Exploring strategies for investigating the underlying mechanisms linking climate and child health

Kathryn Grace, Andrew Verdin, Frank Davenport, Chris Funk and Greg Husak

Introduction

Warming and drying represent the most direct impacts of climate change on humans. Communities reliant on rainfed agriculture to meet their food and nutrition needs are at high risk for negative health and economic outcomes associated with climate change (IPCC 2013, Brown et al. 2015). Subsistence communities in rural Sahelian Africa, where rainfall is inconsistent and where temperatures can spike to extremely high levels, face notable agricultural, health and livelihood challenges associated with climate change (Grace et al. 2015, Davenport et al. 2017). In these contexts, and for these communities, seasonal rainfall is vital for producing the required food needed to meet the family's nutritional and caloric demands. If rains are inadequate then household food production is constrained, putting the health and security of families at risk. High temperatures can impact agricultural yields (in different ways, depending on the setting and the precipitation) or they can can cause heat waves leading to heat stress and associated adverse health outcomes (Amegah et al. 2016, Strand et al. 2011, Muller et al. 2011). Warm temperatures and wet conditions can also create an ideal setting for malaria transmission (Kudamatsu et al. 2012, Tanser et al. 2003). Consequently, a rainy, warm season that may seem positive for agricultural production may result in increased exposure to disease or an increase risk of exposure to heat stress.

Because of these complexities, research related to climate's impacts on individual health outcomes related to malnutrition often struggles to isolate and identify the mechanisms underlying the relationship between a climate measure and a health outcome. In other words, it is difficult to explain why the relationship between seasonal rainfall totals and a measure of malnutrition, for example is negative in some cases and positive in other cases (Grace et al. 2012, Bakhtsiyarava et al. 2018, Davenport et al. 2017). Similarly, high temperatures are generally assumed to have a negative impact on health outcomes but research that investigates temperature conditions and health outcomes are inconsistent, showing both positive and non-significant associations using varying metrics (Xu et al. 2012, Amegah et al. 2016).

The goal of this paper is to isolate and examine the differential pathways that connect climate/weather variability to child health outcomes. This goal will be accomplished through the application of climate indicators designed to capture the complexities of different climate related risks and isolate their impacts based the timing and duration of exposure. Specifically, we focus on infant birthweight outcomes with attention to local weather conditions and climate extremes associated with the three most frequently posited potential drivers of adverse health outcomes: heat stress, malaria, and food insecurity. We focus on Mali, where the vast majority of individuals are dependent on rainfed agriculture and where malaria is endemic. Additionally, Mali's seasonal variability – a hot dry season and a single rainy, warm and short growing season – facilitate temporal isolation of specific types of climate related exposures.

To conduct our analysis, we incorporate three measures of climate conditions that are designed to capture the specific potential pathways of interest. These measures reflect the spatial and temporal complexities of each of the three dimensions and are derived from related research. We modify them somewhat from their original development to accommodate the available data as well as to account for the temporal and geographic aspects of the Malian context. Key to our research design, the composite climate measures reflect spatial and temporal variation as they relate to the three primary pathways hypothesized to link climate to child health and will be matched to individuals to investigate how exposure to specific conditions during pregnancy impacts infant birth weights. Individual level birth weights, an anthropometric measure that varies according to biological and environmental conditions a woman experiences during pregnancy (Vitora et al. Black et al.), come from multiple periods (2000, 2006 and 2012) of the spatially referenced Demographic and Health Survey (DHS) collected for Mali. These data will be merged with the spatially and temporally varying climate measures with close attention to the location and timing of individual exposures.

Background – using climate and weather data to estimate exposure to stressors

Research investigating the impacts of climate on health and development in sub-Saharan Africa has resulted in a range of results (e.g., Bakhtsiyarava et al. 2018, Grace et al. 2012, Kudamatsu et al. 2012; see also Xu et al. 2012, Amegah et al. 2016, Phalkey et al. 2014). Such non-convergent results are very likely a result of inconsistent climate data sources and climate variable definition, and also the nuanced and complex biological response to climate extremes—including acclimatization—and an individual's socioeconomic status, which impacts access to resources to alleviate negative health outcomes. Researchers often focus on aggregate rainfall and temperature trends and theorize that these climate measures impact health outcomes through various pathways - primarily disease (Kudamatsu et al. 2012), food insecurity (Davenport et al. 2017), or heat stress (Asamoah et al. 2018, Xu et al. 2012, Phalkey et al. 2014). However, the linkages between climate and health are complex and difficult to detect using aggregate climate conditions. For example, seasonal or annual total precipitation provides little information on local agricultural yields and annual average maximum temperature provides little information on heatwave frequency and duration.

Seasons when climate conditions are likely to increase the likelihood of malaria transmission can be identified based on historical norms, but monthly climate data can help to refine the spatial and temporal detail allowing for variability across years and over space. In other words, aggregate climate conditions do not always adequately reflect the within-season variability that drives negative health outcomes. Applying measures that have been developed precisely to capture agricultural productivity/food availability, malaria conditions and heat waves to analyses of child health outcomes associated with malnutrition, malaria and heat stress – will help to sort out the different pathways that link climate to adverse health outcomes.

Malaria

Malaria likely increases the risk of stillbirth and spontaneous abortion, but it also is linked to low birth weight and birth defects (Desai 2007, McFalls and McFalls 1984, Kudamatsu et al. 2012). Individual-level disease histories are virtually non-existent for sub-Saharan African countries making it impossible to investigate an individual's specific health background and their later life health. Aggregate measures of disease presence are also non-existent or insufficient because highly detailed community-level data or health surveillance type data on malaria cases or outbreaks is difficult to come by. Ultimately this lack of data leads researchers to develop alternative strategies for measuring the potential for malaria presence in a given area during a given time frame. In some cases (normally smaller-scale studies), researchers will simply identify the typical rainy season months as being high malaria transmission months (for example, Berry et al. 2018). This approach ignores any variability in actual weather patterns and so is not appropriate for spatial or temporal analyses comparing outcomes over time and space. Some analysts, especially in studies where the data spans many countries and years, use different measures of rainfall or more sophisticated composite indicators that consider both temperature trends and rainfall trends together. In the case of the combined temperature/rainfall index, high frequency climate data are used to derive a malaria index capable of identifying, over space and time, climate conditions that support the existence of the parasite and the vector needed to transmit malaria (Tanser et al. 2003, Kudamtsu et al. 2012).

