Weather and Infant Mortality in Africa*

Masayuki Kudamatsu, Torsten Persson, and David Strömberg
IIES, Stockholm University

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Abstract

To what extent have weather fluctuations in Africa affected infant mortality over the last fifty years? We investigate this question by combining individual level data, obtained from retrospective fertility surveys (DHS) for nearly a million births in 28 African countries, with data for weather outcomes, obtained from re-analysis with climate models (ERA-40). The focus is on two mechanisms: malaria and malnutrition. We find robust statistical evidence of quantitatively significant effects. Infants born in areas with epidemic malaria that experience worse malarious conditions during the time in utero than the site-specific seasonal means face a higher risk of death, especially when malaria shocks hit low-exposure geographical areas, or hit mothers in the first trimester of pregnancy. Infants born in arid areas who experience droughts when in utero face a higher risk of death, especially if born in the so-called hungry season just after the start of the rains. We also uncover heterogeneities in the infant moratility effects of growing season rainfall and drought shocks, depending on household occupation or education.

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1 Introduction

To evaluate the desirability of mitigation or adaptation to climate change, we need comprehensive information about the impact of weather and climate on central socioeconomic outcomes, like health. While some impact assessments do exist,[1] many estimates of large-scale socioeconomic impacts rely on bold extrapolation, often from case studies in developed nations. Existing knowledge is particularly incomplete when it comes to developing regions, especially Africa, which is likely to be hit the hardest by changing weather and climate because climate is already harsh and societies are already vulnerable.

In this paper, we do not study climate change, but we do evaluate the health impact of weather shocks in Africa over the last 50 years. The fragmented information we have about such impacts mostly comes from clinical studies in local settings. Large-scale studies are very scant, mostly due to a lack of relevant data. We try to take some steps towards filling this lacuna of knowledge.

Specifically, we focus on the effects on infant mortality. The reason is twofold. On the one hand, alongside HIV, infant death is Africa's largest health problem: still today, close to 100 out of 1000 babies born on the continent die before the age of one year. On the other hand, and unlike the case of HIV, variations in weather most likely play an important role for infant death through channels like malaria and malnutrition.

Aside from its substantive objective, the paper also has a methodological purpose. We show how data from very different sources can be combined to overcome the lack of comparable African data at a continental scale. These data come at high resolutions in time and space. For infant death, we use cross-country retrospective fertility surveys in which the month as well as the year of birth of children is recorded and a geographic coordinate of the survey location is collected. For weather variables, we use the data generated from re-analysis with a global atmospheric weather forecasting model, available at the six-hour frequency on a 1.25×1.25 degree earth grid. When we examine nutritional channels of weather impacts, we also use data on growing seasons from spectral information collected by satellites, available bi-weekly at an 8×8 km resolution. We merge these datasets spatially by using the latitude and the longitude, rather than by the name of countries or sub-national regions.

[1]See Parry et al. (2007) for an overview.

Identifying the causal effects of weather variations on health is not straightforward. We can think of many reasons why weather and health might be non-causally correlated, e.g., due to their joint dependence on geography – places on the coast have different weather than land-locked locations, but people along the coast often have better economic opportunities, higher incomes, and better health. To avoid such statistical pitfalls when analyzing the effects of specific weather events, we only use the temporal deviation from the normal monthly pattern within each given location. As the natural variability of weather over time is, arguably, uncorrelated with any latent determinants of health, we are in effect using a gigantic set of natural experiments to identify the effects on infant mortality.

We focus on two mechanisms, malaria and malnutrition, and uncover statistically and quantitatively significant effects through both of them. Infants born in areas with epidemic malaria, who in utero experience worse malarious conditions than the site-specific seasonal means face a higher risk of death, especially in areas with very low average exposure to malaria, or when malaria shocks hit mothers around the time of conception. Infants born in arid-climate regions of Africa who in utero experience droughts face a much higher risk of death than other babies, especially if born in the so-called hungry season around the start of the rains. We also find marked heterogeneities in the effects of rainfall and drought on infant mortality, depending on household occupation and education.

The results are not only robust to a number of statistical pitfalls. They are also quantitatively important. For example, we estimate that a six-month malaria epidemic in a place with little average exposure to malaria can raise infant mortality by more than 3.5 percentage points. The effect of a drought in an arid area is of similar magnitude and doubles for infants born in the so-called hungry season.

While we are not aware of any studies with a similar scope and methodology for Africa, there are some recent reminiscent studies by economists. Deschenes and Greenstone (2007b) estimate the effect of weather shocks on overall mortality in the United States, but they rely on county-level rather than individual-level data and focus on cardiovascular disease. Burgess et al (2010) look at weather-induced mortality in India, but they too look at overall mortality and mostly rely on district-level data. References to other related work are given in context below.[2]

[2] Artadi (2006) estimates the impact of being born in rainy seasons and hungry seasons

In the following, Section 2 of the paper gives general background on our data. Sections 3 and 4 look separately at the effects of malaria and malnutrition, respectively, while Section 5 combines the analysis of the two channels. Section 6 summarizes our findings and discusses possible extensions.

2 Data – General Overview

Our most important data for this study come from two sources. We use individual data on health and demography outcomes assembled from DHS surveys, and spatially disaggregated data on weather outcomes obtained from ERA-40 re-analysis. In this section, we give some background on these data and how we put them together.

DHS surveys Demographic and Health Surveys (DHS) have been carried out with a similar methodology in many developing countries since 1984 with financial support from USAID. Each survey is carried out to collect information on life and health outcomes by interviews of a nationally representative sample of women in child-bearing age. Because of a standardized survey format, data from different surveys can easily be combined. DHS data have been used in a growing number of microeconomic papers on various topics in economic development.[3]

Each DHS survey employs a two-stage sampling, first selecting clusters – i.e., villages and town districts – and then selecting households within each cluster. In this study, we use a total of 51 DHS surveys, from 28 African countries – all the available surveys in which the geographic coordinate of each cluster is collected by a GPS receiver. These 51 surveys comprise information from a total of 17,772 clusters, located in both rural and urban settings. Figure 1 plots these clusters on a map of Africa. The data cover a pretty large part of the continent, including countries in the North (Morocco and Egypt), many in West Africa (from Senegal to Cameroon) and the Sahel,

on infant mortality in African countries. But her interest is to measure the impact of average monthly weather patterns while our focus is to estimate the weather impact of deviations from the average seasonal pattern.

[3] Detailed information on the DHS surveys and the underlying methodology can be obtained from the website:
`www.measuredhs.com`

and countries in the East of Africa (from Ethiopia to Tanzania), as well in the South (ranging from Namibia to Madagascar).

In the retrospective fertility module of any DHS survey, women of age 15 to 49 in the sampled households are asked about the month and year of birth for each of their children, whether the child died after birth and, if so, in which month. If either the month or the year of birth is not reported or inconsistent, the date of the birth is imputed from auxiliary information. The surveys we exploit contain information about 1.2 million births by about 300,000 mothers that occurred at least 12 months before the survey date, in the period (1957-2002) covered by our weather data (to be described). Dropping all the births with an imputed birth date leaves us with 975,800 births by more than 270,000 mothers.

For each of these births, we construct a binary variable indicating whether the child died as an infant. i.e., at the age of 12 months or less.[4] This is our major dependent variable in the paper. Infant mortality varies quite a bit both across time and place. For the full sample of births, the overall mean is 100.4 deaths per 1000 births, with a standard deviation across clusters of 69.2. But the mean masks a general decline from levels of mortality about 143 in 1970 to about 86 in 2002. Inspection of the data shows that infant mortality also varies quite a bit from year to year in addition to generally declining trends, as well as across groups of clusters (e.g., rural and urban areas) within the same country.

The fact that the surveys are retrospective gives us some causes of concern. While the birth and death of one's children are certainly life-defining events, we cannot rule out measurement error (perhaps more about the year than the month of birth or death). However, our results do not change significantly when we drop all reported births more than 10 years before the survey. Assuming that events nearer in time are more easily recollected, this is encouraging, and suggests that measurement error owing to imperfect recall is not a major problem in practice.

Another cause of concern is that mothers might migrate, so the mother's location at the time of the survey may not coincide with her location when her children were born. Using weather information pertaining to the surveyed cluster may thus attribute incorrect weather conditions to the time around birth. The surveys allow us to drop all births taking place before migrating

[4]The results are robust to excluding death at the age of 12 months from the definition of infant death.

mothers moved to the survey location, and this robustness check does not materially affect the results. Thus, the prospective downward bias of using weather data from the wrong place appears to be small (see further below).

The DHS surveys also give basic information at the moment of the interview about each child's gender and birth-order, their mother's weight, stature, years of education, and occupation, her husband's years of education and occupation, and the household's asset ownership, etc. We exploit some of these variables to investigate if the impact of weather shocks on infant mortality is heterogenous.

ERA-40 re-analysis Development economics research has increasingly relied on shocks to weather, such as rainfall, as a way of isolating exogenous variation in variables like income. The bulk of this research relies on data from weather stations together with various interpolation methods to fill out the missing data.

A well-known weather data set based on weather station observations is the one supplied by the Climate Research Unit (CRU) at the University of East Anglia.[5] The CRU data set indeed includes data at a high temporal and spatial resolution (monthly data at down to 0.5×0.5 degree resolution) for much of Africa. But its interpolation method is problematic for exploiting variation within location over time.[6] Since weather stations with consistent time-series observations in most African countries are few and far in between, and their precise location is not even public information, the CRU data is not appropriate for our purpose.

Miguel et al. (2004) use rainfall data from the Global Precipitation Climatology Project (GPCP), which relies on satellite images of cloud cover to estimate rainfall. However, for our study the GPCP is unsatisfactory: the spatial resolution of the rainfall data is rather coarse at 2.5×2.5 degrees, and we need temperature data to predict malaria transmission risk (see the next section).[7]

For this reason, we have decided to rely on weather data produced by what

[5] See the webpage at `www.cru.uea.ac.uk/cru/data/`

[6] First, changes in the weather outcomes in a given location may be due to the availability of nearby weather station data over time. Second, if the closest weather station with available data is too far, a long-term average value is used. See Climate Research Unit (undated) for details.

[7] The higher resolution data of the GPCP (1.0×1.0 degree) is available only after October 1996.

meteorologists call re-analysis. Specifically, we use a data archive known as ERA-40 supplied by the European Centre for Medium-Term Weather Forecasting (ECMWF).[8] This re-analysis relies on historical data from a variety of sources: weather stations, ships, aircraft, weather balloons, radiosondes, and most importantly – from the late 1970s – satellites orbiting the Earth. Such observations are fed into the ECMWF's large-scale atmospheric circulation model (known as IFS CY23r4) to produce a string of grid-specific forecasts for every six hours. These are statistically combined with available observations to produce a set of weather outcomes for every six hours, over the period from September 1957 through August 2002, on a global grid of quadrilateral cells defined by parallels and meridians at a resolution of 1.25×1.25 degrees (approximately 139×139 kilometers around the equator).[9] We expect this data set to contain among the very best available weather data for Africa, particularly since the poor observations are supplemented with frequent global satellite data, as this becomes available from 1979; in fact, about 88% of the births in our sample occurred 1979 or later.

Each DHS cluster is matched to the ERA-40 grid cell that contains it, by using ArcGIS 9.3's Spatial Join tool. These matched ERA-40 cells and DHS clusters are illustrated in Figure 2. With 17,772 clusters and 743 grid cells, there are almost 24 clusters on average per grid cell. For each grid cell, we extract 6-hourly data on rainfall and temperatures from the ERA-40 archive, and aggregate these data to the monthly frequency. Effectively, this gives us a large, balanced panel data set of rainfall and temperature, with 743 cross-sectional units and 540 (12×45) monthly observations for each unit. Summary statistics for infant mortality and weather outcomes, by clusters and various subgroups, are reported in Table 1.

3 Malaria

In this section, we focus on malaria during pregnancy as the important channel through which weather affects the survival of infants.[10] We start by a

[8]The data were downloaded from ECMWF's Meteorological Archival and Retrieval System. We are grateful for Heiner Körnich for help in this process.

[9]See Uppala et al (2006) for an overview and details on the methodology behind the ERA-40 archive, as well as a (partial) validation of the data.

[10]By malaria, we mean the infection in humans caused by Plasmodium falciparum, the most deadly species of malaria parasites, which is the most prevalent in Africa.

brief and selective overview of the epidemiology, immunology and pathology literatures on malaria and infant death. This suggests that large risks are associated with malaria infected mothers when the child is in utero, and that these risks may differ by malaria prevalence and type of baby. Next, we describe the index that we use to measure the weather conditions suitable for malaria transmission and infection, and how this index can be used to classify different DHS clusters for which we have data into different zones of malaria risk. Then, we present and discuss our econometric methodology and some results for the full sample and different malaria zones within a simple model where the number of malaria months enter linearly. These basic results clearly indicate that site-specific shocks to malarious conditions only have an effect on infant death in African areas with epidemic malaria, a result which is robust to a variety of statistical pitfalls. Thus, we look closer at subsets of these epidemic areas, allowing for a non-linear effect in the number of malaria months. Finally, we ask whether the risk of infant mortality varies systematically with household and mother characteristics, or with the trimester of pregnancy when malaria shocks hit.

Malaria and infant mortality Malaria is one of the major causes of death for children in Africa. Estimates provided by Murray and Lopez (1996, Appendix Table 6f) suggest that malaria caused about 15 % of deaths of children under the age of five in sub-Saharan Africa in 1990. It is estimated that about 75 % of the estimated malaria death toll of nearly one million people in sub-Saharan Africa in 1995 is made up of children less than five years old (Snow et al, 1999). However, infants are known to have a reduced sensitivity to malaria during the first few months of life, and fatal infections are believed to be more likely in the latter half of the first year of life and the first few years of childhood (Maegraith 1984, p. 262).

Malaria in pregnancy[11] is known to raise the likelihood of infant death via low birthweight – a major risk factor for infant death (McCormick, 1985). Guyatt and Snow (2001) show that the risk of low birthweight doubles if a baby's mother is infected with malaria during pregnancy, and that 5.7 % of infant deaths in Africa could be attributed to the low birth weight induced by maternal malaria.[12] The exact mechanism for the association

[11] See Desai et al. (2007) for a recent and extensive review of the medical literature on malaria in pregnancy.

[12] Studies reviewed by Steketee et al. (2001) attribute 3 to 8 % of infant mortality to

between malaria in pregnancy and low birthweight remains unclear, although insufficiency of a malaria-infected placenta is thought to lead to intrauterine growth retardation and premature delivery (Brabin et al. 2004). Placental infection by malaria parasites in African pregnant women is quite frequent. For areas where malaria is endemic, the median infection rate in the studies reviewed by Gyatt and Snow (2004) is 26 %, with a range of 5 to 52 %. Desai et al. (2007) review studies conducted in low malaria transmission areas of Africa and report a median prevalence of placental infection amounting to 6.7 %.

On top of a higher likelihood of low birth weight, babies born to mothers with an infected placenta are reported to be more likely to develop a malaria infection during the first year of life (Le Hesran et al., 1997) and may become susceptible to measles earlier than other babies due to reduced placental transfer of maternal antibody (Owens et al., 2006).[13]

Given the above-mentioned immunity of infants to malaria during the first few months of life, malaria in pregnancy may have a more profound effect on infant survival than infants' own infection after birth.[14] Therefore, we focus on the effects of weather-induced variation in malaria incidence while the child is in utero on the subsequent risk of infant death. However, we discuss exploratory estimates of mortality effects of malarious weather conditions during the first year of life.

