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Using Natural Areas and Empowering Women to Buffer Food Security and Nutrition from Climate Shocks

Evidence from Ghana, Zambia, and Bangladesh

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INTERNATIONAL FOOD POLICY RESEARCH INSTITUTE

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ABSTRACT

As climate change makes precipitation shocks more common, policymakers are becoming increasingly interested in protecting food systems and nutrition outcomes from the damaging effects of droughts and floods (Wheeler and von Braun, 2013). Increasing the resilience of nutrition and food security outcomes is especially critical throughout agrarian parts of the developing world, where human subsistence and well-being are directly affected by local rainfall. In this study, we use data from Feed the Future datasets from Ghana, Zambia, and Bangladesh to examine the impact of precipitation extremes on food security as well as the role of natural land cover and women's empowerment in creating resilience. We first model the effects of extreme rainfall on indicators of nutrition and food security, and then examine whether women's empowerment and environmental land cover types can dampen the effects of rainfall shocks on these food security and nutrition outcomes. Our results find that there is a strong association between extreme precipitation and household hunger. Further, they suggest that in certain contexts land cover types providing ecosystem services can reduce household hunger scores, that empowering women can mitigate the effects of precipitation shocks, and that there may be an interactive effect between ecosystem service availability and women's empowerment.

Keywords: Climate, gender and nutrition

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1. INTRODUCTION

There is a well-established relationship between precipitation shocks and poor child nutrition outcomes in the developing world (Cornwell and Inder, 2015; Maccini and Yang, 2009; Shively, 2017; Tiwari et al., 2017). Similarly, food security, although sometimes less clearly defined than nutrition, has been shown to be greatly affected by climate and precipitation in multiple countries (Afifi et al., 2014; Hillbruner and Egan, 2008; Niles and Brown, 2017; Rosegrant et al., 2009; Warner and Afifi, 2014). Given that climate shocks are to some extent inevitable but also likely to become more severe in many places as a result of climate change (IPCC, 2013), it is critical that policymakers explore how to mitigate the effects of extreme precipitation on nutrition and food security outcomes.

The Feed the Future surveys were designed to measure multiple indices of food security and nutrition, such as the household hunger score and child anthropometry, as well as critical co-variates such as household wealth, agricultural practices and women's empowerment (Feed The Future, 2011). Additionally, some of the Feed the Future surveys collected GPS points for every household, facilitating the extraction of environmental data at the location of each household to explore relationships between household characteristics, environmental characteristics, and nutrition outcomes (Brown et al., 2014).

We utilized geolocated Feed the Future surveys from Ghana (2012), Zambia (2012) and Bangladesh (2011, 2015) to examine whether there is an observable impact of rainfall shocks on child nutrition and household food security. Additionally, we test for whether factors such as the availability of natural land cover and the empowerment of women can support food security and mitigate the impacts of precipitation shocks.

Ecosystem Services

Ecosystem services are fundamental to human well-being (Haines-Young and Potschin, 2010). They are quite varied, and according to the Millennium Ecosystem Assessment, they can be grouped into four categories: (1) Provisioning Services, which are products such as food, fuel and fiber that are sourced directly from nature, (2) Regulating Services, which provide services such as clean water, climate regulation, and crop pollination, (3) Cultural Services, which create a sense of inspiration and heritage and play a role in humanity's spiritual and religious values; and (4) Supporting Services, such as soil formation and the creation of oxygen, which occur across broad time scales and facilitate all other services, (Millenium Ecosystem Assessment, 2005).

A useful framework for analyzing ecosystem services in relation to land cover is that of "bundles" (Raudsepp-Hearne et al., 2010). According to this framework, different land cover types and land uses provide distinct groups, or bundles, of ecosystem services. For example, water bodies provide fish and drinking water, agricultural areas provide soil for cultivation and crops, and forests provide soil formation, clean water, pollinators, and wild foods. This framework is useful for analyzing tradeoff at landscape scales (Raudsepp-Hearne et al., 2010).

We rely on this framework when using land cover classes as a proxy for the availability of various ecosystem services. Specifically, we posit that forests and non-forest natural areas such as shrublands and grasslands can provide both provisioning services such as wild foods as well as regulating services that improve agriculture, such as pollination, pest regulation and soil formation. These land cover types are thus proxies for ecosystem services that contribute to food security and nutrition.

Provisioning Services

Forests and other natural areas play a large role in the diets of rural and agrarian people around the world. A large body of literature exists demonstrating the value of non-timber forest products for rural and agrarian people, as sources of both food and income (Assogbadjo et al., 2012; Kaimowitz, 2003). Some forest products, such as Shea, are collected from local forests, processed regionally, and exported to global markets. Many forest products, however, are consumed locally, and play a significant role in supporting nutrition. These products are especially valuable for more marginalized members of society such as women, who may lack access to agricultural inputs and livestock or may be left with the lowest quality agricultural land in an area (Agarwala et al., 2014). Because forests and other non-agricultural areas are often held as "commons" throughout much of Africa and the developing world (Wily, 2008), they are where the poorest members of rural communities go for both food and products to sell (Pouliot and Treue, 2013). Foods such as bushmeat, fish, insects, wild plants, nuts, seeds, and honey are also especially vital during times of climate-related stress and agricultural failure. Many forest food products are dispreferred, but known by local people to be edible. People rely on these “famine foods” most during hungry seasons and during years when agricultural output is low (Mavengahama et al., 2013; Muller and Almedom, 2008).

Regulating Services

In addition to providing wild foods and other NTFP that can directly improve people’s diets, natural areas also provide ecosystem services that can improve agricultural outcomes and, critically, make agriculture more resilient to climate shocks. Environmental areas are key for agriculture crops that require pollinators, and these crops provide many different micronutrients, as well as much of the Vitamin A in low-income countries (Smith et al., 2015). Crops grown near forests have a greater variety of available pollinator species (Klein, 2009), which has been linked to higher yields (Hoehn et al., 2008). Many forests and grasslands that are habitat for pollinator species are also habitat for species that provide pest regulation. Forests in particular have been found to contribute to pest regulation from Cameroon to Costa Rica (Gidoin et al., 2014; Karp et al., 2013). Additionally, forests and other natural areas contribute to water regulation, often retaining soil moisture during dry periods (De Groot et al., 2002; Wang et al., 2013), or facilitating water runoff and decreasing flooding during wet periods (Keesstra et al., 2018).

Ecosystem Services at Across Multiple Scales

Increasingly, researchers have examined how these products contribute to human nutrition at multiple scales (Myers et al., 2013). Much interesting work has been done at smaller scales using primary data and observing exactly what food sources and nutrients are sourced from forests (Golden et al., 2016). This work often emphasizes the vast increase in dietary diversity that wild foods can provide over only agricultural foods (DeClerck et al., 2011). In areas that might grow at most a dozen crops over the course of a year, natural areas can provide hundreds of different plant and animal species as food sources, each offering a diverse array of micronutrients for humans (Remans et al., 2012; Uusiku et al., 2010). These resources are vital for human nutrition– one study found that losing access to bushmeat would increase anemia by 30% in parts of Madagascar (Golden et al., 2011).

Drawing on these local analyses, other researchers study the linkages between natural areas and human nutrition at larger scales using secondary data. Most commonly, some indicator of land cover or environmental health is derived from satellite imagery and combined with geocoded household surveys containing data on nutrition and food security outcomes, such as dietary diversity or anthropometry (Brown et al., 2014). Such work has found a link between more forest cover and lower rates of stunting in Malawi (Johnson et al., 2013); and an association between greater vegetation productivity and lower infant mortality (Brown et al., 2014); as well as linkages between increased dietary diversity and increased forest cover across 21 African countries (Ickowitz et al., 2014).

In addition to demonstrating how environmental indicators can be associated with positive outcomes, this research has also demonstrated how precipitation shocks are associated with worsened health and nutrition outcomes (Cornwell and Inder, 2015; Thai and Falaris, 2014). Precipitation levels have been shown to affect stunting, an indicator of chronic long-term malnutrition, as well as wasting, an indicator of acute short term malnutrition. This connection has also been demonstrated at multiple time scales – children who spend the first few years of their lives during dryer-than-normal years will be affected (Maccini and Yang, 2009), and children born during annual dry seasons are also more likely to be underweight (Tiwari et al., 2017). At the same time, high levels of precipitation can lead to flooding and crop spoiling, and have been associated with worsened rates of stunting in Bangladesh (Rodriguez-Llanes et al., 2011). However, few studies have examined the interaction of ecosystem services and climate stress to test the hypothesis that forests and other natural areas can mitigate the effects of climate shocks. Despite this lack of research at large scales, research at small scales using primary data has shown how natural food sources can improve the resilience of food security and nutrition outcomes during times of climate stress (Robledo et al., 2012). Increasingly, researchers are calling for more research at large, multi-national scales and emphasizing the predilection towards case studies as a flaw in the literature on the environment and human well-being (Reed et al., 2016).

