year-of-event as a percentage of RDA for children aged 1–3 years

show significant nutrient supply changes during the year-of-event, although they did trend towards negative effects. This finding could be explained by better access to humanitarian response and food aid. Landlocked developing countries have no direct access to water ports, which has explicit implications for food security. Domestic food prices in these countries are up to three times more volatile than in their coastal counterparts.

Landlocked countries are often locked out of the global food market through high tariffs, bureaucratic border crossings, rent-seeking behaviour by authorities and transport sectors, and poor infrastructure.^{35,36} The volume of international trade of a landlocked developing country is, on average, just 60% of the trade volume of a comparable coastal country.³⁷ Current domestic food production is not sufficient compensation, as landlocked developing countries typically have less arable land and

less agricultural land under irrigation, leaving them particularly vulnerable to the effects of climate change and extreme weather events.³⁵ The frequency and type of extreme weather events that occurred in landlocked developing countries from 1964–2010 are visualised in the appendix (p 13).

The implications of our study are especially relevant for pregnant women and children under 5 years in resource-poor settings; it is estimated that chronic and acute child malnutrition, low birthweight, and suboptimal breastfeeding cause the deaths of 3.5 million mothers and young children every year.³⁸ Various micronutrients and macronutrients (ie, protein, fatty acids, iron, copper, zinc, B vitamins) are necessary for the neurodevelopmental processes that occur rapidly during pregnancy and infancy, such as neuron proliferation and myelination.³⁹ Maternal micronutrient deficiencies during lactation can also cause a reduction in the concentration of nutrients in

breastmilk (especially thiamin, riboflavin, vitamin B6, and vitamin A), with subsequent infant depletion.^{40,41} Repercussions of these nutritional deficiencies are long lasting; undernutrition during pregnancy and the first 2 years of life is a major determinant of stunting and poor development, with long-term consequences for adult health and work productivity.²⁹

Although agricultural yields have been consistently increasing since the industrial revolution, the world has also witnessed an increase in the absolute number of people and the percentage of people in the world with insufficient dietary energy consumption in 2017.²³ Current estimates indicate that 250 million children under 5 years in low-income and middle-income countries are at risk of not reaching their developmental potential.⁴² The effects of extreme weather events found in this study could significantly exacerbate current malnutrition burdens, as well as endanger those children who are on the cusp of adequate nutrition. Although there is a clear need to provide nutrient supplementation during and after an extreme weather event, it is also imperative that nations are better equipped to prepare for them. Anticipatory humanitarian aid must include comprehensive nutrient accessibility before an event, to help mitigate shocks on the nutrient supply. Strengthening domestic infrastructure of food supply and health care will also ensure that a nation is self-equipped to establish nutrient security in times of emergency.

The GENUS model has several limitations: (1) it does not directly measure consumption; (2) it is based on FAO data, some of which is interpolated rather than directly measured due to gaps in data collection;⁴³ (3) for some countries, there is absolutely no available data, thus rendering interpolation impossible; and (4) the per capita data used here does not discriminate between age, gender, or socioeconomic status. Certain subpopulations within a country might be more disadvantaged than others, and thus more exposed to the effects of food disruptions.^{44,45} Another major limitation is that our analysis does not cover small island developing states as a subgroup—these are known to be highly vulnerable to extreme weather events and limited in their ability to import fresh foods in the case of an emergency.⁴⁶ One caveat with using EM-DAT is that the database is a compilation of field reports and post-disaster assessments, often carried out by a constellation of government ministries, non-governmental organisations, and international governance agencies. Although measurement units are standardised, the method of collecting and analysing data is not standardised. Lastly, while measuring supply fluctuations is important, measuring actual nutrient consumption would more closely align with health consequences. This could be an important area for future study.

Previous studies have established the negative effect of extreme weather events on food production, but few have made the final link between this food disruption and human nutrition. In this study, we aimed to bridge

extreme weather events and nutrition through the quantification of micronutrient, macronutrient, and fibre supply fluctuations during the year of major extreme weather events. We found modest, but significant micronutrient and macronutrient supply declines in the year-of-event globally and among UN-designated low-income subgroups. We identified landlocked developing countries as an especially vulnerable subgroup, and further contextualised the magnitude of nutrient supply deficits with RDAs for children aged 1–3 years. Children in low-income settings not only face the greatest exposure to environmental risk, but also stand to bear the most severe long-term health consequences. As climate change increases the volatility of extreme weather events worldwide, it is imperative that the international community better prepares for and addresses the nutritional impacts of extreme weather events, especially within low-income settings.

Contributors

CSP designed the study, did the analysis, interpreted the results, and wrote the manuscript. LML, SSM, MD, and B-AB helped conceptualise aspects of the study, and EV was integral to coding the analysis in R. All authors commented on the manuscript draft and approved the final submission.

Declaration of interests

EV reports a PhD scholarship from the University of Melbourne during the conduct of the study. All other authors declare no competing interests.

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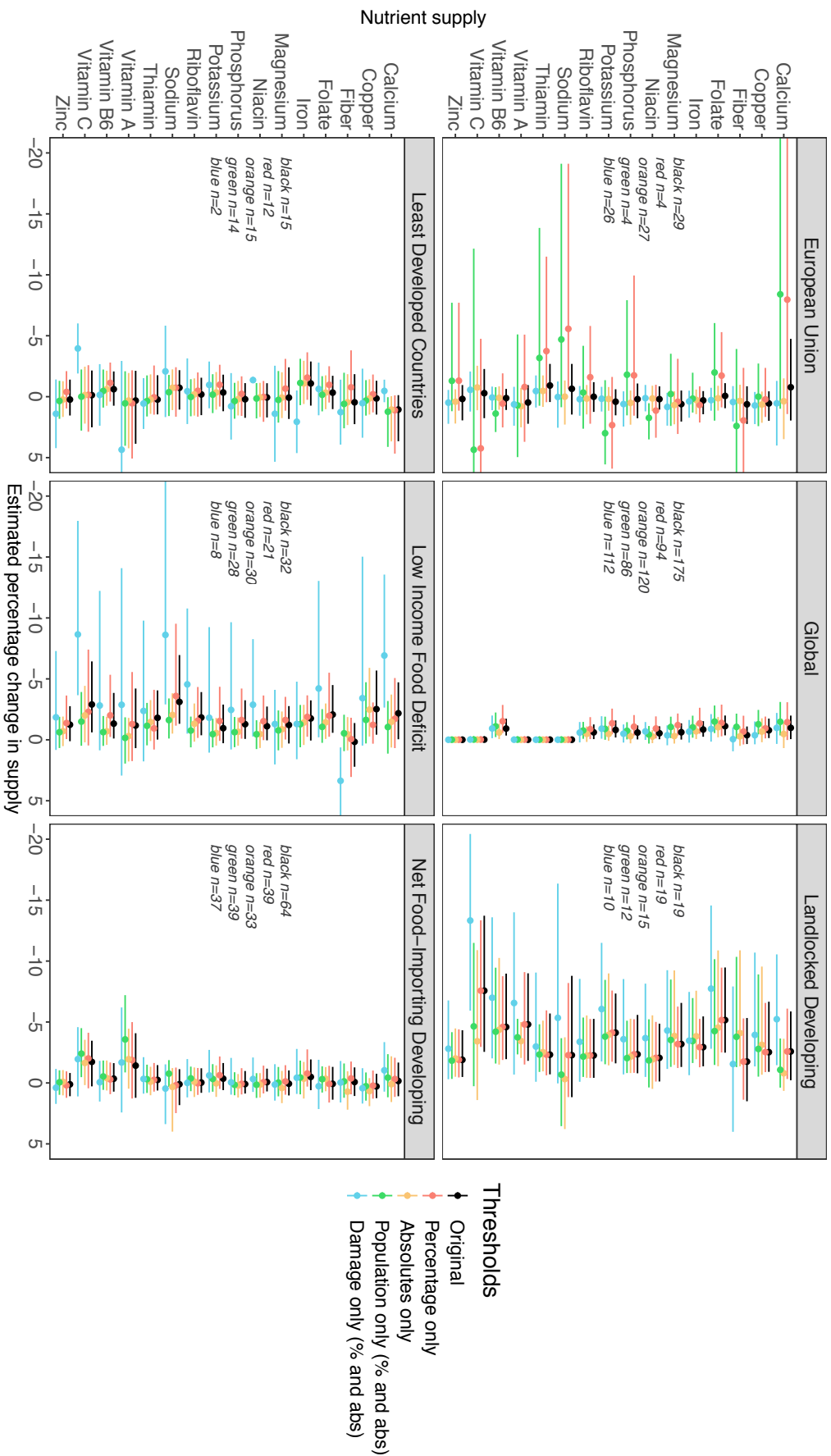
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A.2: Definition of extreme weather events. Source: <https://www.emdat.be/Glossary>

