ABSTRACT

Title of dissertation: PEOPLE AND PIXELS:
INTEGRATING REMOTELY-SENSED
AND HOUSEHOLDS SURVEY DATA
FOR FOOD SECURITY AND NUTRITION

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For several decades now, the study of environmental impacts on human well-being has been informed by what are called "People and Pixels" methods: the combining of remotely sensed data about environmental conditions with geolocated data from household surveys about health and nutrition. However, much of this work has been conducted at the scale of individual countries and often relies on only one or two survey waves, which creates substantial issues around spatial autocorrelation and endogeneity. Furthermore, much of this work uses simple linear regression as its analysis technique, which is limited in its ability to describe spatial variation as well as non-linearities in the relationship between the environment and human well-being. Thus, this dissertation uses several insights from the emerging field of data science to advance these methods. First, this analysis draws on large, multinational datasets from dozens of surveys, making it possible to better estimate the non-linear effects of climate extremes on human well-being as well as examine

spatial heterogeneities in vulnerability. Secondly, this analysis uses techniques at the boundary between traditional econometric regression models and more complex machine learning models, such as using Generalized Additive Models (GAMs) as well as LASSO estimation. This permits the creation of spatially-varying terms as well as nonlinear effects. Applying these techniques, the dissertation has yielded several insights that could be beneficial to policymakers in governments, non-profits, and multinational organizations. The initial chapters analyze the effects of rainfall anomalies on food security and malnutrition, finding that the effect of an anomaly varies considerably depending on the local socioeconomic and environmental contexts, with low-income, poorly-governed, and arid countries, such as Somalia and Yemen, being the most vulnerable. The latter chapters look at the role of ecosystem services in improving human livelihoods, as well as how land cover is associated with dependence on local provisioning ecosystem services.

PEOPLE AND PIXELS: INTEGRATING REMOTELY-SENSED AND HOUSEHOLD SURVEY DATA FOR FOOD SECURITY AND NUTRITION

by

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Dedication

This dissertation is dedicated to all of the people who generously give their time and energy to create high-quality and free open-source software. Open source software like Linux, R, and Python is essential for modern science and the modern world to work. It provides an example of the wonderful things that can happen when we get beyond an economic mindset rooted in scarcity and start operating from an mindset of abundance and sharing.

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This dissertation and all of the research I conducted over the course of this PhD would not have been possible without the help of several organizations and people.

I received financial support from Conservation International and the International Food Policy Research Institute, as well as Azure credits from Microsoft, which allowed me to work with data at a large scale.

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Finally, my committee gave me a a great deal of advice and feedback as my research developed. Nadine Sahyoun and Julie Silva gave great feedback during committee meetings and helped me to consider my research questions from new angles; Alex Zvoleff taught me a ton about data science, from cloud computing to

Bayesian modeling; Molly Brown pushed me to think more systematically about how food systems work and how to model them; and Matt Hansen provided a supportive lab space and academic guidance.

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List of Abbreviations

AEZ	Agro-Ecological Zone
AVHRR	Advanced Very High Resolution Radiometer
CBGPS	Covariate Balancing Generalized Propensity Score
CHIRPS	Climate Hazards Group InfraRed Precipitation with Stations
CI	Conservation International
CIFOR	Center for International Forestry Research
CSI	Coping Strategies Index
DHS	Demographic and Health Surveys
EA	Enumeration Areas
ESA CCI	European Space Agency Climate Change Initiative
ESDA	Exploratory Spatial Data Analysis
FCS	Food Consumption Score
FEWS NET	Famine Early Warning Systems Network
FTF	Feed the Future
GAM	Generalized Additive Model
GDP	Gross Domestic Product
GPS	Global Positioning System
HAZ	Height-for-Age Z-Score
HDDS	Household Dietary Diversity Score
HFIAS	Household Food Insecurity Access Scale
HHS	Household Hunger Scale
IDDS	Individual Dietary Diversity Score
IFPRI	International Food Policy Research Institute
IPCC	Intergovernmental Panel on Climate Change
IPUMS	Integrated Public Use Microdata Series
IUCN	International Union for the Conservation of Nature
LOESS	Locally Estimated Scatterplot Smoothing
LSMS	Living Standards Measurement Survey
METSS	Monitoring, Evaluation and Technical Support Services
MUAC	Mid Upper Arm Circumference
NDVI	Normalized Difference Vegetation Index
NRC	National Research Council
NTFP	Non-Timber Forest Product
OLS	Ordinary Least Squares
PEN	The Population-Environment Network
PCA	Principal Component Analysis
PSU	Primary Sampling Unit
SDG	Sustainable Development Goal
SER	Spatial Error Regression

SLA	Sustainable Livelihoods Approach
SPEI	Standardized Precipitation Evapotranspiration Index
SPI	Standardized Precipitation Index
USAID	United States Agency of International Development

Chapter 1: Introduction

The dissertation aims to push the frontier of the “People and Pixels” approach to human-environment research by incorporating methods from the emerging field of data science to generate policy-relevant insights. The phrase “People and Pixels” comes from a book published by the National Research Council (NRC) in 1998 (Liverman et al., 1998) which showcased a number of studies that take an approach of combining geolocated survey data on “People” with data from remote sensing, aka “Pixels”. This approach has been used to study both how the environment has affected people, in terms of livelihoods, health, and income; as well as how people have affected the environment through land cover change, land degradation, and land restoration. For my dissertation research, the focus is primarily on indicators of human well-being – child nutrition especially, but some chapters also focus on food security and livelihoods more broadly. For the environmental component of my research, which is based on remote sensing and products derived from remote sensing, I am interested in both how the environment can harm human well-being, through climate shocks like heat waves, droughts and flooding, as well as how the environment benefits human well-being, through ecosystem services.

Beyond utilizing geolocated household surveys and remotely-sensed data sources, my research draws on methods and techniques that could be broadly characterized as data science. Data science is a still-emerging field of inquiry, combining statistics, computer science, and domain expertise. It is characterized by facets such as drawing on large volumes of data and integrating disparate data sets in novel ways; using advanced quantitative methods like machine learning with less concern for parametric approaches traditionally used in statistics; as well as a focus on applicability and empiricism, aiming to solve problems and answer questions with data, rather than to speak only to theory. Thus, my research combines household survey data with a variety of global datasets, and, for some chapters, draws on large global datasets of child nutrition outcomes across many countries and surveys. Managing and modeling these datasets would not be possible without using cloud computing approaches, as extracting climate indicators for all those observations or running large models using the entire dataset would not be possible on a personal computer.

Finally, this research seeks to be policy relevant. Thus, each of the chapters of my dissertation is intended to have some application to policymakers and answer questions like "Where could establishing a protected area have the most benefit for local food security?" or "What factors are most important for making child nutrition resilient to future climate shocks?" My dissertation has been funded by small grants from the International Food Policy Research Institute (IFPRI) and Conservation International (CI), and I intend for my research to assist these two organizations in their missions. As a geographer, I am particularly concerned in my research with the question of "where?" and thus an output from two of my chapters are maps highlighting the locations where child nutrition is most vulnerable to climate shocks or most dependent on local ecosystem services.

1.1 Dissertation Structure

This dissertation has two components: one on climate shocks and human well-being, and one on ecosystem services and human well-being. These two halves of the dissertation each have two body chapters: an initial chapter where I use smaller regional datasets to explore associations, and a larger chapter drawing on the entire Demographic and Health Surveys (DHS) dataset with a significant mapping component focused on stunting.

The first half of the dissertation analyzes precipitation shocks, and Chapter 2 focuses on both nutrition and food security in Ghana and Bangladesh. This work draws on Feed the Future datasets from IFPRI, and finds that, in both countries, food security, as measured by the Household Hunger Scale (HHS) is more sensitive to precipitation shocks than child malnutrition is. The study further finds that, as the literature would suggest, the types of climate shocks that most affect food security are dependent on baseline environmental conditions. An innovative aspect of this study was the use of a Spatial Error Regression (SER), which is not often used in national-level surveys of climate and food security, but, I argue, is necessary. This study was published in the summer of 2019 in the journal *Population and Environment*. The second part in this section, Chapter 3 draws on much of the Chapter 2, including modeling the impacts of precipitation shocks on child malnutrition, as well as the role of moderating factors like mean annual precipitation. However, the scope of this study is much larger, drawing on Demographic and Health Survey (DHS) data from 53 different countries and focusing on several factors that mitigate or amplify the effects of climate shocks, such as Gross Domestic Product (GDP), crop production, mean annual precipitation, land cover, stability and violence, government effectiveness, market access, and trade per capita. Having estimated the role that various geographic factors play in moderating the effects of climate shocks, I then combined global datasets on each of these factors to create a map of vulnerability to shocks, measured by how much child malnutrition would be expected to increase in a given location under a given shock. Furthermore, I validated the model with data on food insecurity severity from the Famine Early Warning Systems Network (FEWS NET), finding that my models predictions of where stunting would increase under drought corresponded closely to where food security was observed to deteriorate during recent droughts in East and Southern Africa. Chapter 4 has also been published, in the *Proceedings of the National Academy of Sciences*.

The second half focuses on ecosystem services, the validity of land cover as a proxy for ecosystem services, as well as and their role in buffering nutrition from climate shocks. Thus, Chapter 4 is a study which uses data from the Vital Signs project at Conservation International to show that, across four African countries, households near forests are more likely to collect wild foods and other Non-Timber Forest Products (NTFP). This study, which was published in *Forest Policy and Economics*, helps to bolster the case that, where forests and natural land cover are associated with improved child nutrition outcomes, it is reasonable to assume that people are consuming food and other resources from those areas – a critical assumption I am making the in Chapter 5. This Chapter uses DHS data to test the hypothesis that natural areas provide ecosystem services during climate shocks that can act as a "safety net" when less food would be otherwise available. Because remote sensing can not detect ecosystem services *per se*, but rather land cover, I draw heavily on frameworks that see ecosystem services a being "bundled" in land cover types, with trade-offs between land cover types being congruous to trade-offs in ecosystem services (Raudsepp-Hearne et al., 2010). After sub-setting the data to various agro-ecological zones, under the premise that the ecosystem services offered by natural land vary significantly across zones, I estimate how natural, uncultivated land cover moderates the effect of drought on nutrition outcomes. This component of the analysis highlights areas where the safety net effect is strongest – and thus where conservation organizations should focus their efforts if they want to have co-benefits for food security.

1.2 Background

1.2.1 Food Security and Nutrition

In the 1970s, food security work focused on either mortality (Puffer and Serrano, 1973) or child nutrition as measured by anthropometry (Habicht et al., 1974). Habicht et el showed that environmental conditions play a larger role than ethnic differences in explaining children growth outcomes, and thus child anthropometry is a valid means of studying malnutrition (Habicht et al., 1974). Any efforts to look at food security in adults or independent of child nutrition outcomes usually consisted of national and regional efforts to determine the amount of grain or arable land per capita (Maxwell and Frankenberger, 1992). Much of what was considered food security at that time would now be seen as the study of food availability, a sub-component of food security.

Today, there is still no *sine qua non* metric for food security, largely because it has many different facets that are the result of processes at various scales (ie, national, regional, community, household, individual). A variety of metrics for food security and nutrition have been proposed, many of which developed from objective standards for behavioral markers of adaptation to food insecurity (Webb et al., 2006). In the "Food Security and Livelihoods Field Manual" published by Action Against Hunger, 25 different tools for measuring food security and sustainable livelihoods were mentioned, including Mid Upper Arm Circumference (MUAC), the Coping Strategies Index (CSI), Household/Individual Dietary Diversity Scores (HDDS/IDDS), and the Food Consumption Score (FCS), among others. Increasingly, researchers have called for work examining and validating these different metrics, to see which indicators capture acute or chronic food insecurity as well as which indicators are most useful for needs assessment or measuring the success of an intervention (Webb et al., 2006).

Recently, focus has again returned to anthropometry, often as an outcome variable in regression analyses. This is in part because anthropometric indicators are standardized, comparable, and have been collected in a wide variety of contexts over long periods of time. While some work has associated adult stature with nutrition and health (Steckel, 2009), most work focuses on child anthropometry. A analysis using country-level statistics looked at underlying and basic determinants of malnutrition, and found that health environments, women's education, women's relative status, and per capital food availability were underlying determinants of rates of child underweight, while per capital national incomes and democracy were basic determinants (Smith and Haddad, 2000). Another analysis focused on individual outcomes found that improving food availability was strongly associated with reducing child undernutrition and had the greatest marginal effect in developing countries (Smith and Haddad, 2001).

One of the consequences of poor child nutrition is stunting, which affects more than one in three children in many developing countries (UNICEF et al., 2017). Stunting can lead to a higher risk of mortality as a child (Black et al., 2010), as well as reduced physical, cognitive, and educational attainments and lifelong health problems from reduced immunity and increased disease susceptibility (Arthur et al., 2015). The effects of stunting on a population are long term: the children of parents who experienced early childhood stunting are in turn at higher risk for lower developmental levels (Walker et al., 2015). Due to decreased earnings and economic output, child stunting can hamper a countries long-term economic growth for generations (Heltberg, 2009). Thus, ameliorating child stunting is a critical component of sustainable development (Daelmans et al., 2017). While rates of stunting have been in decline globally over the past few decades, hot-spots of stunting remain in Africa and in South Asia Osgood-Zimmerman et al. (2018), Phalkey et al. (2015), and climate change could stall or even reverse current gains.

1.2.2 Climate Impacts on Food Security and Nutrition

The Intergovernmental Panel on Climate Change (IPCC) states in the Fifth Assessment Report with high confidence that increases in temperature will increase the risk of food insecurity through impacts such as drought, flooding, precipitation variability and precipitation extremes (IPCC, 2013). While rates of undernutrition and food security have been falling overall for the past few decades, there has been an increase in these statistics more recently, which is somewhat attributable to climate shocks (FAO et al., 2018). Currently, the world is not on track to meet nutrition targets such as the second Sustainable Development Goal of zero hunger by 2030 (IFPRI, 2016), and meeting these targets will require significant investments in climate-resilient agriculture and supply chains (WBG, 2016). While increasing precipitation extremes induced by climate change are broadly known to be a threat to nutrition, the interacting effects of short-term rainfall shocks, long-term changes in precipitation patterns, and the current water requirements of livelihood systems, are underexplored.

Substantial literature exists on the pathways by which precipitation shocks can affect food security and nutrition. The most immediate impact of unusually low or high rainfall levels on food security is through harming yields, decreasing the overall food availability in a location (Schlenker and Lobell, 2010, Thornton et al., 2009) (See Figure 1.2.2). Subsistence farmers in low income countries often plant crops that are adapted to local long-term rainfall, but when a given season has rainfall levels that are far from long-term norms, yields can suffer. Insufficient water decreases the overall crop productivity, while at the same time, overabundant water can delay planting, prevent waterlogged roots from absorbing nutrients, increase the presence of crop pests, and increase lodging, rot and spoilage in harvests (Tefera, 2012). In addition to harming the yields of grain and vegetable crops, rainfall shocks can affect the abundance of grazing areas, leading to lower availability of animal protein. A decrease in food available can then cascade to constraints in food access: when yields and livestock productivity decrease, food prices increase, making food access difficult for poor households (Brown and Kshirsagar, 2015). At the same time, households that rely on sales of agricultural products and cash crops can be hit by decreasing incomes, while those relying on agricultural wage labor or trading with farmers can also be negatively affected. Finally, excessive rainfall can increase the risk of infectious diseases such as malarial, parasitic and diarrheal disease, in turn harming proper food utilization and increasing rates of undernutrition (Delpla et al., 2009, Paterson and Lima, 2010). Households often adopt strategies of livelihood and agricultural diversification to protect their income and food security from these shocks (Scoones, 1998).

While climate change is recognized to be a major threat to child nutrition, a 2015 review paper of the effects of climate change on undernutrition noted that current evidence associating climate change and undernutrition is "scattered and limited" (Phalkey et al., 2015). The paper documented 15 studies that used regression techniques to find an association between meteorological or agricultural variables and child stunting (Phalkey et al., 2015). In this literature review, only two studies were multinational, and the largest sample size was about 19,000 chil-

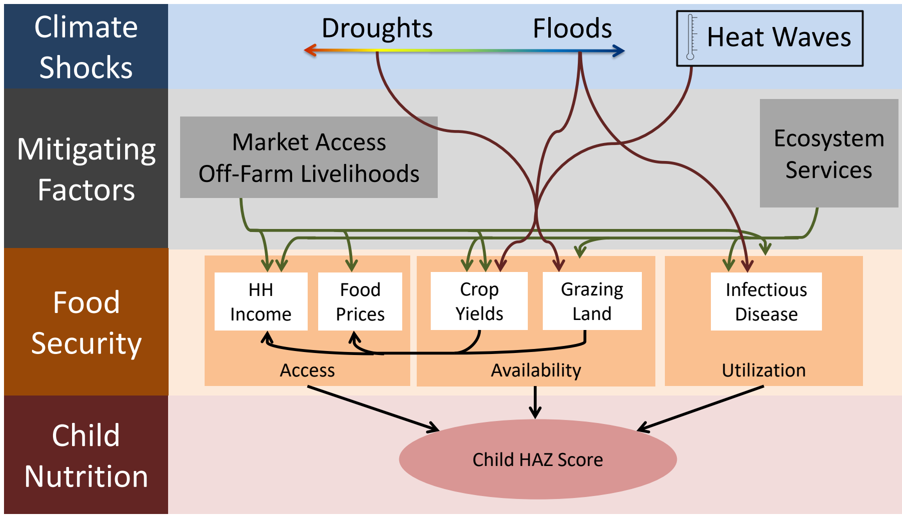

Figure 1.1: Pathways by which precipitation anomalies affect nutrition, as well as mitigating factors. Both low and high precipitation anomalies affect crop yields and grazing land, which in turn affect food prices and household income, while high rainfall can also affect infectious disease conditions, all of which ultimately affect food security and, eventually, child nutrition outcomes. However, factors like access to markets as well as ecosystem services can stabilize food prices, increase income, and raise crop yields, ultimately improving nutrition outcomes or at least stabilizing them in the event of precipitation shocks.

dren. Since 2015, more work has been done to confirm associations between low rainfall and rates of stunting (Kinyoki et al., 2016, Lopez-Carr et al., 2015, Shively et al., 2015), as well as to examine factors that can mitigate the effects of low rainfall (Shively, 2017). Nevertheless, there is still a significant dearth of research that draws on empirical observations of child nutrition and climate impacts, especially using large pools of data with the spatio-temporal variability that is needed to model outcomes across geographies.

1.2.3 Ecosystem Service Impacts on Food Security and Nutrition

Ecosystem services provided by natural areas play a large role in agricultural production, as these areas provide pollination and pest regulation services, create micro-climates via shading and windbreaks, retain soil moisture, and are essential for soil formation in areas that practice swidden agriculture (Reed et al., 2016). In addition to supporting agriculture, natural land cover types also provide wild foods like bushmeat, fish, insects, wild plants, nuts, seeds, and honey. These wild foods are a major part of the diets of agrarian people, and provide a wider range of micronutrients than agricultural foods alone (DeClerck et al., 2011), as well as Non-Timber Forest Products (NTFP), which can supplement income. Ecosystem services availability can be proxied using vegetation indices (Martínez-Harms and Balvanera, 2012) as well as land and tree cover, which is especially useful for measuring tradeoffs at landscape scales (Raudsepp-Hearne et al., 2010).

Another major benefit provided by ecosystem services is that they make livelihoods, and therefore human health and nutrition, more resilient to shocks that affect food production. Natural vegetation retains water and increases soil moisture during dry years, while pest regulation services are critical for crops that are already stressed from heat waves or too much humidity (Reed et al., 2016). Provisioning services like wild foods are a critical safety net for communities during droughts, floods, and heat waves (Robledo et al., 2012). For example, during extreme shocks communities with nearby natural areas can rely on “famine foods” - foods that are not commonly eaten but are known to be edible (Mavengahama et al., 2013). These foods are critical to sustain adequate nutrition during years of agricultural failure.

It has been estimated that NTFP provide income and nutrition for over two-thirds of Africa's population (CIFOR, 2005). These products can provide significant income to households and communities, with some products like shea oil and gum arabic being collected and exported to international markets (Mujawamariya and Karimov, 2014, Rousseau et al., 2017). Many other products, such as fuelwood and building materials, are also sold locally and are an income source. A global literature review of 51 case studies across 17 developing countries estimated that, on average, forests provide 22% of a household's total income (Vedeld et al., 2007). NTFPs can also provide fuel, food and materials to households for free and lessen their dependency on goods purchased from markets – thus, households with less income tend to be the most dependent on forest products (Vedeld et al., 2007).

Thus, ecosystem services like NTFP are critical to human well-being (Haines-Young and Potschin, 2010). Throughout the world, natural and human-impacted areas provide regulating, cultural and provisioning ecosystem services (Bennett et al., 2009). In agrarian parts of the developing world, communities depend significantly on local provisioning ecosystem services for their health and income (Altieri, 2004). While agricultural production often provides the bulk of food and income in these areas, provisioning ecosystem services from forests, shrublands and grasslands also make significant contributions to communities' livelihoods (Ambrose-Oji, 2003, Heubach et al., 2011, Kar and Jacobson, 2012). Understanding the geographic and demographic characteristics of areas that depend on these services is key to conservation priority setting to maximize ecosystem service provisioning and human well-being (Angelsen et al., 2011, Kareiva, 2011).

Chapter 2: Precipitation Anomalies, Nutrition and Food Security

2.1 Introduction

The Intergovernmental Panel on Climate Change (IPCC) states in the Fifth Assessment Report with high confidence that climate change will increase the risk of food insecurity through impacts such as droughts, flooding, and shifting precipitation patterns (IPCC, 2013). While rates of undernutrition and food insecurity have been falling overall for the past few decades, there have been recent increases in these statistics in some locations, which is somewhat attributable to climate shocks (FAO et al., 2018). Currently, the world is not on track to meet nutrition targets such as the second Sustainable Development Goal of zero hunger by 2030 (IFPRI, 2016), and meeting these targets will require significant investments in climate-resilient agriculture and supply chains (WBG, 2016). While increasing precipitation extremes induced by climate change are broadly known to be a threat to food security and nutrition, the interacting effects of rainfall shocks at various temporal scales, overall changes in precipitation patterns, and the current water requirements of livelihood systems, are underexplored. Furthermore, much of the work that has been done has not sufficiently controlled for the effects of spatial autocorrelation in the patterns of precipitation shocks as well as in food security and nutrition outcomes.

Thus, we here explore these interrelationships, taking care to account for spatial autocorrelation.

2.2 Background and Previous Literature

Substantial literature exists on the pathways by which precipitation shocks can affect food security (Funk et al., 2008, Lobell et al., 2008), with smallholder and subsistence farmers being particularly vulnerable (Morton, 2007). The most immediate impact of unusually low or high rainfall levels on food security is through harming yields, decreasing the overall food availability in a location (Afifi et al., 2014, Hanjra and Qureshi, 2010, Schlenker and Lobell, 2010, Thornton et al., 2009). Subsistence farmers in low income countries often plant crops that are adapted to local long-term rainfall patterns (Altieri et al., 2012, Altieri and Nicholls, 2017), but when a given season has rainfall levels that are far from long-term norms, yields can suffer (Amikuzino and Donkoh, 2012, Di Falco and Chavas, 2015). Insufficient water decreases the overall crop productivity, while at the same time, overabundant water can delay planting, prevent waterlogged roots from absorbing nutrients, increase the presence of crop pests, and increase lodging, rot and spoilage in harvests (Alam et al., 2011, Mirza, 2011, Tefera, 2012). In addition to harming the yields of grain and vegetable crops, rainfall shocks can affect the abundance of grazing areas, leading to lower availability of animal protein (Barrett and Santos, 2014, Patton et al., 2007). A decrease in food availability can then cascade to constraints in food access: when yields and livestock productivity decrease, food prices increase, making food access difficult for poor households (Brown and Kshirsagar, 2015, Devereux, 2007, Sen, 1983, Webb, 2010). At the same time, households that rely on sales of agricultural products can experience decreasing incomes, while those relying on agricultural wage labor or trading with farmers can also be negatively affected (Bola et al., 2014, Cunguara et al., 2011, Kazianga and Udry, 2006, Pandey et al., 2007, Udmale et al., 2015). Finally, excessive rainfall can increase the risk of infectious diseases such as malarial, parasitic and diarrheal disease, in turn harming proper food utilization and increasing rates of undernutrition (Delpla et al., 2009, Paterson and Lima, 2010). To deal with such shocks, households often adopt strategies of livelihood and agricultural diversification to protect their income and food security from these shocks (Lay et al., 2009, Maxwell, 2002, Scoones, 1998), while in some areas government social protection programs and international aid can also provide relief (Calow et al., 2010, Haile, 2005, Wilhite et al., 2014).

A recent review paper of research on precipitation and child undernutrition noted that there is "limited comprehensive empirical evidence at the household level" of an association (Phalkey et al., 2015). While it is broadly known that climate change will affect precipitation patterns and food security, much work remains to be done to understand which types of precipitation impacts will affect food security and which populations are most vulnerable. Several studies have found linkages between mean annual precipitation and child anthropometry (Akresh et al., 2011, Grace et al., 2012, Huss-Ashmore and Curry, 1994), suggesting that changing precipitation patterns induced by climate change may affect child nutrition outcomes. Other researchers have focused on deviations from long-term norms, and have found that both droughts and periods of excessive rainfall can impact child nutrition due to the effects of these precipitation extremes on agricultural production and overall food availability (Alderman, 2010, Chotard et al., 2011, Rodriguez-Llanes et al., 2011). However, there is much disagreement about the timescales at which precipitation shocks are most relevant to child undernutrition, with some studies focusing on early-life rainfall (Alderman, 2010, Rodriguez-Llanes et al., 2011), others focusing on prenatal precipitation (Woldehanna and Lives, 2010), others testing for rainfall shocks in recent seasons (Skoufias and Vinha, 2012), and still others looking at rainfall extremes during any single year in an individual's first five years of life (Alderman, 2010). Overall, it seems that little work to date has examined how precipitation extremes at multiple time scales relate to child anthropometry outcomes. The relationship between the timing of precipitation impacts and levels of child stunting is complicated by the fact that while the first thousand days of a child's life are most critical for anthropometric attainment (Black et al., 2013, du Plessis et al., 2016), there is a well-established phenomenon of catch-up growth, whereby a child can experience accelerated linear growth after the cessation of a nutritional shock (Behrman, 2015, Godoy et al., 2010, Stobaugh et al., 2018, Wit and Boersma, 2002). Thus, the linkages between the timing and duration of rainfall shocks and their impact on food security and nutrition merit further study.

While child anthropometry has been used as a metric of food security for decades, some researchers have raised important concerns regarding its lack of information on qualitative aspects of food insecurity (Coates et al., 2003, Maxwell, 1996), and the fact that is a lagged signal of previous household food insecurity

(Carletto et al., 2013). For these reasons, a number of new rapid indicators of food security have been developed, including the Household Hunger Scale (HHS) (Jones et al., 2013). However, linkages between these newer household food security metrics and climate and precipitation shocks, as well as their performance in relation to traditional child anthropometry metrics, remain underexplored.

We begin to address these questions by using geospatial data on precipitation patterns, population densities, and irrigation infrastructure in combination with the United States Agency for International Development (USAID) Feed the Future (FTF) household survey data. These surveys were commissioned by the USAID and conducted by the International Food Policy Research Institute (IFPRI) in Bangladesh and the Monitoring, Evaluation and Technical Support Services (METSS) team in Ghana. By comparing surveys from both Bangladesh and Ghana, we have the opportunity to compare the response of HAZ, WHZ, and HHS scores to precipitation extremes in two very different agro-ecological contexts: in Bangladesh, with high annual precipitation and high levels of irrigation, as well as in northern Ghana, with low annual precipitation and no large-scale irrigation. These surveys were designed to measure food security and child nutrition as well as critical co-variates such as household wealth and demographics (Feed The Future, 2011). Additionally, some FTF surveys collected GPS points at each household, facilitating the extraction of meteorological data at the location of each household to explore relationships between household characteristics, precipitation conditions, and nutrition and food security outcomes (Brown et al., 2014). We utilized geolocated FTF surveys from Ghana (2012) and Bangladesh (2011, 2015) to test for an observable impact of rainfall levels and rainfall extremes on household food security, measured by the HHS, and child undernutrition, measured by child height-for-age Z-scores (HAZ) and weight-for-height Z-scores (WHZ) using Spatial Error Regression (SER) where necessary to account for possible spatial autocorrelation in the regressions.

2.3 Data

2.3.1 Sources

For this analysis we used data on rural households from Feed the Future surveys conducted in Ghana and Bangladesh, taking care to properly account for effects of spatial autocorrelation (see Modeling Methods section). The 2012 survey from Ghana was targeted at the Feed the Future Zone of Influence (ZOI) in the northern part of the country where Feed the Future interventions had taken place, while the survey from Bangladesh was a nationally representative panel survey from the years 2011 and 2015. In Ghana, enumeration areas (EAs) were established in the ZOI in the Upper West, Upper East, and Northern regions, as well as in parts of the Brong-Ahafo region. Households were randomly sampled from these EAs and sampling weights were generated to make the data representative of the ZOI. In Bangladesh, households were selected from 325 primary sampling units (PSUs) throughout the country, and sampling weights were devised based on population census data to make the survey nationally representative. Rural households with less access to high-quality roads and food markets generally have lower agricultural productivity

(Stifel and Minten, 2008). Thus, children in such areas are more affected by local precipitation patterns (Mulmi et al., 2016, Shively, 2017) and typically exhibit higher rates of stunting (Thapa and Shively, 2018). Therefore, we focused our analysis on rural households, as other researchers have done in similar studies (Phalkey et al., 2015). For Ghana, we only use data on households from PSUs designated as rural in the sampling frame of the Ghana survey, while for Bangladesh, because EAs were not classified into urban and rural, we excluded households within 30 minutes travel time to cities of over 20,000 people, with the time to travel to cities calculated using a methodology developed by IFPRI (Guo and Cox, 2014). This yielded a final dataset of 2,362 Ghanaian households and 4,878 unique Bangladeshi households. Of the Bangladeshi households, 4,464 were observed twice, 342 where only observed in 2011, and 72 were only observed in 2015, yielding a dataset of 9,342 observations. Finally, for our analysis of HAZ and WHZ scores, we had a final dataset of 3,271 children from Bangladesh and 1,346 children from Ghana. There were fewer children than households in both countries because not all households had children under 5 years old.

2.3.2 Outcome Variables

Our anthropometric outcome variables were height-for-age z-scores (HAZ) and weight-for-height z-scores (WHZ) of children under five years old. This approach involves comparing the height and weight/height ratio of a child under five years old to the distributions of these measurements for children of the same age and gender in a healthy population and assigning a Z-score (WHO, 1995). A child's HAZ score is a common indicator of stunting, which results from long-term, chronic undernutrition, while a child's WHZ score is an indicator wasting, which results from recent and acute undernutrition (Lewit and Kerrebrock, 1997). These metrics have been used for decades and have been found to be a salient indicator of child health status (Black et al., 2013), and strongly related to agricultural variables (Bezner Kerr et al., 2011, Cunningham et al., 2015, Shively, 2017, Webb and Kennedy, 2014), environmental variables (Akseer et al., 2018, Buttenheim, 2008, Chagomoka et al., 2018, Grace et al., 2017), as well as other child health metrics (Black et al., 2008, Caulfield et al., 2006, Dewey and Begum, 2011). The population-level rates of stunting and wasting can be derived from the percentage of children with HAZ and WHZ scores less than -2, although natural variation in human height as well as the arbitrary cutoff of -2 makes it inappropriate to classify an individual child as stunted or wasted from anthropometry alone (Perumal et al., 2018). Stunting and wasting can bear long-term effects on educational outcomes, disease risk, and potential adult income (Badham and Sweet, 2010, Dewey and Begum, 2011), and so reducing the rates of these indicators of undernutrition is a critical part of sustainable development (Daelmans et al., 2017).

In addition to child HAZ and WHZ scores, we also analyzed the Household Hunger Scale (HHS), a common indicator of household food insecurity (Jones et al., 2013), measured in both the Ghana and Bangladesh surveys. The HHS consists of three questions about a household's experience of insecurity (Ballard, 2011), expressed by:

1. Was there ever no food to eat of any kind in your house because of lack of resources to get food?

2. Did you or any household member go to sleep at night hungry because there was not enough food?

3. Did you or any household member go a whole day and night without eating anything because there was not enough food?

Households report how frequently they had experienced these events over the previous four weeks and a score is given for each question (never: 0, rarely or sometimes: 1; often: 2). The frequency scores across all three questions are summed to yield the final HHS score, with a value of 0 indicating no experiences of hunger, and a value of 6 indicating frequent experiences of all three forms of hunger over the previous four weeks. The HHS was developed from applications of the Household Food Insecurity Access Scale (HFIAS), which consisted of nine questions (Deitchler et al., 2010). Both the HHS and the HFIAS grew out of a recognized need for indicators of food security that could be rapidly deployed and that capture experiential aspects of food insecurity (Carletto et al., 2013, Coates et al., 2003). However, some of the nine questions in the HFIAS were found to be difficult to translate into other languages, while the item-step severity of the scale did not always change monotonically (Deitchler et al., 2010, Jones et al., 2013). Thus, the HHS is based on only three questions from the HFIAS which are most readily translatable and applicable to other cultural settings and are most likely to show item-step severity trends that are monotonic. Overall, compared to the HFIAS, the HHS is recognized to have the highest potential to be internally, externally and cross-culturally valid (Deitchler et al., 2010). While it has been pointed out that the HHS measures hunger and not food security per se (Jones et al., 2013), food security itself cannot be measured directly (Vaitla et al., 2017) and the HHS certainly captures an important aspect of food security. Thus, in this paper we take increased hunger as measured by the HHS score as indicative of worse food security.

2.3.3 Predictor Variables

We used rainfall data from the Climate Hazards Group InfraRed Precipitation with Station (CHIRPS) dataset (Funk et al., 2015), and we calculated the long-term rainfall norm as well as the Standardized Precipitation Index (SPI) at intervals from one to five years for each household. The SPI is a derived measure of wetness/dryness for a given location based on long-term norms at that site, with a positive SPI score indicating a wetter-than-normal period and a negative SPI score indicating a drier-than-normal period (Guttman, 1999). The time scale used to calculate the SPI varies depending upon the application, with studies focusing on agriculture using SPI a shorter timescales of up to 12 months (Brown and Funk, 2008), studies focusing on WHZ scores calculating SPI over shorter windows such as 3 months (Delbiso et al., 2017, Lazzaroni and Wagner, 2016), and studies focusing on other health impacts calculating SPI over longer windows of up to 48 months (Dinkelman, 2017, Hyland and Russ, 2019), with most studies finding a significant association between SPI and various outcome variables of interest.

SPI Range	Interpretation
<-2	Extremely Dry
-1.5 - -2	Moderately Dry
-1 - -1.5	Dry
-1 - 1	Normal Precipitation
1 - 1.5	Wet
1.5 - 2	Moderately Wet
>2	Extremely Wet

Table 2.1: Summary of variables included as co-variates in the regressions as well as their availability by country. Where applicable, variable units are given.

To explore how rainfall aberrations over different time periods can affect food security and nutrition, for our analysis we ran separate regressions with SPI values measured at 12, 24, 36, 48, and 60-month intervals for each country and outcome variable. For each survey analyzed, spatial variation in SPI scores is substantial. The maps in Figure 1 show the observed 48-month SPI values in the Ghana and Bangladesh household surveys. In Ghana, precipitation in the north was slightly higher than normal, and near the Volta Basin in the east it was significantly wetter than normal. Bangladesh had showed similar rainfall patterns in the north in both 2011 and 2015, with households in north and central Bangladesh experiencing drier-than-average periods, with farmers in the northeast of the country in the Sylhet region experiencing wetter-than-average periods. In the south of Bangladesh, precipitation patterns differed between 2011 and 2015. Households in Barisal were experiencing ample rainfall in 2011 but experienced a dry period leading up to 2015, while households in Chittagong in the southeast experienced a mildly wet period in 2011 and a very wet period in 2015.

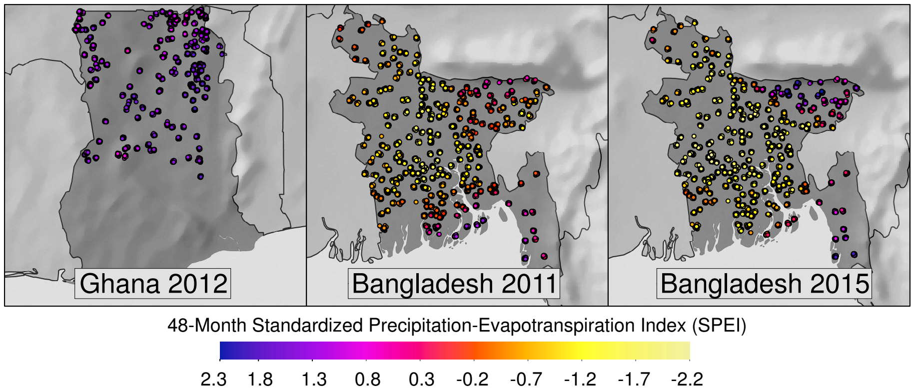

Figure 2.1: Locations of households used in the analysis, as well as observed 48-month SPI values at each household. Figure was made using ArcMap.

2.3.4 Control Variables

To better assess the relationship between precipitation and food security and nutrition, we control for several other geographic-, household-, and individual-level variables. Household wealth is a strong determinant of both household food security status and child nutrition status (Ahmed et al., 2012). Because there was no measure of income or expenditure in the surveys, we constructed an index of household wealth through Principal Component Analysis (PCA) on household assets and other indicators of wealth (Vyas and Kumaranayake, 2006). For each country, the first principal component factor explained a large proportion of the variance (68% and 65% of the variance in Bangladesh and Ghana, respectively). The assets we used varied by country and are summarized in Appendix A.

