Exploring Strategies for Investigating the Mechanisms Linking Climate and Individual-Level Child Health Outcomes: An Analysis of Birth Weight in Mali

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Abstract

The goal of this article is to consider data solutions to investigate the differential pathways that connect climate/weather variability to child health outcomes. We apply several measures capturing different aspects of climate/weather variability to different time periods of *in utero* exposure. The measures are designed to capture the complexities of climate-related risks and isolate their impacts based on the timing and duration of exposure. Specifically, we focus on infant birth weight in Mali and consider local weather and enviromnental conditions associated with the three most frequently posited potential drivers of adverse health outcomes: disease (malaria), heat stress, and food insecurity. We focus this study on Mali, where seasonal trends facilitate the use of measures specifically designed to capture distinct aspects of climate/weather conditions relevant to the potential drivers. Results indicate that attention to the timing of exposures and employing measures designed to capture nuances in each of the drivers provides important insight into climate and birth weight outcomes, especially in the case of factors impacted by precipitation. Results also indicate that high temperatures and low levels of agricultural production

are consistently associated with lower birth weights, and exposure to malarious conditions may increase likelihood of nonlive birth outcomes.

Keywords

Introduction

Warming and drying represent one of 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 (Brown et al. 2015; IPCC et al. 2013). In rural Sahelian Africa, where inconsistent rainfall may result in droughts or flooding events and where temperatures can spike to extremely high levels, subsistence communities face notable agricultural, health, and livelihood challenges associated with climate change (Davenport et al. 2017; Grace et al. 2015). In these contexts and for these communities, seasonal rainfall is vital for producing the food needed to meet the family's nutritional and caloric demands. Inadequate rains constrain household food production, 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 cause heat waves that lead to heat stress and associated adverse health outcomes (Muller et al. 2011; Strand et al. 2011). Warm temperatures and wet conditions can also create an ideal setting for malaria transmission (Kudamatsu et al. 2016; 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 increased risk of exposure to heat stress.

Because of these complexities, research exploring the effects of climate on malnutrition often straggles 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 others (Bakhtsiyarava et al. 2018; Davenport et al. 2017; Grace et al. 2012). Similarly, high temperatures are generally assumed to have a negative impact on health outcomes, but research investigating temperature conditions and health outcomes has been inconsistent, showing both positive associations and nonsignificant associations using varying metrics (Xu et al. 2012; Zhang et al. 2017).

Our goal here is to consider exposure timing to examine the differential pathways that connect climate/weather variability to child health. To this end, we use 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 individual-level infant birth weight with attention to local seasonal weather conditions associated with the three most frequently posited potential drivers of adverse health outcomes: disease (malaria), heat stress, and food insecurity. The approach used here exploits highly spatially and temporally detailed data to examine exposure conditions and isolate different enviromnental factors associated with child health. This project therefore advances spatial

and enviromnental demography because it combines a diverse set of climate and health data capable of capturing a range of factors of importance to child health.[1]

We focus on Mali, where the vast majority of individuals are dependent on rainfed agriculture and where malaria is endemic (WHO 2017). Additionally, Mali's seasonal variability—a hot, dry season and a single rainy, warm, and short growing season— facilitates the temporal isolation of specific types of climate-related exposures (see Figure 1).

To conduct our analysis, we incorporate three measures of climate conditions that are designed to capture the specific potential pathways of interest: disease, heat stress, and food insecurity. These measures reflect the spatial and temporal complexities of each of the three pathways and are derived from related research. We modify the measures somewhat from their original development to accommodate the available data as well as to account for the temporal and geographic aspects of the Mahan context. We match each indicator to individual birth weights to investigate how exposure to specific conditions during pregnancy impacts health outcomes.

Data on individual-level birth weights come from multiple periods (2000, 2006, and 2012) of the spatially referenced Malian Demographic and Health Survey (DHS). These data are merged with the spatially and temporally varying climate measures based on the location and timing of individual exposures.

Background

Climate and Weather and Children's Health Outcomes

In this article, we focus on one child health outcome: birth weight. Birth weight is one of several commonly investigated anthropometric measures of child health (other frequently considered measures are height-for-age and weight-for-age) used to assess overall health of individuals and of a population. Understanding risk factors associated with birth weight variation or low birth weight (when an infant weighs less than 2,500 grams at birth) may also help to identity children at greatest risk for morbidity and mortality (Black et al. 2008; Mosley and Chen 1984; Victora et al. 2008). Conceptual frameworks useful for understanding and designing interventions to improve child health include birth weight as one of many factors of interest. As with other children's health outcomes, birth weight varies by individual child according to biological variations and a wide range of enviromnental conditions experienced during key periods (in this case, pregnancy) (Black et al. 2008; Kramer 1987, 2003). Although child health and development frameworks differ in some ways, the general structure is that broad factors relating to politics, the economy, and (more recently) climate/weather lead to more local region–specific factors; these in turn impact household/individual factors, which then impact biological responses and finally the health outcome (see Grace 2017; Kramer 2003; Mosley and Chen 1984; UNICEF 1991, 2017). In practice, applying these kinds of frameworks implies that broad-level shocks will

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[1]A range of health outcomes could be evaluated using the approaches we describe here as long as the pathways and exposure periods were properly matched.

have differential impacts on birth weight (or other health outcomes) depending on, for example, the socioeconomic status of a household or an individual's educational attaimnent or prenatal care history.

In demographic and social science research, climate and weather are conceptualized more broadly as enviromnental or contextual factors (Kramer 2003; Mosley and Chen 1984; UNICEF 2017). As interdisciplinary research on the climate-health relationship has expanded, the data and tools used to this relationship have resulted in some important shifts in the ways that researchers link climate/weather data to health data. In applied and interdisciplinary research, climate and weather factors are often more directly tied to community-, household-, or individual-level responses and are commonly used to proxy factors of interest related to disease, food security, or climate shocks (Eissler et al. 2019; Sellers and Gray 2019). In fact, in a recent review of climate and undernutrition, Phalkey et al. (2015) reimagined the UNICEF framework to highlight the role of climate/weather factors[2] at individual and household scales, noting "that a large proportion of the mediating factors are climate/weather sensitive" (p. E4526). In this analysis, we focus on birth weight as an outcome variable with established linkages to prenatal exposure to disease, heat stress, and food security. However, noting the connection between birth weight, child health, and mortality, the approach that we use here can easily be expanded to investigate associated outcomes, such as infant mortality, chronic or acute malnutrition, cognitive development, and related factors.

Using Climate and Weather Data to Estimate Exposure to Stressors

Research investigating the impacts of climate on early child health (including birth weight) in sub-Saharan Africa has produced mixed results (e.g., Bakhtsiyarava et al. 2018; Kudamatsu et al. 2016; see also Phalkey et al. 2015; Xu et al. 2012). Three factors may explain the nonconvergent results in climate and health studies: (1) the wide range of climate data sources and climate variable definition; (2) the nuanced and complex biological response to climate conditions (or extremes), including acclimatization; and, likely most importantly, (3) an individual's socioeconomic status, which impacts access to resources to alleviate negative health outcomes. Researchers have often focused on aggregate rainfall and temperature trends and have theorized that these climate measures impact health outcomes through various pathways—primarily disease (Kudamatsu et al. 2016), food insecurity (Davenport et al. 2017), or heat stress (Asamoah et al. 2018; Phalkey et al. 2015; Xu et al. 2012). 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

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[2]The framework proposed by Phalkey et al. (2015) focused on food security, the food system, infectious disease, and the impact of these factors over time and within households.

within-season variability that drives negative health outcomes. Applying measures that have been developed precisely to capture agricultural productivity and food availability, malaria conditions, and heat waves to analyses of child health outcomes associated with malnutrition, malaria, and heat stress will help decipher the different pathways that link climate to adverse health outcomes. Our analyses focus on the three pathways: malaria (disease), food insecurity, and heat stress.

