

FINAL REPORT

Project: How can we produce a time series of country level childhood wasting estimates, accounting for seasonality: exploring the impact of survey timing?

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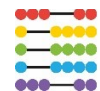
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Executive Summary

Undernutrition in children is assessed from measurements of growth, primarily weight and height. Wasting, or low weight for height, is characterised by a loss or deficit of soft tissue, particularly body fat and skeletal muscle. In 2022 wasting was estimated to affect 45 million (6.8%) children under 5 years of age and 13% of under-five child deaths are attributed to wasting each year. The Joint Malnutrition Estimation group (JME) hold a large amount of data on child wasting. However, the timing of surveys is not focused on capturing the main issues surrounding child nutrition; rather and quite understandably, it is focused on minimising the costs of surveys. This results in inconsistent survey periods and the timing of the surveys can have an impact on measures of wasting. This project explored the seasonal effects of wasting scores with the goal to establish if it is possible to answer the following question: *“what would the wasting score have been had it been measured in a different month of that year?”*. Results indicated the following:

1. Wasting does vary seasonally in each country and that there appears to be a ‘wasting season’;
2. Controlling for wealth and education, the wasting scores still varied monthly;
3. The multi-level logistic regression model provided a list of variables that are correlated with wasting, many of which vary seasonally;
4. The multi-level logistic regression model was able to accurately estimate monthly wasting values using a year and month of survey.

The results indicate that prediction is more accurate when data are available from multiple months and years. The study used data only from the Demographic and Health Survey (DHS) which limited the amount of data available and limited the ability to establish seasonal patterns in some countries. It is recommended that this study be repeated by combining SMART surveys with the DHS data to establish a longer and deeper time series for each country.

Geospatial data had a limited but significant impact on the models. It is recommended that future work should establish proxy metrics for specific issues affected child wasting from geospatial sources. For example, the remotely sensed normalised difference vegetation index (NDVI) is the most commonly used geospatial variable in these types of models across the literature, however, in our



project, it was often not significantly related with wasting. NDVI is an artificially created index, so it cannot be mechanistically linked to wasting or food production. It could be used to generate additional metrics that are more directly related to wasting or food production and availability. For example, converting an NDVI time series into the number of growing days in the year and then linked this to a cropping calendar to see if these days were above or below a threshold for particular crops. Physical access to markets is also important for food supply/access. Furthermore, geospatial variables only focused on food production (temperature, rainfall, drought, and soil moisture) and did not consider food access. In future, estimating travel time/access to markets should also be included.

Overall, the results of the SEASNUT project indicate that there are seasonal patterns and that statistical models can establish these patterns and estimate monthly wasting values using a range of covariates. Therefore, adding further data on wasting to build the time series/seasonal patterns along with further work on the geospatial covariate design should lead to a more accurate set of estimations. Ultimately, this could allow for monthly wasting correction factors/adjustment factors to be created for specific countries.

1. Introduction

Undernutrition in children is assessed from measurements of growth, primarily weight and height (or length in children under 2 years of age). While the immediate determinants of undernutrition of children and their mothers are diet quantity and quality and provision of personal care, the underlying determinants of these, (food and water supply, food habits and health services) ultimately depends on enabling economic, social, and political conditions (Figure. 1).

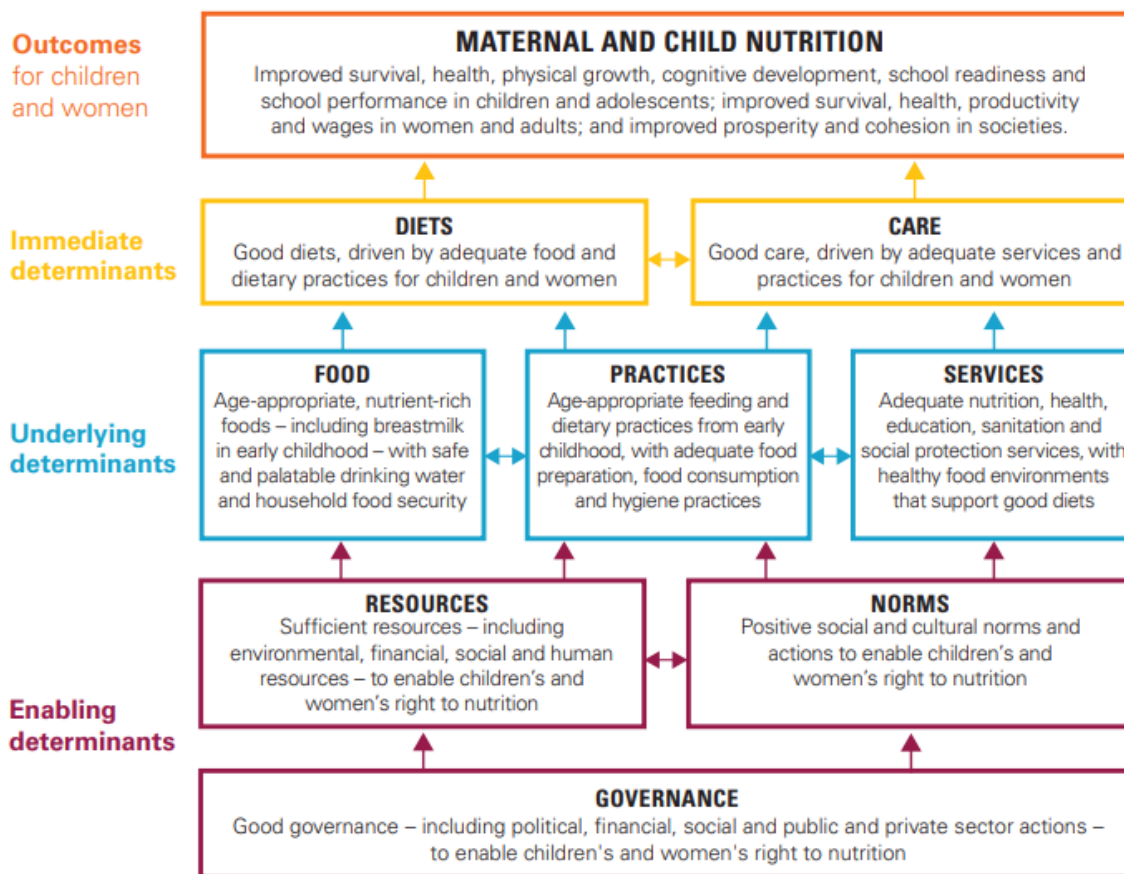


Figure 1 UNICEF conceptual framework, 2020 <https://www.unicef.org/documents/conceptual-framework-nutrition> (2020).

The Joint Malnutrition Estimation (JME) group (UNICEF, World Health Organisation, and the World Bank) that releases annual estimates for child stunting, overweight, underweight, wasting, and severe wasting for Sustainable Development Goals (SDG) reporting have an established database of malnutrition variables contained within several sub-national level surveys. Often the timing of these surveys is focused on minimising the cost and time required to collect as much quality information as possible. This can mean that the survey collection periods are not consistent in terms of hunger periods and agricultural calendars. Child wasting varies inter-annually and can fluctuate rapidly (Johnston et al. 2021), thus the timing of the surveys can have a big impact on measures of the prevalence of wasting. The aim of the project was to identify whether we can correct for the seasonal effect in wasting scores with the ultimate goal to establish if it is possible to answer the following question: “*what would the wasting score have been had it been measured in a different month of*



that year?” To do this, the project had three main objectives:

- Is seasonal variability an issue in the wasting scores?
- To establish if there were “wasting” seasons in the data.
- To investigate if monthly wasting prevalences can be estimated.

The longer-term motivation of the research was to identify if and how wasting data can be corrected for the temporal inconsistencies in sampling. This could allow partial historical trends to be adjusted and a more accurate measurement of wasting prevalence that is adjusted for seasonal fluctuations.

1.1 Project Scope, Objectives

UNICEF have an established database of malnutritional variables associated with other demographic components contained within DHS/MICS and other sub-national regional/district level surveys such as Living Standards Measurement Study (LSMS). These data are consistent from survey to survey (or has been made so by post analysis) however the timing of malnutrition variables (stunting and wasting) is not consistent in terms of the agricultural calendar. This means that surveys have been conducted effectively randomly throughout the year and most surveys have occurred over extended periods of time. For the same country repeat sampling visits different households (except LSMS), so the data are not longitudinal (Table 3). As such, consistency is a problem for comparing between countries as well as establishing patterns overtime in the same country.

Child wasting varies intra-annually and therefore the distribution of sampling directly impacts the comparability of data sets. Child wasting is highly elastic and as such the current methods for collecting data on Child Nutrition (wasting, stunting etc) are problematic. Because wasting is related to food availability and food intake, seasons could have a significant effect on the wasting score. The timing of a survey could have a significant effect on the wasting prevalences and thus using wasting values extracted from survey data may be biased. If seasonal variation can be identified and modelled, then it may be possible to (1) estimate likely wasting scores in non-surveyed months given the measured months and (2) adjust wasting scores across a year to give an average.

Ideally, nutrition data would be collected every month of the year from the same



children to track intra and inter annual changes in child stunting and wasting. However, this is not possible due to time constraints and cost implications of conducting, processing, and analysing such datasets. Therefore, this project sought to identify if wasting scores could be estimated using available data from surveys and geospatial data such as remotely sensed satellite imagery.

1.2 What is Wasting?

The most common form of undernutrition in children is stunting, or low height for age, which reflects delayed bone growth, particularly of the spinal column and lower limbs. In 2022 stunting was estimated to affect 22.3 % of children under 5 years of age globally (145.1 million children: 76.6m in Asia, 63.1m in Africa) (JME 2023). Wasting, or low weight for height, is characterised by a loss or deficit of soft tissue, particularly body fat and skeletal muscle. In 2022 wasting was estimated to affect 6.8% of children under 5 years of age (45.0m children globally: 31.6m in Asia and 12.2m in Africa and 13% of under-five child deaths are attributed to wasting each year [Schoenbuchner et al. 2019]).

Wasting is a condition that can have serious impacts on health, development, and the life of a child (Brown et al. 1982). It occurs when nutrient intake does not meet the demands for physiological and biochemical functions, growth, and capacity to respond to illness. When the body is deprived of food and nutrients it uses body fat, muscle, and other nutrients to maintain essential metabolic processes (Cahill 2006), resulting in weight loss and can lead to a failure to grow. Wasting can occur at any stage of development, including in utero (Black et al. 2013). Furthermore, for those children that survive severe wasting, each occurrence increases the risk of stunting, which is associated with a range of further problems related to development and future economic power.

Stunting and wasting are not exclusive conditions: children can be both stunted and wasted ('WaSt') and in these children the risk of dying is considerably higher than in either stunting or wasting alone (Zaba et al 2022). Longitudinal studies show that children who are wasted are at increased risk of becoming stunted, while the opposite relationship is less commonly observed (Wright et al. 2021). In the four



target countries (Bangladesh, Burkina Faso, Ethiopia, Nigeria) in 2019, 30–40% of children who were wasted were also stunted.

1.3 Major Determinants of Wasting

Most information on determinants of wasting come from cross-sectional studies in which the direction and nature of the causal pathway cannot be determined. The associations and their strength may vary according to the age group of children, the country, region, year and month of data collection and the covariates included in the analysis as well as the number of children included, so only broad generalisations can be made. We conducted a rapid exploratory literature review of peer-reviewed literature since 2010, including key articles from the project team supplemented by searches for relevant peer-reviewed papers on child wasting in: (1) Medline; (2) Web of Science; (3) Google Scholar. Onward literature searches of key articles with AI (Artificial Intelligence) algorithms applied to key papers were also used. The aim of this review was to identify key determinants of child wasting with a particular focus on identifying seasonal drivers of wasting and geospatial proxies that could be used to predict wasting in statistical models.

1.3.1 Non-seasonal factors related to Wasting

Ten widely reported factors are outlined below, with illustrative examples from the target countries, notably Ethiopia and Bangladesh where many published studies have been carried out:

1. **Age.** Wasting is consistently associated with younger age – for example, children aged 24–59 months were 44% less likely to be wasted than those aged 0–6 months in the 2016 Ethiopian DHS (Amare et al. 2019).
2. **Sex.** In most surveys boys have a slightly higher prevalence of wasting than girls – for example, there was an 18% higher prevalence in wasting for boys in a study in Bangladesh (Harding et al. 2018) and 26% higher prevalence in a study in Ethiopia (Dessie et al. 2019).
3. **Household wealth.** Associations of wasting with lower wealth of households are consistently seen. In a meta-analysis of studies in Ethiopia those in the lowest wealth group had a 73% higher prevalence of wasting compared to those in the highest wealth group (Abate and Belachew 2019) while in the 2013 Nigerian DHS



wasting prevalence was 20.2% in the poorest group vs. 14.2% in the richest group (Akombi et al. 2019). However, household wealth was not consistently associated with wasting across South-Asia, and it may be explained more by WaSH conditions and Maternal BMI (Body Mass Index) (Harding et al. 2018)

4. **Maternal education.** Maternal educational levels are consistently associated with the prevalence of wasting. Wasting has a higher prevalence in children of mothers without secondary education in Bangladesh (Sanin et al. 2023). In Ethiopia Habtamu et al. (2022) found a 2.5-fold increased risk of wasting in children of mothers with no formal education. In some but not all studies paternal education level shows a similar, if weaker, association with child wasting.
5. **Maternal nutrition.** Low maternal BMI (weight for height) is consistently associated with a higher prevalence of wasting: for example, 59% higher in children of undernourished mothers (BMI <18.5) in Bangladesh (Sanin et al. 2023) or in Ethiopia albeit under flood conditions (Goudet et al. 2011). Children of mothers of short stature (<145 cm) in Bangladesh were found to have a 28% higher risk of wasting (Khatun et al. 2019).
6. **Size at birth.** In Bangladesh children who were classed as having a low birth weight (<2500g) were 71% more likely to be wasted than others (Rahman (2015), while mother-perceived small size at birth was associated with 58% higher likelihood of being wasted in Ethiopian children Sahiledengle et al. 2022).
7. **Child feeding practices** In many, though not all, studies of poor-quality infant feeding practices have been associated with a higher prevalence of wasting. In Ethiopian children, termination of exclusive breast feeding before 6 months and particularly before 3 months was associated with an increased risk of wasting in children (Nigatu et al. 2019). In another Ethiopian study, children 6-59 months who ate less than 4 times a day were twice as likely to be wasted (Demilew and Alem 2019). However, in a further study in Ethiopia, infant and young child feeding practices were not associated with wasting in 6-11-month-olds (Samuel et al. 2022). In a pooled analysis of DHS data from 32 Sub-Saharan African countries, children 6-23 months who reached minimum diet diversity (consumed items from 4 or more food groups the day previous to the interview being conducted, in addition to breast milk) were 13% less likely to be wasted (Aboagye et al. 2021) but another study using data from 9 countries, (including



Ethiopia and Bangladesh) found that breast feeding indicators were more strongly associated with wasting than complementary feeding indicators e.g. meal frequency and diet diversity (Jones et al. 2014).