In addition to an asset index, other variables included were the household size, household head characteristics such as sex, religion, and education, as well as the fraction of a household not of working age. The two datasets did not have identical information on household or individual characteristics and in some cases, variables were frequently missing or incomplete, so different control variables were used in the country-level analyses. In Bangladesh, the interview month was included in the regressions in order to control for seasonal effects; however, these were not included in Ghana as the entire survey took place over the course of a month. These variables are summarized in Table 2.2.

Variable	**Ghana**	**Bangladesh**
Outcome Variables		
Household Hunger Scale	Yes	Yes
Height-for-Age Z-Score	Yes	Yes
Geographic Variables		
Population within 7.5km (Count of People)	Yes	Yes
Percent of Agricultural Area Irrigated	No	Yes
Household Variables		
HH Size (Number of Individuals)	Yes	Yes
Asset Index	Yes	Yes
HH Head Religion	Yes	Yes
HH Head Age (Years)	Yes	Yes
HH Head Literate	Yes	Yes
HH Head Education Level	No	Yes
HH Head Sex	Yes	Yes
Percentage of Household Under 12 or Over 60 Years of Age	Yes	Yes
Interview Month	No	Yes
Survey Year	n.a.	Yes
Individual Variables (Used in Nutrition Analyses)		
Age (Months)	Yes	Yes
Gender	Yes	Yes
Child's Birth Order	Yes	No
Siblings Born Within 24 Months	Yes	No

Table 2.2: Description of Variables Used in Regressions

2.4 Descriptive Statistics

To generate hypotheses to be tested in the multivariate regression framework and facilitate the interpretation of estimation results, in this section we graph probability density and probability mass functions, as well as summary statistics of several key statistics in the regressions. Additionally, complete summary statistics are provided in Appendix A.

2.4.1 Standardized Precipitation Index

For each country, the SPI values provided ample variation in each regression. SPI scores in Bangladesh varied more than in Ghana, often from less than -2, signaling extremely dry conditions, to 2, signaling moderately wet conditions, depending on the period. In both 2011 and 2015, the majority of households were subject to lower rainfall than the long-term norm for SPI values calculated at all time windows. For Ghana, none of the households experienced drought at the time of the survey, and only a few households had SPI values less than 0 when calculated by the 12 month window, meaning that we can only examine the effects of extreme rainfall on food security and anthropometry outcomes in Ghana and not the effects of drought. For most time windows, SPI values ranged from near-normal to moderately wet conditions.

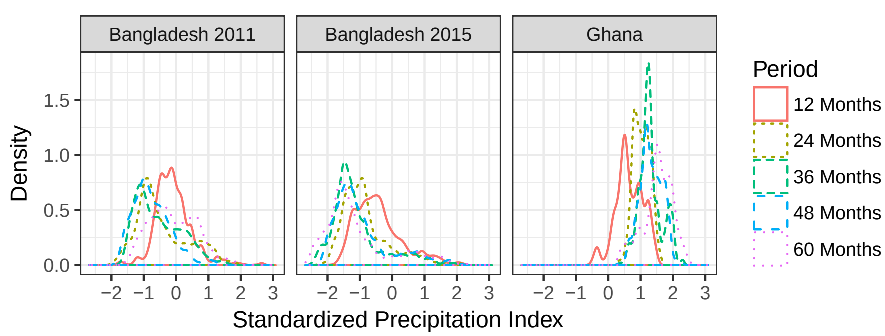

Figure 2.2: Density plots of observed SPI scores, by survey and the period over which the SPI was calculated. Figure was made in R using the ggplot2 library.

2.4.2 Average Annual Precipitation

The density plots below report the distribution of average annual precipitation levels among households in the two countries. Bangladesh receives significantly more rainfall than Ghana, with the minimum rainfall in Bangladesh being similar to the maximum rainfall in Ghana. Bangladesh shows much greater variation in rainfall distribution, from 1420mm to 5000mm per year, whereas Ghana only ranges from 912mm to 1370mm per year.

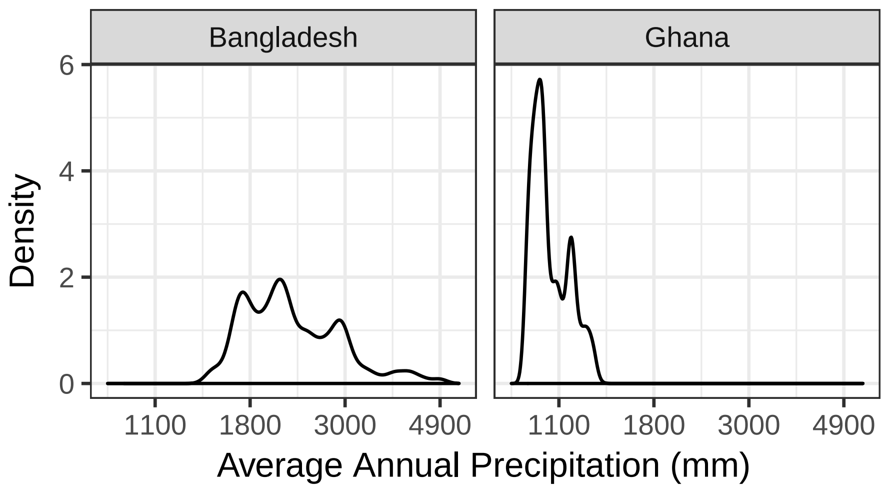

Figure 2.3: Density plots of average annual precipitation levels across observed households, by country. Figure was made in R using the ggplot2 library.

2.4.3 Household Hunger Scale

In Bangladesh, 10.1% of households had experienced hunger in the previous four weeks at the time of the 2011 survey and 11.7% had experienced hunger in the previous four weeks at the time of the 2015 survey, with progressively fewer households at each level of increasing severity. Ghana, on the other hand, showed higher scores, with 56.7% households reporting some level of hunger. The count and percent distribution of households for each value of the hunger scale is provided in Appendix A.

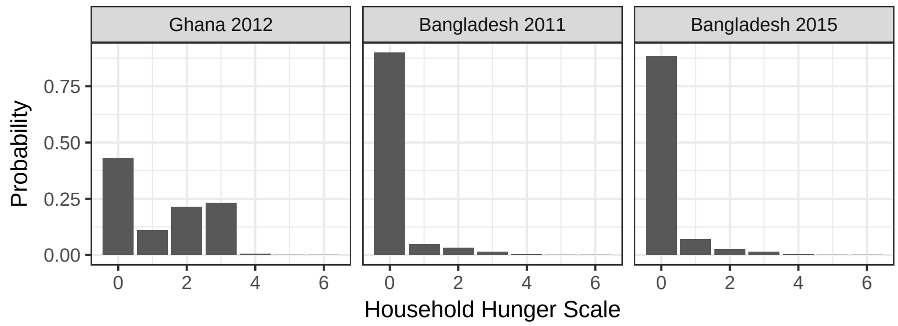

Figure 2.4: Frequency plot of observed Household Hunger Scale (HHS) scores, by survey. Lower scores indicated less hunger.

2.4.4 Child HAZ and WHZ Scores

Rates of stunting and were very high in both Ghana and Bangladesh, at 38% and 43% respectively, while rates of wasting were lower, at 14% in Bangladesh and 11% in Ghana. While the Z-scores of children clustered well below 0 in each country, there was still substantial variation in heights.

2.5 Modeling Methods and Results

In this analysis, we took care to control for spatial autocorrelation. This is because outcomes such as HHS and HAZ scores are often correlated spatially: nearby households are likely to show similar nutrition and food security outcomes. The correlations in outcomes could be due to a variety of factors, such as spatial clustering in the distribution of poverty, disease burden, market access, soil fertility, pest out-

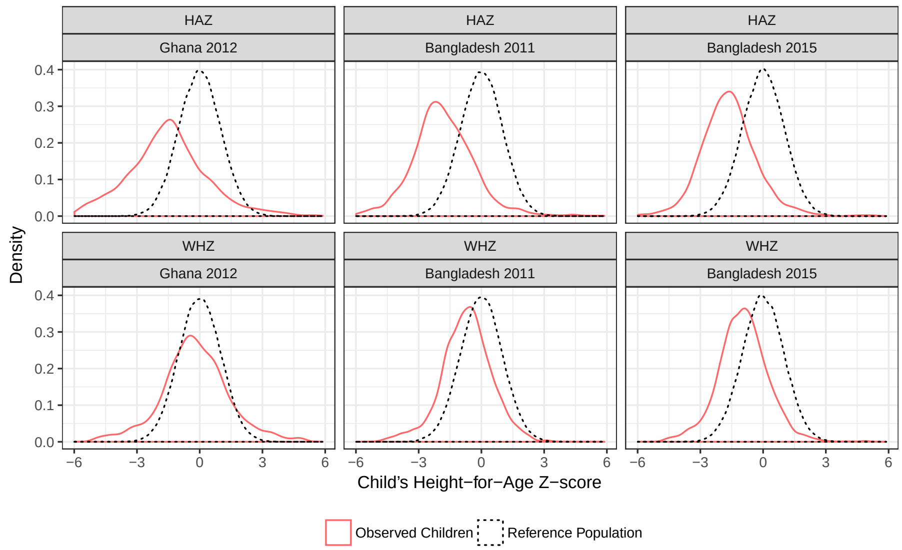

Figure 2.5: Density plot of observed child height-for-age Z-scores (HAZ) and weight-for-age Z-scores in comparison to a reference healthy population, by country. An HAZ score of less than -2 is considered stunted and a WHZ score of less than -2 is considered wasted. Figure was made in R using the ggplot2 library.

breaks, or farming practices. Thus, it is necessary to use a Spatial Error Regression because OLS assumes that each observation is independent. If there is an underlying spatial structure to the error terms, a simple ordinary least-squares (OLS) regression will tend to underestimate the variance and therefore will overestimate the p-values in the model (Ward and Gleditsch, 2008b).

To verify that there is a need to conduct a Spatial Error Regression and to determine the distance cutoffs for the spatial weights matrix, we first conducted an Exploratory Spatial Data Analysis (ESDA). For each outcome and each country, we tested to determine whether or not the residuals of an OLS regression show spatial autocorrelation, and we did this using a Moran's I test. Then, for outcomes for which spatial autocorrelation was detected by a Moran's I test, we plotted a correlogram for the outcome variable to determine the distance at which spatial autocorrelation disappears and then used this distance to construct a spatial weights matrix.

We modeled outcome variables for which we observed spatial autocorrelation using a Spatial Error Regression, which uses a spatial weights matrix to correct the error term and obtained unbiased coefficients and p-value estimates (Anselin, 2001, Bivand et al., 2005, Ward and Gleditsch, 2008b). The SER differs from the Spatially Lagged Regression (SLR) model in that it models spatial correlation in the error term due to unobservable processes affecting households across space, while the SLR explicitly models the spatial correlation in the dependent variable due to observable characteristics spatially correlated across households (Ward and Gleditsch, 2008b). A SLR is more appropriate when the value of one observation affects the value of nearby observations, whereas a SER is more appropriate when the values of observations are independent from each other but affected by unobservable underlying spatial processes. Since child nutrition and household food security statuses are more affected by unobserved spatial conditions than by the correlation of the observed characteristics among children and households across space, we used a SER.

Specifically, a Spatial Error Regression takes the form:

$$y = \beta_0 + \beta X + \lambda W \xi + \epsilon \tag{2.1}$$

where, as in a typical regression, y is the outcome variable, β_0 is the intercept, β is a vector of coefficients, and X is a matrix of observed covariates. In a SER, the error term is decomposed into ϵ, the spatially uncorrelated error component and ξ, the spatial error component, which is estimated using the matrix of spatial connectivities Wand the parameter λ, which indicates the degree to which error terms are spatially correlated. We estimated the matrix of spatial connectivities W for neighbors within the cutoff distance determined by the correlograms. In every regression, we included sample weights.

For each country, we ran separate regressions for child WHZ, HAZ and HHS scores across all 5 SPI windows and included the relevant co-variates in each regression. Due to the number of hypothesis tested (30), we use a Bonferroni correction when testing for statistical significance of the coefficient of the SPI term to avoid the possibility of a Type I error of incorrectly rejecting the null hypothesis and hence we use an alpha value of α=0.05/30=0.00167. In the case of Bangladesh, given the availability of the panel dataset for Household Hunger Scores, we first conducted a Chow test to identify a possible structural change over time, in absence of which it would be appropriate to pool the two waves of data (Wooldrige, 2013). The test statistic was not significant for any SPI value ($\alpha = 0.01$), and there was no a priori reason to expect the effects of precipitation shocks on food security and nutrition to be different between 2011 and 2015, so we pooled the waves and included a fixed effect for the survey year. Parameter estimates and test statistics are presented in Appendix A.

2.5.1 Exploratory Spatial Data Analysis (ESDA)

We tested for spatial autocorrelation in our outcome variables as well as in the residuals of an OLS using a Moran's I test for each outcome variable and each country. This showed that there was spatial autocorrelation for the HHS score in Bangladesh and in Ghana, as well as for the HAZ and WHZ score in Bangladesh; however, there was no autocorrelation for HAZ or WHZ scores in Ghana.

Country	Variables	Observed	Expected	Std. Dev.	P Value
Ghana	HAZ	0.00247	-0.00074	0.00549	0.559
Ghana	WHZ	0.00603	-0.00074	0.00549	0.217
Ghana	HHS	0.0477	-0.00042	0.00384	0
Bangladesh	HAZ	0.00887	-0.00031	0.00236	0.000105
Bangladesh	WHZ	0.00496	-0.00031	0.00236	0.0261
Bangladesh	HHS	0.00422	-0.00011	0.000911	0.00000203

Table 2.3: Results of a Moran's I test for spatial autocorrelation for WHZ, HAZ, and HHS residuals in Bangladesh and Ghana.

For the three outcome variables for which there was spatial autocorrelation, we examined a correlogram to determine the distance at which autocorrelation persists. The distance at which the 95% error bar dips below 0 is the distance at which a Moran's I test no longer shows significant spatial autocorrelation. This showed that there was significant ($p < 0.05$) spatial autocorrelation to 80 kilometers for the HHS score in Bangladesh, to 30 kilometers for the HAZ score in Bangladesh, to 20 kilometers for the WHZ score in Bangladesh, and to 125 kilometers for the HHS score in Ghana. We used these distances to establish the cut-off distances in defining our spatial weights matrices for the Spatial Error Regressions.

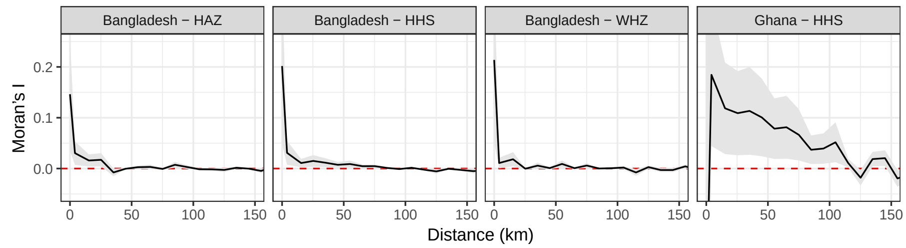

Figure 2.6: Correlograms showing Moran's I at various spatial lags, with a 95% confidence interval shaded in grey. These estimates were used to create the spatial weights matrices used in the regressions.

2.5.2 Ghana

Although we varied the SPI window from one to five years, the covariates remained mostly unchanged and had similar estimates across the regressions. The child's age was a significant predictor of the child's HAZ or WHZ score, with older children having lower HAZ scores but larger WHZ scores. Household size and household religion were significant predictors of HAZ scores, with larger households being associated with higher HAZ scores and households with no religion being associated with children with lower HAZ scores. Various Regions were also significant as fixed effects for child WHZ scores. For HHS scores, significant covariates included the household size, household head age, whether the household head was literate, and the household religion. Additionally, the average annual precipitation was significant across many of the HHS regressions, with households receiving more annual precipitation being associated with less hunger.

For SPI values, excessive rainfall over a short time window of 12 months was associated with lower WHZ scores, whereas excessive rainfall over longer time windows of 36 months were associated with lower HAZ scores. Excessive rainfall over periods of 36 and 48 months were also associated with lower HHS scores.

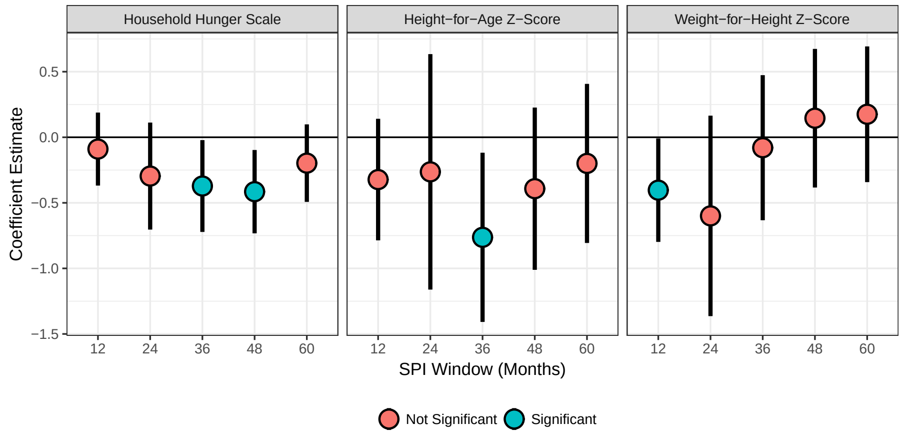

Figure 2.7: Coefficient estimates for Ghana for SPI values calculated at varying windows. Errors bars and significance values are shown after accounting for a Bonferroni correction. Note: while higher HAZ and WHZ scores indicate good nutrition, higher HHS scores indicate poor food security. Figure was made in R using the ggplot2 library.

2.5.3 Bangladesh

Many of the covariates were significant in the Bangladesh regressions. Similar to Ghana, the child's age was significant for both HAZ and WHZ scores, however in Bangladesh, older children had both lower HAZ and WHZ scores. Household head education had significant effects on both WHZ and HAZ scores, with more educated household heads being associated with better nourished children. The month of the household survey also had a significant effect on both HAZ and WHZ scores, especially for months earlier in the calendar year. For covariates of HHS, education played a significant role, with more educated household heads having lower HHS scores, indicating less hunger, and less educated household heads having higher HHS scores, indicating more hunger. Other household demographic factors were also important, with households with a larger fraction of young and old having higher HHS scores, and larger households having lower scores. Many of the Divisions of Bangladesh were also significant predictors of a household's HHS score. Finally, mean annual precipitation was never a significant predictor of a household's HHS score.

For nutrition and food security outcomes across all of the SPI time windows, the recent SPI was never a significant predictor of child nutrition outcomes like HAZ and WHZ. However, the 48-month SPI was a significant predictor of household hunger scores, with greater rainfall being associated with higher scores, indicating more hunger. None of the other time windows were significant predictors of hunger.

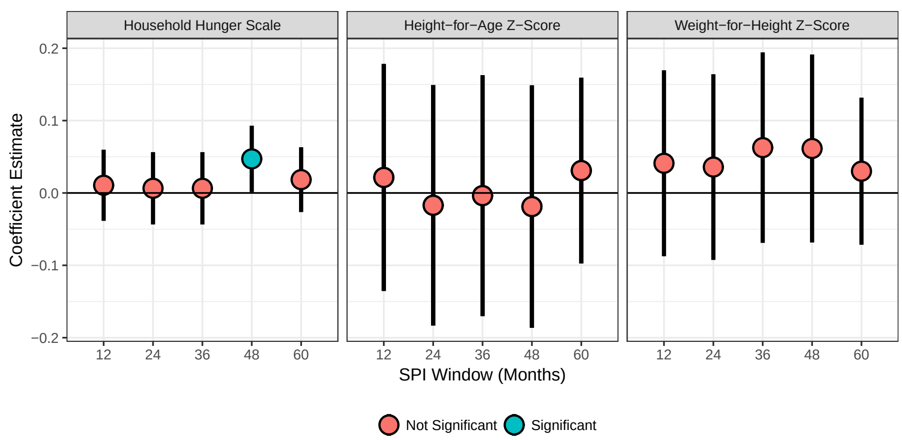

Figure 2.8: Coefficient estimates for Bangladesh for SPI values calculated at varying windows. Errors bars and significance values are shown after accounting for a Bonferroni correction. Note: while higher HAZ and WHZ scores indicate good nutrition, higher HHS scores indicate poor food security. Figure was made in R using the ggplot2 library.

2.6 Discussion

This study has contributed to the literature on precipitation shocks and food security and nutrition in three ways. First, it has demonstrated the utility of Spatial Error Regression in accounting for geographic autocorrelation in food security outcomes. This type of model can reduce the impact of unobserved spatial processes that can confound results in a simple OLS regression. Such an approach is important for disentangling the effects of climate from other variables that also have a spatial component, such as wealth, market access, and livelihood systems. Secondly, this study has compared how shocks over various time periods may affect food security and nutrition outcomes in both an arid country as well as in a country with relatively high average rainfall. Finally, this study has examined how both anthropometric measures and the Household Hunger Scale response to precipitation shocks and demonstrates that the Household Hunger Scale is a useful and informative metric of studying household food security.

The distribution of both precipitation regimes and precipitation shocks have a spatial component – nearby households are likely to have similar precipitation patterns and experience similar precipitation shocks. Similarly, nearby households are likely to have similar levels of food security and nutrition, as these are affected by a variety of underlying spatial processes such as the distribution of wealth, infrastructure, and livelihood systems. Thus, when assessing the relationship between precipitation patterns and food security outcomes, it is important to control for this autocorrelation to minimize the possibility of a Type I error and incorrectly reject the null hypothesis. In this paper, we demonstrate this approach, beginning with an Exploratory Spatial Data Analysis (ESDA) to identify for which regressions a Spatial Error Regression is necessary.

Examining SPI calculated across different windows allowed us to compare how rainfall levels over different periods of time affected child nutrition and household food security. In Ghana, the response of WHZ and HAZ scores to different rainfall windows were in line with what the literature would suggest: short term rainfall shocks over 12 months were significant predictors of WHZ scores, an indicator of short-term undernutrition, whereas longer periods of 36 months were significantly associated with HAZ scores, which indicate long-term, chronic undernutrition (Lewit and Kerrebrock, 1997, WHO, 1995). In both cases, increased rainfall was associated with worse nutrition outcomes. While HAZ and WHZ scores respond differently to rainfall shocks over different time periods, in both Ghana and Bangladesh household hunger was affected by longer term processes. This suggests that most households will not experience food insecurity after a single poor crop season or even a year of poor yields. Rather, in the two countries examined, it is the compounding effects of multiple years of precipitation extremes that make households vulnerable to hunger. This suggests that some studies which have examined the impacts of short-term SPI on malnutrition would benefit from also examining SPI calculated over longer timescales (Delbiso et al., 2017, Lazzaroni and Wagner, 2016). Finally, in Ghana, higher average annual precipitation levels were associated with lower household hunger scores. This suggests that there may be impacts on food security as areas experience gradual drying over multiannual and decadal periods, rather than just precipitation extremes over shorter periods.

By comparing Ghana and Bangladesh – two countries with similar levels of wealth per capita and large agrarian populations but starkly divergent precipitation regimes – we can get a better sense of what kind of precipitation shocks affect food security in which contexts. Overall, with regard to hunger, it seems that in arid Ghana, more rainfall improves food security, as decreased hunger was associated with both increased precipitation over 36 and 48 month windows as well as increased average annual precipitation. It is particularly noteworthy that all households in Ghana were observed during wet periods, and even exceptionally high precipitation levels were not associated with increased hunger. In contrast to Ghana, in Bangladesh, increased rainfall was associated with more hunger. This is not entirely surprising, given that flooding in Bangladesh has been associated with increased stunting and food insecurity (Del Ninno et al., 2003, Douglas, 2009, Monirul Qader Mirza, 2002). These findings indicate that precipitation shocks will not necessarily harm food security in all contexts. Rather, whether or not a shock affects food security is depended on prevailing agro-ecological conditions. In comparing Bangladesh and Ghana, results further indicate that food security and nutrition in northern Ghana may be more sensitive to rainfall deviations from long-term norms than Bangladesh is, as WHZ, HAZ, and HHS scores were affected by precipitation in Ghana, but only HHS scores were affected by precipitation in Bangladesh. This may be due to the fact that Bangladesh has extensive irrigation infrastructure, making agricultural production less affected by local rainfall.

Another contribution of this study to the literature was the comparison of the Household Hunger Scale to child anthropometry. In Ghana, counter-intuitively, greater rainfall was associated with less hunger but more undernutrition. Furthermore, the findings are more robust and less likely to be due to spurious correlation because we controlled for both spatial autocorrelation and testing multiple hypothesis by using a SER regression as well as a Bonferroni correction. These findings may be explained in part by the role that infectious disease can play in affecting child nutrition (Dowell, 2001, Patz et al., 2004). Excess rainfall can lead to increased incidence of malaria (Briët et al., 2008, Odongo-Aginya et al., 2005, Thomson et al., 2005), parasite infections (McCreesh et al., 2015, Raso et al., 2006), diarrheal disease (Carlton et al., 2014), and other infectious diseases (Patz et al., 2005), especially cholera (Hashizume et al., 2008, Moore et al., 2017). These effects may be especially pronounced in areas without the appropriate infrastructure to handle large quantities of rainfall. Thus, it may be that increased rainfall has mixed results for food security, because while it can lead to more food production and agricultural income, it can also hamper food utilization due to an increased disease and parasite burden. These results reinforce the notion that climate change will have complex impacts on human well-being. Furthermore, these results echo previous findings that food security is complex and multidimensional, and is more accurately characterized by using multiple complementary metrics (Coates et al., 2003, Vaitla et al., 2017).

In Bangladesh, only the Household Hunger Scale was related to rainfall patterns, while both HAZ and WHZ scores were uncorrelated with recent rainfall aberrations, even though previous literature had found a relationship between high rainfall and stunting in that country (Rodriguez-Llanes et al., 2011). This may be somewhat due to the fact that the dataset used in the analysis has relatively few households with children under five years old (only 15% in Bangladesh in both 2011 and 2015), meaning that the regressions for HAZ and WHZ scores relied on data sets of significantly reduced size. Thus, the regressions with anthropometric outcomes had less statistical power for inference. These findings suggest that, while much previous literature has focused on the relationship between rainfall and child anthropometry (Cornwell and Inder, 2015, Lopez-Carr et al., 2016, Maccini and Yang, 2009, Rodriguez-Llanes et al., 2011), rapidly deployable metrics of food security at the household level such as the HHS may be more robust indicators of climate change impacts than just child anthropometry, especially as birth rates decline worldwide and households are less likely to have children under five present.

While this study made several contributions to the literature, there remain further avenues for research. For example, while we controlled for additive effects of irrigation in Bangladesh, future work could test for an interactive effect between irrigation levels and SPI. Furthermore, future studies could account for temperature, which has been shown to have a direct effect on child health outcomes (Grace et al., 2015), and also plays a significant role in moderating the severity of drought on agriculture because it affects evapotranspiration (Beguería et al., 2014). Thus, future work could model extend the SPI by using biogeophysical models to estimate local evapotranspiration and calculate the Standardized Precipitation-Evapotranspiration Index (SPEI).

2.6.1 Implications

The present work has many implications for policymakers and researchers. We showcase the utility of Spatial Error Regression and emphasize the importance of testing for spatial autocorrelation in analysis of factors that vary through space, such as food security and nutrition. Our study also highlights the utility of the Household Hunger Scale as tool to measure food security in addition to commonly-used anthropometric metrics such as the child anthropometrics z-scores. This is because we found diverging impacts of excessive of precipitation on anthropometry and household hunger in Ghana, as well as because we found the HHS to be more sensitive than child anthropometry to precipitation extremes in Bangladesh. These findings are indicative of the complex ways in which climate shocks can affect human well-being and highlight the importance of measuring multiple aspects of food security to get a comprehensive characterization of foods security. More research is needed on the HHS and similar rapid food security indicators, as policy tools such as the Integrated Food Security Phase Classification may benefit from incorporating such indicators (IPC/FAO, 2015). Finally, we have presented evidence that both drought and periods of excessive rainfall are significantly correlated with food security outcomes, with dry areas potentially more vulnerable to drought and wetter areas potentially more vulnerable to excessive rainfall. To better understand the role that environmental and infrastructural context plays in moderating the impacts of precipitation shocks and food security and nutrition, more comparative and multinational studies are needed.

Chapter 3: Mapping the Effects of Drought on Child Stunting

3.1 Overview

Currently, one in nine people around the world are undernourished and nearly half of the deaths in children under five are caused by poor nutrition (FAO et al., 2018). One of the consequences of poor child nutrition is stunting, which affects more than one in three children in many developing countries (UNICEF et al., 2017). Stunting can lead to a higher risk of mortality as a child (Black et al., 2010), as well as reduced physical, cognitive, and educational attainments and life-long health problems from reduced immunity and increased disease susceptibility (Arthur et al., 2015). The effects of stunting on a population are long term: the children of parents who experienced early childhood stunting are in turn at higher risk for lower developmental levels (Walker et al., 2015). Due to decreased earnings and economic output, child stunting can hamper long-term economic growth for generations (Heltberg, 2009). Thus, ameliorating child stunting is a critical component of sustainable development (Daelmans et al., 2017). While rates of stunting have been in decline globally over the past few decades, hot spots of stunting remain in Africa and South Asia (Osgood-Zimmerman et al., 2018). Furthermore, because stunting has been shown to be very sensitive to climate shocks (Grace et al., 2012, Shively, 2017), climate change could stall or even reverse current gains (FAO et al., 2018).

Climate change is now widely acknowledged to be a threat to food security and nutrition globally. Rising temperatures due to increased greenhouse gas emissions will change patterns of precipitation and temperature around the world, in turn affecting food production and infrastructure critical to food distribution (Porter et al., 2014). All of these impacts will affect child nutrition outcomes, which is why both the World Health Organization (WHO) and the Intergovernmental Panel on Climate Change (IPCC) have identified undernutrition as a major expected health impact of climate change (Smith et al., 2014, WHO, 2014). Most directly, climate change will affect crop production and therefore food availability (Schlenker and Lobell, 2010). In many parts of the world, precipitation shortfalls will become more frequent and severe, while rising temperatures will increase rates of evapotranspiration and cause drought conditions even in areas with sufficient rainfall (Milly and Dunne, 2016), ultimately leading to lower crop yields and worsened food security and nutrition for vulnerable populations (Wheeler and von Braun, 2013).

While climate change is recognized as a major threat to child nutrition, insufficient research has been conducted associating the effects of precipitation and temperature shocks with worsened nutrition outcomes. A 2015 review paper documented 15 studies that used regression techniques to find an association between meteorological or agricultural variables and child nutrition outcomes, and the paper ultimately characterized the current evidence as "scattered and limited" (Phalkey et al., 2015). In this literature review, only two studies were multinational, and the largest sample size was about 19,000 children. Since 2015, more work has been done to confirm associations between low rainfall and rates of stunting (Shively et al., 2015), as well as to examine factors that can mitigate the effects of rainfall anomalies on child nutrition (Shively, 2017). Nevertheless, there is still a significant dearth of research that draws on empirical observations of child nutrition and climate impacts, especially using large pools of data with the spatio-temporal variability that is needed to model outcomes across geographic contexts.

Because the primary impact of climate change will be on food production, much of the research on the expected impacts of climate change on food security focuses on agricultural yields. While farmers in general and subsistence farmers in particular will be quite affected by climate change, whether or not its impacts lead to increased child undernutrition depends on a variety of factors that ultimately affect food access, such as equitable food distribution, government safety nets, and resilient trade systems (Baro and Deubel, 2006). As recent droughts in Southern and Eastern Africa demonstrate (FEWS NET, 2016, 2017), there can be significant spatial heterogeneity in which populations are most affected and vulnerability is influenced by a variety of political, social, economic, agricultural and environmental factors.

Focusing on these factors influencing vulnerability, some studies have been conducted at global and continental scales to create indicators that highlight hotspots of risk. Such studies include efforts to map drought risk (Carrão et al., 2016), the risk of climate change impacts on food security (Ericksen et al., 2011, Krishnamurthy et al., 2014, Richardson et al., 2018), as well as mapping climate risks for security more broadly (Busby et al., 2014). While these studies recognize the importance of locating the populations most vulnerable to climate impacts, they often rely on highly aggregated data and make no predictions about actual impacts, but simply highlight areas of general risk or severity. Furthermore, because these studies lack an empirical basis to estimate how different factors affect climate change vulnerability, they often weigh diverse variables equally when combining them into an indicator - for example, deriving sub-indicators and taking the average (Carrão et al., 2016, Krishnamurthy et al., 2014). In this study, we improve upon these methods by using an econometric approach to map the anticipated effects of drought on child stunting globally.

To map where child nutrition is vulnerable to precipitation shocks and explore which factors moderate vulnerability, we combine nutrition data from Demographic and Health Surveys (DHS) with climatological data, as well as a variety of global datasets on factors influencing both the sensitivity of local food systems to drought as well as local adaptive capacity from sources such as the World Bank, the FAO, and NASA, as well as datasets published in scientific journals. Deriving the Standardized Precipitation-Evapotranspiration Index (SPEI) from the climatological data, we show how precipitation anomalies are related to increased child stunting (Figure 3.1). We then model how various factors have historically either mitigated or amplified the effect of drought on child stunting (Figure 3.2), and combine global data on these factors to estimate current drought vulnerability (Figure 3.3). Finally, for two areas that have recently experienced drought, we make a qualitative comparison of our model's predictions of increases in stunting with observed increases in food insecurity during those droughts.

3.1.1 Justification for Stunting as an Outcome Variable

While many metrics of food insecurity, undernutrition, and famine exist, using child stunting data in this analysis has several advantages. Stunting has been a widely accepted indicator of child undernutrition for decades, meaning that data on child stunting has been collected in a wide variety of contexts, allowing us to estimate how those contexts contribute to drought vulnerability. This is not the case for newer metrics, such as the Household Hunger Score (HHS) (Ballard, 2011), Household Dietary Diversity Score (HDDS) (Swindale and Bilinsky, 2006), Household Food Insecurity and Access Score (HFIAS) (Coates et al., 2007), or even the Integrated Food Security Phase Classification System (IPC) (IPC/FAO, 2015). Conversely, other metrics of food insecurity that have also been estimated for decades, such as increases in mortality rates or decreases in staple crop production, have the disadvantage that they are often aggregated to the country or provincial level. Given the potential sub-national heterogeneity in drought severity, these food security metrics measured at administrative levels are difficult to match with meteorological data. Using geolocated micro-data on stunting, on the other hand, has the twin advantage of having been collected for many years across a variety of contexts, as well as having the spatial specificity that makes it possible to estimate each individual child's exposure to drought. Child stunting also has advantages over other child health metrics that have been collected for decades in geolocated surveys. Because stunting, measured with Height-for-Age Z Scores, is a continuous variable and is sensitive even to small changes in nutrition, it is possible to measure the impact of minor droughts on children, which would not be possible given dichotomous outcomes that only occur under severe conditions, such as child mortality. Finally, child stunting is a more appropriate outcome variable than other child anthropometry metrics, such as underweight or wasting, because it is affected by the chronic, long-term undernutrition that is likely to occur under drought.

3.2 Data Used

3.2.1 Nutrition Data

We use geolocated child nutrition data from the Demographic and Health Surveys (DHS) program in combination with a variety of geographic datasets. Our dataset consists of 584,662 children from 127 surveys conducted in 53 countries over 26 years, from 1990 to 2016 (See Appendix B). To focus the analysis on children in households with livelihoods that are at least partially agricultural, we excluded children that were from DHS sites in areas with greater than 95% of nearby land cover classified as bare ground (Song et al., 2018) or with greater than 20% of nearby land cover classified as built up (Pesaresi et al., 2015). This excluded 1.1% of the children, and consisted mostly of children from extremely arid places, like the central Sahara desert, or highly urban places. While DHS surveys are often conducted periodically within a given country, they do not intentionally revisit the same communities, so the surveys are not longitudinal and every child is observed only once.

For children under five, environmental factors explain more variation in height than ethnic differences (Habicht et al., 1974). Thus, child heights are a widely accepted indicator of child nutrition. For this analysis, our outcome variable is the height-for-age Z-score (HAZ) for children under 5 years old, which is a standardized measure of child heights and a common indicator of stunting. This indicator compares a child's height to the distribution of heights of healthy children of the same age and gender and assigns a Z-score. The percent of children with a Z-score less than -2 in a given population is the rate of stunting for that population (Lewit and Kerrebrock, 1997). Thus, while exact changes in the rate of stunting in a population cannot be derived from changes in HAZ scores alone, decreases in mean HAZ scores will lead to increases in stunting.

To better estimate the impact of rainfall anomalies on an individual child's HAZ score, it is important to control for individual and household level variables that can also affect child health outcomes, such as the child's birth order or household wealth. The DHS includes many such variables, although few are collected in all surveys. We identified 10 variables that were available in 127 DHS surveys and that robustly predicted child HAZ scores (See Appendix B). While not all the surveys in our dataset asked how long the households had been residing at the site or whether they were visitors, for those that did, if the households were visitors or had been residing at the site for less than three years, we excluded them from the dataset.

3.2.2 Data on Shocks

As an indicator of precipitation extremes, we used the Standardized Precipitation-Evapotranspiration Index (SPEI), a measure of how recent hydrological conditions over a given time frame vary with respect to long-term norms, taking both rainfall and evapotranspiration into account (Beguería et al., 2014). By accounting for water lost to evapotranspiration, the SPEI can more accurately indicate the overall water availability and agricultural stress at a location. Furthermore, because this metric is based on long-term norms for a given location, it characterizes precipitation extremes in a way that is comparable between locations. We used reanalysis datasets of precipitation (Funk et al., 2015) and temperature (Sheffield et al., 2006) to calculate the SPEI, and derived potential evapotranspiration (PET) using the Hargreaves method. Finally, we calculated rainfall levels during the growing season at each site (Kerdiles et al., 2017), and compared models with SPEI scored derived from full year and growing season only precipitation at 12, 24, and 36-month intervals, as well as for the duration each child's lifetime, including time in utero.

