After the Rain - Understanding the Link Between Flood Exposure and Child Undernutrition in West Africa.

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Ethics approval and consent to participate: The analyses for this paper were conducted using publicly available data from the DHS. Consistent with the standards in ensuring the protection of respondents' privacy, the collected data used in the present study were anonymous and acquired with participants' informed consent. Therefore, no additional ethical permission was required.

Consent for publication: The author declares that there are no conflicts of interest relevant to the content of this paper.

Availability of data: The datasets analyzed during the current study are available in the DHS repository for the 14 selected West African countries, https://dhsprogram.com/data/dataset_admin/index.cfm.

Competing Interests: No competing interests exist.

Funding: This research was funded by the Social Sciences and Humanities Research Council (SSHRC)

Authors' contributions: KA was responsible for the concept, design and primary analysis of this study, as well as the written draft of the final manuscript.

Acknowledgements: The author acknowledges the support of her supervisors, Sarah Brauner-Otto and Shelley Clark, throughout the writing of this paper.

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West Africa[1] is one of the world's most climate-vulnerable regions, where the frequency and intensity of extreme weather events are rising rapidly. Although the region contributes minimally to global greenhouse gas emissions, it endures a disproportionate share of the adverse effects of climate change. Temperatures are rising at a faster rate than the global average, and rainfall patterns have become increasingly erratic (USAID, 2018). While the region was once primarily associated with prolonged droughts, particularly in the Sahel,[2] West Africa now faces an important increase in the frequency and severity of flooding events (Barry et al., 2018; Ekolu et al., 2022; Kennedy et al., 2017; Nicholson et al., 2018; Nka et al., 2015; Sylla et al., 2016; Thomas & Nigam, 2018). Floods are now more frequent and intense, as well as intensified in magnitude and duration, causing a greater number of people to be directly and indirectly affected by climate-related shocks. Between 2011 and 2021, more than 14 million people were affected by flooding events across the region, an increase of approximately 7 million compared to the previous decade (CRED, 2025).[3] The growing unpredictability of these events is especially concerning for the region as a whole and, in particular, Sahelian countries, where climate volatility exacerbates long-standing development challenges and strains institutional capacities for climate-related shock preparedness and response.

[1] This region consists of Benin, Burkina Faso, Cape Verde, Côte d'Ivoire, The Gambia, Ghana, Guinea, Guinea-Bissau, Liberia, Mali, Mauritania, Niger, Nigeria, Senegal, Sierra Leone, and Togo.

[2] The Sahel region encompasses West African countries such as Senegal, Gambia, Mauritania, Guinea, Burkina Faso, Niger, and Nigeria.

[3] This is estimated to represent 3 to 4% of West Africa's total population during that period, based on population growth estimates from approximately 350 million in 2011 to over 420 million in 2021 (United Nations, 2025)

West Africa's vulnerability to climate shocks is not rooted only in it's increase environmental exposure but also in persistent structural inequalities. Widespread high poverty rates, weak infrastructure, and limited institutional capacity make it difficult for countries in the region to prepare for or effectively respond to climate-related shocks (Cervigni et al., 2015, 2017; UN et al., 2021). As the region continues to be one of the poorest in the world,[4] it also continues to experience high levels of food insecurity. In 2023, approximately 45 million people were classified as food insecure, highlighting the level of vulnerability across the region (AFD, 2023).[5] Rapid urbanization, inadequate water, sanitation, and hygiene (WASH) systems, and unplanned settlement patterns, especially in newly classified peri-urban areas, further exacerbate the impact of extreme weather events, such as floods, placing weaker infrastructure under even greater strain. Therefore, families across the region are experiencing higher levels of precarity, and exposure to floods poses an important threat to the long-term well-being of vulnerable individuals.

Children are among the most vulnerable to the rising climate crisis. They are confronted with heightened biological vulnerability to both disease and undernutrition and are often the least protected during emergencies. Although West African children represent only 10% of the world's child population, they account for a disproportionate share of global child mortality, malnutrition, and limited educational completion (UNICEF, 2024). In 2021, the region was home to a large share of the under-five deaths and the world's stunted children (UNICEF, 2021). Twelve out of sixteen countries in West Africa rank among the thirty most climate-vulnerable nations for children

[4] It is estimated that in 2025, 8 of the 16 countries in the West African region were among the 20 poorest countries in the world. This includes Niger, Liberia, Sierra Leone, Mali, Burkina Faso, The Gambia, Guinea-Bissau and Nigeria (Focus Economics, 2024).

[5] This represents approximately 10% of West Africa's estimated population of 446 million in 2023 (World Population Prospects, 2025).

(Boutin et al., 2021).[6] In 2024 alone, extreme rainfall displaced four million people and disrupted education for over ten million children across several countries, including Niger, Nigeria, Mali, and the DRC (UNICEF, 2024). As climate change continues to destabilize weather systems, children's lives and well-being will remain threatened.

Although climate-related risks in West Africa have become increasingly well documented, the specific relationship between flooding and child nutrition continues to be underexplored. Much of the existing literature on climate shocks and malnutrition has focused on South Asia, particularly Bangladesh (Baten et al., 2020a; Goudet et al., 2011; Rahman et al., 2024), India (Rodriguez-Llanes et al., 2011, 2016), Nepal (Gaire et al., 2016), and Pakistan (Hossain et al., 2013). Within the West African context, most studies have been confined to single-country analyses and have primarily examined the economic consequences of climate variability, such as agricultural productivity, household consumption, or poverty levels (Atanga & Tankpa, 2021; Brown & Crawford, 2008; Müller et al., 2023; Sawadogo et al., 2024). When cross-country studies in sub-Saharan Africa do exist, they often rely on broader indicators of climate variability, such as deviations in rainfall or temperature (Davenport et al., 2017; Kemajou Njatang et al., 2023; Thiede & Strube, 2020), which are unable to explicitly capture the abrupt effects of flooding events. Moreover, most studies continue to emphasize drought as the dominant climate risk in the region (Cooper et al., 2019; Hoddinott & Kinsey, 2001; Mason et al., 2011), leaving the impacts floods on population health relatively understudied despite their growing prevalence and severity. This has resulted in a limited and fragmented body of research focused on West Africa.

[6] This includes Benin, Burkina Faso, Cote d'Ivoire, Guinea, Guinea-Bissau, Liberia, Mali, Niger, Nigeria, Senegal, Sierra Leone and Togo.

This represents a significant limitation in the existing literature, given the distinct and severe nature of flooding as a climate-related shock. Unlike gradual or seasonal climate stressors observed through climate-variability, flooding constitutes a sudden-onset, high-impact event that can severely disrupt infrastructure, displace families, contaminate water sources, damage agricultural land, undermine household food security, and impede access to health services. These disruptions have important implications for acute forms of childhood malnutrition, especially wasting, which reflects short-term nutritional deprivation and physiological stress. While broader indicators of climate such as rainfall variability provide important insight for understanding the impacts of long-term or seasonal trends, these are often unable to adequately reflect the immediate and severe conditions caused by flooding events. As such, a critical empirical gap persists in the literature, as relatively few studies examine the effects of flooding on child nutritional outcomes in West Africa. As flooding events become a more frequent and prominent threat in this region of Africa, understanding its impacts on child health is the key for developing targeted adaptation and mitigation strategies. Therefore, this study aims to address this gap by examining the impact of flood exposure on childhood acute malnutrition across West Africa, expanding our knowledge of how environmental shocks interact with health vulnerabilities in one of the world's most climate-sensitive regions.

Conceptual framework

Flooding is a climate-related shock that poses both immediate and long-term risks to children's health and nutrition. It heightens exposure to infectious diseases, weakens household economies, disrupts food systems, and restricts individuals' access to essential health services. These climate shocks have important consequences in settings such as West Africa, where existing climate and food security vulnerabilities are exacerbated by weak infrastructure, high dependence to agriculture and limited institutional capacity to mitigate the impacts of environmental hazards.

