# Does climate change affect child malnutrition in the Nile Basin?

Amira Elayouty[1], Hala Abou-Ali[2], Ronia Hawash[3]

## Abstract

Children's nutritional status is expected to be negatively impacted by global climate change given their relative vulnerability to food insecurity shocks. The developing countries in Africa are relatively even more vulnerable to these negative impacts. This study investigates the impact of climate change on the geographical variation of the prevalence of stunting among children under the age of five in the Nile basin region using the Demographic and Health Surveys of the three countries Egypt, Ethiopia and Uganda. Survey data is spatially and temporally merged with high resolution climate change datasets to investigate whether and how the change in temperatures and precipitation has an influence on children's malnutrition. The prevalence of stunting among children under five years of age and its determinants are modelled using Bayesian geospatial regression model. The prevalence and determinants of stunting varied across Egypt, Ethiopia, and Uganda. The result of this paper highlights the fact that public health interventions targeted to reduce the burden of childhood stunting should consider geographical heterogeneity and adaptable risk factors.

## 1. Introduction

Most land areas will experience more frequent hot temperature days and heat waves by 2100 according to the Intergovernmental Panel on Climate Change (IPCC, 2014). These changes in the weather have direct and indirect implications on health and well-being. Climate change can have a direct impact on people's health through changing exposure to heat and cold, air pollution, emerging infections, and respiratory and water-borne diseases (Li et al., 2015; Mayrhuber et al., 2018; Greena et al., 2019). Children are even more vulnerable than adults to these changes; as they have greater metabolic rate, lower cardiac output, and greater body surface area-to-mass-ratio, which makes their bodies more sensitive to temperature changes (Bunyavanich et al., 2003; Sheffield et al., 2014; Varela, Rodríguez-Díaz and DeCastro, 2020). The indirect impacts of high temperature on agriculture, water sources and general productivity levels have also been identified (Hasegawa et al., 2016). Such disturbances in nutritional sources and income levels can eventually threaten food security and hence increase the risk of children malnutrition, including stunting and wasting (Mayrhuber, et al., 2018).

[1] Assistant Professor, Department of Statistics, FEPS, Cairo University, Egypt. a.ayouti@feps.edu.eg

[2] Professor, Department of Economics, FEPS, Cairo University, Egypt.

[3] Assistant Professor, Lacy School of Business, Butler University, Indianapolis, Indiana, USA. rhawash@butler.edu.

There is now evidence from middle- and high-income countries (Greenstone and Guryan, 2009; Deschênes, Gasparrini et al., 2015; Barreca, 2018) that high temperatures are associated with increased mortality and malnutrition rates among children. Yet, little is known about the impacts of high temperatures in developing countries, although the problem is becoming more salient in these countries. Poor populations are less capable of confronting exposure to heat waves and its health associated effects. This is because of their weak hospitalization and medical assistance, weak nutritional status and their strong dependence on agriculture and natural resources which are subject to higher climate risks (Varela, Rodríguez-Díaz and DeCastro, 2020; Xu et al., 2017). It is, therefore, vital to quantify the impacts of climate change on children's health in the developing countries to be able to mitigate its impact efficiently. But the scarcity of data in most developing countries, is the main challenge limiting such studies. This study examines the impact of climate change on children's heath in Egypt, Ethiopia, and Uganda. The choice of the studied countries is not only driven by data availability, but these countries also offer a good diversity and representation in the exploration of the Nile Basin.

This study attempts to examine the association between temperature and precipitation anomalies and under-five child malnutrition in various Nile Basin countries namely, Egypt, Ethiopia, and Uganda, at a smaller spatial scale and analyze the spatial variations in climate change effects across different areas of the studied countries. This will help policy makers evaluate the impacts of changes in climate on the prevalence of poor health conditions among infants and children across the Nile Basin and identify regions that are less resilient to high temperatures. This can be used as an early warning system to guide the public health sector on where and how to distribute its resources to save young generations.

The paper starts by presenting the research problem and a review of the studies performed to examine the impacts of weather variables on children malnutrition at both the global and regional levels. This will be followed by a description of the data and the Bayesian geo-spatial model used to evaluate malnutrition among under-five children in relation to climate at the sub-national level of Egypt, Ethiopia, and Uganda. Subsequent sections report the study empirical results and conclude with the policy implications of these results.

## 2. Background and Literature Review

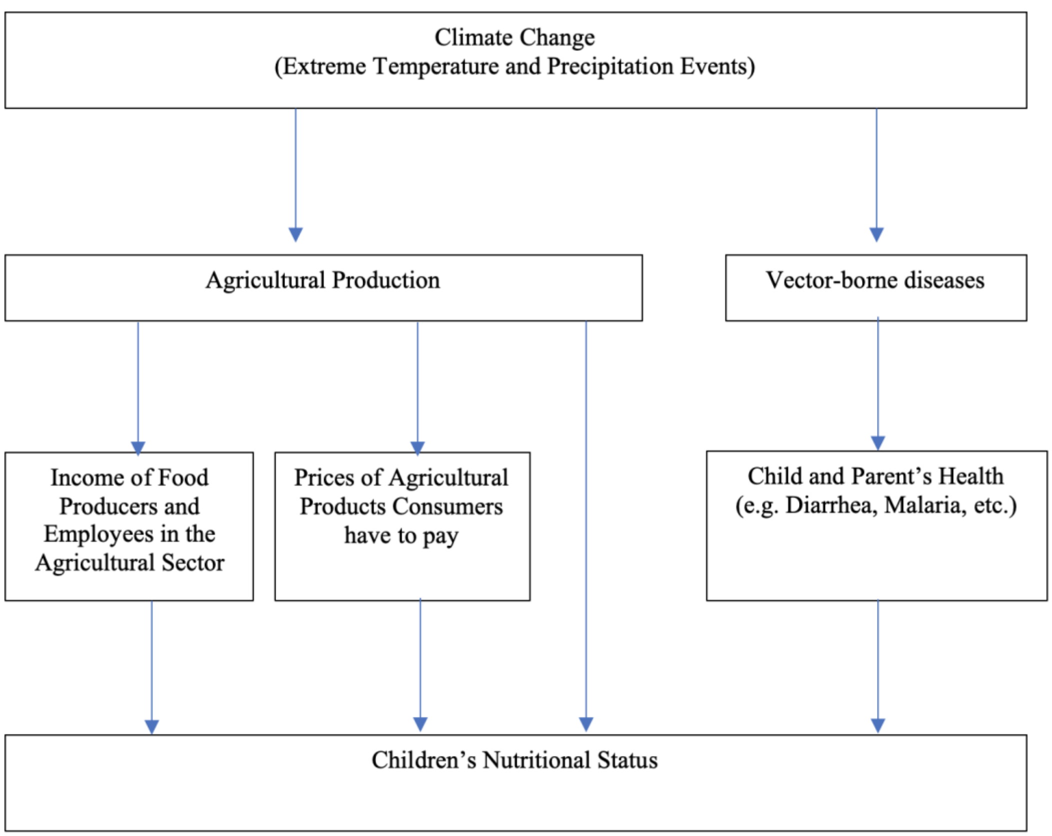
Climate change and its impact on food security has been considered one of the most pressing global challenges. Continuous increase in surface temperature and more intense and frequent heatwaves and precipitation events are expected to have a global impact through reducing water availability, food security, infrastructure, and agricultural incomes. However, the impact on low and middle-income countries is expected to be stronger due to the fact that these countries are more vulnerable to slower economic growth and food shortages which will make poverty reduction more difficult and may increase the risk of violent conflicts (Louis and Hess, 2008). Climate change results in a loss in aggregate crop production but the impact is stronger in tropical and temperate regions that rely on rainfed agriculture to meet their food and nutrition needs (Brown et al., 2015; Challinor et al., 2014). Developing countries in Africa are one of the most vulnerable regions in which agricultural production are negatively highly affected by inconsistent rainfall and extremely high temperatures (Davenport et al., 2017). The frequent flooding and drought events in addition to extremely high temperatures make it more difficult for families that rely on subsistence agriculture to meet their nutritional and caloric demand. The fact that children in the developing world and more specifically in poor communities are more vulnerable to food and nutritional food insecurity, provokes research into how climate change may impact the nutritional status of children living in these regions.

Understanding the impact of climate change on children's nutritional status is important due to malnutrition's short-term and long-term negative impacts. Malnutrition before conception and during early pregnancy has adverse effects on maternal, neonatal, and child health outcomes (Ramakrishnan et al., 2012). Malnutrition in-utero also increases the incidence of disability and lower years of schooling (Almond and Mazumder, 2001; Meng and Qian, 2009). Studies have also shown that malnutrition during early childhood has a negative impact on adult stature and years of schooling, adult health, and mortality rates (Alderman et al., 2006; Hoddinot and Kinsey, 2001; Currie and Vogl, 2013; Van den Berg et al., 2009). Low and middle-income populations relatively have the highest rates of stunting in children in addition to higher risks of maternal and child malnutrition which makes focusing on the developing countries of significance importance (Black et al., 2020).