3.2.3 Data on Factors Influencing Vulnerability

We modeled how various factors mitigate or amplify the impacts of rainfall shocks on child HAZ scores. In our model, we draw on previous frameworks that characterize vulnerability in terms of sensitivity, adaptive capacity and hazard (Krishnamurthy et al., 2014). We thus include geographic variables that describe the sensitivity and adaptive capacity of a system vis-à-vis a hazard (i.e., drought). Variables characterizing the sensitivity of the food system to shocks include primarily agro-ecological variables, while variables characterizing the adaptive capacity of households facing drought include primarily economic, demographic, and geopolitical variables. For each of these geographic variables, we fit the model using data for the year of the DHS survey, or the nearest available year, and for the final map (Figure 3.3), we use data for the closest available year to 2020.

3.2.4 Overview of Geographic Data on Factors Influencing Vulnerability

Official Development Assistance (ODA): ODA consists of financial flows from developed countries to developing countries with the objective of promoting economic development and welfare (Organization for Economic Co-operation and Development, 2008), and can include agricultural and nutritional aid as well as assistance in climate change adaptation. In some developing countries, ODA can be up to a quarter of Gross National Income (GNI) (The World Bank, 2016). While ODA can take many forms, there is some evidence that IMF programs are associated with improved child nutrition outcomes in rural areas when parents have less education (Daoud et al., 2017).

GDP (PPP) Per Capita: Wealth is a major determinant of nutrition outcomes both within and between nations. Countries with a higher Gross Domestic Product (GD)P per capita have diverse economies that are less dependent on agriculture, are better integrated into global trade, and have more infrastructure to support agriculture and distribute food during shocks. A 2000 study found that per capita national incomes were a major determinant of a nation's overall nutrition status (Smith and Haddad, 2000). The dataset we draw on has GDP per capita in purchasing power parity (PPP) at the sub-national level (Kummu et al., 2018), allowing us to explore differences in GDP per capita even within a given country and year. One disadvantage of GDP as an indicator is that is does not take into account income inequality and many resource-rich but highly unequal countries may have both high GDP per capita values and large populations that are impoverished and food insecure. While data on the Gini index or below poverty line estimates was not available for every country and year in our dataset, using sub-national GDP estimates does account for some of the inequality within countries. This variable was log-transformed.

Government Effectiveness: Effective governments are critical for ensuring populations receive adequate nutrition during years of climate shocks and decreased yields. More effective governance can foster improved national infrastructure and support national economies, which in turn have second-order effects on nutrition outcomes. This indicator was developed by the World Bank as a World Development Indicator, and has been used in studies of drought risk (Carrão et al., 2016) as well as the climate change – food security vulnerability index (Krishnamurthy et al., 2014).

Human Development Index (HDI): The HDI is a commonly used metric of development that incorporates financial, educational, and health variables (Sen, 1994), and thus is a proxy for the financial and human capital that may be available to people during periods of shocks. It is based in part on GDP per capita, which has been shown to be a major predictor of a nation's overall nutrition status (Smith and Haddad, 2001). While detailed educational and health data is not available for every country in the DHS for the years in which surveys have been conducted, overall HDI has been estimated annually at sub-national levels for the globe (Kummu et al., 2018).

Political Stability and Absence of Violence: Violence can be a major cause of undernutrition and reduced adaptive capacity to shocks, as it disrupts markets and infrastructure providing access to food and agricultural inputs. There is some evidence that the impacts of violence disproportionately affect children (Ghobarah et al., 2003). For this indicator, which is a proxy for the overall social capital in a country, we use annual national-level data from the World Bank's World Governance Indicators (Kaufmann et al., 2011).

Population Density: Population density can affect child undernutrition and vulnerability to shocks in a variety of ways. In some cases, greater population densities can lead to greater competition for limited resources, smaller farm sizes, and a greater disease burden (Halpenny et al., 2012, Masters et al., 2013). At the same time, population density can be an indicator of greater urbanization, available infrastructure and trade, as well as opportunities for off-farm income (Masters et al., 2013). To measure population density, we use the Gridded Population of the World dataset, with global population estimates given by combining satellite imagery and national censuses for the years 1990, 2000, 2005, 2010, 2015, and 2020 (Doxsey-Whitfield et al., 2015). This variable was log-transformed.

Per Capita Value of Imports: Having access to food via imports can greatly increase overall food availability, even during periods where local agricultural output is low. This can increase a household's options for obtaining foods and overall adaptive capacity. Greater imports per capita is also indicative of an economy integrated into global markets, with more opportunities for off-farm labor. This indicator is from the World Bank and is available annually at the national level (The World Bank, 2016). This variable was log-transformed.

Primary School Enrollment: Rates of education and school attendance in a country is associated with better overall child nutrition (Alderman, 2010, Bhutta et al., 2013). Furthermore, because it increases local human capital and adaptive capacity, education is widely recognized to be a critical part of climate adaptation (Bowen et al., 2012, Laplante et al., 2010). While most studies of impacts on education, climate-related shocks, and nutrition focus on parental education, we use data on rates of primary school attendance, as this metric has greater global coverage (The World Bank, 2016).

Average Monthly Maximum Temperature: Temperatures are rising globally. Higher temperatures have been found to impact economic production (Burke et al., 2015) as well as child birth weight (Grace et al., 2015), a major risk factor for lower child HAZ scores later in life (Wrottesley et al., 2015). To account for the possible effects of changing temperatures and shifting isotherms, we measure the average daily maximum temperature for the decade before a child health observation rather than the multidecadal temperature average. For our data on temperature, we use a reanalysis product combining remote sensing, on-the-ground measurements and geophysical models (Sheffield et al., 2006).

Nutrition Diversity of Agriculture: Consuming a diversity of nutrients is critical for adequate nutrition (Arimond and Ruel, 2004) and at the national level, nutritionally diverse food supplies have been associated with better anthropometric outcomes (Remans et al., 2014). While agricultural production diversity has been underexplored as a factor contributing to resilience during climate shocks, there is some evidence that it mitigates the effects of other types of household-level shocks (Malapit and Quisumbing, 2015). To model nutritional diversity, we draw on a dataset created by Herrero et al (Herrero et al., 2017) which modeled the Modified Functional Attribute Diversity of 8 critical nutrients in agricultural systems worldwide.

Mean Annual Precipitation: The amount of precipitation in a location affects what types of crops can be grown, and what livelihood systems people undertake. Areas that experience unusually high or low levels of annual precipitation, such as the Sahel or areas affected by the South Asian Monsoon, may be particularly sensitive to seasonal extremes (Mirza, 2011, Roudier et al., 2011). For this variable, we use the Climate Hazards Group Infrared Precipitation with Station (CHIRPS) dataset, taking the average annual precipitation for period from 1981 to 2016. This variable was log-transformed.

Normalized Difference Vegetation Index: The Normalized Difference Vegetation Index, or NDVI, is a measure of the productivity of vegetation. It has been associated with child nutrition outcomes in several studies (Brown et al., 2014, Johnson and Brown, 2014). The dataset on NDVI that we used is derived from Advanced Very High Resolution Radiometer (AVHRR) data estimated annually (Song et al., 2018).

Irrigation: Because irrigated agriculture utilizes water from distant sources, irrigated agriculture is much less sensitive to local rainfall deficits than rainfed agriculture. In our model, we use the spatially specific Food and Agricultural Organization (FAO) Global Map of Irrigated Areas, estimated for the year 2000. This dataset was derived and validated using remote sensing observations and irrigation statistics from 10,825 sub-national statistical units (Siebert, S., Döll, P., Feick, S., Frenken, K., Hoogeveen, 2013), and has been used in other assessments of drought risk (Carrão et al., 2016).

Topographic Ruggedness: The topography of a region has a large impact on the hydrology, agricultural practices and infrastructure in a location, all of which influence a systems ability to absorb climate shocks. While topographic variability can increase soil moisture during periods of low rainfall by reducing water lost through evapotranspiration (Cowley et al., 2017). In our model, we use the Topographic Ruggedness Index, which is the difference between the maximum and minimum elevation value in a 3x3 pixel window in a Digital Elevation Model (DEM). This variable was log-transformed.

Bare Land Cover: Bare land cover consists of areas with no vegetation, such as rocky or sandy areas (Gregorio and Jansen, 2005), and has no agricultural potential. Areas that were once vegetated can become bare due to overgrazing and land degradation (Bai et al., 2008), while areas that were previously bare can become vegetated due to irrigation and agricultural expansion (Song et al., 2018). For this variable, we use annual data on land cover dynamics (Song et al., 2018). This variable was log-transformed.

Per Capita Staple Crop Production: Food production is a major factor influencing child nutrition outcomes (Smith and Haddad, 2000). Area with greater food production are also likely to be less sensitive to shocks, given that they are probably using higher-yield varieties of crops and have more agricultural infrastructure. We used annual country-level data on per-capita food production from the FAO and included cereals and grains as well as other starches that are staple foods in some countries, such as roots and tubers (FAOSTAT, 2018). This variable was log-transformed.

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Variable	Organization/Project	Temporal Resolution	Value Min	Value Max	Value Mean	Units	Citation
Variables Characterizing Adaptive Capacity							
Official Development Assistance (ODA)	World Bank Open Data	Annual	2.35	319.68	46.58	Net ODA received per capita in current USD	(The World Bank, 2016)
GDP per Capita (PPP)	Aalto University	Annual (1990-2015)	311.10	24303.63	3685.44	Thousands of 2011 USD	(Kummu et al., 2018)
Government Effectiveness	World Bank – World Governance Indicators	Annual	-1.75	0.23	-0.69	Indicator of Government Effectiveness, lower scores indicating less effective governments	(Kaufmann et al., 2011)
Human Development Index	Aalto University	Annual (1990-2015)	0.25	0.83	0.5	Indicator from 0-1	(Kummu et al., 2018)
Stability and Absence of Violence	World Bank – World Governance Indicators	Annual	-2.19	1.05	-0.72	Indicator of Political Stability and Absence of Violence/Terrorism, with more stable and less violent countries having a higher score	(Kaufmann et al., 2011)
Population Density	NASA Socioeconomic Data and Applications Center (SEDAC)	1990, 2000, 2005, 2010, 2015, 2020	0	639.52	15.17	Thousands of Individuals per 2.5-arcminute pixel	(Doxsey-Whitfield et al., 2015)
Per Capita Value of Imports	World Bank Open Data	Annual	47.05	3186.96	504.77	Current US Dollars	(The World Bank, 2016)
Primary School Enrollment	World Bank Open Data	Annual	19.11	99.55	77.59	Percentage of Children of Primary School Age	(The World Bank, 2016)
Variables Characterizing Sensitivity							
Average Monthly Max Temperature	Princeton University	Monthly	1.07	39.51	29.77	Average maximum temperature over the previous 10 years (Celsius)	(Sheffield et al., 2006)
Nutritional Diversity of Agriculture	CSIRO Australia	2005	0.24	0.81	0.59	Modified functional attribute diversity of various crops, livestock, and fish cultivated at a given pixel	(Herrero et al., 2017)
Mean Annual Precipitation	CHIRPS	Monthly	0.03	7829.52	1076.81	Mean Annual Precipitation for 1981-2016 (1000mm)	(Funk et al., 2015)
NDVI	University of Maryland	Annual	-0.06	1	0.65	Normalized Difference Vegetation Index	(Song et al., 2018)
Irrigation	FAO - Global Map of Irrigated Areas	2000	0	1	0.08	Percent of a given pixel with irrigated agriculture	(Siebert, S., Döll, P., Feick, S., Frenken, K., Hoogeveen, 2013)
Topographic Ruggedness	GTOPO30	Time Invariant	0	1167.79	88.87	Difference between highest and lowest pixel value in 3x3 window	(Riley et al., 1999, USGS, 1996)
Bare Land Cover	University of Maryland	Annual	0	94.89	15.6	Percentage of pixel with bare land cover	(Song et al., 2018)
Per Capita Staple Crop Production	FAO	Annual	2.3	7.07	4.02	Tonnes of grains, roots, and tubers produced per capita	(FAOSTAT, 2018)

Table 3.1: Summary of geographic variables moderating the effects of drought on child stunting. Summary statistics shown are values for before data transformations.

3.3 Methods

3.3.1 Extracting Spatial Data

This analysis relies on combining geolocated DHS surveys with a wide variety of geographic datasets. However, the GPS points given by the DHS are displaced to maintain respondent anonymity. Urban points are displaced by up to 2 km, while 99% of rural points are displaced by up to 5 km and 1% are displaced by up to 10 km (Burgert et al., 2013). To account for this jittering when extracting geospatial data we used the same methodology as Grace et al (Grace et al., 2012). We first resampled all the geographic data to a 3 arc-minute resolution (between a 4 km and 5.5 km resolution, depending on the latitude of the DHS site). We then took the average value of the grid cell in which a GPS point fell, as well as all of the neighboring grid cells. This accounts for the lack of specificity in the location of the DHS GPS points and also reflects the fact that livelihoods can be affected by processes over 5 km away, as households will sometimes farm on distant fields or may travel several kilometers to collect water (Grace et al., 2012).

3.3.2 Rainfall Anomalies and Undernutrition

To control for individual, household, and national factors in our LOESS model of rainfall anomalies and undernutrition, we first modeled HAZ scores as a function of 10 individual and household covariates, with varying intercepts at the country and DHS survey level. We then predicted the residuals from this regression as a function of the 24-month SPEI using a LOESS model with a 2nd degree polynomial and tricubic weighting on a local window size of 75% of the data.

Factors Moderating the Effects of Rainfall Anomalies

Based on the results of the LOESS model, we identified the points at which low and high rainfall levels are associated with worsened child nutrition outcomes, and focused the rest of the analysis on children observed during droughts and during normal rainfall periods. We thus excluded all observations with extremely high SPEI values (SPEI $>$1.4), and created a categorical variable for the remaining observations indicating whether the child was observed during a drought period (SPEI $<$-0.4) or a normal period (-0.4 $<$SPEI $<$1.4).

We modeled child HAZ scores as a function of household, individual, and geographic factors, and we model each geographic factor interacting with the categorical variable for whether the child was observed during a drought. Formally, we ran the following linear regression:

$$y_i = \beta_0 + \beta X_i + \gamma G_{j(i)} D_{j(i)} + \epsilon_i \tag{3.1}$$

Where i is the index for each individual child and j is the index for the DHS site, y_i is a child's HAZ score, β is a vector of coefficients for a matrix of individual, household and geographic factors X_i, and $D_{j(i)}$ is a vector of binary values for whether the observed 24-month SPEI score indicated drought at a DHS site at the time the child health observation was made. The vector of drought conditions $D_{j(i)}$

at each DHS site interacts with a matrix of geographic variables, $G_{j(i)}$, which are in turn moderated by a vector of coefficients γ.

Because the geographic variables included in the regression explained much of the DHS site-level variation in nutrition outcomes, we avoided including terms that are typically used in multinational DHS analyses, such as a term for the interview year, a term for whether the site was urban or rural, as well as varying intercepts at the country or survey level (Shively, 2017). This allowed the spatio-temporal variation in HAZ scores to be explained by only the geographic variables included in the regression. We estimated our model using Least Absolute Shrinkage and Selection Operator (LASSO) regularization, which is particularly apt for cases like this one where regression is being used with a large number of covariates to make predictions (Tibshirani, 2011). Using the LASSO, redundant covariates will drop out of the model. To better fit the model and facilitate comparison between the coefficients of the covariates, we first log-transformed some variables, and then scaled all variables from 0 to 1.

3.3.3 Model Estimation with LASSO Regularization

We estimated the model using the Least Absolute Shrinkage and Selection Operator, or LASSO, method (Tibshirani, 1996). This method performs regularization by penalizing the size of the model coefficients to prevent over-fitting and also facilitates variable selection by shrinking some of the model coefficients to zero (Tibshirani, 1996). The LASSO method involves recasting the regression problem as a convex optimization, which simplifies model estimation (Taylor and Tibshirani, 2015). It solves the problem:

$$\text{minimize}_{\beta_0,\beta}\Big[\frac{1}{2}\sum_{i=1}^{N}\Big(y_i-\beta_0-\sum_j x_{ij}\beta_j\Big)^2+\lambda\sum_{j=1}^{p}|\beta_j|\Big] \tag{3.2}$$

Where β_j is the parameter vector from the regression model [1], including both the β and γ parameters, and the tuning parameter λ moderates the level of penalization and regularization. As is typical, we estimated this parameter through cross-validation (Taylor et al., 2015).

Using the LASSO, variables that are orthogonal to the outcome variable or are correlated with other covariates are estimated with a coefficient of 0 and "drop out" of the model.

3.3.4 Mapping Vulnerability

We use the coefficients γ from Equation 3.1 to predict where HAZ scores would be expected to decrease in the event of a drought, as well as the degree to which they would decrease. Because the individual and household level covariates β were not modeled as interacting with the drought variables $D_{j(i)}$, we only need data on geographic factors to estimate changes in HAZ related to drought. Just as we excluded children from areas with greater than 20% built-up land cover or 95% bare land cover from our nutrition dataset, we excluded these areas from our maps.

3.3.5 Comparison with FEWS NET Reports

As a qualitative out-of-sample validation, we compare our model predictions to observed changes in food security during recent droughts in Southern Africa (FEWS NET, 2016) and East Africa (FEWS NET, 2017) as reported by the Famine Early Warning Systems Network, or FEWS NET and measured with the Integrated Food Security Phase Classification (IPC) 2.0 methodology, which includes a chronic food insecurity component that incorporates rates of stunting (IPC Global Partners, 2012), (Figure 3.4). While food security and child nutrition are not synonymous, because stunting is a consequence of food insecurity, they are likely to co-occur spatially (Baig-Ansari et al., 2006, Isanaka et al., 2007). Furthermore, while geolocated HAZ scores of children across the globe observed before and during droughts are unavailable to validate our model, FEWS NET maps of IPC phases can provide an indication of food security and nutrition with high temporal resolution at multinational scales because FEWS NET publishes food security reports several times a year for key world regions. Thus, data on where IPC phases have changed in response to drought can provide a qualitative validation of our model and contextualize our findings in relation to existing food security monitoring systems.

For these comparisons, we use GIS data published by FEWS NET to estimate changes in IPC phases from before and during a drought for recent droughts in Southern Africa in early 2016 (FEWS NET, 2016) and in East Africa in mid 2017 (FEWS NET, 2017). In the maps for the qualitative validation, we mask from the FEWS NET maps the same areas that were masked in our model, and in our predictions, we mask areas that were excluded from the FEWS NET maps, such as unpopulated natural protected areas. In calculating the differences in food security status from before and during a drought, we use IPC maps from the same time of year, to avoid misinterpreting seasonal changes in food security as drought-induced.

3.4 Results

3.4.1 Rainfall Anomalies and HAZ Scores

We began by determining the time window at which SPEI values best predict child heights, and found that the 24-month SPEI performs better than SPEI values calculated for other time windows, including each child's age (See Appendix B). We then explored the effects of rainfall anomalies on observed child Height-for-Age Z-scores (or HAZ scores), an indicator of child stunting. We used a Locally Estimated Scatterplot Smoothing (LOESS) regression because it can model the anticipated non-linear relationship between anomalies and child stunting. After controlling for the effects of individual, household, annual and national factors, there was a clear relationship between the 24-month SPEI and child HAZ scores, a common indicator of stunting (3.1). The fitted curve shows that children have the highest HAZ scores when rainfall is between the long-term norm (SPEI=0) and a mildly wet period (SPEI=1). As rainfall levels increase relative to long-term norms, HAZ scores decline slightly, and then as the SPEI increases beyond 1.4, child HAZ scores decline sharply. Child HAZ scores decrease monotonically with rainfall deficits at all levels. Even when the previous 24 months were only slightly drier than the long-term norm, HAZ scores were slightly worse, and SPEI scores less than -0.4 were associated with children shorter than other relevant factors would otherwise predict.

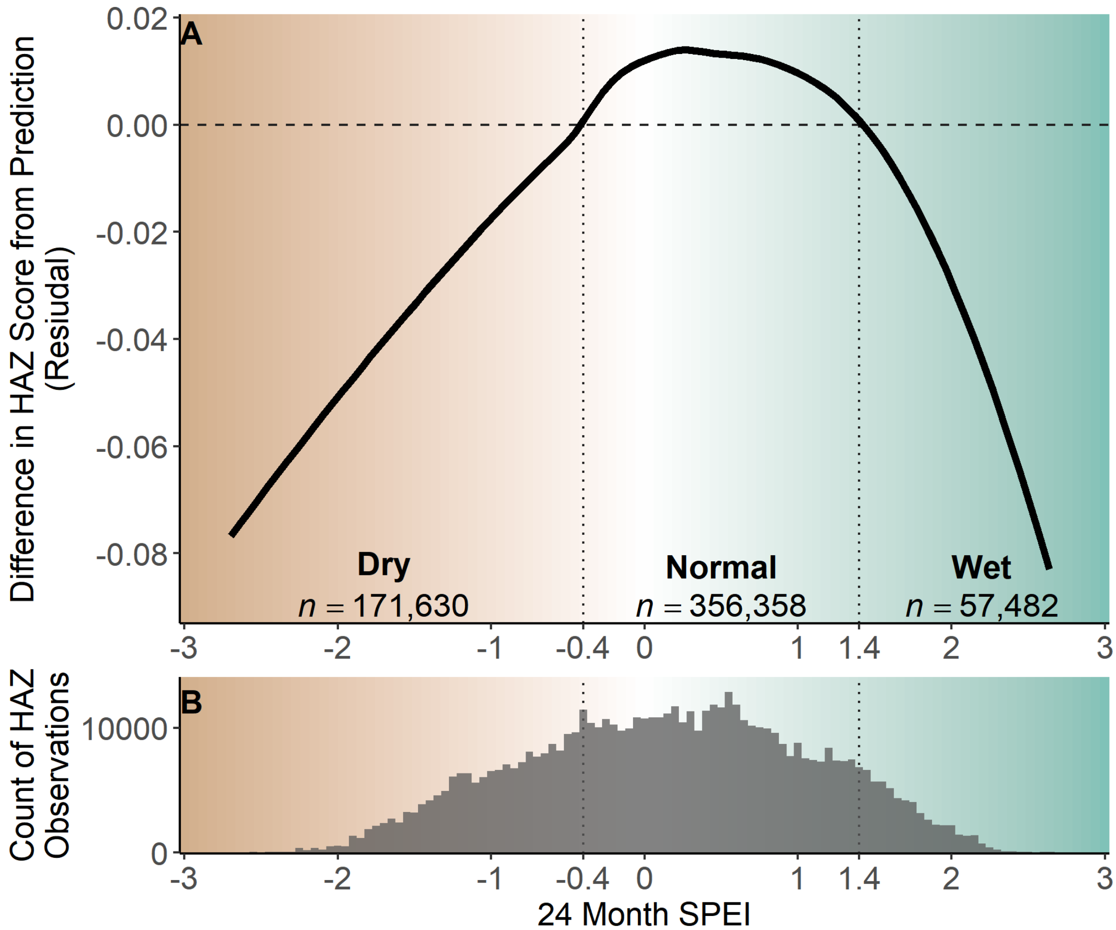

Figure 3.1: A: Relationship between the 24-Month Standardized Precipitation-Evapotranspiration Index (SPEI) and residual Height-for-Age Z-Scores. During periods of normal rainfall, children were typically taller than household and individual factors would otherwise predict (residual >0). Conversely, during periods of minor to severe drought and during periods of severe wetness, children were typically shorter (residual <0). This non-parametric analysis was used the discretize the 24-month SPEI variable into drought and normal periods and to exclude extremely wet periods, based on the cut-offs at -0.4 and 1.4. B: Histogram of child nutrition observations at various SPEI levels.

3.4.2 Modeling Combined Effects of Geographic Factors

Based on the results of the LOESS model, we identified the points at which low and high rainfall levels are associated with worsened child nutrition outcomes, and focused the rest of the analysis on comparing children observed during droughts (SPEI $<$-0.4) to those observed during normal rainfall periods (-0.4 $<$SPEI $<$1.4). This was because higher-than-average rainfall was not related to lower HAZ scores unless it was extreme, while lower-then-average rainfall was related to lower HAZ scores even at minor levels, yielding a large number of children in a wide variety of geographical contexts observed during drought, but fewer children observed during excessively wet periods. Furthermore, the effects of drought on food production occur at the location of the drought, while the effects of excess rainfall, such as flooding and landslides, can be caused by rainfall far upstream from the location of a child nutrition observation.

To determine how various geographic factors moderate this relationship between drought and stunting, we modeled a variety of geographic factors in interaction with whether a child was observed during drought conditions, and we show that many variables influence whether or not a drought will be associated with decreases in HAZ scores (See Figure 3.2). Factors having a large effect on mitigating the impacts of drought on HAZ scores include the nutritional diversity of local agricultural systems, effective governments, greater imports and staple crop production, a higher percentage of irrigated agriculture, political stability, and greater mean annual precipitation. Factors that exacerbate the effects of drought include higher population densities, higher average monthly maximum temperature, a higher percentage of bare land cover, and greater topographic ruggedness. The Normalized Difference Vegetation Index (NDVI), Human Development Index (HDI), and Gross Domestic Product (GDP) dropped out of the model (See Appendix B).

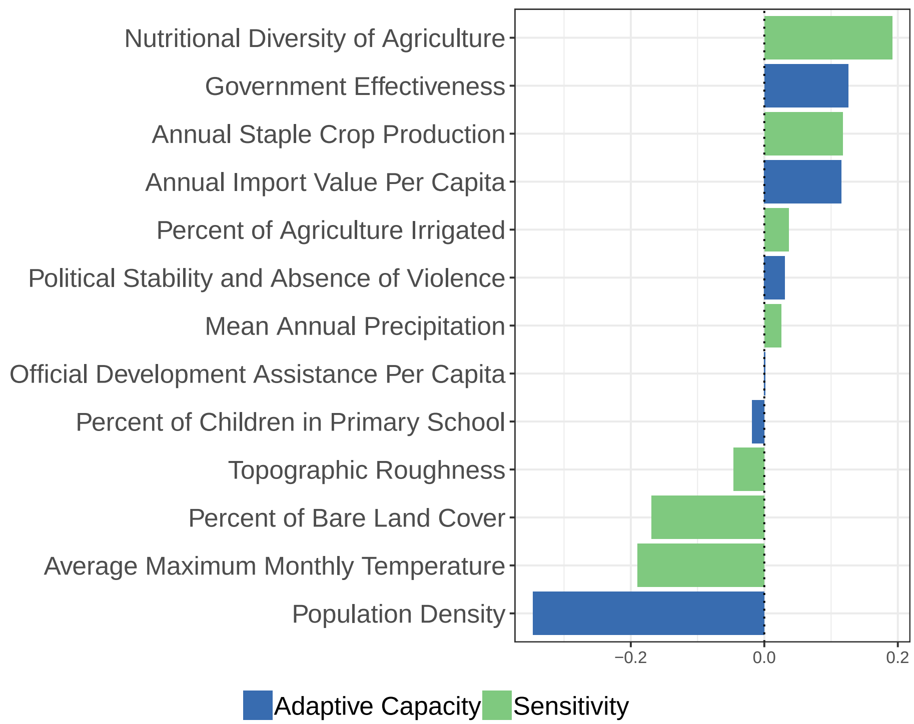

Figure 3.2: Coefficient estimates of geographic variables moderating the effects of drought on child HAZ scores. Positive coefficients mitigate the effects of drought, while negative coefficients exacerbate the effects of drought. Some variables were log-transformed, and then all variables were scaled from 0-1. Variables are color-coded according to whether they characterize a system's sensitivity to shocks (green) or adaptive capacity (blue).

We modeled the impact of drought as being moderated by only geographic factors. Because of this, we were able to then predict changes in HAZ scores under drought globally, including in countries that did not have DHS data, based on geographic data for as close to the year 2020 as possible. Thus, we weighed global data on factors that moderate the effects of drought according to the coefficients estimated from our model to predict changes in HAZ scores under drought (Figure 3.3). This map showed that the most drought vulnerable children are in arid areas with weak governments and little international trade, such as Chad, Sudan, Eritrea, South Sudan, Somalia, and Yemen. In addition to these hot-spots of drought vulnerability, other areas with some vulnerability included other countries throughout Africa, central Asia, and the Middle East, as well as Papua New Guinea, North Korea, and Haiti. Comparing our model's predictions with observed changes in food insecurity during recent droughts in southern and eastern Africa shows that our model performs quite well.

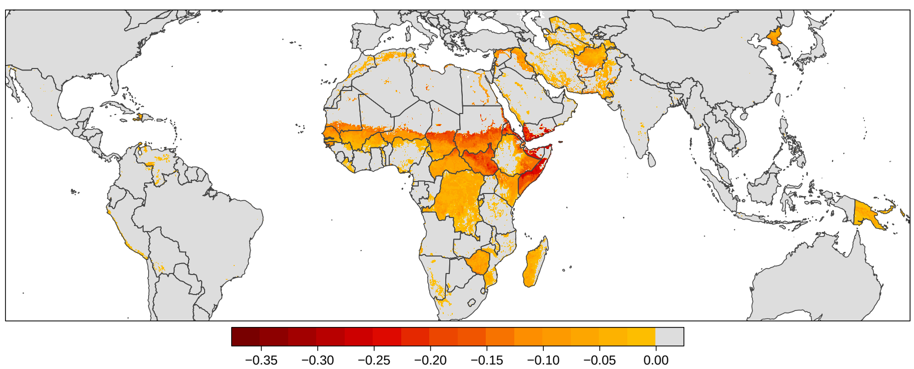

Figure 3.3: Expected decrease in mean child HAZ scores during drought conditions.

Comparing these maps shows broad spatial concordance between areas that FEWS NET reported as having worsened food security during a recent drought and where our model predicts higher rates of stunting during a drought. In southern Africa, FEWS NET reported an increase of one IPC phase in all of Zimbabwe and an increase of two phases in southern Zimbabwe, as well as IPC phase increases in parts of Mozambique. Similarly, our model predicted slightly greater decreases in HAZ scores in southern Zimbabwe, as well as decreases in HAZ scores in the same parts of Mozambique where increases in food insecurity were observed. In eastern Africa, our model's predictions of decreases in HAZ scores broadly concurred with the IPC changes in Somalia, northern and eastern Kenya, eastern Ethiopia, much of South Sudan, as well as coastal and sahelian Sudan.

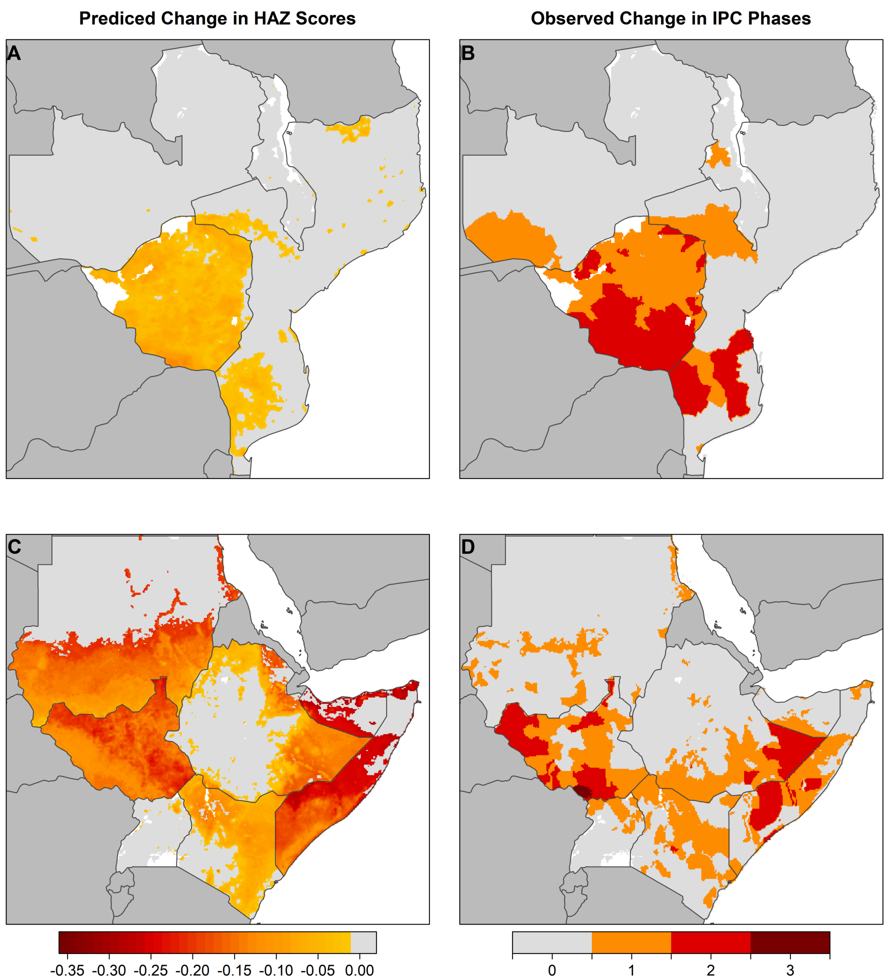

Figure 3.4: Comparison of predicted changes in HAZ scores (A, C) with observed changes in IPC phases (B, D) during recent droughts in Southern Africa and East Africa.

Discussion

A significant advantage of this study was using a very large dataset, which allowed us to draw on child nutrition outcomes during droughts across a range of economic, political, and agro-environmental conditions. We were thus able infer how these conditions moderate the relationship between drought periods and child HAZ scores. We found that precipitation deviations from long-term norms such as minor to severe droughts or severely wet periods were associated with worse child nutrition, as measured by child HAZ scores. Using geographic data associated with the time and location of each child nutrition observation, we modeled how a variety of geospatial factors amplify or mitigate the effects of drought. Finally, we used this model to predict globally where current geographic contexts could contribute to worsened child nutrition outcomes during the event of a drought, based on how those factors have historically moderated the relationship between drought and HAZ scores.

In assessing the relationship between rainfall anomalies and child undernutrition, previous studies have taken varied approaches, with some measuring lifetime growing season precipitation levels (Grace et al., 2012, Shively, 2017) and others looking at rainfall in recent seasons (Skoufias and Vinha, 2012). Thus, we compared precipitation deviations from long-term norms at multiple timescales for both growing season precipitation and full-year precipitation, and we found that the full-year 24-month SPEI performed the best in modeling child HAZ scores. Although a child's HAZ score is affected by chronic, long-term undernutrition, the 24-month

SPEI score performed better than indicators over other time frames, including the SPEI for the child's lifetime. This may be due to children experiencing rapid growth when they receive adequate nutrition following a period of poor nutrition, a phenomenon known as compensatory growth or catch-up growth (Behrman, 2016, Wit and Boersma, 2002).

We found that a variety of factors improve child nutrition outcomes under drought. While many of these factors have been previously associated with positive nutrition outcomes, including agricultural and dietary diversity (Rah et al., 2010), crop production (Smith and Haddad, 2000), and trade (Bryce et al., 2008), relatively little research has been conducted exploring their role in mitigating the effects of drought on child nutrition. Our results indicate that, to build climate-resilient nutrition systems, policymakers at the national level should focus on effective governance and trade, while local interventions should focus on increasing the nutritional diversity of agricultural systems as well as restoring degraded and bare land. Our results further indicate that increasing crop yields in vulnerable countries can improve drought resilience, while climate change may exacerbate vulnerability by raising temperatures and lowering rainfall averages.

Beyond just showing which geographic factors amplify or mitigate vulnerability, this study also mapped the expected impact of precipitation extremes on child HAZ scores. This improves upon previous mapping efforts that have similarly focused on geographic variables that influence vulnerability (de Sherbinin, 2014), but have relied on index-based methods that take an *a priori* approach to combining these variables (Busby et al., 2014, Carrão et al., 2016, Ericksen et al., 2011, Krishnamurthy et al., 2014, Richardson et al., 2018). By using a more empirical approach, we are able to map vulnerability by weighing various geographic factors according to how much they have historically been observed to moderate the relationship between drought and lower HAZ scores.

There are several assumptions and simplifications built into the model. For the purposes of this paper, rainfall deficits across a wide range of levels were combined into the category of drought. Most of these droughts were moderate and not uncommon, with an SPEI between -0.4 and -1.5, and thus this map does not show the anticipated effects of severe droughts that could become more common under climate change. Many areas besides those highlighted in this map would likely see nutritional decreases under severe droughts, and areas shown in this analysis to be vulnerable to moderate drought, like Somalia and the Sahel, would likely see extreme increases in stunting and even famine under severe droughts. Furthermore, this analysis relies on some geographic data that is only available at the national level, which may obscure significant sub-national vulnerability, for example in countries with pockets of instability, such as Nigeria (FEWS NET, 2018). Thus, our map is less useful for local and national policymakers who already have substantial understanding of the spatial distribution of drought vulnerability in the countries where they work. Rather, is most applicable for NGOs, foundations, and multinational organizations seeking to target vulnerable populations and prioritize aid at global and continental scales.

While many of the areas identified by our model as vulnerable to drought have been the location of previous studies associating precipitation and undernutrition (Alderman, 2010, Chotard et al., 2011, Grace et al., 2012, Hagos et al., 2014, Jankowska et al., 2012, Mueller and Mueller, 1999), there were some areas where previous literature had found associations between precipitation shortfalls and worsened nutrition outcomes and where our model predicted little vulnerability, such as Nepal (Panter-Brick, 1997, Shively, 2017), Rwanda (Akresh et al., 2011), Indonesia (Maccini and Yang, 2009), Mexico (Skoufias and Vinha, 2012), and India (Mahapatra et al., 2000). This may be due in part due to the aforementioned issue of our model relying on national indicators for countries with substantial within-country heterogeneity, particularly for large middle-income countries such as Indonesia, Mexico, and India. This suggests that our model might be best taken as a conservative estimate of where drought-induced undernutrition is likely to occur, but not a prediction of where it will *not* occur, given that poorer and more rural sub-populations in many countries may be more vulnerable to climate change than national statistics or historic population-level shifts in HAZ scores would indicate (Dennig et al., 2015). However, another potential reason for our model disagreeing with previous studies is that they may have taken place several years ago using datasets that were even older, and increases in trade, wealth and stability over the previous few decades have led to decreases in drought vulnerability. Indeed, using our model to predict vulnerability based on geographic data from the years 2000 and 1990 (See Appendix B) shows that droughts in those years would have led to greater decreases in mean HAZ scores in many places than a drought would today, and that areas modeled as drought-resilient in 2020, such as India, were previously more drought vulnerable.