EWE main type	EWE sub-type	Glossary definition
Drought		An extended period of unusually low precipitation that produces a shortage of water for people, animals and plants. Drought is different from most other hazards in that it develops slowly, sometimes even over years, and its onset is generally difficult to detect. Drought is not solely a physical phenomenon because its impacts can be exacerbated by human activities and water supply demands. Drought is therefore often defined both conceptually and operationally. Operational definitions of drought, meaning the degree of precipitation reduction that constitutes a drought, vary by locality, climate and environmental sector.
Extreme cold event	Cold wave	A period of abnormally cold weather. Typically a cold wave lasts two or more days and may be aggravated by high winds. The exact temperature criteria for what constitutes a cold wave vary by location.
	Severe winter conditions	Damage caused by snow and ice. Winter damage refers to damage to buildings, infrastructure, traffic (esp. navigation) inflicted by snow and ice in form of snow pressure, freezing rain, frozen waterways etc.
Extreme heat event	Heat wave	A period of abnormally hot and/or unusually humid weather. Typically a heat wave lasts two or more days. The exact temperature criteria for what constitutes a heat wave vary by location.
	Wildfire	Any uncontrolled and non-prescribed combustion or burning of plants in a natural setting such as a forest, grassland, brush land or tundra, which consumes the natural fuels and spreads based on environmental conditions (e.g., wind, topography). Wildfires can be triggered by lightning or human actions.
Flood		A general term for the overflow of water from a stream channel onto normally dry land in the floodplain (riverine flooding), higher-than-normal levels along the coast and in lakes or reservoirs (coastal flooding) as well as ponding of water at or near the point where the rain fell (flash floods).
Storm	Extra-tropical storm	A type of low-pressure cyclonic system in the middle and high latitudes (also called mid-latitude cyclone) that primarily gets its energy from the horizontal temperature contrasts (fronts) in the atmosphere. When associated with cold fronts, extratropical cyclones may be particularly damaging.
	Tropical storm	A tropical storm originates over tropical or subtropical waters. It is characterised by a warm-core, non-frontal synoptic-scale cyclone with a low pressure centre, spiral rain bands and strong winds. Depending on their location, tropical cyclones are referred to as hurricanes (Atlantic, Northeast Pacific), typhoons (Northwest Pacific), or cyclones (South Pacific and Indian Ocean).
	Convective	A type of meteorological hazard generated by the heating of air and the availability of moist and unstable air masses. Convective storms range from localised thunderstorms (with heavy rain and/or hail, lightning, high winds, tornadoes) to meso-scale, multi-day events.

A.3: (on following page) Sensitivity analysis of EWE inclusion criteria, with point estimates and their 95% bootstrapped BCa confidence intervals. Black objects represent the original EWEs included in the study. Red objects represent only those EWEs that fulfilled the percentage criteria (i.e. total financial damage as percentage of GDP and total number of people affected as percentage of population). Orange objects represent only those EWEs that fulfilled the absolute criteria (i.e. total financial damage and total number of people affected). Green objects represent only those EWEs that fulfilled the population criteria (i.e. total number of people affected in absolute terms and as a percentage of population). Blue objects represent only those EWEs that fulfilled the damage criteria (i.e. total financial damage in absolute terms and as a percentage of GDP). Sample sizes for each object are denoted for each subgroup. Note that the blue objects of Least Developed Countries do not have bootstrapped BCa 95% confidence intervals. This is because there are only $n=2$ observations that fit under the damage-only criterion for LDCs; therefore, the CIs shown for this sub-subgroup are simply the two observations set at the end-points. See fully detailed justification for inclusion criteria on page following figure.



Justification for inclusion criteria: By using both absolute and relative thresholds for people affected and financial damage, we are able to isolate EWEs that are likely to be considered “natural disasters” for a region in the world, even if it is subnational (note that we are operating under the IPCC’s definition of “natural disasters” as EWEs that have severe human consequences). We are also able to capture a truly global snapshot – not just of countries where the majority of their populations are affected by EWEs. We conducted subgroup analysis so as to show the difference between the global average and the most vulnerable groups. We expect that high-income countries would not be as affected; thus lowering the average magnitude of effect. Another advantage to using absolute thresholds is that we are able to include more observations in our study, thus lending more power to our study. Another way of adding more observations would be to lower the percentile threshold, but that would dilute the pool of major EWEs.

That said, we acknowledge that including the absolute thresholds involves a trade-off – it allows us to include a comprehensive swath of the global landscape, but it also introduces a potential implicit mismatch of scale. To address fears of bias introduced by implicit mismatches of scale, we did conduct the sensitivity analysis of threshold criteria (see figure above). The global set shows very little difference amongst all five variations of threshold criteria. All point estimates of the colored criteria fit within the 95% CI of the original black criterion; all five criteria CIs also tend to move together, with large overlap. Note also that even in cases where the exact same observations are used under two different threshold criteria (i.e. Landlocked Developing Countries (black object) and (red object), the 95% CIs are not *exactly* identical even though the point estimates are. This discrepancy in CIs arises due to the nature of algorithmic bootstrapping.

For all subgroups, the point estimates and confidence intervals of the five different threshold criteria generally move together. For the instances when they do not move together, we cannot determine if there is an actual difference in effect because the sample sizes are so small. This is also why the CIs of these objects are so large (e.g. blue object for Landlocked Developing Countries has an $n=10$; and blue object for Low Income Food Deficit Countries has $n=8$). Even if the difference in effect for these cases is a real difference, this analysis shows us that if anything, the magnitude of our results are biased downwards – i.e. an underestimation of the true effect – by using the original combination of threshold criteria. This is a better outcome than if our study results were biased upwards.

Lastly, the case of the European Union highlights the trade-off mentioned above. If percentage criteria (red object) or population-only criteria (green object) were used instead of the combined percentage/absolute value criteria (black object), we would not be able to include the EU as a high-income comparator due to small sample size ($n=4$). Once again, if the difference in point estimates between thresholds criteria is a real difference, at the very least, our analysis shows that our study results are underestimated. Additionally, we hope the reviewer’s concerns about Manhattan influencing the final results is assuaged by this sensitivity analysis in that it shows very few observations that may potentially suffer from the implicit mismatch of scale mentioned above.

A.4: Change in micronutrient, macronutrient, and fiber supplies during year-of-event for all countries included in study except Landlocked Developing Countries, with 95% confidence intervals

Nutrient	Percentage change, relative to non-EWE-year averages	Absolute change, in mg/person/day [†]
Calcium	-0.786 (-1.873, 0.225)	-3.798 (-13.726, 5.767)
Copper	-0.571 (-1.475, 0.121)	-0.011 (-0.027, 0.002)
Fiber	-0.218 (-0.842, 0.423)	-0.036 (-0.259, 0.15)
Folate	-0.627 (-1.467, 0.087)	-2.441 (-5.533, -0.35)
Iron	-0.587 (-1.257, 0.018)	-0.102 (-0.212, 0.006)
Magnesium	-0.306 (-0.935, 0.35)	-1.691 (-4.275, 0.746)
Niacin	-0.355 (-0.916, 0.141)	-0.063 (-0.162, 0.023)
Phosphorus	-0.381 (-0.961, 0.208)	-4.792 (-11.99, 3.024)
Potassium	-0.407 (-1.126, 0.162)	-10.245 (-32.697, 9.846)
Riboflavin	-0.414 (-1.073, 0.125)	-0.002 (-0.011, 0.006)
Sodium	-0.642 (-1.655, 0.367)	-2.351 (-6.767, 2.516)
Thiamin	-0.722 (-1.424, -0.113)	-0.009 (-0.018, 0)
Vitamin A	-0.553 (-1.878, 0.73)	-3.542 (-10.792, 3.727)
Vitamin B6	-0.477 (-1.18, 0.137)	-0.011 (-0.025, 0.004)
Vitamin C	-1.018 (-2.236, 0.305)	-0.731 (-2.564, 1.695)
Zinc	-0.401 (-0.962, 0.18)	-0.049 (-0.107, 0.021)
Calories	-0.248 (-0.686, 0.152)	-6.563 (-17.653, 3.272)
Carbohydrates	-0.185 (-0.672, 0.21)	-0.882 (-2.839, 0.683)
Monounsaturated FA	-0.709 (-1.495, 0.045)	-0.183 (-0.404, 0.021)
Protein	-0.302 (-0.832, 0.217)	-0.249 (-0.673, 0.139)
Polyunsaturated FA	-0.731 (-1.566, 0.173)	-0.108 (-0.257, 0.04)
Saturated FA	-0.242 (-1.126, 0.505)	0.018 (-0.266, 0.373)