This more complex and physically-based indicator is capable of capturing variation over time and space that cruder measures are not able to capture. This measure has been used to investigate patterns of infant mortality across sub-Saharan Africa (Kudamatsu et al. 2012). We use this composite, climate-based measure to identify months and locations (spatial resolution of ~5 km) where the parasite and vector are likely to be present and transmission rates are expected to be higher. Please see the Tanser et al. (2003) and Kudamatsu et al. (2012) for specific details on the construction and validation of the malaria index.

Food Insecurity

Food insecurity is associated with adverse health outcomes for pregnant and breastfeeding women and their children. Food insecurity can lead to low birth weight, low height-for-age (stunting), low weight-for-age (wasting), among a wide range of other adverse health outcomes that can last into adulthood. There are a wide range of factors that drive community- or household-level food insecurity, with food availability featuring prominently in studies focused on sub-Saharan Africa and small-scale farming households (Grace et al. 2016, Smith and Haddad 2005, Butt et al. 2005). Ideal measures of household food availability would include information on farm yield, agricultural storage, presence of locally available food for purchase, diversity and quality of available food, perceptions of food security and other factors (Barrett 2010, Myers et al. 2017, Timmer 2010) and would be available at monthly (or finer) or seasonal time-scales for each household. As expected, data of this type is rarely available for sub-Saharan African households and never available with the temporal and spatial detail suitable for a study of individual-level child health outcomes.

A solution that researchers and development agencies have used to estimate food availability and, consequentially food insecurity, is to use remotely sensed data of vegetation. The Normalized Difference Vegetation Index (NDVI) serves as a measure of greenness and because of the way the satellites collect data and the way the measure is calculated, it is available at a fine spatial scale – usually finer than 1 km. The temporal frequency is also fine – and measures of NDVI are available every 8 days. Therefore, NDVI produces a measure of vegetation throughout the year and at a scale that is relevant for a village or community. In rainfed agricultural settings, NDVI indicates which areas (communities or villages or plots) are greener than others and during what time periods. For food availability estimates, the standard approach is to calculate the maximum NDVI value for each spatial unit over the growing season, which has been shown to be a good indicator of agricultural production in some settings (Husak and Grace 2016, Chivasa et al. 2017, Funk and Budde 2009). For estimates of a village's food insecurity, an analyst identifies the area where agriculture is likely to be produced and aggregates the maximum NDVI pixels within that area to calculate annual growing season food production. In years where the NDVI value is lower than other years or than some threshold, that community may have faced food insecurity.

Heat Stress

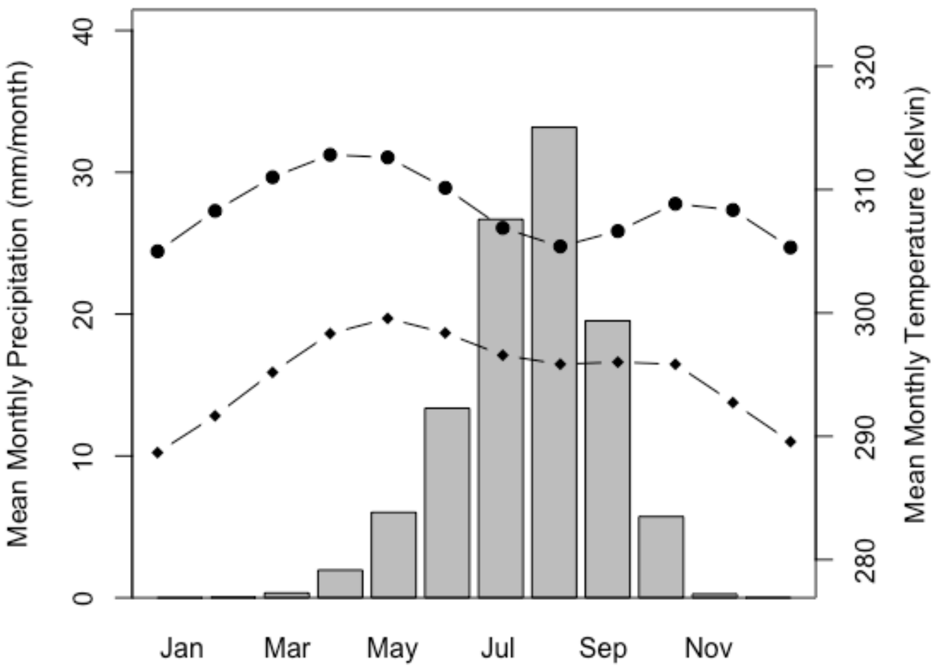
Heat stress is hypothesized to have negative impacts on the placenta and the developing fetus and is therefore related to adverse pregnancy outcomes like low birth weight, pre-term birth, and other related outcomes. The impact of exposures during different stages of pregnancy is not well understood but it is theorized that exposure to high temperatures during conception and early stages of pregnancy may increase the likelihood of miscarriage – ultimately resulting in heavier babies at birth as only the healthiest fetuses result in live birth (cite). Exposure during later stages of pregnancy has inconsistent outcomes but is typically associated with increased risk of pre-term birth, thus resulting in lower birth weights.

Temperature measures used in climate-health analyses rely on relatively coarse-spatial scale (usually 25-50 km) and either fine (daily maximum values, for example) or coarse (monthly or yearly averages) temporal scale. There are several different approaches used to aggregate temperature data with health or other population data. Among the common approaches are to calculate annual, seasonal, or monthly means of daily maximum values. Or to derive heat wave indicators which often identify sequences of days where the daily maximum exceeds a specific threshold or percentile of the temperature distribution for a given location. However, in some subsistence-based farming settings, increased temperatures may correspond to increased agricultural yields which may be associated with higher birth weights.