Floods can pose a direct threat to children's and caregivers' health through increased morbidity and mortality. Drowning and physical shock are immediate risks of flooding events, while longer-term health threats arise from the propagation of waterborne and vector-borne diseases following a flood. Children recently exposed to floods often face a high risk of infections such as cholera and malaria, which can compromise children's nutritional status through repeated periods of diarrhea and fever (Mallett & Etzel, 2018; Naing et al., 2019; Rahman et al., 2024; Sur et al., 2000; Wang et al., 2023). For example, Mallett and Etzel (2018) found that floods were often associated with significant increases in malaria-related morbidities and mortality among exposed children, while Helldén et al. (2021) highlight how shifts in short-term weather patterns, including flooding, create favourable conditions for disease transmission and are strongly associated with undernourishment.[7]

Beyond the immediate health impacts, floods can also disrupt the economic foundations that support household food security and child nutrition. In agrarian economies such as those in much of West Africa, floods can destroy crops, kill livestock populations, and impair soil fertility, directly undermining household agricultural output (Alderman et al., 2012; Carpena, 2019; Dimitrova & Muttarak, 2020). These disruptions result in significant income disruptions and the loss of resources. In some cases, affected families may be forced to redirect household resources

[7] While mortality associated with flooding events may lead to an underestimation of the actual impact of floods on child nutrition, as the most vulnerable children may not survive to be included in survey samples, the analysis still captures broader effects among surviving children, offering critical insight into the health burdens that persist after flood exposure.

toward repairing their damaged home, replacing lost assets, or relocating household goods, which can divert essential household resources away from critical early childhood needs such as nutritious food, preventive services, and medical care. Moreover, flooding often disrupts local markets, constraining food availability and driving up the prices of basic goods, which can exacerbate nutritional stress among young children, even in non-agricultural households (Arndt et al., 2012; Pelser et al., 2022). These economic pressures may lead families to ration food, reduce meal frequency, or lower dietary diversity, all of which have adverse implications for child growth, especially during early developmental periods when nutritional demands are the highest.

Flooding can also put a strain on the supply of healthcare and essential public services. The destructions of health facilities, as well as damages to road networks, and sanitation systems can increase the cost and difficulty of daily life activities and accessing care, particularly in rural areas (Amankwaa & Gough, 2023; Davis et al., 2010). Infrastructural damage not only limits the availability of emergency services but also hampers the delivery of maternal and child health interventions, such as immunizations, as well as nutritional and antenatal care (Baten et al., 2020a; Masbi et al., 2024; Salam et al., 2023). These challenges are further exacerbated in West Africa, where rapid urbanization, poor WASH infrastructure, and unplanned settlement patterns contribute to the region's heightened vulnerability to floods. In such settings, fragile institutional systems are placed under additional pressure during flooding events, which further constrain institutional capacity to respond and deepen the vulnerabilities of populations. The breakdown of WASH systems also elevates children's vulnerability to infectious diseases, thereby intensifying the nutritional and health burdens of children in flood-affected regions.

Together, these interconnected pathways through which climate-related shocks impact populations highlight the complex ways in which flooding impacts child nutrition, particularly through its impact on weight-for-height, a sensitive indicator of acute malnutrition. A weight-for-height z-score below -2 indicates wasting, which reflects recent weight loss or insufficient weight gain and is commonly caused by the mechanisms outlined above: illness, household economic shocks, service disruptions, and compromised care environments. This study builds on this conceptual foundation to empirically examine how recent flood exposure contributes to acute nutritional vulnerability among children across West African countries.

The Heterogenous Effects of Flood Exposure

The relationship between flooding and child nutritional outcomes is not likely to be uniform across populations. Instead, it is likely shaped by a range of intersecting social, biological, and structural factors that condition both exposure to risk and the capacity to cope with this phenomenon. To better understand the varying and complex effects of flooding events, this study examines how the impact of recent flood exposure varies across key sociodemographic groups.

Children's biological characteristics, such as age and sex, may influence their vulnerability to nutritional stress in very distinct ways. Specifically, the association between recent flood exposure and children's weight may vary by children's sex, as gender discrimination may influence how parents ensure children's safety from the adverse effects of flooding (Block et al., 2004; Tiwari et al., 2017), although there is little evidence of discriminatory practices in sub-Saharan Africa. The association between recent flood exposure and children's weight may also vary based on children's age, as young children are more physiologically susceptible to infections, nutrient loss, and growth impairment, making them particularly vulnerable to disruptions in food and health systems.

The socio-economic dimensions of the household environments are also factors that could potentially mediate the effects of flooding, as well as childhood malnutrition. Mothers' education, for instance, is strongly associated with children's health, as typically more educated mothers are better equipped to seek help, navigate and access services, and adjust their caregiving responsibilities when experiencing stressful events (Gbratto-Dobe & Segnon, 2025; Greenaway et al., 2012; Iftikhar et al., 2017; Ohonba et al., 2019). Mothers' employment can also have an important impact on children's health after a flooding occurrence. Children from agricultural households may experience higher risk associated with flooding events due to damaged crops, reduced food availability within affected families, and income constraints (Nankinga et al., 2019; Ukwuani & Suchindran, 2003). In these types of situations, the time that mothers dedicate to caregiving may also be reduced due to them now being required to participate in the household's recovery efforts or explore alternative income-generating activities. In turn, this would potentially limit the attention mother's would give to their children's feeding, hygiene, and healthcare needs. Household wealth level can also help mediate or deepen the impact of environmental shocks on children's nutrition (Chalasani & Rutstein, 2014; Lartey et al., 2016). Families with higher wealth may have greater access to food stocks, healthcare, and safer housing, all of which can buffer the impact of flooding. Similarly, children in lower-income households could be more likely to experience heightened risks. Finally, flood exposure could differ between urban and rural settings (Datar et al., 2013; Rodriguez-Llanes et al., 2016). While urban households may face higher risks of disease transmission due to higher population density, rural households may experience more prolonged disruptions in food systems and health service delivery.

By examining these dimensions together, this paper applies an intersectional lens to identify how social, biological, and structural characteristics could mediate the impact of flood exposure on children's nutritional vulnerability. This approach not only aims to reveal the differential effects within the population but also provides a deeper understanding of the compounded risks experienced by those at multiple points of disadvantage.

Data and methods:

This study utilizes child anthropometric and socioeconomic data from the Demographic and Health Surveys (DHS) program, which has collected nationally representative data on population health and nutrition across more than 90 countries since the 1980s (DHS, 2025). The DHS program is widely recognized for its rigorous survey methodology, high-quality data collection standards, and comprehensive coverage of demographic and health indicators. These surveys provide a valuable source of information for analyzing child nutritional outcomes, as it collects data on the weight and height of children, along with important demographic and socioeconomic information about the children's households.

The pooled dataset consisted of 457,342 children aged 0–59 months across all DHS surveys conducted in 12 West African countries between 2000 and 2023. This includes Benin, Burkina Faso, Côte d'Ivoire, Gambia, Ghana, Guinea, Liberia, Mali, Niger, Nigeria, Senegal, and Sierra Leone. The analytical sample was then restricted to DHS surveys, where anthropometric measurements for children aged 0–59 months were collected. Observations flagged by the DHS (13,590) and observations with missing anthropometric information (169,963) were excluded from the analytical sample due to sampling procedures.[8] Observations with biologically implausible anthropometric values were also excluded from the analytical sample. Specifically, children with

[8] Anthropometric information was missing for a subgroup of children in the original sample for multiple reasons, according to the DHS data records. Specifically, based on DHS records, among the 169,963 children with missing weight measurements, the most common reasons provided was that no measurement was recorded in the household roster (76.01%), followed by the child dying before the survey (15.93%). Other reasons (4.02%) and refusal by the child or mother (1.68%) were additional reasons why the data was recorded as missing.

weight-for-height z-scores (WHZ) greater than 5 (2,874) or ages in days outside plausible limits (65) were excluded from the analytical sample. After applying these restrictions, the final analytical sample consisted of 270,850 child records drawn from 44 DHS surveys conducted in the selected 12 West African countries over a 23-year study period. As recommended by the DHS program, sampling weights were applied in all analyses to account for the complex survey design and ensure nationally representative estimates.

