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RESEARCH ARTICLE

Food and nutrition security trends and challenges in the Ganges Brahmaputra Meghna (GBM) delta

Arnout van Soesbergen[*,§], Kristine Nilsen[†], Neil D. Burgess[*], Sylvia Szabo[‡] and Zoë Matthews[†]

The population of the Ganges Brahmaputra Meghna (GBM) delta is highly vulnerable to food insecurity and malnutrition due to the specific environmental, climatic and human development factors affecting agricultural production and fisheries. To better understand the impacts of climate and environmental change on food security and nutrition in this delta, this study combines spatially explicit data from the 2007 and 2011 Bangladesh Demographic and Health Survey (BDHS) with a standard satellite remotely sensed vegetation greenness index (Normalised Difference Vegetation Index, NDVI), used as a proxy for rice production. The strength of association between NDVI and child nutrition in this tropical mega-delta were tested, showing correlations between two widely used indicators of child malnutrition; stunting and wasting, and deviations from a 10 year mean NDVI (anomalies) for rice crop growing seasons – regarded as critical to individual children's early lives. For children surveyed in 2007 we found that the likelihood of being stunted decreased with increased NDVI as a measure of food production. Similarly, for children surveyed in 2011, the likelihood of being wasted reduced with increased NDVI. However, regression results for stunting in 2011 and wasting in 2007 were not statistically significant. Our findings suggest that NDVI can be regarded as indicative of climatic variability and periods of low food production but is only partly successful as an indicator of climate related impacts on child nutrition in the GBM delta. Furthermore, our study highlights some of the uncertainties and challenges with linking environmental indicators such as the NDVI with household survey data across spatial and temporal scales.

Keywords: GBM Delta; nutrition; climate change; NDVI; stunting; wasting

1. Introduction

It is estimated that more than 20% of the global population remains food insecure (FAO, IFAD, and WFP, 2015; Wheeler and von Braun, 2013) and due to a rise in consumption, rapid urban growth and changing population dynamics, food demand may increase by 70% by 2050 (Royal Society, 2009). The challenge of meeting this increased demand is exacerbated by demographic changes, political instabilities, and environmental change, including the impacts of climate change (Poppy et al., 2014). These challenges are particularly pertinent to the densely populated tropical mega deltas of the global south, dubbed the 'rice bowls' of the world.

* UN Environment World Conservation Monitoring Centre, GB
† Social Statistics and Demography, University of Southampton, GB
‡ Hunger and Nutrition Team, Save the Children, GB
§ Environmental Dynamics Research Group, Department of Geography, King's College London, GB
Corresponding author: Arnout van Soesbergen (arnout.van-soesbergen@unep-wcmc.org)

In the last 20 years many developing countries have made considerable progress towards improving food security and nutrition. However, progress across countries and dimensions of food security have been uneven (FAO et al., 2015). This is particularly true in countries which are home to major tropical deltas, such as Bangladesh where around a third of children are still classified as undernourished (IFPRI, 2015). While challenges to food security in the context of environmental and climate changes have been studied widely, limited evidence exists on their implications for food and nutrition security in tropical deltaic regions. Delta areas are particularly vulnerable to food insecurity and malnutrition due the specific environmental, climatic and human development factors affecting agricultural production and fisheries. These include coastal flooding and storm surges, deforestation, changes to river flow patterns and water tables, increased soil salinity and water quality degradation (Foufoula-georgiou et al., 2013).

Due to the relatively large number of people living in deltaic regions and their importance in regional food production (Szabo et al., 2015), there is a pressing need for a better understanding on how environmental factors affect food security and malnutrition. In this study we address this gap by exploring the potential impacts and challenges posed by environmental and climate change on food and nutrition security in the Bangladesh part of the world's most populated delta, the Ganges-Brahmaputra-Meghna delta. We analyse the relationship between child nutrition outcomes and environmental variability by linking remotely sensed data on green vegetation as a proxy for crop productivity to child growth using geo-referenced household survey data from Bangladesh Demographic Health Surveys (BDHS) for 2007 and 2011. We specifically included the spatial and temporal dimensions of crop productivity and children's growth, to allow for a more detailed analysis of relevant growing seasons for specific children's developmental periods.

2. Background

2.1 Bangladesh and the GBM delta

Bangladesh is one of the poorest and most densely populated countries in the world, covering an area of 144,000 km^2 with a population of over 150 million (2011) which, despite one of the most rapid recent fertility declines of any nation, is still projected to grow to around 200 million by 2050 (Mainuddin and Kirby, 2015). The country faces high levels of child undernutrition and child mortality and a large number of people are living under extreme poverty. The main food crop is rice which accounts for around 70% of daily caloric intake (Ricepedia, 2016). Food insecurity is closely linked to poverty with rural households spending nearly 60% of their household budget on food. Annually, more than 29 million tons of rice are produced in the country on an area of around 10.14 million ha with an additional 2.8 million ha of inundated seasonal rice fields where water remains for around 4–6 months (Ahmed and Garnett, 2011).