Malaria—Malaria likely increases the risk of stillbirth and spontaneous abortion, but it also is linked to low birth weight, especially in the case of first births in malaria-endemic areas (Desai et al. 2007; Kramer 2003; Kudamatsu et al. 2016; McFalls and McFalls 1984). Large-scale,[3] spatially referenced, 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 capturing a country's disease experience are also non-existent or insufficient because highly detailed community-level data on malaria cases or outbreaks are 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 identify the typical rainy season months as those with high malaria transmission (e.g., Berry et al. 2018). At small scales, this approach may be used to capture some shifts in yearly conditions, but it would be challenging to apply to a large sample of communities to compare outcomes over time and space. Some analysts, especially in studies with data spanning many countries and years, use different measures of rainfall or more sophisticated composite indicators that consider temperature trends and rainfall trends together.

In the case of the combined temperature and 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 (for details on the construction and validation of the malaria index, see Kudamatsu et al. 2016; Tanser et al. 2003). This more complex and physically based indicator is capable of capturing variation over time and space that coarser measures are not able to capture. This measure has been used to investigate patterns of infant mortality across sub-Saharan Africa (Kudamatsu et al. 2016). We use this composite climate-based measure to identify months and locations (with a spatial resolution of ~5 kilometers) in which the parasite and vector are likely to be present and transmission rates are expected to be higher.

Table 1 presents the criteria used to define the binary malaria index. All criteria must be satisfied for a location (grid cell) to be considered potentially malarious.

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

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[3]Extensive surveillance data exist for many sites across Africa and worldwide. Surveillance systems (see, e.g., In-Depth Data Repository; http://www.indepth-network.org/) are designed to follow individuals and regularly track different key events, including disease, births, and deaths. Unfortunately, data of this sort are geographically limited to specific communities and can be challenging to combine with other, similar surveys in different places because questionnaires can vary greatly. Furthermore, access to the individual records dramatically varies across sites and over time.

when women are exposed during prepregnancy or early or later stages of pregnancy (Bloomfield et al. 2013; Kramer 2003). Other outcomes of food insecurity include low height-for-age (stunting) and low weight-for-age (wasting), among a wide range of other adverse health outcomes that can last into adulthood (many of which are associated with *in utero* exposures). A wide range of factors drive community- or household-level food insecurity, with food availability featuring prominently in studies focused on sub-Saharan Africa and small-scale farming households (Butt et al. 2005; Grace et al. 2016; Smith and Haddad 2001). 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, migration, and remittances (Barrett 2010; Myers et al. 2017; Timmer 2012), and would be available on a monthly (or finer) scale or a seasonal time scale for each household. As expected, data of this type are rarely available for sub-Saharan African households and are never available with the temporal and spatial detail suitable for a study of individual-level child health outcomes.

As a solution, researchers and development agencies (e.g., USAID Famine Early Warning Systems Network [FEWS NET]) have estimated food availability and, consequentially, food insecurity through the use of remotely sensed data of vegetation (Brown et al. 2012; Brown et al. 2015; Funk and Brown 2006; Funk and Budde 2009; Husak and Grace 2016). In this research, we use the Normalized Difference Vegetation Index[4] (NDVI) as a proxy for community-level food availability. Specifically, we use NDVI data from a data series provided by the Integrated Climate Data Center at Universität Hamburg (Pinzon and Tucker 2014). These data are a quality-controlled version of the NDVI data provided by the National Aeronautics and Space Administration's Global Inventory Monitoring and Modeling System (NASA-GIMMS; Tucker et al. 2005). NDVI serves as a measure of greenness and is available at a relatively fine spatial (1/12-degree grid cell, or roughly 8 kilometers) and temporal (bimonthly) resolution. Thus, NDVI allows for a proxy measure of vegetation that varies throughout the year and at a scale that is fine enough to reflect village- or community-level variation over space and time. Although food security is more complex than food availability alone, NDVI in semiarid zones such as in Mali captures the interannual variability of yield across all crops. NDVI is particularly relevant in Mali because the vast majority of Mahan fanners rely on rainfall as their primary source of moisture, particularly in communities far from surface water (Husak and Grace 2016; FEWS NET livelihood reports for Mali, https://fews.net/west-africa/mali).

For estimates of a village's food security, an analyst identifies the area where agriculture is likely to be produced and spatially aggregates the maximum NDVI of pixels within that area to estimate the annual growing season's crop production. Relative changes in this aggregate NDVI value enable the analyst to identify years when that community likely produced more or less food, with a consequential increase or decrease in food security (Bakhtsiyarava et al. 2018). Although not optimal, NDVI as a proxy for food security allows researchers to

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[4]Under some circumstances, the Moderate Resolution Imaging Spectroradiometer (MODIS) Enhanced Vegetation Index (EVI) might be preferred over NDVI. The EVI has been optimized to have a more sensitive response to densely vegetated regions and to minimize canopy-soil variations. In our data, and in West Africa generally, the EVI and NDVI are highly correlated (Zoungrana et al. 2015) and show negligible differences when used interchangeably in the food insecurity pathway models.

(1) produce more policy-relevant findings through the use of an approach common across development agencies,and (2) address food security research questions in data-poor regions without any time-varying information about smallholder farming practices.

Linking regional aggregate NDVI with food insecurity requires the assumption that the relative changes in NDVI between years are due predominantly to crop health and subsequently agricultural yield. However, it is possible that certain communities transitioned to a drought-tolerant crop, which may lead to a false flag if that drought-tolerant crop is less green than the previous selection. A low NDVI value for a robust harvest of a less-green drought-tolerant crop would appear to indicate food insecurity, when in fact this decline is due entirely to agronomic strategy.

Another potentially confounding factor when considering ND VI as a proxy for food insecurity concerns communities' coping strategies when yields are suboptimal, and the high prioritization of maximizing the health of pregnant women and infants. One such strategy is circular migration, in which one or more family or community members leave to seek wage-earning opportunities elsewhere, thus reducing the number of mouths to feed and increasing the per capita food stores. In some Mahan communities, circular migration is widespread and represents a normal part of the transition to adulthood (Hertrich and Lesclingand 2012, 2013), but it may be less common under certain conditions, including during periods of drought (Findley 1994; Grace et al. 2018). The impacts of migration on food security in the origin communities in Mali is not well understood. The very limited migration data included in standard, country-representative population/health surveys, especially in countries reliant on short-term migration, constrain analyses and prevent us from taking circular migration into account.

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, such as low birth weight and preterm birth (Rylander et al. 2013). 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 delay conceptions or increase the likelihood of miscarriage, possibly resulting in heavier babies at birth given that only the healthiest fetuses result in live births (Barreca et al. 2018; Wilde et al. 2017). Exposure during later stages of pregnancy has inconsistent outcomes but is typically associated with increased risk of preterm birth, thus resulting in lower birth weights (Basu et al. 2016; Schifano et al. 2016). However, in some subsistence-based farming settings, mainly those in the tropics, increased temperatures may correspond to increased agricultural yields, which may be associated with higher birth weights (Davenport et al. 2017; Ray et al. 2019).

Temperature measures used in climate-health analyses in low-income countries rely on a relatively coarse spatial scale (usually 25–50 kilometers) and either a fine (daily maximum values, for example) or coarse (monthly or yearly averages) temporal scale. There are several approaches used to aggregate temperature data with health or other population data. Among the common approaches are calculating annual, seasonal, or monthly means of daily maximum values, or deriving heat wave indicators, which often identify sequences of days when the daily maximum exceeds a specific threshold or percentile of the temperature

distribution for a given location (see Phalkey et al. 2015; Zhang et al. 2017). Where available, hourly measures of temperature data can provide additional context (Jiao et al. 2019), for example, by examining the impact of excessive nighttime or morning temperature on health outcomes.

Pathways in Application—Although the concepts of disease, food insecurity, and heat stress are general, how each 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 to 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. Mali has a clear north-south rainfall gradient, with much lower levels of rainfall in the north and higher levels in the south. In addition, within-country rainfall variability is fairly high: villages as close as 10–20 kilometers apart may experience different rainfall conditions that modify the start, length, and overall quality of the season. As in other malaria-endemic contexts, the primary malaria season occurs during the growing season, with most cases occurring in June-September. However, similar to the situation for food security and agricultural production, within-country variability in rainfall during a given year results in spatial variability in malaria transmission as well. Thus, in research investigating climate and health, spatial and temporal variability in enviromnental conditions and exposures requires a consideration of the conditions where each person lives.