The literature on malaria in pregnancy suggests several factors that raise the risk of infant death due to maternal malaria. One such factor is endemicity of malaria transmission. Where malaria is endemic, adult women develop partial immunity to malaria after repeated infections since childhood and thus avoid symptoms such as fever and anemia during pregnancy. Where malaria is seasonal or epidemic-prone, however, adult women lack in immunity against malaria. As a result, once infected with malaria, pregnant women have fever, which is known to increase the chance of premature delivery and of infant death (Luxemburger et al. 2001). We therefore expect the impact of malaria on infant mortality to be larger in areas where malaria transmission is low.

Firstborn babies are believed to face a higher risk of death due to malaria

maternal malaria.

[13] Measles is estimated to account for about 12 % of deaths of children under the age of five in sub-Saharan Africa in 1990 (Murray and Lopez, 1996, Appendix Table 6f).

[14] Snow et al. (2004) argue that looking only at the direct cause of death would significantly underestimate the impact of malaria on child death.

in pregnancy than those of higher birth order, although this heterogeneity appears to be absent in low malaria transmission areas (McGregor 1984). Rogerson et al. (2000) and Walker-Abbey et al. (2005) find that teenage women are more likely to be infected with malaria during pregnancy in Malawi and in Cameroon, respectively. Infants born to mothers infected with HIV as well as malaria face higher risks of low birth weight (ter Kuile et al., 2004). In general, firstborn babies, female babies, and babies born by stunted mothers, face a particular risk of low birthweight (Kramer, 1987), which makes it plausible that such babies might be particularly at risk in the wake of malaria shocks. We investigate whether these individual-level characteristics result in heterogeneous impacts of malaria-prone weather conditions.

How to measure malarious weather conditions? The incidence and prevalence of malaria in a given area and time depend on a host of factors, including climatic, biological, geographic, and socioeconomic conditions. Based on clinical measurements of malaria prevalence, researchers have tried to combine such information on the spatial distribution of malaria in so-called malaria maps (e.g., Kiezowski et al, 2004, Hay et al, 2009). In this study, we are interested in the weather-induced variability of malaria-prone conditions over time within each area for which we have infant mortality data.

A necessary condition for malaria to spread is the growth and survival of parasites causing the disease and vectors (a certain species of mosquitoes) transmitting the parasites. The rates of growth and survival are known to be heavily dependent on temperature and rainfall, and we want to capture these conditions in a parametric way.

To this end, we follow Tanser, Sharpe, and le Seuer (2003), who propose a relatively parsimonious weather-based index for malarious conditions for Africa in their study of malaria and climate change. This index builds on the comparison of mean long-term (1920-80) monthly rainfall and temperature with monthly profiles of malaria transmission intensity in 15 different locations with differing malaria prevalence rates as well as biological ranges affecting both vector and parasite development. The resulting monthly predictions of malaria transmission are empirically validated against the malaria occurrence data from about 3800 parasite surveys in different African locations. The index correctly predicts 63 % of malaria transmission incidents and 96 % of the absence of malaria transmission.[15]

[15] A high probability of correctly predicting the disease absence is remarkable given

Following the approach of Tanser et al (2003), we adopt the following:

Definition 1 *We set our binary malaria index for month τ in grid cell g, $Z_{g,\tau} = 1$ if and only if all of the following four conditions are satisfied:*

(a) *Average monthly rainfall during the past 3 months ($\tau - 2, \tau - 1, \tau$) is at least 60mm.*

(b) *Rainfall in at least one of the past 3 months is at least 80 mm.*

(c) *No day in the past 12 months ($\tau - 11$ to τ) has an average temperature below $5°C$.*

(d) *The average temperature in the past 3 months ($\tau - 2, \tau - 1, \tau$) exceeds $19.5°C$+SD(monthly temperature in the past 12 months).*

If any one of conditions (a)-(d) fails, we set $Z_{g,\tau} = 0$.

Conditions (a) and (b) ensure the availability of breeding sites for the vector and sufficient soil moisture for the vector to survive; (c) is required for the survival of the vector, as it quickly dies off at lower temperatures; and (d) allows the parasite to become infectious inside the vector's body before the vector dies.[16] The required threshold of temperature is higher, the higher the standard deviation of monthly temperature, because, after a cold winter, the populations of parasites and vectors need to be quickly regenerated to the level sufficient for malaria transmission.[17]

that these parasite survey sites were chosen because of their potential for transmission. A modest probability of correctly predicting the incidence of malaria is presumably due to socio-economic factors that prevent malaria transmission despite the suitable weather conditions.

[16] The vector obtains a parasite by biting a malaria-infected human being. However, it takes a while for the parasite to become infectious and thus for the vector to transmit malaria by biting another human being. Higher temperature shortens the time required for the parasite to become infectious and helps the vector survive long enough.

[17] The definition for our binary malaria index is slightly different from that in Tanser et al (2003). Since these authors have only monthly data, they apply condition (c) to monthly rather than daily temperature, while we use the latter. Unlike Tanser at al (2003), we also treat a non-malarious month based on the four conditions as still unsuitable for malaria transmission even if it is sandwiched by two malarious months. We also tried to implement the index in exactly the same way as Tanser et al, and found somewhat weaker results. By dropping separately each of the four conditions, we found conditions (a) and (d) to be the most relevant ones to predict infant deaths.

Malaria zones in Africa Climatological conditions play a major role for prevalence of malaria. In some areas, malaria is *endemic*, meaning that the risk of malaria is permanently high, or at least a good part of every year. In other *epidemic* areas, malaria spells are more short lived. This can be either because the transmission is seasonal, i.e., it recurs in a particular season due to stable variations in rainfall and temperature, or because it is unstable, i.e., it is present in some years but not in others. Finally, in *non-malarious* areas, the climate is too dry or too cold for malaria to be present or infectious at all.

As already mentioned, we expect a larger effect on infant mortality of seasonal weather shocks in epidemic areas, due to lower immunity rates and more severe malaria infections in such regions. To be able to test this hypothesis empirically, we divide the ERA-40 grid points (and thus DHS clusters) into three different malaria zones. Non-malarious zones have no single malarious month, as defined by the malaria index $Z_{g,\tau}$, over the entire sample period; epidemic areas have strictly positive malaria exposure between 0 and 4 months on average; while endemic areas have higher exposure rates. We have also set the epidemic-endemic split at 6, rather than 4, months with similar results.

Our classification is illustrated in Figure 3. Non-malarious areas, the green circles on the map, entail about 20% of the births in our sample and are found in the very North and South of Africa, and in mountain tracts (which are too cold), and in desert or near-desert regions (which are too dry). The remaining 80% of births are split almost equally between endemic and epidemic areas. The epidemic areas, colored in yellow, are mainly found in the Sahel, in higher terrain in East Africa, and in dry areas of the South. Endemic areas, in red, are mainly found in the tropical parts of Africa with stable warm and humid conditions throughout the year.

The geographical distribution of these three zones, based on weather conditions alone, corresponds reasonably well to the distribution of actual cases of parasite infection in malaria maps, based on cross-sectional clinical observations (see e.g., Hay et al, 2009).

Malaria exposure for individual pregnancies As mentioned above, we focus on the malaria conditions during pregnancy. For each childbirth in our sample, we thus create a measure of maternal malaria exposure of the 12 months up to the birth month. Specifically, for children born in a cluster within ERA-40 grid cell g and in running month t, we define

$$z_{g,t} = \sum_{\tau=t-11}^{t} Z_{g,\tau} \ . \tag{1}$$

In words, we gauge during how many months in the year before birth the child's mother was exposed to malarious weather conditions. This measure varies substantially across areas and time. In endemic areas, mothers are on average exposed to 8.0 months of malarious conditions, with a standard deviation of 1.0 months. In epidemic areas, the corresponding numbers are 1.8 and 1.0 months. Mean-adjusted variability is thus much higher in epidemic areas. (See Table 1, Panel B for summary statistics on $z_{g,t}$).

Basic econometric specifications In our most basic econometric specifications, we estimate panel regressions that are of the following type:

$$m_{i,c,x,t} = \beta z_{g,t} + \alpha_{c,s} + \alpha_{x,y} + \varepsilon_{i,c,x,t} \tag{2}$$

The dependent variable, $m_{i,c,x,t}$, is a binary infant mortality indicator. It indicates death at the age of 12 months or less, for child i, who is born in cluster c, within grid cell g in country x, and in running month t, which is calendar month s of year y.[18] We multiply this indicator by 1000 so that our results square with the conventional way of measuring infant mortality.

On the right-hand side, our parameter of interest is β, which measures how many more children per 1,000 die in the first year of life due to one additional month suitable for malaria transmission during the 12 months leading up to the birth. Further, $\alpha_{c,s}$ is a *fixed effect* for cluster c and calendar month $s = 1, .., 12$. That is, when we run this regression in the full sample, we control for 12 monthly means in each of our 17,772 DHS clusters, making for over 220,000 fixed effects. This way, we are identifying the parameter β from the deviation within each cluster from its site-specific monthly mean. To allow for a non-parametrically declining trend of infant mortality throughout Africa, in line with actual observations, $\alpha_{x,y}$ is a fixed effect for calendar year

[18]The standard definition of infant mortality is death *before* turning the age of 12 months. The distribution of age at death in the DHS data, however, has a peak at 12 months, suggesting some of the babies who died before turning 12 months old are reported to die exactly at the age of 12 months. Using the standard definition of infant mortality, we find somewhat smaller impacts of weather fluctuations.

$y = 1957, ..., 2002$ in country x. This adds another set of 1288 (46×28) fixed effects. That is, we allow infant mortality to have trends in national health systems, policies, or economic conditions, which could conceivably be related to local weather realizations.[19] Finally, $\varepsilon_{i,c,x,t}$ is an error term. We compute Huber-White robust standard errors, allowing for clustering at the grid level (encompassing 743 grid cells in the full sample).

Basic results The results we obtain when running versions of (2) in the full sample are displayed in Columns (1)-(3) of Panel A in Table 2. Column (1) is the result of a "standard" panel regression, with fixed effects for clusters and years, thus allowing for different cluster means and a non-parametric time trend for all of Africa. Column (2) replaces the cluster fixed effects with cluster-by-month fixed effects, whereas Column (3) estimates equation (2) by replacing year fixed effects with country-by-year fixed effects so that non-parametric trends for each country are allowed.

The point estimates of β are all positive, as expected. Evidently, taking the very local seasonal patterns of infant mortality and weather into account in Column (2) raises the point estimate at no loss of precision. But the more general specification in Column (3) cuts the point estimate and renders it statistically insignificant. This specification absorbs all country-by-year malaria shocks in the fixed effect. The lower coefficient makes sense, as country-wide malaria shocks may have more severe consequences than purely local shocks, e.g., because infections might spread from neighboring areas in the same country.

However, this basic specification assumes a treatment effect of malaria shocks that is homogenous across the whole sample – a very strong assumption. To test our prior of a larger effect in epidemic areas, we split the sample into its endemic and epidemic part, dropping from the sample non-malarious areas which by definition have no variation in the malaria index from zero. The corresponding estimates for endemic areas are shown in columns (4)-(6) of panel A. The point estimates for temporary malaria shocks show a similar pattern as those in the full sample, but they are never statistically significant.[20] Note that this does *not* mean that malaria is not a large risk factor

[19] For example, Kudamatsu (forthcoming) finds democratization has reduced infant mortality in sub-Saharan Africa while Bruckner and Ciccone (forthcoming) find negative rainfall shocks led to democratization in Africa.

[20] The result is similar if the boundary between epidemic and endemic is instead drawn at 6 months average exposure.

for infant death in endemic areas. Our identification of the effect hinges on the deviation from the average seasonal pattern of malaria transmission. Year-to-year variation in seasonal malaria transmission for endemic areas is not very large (see Table 1 Panel B), and the bulk of malaria-induced infant deaths are likely absorbed by the cluster or cluster-month fixed effects.

Panel B shows the results in epidemic areas. The estimated coefficients in Columns (1)-(3) follow the same pattern as in Panel A, but now the coefficient in the most general specification with national non-parametric trends is just below one and significantly different from zero at the 10% level. Mothers who face three months higher malaria exposure than normal have a raised infant mortality risk in the average epidemic cluster by just below 3 per thousand (close to the total infant mortality rate for Sweden).

In two remaining specifications in Panel B, we show the results of some robustness analysis for epidemic areas. Clustering of the standard errors at the grid-cell level, as in Column (3), allows for arbitrary serial correlation of infant mortality and weather in each grid cell. While such local serial correlation certainly exists, weather and the survival of babies are likely to be correlated across grid cells and also between a particular cell in a certain month and its neighboring cells in the following months. To allow for simultaneous spatial and temporal correlations, we try an alternative clustering scheme by 5 year-period and average malaria exposure (specifically, we split epidemic areas in those above and below 2 months of exposure north and south of the equator, respectively), giving a total of 36 clusters. As Column (4) shows, this yields standard errors for β, which are slightly lower than those with grid-level clustering.

While the specification looks at the linear effect of different number of malaria months, the definition of a malaria month is highly non-linear in temperature and precipitation. Perhaps this specification really picks up some other non-linear effect of weather on infant mortality. To check for this possibility, in Column (5) we include cubic polynomials in rainfall and in temperature during the 12 months preceding each specific birth.[21] This

[21] Specifically, we include the following terms to the right hand side of equation (2):

$$\rho_3^T T_{g,t}^3 + \rho_2^T T_{g,t}^2 + \rho_1^T T_{g,t} + \rho_3^P P_{g,t}^3 + \rho_2^P P_{g,t}^2 + \rho_1^P P_{g,t}$$

where $T_{g,t}$ and $P_{g,t}$ are the average temperature and the total rainfall, respectively, in grid cell g over the months $t-11$ to t. In subsequent analysis, we always refer to these terms as cubic polynomials in rainfall and in temperature.

is like adding a control function to the specification in equation (2). The resulting estimate of β is a bit above 1 with a slightly higher standard error than in Column (3).

Non-linear effects in epidemic areas? All specifications in Table 2 assume that the impact of malaria shocks is linear in the number of months of malaria exposure. But infant mortality is an extreme outcome, so perhaps it is more closely related to extreme weather events. Table 3 shows estimates that relax the functional-form assumptions. We first disaggregate the epidemic area into two subgroups, above and below 2 months of average exposure per year. This further classification is illustrated in Figure 4. Based on an immunity argument, one could presume that weather shocks increasing the susceptibility to malaria may have their most pronounced effect where malaria occurs the most rarely. Columns (1) and (2) of Table 3 display the results when the linear specification in equation (2) is estimated on the two separate epidemic subsamples. As the estimates show, however, the linear model does not produce very different estimates in the two samples.