Flood exposure is measured using two complementary sources: the Geocoded Disasters (GDIS) Dataset and the Emergency Events Database (EM-DAT). The GDIS dataset serves as the primary data source for constructing the flood exposure variable. Developed as a geospatial extension of EM-DAT, the GDIS provides province-level geographic coordinates for disaster-affected areas. Moreover, by providing standardized information on the geographic location and year of disaster events, this dataset allows me to spatially and temporally match flood occurrences with children in the DHS sample. This matching process forms the basis for constructing a child-level measure of flood exposure.

To supplement the geospatial information provided by the GDIS, I incorporate data from the EM-DAT database. Maintained by the Centre for Research on the Epidemiology of Disasters (CRED) in collaboration with the World Health Organization (WHO), EM-DAT is a globally recognized repository of disaster-related data widely used in disaster and public health research (Baten et al., 2020b; Datar et al., 2013). It provides detailed records on the location, timing (including day, month, and year), and human impact of natural and human-made disasters (Lee et al., 2024). A disaster is recorded in EM-DAT if it meets at least one of the following criteria: (i) 10 or more deaths, (ii) 100 or more individuals affected, (iii) a declared state of emergency, or (iv) a request for international assistance. I integrate data from the EM-DAT database in two key ways, both of which are essential for accurately capturing children's and provinces' recent exposure to a flooding event. First, I use the EM-DAT database to obtain the start and end dates of each flooding event, which are not available in the GDIS dataset. This additional temporal information enables precise identification of whether a flood occurred within the 12-month window to the survey, which is critical for the classification of children recently exposed to a flooding event. Second, because the GDIS only includes disaster occurrences up to 2018, I use the EM-DAT database to incorporate flood events occurring between 2019 and 2023. These dates are provided in the EM-DAT database alongside disaster information including the location of the events, the number of affected people and the total cost of damages. These more recent events are then harmonized with earlier disaster records to ensure consistency in exposure measurement and matched by region and year to the DHS data.

By integrating EM-DAT and GDIS, this study ensures a systematic and spatially accurate assessment of flood exposure. This approach also strengthens the analytical framework by enabling a more precise regional estimation of the relationship between flood exposure and child nutritional outcomes from the DHS across West Africa.

Child Level Measures

The dependent variables used in these analyses are 1) a continuous measure of weight-for-height (WHZ) and 2) a dichotomous measure of wasting, defined as a WHZ of < -2. Weight-for-height z-scores are calculated using the World Health Organization (WHO) growth standards and are directly provided by the DHS. WHZ reflects the child's body mass in relation to height, allowing for the detection of acute nutritional stress. A lower WHZ indicates recent weight loss or insufficient weight gain, typically resulting from short-term disruptions to food intake, illness, or caregiving practices—all of which are commonly exacerbated during and after flooding events.

The binary wasting indicator identifies children who fall below the threshold for acute malnutrition, highlighting those at elevated risk of illness and mortality. Together, these indicators of acute malnutrition capture dimensions of short-term nutritional vulnerability and are well-suited for assessing the immediate impacts of environmental shocks such as floods.

The independent variable of interest for the child-level analyses is flood exposure. Specifically, to assess the short-term impact of flooding on child nutritional outcomes, I constructed a binary indicator of recent flood exposure, defined as exposure to at least one flooding event occurring within the 12 months prior to the DHS interview, including the month of the interview. This measure was developed using spatial and temporal information from the GDIS and EM-DAT datasets. First, I identified whether each child resided in a province where at least one flood event had been recorded during the relevant 12-month window. Second, I used the start and end dates of each flood event, obtained from EM-DAT, to determine whether the child was alive at the time of the flood. A child was coded as exposed (1) if they were alive and lived in a flood-affected region in the 12 months before the DHS interview. Children were coded as not exposed (0) if they did not live in a flood-affected at the time of the DHS data collection or were born after the identified flooding event. The dummy variable approach, which captures whether at least one flood occurred in a child's region within the defined time frame, allows me to avoid double counting a flood that may have occurred over multiple months or recurrent flooding events in the same province. While this measure does not capture variation in flood intensity, this limitation is mitigated by the fact that less than 2% of children in the sample experienced more than one flood in the 12-month period, suggesting that the prevalence of repeated exposure is low and unlikely to bias the findings.

The child-level analyses control for a set of childhood, maternal and household characteristics that may affect the relationship between recent flood exposure and nutritional outcomes.

Childhood controls for my analyses include the child's sex (0 = male, 1 = female), age in months (0-59 continuous), birth order (1-25 continuous), and the number of co-residing children under the age of five (continuous). These variables aim to capture key dimensions of child development, caregiving context, and household demographic composition that may influence both individual vulnerability and intra-household competition for resources and affect children's nutritional status. Maternal-level controls are the mother's age (continuous), educational attainment and employment status. Educational attainment was recoded from four original DHS categories into three analytical groups: (0) no education, (1) primary education, and (2) secondary education or higher. Mother's employment status was coded into three categories: (0) unemployed, (1) employed in the agricultural sector, and (2) employed in the non-agricultural sector. Mother's employment status was created using both the mother's current work status and reported occupation to reflect women's labour force engagement more accurately. Finally, household-level controls include the wealth index, which was collapsed from the original DHS wealth quintiles into three categories (poor, middle, and rich), and a binary measure of urban (0) and rural (1) residence.

To account for unobserved spatial and temporal heterogeneity, I also include province and time controls. For my province control measure, I harmonized provincial administrative units across DHS waves by using the most recent DHS boundaries for each country as the reference framework. Earlier DHS waves were matched to the most recent boundaries using geospatial mapping techniques, whereby cluster-level GPS coordinates from older surveys were overlaid onto the updated DHS regional divisions.[9] This process ensures that regions are consistently defined across

[9] To ensure spatial consistency across survey waves, earlier DHS clusters were matched to the most recent regional boundaries available through the DHS Program's modelled administrative surfaces. These boundaries are based on DHS-modeled surfaces used for survey data collection and are available at https://spatialdata.dhsprogram.com/boundaries. Specifically, Benin 2001 was overlaid and matched to the 2017

time, allowing for more reliable estimation of time-invariant provincial characteristics such as baseline infrastructure, service availability, and historical exposure to environmental shocks. The province control measure captures the provincial characteristics of the 118 provinces across the 12 West African countries. The provinces across the studied West African countries can be broken down as follow: 12 regions in Benin, 13 regions in Burkina Faso, 14 regions in Côte d'Ivoire, eight regions in Gambia, 16 regions in Ghana, eight regions in Guinea, five regions in Liberia, nine regions in Mali,[10] eight regions in Niger, six regions in Nigeria, 14 regions in Senegal, and five regions in Sierra Leone.

Temporal variation is controlled for using a categorical variable grouped into five intervals based on the DHS survey year: 2000–2004, 2005–2009, 2010–2014, 2015–2019, and 2020 onward. These time controls account for trends in nutritional outcomes, national development trajectories, and improvements in health infrastructure that may independently influence child nutrition, irrespective of flood exposure.

Statistical models

To estimate the impact of flood exposure on children's nutritional status, I employ a series of linear and logistic regression models. For the continuous nutritional outcome of weight-for-height z-score, I use OLS regression models. For the binary outcome of wasting, I use logistic regression models. In these specifications, the nutritional status of a child is modelled as a function of exposure to a flooding event in the 12 months prior to the DHS interview while accounting for a

boundaries; Burkina Faso 2003 to 2021; Côte d'Ivoire 2012 to 2021; Ghana 2003, 2008, and 2014 to 2022; Senegal 2005, 2010, 2012, 2014, 2015, 2016, 2018, and 2019 to 2023; and Sierra Leone 2008 and 2013 to 2019.

[10] The 2012 regional sample for Mali consists of six regions rather than nine because the DHS did not sample Tombouctou, Gao, and Kidal.

set of child-, maternal-, and household-level controls. The models also include province-fixed effects to control for time-invariant regional characteristics and time-fixed effects to account for period-specific shocks. This helps reduce bias from unobserved factors that vary across provinces or time.