Identifying the specific mechanism using cross-sectional, observational data is challenging, especially because some of these conditions are interrelated and because 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. As the field of climate-health scholarship rapidly grows, researchers increasingly note the potential for climate and weather conditions to impact health outcomes through many potential pathways (Phalkey et al. 2015). To better isolate the contributions to adverse health outcomes associated with each of these potential drivers, we use different measures derived from different remotely sensed and physically based data sets. Each measure has been validated in other research and is modified here for our study on birth weight outcomes in Mali.

Birth weight is used because it provides an easily identifiable period of risk: the pregnancy (approximately 9 months before a child's birth date) and prepregnancy periods (approximately 9–12 months before a child's birth date). Exposure to disease (malaria), heat stress, and food insecurity during pregnancy may affect infant birth weight. Timing of exposure is important: exposures during prepregnancy and early pregnancy may contribute to failed conceptions or spontaneous abortions and result in a selection bias, resulting in heavier babies at birth (see Catalano et al. 2016; Wilde et al. 2017; Zhang et al. 2017). Using trimester-specific measures of exposure allows us to consider the differential risks associated with each trimester on birth weight outcomes.

To separate temperature effects associated with agriculture from those associated with heat stress, we exploit Mali's unique agricultural calendar. Specifically, the hot season (March–May), when temperatures can exceed 45°C, does not overlap with the rainy growing season (June–September). Focusing on different categories of temperatures conditions allows us to 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 is 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 account for the complicated relationships among rainfall malaria, and food insecurity. Table 2 summarizes the pathways, the measures and data, and timing considerations for use in this analysis. Details on the specific construction of each pathway are presented in the Measures section.

Data

Population Data

The population data used in this research come from the 2000, 2006, and 2012 cross-sectional Demographic and Health Surveys (DHS). Because of ease of use and consistency across periods, we use DHS data from IPUMS DHS (Boyle et al. 2018). DHS data contain highly detailed information on women's 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 attaimnent, 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 kilometers to maintain confidentiality of respondents but can be merged with other spatially referenced data as long as an appropriate spatial buffer[5] is incorporated into an aggregation strategy (see Davenport et al. 2017; Grace et al. 2019).

Environmental Data

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

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[5]The spatial scale of the environmental data (described later) varies. In the cases where the spatial scale is finer than the DHS, we average the values within the buffer. In the case of temperature, for which the spatial scale is coarser, multiple DHS clusters fall within the same temperature pixel.

Temperature Data—We use temperature data provided by Princeton University's Terrestrial Hydrology Research Group (Sheffield et al. 2006). These temperature data were extracted from a data set (version 3)[6] of complete meteorological forcings, including precipitation, air temperatures (minimum, maximum, and average), downward short- and longwave radiation, surface pressure, specific humidity, and wind speed. Since its development, the Princeton University data set 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 (Rodell et al. 2004). These temperature data are provided at 0.25 degrees, which is the finest resolution currently available for daily global temperature data. Although the spatial resolution is coarser than that of the precipitation data, temperatures generally exhibit less spatial variability than precipitation and thus do not require such fine resolution. We use these temperature data to identify and compute heatwave events (i.e., the heat stress pathway), and we combine these temperature data with precipitation totals to quantify malaria risk.

Vegetation Data—The Normalized Difference Vegetation Index (NDVI) is a measure of vegetation health and thus a measure 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 provides 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. 2016; Husak et al. 2008). Here we use NDVI data from the Integrated Climate Data Center at Universitat Hamburg; this data set is a quality-controlled version of the NASA-GIMMS NDVI products (Tucker et al. 2005). The NDVI data are available at bimonthly (~15-day) time steps and 1/12-degree spatial resolution from 1981 to 2015.[7] In this research, we consider seasonal maximum NDVI to be a proxy for crop production and ultimately food security and availability (i.e., the food insecurity pathway).

Measures

Outcome Variable—The outcome variable is birth weight, which reflects a clearly defined period of exposure: approximately nine months of gestation. This defined period allows us to carefully consider specific exposures. Given that DHS data generally do not contain information necessary to calculate exact conception date (or gestational age), we approximate the date of conception as the nine months prior to the birth date. Consistent with the literature on fetal growth and prenatal exposures, we consider each trimester of a pregnancy separately and include the important 0th trimester (the prepregnancy or conception period) (Bloomfield et al. 2013; Kramer 2003; Rylander et al. 2013). Birth

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

[7] This NDVI data series is not updated regularly and currently ends in December 2015. For analyses that require more recent NDVI data, the MODIS satellite imagery has been used to develop NDVI beginning in February 2000.

weight is recorded based either on a respondent's recall of her child's birth or 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 whether the birth weight information was from recall or from the medical card.

Among the 25.5% of respondents who did not report a birth weight for their child—either because they could not remember the child's birth weight or because the child's weight was not measured at birth—57% live in urban areas, and 66% are classified as having no educational attainment. However, 87% of rural and 86% of women living in pastoral areas reported birth weights. When considering birth weight reporting by month of birth, we find some variation, with most months having around 25% to 26% of missing data on birth weight. In the fall (August–November), information on birth weight is somewhat more likely to be missing than in other months, with about 27% to 28% of births having no birth weight recorded. Comparative figures for December and February are 23% and 24%, respectively. Apart from the lower reporting of birth weight among urban women, it does not appear that certain times or places are routinely excluded from the analysis. We therefore do not believe that there is a pattern to this missingness that correlates with any of the pathways investigated here, and we do not consider this limitation to inflate the relationships observed here.

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 Mali DHS questionnaire asks, "How long have you been living continuously in this town/village?"[8] Responses are recorded using an annual time scale. Although not optimal for measuring individual migrations or exposures to different enviromnental risks, this question allows us to link individuals to enviromnental exposures. In terms of pregnancy outcomes, respondents who have lived in the current community at least 12 months preceding childbirth 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 were either not in the current community during the pregnancy period or did not provide a response to the question. This question was excluded in the 2012 survey, and we therefore conducted the analyses separately for those with and without tins residency information. No significant difference in results was detected when we compared results across groups with and without residency information and with and without aligned exposures (results available upon request). The final models presented here use all available data, regardless of residency information.

Independent Variables: Food Insecurity—We use growing season maximum NDVI values as our food insecurity measure. NDVI is best used as a comparative measure to indicate whether one area has more vegetation than a neighboring area or for comparing one period with another. The seasonal maximum NDVI is calculated for a 10-kilometer buffer centered on each DHS cluster. The growing season typically begins in mid-June and lasts through harvest in September. To investigate birth weight outcomes, we consider the

[8]The question about length of time at the current residence is included in DHS surveys in other countries as well, but the question may be worded slightly differently.

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[9] 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*. 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, whereas a higher NDVI value would indicate that agricultural production was relatively improved (compared with other communities) and that more food would be stored, thus delaying and shortening the hunger season.

Independent Variables: Disease (Malaria)—Malaria is measured using the binary malaria index from Tanser et al. (2003), which is based on 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., with the three months leading up to conception considered the 0th trimester, and the 1st–3rd trimesters following the standard definitions). This index ranges from 0 to 3, with lower values indicating lower risk of exposure to malaria during a given trimester and higher values indicating an increased risk.

Independent Variables: Heat Stress—Heat stress is measured using daily maximum temperatures from a data set on meteorological forcings developed by the Terrestrial Hydrology Research Group at Princeton University (Sheffield et al., 2006). Quadratic and cubic approaches have been used in other analyses in addition to a binned approach and a threshold approach (i.e., days above an arbitrary cutoff value). Based on this research, a threshold or binned approach best captures exposure to heat stress in hot and dry enviromnents, with the focus on the hotter end of the distributions. Use of binned temperatures produces highly correlated independent temperature variables that were ultimately not useful. For this analysis, after exploring several temperature thresholds and binned approaches, we use a simple count of the number of hot days above 100°F, which is consistent with other approaches (see Davenport et al. 2017; Deschenes et al. 2009; Grace et al. 2015). Exploratory analysis on the use of wet-bulb temperature, which considers humidity to capture the "feels like" temperature, does not dramatically vary from the analyses using the temperature data set reported here. In addition, 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.

Table 3 provides summary information on the data used in the analysis.