8. **Household food security** is not consistently associated with child wasting. In Bangladeshi children aged 6–59 months the prevalence of wasting was 8.7% in households with severe food insecurity compared with 4.3% in food-secure households (Abdullah et al. 2018) but in two studies in Ethiopia household food insecurity was associated with stunting and underweight but not wasting in similar aged children (Berra 2020; Betebo et al. 2017).
9. **Child infectious disease**. Wasting is consistently and often strongly associated with gastro-intestinal and other infectious diseases in young children. Bangladeshi children with rotavirus were over 2 times more likely to be wasted than uninfected children (Yeasim et al. 2022), while children who had had a fever in the past 2 weeks were 30% more likely to be wasted than others (Sanin et al. 2023). A meta-analysis of studies mostly from LMICs found that children with Giardiasis were 2.9 times more likely to be wasted (Fauziah et al. 2022). In Burkina Faso child wasting was found to be strongly associated with HIV infection (Poda et al. 2017); children under 5 with malaria in Ethiopia were twice as likely to be wasted compared to a control group (Shikur et al. 2016) though in Burkina Faso no association between wasting and subsequent malaria infection was seen (de Wit et al. 2021). In a study in Ethiopia, mothers who did not have access to a health facility were 2.2 times more likely to be wasted (Fentahun et al. 2016).
10. **Water, sanitation, and hygiene** ('WaSH'). Water quality and hygiene practices, where measured, are frequently but not invariably associated with child wasting. Under 5 children in Northern Ethiopia in households with water contaminated by E Coli were 2.5 times more likely to be wasted than others (Usman and Gerber 2020), but in an analysis of DHS data from 2000–2016 in Ethiopia no associations between water, sanitation and hygiene and wasting were detected (Sahiledengle et al. 2022). In Burkina Faso, children who were visibly clean and in compounds without chicken faeces were less likely to be wasted (Gelli et al. 2015). Bangladeshi children in households lacking an improved water supply had a 78% increased risk of wasting (Harding et al. 2018).



1.3.2 Other factors

Family size/structure. Short birth interval (<24 months) and large family size/birth order are found to be associated with an increased risk of wasting in some but not all studies. **Rural/urban residence. Rural-urban differences** in wasting prevalence vary widely within and between countries: some report higher prevalence in rural areas (Tesfaw and Dessie 2022) while others find no difference (Dessie et al. 2019; Sanin et al. 2023) or lower prevalence in rural areas (Chagomoka et al. 2016). Other associations found with child wasting in some studies include women's empowerment (Heckert et al. 2019; Kisso et al. 2022; Mekonnen et al. 2021); displacement (Tadesse et al. 2022; Islam and Biswas 2020; Idowu et al. 2020); conflict (Howell et al. 2020; Dunn 2018; Delbiso et al. 2017) and particulate air pollution (Johnson and Brown 2014; Goyal and Canning 2018). **Land tenure** child wasting was lower in Nigerian households with formal documents showing land tenure, perhaps due to ability to raise credit (Ibrahim et al. 2022).

1.3.3 Seasonal factors

1. **Agricultural production:** High or low commercialisation of agriculture are associated with lower child wasting in Ethiopia (Haji 2022). Off-farm income was associated with improved food security and reduced child wasting in Nigeria, partly by boosting agricultural productivity (Kabalo and Lintjörn 2022). In Bangladesh, wasting decreased with increasing NDVI (taken as a proxy for rice production) in data from 2011 but not 2007 (van Soesbergen et al. 2017). In Bangladesh lower child wasting was associated with increased agriculture productivity (rice yield), which was associated with complementary feeding, rainfall, and household assets (Headey and Hodinott 2016).
2. **Food price:** In Ethiopia rising cereal prices were associated with reduced child stunting but not wasting (Brenten and Nyawo 2021).
3. **Drought/rainfall:** Seasonal drought in Ethiopia increased risk of wasting in rural areas (Dimitrova 2021). In Burkina Faso, increased rainfall variability was associated with an increase in child weight-for-height z-score (Mank et al. 2020). Rainfall shocks were not associated with child wasting in Ethiopia (Ledlie et al. 2018). Moderate, but not severe drought, was associated with child wasting in Ethiopia (Agabiirwe et al. 2022).
4. **Flooding:** In South Asia, some evidence for an increased prevalence of



wasting immediately after floods, possibly linked to diarrhoea (Rodriguez-Llanes et al. 2016). In India, frequent floods were associated with increased wasting one year after a large flood due to lower agriculture production (Rodriguez-Llanes et al. 2016), however the long-term effect of floods on wasting is inconsistent (Agabiirwe et al. 2022).

5. **Cyclone:** There was no increase in wasting post cyclone in Bangladesh, probably due to effective food aid distribution (Paul et al. 2012).

1.3.4. Geospatial influences on wasting.

Table 1 shows the seasonality pathways and related geospatial variables that are associated with child wasting. Dry season, drought areas, and frequently flooded areas have higher wasting prevalence due to lower agriculture yields that tend to reduce food intake among children. Further, lack of labour work in the lean agriculture season and the absence of non-agricultural livelihoods in these contexts can aggravate food insecurity leading to child wasting. A recent systematic review of studies in drought affected areas of Africa found a positive relationship between climate change (rising temperature, variable rainfall) and reduction in agricultural yields (Asmall et al. 2021) meaning that geospatial proxies for climate change could also be related to wasting.

Worldwide, food systems are undergoing a broad and significant transition where there is an increased reliance on markets for food even among the traditional food producers in rural areas. In this context, studies have found a positive relationship between improved market access and reduction in wasting. The pathway for this association is two-fold, one is a general improvement in food availability through the markets especially during the dry or lean agriculture season and the other is through an expansion in the diversity of foods. Increase in diet diversity among children in the wet and dry season assists in building immunity that leads to a reduction in diarrhoeal diseases.



Table 1 Geospatial factors associated with child wasting

Pathways associated with wasting	Geospatial variables/factors	Studies	Context/Demography
Lower agriculture yields reduces food intake	Agriculture yield; Number of days between cultivation and harvest	(Headey 2016); (Abdulahi 2017); (Martin-Canavate, 2020); (Agabiirwe 2022); (Kabalo 2022);	Dry season; floods; droughts
Production diversity (crops/livestock) improves food security	Vegetation Index; Availability of livestock	(Sibhatu 2015); (Cafer 2015); (Kinyoki 2016); (Asmail 2021)	Droughts
Lower agriculture yields reduces food availability	Number of markets/retail shops in the local area	(Abdulahi 2017); (Schoenbuchner 2019); (Chowdhury 2020);	Floods; Landslide
Non-agriculture livelihoods or lack of dry season livelihoods reduces child diet diversity in areas with remote access to markets	Density and types of food vendors in the local area; Access: Roads/Transport and their seasonal accessibility;	(LLanes 2016) (Roba 2016) (Abdulahi 2017) (Cattaneo 2021) (Hasan 2022) (Headey 2022) (Nahalomo 2022) (Mohsena 2022)	Dry or lean season; remote areas; food-insecure households
Economic growth affects diet diversity and helps build child immunity against diseases and infection	Nightlights	(Headey 2022)	
Climate change affects food production	Rainfall; Temperature	(Asmail 2021)	Droughts
Climate change affects diarrhoeal disease	Temperature, vapor pressure (a measure of the specific humidity), climatic index for aridity (Tmin/vapor pressure), lagged monthly precipitation	(Alexander 2013) (Waage 2022)	Dry-season and Wet season



2. Data and study locations

The project focused four countries: Bangladesh; Burkina Faso; Ethiopia; Nigeria. The inconsistent timing of data collection from the DHS is demonstrated in Table 3. Bangladesh is the most sampled country in our dataset. It has five years in which surveys were conducted and for which GPS locations were collected for the village centres (2004, 2007, 2011, 2014, 2017). Most months have 2 separate years in which wasting data is available (Table 2) with the most being three (March, July, August, October, and November). The data is sparser in the other countries; Burkina Faso had almost no DHS surveys conducted between January and May in either year that the DHS was available. Ethiopia had no DHS survey conducted in January, February, or March (Table 2). This will make it more challenging to establish if there are seasonal patterns in wasting because the data gaps prevent a complete picture of how wasting varies across a year (Figure 2a). The data for Bangladesh indicates that the prevalence of wasting appears to be higher in May, July, and September whilst it is lower in June and November through to January, but this picture is complicated by the fact that June has a lower sample size than other months (Figure 2B).

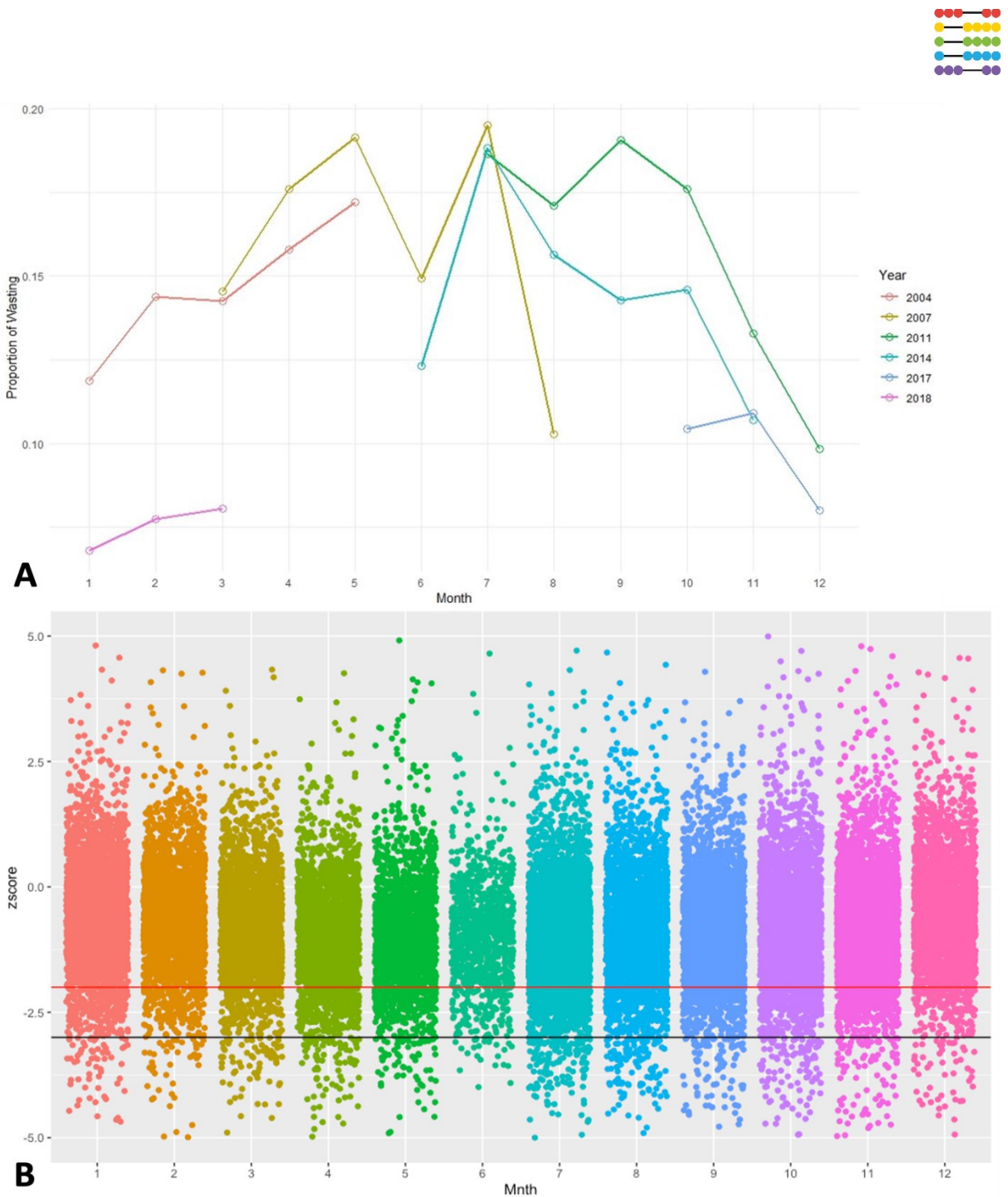


Figure 2 (A) Proportion of children in Bangladesh DHS Surveys that were wasted. Showing the number of times data are collected in each month – Most months have two data points with March, July, August, October, and November having three. (B) showing the z scores for wasting in each month of the year across all years that the DHS was conducted. The grey line (< -2) and the black line (< -3) indicate wasting and severe wasting, respectively. June has fewer children classed as severely wasted compared to other months but also has fewer samples.