Data on HAZ scores with high temporal frequency is unavailable at the global scale to validate our model, so we used reports on IPC phases from FEWS NET in food insecure regions to perform a qualitative ground-truthing of our model's predictions. Indeed, we found that our model broadly agrees with FEWS NET's reports of where food security worsened after the onset of recent droughts in Southern Africa and East Africa. This suggests that our model is useful as a framework for using empirical methods to estimate vulnerability spatially and also suggests that there is validity to the geographic factors that our model identified as amplifying or moderating the effects of drought.

Overall, our findings have significant implications for policymakers, foundations, and multinational organizations interested in targets such as Sustainable Development Goal (SDG) 2 of achieving zero hunger, as well as SDG 13 of taking action to combat climate change impacts. First, we show that precipitation extremes are associated with worse child nutrition outcomes throughout much of the developing world. This supports the assertions of the WHO and IPCC that climate change, which will make extremes both more common and more severe, is a significant threat to adequate nutrition for much of the world (Smith et al., 2014, WHO, 2014). Secondly, we highlight the factors that can increase both vulnerability and resilience to droughts. Nutritionally diverse agricultural systems and effective governance, staple crop production and international trade were found to have a large impact on drought resilience, and thus investing in these aspects of food systems would be expected to pay large dividends in increasing climate resilience. Finally, we mapped areas where droughts would be expected to lead to increased rates of undernutrition, with the expectation that such maps would assist global policymakers in targeting aid to improve climate resilience for the world's most vulnerable populations.

Chapter 4: Geographic Factors and Provisioning Ecosystem Services

4.1 Introduction

Ecosystem services are critical to human well-being (Haines-Young and Potschin, 2010). Throughout the world, natural and human-impacted areas provide regulating, cultural and provisioning ecosystem services (Bennett et al., 2009), and non-timber forest products (NTFPs) are a provisioning ecosystem service that supports human livelihoods in both developed and developing countries (Shackleton et al., 2015, Sisak et al., 2016, Živojinović et al., 2017). In agrarian parts of the developing world, communities depend significantly on local provisioning ecosystem services for their health and income (Altieri, 2004, Zenteno et al., 2013). While agricultural production often provides the bulk of food and income in these areas, provisioning ecosystem services from forests, shrublands and grasslands also make significant contributions to communities' livelihoods (Ambrose-Oji, 2003, Heubach et al., 2011, Kar and Jacobson, 2012). Understanding the geographic and demographic characteristics of areas that depend on provisioning services in the form of NTFPs is key to conservation strategies that maximize NTFP availability to support human livelihoods and well-being (Angelsen et al., 2011, Kareiva, 2011).

It has been estimated that NTFPs provide income and nutrition for over two-thirds of Africa's population (CIFOR, 2005). These products provide significant income to households and communities, with some products like shea oil and gum arabic being collected and exported to international markets (Mujawamariya and Karimov, 2014, Rousseau et al., 2017). Many other products, such as fuelwood and building materials, are also sold locally and are an income source. A global literature review of 51 case studies across 17 developing countries estimated that, on average, forests provide 22% of a household's total income (Vedeld et al., 2007). While access to NTFPs is often moderated by political and cultural institutions (Lambini and Nguyen, 2014, Ludvig et al., 2016), a common feature of NTFPs is that they do not require financial capital to procure. Thus, households with less income tend to be the most dependent on forest products for food, fuel and materials (Vedeld et al., 2007).

In addition to providing income and supplying goods that households would otherwise have to purchase from markets, NTFPs also support nutrition outcomes, and many wild foods are consumed directly by the household that collected them. Given that forests and other natural areas offer significantly more species for consumption than agriculture alone, wild foods can significantly increase a household's dietary diversity (Powell et al., 2015, Remans and Smukler, 2013) and also provide an income source (Ingram et al., 2017). A study in Madagascar found that removing households' access to wildlife for consumption would increase rates of child anemia by 29% due to decreased meat consumption (Golden et al., 2011). While some wild foods are consumed continuously, many others are a reserve food supply used during times of famine. These "famine foods" are not preferred but are essential for households during hungry seasons or years when agricultural output is low (Mavengahama et al., 2013). Such foods increase household resilience to climate shocks. In surveys of households' climate adaptation strategies in Mali, Tanzania, and Zambia, forests were found to play a key role in reducing vulnerability during droughts and floods by providing alternative food and income sources (Robledo et al., 2012).

While forests are significant providers of NTFP and provisioning ecosystem services, products sourced from other natural areas like shrublands and grasslands also play a significant role in households' livelihoods (Pouliot and Treue, 2013). Because access to forested land is sometimes more regulated than access to grassland and shrubland, these non-forested areas can be a significant resource to less well-connected or less wealthy rural people, such as women or ethnic minorities (Pouliot and Treue, 2013). Whether products sourced from these areas can be included in the term "NTFP" is debatable, as a NTFP can often refer to many types of products sourced from a wide variety of environmental areas and land cover types (Belcher, 2003). For example, some trees that provide products typically classified as NTFPs, such as the Gum Arabic tree (*Senegalia senegal*), often grow in areas with less than the 10% canopy cover required to meet the FAO definition of a forest (FAO, 2012). Furthermore, products sourced from uncultivated non-forest areas have the basic fundamental economic characteristics of NTFPs identified in a comprehensive paper from the Center for International Forestry Research (CIFOR) on NTFPs and rural livelihoods: (i) they have low returns per unit area; (ii) they are primarily used for subsistence and often fill income gaps; and (iii) they are not planted, and are only managed indirectly, if at all (Angelsen and Wunder, 2003). Thus, while this paper examines foods from both forested and non-forested areas like grasslands and shrublands, we use the term NTFP to refer to provisioning ecosystem services sourced from any natural area following the characterization laid out by CIFOR (Angelsen and Wunder, 2003). In our analyses, we split NTFP into two categories: "wild foods" for NTFP like nuts, seeds, bushmeat, honey, or insects, and "nonfood NTFP" for other products such as building materials, medicines, and fibers. When speaking about both wild foods and nonfood NTFP, we use the general term NTFP.

While the benefit that NTFPs provide in supporting rural livelihoods has been clearly demonstrated in many case studies, few studies have been conducted at national and multinational scales relevant to policymakers or conservation and development practitioners (Reed et al., 2016). Indeed, a recent literature review lamented that this body of work is "limited by the propensity for small-scale and short-term evaluations" (Reed et al., 2016). Some notable exceptions to the preponderance of case studies include literature reviews on topics like wild food consumption (Powell et al., 2015) and environmental income from forests (Vedeld et al., 2007), as well as the Population-Environment Network (PEN) dataset on household NTFP use based on surveys conducted in 24 developing countries (Angelsen et al., 2014, Hickey et al., 2016). While these literature reviews and the PEN study have made significant contributions to our understanding of characteristics of households that depend on NTFPs and the degree of their dependence, they have a significant sampling bias, with most of the case studies and sample sites established opportunistically in areas with significant forest cover and where communities were already known to utilize forest resources. Thus, findings from these studies showing that NTFPs provide

22% of total income (Vedeld et al., 2007) or 28% of total income (Angelsen et al., 2014) cannot be taken as representative of all rural developing countries or as representative of any one country.

The fact that studies of household use of NTFPs are usually only conducted in highly localized case studies is unfortunate, as a growing body of literature is beginning to associate various environmental data metrics from satellite imagery with indicators of income, health, and food security from household surveys. Such research has found relationships between an increased Normalized Difference Vegetation Index (NDVI) and decreased child mortality (Brown et al., 2014); more forest cover and greater dietary diversity (Ickowitz et al., 2014); and more forest cover and decreased child stunting (Johnson et al., 2013). Many of these studies have found significant associations, but the specific mechanisms underlying linkages between environmental indicators like NDVI and forest cover with human well-being remain under-explored at relevant scales. This is largely because multinational surveys on human well-being, such as Demographic and Health Surveys (DHS) and Living Standards Measurement Surveys (LSMS), do not collect data on the accessibility and collection of wild foods and non-food products in a standardized manner across countries. On the other hand, datasets that do include data on NTFP use, such as individual case studies or the PEN dataset, do not include detailed data on key measures of human well-being, such as agricultural production, health, and food security. Thus, datasets that can be used to find a significant relationship between vegetation indices or land cover and human well-being at multinational scales are often lacking data on the exact causal linkages. For example, a recent study showed that forest cover was associated with dietary diversity across 21 African countries (Ickowitz et al., 2014), but could not explain the exact linkages, stating:

> While we have found clear evidence linking tree cover and indicators of diet quality, we are not able to determine the drivers of this relationship. Our data do not allow us to distinguish between natural forests, old fallows, and agro-forests; thus we cannot ascertain if people living near forests are collecting more nutritious foods from the forest or if they are cultivating them on farms and in agroforests, or a combination.

This paper aims to bridge these gaps – to provide a characterization of households that gather both food and nonfood NTFP in terms of both household characteristics and environmental characteristics. We do this by examining which geographical and household level variables are significant predictors of household wild food and nonfood gathering from 25 agro-ecological landscapes in 4 countries. While the landscapes in this study were not selected at random, they were selected purposively to monitor a variety of topics such as agricultural intensification, livelihoods, and environmental quality. Thus, landscapes were not selected with the specific intention of examining wild food or NTFP collection, and some of the landscapes selected had no households that reported collecting any NTFPs. This dataset therefore provides a unique opportunity to examine variation in NTFP gathering across and within multiple African countries and agro-ecological regions, as well as the factors associated with that variation, without relying on sample data that was collected in areas already known to have high levels of NTFP gathering. A geographic characterization of households that collect NTFP can, in turn, begin to fill in gaps in knowledge of the mechanisms by which ecosystem provisioning services (measured by satellite-derived environmental indices) could be contributing to positive human health outcomes. Finally, an understanding of which landscapes contain households that collect NTFP in significant numbers can aid conservation priority setting efforts that aim to maximize ecosystem service provision.

4.2 Methods and Data

For household survey data, we used data from the Vital Signs project (Scholes et al., 2013). Vital Signs is an integrated monitoring system that collects data on agriculture, the environment and livelihoods in a number of agricultural landscapes in Africa. The sampling design involves six to seven 10 x 10 km agricultural landscapes per country, with about 30 households per landscape. Landscapes were purposively placed within the identified regions in each country with the intention to cover a wide distribution of agro-ecological zones in areas where smallholder agriculture predominates (Scholes et al., 2013). Each household was interviewed about agricultural practices and production, off-farm and on-farm income, food security, and collection of food and nonfood NTFPs. A total of 751 households were interviewed across 25 landscapes in Ghana, Uganda, Rwanda and southern Tanzania (See Fig 4.1). Data was collected from 2013 to 2016, with interview dates varying by landscape and country. The median amount of time spent in a landscape conducting household surveys was 20 days.

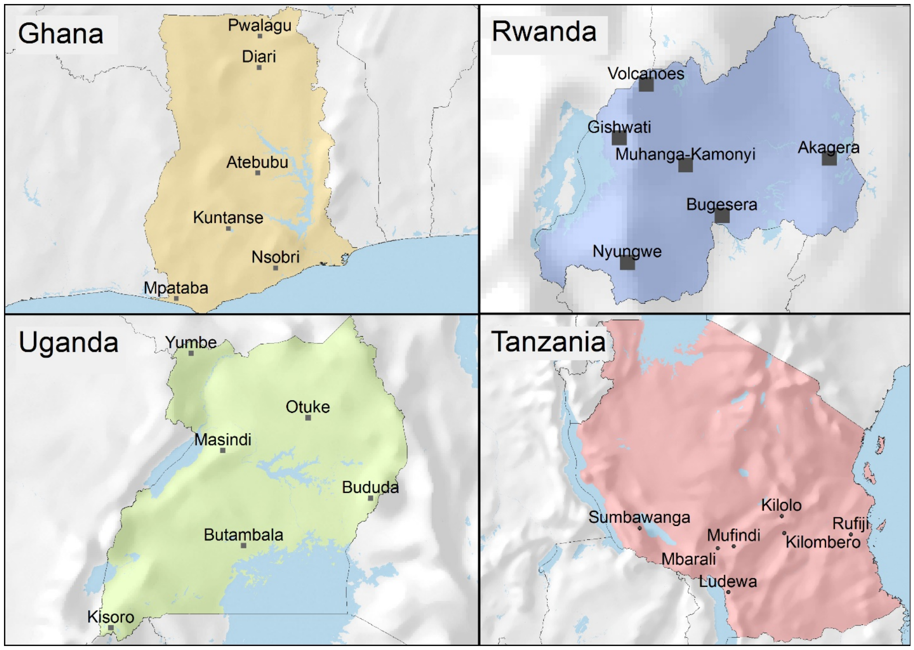

Figure 4.1: Location of landscapes within the four Vital Signs countries. Each landscape is 10x10km.

This study used multilevel logit models to determine the most significant geographic and household predictors of whether a household reported collecting NTFPs. Two separate regressions were run: one for whether the household collected wild foods and one for whether the household collected any nonfood NTFPs. The regressions were based on 751 households from Ghana, Uganda, Rwanda, and southern Tanzania.

While many analyses of wild foods include all undomesticated species, including those sourced from farmlands and villages (Powell et al., 2015), the Vital Signs questionnaire specifically asked about wild foods and other nonfood products collected from "nearby fallow lands, forest, woodland, shrubland, rivers, creeks, or other areas." Households were specifically asked about wild meat, wild insects, fish from local rivers/creeks, nuts or seeds, honey, building materials and medicinal plants but were also given the option to specify other NTFPs. Other products specified were snails, crabs, mushrooms, green vegetables, sisal, and palms for making mats. Because the particular NTFPs that households collected varied widely from one area to another, regressions were not run for each individual product. We used the same predictor variables for both regressions and allowed intercepts to vary at the landscape level and the country level. Additionally, although ancillary data was collected on frequency of collection and market value of NTFPs, the questionnaires were not designed to allow accurate estimation of values or quantities of all food products. To avoid the possibility of erroneous comparisons between areas, we only used simple binary outcomes.

4.2.1 Household Survey Data

Household-level data used in the regressions included measures of food security and household wealth, as well as demographic characteristics that have been shown in the literature to be significant predictors of wild product use, including the gender of the household head, average household age, household size, and education as measured by the percent of the household that could read in any language and the average years of schooling for all household members (Coulibaly-Lingani et al., 2009). All household-level data was collected using the Vital Signs household survey questionnaire (Scholes et al., 2013).

As a measure of household food security, an adjusted version of the Household Food Insecurity and Access Scale (HFIAS) was used (Coates et al., 2007). This consisted of eight different coping strategies that a household might have to take in response to food insecurity, such as skipping meals or limiting the variety of food eaten. The scale was calculated as the total number of days in the past week the household had to undertake a given coping strategy, summed across all eight coping strategies. In addition to the HFIAS, because food security does not just consist of food access, availability, and utilization, but also requires temporal stability (Wheeler and von Braun, 2013), we added a temporal aspect with a binary variable of whether the household reported not having enough food to feed the household at any point in the previous year.

For measures of household economic status, we included household income from non-agricultural sources, such as off-farm wage labor and running a household business; the total cost of all expenditures made in the previous year by a household for both food and nonfood products; and the total estimated value of all agricultural products produced in the previous year by a household, estimated as the summed production value of field crops, permanent crops, crop byproducts, crop residue, livestock, and livestock byproducts. Monetary estimates were calculated in local currencies for each country, and then converted to 2015 US dollars.

4.2.2 Household-Level Geographic Data

Because not all of the households fell perfectly within the 10 x 10 km landscape in which they were intended to be sampled, and because there was significant within-landscape variation in land cover types, land cover was measured as a household-level variable. Land cover and protected area data was summarized within a given distance of a household. Regression results for land cover within 7.5 km of a household are included in the body of this paper. However, because the distance people travel to collect resources can vary significantly based on the resource and location (Maukonen et al., 2014) regression results within 2.5km, 5km, 10km, and 15km are included in Appendix C.

Two variables were generated at the household level as indicators of the prevalence of land cover types that might provide wild foods and nonfood NTFPs: one for area covered by only forest and another for area covered by any non-forest, non-agricultural land cover types. Land cover data came from the 300 m spatial resolution European Space Agency Climate Change Initiative (ESA CCI) land cover dataset (Defourny et al., 2017). Forest categories consisted of any land cover type with greater than 15% tree cover, including broadleaved, needleleaved, evergreen, deciduous, and flooded areas, while non-forest, non-agricultural categories (henceforth referred to as "grassland") consisted of shrubland, grassland, herbaceous and sparsely vegetated areas with less than 15% tree cover. Because the ESA CCI dataset has annualized data, land cover was extracted for each household for the year in which the survey was conducted.

Additionally, data on protected areas was collected from the World Database of Protected Areas (UNEP-WCMC and IUCN, 2017) and all areas within protected areas (PAs) with International Union for the Conservation of Nature (IUCN) categories I through V were counted as protected, while areas permitting sustainable resource use (category VI) or areas unclassified within the IUCN system were not counted as protected. The variable was calculated as the percentage of total area protected within a given distance of a household. Finally, the 12-month Standardized Precipitation Index (SPI) (Mckee et al., 1993) was calculated for each household at the landscape centerpoint using the 1 km spatial resolution CHIRPS dataset (Funk et al., 2015). The SPI was originally developed to allow inter-comparison of drought and wet periods between stations. The 12-month SPI compares the precipitation total for each set of 12 months to all other 12-month periods in the record. The value of the 12-month SPI in a given month is equal to the number of standard deviations above or below the mean of the total precipitation received in the 12 preceding months (Guttman, 1999). Because households were not all interviewed within the same month, two households in the same landscape could have different SPI values.

4.2.3 Landscape-Level Geographic Data

For each of the 25 landscapes, data on distance to cities and population density were extracted using Google Earth Engine. These factors were selected because they could have an impact on household use of NTFPs, and they were measured at the landscape level because they do not vary significantly over a distance of 10km. Market distance was counted as the travel time in hours to the nearest town with a population greater than fifty thousand people, and was sourced from the Harvest Choice Market Distance dataset (Harvest Choice, 2011). Population density was measured as the total number of people within each 10 x 10 km landscape in the year 2015, as measured in the 100 km resolution WorldPop dataset (Tatem, 2017).

Variable	**Source**	**Description**
Household Survey Data		
Head Gender	Vital Signs Survey (Scholes et al., 2013)	Whether the head of household, defined as the household member who occupies the role of decision maker, is male.
Age	Vital Signs Survey	The average age of all household members.
Years of Schooling	Vital Signs Survey	The average years of schooling for household members over 5 years old.
Literacy	Vital Signs Survey	The percentage of individuals over 5 years old who can read in any language.
Household Size	Vital Signs Survey	The number of individuals in the household.
Critical Food Shortage	Vital Signs Survey	Whether the household was unable to meet their basic dietary needs at any point within the past year.
HFIAS	Vital Signs Survey	Household Food Insecurity and Access Score
Total Ag Production	Vital Signs Survey	The total value of all agricultural products produced in the past year, including field crops, permanent crops, crop byproducts, livestock and livestock byproducts in 2015 US dollars
Net Business Income	Vital Signs Survey	The net income from any business run by the household from the previous year in 2015 US dollars
Wage Income	Vital Signs Survey	The total income from wage labor conducted by members of the household over the past year in 2015 US dollars
Nonfood Spending	Vital Signs Survey	The total amount spent on nonfood items over the previous year in 2015 US dollars
Food Spending	Vital Signs Survey	The total amount spent on food over the previous year in 2015 US dollars
Household-Level Geographic Data		
Area Protected	WDPA (UNEP-WCMC and IUCN, 2017)	The percentage of land area within a given distance from a household that falls inside of a protected area.
Forest Cover	ESA-CCI (Defourny et al., 2017)	The percentage of land area within a given distance from a household that is of a forest land cover type.

Grassland	ESA-CCI	The percentage of land area within a given distance from a household that is of a grass, shrub, or herbaceaous land cover type.
12 – month SPI	CHIRPS (Funk et al., 2015)	The Standardized Precipitation Index (SPI) for the 12 months before a survey was conducted.
Landscape-Level Geographic Data		
Market Distance (Landscape Level)	Travel Time to Market Centers (Harvest Choice, 2011)	The number of hours it would take to travel to a town with over 50,000 people from the center of a landscape.
Population Density (Landscape Level)	WorldPop (Tatem, 2017)	The total population of the 10km x 10km landscape from which the households were selected.

Table 4.1: Description of Variables Used in Regressions

Although we used multiple indices of household food security and household income, none of these variables used were found to be multicollinear; however, other potential indices were excluded because of multicollinearity with the indices that we did use. The regression was run in R using the lme4 package version 1.1.12 (Bates et al., 2015) and significance estimates were generated using the lmerTest package version 2.0.32, which uses Satterthwaite's degrees of freedom method to generate significance estimates (Kuznetsova et al., 2014). Variables were rescaled and centered to yield values from -1 to 1 to facilitate model estimation.

4.3 Results

The households in the dataset had significant variation in income, agricultural production, forest cover, and rates of NTFP collection. For example, in Mpataba,

Product	Number of Households	Percentage of Households
Nuts or seeds	57	7.60%
Wild meat	54	7.20%
Honey	41	5.50%
Wild insects	18	2.40%
Fish from local rivers/creeks	13	1.70%
Other - Vegetables	7	0.90%
Other - Mushrooms	5	0.70%
Other - Snails	3	0.40%
Other - Crabs	3	0.40%
Any Wild Food	126	16.90%

Table 4.2: Number and percentage of households that collected specific wild foods.

Ghana the average agricultural production value per household was \$5,994 over the previous year, while it was only \$286 in Kisoro, Uganda. Similarly, forest cover within 7.5km of a household ranged from 0.004% in Nsobri, Ghana to 92.7% in Atebubu, Ghana, and rates of NTFP gathering ranged from 0% in Nyungwe and Volcanoes, Rwanda to 87% in Yumbe, Uganda. Finally, the landscapes were placed in areas with ample variation in precipitation, from 861 mm/yr in Sumbawanga, Tanzania to 1618 mm/yr in Mpataba, Ghana.

4.3.1 Types and Rates of NTFP Collecting

Our surveys find wide variability in the rates of collecting wild foods and non-food NTFPs. The most common NTFP collected was building materials, followed by medicinal plants, while the most common wild food collected was nuts or seeds, followed closely by wild meat.

In looking at the rates of households collecting only wild foods, only nonfood NTFPs, both types of NTFP, or neither wild food nor nonfood NTFPs, over half of

Product	Number of Households	Percentage of Households
Building Materials	209	27.80%
Medicinal Plants	170	22.60%
Palms for Mats	2	0.26%
Sisal	1	0.13%
Any Nonfood NTFP	284	37.90%

Table 4.3: Number and percentage of households that collected specific nonfood NTFPs.

	Number of Households	Percentage of Households
No NTFPs At All	426	56.60%
Only Nonfood NTFPs	200	26.60%
Only Wild Foods	42	5.60%
Both Wild Food	84	11.20%

Table 4.4: Tabulation of households that collected only wild foods, only nonfood NTFPs, both wild foods and nonfood NTFPs, or no NTFP at all.

households reported collecting no NTFP at all. Additionally, many more households collected nonfood NTFPs than wild foods.

4.3.2 Regression Results

Across the 25 landscapes, the most significant predictors of whether a household would report collecting wild foods were the presence of forests or grasslands. Household characteristics like demographics, education, income, spending, and food security had little significance in determining whether a household would report collecting wild foods when geographic variables were included in the regressions.

	Estimate	Std. Error	z value	$\Pr(<\lvert z\rvert)$
(Intercept)	-3.4	1.24	-2.74	0.01**
Head Gender	0.59	0.45	1.33	0.18
Age	-0.45	0.9	-0.5	0.62
Years of Schooling	-1.61	1.13	-1.42	0.15
Literacy	0.07	0.92	0.08	0.94
Household Size	-0.05	0.75	-0.07	0.94

Critical Food Shortage	-0.04	0.35	-0.11	0.91
HFIAS	0.64	1.38	0.47	0.64
Total Ag Production	0.26	1.76	0.15	0.88
Net Business Income	-0.01	1.4	-0.01	1
Wage Income	-2.76	2.26	-1.22	0.22
Nonfood Spending	-0.61	1.88	-0.32	0.75
Food Spending	-0.52	0.99	-0.52	0.6
Area Protected	-1.27	1.46	-0.87	0.39
12 – month SPI	0.07	0.49	0.14	0.89
Forest Cover	2.03	0.95	2.14	0.03*
Grassland	2.7	1.19	2.27	0.02*
Market Distance	0.19	2.35	0.08	0.93
Population Density	1.18	1.34	0.88	0.38

Table 4.5: Predictors of whether a household reported collecting wild food NTFP. Note: variables were centered and rescaled. n = 751. A p-value of less than 0.001 is indicated with three stars (***), a p-value of less than 0.01 is indicated with two stars (**), a p-value of less than 0.05 is indicated with one star (*), and a p-value of less than 0.1 is indicated with a period (.).

Similar to wild foods, household characteristics had little significance for whether a household would report collecting nonfood NTFP. Unlike wild foods, however, land cover (forest cover or grassland) was not a significant predictor. Rather, the best predictor of whether a household would report collecting nonfood NTFP across the 25 landscapes and four countries was lower population density. Additionally, lower household literacy rates and higher HFIAS scores were both somewhat associated with nonfood NTFP collection.

	Estimate	Std. Error	z value	Pr(<|z|)
(Intercept)	-1.87	1.09	-1.71	0.09.
Head Gender	0.35	0.29	1.2	0.23
Age	-0.4	0.72	-0.55	0.58
Years of Schooling	0.17	0.83	0.2	0.84
Literacy	-1.23	0.74	-1.67	0.1.
Household Size	-0.35	0.52	-0.67	0.5
Critical Food Shortage	0.37	0.25	1.49	0.14
HFIAS	1.81	0.99	1.83	0.07.

Total Ag Production	2.08	1.48	1.4	0.16
Net Business Income	1.36	1.45	0.94	0.35
Wage Income	1.91	1.69	1.13	0.26
Nonfood Spending	0.94	1.38	0.68	0.49
Food Spending	-0.06	0.9	-0.06	0.95
Area Protected	-1.19	0.99	-1.21	0.23
12 – month SPI	-0.09	0.43	-0.21	0.83
Forest Cover	-0.68	0.97	-0.7	0.48
Grassland	0.41	1.07	0.38	0.7
Market Distance	-1.25	1.42	-0.88	0.38
Population Density	-3.09	1.42	-2.17	0.03*

Table 4.6: Predictors of whether a household reported collecting nonfood NTFP. Note: variables were centered and rescaled. n = 751. A p-value of less than 0.001 is indicated with three stars (***), a p-value of less than 0.01 is indicated with two stars (**), a p-value of less than 0.05 is indicated with one star (*), and a p-value of less than 0.1 is indicated with a period (.).

Regressions were also run at 2.5km, 5km, 10km, and 15km spatial scales, and these results were included in Appendix C. Many of the variables that were significant predictors at a 7.5km scale remained significant at all scales. Lower population densities remained a significant predictor of nonfood NTFP collection, even as forest cover, grassland area, and area protected were measured at different scales. For wild food collection, forests were a significant predictor of NTFP collection at all spatial scales and increased in significance at smaller scales. Grassland was most significant at 7.5 and 10km scales, but lost significance at both larger and smaller scales. Additionally, a lower percentage of area protected was somewhat significant as a predictor of wild food collection at 5km scales and was significant as a predictor of nonfood NTFP collection at 10 and 15km scales.

4.4 Discussion

One of the most striking results in this analysis is that geographic variables like land cover and population density are better predictors of whether a household will report collecting NTFP than any household level variables that have been shown to be related to wild product gathering in other contexts (Bakkegaard et al., 2017, Coulibaly-Lingani et al., 2009, Melaku et al., 2014). These findings are in line with a similar study conducted in China, which found that geographic factors like soil quality and forest distance were significant predictors of whether a household would collect NTFP, while household socio-economic factors, such as annual per capital income or education levels, were not (Zhu et al., 2017). The presence of both forests and grasslands were significant predictors of whether a household would report collecting wild foods, while lower population density was significantly associated with higher collection of nonfood NTFPs. Given that there is also substantial variability between landscapes in terms of socio-economic characterization, it is also apparent that the geographic context, rather than socio-economic factors, is the greatest determinant of whether households in that landscape will report gathering NTFP.

Interestingly, very different contexts determine whether a household will report collecting wild foods or nonfood NTFPs. The fact that environmental land cover types predicted whether a household will report collecting wild food suggest that this land cover variable is likely capturing availability of wild foods in particular land cover types. Both wild meats and wild nuts and seeds, the two most frequently reported types of wild food collected, require some amount of natural habitat in order to grow, and thus are unavailable in areas without these land cover types. Building materials, on the other hand, can often consist of mud bricks or other products that don't necessarily require the presence of a particular land cover type. Even organic building materials, like thatch and wood, can be sourced from marginal areas or small plots, whereas food species of wild meat and plants like shea (*Vitellaria paradoxa*), locust bean (*Parkia biglobosa*), and *Syzygium* fruits require some natural habitat (Naughton et al., 2015). The fact that lower population densities were associated with greater collection of nonfood NTFPs could be duo to a number of factors. It possible that in densely populated areas artificial building materials and medicines are more readily available, that households have higher incomes in densely populated areas to purchase these resources, that there is greater competition for natural building materials and medicines in these areas, or that NTFP availability is quickly exhausted in densely populated areas.

Another significant finding was that household level variables related to demographics, education, food security, and income had little predictive power in determining whether a household would report collecting NTFPs. This stands in opposition to pre-existing work on household determinants, which has found that factors like age, household size, education levels, and income sources are significant determinants of whether a household would report having access to NTFPs (Coulibaly-Lingani et al., 2009). Where our models did find that household level predictors were somewhat significant, they concurred with previous literature: both decreased household literacy and decreased food security were somewhat associated with greater collection of nonfood NTFPs. This is likely because illiteracy and food insecurity are associated with poorer and marginalized members of communities, which previous studies have found to be more likely to depend on NTFPs (Pouliot and Treue, 2013). It is possible that household-level variables do have significant effects within a landscape, as prior research suggests, but that our sample size was not large enough to detect these relationships. Coulibaly-Lingani sampled over 1800 households in one province of Burkina Faso, and showed that within this small area many household characteristics were significant predictors of NTFP access (Bakkegaard et al., 2017, Coulibaly-Lingani et al., 2009). However, when comparing between countries and agro-ecological zones, as the Vital Signs dataset does, it seems that land cover and population density have more explanatory power than household characteristics when determining if NTFP gathering is part of a given household's livelihood strategy. Thus, these geographic and land cover variables should be taken into account in future econometric work on NTFP access and utilization.

Assessing the presence of forests, grasslands and protected areas within varying distances (see Appendix C) also revealed interesting results. The percent of the land covered by forest was most significant as a predictor of wild food collection at very local scales, around 2.5km, while the percent of land covered by forest within 10 and 15 km of a household had a less significant effect. Grassland was only significant at 7.5 and 10 km scales. Interestingly, the presence of protected areas was also significant at some scales for both wild foods and nonfood NTFP, with a greater presence of protected areas associated with less NTFP gathering. This could be due to a variety of factors, such as exclusion of households from access to NTFPs within protected areas to greater competition for the NTFPs that fall outside of PAs. It could also be due to respondent bias, with households being reluctant to admit to behavior that is illegal or that may appear illegal. Nevertheless, our findings at multiple scales do suggest that PAs have an effect on household's reported NTFP gathering, although not as salient of an effect as the presence of forests and grasslands. This has significant implications for conservation policy, suggesting that restrictive protected areas, such as those with IUCN categories I through IV, may decrease local peoples access to wild foods and nonfood NTFPs. Thus, more research is needed on policy strategies that allow people to maintain their livelihoods while also meeting conservation goals, such as community-based forest management and protected areas permitting sustainable use of resources (Ellis and Porter-Bolland, 2008).

While greater presence of forests and grasslands is significantly associated with wild food collection and low population densities are associated with nonfood NTFP collection, there are many areas in Africa with high population densities where agricultural land use is predominant. In these areas households likely do not collect NTFP, not only because forests and grasslands are less common, but also because they are well protected or highly fragmented and not as productive of wild food species. This is especially true in Rwanda and southwest Uganda, where the Vital Signs data indicates very little wild food or nonfood NTFP collection and there is little substantial natural land cover outside of national parks like Nyungwe and Volcanoes in Rwanda or Bwindi Impenetrable forest in Uganda. Thus, our results show there may be significant populations of smallholder farmers in Africa that rely on little to no NTFP resources. This suggests that the contribution of NTFP to local incomes across all rural households in sub-Saharan Africa may be much lower than the 22% calculated by Vedeld in a literature review or the 28% calculated by the PEN study (Angelsen et al., 2014, Vedeld et al., 2007). At the very least, our data and analyses suggest that NTFP dependence varies widely across different parts of the continent.

One benefit of this study was its multinational approach, providing significant variety in landscape characterization in terms of factors like landcover type, market distance, and population density. This allows us to build on previous studies that have mostly taken place in one country or setting and compare between landscapes and countries to determine which geographical contexts are most associated with households that collect NTFPs. The multilevel models used in this study take advantage of the multinational approach to allow estimates in one country to borrow strength from the other countries in the analysis. Conducting an analysis at this scale also allows us to speak to previous studies conducted at similar scales finding associations between natural landcover and positive human well-being outcomes (Ickowitz et al., 2014, Johnson and Brown, 2014).

Furthermore, increasing food security and access to provisioning ecosystem services is an increasing goal of conservation in developing countries (Shackleton et al., 2015, Tscharntke et al., 2012), and this research can justify conservation schemes designed to increase availability of provisioning ecosystem services to communities, even in areas where case studies of NTFP collection have not been conducted. Nevertheless, there are some risks to missing important local variables when creating multinational statistical models. While we did not have data on cultural diversity, for example, we did allow for intercepts in the model to vary at the landscape scale and the nation scale, with the intent to account for variation in community and national factors among landscapes and countries.

This study had some limitations that must be noted. One issue is that while the landscape locations were not sampled in a way that targets communities that are known to collect NTFP, they were also not randomly sampled, and therefore may exhibit some bias in the representativeness of the households interviewed. Another limitation was that while this survey asked respondents if they collected NTFPs and what kind they collected, it did not explore questions of frequency, uses, and domestication status of NTFP that were collected, as previous work has done (Casas et al., 2007, Heubach et al., 2011, Kar and Jacobson, 2012). Future work could build on our findings to explore factors like how distance to natural land cover relates to NTFP outcomes, how geographic factors affect outcomes such as the frequency of collection of NTFPs or the market value of NTFPs, as well as how different land cover types correspond to the types of NTFPs collected. Such initiatives should increase the sample size to provide a reliable estimate of household characteristics that are related to NTFP collection, and how these characteristics are affected by geographic factors. Additionally, future work could provide more detailed analyses of how the presence of protected areas and the severity of their restrictions affect households' propensity to collect various types of NTFPs. A final limitation in the data is that it is a cross section that does not allow us to examine inter-annual variability. Collection of data with higher frequency is recommended to control for heterogeneity among households as well as to examine trends in the supply of NTFPs in a given region.

Overall, our findings suggest that the presence of forests and grasslands are significant predictors of whether a household will report collecting wild foods, that a greater presence of these areas leads to a greater likelihood that a household will collect wild foods, and that these geographic variables in fact play a more significant role than a household's income levels or food security status. This is especially true in the four countries where Vital Signs collected data but also likely true for households in areas with similar agro-ecological systems in sub Saharan Africa. These findings are relevant to recent literature associating forest cover with positive outcomes in terms of dietary diversity and child nutrition (Ickowitz et al., 2014, Johnson et al., 2013), suggesting that the collection of wild foods may be playing a role in these positive food security outcomes. This has implications for conservation policy, suggesting that forests and grasslands in Africa with a nearby human presence are very likely providing wild foods to supplement people's incomes and diets. Restrictive conservation and protected area policies could harm communities' access to these livelihood-supporting resources. Thus, the provisioning ecosystem services offered by these areas could be a justification for supporting conservation efforts and for sustainable use (IUCN Category VI) type protected areas.

4.5 Conclusion

This study shows that communities in areas in Africa with low population densities and high rates of forest and other natural areas are most likely to report collecting wild foods and NTFP. This offers a useful counterpoint to literature drawing only on areas known to have high rates of NTFP collection to examine household characteristics that predict NTFP collection. Furthermore, the observed association between forest cover and wild food collection suggests that wild foods may be playing some role in previously observed associations between forest cover and positive dietary and nutrition outcomes. This has implications for conservation efforts in Africa, suggesting that increased food security via wild food collection can be a justification for conservation, but also that protected areas permitting sustainable use of natural resources will be more beneficial to communities than protected areas that do not give locals access to wild foods or NTFP. Finally, it shows that NTFPs make important contributions to livelihoods in rural landscapes throughout Africa and provides a characterization of landscapes where policy instruments could be targeted to support livelihoods via NTFP.

Chapter 5: Mapping the Safety Net Effect

5.1 Introduction

Currently, an estimated 58.8 million African children, representing nearly one third of the continent's under-5 population, suffer from chronic undernutrition (United Nations Children's Fund (UNICEF) et al., 2019). While progress has been made in the past several decades to improve nutrition and food security outcomes, climate change threatens to stall or even reverse current trends (FAO et al., 2018). As climate change continues, the frequency and intensity of meteorological extremes will affect food production, ultimately harming food security and nutrition for many vulnerable communities. No continent is more vulnerable to these changes than sub-Saharan Africa, where an estimated 95% of agriculture is rainfed (Wani et al., 2009) and about 65% of households produce food for their own consumption (Runge et al., 2004).