To get further, we allow for a more general non-linear response within each subsample, by allowing for five bins of malaria exposure, setting the omitted default bin at average exposure. In Column (3), we look at the 0-2 month exposure sample, the cream-colored regions in Figure 4. The sign and size pattern of the point estimates is exactly what one might expect: exposure above the average is associated with a positive point estimate, even though the estimates are quite noisy. The most striking finding is the comparison of those pregnancies that have more than 6 vs. 1-2 (or 0) months of malaria exposure. A temporary weather pattern exposing a set of mothers to a potential more-than-six-months malaria epidemic raises infant mortality by about 38 per 1000, compared to a control group of pregnancies with no or little exposure at all. This is a huge effect, given an average infant mortality rate of about 100 per 1000 in the sample. Column (4) shows that these results are robust to including cubic polynomials in rainfall and in temperature during each pregnancy. Interestingly, the impact on infant mortality of reducing exposure from 6 to 0 (or 1-2) malaria months is similar in magnitude to the impact of the protection by insecticide-treated bed nets on the reduction in infant mortality, which is 31 per 1000 according to a randomized controlled trial conducted in endemic areas of western Kenya by Phillips-Howard et al. (2003).

In Columns (5) and (6), we show analogous estimates for DHS clusters with 2-4 months average exposure, the orange regions in Figure 4. The sign pattern is similar to that in Column (3). That is, zero or very little exposure is associated with much lower infant mortality rates than above 6 months exposure, even though the difference between the highest and lowest bin is smaller than in the 0-2 month sample – about 28 or 19 per 1000, depending on whether the cubic polynomials are included or not. Unlike in the earlier specifications, Column (6) rejects that both cubic polynomials in temperature and in rainfall are insignificant (see the F-statistic at the foot of the table), but the implied effect on infant mortality is larger than in the specification omitting the polynomials in Column (5).

We have also tried to distinguish areas with seasonal and unstable malaria, based on the standard deviation of the number of annual malaria months, within the epidemic sample. But this has not produced any stark differences in the estimated effect of malaria shocks.

The findings on non-linear effects are potentially very important for the consequences of future climate change. Projections of future climate indicate that Africa will get significantly warmer.[22] This means that areas which are hitherto non-malarious due to cold temperature – mountainous regions in Ethiopia, Kenya, Madagascar, and Zimbabwe close to the yellow dots in Figure 4 – are likely to become new marginal epidemic areas, where mothers will have little immunity and infants will be very vulnerable to temporary malaria epidemics. Moreover, if future climate change leads to more dramatic variations in the annual fluctuations of rainfall in the dry parts of Africa, then malaria epidemics may become more frequent in low-prevalence areas, with potentially large effects on infant mortality.

Heterogeneity by individual characteristics Following the medical literature discussed at the beginning of this section, we have also investigated if the impact of maternal malaria exposure is heterogeneous across different types of babies, mothers, or households. In particular, we have estimated extensions of our basic econometric specification in equation (2), where all right-hand side variables are interacted with indicators for female babies, firstborn babies, young mothers (under 18), stunted mothers (2 standard deviations below the median stature of the WHO Child Growth Standard by

[22]By the end of the 21st century, the average temperature in Africa is predicted to go up by 2.6 to 5.3 degrees Centigrade (Tanser et al. 2003, Table 2).

WHO Multicenter Growth Reference Study Group, 2006), and households living in regions with high HIV prevalence rate (10 % or higher according to the DHS HIV test results conducted in the 2000s). We have also investigated the heterogeneous impact by the education level of the household (whether both the baby's mother and her husband went to school for more than 8 years) and by affluence of the household (owning a majority of the consumer durables listed in the survey questionnaire). In these regressions, we always split the sample between endemic and epidemic areas. However, we find no significant patterns of heterogeneity in the data, while we always continue to find a significant effect of malaria shocks in epidemic areas but no such effects in endemic areas. This lack of heterogeneity across mothers and households is a bit surprising given the clinical evidence cited above.[23]

Heterogeneity by timing of malaria shocks Our findings above relate to the number of malaria months during the entire year preceding each birth. It is also of interest to gauge whether and how the exposure to malaria shocks at different times in pregnancy might matter. To this end, we split up the malaria-exposure index $z_{g,t}$ above into four parts – one for each trimester of pregnancy, and one for the quarter just before conception. In addition, we calculate the number of malaria months during 12 to 14 months before the birth. We then estimate a regression analogous to our basic formulation for epidemic areas, in Column (3) of Panel B in Table 2, except that the months of exposure in each of the five quarters preceding the birth enter as separate regressors.

Figure 5 plots the estimated coefficients on these quarterly exposure variables and their 95% confidence intervals. The message is pretty clear: an additional month with malarious conditions in the quarter before pregnancy, or the first trimester of pregnancy, is associated with a substantial increase in infant mortality. But there is no such effect for malaria shocks, neither in the second or third trimester, nor in the second-to-last quarter before pregnancy. Each of the two significant coefficients has a value around 2.5, more than double the estimate in Table 2. Quantitatively, this would mean that a six-month spell of malarious conditions, relative to the complete absence

[23]Our failure to find heterogeneous impacts of malaria in pregnancy across parities in endemic areas, however, is consistent with Guyatt and Snow (2001), who report malaria in pregnancy doubles the risk of low birthweight across all parities as well as for first pregnancies. Mutabingwa et al. (2005) also find that infants born to women with malaria-infected placenta are susceptible to malaria infection even if they are of higher birth order.

of malarious weather, in the two critical quarters raises infant mortality by about 15 per 1000.

These findings are interesting in that epidemiological research has produced few findings on the effects of malaria in the early part of pregnancy (Desai et al, 2007). However, the findings appear to be consistent with clinical studies showing that malaria infection in pregnant women tends to peak at the end of the first trimester (Brabin, 1983).

Malaria shocks in the first year of life For each child, we have focused on malaria shocks during the year before birth and we have seen that these shocks in utero have a significant effect on the likelihood of survival. Do malaria shocks after birth affect the probability that a child dies before age one, directly or indirectly through the health of the mother? To analyze this question, we have run regressions where malaria exposure during the first year of life – either month by month or the cumulated number of months with a positive malaria index – is added as its own term and as its interaction term with $z_{g,t}$ to the right hand side of equation (2).[24] We find no significant effects on infant mortality of in-life shocks neither in epidemic areas, nor in endemic areas. On the other hand, in-utero malaria exposure continues to exercise a significant effect on infant death in epidemic areas of similar magnitude as in our earlier estimates.

Summary To summarize, we find that weather shocks which raise exposure to malaria, as measured by the Tanser et al (2003) malaria index, significantly raise the incidence of infant death. The largest effects arise from exposure for more than six months in areas where malarious conditions are otherwise rare, and from exposure just before conception or in the first trimester of pregnancy.

[24] Malaria exposure in the n-th month after birth does not affect the survival of babies who died before turning n months. Therefore, including the 12-month exposure to malaria infection during the first year of life as a regressor to the whole sample will bias the estimated effects towards zero. To deal with this problem, for each n from 1 to 12, we restrict the sample to babies who survive at least the first n months after birth and use how many months are malarious during the n months after birth as a regressor.

4 Malnutrition

In this section, we continue to explore how past weather events in our ERA-40 data impact on infant death in our DHS data. But here, we focus on the prospective mechanism through malnutriton. Following a brief literature review, we discuss how to measure weather-induced crop-yield fluctuations in agricultural societies highly dependent on rainfall during a limited growing season, and how to partition the African continent into different climate zones. Next, we describe our measure of weather conditions conducive to more or less malnutrition during a child's period in utero and validate it against the data on crop prices in a subset of the countries in the infant mortality sample. Our econometric estimates show that a simple measure of rainfall during the growing season(s) tied to each childbirth are significantly related to infant mortality. In addition, we find a large effect of extreme events in the form of droughts (but not of floods), in Africa's arid climate zone. When we allow for heterogenous effects for different types of households, we uncover a significant linear effect of rainfall among agricultural households in tropical and temperate climate zones; we also find drought effects in the arid areas to be weaker in households dependent on agriculture and in well-educated households. Finally, the data suggest that babies born in the hungry season – the time just after the start of the rains – are particularly sensitive to malnutrition in utero.

Infant mortality and malnutrition Maternal and child malnutrition poses a major risk for child health, particularly in poor countries – for a recent review see Black et al. (2008). Because maternal intake is the sole source for fetal energy requirements, a lack of food during pregnancy negatively affects the growth of fetus in utero due to deficiencies of calories and important micro-nutrients. As a result, maternal malnutrition increases the risk of low birth weight, which in turn raises the risk of infant death through birth asphyxia and infections (McCormick, 1985, Black et al., 2008). The medical literature finds that low weight gain during pregnancy increases the chance of low birth weight (Kramer 1987 for a review). This effect is found to be stronger for women whose nutritional status is already poor before pregnancy (Krasovec and Anderson, 1991 for a review) and during the second and third trimesters (Strauss and Dietz, 1999).

Most African children are breast-fed during the period after birth, which is known to lower mortality risk compared to children who obtain non-breast milk liquid or solid food during the first six months of life (see e.g., Black et al. 2008, Table 4)[25] Consequently, and in analogy to the previous section on malaria, we do not focus on variations in food supply after birth, but rather on weather-induced variations in the risk of maternal malnutrition during pregnancy and their subsequent effects on infant survival.

Crop yield and growing seasons Most African countries are agricultural economies – in 2004, some 55% of people on the continent are employed in agriculture (Frenken 2005, Table 2), and many more depend on agriculture in other ways. In addition, transportation infrastructure in Africa is poorly developed.[26] Most people are thus largely dependent on the local yields of subsistence crops for nutritional intake (or of cash crops for earning income to buy foods). Moreover, irrigation of land plays a minor role in crop production, especially in Sub-Saharan Africa – only 6.4% of cultivated land was irrigated in 2004 (Frenken, 2005, Table 12). These stylized facts about Africa suggest that maternal nutritional intake largely depends on local rainfall.

While predictably rich throughout the year in tropical Africa, rainfall in many arid and semi-arid areas is much more erratic. General African rainfall patterns are largely governed by the so-called Inter Tropical Convergence Zone (ITCZ), in which the trade winds from the northeast and the southeast converge (Griffiths, 1972). As a result of the low pressures along the ITCZ, convectional thunderstorms form daily and dump large amounts of precipitation in scattered afternoon rains. Over land, the ITCZ moves north and south with the seasons, following the hottest part of the continent, which causes large variations in rainfall between dry and wet periods in a typical year. This is illustrated in Figure 6, which shows the average amount of rainfall across Africa in four different months. On top of this regular seasonal cycle, however, one finds considerable fluctuations across years in the precise timing and amount of rainfall. These are more marked in the areas that receive little rain owing to the unpredictable movements of the ITCZ from one year to the next.

In many non-tropical areas of Africa, crop yields are thus crucially depen-

[25] One might think that food availability after the birth of a child is important for his or her mother to produce breast milk. However, as long as it is not very severe, maternal malnutrition is known to have little impact on the volume and composition of breast milk (see Brown and Dewey, 1992 for a review).

[26] Herbst (2000, Table 5.3) reports that the road density for the median African country around the year of 1997 is merely 0.07 kilometers per square kilometers of land.

dent on the seasonal rains falling in the *growing season* – i.e., the rainy period of the year. We therefore use the total amount of rainfall during the growing season as a proxy for the amount of nutrition available for pregnant women in the analysis below. We have also experimented with various measures of temperature during the growing season, but with little success.[27]

The literature on agriculture and rural poverty in sub-Saharan Africa and elsewhere in the developing world stresses the concept of the "hungry season", the period just after the start of the annual rains, when food stocks from the previous harvest are on the decline at the same time as the calorie expenditures are peaking due to extensive agricultural work (see e.g., the contributions in Chambers, Longhurst and Pacey, 1981 and in Sahn, 1989). Low birth weights are found to be more likely to happen during rainy seasons than during dry seasons (Bantje, 1983 and Kinabo, 1993 for Tanzania, Fallis and Hilditch, 1989 for Zaire). This suggests that annual fluctuations in weather-induced nutritional availability may have heterogeneous impacts on infant survival across which season babies are born in.

How to measure the growing season? The growing season in a particular location is likely to depend on many other factors than the extent of rainfall, including soil qualities, crop types and the use of fertilizers. While some gridded information on these other factors exists, we take a convenient short cut to determine the relevant growing season for each of our DHS clusters, by employing the data measuring photosynthetic activity from remote sensing by satellite.

Photosynthesis is identifiable from a long distance, because growing plants reflect light at the infrared part of the spectrum and absorb light at the near-red part of the spectrum. Therefore, ecologists often use data collected by satellites to measure plant growth through ongoing photosynthesis. We use such satellite data made available through the Global Inventory of Modeling and Mapping Studies or GIMMS (Tucker et al. 2005), namely the so-called normalized difference vegetation index (NDVI). The NDVI index is globally available as bi-weekly series from 1982 and onwards on a resolution of 8×8 kilometers. In the ecology and biology literature, the integral of NDVI

[27] We are certainly not the first to use growing season rainfall as a proxy for crop yields. Lobell et al. (2008) use the growing season rainfall (and temperature) to predict crop yields in developing countries under the future climate change scenarios. Deschenes and Greenstone (2007a) also use growing season rainfall to predict agricultural profits in the United States.

values over the growing season is often used as a proxy for crop yields (e.g. Rasmussen, 1992 for millet yields in Burkina Faso, Rasmussen, 1997 and Rasmussen, 1998 for millet yields in Senegal).

The map in Figure 7 shows the distribution of the average annual integrated NDVI across Africa, with bluer areas denoting areas with a low value – little photosynthetic activity over the year – and redder areas a high value. The two graphs in Figure 7 plot observed NDVI values as the jagged thin curves over two years, 1982 and 1983, in two locations: one in Burkina Faso just at the boundary to Niger, and one in Tanzania just south of the Victoria Lake. In these graphs, the horizontal axis shows time measured in two-week periods; the vertical axis shows the NDVI value (multiplied by 10,000). Clearly, the peaks are much lower (note the different scales) for the Burkina Faso location than the Tanzania location, reflecting a lower amount of rainfall.

To obtain the growing season from this time-series NDVI data, we use the TIMESAT program (Jonsson and Eklundh, 2004).[28] The two graphs in Figure 7 demonstrate how this program works. The TIMESAT program first produces smoothed (filtered) values of NDVI (shown as the thick curve in the graphs), where the smoothing is meant to eliminate temporary random fluctuations, for example, due to variations in cloud cover. Following the common practice among ecologists (e.g. Heumann et al., 2007), the program then produces the times for the start and the end of the growing season defined as the time period in between 20% above one trough to 20 % above the next, as shown by the points on the smooth curves in Figure 7. Notice that the duration of the growing season is much shorter in Burkina Faso than in Tanzania. Finally, to deal with the potential endogeneity of the observed annual growing seasons, we average the start and end dates over the 25 years available for each location, and use the calendar months between these two average dates as our measure of the *fixed* growing season.[29]

Climate zones Because the seasonality of weather and agriculture differs so much, crop types, cultivating practices, and lifestyles have most likely adapted to the local conditions in different parts of Africa. We would there-

[28] We are grateful to Lars Eklundh, Department of Earth and Ecosystem Sciences, Lund University for his assistance with this program and the data.

[29] In areas where there are two growing seasons per year, we use every odd growing season in our calculation of the fixed growing season.

fore like to allow the effects of weather on nutrition and health to depend on the prevailing climate. A straightforward way of making such conditioning operational is to follow the approach originating with German climatologist Wladimir Köppen, who was the first to classify different areas on Earth into different climate zones.