Women's Empowerment

Empowering women has been shown to improve nutrition outcomes, as women often devote more household resources to child care (Choudhury et al., 2000; Jin and Iannotti, 2014) and focus on growing more nutritious crops (Howard, 2003), when given the opportunity. Women's empowerment has been associated with child dietary diversity and maternal BMI in Benin (Alaofè et al., 2017), and a literature review of women's empowerment across all of South Asia similarly found that women's empowerment is related with more healthy outcomes in terms of child anthropometry (Cunningham et al., 2015).

To better understand the role that women's empowerment can play in food security and nutrition outcomes, an indicator called the Women's Empowerment in Agriculture Index was developed to support USAID's Feet the Future projects (Alkire et al., 2013). The indicator looks at empowerment of women across five domains, such as decision-making in agricultural production and control of productive resources, control of income, leadership in the community and time allocation as well as the gap between women's empowerment and men's empowerment within households (Alkire et al., 2013). Improvements in women's empowerment as measured by this indicator have been associated weakly with improved nutrition and strongly with improved dietary diversity in Ghana (Malapit and Quisumbing, 2015) as well as with calorie availability and dietary diversity in Bangladesh (Sraboni et al., 2014). Furthermore, the indicator has been analyzed as a possible mitigating factor in other determinants of poor nutrition and food security. For example, the indicator was found to be related to the mitigation of the effects of low production diversity on maternal and child nutrition in Nepal (Malapit et al., 2015).

Women's Empowerment and Ecosystem Services

This analysis is further informed by literature that shows that women's empowerment and ecosystem services are not independent. Often women spend more time gathering natural products than men as both a food source and income source (Kassa and Yigezu, 2015). The food and income from non-timber forest products (NTFPs) gathered by women are, in turn, more likely to be channeled into child care. Additionally, in cases where women are not empowered through means such as wage labor or agricultural production, provisioning ecosystem services such as NTFPs can provide a way for women to obtain food and other resources and even goods that can be sold to generate income (Agarwala et al., 2014; Naughton et al., 2017).

2. METHODS – INDICATORS AND ANALYSIS

For this analysis we used Feed the Future datasets from Ghana, Bangladesh, and southeast Zambia, taking care to properly account for effects of spatial autocorrelation. The survey from Ghana was nationally representative from the year 2011 and had 1612 households as well as 1166 child nutrition observations. The survey from Bangladesh was a nationally representative panel survey of 2794 households from the years 2012 and 2015, as well as 892 child nutrition observations from across both years. Finally, the survey from Zambia was from the year 2011, included 745 households and 644 child health observations, and was only conducted within the Zone of Influence in rural areas near the city of Chipata. In each country, we first tested for relationships between rainfall deficits and worsened nutrition and food security outcomes. Then, for outcomes which were shown to be significantly affected by rainfall deficits in a given country, we further tested for the mitigating effects of land cover types providing ecosystem services, women's empowerment, as well as possible interactions between women's empowerment and natural land cover types.

Indicators

To look at associations between precipitation deficits and malnutrition and food security as well as the role that ecosystem services or women's empowerment could play in buffering these effects, we relied on several different indicators to approximate relevant outcome variables, predictor variables and control variables.

Outcome Variables

For a child's nutrition status, we looked at stunting in terms of the Z-score for that child's height for their age (Lewit and Kerrebrock, 1997). Stunting is typically examined only for children less than 60 months of age, with any child having a Z-score of less than -2 being defined as stunted and any child with a Z-score less than -3 being defined as severely stunted. Measuring and mitigating stunting is important because it can have long-term effects on an individual's educational outcomes, adult income, and disease risk (Badham and Sweet, 2010; Dewey and Begum, 2011). Rates of stunting have been shown to be significantly related to environmental quality (Johnson et al., 2013), as well as women's empowerment (Malapit et al., 2015). For the Bangladesh and Zambia datasets, Z-scores were already provided by IFPRI, while for the Ghana dataset, they were calculated using reference tables from the WHO.

The other outcome we examined in each country was the household hunger score (HHS), a common indicator of household food security. The HHS consists of three questions about a household's experience of not having adequate food supplies, in terms of going to sleep hungry, going for periods without eating, or not having any food in the home over the previous month. Aggregating a households reports of frequency of these experiences yields a score from 0 to 6, where a 0 means that the household has not had any of the three experiences and 6 means that a household has frequently had all three experiences (Ballard, 2011; Jones et al., 2013). The HHS grew out of validations of the Household Food Insecurity and Access Score (HFIAS), which consisted of 9 questions (Deitchler et al., 2010). Today, the creators of the HFIAS now recommend the HHS, as they believe it has the highest potential to be internally, externally and cross-culturally valid (Jones et al., 2013). While it is somewhat lacking in nuance, it is designed to be rapidly applicable at the household level to assess the locations and characteristics of households that are food insecure and was developed through a decade of exploratory, theoretic and evidence-based research and later validation (Deitchler et al., 2010). One criticism of the HHS as food security metric is that it measures hunger more than food security per se (Jones et al., 2013). The three HHS questions were asked in all three Feed the Future datasets that we used in our analysis.

Predictor Variables

To measure precipitation deficits, we calculated the Standardized Precipitation Index (SPI) using the Climate Hazards Group InfraRed Precipitation with Station (CHIRPS) data (Funk et al., 2015). The SPI for a given location is similar to a Z-score, although because rainfall is not normally distributed, the distribution of historical rainfall is transformed from a gamma distribution before calculating the score (Guttman, 1999). The SPI can be calculated for a number of different time windows, and for our analysis we used the 24-month SPI, as rainfall deficits over shorter periods – such as six or twelve months – are less likely to have a noticeable impact on human food security or nutrition. Critically, for each of the countries analyzed, there was significant enough variation in SPI to facilitate analyses.

To measure the availability of both provisioning and regulating ecosystem services, we examined the presence of forest cover and other natural land cover types, as many ecosystem services come in "bundles" associated with specific land cover types (Raudsepp-Hearne et al., 2010). Data was extracted using Google Earth Engine from the European Space Agency Climate Change Initiative (ESA CCI) land cover dataset (Defourny et al., 2017). Because the ESA CCI data product is annualized, we were able to extract land cover for the year that a given survey was conducted. Land cover types classed as providing ecosystem services included forests, which were defined as any land cover type with greater than 15% tree cover, including broadleaved, needleleaved, evergreen, deciduous, and flooded areas. Other natural areas classed as providing ecosystem services included categories that were non-agricultural, non-urban and non-forests, such as shrubland, grassland, herbaceous and sparsely vegetated areas with less than 15% tree cover. For each household, we calculated the percent of pixels within 7.5.km that fell into any of the forest land cover types or other natural land cover types.

As a metric of women's empowerment, we used the uncensored empowerment scores that are precursors to calculating the Women's Empowerment in Agriculture Index (WEAI). The WEAI was a flagship indicator of the Feed the Future surveys, and was therefore provided for each household in the dataset. Specifically, we used the five domains of empowerment (5DE) sub-indicator for the women in a given household, which measures whether women are empowered in (1) decisions about agricultural production, (2) access to and decision-making power about productive resources, (3) control of use of income, (4) leadership in the community, and (5) time allocation (Alkire et al., 2013).

Control Variables

To better assess the relationship between precipitation, nutrition and food security, ecosystem service provision, and women's empowerment, several other geographic and household variables should be controlled for, as they can affect both the predictor and outcome variables and thus models can have endogeneity issues when these variables are not controlled for.

A household's wealth can correlate with food security and nutrition, as well as ecosystem service availability and women's empowerment. Thus, it is an important variable to control for. Because there was no uniform measure of income or expenditures across the three surveys, we developed an index of household wealth by conducting a Principal Component Analysis (PCA) on the household's assets and other indicators of wealth (Vyas and Kumaranayake, 2006). For each country, the first principal component explained a large proportion of the variance (68.46% in Bangladesh, 70.81% of the variance in Zambia, and 65.12% of the variance in Ghana). The assets we used varied by country, and are summarized in Appendix 1.

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 number of workers and dependents in a household. Similarly, for regressions with child nutrition as the outcome variable, we included relevant co-variates such as the child's age, gender, birth order, and the number of siblings born within 24 months of the child. Because some datasets did not have data on every household or individual characteristic (i.e., the Zambia Feed the Future survey did not collect data on the religion of the household head), in some cases not all household or individual co-variates could be included.