Pathways in application

While these concepts are general, the ways in which the specific stressor is measured is context dependent. Therefore, to appropriately investigate these pathways in application, we must consider the particular context of Mali as it relates to each pathway. Figure 1 highlights general rainfall and temperature trends over a given year in Mali. Notably, the hot season occurs from March-May, with temperatures decreasing as the rains begin in May. The rainy season is the primary agricultural growing season for Malians. Planting typically occurs sometime in June and harvest follows in September. There is a clear north-south rainfall gradient with much lower levels of rainfall in the north and higher levels in the south. Apart from the north-south gradient, within country rainfall variability is fairly high – villages as close as 10-20km apart may experience different rainfall conditions that modify the start, length and overall quality of the season. Maize, millet and sorghum are the primary cereal crops. In some cases, rice, cotton and vegetables (tomatoes, onions, and garlic) serve as higher valued cash crops. As in other contexts where malaria is endemic, the primary malaria season occurs during the growing season with most cases occurring in June-September. Because of within country variability in rainfall during a given year, there is spatial variability in malaria transmission as well.

Figure 1: Mali climatology from 1981-2016 averaged over all DHS clusters



Identifying the specific mechanism using cross-sectional, observational data is challenging especially because some of these conditions are interrelated and, the climate measures used to capture rainfall and temperature variability, are necessarily proxy measures which may reflect factors that are not explicitly accounted for in the theoretical design. To better isolate the contributions to adverse health outcomes associated with each of these different potential drivers, we use different measures that are derived from different remotely sensed and physically-based data sets. Each measure has been validated in other research and is being modified for use in our particular case focused on Mali and birth weight outcomes.

Birth weight is used because it provides a very identifiable time period of risk – the pregnancy (approximately 9 months before a child's birth date) and pre-pregnancy/conception periods (approximately 12-9 months before a child's birth date). When a pregnant person is exposed to food insecurity, malaria, and heat stress during their pregnancy – the weight of the infant at birth may be impacted. Timing of exposure is important – as exposures during pre-

pregnancy/conception periods and early pregnancy may actually contribute to failed conceptions or spontaneous abortions and result in a selection bias producing heavier babies at birth (see Wilde et al. 2017 and Berecca et al. 2019). Using trimester specific measures of exposure allows us to consider the differential risks associated with each trimester on birth weight outcomes.

To separate out temperature effects associated with agriculture versus those associated with heat stress, we exploit Mali's unique agricultural calendar. Specifically, the hot season (from March-May) – where temperatures can exceed 45C – does not occur during the rainy growing season (June – September). Focusing on different categories of temperatures conditions allows for us to separately examine the impact of heat waves on pregnancy outcomes separately from the food production pathway. Similarly, considering rainfall alone combines conditions that are ideal for malaria and for agricultural production. However, NDVI serves as an established measure of agricultural production in Mali, where vegetation is almost always indicative of a source of food (or cash, in the case of cash crops).   Using NDVI to measure seasonal quality of the prior growing season will help to account for the complicated relationship between rainfall, malaria, and food insecurity. Details on the specific construction of each pathway are presented in the measures section.

Table 1 summarizes the pathways, measures/data, and timing considerations for use in this analysis.

Table 1: Primary mechanisms linking climate and infant health

Pathway	Data/Measure	Hypotheses and Associated Timings
Food Insecurity	Normalized Difference Vegetation Index	High vegetation during growing season produces better/more crops which allows for greater food storage. Potential for a **positive** relationship during the following year's hunger season because more agricultural production implies improved household food availability. The results of improved storage/food availability would likely be experienced 9-12 months AFTER the growing season where higher birth weights may be observed.
Disease (Malaria)	Rainfall and Temperature	Increased risk of disease occurs during the key malarious months. Potential for exposure to more months with malaria conditions to have a **negative** impact on birth weight.
Heat Stress	Consecutive Days of High Temperatures	High temperatures during hot part of year could indicate exposure to heat stress. Potential for **negative** impacts on birth weight if a pregnant woman is exposed to heat stress during early pregnancy (impacts on placenta and uterus) and during late pregnancy (associated with pre-term birth).

Data

Population data

The population data used in this research come from the 2000, 2006 and 2012 cross-sectional Demographic and Health Surveys (DHS) (INSTAT 2006 and 2012). Because of ease of use and consistency across time periods, we use DHS data from the Integrated Demographic and Health Surveys (IDHS) (Boyle et al. 2018). DHS data contain highly detailed information on women and children's health for the poorest countries in the world. These data are widely used for research and policy investigations related to health and development. The data contain information on individual and household-level characteristics including educational attainment, health, and household assets. The data also contain retrospective information on child and infant health outcomes as reported by the mother. The data are georeferenced at the level of the DHS community cluster. Clusters are spatially shifted (offset) up to 10 km to maintain confidentiality of respondents but can be merged with other spatially referenced data as long as an appropriate spatial buffer is incorporated into an aggregation strategy (see Grace et al. 2019, Davenport et al. 2017).

A final, and vitally important aspect of DHS data, is the inclusion of information on length of time at current residence. A single question in the DHS questionnaire asks "how long have you been living continuously in this town/village?"[1]. Responses are recorded using an annual time scale. While not the optimal way of measuring individual migrations or exposures to different environmental risks, this question allows us to link individuals to environmental exposures. In terms of pregnancy outcomes, if a respondent has lived in the current community at least 12 months preceding the birth of the child, then they are included in the analysis because the conditions that they were exposed to during pregnancy can be inferred.

For the 2000 and 2006 surveys, around 7% of the respondents included in this study, were excluded because the were not in the current community during the pregnancy period or because this information was not known. This question was excluded in the 2012 survey and we therefore separate the analyses of the data with and without this residency information.