Bangladesh makes up around two thirds of the Ganges-Brahmaputra-Meghna (GBM) delta, one of the world's largest deltas with an area of around 100,000 km^2 draining land from Bangladesh, Bhutan, China, India and Nepal (Goodbred and Kuehl, 2000). The remaining third of the delta falls within the Indian province of West Bengal (**Figure 2**). A large part of the delta is less than three metres above sea level and tidal influence reaches up to 100 km inland, therefore nearly a quarter of the country of Bangladesh can be considered coastal. On the coast lies the world's largest stretch of mangrove forests, the Sundarbans Reserve Forest which is strictly protected.

2.2 Food security challenges

Bangladesh faces many food security challenges. Coastal flooding is common and each year during the high monsoon (July–September) nearly 18% of the country is flooded with loss of lives and destruction of property and crops. While annual flooding is normal, so-called hazardous floods (flooding about one-fourth of the country) have become more frequent in recent years, happening about every 4 years in the late 1990s compared to roughly every 30-years prior to the 1940s (Ali, 2007). In the last 15 years, the country was hit by a number of devastating flood events and cyclonic events causing storm surges and flooding. In September 2004, a major flood hit the normally dry and drought prone south-western districts of Jessore, Satkhira, Khulna, Magura and Chuadanga affecting over 5 million people as well as the Aman rice crop of that year. In November 2007, cyclone Sidr, one of the worst to hit the country since 1991 caused up to 15,000 fatalities and severe loss of homes and crops. The next biggest event happened in May 2009 when cyclone Aila caused severe flooding in the coastal regions of Bangladesh resulting in extensive damage to houses, rendering an estimated 1 million people homeless (Panda and Nair, 2011). As well as direct loss of life and damage, these cyclones were followed by outbreaks of a number of diseases such as diarrhoea, pneumonia and typhoid, mainly due to a shortage of drinking water in the affected areas (Kouadio et al., 2010).

Due to climate change and accelerated sea-level rise, the frequency and severity of floods associated with cyclones and other major coastal storms are likely to increase in the future (Dasgupta et al., 2011; Woodruff et al., 2013; IPCC, 2014), ranking Bangladesh the most vulnerable country to climate change with potential negative impacts on agricultural production, including fisheries (Allison et al., 2009; Maplecroft, 2014). As well as the indirect impacts on agriculture through storms and associated flooding, changing temperatures are projected to reduce crop yields, for example, Hossain and da Silva (2013) found that climate change could potentially reduce grain yields in the region between 3 and 15 percent (by 2050) while Basak et al., (2010) found that increasing temperatures have a potential negative impact on Boro rice crop yields.

One of the main food security challenges in Bangladesh and the GBM delta is salt water intrusion caused by sea level rise and reduction in flow of the Ganges as a result of upstream dams. Salt water intrusion into surface and groundwater in the coastal region results in greater soil salinity which is negatively affecting livelihoods, especially of the poorest, as farmers abandon agriculture or convert fields to shrimp ponds (Rabbani et al., 2013).

2.3 Environment-nutrition linkages

Well-nourished children under the age of five tend to show similar heights and weights in their growth trajectories, despite geographic, ethnical and cultural differences (Habicht et al., 1974). Therefore, any differences between children's growth rates can be attributed to socio-economic and environmental factors (Shively et al., 2015). Stunting, or low height-for-age is an indicator of long-term nutritional status of a child, indicating nutritional deficiencies as well as repeated illness. Stunting is associated with insufficient food intake and unhealthy physical environments. Wasting, or low weight-for-height is an indicator of the short-term nutritional status of a child and is very sensitive to recent and severe events. Stunting is mostly determined by conditions during the first two years of a child's life and effects are largely irreversible. The World Health Organization (WHO) defines stunting and wasting respectively as a child having a height-for-age or weight-for-height score of less than 2 standard deviations below the WHO child growth standards median (World Health Organization, 2006).

In Bangladesh, the prevalence of stunting and wasting in children under five years of age are among the worst in the world. According to the 2011 Bangladesh Demographic Health Survey (BDHS), 36% of children under five are underweight and as much as 41% are considered stunted (NIPORT/MITRA/ICF, 2013). Globally, an estimated 27% of children were stunted in 2010, around 38% in Africa and around 27% in South East Asia (De Onis et al., 2011).

Drivers of child nutrition are often explained by analysing associations between children's anthropometric data and household, maternal and child characteristics using sample survey data. To assess the impacts of environmental and climate variability on food security and nutritional outcomes it is necessary to use quantitative, spatially explicit data on environmental indicators and combine these with nutrition indicators. Conceptual linkages between environmental conditions and child nutrition and health are illustrated in **Figure 1**. Climatic variability and extreme events such as cyclones and floods reduce crop yields and environmental productivity which lead to a reduction in availability of food as well as a reduction in family resources and thus access to food which in turn can lead to child under-nutrition. As well as impacting crops, climatic variability can directly impact on health and activity in turn affecting child nutrition, e.g. low rainfall has been shown to cause an increase in malaria due to drying up of rivers and streams resulting in increased breeding sites (Haque et al., 2010). It is important however to assess these linkages in a spatial context. In Bangladesh poor rural households rely on agriculture for their livelihoods which means that access to food is determined by household's capacity to grow or sell crops from their own farmland or supported by agricultural labour on farms nearby. In this study we use the Normalised Difference Vegetation Index (NDVI) from satellite data as a spatially explicit measure of the production and yield of rice as the main food crop in Bangladesh. The NDVI is a measure of photosynthetic activity or greenness and is calculated as a ratio of light reflected in the red portion of the electromagnetic spectrum versus light reflected in the near infrared spectrum. The index is then calculated as.