Even though it may seem clear that climate change must have an impact on children's nutritional status; yet the relationship involves several complex pathways and direct and indirect mechanisms between both variables as shown in Figure 1. Changing climate disrupts the food system by impacting agricultural production, health, socioeconomic status of agricultural laborers and consumers. Extreme weather events such as: heat waves, droughts, and floods are expected to impact food availability by reducing agricultural production and increasing the likelihood of crop and pest diseases. The adverse impact on agricultural production not only directly increase the risk of famines and malnourishment, but it also impacts nutrition indirectly by reducing the incomes of food producers and labor in the agricultural sector (Maccini and Yang, 2009). It also increases the prices of food, which in turn reduces access to food and increases the likelihood of child malnourishment. These extreme weather events also increase the spread of vector-borne diseases such as diarrhea and malaria among children which reduces their biological ability of food utilization and make parents less capable of working and taking care of their children, and hence adversely impact their nutritional status (Louis and Hess, 2008).

Previous literature attempted to capture the relationship between exposure to climate changes in-utero and as children under the age of five and their short-term and long-term health status measured by their height-for-age and weight-for-age. Studies have examined the impact of climate variability during pregnancy on child health outcomes. Pregnancies conceived in months with lowest precipitation have shorter gestation periods and increased risk of having pre-term babies (Rayco-Solon et al., 2005). Grace et. al (2021) show that high temperatures and low levels of agricultural production in Mali are associated with lower birth weights and that living in malarious conditions may increase the likelihood of non-live birth outcomes. While McMahon and Gray (2021) find that precipitation extremes in South Asia in the first year of life reduces children's height-for-age with the highest impact concentrated in under-resourced households such as those lacking access to proper sanitation and households with women with lower education. Thiede and Strube (2020) examine the impact of temperature and precipitation anomalies on the weight and wasting of children below the age of five in Sub-Saharan Africa concluding that high temperatures are associated with lower weights and increased risk of wasting, whereas low precipitation is associated with reductions in weight. Hoddinott and Kinsey (2001) reach similar results by investigating the impact of rainfall shocks on children growth finding that children ages 12 to 24 months are the most vulnerable as they lose 1.5-2cm of growth in the aftermath of a drought. Grace et al. (2012) shows that drying conditions continue to prevail in Kenya increasing stunting levels for children aged 1 to 5. Another study tested the relationship between temperature, precipitation and stunting in Ethiopia concluding that increasing rainfall during rainy seasons is associated with increasing height-for-age. Moreover, exposure to higher temperature during the first and third trimester is positively associated with severe stunting (Randell et al., 2020). In brief, several studies have shown that lower precipitation and higher temperature are associated with increased stunting, wasting, and other adverse health outcomes.

**Figure 1: Mechanisms by which climate change impacts children's nutritional status**



Conversely, Cooper et al. (2019) find that higher rainfall is associated with poorer child nutrition in Ghana due to its increasing threat to food security and nutrition. Singh et al. (2001) examine the relationship between extreme rainfall and incidence of diarrhea in Fiji concluding that there is a positive association between both variables. Tiwari and Skoufias (2017) examine the relationship between monsoon rainfall shocks and height and weight in early childhood in rural Nepal. Their results indicate that more rainfall is associated with higher weight in children due to more agricultural production "positive income effect" but it also results in lower weight due to higher transmission of disease "negative disease effect". However, the positive income effects outweigh the negative disease effect resulting in positive net weight gain for children during the higher precipitation episodes. Cornwell and Inder (2015) also find that rainfall has a positive impact on height-for-age but also a negative impact through higher transmission of disease in urban children aged 10 and under in Indonesia.

Previous literature indicates contradicting results when examining the relationship between climate change and children's nutritional status. More specifically, the relationship between precipitation and height and weight in children seems to be non-linear. This is because too little rainfall negatively impacts child health by affecting agricultural incomes and food availability but also too much rainfall results in more disease transmission which also in turn increases child malnourishment. Moreover, the relationship between climate and nutrition tends to differ from one region to another. To our knowledge, there have not been any previous studies that explored the relationship between climate change and stunting in Egypt. Our study examines the non-linear relationship between temperature and precipitation anomalies and stunting in Egypt, Ethiopia, and Uganda using spatial modeling, which allows us to control spatial and temporal confounders more rigorously. We attempt to examine the impact of climate change on height-for-age and stunting in children aged 5 and under in the three countries under study using the Demographic and Health Survey (DHS) which is a high quality nationally representative dataset with high resolution geographic identifiers.

## 3. Data and Method

### 3.1. Data Description

Child anthropometric and socio-economic data are obtained from the latest available Demographic and Health Surveys (DHS) in Egypt, Ethiopia and Uganda; which were accessed using the DHS program database (`https://dhsprogram.com/`). DHS data are considered among the highest quality population health surveys in the developing countries. One advantage of DHS data is that they are collected using standardized core questionnaire that facilitates comparisons across countries (Headey, 2013). Another advantage of DHS data is that they include the latitude and longitude of DHS clusters which allows linking individual records to high-resolution temperature and precipitation data.

It is worth noting here that the DHS program randomly displaces cluster geo-coordinates (0-2 km for urban clusters; and 0-5 km for rural clusters with 1-5% of all clusters shifted by 10 km) to protect respondent confidentiality. This can introduce bias in the estimates but proved to be of relatively small magnitude. To account for this location shift, climate data in and around the community cluster location are aggregated. That is, households are linked with climate data for an approximate 10 square kilometer grid cell, including where the DHS cluster lies and all grid cells congruent to the cluster grid cell (Grace et al., 2012). Linking the cluster grid cell to the climate information of the cluster itself and its neighboring grid cells accounts for the location shift and the fact that temperature and precipitation outside of a household's immediate area may still influence that household's ability to meet the nutritional requirements of its children.

The analysis in this paper is restricted to the children under 5 for which anthropometric measures are available and to children born to mothers who had usually resided in their cluster of enumeration and as a result have been exposed to the climatic conditions in these clusters. Twins and observations with biologically impossible height-for-age z-score (HAZ) values (>|5|) were also excluded from the sample. After these restrictions, the analysis in this paper is based on a sample that includes 11995 child records from Egypt 2014 DHS, 8000 from Ethiopia 2016 DHS and 3536 from Uganda 2016 DHS. As recommended by the DHS program, sampling weights are applied to all analyses. The sample characteristics are illustrated in Table 1 and the geographic distribution of the clusters included in the sample is depicted in Figure 2.

Climate variability is measured using data from the University of East Anglia Climate Research Unit's Time Series (CRU TS). CRU TS is a global dataset of monthly weather conditions (Harris et al., 2014) constructed at 0.5$^{\circ}$ resolution based on statistical interpolations of data from over 4000 weather stations across the globe. Maximum temperature and precipitation records are extracted from 1951 through 2015 for grid cells that DHS clusters fall in, and maximum temperature and precipitation anomalies are calculated as described below.