One factor that can play a major role in fostering food systems that are resilient to climate shocks is the presence of ecosystem services provided by forests, savannas, and other natural, uncultivated land use types (Daily and Matson, 2008, Pascual et al., 2017, Reed et al., 2016). Uncultivated areas provide a suite of regulating services that can buffer agricultural yields from the effects of shocks. For example, natural vegetation can provide shade and cooler temperatures during heat waves, absorb water and protect against erosion during floods, as well as retain soil moisture during droughts. Furthermore, natural areas can provide habitat for pollinators and species that regulate pest outbreaks. Beyond regulating services, natural, uncultivated land provides provisioning services in the form of wild foods and other inedible Non-Timber Forest Products that can support local incomes and food security when agricultural output is low.

While a great deal of literature has focused on the benefit that ecosystem services can provide, much of this work has relied on studies that are site specific. For example, detailed work conducted in case studies across Africa have found instances of ecosystem services improving child nutrition (Golden et al., 2011), regulating crop pests (Girma et al., 2000), improving yields through pollination (Gemmill-Herren and Ochieng', 2008, Munyuli, 2012), and improving soil nutrient quality (Boffa et al., 2000, Sileshi et al., 2012, Siriri et al., 2009). Some work that is particularly relevant to climate resilience has found that natural land cover can improve soil water storage (Lott et al., 2009, Siriri et al., 2013), but nevertheless few empirical studies have observed how ecosystem services affect human outcomes during climate shocks. Rather, most studies that focus on ecosystems as a form of climate resilience use surveys that ask respondents if they would rely on ecosystem services in the event of a hypothetical shock (Robledo et al., 2012), with some studies indicating that many people do not think of ecosystem services as an asset that they would rely on during a shock (Wunder et al., 2014).

Beyond a multitude of case studies, an emerging body of work has begun to assess whether the benefits provided by various ecosystem services can be observed at large multinational scales. This work typically draws on geolocated Demographic and Health Surveys and tends to focus on Africa in particular, where DHS data is particularly rich and where low levels of economic development mean that people are particularly dependent on local ecosystem services. Such work has shown that forest cover is associated with improved dietary diversity (Ickowitz et al., 2014, Rasolofoson et al., 2018), that forested watersheds are associated with less diarrheal disease (Herrera et al., 2017), and that protected areas are associated with a number of positive benefits (Naidoo et al., 2019).

This study aims to build on this existing multinational work by examining whether natural, uncultivated land cover types are associated with drought-resilient nutrition outcomes in Africa. Furthermore, this study does not model the effects of ecosystem services as uniform over space, but explores how the effects of ecosystem services on fostering drought resilience varies across Agro-Ecological Zones (AEZs) in Africa in order to identify where people are particularly dependent on local ecosystem services. This research will therefore inform conservation priority setting by highlighting where environmental conservation is most likely to lead to improved nutrition outcomes during drought.

5.2 Theoretical Framework

5.2.1 Land Cover and Ecosystem Services

The ecosystem services provided by nature are highly varied and operate across different spatial scales. They are typically classified into provisioning, supporting, regulating, and cultural services (Martínez-Harms and Balvanera, 2012), although other typologies exist (Fisher and Kerry Turner, 2008). A common approach for mapping ecosystem services is to focus on land cover types, especially when primary data is unavailable (Martínez-Harms and Balvanera, 2012). One approach is to analyze each land cover type as providing a "bundle" of associated ecosystem services (Raudsepp-Hearne et al., 2010). Thus, in an African context, cultivated land provides food crops as a service, grasslands provide grazing for livestock as well as habitat for pollinators and pest regulation services, while forests provide a variety of wild foods, soil formation, cooking fuels, water quality regulation, and non-timber forest products. This framework is especially useful for analyzing trade-offs: as natural vegetation is cleared to make room for crop production, the increase in food crops necessitates a decrease in habitat for pollinators and wild food species, as well as the regulating services provided by uncultivated land. Conversely, as agricultural land is abandoned, it stops providing food crops but becomes available again for timber production, water quality regulation, erosion protection, pollinator habitat, and livestock grazing. Finally, previous work has shown that the presence of natural, uncultivated land is one of the best geographic predictors of whether households in Africa report collecting both wild foods as well as other provisioning ecosystem services (Cooper et al., 2018).

5.2.2 Uncultivated Land and Commons

The regulating and supporting services provided by uncultivated land, such as soil formation, pollination, and water retention are, by their very nature, beneficial across boundaries of property and ownership. However, in cases when land is privately held, provisioning services such as food crops or timber only provide benefits to landowners, who reserve the right to collect these goods.

In Africa, uncultivated land is often held as a commons, providing resources to multiple members of a community rather than just one landowning household, although specific practices of land tenure, ownership, access rights, and communal domain vary widely across cultural contexts (Wily, 2008). This means that not only regulating and supporting services but even provisioning services such as wild foods and fuelwood provided by uncultivated land are available to many members of a community. Thus, these areas are especially critical for the poorest members of communities, and these commons are often framed as "possibly the only capital asset of the poor" (Wily, 2008). Furthermore, empirical research has shown that provisioning services provided by such areas are critical for the livelihoods of women, migrants, and other marginalized groups in rural Africa (Coulibaly-Lingani et al., 2009, Pouliot and Treue, 2013).

Thus, as cropland expands into previously uncultivated areas in Africa due to pressures of both population growth and agricultural commodification (Laurance et al., 2014, Rudel, 2013), commons and the services they provide for communities and the poor are becoming increasingly depleted. The conversion of communal land to privately held, cultivated land often happens with no benefit to marginalized community members because communally held land and commons are not well-recognized or protected by African legal systems (Wily, 2011). Similarly, as agricultural land is abandoned and is reforested through processes like shrub encroachment, provisioning ecosystem services can become publicly available to communities again (Eldridge et al., 2011, Laris, 2008, Venter et al., 2018).

5.3 Data Sources

5.3.1 Nutrition Data

For this analysis, we use data from Demographic and Health Surveys (DHS) from throughout Africa. The DHS is often considered the “gold standard” of data on health and nutrition from developing countries and is often used in environmental health studies, because the GPS coordinates associated with each DHS cluster make it possible to infer the environmental context at the time and location of the survey (Brown et al., 2014). We utilize all surveys from sub-Saharan Africa that meet the following criteria: (1) they have geolocated coordinates, to facilitate the extraction of climate conditions and local land cover at the site of each DHS cluster, (2) they have data on child nutrition outcomes, and (3) they have data on relevant household and individual co-variates of malnutrition.

As our metric of child nutrition, we use Height-for-Age Z-Scores (HAZ Scores). This is an indicator of stunting, a consequence of long-term malnutrition, and has been collected in the majority of DHS surveys for decades. HAZ Scores are derived by comparing the height of a child under five years of age to the distribution of heights of well-nourished children of the same age and gender, and then deriving a Z-score. While natural variation in human height makes it impossible to diagnose any one individual as stunted (Perumal et al., 2018), stunting can be defined at the population level as the percentage of a population with an HAZ score less than -2, and severe stunting is the percentage of a population with an HAZ score less than -3. While human populations do vary in potential attainable height, for children under 5, differences in height are mostly explained by environmental and dietary conditions (Habicht et al., 1974).

5.3.2 Drought Data

For our data on drought, we use precipitation data from the Climate Hazards Infrared Precipitation with Stations (CHIRPS) dataset (Funk et al., 2015) and temperature data from a land surface re-analysis model (Sheffield et al., 2006). Because direct observations of long-term climate conditions in Africa are scarce, both of these datasets rely on remote sensing in combination with ground-truthed data as well as modeling to infer meteorological conditions across space.

Using monthly estimates of precipitation as well as average daily monthly maximum and minimum temperatures, we calculate the monthly water balance using the Hargreaves method (Hargreaves and Samani, 1982) and then derive the 24-month Standardized Precipitation-Evapotranspiration Index (SPEI) (Beguería et al., 2014). This metric compares the water balance over the previous 24 months and compares it to long-term trends in that location, deriving an index that can be interpreted like a Z-Score. In previous studies of precipitation anomalies and child malnutrition, the SPEI calculated for the 24 months before a survey was the best predictor of child health outcomes (Cooper et al., 2019). Because the SPEI accounts for both precipitation anomalies as well as water lost through heat-induced evapotranspiration, it can characterize both meteorological and hydrological droughts, both of which are expected to become more common under climate change (Dai, 2013).

While drought has a strong and clear impact on children's nutrition status in many parts of Africa, excessive rainfall can also affect health outcomes (Cooper et al., 2019). To focus only on the effects of drought relative to normal periods, we exclude from our analysis children observed during relatively high levels of rainfall (SPEI >1).

5.3.3 Land Cover

For data on land cover near a DHS cluster, we use a dataset created by the European Space Agency Climate Change Initiative (Defourny et al., 2017), which is available annually for the years 1992 to 2015 at a 300m resolution for 22 distinct land cover classes. For uncultivated land providing regulating, supporting, and communal provisioning ecosystem services, we use all forms of tree, shrub and herbaceous cover, as well as shrubland, grassland, and water bodies. Additionally, for mosaic land cover types with both cropland and natural vegetation, we counted each pixel as cultivated if it contained more than 50% cropland and uncultivated if it contained less than 50% cropland. Finally, we do not count urban, bare, or permanent snow and ice areas as uncultivated land, as they do not provide most of the local ecosystem services that uncultivated land cover types do.

As our metric for the availability of ecosystem services, we determine the fraction of land within 15 km of each DHS cluster that was uncultivated at the time of the survey. We use a 15 km radius for three reasons. For one, DHS clusters are spatially distorted to preserve respondent anonymity, with 99% of sites displaced by up to 5 km and 1% of sites displaces by up to 10 km (Grace et al., 2012). Thus, a 15 km radius more accurately captures landscape-scale land cover characteristics, because the land cover in the immediate vicinity of a community can't be known. We also focus on a 15 km, landscape-scale area because many ecosystem services flow over large scales, especially abiotic resources that move through space, such as water, as well as ecosystem services from animals, such as bushmeat and pollination (López-Hoffman et al., 2010). Finally, many individuals will travel significant distances to farm and to collect resources, especially in swidden cropland systems as well as when resources are scarce (Arku and Arku, 2010, Felardo and Lippitt, 2016).

Having derived nearby land-cover categories for each DHS cluster, we exclude sites from our analysis that have greater than 1% of nearby land cover as urban (19.1% of the original data) or greater than 5% of nearby land cover as water (14.1%

of the original data). This is to ensure that we are basing our analysis only on rural, agrarian households that are largely dependent on rainfed agriculture and ecosystem services from non-agricultural areas, rather than households that have livelihoods based on off-farm labor (such as those in urban areas) or livelihoods based on fishing (such as those near coasts or large bodies of water). Excluding DHS clusters that were either observed during a significantly wet period (SPEI >1) or in urban or coastal areas, yields a dataset of 221,885 observations, or 59.6% of the original 372,197 observations.

5.3.4 Agro-Ecological Zones

Because both farm systems and ecosystem services vary according to local biophysical variables, especially temperature, precipitation and elevation, we analyze the effect of ecosystem services in providing drought resilience at the scale of Agro-Ecological Zones (AEZs). We use AEZs rather than other potential groupings, such as livelihood zones, because the response of agriculture to drought and the ecosystem services that natural areas can provide are primarily determined by biophysical conditions. Furthermore, most data on livelihood zones available at a continental scale is broadly similar to any AEZ characterization (Lynam, 2002). Using the FAO methodology (Fischer et al., 2006) AEZs are defined by elevation and length of growing period, where the growing period is defined as days where precipitation plus moisture stored in the soil exceeds half of potential evapotranspiration (Fischer et al., 2006). In other parts of the world, temperature is an important factor in determining

AEZ, but as nearly all of Africa is warm, it is not an important determinant in this analysis. In cases where there are ample observations (Savanna and Sub-Forest), we disaggregate each zone into roughly contiguous northern and southern hemisphere zones. Conversely, in the case of arid zones, where there was fewer observations we aggregated across across the entire continent to create one discontinuous zone, assuming that the relationships between drought, ecosystem services, and nutrition outcomes are comparable across all of arid Africa. In the end, each zone in our analysis had over 10,000 child nutrition observations from multiple countries and surveys (See Table 5.1).

Briefly, here is an overview of each AEZ in our analysis:

- **Arid**: This AEZ includes all parts of Africa with a growing period of less than 70 days a year throughout the Sahel and Sahara, the Horn of Africa as well as the Kalahari desert. Livelihood systems in arid parts of Africa are often completely pastoral, although in some cases arid-adapted crops like Sorghum and Millet are grown. Population is typically quite sparse.

- **Forest**: This AEZ includes all areas over 270 days of growing period in a year. Forests are primarily found in central Africa, but are also in mountainous and coastal parts of West Africa, in Liberia and Sierra Leone, as well is in coastal Southeast Africa, in Mozambique and Madagascar. Farming activities in these areas are based around crops like rice and cassava, as well as commodity tree crops like rubber and palm oil. Populations in agricultural areas are typically sparse, although greater population density can be found along coasts and rivers.

- **Highlands**: For highlands, we included all areas at greater than 1200m of elevation, irrespective of growing period. This included much of the highlands of Ethiopia, Eastern and Southern Africa, as well as Lesotho. Livelihood systems in mountainous regions are primarily crop-based, although the particular crops vary, with Teff and Wheat being prevalent in Ethiopia and crops like Potatoes, Maize and Bananas being more prevalent in Southern and Eastern Africa. Cash crops include Coffee and Tea. In much of the highlands of Africa population and agriculture are quite dense.

- **Northern Savanna**: The Northern African Savanna, typically called Sahelian Savanna is characterized by 70-180 day growing seasons and extends from Senegal to the Sudan. Crops include maize, groundnuts, millet, and sesame, and cattle production is high. Population densities vary substantially from the dense Hausalands of northern Nigeria to more remote parts of Chad, but generally high.

- **Southern Savanna**: Also characterized by 70-180 day growing seasons, Southern African Savanna occupies a swath of lowlands from southern Kenya, through Tanzania and Zambia to the Victoria falls region of Southern Africa. Agriculture includes maize and cattle. Population densities vary but are generally more sparse than the savannas of Northern Africa, with significant amounts of uncultivated land providing habitat to wildlife.

- **Northern Sub-Forest**: The Northern African Sub-Forest AEZ, sometimes referred to as the Guinean Forest-Savanna Mosaic, is less densely populated that the savannas farther north or the coastal forests farther south. Root crops like yams and cassava are common, as are maize, sorghum and millet. Pastoralism is practiced, and is more common in South Sudan. Population densities vary widely, from Nigeria to the almost uninhabited border of the Central African Republic and South Sudan.

- **Southern Sub-Forest**; The Southern African Sub-Forest AEZ often referred to as Miombo woodlands, exists on the southern periphery of Central African forests in northern Angola and Southeastern DRC, as well as in the region of Tanzania, Mozambique and Malawi. Crops include cassava and maize, and population densities are generally low.

AEZ	Children	Countries	Surveys
Arid	11,739	9	25
Forest	20,203	17	38
Highlands	56,504	18	45
Northern Savanna	58,392	14	41
Northern Sub-Forest	32,815	15	42
Southern Sub-Forest	22,767	11	23
Southern Savanna	19,465	9	21

Table 5.1: Number of child nutrition observations per AEZ

5.4 Methods

For this analysis we model how access to ecosystem services affects the vulnerability of nutrition to drought in each agro-ecological zone. We start by using

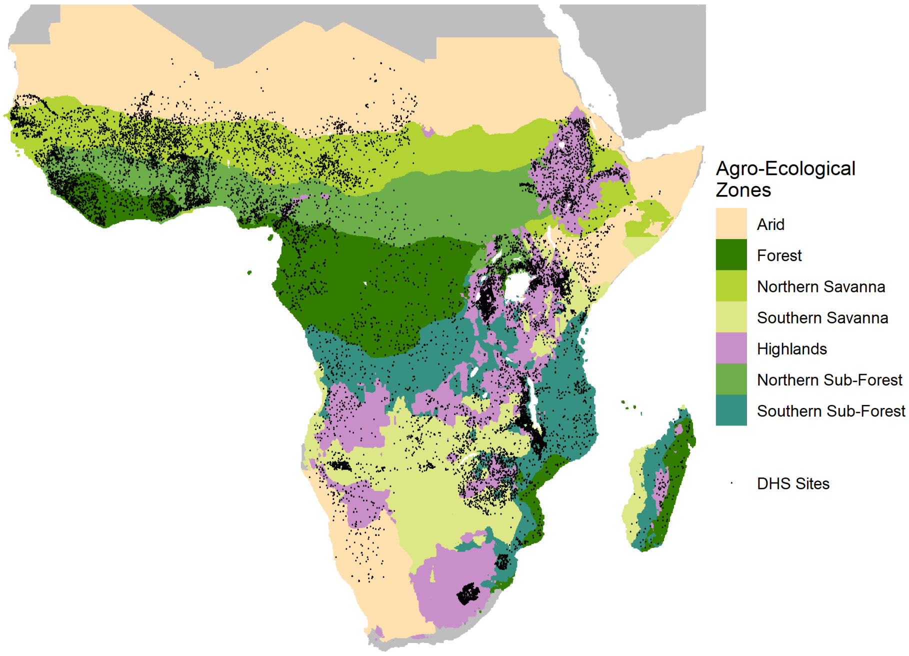

Figure 5.1: Agro-Ecological Zones and DHS clusters included in the study.

Covariate Balancing Generalized Propensity Scoring (CBGPS) (Fong et al., 2018a) to derive weights for each observation to control for the effects of other geographic factors that affect drought vulnerability and may be correlated with land cover and land use, including population, subnational GDP per capita, access to larger cities, and international trade. For example, because higher population densities are correlated with less natural land cover, we weight the observations such that high-population, high-natural land cover sites are given more weight. Using these weights, we then use a special class of Generalized Additive Model (GAM) known as a Varying-Coefficient model (Wood, 2017) with a nonlinear smooth to model how the impact of droughts on HAZ scores varies according the amount of nearby natural land cover. In the following sections, we give an overview of the CBGPS weighting methodology as well as the modeling framework.

5.4.1 Covariate Balancing Generalized Propensity Scoring

A number of factors are associated with the presence or absence of uncultivated land cover that also affect drought vulnerability. Thus, to be able to infer that it is uncultivated land and the ecosystem services it provides that is having a causal effect on reducing drought vulnerability, it is important to control for these variables. Propensity score weighting is a common method to deal with this issue; however, most traditional methods involve a binary treatment variable, which must be dichotomized if it is initially measured in continuous terms (Hirano et al., 2003, Robins et al., 2000). Because our treatment variable, uncultivated land, is continuous, and we have no theoretical priors on how it could be dichotomized, we opt instead to use Covariate Balancing Generalized Propensity Scoring (CBGPS), which can be used for continuous treatments and is more robust to mis-specification (Fong et al., 2018a). Moreover, we use the non-parametric method to estimate the generalized propensity score, which finds weights that leave each confounding variable uncorrelated with the treatment variable, while maximizing the empirical likelihood of observing the data. The non-parametric approach makes it possible to avoid assumptions about the functional form of the propensity score, but is more computationally costly (Fong et al., 2018a).

We balance for demographic and economic factors that can influence both drought vulnerability as well as land cover. These are: population, from the WorldPop project (Tatem, 2017), which can affect land cover by increasing pressure for agricultural production, as well as drought vulnerability by increasing access to off-farm labor opportunities but also increasing pressure for resources; subnational GDP per capita (Kummu et al., 2018), which can drive agricultural expansion, while also decreasing drought resilience through financial capital; national imports per capita (World Bank, 2017), which can drive agricultural expansion (Meyfroidt et al., 2013) while also increasing food access, even when local food production is low; and time to travel distance to major cities (Uchida and Nelson, 2008, Weiss et al., 2018), which is an indicator of both market pressure on agriculture as well as access to financial capital that can buffer child nutrition from the effects of droughts. By balancing for these factors at the AEZ level, we can draw on such a large data set of over 200,000 children rather than having to subset the data to specific AEZ or socio-economic contexts.

After using the non-parametric CBGPS methodology to generate weights for each of these variables with respect to the availability of uncultivated land, we tested to see whether the correlation between these variables and uncultivated land cover decreased (Fong et al., 2018a). We run the algorithm separately for each AEZ in our analysis. To conduct the balancing we use the CBPS package for R (Fong et al., 2018b), with the default value of $0.1/N$ for the tuning parameter ρ, which moderates the trade-off between completely reducing correlation and avoiding extreme outlier weights.

5.4.2 Modeling Framework

Having derived weights for the propensity of each observation to have uncultivated land in its vicinity, we then model nutrition outcomes as a function of the local 24-month SPEI score, where the coefficient for SPEI is modeled as a function of uncultivated land cover, controlling for typical household and individual factors as well as the spatially-varying rate of malnutrition using a spherical spline. This is a specific form of Generalized Additive Model (Hastie and Tibshirani, 1986) known as a varying coefficient model (Wood, 2017). Specifically, our model takes the following form:

$$y = \beta_0 + \beta X + s(latitude, longitude) + s(\nu)spei + \epsilon \tag{5.1}$$

Where y is a given child's HAZ score, β_0 is a fixed intercept, X is a matrix of individual and household covariates, modified by a vector of fixed coefficients β, $s(latitude, longitude)$ is a spatially varying effect estimated by a spherical spline basis (Wahba, 1982), and $s(\nu)$ is a coefficient for the effect of the 24-month SPEI on nutrition outcomes, with the coefficient varying as a function of uncultivated land cover ν, and with each function $s(\nu)$ estimated separately for each AEZ. The basis we use for the varying coefficient $s(\nu)$ is estimated using thin plate splines (Duchon, 1977), and the smoothing parameter for this smooth is estimated through Generalized Cross Validation (GCV) (Wood, 2017).

5.4.3 Modeling Contribution of Uncultivated Land to Drought-Resilient Nutrition

To estimate the contribution of uncultivated land to nutrition outcomes, we model two scenarios for every AEZ where natural land cover was found to buffer children from the effects of drought: one estimating the impact of drought on child HAZ scores based on current levels of natural land cover, and one counterfactual scenario estimating the impact of drought on child HAZ scores if natural land cover were converted to agriculture.

Our model estimates changes in mean HAZ scores under drought conditions, but not increases in rates of stunting, which is a more familiar metric for policy-makers. Given that HAZ scores are normally distributed and the rate of stunting is the percentage of children under 5 years old with an HAZ score of less than -2, it is possible to convert changes in mean HAZ scores into increases in rates of stunting given prevailing mean HAZ scores, which can in turn be derived from prevailing rates of stunting and the standard deviation of HAZ scores. Thus, for estimates of current HAZ scores, we use data from a recent analysis of rates of stunting in Africa (Osgood-Zimmerman et al., 2018). Because this analysis estimated rates of stunting for the years 2000-2015, we draw on trend analysis methods common in epidemiology to conduct a pixel-wise forecast to the year 2020 (Fullman et al., 2017, Osgood-Zimmerman et al., 2018). For standard deviation, overall standard deviations in HAZ scores have been observed to vary independently of mean HAZ scores (Mei and Grummer-Strawn, 2007) and to not change significantly over time. Thus, we simply use the standard deviation for our dataset (1.62), which matches previous literature on the standard deviation of HAZ scores in surveys in Africa (Mei and Grummer-Strawn, 2007).

Using these values and the definition of a normal distribution, we estimate the current HAZ scores as well as the decrease in HAZ scores under drought for scenarios of natural land cover as well as a counterfactual scenario with no natural land cover. Then we derive a pixelwise estimate of increases in rates of stunting under drought in the absence of natural land cover providing ecosystem services.

5.5 Results

5.5.1 Covariate Balancing

After estimating weights using CBGPS, the correlation between uncultivated land cover and the various confounding variables that we attempted to control for was significantly reduced. Tables 5.2 and 5.3 show the reduction in correlation between these variables based on the weighting.

	Import Value Per Capita		Population Density	
AEZ	Unweighted	Weighted	Unweighted	Weighted
Arid	0.22	0.01	0.27	0
Forest	0.1	0.1	-0.47	0.04
Highlands	0.37	0.03	-0.64	-0.14
Northern Savanna	0.02	0.03	-0.45	0.02
Northern Sub-Forest	0.16	-0.03	-0.41	-0.01
Southern Savanna	0.45	0.01	-0.62	-0.03
Southern Sub-Forest	0.46	-0.09	-0.7	0.18

Table 5.2: Summary of correlation between uncultivated land cover and confounding variables before and after weighting using CBGPS

	Subnational GDP Per Capita		Time to Travel to Major City	
AEZ	Unweighted	Weighted	Unweighted	Weighted
Arid	0.16	-0.01	-0.15	0
Forest	0.19	0.08	0.31	-0.03
Highlands	0.17	-0.04	0.33	0.12
Northern Savanna	-0.16	0.02	0.24	0.01
Northern Sub-Forest	-0.03	-0.04	0.12	0.03
Southern Savanna	0.47	0.02	0.24	0.05
Southern Sub-Forest	0.22	0.06	0.17	0.05

Table 5.3: Summary of correlation between uncultivated land cover and confounding variables before and after weighting using CBGPS

5.5.2 Role of Natural Land Cover in Moderating Drought by AEZ

Having estimated the model, we here graph the smooths for how uncultivated land cover affects the impact of drought in each AEZ (Figure 5.2), and include full model results in the Appendix.

Figure 5.2 shows how the coefficient for the 24-month SPEI varies as a function of the percent of nearby natural land cover. The error band around the parameter indicates the 95% confidence interval, so areas where the error band does not cross 0 (at the dotted line) indicates that, at that level of natural land cover, precipitation anomalies have a significant effect on child nutrition outcomes at $\alpha = 0.05$. Thus, for example, in the Southern Sub-Forest AEZ, when 100% of nearby landcover is cultivated, an a decrease of -1 in the SPEI score is associated with a decrease in HAZ scores of 0.2 and this effect is significant. However, in the same AEZ, when only 50% of nearby landcover is cultivated, a decrease of -1 in the SPEI score is only associated with a very small decrease in HAZ scores, and this effect is not

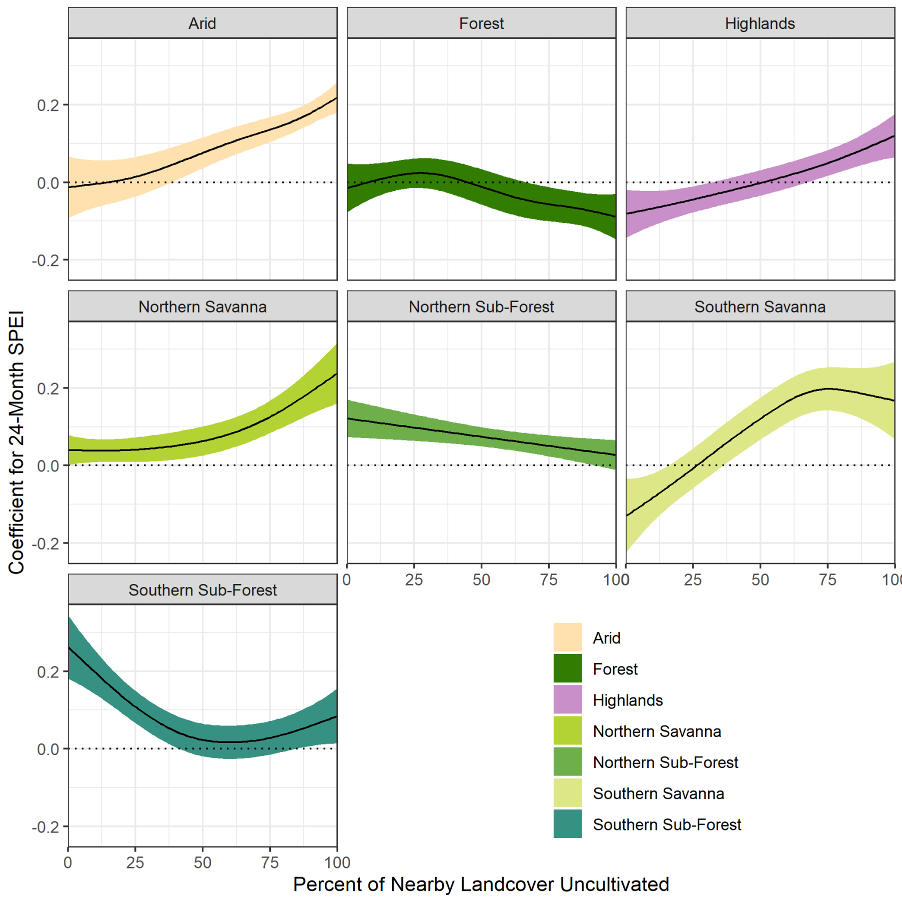

Figure 5.2: Varying effect of droughts on child nutrition outcomes by Agro-Ecological Zone (AEZ). In arid, savanna, and highland zones, more natural land cover was associated with greater drought vulnerability, while in sub-forest zone, natural land cover was associated with less drought vulnerability. Error bands indicate the 95% confidence interval.

significant because the 95% confidence interval crosses 0 and is not entirely positive. For studies from the environmental sciences and epidemiology that used a similar model, see Zhao et al. (2014) and Snickars et al. (2015).

In many AEZs, increasing rates of natural land cover are modeled to have a higher coefficient for the 24-month SPEI, signaling greater drought vulnerability. However, in the sub-forest AEZ of both northern and southern Africa, decreasing natural land cover is associated with greater drought vulnerability. At low levels of natural land cover in both northern and southern sub-forest Africa, a moderate drought (SPEI = -2) decreases mean HAZ scores by 0.2 to 0.4, whereas at high levels of natural land cover, drought has no significant effect on nutrition outcomes.

5.5.3 Modeling Ecosystem Service Dependence Over Space

Our model indicates that in sub-forest parts of Africa, natural land cover buffers child nutrition from the effects of drought. Thus, focusing on these AEZs, we model the impact of drought on child nutrition outcomes in scenarios of both current natural land cover levels as well as with no natural land cover, and estimate potential increases in stunting.

Figure 5.3 shows several outputs from the steps from extrapolating the parameters from our model to estimating the total number of children dependent on local ecosystem services for drought resilience per country. The most drought vulnerable areas are arid and savanna AEZs, especially in the Sahel, the Horn of Africa, as well as in arid parts of Southwest Africa. However, the areas that would see an increase in stunting in the absence of local natural land cover were mostly in the sub-forest regions on Northern and Southern Africa, such as the Guinean forest-savanna mosaic of Northern and Western Africa as well as the Miombo Woodlands of Southern Africa. Examining the potential increase in stunted child under drought in each of these eco-regions shows that many of them would be located in the woodlands of southern DRC and northern Angola, as well as in parts of Mozambique and southern Tanzania. Throughout Africa, an additional 1.5 million children would

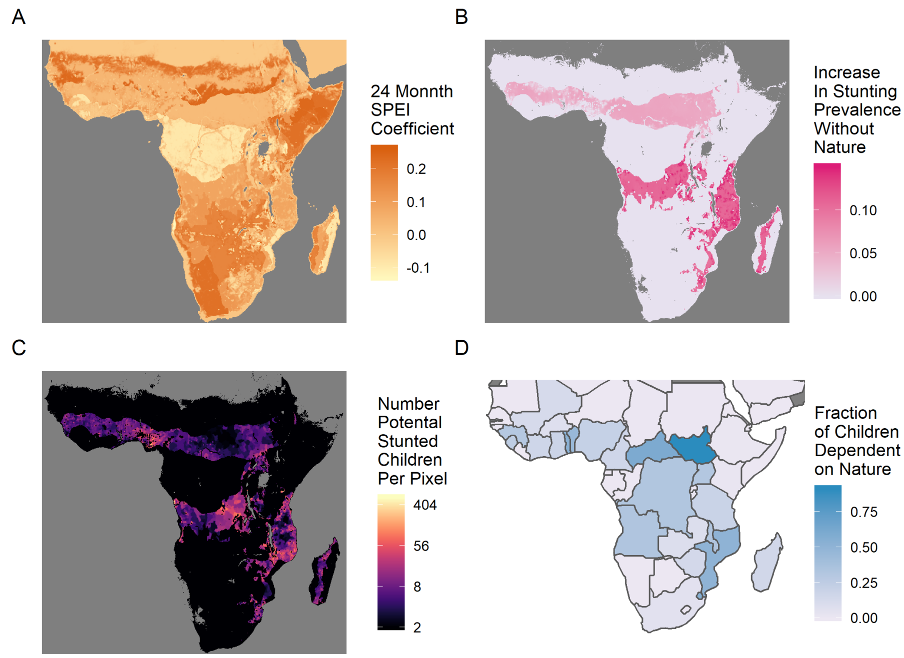

Figure 5.3: **A**) The effects of the 24-month SPEI on HAZ scores across Africa. Positive values indicate drought vulnerability. **B**) Increase in the rate of stunting under drought if local uncultivated land were entirely converted to agriculture. **C**) The gross number of additional stunted children per pixel in a no natural land cover scenario. **D**) The fraction of children under 5 dependent on local natural land cover for drought resilience by country.

be stunted under drought without local ecosystem services. Finally, examining the total number of vulnerable children, which would see any decrease in HAZ scores without necessarily becoming stunted without local ecosystem services shows that the countries with the highest rates of dependence on natural land cover are South Sudan, Central African Republic, Swaziland, Togo, and Mozambique.

5.6 Discussion

This paper assessed how the prevalence of uncultivated land cover moderated the impact of drought on child nutrition outcomes throughout several agro-ecological zones in Africa. We took care to control for the potential confounding effects of several factors that could influence both the presence of uncultivated land as well as drought vulnerability, such as GDP per capita, distance to major cities, population density, and the per capita value of national imports. We found that the manner in which natural land cover moderated the effect of drought on child nutrition outcomes varied by AEZ, and that there is an observable "safety net" effect in semi-forested landscapes throughout Africa, although natural land cover is associated with greater drought vulnerability in arid and savanna AEZs. Finally, examining a counterfactual scenario of the impact of droughts without uncultivated land cover and the ecosystem services it provides shows that millions of children are dependent on ecosystem services to meet their nutrition needs in times of drought.

A major contribution of this paper to the literature is its scale. Most other studies of the role in ecosystem services in buffering human well-being from climate shocks tends to focus on case studies (Debela et al., 2012) as well as use hypothetical scenarios (Robledo et al., 2012) or retrospective analyses (Muller and Almedom, 2008). This paper provides a large scale analysis of nutrition outcomes observed during varying levels of drought as well as across sites with varying access to ecosystem services.

While a large body of research attests to the fact that ecosystem services play a large role in food production and nutrition, especially for smallholder farmers, comparatively little work in the field of environmental conservation has been conducted to identify areas where conservation interventions could lead to improved food security and nutrition outcomes. This is in spite of the fact that the practice of conservation relies heavily on mapping for priority setting - for example, mapping ecosystem services such as carbon sequestration and storage or water provision as well as mapping biodiversity hot spots. Thus, mapping which natural areas contribute the most to climate-resilient nutrition systems could further catalyze conservation investment, as well as identify locations where conservation interventions could lead to synergies between Sustainable Development Goals (SDGs) related to environmental conservation (13 & 15) and human well-being (1 & 2).

One of the only multinational analyses of the role of ecosystem services as a buffer during shocks found that households did not rank forest resources as a very important resource during shocks (Wunder et al., 2014). This paper differed in significant ways from our analysis: it focused on forests rather than all uncultivated land cover types, it focused on a variety of types of shocks beyond just drought, it asked households retrospectively about previous shocks rather than observing them *in situ*, and it asked households about their preferences. Thus, there are several possible reasons why we observed natural land cover as playing as significant effect in buffering households from drought in semi-forested landscapes while Wunder et al. did not find such an effect. First, it may be that households do not pivot towards forest resources during drought; rather, households that are always using forest resources are simply less affected by agricultural shocks like drought. Second, by focusing only on forest resources like timber, Wunder et al. are unable to explore the benefit that supporting and regulating ecosystem services have on local agricultural production.

An important aspect of this analysis was using weighting to ameliorate the effects of potential confounding variables. Because we controlled for the effects of several demographic and economic variables, we can more confidently ascribe the observed drought mitigation to the land cover itself rather than to another factor that is correlated with land cover. However, given that weighting each covariate to achieve a correlation of perfectly 0 would be either impossible or would require extreme weights, we did not reduce the correlation between our confounding variables and natural land cover all the way to 0 (See Tables 5.2 and 5.3). Nevertheless, we diminished the correlation to the extent that a causal interpretation of the observed mitigation effect of natural land cover is now more plausible. This, combined with the fact that we excluded households with greater than 1% urban land cover and greater than 5% water land cover means that we are making the best apples-to-apples comparison we can.

While the model estimated the moderating effect of natural land cover on drought vulnerability as varying across AEZs, we found that natural land cover played a similar function in ecologically similar zones. In arid and savanna zones, greater natural land cover was associated with greater drought vulnerability. On the other hand, in the ecologically similar but geographically disjoint semi-forested regions, natural land cover had a safety net effect during drought. The fact that ecologically similar eco-regions were modeled as having similar effects in terms of drought vulnerability, even though they were modeled with independently estimated smoothing splines, suggests that this effect is real and is ecologically based.