In addition to household and individual characteristics, two geographic variables that we accounted for at the household level were population density and market distance. Both were extracted using Google Earth Engine. For population density, we used the World Pop dataset (Tatem, 2017). Because it is available for five-year intervals, for Feed the Future surveys conducted in 2011 and 2012, we used population estimates for 2010, and for surveys conducted in 2015, we used the estimates for 2015. For a metric of urbanization and market access, we used the Time Travel to Major Cities dataset published by the World Bank (Uchida and Nelson, 2008)

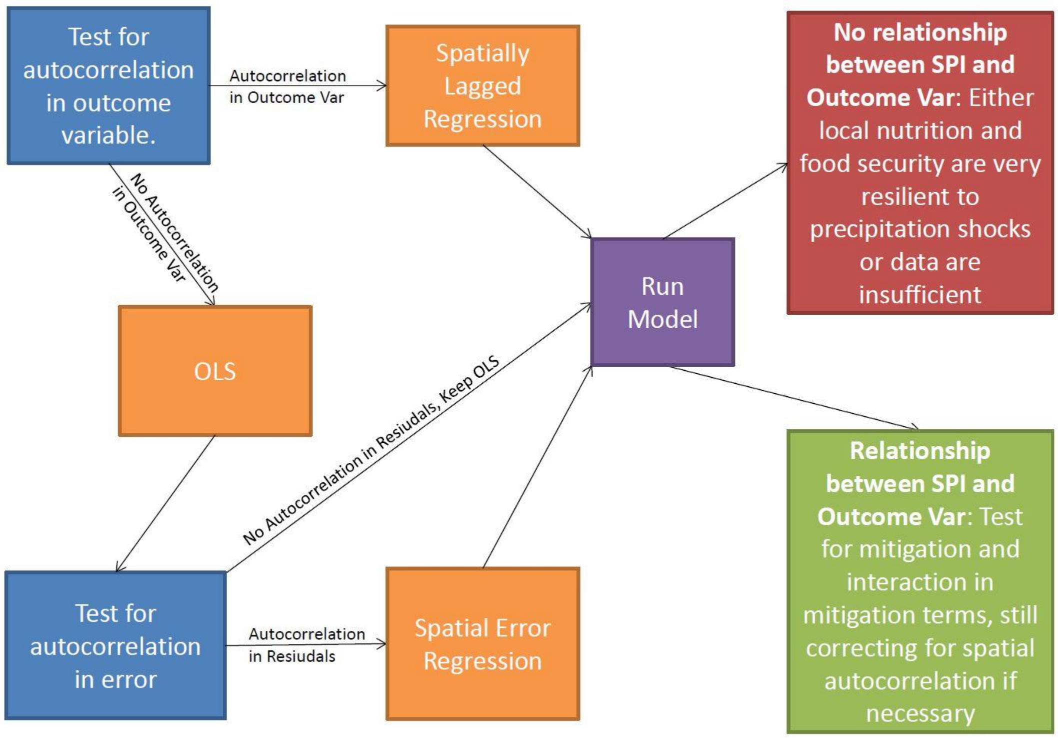
Finally, for only Bangladesh, an indicator of irrigation as well as a dummy variable for the year of the survey was included. This is because irrigated agriculture is common in Bangladesh and can make households less affected by rainfall shocks and because the Bangladesh survey was conducted over two separate waves for each household. Our metric for prevalence of irrigation for a household was the percent of the area of rice cultivation that was irrigated, which was included in the Feed the Future dataset.

Analysis

For each country, we first tested to see if there was a relationship between the 24-month SPI and either child stunting or a household's hunger score. For countries and outcomes for which there was a significant relationship between rainfall patterns and the given outcome, we used separate regressions testing for whether ecosystem services or women's empowerment could mitigate the effects of precipitation shocks. To test for mitigation from a statistical perspective, we used a similar approach as Shively in a recent paper on infrastructure mitigating the effects of low precipitation on child nutrition (Shively, 2017). We ran two separate regressions: one without the mitigating variable, and a second one with the mitigating variable. If, in the second regression, the mitigating variable is statistically significant, and the significance of the predictor variable that we are seeking to mitigate is reduced, then we can say that the mitigating variable has reduced the effect of the predictor variable on the outcome variables. Finally, we then tested for an interaction effect between the ecosystem services variable and the women's empowerment variable.

When running these regressions, we took care to control for spatial autocorrelation. Many of the variables involved in this analysis, including nutrition, food security, precipitation deficits, and land cover, have significant spatial autocorrelation. Without controlling for this, a model can have substantial bias and many predictor variables appear to be more significant than they actually are (Ward and Gleditsch, 2008). Thus, before running models, we first conducted a Moran's I test on the outcome variable. For models where the outcome variable was significant, we ran a spatial-lag regression. If the Moran's I test on the outcome variable was not significant, we instead ran an OLS regression, but also checked the error terms from that regression to ensure that the error terms did not have any autocorrelation as well. The workflow of our approach can be summarized in the following flowchart.

Figure 2.1 Summary of Workflow for Accounting for Spatial Autocorrelation



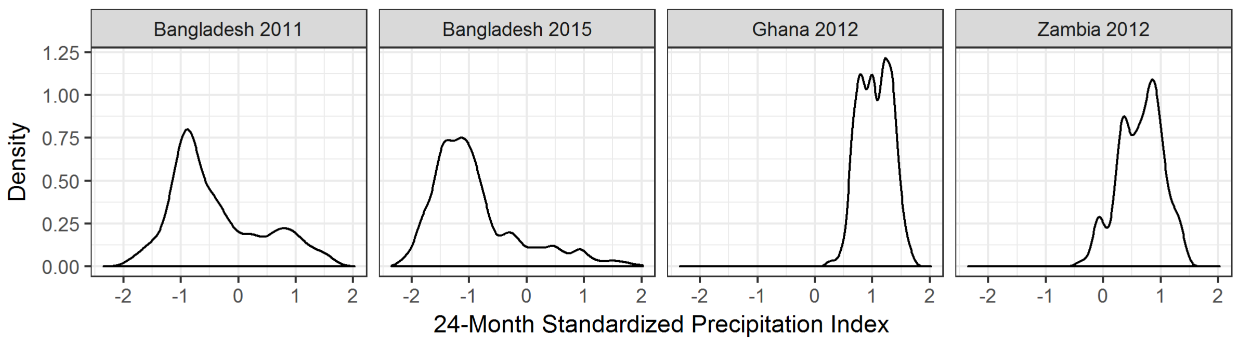
Regressions were run in R version 3.3.1, and Spatially Lagged Regressions, Spatial Error Regressions and Moran's I tests were run using the spdep package (Bivand et al., 2005)

3. RESULTS

Descriptive Statistics

To provide context to the models and facilitate the interpretation of model results, we here give the probability density graphs, probability mass functions, and summary statistics of several of the key statistics in the regressions. Additionally, summary statistics are given for every variable included in the regressions in the tables in Appendix 3.

Figure 3.1 Probability Density Function of the Standardized Precipitation Index

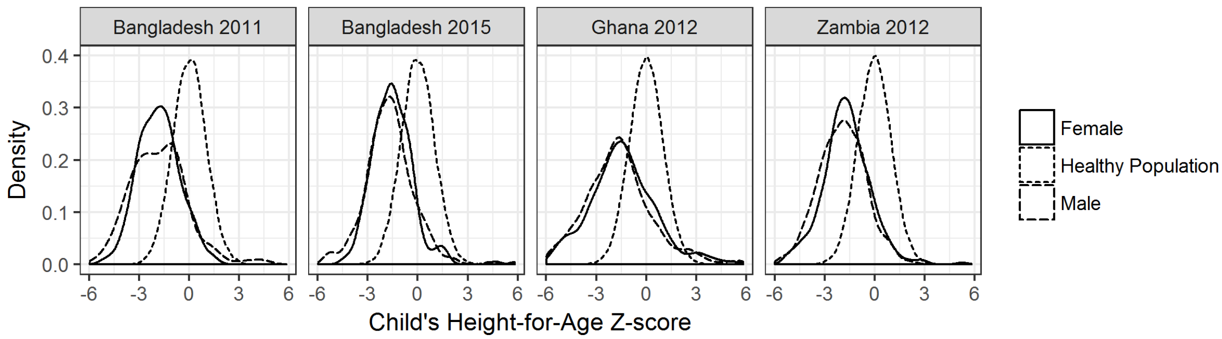


For each country, the SPI values ranged over at least two points, providing ample variation in each regression. SPI scores in Bangladesh varied most significantly, from less than -2, signaling drought, to 2, signaling abnormally high levels of rainfall. In both 2011 and 2015, the majority of households had less rainfall than the long-term norm. For Zambia and Ghana, none of the households was experiencing drought at the time of the survey, although the sample of households did provide a range from a normal or near-normal period of precipitation to households experiencing a substantially wet year. These SPI values should be interpreted in the context of the long-term average from which they were derived. The table below gives the distribution of average annual rainfall across all the households in the three countries in millimeters. Bangladesh receives significantly more rainfall than Ghana or Zambia, with the driest household in Bangladesh receiving more rainfall than wettest household in Ghana. Unsurprisingly, land cover varies significantly across these countries: an ANOVA test of between-country differences in rates of natural land cover has an extremely significant p-value of $<2 \times 10^{-16}$.