### 3.2. Variables

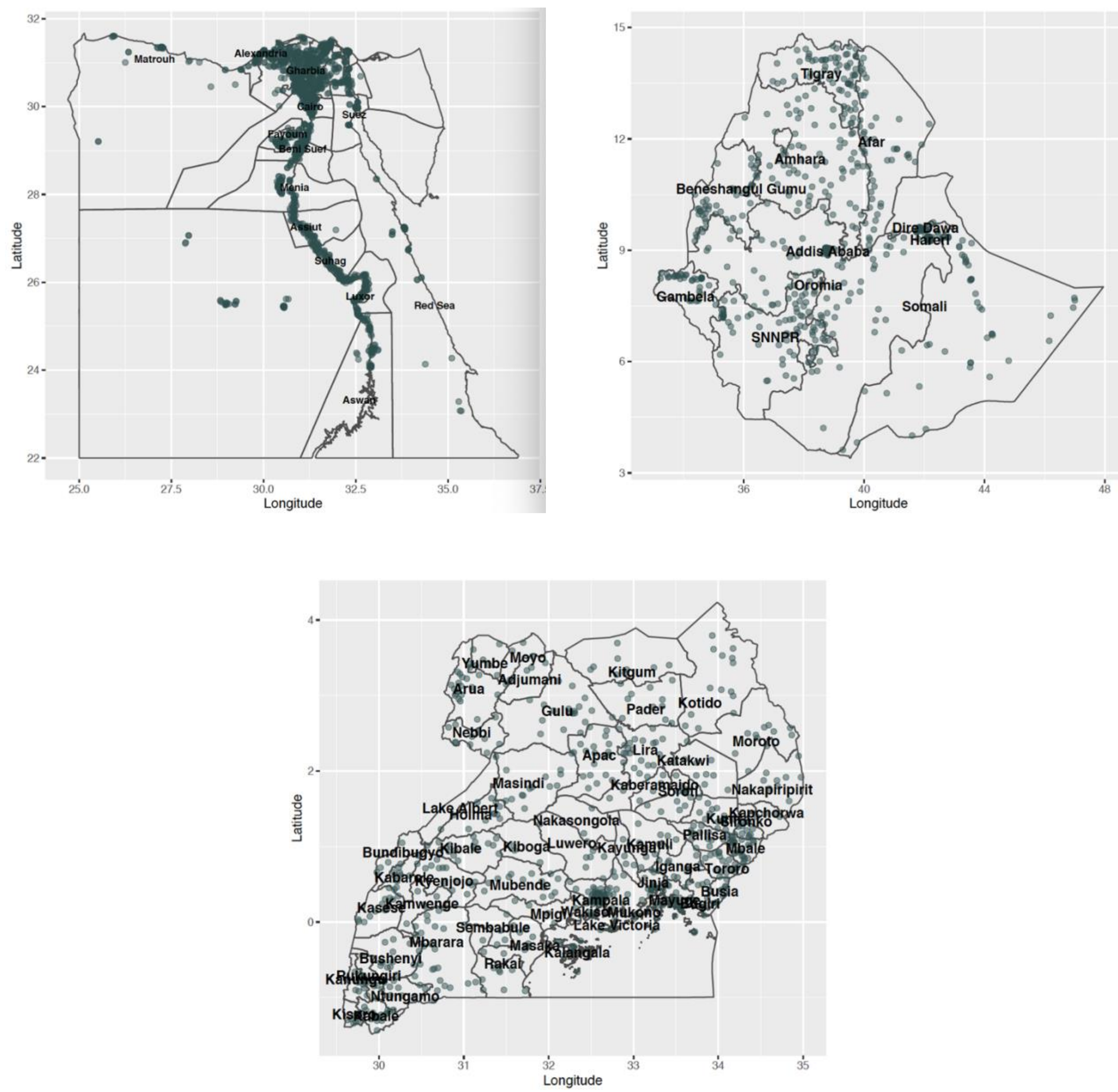
The dependent variable in this study is stunting, defined as having a height-for-age z-score (HAZ) less than -2. HAZ is calculated by subtracting an age- and sex-appropriate median value from a standard population and dividing by the standard deviation (SD) of the standard population. The z-scores are calculated using the World Health Organization (WHO) standards (World Health Organization, 2006). For this study, the nutritional status of children was classified on a binary scale ("1 = Yes/stunted" or "0 = No/not stunted"). Stunting is often associated with several negative outcomes, including suppressed immunity, increased risk of morbidity and mortality, and lower school performance. This, in turn, has implications on human development over both the short- and long-run terms.

**Table 1: Summary of Variables**

| | Ethiopia | | | | Egypt | | | | Uganda | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Variables** | **Mean** | **SD** | **Min** | **Max** | **Mean** | **SD** | **Min** | **Max** | **Mean** | **SD** | **Min** | **Max** |
| ***Average lifetime climate anomalies*** | | | | | | | | | | | | |
| Temperature | 1.803 | 0.006 | 1.21 | 3.27 | 1.993 | 0.006 | 0.65 | 3.38 | 1.795 | 0.006 | 1.04 | 2.35 |
| Precipitation | 0.261 | 0.009 | -1.18 | 1.84 | -0.480 | 0.004 | -1.38 | 1.00 | 0.548 | 0.007 | -0.32 | 1.43 |
| ***Historical average climate*** | | | | | | | | | | | | |
| Temperature | 26.247 | 0.041 | 20.29 | 35.96 | 28 | 0.019 | 24.25 | 33.93 | 28.827 | 0.03 | 22.59 | 31.71 |
| Precipitation | 91.705 | 0.346 | 15.57 | 149.63 | 4.099 | 0.048 | 0.20 | 23.96 | 107.34 | 0.228 | 56.56 | 139.76 |
| ***Child characteristics*** | | | | | | | | | | | | |
| Age (months) | 28.822 | 0.28 | 0 | 59 | 28.589 | 0.17 | 0 | 59 | 29.103 | 0.32 | 0 | 59 |
| %Females | 0.490 | - | 0 | 1 | 0.473 | - | 0 | 1 | 0.496 | - | 0 | 1 |
| Birth order | 4.018 | 0.04 | 1 | 14 | 2.457 | 0.01 | 1 | 15 | 4.041 | 0.05 | 1 | 18 |
| ***Mother characteristics*** | | | | | | | | | | | | |
| %Primary education | 0.061 | - | 0 | 1 | 0.183 | - | 0 | 1 | 0.321 | - | 0 | 1 |
| %Secondary & higher education | 0.026 | - | 0 | 1 | 0.587 | - | 0 | 1 | 0.067 | - | 0 | 1 |
| BMI | 20.576 | 0.04 | 11.73 | 46.43 | 28.896 | 0.05 | 10 | 49.96 | 23.135 | 0.09 | 14.16 | 48.63 |
| Age (years) | 27.135 | 0.10 | 13.33 | 48.17 | 26.199 | 0.05 | 13.17 | 47.17 | 26.876 | 0.13 | 13.50 | 45.75 |
| %Working | 0.446 | - | 0 | 1 | 0.133 | - | 0 | 1 | 0.841 | - | 0 | 1 |
| ***Household Characteristics*** | | | | | | | | | | | | |
| %Urban | 0.105 | - | 0 | 1 | 0.305 | - | 0 | 1 | 0.196 | - | 0 | 1 |
| %Middle income group | 0.213 | - | 0 | 1 | 0.255 | - | 0 | 1 | 0.202 | - | 0 | 1 |
| %Rich income group | 0.319 | - | 0 | 1 | 0.372 | - | 0 | 1 | 0.356 | - | 0 | 1 |
| %With protected water source | 0.524 | - | 0 | 1 | 0.974 | - | 0 | 1 | 0.693 | - | 0 | 1 |
| %With improved toilet facility | 0.082 | - | 0 | 1 | 0.916 | - | 0 | 1 | 0.330 | - | 0 | 1 |

The main goal of this study is to investigate whether and how climate change impacts the rates of stunting in the Nile Basin countries: Egypt, Ethiopia and Uganda. Therefore, the independent variables of interest are temperature and precipitation anomalies that capture the deviations of the climate patterns over each child's lifetime from the long-term average conditions within each cluster in the sample. These variables are measured respectively as the average of the yearly mean temperature and yearly total precipitation observed for a given cluster over the life span of each child prior to the year of each DHS survey, standardized over all consecutive 12-month periods from 1950 to 2000 for that location. This approach is used to assess the irreversible impacts of climatic variability on the child's health and nutritional status throughout his life.

**Figure 2: Maps of the location of under five children in the investigative sample in Egypt (top left), Ethiopia (top right) and Uganda (bottom)**




Other independent variables that have been considered in this study as control variables include child gender, birth order and age in months; maternal age, Body Mass Index (BMI) and school attainment; the place of residence controlling for rural/urban disparities, wealth, toilet facility and water source status of the household's cluster of residence; and the historical climate of the cluster of residence as measured by the respective means and standard deviations of temperature and precipitation across history (1950-2015). These variables may be correlated with child malnutrition (Behrman and Skoufias, 2004; Grace et al., 2012; Rieger and Trommlerova, 2016; Thiede and Strube, 2020), and hence their inclusion in the model increases the estimates precision.

In addition to the control variables described above, we included a series of random effects to control for the cluster effect as well as spatially structured random effects. These latter random effects are incorporated into the model to account for the geographical dependence between clusters, assuming that spatial autocorrelation decays as the distance between clusters increases.