Environmental Data

Rainfall data: For the rainfall data, we use the Climate Hazards Group InfraRed Precipitation with Station (CHIRPS) dataset (Funk et al. 2014a). The CHIRPS data set, developed by USGS scientists in collaboration with the Climate Hazards Group at the University of California Santa Barbara, combines a high-resolution (0.05°) climatology (Funk et al. 2015) with time-varying station data and observations from geostationary weather satellites. CHIRPS period of record, 1981-present, compares reasonably well with in situ rain gauge observations in Africa. Research projects supported by the United States Agency for International Development use CHIRPS for monitoring and forecasting rainfall across Africa (Funk et al. 2014b). These rainfall data are combined with temperature to quantify malaria risk.

---

[1] This refers to the particular way that the question is framed in the Mali DHS surveys – other countries also record this information but may ask the question slightly differently.

Temperature data: We use temperature data provided by Princeton's Terrestrial Hydrology Research Group (Sheffield et al. 2006). These temperature data were extracted from a dataset (v3[2]) of complete meteorological forcings, which includes precipitation, air temperatures (minimum, maximum, and average), downward short- and longwave radiation, surface pressure, specific humidity, and wind speed. Since its development, the Princeton dataset has been used extensively in the literature. Most recently, it has been used to study health outcomes in sub-Saharan Africa (Davenport et al. 2017), characterize heat waves in West Africa (Odoulami et al. 2017), inform projections of climate and land use change in West Africa (Wang et al. 2017), quantify crop yield uncertainty in sub-Saharan Africa (Dale et al. 2017; Srivastava et al. 2017), and drive the Global Land Data Assimilation System (GLDAS; Rodell et al. 2004). These temperature data are provided at 0.25°, which is the finest resolution currently available for daily global temperature data. While the spatial resolution is coarser than the precipitation data, temperatures are generally exhibit less spatial variability than precipitation, thus do not require such fine resolution. We use these temperature data to identify and compute heatwave events (i.e., Heat Stress pathway), and combine these temperature data with precipitation totals to quantify malaria risk.

Vegetation data: The Normalized Difference Vegetation Index (NDVI) serves as a measure of vegetation health and subsequently of crop production in a community. NDVI is a measure of greenness, which has been shown to be related to primary productivity and leaf area of plants (Sellers, 1985; Townshend and Justice, 1986) and provide a way to directly measure the impact of moisture and temperature conditions on vegetation health. In application, NDVI has been linked to local agricultural production and can be used to proxy variations in locally produced food (Grace et al. 2014, Husak et al. 2008). Here we use NDVI data from the Advanced Very-High Resolution Radiometer (AVHRR) instrument aboard NASA's family of polar orbiting platforms and European MetOp satellites. These NDVI data are available from 1981-2015 at bimonthly (~15-day) time steps and 8km spatial resolution. In this research, we consider seasonal maximum NDVI to be a proxy for crop production and ultimately food security and availability (i.e., Food Insecurity pathway).

Measures

The outcome variable is birth weight. Unlike other anthropometric measures of food insecurity (e.g., stunting), a child's weight at birth reflects a clearly defined period of exposure – approximately 9 months of gestation. This defined time period allows us to carefully consider specific exposures. DHS data generally does not contain information to calculate exact conception date. We therefore approximate the date of conception as the 9 months prior to the birth date. Birth weight is recorded either based on a respondent's recall of her child's birth or based on a health card. Recall may be impacted by other factors and may not be completely accurate. We therefore include a dummy variable in the models indicating if the birth weight information was from recall or from the medical card.

There is a relatively large amount of missing data on birth weight – either because a respondent was not able to remember the child's birth weight or because the child's weight was not

---

[2] http://hydrology.princeton.edu/data.pgf.php

measured at birth. This missing data does reduce the sample size and, in our sample, results in greater representation of birth weights of the children of urban women with more education and better access to health care. We do not believe that there is a pattern to this missingness that correlates with any of the pathways investigated here.

Pathway Measures

Food insecurity is measured using NDVI. NDVI is best used as a comparative measure – to indicate if there is more vegetation in a given area than a neighboring area or for comparing one time period to another. The seasonal maximum NDVI is calculated for a 10 km buffer centered on each DHS cluster. The growing season typically begins in mid-June and lasts through harvest in September. To investigate birthweight outcomes, we consider the maximum NDVI of the growing season that occurred just before the pregnancy. This is the growing season that would impact the severity of food insecurity during the hunger season[3] occurring during the pregnancy. For a pregnancy that resulted in a birth in October of year t, we consider the NDVI from the growing season of year t. While for a birth occurring in March of year t, we consider the growing season of year $t-1$. In this way we consider a buffering time between when the food was actually harvested and when the harvest may begin to be depleted. A lower NDVI value would indicate that the hunger season would start earlier for a given community, while a higher NDVI value would indicate that agricultural production was relatively improved (as compared to other communities) and that more food would be stored, delaying and shortening the hunger season.

Malaria is measured using the binary malaria index from Tanser et al. (2003), which is based upon physically-derived critical weather thresholds determined to sustain transmission of the vector. For each birth in our data set, we compute the number of malarious months for each of four trimester periods (i.e., the three months leading up to conception is considered the 0th trimester; the 1st-3rd trimesters are standard definitions). The range of this index is [0,3]: lower values indicate lower risk of exposure to malaria during a given trimester; higher values indicate an increased risk in exposure to malaria.