NDVI = (NIR – RED)/(NIR + RED). The possible range of values is between –1 and 1, where values increase from 0 to 1 as vegetation increases while negative or zero values indicate an absence of vegetation.

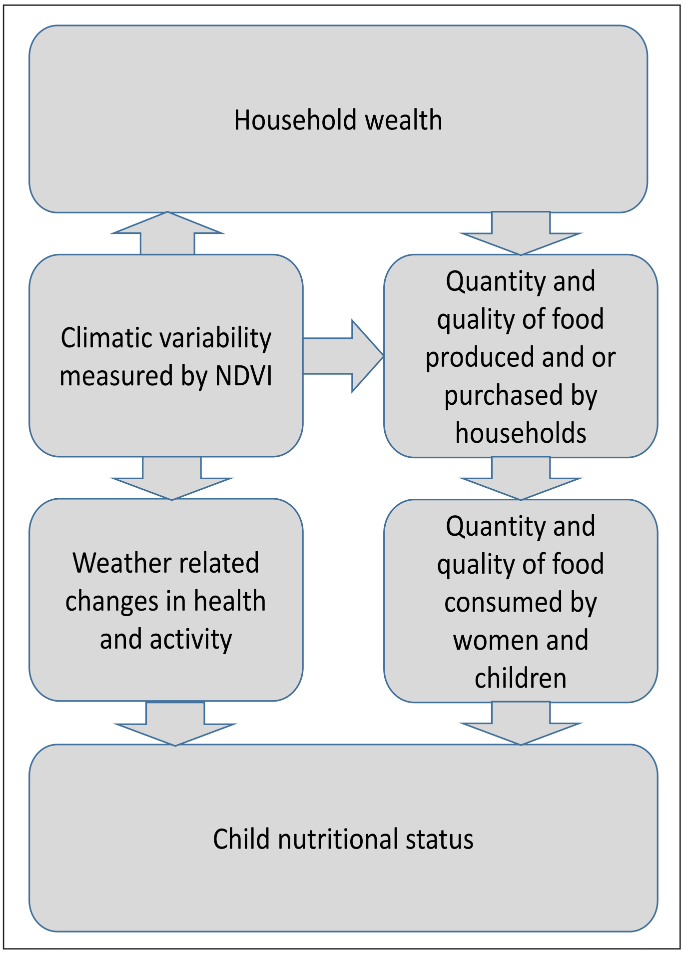

Figure 1: Conceptual linkages between climatic variability and child nutritional status. Climatic variability and extreme events such as cyclones and floods reduce crop yields and environmental productivity which lead to a reduction in availability of food as well as a reduction in family resources and thus access to food which can impact child nutritional status. As well as impacting crops, climatic variability can directly impact on health and activity in turn affecting child nutrition (adapted from Shively et al., 2015). DOI: https://doi.org/10.1525/elementa.153.f1

The NDVI can be considered a good indicator of the combined effects of rainfall, temperature and land cover as it captures moisture and temperature stress and allows for comparison of growing conditions across regions (Hoefsloot et al., 2012; Shively et al., 2015). NDVI data are used by food security analysts in early warning and vulnerability information, e.g. the Famine Early Warning Systems Network (FEWS NET) funded by USAID (Brown, 2008). Here we use the NDVI as a proxy for maternal food access and availability during gestation and child food access after birth (Grace et al., 2014; Shively et al., 2015). NDVI values are assumed to be indicative of rice yield and production in this region, which is supported by a number of studies (e.g. Rahman et al., 2012; Son et al., 2014). Ideally, this assumption is validated using ground observations of rice yield and production in the years and seasons studied. However, this was beyond the scope of this exploratory study. NDVI values have been used in a few other recent studies linking environmental variables with child nutrition outcomes, for example Johnson and Brown (2014) found higher rates of stunting and wasting in children under five years of age under dry conditions with low NDVI values for several countries in West Africa and Shively et al., (2015), using NDVI anomalies found heterogeneous relationships between environmental conditions and child growth across Nepal.