Table 2 Number of households sampled in each DHS year for each country, by month. In Bangladesh, the DHS V survey was split over 2017 and 2018; it was not two separate survey rounds, but the same survey conducted over 6 months but spanning the two years. In Burkina Faso, Ethiopia, and Nigeria there are clearly some months where no data was ever collected within the DHS

Country	Year	Jan	Feb	Mar	Apr	May	June	July	Aug	Sept	Oct	Nov	Dec	Total	
Bangladesh	2004	1,134	691	861	824	550	-	-	-	-	-	-	-	4,060	
	2007	-	-	301	893	807	602	596	178	-	-	-	-	3,377	
	2011	-	-	-	-	-	-	1,154	774	903	1,097	747	527	5,202	
	2014	-	-	-	-	-	105	1,301	1,276	1,031	863	140	-	4,716	
	2017	-	-	-	-	-	-	-	-	-	-	211	1,414	1,213	2,838
	2018	1,081	773	386										2,240	
Burkina Faso	2003	-	-	-	-	-	47	490	1,092	1,506	1,815	566	-	5,516	
	2010	5	-	-	-	19	31	338	785	857	724	927	525	4,211	
Ethiopia	2000	-	-	-	-	-	1,372	1,567	1,644	990	88	-	-	5,661	
	2005	-	-	-	-	-	-	-	304	827	731	656	142	2,660	
	2011	-	-	-	468	1,344	1,519	1,753	1,224	-	-	-	-	6,308	
	2016	-	-	-	-	382	1,271	1,374	1,360	1,255	158	-	-	5,800	
Nigeria	2003	-	-	255	269	424	480	626	78	-	-	-	-	2,132	
	2008	-	-	-	-	-	729	3,231	3,352	2,100	1,312	21	-	10,745	
	2013	-	510	3,336	4,515	4,149	266	-	-	-	-	-	-	12,776	
	2018	-	-	-	-	-	-	-	231	1,492	1,427	1,322	1,007	5,479	



2.1 Covariate Selection for modelling Wasting

The rapid review informed the identification of covariates for use in statistical modelling. These were extracted from the DHS survey data and open-source geospatial databases. For the DHS data, covariates were dropped if:

- A covariate was not available in each year of survey (i.e. questions were dropped in later surveys or new questions appeared in later surveys);
- Covariates had high levels of correlation with other covariates deemed more suitable for the models (i.e. variables on household asset ownership were dropped as these were included already in the DHS Wealth Index variable);
- Covariates that did not appear in all countries (i.e. when child is sick respondent can decide to get medical treatment was not asked in most surveys);
- Variables had a high number of NoData, NA or Don't Know answers.

For a full breakdown of the process followed to select covariates see Appendix 1.

2.2.1 DHS Covariates Used in models

- **Respondent Education:** provides education level of the respondent as no education (coded as 0), primary (1), secondary (2) and higher education (3).
- **Partners' Education:** this variable explains the educational achievement of the partner and was categorized as none, incomplete primary, complete primary, incomplete secondary, complete secondary, higher education, and unknown level of education.
- **Religion: category 1 was generally the most common religion within the country and was used as the reference category in subsequent models.**
 - For Bangladesh, codes were: Islam (1*), Hinduism (2), Buddhism (3), Christianity (4) and Other (6);
 - For Burkina Faso, the codes were: Catholic (1*), Protestant (2), Muslim (3), Traditional (4), Sans religion/Aucune (5) and Others (96);
 - For Ethiopia, codes were: Orthodox (1*), Catholic (2), Protestant (3), Muslim (4), Traditional (5) and other (6/96);
 - For Nigeria, the codes were: Catholic (1*), Other Christian (2), Islam (3), Traditionalist (4) and Other (96);
 - Code 0 represented no religion as code 0.



- **Note that each religion categorised at 1 was used as the reference value in subsequent models.*
- **Frequency of listening to radio:** This variable was categorized into: Not at all (0), everyday (1), at least once a week (2) and less than once a week (3).;
- **Occupation of Respondent:** This variable explains whether the respondent was currently working or not and was responded as yes or no; Partner's **Occupation:** partner's occupation groups. Country specific categories;
- **Number of Women in Household:** this variable was coded as 1 for 1 woman in household otherwise ≥ 2 (if number of women is ≥ 2 in the household).

2.2 DHS GPS Repositioning

DHS GPS points are collected in a central location for each surveyed settlement/cluster. To protect the confidentiality of respondents, these points are displaced before being published on the DHS website. The displacement applied is between 0 and 2 km in Urban areas and 0 and 5 km in rural areas. However, 1% of points are moved up to 5 km in urban areas and up to 10 km in rural areas (Burgert et al. 2013). Most points are displaced over a small distance from their original locations (Brumhead 2020). Whilst protecting respondent confidentiality well, this approach can affect the use of the data for spatial analyses. Part of the aim of the SEASNUT project was to identify if the seasonality of wasting could be predicted using geospatial data proxies. To test this, we extracted metrics from the remotely sensed data to act as proxies for seasonal factors. However, these proxies have to be located within the same area as the household survey data was collected to ensure that the geospatial proxies are representative of the landscape characteristics surrounding the surveyed locations. Some geospatial variables are capturing heterogeneous biophysical parameters that will vary over small spatial areas such as agricultural productivity. Some variables are less heterogeneous such as rainfall and temperature and so the displacement from original location to published location is less problematic. The geospatial data that we shortlisted for use in the modelling ranged in spatial resolution from 250m to 55.5km and therefore it was necessary to relocate the GPS points to a known settlement.

The DHS recommends aggregating or averaging all geospatial data over a 5-10km area around the displaced points. However, Grace et al. (2019) indicated that



manually moving the point back to the nearest settlement viewed on satellite base maps may be an adequate approach for the majority of places which has been used in Wahab and Hall (2023). We developed a model in ESRI ArcPro (ESRI 2022) that relocated (snapped) a DHS cluster GPS point to the nearest Open Street Map (OSM) place point. The script snaps only rural DHS points to the nearest OSM place (village or town as Urban is removed), the initial search radius around the displaced point was 5 km as this is the maximum distance that 99% of rural DHS points are displaced by (Burgert et al. 2013). However, if no OSM place point could be found within 5km the model expands the search radius to 10km. Finally, if no place point can be found within 10km then the DHS point was manually assigned using the high-spatial resolution base maps available in ArcPro. The model produced interim outputs that can be used to identify the distances that points have been moved (Figure 4).

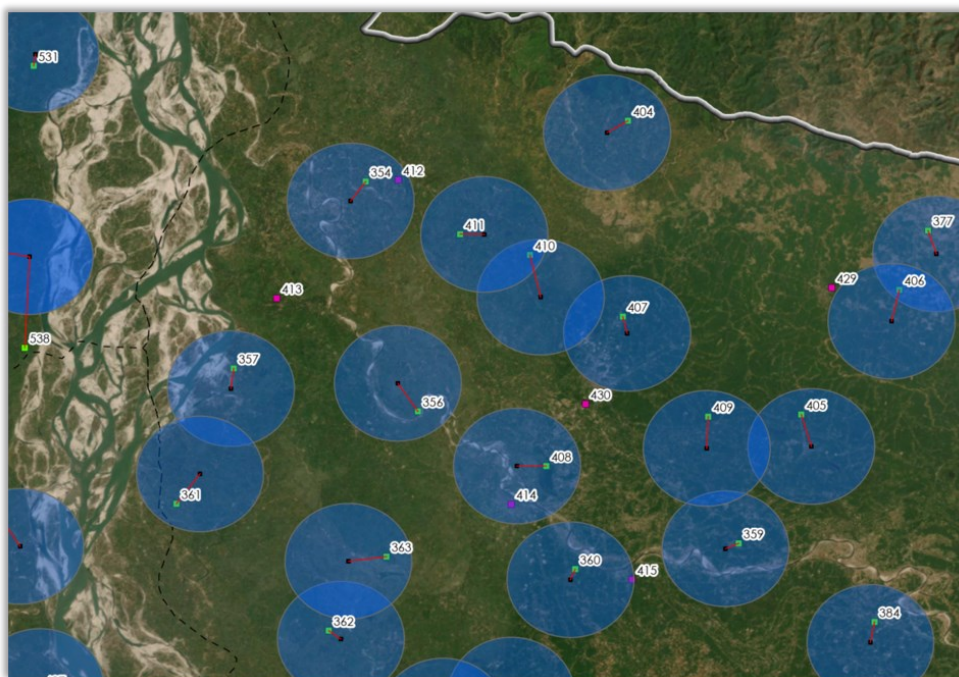


Figure 3 Each DHS point (black dot) was linked to the nearest rural OSM settlement point (green dot) within a 5 km radial buffer (blue area)

The approach is limited by the quality of OSM data and as such checks should be made in each country. For example, OSM data does not provide settlement locations for every settlement in a country; data can be of dubious categorisation, and often the settlement points are unevenly spread across a county (Figure 5b). The DHS random location can introduce, in a few cases, a scenario where multiple DHS



clusters can snap to the only available OSM place point within the search distance. Our model does not currently reposition points that are relocated to the same OSM settlement location.

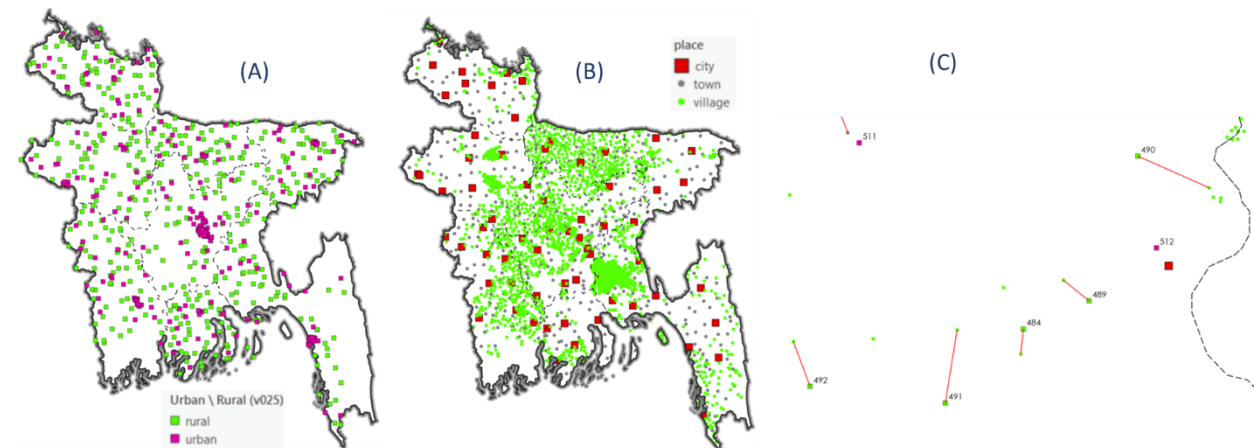


Figure 4 Example of 2018 DHS data snapped to OSM in Bangladesh. (A) DHS locations, (B) OSM locations, some places have dense settlement points, but others have sparse to none, and (C) the “snap to nearest” OSM visualized by red line.

2.3 Geospatial data preparation

The results of the rapid review informed the identification of a series of geospatial data that could act as proxies for seasonal drought, rainfall variability, and agricultural productivity (Table 3). The Dartmouth flood data set was explored but the structure of the data was not appropriate for this study and required in-depth further analysis. Drought can be a key cause of food insecurity but relying on weather data alone is not sufficient for drought monitoring, especially in developing countries where weather stations are scattered and incomplete. Therefore, we identified proxies from remotely sensed satellite data; the Normalised Difference Vegetation Index (NDVI), Rainfall, Soil Moisture, Land surface temperature and the SPEI drought index (Table 3).



Table 3 Summary of EO (Earth Observation) dataset sources for assessment impacts of drought on child wasting

Indicator	Data source	Spatial resolution	Temporal resolution available	Temporal resolution selected	Length of time series	Link to source
EO drought indicators						
Crop/vegetation condition (NDVI)	MODIS (MYD13Q1.6)	250 m	16-day/monthly aggregate	monthly	2000 – present	https://earthdata.nasa.gov/ https://earlywarning.usgs.gov/
Rainfall	CHIRPS	0.05° (5.5 km)	Pentadal/monthly	monthly	1981– present	https://data.chc.ucsb.edu/products/CHIRPS-2.0/ https://earlywarning.usgs.gov/fews/datadownloads/Global/CHIRPS%202.0 ftp://chg-ftpout.geog.ucsb.edu/pub/org/chg/products/CHIRPS-2.0/
Soil moisture	GLDAS-SM	0.25° (27.75km)	Monthly	monthly	2000– present	https://disc.gsfc.nasa.gov/datasets/GLDAS_NOAH025_M_2.1/summary
Land surface temperature	GLDAS-SM	0.25° (27.75km)	Monthly	monthly	2000– present	https://disc.gsfc.nasa.gov/datasets/GLDAS_NOAH025_M_2.1/summary
Drought index	SPEI	0.5° (55.5km)	1-, 2- to 48-month time scale	3 monthly (agricultural drought)	1901–2018	https://spei.csic.es/spei_database/#map_name=spei01#map_position=1415

2.3.1 Rainfall

Rainfall is a key input for agricultural growth and remotely sensed estimates of rainfall provide an outlook of one of the climatic drivers of vegetation growth (Rembold et al., 2019). Agriculture is a significant contributor to livelihoods, incomes, and food supply in rural areas of many LMICs. Rainfall was hypothesised to be



related to wasting because too much or too little rainfall can lead to crops not being planted at all or failing to produce expected.