Table 3.1 Summary of Annual Rainfall Levels by Country (mm)

Survey Country	Mean	Standard Deviation	Max	Min
Bangladesh	2300	670	5100	1500
Ghana	1100	110	1400	910
Zambia	970	190	1600	560

Figure 3.2 Probability Density Function of Child's Height-for-Age Z scores

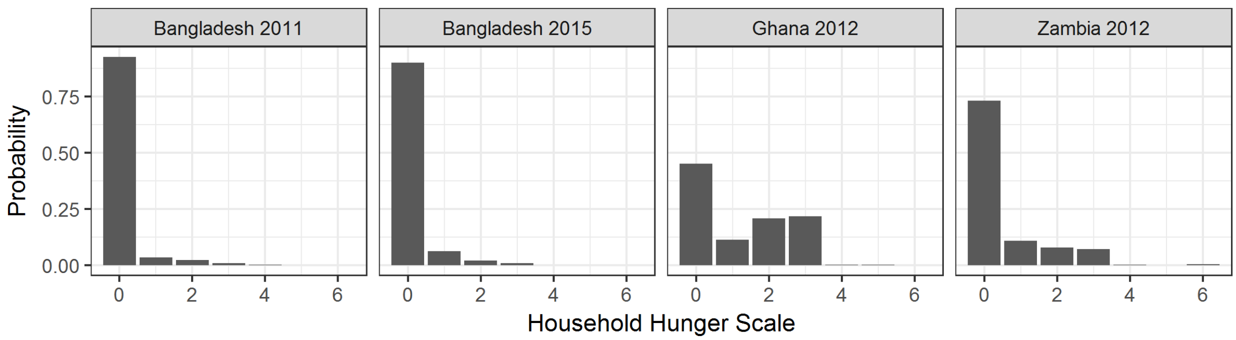


The distributions of Z-score by gender of the children compared to a healthy population of children are shown. Additionally, the table below gives the percentage of male and female children stunted for each survey, as well as the p-value of an ANOVA test for whether male and female height-for-age Z-scores were significantly different. In this table, stunting is defined as a child having a height-for-age z-score of less than -2. There is some evidence that male and female children have significantly different z-scores in Ghana, and strong evidence that they have significantly different scores in Zambia. Further summary statistics for the distributions are given in Appendix 2.

Table 3.2 Rates of Stunting by Survey and Gender

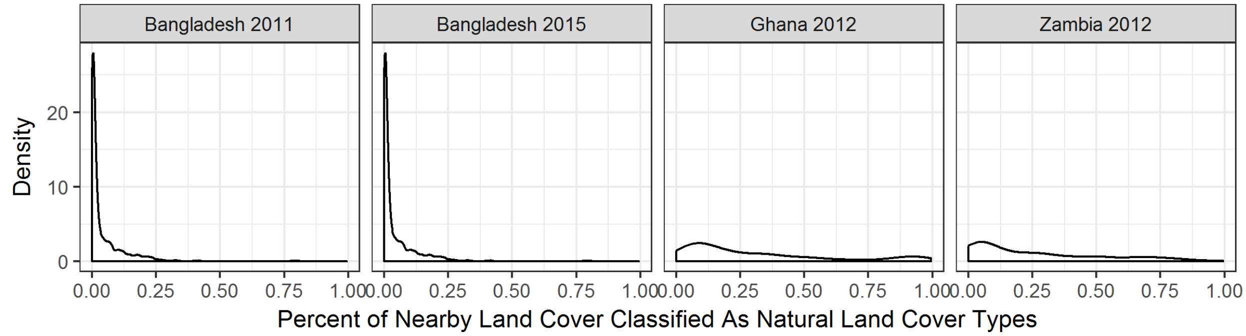
Survey Country and Year	Percent of Children Stunted by Gender			P-value of ANOVA test
	Male	Female	Both	
Bangladesh 2011	47%	46%	47%	0.91
Bangladesh 2015	40%	37%	39%	0.27
Ghana 2012	42%	38%	40%	0.052
Zambia 2012	47%	41%	44%	0.016

Figure 3.3 Probability Mass Function of the Household Hunger Scale



In Bangladesh, 7.3% of households were experiencing hunger in 2011 and 9.8% were experiencing hunger in 2015, with progressively fewer households at each level of the household hunger scale. Ghana and Zambia, on the other hand, had more variable scores, with many households scoring some level of hunger but towards the lower end of the scale. Overall, Ghana had the worst household hunger scores across the three countries. A breakdown of the percentage of households with each hunger score is given in Appendix 2.

Figure 3.4 Probabiltiy Density Function of the Percent of Nearby Land Cover Classified as Natural Land Cover Types

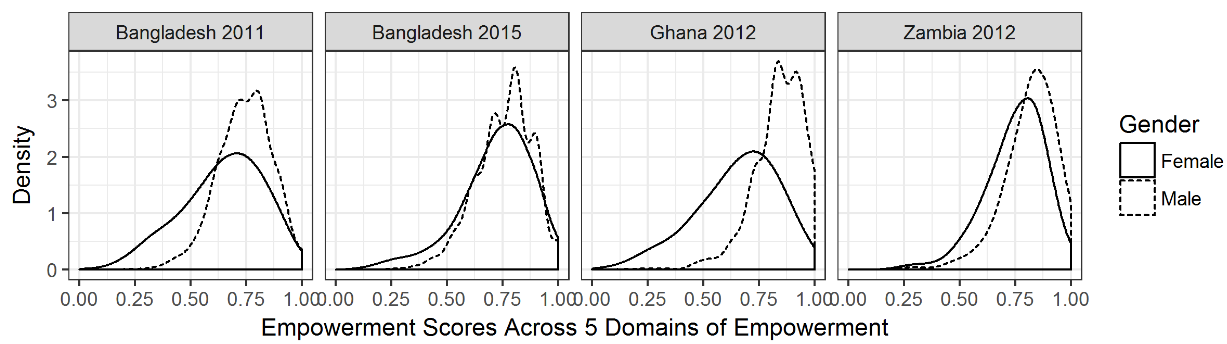


Both Ghana and Zambia are associated with a wide distribution in the share of natural land cover over total, while Bangladesh had few areas with large amounts of natural land cover. The table below also shows the mean and standard deviation for nearby natural land cover for each household, as well as the percentage of households with no natural land cover for each survey.

Table 3.3 Percent of Nearby Areas Classified as Natural Land Cover by Survey

Survey Country and Year	Mean	Standard Deviation	Percent of Households with None
Bangladesh 2011	5.4%	9.2%	15%
Bangladesh 2015	5.4%	9.2%	15%
Ghana 2012	52%	32%	0.062%
Zambia 2012	32%	29%	0.0%

Figure 3.5 Probabiltiy Density Function of Empowerment Scores across Five Domains of Empowerment



For these scores, 1 signifies a fully empowered individual. Women's empowerment varied significantly within and between the countries, and was always lower than Men's empowerment in those countries. This is especially evident for less-empowered individuals, as the majority of individuals with empowerment scores less than 0.5 were women in every country. Ghana had the greatest gap between women's and men's empowerment, and women's empowerment improved noticeably between 2011 and 2015 in Bangladesh.

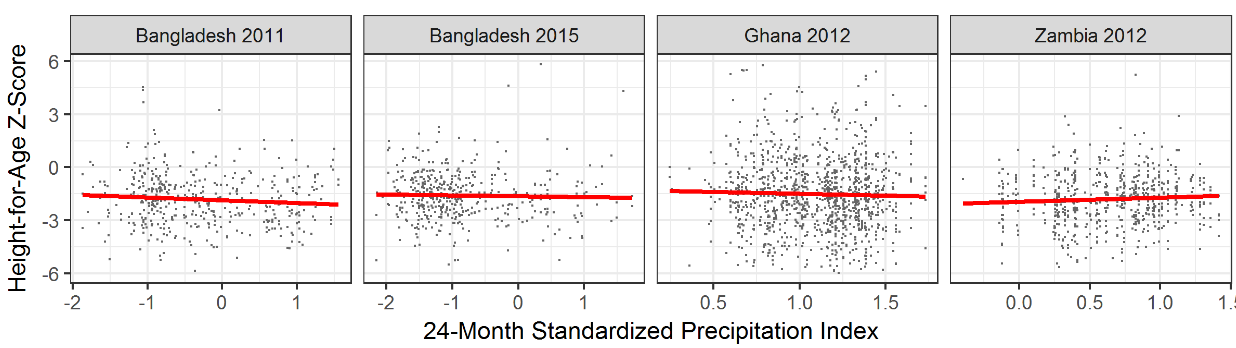
Table 3.4 Summary of Empowerment Scores by Survey and Gender

Survey Country and Year	Mean Empowerment Score		
	Male	Female	Both
Bangladesh 2011	0.74	0.64	0.70
Bangladesh 2015	0.76	0.72	0.74
Ghana 2012	0.84	0.65	0.75
Zambia 2012	0.82	0.75	0.79