3. Data and methods

3.1 Study area

Our study focuses only on the Bangladesh portion of the GBM delta (**Figure 2**) as geo-referenced household survey data from DHS was not available for the Indian

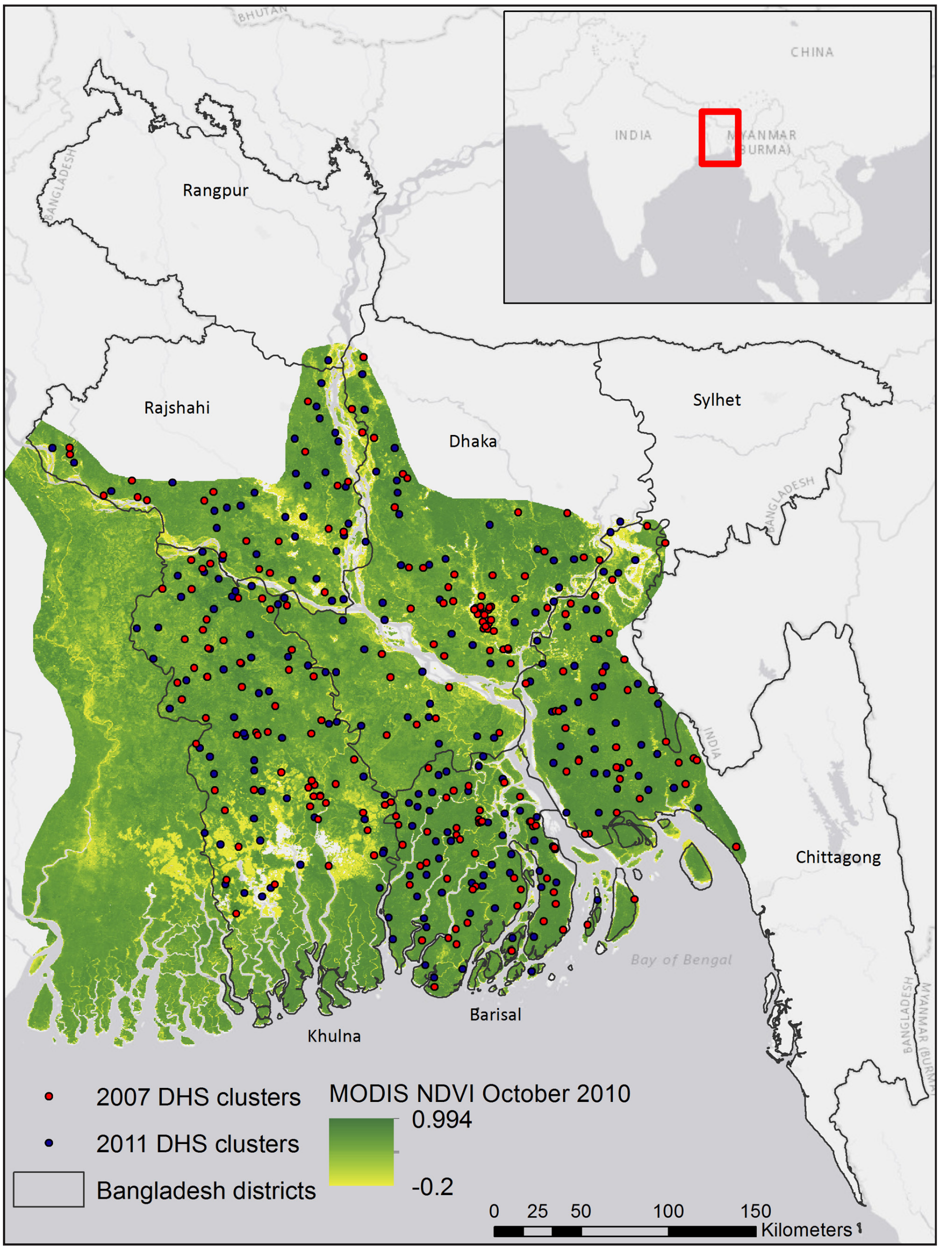

Figure 2: Location of Demographic Health Survey clusters within the GBM delta. Our study area encompasses the GBM delta within Bangladesh only. The extent of the GBM delta is outlined by the MODIS NDVI for the month of October 2010. DOI: https://doi.org/10.1525/elementa.153.f2

West Bengal region. The boundary of the GBM delta was defined based on Goodbred and Kuehl (2000). The delta boundary fully covers the Bangladesh administrative divisions of Khulna and Barisal but only partly covers the divisions of Rajshahi, Dhaka, Chittagong, Rangpur and Sylhet.

3.2 The 2007 and 2011 Bangladesh Demographic and Health Survey

We obtained nutritional status and other individual and household level characteristics from the 2007 and 2011 Bangladesh Demographic Health Surveys (BDHS). The BDHSs are nationally and sub-nationally representative cross-sectional household surveys with samples selected using a stratified two-stage cluster sampling design. Each cluster with samples is geo-referenced with a total of 215 and 213 sample clusters for 2007 and 2011 survey years respectively falling within the boundaries of the GBM delta (**Figure 2**). While the BHDSs include samples in both urban and rural areas, only clusters in rural areas are included in the analysis. The total number of households included in the 2007 and 2011 BDHS samples in the rural GBM delta were 9,190 in 2007 and 9,128 in 2011.