The well-known Köppen climate classification system distinguishes between different climate types based on annual and monthly temperature and precipitation, as well as the seasonality of precipitation (see, e.g., Peel et al., 2007 for more details). Using the Köppen classification criteria and our ERA-40 weather data, we subdivide all the DHS clusters in our sample into two climate zones: *rainy* areas, which include rainforest, monsoon, savannah and temperate climates, and *arid* areas, which include steppe and desert climates. The resulting classification of our DHS clusters is shown in Figure 8.

Malnutrition exposure for individual pregnancies We want to determine how weather affects each mother's nutritional intake for the 12 months before her child is born. When doing so, we focus on effects through local crop yields driven by variations in rainfall during the relevant growing seasons, as summarized by a simple index.

The relevant growing season(s) of an individual birth depends on its timing relative to local harvest time. As an example, suppose a child is born in September 2000, one month after the last harvest in this location (August 2000). In the last year before giving birth, the mother has consumed food for one month from that harvest and for eleven months from last year's harvest. In general, the mother's nutritional intake during the year before giving birth depends on the two last harvests. We weight these by the number of months the mother had the ability to consume from each harvest. In the example, our rainfall exposure index weights rainfall during the growing seasons of 2000 and 1999 by the weights 1/12 and 11/12, respectively.

To be more precise, we define a simple *rainfall exposure index*, proxying for the nutritional dependence during the 12-month period up to birth as follows.

Definition 2 *Consider babies born in location g in running month t. Let $r_1^{g,t}$ and $r_2^{g,t}$ be the total rainfall during the last and second-to-last (respectively) completed growing seasons preceding date t for location g. Further, let $h^{g,t}$ be the running month of the last harvest preceding date t in location g. We* *proxy the nutritional dependence on weather during the 12-month period up to the birth date t in location g by the rainfall exposure index, defined as*

$$r_{g,t} = \omega_{g,t} r_1^{g,t} + (1 - \omega_{g,t})\, r_2^{g,t} \ , \tag{3}$$

where weight $\omega_{g,t}$ *is given by* $\omega_{g,t} = \frac{t - h^{g,t}}{12}$.

Underlying this index are three simplifying assumptions that we wish to highlight. First, the construction of the index assumes that all crop yield in location g becomes available at the final month of the growing season, and this harvest month, $h^{g,t}$, is the same calendar month every year. Second, it assumes that yields harvested in months $h^{g,t}$ and $h^{g,t} - 12$ depend directly only on the cumulated rainfalls during the growing seasons that ended in those months ($r_1^{g,t}$ and $r_2^{g,t}$, respectively). Third, it assumes that the marginal effect of weather variation on nutritional intake is constant across the year of exposure.

Below we will compare the performance of our rainfall exposure index with a simpler measure – the past 12-month rainfall – to provide suggestive evidence for the validity of the first two assumptions. We will also relax the third assumption and investigate whether the marginal impact of harvested crop yields on children's health is larger during the hungry season as discussed above.

The mean rainfall exposure index in the sample is 72.3 centimeters (cm) of rainfall, while the average grid-level standard deviation is 19.2 cm. The corresponding statistics for the rainy climate zone sample are 126.2 and 28.4 while they are 17.4 and 5.9 for the arid climate zone. As mentioned above, mean-adjusted variability is much larger for the arid climate zone. See Table 1, Panel C for summary statistics.

Validation of the rainfall exposure index How can we make sure that this index based on growing season rainfall that we have just defined is a relevant measure of the scarcity of local crop yield? One way is to relate it to observed crop prices. In doing so, we exploit monthly crop price data between 1970 and 2002 for six major African crops in 424 local markets located in eight of the countries where we measure infant mortality. These data are compiled from the data in the USAID Famine Early Warning Systems Network (FEWS NET).

We then relate these local crop prices to local rainfall and drought incidence (to be defined in the next subsection), exploiting only the within-market monthly deviations from the local seasonal mean, relying on an empirical strategy that is fully analogous to our infant-mortality analysis. See the Appendix for more on the data construction and the econometric specification.

Table 4 reports the estimation results. Column (1) shows that in rainy areas the crop price significantly goes down by 2.1 percent with a one standard deviation increase in rainfall during the previous completed growing season, i.e., $r_1^{g,t}$ in equation (3). A drought incident significantly increases the crop price by 6.7 percent. Column (2) shows that in arid areas the linear impact of growing-season rainfall on crop prices is insignificant, but a drought incident significantly raises crop prices by 9.5 percent. These results give support to our assumption that local rainfall affects the availability of foods due to the lack of irrigation and transportation infrastructure.

Basic results In Table 5, we report estimates from running panel regressions with specifications like (2) in Section 3, except that we replace the malaria exposure index $z_{g,t}$ with the rainfall exposure index $r_{g,t}$. Columns (1)-(3) show the estimates of the coefficient of interest in the full sample, with only cluster fixed effects or cluster-by-month fixed effects included, and with different treatment of trends. The point estimates always have the expected negative sign – i.e., more rainfall in the growing seasons before birth cuts the risk of infant mortality. In the most conservative specification with country-specific non-parametric trends in Column (3), the coefficient is the highest in absolute value and is significantly different from zero at the 10% level.

Column (4) shows that the point estimate is lower in absolute value and not significantly different from 0, if we replace $r_{g,t}$ with the cumulated rainfall over the 12 months preceding birth, with no allowance for the location-specific growing seasons. This indicates that our rainfall exposure index, following from the first two assumptions underlying Definition 2, captures the mothers' nutritional intake better than 12-month average rainfall.

Columns (5) and (6) report corresponding estimates when the same specification is estimated on the subsamples of babies born in rainy and arid climate zones, respectively. In both areas, the point estimates have the same negative sign as in the full sample, but both estimates are too noisy to be statistically significant.

Non-linear effects: droughts and floods Since infant death is an extreme health outcome, we might think that it is closely related to extreme precipitation events, such as droughts or floods – in analogy with the malaria epidemics discussed in Section 3. The linear specifications estimated in Table 4 do not allow for disproportional effects of extreme events, however.

We use a drought index based on extreme growing season rainfall outcomes, which is defined as follows.

Definition 3 *In each grid cell, we first compute the average value of our rainfall exposure index, $\overline{r}^g$, as well as its standard deviation, $\sigma^{r,g}$, using the full 45 years of ERA-40 data from 1957 to 2002 (irrespective of whether we observe child births or not). We then define a binary drought indicator variable for babies born in location g and running month t by*

$$d_{g,t} = I\left[r_{g,t} < \overline{r}^g - 2\sigma^{r,g}\right] \ . \tag{4}$$

That is, the birth is associated with a drought indicator of unity if its rainfall exposure index falls two standard deviations below the local mean. For convenience, we define a flood symmetrically, as an extreme event in the opposite direction.[30]

Table 6 displays the results from adding the drought and flood indexes defined above to the econometric specification used in Column (3) of Table 5. The full-sample estimates in Column (1) – in the most conservative specification with cluster-month plus country-year fixed effects – show a positive, albeit statistically insignificant, point estimate for drought and an insignificant, negative estimate for floods. The results for rainy areas in Column (2) are similar.

When we restrict the sample to arid areas in Column (3), the results are different. While the rainfall coefficient is insignificant, as in Table 5, the estimated coefficient on drought is positive and precisely estimated. The

[30] Our drought measure is similar to the Standardized Precipitation Index (McKee et al., 1993), but is based on our rainfall exposure index rather than just average rainfall. For a discussion of drought indices and their application to Africa, see Ntale and Gan (2003). We also interacted our drought index with the indicator of vulnerability to drought and flood from Dilley et al. (2005). However, this interaction variable did not significantly affect infant mortality.

effect of a drought is now estimated to be quite powerful: it raises infant mortality by 23.4 per 1000, an amount equal to nearly a quarter of the sample mean. But we do not find any effect of extreme positive amounts of rainfall.

The remaining two columns in Table 6 check the robustness of the result in Column (3) in an analogous way to Columns (4) to (5) in Panel B of Table 2. Column (4) shows that these estimates for arid areas are robust to clustering the standard errors at climate zones by 5-year periods.[31] In Column (5), we add cubic polynomials in the past 12-month temperature and rainfall to the regression, and obtain a point estimate for droughts almost identical to that in Column (3).

Our results suggest that, in arid areas, extreme shortfalls of rain have large effects while more piecemeal variations in precipitation do not have any measurable effects on infant mortality. These results are consistent with Susser (1991), who reviews studies on the relationship between maternal nutrition and birth weight and concludes that nutritional intake by mothers significantly affects birth weight only in famine conditions.

As in Section 3, these results appear to have important implications for climate change. When it comes to the effects on infant mortality, the main threat seems to be associated with future extreme events in the form of droughts in the arid areas of Africa, such as those bordering to the Sahara and the Kalahari deserts and some regions in East Africa. To the extent that climate change increases extreme weather events, these areas are expected to be hit the hardest. Note also that the arid areas and the areas where malaria is epidemic largely overlap, as can be seen by comparing Figures 3 and 8.

Heterogeneity by household characteristics? The specifications in Tables 5 and 6 do not allow for any heterogeneous effects across households, mothers and babies (beyond a difference across climate zones). We now turn to these issues. It is natural to believe that the vulnerability of the offspring to maternal malnutrition might differ with mother or household characteristics, such as occupation, income, or education. Table 7 presents some estimates relevant to this hypothesis. We focus on two specific sources of heterogeneity, which appear important a priori and reasonably measurable in the DHS data at our disposal. One is occupation: we call a baby's

[31] The arid areas are divided into 4 zones by northern versus southern hemispheres and by steppe versus desert climate zones, as defined by the Köppen climate classification.

household *agricultural*, when parents of this baby earn a living only from agriculture at the time of the survey. In the full sample, about 42% of all children, excluding those with missing information on their parents' occupation, are born in agricultural households. Measurement error in the classification of agricultural households is inevitable: parents may have changed the job since the baby's birth, and the definition of agriculture in the DHS data also includes forestry and fishery. These factors, however, would bias our results against finding heterogeneous effects of weather fluctuations.

We also consider education, and define a baby's household as *well-educated* if both the baby's mother and her husband (if relevant) have more than eight years of education. Eight years is chosen as the cutoff because we see a marked drop in the cross-sectional distribution of infant mortality above this level of education. In the DHS sample, only slightly more than 8% of the babies are born to well-educated households. The retrospective nature of the survey is unlikely to be a major source of mismeasurment when it comes to education. See Table 1, Panel A for summary statistics by subgroup.

We then run the following regression:

$$\begin{aligned} m_{i,c,x,t} = {} & \beta r_{g,t} + \beta^f r_{g,t} \cdot f_i + \gamma d_{g,t} + \gamma^f d_{g,t} \cdot f_i \\ & + \alpha_{c,s} + \alpha^f_{c,s} \cdot f_i + \alpha_{x,y} + \alpha^f_{x,y} \cdot f_i + \varepsilon_{i,c,x,t} \ , \end{aligned} \tag{5}$$

where f_i is an indicator of baby i's household type (agricultural or well-educated). Note that this specification allows cluster-by-month and country-by-year fixed effects to differ across different household types. Table 7 reports the estimated coefficients: β, β^f, γ, and γ^f.

Column (1) shows the estimates for the occupational breakdown in the rainy sample. In contrast to the results in Tables 5 and 6, the results suggest that rainfall exerts a significant negative linear effect on infant mortality if we look at agricultural households. The sum of the two coefficients on rainfall ($\beta + \beta^f$) – the total linear effect of rainfall for agricultural households – is statistically significant at the 5 percent level. The non-interacted coefficient (β) shows that the effect is statistically insignificant and close to zero for non-agricultural households. To the contrary, droughts have no effect on infant mortality in either groups in rainy areas.

In arid areas, the results in Column (2) show something close to the opposite. There is no linear effect of rainfall on infant mortality in either group. But a drought has a large effect in non-agricultural households, whereas it has no significant effect in agricultural households (the sum of γ and γ^f is not significantly different from zero).

A reasonable interpretation of these results is that normal variations in rainfall tend to make agricultural households in rainy areas better off nutritionally. On the other hand, in arid areas such households have better access to whatever little crop yield there may be at the time of drought, when the main burden is borne by non-agricultural households.

Columns (3) and (4) repeat the same exercise for the breakdown of household type by education. The main result here is two-fold. It is primarily the non-educated that benefit from more rainfall in rainy areas. And – as might be expected – the well-educated appear to be protected from the high infant mortality effects of a drought shock in arid areas, perhaps as a result of higher purchasing power or better opportunities.

As in the malaria section, we have also experimented with conditioning on various baby and mother characteristics (gender, birth order of child, age or stature of mother, etc.), on the notion that some types of babies or mothers may be more vulnerable to malnutrition shocks than others. But this has produced no robust results.

Heterogeneity by timing of birth As mentioned after Definition 2, our simple rainfall and drought exposure indexes implicitly assume that the marginal effects on infant mortality are constant across time. We now relax this assumption by conditioning the effects of shocks on the time of birth relative to the beginning of the growing season. Given the earlier results, we focus on the drought effects in arid areas and run the regression:

$$m_{i,c,x,t} = \sum_{k=0}^{3} \beta^k r_{g,t} \cdot q^k_{g,s} + \sum_{k=0}^{3} \gamma^k d_{g,t} \cdot q^k_{g,s} + \alpha_{c,s} + \alpha_{x,y} + \varepsilon_{i,c,x,t} \ , \qquad (6)$$

where $q^k_{g,s}$ is a dummy that equals one if calendar month s of date t falls within the k^{th} quarter since the beginning of the growing season in grid g ($k = 0$ for the quarter immediately before the growing season starts).

Figure 9 plots estimated coefficients of the γ^ks and their 95% confidence intervals. The vertical line in the figure indicates the beginning of the growing season – recall Figure 7 and our definition of this as the time when the NDVI value is 20% above its last trough. The babies born in the quarters around the beginning of the growing season, marked 0 and 1 in Figure 9, seem to fare much worse in the wake of a drought shock than the babies born closer to the harvest. The estimated hike in death rates for these babies – on the order of 60 per 1000 births – is a stunning number indeed.

These results are interesting in view of the notion of a "hungry season", which is discussed in the literature on food availability and poverty. The average length of the growing season in arid areas is about 6 months in our sample, and the actual harvest may start before the end of the fixed growing season we use in the analysis. Therefore, food is the least available in the period around (in particular, after) the beginning of the growing season. On top of that, the beginning of the growing season is the time when energy expenditure of people – including pregnant women – reaches its peak over the year owing to the need for clearing the land and planting the seeds.

A study on pregnant women in a Gambian village shows that pregnancy, even in the last month before giving birth, does not reduce the time women spend at their farms (Roberts et al., 1982). Studying the same rural area in Gambia, Rayco-Solon et al. (2005) find that the incidence of premature birth (a major cause of low birth weight) significantly increases during the first few months of the rainy season, which suggests a possible causation from increased amount of workload for pregnant women to low birth weight. Moreover, randomized controlled trials in the same area show that the impact of dietary supplements to pregnant women on the incidence of low birth weight and early infant death are both significantly larger for babies born in the hungry season (Ceesay et al., 1997). Our empirical findings suggest that these results from particular Gambian villages may be applicable to other arid areas of Africa.