[†] = All vitamins measured in mg/person/day except vitamin A (µg RAE/person/day) and folate (µg/person/day); Fiber measured in g/person/day; Calories measured in kcal/person/day

A.5: Absolute change of micronutrient, macronutrient, and fiber supplies during year-of-event, measured in mg/person/day[†], with 95% confidence intervals

Nutrient	All countries incl. in study	European Union	Landlocked Developing Countries	Least Developed Countries	Low Income Food Deficit Countries	Net Food-Import Developing Countries
Calcium	-4.87 (-13.64, 3.67)	-4.68 (-48.4, 38.8)	-13.67 (-35.4, -3.24)	4.71 (-0.6, 22.69)	-12.3 (-27.63, -1)	1.79 (-3.25, 7.18)
Copper	-0.01 (-0.03, 0)	0.01 (-0.01, 0.04)	-0.04 (-0.09, -0.01)	0 (-0.02, 0.02)	-0.04 (-0.1, -0.01)	0.01 (-0.01, 0.02)
Fiber	-0.08 (-0.27, 0.11)	0.22 (-0.2, 0.78)	-0.44 (-1.23, 0.29)	-0.02 (-0.46, 0.35)	0.07 (-0.31, 0.56)	0.07 (-0.22, 0.43)
Folate	-3.69 (-6.89, -1.69)	-0.3 (-4.21, 3.11)	-13.92 (-25.91, -6.11)	-1.17 (-5.35, 2.91)	-5.48 (-11.47, -1.37)	-0.17 (-2.98, 2.73)
Iron	-0.14 (-0.26, -0.04)	0.03 (-0.09, 0.17)	-0.48 (-0.94, -0.24)	-0.22 (-0.53, 0.13)	-0.29 (-0.53, 0.02)	-0.07 (-0.29, 0.11)
Magnesium	-2.69 (-5.04, -0.44)	2.49 (-1.98, 9.89)	-10.9 (-19.98, -5.27)	-1.48 (-10.34, 6.6)	-6.04 (-12.51, 1.22)	0.2 (-3.22, 3.9)
Niacin	-0.09 (-0.18, -0.01)	0.03 (-0.2, 0.22)	-0.33 (-0.75, -0.01)	0.01 (-0.14, 0.24)	-0.15 (-0.36, 0.03)	0 (-0.16, 0.12)
Phosphorus	-7.36 (-15.05, 0.15)	3.61 (-19.04, 35.51)	-28.4 (-63.79, -11.44)	0.51 (-15.97, 16.57)	-14.57 (-35.15, 1.23)	2.12 (-8.07, 10.45)
Potassium	-21.9 (-43.94, -3.27)	10.89 (-33.91, 50.6)	-117.56 (-220.03, -47.02)	-18.56 (-68.18, 17.87)	-22.43 (-71.58, 15.05)	-9.85 (-49.27, 17.78)
Riboflavin	0 (-0.01, 0)	0 (-0.02, 0.03)	-0.03 (-0.06, 0)	0 (-0.01, 0.02)	-0.01 (-0.03, 0)	0 (-0.01, 0.01)
Sodium	-2.85 (-7.04, 1.7)	-3.7 (-17.9, 18.51)	-6.97 (-31.72, 3.3)	-0.26 (-2.5, 4.05)	-7.43 (-22.89, -2.28)	1.47 (-1.61, 6.62)
Thiamin	-0.01 (-0.02, 0)	-0.02 (-0.05, 0.01)	-0.03 (-0.07, -0.01)	0 (-0.02, 0.02)	-0.01 (-0.03, 0.01)	0 (-0.02, 0.01)
Vitamin A	-5.88 (-13.65, 0.69)	6.24 (-8.08, 25.48)	-25.12 (-56.1, -9.75)	-0.09 (-10.55, 11.97)	-6.78 (-28.41, 2.84)	-8.23 (-21.53, 4.72)
Vitamin B6	-0.02 (-0.03, 0)	0 (-0.02, 0.02)	-0.08 (-0.14, -0.03)	-0.02 (-0.05, 0.01)	-0.03 (-0.07, -0.01)	-0.01 (-0.03, 0.03)
Vitamin C	-1.21 (-2.9, 0.94)	-0.74 (-3.1, 1.95)	-5.17 (-10.58, -0.12)	0.12 (-0.99, 1.46)	-2.02 (-4.37, 0.32)	-2.04 (-5.16, 0.54)
Zinc	-0.06 (-0.12, 0)	0.03 (-0.11, 0.27)	-0.18 (-0.41, -0.05)	-0.01 (-0.15, 0.12)	-0.13 (-0.27, -0.01)	0.01 (-0.08, 0.1)
Calories	-10.24 (-23.69, -0.41)	-11.5 (-49.86, 22.09)	-40.41 (-150.36, -3.15)	9.49 (-7.57, 34.41)	-26.38 (-88.24, -0.29)	5.14 (-7.72, 16.62)
Carbohydrates	-1.46 (-3.28, 0.32)	-1.1 (-4.66, 3.51)	-6.23 (-15.22, -1.82)	0.64 (-1.9, 3.85)	-3.36 (-8.86, 0.74)	0.39 (-2.32, 2.56)
Monounsaturated FA	-0.21 (-0.49, 0.02)	-0.51 (-1.35, 0.42)	-0.46 (-3.37, 0.57)	0.2 (-0.15, 0.55)	-0.45 (-1.94, 0.05)	0.03 (-0.21, 0.29)
Polyunsaturated FA	-0.11 (-0.23, 0.04)	-0.13 (-0.42, 0.23)	-0.09 (-0.71, 0.35)	0.35 (-0.02, 0.93)	-0.01 (-0.33, 0.34)	-0.06 (-0.27, 0.19)
Protein	-0.36 (-0.77, 0.07)	-0.25 (-1.85, 1.54)	-1.31 (-4.3, -0.31)	0.05 (-0.53, 0.6)	-0.87 (-2.49, -0.15)	0.22 (-0.24, 0.64)
Saturated FA	-0.02 (-0.35, 0.27)	0.16 (-1.01, 1.65)	-0.32 (-2.45, 0.51)	0.18 (-0.09, 0.58)	-0.38 (-1.87, 0.08)	0.23 (-0.02, 0.51)

[†] = All vitamins measured in mg/person/day except vitamin A (μg RAE/person/day) and folate (μg/person/day); Fiber measured in g/person/day; Calories measured in kcal/person/day

A.6: Percentage change of nutrient supply during year-of-event, as a percentage of Recommended Dietary Allowance for children aged 1-3 years, with 95% confidence intervals