One potential interpretation of these findings is that the ecosystem services in arid and savanna environments are more vulnerable to drought and therefore less able to provide a safety net effect. This could be due to lower overall biodiversity leading to a smaller range of functional responses to drought as well as fewer available ecosystem services. In more humid environments, many plant species are perennial and continue to provide services even during drought, whereas in arid and savanna environments, the primary plant species are annual grasses, which are more drought affected. Moreover, many of the regulating and supporting ecosystem services provided by natural land cover, such as wind breaking, shading and temperature regulation, and moisture retention are specifically a function of trees (Reed et al., 2016), where as the primary ecosystem service provided by grasses is grazing for animals. Thus, areas lacking in trees and biodiversity are not only unable to provide a safety net in times of drought but are in fact as drought-vulnerable as agricultural land. Finally, for very humid and mesic areas, drought vulnerability does not seem to be a major issue: even when precipitation is well below historic norms, it is still high enough to support food production. This may be why there was almost no effect of SPEI in the forest AEZ. Thus, the semi-forested parts of Africa present a middle ground, where rainfall levels are low enough that a precipitation anomaly can lead to increases in stunting, but rainfall is still high enough that natural land cover has both the biodiversity and biomass to provide a safety net.

While the association between natural land cover and reduced drought vulnerability in certain AEZs is certainly suggestive that people are relying on ecosystem services as a safety net, this analysis cannot speak to the particular pathways through which people are benefiting from nature. For example, the relative importance of provisioning ecosystem services such as wild foods versus regulating services such as shading to prevent moisture loss cannot be ascertained. Nevertheless, previous work in Africa has found that greater natural land cover is associated with greater collection of wild foods and nonfood NTFPs, suggesting that provisioning ecosystem services are a part of the pathway (Cooper et al., 2018).

5.7 Conclusion

These findings are have important implications for the study of food security, climate change vulnerability, and environmental conservation. We showed that nature can be a critical part of reducing climate change vulnerability, but the specific role that nature plays is highly context-specific. While mapping ecosystem services has traditionally focused on variables like carbon stocks and biodiversity hotspots, this analysis shows that the contributions of nature to food security can also be mapped to support greater food security. Given the increasing threat of a more drought prone world under climate change (Dai, 2013) combined with the severe precarity of Africa's agrarian poor, dampening the effects of drought and providing alternative food and income sources when agriculture fails may indeed be one of nature's most important contributions to people.

Chapter 6: Conclusion

6.1 Summary of Findings

The four chapters in this dissertation, which focused on the role of precipitation shocks and ecosystem services in affecting livelihoods, food security, and nutrition, had several novel findings, methodological innovations, and contributions to the academic literature.

The analysis of rainfall anomalies and food security and nutrition in Ghana and Bangladesh in Chapter 2 made the important insight that the impacts of precipitation anomalies depend on local baselines, with wetter countries like Bangladesh potentially more vulnerable to excessive rainfall and drier countries like Ghana more vulnerable to droughts. This analysis also used a Spatial Error Regression (SER), which corrects for spatial auto-correlation, a method that is not used enough in national-level analyses of the environment and human well-being.

Building on the analysis in Ghana and Bangladesh, the analysis in Chapter 3 used data from 53 countries to map drought vulnerability globally. This greatly improved on existing studies, which are typically at the nation scale with much smaller sample sizes, and estimate a linear and spatially uniform effect of precipitation anomalies on health outcomes (Phalkey et al., 2015). Furthermore, by examining the factors that mitigate vulnerability, this analysis provided several policy-relevant insights, especially that nutritionally diverse agricultural systems are key for resilience. This study also illustrates the values of a "big data" approach: only by drawing on 600,000 child nutrition observations under a wide range of climatological, agricultural, economic, political and demographic conditions was it possible to estimate the non-linear relationship between drought and stunting, as well as how a variety of different factors moderate this relationship. Finally, this analysis disagreed with some of the conventional wisdom around the timing and duration of shocks and child nutrition outcomes. While much of the child nutrition literature focuses on the first thousand days of a child's life, we found that rainfall during this period had a lesser explanatory effect on child heights than rainfall in the two years before a survey, no matter the child's age. We attributed this to the oft-overlooked phenomenon of catch up growth (Behrman, 2016, Wit and Boersma, 2002).

The analysis of users of provisioning ecosystem services and land cover in Chapter 4 was the first-ever analysis of geographic predictors of households collecting wild foods and nonfood ecosystem services. This is significant, given that much of the previous work on access to such resources focused on household and individual characteristics, often finding that women and the poor are more dependent on these provisioning ecosystem services (Pouliot and Treue, 2013). However, given the substantial between-landscape variation in rates of access to ecosystem services, this analysis made the important step of examining correlates of this variation, and set the stage for an analysis of geographic correlates of drought resilience.

The final study, in Chapter 5, drew on insights from all of the previous chapters, synthesizing approaches and findings related to both precipitation anomalies and ecosystem services. It is potentially the first ever map of ecosystem services relevant to climate-resilient food security conducted at a continental scale with the aim to improve conservation priority setting. While most large scale analysis of the environment and human health and nutrition estimate a linear and spatially uniform effect (Herrera et al., 2017, Ickowitz et al., 2014, Naidoo et al., 2019, Rasolofoson et al., 2018), we estimated a nonlinear effect of natural land cover as well as a separate effect according to Agro-Ecological Zone, finding substantial heterogeneity across zones.

6.2 Overall Synthesis and Contribution to the Literature

This dissertation has built on existing research in several ways. For the two chapters drawing on larger data sets (Chapters 3 and 5), my work made the contribution of potentially being the first People and Pixels papers to (1) use global empirical data, (2) create bivariate analyses and (3) have a spatial component (Figure 6.2). Many different studies have done significant work drawing on two of these themes, but my work has sought to incorporate all them. For example, there are many bivariate analyses that draw on large, multinational datasets, including work showing relationships between forest cover and dietary diversity, (Ickowitz et al., 2014, Rasolofoson et al., 2018); work showing that forested watersheds are associated with lower rates of diarrheal disease (Herrera et al., 2017); work showing precipitation impacts on food security (Niles and Brown, 2017); and work showing that higher temperatures are associated with low birthweights in Africa (Grace et al., 2015). However, each of these studies simply show an association between two important variables at large scales, rather than look at how this association varies over space in order to map “hot spots” of climate vulnerability or ecosystem service dependency. Most human-environment studies with a significant mapping component, on the other hand, take one of two approaches. Many use empirical datasets like the DHS to map single variable over space, using methods like kriging. This include maps of malaria prevalence (Bhatt et al., 2015), child mortality (Burke et al., 2016), and child stunting (Osgood-Zimmerman et al., 2018), all of which were published in premier journals. However, they merely show an outcome variable, rather than how that variable would be expected to respond to climate shocks or deforestation. Other mapping approaches are index-based (Busby et al., 2014, Carrão et al., 2016, Ericksen et al., 2011, Krishnamurthy et al., 2014, Richardson et al., 2018). They consider all the factors that would be expected to moderate the relationship between two variables – i.e., factors influencing vulnerability. However, they combine these variables in simple ways, often scaling variables from 0-1 and taking the average, with little empirical support. Both Chapters 3 and 5, on the other hand, aim to synthesize all three of these themes, whereas previous work has only incorporated up to two themes in any one of these studies.

One major consideration in each of these studies was selecting an outcome variable to model. In three of the four studies, child stunting, measured with HAZ scores, was one of the outcome variables. This was largely because the HAZ score is a standardized metric that has been collected around the world for decades. However,

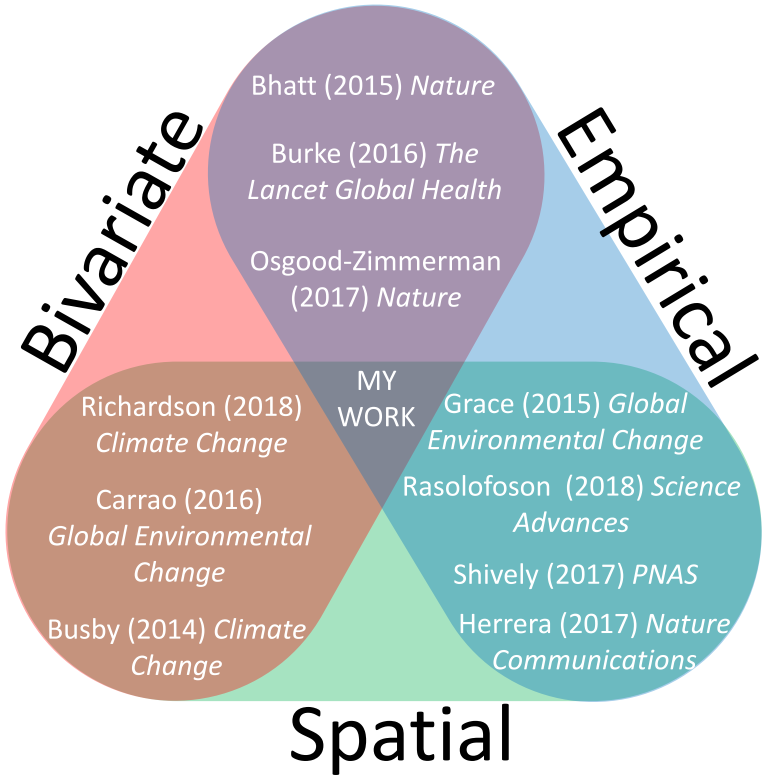

Figure 6.1: Schematic representation of the various components of previous studies that my work brings together, resulting in some of the first ever People-and-Pixels analyses that were spatial, bivariate, and global.

the HAZ is only indicative of child malnutrition, and while increases in child stunting certainly imply concurrent increases in adult malnutrition, this is not necessarily the case. Thus, an ideal metric would take into account adult malnutrition. Potential alternative metrics that are indicative of household food security are dietary diversity scores, which have been associated with both ecosystem services (Ickowitz et al., 2014, Rasolofoson et al., 2018), as well as child stunting (Arimond and Ruel, 2004). Other potential newer metrics include the Food Insecurity Experience Score (FIES), Household Food Insecurity and Access Scale (HFIAS), and Household Hunger Score

(HHS), used in Chapter 2. However, there are several issues with these metrics that would make it challenging to incorporate them into a global analysis of the environment and food security. For one, that they have not been collected for long enough to truly observe how they respond to climate shocks in a variety of contexts, although this could be solved with time. Secondly, they are often discrete or integer based measurements, and are therefore not measured with as much precision as an anthropometric Z-Score. Given the amount of variance in food security outcomes that must be controlled with household and individual variables to measure the effects of the environment on nutrition outcomes, this imprecision may make it impossible to see an effect of the environment on food security without a very large dataset. Finally, many alternative food security metrics are not even collected by the DHS, including the FIES, HFIAS, and HHS, as well as other key variables, such as gathering forest resources used in Chapter 4. These variables are more frequently used in specialized surveys conducted by smaller organizations, such as the Feed the Future surveys by IFPRI and the Vital Signs surveys conducted by Conservation International.

These four analyses also drew on different but related methodological approaches. Two issues were of primary concern for these approaches: one was finding a modeling approach with enough flexibility to make accurate predictions, describe non-linearities, and perform feature selection where necessary, while the other concern was controlling for spatial autocorrelation and endogenous variables to make a causal interpretation of any observed relationships more valid.

In modeling, there is, to some extent, a trade-off between flexibility and interpretability of models (See Figure 6.2). Many models more generally referred to as machine learning models, such as neural networks and random forests, are very flexible in their structure, accounting for interactions between predictor variables and making predictions with great accuracy. However, these models are difficult to interpret and are not very informative about the actual structure of a system. Conversely, many regression-type econometric models allow the analyst to interpret exactly why the model is making certain predictions, but are less accurate and can only incorporate simple interactions between variables. Finally, to model estimates of complex interactions between variables and make predictions in machine learning models, large data sets are necessary, while econometric models can be estimated from smaller datasets.

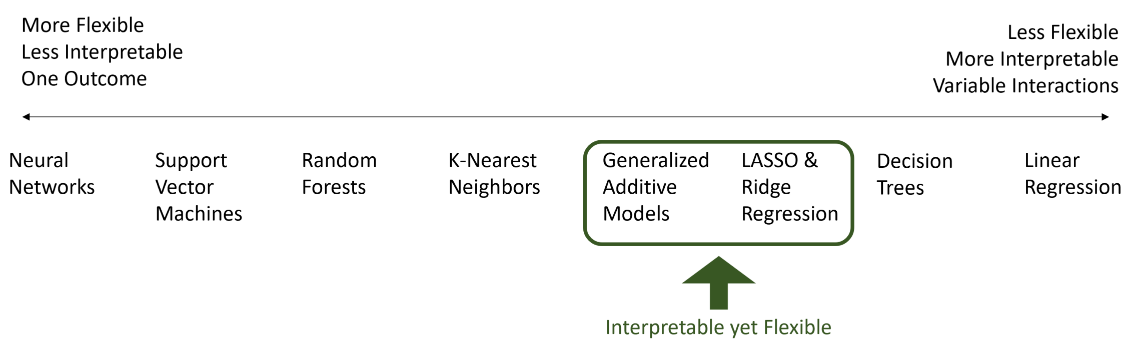

Figure 6.2: This graphic illustrates the trade-off between more flexible but less interpretable approaches, often referred to as "Machine Learning," and less flexible but more interpretable and structured approaches, often referred to as "Econometric Modeling."

For Chapters 2 and 4, due to the available data size, which in both cases was no more than several hundred observations, econometric models were used and a linear effect was estimated between each predictor variables and the outcome variables of interest. While these were not as simple as OLS regression (Chapter 2 use Spatial

Error Regression and Chapter 4 used Hierarchical Regression), they were still linear models.

For Chapters 3 and 5, I had the data size to estimate more complex models. However, I also wanted to specify some structure in the models. If I simply wanted to predict rates of malnutrition on a per-pixel basis, a "black box" machine learning approach like neural networks or random forests would have been the most appropriate. However, my research questions were not "What are the rates of malnutrition globally?" but "Where is malnutrition vulnerable to drought?" and "Where do ecosystem services support nutrition during drought?" Thus, because my research questions had some structure as part of their premise, it was necessary to use an approach that let me control the model structure to some extent. However, I still wanted to perform feature selection and regularization in Chapter 3, and I also wanted to model non-linearities in 5. Thus, I ended up using LASSO regression and Generalized Additive Models, two approaches that balance the flexibility/interpretability trade-off (See Figure 6.2). Interestingly, these approaches were both invented by the same researchers at Stanford University, who often refer to this class of models as *Statistical Learning* (Hastie et al., 2009).

Another concern with respect to modeling approaches beyond the structure of the model is appropriately controlling for both spatial autocorrelation as well endogenous variables. Spatial autocorrelation is when there is a spatial structure to predictor and outcome variables in a way that biases the model. This can arise for a number of reasons, such as when variables are inherently spatial and thus model errors have a spatial component, as well as when a variable can have "spillover" effects and influence the values of observations that are nearby spatially (Ward and Gleditsch, 2008a). An example of the former would be when mean annual precipitation is a predictor variable, as this obviously has a spatial component. An example of the latter would be an outcome variable like wealth, which can spillover to affect the wealth of nearby areas. The chapter that most thoroughly assessed for spatial autocorrelation was Chapter 2, which showed the distance at which autocorrelation could be detected in various outcome variables in Figure 2.6.

I dealt with spatial autocorrelation in a variety of ways, depending on the specific chapter. Across the four chapters, the techniques I used to control for spatial autocorrelation grew more advanced over time. In Chapter 4, I simply used landscape-level fixed effects, making the reasonable assumption that any within-landscape autocorrelation was negligible, while in Chapter 3 I simply assumed that including a large number of geographic variables related to malnutrition and nutritional vulnerability to climate shocks would be sufficient to explain global-scale heterogeneity. In Chapter 2, on the other hand, I specifically used a Spatial Error Regression to deal with spatial autocorrelation in Bangladesh and Ghana, where much of the drivers of subnational spatial variation of nutrition and food security outcomes, such as cultural practices, are more difficult to quantify and include in a model. Finally, in Chapter 5, I control for spatial autocorrelation in Africa using a spherical spline (Wahba, 1982).

Beyond spatial autocorrelation is the issue of endogeneity. An endogenous variable is one that can affect both the predictor variable and the outcome variable in a way that makes the two variables correlated. Thus, a correlation between two variables cannot be interpreted as causal unless these variables are accounted for. This was primarily a concern in Chapter 5, where I used Covariate Balancing Generalized Propensity Scores (CBGPS). In Chapter 4, we were unconcerned with ascribing causality to the gathering of provisioning ecosystem services; rather we simply interested in the correlates. In Chapters 2 and 3, on the other hand, the occurrence of drought or excessive rainfall is independent of other drivers of malnutrition outcomes such as wealth or maternal education. Thus, there is no other underlying variable that could be theoretically having an endogenous effect on both drought and malnutrition, and we can interpret the relationship as causal on *a priori* grounds.

6.3 Future Work

There are several ways this work could be improved upon in future studies. Newer outcome variables based on richer DHS data, such as on child mortality, could be incorporated. Whereas many geolocated DHS do not include data on nutrition or relevant nutrition covariates, nearly every DHS collects data on the children born to each woman. Furthermore, because this data is longitudinal, it allows for a retrospective analysis of mortality. Thus, with nutrition, data is only available for children at the time of a survey, but mortality outcomes are available on a monthly basis for up to several years before a survey. This has significant implications for data completeness. For example, if a major drought happened a couple of years before a survey and there was an associated increase in mortality, this would be reflective in the mortality data. However, it would not be apparent in the nutrition data. Thus, child mortality presents a promising future avenue for people and pixels research.

Additionally, future work should take into account the effect of temperature on food security and nutrition. A number of studies have linked temperature with decreased crop yields (Asseng et al., 2011, Peng et al., 2004, Schlenker and Roberts, 2009) as well as with worse health outcomes (Chen et al., 2016, Gasparrini et al., 2017, Green et al., 2019, Guo et al., 2017). However, temperature can be more difficult to model, because it is often absolute temperature that leads to increased mortality and harmed crop yields, whereas it is precipitation anomalies that are most associated with negative human outcomes. This presents an endogeneity issue for estimating the effects of temperature on human well-being. For example, a simple model would associate higher temperatures with higher mortality, and an analyst must take care to tease apart whether this effect is causal (i.e., higher temperatures cause more malnutrition) or simply correlative (i.e., less developed areas tend to be in warmer places and also tend to have higher rates of malnutrition).

A further challenge of working with temperature data is that many of the effects of temperature on human outcomes are based on daily temperatures. For example, daily temperature has been associated with mortality (Gasparrini et al., 2017), intimate-partner violence (Sanz-Barbero et al., 2018), and suicide (Burke et al., 2018). However, most data on nutrition and food security outcomes from household surveys like the DHS are collected with monthly but not daily specificity. Thus, it is not possible to pair an event like child mortality with the temperature on the day of the mortality event. Nevertheless, it would be possible to aggregate temperature to a monthly scale, for example by taking the average maximum temperature for the month or by taking the count of days above a given threshold, and such metrics have already been used in DHS analyses (Geruso and Spears, 2018).

Finally, future work could take into account future scenarios of climate and development to estimate future impacts of climate change on food security and nutrition. Models could be trained on historic data from the entire DHS, and these models could be used to derive estimates of the future malnutrition burden under different scenarios. Such an analysis could answer questions like: How many more people will be malnourished if we do not meet the Paris targets? What does malnutrition look like in a high-emissions, high-development world versus a low-emissions, low-development world? Shared Socioeconomic Pathway (SSP) projections have already been developed at the country level for variables like demographic structure and education (KC and Lutz, 2017), wealth (Dellink et al., 2017), and inequality (Rao et al., 2019), while spatially explicit projections exist for urbanization (Jiang and O'Neill, 2017) and population (Jones and O'Neill, 2016). Similarly, bias-corrected climate projections from the Inter-Sectoral Model Inter-Comparison Project (ISIMIP) as well as forthcoming models from the 6th Climate Model Inter-Comparison Project (CMIP6) would enable predictions of the future exposure to climate shocks under various RCPs. Based on a model trained with historic data on these variables, one could make projections of a variety of outcomes under various combinations of SSPs and RCPs. This analysis could inform policymaking by estimating which scenarios meet the child mortality objectives set forth in the SDGs, as well as in analyzing trade-offs between economic development, pollution reduction (Goodman et al., 2004, Heft-Neal et al., 2018, Roberts, 2004), and climate mitigation. Furthermore, because it is spatially explicit, such a model would provide maps of future vulnerability to climate shocks, based on location-specific estimates of how vulnerability and the local climate will change in the coming years.

6.4 Policy Recommendations

This work has several critical implications for policymakers at various scales. The work on the effects of precipitation on food security and nutrition in Chapters 2 and 3 shows that precipitation anomalies and drought in particular can have a major impact on food security and nutrition, but that the particular impact of drought varies significantly based on the specific food system. For example, Chapter 2 found that drought is associated with worsened food security in Ghana while flooding is associated with worsened food security in Bangladesh. Chapter 3, on the other hand, found many places where drought is associated with worsened nutrition, with some of the most vulnerable places being in the horn of Africa. Chapter 3 also identified factors associated with increased nutritional resilience, including government effectiveness, nutritionally diverse cropping systems, and increased international trade. Thus, that study provides clear insights for improved policies around drought resilience at different scales, suggesting that national actors should focus on governance and trade, while more local actors should focus on mitigating land degradation and improving agricultural diversity.

In addition to the chapters on precipitation anomalies, Chapters 4 and 5 provide policy-relevant insights related to the role of ecosystem services in improving food security. Chapter 4 showed that people all over Africa collect provisioning ecosystem services from forests and grasslands to supplement their livelihoods and food security, and that the greater the amount of nearby forests and grasslands, the more likely people were to report collecting these provisioning ecosystem services. Chapter 5, on the other hand, demonstrated that in certain African ecosystems, particularly the semi-forested areas on the periphery of the equatorial tropical forests, natural, uncultivated land cover can provide a safety during drought, and this safety net effect is likely through the pathways of both provisioning and regulating ecosystem services. Thus, both of these chapters indicate that natural, uncultivated areas like forests and grasslands can provide a significant improvement to food security and nutrition in Africa, and policymakers should seek to implement conservation schemes that encourage community-based protected area management as well as protected areas that permit the sustainable harvesting of some ecosystem services (Porter-Bolland et al., 2012).

This analysis relied in large part on household survey data, and thus provides several insights with regards to the type of household survey variables that are valuable for food security and nutrition research. For one, having household-specific GPS points is tremendously useful or any type of research related to health, food security, and the environment. For both the DHS and Feed the Future surveys used in these studies, a large number of household surveys were collected without GPS data. Thus, these surveys were not included in the analyses, and the statistical power of the analyses were significantly diminished.

Other variables that should be included in household surveys include those that are useful for determining the vulnerability of livelihoods to climate shocks, such as where they source their food. The Vital Signs household surveys asked about collecting wild foods, which provided an immensely useful outcome variable in Chapter 4, but this data is not collected in other household surveys like the DHS. Other questions that could be included in such household surveys include those that address the provenance of food - how much of it is purchased at the market, and how much of it comes from own production? While the DHS has begun including questions about dietary diversity in its household surveys, including more data on the diversity of food origins would be important for better assessing households' vulnerability to local food production shocks.

6.5 Conclusion

Perhaps the most important contribution of this dissertation to the scientific literature was to highlight the agrarian poor are affected by the twin processes of ecological and climatological change. For high income countries, the weather outside or the local land cover have little impact on people's food security and nutrition. Whether it is hot or cold, wet or dry outside, individuals in rich countries will have the same access to food, often sourced from thousands of miles away. Similarly, while the loss of nearby public and natural land may be a pedestrian concern for people in high income countries, it hardly means diminished access to foods, medicines, building materials, and income sources. In poor countries, on the other hand, climate shocks and environmental degradation can lead to higher rates of malnutrition, as this dissertation has shown. Thus, the actions of consumers and policymakers in rich countries can have distal effects that can either mitigate or amplify human suffering in poorer countries. It is my hope that the research contained here plays a small role in improving our understanding of patterns of vulnerability among the worlds poor so that we might work to mitigate that suffering.

Appendix A: Appendix A

Asset Index Variables

Ghana

The asset index for Ghana included: dwelling conditions; whether the house was rented, owned or borrowed; water treatment, source for light and fuel; garbage disposal; roof and walls material; type of toilet; and water sources, all variables reported in Module 9.

Bangladesh

The asset index for Bangladesh included: the household's total land area cultivated, rented, owned; house ownership, number of rooms in the house; whether house had electricity; water source; toilet type; roof, walls, and floor material; number of cattle, poultry, sheet, goats, and other livestock owned; television, radio, motorbike, telephone, tractor, or cart plough ownership; and whether the household used organic or chemical fertilizer.

Summary Statistics

		Ghana	Bangladesh
	max	59	60
Child's Age (Months)	mean	32.4	29
	min	7	0
Child's Sex (%)	Female	49.6	49.1
	Male	50.4	50.9
	max	18	
Child's Birth Order	mean	4.2	
	min	1	
	max	4	
Number of Siblings Born Within 24 Months	mean	0.4	
	min	0	
	max	5.5	5.9
Child's Height-for-Age Z-Score	mean	-1.5	-1.7
	min	-6	-5.9
	max	4.9	4.9
Child's Weight-for-Age Z-Score	mean	-0.2	-0.8
	min	-5	-4.9
	max	5	5
Asset Index	mean	3	3.1
	min	1	1
	max	0.9	1
Fraction of Dependent Age Individuals in Household	mean	0.5	0.5
	min	0.1	0.1
	max	28	14
Household Size	mean	7.6	5.2
	min	2	2
	max	97	90
Household Head Age (Years)	mean	39.2	39.2
	min	18	18
	High School		2.6
	Never		41.9
Household Head's Education (%)	Primary		49.5
	Secondary		5.4
	University		0.6
Household Head Sex (%)	Female	12.2	15.9
	Male	87.8	84.1
Household Head Literacy (%)	Illiterate	79.6	18
	Literate	20.4	82
	Christian	37.1	0.3
	Hindu		9.5
Household Head Religion (%)	Muslim	40.4	90.2
	None	1.6	

	Traditional	20.9	
Percent of Rice Area Irrigated	max		1
	mean		0.5
	min		0
Population Within 7.5km of Household (1000 people)	max	43	529
	mean	10.2	185
	min	1.3	11.9
Year (%)	2011		52.7
	2012	100	
	2015		47.3
12-Month Standardized Precipitation Index	max	1.5	2.6
	mean	0.8	-0.2
	min	-0.5	-1.7
24-Month Standardized Precipitation Index	max	1.7	2.2
	mean	1.1	-0.5
	min	0.3	-2.3
36-Month Standardized Precipitation Index	max	2.3	2.3
	mean	1.4	-0.6
	min	0.4	-2.3
48-Month Standardized Precipitation Index	max	2.2	2.3
	mean	1.4	-0.7
	min	0.3	-2.2
60-Month Standardized Precipitation Index	max	2.5	3.1
	mean	1.6	-0.4
	min	0.4	-2.5
Average Annual Precipitation (1000mm)	max	1.4	5
	mean	1.1	2.5
	min	0.9	1.4

Table A.1: Child Stunting

		Ghana	Bangladesh
Asset Index	max	5	5
	mean	3	3
	min	1	1
Fraction of Dependent Age Individuals in Household	max	1	1
	mean	0.4	0.4
	min	0	0
Household Size	max	28	14
	mean	5.8	4.4
	min	1	1
Household Head Age (Years)	max	100	105
	mean	45.1	45.2
	min	15	17

Household Head Gender (%)	Female	18.2	18.6
	Male	81.8	81.4
Household Head Literacy (%)	Literate	21	78.3
	Illiterate	79	21.7
Household Head Education (%)	Primary		44.9
	Education		5.8
	High School		2.3
	University		0.6
	None		46.3
Household Head Religion (%)	Christian	40.9	0.3
	Hindu		11.2
	Muslim	35.1	88.6
	None	2.1	
	Traditional	21.9	
Household Hunger Scale (HHS) Score	0	1022 (43.2%)	8328 (89.1%)
	1	261 (11.0%)	548 (5.9%)
	2	507 (21.5%)	269 (2.9%)
	3	549 (23.2%)	140 (1.5%)
	4	15 (0.6%)	32 (3.4%)
	5	5 (0.2%)	10 (0.1%)
	6	3 (0.2%)	15 (0.2%)
Percent of Rice Area Irrigated	max		1
	mean		0.5
	min		0
Population Within 7.5km of Household	max	43000	577000
	mean	10700	185000
	min	1340	11900
Year (%)	2011		51.4
	2012	100	
	2015		48.6
12-Month Standardized Precipitation Index	max	2.6	1.5
	mean	-0.2	0.7
	min	-1.9	-0.5
24-Month Standardized Precipitation Index	max	2.2	1.7
	mean	-0.6	1
	min	-2.3	0.3
36-Month Standardized Precipitation Index	max	2.3	2.3
	mean	-0.8	1.3
	min	-2.5	0.4
48-Month Standardized Precipitation Index	max	2.3	2.2
	mean	-0.8	1.3
	min	-2.2	0.3
60-Month Standardized Precipitation Index	max	3.1	2.5
	mean	-0.6	1.5

	min	-2.7	0.4
Average Annual Precipitation (1000mm)	max	1.4	5
	mean	1.1	2.3
	min	0.9	1.4

Table A.2: Household Hunger Scale

Parameter Estimates for Regressions

Parameter estimates for models run predicting HAZ, WHZ, and HHS scores in Ghana and Bangladesh from SPI calculated at 12, 24, 36, 48, and 60 month windows. For Spatial Error Regressions, the parameter Lambda is given. Stars denote significance at α=0.1 (.), α=0.05 (*), and α=0.01 (**). Significance estimates for SPI variables have been Bonferroni corrected

	HAZ	WHZ	HHS
(Intercept)	-0.66	0.18	2.68^{***}
	(0.94)	(0.80)	(0.63)
asset_index	0.05	-0.01	0.01
	(0.04)	(0.03)	(0.02)
admin1Northern	0.15	-0.12	-0.01
	(0.22)	(0.19)	(0.14)
admin1Upper East	0.55	-1.02^{***}	0.06
	(0.34)	(0.29)	(0.18)
admin1Upper West	0.44	-0.15	-0.30
	(0.27)	(0.23)	(0.24)
hh_size	0.07^{*}	-0.03	0.02^{*}
	(0.03)	(0.03)	(0.01)
hhhead_religionMuslim	-0.05	-0.06	-0.05
	(0.12)	(0.10)	(0.06)
hhhead_religionNone	-0.87^{*}	0.30	-0.19
	(0.42)	(0.36)	(0.17)
hhhead_religionTraditional	0.12	0.16	0.35^{***}
	(0.15)	(0.13)	(0.07)
mean_annual_precip	0.00	-0.00	-0.00^{**}
	(0.00)	(0.00)	(0.00)
hhhead_age	0.00	-0.00	0.00^{**}
	(0.01)	(0.00)	(0.00)
hhhead_literateTRUE	0.22	0.12	-0.26^{***}
	(0.13)	(0.11)	(0.06)
hhhead_sexfemale	0.22	-0.21	0.11
	(0.17)	(0.14)	(0.06)
dependents	-0.62	0.12	-0.17
	(0.41)	(0.35)	(0.11)
genderMale	-0.11	0.15	
	(0.10)	(0.09)	
age	-0.02^{***}	0.02^{***}	
	(0.00)	(0.00)	
pop	-0.00	0.00^{*}	0.00
	(0.00)	(0.00)	(0.00)
birth_order	-0.10^{*}	0.05	
	(0.04)	(0.04)	
within24	0.10	0.05	

	(0.09)	(0.07)	
spi12	-0.32^{*}	-0.40^{**}	-0.09
	(0.15)	(0.13)	(0.09)
λ			0.92^{***}
			(0.05)
R^2	0.05	0.05	
Adj. R^2	0.04	0.04	
Num. obs.	1346	1346	2362
RMSE	1.84	1.56	
Parameters			18
Log Likelihood			-3894.58
AIC (Linear model)			7841.57
AIC (Spatial model)			7825.16
LR test: statistic			18.41
LR test: p-value			0.00

Table A.3: spi12 in Ghana

	HAZ	WHZ	HHS
(Intercept)	-0.32	0.48	2.77^{***}
	(0.93)	(0.79)	(0.62)
asset_index	0.04	-0.02	0.01
	(0.04)	(0.03)	(0.02)
admin1Northern	-0.04	-0.28	-0.01
	(0.20)	(0.17)	(0.13)
admin1Upper East	0.39	-1.21^{***}	0.01
	(0.33)	(0.28)	(0.18)
admin1Upper West	0.31	-0.29	-0.35
	(0.26)	(0.22)	(0.23)
hh_size	0.07^{*}	-0.04	0.02^{*}
	(0.03)	(0.03)	(0.01)
hhhead_religionMuslim	-0.02	-0.03	-0.05
	(0.12)	(0.10)	(0.06)
hhhead_religionNone	-0.85^{*}	0.31	-0.20
	(0.42)	(0.36)	(0.17)
hhhead_religionTraditional	0.12	0.16	0.35^{***}
	(0.15)	(0.13)	(0.07)
mean_annual_precip	0.00	-0.00	-0.00^{*}
	(0.00)	(0.00)	(0.00)
hhhead_age	0.00	0.00	0.00^{**}
	(0.01)	(0.00)	(0.00)
hhhead_literateTRUE	0.21	0.11	-0.26^{***}
	(0.13)	(0.11)	(0.06)
hhhead_sexfemale	0.25	-0.16	0.12

	(0.17)	(0.14)	(0.06)
dependents	−0.69	0.05	−0.16
	(0.41)	(0.35)	(0.11)
genderMale	−0.10	0.16	
	(0.10)	(0.09)	
age	−0.02***	0.02***	
	(0.00)	(0.00)	
pop	−0.00*	0.00	0.00
	(0.00)	(0.00)	(0.00)
birth_order	−0.10*	0.04	
	(0.04)	(0.04)	
within24	0.10	0.04	
	(0.09)	(0.07)	
spi24	−0.26	−0.60*	−0.30*
	(0.29)	(0.24)	(0.13)
λ			0.91***
			(0.05)
R^2	0.05	0.05	
Adj. R^2	0.04	0.04	
Num. obs.	1346	1346	2362
RMSE	1.84	1.57	
Parameters			18
Log Likelihood			-3892.52
AIC (Linear model)			7836.29
AIC (Spatial model)			7821.03
LR test: statistic			17.26
LR test: p-value			0.00

Table A.4: spi24 in Ghana

	HAZ	WHZ	HHS
(Intercept)	−1.39	0.64	2.36***
	(0.97)	(0.83)	(0.58)
asset_index	0.05	−0.02	0.01
	(0.04)	(0.03)	(0.02)
admin1Northern	0.53*	−0.38	0.09
	(0.25)	(0.22)	(0.13)
admin1Upper East	0.80*	−1.18***	0.15
	(0.35)	(0.30)	(0.18)
admin1Upper West	0.59*	−0.32	−0.16
	(0.27)	(0.23)	(0.22)
hh_size	0.07*	−0.04	0.02*
	(0.03)	(0.03)	(0.01)
hhhead_religionMuslim	−0.03	−0.02	−0.07

	(0.12)	(0.10)	(0.06)
hhhead_religionNone	-0.88^{*}	0.34	-0.20
	(0.42)	(0.36)	(0.17)
hhhead_religionTraditional	0.16	0.17	0.36^{***}
	(0.15)	(0.13)	(0.07)
mean_annual_precip	0.00	-0.00	-0.00
	(0.00)	(0.00)	(0.00)
hhhead_age	0.00	-0.00	0.00^{**}
	(0.01)	(0.00)	(0.00)
hhhead_literateTRUE	0.22	0.09	-0.26^{***}
	(0.12)	(0.11)	(0.06)
hhhead_sexfemale	0.25	-0.17	0.12
	(0.17)	(0.14)	(0.06)
dependents	-0.63	0.02	-0.17
	(0.41)	(0.35)	(0.11)
genderMale	-0.11	0.16	
	(0.10)	(0.09)	
age	-0.02^{***}	0.02^{***}	
	(0.00)	(0.00)	
pop	-0.00	0.00^{*}	0.00
	(0.00)	(0.00)	(0.00)
birth_order	-0.11^{*}	0.04	
	(0.04)	(0.04)	
within24	0.10	0.04	
	(0.09)	(0.07)	
spi36	-0.76^{***}	-0.08	-0.37^{***}
	(0.21)	(0.18)	(0.11)
λ			0.86^{***}
			(0.07)
R^2	0.06	0.05	
Adj. R^2	0.05	0.03	
Num. obs.	1346	1346	2362
RMSE	1.83	1.57	
Parameters			18
Log Likelihood			-3889.86
AIC (Linear model)			7825.60
AIC (Spatial model)			7815.71
LR test: statistic			11.89
LR test: p-value			0.00

Table A.5: spi36 in Ghana

	HAZ	WHZ	HHS
(Intercept)	-0.19	0.77	2.76^{***}

	(0.92)	(0.79)	(0.56)
asset_index	0.04	−0.02	0.01
	(0.04)	(0.03)	(0.02)
admin1Northern	0.08	−0.51**	0.06
	(0.21)	(0.18)	(0.13)
admin1Upper East	0.45	−1.24***	0.15
	(0.33)	(0.28)	(0.17)
admin1Upper West	0.21	−0.33	−0.25
	(0.26)	(0.22)	(0.21)
hh_size	0.07*	−0.04	0.02*
	(0.03)	(0.03)	(0.01)
hhhead_religionMuslim	0.00	−0.03	−0.05
	(0.12)	(0.10)	(0.06)
hhhead_religionNone	−0.84*	0.35	−0.18
	(0.42)	(0.36)	(0.17)
hhhead_religionTraditional	0.12	0.17	0.35***
	(0.15)	(0.13)	(0.07)
mean_annual_precip	0.00	−0.00	−0.00*
	(0.00)	(0.00)	(0.00)
hhhead_age	0.00	−0.00	0.00**
	(0.01)	(0.00)	(0.00)
hhhead_literateTRUE	0.21	0.09	−0.26***
	(0.13)	(0.11)	(0.06)
hhhead_sexfemale	0.28	−0.18	0.12
	(0.17)	(0.14)	(0.06)
dependents	−0.70	0.01	−0.17
	(0.41)	(0.35)	(0.11)
genderMale	−0.11	0.16	
	(0.10)	(0.09)	
age	−0.02***	0.02***	
	(0.00)	(0.00)	
pop	−0.00*	0.00	0.00
	(0.00)	(0.00)	(0.00)
birth_order	−0.10*	0.05	
	(0.04)	(0.04)	
within24	0.10	0.04	
	(0.09)	(0.07)	
spi48	−0.39*	0.15	−0.41***
	(0.20)	(0.17)	(0.10)
λ			0.82***
			(0.09)
R^2	0.05	0.05	
Adj. R^2	0.04	0.03	
Num. obs.	1346	1346	2362
RMSE	1.84	1.57	