We used the Climate Hazards Group Infrared Precipitation with Station data (CHIRPS) to estimate rainfall at 0.05° spatial resolution (approximately 5.6 km at the equator). CHIRPS is a 30+ year freely available global rainfall estimate (RFE) dataset which incorporates satellite imagery (thermal infrared and passive microwave) with in-situ station (gauge) data to create gridded rainfall time series. Given the consistency in data acquisition over a long period of time, CHIRPS RFE data is well suited for meteorological monitoring, as well as examining how rainfall affects agricultural crop production and forage availability for livestock. For the SEASNUT project we used monthly estimates of rainfall and converted these into anomalies using the z-score approach described in section 2.5 below. The monthly anomalies were categorized in the following way:

- -2 to 2 – classed as normal rainfall conditions;
- > -2 classed as drier than normal;
- > 2 classed as wetter than normal.

The rainfall anomaly is again calculated with local context in mind comparing the rainfall for a particular month and pixel to the long-term average for that particular pixel. We chose to use monthly rather than 3-monthly average for the rainfall since we used the 3-month time horizon for the drought calculations (section 2.4.3)

2.3.2 Soil moisture (SM) and Land Surface Temperatures (LST)

Soil moisture and surface temperature can be acquired using active and passive microwave satellite sensors. Soil moisture availability affects changes in crop growth (phenology) and is therefore considered an important indicator when assessing seasonality in agricultural areas. The Global Land Data Assimilation System (GLDAS) soil moisture and surface temperature datasets are gridded with a spatial resolution of 0.25 x 0.25-degree spatial resolution (approximately 27.75km at the equator) and monthly temporal resolution. The GLDAS soil moisture product can be used to characterize the variability of soil moisture at a regional scale and its ability to capture anomalies compares favourably with other proxies such as the standardized precipitation index (Pennemann et al. 2015). Since GLDAS requires lower computational time than the standardized precipitation index (Rodel et al. 2004) we



chose to utilise this indicator. Furthermore, the global availability at a relatively fine resolution (both temporal and spatial) and its integration of satellite with ground-based data sources make this dataset well suited for drought monitoring. In the SEASNUT project we used the GLDAS Land Surface Model version 2 soil moisture dataset.

2.3.3 Drought

Rainfall is not the only factor affecting water availability as temperature drives evapotranspiration rates which affect water availability in a particular location. Drought indicators that are solely based on precipitation are less sensitive than those based on precipitation and temperature (Tirivarombo et al. 2018, SPEI 2020). The Standardized Precipitation and Evapotranspiration Index (SPEI) combines long-term time series information on rainfall and temperature to generate an index that is more sensitive in identifying droughts than a simple rainfall index (Pei et al., 2020; Bezdán et al., 2019). The SPEI accounts for local context when identifying drought conditions and the values of the SPEI can be categorized as shown in Table 4.

Table 4 Categorization of Standardized Precipitation and Evapotranspiration Index (SPEI) based on values in Wang et al, 2021

Categorization (based on Wang et al. 2021)	SPEI Value
Extremely Wet	≥ 2
Severely Wet	≥ 1.5 and < 2
Moderately Wet	≥ 1 and < 1.5
Mildly Wet	≥ 0.5 and < 1
Normal	≥ -0.5 and < 0.5
Mild Drought	> -1 and ≤ -0.5
Moderate Drought	> -1.5 and ≤ -1
Severe Drought	> -2 and ≤ -1.5
Extreme Drought	≤ -2



SPEI provides long-term, robust information about drought conditions at the global scale, with a 1-degree spatial resolution and a monthly temporal resolution. There are a variety of time-horizons that can be used to assess the SPEI allowing it to be used for identifying short/meteorological droughts (one month), agricultural droughts (3 months), and hydrological droughts (12 months) (Vicente-Serrano et al. 2010) to long-term (up to 48 months) drought episodes. We used the 3-month time horizon as this is used to identify 'agricultural droughts'. Thus, if a monthly value of SPEI is -2 this indicates that there was an extreme drought during the 3 months leading up to the date in-question for that particular pixel (i.e. if April 2010 has an SPEI value of -2 this means that February, March, and April 2010 was a drought period). We include SPEI in the analysis because we hypothesise that wasting will be associated with dry and wet conditions through damage to crops and reduced harvests. This results in less food being available in rural markets and thus less food to eat and lower incomes, meaning less food can be bought by those reliant on agricultural production for their livelihoods and/or food intake.

2.3.4 Vegetation condition - Normalized Difference Vegetation Index (NDVI)

Time series of satellite-based biophysical indicators such as vegetation greenness can provide information about vegetation status, including crops and forage over large areas (Rembold et al., 2019). Optically derived NDVI data has been used as a proxy for vegetation cover, greenness, and vigour with applications in crop and rangeland browse or forage condition assessment and monitoring, and more recently gaining significance in drought monitoring at both regional and global scales. NDVI converts the spectral bands into a unit-less measure (Rouse et al., 1974). NDVI is computed as a normalized difference of the near infrared (NIR) and the red reflectance because healthy green leaves have a high level of reflectance in the NIR band and a low level of reflectance in the red band. The index values range between -1 and 1 with vegetated surfaces having a positive value and it can be measured by any sensor that measures in these spectral bands (red and NIR). The [MODIS NDVI product version 6](#) used in the SEASNUT project, available in Google Earth Engine. These are generated every 16 days at a spatial resolution of 250 m. The data were



aggregated to the DHS cluster for each month of the year of the DHS survey. We extracted the NDVI value for the following time horizons:

- Month of the survey;
- Average of the 2 months leading up to the survey;
- Average of the 3 months leading up to the survey.

The NDVI was assumed to have a relationship with agricultural productivity, whereby higher levels of greenness could indicate a higher harvest. However, given that Bangladesh has a large reliance on Rice Padi it was likely that this may not be the case and so we tested these in the model. None of the NDVI data were significant, therefore, it was dropped from the model in Bangladesh, and we did not process the data for Burkina Faso, Ethiopia, or Nigeria. Since vegetation is affected by rainfall, soil moisture, and temperature it was felt that these measures already included in the models were more reliable geospatial variables to use as are more directly linked to agricultural productivity than vegetation greenness.

2.4 Earth Observation data processing

Each of the datasets were processed at the pixel level before being aggregated to the DHS Cluster. For the rainfall, soil moisture, and surface temperature, the data were subset to the years 2000 to 2019, providing 19 years of data. The z-score was calculated for each of these (except the SPEI). Z-scores are deviations of observed monthly and seasonal indicators from long term averages (LTAs), also known as anomalies. The whole process, applicable in computing monthly anomalies for the EO drought indicators, can be summarized in 2 basic steps:

1. Temporal aggregation to a harmonized temporal resolution of monthly and seasonal indicators;
2. Normalization through computation of z-scores to compare the condition at the time (month/season) under investigation to long term average, or distance from mean. This shows how many standard deviations a monthly or seasonal observed score is below or above the long-term average (LTA) Negative z-Scores show below-normal conditions, while positive values depict above-normal conditions.

A Python script was developed to automate the extraction of the sum of the values of the Standardised Precipitation & Evaporation Index (SPEI), Soil Moisture (SM), Surface Temperature (ST) and Rainfall Estimates. Rasters were converted to polygons and



then intersected with buffers around each repositioned DHS cluster point.

2.5 Multilevel Modelling of Child Wasting at the cluster level

DHS surveys for every year with GPS data available were pooled for each country (Bangladesh, Burkina Faso, Ethiopia, Nigeria) to examine if there was a seasonal pattern in the wasting prevalence and the extent to which geospatial covariates could be used to estimate the wasting prevalence. The aim was to investigate the individual, household, and cluster level variables that affect the wasting among children under five years of age, and whether the geospatial factors can explain the variation in wasting, severe wasting, and Z-scores of wasting among children under five years of age.

2.5.1 Shortlisting of covariates for the models

The selection of covariates from the DHS dataset, which may exert an influence on the prevalence of wasting among children under the age of five, was carried out through a comprehensive literature review and our domain expertise giving us a comprehensive list of covariates (Section 2.2.1). Thereafter, a correlation analysis was conducted on the selected covariates to identify and subsequently eliminate variables exhibiting a high degree of correlation with each other. This was done to mitigate the issue of multicollinearity in the multilevel regression models.

Covariates demonstrating substantial correlation (correlation coefficients exceeding ± 0.7) were investigated further and the covariate that had the highest number of missing values or that were deemed of lower importance from the literature were removed from further analysis. For example, the covariates pertaining to mosquito bed nets were excluded due to their absence in the surveys across all four countries. The variable representing the total number of household members was omitted given its high correlation with the count of *de jure* members. In the domain of religion and ethnicity, the ethnicity variable was removed because it was highly correlated with religion and religion had a higher number of reported cases than ethnicity. Covariates concerning the type of toilet facility and those associated with the number of livestock were excluded from consideration, as they were already factored into the calculation of the wealth index. Covariates pertaining to



respondents' ownership of a mobile phone and their internet usage were removed due to their presence only in the most recent survey years.

2.5.2 Model description

We used a linear model that takes into account individual, household, and cluster level variables to predict z-scores, wasting, and severe wasting where the former outcome is continuous while the latter two outcomes are binary. We modelled these variables as fixed effects (i.e., the respective coefficients are explicitly estimated) and also allowed cluster specific variations in the model. Since there were a high number of clusters in most countries, we modelled the cluster specific variation as a random effect (i.e. we do not explicitly estimate the cluster level coefficients but their mean value and standard deviation over all clusters). We also assumed that the outcomes (wasting, severe wasting, and Z-scores of wasting) could vary over months, and we modelled this variation as a fixed effect. Similarly, we assumed that the outcomes could vary over years, and we modelled this variation as another fixed effect. Detailed model descriptions are available in Appendix 4. We created 3 separate multi-level models:

1. The WHZ-score wasting values;
2. The prevalence of wasting;
3. The prevalence of severe wasting.

We included certain covariates at the household level, others at the child level, and others at the cluster level to account for the fact that these covariates vary at different spatial scales. For example, each child within a household will have a unique age, birth interval, breastfeeding duration, and wasting score. But most children within a household will have the same parents and therefore the respondent education, religion of mother, literacy of respondent will be the same for most children in a household whilst differing between households. All geospatial variables were the same for each cluster because they were extracted for the buffer zone around the GPS cluster location; the final variables that were considered for each model are listed in Table 5 and Table 6.



Table 5 Household level features included in the models for each country, those marked as 'N' had missing data and were not considered in the models.

Household level feature	Bangladesh	Burkina Faso	Ethiopia	Nigeria
Respondent Education	Y	Y	Y	Y
Partners' Education	Y	Y	Y	Y
Religion of mother	Y	Y	Y	Y
Frequency of radio listening	Y	N	Y	Y
Occupation of mother	Y	Y	Y	Y
Number of women in the household	Y	Y	Y	Y
Literacy	N	N	Y	Y
Wealth Index quintile of the household	Y	Y	Y	Y
Household in urban or rural area	N	Y	Y	Y
Sex of head of household	Y	Y	Y	Y

Table 6 Child level features included in each model, those marked as 'N' had missing data and were not considered in the models.

Child level feature	Bangladesh	Burkina Faso	Ethiopia	Nigeria
Birth order	Y	Y	Y	Y
Breastfeeding duration	Y	N	N	N
Age of child	Y	Y	Y	Y
Sex of child	Y	Y	Y	Y
Preceding birth interval (months)	N	Y	Y	Y
Number of entries in immunization roster	Y	Y	Y	Y

All models were run for a maximum 10,000 iterations with a tolerance of 0.00001 was used for declaring convergence. For each outcome variable, we generated three models:

- with only DHS covariates including individual, household and cluster level covariates;
- with only geospatial covariates;
- a full model with both DHS covariates and geospatial covariates.



NDVI was included in the full model of Bangladesh for all three outcomes as described above (WHZ score model, wasting model and severe wasting model) in different forms to understand the role of NDVI in determining the wasting prevalence. NDVI was treated differently to other geospatial covariates for two reasons: (1) it is less directly linked to food production than others as it is a unitless index that shows vegetation vigour rather than a particular input required for plant growth (temperature, rainfall, soil moisture); (2) it is commonly used in studies like SEASNUT but in different ways. Thus, we wanted to see if (1) NDVI was correlated with wasting and (2) if the correlation differed depending on the way that NDVI was treated. The NDVI was aggregated to the cluster in the following ways:

- lag1 month (BD-lag1) NDVI value one month prior to the DHS month of data collection;
- lag2 (BD-lag2) - NDVI value two months prior to DHS the month of data collection;
- lag3 (BD-lag3) NDVI value three months prior to the DHS month of data collection;
- average of lag two months (BD-avglag2) i.e., average of two months of NDVI prior to the month of data collection for child anthropometric indices – typically four to five individual NDVI values per pixel;
- average of lag three months (BD-avglag3) i.e., average of three months of NDVI prior to the month of data collection for child anthropometric indices. Typically, six to seven individual NDVI values per pixel.

2.6 Actual versus Predicted Wasting Prevalence

To identify if the model can be used to estimate wasting prevalence we calculated prevalence as:

$$v_{cl,mm-yy} = \frac{N_{wasted,cl,mm-yy}}{N_{total,cl,mm-yy}}$$

This prevalence is then modelled as in [M3] and [M3'].