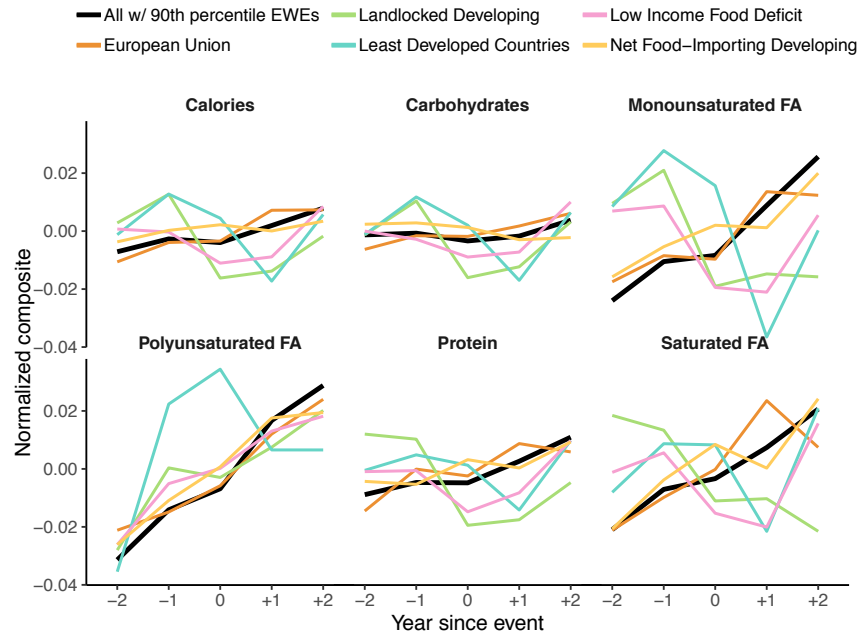
Nutrient	Child RDA, mg/person/day [†]	Change during year-of-event, all countries incl. in study		Change during year-of-event, Landlocked Developing Countries	
		in mg/person/day [†]	as percentage of RDA	in mg/person/day [†]	as percentage of RDA
Calcium	700	-4.87 (-13.64, 3.67)	-0.7 (-1.95, 0.52)	-13.67 (-35.4, -3.24)	-1.95 (-5.06, -0.46)
Copper	340	-0.01 (-0.03, 0)	0 (-0.01, 0)	-0.04 (-0.09, -0.01)	-0.01 (-0.03, 0)
Fiber	19	-0.08 (-0.27, 0.11)	-0.42 (-1.41, 0.56)	-0.44 (-1.23, 0.29)	-2.3 (-6.47, 1.54)
Folate	150	-3.69 (-6.89, -1.69)	-2.46 (-4.59, -1.13)	-13.92 (-25.91, -6.11)	-9.28 (-17.28, -4.08)
Iron	7	-0.14 (-0.26, -0.04)	-2.05 (-3.76, -0.57)	-0.48 (-0.94, -0.24)	-6.9 (-13.43, -3.39)
Magnesium	80	-2.69 (-5.04, -0.44)	-3.36 (-6.3, -0.55)	-10.9 (-19.98, -5.27)	-13.63 (-24.97, -6.58)
Niacin	6	-0.09 (-0.18, -0.01)	-1.53 (-3.03, -0.13)	-0.33 (-0.75, -0.01)	-5.42 (-12.52, -0.2)
Phosphorus	460	-7.36 (-15.05, 0.15)	-1.6 (-3.27, 0.03)	-28.4 (-63.79, -11.44)	-6.17 (-13.87, -2.49)
Potassium	300	-21.9 (-43.94, -3.27)	-7.3 (-14.65, -1.09)	-117.56 (-220.03, -47.02)	-39.19 (-73.34, -15.67)
Riboflavin	0.5	0 (-0.01, 0)	-0.99 (-2.74, 0.67)	-0.03 (-0.06, 0)	-5.31 (-12.46, -0.73)
Sodium	120	-2.85 (-7.04, 1.7)	-2.38 (-5.87, 1.42)	-6.97 (-31.72, 3.3)	-5.81 (-26.43, 2.75)
Thiamin	0.5	-0.01 (-0.02, 0)	-2.21 (-4.02, -0.61)	-0.03 (-0.07, -0.01)	-6.11 (-13.53, -1.81)
Vitamin A	300	-5.88 (-13.65, 0.69)	-1.96 (-4.55, 0.23)	-25.12 (-56.1, -9.75)	-8.37 (-18.7, -3.25)
Vitamin B6	0.5	-0.02 (-0.03, 0)	-3.56 (-6.8, -0.69)	-0.08 (-0.14, -0.03)	-15.24 (-27.34, -6.53)
Vitamin C	15	-1.21 (-2.9, 0.94)	-8.08 (-19.33, 6.24)	-5.17 (-10.58, -0.12)	-34.44 (-70.54, -0.8)
Zinc	3	-0.06 (-0.12, 0)	-2.12 (-4.03, -0.15)	-0.18 (-0.41, -0.05)	-6.1 (-13.62, -1.64)
Calories [‡]	950	-10.24 (-23.69, -0.41)	-1.08 (-2.49, -0.04)	-40.41 (-150.36, -3.15)	-4.25 (-15.83, -0.33)
Carbohydrates	130	-1.46 (-3.28, 0.32)	-1.12 (-2.52, 0.25)	-6.23 (-15.22, -1.82)	-4.79 (-11.71, -1.4)
Monounsaturated FA	NA	-0.21 (-0.49, 0.02)	NA	-0.46 (-3.37, 0.57)	NA
Protein	7.7	-0.36 (-0.77, 0.07)	-4.73 (-9.95, 0.92)	-1.31 (-4.3, -0.31)	-17.03 (-55.79, -4.06)
Polyunsaturated FA [‡]	13	-0.11 (-0.23, 0.04)	-0.81 (-1.8, 0.32)	-0.09 (-0.71, 0.35)	-0.68 (-5.44, 2.67)
Saturated FA	NA	-0.02 (-0.35, 0.27)	NA	-0.32 (-2.45, 0.51)	NA

See footnotes on next page

† = All vitamins measured in mg/person/day except vitamin A ($\mu\text{g RAE/person/day}$) and folate ($\mu\text{g/person/day}$); Fiber measured in g/person/day; Calories measured in kcal/person/day

* = Bold denotes significance at the 0.05 level

‡ = There is no official RDA for potassium, so Adequate Intake (AI) indicator is used instead. AI is the recommended average daily intake level of a nutrient based on observed or experimentally determined approximations of intakes that are assumed to be adequate for a group of healthy people. For recommended daily estimated calories, see Gidding et al (2006).¹²⁶



A.7: Percentage change of macronutrient supply for each five-year window (global $n=175$, European Union $n=29$, Landlocked Developing $n=19$, Least Developed Countries $n=15$, Low Income Food Deficit $n=32$, and Net Food-Importing Developing $n=64$), composited and centered around the year-of-event.

A.8: Percentage change of nutrient supply during year-of-event, as a percentage of Adequate Intake for infants aged 0-12 months, with 95% confidence intervals

Nutrient	Infant AI, mg/person/day [†]	Change during year-of-event, all countries incl. in study		Change during year-of-event, Landlocked Developing Countries	
		in mg/person/day [†]	as percentage of AI	in mg/person/day [†]	as percentage of AI
Calcium	230	-4.87 (-13.64, 3.67)	-2.12 (-5.93, 1.6)	-13.67 (-35.4, -3.24)	-5.94 (-15.39, -1.41)
Copper	210	-0.01 (-0.03, 0)	-0.01 (-0.01, 0)	-0.04 (-0.09, -0.01)	-0.02 (-0.04, -0.01)
Fiber	NA	-0.08 (-0.27, 0.11)	NA	-0.44 (-1.23, 0.29)	NA
Folate	72.5	-3.69 (-6.89, -1.69)	-5.09 (-9.5, -2.33)	-13.92 (-25.91, -6.11)	-19.2 (-35.74, -8.43)
Iron	5.635	-0.14 (-0.26, -0.04)	-2.55 (-4.67, -0.71)	-0.48 (-0.94, -0.24)	-8.58 (-16.68, -4.21)
Magnesium	52.5	-2.69 (-5.04, -0.44)	-5.13 (-9.59, -0.84)	-10.9 (-19.98, -5.27)	-20.77 (-38.05, -10.03)
Niacin	3	-0.09 (-0.18, -0.01)	-3.06 (-6.07, -0.27)	-0.33 (-0.75, -0.01)	-10.84 (-25.04, -0.4)
Phosphorus	187.5	-7.36 (-15.05, 0.15)	-3.92 (-8.02, 0.08)	-28.4 (-63.79, -11.44)	-15.15 (-34.02, -6.1)
Potassium	550	-21.9 (-43.94, -3.27)	-3.98 (-7.99, -0.6)	-117.56 (-220.03, -47.02)	-21.38 (-40.01, -8.55)
Riboflavin	0.35	0 (-0.01, 0)	-1.41 (-3.91, 0.96)	-0.03 (-0.06, 0)	-7.59 (-17.8, -1.04)
Sodium	245	-2.85 (-7.04, 1.7)	-1.16 (-2.87, 0.7)	-6.97 (-31.72, 3.3)	-2.85 (-12.95, 1.35)
Thiamin	0.25	-0.01 (-0.02, 0)	-4.42 (-8.05, -1.21)	-0.03 (-0.07, -0.01)	-12.22 (-27.05, -3.62)
Vitamin A	450	-5.88 (-13.65, 0.69)	-1.31 (-3.03, 0.15)	-25.12 (-56.1, -9.75)	-5.58 (-12.47, -2.17)
Vitamin B6	0.2	-0.02 (-0.03, 0)	-8.91 (-17, -1.72)	-0.08 (-0.14, -0.03)	-38.1 (-68.36, -16.33)
Vitamin C	45	-1.21 (-2.9, 0.94)	-2.69 (-6.44, 2.08)	-5.17 (-10.58, -0.12)	-11.48 (-23.51, -0.27)
Zinc	2.5	-0.06 (-0.12, 0)	-2.54 (-4.84, -0.18)	-0.18 (-0.41, -0.05)	-7.32 (-16.34, -1.96)
Calories	636.4	-10.24 (-23.69, -0.41)	-1.61 (-3.72, -0.06)	-40.41 (-150.36, -3.15)	-6.35 (-23.63, -0.5)
Carbohydrates	77.5	-1.46 (-3.28, 0.32)	-1.89 (-4.24, 0.41)	-6.23 (-15.22, -1.82)	-8.03 (-19.64, -2.35)
Monounsaturated FA	NA	-0.21 (-0.49, 0.02)	NA	-0.46 (-3.37, 0.57)	NA
Protein	10.05	-0.36 (-0.77, 0.07)	-3.63 (-7.62, 0.7)	-1.31 (-4.3, -0.31)	-13.04 (-42.75, -3.11)
Polyunsaturated FA	4.5	-0.11 (-0.23, 0.04)	-2.35 (-5.21, 0.92)	-0.09 (-0.71, 0.35)	-1.96 (-15.7, 7.72)
Saturated FA	NA	-0.02 (-0.35, 0.27)	NA	-0.32 (-2.45, 0.51)	NA