The child-level regression model takes the following form:

$$\boldsymbol{OLS\ model:}\ \boldsymbol{Y_{ipt} = \beta_0 + \beta_1 F_{ipt} + X_{ipt}\beta + \delta_p + \lambda_t + \epsilon_{ipt}}$$

&

$$\boldsymbol{Logistic\ model: Pr(Y_{ipt}) = \frac{exp(\beta_0 + \beta_1 F_{ipt} + X_{ipt}\beta + \delta_p + \lambda_t)}{1 + exp(\beta_0 + \beta_1 F_{ipt} + X_{ipt}\beta + \delta_p + \lambda_t)}}$$

where $\boldsymbol{Y_{ipt}}$ represents the nutritional outcome of interest (WHZ or wasting) for child i in province $\boldsymbol{p}$ at survey time $\boldsymbol{t}$. The variable $\boldsymbol{F_{ipt}}$ is a binary indicator for flood exposure in the 12 months before the survey interview. The term $\boldsymbol{X_{ipt}\beta}$ is a vector of control variables capturing child, maternal, and household characteristics. The term δ_p denotes a vector of province fixed effects, implemented as a set of province dummies for each of the 118 unique provinces in the sample. The term $\boldsymbol{\lambda_t}$, represents a vector of time-fixed effects that include a set of survey-year dummies grouped into five intervals (2000–2004, 2005–2009, 2010–2014, 2015–2019, 2020 onward). Finally, $\boldsymbol{\epsilon_{ipt}}$ represents the regression error term for the OLS model.

Table 1 presents weighted descriptive statistics for the child-level analyses. Approximately 11% of children in the analytical sample were wasted. The average weight-for-height-z-score in the sample was -0.41. Within this sample, one-third (33%) of children resided in areas that experienced a flooding event in the 12 months to the DHS interview.

Table 1: Child-level Variables

Variables	Mean	SD	Min	Max
Outcomes				
Wasted (WHZ <-2)	0.11	0.31	0.00	1.00
Weight for height z-score	-0.41	1.39	-5.00	5.00
Childhood Flood Exposure				
Flood Exposure in the last 12 months	0.33	0.47	0.00	1.00
Control Variables				
Childhood Characteristics				
Age (0-59 months)	28.13	17.21	0.00	59.00
Sex = Female	0.49	0.50	0.00	1.00
Child's birth order	3.75	2.43	1.00	18.00
Coresident with under five children	2.55	1.64	0.00	27.00
Maternal Characteristics				
Mother's age (years)	29.45	6.92	15.00	49.00
Mother's education				
No education	0.63	-	-	-
Primary	0.18	-	-	-
Secondary +	0.19	-	-	-
Mother's employment				
Unemployed	0.35	-	-	-
Non-Agriculture Sector	0.42	-	-	-
Agriculture Sector	0.23	-	-	-
Household Characteristics				
Household wealth				
Low	0.43	-	-	-
Middle	0.20	-	-	-
High	0.36	-	-	-
Place of residence				
Rural	0.67	0.47	0.00	1.00
Sample size:	270,850			

Note: Weighted descriptive statistics.

Results:

Overall estimates for child analyses

I begin my analysis by examining the association between recent flood exposure and children's weight-for-height. Table 3, Model 1 presents the estimates from my OLS regression, which reveals a negative and statistically significant association between flood exposure and weight-for-height (WHZ). Specifically, I find that children exposed to a flooding event within the 12 months preceding the DHS interview had WHZ scores that were 0.11 standard deviations lower than those of children who had not experienced a recent flooding event. This suggests that flood exposure contributes to acute nutritional stress.

I next estimated a logistic regression model that assessed whether flood exposure is associated with an increased likelihood of wasting. The estimates of this analysis are presented in Table 3, Model 2. As shown in Table 3, Model 2, the results indicate a statistically significant increase in the likelihood of wasting among children exposed to floods. Specifically, children exposed to flooding were 20% more likely to be wasted compared to their non-exposed counterparts. This finding highlights the short-term nutritional consequences of environmental shocks.

Overall, the estimates presented in Table 3 provide evidence that flood exposure has adverse effects on children's nutrition, particularly on acute malnutrition. The declines in WHZ and increases in wasting highlight the heightened vulnerability of young children to environmental shocks. Moreover, these findings suggest that recent floods may play an important role in shaping children's nutritional vulnerability by increasing the odds of wasting by 20%. This highlights how floods may cause heightened risks of illness, developmental delays, and mortality in affected populations.

Table 3: Impact of recent flood exposure on child nutritional growth

Variables	Model 1 Coef WHZ		Model 2 OR Wasting	
Recent flood exposure	-0.11	***	1.20	***
	(0.01)		(0.03)	
Age in months	0.00	***	0.98	***
	(0.00)		(0.00)	
Childhood controls	Yes		Yes	
Maternal Controls	Yes		Yes	
Household Controls	Yes		Yes	
Year fixed effects	Yes		Yes	
Provincial fixed effects	Yes		Yes	
Joint test, recent flood exposure	***		***	
Observations	270,834		270,834	

Robust standard errors are in parentheses. Weighted analyses.
*** $p<0.001$, ** $p<0.01$, * $p<0.05$, † $p<0.1$

Variation in the individual effects of recent floods

To examine whether the impact of recent flood exposure varies across sociodemographic groups with differing levels of vulnerability, I estimate a series of interaction models. Results from these analyses are presented in Table 5 for weight-for-height and in Table 6 for wasting.

Models 1 and 2 in both Table 5, for weight-for-height, and Table 6, for wasting, explore whether the effects of flood exposure differ by child children and age. Unsurprisingly, I find no evidence of gendered differences in nutritional vulnerability: the interaction between flood exposure and female sex is small and statistically insignificant for both WHZ and wasting. While no gendered differences were found, child age emerged as a significant moderator in the interaction between child age and flood exposure, which suggests age-related differences in vulnerability. In the WHZ model (Table 5, Model 2), the positive coefficient on the interaction term ($\beta = 0.009$, *p*

< 0.001) indicates that the negative effect of flooding on weight-for-height becomes progressively smaller as children age. Similarly, in the wasting model (Table 6, Model 2), the interaction term (OR = 0.991, $p < 0.001$) suggests that the probability of wasting decreases slightly with each additional month of age. These findings imply that older children are somewhat more resilient to the immediate nutritional impacts of flooding, possibly due to greater dietary independence, stronger immune function, or reduced reliance on caregivers during disruptions.

Model 3 assesses whether maternal education buffers the adverse effects of flooding. Specifically, in this model, I test for differences in the relationship between recent flood exposure based on whether children's mothers had primary education or secondary and above education. Compared to children of mothers with no formal education, those whose mothers have attained primary education experience significantly smaller declines in WHZ (β = 0.103, $p < 0.001$) and were also less likely to be wasted (OR = 0.859, $p < 0.001$). The protective effect observed in mothers with primary education is shown to extend to those with secondary or higher education, where modest improvements in WHZ (β = 0.027, $p < 0.1$) and reduced odds of wasting (OR = 0.869, $p < 0.001$) were observed. However, the effects of secondary education are also shown to be smaller than those of primary education. Overall, these findings suggest that maternal education acts as a protective factor for children's nutritional health, potentially enabling households to better safeguard child nutrition in the face of environmental shocks.

In Model 4, I investigate whether maternal employment moderates the flood-related impacts on children's nutrition. The results show a modest protective effect for children of unemployed motherscocmpared to employed mothers in the non-agricultural sector, suggesting possible compensatory caregiving behaviours when mothers are home. Specifically, children of unemployed mothers exhibit a slightly less negative WHZ trajectory following flooding (β = 0.040,

$p < 0.01$). However, I find no evidence of a significant association between recent flood exposure and mothers employed in the agricultural sector, suggesting that despite direct vulnerability to crop loss or income disruption, this group may not experience additional disadvantage in children's short-term nutrition.