Bivariate Descriptive Statistics

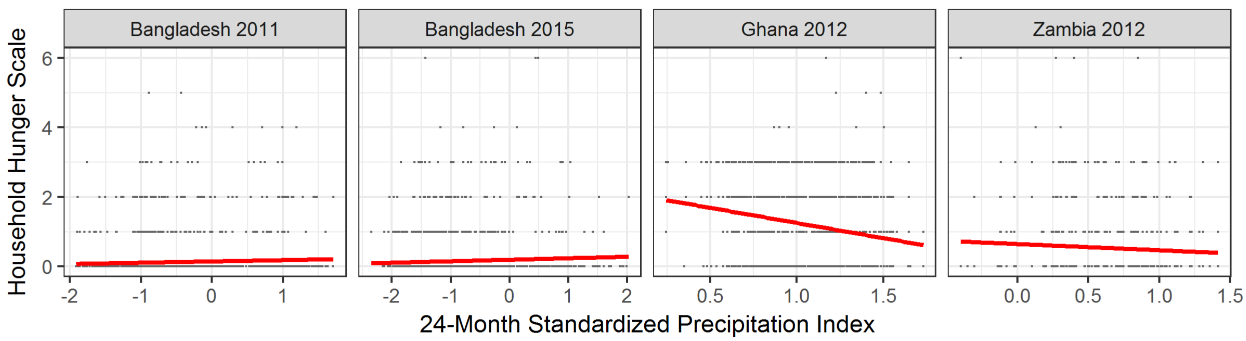
A key premise of this paper is that rainfall variation from the long-term norm is associated with food security and nutrition outcomes. Below we show bivariate plots of the 24-month Standardized Precipitation Index with (1) children's height-for-age Z-score and (2) the Household Hunger Score, with non-parametric trend lines.

Figure 3.6 Height-For-Age Z Scores vs 24-Month Standardized Precipitation Index



We find surprisingly little association between the 24-month SPI and children's height-for-age Z-scores. In Zambia, there is a somewhat positive association between the two, while in both Bangladesh surveys and in Ghana the two variables have a negative association. While the relationship is very weak, with all of the trend lines nearly horizontal, the direction of the association is consistent with the findings for the household hunger score in Zambia and Bangladesh.

Figure 3.7 Household Hunger Score vs 24-Month Standardized Precipitation Index



The Household Hunger Score is more strongly associated with the 24-month SPI than child nutritional outcomes. This is especially true in Ghana, where higher SPI scores are clearly associated with lower hunger scores. In the two Bangladesh surveys and in Zambia there is also a relationship, although not as strong. In Bangladesh, increased rainfall is associated with higher rates of hunger, while in Ghana and Zambia, increased rainfall is associated with lower rates of hunger. This implies that low levels of rainfall are associated with worse hunger scores in Ghana and Zambia, while high precipitation is associated with worse hunger scores in Bangladesh. We will explore these relationships further in multivariate regressions in the next section.

Modeling Rainfall Deficits and Food Security

We ran several regressions for each country, attempting to keep approximately the same variables and methodology for each country. The results for each regression as well as Moran's I test and Chow test results are presented in Appendix 3.

Ghana

For Ghana, we began by testing for spatial autocorrelation in children's Z-scores with a Moran's I test. The Moran's I statistic was 0.013 and the p-value was 0.000008, signifying that there was significant autocorrelation and therefore a spatial lag regression was most appropriate. This model found the twenty-four month SPI had an insignificant effect on children's Z-scores, with a p-value of 0.97. The most significant variables were individual-level variables, such as the child's age, birth order, and the number of siblings born within 24 months. Additionally, increases in market distance as well as literate household heads were found to be significantly associated with higher Z-scores while household heads with no religion were associated with significantly worse Z-scores. Because there was no clear association between precipitation trends and stunting, we did not run further models to look for the mitigating effects of ecosystem services or women's empowerment.

In addition to height-for-age Z-scores, we also looked at the effects of precipitation trends on the reported household hunger scores (HHS). The HHS for Ghana was also found to have very significant autocorrelation, with a Moran's I statistic of 0.089 and an extremely significant p-value of 2.2×10^{-16}, again necessitating a spatial lag regression.

The first regression testing for a significant association between precipitation trends and household hunger found that an increase in rainfall over the previous 24 months significantly (p=0.003) decreased the household's hunger score. The other significant variables included the household's size, whether the household head was literate, the number of dependents and workers, as well as whether the household was urban or rural.

Because there was a significant relationship between precipitation trends and HHS, we then tested for the role of ecosystem services and women's empowerment in mitigating that relationship. We ran regressions similar to the first one, but included terms for the percent of nearby land cover that was a natural land cover type, the women's empowerment score, and any interaction between natural land cover and women's empowerment. While none of the terms were very significant, natural land cover types were somewhat associated (p=0.050) with worse hunger scores and women's empowerment was somewhat associated (p=0.070) with better hunger scores.

Zambia

In Zambia, we tested for a relationship between children's height-for-age Z-Scores and SPI, as well as between HHS and SPI. For children's height-for-age Z-scores, we found very significant spatial autocorrelation, with a Moran's I statistic of 0.017 and a p-value of 0.000006, and therefore used a spatial lag model. For this model, we found no relationship between the SPI and children's Z-scores, although individual factors such as the child's age and gender, as well as the household head's gender and education levels were found to be significant.

In testing for spatial autocorrelation in reported HHS, we found no significant autocorrelation (Moran's I statistic = -0.0014, p-value=0.51), and so we used a simple OLS regression in looking at the relationship between precipitation and HHS. To ensure that there were no issues of spatial autocorrelation, we tested the error terms of each regression for spatial autocorrelation, each time finding none. Similar to Ghana, we found that an increase in SPI significantly reduced a household's hunger score. In addition to SPI, we found that greater education of the household head was associated with a lower hunger score.

Having found a relationship between low rainfall and an increased hunger score, we then tested for whether natural land cover types could moderate this relationship. Adding this parameter to the regression showed that natural land cover was significantly associated with reduced hunger scores, although the significance of SPI term was not reduced, providing no evidence of mitigation effects. We further tested for whether women's empowerment could moderate SPI's effect on household hunger. While women's empowerment had a negative coefficient meaning that households with more empowered women had less hunger, the term was not significant (p=0.70).

Finally, we tested for an interaction between women's empowerment and natural land cover types. In this case, there was a significant interaction (p=0.017) with a negative coefficient. Furthermore, the magnitude of the coefficient was greater than the coefficients for the individual terms, showing that in Zambia there is a strong interaction between women's empowerment and natural land cover. This shows that households with empowered women near significant natural land cover have better food security than either of those two factors alone would predict.

Bangladesh

Finally, we ran a similar analysis on the surveys from Bangladesh. However, because the data from Bangladesh involved two separate surveys, we first tested for whether these surveys could be pooled with Chow tests. This test gave an F statistic of 1.4 and p-value of 0.13 for children's height-for-age Z-scores and an F statistic of 1.2 and p-value of 0.29 for the household hunger scores, showing that the coefficients were not significantly different between the first and second round of surveys and that the data could be pooled. Thus, we only included a dummy variable for the year of the survey and did not control for other random effects between years.

We first ran a Moran's I test on children's Z-scores to determine if a spatial lag regression would be necessary, and found that there was somewhat significant spatial autocorrelation (Moran's I = 0.008, p-value= 0.069) and that a spatial lag regression would be necessary. This regression found no significant association between 24-month SPI and child height-for-age Z-scores, although, similar to the Zambia and Ghana cases, individual characteristics and household head education levels were significant predictors of children's Z-scores.

We also found significant spatial autocorrelation for the HHS (Moran's I = 0.014, p-value<2.2 x $^{-16}$), and therefore conducted a spatial lag regression. In contrast to Ghana and Zambia, this regression indicated that an increase in SPI was associated with an increased household hunger score. Households in the year of the second survey, 2015, were modeled to have higher household hunger scores, while increasing household head education and higher numbers of available workers were associated with lower household hunger scores.

In testing for whether land cover types associated with ecosystem services could mitigate the effect of precipitation on household hunger, we found no association with household hunger.

After testing for the effect of ecosystem service availability, we tested for whether women's empowerment could mitigate the effects of precipitation shocks on household hunger. In this regression, we found that a higher individual empowerment score across the five domains of empowerment was significantly associated with lower rates of household hunger. Furthermore, the significance and the coefficient of the 24-month SPI was also somewhat diminished (from a p-value of 0.02 to 0.034 and from a coefficient of 0.22 to 0.20), suggesting that women's empowerment may mitigate some of the effects of low rainfall, although the impact is quite small.

Additionally, we tested for an interaction between these two terms, but found no significant interaction between women's empowerment scores and natural land cover types.

4. DISCUSSION

Our regressions showed no relationship between stunting and the Standardized Precipitation Index (SPI) in any of the countries, although we did find strong linkages between SPI and the household hunger scale in all three of the countries analyzed. Additionally, we found evidence that ecosystem services provided by natural areas in Zambia are related to lower household hunger scores, that empowering women in Bangladesh might have a small effect in mitigating the relationship between SPI and household hunger, and that there is an interaction between natural land cover and women's empowerment in Zambia.