[†] = All vitamins measured in mg/person/day except vitamin A (µg RAE/person/day) and folate (µg/person/day); Fiber measured in g/person/day; Calories measured in kcal/person/day

* = Bold denotes significance at the 0.05 level

A.9: List of all Land Locked Developing Countries

ISO3 Code and Country Identifier					
AFG	Afghanistan	ETH	Ethiopia	MDA	Republic of Moldova
ARM	Armenia	KAZ	Kazakhstan	RWA	Rwanda
AZE	Azerbaijan	KGZ	Kyrgyzstan	SSD	South Sudan
BTN	Bhutan	LAO	Lao People's Democratic Republic	SWZ	Swaziland
BOL	Bolivia (Plurinational State of)	LSO	Lesotho	TJK	Tajikistan
BWA	Botswana	MWI	Malawi	MKD	The former Yugoslav Republic of Macedonia
BFA	Burkina Faso	MLI	Mali	TKM	Turkmenistan
BDI	Burundi	MNG	Mongolia	UGA	Uganda
CAF	Central African Republic	NPL	Nepal	UZB	Uzbekistan
TCD	Chad	NER	Niger	ZMB	Zambia
SWZ	Eswatini	PRY	Paraguay	ZWE	Zimbabwe

A.10: List of EWE descriptions that were analyzed in global nutrient supply SEA

Country	Start year	End year	EWE type	Total affected* (persons)	Total financial damage* (\$)	Total affected as %age of population	Total financial damage as %age of GDP	Group(s) ¹
ARG	1992	1993	Flood	44037	801000	0.13	0.34	
ARG	1997	1998	Flood	186250	550000	0.52	0.19	
ATG	1989	1990	Storm	4015	40000	6.02	8.91	5817
ATG	1998	1999	Storm	3991	50000	4.94	6.69	5817
BHS	1965	1966	Storm	602	8100	0.42	2.53	
BHS	2004	2005	Storm	5250	775000	1.61	10.47	
BOL	2006	2007	Flood	475548	312500	5.08	2.54	5802
CHE	1998	1999	Storm	0	750500	0.00	0.26	
CHE	2005	2007	Flood	1867	816667	0.02	0.19	
CHN	1978	1979	Drought	3000000	0	0.31	0.00	
COL	1969	1971	Flood	1726333	46450	7.83	0.65	
CZE	1996	1998	Flood	34056	646000	0.33	0.99	5706
DEU	1990	1991	Storm	0	2222500	0.00	0.12	5706
DOM	1979	1980	Storm	777000	98500	13.53	1.62	5817
ESP	2003	2006	Extreme heat	325	678000	0.00	0.06	5706
FJI	1972	1973	Storm	63075	11250	11.50	3.03	
FJI	1992	1993	Storm	81002	50800	10.80	3.21	
ITA	1965	1966	Flood	650000	1000000	1.24	1.41	5706
JAM	2004	2005	Storm	180261	464750	6.59	4.35	5817
JPN	1964	1965	Flood	1500000	45000	1.53	0.05	
JPN	1998	2001	Flood	102105	1886750	0.08	0.04	
KEN	2004	2005	Drought	2900000	0	8.15	0.00	5815, 5817
KNA	1998	1999	Storm	5590	220700	12.54	58.47	5817
KOR	1998	2005	Storm	22319	1262694	0.05	0.21	
LKA	1987	1988	Drought	1503000	0	9.13	0.00	5817
MEX	1995	1996	Drought	0	650000	0.00	0.18	
NLD	1994	1995	Storm	125000	591000	0.81	0.14	5706
PAK	1976	1984	Flood	999967	56111	1.27	0.24	5815, 5817
PER	2003	2004	Extreme cold	1988678	0	7.34	0.00	5817
POL	1997	1998	Flood	112850	1750000	0.29	1.05	5706
USA	1986	1987	Extreme heat	0	875000	0.00	0.02	
VEN	1999	2000	Flood	285254	1580000	1.18	1.47	5817
ALB	2005	2005	Storm	400000		13.28		
ARM	2000	2000	Drought	297000	100000	9.68	5.23	5802
ATG	1995	1995	Storm	3702	350000	5.03	60.63	5817
ATG	2008	2008	Storm	25800		27.90		5817
AUS	1967	1967	Drought		600000		1.97	
AUS	1981	1981	Drought	80000	6000000	0.54	3.39	
AUT	2002	2002	Flood	60000	2400000	0.74	1.12	5706
AZE	1995	1995	Flood	1658800	16200	21.58	0.53	5802
BEL	1990	1990	Storm		980000		0.47	5706
BGD	1964	1964	Flood	1000000	5000	1.85	0.09	5801, 5815, 5817
BGD	1983	1983	Drought	20000000		22.64		5801, 5815, 5817
BGD	1989	1989	Drought	5000000		4.83		5801, 5815, 5817
BHS	1992	1992	Storm	1700	250000	0.64	8.04	
BIH	2000	2000	Drought		158000		2.87	
BLZ	2008	2008	Flood	38000	9697	12.41	0.71	
BOL	1983	1983	Drought	3083049	917200	51.73	16.91	5802
BOL	1992	1992	Flood	40050	200000	0.56	3.54	5802
BRA	1970	1970	Drought	10000000	100	10.49	0.00	
BRA	1998	1998	Drought	10000000	122000	5.88	0.01	
CAN	1977	1977	Drought		3000000		1.42	
CAN	1984	1984	Drought	30000	1000000	0.12	0.28	
CAN	1992	1992	Extreme cold		2000000		0.34	
CHN	1988	1988	Drought	49000000	942887	4.45	0.30	
CZE	2002	2002	Flood	200000	2400000	1.96	2.93	5706
DMA	1984	1984	Storm	10000	2000	13.47	2.23	5817
DMA	1989	1989	Storm	710	20000	1.00	13.04	5817
DMA	1995	1995	Storm	5001	195000	7.01	87.04	5817
DMA	2007	2007	Storm	7530	20000	10.61	4.75	5817
DNK	1992	1992	Drought		751700		0.49	5706
DNK	1999	1999	Storm		2604939		1.46	5706
DNK	2005	2005	Storm		1300000		0.49	5706
DOM	1988	1988	Flood	1191150		17.25		5817

Table A.10 continued: List of EWE descriptions that were analyzed in global nutrient supply SEA