3.3 Normalised Difference Vegetation Index

We use the satellite remote sensing derived NDVI index as a spatially explicit proxy for yield and production of rice. Rice production can successfully be monitored using NDVI values, e.g. Shapla et al., (2015) use MODIS NDVI data to estimate rice production in five districts in Bangladesh for the time periods 2001–2003 and 2011–2013. Gumma et al., (2014) also used MODIS NDVI data to map the rice crop extent and area for the year 2010, finding slightly higher rice area estimates (3–6%) than sub-national statistics. Similar studies have been carried out in other rice dominated areas such as the Mekong delta (Nguyen et al., 2015; Son et al., 2014). Whilst the production of irrigated rice can be assessed with NDVI, the response to variation in rainfall may be different than that of non-irrigated rice due to the potentially different timings of water availability.

The possible range of the NDVI index is between –1 and 1, where values increase from 0 to 1 as vegetation increases while negative or zero values indicate an absence of vegetation. The typical range of values in the GBM delta varies between 0.2 and 0.7. Values tend to be high in October due to the Aman rice growing season. February sees the lowest values mostly due to low rainfall (Shapla et al., 2015).

Rice is the staple crop in Bangladesh, accounting for nearly 70% of the daily caloric intake relative to other sources such as wheat and maize in 2009 (Ricepedia, 2016). There are three main rice types grown in the country. The rain-fed transplanted Aman (T. Aman or monsoon rice) is grown from July to December, making it particularly prone to monsoon floods. Boro, or winter rice which is irrigated rice grown from January to June and Aus rice which is grown between March and August. Aman rice makes up around 50% of the total rice area in Bangladesh, contributing 40% of the total rice yield in the country (Kwak et al., 2015). All three rice types are grown throughout the country and the delta with the exception of the Sundarbans.

Here we focus on the Boro and Aman rice types. Together these make up more than 80% of rice production in Bangladesh, occupying a total production area of 10.37 million ha in 2013 (Bangladesh Bureau of Statistics, 2016). To capture the growing season for these rice types, we use the mean NDVI for the months of April and May for Boro rice and September–November for Aman rice.

We use NDVI data derived from NASA's MODerate resolution Imaging Spectroradiometer (MODIS) instruments on board NASA's Terra and Aqua satellites. Data are collected twice daily since the year 2000 and raw data from these sensors are composited into daily, 8-day, 16-day and annual imagery. We obtained the 16-day composited NDVI data from the MOD13Q1 NDVI product at 250 metre spatial resolution from the Oak Ridge National Laboratory Distributed Active Archive Center (ORNL DAAC) using the MODISTools R package (Tuck et al., 2014) which allows for easy access, downloading and processing of MODIS data. Data were downloaded for each household survey cluster location in the 2007 and 2011 DHS surveys.

3.4 Combining BDHS and NDVI data

The BDHS surveys record GPS coordinates for each centre of populated area surveyed (cluster centroid). To ensure confidentiality, a random displacement is applied to these data. Therefore, rural points contain a minimum of 0 and a maximum of 5 kilometre error. Another 1% of rural points is offset to a maximum of 10 kilometre. Urban locations are offset with a minimum of 0 and a maximum of 2 kilometres. To account for the potential displacement of BDHS cluster points, mean NDVI data for 16-day composites was calculated for each cluster centroid and the surrounding 625 pixels, representing an area of 6.25 × 6.25 kilometres for the period 2000–2011. The 16-day data was then combined into monthly means and long-term monthly means for the whole data period were calculated.

3.5 Variables in the analysis

Dependent variables

Our analysis included two dependent variables indicative of child malnutrition: stunting and wasting. The BDHS survey data includes information on stunting and wasting for children aged five years and younger at the time of survey. Stunting or low height-for-age (HAZ) and wasting or low weight-for-height (WHZ) Z-scores are calculated using the WHO Child Growth Standards (World Health Organization, 2006). Children are considered stunted or wasted with Z-scores below –2 standard deviations. Stunting is generally associated with insufficient food intake and unhealthy physical environments. Wasting, or low weight-for-age is an indicator of acute undernutrition of a child and is very sensitive to recent and severe events. Stunting is mostly determined by conditions during the first two years of a child's life and effects are largely irreversible. We extracted values for stunting for all children aged 6–59 months old at the time of survey (n = 1,650 for 2007 and n = 2,683 for 2011). For the analysis on wasting we used WHZ values for all children under five years of age for the full sample of both the 2007 and 2011 surveys.

The continuous Z-scores were transformed into binary values with children stunted or wasted (Z < = 2) coded '1' and all other children coded '0'. This transformation does result in a loss of information. However, the objective of the study is to explore the relationship between NDVI and child stunting and wasting and not partial effects on Z-score outcomes.

Independent variables

We used the mean NDVI and NDVI anomaly (defined as a departure of an observed monthly NDVI from a long term (11 year) average, i.e. if rice production is more or less than the long term average) for relevant growing season months based on individual childrens' birth month for both Boro and Aman rice as independent variable. Similar to Shively et al., (2015) we use NDVI anomalies rather than actual mean NDVI values for growing season months due to the similarity of NDVI values for the years of interest creating a potential for collinearity with repeated measurements. For our stunting model, we used the NDVI anomaly for growing seasons months for the year of conception and the first and second year of life (n = 0, n + 1 and n + 2). For the wasting model we used the mean of the most recent growing season of Boro and Aman rice in relation to the interview date.