Summary Let us briefly summarize. Extreme negative rainfall shocks (droughts) have a powerful effect on infant death in areas with steppe and desert climates. Rainfall above the site-specific seasonal mean in the relevant growing season diminishes infant mortality only for babies born in agricultural households in the rainy parts of Africa. Drought shocks impinge especially hard on babies to parents that do not work in agriculture, are not well educated, and on babies born around the start of the rains.

5 Malaria and Malnutrition

In the two previous sections, we have investigated separately two channels – malaria and malnutrition – whereby local seasonal weather shocks affect infant mortality rates in Africa. We have taken care to define these weather shocks according to the mechanism under investigation, but ultimately all the shock measures emanate from the same weather data. It is thus legitimate to ask if the main results hold up when we allow both types of shocks to occur simultaneously. For example, more rainfall can potentially have two opposite effects on infant mortality: more rain may be good through increased nutrition but bad through increased malaria. For the babies in our sample, the malaria exposure index $z_{g,t}$ is indeed positively correlated with the rainfall exposure index $r_{g,t}$ with a correlation coefficient in the full sample of 0.77.[32]

Table 8 revisits the two main results above: the effect of malaria shocks in epidemic areas and the effect of droughts in arid areas. Comparing the epidemic malaria zone in Figure 3 with the arid climate zone in Figure 8, we see that these zones spatially overlap but not perfectly so. In Column (1), we reproduce the malaria results from Column (3) of Panel B in Table 2. In Column (2), we add $r_{g,t}$ and $d_{g,t}$ as regressors. Column (3) further adds the cubic polynomials in the past 12-month temperature and rainfall. As the estimates show, the malaria result is essentially the same, while we find no significant effects of rainfall exposure in the growing season(s).

In Column (4), we estimate the effect of drought in arid areas in the same specification as in Column (3) of Table 6 except that we now drop the flood indicator. In Column (5), we add $z_{g,t}$ as a regressor. Here, we find a positive and large effect of malaria shocks, 40% higher than in the epidemic areas, while the coefficient on the linear rainfall term increases its size in absolute terms by about 75% of its previous value (still insignificant, though). The coefficient on the drought indicator does not change while its precision increases. Column (6) further adds the cubic polynomials and shows these results are robust. This change in the coefficient is natural, given the positive correlation between the rainfall exposure and the malaria exposure indexes: in Tables 5 and 6 we were most likely under-estimating the (absolute value of the) negative effect of rainfall, thereby falsely attributing some infant deaths caused by malaria to a weaker nutritional channel.

[32] If we drop duplicated observations (multiple babies are assigned the same values of $z_{g,t}$ and $r_{g,t}$ if they are born in the same grid cell in the same month), we still obtain the correlation coefficient of 0.74.

A memento for economists The result in the last part of Table 8 can perhaps also serve as a memento for development economists, who have increasingly relied on research designs in which rainfall is used as an instrument/indicator of income or poverty shocks. Take, for example, Miguel et al. (2004), who use rainfall as an instrument for national income as a determinant of civil conflicts in sub-Saharan Africa. Because malaria is common in many war-ridden states, its dependence on rainfall calls into question the exclusion restriction underlying the IV strategy to the extent that a higher disease burden has a separate effect on conflict, beyond its effects on income. Another example might be the recent study by Maccini and Yang (2009), who use negative rainfall shocks as an indicator of negative early-life nutrition shocks in Indonesia. Since malaria is common in Indonesia, failing to account for the effect of rain on malaria infection might lead the authors to underestimate the effect of early life shocks on adult outcomes.

6 Final Remarks

We believe this paper makes substantive as well as methodological contributions. In terms of substance, we uncover two channels whereby weather might impact on infant mortality in African countries. Weather shocks that raise malaria exposure of pregnant mothers have a large impact on infant death, especially when they strike early in pregnancy and when they sow the seeds of a malaria epidemic in areas where malaria is rare. Rainfall shocks in the growing seasons that affect maternal nutrition when the child is in utero only appear to affect babies born to agricultural households in Africa's rainy climate zones. Drought shocks have a pronounced effect on infant death in arid areas, especially for babies whose parents are not well educated, not dependent on agriculture, and for babies who are born in the hungry season. The malaria and drought effects we estimate are statistically robust and quantitatively large.

These results paint a dismal picture for certain parts of Africa, especially the areas with scant rainfall that also suffer from epidemic malaria, such as the Sahel and mountainous areas in East Africa. Due to the erratic movements of the Intertropical Convergence Zone, these areas face large variations in annual rainfall. When it rains a lot this may cause a malaria epidemic, when it rains a little this may cause a drought – whichever way with bad outcomes for infant mortality.

In terms of methodology, we hope to have outlined a possible research design for impact research, showing how one may combine very different data sources for large-scale statistical work, when conventional data sources are absent or poor. A similar approach and statistical methodology may be used to study other outcomes of interest in Africa or other regions. For example, further research on Africa could use DHS data to look at the weather dependence of other outcomes, such as child mortality, child health, or fertility. Perhaps one may also look at more complex issues, such as generational spillovers, whereby girls with negative weather shocks in early life become physically or cognitively impaired adults and thus face a larger risk of bad outcomes when they give birth themselves.

There is certainly scope for improvement on the natural-science side of our measurement. For example, one could try to use re-analysis from *regional* rather than *global* climate models to obtain more recent and fine-gridded weather data, so as to better pick up the spatial distribution of rainfall. As another example, one could try to use structural crop-yield models to get a better handle on the interplay between temperature and rainfall in producing local crop yields.

Our results also give some hints on the analysis of future climate change. Most climate projections suggest that Africa will get a great deal warmer over time, and that its rainfall patterns will become more erratic especially in arid areas. Warming means that new parts of Africa, such as mountainous regions, will be subject to weather-induced malaria epidemics. More erratic rain patterns mean that arid/epidemic areas will be subject to larger changes in annual rainfall. Our results on the exposure to malaria epidemics and droughts give a strong hint that both types of change might seriously threaten infant survival. However, we do not believe that the right way to obtain clearer results about these risks is to carry out a simple statistical forward projection of the current results. Serious analysis will have to consider mechanisms of adaptation, like migration or better health protection, as the climate changes and income grows over time. This task is left for future research.

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Appendix

Data We use crop-price data compiled by the USAID Famine Early Warning Systems Network (FEWS NET).[33] Specifically, we sample six major crops in Africa (maize, rice, wheat, cassava, millet, and sorghum) and markets in eight countries, for which we also have data for infant mortality (Burkina Faso, Ethiopia, Kenya, Malawi, Mali, Tanzania, Uganda, and Zambia).[34] Price data is aggregated to the monthly frequency if the original data is daily or weekly. The geographic coordinate of each market in the data is obtained by searching the name of the market in the National Geospatial-Intelligence Agency's Geonames Search.[35] The ERA-40 weather data used in our infant-mortality analysis is then matched spatially with each market in ArcGIS 9.3 (the Spatial Join tool). Figure A1 shows the locations of 424 markets in the sample with the color indicating which climate zone (rainy or arid) the market belongs to. The sample period is from 1970 to 2002.

Empirical strategy We estimate the following regression equation:

$$\ln p^p_{m,t} = \alpha^p_{m,s} + \beta^p_{c,y} + \gamma {r_1^{g,t}} + \delta D_{g,t} + \varepsilon^p_{m,t}$$

where $p^p_{m,t}$ is the price (in domestic currency units) of crop p in market m (located within grid cell g and in country c) in running month t (which is month s of year y), $r^1_{g,t}$ the total amount of rainfall during the previous completed growing season (corresponding to the first term on the right-hand side of equation (3)) in grid cell g, and $D_{g,t}$ the indicator for $r^1_{g,t}$ being two standard deviations below the location-specific mean.[36] We control for crop-by-market-by-month fixed effects, $\alpha^p_{m,s}$, so that the impact of weather is

[33] We downloaded the data from `earlywarning.usgs.gov/adds` in October 2009. Since then, the FEWS NET has decided to discontinue the data distribution because, according to James Rowland at USGS, they are unable to keep the data up-to-date.

[34] These six major crops account for 57% of calorie availability in Africa in 2000 according to FAO's Food Balance Sheets. In the price data, each crop has subcategories (in flour, dried, fresh, etc.). We treat each subcategory as a single crop when we create fixed effects. Therefore, there are more than 6 crops in the sample.

[35] The address is `geonames.nga.mil`. If the name of the market cannot be found, we use Global Gazetteer Version 2.1 (`www.fallingrain.com/world`), Wikipedia and then the Google search as the final resort.

[36] Note that $D_{g,t}$ is different from $d_{g,t}$ defined in equation (4). It is defined over ${r_1^{g,t}}$, not over $r_{g,t}$.

identified from year-to-year deviations from the average location-by-crop specific seasonal pattern. We also control for crop-by-country-by-year fixed effects, $\beta^p_{c,y}$, so as to take into account crop-by-country-specific non-parametric trends, as well as national price inflation and exchange-rate changes. The coefficients of interest, γ and δ, measure the percentage change in price due to a one-centimeter increase in growing-season rainfall and due to unusually low growing-season precipitation, respectively. We estimate this equation separately for rainy and arid areas with standard errors clustered at the ERA-40 grid-cell level.

The results are displayed in Table 4.

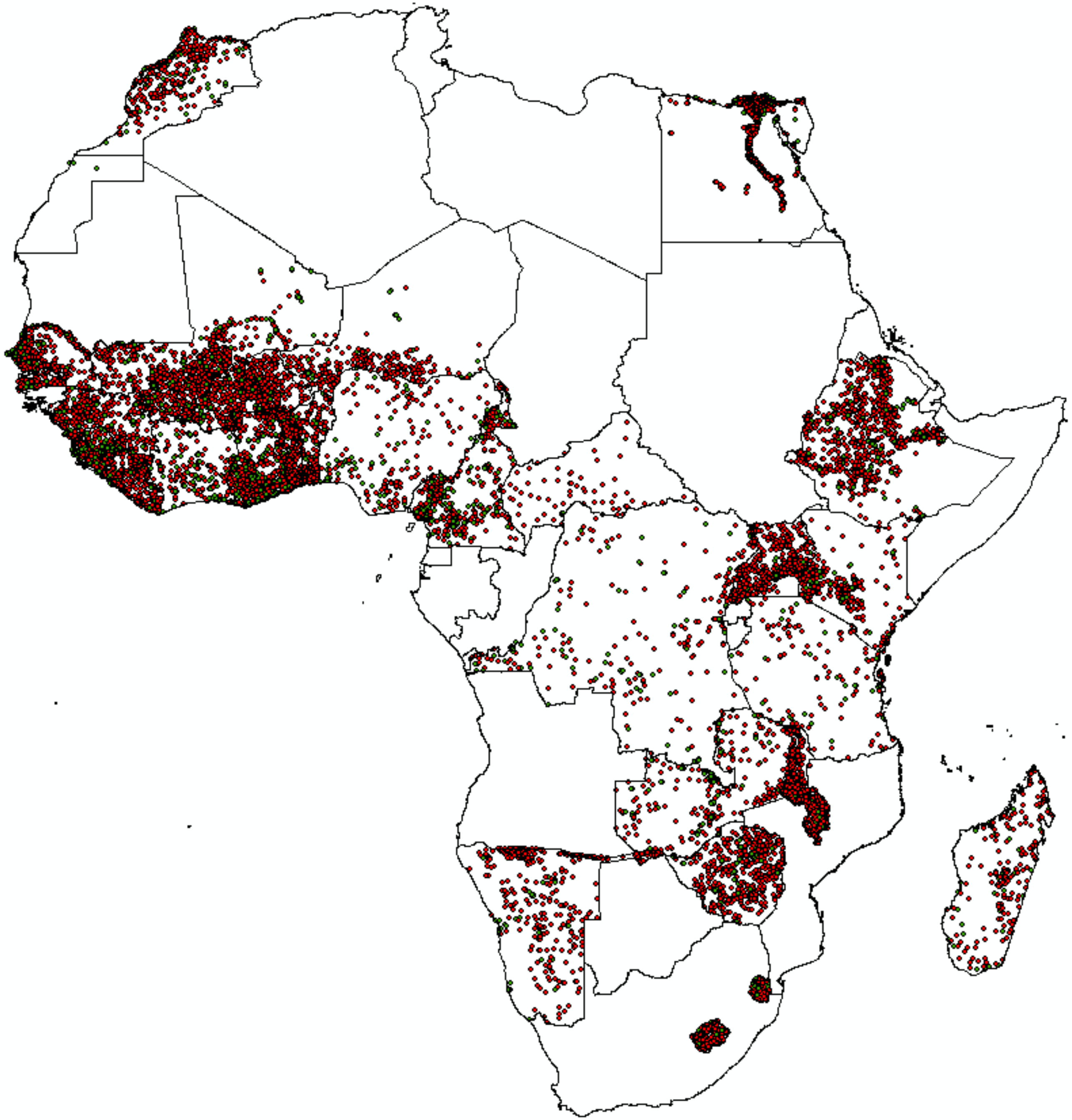


Figure 1 – DHS Clusters in the Sample

Notes: Green circles indicate urban clusters; red ones indicate rural clusters

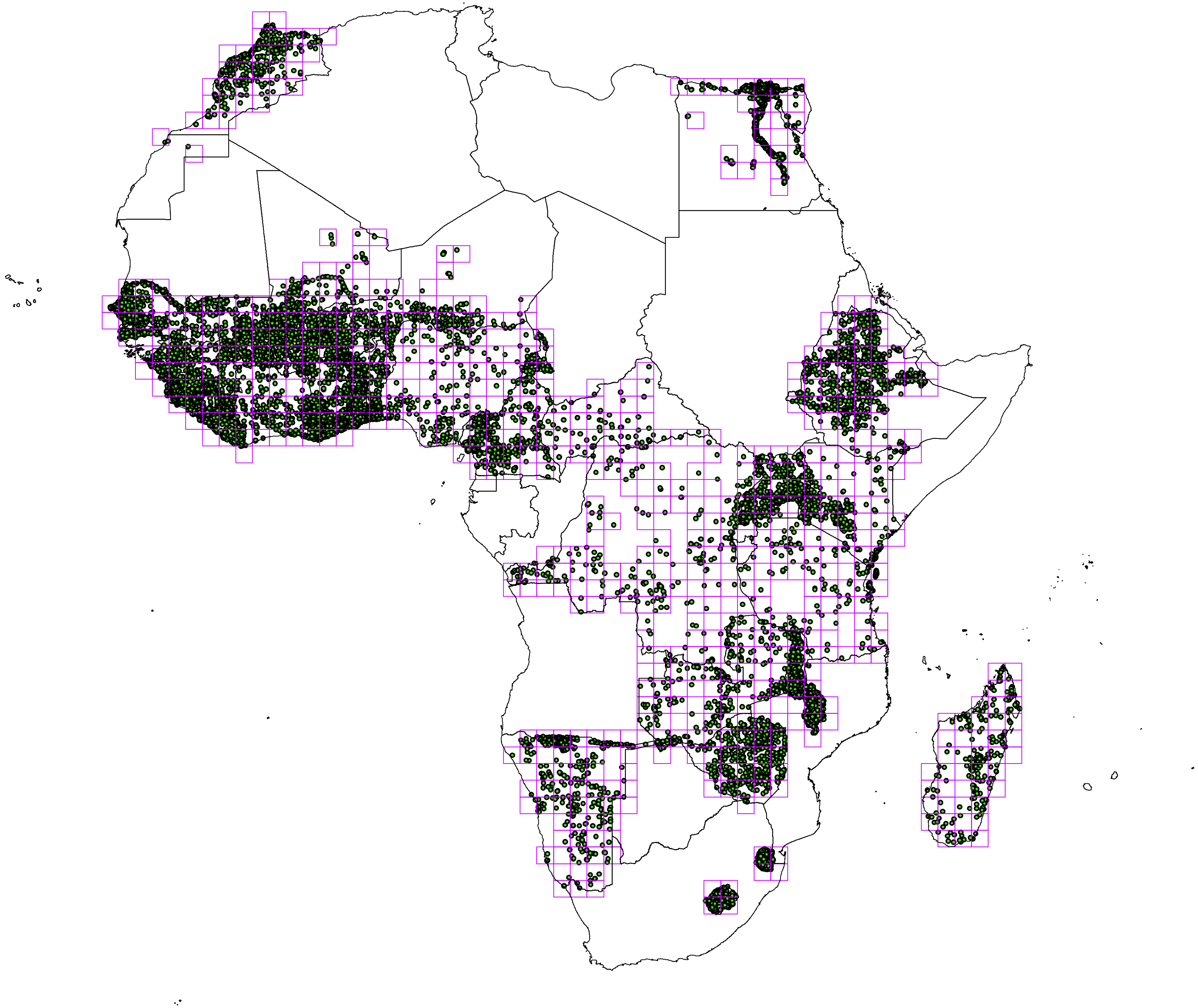


Figure 2 – ERA-40 Grid and DHS Clusters in the Sample

Notes: Purple squares indicate ERA-40 grid cells; green circles indicate DHS clusters.