3. Results

Overall, the models with the lowest AIC values across all countries were those containing both DHS and geospatial covariates (Table 7). The geospatial only model outperformed the DHS only model in Ethiopia for wasting and severe wasting but in Nigeria the results were more varied. In all cases the difference between all of the models is relatively small.

The marginal and conditional r^2 values indicate that the WHZ-Score models all have a limited ability to explain the variance in the observed values. However, they do indicate that for both Nigeria and Ethiopia the geospatial only model is the worst performing model which is to be expected as it contains only information on NDVI, rainfall, drought and soil moisture which is expected to only explain a small amount of the child nutrition patterns seen in the data.

The best performing models were selected based on model performance statistics – conditional R squared, marginal R squares, (Akaike's Information Criteria) AIC and Bayes Information Criteria (BIC) values for WHZ score models and AUC, F1-Score (threshold of 0.2), and AIC and BIC values for wasting and severe wasting models. Finally, only the covariates which were found to be significantly correlated to the output in the best performing models were used in a final model for interpreting covariate relationships. The covariates month and year were included in all the models irrespective of whether they were significantly affecting the output or not. The model performance statistics for models with all the significant covariates including month and year are presented in Table 7. Further, from the analysis of BD models it was observed that NDVI did not significantly affect the output in any of the Bangladesh models thus, NDVI was not included as a covariate for Ethiopia, Nigeria, and Burkina Faso.



Table 7 Model Performance statistics for WHZ-score, wasting and severe wasting models without geospatial covariates, with only geospatial covariates and with all covariates including geospatial

Region	Model	AUC	F1-Score (threshold of 0.2)	Conditional R squared	Marginal R squared	AIC	BIC
Bangladesh (WHZ-score Model)	No Geo Model	-	-	0.097	0.071	67717.6	68030.3
	Only Geo Model	-	-	0.058	0.007	54580.3	54673.8
	Full Model with Geo	-	-	0.096	0.070	67750.9	68071.6
Bangladesh (Wasting Model)	No Geo Model	0.690	0.319	-	-	18043.8	18348.5
	Only Geo Model	0.719	0.286	-	-	15213.9	15299.6
	Full Model with Geo	0.690	0.319	-	-	18055.9	18368.6
Bangladesh (Severe Wasting Model)	No Geo Model	0.748	0.029	-	-	5879.3	6176.0
	Only Geo Model	0.873	0.039	-	-	5147.4	5217.6
	Full Model with Geo	0.842	0.052	-	-	5836.1	6084.7
Ethiopia (WHZ-score Model)	No Geo Model	-	-	0.098	0.049	66676.4	67064.7
	Only Geo Model	-	-	0.068	0.003	65780.6	65914.8
	Full Model with Geo	-	-	0.095	0.050	64988.3	65438.5
Ethiopia (Wasting Model)	No Geo Model	0.749	0.382	-	-	15379.7	15760.1
	Only Geo Model	0.754	0.256	-	-	15478.4	15604.8
	Full Model with Geo	0.745	0.371	-	-	14840.5	15282.9
Ethiopia (Severe Wasting Model)	No Geo Model	0.750	0.029	-	-	6728.6	7053.5
	Only Geo Model	0.858	-	-	-	6716.8	6811.6
	Full Model with Geo	0.825	0.080	-	-	6438.3	6825.4
Nigeria (WHZ-score Model)	No Geo Model	-	-	0.124	0.053	114740.9	115166.5
	Only Geo Model	-	-	0.097	0.006	112667.2	112792.0
	Full Model with Geo	-	-	0.124	0.055	112053.2	112519.2
Nigeria (Wasting Model)	No Geo Model	0.779	0.424	-	-	23993.2	24410.5
	Only Geo Model	0.770	0.399	-	-	24390.3	24506.8
	Full Model with Geo	0.779	0.425	-	-	23414.2	23872.0
Nigeria (Severe Wasting Model)	No Geo Model	0.78	0.228	-	-	14220.1	14645.8
	Only Geo Model	0.833	0.256	-	-	14215.8	14315.6
	Full Model with Geo	0.823	0.273	-	-	13675.8	14141.9



3.1 Bangladesh

In Bangladesh, the WHZ-Score models indicated a complex relationship between child age and wasting. Wasting WHZ-scores were generally lower in children aged 12-23 months compared to 0-11 months indicating that Wasting prevalence was higher in children between 12 and 23 months than those between 0 and 12 months. Wasting prevalence was lower in children between 24 and 47 months (Figure 7). This corresponds to the wider understanding of Wasting for age as it generally starts low during early months of life, increases initially after weaning, and then decreases to almost zero by the age of 5. However, in Bangladesh, increased once again in the oldest age group (48-59 months) which is not expected. However, the observed data in Bangladesh clearly showed that in 2011, 2014 and 2017 the percentage of children wasted was high in younger age groups, reduced in the middle age groups and increased once again in the oldest age group (Table 8).



Table 8 Observed Wasting percentages per age group in Bangladesh showing the unexpected result of the oldest age group (4) corresponding to children aged between 47 and 59 months having higher rates in 2011, 2014 and 2017

Year	Age (Years)	Total no. of Children	No. of Wasted Children	No. of Severely wasted Children	Wasting (%)	Severe Wasting (%)
2004	0	816	136	41	16.66667	5.02451
2004	1	803	168	38	20.92154	4.732254
2004	2	818	112	33	13.69193	4.03423
2004	3	831	95	13	11.43201	1.56438
2004	4	792	96	10	12.12121	1.262626
2007	0	675	131	36	19.40741	5.333333
2007	1	673	168	35	24.96285	5.200594
2007	2	682	121	15	17.74194	2.199413
2007	3	660	93	17	14.09091	2.575758
2007	4	687	105	7	15.28384	1.018923
2011	0	1034	155	51	14.99033	4.932302
2011	1	955	165	41	17.27749	4.293194
2011	2	957	145	32	15.15152	3.343783
2011	3	1153	200	49	17.34605	4.249783
2011	4	1103	188	37	17.04442	3.354488
2014	0	915	172	44	18.79781	4.808743
2014	1	986	180	45	18.25558	4.563895
2014	2	949	128	21	13.48788	2.212856
2014	3	929	119	19	12.80947	2.04521
2014	4	937	150	20	16.00854	2.134472
2017	0	1126	90	22	7.992895	1.953819
2017	1	1068	89	22	8.333333	2.059925
2017	2	976	77	18	7.889344	1.844262
2017	3	938	85	10	9.061834	1.066098
2017	4	970	100	4	10.30928	0.412371

Wasting was higher in children who had suffered diarrhoea in the 2 weeks preceding the survey, if they were male, if their mother was underweight and if their mother had lower education. Compared to the poorest households (comparison) wasting was lower in each wealth quintile (Figure 5).



None of the geospatial covariates showed a significant association with WHZ score (Figure 5) in the full model (including DHS and geospatial covariates). However, the model with only geospatial variables showed significant relationships between pre-ndvi-lag1 month, soil temperature and SPEI with WHZ scores (Appendix 6). The WHZ scores improved with an increase in pre-NDVI-lag1 month values, and as the SPEI shifts from moderately wet to mildly wet and drier conditions. The seasonal variation in the WHZ scores was visible when comparing between months of data collection. Wasting was highest in July and lowest in February in Bangladesh when January was used as the reference month. But the interpretation of the results means that compared to January, the wasting started increasing as the year progresses with the worst months being July to September but better (i.e., less wasting) in October, November, and December. The WHZ score model with only DHS covariates without any geospatial covariates is provided in Appendix 6.



Bangladesh - WHZ Score (Full Model)

Ref. Month: January, Ref. Year: 2004

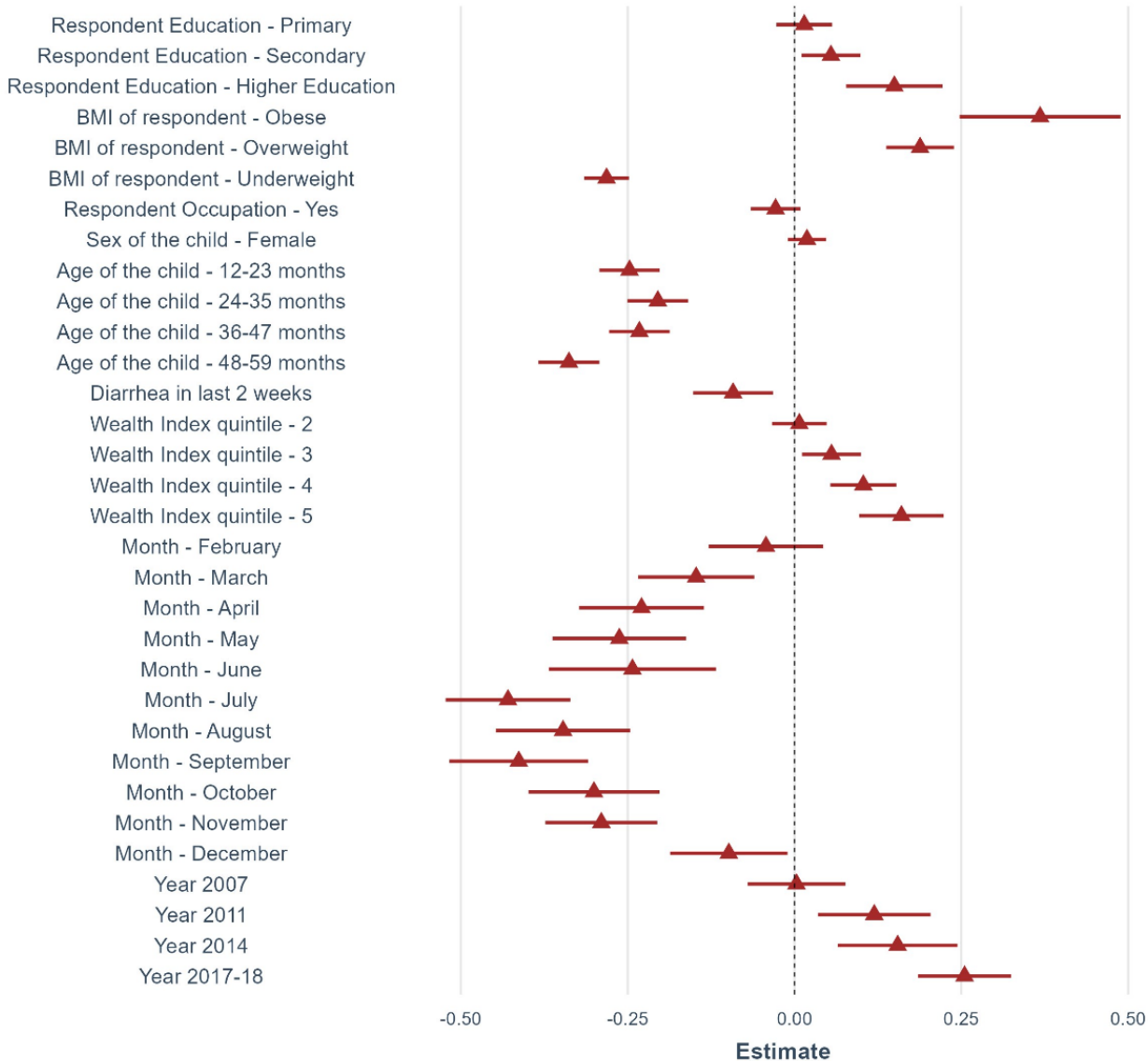


Figure 5 Bangladesh WHZ score for the best performing model. For the WHZ-score model, a variable was associated with increased wasting if it was to the left of the 0.0 line. Wasting is higher the further to the left of the plot a variable appears

The likelihood of being wasted and severely wasted was lower in ages over 11 months with the lowest likelihood of being severely wasted being in the oldest two age groups which is as would be expected (Figure 6). However, the likelihood of becoming wasted increased again in the age group of 47-59 months. Further,



children had a higher likelihood of wasting if they had diarrhoea in last two weeks preceding the day of survey (odds ratio (OR) = 1.33, confidence interval (CI) = 1.15–1.54 indicating 33% more likelihood of getting wasted) or if their mother had no formal education although, these two covariates did not show any significant association in severe wasting model (Figure 6). Whilst the likelihood of a child being wasted or severely wasted was lower in children whose mothers were overweight (OR = 0.66, CI = 0.57–0.79 meaning 34% less likely in case of wasting and OR = 0.80, CI = 0.56–1.14 for severe wasting) and higher when mothers were underweight (OR = 1.56, CI = 1.44–1.70 for wasting and OR = 1.52, CI = 1.29–1.80 for severe wasting). There was little difference in the likelihood of wasting or severe wasting between wealth quintile 1 (poorest) and 2 and 3, but the likelihood was lower in quintile 4 and 5 (highest wealth). In the full models for prevalence of wasting and severe wasting, none of the geospatial variables showed a significant relationship with the likelihood of wasting and severe wasting. The likelihood of wasting was slightly higher in each month of the year except December (OR = 1.04, CI = 0.79–1.35) and peaked in July (OR = 2.11, CI = 1.65–2.69) compared to January (reference month). However, the likelihood of severe wasting was highest in the month of November (OR = 1.68, CI = 0.99–2.87) (Figure 6).