Model 5 examines whether wealth moderates the effects of flood exposure by comparing children from middle- and high-wealth households to those from the poorest category. While wealthier households are often assumed to have a greater capacity to absorb shocks, I find no statistically significant differences in the effect of recent flood exposure on WHZ and wasting across these wealth categories, indicating that household economic standing alone may not mitigate flood-related nutritional vulnerabilities.

Finally, in Tables 5 and 6, Model 6 examines the moderating effect of rural residence. The interaction between flood exposure and rural location is negative and statistically significant for WHZ ($\beta = -0.025$, $p < 0.05$), but no significant association is observed in the wasting model. This suggests that children in rural areas may suffer more weight loss following flooding events. The findings highlights the persistent structural vulnerabilities of rural households.

Table 5. Interaction Effects of Recent Flood Exposure on Child Weight-for-height Z-Scores (WHZ)

Variables	Model (1)		Model (2)		Model (3)		Model (4)		Model (5)		Model (6)	
Recent flood exposure	-0.119	***	-0.388	***	-0.142	***	-0.136	***	-0.123	***	-0.102	***
	(0.01)		(0.02)		(0.01)		(0.01)		(0.01)		(0.01)	
Interaction Terms												
Female x Recent flood exposure	0.0003											
	(0.01)											
Age in months x Recent flood exposure			0.009	***								
			(0.00)									
Primary x Recent flood exposure					0.103	***						
					(0.016)							
Secondary+ x Recent flood exposure					0.027	*						
					(0.02)							
Unemployed x Recent flood exposure							0.040	**				
							(0.014)					
Agricultural sector x Recent flood exposure							0.008					
							(0.02)					
Middle wealth x Recent flood exposure									0.002			
									(0.016)			
High wealth x Recent flood exposure									0.009			
									(0.01)			
Rural x Recent flood exposure											-0.025	*
											(0.01)	
Childhood controls	Yes		Yes		Yes		Yes		Yes		Yes	
Maternal Controls	Yes		Yes		Yes		Yes		Yes		Yes	
Household Controls	Yes		Yes		Yes		Yes		Yes		Yes	
Year Fixed effects	Yes		Yes		Yes		Yes		Yes		Yes	
Province-Level Fixed effects	Yes		Yes		Yes		Yes		Yes		Yes	
R-Squared	0.0354		0.0377		0.0355		0.0354		0.0354		0.0354	
Observations	270,834		270,834		270,834		270,834		270,834		270,834	

Robust standard errors are in parentheses. Weighted analyses.
*** p<0.001, ** p<0.01, * p<0.05, t p<0.1

Table 6. Interaction Effects of Recent Flood Exposure on Childhood Wasting

Variables	Model (1)		Model (2)		Model (3)		Model (4)		Model (5)		Model (6)	
Recent flood exposure	1.206	***	1.492	***	1.261	***	1.213	***	1.227	***	1.179	***
	(0.03)		(0.04)		(0.03)		(0.03)		(0.03)		(0.04)	
Interaction Terms												
Female x Recent flood exposure	1.001											
	(0.03)											
Age in months x Recent flood exposure			0.991	***								
			(0.00)									
Primary x Recent flood exposure					0.859	***						
					(0.033)							
Secondary+ x Recent flood exposure					0.869	***						
					(0.04)							
Unemployed x Recent flood exposure							0.949					
							0.030					
Agricultural sector x Recent flood exposure							1.059					
							(0.04)					
Middle wealth x Recent flood exposure									0.981			
									(0.035)			
High wealth x Recent flood exposure									0.957			
									(0.03)			
Rural x Recent flood exposure											1.031	
											(0.03)	
Childhood Controls	Yes		Yes		Yes		Yes		Yes		Yes	
Maternal Controls	Yes		Yes		Yes		Yes		Yes		Yes	
Household Controls	Yes		Yes		Yes		Yes		Yes		Yes	
Year Fixed effects	Yes		Yes		Yes		Yes		Yes		Yes	
Provincial Fixed effects	Yes		Yes		Yes		Yes		Yes		Yes	
R-Squared												
Observations	270,834		270,834		270,834		270,834		270,834		270,834	

Robust standard errors are in parentheses. Weighted analyses.
*** p<0.001, ** p<0.01, * p<0.05, t p<0.1

Sensitivity Analyses:

To assess whether the main findings are robust to alternative modelling choices, I conduct a series of sensitivity analyses. These tests examine whether the relationship between flood exposure and child nutritional outcomes holds across different model specifications. I summarize the results of these sensitivity analyses here and include the full results in the Supplemental information.

First, to explore whether the timing of flood exposure affects child nutritional outcomes, I constructed a categorical variable disaggregating flood exposure into five intervals: (0) no exposure, (1) exposure within 1 month, (2) exposure within 2–3 months, (3) exposure within 4–6 months, (4) exposure within 7–9 months, and (5) exposure 10+ months before the DHS interview.[11] These thresholds allow for a finer-grained inspection of the immediate and delayed effects between flooding on children's nutritional growth.[12] The results of this threshold analysis (Table S1) are mainly consistent with the primary binary analysis of flood exposure, where flood exposure was significantly associated with both declines in WHZ (Model S1) and increased risk of wasting (Model S2). However, this disaggregated specification revealed both immediate and delayed effects. Specifically, children exposed to floods 1 month before the DHS data collection show significantly elevated odds of wasting and a decline in WHZ, indicating that the nutritional

[11] To construct the categorical threshold variable for flood exposure, several alternative groupings were tested to ensure that the selected categories captured substantively distinct exposure periods. A series of post-estimation tests confirmed that most thresholds were statistically different from one another. Overall, the results support the use of five mutually exclusive exposure periods: 1 month, 2–3 months, 4–6 months, 7–9 months, and 10 months or more before the DHS interviews.

impacts of flooding can emerge quickly. Similar decreases in WHZ and increases in the likelihood of wasting were also observed for children exposed 2 to 3 months before the DHS data collection. The results of this analysis also showed that children exposed 7–9 months earlier also experienced a significant rise in wasting and one of the largest declines in WHZ, suggesting that some consequences may be delayed and intensify over time, possibly due to cumulative resource depletion, prolonged food insecurity, or persistent disease exposure following the flood. An interesting pattern also emerged in the wasting threshold analysis for the 4–6 month exposure window. The threshold analysis reveals that for the 4-6 month exposure window, the odds of wasting are significantly lower. This divergence may reflect short-term coping strategies or targeted relief interventions, such as food distribution, mobile health units, or humanitarian aid, that are often mobilized a few months after a major disaster. Alternatively, this pattern may be associated with seasonal variation in households' food availability or individual household resilience, where the flood aligns with a harvest or income cycle that temporarily buffers nutritional stress.

I then investigated whether the findings were sensitive to how the exposure window in the primary analysis was defined. Specifically, to examine whether the relationship between flood exposure and child nutritional outcomes is sensitive to the specific definition of the exposure window utilized in the primary analyses, I re-estimate my models using shorter exposure windows of 8 and 10 months rather than the 12-month window. While a 12-month exposure window is commonly used in studies of environmental shocks and disasters, alternative specifications of 8 and 10 months are considered to account for the possibility that more recent exposure to flooding events may have a greater impact on children's nutritional development, particularly since WHZ and wasting capture acute and short-term deprivation. In each specification, children were coded as exposed if they lived in a flood-affected province during the defined 8- or 10-month period before the DHS interviews. Children who had no flood exposure within that window were coded as unexposed. To avoid exposure misclassification, children who experienced a flood outside the defined time window (e.g., 11–12 months before the survey in the 10-month model) were excluded from the analysis. This ensured that only children whose flood exposure timing fell within the defined risk window were included. The results of these analyses are presented in Table S2. While the point estimates slightly varied with changes in the exposure window, the substantive findings of the primary analyses remained largely unchanged, although slightly stronger. Flood exposure continued to be significantly associated with decreased WHZ (Model S3) and increased levels of wasting (Model S4). Estimates for provincial analysis were also consistent with the original results.