To control for potentially confounding factors in our analysis of the relationship between child nutrition outcomes and environmental variability we included the following control variables: geography (division), household wealth (measured as an asset index constructed by DHS), child's age and sex, birth order, preceding birth interval and mother's age, education and nutritional status. A mother is considered underweight if she had a BMI of less than 18.5 (Freedman et al., 2006). The full set of dependent variables used in the analysis are provided in tables S1 and S2 for the stunting and wasting analysis respectively with standard deviations, minimums and maximums reported for all variables.

3.6 Statistical methods

We used multivariate logistic regression to examine the associations in each of the two years (2007 and 2011) between the independent variable (NDVI anomaly for growing season months) and the dependent variables stunting and wasting while controlling for background characteristics (i.e. four models in total).

Before each model was fitted, bivariate analyses, using chi-squared tests were performed to assess the associations between each of the dependent variables and each of the categorical independent variables. Because all analyses adjusted for clustering, chi-squared statistics were converted into F-statistics. Independent variables that had significant associations (p-value < 0.05) were then considered for inclusion into the relevant multivariate logistic regression. Forward selection method was used in the regression modelling process and log likelihood ratio test to assess covariate significance. Interactions between dependent variables were then explored. The aim of the modelling process was to obtain parsimony i.e. only covariates with a significant effect in either year were retained in the models, for each independent variable respectively.

The logistic regression equation is given as:

$$log\left(\frac{\pi}{1-\pi_i}\right) = \beta_0 + \beta_1 + \beta_2 x_i + \ldots + \beta_k x_i$$

Where β_0 is the intercept and β_k is the value of the regression coefficient measuring the effect of the independent variable *x*, on the dependent variable *y* for individual *i*. Results are presented as odds ratios and predicted probabilities were calculated to describe the associations between child nutrition outcomes and independent variables without attributing causality. Odds ratios are the exponentials of each coefficient β_k given the above equation, and is interpreted as the effect of a one unit increase in x_k on the odds that $y_i = 1$, holding other all other variables constant. For categorical variables, a reference category is defined, for ease of interpretation. In the case of NDVI anomalies, predicted probabilities are also used to interpret the effect on stunting and wasting if the effect is significant at $p < 0.05$. Predicted probabilities vary between zero and one and are calculated as:

$$\pi = \frac{\exp(\beta_0 + \beta_k)}{1 + \exp(\beta_0 + \beta_k)}$$

The analysis was adjusted for the multistage cluster design of the DHS samples and weights were applied to account for unequal selection probabilities of households. All statistical analyses were performed with Stata 14 software (StataCorp, 2015).

4. Results

4.1 NDVI results

The mean NDVI anomaly for the growing season of Boro rice (April–May) and Aman rice (Sep–Nov) for all sampling points for the 2007 and 2011 BDHS surveys for the period 2000–2011 (**Figure 3b** and **3c**) show a strong inter-annual variability with particular low values for the years 2004 and 2007 for Aman rice. These years correspond to the occurrence of floods and cyclones which affected production of all crops and a reported reduction of up to 50% of Aman rice production in some areas in 2007 (FAO and WFP, 2008). Particular anomalies for the Boro rice growing season appear in 2006 and 2010 (negative) and 2011 (positive). There are no significant climatic events related to the Boro rice anomalies. However, reported Boro rice yields for 2006, particularly for the more traditional varieties are much lower (>1SD) than the mean for the period 2000–2009 (Alam and Islam, 2013), therefore the anomalies are likely to be indicative of lower production.

4.2 Characteristics of the BDHS sample

More than 45 percent of children were stunted in 2007 with slightly lower values for 2011 (43%) (Table S1). The percentage of male and female children in the samples are

Figure 3: Rainfall and NDVI during growing seasons of Boro and Aman rice for the period 2000–2011. Mean rainfall during growing season for Boro (April–May) and Aman (Sep–Nov) rice and 10-year means (in grey) **(a)** and mean NDVI anomaly for all cluster areas for 2007 **(b)** and 2011 **(c)** for growing season months of Boro and Aman rice for the years 2000–2011. DOI: https://doi.org/10.1525/elementa.153.f3

roughly the same with a mean age of about 32 months. In both samples, the majority of mothers were aged 20–29 years old with about 15% aged below 19 years old. About one-third of mothers were underweight in both survey years. About 25–30% of children in the samples resided in Chittagong or Dhaka, respectively. Mean NDVI anomalies are negative for the period before the 2007 survey but slightly positive in the period up to the 2011 survey. Just under 20 percent of children are considered wasted in the 2007 survey (Table S2), again with slightly lower values for the 2011 survey (16%). Similar values to the stunting model are found for the other variables in the wasting model.

Figure 4 shows the percent of children stunted or wasted by age of the child in months. Not unexpectedly, the trend in the percentage of children stunted tends to increase between 5–10 months to 20 months before stabilising, reflecting that stunting is a long-term effect of malnutrition. The trend in the percentage of children wasted is higher at early ages in 2007 compared to 2011 before stabilising around roughly 20%. Such high fluctuations in the proportion of children wasted and stunted by age has been observed in previous studies (e.g. Shively et al., 2015).