Food Security, Nutrition, and Precipitation

These results around relationships between the 24-month SPI and household hunger scores must be interpreted in light of the observed SPIs and hunger scores for each country. While variation in SPI across space provided some variation in SPI for each country, both Zambia and Ghana had SPI scores that were almost entirely positive, meaning that no households were observed to be experiencing a drought. Rather, the households in these two countries ranged from having experienced two years of normal rainfall in line with the long-term trends to having experienced significantly more abundant rainfall than normal over the previous two years. Thus, our interpretation of the regressions for these two countries should not be that drought worsens hunger, but rather that abundant rainfall ameliorates hunger in these arid countries. In Bangladesh on the other hand, there was a wide distribution of SPI values with a slight predominance of lower SPI values and some households experiencing real drought at the time of the survey. However, because a higher SPI was associated with worse household hunger scores, it seems that ample-to-high rainfall can worsen food security, perhaps due to flooding or higher risk of food spoilage.

The most striking feature of these results is that the household hunger scale was related to SPI in all three countries whereas children's height-for-age Z-scores wasn't. This is especially surprising given previous studies finding linkages between precipitation shocks and rates of stunting, including in Bangladesh (Cornwell and Inder, 2015; Lopez-Carr et al., 2016; Maccini and Yang, 2009; Rodriguez-Llanes et al., 2011). However, in each country, few households had children under five years old (only

14.8% in Bangladesh in 2011, 15% in Bangladesh in 2015, 64.2% in Zambia, and 50.9% in Ghana), meaning that the regressions for stunting relied on data sets of substantially reduced size. Thus, one possible explanation for why no linkages were found between stunting and SPI is that there were not enough data on stunting specifically to show an effect. This could also be an effect of the limited variation in SPI in Zambia and Ghana or the time span that we chose to use (24 months) when examining SPI, as the height of children over two years old could have been affected by rainfall levels earlier than 24 months ago. Therefore, even though we found no linkages in our dataset between low rainfall and child stunting, we would caution against the conclusion that there is no association between rainfall shortages and malnutrition.

Household hunger, on the other hand, appears to be strongly associated with precipitation patterns in all of the countries we examined. There are clear theoretical linkages between precipitation availability and food production in subsistence households, and this research now provides empirical evidence for these linkages. However, the relationship between rainfall and hunger is not consistent in all countries: in Bangladesh worsened hunger scores were associated with more rainfall, whereas in Zambia and Ghana they were associated with less rainfall. This likely has to do with the fact that Bangladesh is already quite humid and receives significant quantities of agricultural water via irrigation. Thus, it is more susceptible to flooding and spoilage, while low SPI levels may not have as significant impacts on nutrition outcomes. Ghana and Zambia, on the other hand, are more arid and depend more on rain-fed crops, and thus are more dramatically affected by droughts and are not as susceptible to flooding.

Mitigating Precipitation Shocks

In addition to showing that household hunger is sensitive to changes in rainfall, our study also highlighted some factors that can contribute to improving hunger outcomes and possibly mitigate the effects of lower precipitation. We found that natural land cover types were associated with lower household hunger scores in Zambia. As discussed previously, these land cover types contribute in demonstrable ways to agricultural production while also providing wild foods directly to some communities. Thus, it is unsurprising that they were associated with better hunger outcomes in some contexts. However, these natural land cover types could not be shown to mitigate the effects of SPI on household hunger and contribute to overall resilience, as including these land cover types did not reduce the effects of SPI. Furthermore, these land cover types were only found to be significant in Zambia.

The other mitigating factor tested was women's empowerment. In Bangladesh, this was shown to improve household hunger scores while simultaneously reducing the explanatory power of SPI in our model. Thus, empowering women may make households resilient against hunger and rainfall shocks and is an outcome that policymakers could support as a contribution to food security.

Finally, our results indicated that there is interaction between available natural land cover and women's empowerment/disempowerment in Zambia. Specifically, the interaction of women's disempowerment and the presence of natural land cover types were shown to lower the household hunger score, suggesting that perhaps ecosystem services such as wild foods or NTFP provided by these areas are a resource to women who are disempowered and cannot ensure food security through conventional avenues such as agriculture or wage labor.

Issues and Caveats

One issue with these regressions was that the asset index was never a significant predictor of stunting or hunger. The index was intended to account for households' income and wealth and was derived from a Principal Components Analysis on the various assets and household materials reported in the household surveys. This is surprising, as there was a significant trend in the different countries and the first principal component always explained at least 65% of the variance observed. However, if the asset index did not fully account for a household's wealth or income, which could in turn affect nutrition and food security outcomes, then the models could be improved by better accounting for this factor.

In these models, we took care to account for spatial autocorrelation. Nearly all of the factors we included in the models would be expected to have some spatial component, as the countries vary significantly over space in terms of climate, nutrition and food security, income, natural land cover, and women's empowerment. Only Zambia had no spatial autocorrelation in the outcome variable or in the error terms for the HHS regressions. This is likely because the households surveyed in Zambia were all in one specific province where the Feed the Future Zone of Impact was located, and therefore were much more uniform and did not vary significantly over space. We also took care to deal with the fact that Bangladesh had two waves by using a Chow test to determine if they should be pooled, and ultimately deciding based on the Chow test to pool the two waves and only use a dummy variable for the year of the survey.

Implications

Overall, our results have significant policy implications. First and foremost, household hunger is very susceptible to rainfall shocks. Excessively high rainfall is associated with higher hunger scores in Bangladesh, while in semi-arid African countries such as Zambia and Ghana even unusually wet years continue to have a reducing effect on hunger. Thus, policymakers should take climate change as a serious threat to food security for subsistence and smallholder farmers, especially if rainfall is predicted to decrease in arid areas or if rainfall is predicted to increase in areas that already receive substantial rainfall. We found that in Zambia, natural land cover types were associated with lower hunger scores and these areas interact with women's empowerment to lower household hunger. In Bangladesh, on the other hand, women's empowerment could buffer household hunger from high rainfall and flooding. Thus, supporting protected areas that permit sustainable use of resources as well as supporting women's empowerment could have real benefits in terms of food security.

5. CONCLUSION

Climate shocks are inevitable – statistically speaking, for any given location on earth, one in 12 years will have a drought with an SPI score of less -2 or an excessively wet year with a score of greater than 2. Thus, it is imperative that we support food systems that are resilient to these shocks. This is even more critical as climate change causes rainfall to deviate from long-term trends and make droughts and floods even more likely in some locations. This research demonstrated that household hunger is strongly affected by rainfall and posits some factors that policymakers can support to improve household hunger scores and increase resilience. We found that areas with more natural land cover types had lower rates of hunger, suggesting that those areas play a real role in contributing to food security for agrarian and subsistence households. Additionally, we found some evidence that empowering women might buffer household hunger from climate shocks. Perhaps most importantly, we found of an interaction between women's empowerment and natural land cover types in some contexts, suggesting that supporting both of these factors can have a synergistic effect, leading to greater food security improvements than either factor alone would predict.

APPENDIX 1: ASSET INDEX VARIABLES

Ghana

The assets index for Ghana included the condition of the house, whether they house was rented, owned or borrowed, how they treated their water, the source they used for light, the source they used for fuel, how they disposed of their garbage, what their roof was constructed from, what their walls were constructed from, the type of toilet the household had, and where the household got their water. These variables came from Module 9, and variables with categorical answers were pivoted into multiple binary variables.

Zambia

The asset index for Zambia included the household's roof material, floor material, exterior wall material, number of rooms in the dwelling, type of toilet, drinking water source, whether the household had electricity, and source of cooking fuel. These variables came from Module D, and variables with categorical answers were pivoted into multiple binary variables.

Bangladesh

The asset index for Bangladesh included the household's total land area, total land rented, what they did with land they owned, whether they owned their house, the number of rooms in the house, whether the house had electricity, the water source, the toilet type, the material of the roof, walls, and floor, the number of cattle, poultry, sheet, goats, and other livestock owned, whether the household had a television, radio, motorbike, telephone, tractor, or cart plough, and whether the household used organic or chemical fertilizer. Again, categorical answers were pivoted into multiple binary variables.