To account for potential bias arising from household mobility, I conduct an additional robustness check, excluding all households that reported residing in their current location for less than one year, which aligns with the length of the studied exposure window. This exclusion criteria for households was chosen to match the 12-month exposure window used in the primary analysis, ensuring that children classified as exposed (or unexposed) to flooding had lived in a specific area during the entire period when flood exposure was assessed. Without this restriction, recent in-migration or out-migration could result in the misclassification of childhood exposure. This restriction was applied using information on the length of time a household has lived in its current place of residence from the DHS survey. While existing research suggests that migration in response to environmental shocks is relatively uncommon (Bohra-Mishra et al., 2014), this test aimed to ensure that recent migrating households were not disproportionately influencing the results. The results of this analysis (Table S3), excluding recent migrant households, do not substantively change the main findings of the primary analysis. Flood exposure remained significantly and negatively associated with WHZ (Model S7) and positively associated with wasting (Model S8). The findings thereby reinforced the robustness of the primary analyses.

Finally, to investigate whether the functional form of child age influences the estimated relationship between flood exposure and nutritional outcomes, I re-estimate the primary models by including a quadratic term for child age. This specification accounts for potential nonlinearity in the relationship between age and nutritional status, which may be particularly relevant during early childhood due to the rapid developmental changes that occur during this period. As shown in Table S4, the squared age term is not statistically significant in the WHZ model (Model S9), which suggest that the linear specification in the primary analyses is sufficient. In this model, I also find that adding the squared age term does not alter the estimated association between flood exposure and WHZ. The estimated effect remains a 0.11 standard deviation decline in WHZ for flood-exposed children, identical to the baseline model. These results suggest that for the WHZ model, the linear specification of child age sufficiently captures its relationship with WHZ. For wasting (Model S10), the age-squared term is statistically significant but substantively negligible. The estimated odds ratio for the quadratic age term is 1.00. However, the inclusion of the quadratic term yields a slightly stronger estimated association between flood exposure and child wasting, where flood exposure increases from 1.20 to 1.22 in the nonlinear specification. Although the inclusion of the quadratic does yield a modest change in the magnitude of the coefficient for flood exposure, the overall results from this sensitivity analysis align with the main findings of the primary analysis. That is, recent flood exposure is associated with poorer child nutritional outcomes.

References:

AFD. (2023, June 14). *Lutte contre l'insécurité alimentaire en Afrique de l'Ouest : l'action du groupe AFD en 5 projets | AFD - Agence Française de Développement*. https://www.afd.fr/fr/actualites/insecurite-alimentaire-afrique-ouest-action-groupe-afd-5-projets

Alderman, K., Turner, L. R., & Tong, S. (2012). Floods and human health: A systematic review. *Environment International*, *47*, 37–47. https://doi.org/https://doi.org/10.1016/j.envint.2012.06.003

Amankwaa, E. F., & Gough, K. V. (2023). 'We are at the mercy of the floods!' : Extreme weather events, disrupted mobilities, and everyday navigation in urban Ghana. *Singapore Journal of Tropical Geography*, *44*(2), 235–254. https://doi.org/10.1111/SJTG.12482

Arndt, C., Farmer, W., Strzepek, K., & Thurlow, J. (2012). *Climate Change, Agriculture and Food Security in Tanzania* (Policy Research Working Papers). World Bank, Washington, DC. https://doi.org/10.1596/1813-9450-6188

Atanga, R. A., & Tankpa, V. (2021). Climate Change, Flood Disaster Risk and Food Security Nexus in Northern Ghana. In *Frontiers in Sustainable Food Systems* (Vol. 5). Frontiers Media S.A. https://doi.org/10.3389/fsufs.2021.706721

Barry, A. A., Caesar, J., Klein Tank, A. M. G., Aguilar, E., McSweeney, C., Cyrille, A. M., Nikiema, M. P., Narcisse, K. B., Sima, F., Stafford, G., Touray, L. M., Ayilari-Naa, J. A., Mendes, C. L., Tounkara, M., Gar-Glahn, E. V. S., Coulibaly, M. S., Dieh, M. F., Mouhaimouni, M., Oyegade, J. A., … Laogbessi, E. T. (2018). West Africa climate extremes and climate change indices. *International Journal of Climatology*, *38*, e921–e938. https://doi.org/10.1002/joc.5420

Baten, A., Wallemacq, P., van Loenhout, J. A. F., & Guha-Sapir, D. (2020a). Impact of Recurrent Floods on the Utilization of Maternal and Newborn Healthcare in Bangladesh. *Maternal and Child Health Journal*, *24*(6), 748–758. https://doi.org/https://doi.org/10.1007/s10995-020-02917-3

Baten, A., Wallemacq, P., van Loenhout, J. A. F., & Guha-Sapir, D. (2020b). Impact of Recurrent Floods on the Utilization of Maternal and Newborn Healthcare in Bangladesh. *Maternal and Child Health Journal*, *24*(6), 748–758. https://doi.org/10.1007/S10995-020-02917-3/TABLES/5

Block, S. A., Kiess, L., Webb, P., Kosen, S., Moench-Pfanner, R., Bloem, M. W., & Timmer, C. P. (2004). Macro shocks and micro outcomes: child nutrition during Indonesia's crisis. *Economics & Human Biology*, *2*(1), 21–44. https://doi.org/10.1016/J.EHB.2003.12.007

Bohra-Mishra, P., Oppenheimer, M., & Hsiang, S. M. (2014). Nonlinear permanent migration response to climatic variations but minimal response to disasters. *Proceedings of the National Academy of Sciences of the United States of America*, *111*(27), 9780–9785. https://doi.org/10.1073/PNAS.1317166111/-/DCSUPPLEMENTAL

Boutin, G., Escudero, P., Ganesh, V., Hereward, M., Ann Naylor, K., Otmacic, V., Wijesekera, S., Bernd, L., Mi Choi, S., Da Silva, J., Engilbertsdottir, S., Grandjean, A., Hassan, T., Healy, L., Krishnamurthy, K., Girma Mamo, B., Raquel Narvaez, D., Russell, K., Solomon, A., … Zuehlke, E. (2021). *Overall Leadership and Guidance: Gautam Narasimhan (Climate,* *Energy, Environment & Disaster Risk Reduction) and Toby Wicks (Data Use) Special thanks to*.

Brown, Oli., & Crawford, Alec. (2008). *Assessing the security implications of climate change for West Africa : country case studies of Ghana and Burkina Faso*. International Institute for Sustainable Development.

Carpena, F. (2019). How do droughts impact household food consumption and nutritional intake? A study of rural India. *World Development*, *122*, 349–369. https://doi.org/10.1016/J.WORLDDEV.2019.06.005

Cervigni, R., Liden, R., Neumann, J. E., & Strzepek, K. M. (2015). *Enhancing the Climate Resilience of Africa's Infrastructure The Power and Water Sectors*.

Cervigni, R., Losos, A., Chinowsky, P., & Neumann, J. E. (2017). *Enhancing the Climate Resilience of Africa's Infrastructure Enhancing the Climate Resilience of Africa's Infrastructure : The Roads and Bridges Sector*. https://doi.org/10.1596/978-1-4648-0466-3

Chalasani, S., & Rutstein, S. (2014). Household wealth and child health in India. *Population Studies*, *68*(1), 15–41. https://doi.org/10.1080/00324728.2013.795601

Cooper, M. W., Brown, M. E., Hochrainer-Stigler, S., Pflug, G., McCallum, I., Fritz, S., Silva, J., & Zvoleff, A. (2019). Mapping the effects of drought on child stunting. *Proceedings of the National Academy of Sciences of the United States of America*, *116*(35), 17219–17224. https://doi.org/10.1073/PNAS.1905228116/SUPPL_FILE/PNAS.1905228116.SAPP.PDF

CRED. (2025). *EM-DAT: The international disaster database – Floods in West Africa (2000–2024)*. Université catholique de Louvain. https://www.emdat.be

Datar, A., Liu, J., Linnemayr, S., & Stecher, C. (2013). The impact of natural disasters on child health and investments in rural India. *Social Science & Medicine*, *76*(1), 83–91. https://doi.org/https://doi.org/10.1016/j.socscimed.2012.10.008

Davenport, F., Grace, K., Funk, C., & Shukla, S. (2017). Child health outcomes in sub-Saharan Africa: A comparison of changes in climate and socio-economic factors. *Global Environmental Change*, *46*, 72–87. https://doi.org/10.1016/J.GLOENVCHA.2017.04.009

Davis, J. R., Wilson, S., Brock-Martin, A., Glover, S., Svendsen, E. R., & Davis, J. (2010). *The Impact of Disasters on Populations With Health and Health Care Disparities*. *4*(1), 30–38.