### 3.3 Statistical Modelling

To evaluate the effects of temperature and precipitation variability on children's stunting status while accounting for the spatial dependence between DHS clusters within each of the three Nile Basin countries, a spatial modelling approach is used. In this modelling approach, the stunting status of child $i$ is estimated as a function of temperature and precipitation anomalies in the cluster of residence $c$ throughout the life span of child $i$ until the year of the survey; while controlling for the child characteristics including the maternal and household corresponding characteristics and the historical climate in cluster $c$. That is, let $Y_i$ be the binary variable taking value 1, if the $i$-th child is stunted and 0 if not. This variable can thus be assumed to be distributed as a Bernoulli random variable with unknown probability $\pi_i$ that the child is stunted; i.e. $Y_i \sim Bern(\pi_i)$. Thus, the risk of being stunted can be modelled using a spatial logistic regression model that accounts for excess heterogeneity and spatial dependence between areas within the same country as follows:

$$\text{logit}(\pi_i) = \log\left(\frac{\pi_i}{1-\pi_i}\right) = \beta_0 + X_i^{\top\beta} + X_{c_i}^{\top\alpha} + f_s(c_i) + f_u(c_i),$$

where $\beta = (\beta_1, \dots, \beta_p)^\top$ is the $(p \times 1)$ vector of regression coefficients that corresponds to the vector of child specific covariates $X_i$, $\alpha = (\alpha_1, \dots, \alpha_k)^\top$ is the $(k \times 1)$ vector of regression coefficients that corresponds to the vector of cluster covariates $X_{c_i}$ such as temperature and precipitation anomalies, $f_u(c_i)$ is a spatially unstructured random component which is independent and identically normally distributed with zero mean and unknown precision[4], $\tau_u$, and $f_s(c_i)$ is spatially structured component which is assumed to vary smoothly from one location to another. The smoothness of $f_s(c_i)$ is accounted for by modelling it as an intrinsic Gaussian Markov random field with a stationary and isotropic Matérn covariance matrix with unknown precision, $\tau_s$ and range $\rho$ parameters. This Matérn covariance matrix is defined as follows:

$$cov\left(f_s(c_i), f_s(c_j)\right) = \frac{\sigma_s^2}{2^{v-1}\Gamma(v)}\left(\kappa|c_i - c_j|\right)^v K v\left(\kappa|c_i - c_j|\right),$$

where $|c_i - c_j|$ denotes the distance between locations $c_i$ and $c_j$, $\sigma_s^2 = 1/\tau_s$ is the variance of the spatial field, and $K(\cdot)$ is the modified Bessel function of second kind and order $v > 0$. The integer value of $v$ determines the mean square variability of the process. $K > 0$ is related to the range $\rho$,

[4] Precision ($\tau$ ) =1/variance

the distance at which the correlation between two points is approximately zero referred to as a spatial decay parameter. A similar modelling approach that accounts for the geographic dependence between DHS clusters was used to examine associations between stunting and other potential health, socio-economic and environmental factors in Ethiopia (Ahmed et al., 2021), Mali (Benedict et al., 2020) and Rwanda (Uwiringiyimana, 2019).

The spatial models described above are fitted within a Bayesian framework by specifying non-informative priors for estimating the posterior distribution of fixed effects and spatial random effects' variance parameters. For the fixed effects' regression coefficients non-informative priors with normal distributions of mean and precision N(0, 0.001) are specified. Whereas, for the spatially structured random effects, vague gamma prior of (1, 0.00005) for the spatial decay parameter and inverse gamma prior for the precision parameter are specified. Another highly dispersed inverse gamma distribution is specified to the variance of the spatially unstructured random effects. The Bayesian inference is carried out using the R library INLA which implements the Integrated Nested Laplace Approximation (INLA) approach for latent Gaussian models (Rue et al., 2009). Bayesian inference using INLA is a computationally efficient alternative to the Markov Chain Monte Carlo (MCMC) that is designed to approximate the MCMC estimations in latent Gaussian models, including generalized linear mixed models and spatial models (Rue et al., 2009).

## 4. Results

### 4.1. Model Validation

For model comparison and selection, the deviance information criterion (DIC), developed by Spiegelhalter et al. (2002) as a measure of model complexity and fit, is used. Smaller values of DIC indicate a better trade-off between the model complexity and fit. The models with spatially structured and unstructured random effects yielded the smallest DIC relative to the traditional logistic models with independent random errors and logistic models with random intercepts (Table 2). For the final spatial models, the odds ratio of stunting with 95% credible intervals are estimated and reported for the different child, maternal, household, and climatic factors in Table 3. A credible interval is the Bayesian equivalent of the confidence interval, in which an unobserved parameter value falls with a given probability. However, unlike confidence intervals, credible intervals are dependent on the prior distribution specified for the parameter (Edwards et al., 1963).

**Table 2: DIC of logistic regression, logistic regression with independent random intercept for clusters and logistic regression with spatially random effects**

| | Basic Logistic | Logistic + IREE | Logistic + IRE+SRE |
|---|---|---|---|
| **Ethiopia** | 11578 | 11120 | 11099 |
| **Egypt** | 12498 | 11228 | 11042 |
| **Uganda** | 3913 | 3842 | 3833 |

### 4.2. Overall estimates

The average effects of climatic variability as well as the child, mother and household characteristics on stunting status are estimated across each country's population using different models with different sets of climatic covariates. That is, for each country, a series of models are fitted to test for non-linearities in temperature and precipitation and interactions between them. This includes the estimation of models that include only linear temperature and precipitation terms, models that include quadratic climate terms, and models that include quadratic climate terms and temperature-precipitation interaction term. Also models with historical average temperature and precipitation are examined. By evaluating these models, the preferred model specification appeared to be the one with quadratic temperature and precipitation anomalies terms which excludes the interaction term and the average historical climate averages, which are not statistically significant. The effect of the enhanced vegetation index (EVI) is also tested but turned to be insignificant in the three countries. One reason for this result is that EVI is considered as a mediator variable between climate and malnutrition.

Figure 3 illustrates the parameter estimates and their 95% credible intervals for the preferred model specification for all three studied countries. In Ethiopia and Uganda, middle and high-income households have the lowest rates of stunting in children under the age of five relative to poor households. The results show that mother education plays a significant role in child nutritional status. Mothers with secondary education or higher significantly reduces the probability of stunting in Egypt, Ethiopia and Uganda by approximately 27%, 36% and 64%, respectively relative to those without education. Mother's Body Mass Index (BMI) seems to be significantly important only in Ethiopia and Uganda in reducing the probability of under five children stunting. Child's age depicts a quadratic relationship with the log odds of stunting in Ethiopia and Uganda in contrast to Egypt where the association is linear. The model also indicates that female children are less likely to be stunted relative to male children.

Table 3 represents the odds ratio (OR) and the associated 95% credible interval (CI) estimated from the geospatial regression model, which accounts for the spatial autocorrelation structure. Children with at least secondary educated mothers (OR = 0.73; CI: 0.63, 0.84), (OR = 0.64; CI: 0.42, 0.96) and (OR = 0.36; CI: 0.22, 0.57) are less likely to be stunted compared to their counterparts for Egypt, Ethiopia, and Uganda, respectively. In Egypt, it is found that children who reside in geographic areas with precipitation anomalies below the long-term average conditions (OR = 1.66; CI: 1.11, 2.47) are less likely to be stunted compared to their counterparts. Maintaining the influence of spatial autocorrelation and other covariates constant, children who live in warmer clusters (OR = 3.2; CI: 1.17, 8.85), are more likely to be stunted compared to their counterparts. In Ethiopia, children from rich households (OR = 0.65; CI: 0.57, 0.75), and those with working mothers (OR = 0.87; CI: 0.78, 0.97) have a lower odd of stunting. The model results highlight also that Ethiopian children who resided in the "arid" geographic locations are more likely to be stunted compared to those who resided in the "wet" geographic locations.