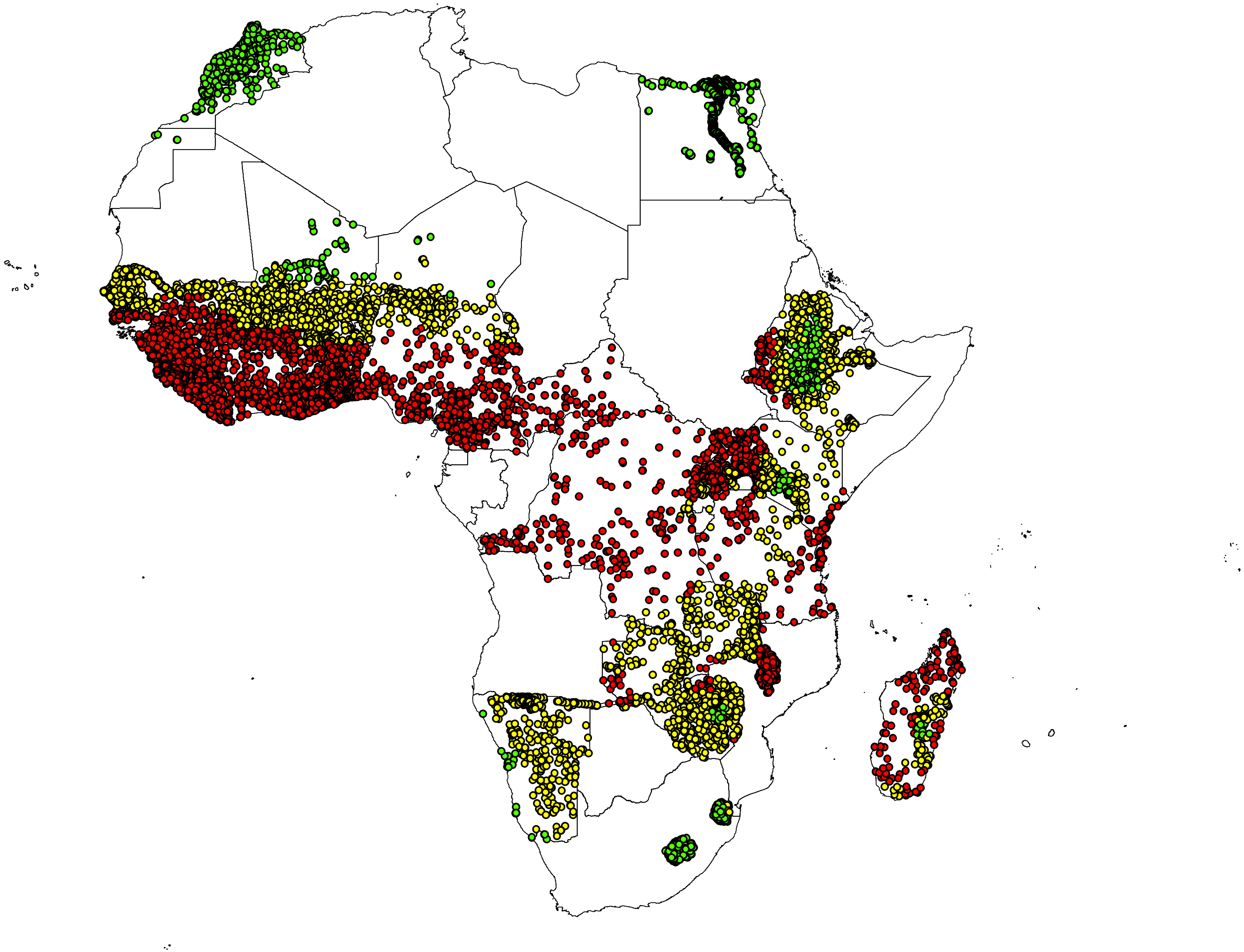


Figure 3 – Malaria Exposure Zones in Africa

Notes: Red, yellow, and green circles indicate DHS clusters in endemic, epidemic, and non-malarious areas, respectively.

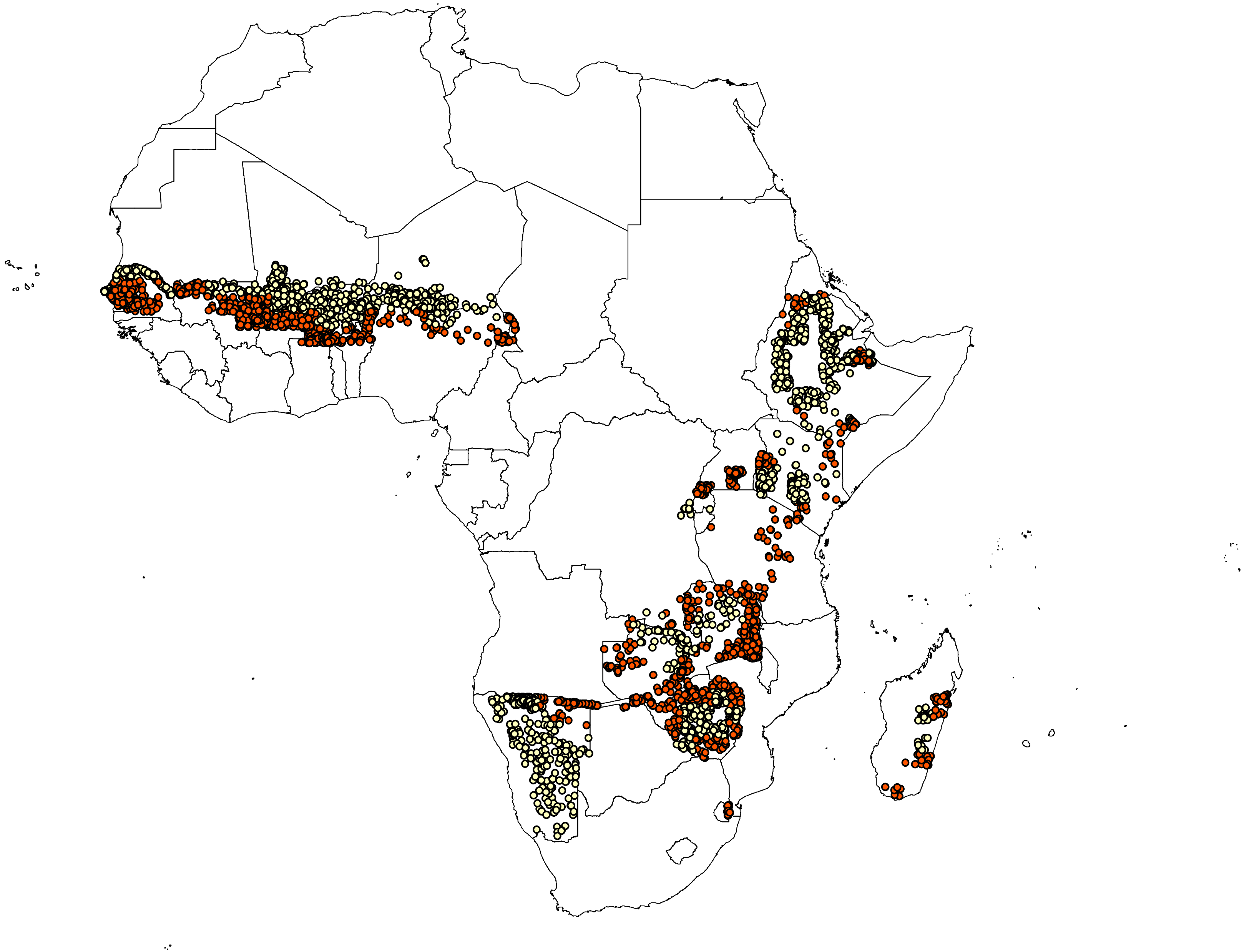


Figure 4 – Low and High Epidemic Malaria Exposure

Notes: Orange and cream-colored circles indicate DHS clusters with the average number of malarious months being 0-2 and 2-4 months per year, respectively.

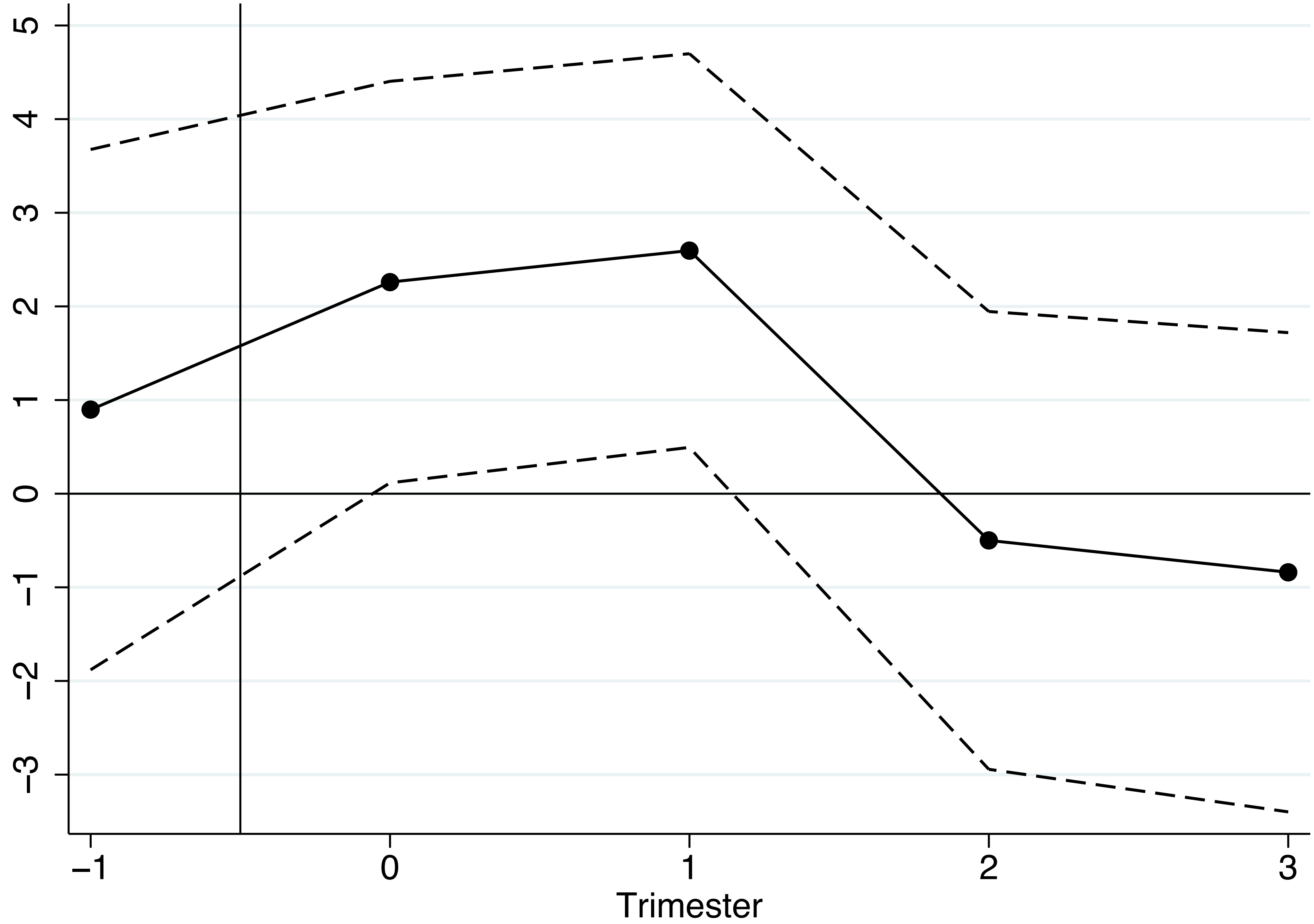


Figure 5 – Infant Death and Malaria Shocks by Trimester

Notes: Plotted are the estimated coefficients on the number of malaria months in each trimester in a regression of the infant death indicator (multipled by 1000) on these variables and cluster-by-month fixed effects and country-by-year fixed effects. Dashed lines indicate the 95 percent confidence intervals where the standard errors are clustered at the ERA-40 grid cell level.