Heat stress is measured using daily maximum temperatures from the Princeton Global Meteorological Forcings dataset (Sheffield et al., 2006). We define two variables for each of the four trimester periods defined: the total number of days within 90-100F, and the total number of days above 100F. The range of these indices is [0,92]: lower values indicate that there was adequate relief from extreme temperatures; higher values indicate there was less relief from extreme temperatures a given trimester. Quadratic and cubic approaches have been used in other analyses in addition to a binned approach (used here) and a threshold approach (i.e., days above an arbitrary cut-off value). Based on this research a threshold or binned approach best captures exposure to heat stress with the focus on the hotter ends of distributions. Biological and public health research indicating that exposure to hot days increases risk of adverse health outcomes further supports the focus on very hottest days of the year (cite). Exploratory analysis on the use of "wet bulb temperature" which considers humidity to capture the "feels like" temperature does not dramatically vary from the temperature dataset used here. It is also

[3] The Hunger Season is defined as the period when food stores from the previous year are depleted but harvests from the current year are not yet available. In a setting with a single growing season, like Mali, the hunger season tends to overlap with the growing season. FEWS.NET provides Hunger Season calendars.

important to note that the hottest time of year in Mali is also the driest time of year indicating that wet bulb temperature would not provide a better measure of the lived conditions.

Analytic Approach
To investigate the differential impact of these different pathways linking climate and health outcomes we estimated a suite of regression models using birth weight as the continuous outcome variable. We use a random effects model with the mother as the random effect[4] which allows us to compare multiple births to a single mother and also to compare birth weights between mothers. Because individual factors related to health and development are of known significance, we will include these variables in the models to account for the variability in the outcome associated with them. Specific control variables are maternal education and age at birth, infant sex, infant's birth order and flooring type as a measure of household wealth/development (citations). We also adjust for month and year of birth and the livelihood zone[5] where the household is located.

The first set of regression models (models 1-3) includes these specific control variables and the climate indicators for the four pathways described in Table 1. Subsequent models include interactions between the climate indicator variables to determine the compounded effects of these environmental conditions on birth weight and stunting.

Results
In Figure 1, we present the results from the four different models corresponding to the three different pathways of potential impact. Beginning with the food insecurity pathway, where agricultural production is measured by NDVI, we see a positive association between birth weight and seasonal maximum NDVI value of the preceding year. For example, a child born in year *t* is likely to weigh more when the *t-1* seasonal maximum NDVI value is higher. In our analysis we look at births that occur at any point during the 12 months after the growing season. The timing indicates that some women were exposed to the growing season conditions during their pregnancy[6] as well as to the resulting agricultural production from the harvests.

In the second model, Figure 2, we investigate the relationship between malaria exposure over the course of the pregnancy and birth weights. The results indicate that when a woman is exposed to more malarious months during the pre-pregnancy period the birth weight of her infant is likely not impacted. This result is also found for exposures during the first and second trimesters. Alternatively, for the third trimester, greater exposure to malarious months is associated with an increased birth weight.

In the third model, Figure 3, we investigate the relationship between heat stress and birth weight outcomes. In this model, if a mother was exposed to more very hot days during some stages of pregnancy – the birth weight of the infant is likely to be lower than for those women who were

---

[4] We also use multi-level regression models and nest individuals within clusters. In other words, we treat the cluster as a random effect. No significant difference in our findings results from these different analytic approaches.
[5] Livelihood zones info should be included here.
[6] For births occurring January-May of year t, some portion of their pregnancy was experienced during the growing season of t-1. Births occurring June-Aug of year t occur during the hunger season which corresponds to the growing

exposed to fewer hot days. While exposure during any of the four trimesters considered in this analysis result in negative coefficients (indicating a negative association with birth weight), greater exposure during the second and third trimesters produces confidence intervals with all or most values as negative. Therefore, even after accounting for the distribution of coefficients, the majority of coefficient result in a negative association between heat waves and birth weight outcomes.

Discussion

Demographic and public health research on the negative impacts of climate change continues to reveal vulnerabilities and highlight groups at great risk for adverse health impacts. Frequently pregnant women and children are identified as those at greatest risk. In sub-Saharan Africa when children are born with decreased birth weight or low birth weight, they potentially face a lifetime of ill health and reduced earnings – factors which may be felt by subsequent generations. In sub-Saharan Africa, health risks associated with climate change, like reduced birth weight, are compounded because, in addition to direct effects associated with heat stress, so many families and individuals rely on rainfed agriculture to meet their nutrition needs. Furthermore, in some countries, malaria serves as a constant cause of major illness, sometimes resulting in death.

Ongoing and dramatic improvements in the quantity and quality of high frequency remotely sensed data has facilitated dramatic improvements in climate data for use in population-environment research in sub-Saharan Africa. This data has been used in many disciplines to help address some of the major limitations in the availability of fine-scale, temporally varying quantitative data used to proxy food insecurity and disease exposure which is not included in the standard survey dataset. Merging spatially-referenced survey data with these high frequency datasets has produced a growing body of research that generally indicates that climate and weather influence health outcomes with many lingering questions about the directions of the relationships and mechanisms linking climate and health.

In this project we selected a country with a very defined growing season (which is not the hot season), high temperatures during the hot season, and where malaria is endemic to examine different strategies for sorting out some of the most frequently cited mechanisms that linking population, health, and the environment. The climate, topography and development level of Mali is relatively consistent with other land-locked West African countries and so these results can potentially be generalized to neighboring countries. Central, Eastern, and Southern Africa face different conditions (multiple growing seasons, highly variable topography within the country, presence of irrigated agriculture, and so forth) which may make the results less applicable. Nonetheless, the approach that we have outlined in terms of specifying the mechanisms connecting individual health outcomes documented in surveys and their climate/environmental contexts may be useful for structuring related questions in other contexts.

Overall our research demonstrates the importance of local food production on the health outcomes of pregnant women. Because we use random-effects models we are able to consider multiple children born to the same mother, in general, our results indicate that when there is more vegetation (as measured by NDVI) then there is a positive impact on birth weight outcomes. Notably, we constructed this variable with the idea of measuring food in the community during the hunger period, therefore, the results indicate that when women experience pregnancies following a relatively better season, they birth babies with a higher birth weight. This result was consistent across all model specifications and after accounting for individual education or wealth levels.