**Figure 3: Parameter estimates along with 95% credible intervals for the preferred model specification**

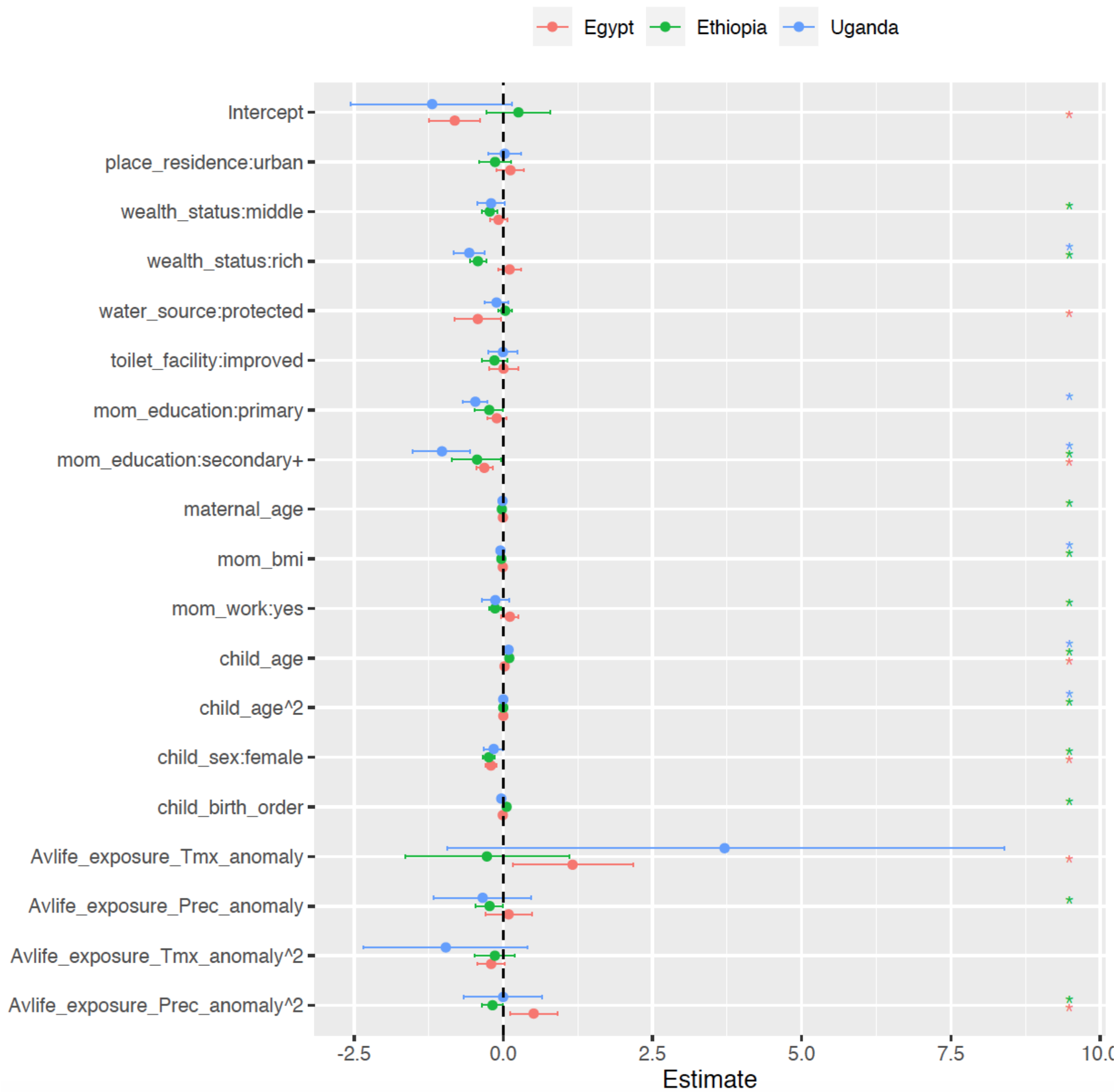


**Table 3: Odds ratios and associated 95% Credible Intervals (CI) for the association between stunting and the climate variables as well as the child, mother and household characteristics**

| | Ethiopia | | | Egypt | | | Uganda | | |
|---|---|---|---|---|---|---|---|---|---|
| **Variables** | **Mean** | **0.025** | **0.975** | **Mean** | **0.025** | **0.975** | **Mean** | **0.025** | **0.975** |
| *Place of residence (reference: Rural)* | | | | | | | | | |
| Urban | 0.87 | 0.66 | 1.14 | 1.13 | 0.90 | 1.42 | 1.02 | 0.77 | 1.35 |
| *Wealth Status (reference: Poor)* | | | | | | | | | |
| Middle | 0.80* | 0.70 | 0.90 | 0.92 | 0.80 | 1.07 | 0.81 | 0.65 | 1.02 |
| Rich | 0.65* | 0.57 | 0.75 | 1.11 | 0.91 | 1.35 | 0.56* | 0.44 | 0.73 |
| *Water Source (reference: Not protected)* | | | | | | | | | |
| Protected | 1.03 | 0.92 | 1.16 | 0.65* | 0.44 | 0.97 | 0.89 | 0.73 | 1.09 |
| *Toilet facility (reference: Not improved)* | | | | | | | | | |
| Improved | 0.86 | 0.69 | 1.07 | 1.00 | 0.78 | 1.29 | 0.99 | 0.78 | 1.27 |
| *Mom Education (reference: No education)* | | | | | | | | | |
| Primary | 0.79* | 0.62 | 0.99 | 0.9 | 0.76 | 1.05 | 0.63* | 0.51 | 0.77 |
| Secondary or higher | 0.64* | 0.42 | 0.96 | 0.73* | 0.63 | 0.84 | 0.36* | 0.22 | 0.57 |
| *Maternal age* | 0.98* | 0.96 | 0.99 | 0.99 | 0.98 | 1.01 | 0.99 | 0.96 | 1.01 |
| *Mother's BMI* | 0.97* | 0.95 | 0.99 | 0.99 | 0.98 | 1.002 | 0.95* | 0.93 | 0.97 |
| *Mother is working (reference: No)* | | | | | | | | | |
| Yes | 0.87* | 0.78 | 0.97 | 1.12 | 0.96 | 1.29 | 0.87 | 0.69 | 1.10 |
| *Child's age (months)* | 1.11* | 1.09 | 1.12 | 1.02* | 1.01 | 1.03 | 1.09* | 1.05 | 1.13 |
| *Child's age*$^2$ | 0.999 | 0.998 | 0.999 | 0.999* | 0.998 | 1.00 | 0.999* | 0.998 | 1.00 |
| *Child's gender (reference: Boy)* | | | | | | | | | |
| Girl | 0.78* | 0.71 | 0.86 | 0.81* | 0.74 | 0.90 | 0.85* | 0.72 | 0.9999 |
| *Child's birth order* | 1.06* | 1.02 | 1.09 | 0.99 | 0.94 | 1.04 | 0.97 | 0.91 | 1.03 |
| *Average lifetime temp anomaly* | 0.76 | 0.19 | 3.05 | 3.20* | 1.17 | 8.85 | 40.8 | 0.39 | 4404.5 |
| *Average lifetime temp anomaly*$^2$ | 0.87 | 0.62 | 1.21 | 0.82 | 0.65 | 1.02 | 0.38 | 0.096 | 1.50 |
| *Average lifetime precip anomaly* | 0.79* | 0.63 | 0.996 | 1.09 | 0.74 | 1.61 | 0.71 | 0.31 | 1.60 |
| *Average lifetime precip anomaly*$^2$ | 0.83* | 0.70 | 0.999 | 1.66* | 1.11 | 2.47 | 0.997 | 0.52 | 1.92 |
| *Random Effects* | | | | | | | | | |
| Unstructured variance ($1/\boldsymbol{\tau_u}$) | $5.7\times10^{-5}$ | 0.0008 | $1.5\times10^{-5}$ | 0.699 | 0.561 | 0.884 | 0.016 | 0.015 | 0.017 |
| Structured variance ($1/\boldsymbol{\tau_s}$) | 0.371 | 0.278 | 0.528 | 0.719 | 0.529 | 0.992 | 0.887 | 0.873 | 0.899 |
| Range (in Km) | 50.00 | 31.77 | 74.17 | 27.33 | 19.5 | 39.31 | 122.1 | 115.6 | 124.0 |

**(*) indicates the significance of the coefficient at 0.05 level of significance.**

### 4.3. Variation in Climate Effects

To further understand the climate change patterns on stunting, the probability of under five children being stunted is plotted across the range of temperature and precipitation anomalies, left and right panels of Figure 4, respectively, holding all categorical variables at the reference level and the other continuous variables at their means. Inspecting the estimation results, an increase in temperature anomalies in Egypt is associated with an increase in the probability of stunting. Contrary to the expectation, higher precipitation levels than average in Egypt increases child stunting, possibly due to the surge in waterborne sicknesses. This is in line with the findings of Cornwell and Inder (2015) in urban Indonesia. However, larger standard errors are associated with this increasing effect indicating higher uncertainty about such effect. It is also expected that precipitation deficits are associated with poor nutritional outcomes and leads to increased stunting, which is in line with the results of Ethiopia. It is also found that the average life-time precipitation exposure is a statistically significant predictor of stunting in the sense that dry spells are associated with higher likelihood of stunting relative to droughts. According to the model estimates, a decline in precipitation to below the average historical level by 1 standard deviation is associated with an increase in the probability of stunting by 1%. It is also evident that during spells of excess rainfall that the probability of stunting may increase or decrease due to the existence of two opposite forces. One is the increase in disease transmission that reduces child nutritional health. The second is the increase in crop production that improves child nutritional health through increased food availability. If the former effect outweighs the latter, it will result in an increase in the probability of child stunting during spells of high precipitation, whereas the probability of stunting will be reduced if the latter offsets the former. Those associations are robust across the studied Nile Basin countries, which is quite important given the detrimentally vulnerable characteristic of the region to food insecurity and climate change (FAO 2018).

### 4.4. Geographical Patterns of Stunting and Significant Subnational Variations

The posterior mean of the spatial effects is shown in the left panels of Figure 5 with darker colors indicating higher spatial effects. The right panels show the associated standard errors which are clearly lower in densely sampled regions. The figure depicts spatial variations in the odds of stunting across the three countries. It is evident from Figure 5 that Lower Egypt (except the west of the Delta) exhibits higher risk of stunting among children aged 0-59 months relative to upper Egypt. Whereas the highest risks of stunting in Ethiopia are spotted in Amhara followed by the southern Ethiopian regions. In Uganda, it is most of the south-west part of the country that exhibits high risks of stunting among children aged 0-59 months.