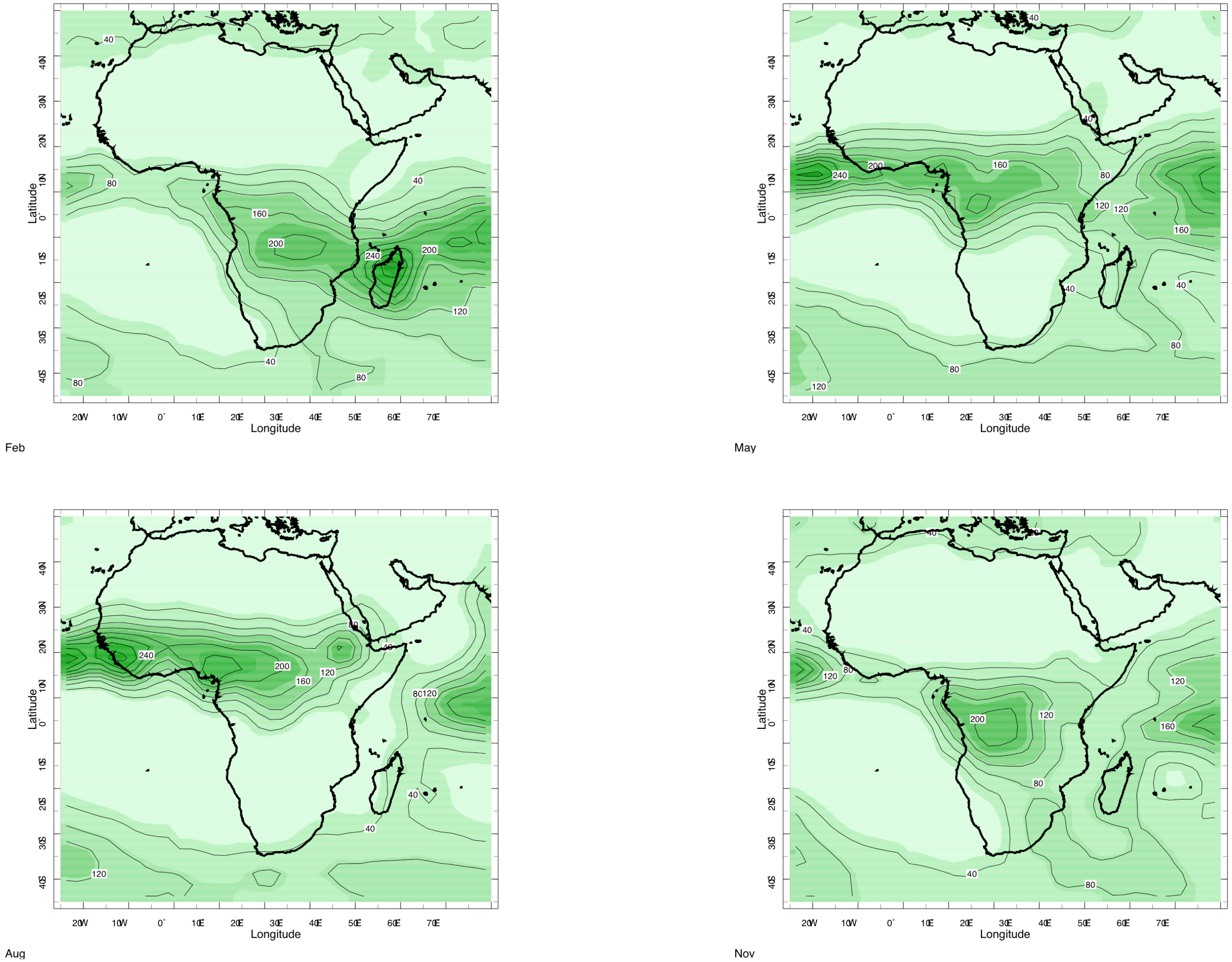


Figure 6 – Total monthly rainfall (in mm) in Africa for February, May, August, and November

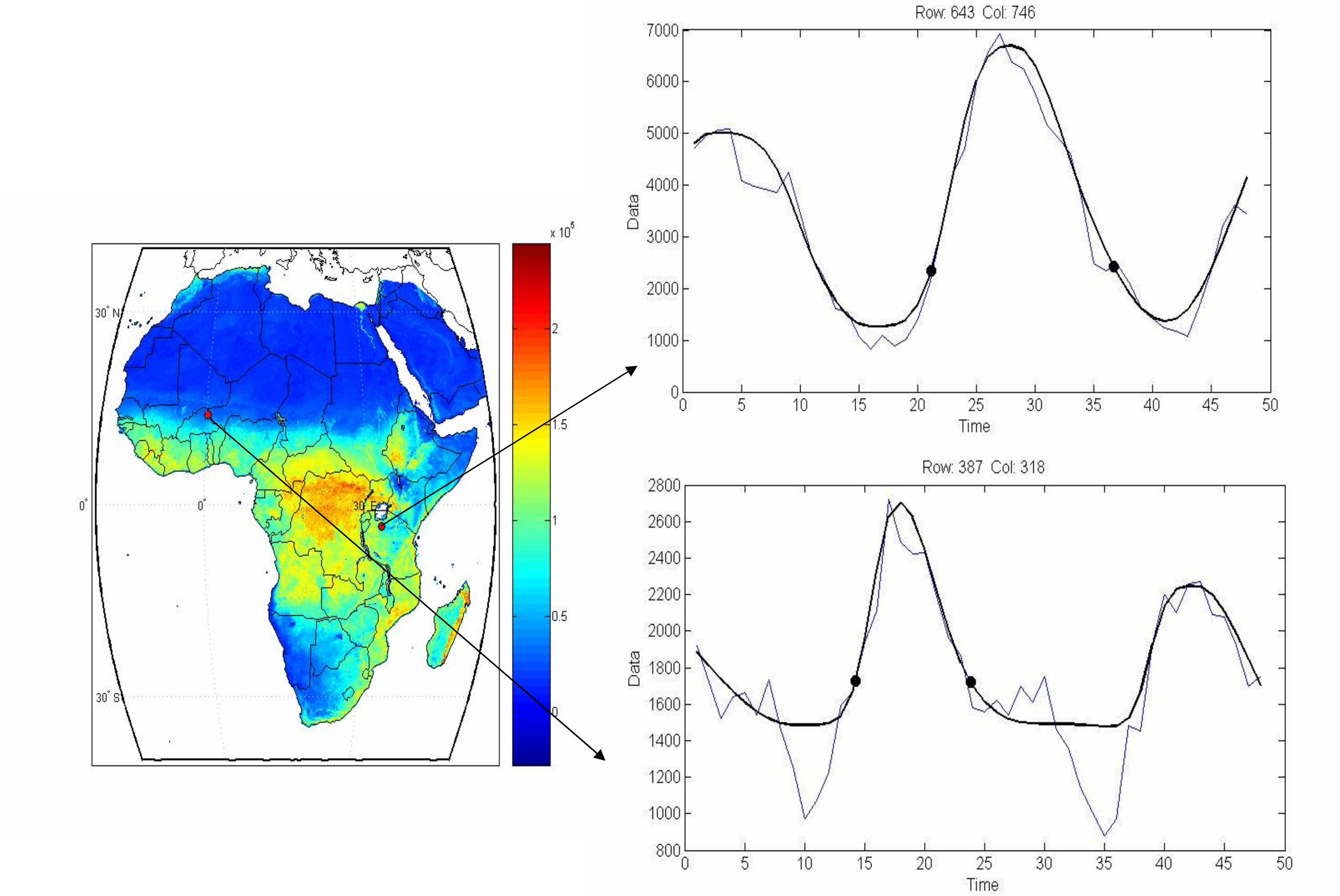


Figure 7 – Actual and fitted NDVI in Burkina Faso and Tanzania

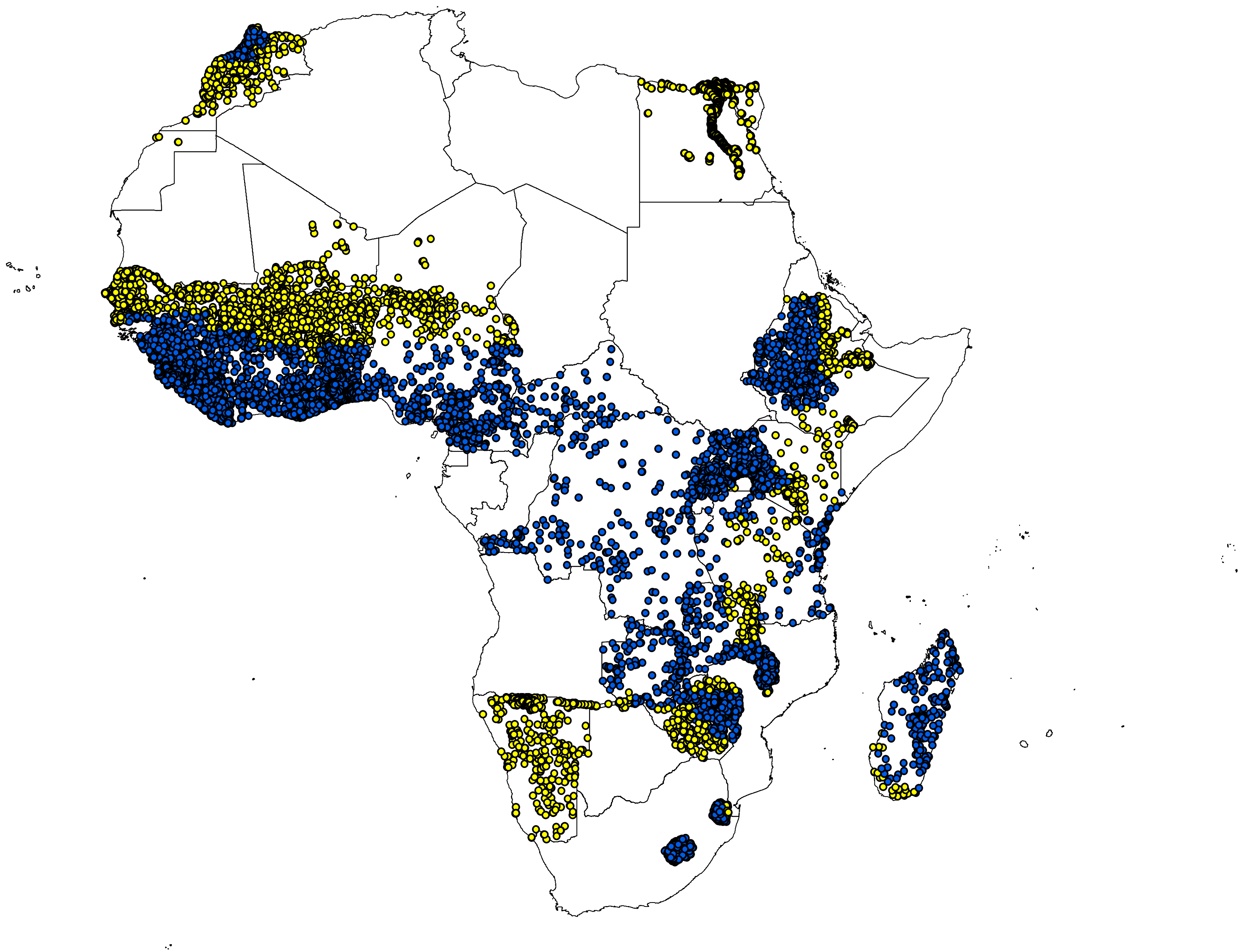


Figure 8 – Arid and Rainy Climate Zones in Africa

Notes: Blue circles indicate DHS clusters in rainy climate zones (Af, Am, Aw, Cs, Cw, and Cf in Koppen climate classification); yellow circles indicate those in arid climate zones (BS and BW). These climate zones are based on the average monthly temperature and total rainfall calculated from ERA-40.

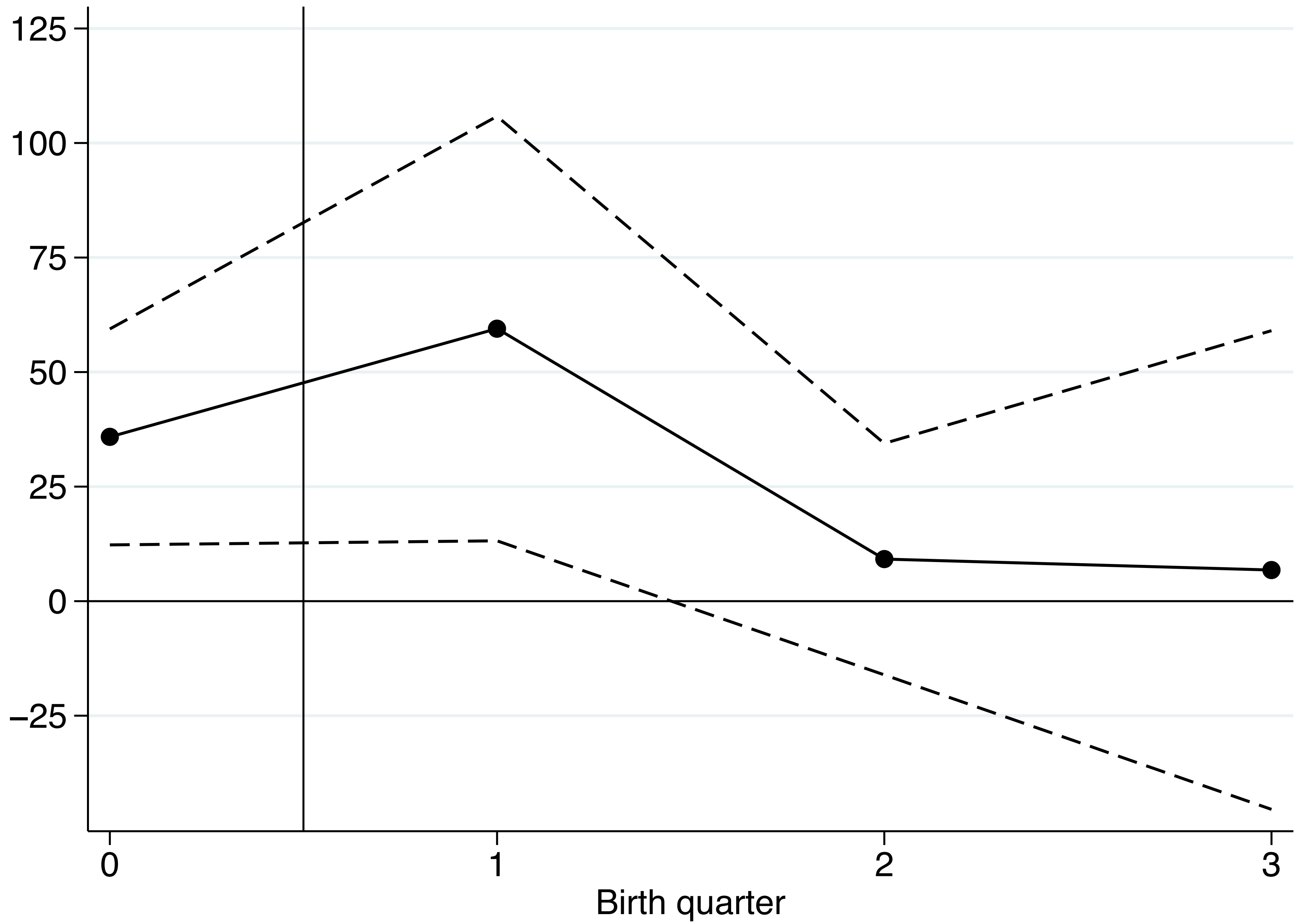


Figure 9 – Infant Death and Drought by Birth Quarter relative to the Beginning of the Growing Season

Notes: Plotted are the estimated coefficients of γ_κ's in equation (6) in the text. Dashed lines indicate the 95% confidence intervals where standard errors are clustered at the ERA-40 grid cell level. The vertical line indicates the beginning of the growing season.