Country	Start year	End year	EWE type	Total affected* (persons)	Total financial damage* (\$)	Total affected as percentage of population (%)	Total financial damage as percentage of GDP (%)	Group(s) ¹
DOM	1998	1998	Storm	975595	1981500	11.76	9.36	5817
ECU	1964	1964	Drought	600000		11.77		
ESP	1987	1987	Flood	2000	1283000	0.01	0.40	5706
ESP	1990	1990	Drought	6000000	4500000	15.44	0.84	5706
ESP	1995	1995	Extreme cold		824300		0.13	5706
ESP	1999	1999	Drought		3200000		0.51	5706
FJI	1998	1998	Drought	263455		32.92		
FRA	1983	1983	Flood	3712	609500	0.01	0.11	5706
GEO	2000	2000	Drought	696000	200000	15.75	6.54	
GHA	1968	1968	Flood	25000	74700	0.30	4.48	5815
GHA	1983	1983	Drought	12500000		105.09		5815
GHA	1991	1991	Flood	2000000		13.30		5815
GRC	1990	1990	Drought		1000000		1.02	5706
GRC	1998	1998	Extreme heat	300	675000	0.00	0.47	5706
GRC	2007	2007	Extreme heat	5396	1750000	0.05	0.55	5706
GRD	1980	1980	Storm		5300		4.78	5817
GRD	2004	2004	Storm	60000	889000	58.45	148.38	5817
GTM	1998	1998	Storm	105700	748000	0.95	3.86	
GTM	2005	2005	Storm	475314	988300	3.63	3.63	
GUY	1997	1997	Drought	607200	29000	79.84	3.87	
HND	1969	1969	Storm	8002	19000	0.30	2.84	5817
HND	1974	1974	Storm	600000	540000	19.61	52.20	5817
HND	1982	1982	Storm	20000	101000	0.51	3.48	5817
HND	1990	1990	Flood	48000	100000	0.97	3.28	5817
HND	1998	1998	Storm	2112000	3793600	34.11	72.92	5817
IDN	1972	1972	Drought	3500000	70000	2.89	0.60	
IDN	1994	1994	Extreme heat	3000000		1.55		
IND	1979	1979	Drought	10000000	200000	1.47	0.13	5815
IND	1982	1982	Drought	100000000		13.70		5815
IND	1987	1987	Drought	300000000		36.73		5815
IND	1993	1993	Drought	1175000		0.13		5815
IND	1996	1996	Drought		542400		0.14	5815
IRN	1999	1999	Drought	37000000	3300000	56.87	2.90	
ISR	1992	1992	Extreme cold		550000		0.73	
ITA	1970	1970	Flood	1301650	268300	2.42	0.24	5706
ITA	1987	1987	Storm		1203700		0.15	5706
ITA	1997	1997	Drought		800000		0.06	5706
JAM	1988	1988	Storm	810000	1000000	33.84	26.12	5817
JAM	1991	1991	Flood	551340	30000	22.56	0.74	5817
JOR	1992	1992	Extreme cold		400000		7.53	5817
KEN	1994	1994	Drought	1200000		4.52		5815, 5817
KEN	2008	2008	Drought	3800000		9.71		5815, 5817
KOR	1967	1967	Drought	2800000		9.29		
KOR	1972	1972	Flood	1128339	73434	3.37	0.68	
LBN	1992	1992	Storm	104075	155000	3.69	2.79	
LCA	2007	2007	Storm		40000		3.13	5817
LKA	1964	1964	Storm	380000	37300	3.49	2.85	5817
LKA	1969	1969	Flood	1000000	8500	8.16	0.43	5817
LKA	1978	1978	Storm	1005000	100000	7.08	3.66	5817
LKA	2001	2001	Drought	1000000		5.32		5817
LTU	1993	1993	Storm	780000	4600	21.18		5706
LUX	1990	1990	Storm		370000		2.80	5706
MAR	1999	1999	Drought	275000	900000	0.96	2.16	5817
MDA	1997	1997	Flood	2244	50000	0.06	2.59	5802
MDA	2000	2000	Storm	2600000	31600	71.44	2.45	5802
MDA	2007	2007	Drought	210394	406000	5.88	9.22	5802
MKD	1995	1995	Flood	1500	245000	0.08	5.51	5802
MKD	2007	2007	Extreme heat	1000000		48.42		5802
MLI	1980	1980	Drought	1500000		21.16		5802, 5801, 5815, 5817
MRT	2001	2001	Drought	1000000		35.83		5801, 5815, 5817
MUS	1975	1975	Storm	826258	200000	92.63		5817
MUS	1979	1979	Storm	105257	175000	11.08	14.39	5817

Table A.10 continued: List of EWE descriptions that were analyzed in global nutrient supply SEA

Country	Start year	End year	EWE type	Total affected* (persons)	Total financial damage* (\$)	Total affected as percentage of population (%)	Total financial damage as percentage of GDP (%)	Group(s) [†]
MUS	1989	1989	Storm	4507	60000	0.43	2.74	5817
MUS	1994	1994	Storm	2300	135400	0.21	3.81	5817
MUS	1999	1999	Drought		175000		4.08	5817
MWI	1987	1987	Drought	1429267		17.60		5802, 5801, 5815, 5817
MWI	2002	2002	Drought	2829435		23.55		5802, 5801, 5815, 5817
MWI	2005	2005	Drought	5100000		39.11		5802, 5801, 5815, 5817
NER	2005	2005	Drought	3000000		22.03		5802, 5801, 5815, 5817
NGA	1983	1983	Drought	3000000	71103	3.78	0.20	5815
NIC	1998	1998	Storm	868228	987700	17.83	21.31	5815
NLD	1990	1990	Storm		1750000		0.56	5706
PAK	1973	1973	Flood	4800000	661500	7.61	10.46	5815, 5817
PHL	1980	1980	Drought	1002100		2.11		
PHL	1983	1983	Drought	1691060		3.29		
PHL	1987	1987	Drought	1002100		1.75		
PHL	1998	1998	Drought	2600000		3.48		
POL	2001	2001	Flood	15000	700000	0.04	0.37	5706
PYF	1983	1983	Storm	5050	37000	3.05	2.77	
ROU	1975	1975	Flood	1000000	50000	4.70		5706
RUS	2003	2003	Drought	1000000		0.69		
RUS	2006	2006	Extreme cold	14	1000000	0.00	0.10	
RWA	2003	2003	Drought	1000000		11.52		5802, 5801, 5815, 5817
SDN	1983	1983	Drought	8400000		52.15		5801, 5815, 5817
SDN	2000	2000	Drought	2000000		7.34		5801, 5815, 5817
SEN	1969	1969	Drought	1400000	74800	33.87	7.60	5801, 5815, 5817
SEN	1982	1982	Drought	1200000		20.27		5801, 5815, 5817
SLV	1982	1982	Flood	68000	280000	1.44	8.24	5817
SWE	2005	2005	Storm		2800000		0.72	5706
SWZ	2007	2007	Drought	410000		36.01		5802, 5817
SYR	2008	2008	Drought	1300000		6.40		
THA	1975	1975	Flood	3000093	45000	7.09	0.30	
THA	1978	1978	Flood	2028400	400000	4.47	1.67	
THA	2002	2002	Drought	5000000	2300	7.80	0.00	
TJK	1992	1992	Flood	63500	300000	1.15	15.71	5802, 5815
TJK	2008	2008	Extreme cold	2000000	840000	27.36	16.27	5802, 5815
TUN	1969	1969	Flood	271269	100000	5.48	7.75	5817
TUR	1998	1998	Flood	1241047	1000000	2.02	0.36	
UKR	2008	2008	Flood	224725	1000000	0.49	0.56	
URY	1967	1967	Flood	38063	39000	1.38	2.44	
USA	1964	1964	Flood		820000		0.12	
USA	1977	1977	Extreme cold		2800000		0.13	
USA	1980	1980	Extreme heat		2000000		0.07	
VCT	1967	1967	Storm		4500		28.42	5817
VCT	1980	1980	Storm	20500	16300	20.40	19.80	5817
VCT	1987	1987	Storm	208	5300	0.20	3.02	5817
VCT	2002	2002	Storm		11000		2.38	5817
YEM	1996	1996	Flood	243210	1210000	1.53	20.91	5801, 5815, 5817
ZAF	1988	1988	Drought	1320000		3.75		
ZAF	1991	1991	Drought		1000000		0.81	
ZAF	2004	2004	Drought	15000000		31.91		

* = For multiyear events, total affected and total financial damage were calculated as an average of the reported annual figures for each year that the EWE spanned

[†] Group codes:

5706 = European Union

5801 = Least Developed Countries

5802 = Land Locked Developing

5815 = Low Income Food Deficit Countries

5817 = Net Food Importing Developing Countries

A.11: All variables included in the PCA

Physical environment		Census	Climate
Accommodation		Tot_p_Indig_M	EHFHeatwavedays_count_anav
Agecared		Tot_p_Indig_F	EHFHeatwavedays_max_anav
BuildingNEC		Tot_p_Indig_P	EHFHeatwavedays_max_anav
ChildCare		Tot_p_NonInd_M	EHFduration_max_anav
Community		Tot_p_NonInd_F	EHFduration_max_anav
Disused		Tot_p_NonInd_P	EHFduration_max_anav
Education		Tot_p_TotM	swbgt_min_av_anav
Health		Tot_p_TotF	swbgt_max_av_anav
Industry		Tot_p_TotP	swbgt_min_av_anav
InfrastructureCommunications		ty_ur_occ_pri_dw_Tot_Ind_P	swbgt_max_av_anav
InfrastructurePower		ty_ur_occ_pri_dw_Tot_No_Ind_P	swbgt_max_av_anav
InfrastructureSewage		ty_ur_occ_pri_dw_Tot_TotP	swbgt_max_av_anav
InfrastructureShelter		ty_ur_Non_pri_dw_Ind_P	swbgt_max_av_anav
InfrastructureToilet		ty_ur_Non_pri_dw_NonInd_P	swbgt_max_av_anav
InfrastructureTransport		ty_ur_Non_pvt_dw_TotP	swbgt_max_av_anav
InfrastructureWater		Med_ag_pe_In_pe_h_L_P	swbgt_max_av_anav
NEC		Me_ag_ps_N_In_ps_ot_hh	swbgt_max_av_anav
Office		Med_age_psn_Tot	swbgt_max_av_anav
Religion		Me_hh_in_wk_In_ps_hh_In_ps	swbgt_max_av_anav
Retail		Me_hh_in_wk_No_In_ps_ot_hh	swbgt_max_av_anav
Services		Med_hhd_inc_wk_Tot	swbgt_max_av_anav
Sport&Recreation		Me_mo_re_mt_In_ps_hh_In_ps	swbgt_max_av_anav
Storage		Med_mort_repay_mth_Tot	swbgt_max_av_anav
Transport		Me_re_wk_In_ps_hh_Ind_psn	swbgt_max_av_anav
unfurnishedbuilding		Me_re_wk_No_In_psn_oth_hh	swbgt_max_av_anav
Neighbours10KM		Med_rent_wk_Tot	swbgt_max_av_anav
Neighbours20KM		Av_N_p-pe_be_In_ps_hh_wi_In_p	swbgt_max_av_anav
Neighbours50KM		Av_Nu_ps-pe_be_No_In_ps_ot_hh	swbgt_max_av_anav
Neighbours100KM		Avg_Nu_psn_per_bed_Tot	swbgt_max_av_anav
Neighbours150KM		Av_hh_si_In_ps_hh_wi_Ind_psn	swbgt_max_av_anav
Neighbours200KM		Avg_hh_si_No_Ind_psn_othr_hhd	swbgt_max_av_anav
Neighbours300KM		Avg_household_size_Tot	swbgt_max_av_anav
ARIA2011		P_d_n_x_b_In_ps_hh_wi_In_p	swbgt_max_av_anav
		P_d_n_x_b_No_In_p_oth_hh	swbgt_max_av_anav
		Perc_dwg_need_extra_bedrm_HH_Tot	swbgt_max_av_anav
		Perc_Y12_equiv_Indig	swbgt_max_av_anav
		Perc_Y12_equiv_Tot	swbgt_max_av_anav
		P_Y12-equivalent_Indigenous	swbgt_max_av_anav
		P_Y12-equivalent_Non_Indig	swbgt_max_av_anav
		P_Y12-equivalent_Tot	swbgt_max_av_anav

A.12: EnRICH health outcomes documentation

****For A1 Inpatient Activity (diagnosis and procedures at a hospital), and A2 Emergency Department Data Collection (presentation at a hospital emergency department):***

Study population = all patients with ICD-10 diagnosis codes

E11 Type 2 diabetes mellitus
E16 Other disorders of pancreatic internal secretion
E66 Obesity
E78 Disorders of lipoprotein metabolism and other lipidaemias
E88 Other metabolic disorders
I10 Essential (primary) hypertension
I11 Hypertensive heart disease
I12 Hypertensive renal disease
I13 Hypertensive heart and renal disease
I15 Secondary hypertension
I20 Angina pectoris
I21 Acute myocardial infarction
I22 Subsequent myocardial infarction
I23 Certain current complications following acute myocardial infarction
I24 Other acute ischaemic heart diseases
I25 Chronic ischaemic heart disease
I26 Pulmonary embolism
I27 Other pulmonary heart diseases
I28 Other diseases of pulmonary vessels
I60 Subarachnoid haemorrhage
I61 Intracerebral haemorrhage
I62 Other nontraumatic intracranial haemorrhage
I63 Cerebral infarction
I64 Stroke, not specified as haemorrhage or infarction
I65 Occlusion and stenosis of precerebral arteries, not resulting in cerebral infarction
I66 Occlusion and stenosis of cerebral arteries, not resulting in cerebral infarction
I67 Other cerebrovascular diseases
I68 Cerebrovascular disorders in diseases classified elsewhere
I69 Sequelae of cerebrovascular disease
I70 Atherosclerosis
I71 Aortic aneurysm and dissection
I72 Other aneurysm and dissection
I74 Arterial embolism and thrombosis
I77 Other disorders of arteries and arterioles
I79 Disorders of arteries, arterioles and capillaries in diseases classified elsewhere
N00 Acute nephritic syndrome
N01 Rapidly progressive nephritic syndrome
N02 Recurrent and persistent haematuria
N03 Chronic nephritic syndrome
N04 Nephrotic syndrome
N17 Acute renal failure
N18 Chronic renal failure
N19 Unspecified kidney failure

Inpatient Activity coded for patient unique ID, DOB, gender, Indigenous status, Community name (suburb or locality) as text (usual or most recent residence), *discharge* date, all discharge diagnoses – ICD-coded, all discharge diagnoses – text, ICD version number.

Emergency Department Data Collection coded for patient unique ID, DOB, gender, Indigenous status, Community name (suburb or locality) as text (usual or most recent residence), *presentation diagnosis* date, presentation diagnosis – ICD-coded, ICD version number.

For A3 **Primary Health Care Collection** (diagnosis/clinical assessment at primary health care centre)

Study population = ICPC Diagnosis code relating to cardiometabolic and behavioural risk factors

ICPC-2 Rubric including ICPC-2 PLUS codes where indicated (ICPC-2 Rubric label)

T89 (Diabetes; insulin-dependent)

T90 (Diabetes; non-insulin-dependent)

T89 (Diabetes; insulin-dependent)

T90 (Diabetes; non-insulin-dependent)

W85 (Gestational diabetes)

K85 (Elevated blood pressure (without hypertension))

K86 (Hypertension; uncomplicated)

K87 including ICPC-2 PLUS codes W81002-W81003 (Hypertension; complicated)

K86 (Hypertension; uncomplicated)

K87 including ICPC-2 PLUS codes W81002-W81003 (Hypertension; complicated)

K74 (Ischaemic heart disease with angina)

K76 (Ischaemic heart disease without angina)

A34005 (Test; C reactive protein)

D34005 (Test; aspartate aminotransferase)

K34003 (Test; cardiac enzymes)

K34004 (Test; creatine kinase)

T34010 (Test; HbA1c)

T34017 (Test; fructosamine)

T34022 (Test; HBA1)

T34005 (Test; glucose)

T34009 (Test; glucose tolerance)

T34023 (Test; glucose (fasting/random))

T34025 (Test; glucose; fasting)

T34026 (Test; glucose; random)

B34026 (Test; fibrinogen)

K86 (Hypertension; uncomplicated)

K87 (Hypertension; complicated)

K74 (Ischaemic heart disease with angina)

K75 (Acute myocardial infarction)

K76 (Ischaemic heart disease without angina)

T93 including ICPC-2 PLUS codes T99075 (Lipid disorder)

T82 (Obesity)

T83 (Overweight)

K84017 (Cardiomyopathy; primary)

K84034 (Cardiomyopathy; secondary)

K84035 (Cardiomyopathy; congestive)

K84036 (Cardiomyopathy; restrictive)