Bangladesh - Wasting and Severe Wasting (Full Model)

Ref. Month: January, Ref. Year: 2004

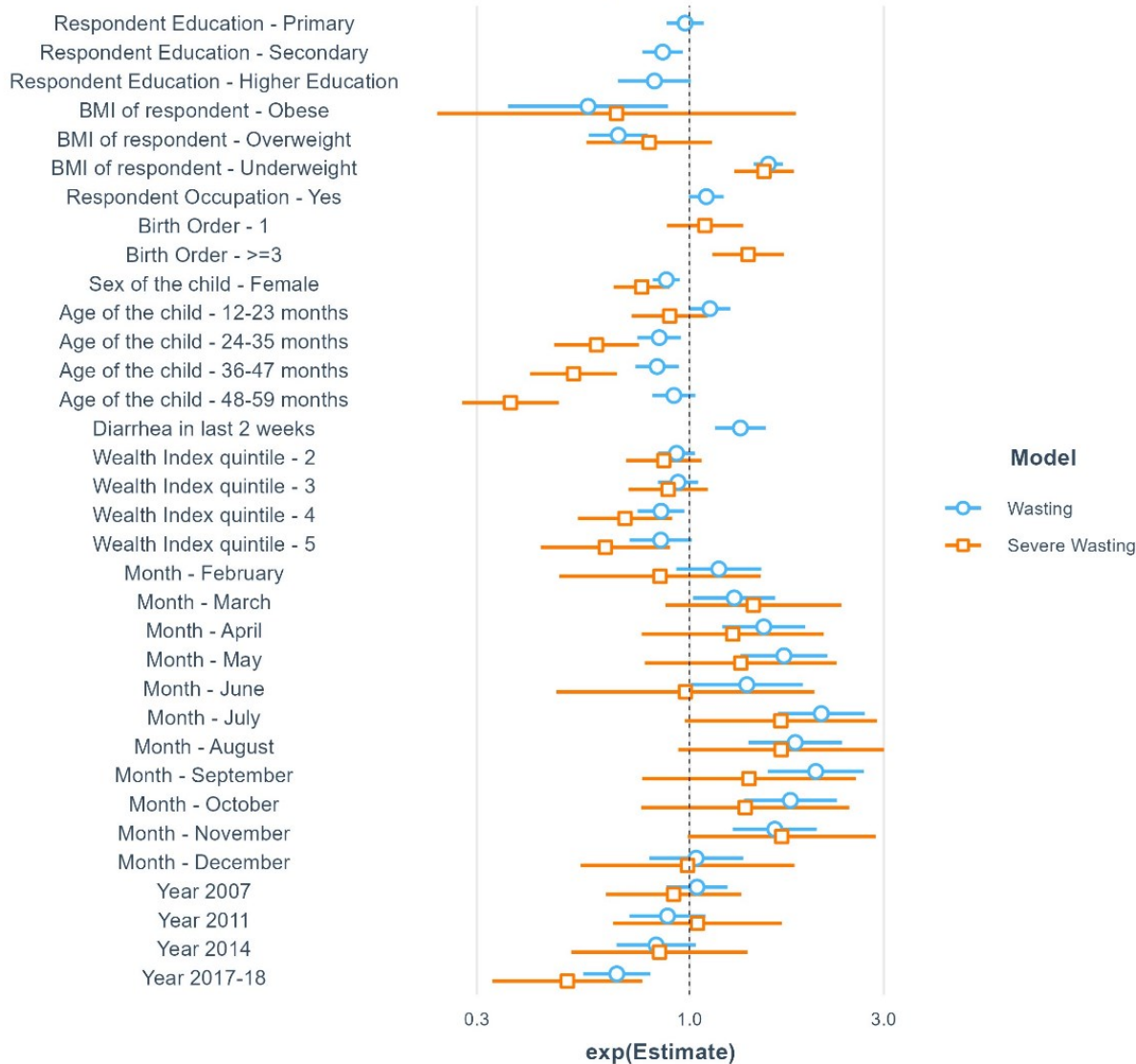


Figure 6 Bangladesh Wasting and Severe Wasting models. These models were both Logistic regression models and the plots show the likelihood of a child being wasted or severely wasted.

3.2 Ethiopia

In Ethiopia, the WHZ-Score models indicated a complex but expected relationship between child age and wasting. Wasting WHZ-scores were generally lower in



children aged 12–23 months compared to 0–12 months indicating that Wasting was higher in children between 12 and 23 months than those between 0 and 12 months (Figure 7). Wasting was low in children between 24 and 47 months. This corresponds to the wider understanding of Wasting for age as it generally starts low during early months of life, increases initially after weaning and then decreases to almost zero by the age of 5. Wasting was higher in children that had suffered diarrhoea in the 2 weeks preceding the survey, if they were male, if their mother was underweight and if their mother had lower education. Results for Ethiopia indicated that the higher the mother’s education the higher chances of the child having higher WHZ score (Habtamu et al., 2022). Compared to the poorest households (comparison) wasting was lower in each wealth quintile.

Among the geospatial variables, the SPEI showed that as the conditions become drier the WHZ score decreased whereas the wetter conditions were beneficial for WHZ score (Figure 7). None of the other geospatial variables (temperature, soil moisture or rainfall) showed any relationship with WHZ score. However, the seasonal variation in the WHZ scores is visible when comparing between months of data collection. Wasting was highest in August and lowest in November and December in Ethiopia. April was used as the reference month for Ethiopia as none of the surveys had data for the months of January, February and March indicating the need to collect data from these months as well to better understand the patterns of wasting in Ethiopia. But the interpretation of the results means that compared to April, Wasting is worse in May to August but better (i.e., less wasting) in September, October, November, and December. The WHZ score model with only DHS covariates without any geospatial covariates is provided in Appendix 6.



Ethiopia - WHZ Score (Full Model)

Ref. Month: April, Ref. Year: 2000

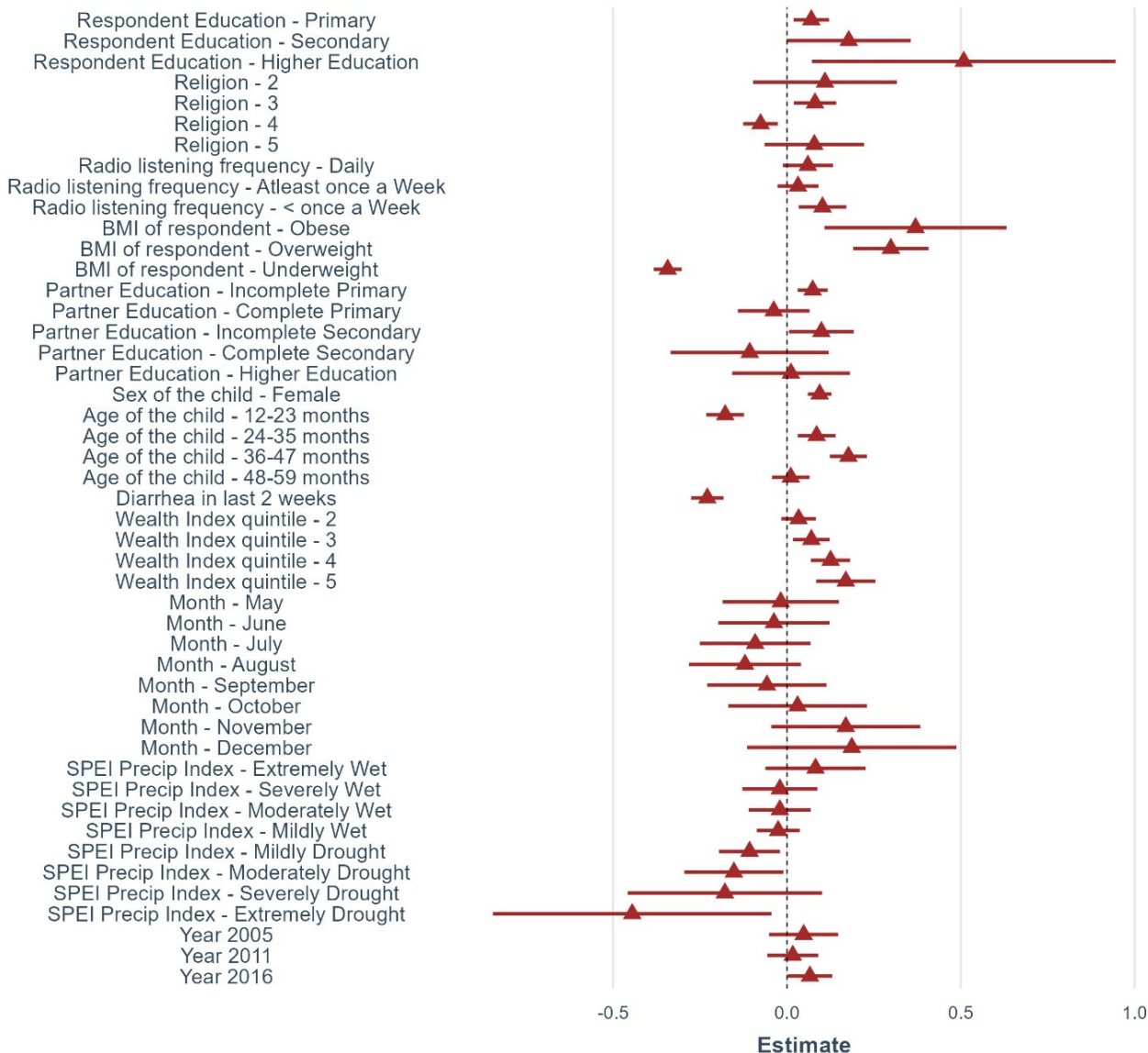


Figure 7 Ethiopia WHZ score for the best performing model. For the WHZ-score model, a variable was associated with increased wasting if it was to the left of the 0.0 line. Wasting is higher the further to the left of the plot a variable appears.

The likelihood of being wasted or severely wasted was lower in ages over 11 months with the lowest likelihood being in the oldest two age groups which is as would be expected (Figure 8). Whilst the likelihood of a child being wasted or severely wasted was lower in children whose mothers were overweight (odds ratio (OR) = 0.59, confidence interval (CI) = 0.41–0.84 for wasting indicating 41% less likelihood of



getting wasted; OR = 0.54, CI = 0.27-0.11 for severe wasting) and higher when mothers were underweight (OR = 1.77, CI = 1.61-1.94 for wasting and OR = 1.42, CI = 1.21-1.68 for severe wasting). There was little difference in the likelihood of wasting or severe wasting between wealth quintile 1 (poorest) and 2 and 3, but the likelihood was lower in quintile 4 and 5 (highest wealth). Like in the WHZ-Score model, the likelihood of a child being wasted or severely wasted was higher when the child had suffered from diarrhoea in the 2 weeks preceding the survey (OR = 1.42, CI = 1.28-1.58 for wasting and OR = 1.50, CI = 1.25-1.80 for severe wasting).

The SPEI was the only geospatial covariate that showed significant association with wasting and severe wasting as the likelihood of both wasting and severe wasting was higher when drought was worse. The likelihood of wasting was slightly higher in each month of the year (OR = 1.02, CI = 0.68-1.53 for May to OR = 1.26, CI = 0.64-2.47 for December in case of wasting and OR = 0.71, CI = 0.36-1.38 for May to OR = 1.56, CI = 0.56-4.34 for December in case of severe wasting) compared to April (reference month). However, the likelihood of severe wasting was lower from May to October compared to April but is higher in December (Figure 8).



Ethiopia - Wasting and Severe Wasting (Full Model)

Ref. Month: April, Ref. Year: 2000

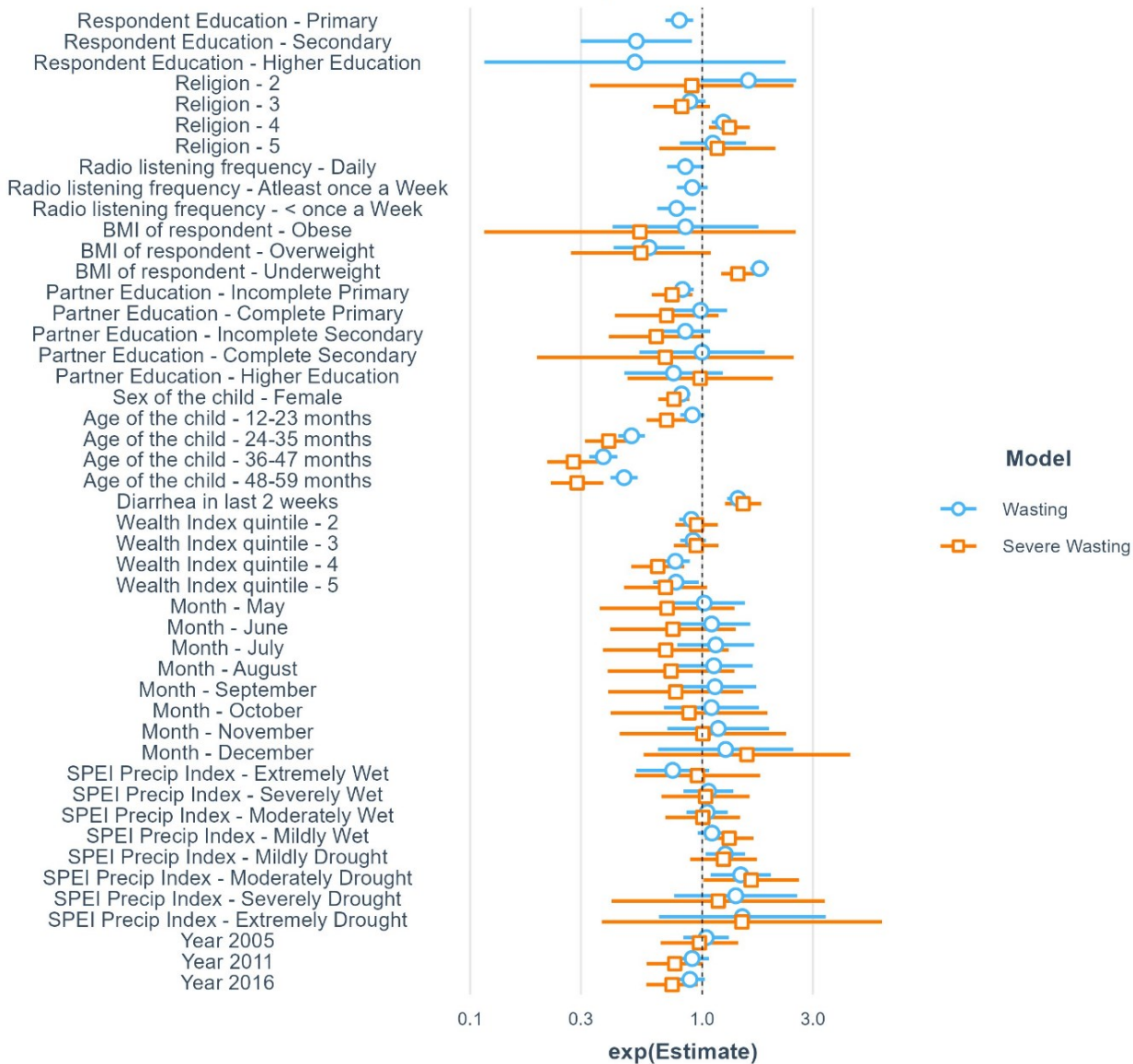


Figure 8 Ethiopia Wasting and Severe Wasting models. These models were both Logistic regression models and the plots show the likelihood of a child being wasted or severely wasted.