Table 1 shows the bivariate relationship between stunting and wasting by background characteristics according to year for categorical variables. Birth order, mother's nutritional status, mother's educational status, wealth and division are significantly associated with stunting irrespective of year. In 2011, the length of the preceding birth interval was also significantly associated with stunting. Only mother's nutritional status was significantly associated with wasting in 2007. In contrast, birth order, mother's education, nutritional status and wealth status were significantly associated with wasting in 2011.

4.3 Regression results

Stunting and NDVI

Controlling for background characteristics, NDVI anomaly is a significant predictor of stunting in 2007 ($p < 0.05$) (**Table 4**). The probability of being stunted in 2007 is negatively associated with NDVI anomaly whereby negative values of NDVI anomalies averaged over 3 years are associated with a higher probability of being stunted (**Figure 5**). For example the probability of being stunted in an area with an NDVI anomaly of –0.5 is about 0.6. In contrast, the probability of being stunted in an area with an NDVI anomaly of 0.3 is around 0.4. This supports our hypothesis that lower than average NDVI values over multiple growing seasons increase the odds of being stunted. However, no significant associations between stunting and actual NDVI values in either year or between stunting and NDVI anomalies in 2011 were found (**Table 2**). For both 2007 and 2011, household socio-economic status (wealth) is a key determinant of stunting, whereby the odds of being stunted reduce with wealth. For example, the odds of being stunted among Q5 (the richest quintile) are reduced by 81% in 2007 and by 72% in 2011 compared to Q1 (the poorest quintiles), respectively (**Table 2**). Significant relationships between wealth and stunting have been reported in numerous studies (e.g. Hong and Mishra, 2006; Johnson and Brown, 2014; Srinivasan et al., 2013). Wealthier households are likely to have greater access to food or may be less reliant on rice alone. Child's age was also found to be a significant predictor of stunting irrespective of year and this has also been reported in similar studies (e.g. Johnson and Brown, 2014).

The likelihood of being stunted is also significantly associated with mother's nutritional status in 2011 but not in 2007. In 2011 the odds of a child being stunted increase by around 48% when the mother is underweight compared to a child to a mother that has a normal BMI/overweight.

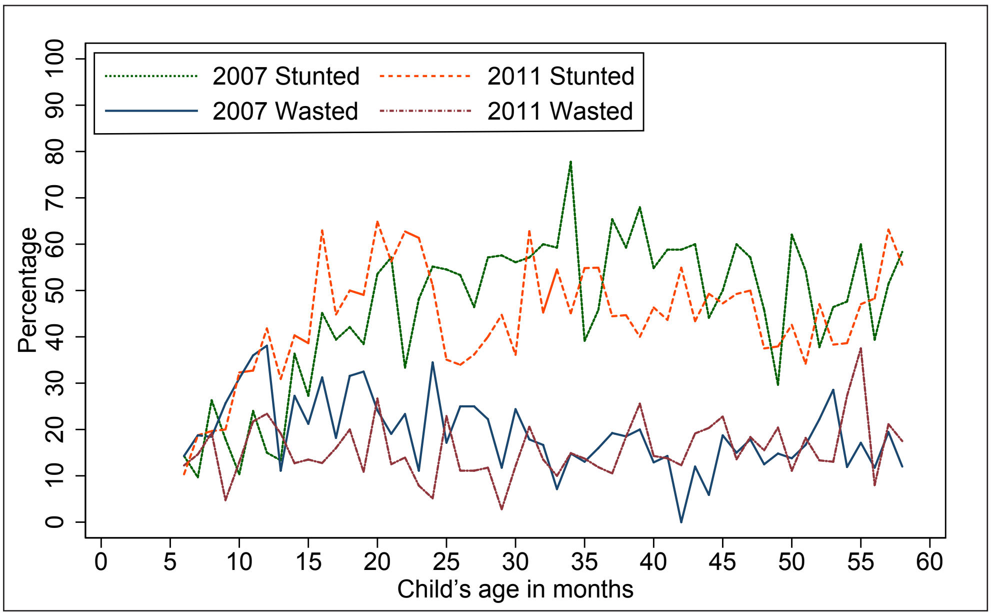

Figure 4: Percentage of children stunted or wasted according to age of the child. The percentage of children that are stunted and wasted by age in months from the BDHS dataset for the survey years 2007 and 2011. DOI: https://doi.org/10.1525/elementa.153.f4

Table 1: Percentage of children stunted or wasted according to year and background characteristics. DOI: https://doi.org/10.1525/elementa.153.t1