DHS. (2025). *The DHS Program - Quality information to plan, monitor and improve population, health, and nutrition programs*. DHS. https://dhsprogram.com/

Dimitrova, A., & Muttarak, R. (2020). After the floods: Differential impacts of rainfall anomalies on child stunting in India. *Global Environmental Change*, *64*. https://doi.org/10.1016/j.gloenvcha.2020.102130

Ekolu, J., Dieppois, B., Sidibe, M., Eden, J. M., Tramblay, Y., Villarini, G., Peña-Angulo, D., Mahé, G., Paturel, J. E., Onyutha, C., & van de Wiel, M. (2022). Long-term variability in hydrological droughts and floods in sub-Saharan Africa: New perspectives from a 65-year daily streamflow dataset. *Journal of Hydrology*, *613*, 128359. https://doi.org/10.1016/J.JHYDROL.2022.128359

Focus Economics. (2024, November 6). *Top 20 Poorest Countries in the World 2025*. https://www.focus-economics.com/blog/the-poorest-countries-in-the-world/

Gaire, S., Delbiso, T. D., Pandey, S., & Guha-Sapir, D. (2016). Impact of disasters on child stunting in Nepal. *Risk Management and Healthcare Policy*, *9*, 113–127. https://doi.org/10.2147/RMHP.S101124

Gbratto-Dobe, S. A. W., & Segnon, H. B. (2025). Is mother's education essential to improving the nutritional status of children under five in Côte d'Ivoire? *SSM - Health Systems*, *4*, 100056. https://doi.org/10.1016/J.SSMHS.2025.100056

Goudet, S. M., Griffiths, P. L., Bogin, B. A., & Selim, N. (2011). Impact of flooding on feeding practices of infants and young children in Dhaka, Bangladesh Slums: What are the coping strategies? *Maternal and Child Nutrition*, *7*(2), 198–214. https://doi.org/10.1111/j.1740-8709.2010.00250.x

Greenaway, E. S., Leon, J., & Baker, D. P. (2012). Understanding the association between maternal education and use of health services in Ghana: exploring the role of health knowledge. *Journal of Biosocial Science*, *44*(6), 733–747. https://doi.org/10.1017/S0021932012000041

Helldén, D., Andersson, C., Nilsson, M., Ebi, K. L., Friberg, P., & Alfvén, T. (2021). Climate change and child health: a scoping review and an expanded conceptual framework. *The Lancet Planetary Health*, *5*(3), e164–e175. https://doi.org/10.1016/S2542-5196(20)30274-6/ATTACHMENT/B98ABF91-EEA8-4815-BBAF-47A79BB1E685/MMC1.PDF

Hoddinott, J., & Kinsey, B. (2001). Child growth in the time of drought. *Oxford Bulletin of Economics and Statistics*, *63*(4), 409–436. https://doi.org/10.1111/1468-0084.T01-1-00227;WGROUP:STRING:PUBLICATION

Hossain, S. M. M., Talat, M., Boyd, E., Chowdhury, S. R., Soofi, S. B., Hussain, I., Ahmed, I., Salam, R. A., & Bhutta, Z. A. (2013). Evaluation of Nutrition Surveys in Flood-affected Areas of Pakistan: Seeing the Unseen! *IDS Bulletin*, *44*(3), 10–20. https://doi.org/10.1111/1759-5436.12026

Iftikhar, A., Bari, A., Bano, I., & Masood, Q. (2017). Impact of maternal education, employment and family size on nutritional status of children. *Pak J Med Sci* , *33*(6). https://doi.org/10.12669/pjms.336.13689

Kemajou Njatang, D., Bouba Djourdebbé, F., & Adda Wadou, N. D. (2023). Climate variability, armed conflicts and child malnutrition in sub-Saharan Africa: A spatial analysis in Ethiopia, Kenya and Nigeria. *Heliyon*, *9*(11). https://doi.org/10.1016/j.heliyon.2023.e21672

Kennedy, J., Dunn, R., McCarthy, M., Titchner, H., & Morice, C. (2017). Global and regional climate in 2016. *Weather*, *72*(8), 219–225. https://doi.org/10.1002/WEA.3042

Lartey, S. T., Khanam, R., & Takahashi, S. (2016). The impact of household wealth on child survival in Ghana. *Journal of Health, Population, and Nutrition*, *35*(1), 38. https://doi.org/10.1186/S41043-016-0074-9/TABLES/6

Lee, R., White, C. J., Adnan, M. S. G., Douglas, J., Mahecha, M. D., O'Loughlin, F. E., Patelli, E., Ramos, A. M., Roberts, M. J., Martius, O., Tubaldi, E., van den Hurk, B., Ward, P. J., & Zscheischler, J. (2024). Reclassifying historical disasters: From single to multi-hazards. *Science of the Total Environment*, *912*. https://doi.org/10.1016/j.scitotenv.2023.169120

Mallett, L. H., & Etzel, R. A. (2018). Flooding: what is the impact on pregnancy and child health? *Disasters*, *42*(3), 432–458. https://doi.org/10.1111/disa.12256

Masbi, M., Tavakoli, N., & Dowlati, M. (2024). Challenges of providing of special care services in hospitals during emergencies and disasters: a scoping review. *BMC Emergency Medicine*, *24*(1), 1–16. https://doi.org/10.1186/S12873-024-01160-1/TABLES/2

Mason, J. B., Chotard, S., Bailes, A., Mebrahtu, S., & Hailey, P. (2011). Impact of drought and HIV on child nutrition in Eastern and Southern Africa. *Food and Nutrition Bulletin*, *32*(3 SUPPL.). https://doi.org/10.1177/15648265100313S301;JOURNAL:JOURNAL:FNBA

Müller, C., Ouédraogo, W. A., Schwarz, M., Barteit, S., & Sauerborn, R. (2023). The effects of climate change-induced flooding on harvest failure in Burkina Faso: case study. *Frontiers in Public Health*, *11*. https://doi.org/10.3389/fpubh.2023.1166913

Naing, C., Reid, S. A., Aye, S. N., Htet, N. H., & Ambu, S. (2019). Risk factors for human leptospirosis following flooding: A meta-analysis of observational studies. *PLoS ONE*, *14*(5). https://doi.org/10.1371/journal.pone.0217643

Nankinga, O., Kwagala, B., & Walakira, E. J. (2019). Maternal employment and child nutritional status in Uganda. *PLOS ONE*, *14*(12), e0226720. https://doi.org/10.1371/JOURNAL.PONE.0226720

Nicholson, S. E., Funk, C., & Fink, A. H. (2018). Rainfall over the African continent from the 19th through the 21st century. *Global and Planetary Change*, *165*, 114–127. https://doi.org/10.1016/J.GLOPLACHA.2017.12.014

Nka, B. N., Oudin, L., Karambiri, H., Paturel, J. E., & Ribstein, P. (2015). Trends in floods in West Africa: Analysis based on 11 catchments in the region. *Hydrology and Earth System Sciences*, *19*(11), 4707–4719. https://doi.org/10.5194/HESS-19-4707-2015, Ohonba, A., Ngepah, N., & Simo-Kengne, B. (2019). Maternal education and child health outcomes in South Africa: A panel data analysis. *Development Southern Africa*, *36*(1), 33–49. https://doi.org/10.1080/0376835X.2018.1456908;PAGE:STRING:ARTICLE/CHAPTER