3.3 Nigeria

The full model for WHZ score with only significant covariates included is presented in figure 9. The Z-Score models indicated that wasting was higher in children aged 12-



23 months compared to 0-11 months. However, it was lower in children aged 24 to 59 months compared with children under 12 months. Wasting was higher in children that had suffered diarrhoea in the 2 weeks preceding the survey, if they were male, if their mother was underweight. Among the household covariates, the wealth index was the most significant covariate affecting the WHZ score in Nigeria. Compared to the poorest household (wealth quintile 1 as reference) wasting was lower in households from quintile 2 and 3 but it appears that wasting is higher in the wealthiest households (quintile 5) compared to the poorest. This was opposite to the trend reported for Nigeria DHS-2013 survey only where wasting prevalence was 20.2% in the poorest group vs. 14.2% in the richest group (Akombi et al. 2019). This was due to small numbers of households being present in the wealthiest quintiles in our dataset because we only used rural households/clusters and had removed urban clusters from the analysis. The month of data collection also showed a variation in WHZ scores such that the WHZ scores decrease in the latter half of the year with the worst scores in the month of October.

In the WHZ score model without geospatial variables, mothers' education had a significant association with WHZ scores (Appendix 6). Thus, children born to educated mothers have higher WHZ scores (lower wasting). Among the geospatial variables included, only SPEI was significantly associated with the WHZ scores where wet conditions and moderate to severe drought conditions showed beneficial effects in the WHZ scores.

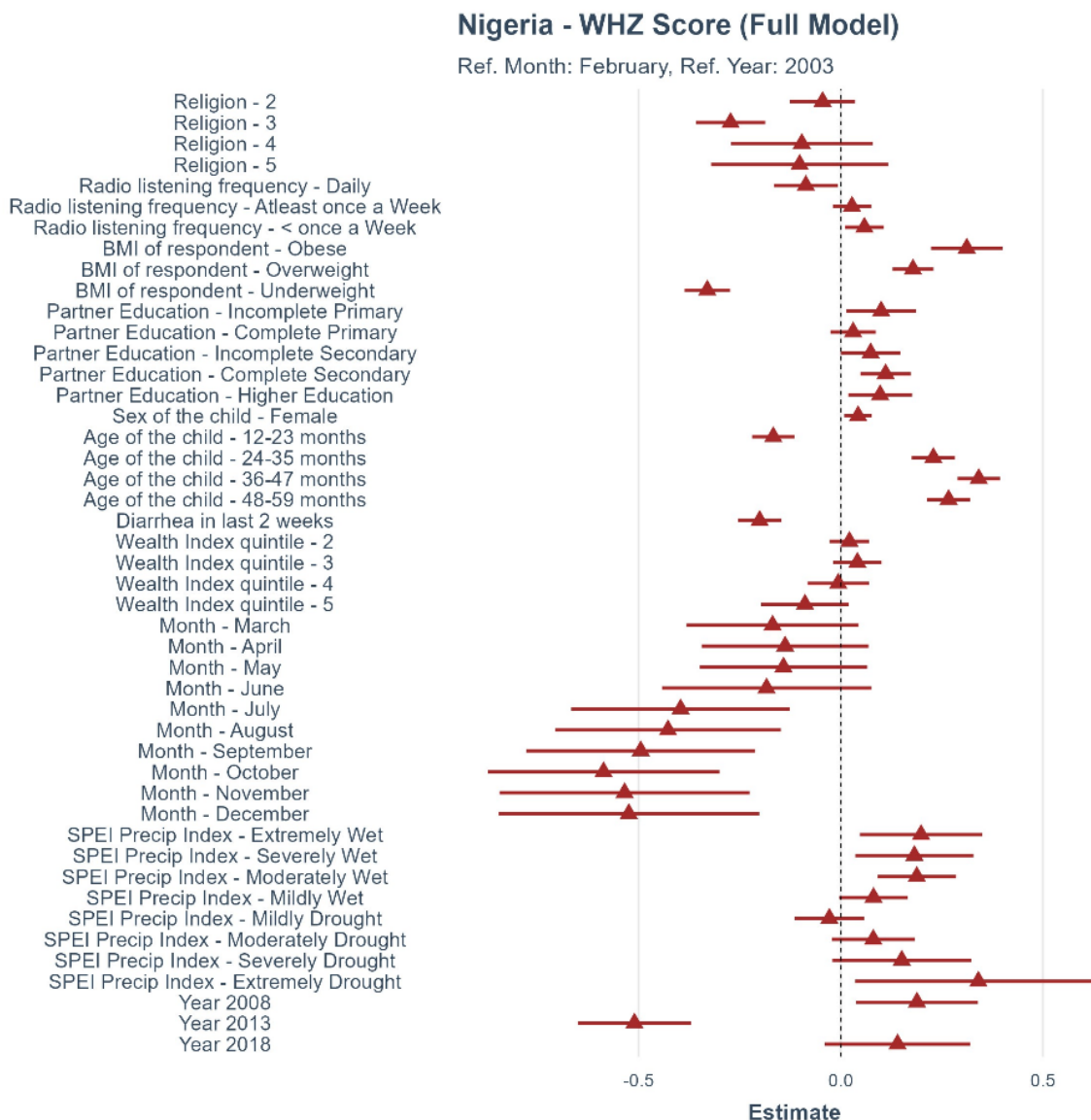


Figure 9 Nigeria WHZ score model forest plot. Higher wasting is seen to the left of the 0.0 line and lower wasting above.

The results of multilevel logistic regression model showed significant association between several household and individual level variables (Figure 10) and likelihood of wasting and severe wasting among children (<5 years). Among the household variables, religion and wealth index showed significant associations with wasting and severe wasting. The likelihood of wasting decreased with an increase in wealth



index quintile until the 4th quintile (odds ratio (OR) = 0.78, confidence interval (CI) = 0.67-0.92 meaning 28% likelihood of developing wasting and OR = 0.72, CI = 0.56-0.91 for severe wasting) followed by an increase in likelihood of wasting (OR = 1.00, CI = 0.79-1.26) and severe wasting (OR = 0.78, CI = 0.54-1.12) among children in households belonging to richest 20% of the population sampled. The sex and the age of the child was also significantly associated with the likelihood of wasting and severe wasting wherein female children were less likely to be wasted (OR = 0.88, CI = 0.82-0.94) or severely wasted (OR = 0.85, CI = 0.78-0.94). However, wasting/severe wasting was less likely in older children. As in the WHZ score model, the BMI of the women is associated with the likelihood of wasting/severe wasting demonstrating the role of mother's nutrition in determining children nutritional status. The seasonal variation in the wasting and severe wasting can be seen from the analysis with a significant increase in the likelihood of wasting/severe wasting from June (OR = 1.74, CI = 1.07-2.85 for wasting and OR = 1.90, CI = 0.92-3.90 for severe wasting) compared to February (reference month) peaking in October (OR = 3.71, CI = 2.15-6.38 for wasting and OR = 5.36, CI = 2.43-11.82 for severe wasting) followed by a decreasing trend until December (OR = 3.02, CI = 1.58-5.77 for wasting and OR = 3.88, CI = 1.41-10.66 for severe wasting). The results also showed increased wasting (OR = 2.56, CI = 1.71-2.97) and severe wasting (OR = 2.43, CI = 1.63-3.62) prevalence in the year 2013 followed by a significant reduction in the year 2018 (OR = 0.39, CI = 0.27-0.55 for wasting and OR = 0.24, CI = 0.14-0.40 for severe wasting).



Nigeria - Wasting and Severe Wasting (Full Model)

Ref. Month: February, Ref. Year: 2003

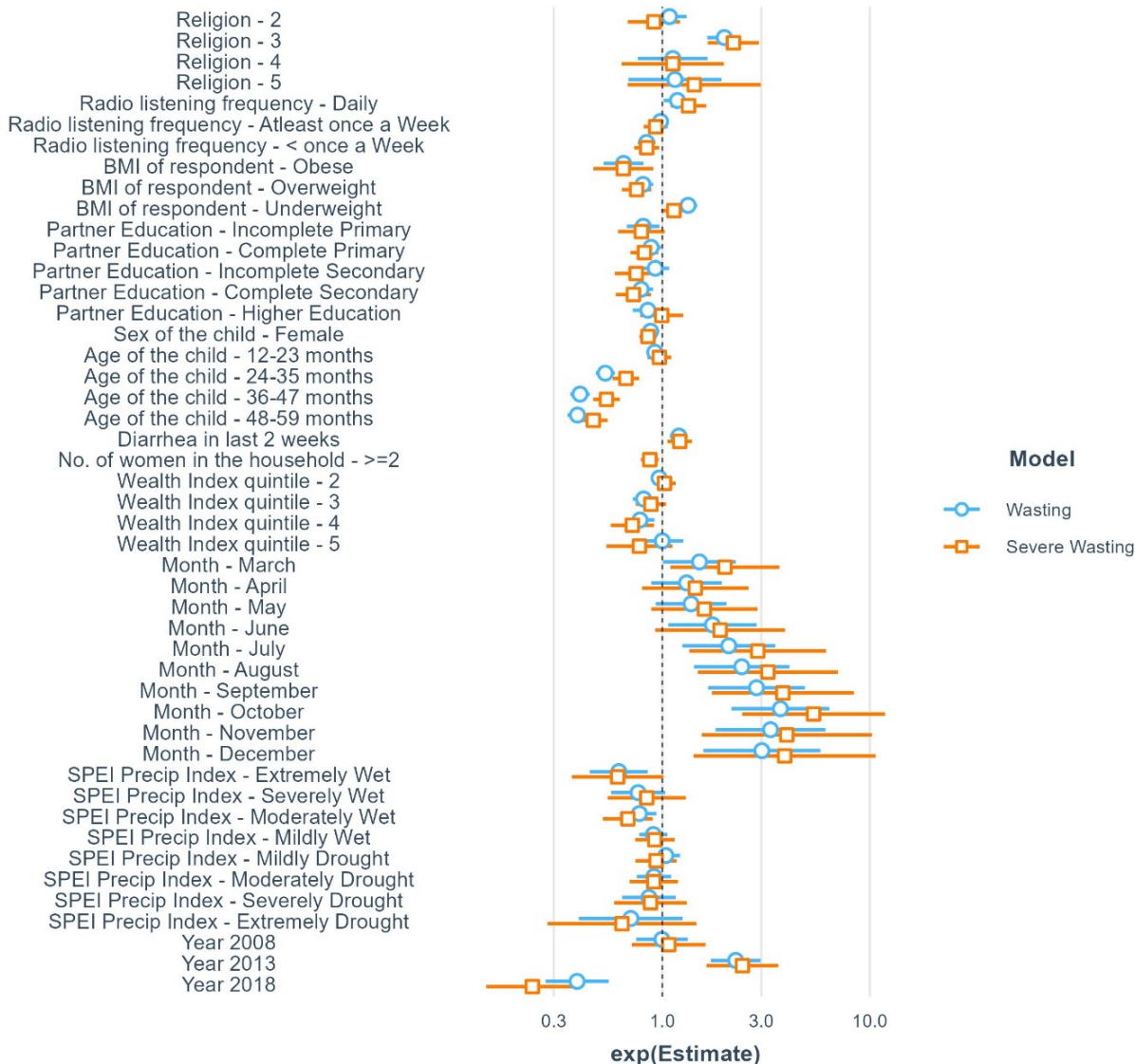


Figure 10 Nigeria Wasting and Severe Wasting models. These models were both Logistic regression models and the plots shows the likelihood of a child being wasted or severely wasted.

3.4 Actual versus Predicted prevalence

We observed a bimodal trend of wasting prevalence in Bangladesh whereby the prevalence increased from a low in January to a high in May, followed by a drop in June and a higher prevalence again in July which is often similar to the prevalence in May. From the second peak in July the fitted/predicted values then drop through to



the end of the year (December which often has the lowest wasting prevalence). The plot (Figure 11) includes the actual/observed wasting prevalence values that are available for Bangladesh, which shows a close match between the model predictions and the actual prevalence for most months across the time period.