Analytic Approach

To investigate the differential impact of these different pathways linking climate and health outcomes, we estimate a suite of regression models using reported birth weight as the

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[9]The *hunger season* is 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. For this project, we use the hunger season calendars from FEWS NET.

continuous outcome variable. We use ordinary least squares (OLS) regression and adjust for clustering at the level of the mother (due to multiple children birthed to the same mother).[10] Because individual factors related to health and development are of known significance, we include these variables in the models to account for the variability in the outcome associated with them. Control variables are maternal education and age at birth, infant sex, infant's birth order, and flooring type. The latter can be used as a measure of household wealth and development. Rather than include the DHS wealth indicator, which is designed for use when considering a single survey period and which may capture broad urban-rural differences in development, we use flooring type along with education level as coarse indicators to distinguish the poorest respondents (those with unfinished flooring and no educational attaimnent) from other respondents (those with finished flooring and primary or secondary education).We also adjust for month and year of birth, length of time at current residence, survey year, and the livelihood zone where the household is located.[11] The first set of regression models (Models 1–3) includes these control variables and the climate indicators for the three pathways described in Table 2.

Finally, we consider the results using the OLS models but where the relevant exposure period associated with the particular characteristics of the location is not considered in the ways that we have described. In other words, instead of looking specifically at hot season temperature conditions during the pregnancy, we look at average monthly maximum temperature during each trimester of pregnancy. We consider rainfall similarly and look at average monthly rainfall during each trimester of pregnancy. We investigate the results from this more general approach that does not address specific pathways associated with the enviromnental measures to determine whether any significant differences in model performance emerge when we use the exposure-based approach focused on the different pathways.

Results

We present the results from the four models corresponding to the three pathways of potential impact: malaria, heat stress, and food insecurity. We present partial dependence plots for the key pathway variables; regression tables can be found in the appendix. Beginning with the food insecurity pathway, we measure agricultural production by NDVI and focus on trimester-specific exposures to the hunger season. Figure 2 presents the NDVI results four separate models corresponding to the period of pregnancy when the exposure occurred.

Our assumption is that a child born in year t is likely to weigh more when the $t-1$ seasonal maximum NDVI value is higher. When the conception period (what we call the 0th trimester, occurring during year t) occurs during the hunger season, we see a positive association between birth weight (for the birth occurring around 12 months later) and the seasonal maximum NDVI value (from year $t-1$) ($p = .14$). For the cases when the first

[10]We also use multilevel regression models and conduct two separate models. We nest individuals within clusters in one model, and we nest individuals within mothers. In other words, we treat the cluster or the mother as a random effect. No significant difference in our findings results from these different analytic approaches.
[11]Data on livelihood zones come from FEWS NET and are used to capture broad trends in the ways that people produce food or earn money.

trimester occurs during the hunger season, we see a similarly positive relationship ($p = .10$) between NDVI (from $t - 1$) and birth weight. We similarly see positive associations for both the second and third trimesters as well ($p < .05$ for both cases). Fetal weight gain occurs during the later stages of pregnancy, and the results indicate that a stronger prior agricultural season is associated with a heavier infant (Bloomfield et al. 2013).

To investigate the relationship between malaria and birth weight outcomes, we use an indicator variable that combines rainfall and temperature characteristics as a measure of conditions that would support the presence of malaria. In this case, each birth that resulted in a live birth (with a birth weight) is included in a single regression model, and the number of months during each trimester (again, including a Oth trimester) is considered. Figure 3 shows these results and highlights a positive association between birth weight and exposure to malarious months in the third trimester. In other words, when a respondent was exposed to more malarious months during the last stage of pregnancy, her child's birth weight was larger ($p < .01$).

This result is inconsistent with our initial expectation that exposure to malaria would reduce birth weight. We believe that this counterintuitive result is explained by the association between greater exposure to malaria and an increased risk of spontaneous abortion during later trimesters. In other words, we speculate that the process by which malarious conditions impact pregnancy is through reducing the likelihood that less healthy pregnancies are carried to term and ultimately producing a group of healthier infants. Although the result initially seems counterintuitive, in fact, this idea is not new.

The potential that adverse enviromnental conditions contribute to miscarriages and stillbirths, or even prevent conceptions, and therefore result in infants who are healthier has been explored and documented in numerous studies focused on wealthy countries (Catalano and Bruckner 2006; Catalano et al. 2016; Wilde et al. 2017). Although not the central focus of our research (consequently detailed results are not presented but are available from the first author), we investigate this possibility in simple ways by considering how changes in malarious conditions during pregnancy relate to the sex of an infant: more malarious months associated with increased likelihood of female infants may indicate some prenatal selection. We also use data from the DHS on nonlive birth outcomes for Mali and investigate whether the risk of nonlive birth outcomes is associated with malarious conditions.

In terms of malarious conditions impacting the sex of an infant, results indicate that when the third trimester of a pregnancy has a greater share of malarious months, the likelihood of a female infant birth increases. No similar impact is observed in earlier stages of pregnancy. In terms of evaluating the impact of malarious exposure on pregnancy outcomes that do not result in live births, our analysis indicates that women who were exposed to more malarious conditions after Month 2 of pregnancy were more likely to experience a nonlive birth. Both sets of results support the notion that malarious exposure has a positive impact on birth weight through a selection process.

In the third model presented in Figure 4, we investigate the relationship between heat stress during each trimester and birth weight outcomes. To measure heat stress, we count the

number of hot days that each respondent was exposed to during her pregnancy. Here we look at all births and consider the count of hot days during each of the four trimesters. As discussed earlier, the hot season in Mali does not occur during the growing season but rather before the growing season. This setting then allows us to investigate high temperatures as an aspect of heat stress separately from considering how temperature conditions relate to agricultural production. Although the exact magnitude of the effect of heat stress on birth outcomes is highly uncertain, the general trend is a negative slope for exposures, indicating that an infant is likely to have lower birth weight when exposed to more days over 100°F during the third trimester ($p < .01$) and first trimester ($p = .06$). Heat stress experienced by a pregnant woman during these two trimesters could potentially lead to preterm birth or intrauterine growth restriction, thereby increasing the risk of low birth weight (Rylander et al. 2013).

Finally, to improve our understanding of these results, we explore one final modeling approach: we calculate general average rainfall and temperature conditions during each trimester of the births in our sample. This approach, which mirrors commonly used approaches that have produced a range of different outcomes, is a simple and straightforward strategy that makes no assumptions about the pathways linking environmental conditions to health outcomes. The aim of this approach is to determine whether variability in weather conditions during pregnancy is associated with variability in birth weight outcomes. Figure 5 displays the relationship between average monthly rainfall averaged over each trimester, and Figure 6 displays the relationship between average maximum temperature over each trimester.

The temperature results are consistent across the two models and suggest that either count of hot days or average temperature conditions experienced during a pregnancy could be used in related analyses. This finding makes sense given that Mali is a relatively warm place and that average temperature conditions are correlated with counts of hot days when hot days are defined as >100°F (correlation = .94 for all trimesters). Thus, higher counts of hot days will occur during the time when the average temperature is greater. In a place with more seasonal variability in temperatures or a growing season that corresponds with the hottest time of year, we anticipate that these different measures would produce more distinct results. The precipitation model, however, produces results that do not align with either the malaria pathway or the food security pathway. (The correlation between NDVI and precipitation is less than +/−.08 for all trimesters, which is not entirely surprising considering the disparate temporal scales between the variables.) Relative to this commonly used averaging approach, the pathway approach seems to reveal distinctly different patterns in the data. In fact, the direction and magnitude of results vary by trimester when the average precipitation approach is used. Because the pathway approach relies on measures that are more closely aligned with the ways that individuals living in Mali interact with the landscape, the pathway-specific results are likely to provide greater insight into the effect of precipitation and weather on children's health. The pathways approach provides a way of directly quantifying the nonlinear and often indirect relationship between precipitation and agricultural yield, and thereby children's health.