APPENDIX 2: SUMMARY STATISTICS

Table A2.1 Child Stunting Analysis

		Ghana	Zambia	Bangladesh
	min	-6	-5.7	-5.9
	mean	-1.5	-1.8	-1.7
Child's Height-for-Age Z-Score	max	5.8	5.2	5.8
	min	1		
	mean	4.5		
Child's Birth Order	max	28		
	min	0		
	mean	0.53		
Number of Siblings Born Within 24 Months	max	7		
	min	7	1	0
	mean	33	31	29
Child's Age (month)	max	59	59	60
	Female	0.48	0.51	0.48
Child's Gender	Male	0.52	0.49	0.52
	min	1	1	1
Number of Dependent Age Individuals in Household	mean	4.1	4	2.4
	max	19	11	7
	min	1	0	1
Number of Working Age Individuals in Household	mean	3.6	2.9	2.5
	max	15	9	7
	min	3	2	3
	mean	8	7.1	5.1
Household Size	max	35	16	13
	Christianity	0.33		0.0067
	Islam	0.45		0.87
	None	0.015		
	Traditional	0.2		
Household Head Religion	Hindu			0.12
	Female	0.023	0.23	
Household Head Gender	Male	0.98	0.77	

Table A2.1 Continued

		Ghana	Zambia	Bangladesh
	Form		0.32	
	None		0.0062	
	Standard		0.66	
	University		0.014	0.0078
	high school			0.027
	never			0.44
	primary			0.46
Household Head Education (School Attended)	secondary			0.063
	FALSE	0.31		
Household Head Has Attended School	TRUE	0.69		
	min	19	18	
	mean	41	38	
Household Head Age	max	97	99	
	min	0	0	0
	mean	0.26	0.74	0.82
Household Head is Literate (0: no; 1: yes)	max	1	1	1
	Rural	0.87		
Household is Urban or Rural	Urban	0.13		
	min			0
	mean			0.49
Percent of Rice Area Irrigated	max			1
	min	0.79	2.2	29
	mean	58	40	660
Population Within 7.5km of Household / 1,000	max	420	260	2100
	min	0.029	0.036	0.011
	mean	0.2	0.26	0.12
Market Distance (1,000 km)	max	0.75	0.78	0.48
	min	0.24	-0.4	-2.2
	mean	1.1	0.64	-0.58
24-Month Standardized Precipitation Index	max	1.7	1.4	1.7

Table A2.2 Household Hunger Analysis

		Ghana	Zambia	Bangladesh
	0	0.45	0.73	0.91
	1	0.11	0.11	0.05
	2	0.21	0.079	0.023
	3	0.22	0.072	0.010
	4	0.0031	0.027	0.0019
	5	0.0019	0	0.0003
Household Hunger Scale	6	0.00062	0.0051	0.0005
	min	0	0	0
	mean	2.9	3.2	1.8
Number of Dependent Age Individuals in Household	max	19	14	7
	min	0	0	0
	mean	3.4	2.9	2.7
Number of Working Age Individuals in Household	max	15	9	12
	min	2	2	2
	mean	6.5	6.3	4.6
Household Size	max	35	24	18
	min	18	18	
	mean	46	42	
Household Head Age	max	100	99	
	min	0	0	0
	mean	0.27	0.73	0.78
Household Head Is Literate (0: no; 1: yes)	max	1	1	1
	Christianity	0.36		0.0029
	Islam	0.41		0.88
	None	0.016		
	Traditional	0.22		
Household Head Religion	Hindu			0.12
	Female	0.039	0.23	0.0023
Household Head Sex	Male	0.96	0.77	1
Household Head Has Attended School	FALSE	0.26		
	TRUE	0.74		
	Form		0.27	
	None		0.0067	
	Standard		0.7	
	University		0.02	0.0063
	high school			0.026
	never			0.5
	primary			0.41
Household Head Education (School Attended)	secondary			0.06

Table A2.2 Continued

		Ghana	Zambia	Bangladesh
	min			0
	mean			0.5
Percent of Rice Area Irrigated	max			1
	Rural	0.84		
Urban or Rural (%)	Urban	0.16		
	min	0.00056	2.2	29
Population Within 7.5km of Household / 1,000	mean	0.069	40	680
	max	0.42	260	2700
	min	0.029	0.036	0.011
	mean	0.19	0.26	0.11
Market Distance (1,000 km)	max	0.75	0.78	0.48
	min	0.24	-0.4	-2.4
24-Month Standardized Precipitation Index	mean	1	0.65	-0.65
	max	1.7	1.4	2
	min	0	0.0033	0
Natural Land Cover (% on land within 7.5km of household with natural cover)	mean	0.52	0.32	0.054
	max	1	1	0.81
	min	0	0.2	0
Women's Empowerment (Individual score across 5 domains of empowerment)	mean	0.65	0.75	0.68
	max	1	1	1

APPENDIX 3: MODEL RESULTS

Ghana

Moran's I test for spatial autocorrelation in child height-for-age z-score

Moran I statistic: 0.013
Expectation: -0.0085
Variance: 0.000010
P-Value: 0.0000084

Table A3.1 Child height-for-age z-score spatial lagged regression results

Variable	Stunting Z-Scores
(Intercept)	-1.3*
	(0.59)
Child's Age	-0.021***
	(0.0041)
Child's Birth Order	-0.18
	(0.11)
Child's Gender - Male	-0.091*
	(0.046)
Number of Siblings Born Within 24 Months	0.23**
	(0.08)
Asset Index	0.063
	(0.04)
Number of Dependent Age Individuals in Household	-0.16
	(0.13)
Number of Working Age Individuals in Household	-0.037
	(0.13)
Household Size	0.18
	(0.13)
Household Head Age	0.0066
	(0.0053)
Household Head Is Literate	0.29
	(0.38)
Household Head Religion - Islam	0.25.
	(0.13)
Household Head Religion - None	-0.2
	(0.13)
Household Head Religion - Traditional	-1.1*
	(0.48)

Table A3.1 Continued

Variable	Stunting Z-Scores
Household Head Gender - Male	-0.1
	(0.16)
Market Distance (1,000 km)	0.13
	(0.21)
Household Is Urban	1.1*
	(0.56)
Population Within 7.5km of Household / 1,000	0.0016
	(0.001)
24-Month Standardized Precipitation Index	-0.0075
	(0.23)
Rho	0.53
AIC	4864.39
r^2	0.066

Moran's I test for spatial autocorrelation in Household Hunger Scores

Moran I statistic: 0.089
Expectation: -0.00062
Variance: 0.0000057
P-Value: $< 2.2 \times 10^{-16}$

Table A3.2 Household Hunger Score spatially lagged regression results

Variable	1	2 (Natural Land Cover)	3 (Women's Empowerment)	4 (NLC + WE)
(Intercept)	0.51*	0.38	0.71**	0.58*
	(0.23)	(0.23)	(0.25)	(0.3)
Asset Index	0.012	0.013	0.011	0.012
	(0.021)	(0.021)	(0.02)	(0.02)
Number of Dependent Age Individuals in Household	-0.16*	-0.15*	-0.16*	-0.15*
	(0.063)	(0.063)	(0.063)	(0.063)
Number of Working Age Individuals in Household	-0.18**	-0.17**	-0.18**	-0.17**
	(0.064)	(0.064)	(0.064)	(0.064)
Household Size	0.18**	0.17**	0.18**	0.17**
	(0.06)	(0.06)	(0.06)	(0.06)
Household Head Age	0.002	0.0019	0.0023	0.0022
	(0.0019)	(0.0019)	(0.0019)	(0.0019)
Household Head Is Literate	0.12	0.099	0.14	0.12
	(0.15)	(0.15)	(0.15)	(0.15)

Table A3.2 Continued

Variable	1	2 (Natural Land Cover)	3 (Women's Empowerment)	4 (NLC + WE)
Household Head Religion - Islam	-0.24***	-0.23***	-0.23***	-0.23***
	(0.068)	(0.068)	(0.068)	(0.068)
Household Head Religion - None	-0.056	-0.031	-0.073	-0.048
	(0.068)	(0.069)	(0.069)	(0.07)
Household Head Religion - Traditional	-0.028	-0.04	-0.041	-0.054
	(0.23)	(0.23)	(0.23)	(0.23)
Household Head Gender - Female	0.35***	0.38***	0.34***	0.36***
	(0.083)	(0.083)	(0.083)	(0.083)
Market Distance (1,000 km)	-0.21*	-0.22*	-0.21*	-0.22*
	(0.098)	(0.098)	(0.098)	(0.098)
Population Within 7.5km of Household / 1,000	0.12	0.0076	0.11	-0.013
	(0.3)	(0.31)	(0.3)	(0.31)
Household Is Urban	-0.58	-0.17	-0.56	-0.11
	(0.46)	(0.51)	(0.46)	(0.51)
24-Month Standardized Precipitation Index	-0.35**	-0.37**	-0.36**	-0.39**
	(0.12)	(0.12)	(0.12)	(0.12)
Natural Land Cover		0.23.		0.24
		(0.12)		(0.33)
Women's Empowerment			-0.29.	-0.31
			(0.16)	(0.28)
Women's Empowerment: Natural Land Cover				0.0022
				(0.48)
Rho	0.74	0.76	0.74	0.76
AIC	5086.94	5085.12	5085.59	5085.26
r^2	0.14	0.15	0.15	0.15

Zambia

Moran's I test for spatial autocorrelation in child height-for-age z-score

Moran I statistic: 0.017
Expectation: -0.0015
Variance: 0.000019
P-Value: 0.0000069