Based on the preferred model specification that accounts for the spatial variations within each country, maps of the predicted probabilities of stunting at the observed clusters are produced in Figure 6. The results highlight that the highest probabilities of stunting are clustered in Egypt mainly in Fayoum, Sharqia and Suhag, which are densely populated governorates characterized by higher levels of poverty. Whereas for Ethiopia, the highest probabilities of stunting are likely to be observed in the region of Amhara which is a region that experience more than usual natural and manmade distresses, including recurring droughts and famines, civil conflicts, and revolutions. These incidents have significant effects on agricultural production, food insecurity and child nutrition. In Uganda, it is the south-west region that suffers from higher risks of stunting relative to the rest of the country. This region of Uganda has a persistently high level of child stunting (Bukusuba et al., 2017; and Vella et al., 1995). This is due to several risk factors mainly poor socio-economic ability of households, lack of good child health feeding practices, and poor hygiene practices. This further justifies why climate change variables have no significant effect in Uganda and calls for more targeted interventions into poverty alleviation with a nutrition focus.

## 5. Discussion and Conclusion

Given the global concern regarding climate change and its impacts on health, this paper attempts to fill a gap in the existing literature on nutrition vulnerability of children of age five and under in developing countries, and more specifically in the Nile Basin countries. Understanding how climate impacts this particularly vulnerable group will significantly contribute to the decision-making process of policymakers in Egypt, Ethiopia and Uganda. This is achieved by answering key research questions such as, whether and how climate change impacts child nutrition in the Nile Basin countries as reflected in higher stunting rates. It is also necessary to identify which regions of the studied countries are particularly more vulnerable or most impacted by climate change.

This paper draws attention to the relationship between climatic change and under five child malnutrition, utilizing a methodological structure that takes into consideration spatial and temporal confounders for three countries of the Nile Basin. This study contributes to the climate-nutrition literature (Andalón et al. 2016; Davenport et al. 2018; Groppo and Kraehnert 2016; Randell et al. 2020; Thiede and Gray 2020; Thiede and Stube 2020) by investigating the relationships between temperature and precipitation variability and child stunting across a diverse set of Nile Basin countries. Prevailing literature mostly supports that warmer and arid circumstances increase child stunting. This paper underlines the complexity of this association through results that contradicts the above-mentioned assumption in some of the countries and results that are in line with it in others. On the one hand, Egypt's warmer weather increases the probability of stunting while periods of above average precipitation are detrimental to child nutrition. This could be due to increased localized flooding that reduces food accessibility and availability in addition to increased waterborne diseases. On the other hand, the results for Ethiopia show that the relationship between precipitation and stunting follows an inverted-U-shaped pattern which is consistent with the findings of Cooper et al. (2019a) and Thiede and Stube (2020). This indicates that the impacts of changes in the climate on children malnutrition vary by region. The strength of this paper lies in its significance for policymaking. The results of the model adopted in this study are expected to aid in cluster-level planning for child health. The mapping of the variation in child malnutrition associated with climate change can help with improving the allocation of limited resources to clusters with varying needs of healthcare.

**Figure 4: Effects of the average life exposure anomalies (temperature on the left and precipitation on the right) on stunting along with 95% credible intervals in Egypt (top), Ethiopia (middle) and Uganda (bottom).**

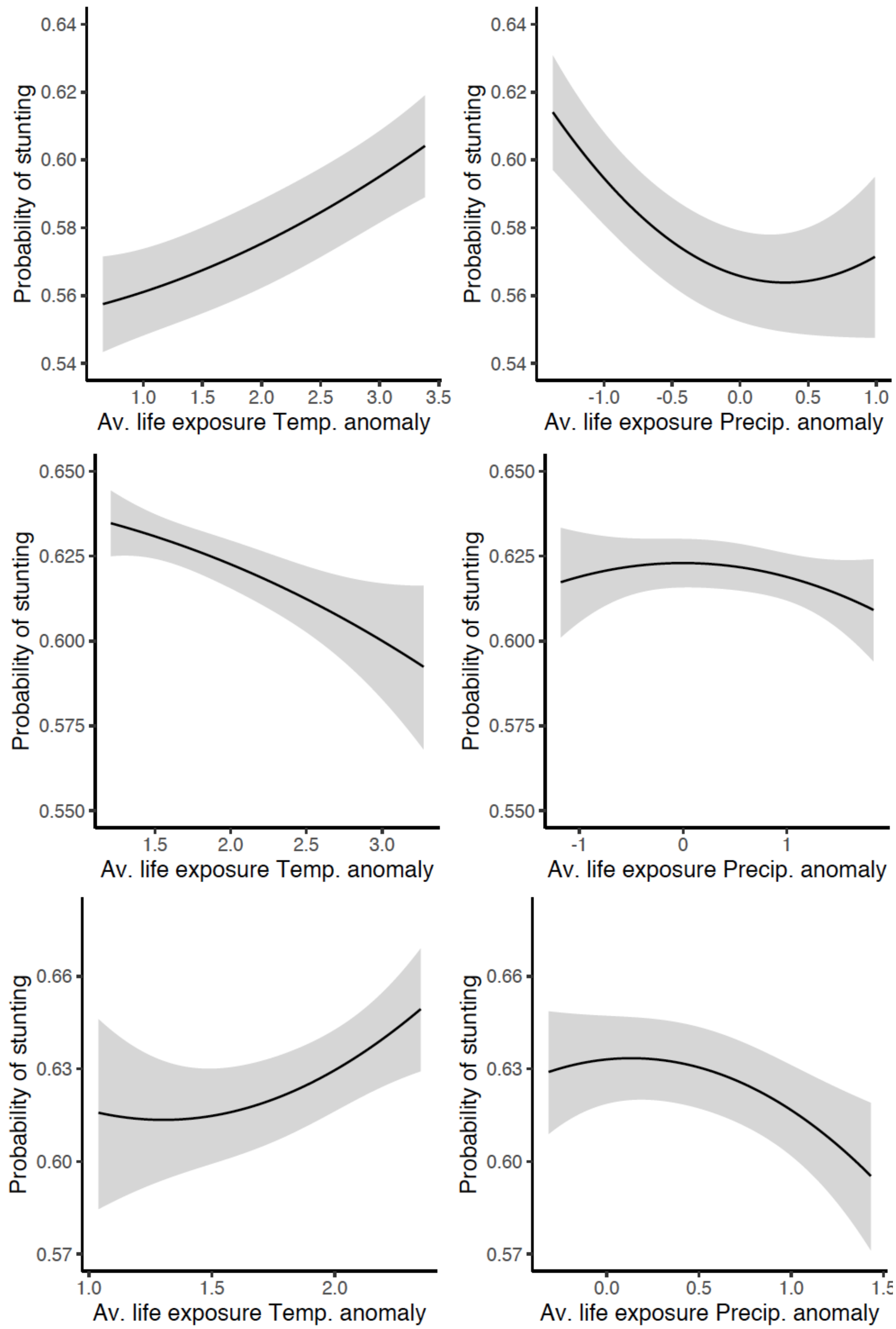


**Figure 5: Posterior mean (left) and standard deviation (right) of the spatial random effects in Egypt (top), Ethiopia (Middle) and Uganda (Bottom)**