Finally, we consider the outcome variable as a categorical variable, comparing low birth weight (LBW) infants with healthy birth weight infants. To construct this variable, we use the World Health Organization's threshold by which any child with a weight below 2,500 grams is considered LBW. With respect to the pathway variables, the results are generally consistent in terms of the direction of the relationship and the level of significance when the categorical variable rather than the continuous variable is used. A notable exception is when evaluating the impact of hot days. During the 0th trimester, if a woman is exposed to more hot days while pregnant, the risk of a LBW birth increases (a relationship that is not significant in the case of the continuous variable, although the direction of the relationship is the same). Another noteworthy finding is the significance of the birth weight recall variable. Using the continuous variable, we do not find any significant differences in birth weight depending on whether a respondent recalls the birth weight or has it documented on a health card. Alternatively, individuals who recall the birth weight of their infant are more likely to recall a LBW compared with those women who had the birth weight information documented on a health card.

Discussion

Demographic and public health research examining the negative impacts of climate change continues to reveal vulnerabilities and highlight groups at great risk for adverse health impacts. Pregnant women and children are frequently identified as those facing some of the greatest risks associated with climate change through factors associated with food security, disease, and heat stress (Phalkey et al. 2015; Rylander et al. 2013). In sub-Saharan Africa, children born with decreased birth weight or low birth weight potentially face a lifetime of ill health and reduced earnings—factors that may be felt by subsequent generations (Rylander et al. 2013). In sub-Saharan Africa, health risks associated with climate change, such as reduced birth weight, are compounded because in addition to direct effects associated with heat stress, many families and individuals rely on rainfed agriculture to meet their nutrition needs. Furthermore, in some countries, malaria is 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 have facilitated dramatic improvements in climate data for use in population-enviromnent and climate-health research centered in sub-Saharan Africa. These data have 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 not included in the standard survey data set. Merging spatially referenced survey data with these high-frequency data sets 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 and hunger season (distinct from the hot season), high temperatures during the hot season, and high disease prevalence (with malaria being endemic) to examine an approach for isolating some of the most frequently cited mechanisms linking population, health, and the enviromnent.

We also focused specifically on infant birth weight. The approach we used here focused on measuring the pathways of interest using different data or indicators that are more closely aligned with the specific pathway of interest. Because the climate, topography, and development level of Mali is relatively consistent with other landlocked West African countries, 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 timing of exposure to better evaluate mechanisms connecting individual health outcomes documented in surveys and their climate/environmental contexts may be useful for structuring related questions in other contexts. Other outcomes beyond birth weight can be used as well, including chronic or acute health outcomes. The only requirements are that place of residence and exposure conditions be considered and that specific timing of exposures be appropriately linked to the pathways of interest.

Overall, our research demonstrates the complexity involved in quantitative studies of climate-health that rely on merging survey data and diverse sources of environmental data. Our results demonstrate the usefulness of deriving different contextually relevant measures capturing pathways linking precipitation variation and health. Based on our use of different enviromnental measures, the results of this research demonstrate the importance of local food production on the health outcomes of pregnant women. In general, our results indicate that more vegetation (as measured by NDVI) has a positive impact on birth weight outcomes. Notably, we constructed this as a lagged variable with the idea of measuring food in the community during the hunger period; therefore, the results indicate that women who experience pregnancies following a relatively (over time or over space) better season have babies with a higher birth weight. Malaria exposure, which is related to rainfall, produced results that seem to support a selection (or "culling") hypothesis. When more months within a trimester (especially the third trimester) were characterized as malarious, we observed an increase in birth weight. These results were consistent across all model specifications and after we accounted for individual education or livelihood zones. Our analytic approach, which relies on different measures to capture different but related enviromnental conditions, highlights the ways that enviromnental conditions impact human health outcomes, especially with regard to conditions related to rainfall. These results can be useful for policy development because they highlight specific periods of greater risk: women in later stages of pregnancy seem to be at greater risk for adverse outcomes related to heat waves, whereas the second trimester of pregnancy may be when exposures to inadequate nutrition and malaria have the greatest impacts on birth outcomes.

This research provides insights into climate-health modeling, but the study's limitations must also be considered. Birth weight data were reported in 75% of cases in the data we used, with the majority of the missing birth weight information concentrated among urban respondents. We included urban residence as a fixed effect in the models, and the concentration of missing birth weight among urban respondents likely resulted in biasing the results toward the null rather than in overinflating significance. Still, it represents a real limitation of the DHS data on birth weight.

Further, the malaria index is not ideal (Tanser et al. 2003), likely mismeasuring some months. 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 from malaria and using completely different timings and data should help to distinguish the effects of food availability from those of malaria exposure, but only to an extent. The malaria indicator is likely best suited for identifying malaria risks in places where malaria is epidemic or where there are historically few outbreaks. Therefore, the positive association observed between the third trimester and malaria exposure may capture some aspect of growing season conditions or some other artifact of the climatological conditions that make up the index.

Finally, at the beginning of this article, we discussed the methodological opportunities associated with using high-frequency spatial data of different spatial and temporal scales to better capture local contexts. In fact, this research largely focuses on the importance of considering local contexts—specifically, the geophysical and landscape contexts—to advance climate-health research. And although conceptual frameworks that highlight social, behavioral, and cultural factors underpin our research, the specific ways that individuals interact and respond to different environmental or health conditions and events is not captured here. We acknowledge that it is of fundamental importance to consider the social and cultural aspects of health with attention to how those factors vary over space and time. In Mali, for example, research has shown that child health is related to the marital and household status of the child's mother and to factors related to the mother's household status when she was a child herself (specifically, whether the mother was a fostered youth) (Castle 1995; Dettwyler 1993). Research also shows that poor water quality, time required to collect fuelwood for cooking, and inadequate financial resources to afford medical care during pregnancy, birth, and later on have significant impacts on children's health and development (Adams et al. 2002; Bove et al. 2014; Dettwyler 1993). Furthermore, farmers and households may respond differently to similar enviromnental conditions, resulting in differing health and economic outcomes.

Thus, within these areas of research, not all individuals face the same outcomes despite sharing similar enviromnental exposures. It is clear from the research that adverse health outcomes, such as low birth weight, result from multiple interacting factors. Dettwyler (1993:36) noted that there is a culturally and contextually important "safety net of overlapping support systems" created by a family and community to guard the health of children. In the case of adverse health outcomes such as low birth weight, these children have slipped through the complex safety net. Among researchers, very little is known about locally relevant safety nets or how pregnant women manage extreme heat, exposure to malaria, or food insecurity. It is a challenge for quantitative data and analyses to capture and measure the range of safety nets, and it is one of the important limitations of this research and the growing field of climate-health research. None of the data sets used in this analysis provide insight into management or coping strategies associated with health decisions used in the face of climate change. In addition to worthwhile and ongoing efforts by quantitative researchers to use existing data to better capture important climate features, qualitative research that investigates resource management and climate adaptation strategies

at the household and individual levels is greatly needed to further advance research in this area. ■

Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

Acknowledgments

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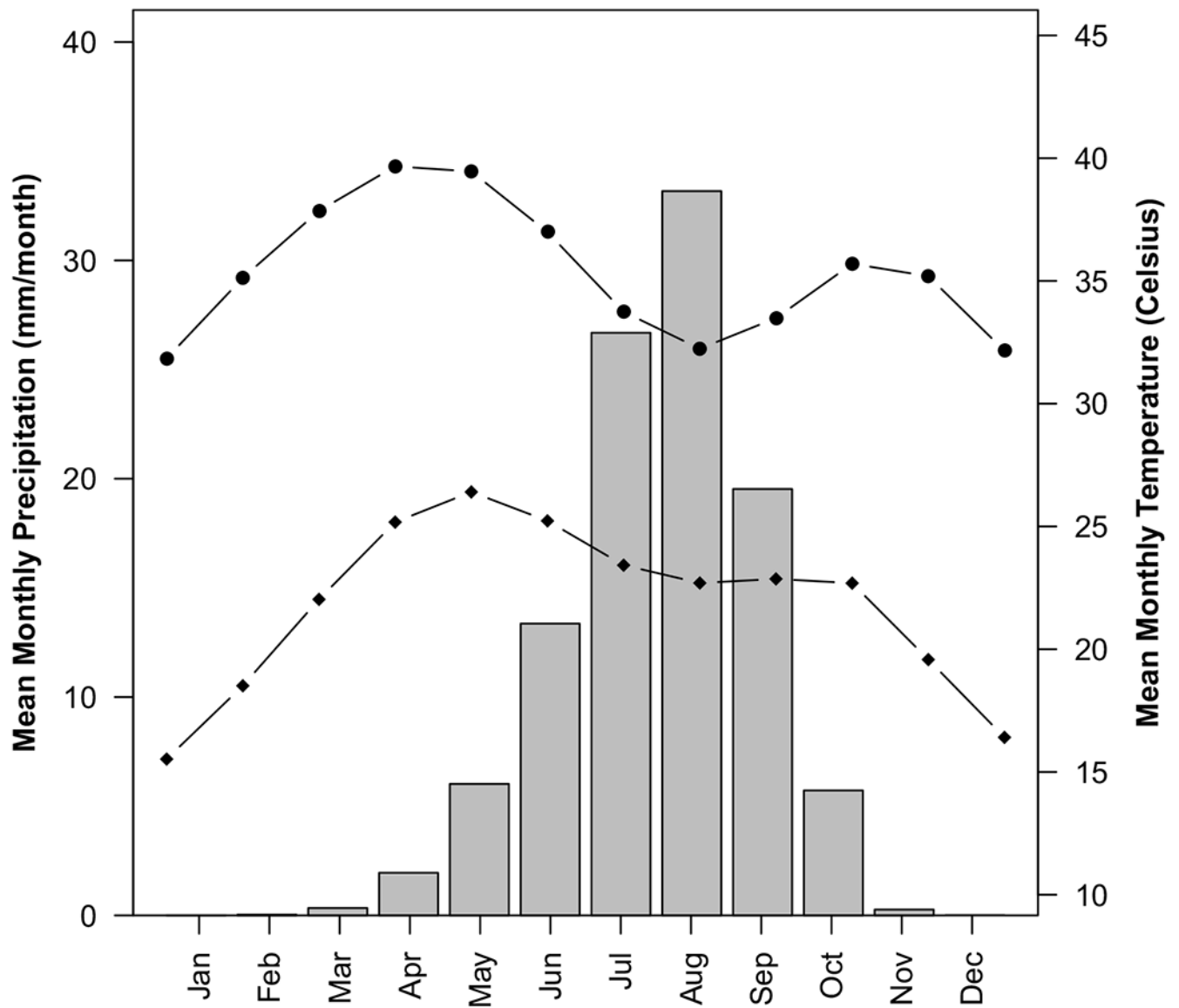
Fig. 1.
Mali climatology from 1981–2016 (averaged over DHS clusters). The bolded line with dots represents daily maximum temperature averaged over the month. Finer line with diamonds represents daily minimum temperature averaged over the month. Bars represent average monthly precipitation totals. Temperature data are obtained from the Global Meteorological Forcing data set (Sheffield et al. 2006). Precipitation data are obtained from the Climate Hazards Infrared Precipitation with Stations (Funk et al. 2014b).
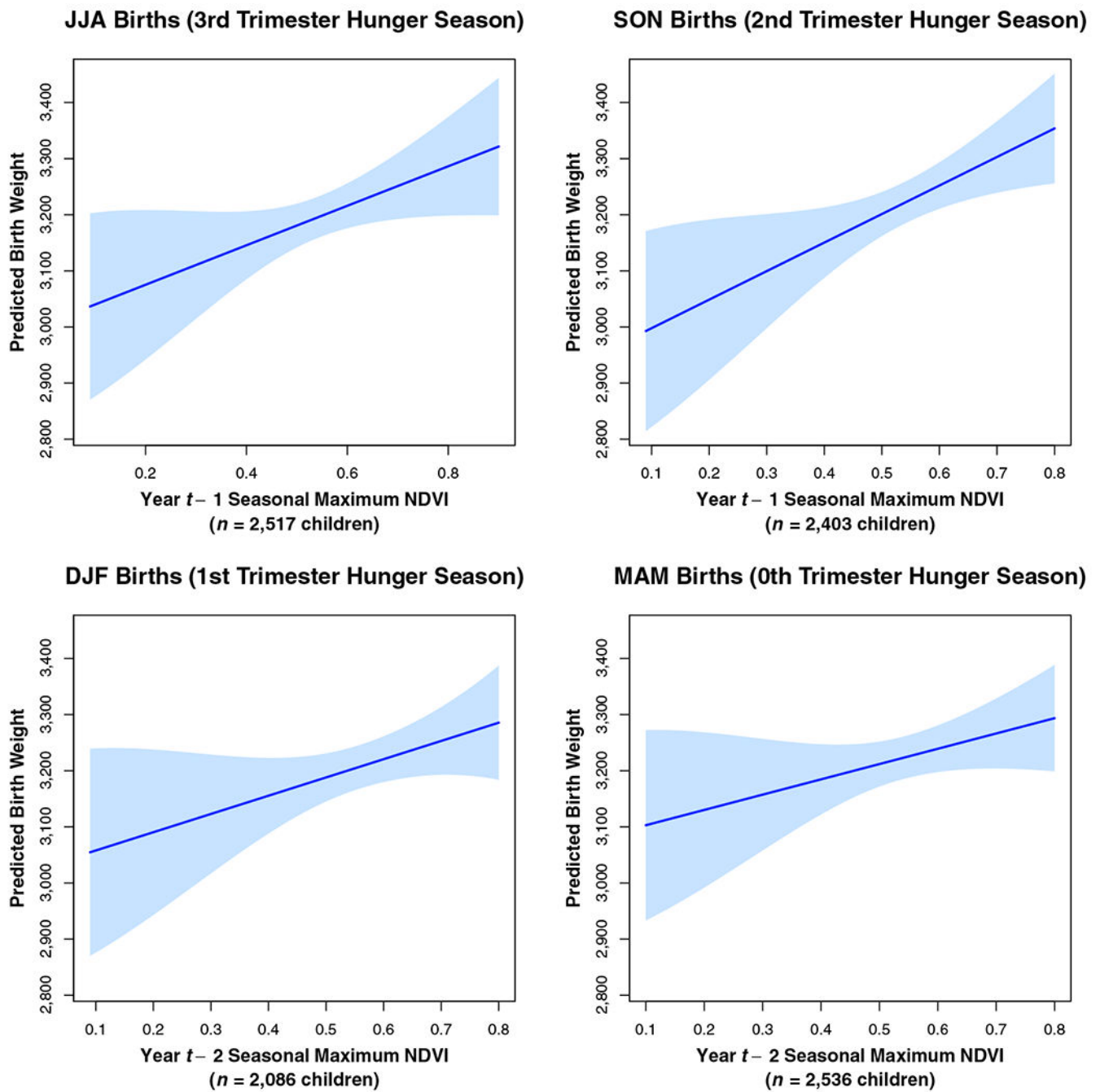
Fig. 2.