Pelser, A. J., Chimukuche, R. S., Pelser, A. J., & Chimukuche, R. S. (2022). *Climate Change, Rural Livelihoods, and Human Well-Being: Experiences from Kenya*. https://doi.org/10.5772/INTECHOPEN.104965

Rahman, M., Sarkar, P., Islam, M. J., Adam, I. F., Duc, N. H. C., & Al-Sobaihi, S. (2024). Factors mediating the association between recurring floods and child chronic undernutrition in northern Bangladesh. *Nutrition*, *119*. https://doi.org/10.1016/j.nut.2023.112300

Rodriguez-Llanes, J. M., Ranjan-Dash, S., Degomme, O., Mukhopadhyay, A., & Guha-Sapir, D. (2011). Child malnutrition and recurrent flooding in rural eastern India: A community-based survey. *BMJ Open*, *1*(2). https://doi.org/10.1136/bmjopen-2011-000109

Rodriguez-Llanes, J. M., Ranjan-Dash, S., Mukhopadhyay, A., & Guha-Sapir, D. (2016). Flood-exposure is associated with higher prevalence of child Undernutrition in rural Eastern India. *International Journal of Environmental Research and Public Health*, *13*(2). https://doi.org/10.3390/ijerph13020210

Salam, A., Wireko, A. A., Jiffry, R., Ng, J. C., Patel, H., Zahid, M. J., Mehta, A., Huang, H., Abdul-Rahman, T., & Isik, A. (2023). The impact of natural disasters on healthcare and surgical services in low- and middle-income countries. *Annals of Medicine and Surgery*, *85*(8), 3774. https://doi.org/10.1097/MS9.0000000000001041

Sawadogo, W., Neya, T., Semde, I., Korahiré, J. A., Combasséré, A., Traoré, D. E., Ouedraogo, P., Diasso, U. J., Abiodun, B. J., Bliefernicht, J., & Kunstmann, H. (2024). Potential impacts of climate change on the sudan-sahel region in West Africa – Insights from Burkina Faso. *Environmental Challenges*, *15*. https://doi.org/10.1016/j.envc.2024.100860

Sur, D., Dutta, P., Nair, G. B., & Bhattacharya, S. K. (2000). Severe cholera outbreak following floods in a northern district of West Bengal. *Indian Journal of Medical Research*, *112*(NOV), 178–182.

Sylla, M. B., Nikiema, P. M., Gibba, P., Kebe, I., & Klutse, N. A. B. (2016). Climate change over West Africa: Recent trends and future projections. In *Adaptation to Climate Change and Variability in Rural West Africa* (pp. 25–40). Springer International Publishing. https://doi.org/10.1007/978-3-319-31499-0_3

Thiede, B. C., & Strube, J. (2020). Climate variability and child nutrition: Findings from sub-Saharan Africa. *Global Environmental Change*, *65*. https://doi.org/10.1016/j.gloenvcha.2020.102192

Thomas, N., & Nigam, S. (2018). Twentieth-Century Climate Change over Africa: Seasonal Hydroclimate Trends and Sahara Desert Expansion. *Journal of Climate*, *31*(9), 3349–3370. https://doi.org/10.1175/JCLI-D-17-0187.1

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. https://doi.org/10.2307/26545240

Ukwuani, F. A., & Suchindran, C. M. (2003). Implications of women's work for child nutritional status in sub-Saharan Africa: a case study of Nigeria. *Social Science & Medicine*, *56*(10), 2109–2121. https://doi.org/10.1016/S0277-9536(02)00205-8

UN, ECOWAS, & WFP. (2021). *Monitoring report on the impacts of COVID-19 in West Africa*. https://hdl.handle.net/10855/47581

UNICEF. (2024). *West and Central African Region - Flooding situation overview*. https://www.unicef.org/media/165346/file/UNICEF%20West%20and%20Central%20Africa%20Region%20(Flooding%20situation%20overview)%20-%201%20Nov%202024.pdf.pdf

United Nations. (2025, May 30). *World Population Prospects*. https://population.un.org/wpp/

USAID. (2018). *Climate Risk Profile: West Africa*. https://www.climatelinks.org/resources/climate-risk-profile-west-africa

Wang, P., Asare, E. O., Pitzer, V. E., Dubrow, R., & Chen, K. (2023). Floods and Diarrhea Risk in Young Children in Low- and Middle-Income Countries. *JAMA Pediatrics*, *177*(11), 1206–1214. https://doi.org/10.1001/jamapediatrics.2023.3964

Supplemental information

Table S1: Coefficient estimates from linear regression models predicting weight-for-height (Model S1) and wasting (Model S2) by month threshold since flood exposure

Variables	S1 WHZ		S2 Wasting	
1 month since exposure	-0.16	***	1.36	***
	(0.02)		(0.06)	
2 to 3 months since exposure	-0.08	***	1.10	*
	(0.02)		(0.05)	
4 to 6 months since exposure	-0.03		0.87	**
	(0.02)		(0.03)	
7 to 9 months since exposure	-0.22	***	1.34	***
	(0.02)		(0.04)	
10+ months since exposure	-0.05	**	1.19	***
	(0.02)		(0.04)	
Childhood Controls	Yes		Yes	
Maternal Controls	Yes		Yes	
Household Controls	Yes		Yes	
Year Fixed Effects	Yes		Yes	
Provincial Fixed Effects	Yes		Yes	
Observations	270,834		270,834	

Robust standard errors in parentheses. Weighted analyses.
*** p<0.001, ** p<0.01, * p<0.05, † p<0.1

Table S2: Coefficient estimates from linear regression models predicting weight-for-height (Models S5 and S7) and wasting (Models S6 and S8), using alternative flood exposure windows (8 and 10 months)

Variables	S5 WHZ		S6 Wasting		S7 WHZ		S8 Wasting	
Flood exposure, 8 months before the survey	-0.13	***	1.21	***				
	(0.01)		(0.03)					
Flood exposure, 10 months before the survey					-0.12	***	1.20	***
					(0.01)		(0.03)	
Childhood Controls	Yes		Yes		Yes		Yes	
Maternal Controls	Yes		Yes		Yes		Yes	
Household Controls	Yes		Yes		Yes		Yes	
Year Fixed Effects	Yes		Yes		Yes		Yes	
Provincial Fixed Effects	Yes		Yes		Yes		Yes	
Observations	250,865		250,865		260,456		260,456	

Robust standard errors are in parentheses. Weighted Results
*** p<0.001, ** p<0.01, * p<0.05, † p<0.1

Table S3: Coefficient estimates from linear regression models predicting weight-for-height (Model S13) and wasting (Model S14), restricted to non-migrant households

Variables	S13 WHZ		S14 Wasting	
Flood exposure	-0.14	***	1.32	***
	(0.02)		(0.04)	
Childhood Controls	Yes		Yes	
Maternal Controls	Yes		Yes	
Household Controls	Yes		Yes	
Year Fixed Effects	Yes		Yes	
Provincial Fixed Effects	Yes		Yes	
Observations	148,548		148,548	

Robust standard errors are in parentheses. Weighted Results
*** p<0.001, ** p<0.01, * p<0.05, † p<0.1

Table S4: Coefficient estimates from nonlinear regression models predicting weight-for-height (Model S18) and wasting (Model S19), including quadratic specification for child age

Variables	S18 WHZ		S19 Wasting	
Flood exposure	-0.11	***	1.22	***
	(0.01)		(0.03)	
Age in months	0.00	***	0.97	***
	(0.00)		(0.00)	
Age in months squared	0.00		1.00	***
	(0.00)		(0.00)	
Childhood Controls	Yes		Yes	
Maternal Controls	Yes		Yes	
Household Controls	Yes		Yes	
Year Fixed Effects	Yes		Yes	
Provincial Fixed Effects	Yes		Yes	
Observations	270,834		270,834	

Robust standard errors are in parentheses. Weighted Results
*** p<0.001, ** p<0.01, * p<0.05, † p<0.1