Table A3.3 Child height-for-age z-score spatial lagged regression results

Variable	Stunting Z-Scores
(Intercept)	-1.6.
	(0.87)
Child's Age	-0.011**
	(0.0036)
Childs Is Female	0.31**
	(0.11)
Asset Index	-0.018
	(0.038)
Number of Dependent Age Individuals in Household	0.043
	(0.14)
Number of Working Age Individuals in Household	0.11
	(0.14)
Household Size	-0.056
	(0.13)
Household Head Age	-0.0047
	(0.0052)
Household Head Is Female	0.38**
	(0.14)
Household Head Is Literate	0.2
	(0.14)
Household Head Education - Form	0.74
	(0.71)
Household Head Education - Standard	0.67
	(0.7)
Household Head Education - University	1.9*
	(0.84)
Market Distance (1,000 km)	-0.43
	(0.61)
Population Within 7.5km of Household / 1,000	0.0019
	(0.0019)
24-Month Standardized Precipitation Index	-0.058
	(0.18)
Rho	0.42
AIC	2265.52
R-Squared	0.07

Moran's I test for spatial autocorrelation in Household Hunger Score

Moran I statistic: 0.0014
Expectation: -0.0013
Variance: 0.000014
P-Value: 0.51

Table A3.4 Household Hunger Score regression results

Variable	1	2 (Natural Land Cover)	3 (Women's Empowerment)	4 (NLC + WE)
(Intercept)	1.4**	1.4**	1.5**	0.95
	(0.5)	(0.5)	(0.54)	(0.59)
Asset Index	-0.0037	-0.0023	-0.0037	0.00018
	(0.026)	(0.026)	(0.026)	(0.026)
Number of Dependent Age Individuals in Household	0.1	0.096	0.1	0.084
	(0.088)	(0.088)	(0.089)	(0.088)
Number of Working Age Individuals in Household	0.13	0.12	0.13	0.12
	(0.088)	(0.088)	(0.089)	(0.088)
Household Size	-0.1	-0.094	-0.097	-0.083
	(0.084)	(0.084)	(0.085)	(0.085)
Household Head Is Female	0.054	0.05	0.059	0.056
	(0.091)	(0.091)	(0.093)	(0.092)
Household Head Is Literate	-0.12	-0.13	-0.12	-0.13
	(0.091)	(0.091)	(0.091)	(0.091)
Household Head Education - Form	-0.58	-0.54	-0.59	-0.52
	(0.47)	(0.47)	(0.47)	(0.47)
Household Head Education - Standard	-0.51	-0.48	-0.52	-0.47
	(0.46)	(0.46)	(0.46)	(0.46)
Household Head Education - University	-1	-0.98.	-1	-0.95.
	(0.54)	(0.53)	(0.54)	(0.53)
Market Distance (1,000 km)	-0.61	-0.41	-0.6	-0.42
	(0.43)	(0.44)	(0.43)	(0.44)
Population Within 7.5km of Household / 1,000	-0.00072	-0.00074	-0.00071	-0.00069
	(0.0013)	(0.0013)	(0.0013)	(0.0013)
24-Month Standardized Precipitation Index	-0.24*	-0.26*	-0.24*	-0.28*
	(0.12)	(0.12)	(0.12)	(0.12)
Natural Land Cover	NA	-0.28*	NA	1.4.
	NA	(0.14)	NA	(0.74)
Women's Empowerment	NA	NA	-0.11	0.63
	NA	NA	(0.29)	(0.42)

Table A3.4 Continued

Variable		1	2 (Natural Land Cover)	3 (Women's Empowerment)	4 (NLC + WE)
Women's Empowerment:Natural Land Cover		NA	NA	NA	-2.3*
		NA	NA	NA	(0.96)
Moran's I Test of Residuals	Moran's I Statistic	-0.0057	-0.0069	-0.0058	-6.4
	Expectation	-0.0013	-0.0013	-0.0013	-0.0013
	Variance	0.000014	0.000014	0.000014	0.000014
	P-Value	0.88	0.93	0.88	0.91
AIC		2151.15	2148.93	2153	2146.96
R-Squared		0.023	0.028	0.023	0.036

Bangladesh

Moran's I test for spatial autocorrelation in child height-for-age z-score

Moran I statistic: 0.0087
Expectation: -0.0011
Variance: 0.000044
P-Value: 0.069

Chow test for equality of coefficients between 2011 and 2015 survey

F: 1.38
P-Value: 0. 12

Table A3.5 Child height-for-age z-score spatial lagged regression results

Variable	Stunting Z-Scores
(Intercept)	-1.7***
	(0.4)
Child's Age	-0.017***
	(0.0028)
Childs Is Male	-0.12
	(0.094)
Asset Index	0.038
	(0.034)
Number of Dependent Age Individuals in Household	0.047
	(0.12)
Number of Working Age Individuals in Household	0.11
	(0.12)
Household Size	-0.048
	(0.11)

Table A3.5 Continued

Variable	Stunting Z-Scores
Household Head Is Literate	0.014
	(0.14)
Household Head Education - Primary	0.19.
	(0.11)
Household Head Education - Secondary	0.36.
	(0.21)
Household Head Education - High School	0.81**
	(0.3)
Household Head Education - University	0.78
	(0.53)
Household Head Religion - Christian	-0.7
	(0.57)
Household Head Religion - Hindu	0.1
	(0.15)
Percent of Rice Area Irrigated	0.2
	(0.16)
Market Distance (1,000 km)	-0.66
	(0.67)
Population Within 7.5km of Household / 1,000	0.00011
	(0.00017)
Year 2015	0.35**
	(0.11)
24-Month Standardized Precipitation Index	-0.081
	(0.064)
Rho	0.11
AIC	3143.47
R-Squared	0.071

Moran's I test for spatial autocorrelation in Household Hunger Scores

Moran I statistic: 0.014
Expectation: -0.00017
Variance: 0.0000019
P-Value: $< 2.2 \times 10^{-16}$

Chow test for equality of coefficients between 2011 and 2015 survey

F: 1.152
P-Value: 0.29

Table A3.6 Household Hunger Score regression results

Variable	1	2 (Natural Land Cover)	3 (Women's Empowerment)	4 (NLC + WE)
(Intercept)	0.16***	0.16***	0.22***	0.24***
	(0.041)	(0.041)	(0.047)	(0.05)
Asset Index	-0.00072	-0.00072	-0.00046	-0.00044
	(0.0049)	(0.0049)	(0.0049)	(0.0049)
Number of Dependent Age Individuals in Household	0.015	0.015	0.015	0.016
	(0.015)	(0.015)	(0.015)	(0.015)
Number of Working Age Individuals in Household	-0.028.	-0.028.	-0.026.	-0.026.
	(0.016)	(0.016)	(0.016)	(0.016)
Household Size	-0.0029	-0.0033	-0.0041	-0.0048
	(0.014)	(0.014)	(0.014)	(0.014)
Household Head Is Female	0.82***	0.81***	0.82***	0.82***
	(0.14)	(0.14)	(0.14)	(0.14)
Household Head Is Literate	-0.033.	-0.033.	-0.032	-0.031
	(0.02)	(0.02)	(0.02)	(0.02)
Household Head Education - Primary	-0.081***	-0.084***	-0.081***	-0.084***
	(0.017)	(0.017)	(0.017)	(0.017)
Household Head Education - Secondary	-0.16***	-0.16***	-0.16***	-0.16***
	(0.031)	(0.031)	(0.031)	(0.031)
Household Head Education - High School	-0.17***	-0.17***	-0.16***	-0.16***
	(0.045)	(0.045)	(0.045)	(0.045)
Household Head Education - University	-0.19*	-0.2*	-0.2*	-0.2*
	(0.088)	(0.088)	(0.088)	(0.088)
Household Head Religion - Christian	-0.041	-0.04	-0.036	-0.039
	(0.13)	(0.13)	(0.13)	(0.13)
Household Head Religion - Hindu	0.0086	0.0082	0.0083	0.0064
	(0.022)	(0.022)	(0.022)	(0.022)
Percent of Rice Area Irrigated	0.014	0.017	0.017	0.02
	(0.023)	(0.023)	(0.023)	(0.023)
Market Distance (1,000 km)	0.072	0.053	0.086	0.063
	(0.11)	(0.11)	(0.11)	(0.11)
Population Within 7.5km of Household / 1,000	3e-05	3e-05	3e-05	3e-05
	(2e-05)	(2e-05)	(2e-05)	(2e-05)
Year 2015	0.046**	0.044**	0.052***	0.05**
	(0.016)	(0.016)	(0.016)	(0.016)
24-Month Standardized Precipitation Index	0.022*	0.019.	0.02*	0.018.
	(0.0096)	(0.0097)	(0.0096)	(0.0098)
Natural Land Cover		0.14.		-0.28
		(0.079)		(0.25)
Women's Empowerment			-0.096*	-0.13**
			(0.039)	(0.046)
Women's Empowerment: Natural Land Cover				0.64.
				(0.38)
Rho	0.48	0.48	0.47	0.46
AIC	8454.78	8453.58	8450.89	8449.78
R-Squared	0.036	0.037	0.037	0.038

Note: For these regressions, 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 (**) and a p-value of less than 0.05 is indicated with one star (*).

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