The relationship between NDVI values (year *t* − 1) and birth weight according to trimester-specific exposure to the hunger season (year *t*)
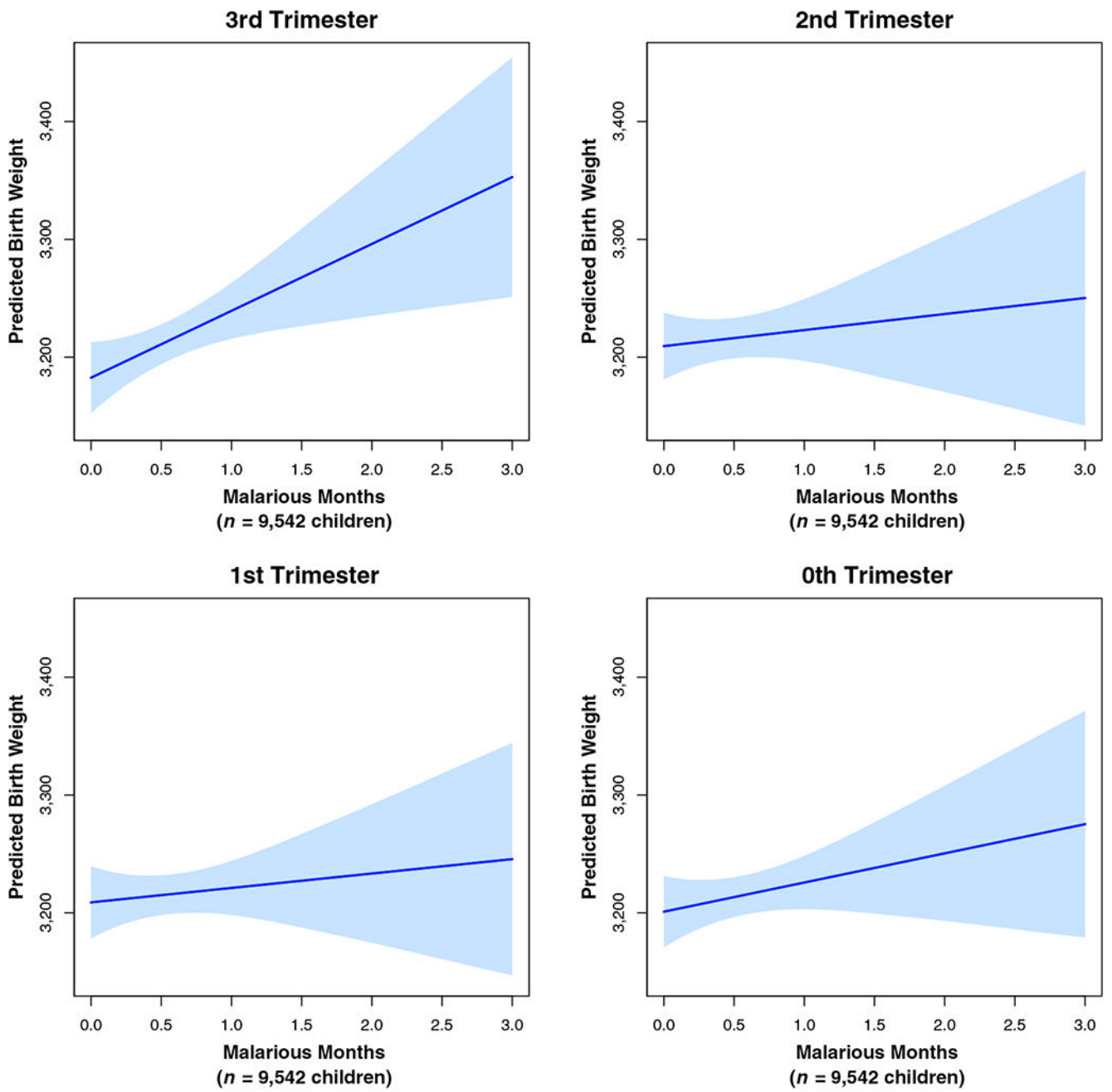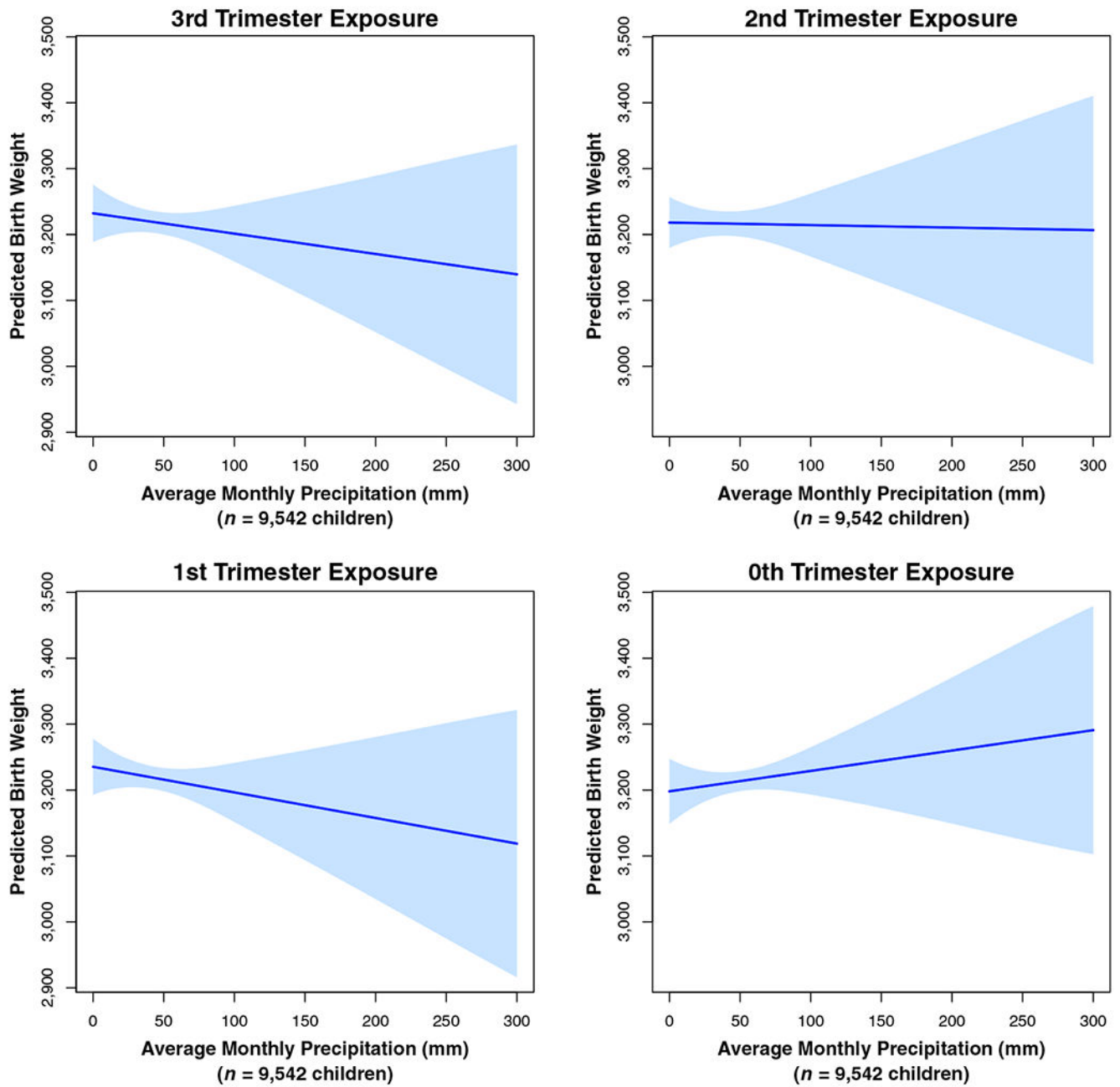
Fig. 3.
The relationship between malarious conditions during each trimester of pregnancy and birth weight for all children in the sample
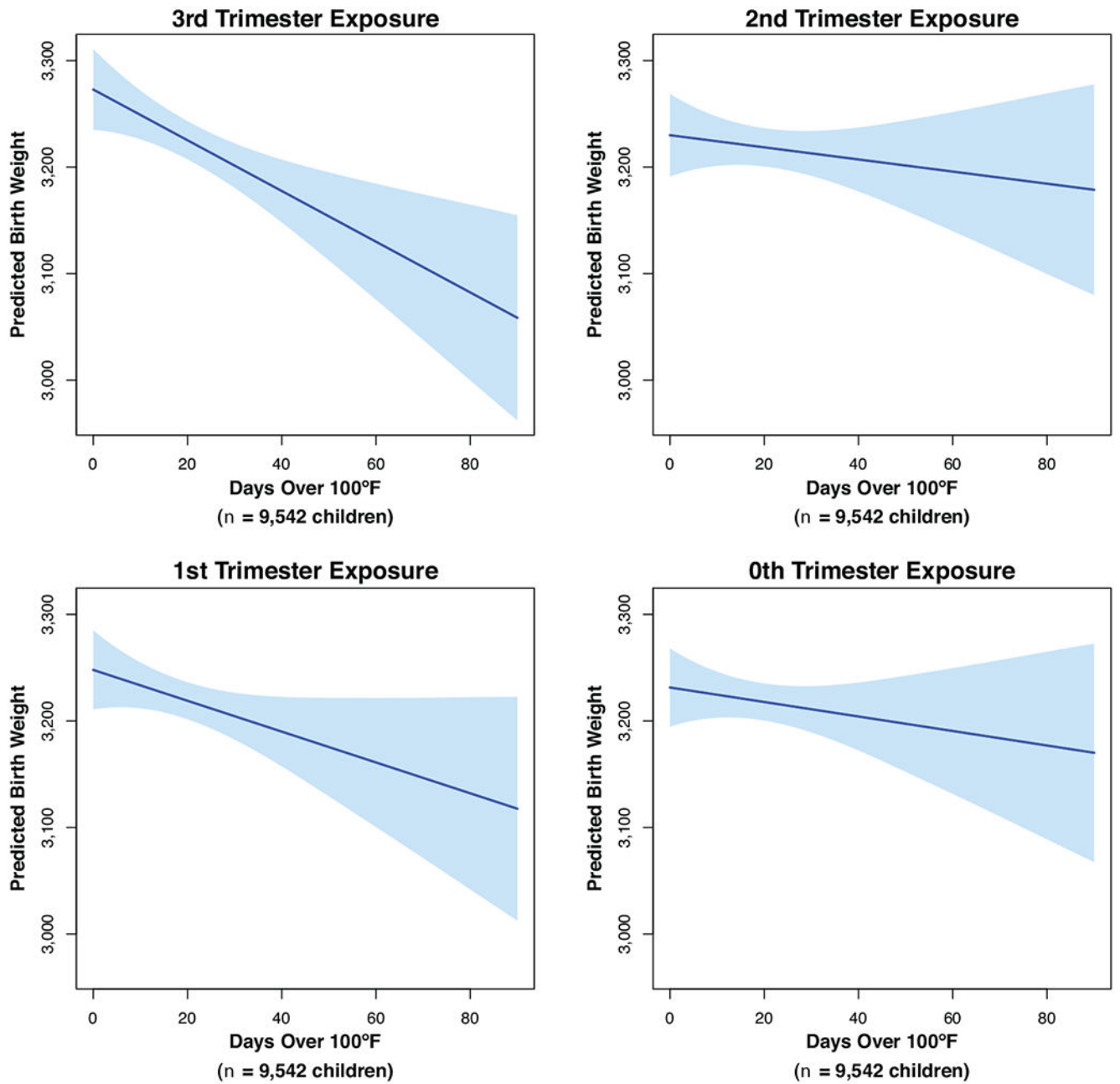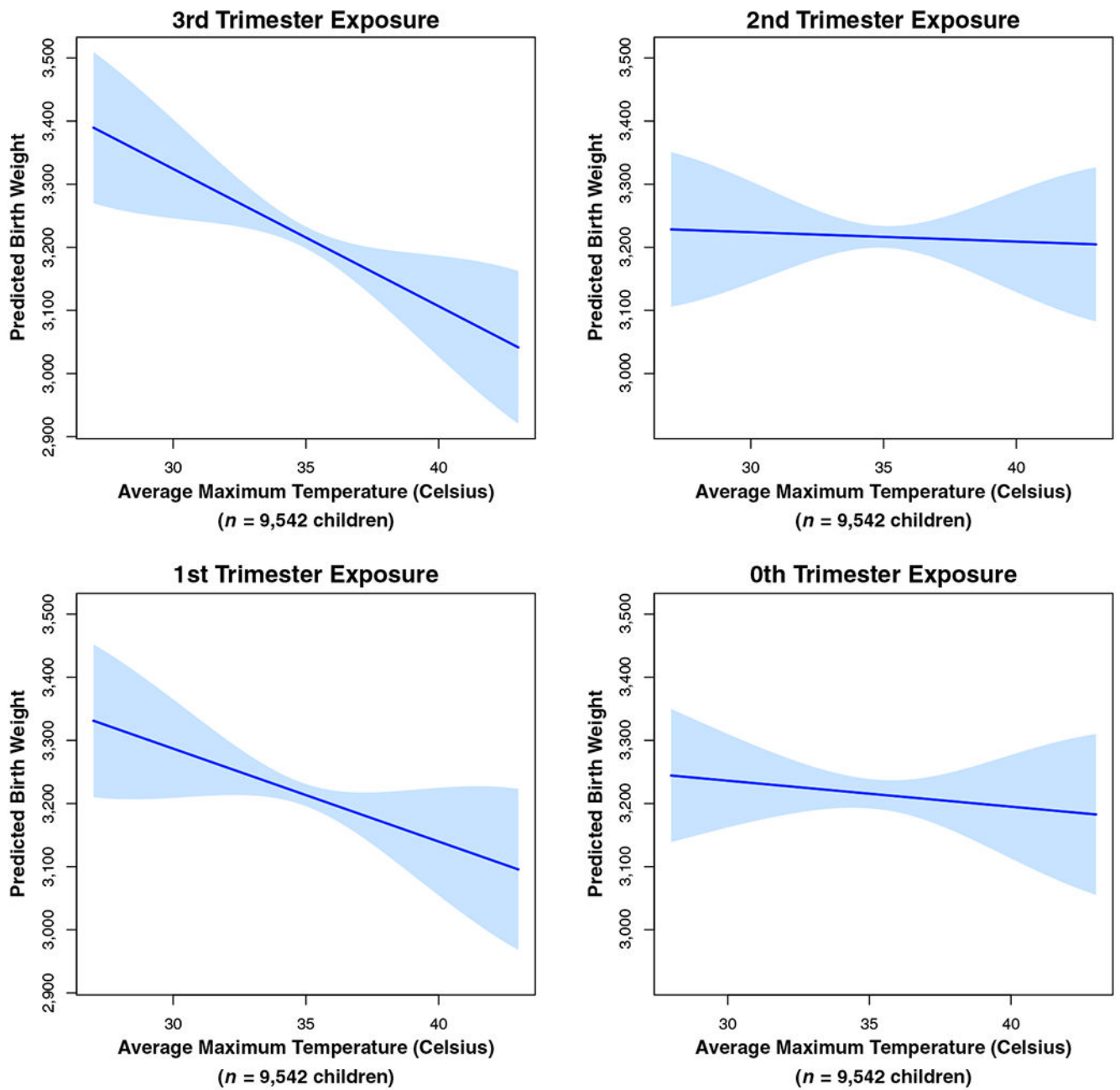
Fig. 4.
The relationship between exposure to days above 100°F during each trimester of pregnancy and birth weight