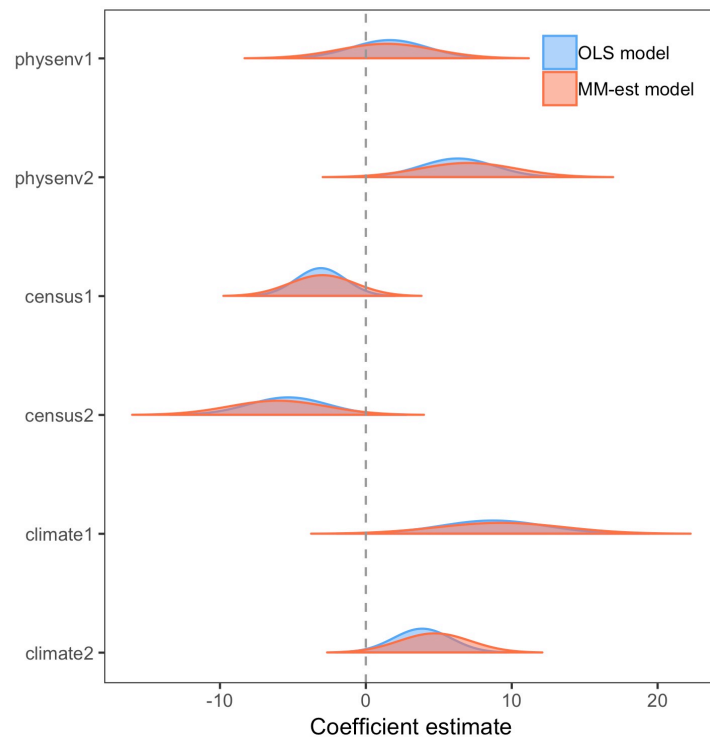
K84037 (Cardiomyopathy; hypertrophic)
 K84041 (Cardiomyopathy)
 K74 (Ischaemic heart disease with angina)
 K75 (Acute myocardial infarction)
 K76 (Ischaemic heart disease without angina)
 K77 (Heart failure)
 K78 (Atrial fibrillation/flutter)
 K79 (Paroxysmal tachycardia)
 K80 (Cardiac arrhythmia NOS)
 K83 (Heart valve disease NOS)
 K84 including ICPC-2 PLUS codes K03001 - K99032 (Heart disease, other)
 K06 (Prominent; veins)
 K22 (Risk factor; cardiovascular disease)
 K85 (Elevated blood pressure)
 K86 (Hypertension, uncomplicated)
 K87 (Hypertension, complicated)
 K88 (Postural hypotension)
 K92 (Atherosclerosis/peripheral vascular disease)
 K93 (Pulmonary embolism)
 K94 (Phlebitis/thrombophlebitis)
 K89 (Transient cerebral ischaemia)
 K90 (Stroke/cerebrovascular accident)
 K91 (Cerebrovascular disease)
 W85 (Gestational diabetes)

Primary Health Care Collection coded for patient unique ID, current age, *diagnosis date*, Indigenous status, usual clinic name (attributed to suburb/locality and aggregated to form community-level outcomes), suburb/locality associated with clinic, residency status (resident, visitor, or tourist), ICPC Diagnosis code.

****For B Territory-wide *Mortality* data**

- 1) all-cause mortality (see: <http://apps.who.int/classifications/icd10/browse/2010/en>)
- 2) cardiovascular-specific mortality, including:
 - ischaemic heart disease (ICD-10 codes I20–I25)
 - cerebrovascular disease (ICD-10 codes I60–I69), and
 - diseases of the arteries, arterioles and capillaries (ICD-10 codes I70–I78)

Word count: 862



A.13: Normally distributed coefficients for the OLS and MM-estimator models of primary health-care rates.

A.14: Memoir

1 December 2018

When I landed on Leyte Island in 2014, 7 months had passed since Typhoon Haiyan. Yet many villages looked exactly as they had on the day of the disaster – ravaged and forsaken. It is a far-too-common-story: after the cameras turn away and the international media moves on, the persistent poor quality of life among survivors in the near- and long-term blurs the distinction between natural disasters and man-made ones.

Standing in the doorway of a collapsed clinic that had yet to be rebuilt, I swore in that moment that even if the rest of the world had abandoned these people, I would not.

Therefore, funded by the Fulbright Anne Wexler Master's Award in Public Policy, I based myself in Australia upon graduating college. I set out to learn how people operate within the Asia-Pacific, the most geographically volatile region of the world. I approached research through “planetary health”, or the study of how human wellbeing is intrinsically linked to the health of the natural world. Just as we shape our environment, it too shapes us; and to solve the health crises of today, we must expand our conception of health to beyond the human body, whether that is teasing out the causality between air pollution and asthma incidence or identifying the maximum heat threshold for safety during a heat wave.

Coming from a biology and economics background, I smoothly transitioned into epidemiology and other statistical methods to test my hypothesis that extreme weather causes a significant increase in the burden of metabolic complications within vulnerable communities. For my first research article, I estimated global nutrient consumption patterns from 1961-2011 in response to extreme weather events (i.e. droughts, extreme heat, floods). My strongest finding is among Landlocked Developing Countries, where a cluster of 14 extreme weather events dramatically reduced vitamin and mineral intake from baseline, especially potassium, vitamin C, and iron. That micronutrients are significantly reduced while total calorie, fat, and carbohydrate intake remain unaffected, supports the conclusion that populations substitute away from micronutrient-rich foods (due to unavailability or financial inaccessibility of fresh produce) and towards processed, nutrient-deficient foods.

Now zeroing in on Australia, my second analysis looks at its most disadvantaged and environmentally exposed group – Aboriginal and Torres Strait Islander Australians. Indigenous Australians have twice the mortality rate from coronary heart disease and nearly 5 times the mortality rate from diabetes compared to non-Indigenous Australians. This manifests as a 10-year gap in life expectancy at birth between non-Indigenous and Indigenous Australians. Among this population, I am uncovering linkages between extreme weather (i.e. excess heat factor, precipitation totals) and cardiometabolic indicators. I am using the EnRICH database tracking the physical, social, and ecological environments of 150 remote Aboriginal communities in the Northern Territory from 2010 – 2015.

As I wrap up my analyses, I am also preparing to return home. Though I have continuously thrived under the Australian sun, I have not done so well under its moon. I often go to bed

feeling extremely uneasy, and I have realised that it is due to a genuine fear of waking up.

Because when I do, I wake up in Melbourne, February 15th, 2018, and cry for the lives taken at Stoneman Douglas High School while I slept, and for any more that must be lost before we enact meaningful legislative change.

I wake up in Melbourne to learn that thousands of American migrant children are being forcibly separated from their parents and detained in shelters.

I wake up in Melbourne to discover that Brett Kavanaugh is my nation's highest justice.

Everyday, I wake up in Melbourne one day ahead of everyone back home. The worst part about living in the "future" is that I cannot stop horrible things from happening in the "past"; nor can I respond in the present. Back in the States, however, I can continue my planetary health research while also returning to the picket line in my off-hours. Not built as an armchair activist, I need my boots on the ground, either knocking on doors or knocking them down. I now fully appreciate how important this part of my identity is, and I no longer believe that I must choose to care about either my country or my world. I can do – and will – do both.

In August 2019, I will begin my PhD in Population Health Sciences at the Harvard T.H. Chan School of Public Health, specialising in Environmental Health under Dr. Sam Myers. Sam was the one who introduced me to the term "planetary health" – a concept I had instinctively internalized but never identified by a name. Sam's brainchild, the Planetary Health Alliance, is a global consortium of over 120 NGOs, government entities, and research institutes committed to advancing planetary health knowledge and policies.

My early career goal is simple: to hone a skill that will make me a source of change, not just a dreamer of it. With Margaret Chan, Jim Kim, and Ban Ki-Moon at the frontline of international policy, I have faith that one day I can join their ranks, and that my voice, too, can penetrate both the glass and bamboo ceiling. Up to this point in my life, I have traveled through various parts of the developing world in search of the faces behind the surveys and the stories beyond the statistics. It is time to piece together these stories – the fragments of others' lives that I was privileged enough to witness – and create something with them.

Colophon

THIS THESIS WAS TYPESET using $\LaTeX$, originally developed by Leslie Lamport and based on Donald Knuth's $\TeX$. A template, which can be used to format a PhD thesis with this look and feel, has been released under the permissive MIT (x11) license, and can be found online at github.com/suchow/ or from the author at suchow@post.harvard.edu.