Table 1 – Summary Statistics

Panel A: Infant Mortality per 1000 live births

	Sample mean	S.D. cluster-level means	Number of clusters	Number of observations
Full sample	100.4	69.2	17772	975800
By area				
Endemic	107.6	73.4	7565	401202
Epidemic	107.2	68.8	6013	378543
Non-malarious	72.5	56.1	4194	196055
Rainy	102.5	71.4	9633	493165
Arid	98.3	66.1	8139	482635
By HH type				
Agricultural	119.4	111.2	12287	392444
Non-agricultural	85.4	92.1	17027	541187
Highly educated	46.3	118.4	9113	80079
Not highly educated	105.4	74.2	17623	891759

Panel B: Malaria Exposure Index (months)

	Sample mean	Mean S.D. within-grid	Number of grids	Number of observations
Endemic	8.0	1.0	365	401202
Epidemic	1.8	1.0	275	378543

Panel C: Nutrition Exposure Index (cm of rainfall)

	Sample mean	Mean S.D. within-grid	Number of grids	Number of observations
Rainy	126.2	28.4	439	493165
Arid	17.4	5.9	304	482635

Table 2 – Infant Mortality and Malaria: Basic Results

Dependent Variable: Infant death indicator (multiplied by 1000)

Panel A

	(1)	(2)	(3)	(4)	(5)	(6)
Sample	Full	Full	Full	Endemic	Endemic	Endemic
Malaria index in	0.53*	0.75**	0.27	0.06	0.11	-0.28
year before birth	(0.32)	(0.34)	(0.38)	(0.43)	(0.45)	(0.53)
Fixed effects	Cluster, Year	Cluster-month, Year	Cluster-month, Country-Year	Cluster, Year	Cluster-month, Year	Cluster-month, Country-Year
S.E. clustered at	ERA-40 cells	ERA-40 cells	ERA-40 cells	ERA-40 cells	ERA-40 cells	ERA-40 cells
# of S.E. clusters	743	743	743	365	365	365
# of obs.	975800	975800	975800	401202	401202	401202

Panel B

	(1)	(2)	(3)	(4)	(5)
Sample	Epidemic	Epidemic	Epidemic	Epidemic	Epidemic
Malaria index in	1.17**	1.55***	0.94*	0.94**	1.22*
year before birth	(0.49)	(0.52)	(0.53)	(0.42)	(0.67)
Fixed effects	Cluster, Year	Cluster-month, Year	Cluster-month, Country-Year	Cluster-month, Country-Year	Cluster-month, Country-Year
Polynomials	No	No	No	No	Yes
S.E. clustered at	ERA-40 cells	ERA-40 cells	ERA-40 cells	5-year by exposure	ERA-40 cells
# of S.E. clusters	275	275	275	36	275
# of obs.	378543	378543	378543	378543	378543

Notes: Robust standard errors in parentheses, clustered as indicated. * significant at the 10 percent level, ** 5 percent, *** 1 percent. Fixed effects included as indicated. The row "Polynomials" in Panel B indicates whether the cubic polynomials in the average monthly temperature and total precipitation over the 12-month period up to the birth month are included. In Panel B column (4), "exposure" refers to four areas with above or below 2 malaria months per year, north and south of the equator, respectively.

Table 3 – Infant Mortality and Epidemic Malaria: Non-linear Effects

Dependent Variable: Infant death indicator (multiplied by 1000)

	(1)	(2)	(3)	(4)	(5)	(6)
Sample	0-2 months avg. malaria	2-4 months avg. malaria	0-2 months avg. malaria	0-2 months avg. malaria	2-4 months avg. malaria	2-4 months avg. malaria
Malaria months in year before birth	0.42	0.92				
	(1.14)	(0.59)				
0 malaria months			0.30	0.93	-3.09	-7.09**
			(2.76)	(2.85)	(2.98)	(3.44)
1-2 malaria months					-6.92***	-8.59***
					(2.23)	(2.37)
3-4 malaria months			1.31	1.20		
			(3.80)	(3.87)		
5-6 malaria months			15.62	14.14	-4.59	-3.33
			(11.89)	(11.49)	(3.68)	(3.83)
>6 malaria months			38.44**	36.56**	15.89**	20.75**
			(15.62)	(15.74)	(7.69)	(8.18)
F-test(polynomials)				1.48		2.61
				[0.190]		[0.020]
Fixed effects	Cluster-month, Country-year	Cluster-month, Country-year	Cluster-month, Country-year	Cluster-month, Country-year	Cluster-month, Country-year	Cluster-month, Country-year
Polynomials	No	No	No	Yes	No	Yes
S.E. clustered at	ERA-40 cells	ERA-40 cells	ERA-40 cells	ERA-40 cells	ERA-40 cells	ERA-40 cells
# of S.E. clusters	150	125	150	150	125	125
# of obs.	187858	190685	187858	187858	190685	190685

Notes: Robust standard errors in parentheses, clustered as indicated. * significant at the 10 percent level, ** 5 percent, *** 1 percent. Fixed effects included as indicated. The row “Polynomials” indicates whether the cubic polynomials in the average monthly temperature and total precipitation over the 12-month period up to the birth month are included. The null for F-test(polynomials) is that the coefficients on polynomial terms are all zero.

Table 4 – Crop Price and Growing-season Rainfall

The Dependent Variable: Log Crop Price

	(1)	(2)
Sample	Rainy	Arid
Rainfall in previous completed growing season (centimeters)	-0.00046***	0.00005
	(0.00015)	(0.00036)
Indicator for rainfall in previous completed growing season < Mean - 2 SD	0.067***	0.095***
	(0.022)	(0.021)
Mean and SD of rainfall in previous completed growing season (centimeters)	85.5	25.2
	(45.7)	(18.4)
# of ERA-40 cells	85	75
# of obs.	109124	74631

Notes: Robust standard errors in parentheses, clustered at the ERA-40 cell level. * significant at the 10 percent level, ** 5 percent, *** 1 percent. Fixed effects for crop-by-market-by-month and for crop-by-country-by-year are included in both regressions.

Table 5 – Infant Mortality and Nutrition: Linear Effects

Dependent Variable: Infant death indicator (multiplied by 1000)

	(1)	(2)	(3)	(4)	(5)	(6)
Sample	Full	Full	Full	Full	Rainy	Arid
Rainfall (centimeters) in growing seasons associated with birth	-0.015	-0.018	-0.044*		-0.034	-0.067
	(0.018)	(0.019)	(0.023)		(0.025)	(0.104)
Rainfall (centimeters) in last 12 months				-0.017		
				(0.013)		
Fixed effects	Cluster, Year	Cluster-month, Year	Cluster-month, Country-year	Cluster-month, Country-year	Cluster-month, Country-year	Cluster-month, Country-year
S.E. clustered at	ERA-40 cells	ERA-40 cells	ERA-40 cells	ERA-40 cells	ERA-40 cells	ERA-40 cells
# of S.E. clusters	743	743	743	743	439	304
# of obs.	975800	975800	975800	975800	493165	482635

Notes: Robust standard errors in parentheses, clustered as indicated. * significant at the 10 percent level, ** 5 percent, *** 1 percent. Fixed effects included as indicated.

Table 6 – Infant Mortality and Nutrition: Nonlinear Effects

Dependent Variable: Infant death indicator (multiplied by 1000)

	(1)	(2)	(3)	(4)	(5)
Sample	Full	Rainy	Arid	Arid	Arid
Rainfall (centimeters) in growing season	-0.039*	-0.030	-0.036	-0.036	-0.052
	(0.024)	(0.026)	(0.10)	(0.067)	(0.10)
Drought (0,1) in growing season	8.22	-2.81	23.4***	23.4***	22.7***
	(8.04)	(12.2)	(8.49)	(7.36)	(8.52)
Flood (0,1) in growing season	-1.54	-1.95	-1.57	-1.57	-1.57
	(2.67)	(3.91)	(3.80)	(3.42)	(3.75)
F-test (polynomials)					0.72
					[0.633]
Fixed effects	Cluster-month Country-Year	Cluster-month, Country-Year	Cluster-month, Country-Year	Cluster-month, Country-Year	Cluster-month, Country-Year
Polynomials	No	No	No	No	Yes
S.E. clustered at	ERA-40 cell	ERA-40 cell	ERA-40 cell	5-year by climate zone	ERA-40 cells
# of S.E. clusters	743	439	304	35	304
# of obs.	975800	493165	482635	482635	482635

Notes: Robust standard errors in parentheses, clustered as indicated. * significant at the 10 percent level, ** 5 percent, *** 1 percent. Fixed effects included as indicated. The row "Polynomials" indicates whether the cubic polynomials in the average monthly temperature and total precipitation over the 12-month period up to the birth month are included. In column (4), "climate zone" refers to "steppe" and "desert" climates types, north and south of the equator, respectively. The null for F-test(polynomial) is that the coefficients on polynomial terms are all zero.

Table 7 – Infant Mortality and Nutrition: Heterogeneous Effects

Dependent Variable: Infant death indicator (multiplied by 1000)

	(1)	(2)	(3)	(4)
Sample	Rainy	Arid	Rainy	Arid
Household type	Agriculture	Agriculture	Educated	Educated
Rainfall (centimeters) in growing season	0.007	0.021	-0.049*	-0.049
	(0.031)	(0.176)	(0.028)	(0.101)
Rainfall (centimeters) x Household type	-0.106**	-0.205	0.153**	0.395
	(0.045)	(0.246)	(0.069)	(0.395)
Drought (0,1) in growing season	-1.448	30.947**	-2.277	27.290***
	(16.450)	(12.410)	(13.252)	(9.399)
Drought(0,1) x Household type	0.611	-17.827	-63.765	-62.504***
	(17.210)	(22.540)	(88.540)	(19.040)
F-test (rainfall)	5.89	1.52	2.67	0.82
	[0.016]	[0.218]	[0.103]	[0.365]
F-test (drought)	0.00	0.46	0.61	4.81
	[0.953]	[0.498]	[0.434]	[0.029]
# of ERA-40 cells	439	304	439	304
# of obs.	469600	464031	490908	480930

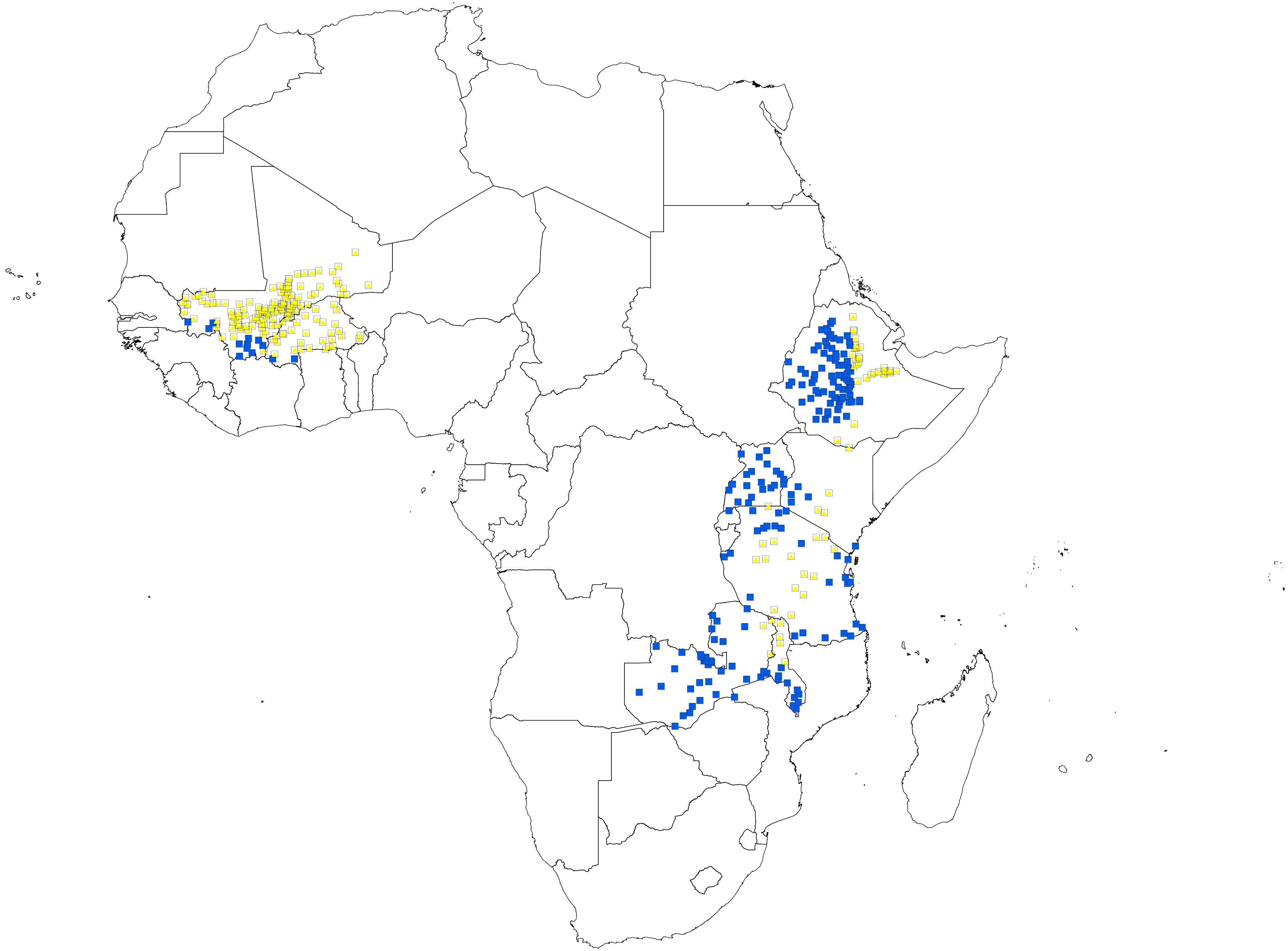
Notes: Robust standard errors in parentheses, clustered at the ERA-40 cell level. * significant at the 10 percent level, ** 5 percent, *** 1 percent. Fixed effects for cluster-month and country-year interacted with household type indicators are included (see equation (5) in the text for the exact speficiation). The nulls for F-test (rainfall) and F-test (drought) are that the sum of rainfall and drought coefficients, respectively, is equal to zero.

Table 8 – Infant Mortality, Nutrition and Malaria

Dependent Variable: Infant death indicator (multiplied by 1000)

	(1)	(2)	(3)	(4)	(5)	(6)
Sample	Epidemic	Epidemic	Epidemic	Arid	Arid	Arid
Malaria index in year before birth	0.94*	0.94*	1.22*		1.34*	2.25***
	(0.53)	(0.53)	(0.66)		(0.71)	(0.81)
Rainfall (centimeters) in growing seasons associated with birth		-0.016	-0.025	-0.046	-0.080	-0.064
		(0.060)	(0.064)	(0.10)	(0.10)	(0.098)
Drought (0,1) in growing seasons associated with birth		7.61	7.55	23.3***	23.3***	22.2***
		(14.3)	(14.5)	(8.47)	(8.33)	(8.38)
F-test (polynomials)			0.36			1.33
			[0.903]			[0.244]
Fixed effects	Cluster-month, Country-Year	Cluster-month, Country-Year	Cluster-month, Country-Year	Cluster-month, Country-Year	Cluster-month, Country-Year	Cluster-month, Country-Year
Polynomials	No	No	Yes	No	No	Yes
S.E. clustered at	ERA-40 cells	ERA-40 cells	ERA-40 cells	ERA-40 cells	ERA-40 cells	ERA-40 cells
# of S.E. clusters	275	275	275	304	304	304
# of obs.	378543	378543	378543	482635	482635	482635

Notes: Robust standard errors in parentheses, clustered as indicated. * significant at the 10 percent level, ** 5 percent, *** 1 percent. Fixed effects included as indicated. The row "Polynomials" indicates whether the cubic polynomials in the average monthly temperature and total precipitation over the 12-month period up to the birth month are included. The null for F-test (polynomials) is that the coefficients on polynomial terms are all zero.



Appendix Figure A1 – Crop markets in the Sample

Notes: Blue and yellow squares indicate markets in rainy and arid areas, respectively.