Fig. 5.

The relationship between exposure to average monthly precipitation averaged over each trimester of pregnancy and birth weight

Fig. 6.
The relationship between exposure to average temperature conditions during each trimester of pregnancy and birth weight

Table 1

Criteria used to calculate months suitable for P falciparum malaria transmission in Africa

Simulated Effect	Variable	Threshold
Parasite Development and Vector Survival	Three-month moving average temperature	(19.5°C + yearly SD of mean monthly temperature)
Frost	Minimum yearly temperature	5°C
Availability of Vector Breeding Sites	Three-month moving average rainfall	60 millimeters
Catalyst Month	Three-month moving average rainfall	At least one month 80 millimeters

Note: Modified from Tanser et al. (2003).

Table 2

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. A **positive** relationship during the following year's hunger season is possible 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, when higher birth weights may be observed.
Disease (Malaria)	Rainfall and Temperature	Increased risk of disease occurs during the key malarious months. Exposure to more months with malaria conditions will potentially have a **negative** impact on birth weight.
Heat Stress	Count of Days of High Temperatures	High temperatures during hot part of year could indicate exposure to heat stress. **Negative** impacts on birth weight are possible if a pregnant woman is exposed to heat stress during early pregnancy (impacts on placenta and uterus) and during late pregnancy (associated with preterm birth).

Table 3

Variables used in the analyses

	Mean	SD	%
Dependent Variable			
Birth weight (grams)	3,217	864	
Low birth weight (<2,500 grams)	1,930	411	
Key Independent Variables			
Seasonal maximum NDVI	0.56	0.17	
Count of malarious months	0.59	0.91	
Count of hot days	22.7	24.6	
Control Variables			
Child's birth order	3.7	2.4	
Child's sex (%)			
Male			52
Female			48
Mother's age (years)	28.4	6.9	
Mother's educational attainment (%)			
Never attended			66
Completed primary or beyond			34
Birth weight source (%)			
Card			31
Memory			69
Floor material (%)			
Dirt			52
Finished			48
Livelihood zone (%)			
Agriculturalists			34
Urban			33
Agropastoralists			27
Pastoralists			2
Irrigated			4
Survey year (%)			
2001			26
2006			40
2012			34

Notes: The sample used for each analysis varies based on exposure timing. We calculate descriptive information using the sample for the analysis of hot days.