Heat exposure, when looking at temperatures exceeding 100F, during some key periods, of pregnancy seems to negatively impact birth weights – especially during the first and third trimesters. Exposures during the 0^{th} trimester are positive for the very hot days – consistent with related results that suggest there may be a selection effect from heat (conceptions may be delayed under hot temperatures). The cooler days (between 90F and 100F) generally have no, or positive impacts on birthweight – however high numbers of these days most likely occur during the growing season, where higher temperatures and plentiful rainfall support agricultural production.

Malaria exposure produces the least consistent and clear results. There are two reasons for this, the malaria index is not ideal (Tanser et al.) and so is likely miss measuring some months. Second, the malaria index considers temperature and rainfall and most of the months that are assigned a value of "1" are growing season months. Our strategy of separating NDVI out from malaria and using completely different timings and data, should help to sort out food availability from malaria exposure, but only to an extent. It is very likely that the positive association observed between the third trimester and malaria exposure is actually capturing growing season conditions or some other artifact of the climatological conditions comprising the index.

Figure 1: NDVI and birthweight

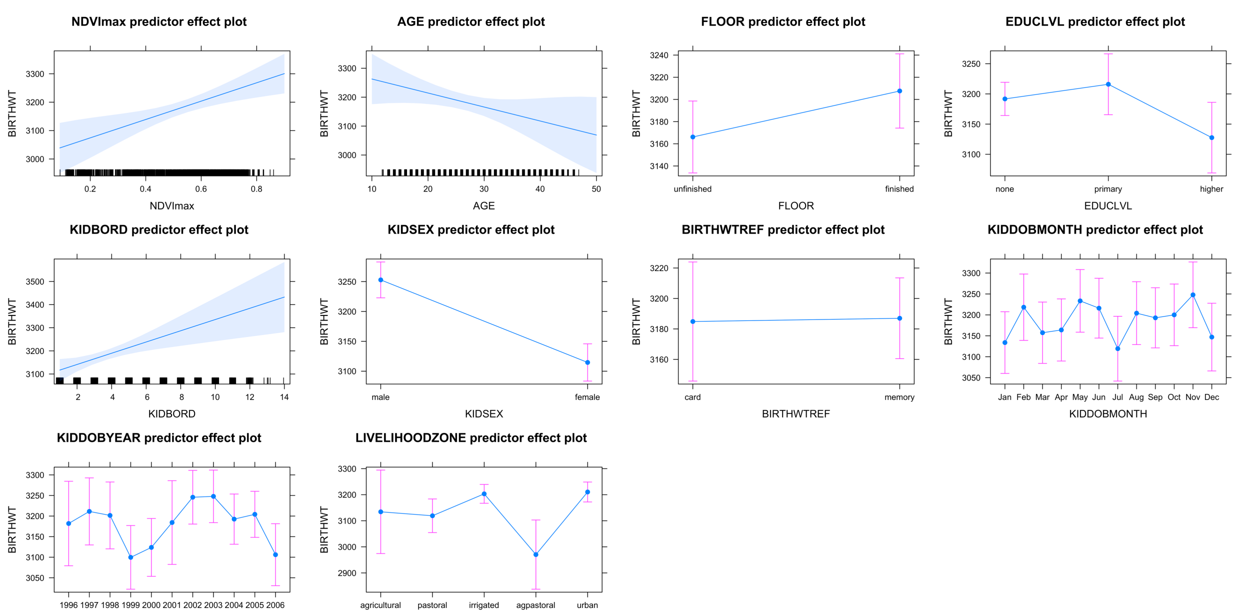


Figure 2: Malaria and birthweight

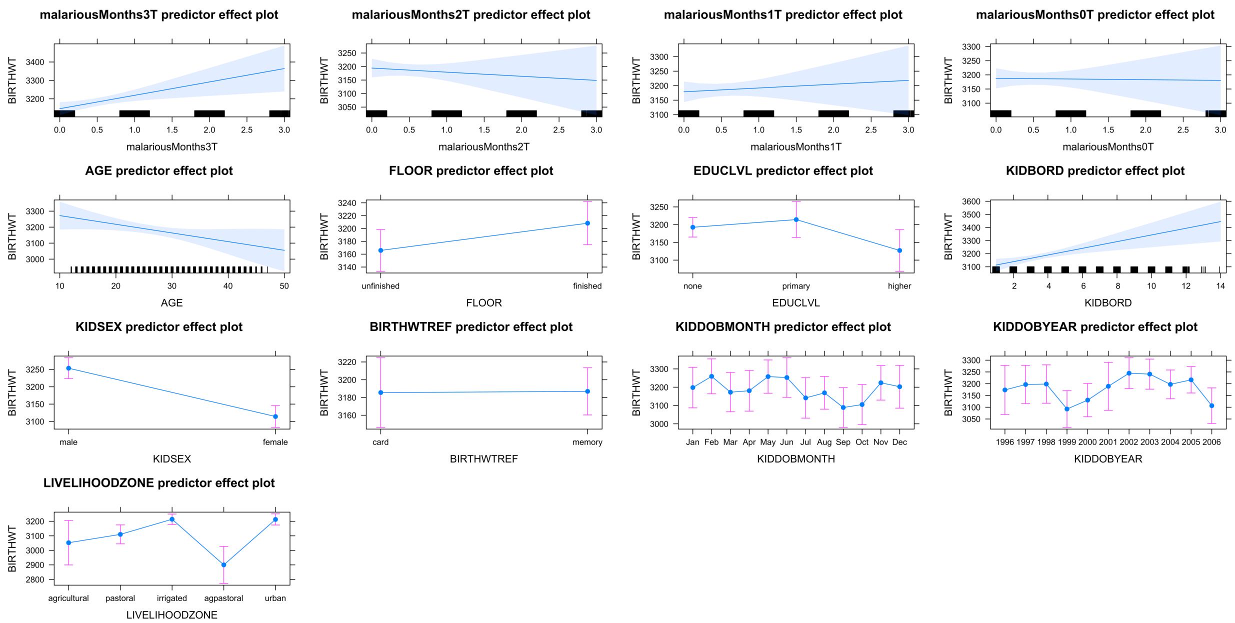
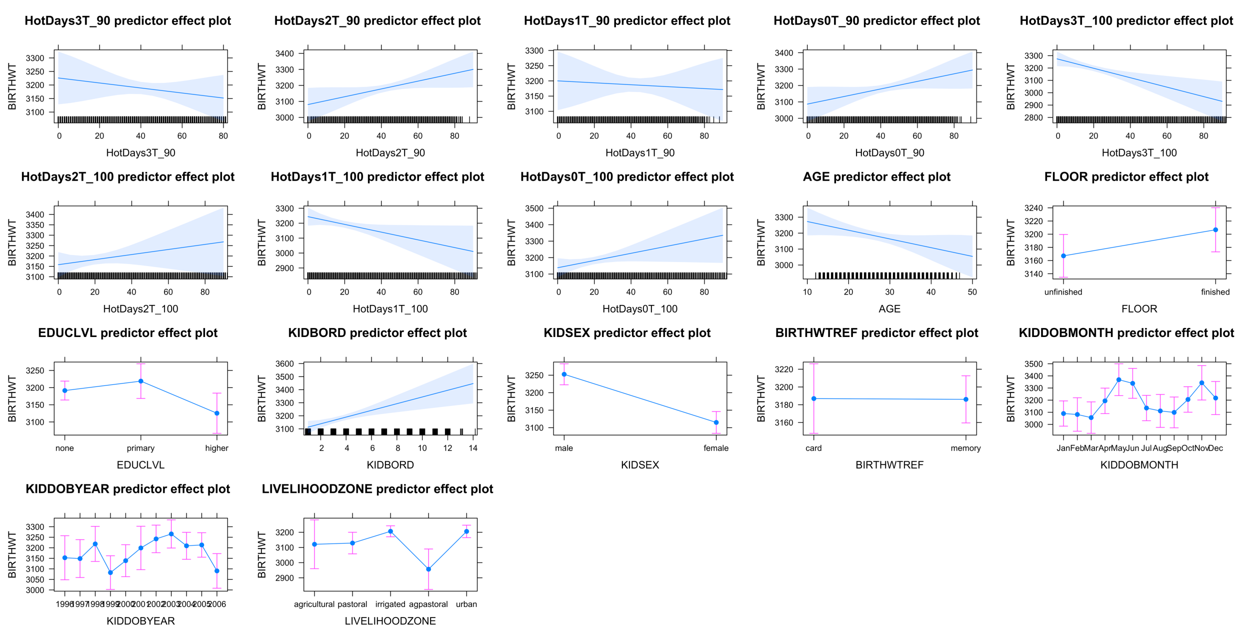


Figure 3: Temperature and birthweight



References

Asamoah, B., Kjellstrom, T., & Östergren, P. O. (2018). Is ambient heat exposure levels associated with miscarriage or stillbirths in hot regions? A cross-sectional study using survey data from the Ghana Maternal Health Survey 2007. *International journal of biometeorology*, *62*(3), 319-330.

Barrett, C. B. (2010). Measuring food insecurity. *Science*, *327*(5967), 825-828.

Bakhtsiyarava, M., Grace, K. and Nawrotzki, R.J. (2018). Climate, Birth Weight, and Agricultural Livelihoods in Kenya and Mali. *American journal of public health*, *108*(S2), S144-S150.