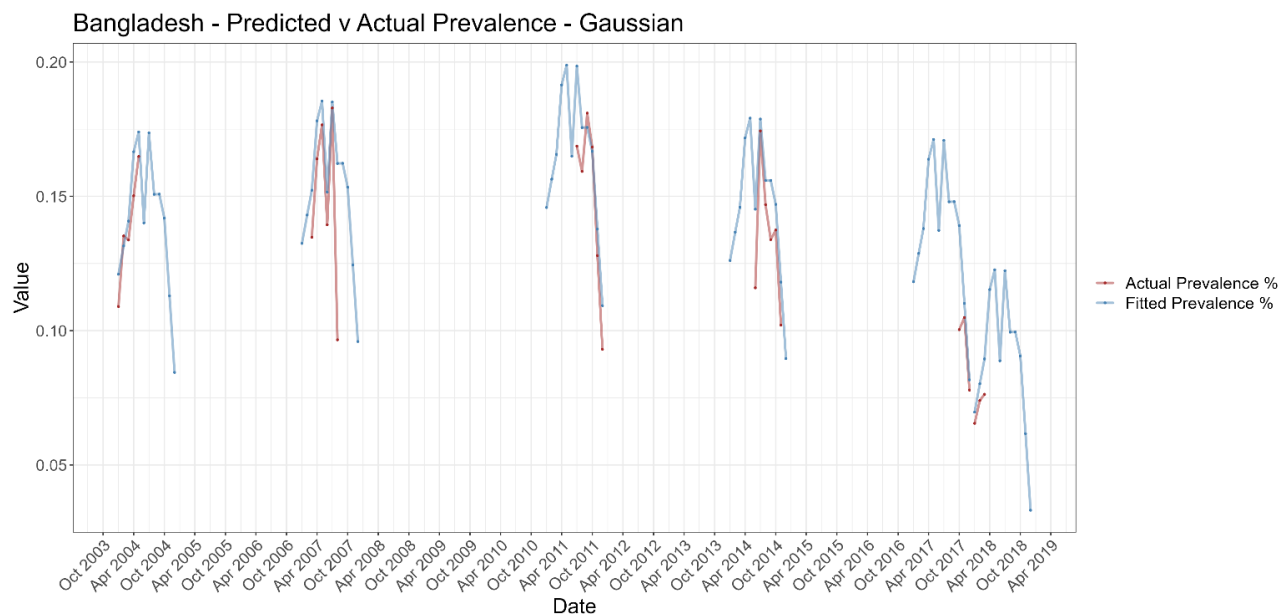


Figure 11 Predicted vs actual wasting prevalence for Bangladesh.

4. Discussion

Overall, the results indicate that the wasting scores do vary seasonally and that the month in which household surveys are conducted does impact the wasting scores and prevalence in all countries. The multi-level models for Burkina Faso, Ethiopia and Nigeria indicate that models using geospatial variables and survey responses perform better than models containing only geospatial variables or only survey responses. However, in Bangladesh the models using only geospatial variables have the lowest overall AIC/BIC values (Table 7) indicating a better overall model performance.



The actual vs predicted model for Bangladesh shows that we are able to estimate monthly wasting prevalence using the multi-level models that we have created (Figure 11). Models for Burkina Faso, Ethiopia and Nigeria are not shown as there was not enough data from enough time periods to establish accurate predictions. This model and the plot of actual vs predicted wasting scores also establishes that there is a wasting season in the data. Combining these with the forest plots for Bangladesh (Figure 5 and Figure 6) it is clear that Wasting scores and prevalence vary seasonally. For example, the month in which the survey was conducted is significantly correlated with wasting score and prevalence. January regularly had the lowest wasting values and was held as the reference value. Each other month had a higher wasting score, and this can be seen in the forest plots, with the double peak being captured in the plot between July and September (Figure 5).

Results for Burkina Faso, Ethiopia and Nigeria are less clear due to the lower amounts of DHS data available. However, the forest plots show that for the full models some of the seasonal variables are significantly related to wasting values. In Ethiopia and Nigeria, the SPEI index indicating extreme drought is significantly associated with wasting values. This is expected as rainfed agriculture dominates in these two countries and thus extreme drought will affect food production and indirectly it will also have an impact in incomes of rural communities reliant on food production. Extreme drought will also have a significant impact on child health more generally. All combined together this will lead to reduced food security and potentially higher levels of child wasting.

The models for Bangladesh revealed two additional unexpected results. The first was that wasting was higher in some of the older age groups which is unexpected. The usual pattern in wasting is that it is highest shortly after weaning from breast feeding and then declines to almost zero by the age of five. However, in Bangladesh the models predicted higher rates of wasting in older children (it was increasing throughout the age categories) – see figure 5. This is not expected and is counter to the evidence that we have in the wider literature. However, it is a feature of the DHS data (Table 8) which for Bangladesh shows a more complex pattern than the one traditionally seen. The second was that in 2017/2018 the wasting values in Bangladesh were unusually high across the country. However, this appears to be



related to the extensive flooding across almost all of Bangladesh around this time. The Dartmouth flood data confirms this, but the flood data was difficult to standardise and use in the modelling for this project. These unexpected results do however give us more confidence in the model performance as they are borne out in the data and are not artefacts of the modelling.

4.1 Geospatial covariate performances

The only geospatial covariate that appeared to be significantly associated with wasting was SPEI. Drought was associated with higher wasting in Ethiopia and Nigeria (Dimitrova 2021; Agabiirwe et al. 2022). Drought is not such a problem in Bangladesh where floods related to monsoonal rains are more often found to cause localized issues around food security. The fact that no other geospatial variables were significant in the models could be because SPEI covers aspects of three other covariates in that it considers rainfall and temperature within its calculation. Furthermore, NDVI and soil moisture will be associated with SPEI values. If SPEI shows extreme droughts, then soil moisture will be lower and NDVI will be less green.

The fact that few of the geospatial covariates were significant could be because of the spatial resolution of the data. This ranged from 5km to 55.5 km in climatic variables and 250 m in the NDVI. NDVI was only available on monthly averages in the year of each survey. It may be that more can be done with this variable in the future to look at how it is able to capture some of the seasonality in the wasting scores. We think there is some evidence that it can be used for this because NDVI was significant in most of the geospatial only models, but dropped out of the full models presumably because month of the year was added. In future, attention should be given to identifying if NDVI can be used as a proxy for month of the year and if so then it could be used to help inform the wasting levels. For the other climatic covariates (SPEI, soil moisture, temperature, and rainfall) it is likely that the spatial resolution of the data was a limiting factor. There is very little evidence that any of the geospatial covariates differed when split between wasted and not-wasted (Figure 12). The cluster points had a 5km radial buffer zone used to extract the climatic variables. But if the data has a spatial resolution of 27 or 55 km then the values will be the same for many clusters. This can create statistical artefacts in the



data whereby clusters with very different wasting scores are being modelled with climatic variables that are the same. In many cases the climatic variables may be very similar as they tend not to vary over short distances but in some cases, it may have an impact on the ability to model the outcome as you are effectively trying to predict different outcomes using the same predictors.

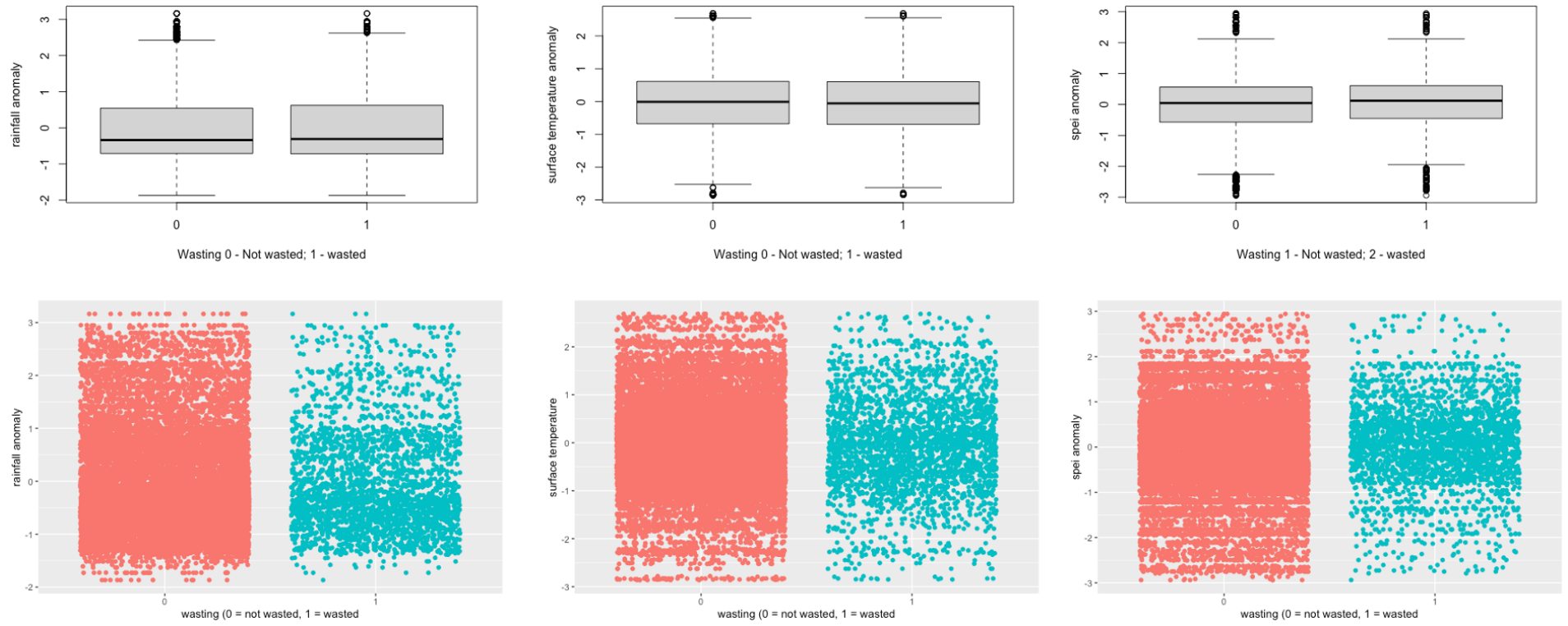


Figure 12 Bivariate plots between wasting and geospatial variables



4.2 Evidence of Seasonality in the Wasting Data

The increased likelihood of wasting and severe wasting in Bangladeshi children during the months of July and August may be attributed to the recurrent monsoon-induced flooding spanning from June to September. This substantially impacts agricultural yields and livelihoods, thereby diminishing the accessibility of sustenance and the economic capacity of households, consequently influencing the health of children. Furthermore, the escalation in food prices during this period, prompted by food scarcity, exacerbates issues related to food insecurity ([Food and Agricultural Organization of the United Nations \[FAO\], 2017](#)).

In Nigeria, the analysis showed an increased likelihood of a child being wasted based on the month as wasting was higher through March to July with a peak in October followed by a decrease through to December. Evidence suggests a slightly different lean period in the North of Nigeria compared to South. For instance, northern areas witnessed the lean period in the month of August in the year 2008 while hunger period peaks in June in South of Nigeria ([Famine Early Warning Systems Network, 2008](#)). Further, the repeated episodes of climate shocks and conflict aggravate the food insecurity in the country ([International Food Policy Research Institute, 2019](#)). This coupled with increase in food prices during lean season make the food insecurity even worse leading to increase in incidence of wasting during this time of the year ([FAO, 2013](#)). Moreover, household variables such as religion and wealth index of the child are the main contributor determining the wasting prevalence at the household level. The wealth index again directly influences the purchasing power of the household.

4.3 Model Assumptions/limitations

The multi-level model we used assumes linear relationships between the covariates and wasting. This is clearly not going to be true of all covariates. For example, soil moisture is not linearly related to wasting because there is a threshold at both the top and bottom of soil moisture whereby wasting is likely to increase because either the soil is too dry to for crops to grow or survive or it is too wet. Our model currently



assumes that as soil moisture increases the relationship with wasting is either positive and negative but crucially it does not allow for the fact that eventually the relationship will switch and become a problem for wasting when it is either too dry or too wet. We, however, fit a linear model for better interpretability of the effect of different covariates.

The project overall suffered from using only the DHS data on wasting. All countries were selected based on the availability of SMART surveys, MICS and DHS data. However, due to formatting differences and a short project time frame only the DHS data could be used. This led to a lack of data available for Ethiopia, Nigeria, and Burkina Faso. Each of these countries had certain months where no wasting scores were available and thus it was not possible to examine seasonal cycles to the same level as Bangladesh.

5. Conclusion

Child wasting varies intra-annually as well as annually and the multi-level models show that wasting, severe wasting and wasting z-scores vary by month and on clearly visible seasonal cycles. Thus, there does appear to be a wasting season in the countries examined in this study. Our models for Bangladesh were able to identify this seasonal pattern in Wasting prevalence and could predict the values on a monthly basis. Often these patterns are linked to prevailing harvest times in each country. Geospatial data on drought and in particular extreme drought was a significant predictor of wasting in Ethiopia and Nigeria where water is a limiting factor for rainfed agriculture. However, it was less relevant in Bangladesh, we think because drought is less of a problem. Overall, this study finds that using DHS data it is clear that the wasting scores do vary depending on the month in which the household surveys are collected, this variation does appear to have a seasonal component and our multi-level logistic regression models were able to estimate these variations using a combination of DHS survey responses and geospatial covariates extracted from satellite imagery. To establish if monthly wasting score adjustment factors can be developed, we recommend further work to combine MICS, SMART and other surveys that contain child nutrition data.



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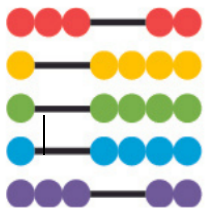
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