Parameters	18
Log Likelihood	-3887.41
AIC (Linear model)	7816.82
AIC (Spatial model)	7810.81
LR test: statistic	8.01
LR test: p-value	0.00

Table A.6: spi48 in Ghana

	HAZ	WHZ	HHS
(Intercept)	-0.09	0.68	2.83^{***}
	(0.93)	(0.79)	(0.58)
asset_index	0.04	-0.02	0.01
	(0.04)	(0.03)	(0.02)
admin1Northern	-0.10	-0.46^{**}	-0.02
	(0.19)	(0.16)	(0.13)
admin1Upper East	0.37	-1.21^{***}	0.08
	(0.33)	(0.28)	(0.18)
admin1Upper West	0.11	-0.20	-0.32
	(0.31)	(0.26)	(0.23)
hh_size	0.07^{*}	-0.04	0.02^{*}
	(0.03)	(0.03)	(0.01)
hhhead_religionMuslim	-0.00	-0.03	-0.05
	(0.12)	(0.10)	(0.06)
hhhead_religionNone	-0.83^{*}	0.34	-0.18
	(0.42)	(0.36)	(0.17)
hhhead_religionTraditional	0.12	0.18	0.35^{***}
	(0.15)	(0.13)	(0.07)
mean_annual_precip	-0.00	-0.00^{*}	-0.00^{**}
	(0.00)	(0.00)	(0.00)
hhhead_age	0.00	-0.00	0.00^{**}
	(0.01)	(0.00)	(0.00)
hhhead_literateTRUE	0.21	0.09	-0.26^{***}
	(0.13)	(0.11)	(0.06)
hhhead_sexfemale	0.27	-0.19	0.12
	(0.17)	(0.14)	(0.07)
dependents	-0.71	0.02	-0.17
	(0.41)	(0.35)	(0.11)
genderMale	-0.10	0.16	
	(0.10)	(0.09)	
age	-0.02^{***}	0.02^{***}	
	(0.00)	(0.00)	
pop	-0.00^{*}	0.00^{*}	0.00
	(0.00)	(0.00)	(0.00)

birth_order	-0.10^{*}	0.04	
	(0.04)	(0.04)	
within24	0.10	0.04	
	(0.09)	(0.07)	
spi60	-0.20	0.18	-0.20^{*}
	(0.19)	(0.16)	(0.09)
λ			0.86^{***}
			(0.07)
R^2	0.05	0.05	
Adj. R^2	0.04	0.03	
Num. obs.	1346	1346	2362
RMSE	1.84	1.57	
Parameters			18
Log Likelihood			-3893.21
AIC (Linear model)			7828.86
AIC (Spatial model)			7822.42
LR test: statistic			8.44
LR test: p-value			0.00

Table A.7: spi60 in Ghana

	HAZ	WHZ	HHS
(Intercept)	-1.41^{***}	-0.71^{**}	0.26^{*}
	(0.31)	(0.24)	(0.10)
asset_index	0.04^{*}	-0.00	0.00
	(0.02)	(0.01)	(0.00)
admin1Chittagong	-0.03	-0.09	-0.07
	(0.16)	(0.11)	(0.05)
admin1Dhaka	-0.04	-0.04	-0.12^{**}
	(0.15)	(0.10)	(0.04)
admin1Khulna	0.16	0.10	-0.11^{*}
	(0.18)	(0.12)	(0.05)
admin1Rajshahi	-0.19	-0.03	-0.14^{**}
	(0.17)	(0.12)	(0.06)
admin1Rangpur	-0.07	-0.08	0.14^{*}
	(0.16)	(0.11)	(0.07)
admin1Sylhet	-0.01	-0.06	-0.05
	(0.20)	(0.14)	(0.07)
hh_size	-0.01	-0.01	-0.02^{***}
	(0.02)	(0.01)	(0.00)
hhhead_age	0.01^{*}	0.00	0.00
	(0.00)	(0.00)	(0.00)
interview_month2	0.11	-0.16^{*}	0.01
	(0.08)	(0.07)	(0.02)

interview_month3	0.27**	−0.27***	−0.05
	(0.09)	(0.08)	(0.03)
interview_month4	0.32***	−0.47***	−0.02
	(0.09)	(0.07)	(0.04)
interview_month5	0.21*	−0.48***	−0.08
	(0.09)	(0.08)	(0.04)
interview_month6	0.34	−0.65***	−0.07
	(0.18)	(0.15)	(0.06)
interview_month8	0.39	−0.59	−0.41
	(0.58)	(0.50)	(0.31)
interview_month9	0.21	−0.21	−0.14
	(0.68)	(0.59)	(0.35)
interview_month11	0.19	−0.29	0.07*
	(0.18)	(0.15)	(0.03)
interview_month12	−0.10	−0.21**	0.03
	(0.09)	(0.07)	(0.02)
hhhead_religionHindu	−0.01	0.12	−0.01
	(0.09)	(0.08)	(0.02)
hhhead_religionChristian	0.32	0.13	−0.28*
	(0.48)	(0.41)	(0.14)
hhhead_literateTRUE	0.11	−0.05	−0.10***
	(0.07)	(0.06)	(0.02)
hhhead_educationprimary	0.09	0.06	−0.11***
	(0.06)	(0.05)	(0.02)
hhhead_educationsecondary	0.38***	0.20*	−0.19***
	(0.11)	(0.10)	(0.03)
hhhead_educationhigh school	0.73***	0.19	−0.19***
	(0.16)	(0.14)	(0.04)
hhhead_educationuniversity	1.36***	0.05	−0.21**
	(0.33)	(0.29)	(0.08)
hhhead_sexfemale	0.12	0.16*	0.13***
	(0.07)	(0.06)	(0.02)
dependents	−0.19	−0.30	0.17***
	(0.17)	(0.15)	(0.03)
genderMale	−0.12**	0.06	
	(0.05)	(0.04)	
age	−0.01***	−0.00***	
	(0.00)	(0.00)	
pop	0.00	0.00***	−0.00
	(0.00)	(0.00)	(0.00)
mean_annual_precip	−0.00	0.00	0.00
	(0.00)	(0.00)	(0.00)
spi12	0.02	0.04	0.01
	(0.05)	(0.04)	(0.02)
irrigation	0.11	0.00	0.01

	(0.10)	(0.08)	(0.03)
λ	0.25^{**}	-0.07	0.85^{***}
	(0.08)	(0.13)	(0.06)
survey_year2015			0.10^{**}
			(0.03)
interview_month7			-0.07
			(0.64)
interview_month10			0.16^{***}
			(0.04)
Num. obs.	3271	3271	9342
Parameters	36	36	37
Log Likelihood	-5706.41	-5256.83	-8890.70
AIC (Linear model)	11491.77	10584.04	17857.02
AIC (Spatial model)	11484.83	10585.66	17855.40
LR test: statistic	8.94	0.37	3.61
LR test: p-value	0.00	0.54	0.06

Table A.8: spi12 in Bangladesh

	HAZ	WHZ	HHS
(Intercept)	-1.47^{***}	-0.68^{**}	0.27^{*}
	(0.33)	(0.25)	(0.11)
asset_index	0.04^{*}	-0.00	0.00
	(0.02)	(0.01)	(0.00)
admin1Chittagong	-0.02	-0.09	-0.07
	(0.16)	(0.11)	(0.05)
admin1Dhaka	-0.04	-0.04	-0.12^{**}
	(0.15)	(0.10)	(0.04)
admin1Khulna	0.16	0.09	-0.11^{*}
	(0.17)	(0.12)	(0.05)
admin1Rajshahi	-0.18	-0.02	-0.14^{**}
	(0.17)	(0.11)	(0.06)
admin1Rangpur	-0.08	-0.09	0.14^{*}
	(0.16)	(0.11)	(0.07)
admin1Sylhet	-0.00	-0.07	-0.05
	(0.20)	(0.14)	(0.08)
hh_size	-0.01	-0.01	-0.02^{***}
	(0.02)	(0.01)	(0.00)
hhhead_age	0.01^{*}	0.00	0.00
	(0.00)	(0.00)	(0.00)
interview_month2	0.11	-0.17^{*}	0.01
	(0.08)	(0.07)	(0.02)
interview_month3	0.26^{**}	-0.28^{***}	-0.05
	(0.09)	(0.08)	(0.03)

interview_month4	0.31***	−0.46***	−0.01
	(0.09)	(0.08)	(0.04)
interview_month5	0.21*	−0.44***	−0.07
	(0.10)	(0.08)	(0.04)
interview_month6	0.32	−0.64***	−0.06
	(0.18)	(0.16)	(0.06)
interview_month8	0.44	−0.53	−0.38
	(0.58)	(0.50)	(0.31)
interview_month9	0.23	−0.21	−0.13
	(0.68)	(0.59)	(0.35)
interview_month11	0.21	−0.28	0.08*
	(0.18)	(0.15)	(0.03)
interview_month12	−0.10	−0.21**	0.03
	(0.09)	(0.07)	(0.02)
hhhead_religionHindu	−0.01	0.12	−0.01
	(0.09)	(0.08)	(0.02)
hhhead_religionChristian	0.32	0.13	−0.28*
	(0.48)	(0.41)	(0.14)
hhhead_literateTRUE	0.11	−0.04	−0.10***
	(0.07)	(0.06)	(0.02)
hhhead_educationprimary	0.09	0.06	−0.11***
	(0.06)	(0.05)	(0.02)
hhhead_educationsecondary	0.38***	0.20*	−0.19***
	(0.11)	(0.10)	(0.03)
hhhead_educationhigh school	0.73***	0.19	−0.19***
	(0.16)	(0.14)	(0.04)
hhhead_educationuniversity	1.36***	0.05	−0.21**
	(0.33)	(0.29)	(0.08)
hhhead_sexfemale	0.12	0.16*	0.13***
	(0.07)	(0.06)	(0.02)
dependents	−0.19	−0.30*	0.17***
	(0.17)	(0.15)	(0.03)
genderMale	−0.12**	0.06	
	(0.05)	(0.04)	
age	−0.01***	−0.00***	
	(0.00)	(0.00)	
pop	−0.00	0.00***	−0.00
	(0.00)	(0.00)	(0.00)
mean_annual_precip	−0.00	0.00	0.00
	(0.00)	(0.00)	(0.00)
spi24	−0.02	0.04	0.01
	(0.05)	(0.04)	(0.02)
irrigation	0.11	0.00	0.01
	(0.10)	(0.08)	(0.03)
λ	0.24**	−0.09	0.86***

	(0.08)	(0.13)	(0.06)
survey_year2015			0.09^{**}
			(0.03)
interview_month7			-0.05
			(0.64)
interview_month10			0.17^{***}
			(0.04)
Num. obs.	3271	3271	9342
Parameters	36	36	37
Log Likelihood	-5706.46	-5256.97	-8890.85
AIC (Linear model)	11490.93	10584.50	17857.66
AIC (Spatial model)	11484.91	10585.93	17855.69
LR test: statistic	8.02	0.57	3.97
LR test: p-value	0.00	0.45	0.05

Table A.9: spi24 in Bangladesh

	HAZ	WHZ	HHS
(Intercept)	-1.44^{***}	-0.61^{*}	0.27^{*}
	(0.33)	(0.25)	(0.11)
asset_index	0.04^{*}	-0.00	0.00
	(0.02)	(0.01)	(0.00)
admin1Chittagong	-0.02	-0.09	-0.07
	(0.16)	(0.11)	(0.05)
admin1Dhaka	-0.04	-0.03	-0.12^{**}
	(0.15)	(0.10)	(0.04)
admin1Khulna	0.16	0.11	-0.11^{*}
	(0.17)	(0.12)	(0.05)
admin1Rajshahi	-0.18	-0.02	-0.14^{**}
	(0.17)	(0.11)	(0.06)
admin1Rangpur	-0.07	-0.08	0.14^{*}
	(0.16)	(0.11)	(0.07)
admin1Sylhet	-0.01	-0.05	-0.05
	(0.20)	(0.14)	(0.08)
hh_size	-0.01	-0.01	-0.02^{***}
	(0.02)	(0.01)	(0.00)
hhhead_age	0.01^{*}	0.00	0.00
	(0.00)	(0.00)	(0.00)
interview_month2	0.11	-0.16^{*}	0.01
	(0.08)	(0.07)	(0.02)
interview_month3	0.26^{**}	-0.26^{***}	-0.05
	(0.09)	(0.08)	(0.03)
interview_month4	0.31^{***}	-0.44^{***}	-0.01
	(0.09)	(0.08)	(0.04)

interview_month5	0.22^{*}	-0.45^{***}	-0.07
	(0.09)	(0.08)	(0.04)
interview_month6	0.33	-0.62^{***}	-0.06
	(0.18)	(0.16)	(0.06)
interview_month8	0.43	-0.51	-0.38
	(0.58)	(0.50)	(0.31)
interview_month9	0.22	-0.21	-0.13
	(0.68)	(0.59)	(0.35)
interview_month11	0.20	-0.28	0.08^{*}
	(0.18)	(0.15)	(0.03)
interview_month12	-0.10	-0.22^{**}	0.03
	(0.09)	(0.07)	(0.02)
hhhead_religionHindu	-0.01	0.11	-0.01
	(0.09)	(0.08)	(0.02)
hhhead_religionChristian	0.32	0.13	-0.28^{*}
	(0.48)	(0.41)	(0.14)
hhhead_literateTRUE	0.11	-0.04	-0.10^{***}
	(0.07)	(0.06)	(0.02)
hhhead_educationprimary	0.09	0.06	-0.11^{***}
	(0.06)	(0.05)	(0.02)
hhhead_educationsecondary	0.38^{***}	0.20^{*}	-0.19^{***}
	(0.11)	(0.10)	(0.03)
hhhead_educationhigh school	0.73^{***}	0.19	-0.19^{***}
	(0.16)	(0.14)	(0.04)
hhhead_educationuniversity	1.36^{***}	0.05	-0.21^{**}
	(0.33)	(0.29)	(0.08)
hhhead_sexfemale	0.12	0.16^{*}	0.13^{***}
	(0.07)	(0.06)	(0.02)
dependents	-0.19	-0.30^{*}	0.17^{***}
	(0.17)	(0.15)	(0.03)
genderMale	-0.12^{**}	0.05	
	(0.05)	(0.04)	
age	-0.01^{***}	-0.00^{***}	
	(0.00)	(0.00)	
pop	-0.00	0.00^{***}	-0.00
	(0.00)	(0.00)	(0.00)
mean_annual_precip	-0.00	0.00	0.00
	(0.00)	(0.00)	(0.00)
spi36	-0.00	0.06	
	(0.05)	(0.04)	
irrigation	0.11	-0.01	0.01
	(0.10)	(0.08)	(0.03)
λ	0.24^{**}	-0.11	0.86^{***}
	(0.08)	(0.13)	(0.06)
survey_year2015			0.09^{**}

			(0.03)
interview_month7			−0.05
			(0.64)
interview_month10			0.17***
			(0.04)
spi24			0.01
			(0.02)
Num. obs.	3271	3271	9342
Parameters	36	36	37
Log Likelihood	-5706.50	-5256.26	-8890.85
AIC (Linear model)	11491.34	10583.25	17857.66
AIC (Spatial model)	11485.00	10584.51	17855.69
LR test: statistic	8.33	0.74	3.97
LR test: p-value	0.00	0.39	0.05

Table A.10: spi36 in Bangladesh

	HAZ	WHZ	HHS
(Intercept)	−1.47***	−0.62*	0.39***
	(0.33)	(0.25)	(0.08)
asset_index	0.04*	−0.00	0.00
	(0.02)	(0.01)	(0.00)
admin1Chittagong	−0.02	−0.08	−0.12***
	(0.16)	(0.11)	(0.04)
admin1Dhaka	−0.05	−0.01	−0.13***
	(0.15)	(0.10)	(0.03)
admin1Khulna	0.16	0.10	−0.05
	(0.17)	(0.12)	(0.03)
admin1Rajshahi	−0.18	−0.01	−0.13***
	(0.17)	(0.11)	(0.04)
admin1Rangpur	−0.08	−0.07	−0.01
	(0.16)	(0.11)	(0.04)
admin1Sylhet	−0.02	−0.02	−0.05
	(0.20)	(0.14)	(0.05)
hh_size	−0.01	−0.01	−0.02***
	(0.02)	(0.01)	(0.00)
hhhead_age	0.01*	0.00	0.00
	(0.00)	(0.00)	(0.00)
interview_month2	0.11	−0.16*	0.02
	(0.08)	(0.07)	(0.02)
interview_month3	0.26**	−0.28***	−0.06
	(0.09)	(0.08)	(0.03)
interview_month4	0.32***	−0.47***	−0.03
	(0.09)	(0.07)	(0.04)

interview_month5	0.22*	−0.46***	−0.10*
	(0.09)	(0.08)	(0.04)
interview_month6	0.33	−0.66***	−0.07
	(0.18)	(0.15)	(0.06)
interview_month8	0.44	−0.52	−0.39
	(0.58)	(0.50)	(0.31)
interview_month9	0.23	−0.21	−0.15
	(0.68)	(0.59)	(0.35)
interview_month11	0.20	−0.27	0.09**
	(0.18)	(0.15)	(0.03)
interview_month12	−0.10	−0.22**	0.03
	(0.09)	(0.07)	(0.02)
hhhead_religionHindu	−0.01	0.11	−0.02
	(0.09)	(0.08)	(0.02)
hhhead_religionChristian	0.33	0.13	−0.28*
	(0.48)	(0.41)	(0.14)
hhhead_literateTRUE	0.11	−0.04	−0.10***
	(0.07)	(0.06)	(0.02)
hhhead_educationprimary	0.09	0.06	−0.11***
	(0.06)	(0.05)	(0.02)
hhhead_educationsecondary	0.38***	0.20*	−0.19***
	(0.11)	(0.10)	(0.03)
hhhead_educationhigh school	0.73***	0.19	−0.19***
	(0.16)	(0.14)	(0.04)
hhhead_educationuniversity	1.36***	0.05	−0.21**
	(0.33)	(0.29)	(0.08)
hhhead_sexfemale	0.12	0.17**	0.13***
	(0.07)	(0.06)	(0.02)
dependents	−0.19	−0.29	0.17***
	(0.17)	(0.15)	(0.03)
genderMale	−0.12**	0.05	
	(0.05)	(0.04)	
age	−0.01***	−0.00***	
	(0.00)	(0.00)	
pop	−0.00	0.00***	−0.00
	(0.00)	(0.00)	(0.00)
mean_annual_precip	−0.00	0.00	0.00
	(0.00)	(0.00)	(0.00)
spi48	−0.02	0.06	0.05**
	(0.05)	(0.04)	(0.01)
irrigation	0.11	−0.00	0.02
	(0.10)	(0.08)	(0.03)
λ	0.24**	−0.11	0.15
	(0.08)	(0.13)	(0.21)
survey_year2015			0.12***

			(0.03)
interview_month7			-0.08
			(0.64)
interview_month10			0.17^{***}
			(0.04)
Num. obs.	3271	3271	9342
Parameters	36	36	37
Log Likelihood	-5706.44	-5256.28	-8888.13
AIC (Linear model)	11491.03	10583.33	17848.36
AIC (Spatial model)	11484.89	10584.55	17850.26
LR test: statistic	8.14	0.78	0.10
LR test: p-value	0.00	0.38	0.75

Table A.11: spi48 in Bangladesh

	HAZ	WHZ	HHS
(Intercept)	-1.39^{***}	-0.71^{**}	0.28^{**}
	(0.31)	(0.24)	(0.10)
asset_index	0.04^{*}	-0.00	0.00
	(0.02)	(0.01)	(0.00)
admin1Chittagong	-0.03	-0.09	-0.07
	(0.16)	(0.11)	(0.05)
admin1Dhaka	-0.03	-0.03	-0.12^{**}
	(0.15)	(0.10)	(0.04)
admin1Khulna	0.16	0.11	-0.10^{*}
	(0.18)	(0.12)	(0.05)
admin1Rajshahi	-0.17	-0.00	-0.14^{*}
	(0.17)	(0.11)	(0.06)
admin1Rangpur	-0.06	-0.08	0.14^{*}
	(0.17)	(0.11)	(0.07)
admin1Sylhet	-0.01	-0.06	-0.05
	(0.20)	(0.14)	(0.07)
hh_size	-0.01	-0.01	-0.02^{***}
	(0.02)	(0.01)	(0.00)
hhhead_age	0.01^{*}	0.00	0.00
	(0.00)	(0.00)	(0.00)
interview_month2	0.12	-0.16^{*}	0.02
	(0.08)	(0.07)	(0.02)
interview_month3	0.29^{**}	-0.27^{**}	-0.05
	(0.10)	(0.08)	(0.03)
interview_month4	0.34^{***}	-0.45^{***}	-0.03
	(0.09)	(0.08)	(0.04)
interview_month5	0.24^{*}	-0.44^{***}	-0.09^{*}
	(0.09)	(0.08)	(0.04)

interview_month6	0.36*	−0.64***	−0.08
	(0.18)	(0.15)	(0.06)
interview_month8	0.44	−0.50	−0.40
	(0.58)	(0.50)	(0.31)
interview_month9	0.20	−0.20	−0.16
	(0.68)	(0.59)	(0.35)
interview_month11	0.19	−0.27	0.07*
	(0.18)	(0.15)	(0.03)
interview_month12	−0.11	−0.21**	0.03
	(0.09)	(0.07)	(0.02)
hhhead_religionHindu	−0.01	0.12	−0.01
	(0.09)	(0.08)	(0.02)
hhhead_religionChristian	0.31	0.13	−0.28*
	(0.48)	(0.41)	(0.14)
hhhead_literateTRUE	0.11	−0.05	−0.10***
	(0.07)	(0.06)	(0.02)
hhhead_educationprimary	0.09	0.06	−0.11***
	(0.06)	(0.05)	(0.02)
hhhead_educationsecondary	0.38***	0.20*	−0.19***
	(0.11)	(0.10)	(0.03)
hhhead_educationhigh school	0.73***	0.19	−0.19***
	(0.16)	(0.14)	(0.04)
hhhead_educationuniversity	1.36***	0.05	−0.21**
	(0.33)	(0.29)	(0.08)
hhhead_sexfemale	0.12	0.17**	0.13***
	(0.07)	(0.06)	(0.02)
dependents	−0.19	−0.30	0.17***
	(0.17)	(0.15)	(0.03)
genderMale	−0.12*	0.06	
	(0.05)	(0.04)	
age	−0.01***	−0.00***	
	(0.00)	(0.00)	
pop	0.00	0.00***	−0.00
	(0.00)	(0.00)	(0.00)
mean_annual_precip	−0.00	0.00	0.00
	(0.00)	(0.00)	(0.00)
spi60	0.03	0.03	0.02
	(0.04)	(0.03)	(0.01)
irrigation	0.11	0.00	0.01
	(0.10)	(0.08)	(0.03)
λ	0.26***	−0.10	0.84***
	(0.08)	(0.13)	(0.06)
survey_year2015			0.12***
			(0.04)
interview_month7			−0.08

			(0.64)
interview_month10			0.16***
			(0.04)
Num. obs.	3271	3271	9342
Parameters	36	36	37
Log Likelihood	-5706.23	-5256.93	-8890.12
AIC (Linear model)	11491.75	10584.49	17854.39
AIC (Spatial model)	11484.46	10585.85	17854.23
LR test: statistic	9.29	0.64	2.16
LR test: p-value	0.00	0.43	0.14

Table A.12: spi60 in Bangladesh

Comparison of Regression Results for Aspatial Ordinal Logistic Regression and Ordinary Least-Squares Regression

	OLS	Logistic
(Intercept)	0.58^{***}	
	(0.06)	
asset_index	0.01	0.13
	(0.01)	(0.14)
hh_size	0.08^{*}	0.80^{*}
	(0.04)	(0.35)
mean_annual_precip	-0.53^{***}	-4.60^{***}
	(0.06)	(0.58)
hhhead_religionMuslim	-0.03^{***}	-0.30^{**}
	(0.01)	(0.09)
hhhead_religionNone	-0.04	-0.35
	(0.03)	(0.29)
hhhead_religionTraditional	0.05^{***}	0.47^{***}
	(0.01)	(0.11)
hhhead_age	0.03	0.17
	(0.03)	(0.24)
hhhead_literateTRUE	-0.05^{***}	-0.40^{***}
	(0.01)	(0.10)
pop	0.07^{**}	0.64^{**}
	(0.02)	(0.21)
hhhead_sexfemale	0.00	0.04
	(0.01)	(0.10)
dependents	0.00	0.11
	(0.02)	(0.18)
spi12	-0.02	-0.19
	(0.02)	(0.14)
R^2	0.11	
Adj. R^2	0.10	
Num. obs.	2362	2362
RMSE	0.20	
AIC		6061.85
BIC		6165.66
Log Likelihood		-3012.92
Deviance		6025.85

Table A.13: spi12 in Ghana

	OLS	Logistic
(Intercept)	0.58^{***}	
	(0.05)	
asset_index	0.02	0.14

	(0.01)	(0.14)
hh_size	0.08^{*}	0.81^{*}
	(0.04)	(0.35)
mean_annual_precip	-0.42^{***}	-3.68^{***}
	(0.07)	(0.62)
hhhead_religionMuslim	-0.03^{***}	-0.28^{**}
	(0.01)	(0.09)
hhhead_religionNone	-0.04	-0.37
	(0.03)	(0.29)
hhhead_religionTraditional	0.05^{***}	0.47^{***}
	(0.01)	(0.11)
hhhead_age	0.03	0.18
	(0.03)	(0.24)
hhhead_literateTRUE	-0.05^{***}	-0.40^{***}
	(0.01)	(0.10)
pop	0.04	0.38
	(0.02)	(0.22)
hhhead_sexfemale	0.00	0.04
	(0.01)	(0.10)
dependents	0.00	0.12
	(0.02)	(0.18)
spi24	-0.14^{***}	-1.18^{***}
	(0.03)	(0.31)
R^2	0.11	
Adj. R^2	0.11	
Num. obs.	2362	2362
RMSE	0.20	
AIC		6049.28
BIC		6153.09
Log Likelihood		-3006.64
Deviance		6013.28

Table A.14: spi24 in Ghana

	OLS	Logistic
(Intercept)	0.59^{***}	
	(0.05)	
asset_index	0.01	0.13
	(0.01)	(0.14)
hh_size	0.09^{*}	0.89^{*}
	(0.04)	(0.35)
mean_annual_precip	-0.46^{***}	-4.01^{***}
	(0.06)	(0.59)
hhhead_religionMuslim	-0.03^{**}	-0.24^{*}

	(0.01)	(0.09)
hhhead_religionNone	−0.04	−0.37
	(0.03)	(0.29)
hhhead_religionTraditional	0.06***	0.54***
	(0.01)	(0.11)
hhhead_age	0.02	0.12
	(0.03)	(0.24)
hhhead_literateTRUE	−0.05***	−0.42***
	(0.01)	(0.10)
pop	0.08**	0.68**
	(0.02)	(0.21)
hhhead_sexfemale	−0.00	−0.00
	(0.01)	(0.10)
dependents	0.00	0.12
	(0.02)	(0.18)
spi36	−0.13***	−1.20***
	(0.03)	(0.27)
R^2	0.11	
Adj. R^2	0.11	
Num. obs.	2362	2362
RMSE	0.20	
AIC		6044.28
BIC		6148.09
Log Likelihood		-3004.14
Deviance		6008.28

Table A.15: spi36 in Ghana

	OLS	Logistic
(Intercept)	0.60***	
	(0.05)	
asset_index	0.02	0.16
	(0.01)	(0.14)
hh_size	0.09*	0.88*
	(0.04)	(0.35)
mean_annual_precip	−0.43***	−3.67***
	(0.06)	(0.59)
hhhead_religionMuslim	−0.02*	−0.17
	(0.01)	(0.09)
hhhead_religionNone	−0.03	−0.33
	(0.03)	(0.29)
hhhead_religionTraditional	0.06***	0.54***
	(0.01)	(0.11)
hhhead_age	0.02	0.15

	(0.03)	(0.24)
hhhead_literateTRUE	-0.05^{***}	-0.41^{***}
	(0.01)	(0.10)
pop	0.06^{**}	0.57^{**}
	(0.02)	(0.21)
hhhead_sexfemale	0.00	0.04
	(0.01)	(0.10)
dependents	0.01	0.12
	(0.02)	(0.18)
spi48	-0.19^{***}	-1.75^{***}
	(0.03)	(0.27)
R^2	0.12	
Adj. R^2	0.12	
Num. obs.	2362	2362
RMSE	0.20	
AIC		6021.14
BIC		6124.95
Log Likelihood		-2992.57
Deviance		5985.14

Table A.16: spi48 in Ghana

	OLS	Logistic
(Intercept)	0.50^{***}	
	(0.06)	
asset_index	0.02	0.15
	(0.01)	(0.14)
hh_size	0.09^{*}	0.82^{*}
	(0.04)	(0.35)
mean_annual_precip	-0.32^{***}	-2.65^{***}
	(0.07)	(0.66)
hhhead_religionMuslim	-0.02^{*}	-0.19^{*}
	(0.01)	(0.09)
hhhead_religionNone	-0.03	-0.30
	(0.03)	(0.29)
hhhead_religionTraditional	0.05^{***}	0.51^{***}
	(0.01)	(0.11)
hhhead_age	0.03	0.17
	(0.03)	(0.24)
hhhead_literateTRUE	-0.04^{***}	-0.39^{***}
	(0.01)	(0.10)
pop	0.08^{**}	0.70^{***}
	(0.02)	(0.21)
hhhead_sexfemale	0.01	0.10

	(0.01)	(0.10)
dependents	0.01	0.13
	(0.02)	(0.18)
spi60	-0.16^{***}	-1.49^{***}
	(0.03)	(0.25)
R^2	0.12	
Adj. R^2	0.12	
Num. obs.	2362	2362
RMSE	0.20	
AIC		6026.46
BIC		6130.27
Log Likelihood		-2995.23
Deviance		5990.46

Table A.17: spi60 in Ghana

	OLS	Logistic
(Intercept)	-4.00^{***}	
	(1.21)	
asset_index	-0.00	-0.08
	(0.00)	(0.12)
hh_size	-0.04^{***}	-1.14^{***}
	(0.01)	(0.32)
hhhead_age	0.00	-0.29
	(0.01)	(0.27)
survey_year	4.07^{***}	208.89^{***}
	(1.21)	(38.19)
interview_month	0.01^{***}	0.50^{***}
	(0.00)	(0.12)
hhhead_religionHindu	0.00	0.09
	(0.00)	(0.11)
hhhead_religionChristian	-0.03	-14.64^{***}
	(0.02)	(0.00)
mean_annual_precip	0.02	0.42
	(0.01)	(0.29)
hhhead_literateTRUE	-0.02^{***}	-0.36^{***}
	(0.00)	(0.09)
hhhead_educationprimary	-0.02^{***}	-0.71^{***}
	(0.00)	(0.09)
hhhead_educationsecondary	-0.03^{***}	-2.24^{***}
	(0.01)	(0.34)
hhhead_educationhigh school	-0.03^{***}	-2.36^{***}
	(0.01)	(0.59)
hhhead_educationuniversity	-0.03^{*}	-14.51^{***}

	(0.01)	(0.00)
hhhead_sexfemale	0.02***	0.46***
	(0.00)	(0.09)
dependents	0.03***	0.79***
	(0.01)	(0.15)
pop	−0.05***	−1.65***
	(0.01)	(0.31)
spi12	−0.00	0.01
	(0.01)	(0.15)
R^2	0.04	
Adj. R^2	0.04	
Num. obs.	9342	9342
RMSE	0.10	
AIC		8403.10
BIC		8567.37
Log Likelihood		-4178.55
Deviance		8357.10

Table A.18: spi12 in Bangladesh

	OLS	Logistic
(Intercept)	−4.96***	
	(1.25)	
asset_index	−0.00	−0.08
	(0.00)	(0.12)
hh_size	−0.04***	−1.15***
	(0.01)	(0.32)
hhhead_age	0.00	−0.29
	(0.01)	(0.27)
survey_year	5.04***	218.37***
	(1.25)	(40.05)
interview_month	0.01***	0.50***
	(0.00)	(0.11)
hhhead_religionHindu	−0.00	0.08
	(0.00)	(0.11)
hhhead_religionChristian	−0.03	−14.57***
	(0.02)	(0.00)
mean_annual_precip	−0.00	0.23
	(0.01)	(0.37)
hhhead_literateTRUE	−0.02***	−0.36***
	(0.00)	(0.09)
hhhead_educationprimary	−0.02***	−0.71***
	(0.00)	(0.09)
hhhead_educationsecondary	−0.03***	−2.24***

	(0.01)	(0.34)
hhhead_educationhigh school	-0.03^{***}	-2.37^{***}
	(0.01)	(0.59)
hhhead_educationuniversity	-0.03^{*}	-14.50^{***}
	(0.01)	(0.00)
hhhead_sexfemale	0.02^{***}	0.46^{***}
	(0.00)	(0.09)
dependents	0.03^{***}	0.79^{***}
	(0.01)	(0.15)
pop	-0.05^{***}	-1.60^{***}
	(0.01)	(0.31)
spi24	0.01^{*}	0.11
	(0.00)	(0.14)
R^2	0.04	
Adj. R^2	0.04	
Num. obs.	9342	9342
RMSE	0.10	
AIC		8402.54
BIC		8566.82
Log Likelihood		-4178.27
Deviance		8356.54

Table A.19: spi24 in Bangladesh

	OLS	Logistic
(Intercept)	-5.05^{***}	
	(1.32)	
asset_index	-0.00	-0.08
	(0.00)	(0.12)
hh_size	-0.04^{***}	-1.16^{***}
	(0.01)	(0.32)
hhhead_age	0.00	-0.29
	(0.01)	(0.27)
survey_year	5.12^{***}	230.64^{***}
	(1.32)	(41.03)
interview_month	0.01^{***}	0.48^{***}
	(0.00)	(0.12)
hhhead_religionHindu	0.00	0.08
	(0.00)	(0.11)
hhhead_religionChristian	-0.03	-14.61^{***}
	(0.02)	(0.00)
mean_annual_precip	-0.00	0.02
	(0.01)	(0.40)
hhhead_literateTRUE	-0.02^{***}	-0.36^{***}

	(0.00)	(0.09)
hhhead_educationprimary	-0.02^{***}	-0.71^{***}
	(0.00)	(0.09)
hhhead_educationsecondary	-0.03^{***}	-2.24^{***}
	(0.01)	(0.34)
hhhead_educationhigh school	-0.03^{***}	-2.37^{***}
	(0.01)	(0.59)
hhhead_educationuniversity	-0.03^{*}	-14.49^{***}
	(0.01)	(0.00)
hhhead_sexfemale	0.02^{***}	0.46^{***}
	(0.00)	(0.09)
dependents	0.03^{***}	0.79^{***}
	(0.01)	(0.15)
pop	-0.05^{***}	-1.58^{***}
	(0.01)	(0.31)
spi36	0.01	0.21
	(0.01)	(0.15)
R^2	0.04	
Adj. R^2	0.04	
Num. obs.	9342	9342
RMSE	0.10	
AIC		8401.20
BIC		8565.47
Log Likelihood		-4177.60
Deviance		8355.20

Table A.20: spi36 in Bangladesh

	OLS	Logistic
(Intercept)	-4.65^{***}	
	(1.19)	
asset_index	-0.00	-0.08
	(0.00)	(0.12)
hh_size	-0.04^{***}	-1.20^{***}
	(0.01)	(0.32)
hhhead_age	0.00	-0.29
	(0.01)	(0.27)
survey_year	4.74^{***}	219.34^{***}
	(1.19)	(37.94)
interview_month	0.01^{**}	0.40^{***}
	(0.00)	(0.12)
hhhead_religionHindu	-0.00	0.04
	(0.00)	(0.11)
hhhead_religionChristian	-0.03	-14.65^{***}

	(0.02)	(0.00)
mean_annual_precip	−0.02	−0.69
	(0.01)	(0.36)
hhhead_literateTRUE	-0.02^{***}	-0.36^{***}
	(0.00)	(0.09)
hhhead_educationprimary	-0.02^{***}	-0.72^{***}
	(0.00)	(0.09)
hhhead_educationsecondary	-0.03^{***}	-2.25^{***}
	(0.01)	(0.34)
hhhead_educationhigh school	-0.03^{***}	-2.37^{***}
	(0.01)	(0.59)
hhhead_educationuniversity	-0.03^{*}	-14.49^{***}
	(0.01)	(0.00)
hhhead_sexfemale	0.02^{***}	0.46^{***}
	(0.00)	(0.09)
dependents	0.03^{***}	0.81^{***}
	(0.01)	(0.15)
pop	-0.04^{***}	-1.28^{***}
	(0.01)	(0.31)
spi48	0.02^{***}	0.65^{***}
	(0.00)	(0.14)
R^2	0.05	
Adj. R^2	0.04	
Num. obs.	9342	9342
RMSE	0.10	
AIC		8381.40
BIC		8545.67
Log Likelihood		-4167.70
Deviance		8335.40

Table A.21: spi48 in Bangladesh

	OLS	Logistic
(Intercept)	-6.75^{***}	
	(1.41)	
asset_index	−0.00	−0.08
	(0.00)	(0.12)
hh_size	-0.04^{***}	-1.22^{***}
	(0.01)	(0.32)
hhhead_age	0.00	−0.30
	(0.01)	(0.27)
survey_year	6.83^{***}	281.70^{***}
	(1.41)	(43.55)
interview_month	0.01^{**}	0.39^{***}

	(0.00)	(0.12)
hhhead_religionHindu	-0.00	0.05
	(0.00)	(0.11)
hhhead_religionChristian	-0.03	-14.63^{***}
	(0.02)	(0.00)
mean_annual_precip	-0.01	-0.34
	(0.01)	(0.35)
hhhead_literateTRUE	-0.02^{***}	-0.37^{***}
	(0.00)	(0.09)
hhhead_educationprimary	-0.02^{***}	-0.72^{***}
	(0.00)	(0.09)
hhhead_educationsecondary	-0.03^{***}	-2.25^{***}
	(0.01)	(0.34)
hhhead_educationhigh school	-0.03^{***}	-2.37^{***}
	(0.01)	(0.59)
hhhead_educationuniversity	-0.03^{*}	-14.52^{***}
	(0.01)	(0.00)
hhhead_sexfemale	0.02^{***}	0.45^{***}
	(0.00)	(0.09)
dependents	0.03^{***}	0.80^{***}
	(0.01)	(0.15)
pop	-0.05^{***}	-1.46^{***}
	(0.01)	(0.31)
spi60	0.02^{***}	0.54^{***}
	(0.01)	(0.16)
R^2	0.04	
Adj. R^2	0.04	
Num. obs.	9342	9342
RMSE	0.10	
AIC		8391.34
BIC		8555.61
Log Likelihood		-4172.67
Deviance		8345.34

Table A.22: spi60 in Bangladesh

Appendix B: Appendix B

Comparison of SPEI Calculated at Different Windows Based on the date of each child nutrition observation, we calculated the SPEI at 12, 24, 36 month intervals, as well as for the childs age, including 9 months in utero. This reflects the fact that children's HAZ scores are an indicator of long-term, chronic undernutrition. Some researchers have found that child undernutrition is particularly sensitive to growing season rainfall (Hagos et al., 2014, Shively, 2017), so we also tested the SPEI across all time intervals for both annual rainfall totals and growing-season only rainfall.