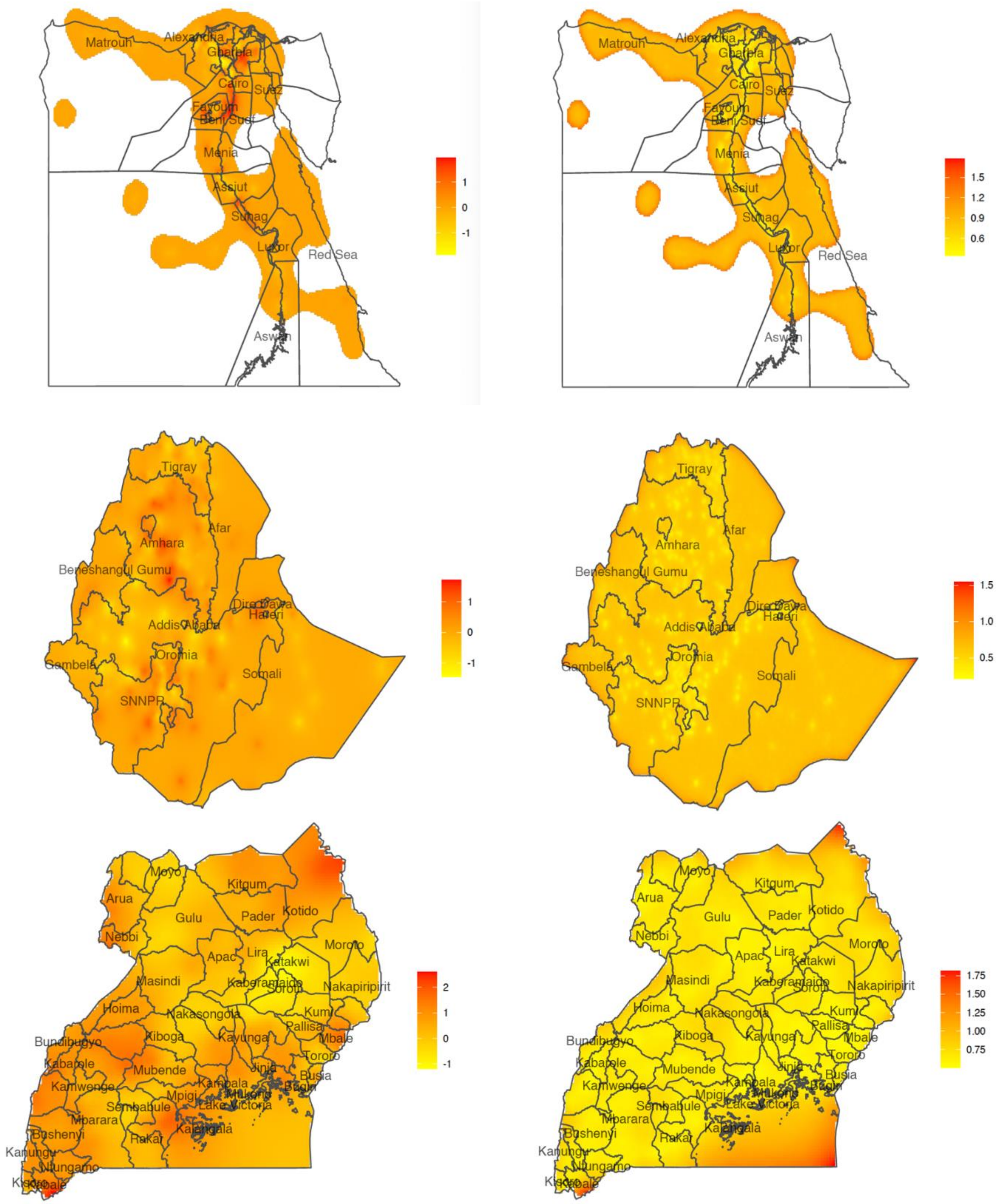
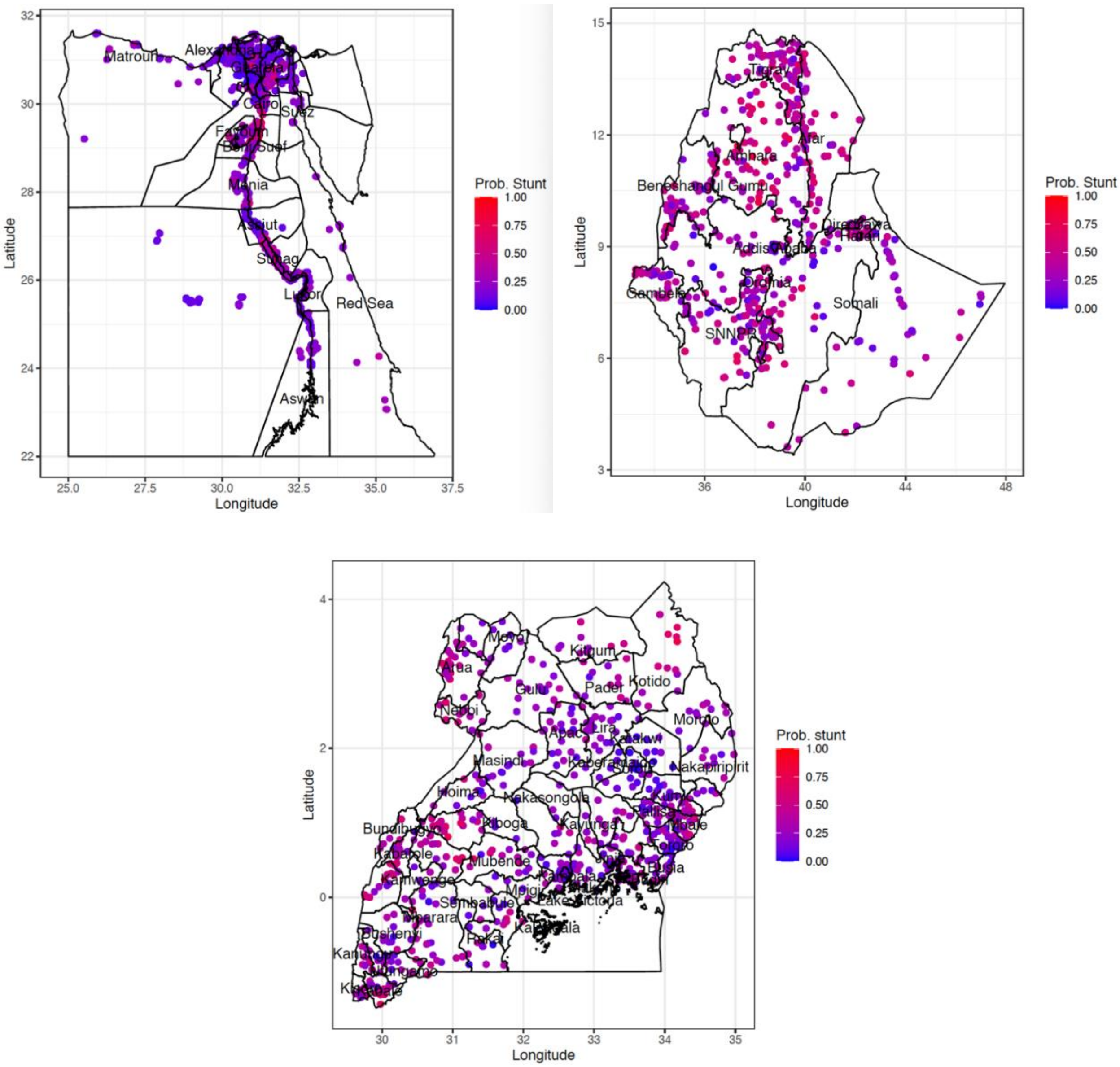


**Figure 6: Estimated probabilities of stunting at observed clusters in Egypt (top left), Ethiopia (top right) and Uganda (bottom).**




## List of References:


Ahmed, K.Y., Agho, K.E., Page, A., Arora, A., Ogbo, F.A., & on behalf of the Global Maternal and Child Health Research Collaboration. (2021). Mapping Geographical Differences and Examining the Determinants of Childhood Stunting in Ethiopia: A Bayesian Geostatistical Analysis. *Nutrients*, 13.

Alderman, H., Hoddinott, J., & Kinsey, B. (2006). Long term consequences of early childhood malnutrition. *Oxford Economic Papers*, *58*(3), 450-474.

Almond, D., & Mazumder, B. (2011). Health Capital and the Prenatal Environment: The Effect of Ramadan Observance During Pregnancy. *American Economic Journal: Applied Economics, 3*(4), 56-85.

Barreca, A. (2018). From Conduction to Induction: How Temperature Affects Delivery Date and Gestational Lengths in the United States. UCLA working paper.

Behrman, J. R., & Skoufias, E. (2004). Correlates and determinants of child anthropometrics in Latin America: background and overview of the symposium. *Economics and Human Biology*, 2(3), 335-351.

Benedict, R.K., Mayala, B.K., Bizimana, J.d., Cisse, I., Diabate, I., & Sidibe, K. (2020). Geospatial Modelling of Changes and Inequality in Nutrition Status among Children in Mali: Further Analysis of the Mali Demographic and Health Surveys 2006–2018, ICF International: Rockville, MD, USA.

Benmarhnia, T., Deguen, S., & Jay S. Kaufman, D. (2015). Vulnerability to Heat-related Mortality: A Systematic Review, Meta-analysis, and Meta-regression Analysis. *Epidemiolog*y, 781-793.

Bharti, R., Dhillon, P., & Narzary, P.K. (2019). A spatial analysis of childhood stunting and its contextual correlates in India, *Clinical Epidemiology and Global Health,* 7(3), 488-495.

Black, R. E., Victora, C. G., Walker, S. P., Bhutta, Z. A., Christian, P., Onis, M. D., . . .& Uauy, R. (2013). Maternal and child undernutrition and overweight in low-income and middle-income countries. *The Lancet, 382*(9890), 427-451.

Blom, S., Ortiz-Bobea, A., & Hoddinott, J. (2019). Heat Exposure and Children's Nutrition: Evidence from Wesr Africa. Paper presented at the 2019 Agricultural & Applied Economics Association Annual Meeting, Atlanta, GA, July 21-23.