Boyle, E.H., King, M., and Sobek, M. IPUMS-Demographic and Health Surveys: Version 5 [dataset]. IPUMS and ICF International, 2018. http://doi.org/10.18128/D080.V5

Brown, M. E., Antle, J. M., Backlund, P. W., Carr, E. R., Easterling, W. E., Walsh, M., Ammann, C.M., Attavanich, W., Barrett, C.B., Bellemare, M.F., and Dancheck, V. (2015). Climate Change and Global Food Security: Food Access, Utilization, and the US Food System. In *AGU Fall Meeting Abstracts*.

Butt, T. A., McCarl, B. A., Angerer, J., Dyke, P. T., & Stuth, J. W. (2005). The economic and food security implications of climate change in Mali. *Climatic change*, *68*(3), 355-378.

Chivasa, W., Mutanga, O., & Biradar, C. (2017). Application of remote sensing in estimating maize grain yield in heterogeneous African agricultural landscapes: a review. *International journal of remote sensing*, *38*(23), 6816-6845.

Dale, A., Fant, C., Strzepek, K., Lickley, M. and Solomon, S. (2017). Climate model uncertainty in impact assessments for agriculture: A multi-ensemble case study on maize in sub-Saharan Africa. *Earth's Future*, 5(3), 337-353.

Davenport, F., Grace, K., Funk, C., and Shukla, S. (2017). Child health outcomes in sub-Saharan Africa: A comparison of changes in climate and socio-economic factors. *Global Environmental Change*, *46*, 72-87.

Funk, C. C., Peterson, P. J., Landsfeld, M. F., Pedreros, D. H., Verdin, J. P., Rowland, J. D., Romero, B.E., Husak, G.J., Michaelsen, J.C., and Verdin, A. P. (2014a). A quasi-global precipitation time series for drought monitoring. *US Geological Survey Data Series,* 832(4).

Funk, C., Hoell, A., Shukla, S., Blade, I., Liebmann, B., Roberts, J. B., Robertson, F.R., and Husak, G. (2014b). Predicting East African spring droughts using Pacific and Indian Ocean sea surface temperature indices. *Hydrology and Earth System Sciences*, *18*(12), 4965-4978.

Funk, C., Verdin, A., Michaelsen, J., Peterson, P., Pedreros, D., and Husak, G. (2015). A global satellite-assisted precipitation climatology. *Earth System Science Data Discussions,* 8(1)
Gidwani, Vinay, and Kalyanakrishnan Sivaramakrishnan. "Circular migration and the spaces of cultural assertion." *Annals of the Association of American Geographers* 93, no. 1 (2003): 186-213.