We assessed the regressions using both the Akaike Information Criterion (AIC) and Log Likelihood as well as by running Locally Estimated Scatterplot Smoothing (LOESS) regressions to determine which indices were observed to be related to worse nutrition outcomes during extremes. For the AIC and Log Likelihood tests, we ran hierarchical linear models with the child's HAZ score as the outcome variable, the precipitation index, the square of the precipitation index, and relevant covariates as predictors, as well as varying intercepts at the country, interview year, and survey level. For the LOESS regression models, we first modeled HAZ scores as a function of the household covariates, again using a hierarchical linear model, and then modeled the relationship between the residuals from that model and each precipitation index. After conducting these tests, we found that the 24-month SPEI using annual rainfall performed best by both the shape of the LOESS curve as well as the AIC and Log Likelihood in a linear regression.

Table B.1: Modeling Child Nutrition With SPEI Calculated at Various Timeframes (Part 1)

	12-Month	12-Month Growing Season	24-Month	24-Month Growing Season
	(1)	(2)	(3)	(4)
Age	-0.015^{***}	-0.015^{***}	-0.015^{***}	-0.015^{***}
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Birth Order	-0.004^{***}	-0.004^{***}	-0.004^{***}	-0.004^{***}
	(0.001)	(0.001)	(0.001)	(0.001)
Child is Male	-0.105^{***}	-0.105^{***}	-0.105^{***}	-0.105^{***}

	(0.004)	(0.004)	(0.004)	(0.004)
Birthmonth - February	0.011	0.011	0.011	0.011
	(0.010)	(0.010)	(0.010)	(0.010)
Birthmonth - March	0.034***	0.034***	0.034***	0.034***
	(0.009)	(0.009)	(0.009)	(0.009)
Birthmonth - April	0.057***	0.057***	0.057***	0.057***
	(0.010)	(0.010)	(0.010)	(0.010)
Birthmonth - May	0.082***	0.082***	0.082***	0.082***
	(0.010)	(0.010)	(0.010)	(0.010)
Birthmonth - June	0.100***	0.100***	0.100***	0.100***
	(0.010)	(0.010)	(0.010)	(0.010)
Birthmonth - July	0.102***	0.102***	0.102***	0.102***
	(0.010)	(0.010)	(0.010)	(0.010)
Birthmonth - August	0.127***	0.127***	0.127***	0.127***
	(0.010)	(0.010)	(0.010)	(0.010)
Birthmonth - September	0.144***	0.144***	0.144***	0.144***
	(0.009)	(0.009)	(0.009)	(0.009)
Birthmonth - October	0.194***	0.195***	0.194***	0.194***
	(0.010)	(0.010)	(0.010)	(0.010)
Birthmonth - November	0.200***	0.200***	0.200***	0.200***
	(0.010)	(0.010)	(0.010)	(0.010)
Birthmonth - December	0.236***	0.236***	0.235***	0.236***
	(0.010)	(0.010)	(0.010)	(0.010)
Mother's Years of Education	0.032***	0.032***	0.032***	0.032***
	(0.001)	(0.001)	(0.001)	(0.001)
Toilet - No Facility	−0.076***	−0.076***	−0.077***	−0.076***
	(0.007)	(0.007)	(0.007)	(0.007)

Toilet - Other	0.019	0.018	0.018	0.019
	(0.019)	(0.019)	(0.019)	(0.019)
Toilet - Pit Latrine	-0.101^{***}	-0.102^{***}	-0.101^{***}	-0.101^{***}
	(0.006)	(0.006)	(0.006)	(0.006)
Household Size	-0.004^{***}	-0.004^{***}	-0.004^{***}	-0.004^{***}
	(0.001)	(0.001)	(0.001)	(0.001)
Household Head Age	0.002^{***}	0.002^{***}	0.002^{***}	0.002^{***}
	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Household Head is Male	-0.023^{***}	-0.023^{***}	-0.023^{***}	-0.023^{***}
	(0.006)	(0.006)	(0.006)	(0.006)
Wealth Index - Poorer	-0.103^{***}	-0.103^{***}	-0.102^{***}	-0.103^{***}
	(0.006)	(0.006)	(0.006)	(0.006)
Wealth Index - Poorest	-0.206^{***}	-0.206^{***}	-0.206^{***}	-0.206^{***}
	(0.006)	(0.006)	(0.006)	(0.006)
Wealth Index - Richer	0.131^{***}	0.131^{***}	0.131^{***}	0.131^{***}
	(0.007)	(0.007)	(0.007)	(0.007)
Wealth Index - Richest	0.400^{***}	0.400^{***}	0.399^{***}	0.400^{***}
	(0.007)	(0.007)	(0.007)	(0.007)
SPEI	0.010^{***}	0.006^{**}	0.023^{***}	0.017^{***}
	(0.003)	(0.003)	(0.003)	(0.003)
SPEI Squared	-0.001	-0.001	-0.019^{***}	-0.009^{***}
	(0.002)	(0.002)	(0.002)	(0.002)
Intercept	-1.003^{***}	-1.003^{***}	-0.988^{***}	-0.998^{***}
	(0.055)	(0.055)	(0.055)	(0.055)
Observations	567,065	567,065	567,065	567,065
Log Likelihood	−1028015	−1028018	−1027971	−1028003
Akaike Inf. Crit.	2056094	2056101	2056006	2056069
Bayesian Inf. Crit.	2056454	2056461	2056366	2056429

Note:	*p<0.1; **p<0.05; ***p<0.01

Table B.2: Modeling Child Nutrition With SPEI Calculated at Various Timeframes (Part 2)

	36-Month	36-Month Growing Season	Child's Age	Child's Age Growing Season
	(1)	(2)	(3)	(4)
Age	−0.015***	−0.015***	−0.015***	−0.015***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Birth Order	−0.004***	−0.004***	−0.004***	−0.004***
	(0.001)	(0.001)	(0.001)	(0.001)
Child is Male	−0.105***	−0.105***	−0.105***	−0.105***
	(0.004)	(0.004)	(0.004)	(0.004)
Birthmonth - February	0.011	0.011	0.011	0.011
	(0.010)	(0.010)	(0.010)	(0.010)
Birthmonth - March	0.034***	0.034***	0.034***	0.034***
	(0.009)	(0.009)	(0.009)	(0.009)
Birthmonth - April	0.057***	0.057***	0.057***	0.057***
	(0.010)	(0.010)	(0.010)	(0.010)
Birthmonth - May	0.082***	0.082***	0.082***	0.082***
	(0.010)	(0.010)	(0.010)	(0.010)
Birthmonth - June	0.100***	0.100***	0.100***	0.100***
	(0.010)	(0.010)	(0.010)	(0.010)
Birthmonth - July	0.102***	0.102***	0.102***	0.102***
	(0.010)	(0.010)	(0.010)	(0.010)
Birthmonth - August	0.127***	0.127***	0.127***	0.127***
	(0.010)	(0.010)	(0.010)	(0.010)
Birthmonth - September	0.144***	0.144***	0.144***	0.144***
	(0.009)	(0.009)	(0.009)	(0.009)

Birthmonth - October	0.194***	0.195***	0.195***	0.195***
	(0.010)	(0.010)	(0.010)	(0.010)
Birthmonth - November	0.200***	0.200***	0.201***	0.201***
	(0.010)	(0.010)	(0.010)	(0.010)
Birthmonth - December	0.235***	0.236***	0.236***	0.236***
	(0.010)	(0.010)	(0.010)	(0.010)
Mother's Years of Education	0.032***	0.032***	0.032***	0.032***
	(0.001)	(0.001)	(0.001)	(0.001)
Toilet - No Facility	−0.076***	−0.076***	−0.076***	−0.076***
	(0.007)	(0.007)	(0.007)	(0.007)
Toilet - Other	0.019	0.018	0.018	0.018
	(0.019)	(0.019)	(0.019)	(0.019)
Toilet - Pit Latrine	−0.101***	−0.102***	−0.102***	−0.102***
	(0.006)	(0.006)	(0.006)	(0.006)
Household Size	−0.004***	−0.004***	−0.004***	−0.004***
	(0.001)	(0.001)	(0.001)	(0.001)
Household Head Age	0.002***	0.002***	0.002***	0.002***
	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Household Head is Male	−0.023***	−0.023***	−0.023***	−0.023***
	(0.006)	(0.006)	(0.006)	(0.006)
Wealth Index - Poorer	−0.103***	−0.103***	−0.103***	−0.103***
	(0.006)	(0.006)	(0.006)	(0.006)
Wealth Index - Poorest	−0.206***	−0.206***	−0.206***	−0.206***
	(0.006)	(0.006)	(0.006)	(0.006)
Wealth Index - Richer	0.131***	0.131***	0.131***	0.131***
	(0.007)	(0.007)	(0.007)	(0.007)

Wealth Index - Richest	0.400***	0.400***	0.400***	0.400***
	(0.007)	(0.007)	(0.007)	(0.007)
SPEI	0.010***	0.005*	−0.007**	−0.007**
	(0.003)	(0.003)	(0.003)	(0.003)
SPEI Squared	0.004*	−0.005**	0.007***	0.007***
	(0.002)	(0.002)	(0.002)	(0.002)
Intercept	−1.008***	−1.000***	−1.008***	−1.008***
	(0.055)	(0.055)	(0.055)	(0.055)
Observations	567,065	567,065	567,065	567,065
Log Likelihood	−1028012	−1028018	−1028014	−1028014
Akaike Inf. Crit.	2056088	2056099	2056092	2056092
Bayesian Inf. Crit.	2056448	2056459	2056452	2056452

Note: *p<0.1; **p<0.05; ***p<0.01

Variable	Coefficient Estimate
Intercept	-0.992
Child's Age (Months)	-0.017
Child Birthmonth - February	0.002
Child Birthmonth - March	0.018
Child Birthmonth - April	0.034
Child Birthmonth - May	0.055
Child Birthmonth - June	0.070
Child Birthmonth - July	0.077
Child Birthmonth - August	0.098
Child Birthmonth - September	0.116
Child Birthmonth - October	0.162
Child Birthmonth - November	0.184
Child Birthmonth - December	0.231
Child's Birth Order	-0.006
Child's Sex - Male	-0.104
Mother's Years of Education	0.030
Household Size	-0.001
Household Toilet - No Facility	-0.149
Household Toilet - Other	-0.138
Household Toilet - Pit Latrine	-0.153
Household Head Age (Years)	0.003
Household Head Sex - Male	-0.022
Household Wealth - Poorer	-0.076
Household Wealth - Poorest	-0.154
Household Wealth - Richer	0.115
Household Wealth - Richest	0.374
Child Was Observed During Drought	-0.042
NDVI	0.118
Government Effectiveness	0.217
GDP (PPP) Per Capita	0.857
Human Development Index (HDI)	-0.067
Mean Annual Precipitation	-0.010
Nutritional Diversity of Agriculture	-0.860
Population	0.100
Topographic Roughness	-0.163
Political Stability and Freedom From Violence	-0.271
Percent of Nearby Agriculture Irrigated	0.319
Average Maximum Monthly Temperature	0.483
Official Development Assistance (ODA) Per Capita	0.248
Crop Production Per Capita	-0.197
Value of Imports Per Capita	0.353
Percent of Nearby Land Cover Bare	0.132
Rate of Primary School Enrollment	-0.139
Drought * Government Effectiveness	0.126
Drought * Mean Annual Precipitation	0.025
Drought * Nutritional Diversity	0.192
Drought * Population	-0.347
Drought * Topographic Roughness	-0.046
Drought * Stability and Absence of Violence	0.031

Model Predictions for 2000 and 1990

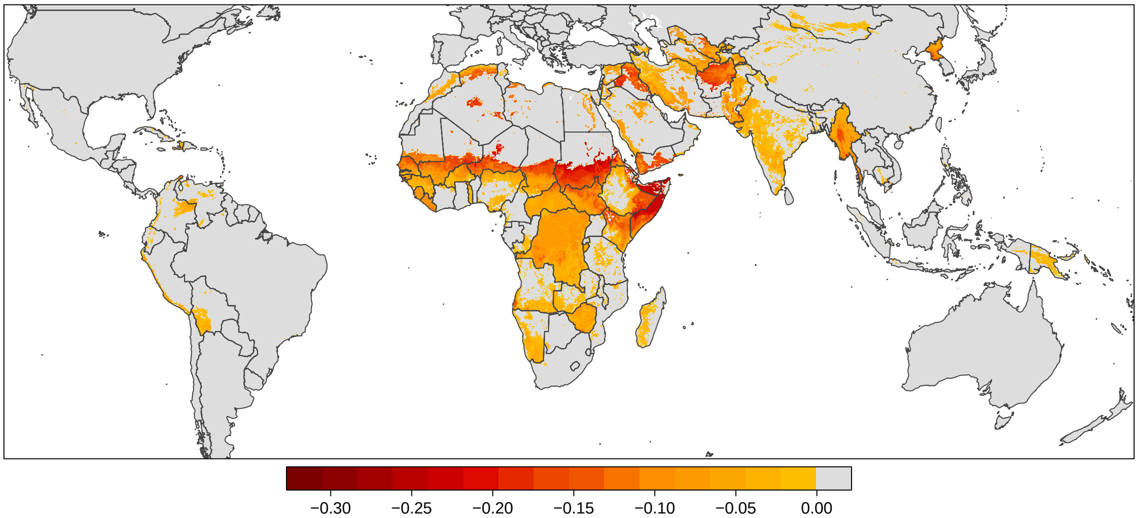

Figure B.1: Expected change in mean child HAZ scores during drought conditions in the year 2000.

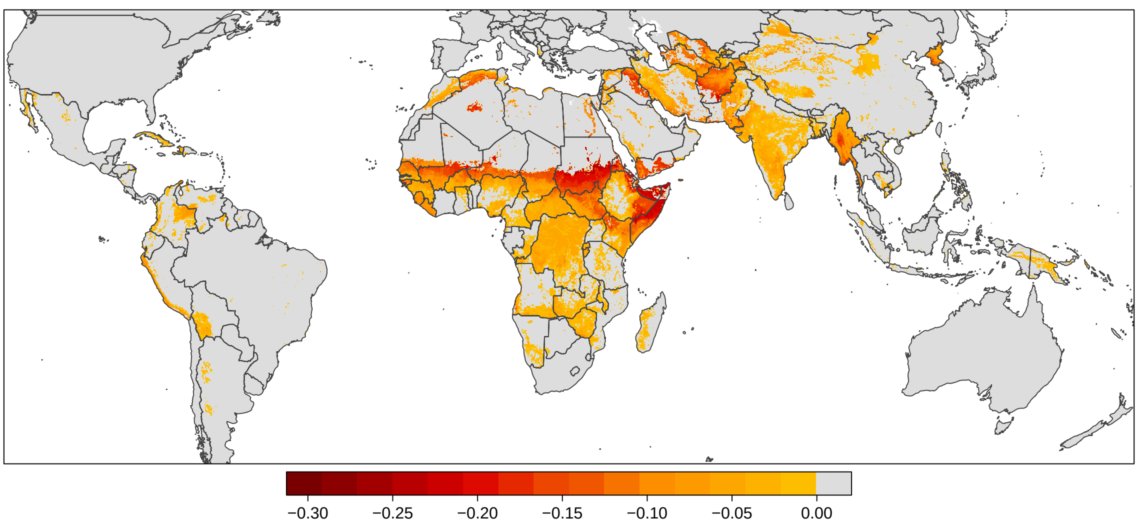

Figure B.2: Expected change in mean child HAZ scores during drought conditions in the year 1990.

Overview of Nutrition Data

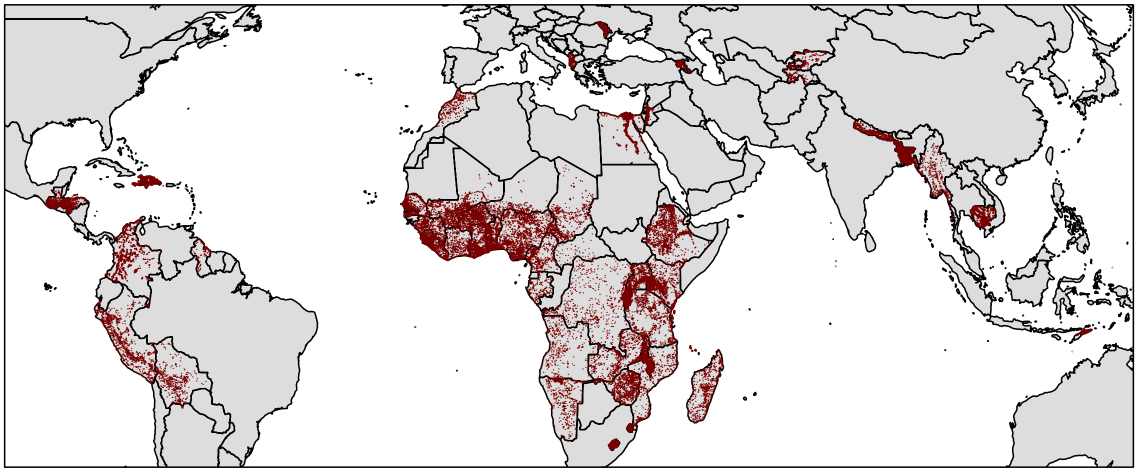

Figure B.3: Locations of all DHS sites used in the study.

Comparison of Household and Individual Variables

We first selected 10 variables that were included across a wide range of DHS surveys that are commonly included in analyses of child nutrition. To determine whether we should include more covariates at the expense of excluding all DHS surveys that did not collect data on these additional covariates, we sub-set the data to only surveys that included other covariates commonly used in child nutrition regression models: whether the child was breastfed, had diarrhea in the past two weeks, or was a twin, as well as household water sources. We found that including these additional covariates improved the Mean Absolute Error (MAE) from 1.152 to 1.145. This represented a marginal improvement of only 0.007 while necessitating the omission of hundreds of thousands of observations. Thus, we include only the original 10 variables available across a broad range of DHS surveys in all our models.

Table B.5: Comparison of Model with 10 vs 14 Covariates

	10 Covariates	14 Covariates
	(1)	(2)
Age	-0.017^{***}	-0.018^{***}
	(0.0001)	(0.0001)
Birth Order	-0.013^{***}	-0.009^{***}
	(0.001)	(0.001)
Child is Male	-0.098^{***}	-0.097^{***}
	(0.005)	(0.005)

Birthmonth - February	0.004	0.008
	(0.012)	(0.012)
Birthmonth - March	0.022^{*}	0.024^{**}
	(0.011)	(0.011)
Birthmonth - April	0.048^{***}	0.053^{***}
	(0.011)	(0.011)
Birthmonth - May	0.059^{***}	0.065^{***}
	(0.011)	(0.011)
Birthmonth - June	0.081^{***}	0.086^{***}
	(0.011)	(0.011)
Birthmonth - July	0.099^{***}	0.100^{***}
	(0.012)	(0.011)
Birthmonth - August	0.105^{***}	0.106^{***}
	(0.011)	(0.011)
Birthmonth - September	0.134^{***}	0.135^{***}
	(0.011)	(0.011)
Birthmonth - October	0.176^{***}	0.179^{***}
	(0.011)	(0.011)
Birthmonth - November	0.179^{***}	0.179^{***}
	(0.012)	(0.012)
Birthmonth - December	0.223^{***}	0.223^{***}
	(0.012)	(0.011)
Mother's Years of Education	0.047^{***}	0.042^{***}
	(0.001)	(0.001)
Toilet - No Facility	-0.410^{***}	-0.314^{***}
	(0.007)	(0.007)
Toilet - Other	-0.334^{***}	-0.274^{***}
	(0.022)	(0.022)
Toilet - Pit Latrine	-0.371^{***}	-0.294^{***}
	(0.006)	(0.006)

Household Size	0.005^{***}	0.005^{***}
	(0.001)	(0.001)
Household Head Age	0.003^{***}	0.003^{***}
	(0.0002)	(0.0002)
Household Head is Male	-0.029^{***}	-0.029^{***}
	(0.006)	(0.006)
Wealth Index - Poorer	-0.026^{***}	-0.022^{***}
	(0.007)	(0.007)
Wealth Index - Poorest	-0.037^{***}	-0.031^{***}
	(0.007)	(0.007)
Wealth Index - Richer	0.055^{***}	0.040^{***}
	(0.008)	(0.008)
Wealth Index - Richest	0.220^{***}	0.168^{***}
	(0.008)	(0.009)
Child Was Ever Breastfed		-0.167^{***}
		(0.016)
Child Had Diarrhea in Previous Two Weeks		-0.219^{***}
		(0.006)
Child Is Twin		-0.471^{***}
		(0.015)
Other Water Source - Purchased		0.083^{***}
		(0.013)
Other Water Source - Surface Water		-0.227^{***}
		(0.008)
Other Water Source - Tube Well		-0.269^{***}
		(0.006)
Intercept	-0.886^{***}	-0.542^{***}
	(0.015)	(0.022)

MAE	1.152	1.145
AIC	1490016.4165027	1485392.38717835
Observations	406,955	406,955
R^2	0.101	0.111
Adjusted R^2	0.101	0.111
Residual Std. Error	1.509 (df = 406929)	1.501 (df = 406923)
F Statistic	1,832.785*** (df = 25; 406929)	1,645.358*** (df = 31; 406923)

Note: *p<0.1; **p<0.05; ***p<0.01

Level	Variable
Individual	Age
Individual	Birth Order
Individual	Birth Month
Individual	Sex
Household	Toilet facilities
Household	Household Head Age
Household	Household Head Sex
Household	Household Size
Household	Household Wealth Quintile
Household	Mother's Years of Education

Table B.4: Individual and Household Variables Included in Model.

Appendix C: Appendix C

	Estimate	Std. Error	z value	Pr($<\vert z\vert$)
(Intercept)	-3.43	1.07	-3.19	0 **
Area Protected	-2.22	2.07	-1.07	0.28
Forest Cover	2.29	0.85	2.7	0.01 **
Grassland	0.31	1.32	0.23	0.82
Head Gender	0.58	0.45	1.27	0.2
Age	-0.52	0.89	-0.58	0.56
Years of Schooling	-1.63	1.14	-1.43	0.15
Literacy	0.15	0.93	0.16	0.88
Household Size	-0.09	0.75	-0.12	0.9
Market Distance	-1.61	2.42	-0.67	0.51
Population Density	-0.22	1.43	-0.15	0.88
12 – month SPI	0.1	0.53	0.19	0.85
Critical Food Shortage	-0.03	0.35	-0.08	0.94
HFIAS	0.5	1.39	0.36	0.72
Total Ag Production	0.34	1.78	0.19	0.85
Net Business Income	-0.11	1.41	-0.08	0.94
Wage Income	-2.83	2.28	-1.24	0.22
Nonfood Spending	-0.55	1.87	-0.29	0.77
Food Spending	-0.51	0.99	-0.52	0.61

Table C.1: Regression for wild foods with geographic variables measured at a 2.5km buffer around each household. A p-value of less than 0.001 is indicated with three stars (***), a p-value of less than 0.01 is indicated with two stars (**), a p-value of less than 0.05 is indicated with one star (*), and a p-value of less than 0.1 is indicated with a period (.).

	Estimate	Std. Error	z value	Pr(¿—z—)
(Intercept)	-3.46	1.17	-2.95	0 **
Area Protected	-3.57	1.96	-1.82	0.07 .
Forest Cover	2.02	0.93	2.16	0.03 *
Grassland	2.07	1.22	1.7	0.09 .
Head Gender	0.65	0.45	1.43	0.15

Age	-0.55	0.89	-0.62	0.54
Years of Schooling	-1.46	1.13	-1.29	0.2
Literacy	0.14	0.93	0.15	0.88
Household Size	-0.12	0.75	-0.16	0.88
Market Distance	-0.19	2.31	-0.08	0.93
Population Density	0.74	1.33	0.56	0.58
12 – month SPI	0.07	0.5	0.15	0.88
Critical Food Shortage	-0.06	0.35	-0.18	0.86
HFIAS	0.56	1.39	0.41	0.68
Total Ag Production	0.22	1.77	0.12	0.9
Net Business Income	-0.09	1.4	-0.06	0.95
Wage Income	-2.83	2.31	-1.23	0.22
Nonfood Spending	-0.57	1.87	-0.3	0.76
Food Spending	-0.61	0.99	-0.61	0.54

Table C.2: Regression for wild foods with geographic variables measured at a 5km buffer around each household. A p-value of less than 0.001 is indicated with three stars (***), a p-value of less than 0.01 is indicated with two stars (**), a p-value of less than 0.05 is indicated with one star (*), and a p-value of less than 0.1 is indicated with a period (.).

	Estimate	Std. Error	z value	Pr(<|z|)
(Intercept)	-3.36	1.23	-2.74	0.01 **
Area Protected	-0.43	1.28	-0.33	0.74
Forest Cover	2.17	1.02	2.13	0.03 *
Grassland	2.47	1.18	2.09	0.04 *
Head Gender	0.56	0.45	1.25	0.21
Age	-0.43	0.89	-0.48	0.63
Years of Schooling	-1.62	1.13	-1.43	0.15
Literacy	0.08	0.92	0.09	0.93
Household Size	-0.07	0.75	-0.09	0.93
Market Distance	-0.07	2.45	-0.03	0.98
Population Density	1.05	1.38	0.76	0.45
12 – month SPI	0.11	0.49	0.23	0.82
Critical Food Shortage	-0.04	0.35	-0.11	0.91
HFIAS	0.61	1.37	0.45	0.66
Total Ag Production	0.31	1.75	0.18	0.86
Net Business Income	-0.02	1.41	-0.02	0.99
Wage Income	-2.79	2.26	-1.23	0.22
Nonfood Spending	-0.63	1.89	-0.33	0.74
Food Spending	-0.47	1	-0.47	0.64

Table C.3: Regression for wild foods with geographic variables measured at a 10km buffer around each household. A p-value of less than 0.001 is indicated with three stars (***), a p-value of less than 0.01 is indicated with two stars (**), a p-value of less than 0.05 is indicated with one star (*), and a p-value of less than 0.1 is indicated with a period (.).

	Estimate	Std. Error	z value	Pr(¿—z—)
(Intercept)	-3.38	1.2	-2.82	0 **
Area Protected	-0.79	1.22	-0.65	0.52
Forest Cover	2.16	1.11	1.95	0.05 .
Grassland	2.27	1.29	1.76	0.08 .
Head Gender	0.59	0.45	1.31	0.19
Age	-0.37	0.89	-0.42	0.68
Years of Schooling	-1.63	1.13	-1.44	0.15
Literacy	0.19	0.92	0.21	0.83
Household Size	-0.08	0.75	-0.1	0.92
Market Distance	-0.16	2.52	-0.06	0.95
Population Density	1.11	1.42	0.79	0.43
12 – month SPI	0.13	0.48	0.28	0.78
Critical Food Shortage	-0.01	0.34	-0.04	0.97
HFIAS	0.58	1.37	0.42	0.67
Total Ag Production	0.4	1.74	0.23	0.82
Net Business Income	-0.04	1.41	-0.03	0.98
Wage Income	-2.82	2.26	-1.24	0.21
Nonfood Spending	-0.62	1.87	-0.33	0.74
Food Spending	-0.48	0.99	-0.48	0.63

Table C.4: Regression for wild foods with geographic variables measured at a 15km buffer around each household. A p-value of less than 0.001 is indicated with three stars (***), a p-value of less than 0.01 is indicated with two stars (**), a p-value of less than 0.05 is indicated with one star (*), and a p-value of less than 0.1 is indicated with a period (.).

	Estimate	Std. Error	z value	Pr(<|z|)
(Intercept)	-2.33	1	-2.33	0.02 *
Area Protected	1.05	0.91	1.15	0.25
Forest Cover	0.41	0.84	0.49	0.63
Grassland	1.03	0.83	1.24	0.21

Head Gender	0.34	0.29	1.16	0.24
Age	-0.36	0.73	-0.5	0.62
Years of Schooling	0.21	0.83	0.25	0.8
Literacy	-1.25	0.74	-1.68	0.09 .
Household Size	-0.35	0.52	-0.67	0.51
Market Distance	-1.06	1.52	-0.7	0.49
Population Density	-2.99	1.49	-2	0.05 *
12 – month SPI	-0.1	0.45	-0.21	0.83
Critical Food Shortage	0.37	0.25	1.51	0.13
HFIAS	1.91	0.98	1.95	0.05 .
Total Ag Production	2.09	1.47	1.42	0.16
Net Business Income	1.5	1.47	1.02	0.31
Wage Income	2.03	1.71	1.19	0.24
Nonfood Spending	1.01	1.39	0.73	0.46
Food Spending	-0.03	0.91	-0.03	0.98

Table C.5: Regression for nonfood NTFP with geographic variables measured at a 2.5km buffer around each household. A p-value of less than 0.001 is indicated with three stars (***), a p-value of less than 0.01 is indicated with two stars (**), a p-value of less than 0.05 is indicated with one star (*), and a p-value of less than 0.1 is indicated with a period (.).

	Estimate	Std. Error	z value	Pr(<|z|)
(Intercept)	-2.11	1.06	-1.98	0.05 *
Area Protected	-0.17	0.98	-0.18	0.86
Forest Cover	-0.34	0.96	-0.36	0.72
Grassland	0.72	0.98	0.74	0.46
Head Gender	0.34	0.29	1.17	0.24
Age	-0.36	0.72	-0.5	0.62
Years of Schooling	0.16	0.83	0.19	0.85
Literacy	-1.23	0.74	-1.66	0.1 .
Household Size	-0.34	0.52	-0.65	0.51
Market Distance	-1.18	1.48	-0.8	0.43
Population Density	-3.07	1.45	-2.12	0.03 *
12 – month SPI	-0.07	0.44	-0.16	0.87
Critical Food Shortage	0.37	0.25	1.5	0.13
HFIAS	1.88	0.98	1.91	0.06 .
Total Ag Production	2.09	1.48	1.41	0.16
Net Business Income	1.42	1.46	0.98	0.33
Wage Income	2	1.71	1.17	0.24
Nonfood Spending	0.96	1.38	0.69	0.49
Food Spending	-0.04	0.91	-0.04	0.97

Table C.6: Regression for nonfood NTFP with geographic variables measured at a 5km buffer around each household. A p-value of less than 0.001 is indicated with three stars (***), a p-value of less than 0.01 is indicated with two stars (**), a p-value of less than 0.05 is indicated with one star (*), and a p-value of less than 0.1 is indicated with a period (.).

	Estimate	Std. Error	z value	Pr(<|z|)
(Intercept)	-1.96	1.11	-1.77	0.08 .
Area Protected	-1.78	0.95	-1.87	0.06 .
Forest Cover	-0.84	0.97	-0.86	0.39
Grassland	0.5	1.11	0.45	0.65
Head Gender	0.36	0.29	1.24	0.22
Age	-0.43	0.72	-0.59	0.55
Years of Schooling	0.17	0.83	0.21	0.83
Literacy	-1.24	0.74	-1.68	0.09 .
Household Size	-0.36	0.52	-0.7	0.49
Market Distance	-1.45	1.37	-1.06	0.29
Population Density	-3.12	1.41	-2.22	0.03 *
12 − month SPI	-0.11	0.42	-0.26	0.8
Critical Food Shortage	0.37	0.25	1.5	0.13
HFIAS	1.78	0.99	1.79	0.07 .
Total Ag Production	2.09	1.49	1.4	0.16
Net Business Income	1.32	1.44	0.92	0.36
Wage Income	1.91	1.69	1.13	0.26
Nonfood Spending	0.93	1.38	0.67	0.5
Food Spending	-0.04	0.9	-0.05	0.96

Table C.7: Regression for nonfood NTFP with geographic variables measured at a 10km buffer around each household. A p-value of less than 0.001 is indicated with three stars (***), a p-value of less than 0.01 is indicated with two stars (**), a p-value of less than 0.05 is indicated with one star (*), and a p-value of less than 0.1 is indicated with a period (.).

	Estimate	Std. Error	z value	Pr(<|z|)
(Intercept)	-2.32	1.15	-2.02	0.04 *
Area Protected	-2.12	0.86	-2.46	0.01 *
Forest Cover	-0.95	1.09	-0.87	0.38
Grassland	0.96	1.18	0.81	0.42

Head Gender	0.37	0.29	1.28	0.2
Age	-0.48	0.72	-0.67	0.51
Years of Schooling	0.18	0.82	0.22	0.82
Literacy	-1.23	0.74	-1.66	0.1 .
Household Size	-0.36	0.52	-0.7	0.49
Market Distance	-1.79	1.3	-1.37	0.17
Population Density	-3.07	1.36	-2.26	0.02 *
12 – month SPI	-0.07	0.4	-0.18	0.86
Critical Food Shortage	0.37	0.25	1.51	0.13
HFIAS	1.82	0.99	1.83	0.07 .
Total Ag Production	2.13	1.49	1.43	0.15
Net Business Income	1.33	1.44	0.92	0.36
Wage Income	1.93	1.71	1.13	0.26
Nonfood Spending	0.89	1.39	0.64	0.52
Food Spending	-0.02	0.9	-0.03	0.98

Table C.8: Regression for nonfood NTFP with geographic variables measured at a 15km buffer around each household. A p-value of less than 0.001 is indicated with three stars (***), a p-value of less than 0.01 is indicated with two stars (**), a p-value of less than 0.05 is indicated with one star (*), and a p-value of less than 0.1 is indicated with a period (.).

Appendix D: Appendix D

age	-0.02^{***}
	(0.00)
birth_order	0.01^{***}
	(0.00)
hhsize	-0.00
	(0.00)
sexFemale	-17.07^{***}
	(1.44)
sexMale	-17.19^{***}
	(1.44)
mother_years_ed	0.03^{***}
	(0.00)
toiletNo Facility	-0.16^{***}
	(0.01)
toiletOther	-0.14^{***}
	(0.03)
toiletPit Latrine	-0.13^{***}
	(0.01)
interview_year	0.01^{***}
	(0.00)
as.factor(calc_birthmonth)2	-0.02
	(0.02)
as.factor(calc_birthmonth)3	0.04^{*}
	(0.02)
as.factor(calc_birthmonth)4	0.03^{*}
	(0.02)
as.factor(calc_birthmonth)5	0.03^{*}
	(0.02)
as.factor(calc_birthmonth)6	0.15^{***}
	(0.02)
as.factor(calc_birthmonth)7	0.11^{***}
	(0.02)
as.factor(calc_birthmonth)8	0.18^{***}
	(0.02)

as.factor(calc_birthmonth)9	0.17***
	(0.02)
as.factor(calc_birthmonth)10	0.23***
	(0.02)
as.factor(calc_birthmonth)11	0.23***
	(0.02)
as.factor(calc_birthmonth)12	0.44***
	(0.02)
head_age	0.00***
	(0.00)
head_sexMale	−0.07***
	(0.01)
wealth_norm	0.54***
	(0.02)
AEZ_newafr.forest.4	−0.11***
	(0.03)
AEZ_newafr.high.7	−0.22***
	(0.03)
AEZ_newnafr.sav.5	0.00
	(0.02)
AEZ_newnafr.subforest.8	0.03
	(0.03)
AEZ_newsafr.subforest.9	0.06*
	(0.03)
AEZ_newseafr.sav.6	−0.17***
	(0.03)
EDF: s(latitude,longitude)	45.17***
	(49.00)
EDF: s(natural):afr.arid.123	3.24***
	(3.74)
EDF: s(natural):afr.forest.4	3.20**
	(3.74)
EDF: s(natural):nafr.sav.5	2.73***
	(3.16)
EDF: s(natural):seafr.sav.6	3.20***
	(3.75)
EDF: s(natural):afr.high.7	2.76***
	(3.20)
EDF: s(natural):nafr.subforest.8	2.00***
	(2.00)
EDF: s(natural):safr.subforest.9	2.97***
	(3.46)
AIC	890428.85
BIC	891421.48

Log Likelihood	-445118.15
Deviance	16.37
Deviance explained	0.48
Dispersion	0.00
R^2	0.11
GCV score	0.00
Num. obs.	221885
Num. smooth terms	8

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

Table D.1: Statistical models

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