Bukusuba, J., Kaaya, A. N., & Atukwase, A. (2017) Predictors of Stunting in Children Aged 6 to 59 Months: A Case–Control Study in Southwest Uganda. *Food and Nutrition Bulletin*, 38(4) 542-553.

Bunyavanich, S., Landrigan, C. P., McMichael, A. J., & Epstein, P. R. (2003). The impact of climate change on child health. *Ambulatory Pediatrics*, 44-52.

Burgess, R. et al. (2017). Weather, Climate Change and Death in India. Working paper. London School of Economics.

Challinor, A. J., Watson, J., Lobell, D. B., Howden, S. M., Smith, D. R., & Chhetri, N. (2014). A meta-analysis of crop yield under climate change and adaptation. *Nature Climate Change, 4*(4), 287-291.

Chen R. et al. (2018). Association between ambient temperature and mortality risk and burden: time series study in 272 main Chinese cities. BMJ, 363.

Cooper, M. W., Brown, M. E., Hochrainer-Stigler, S., Pflug, G., McCallum, I., Fritz, S., ... & Zvoleff, A. (2019a). Mapping the effects of drought on child stunting. *Proceedings of the National Academy of Sciences*, *116*(35), 17219-17224.

Cooper, M., Brown, M. E., Azzarri, C., & Meinzen-Dick, R. (2019). Hunger, nutrition, and precipitation: Evidence from Ghana and Bangladesh. *Population and Environment, 41*(2), 151-208.

Cornwell, K., & Inder, B. (2015). Child Health and Rainfall in Early Life. *The Journal of Development Studies, 51*(7), 865-880.

Currie, J., & Vogl, T. (2013). Early-life health and adult circumstance in developing countries. *Annual Review of Economics*, 5(1), 1-36.

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

Deschênes, O., Michael G., & Jonathan, G. (2009). Climate Change and Birth Weight. In: *American Economic Review*, 99 (2), 211–17.

Edwards, W., Lindman, H., & Savage, L.J. (1963). Bayesian statistical inference in psychological research. *Psychological Review*, 70, 193-242

Gasparrini, A. et al. (2015). Mortality risk attributable to high and low ambient temperature: a multicountry observational study. *The Lancet, 386*, 369–375.

Geruso, M., & Spears, D. (2017). Heat, humidity and infant mortality in the developing world. Economics Working Paper. University of Texas-Austin.

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

Grace, K., Verdin, A., Dorélien, A., Davenport, F., Funk, C., & Husak, G. (2021). Exploring Strategies for Investigating the Mechanisms Linking Climate and Individual-Level Child Health Outcomes: An Analysis of Birth Weight in Mali. *Demography, 58*(2), 499-526.

Greena, H., Bailey, J., Schwarz, L., Vanos, J., Ebi, K., & Benmarhnia, T. (2019). Impact of heat on mortality and morbidity in low- and middle -income countries: A review of the epidemiological evidence and consideration for future research. *Environmental Research*, 80-91.

Harris, I. P. D. J., Jones, P. D., Osborn, T. J., & Lister, D. H. (2014). Updated high-resolution grids of monthly climatic observations–the CRU TS3. 10 Dataset. *International Journal of Climatology*, 34(3), 623-642.

Hasegawa, T., Fujimori, &. S., Takahashi, K., Yokohata, T., & Masui, T. (2016). Economic implications of climate change impacts on human health through undernourishment. *Climate change*, 189-202.

Headey, D. D. (2013). Developmental drivers of nutritional change: a cross-country analysis. *World Development*, 42, 76-88.

Hoddinott, J., & Kinsey, B. (2001). Child Growth in the Time of Drought. *Oxford Bulletin of Economics and Statistics*, *63*(4), 409-436.

Isen, A., Rossin-Slater, M., & Walker, R. (2017). Relationship between season of birth, temperature exposure, and later life wellbeing. *Proceedings of the National Academy of Sciences*, 114 (51), 13447–13452.

IPCC. (2014). Climate Change 2014: Synthesis Report. Contribution of Working Groups I, II, and III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change. IPCC, Geneva, Switzerland.

Li, M., Gu, S., P. B., Yang, J., & Liu, Q. (2015). Heat Waves and Morbidity: Current Knowledge and Further Direction- A comprehensive literature review. *Public Health*, 5256-5283.

Longden, T. (2019) The impact of temperature on mortality across different climate zones. *Climatic Change*, 157, 221–242.

Louis, M. E. S., & Hess, J. J. (2008). Climate change: impacts on and implications for global health. *American Journal of Preventive Medicine*, 35(5), 527-538.

McMahon, K., & Gray, C. (2021). Climate change, social vulnerability and child nutrition in South Asia. *Global Environmental Change, 71*, 102414.

Maccini, S., & Yang, D. (2009). Under the weather: Health, schooling, and economic consequences of early-life rainfall. *American Economic Review*, 99(3), 1006-26.

Mayrhuber, E.A.S., et al. (2018). Vulnerability to heatwaves and implications for public health interventions- A scoping review. *Environmental Research*, 42-54.

Meng, X., & Qian, N. (2009). The Long Term Consequences of Famine on Survivors: Evidence from a Unique Natural Experiment using Chinas Great Famine. NBER Work Pap 14917.

Ramakrishnan, U., Grant, F., Goldenberg, T., Zongrone, A., & Martorell, R. (2012). Effect of Women Nutrition before and during Early Pregnancy on Maternal and Infant Outcomes: A Systematic Review. *Pediatric and Perinatal Epidemiology, 26*, 285-301.

Randell, H., Gray, C., & Grace, K. (2020). Stunted from the start: Early life weather conditions and child undernutrition in Ethiopia. *Social Science & Medicine*, *261*, 113234.

Rieger, M., & Trommlerova, S. K. (2016). Age-specific correlates of child growth. *Demography*, 53(1), 241-267.

Rue, H., Martino, S., & Chopin, N. (2009). Approximate Bayesian inference for latent Gaussian models by using integrated nested Laplace approximations. *J. R. Stat. Soc. Ser. B Stat. Methodol.*, 71, 319–392.

Rayco-Solon, P., Fulford, A. J., & Prentice, A. M. (2005). Maternal preconceptional weight and gestational length. *American Journal of Obstetrics and Gynecology, 192*(4), 1133-1136.

Sheffield, Z. X., Su, H., Wang, X., Su, S. &., & Wang, X. (2014). The impact of heat waves on children's health: a systematic. *Int J Biometeorol*.

Singh, R. B., Hales, S., Wet, N. D., Raj, R., Hearnden, M., & Weinstein, P. (2001). The influence of climate variation and change on diarrheal disease in the Pacific Islands. *Environmental Health Perspectives*, *109*(2), 155-159.

Song, X., Wang, S., Hu, Y., M. Y., T. Z., Liu, Y., . . . Shang, K. (2017). Impact of ambient temperature on morbidity and mortality: An overview of reviews. *Science of the Total Environment*, 241-254.

Spiegelhalter, D.J., Best, N.G., Carlin, B.P., & Van der Linde, A. (2002). Bayesian measures of model complexity and fit (with discussion). *Journal of the Royal Statistical Society, Series B.*, 64(4), 583–639.

Thiede, B.C., & Strube, J. (2020). Climate variability and child nutrition: Findings from sub-Saharan Africa. *Global Environmental Change*, 65, 1-10.

Tiwari, S., Jacoby, H. G., & Skoufias, E. (2017). Monsoon Babies: Rainfall Shocks and Child Nutrition in Nepal. *Economic Development and Cultural Change*, *65*(2), 167-188.

Tusting, L. et al. (2020). Environmental temperature and growth faltering in African children: a cross-sectional study. *Lancet Planetary Health*, 4 (1), 16–23.

Uwiringiyimana, V., Veldkamp, A., & Amer, S. (2019). Stunting spatial pattern in Rwanda: An examination of the demographic, socioeconomic and environmental determinants. *Geospatial Health*, 14.

Van den Berg, G. J., Doblhammer, G., & Christensen, K. (2009). Exogenous determinants of early-life conditions, and mortality later in life. *Social Science & Medicine*, 68(9), 1591– 1598.

Varela, R., Rodríguez-Díaz, L., & DeCastro, M. (2020). Persistent heat waves projected for Middle East and North Africa by the end of the 21st century. *PloS one*, 15(11), e0242477.

Vella, V., Tomkins, A., Nviku, J., & Marshall, T. (1995). Determinants of Nutritional Status in South-west Uganda, *Journal of Tropical Pediatrics*, 41 (2), 89 – 98.

Xu, Z., Crooks, J. L., D. B., Hu, W., & Tong, S. (2017). Heatwave and infants' hospital admissions under different heatwave definitions. *Environmental Pollution*, 525-530.