Funk, C., & Budde, M. E. (2009). Phenologically-tuned MODIS NDVI-based production anomaly estimates for Zimbabwe. *Remote Sensing of Environment*, *113*(1), 115-125.

Grace, K., Davenport, F., Funk, C. and Lerner, A.M. (2012). Child malnutrition and climate in Sub-Saharan Africa: An analysis of recent trends in Kenya. *Applied Geography*, *35*(1-2), 405-413.

Grace, K., Husak, G., and Bogle, S. (2014). Estimating agricultural production in marginal and food insecure areas in Kenya using very high resolution remotely sensed imagery. *Applied Geography*, 55, 257-265.

Grace, K., Davenport, F., Hanson, H., Funk, C. and Shukla, S. (2015). Linking climate change and health outcomes: examining the relationship between temperature, precipitation and birth weight in Africa. *Global Environmental Change*, 35, 125-137.

Grace, K. (2017). Considering climate in studies of fertility and reproductive health in poor countries. *Nature climate change*, 7(7), 479.

Grace, K., Frederick, L., Brown, M.E., Boukerrou, L. and Lloyd, B. (2017). Investigating important interactions between water and food security for child health in Burkina Faso. *Population and Environment*, 39(1), pp.26-46.

Grace, K., Nagle, N.N., Burgert-Brucker, C.R., Rutzick, S., Van Riper, D.C., Dontamsetti, T. and Croft, T. (2018). Integrating Environmental Context into DHS Analysis While Protecting Participant Confidentiality: A New Remote Sensing Method. *Population and Development Review*.

Husak, G. J., Marshall, M. T., Michaelsen, J., Pedreros, D., Funk, C., and Galu, G. (2008). Crop area estimation using high and medium resolution satellite imagery in areas with complex topography. *Journal of Geophysical Research: Atmospheres (1984–2012)*, *113*(D14).

INSTAT 2006. Cellule de Planification et de Statistique du Ministere de la Sante' (CPS/MS) [Mali], Direction Nationale de la Statistique et de l'Informatique du Ministere de l'Economie, de l'Industrie et du Commerce (DNSI/MEIC) [Mali], and Macro International Inc. Mali Demographic and Health Survey 2006 [Dataset]. Data Extract from MLIR52.SAV, MLHR52.SAV, MLKR52.SAV, MLBR52.SAV, and MLPR52.SAV. IPUMS-Demographic and

Health Surveys (IPUMS-DHS), version 5, IPUMS and ICF International [Distributors]. Accessed from http://IPUMS-DHSdata on November 5, 2018.

INSTAT 2012. Cellule de Planification et de Statistiques (CPS/SSDSPF), Institut National de la Statistique (INSTAT), Centre d'Études et d'Information Statistiques (INFO-STAT) [Mali] and ICF International. Mali Demographic and Health Survey 2012-13 [Dataset]. Data Extract from MLIR6H.SAV, MLHR6H.SAV, MLKR6H.SAV, MLBR6H.SAV, and MLPR6H.SAV. IPUMS-Demographic and Health Surveys (IPUMS-DHS), version 5, IPUMS and ICF International [Distributors]. Accessed from http://idhsdata.org on November 5, 2018.

IPCC, 2013: Climate Change 2013: The Physical Science Basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change, 1535 pp.

Kudamatsu, M., Persson, T., and Strömberg, D. (2012). Weather and infant mortality in Africa. *CEPR Discussion Paper No. DP9222*.

Myers, S. S., Smith, M. R., Guth, S., Golden, C. D., Vaitla, B., Mueller, N. D., ... & Huybers, P. (2017). Climate change and global food systems: potential impacts on food security and undernutrition. *Annual review of public health*, *38*, 259-277.

Odoulami, R.C., Abiodun, B.J., Ajayi, A.E., Diasso, U.J., and Saley, M.M. (2017). Potential impacts of forestation on heatwaves over West Africa in the future. *Ecological Engineering*, 102, 546-556.

Rodell, M., Houser, P.R., Jambor, U.E.A., Gottschalck, J., Mitchell, K., Meng, C.J., Arsenault, K., Cosgrove, B., Radakovich, J., Bosilovich, M. and Entin, J.K. (2004). The global land data assimilation system. *Bulletin of the American Meteorological Society*, 85(3), 381-394.

Sellers, P.J. (1985) Canopy Reflectance, Photosynthesis, and Transpiration. *International Journal of Remote Sensing*, 6(8), 1335-1372.

Sheffield, J., Goteti, G., and Wood, E. F. (2006). Development of a 50-year high-resolution global dataset of meteorological forcings for land surface modeling. *Journal of Climate*, 19(13), 3088-3111.

Smith, L. C., & Haddad, L. (2001). How important is improving food availability for reducing child malnutrition in developing countries?. *Agricultural Economics*, *26*(3), 191-204.

Srivastava, A.K., Mboh, C.M., Gaiser, T. and Ewert, F. (2017). Impact of climatic variables on the spatial and temporal variability of crop yield and biomass gap in Sub-Saharan Africa – a case study in Central Ghana. *Field Crops Research*, *203*, 33-46.

Tanser, F.C., Sharp, B., and Le Sueur, D. (2003). Potential effect of climate change on malaria transmission in Africa. *The Lancet,* 362(9398, 1792-1798.

Timmer, C. Peter. "Behavioral dimensions of food security." *Proceedings of the National Academy of Sciences* 109, no. 31 (2012): 12315-12320.

Townshend, J.R.G. and Justice, C.O. (1986). Analysis of the Dynamics of African Vegetation Using the Normalized Difference Vegetation Index. *International Journal of Remote Sensing,* 7(11):1435-1445.

Wang, G., Ahmed, K.F., You, L., Yu, M., Pal, J. and Ji, Z. (2017). Projecting regional climate and cropland changes using a linked biogeophysical-socioeconomic modeling framework: 1. Model description and an equilibrium application over West Africa. *Journal of Advances in Modeling Earth Systems*, 9(1), 354-376.