	Stunted				Wasted			
	2007		2011		2007		2011	
	Mean	Test statistic	Mean	Test statistic	Mean	Test statistic	Mean	Test statistic
Child								
Sex								
Male (ref. category)	44.7	0.22	40.9	2.65	20.3	2.60	15.8	0.14
Female	46.2		44.7		17.0		15.4	
Birth order								
1 (ref. category)	42.7	2.81*	39.4	5.12**	18.0	0.58	13.8	4.92**
2–3	44.2		42.4		18.9		14.9	
4–5	51.1		47.7		20.4		22.5	
6+	54.9		58.4		14.9		16.0	
Preceding birth interval								
<12 months (ref. category)	43.0	1.52	39.3	3.15*	18.4	0.79	14.1	0.94
12–23 months	53.4		49.7		14.1		17.4	
24–35 months	47.8		48.3		17.5		16.6	
36 + months	45.3		43.1		19.9		16.3	
Mother								
Age								
>19 years	41.3	1.29	39.0	1.32	17.8	1.00	13.0	1.40
20–29	44.9		43.5		19.9		15.4	
30–39	48.7		41.6		16.0		17.2	
40+	54.0		50.7		14.2		21.8	
Nutritional status								
Normal/overweight (ref. category)	43.5	4.50*	39.1	26.99**	16.4	8.18**	13.7	15.13**
Underweight	49.0		51.1		22.6		20.4	
Education								
None	54.2	10.03**	48.8	7.05**	21.0	1.34	19.8	5.18**
Primary	50.5		47.2		19.8		17.6	
Secondary	38.8		39.0		16.9		13.4	
Higher	26.2		27.7		13.9		7.3	
Household								
Division								
Barisal (ref.category)	53.8	2.64*	49.1	3.92**	19.6	1.14	14.6	0.99
Chittago	49.0		40.7		18.6		13.2	
Dhaka	45.2		47.0		17.2		16.2	
Khulna	38.5		37.3		20.9		16.5	
Rajshahi	41.2		35.9		16.3		17.6	
Sylhet	59.5		41.2		35.2		29.4	
Wealth quintiles								
Q1(Poorest) (ref.category)	55.8	15.45**	55.3	16.14**	21.2	1.18	18.9	3.41*
Q2	53.7		44.8		19.6		15.9	
Q3	41.9		41.3		16.7		17.4	
Q4	39.1		35.3		18.3		12.6	
Q5(Richest)	20.0		22.7		13.7		8.2	

Significance *p < 0.05 **p < 0.01.

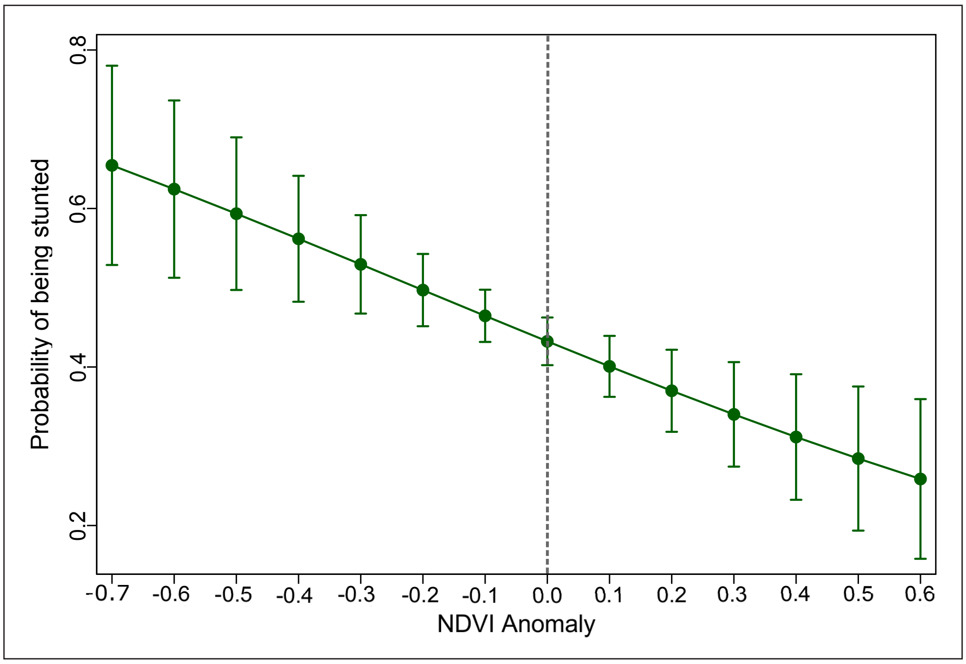

Figure 5: Predicted probabilities of being stunted. The predicted probabilities of being stunted according to NDVI anomaly with 95% confidence interval for the 2007 BDHS survey year. Dashed grey line represents the transition from negative to positive NDVI anomaly. DOI: https://doi.org/10.1525/elementa.153.f5

This indicates the importance of a mother's nutritional status in ameliorating a child from poor nutritional status outcomes. There is also some regional variation in stunting. In both 2007 and 2011 the odds of being stunted are significantly lower (35–50%) in Khulna and Rajshabi divisions in addition to Rangpur in 2011 compared to the reference category, Barisal division.

Wasting and NDVI

For wasting, a significant association with NDVI anomalies is found in 2011 (**Table 3**). As expected, the association is negative indicating that higher values of NDVI anomalies are associated with lower probabilities of wasting (**Figure 6**). This supports the view that NDVI is indicative of current growing conditions and a child's access to food in the short term. While significant ($p < 0.05$), the effect of NDVI anomalies on wasting is weaker compared to the effect of NDVI anomalies on stunting in 2007. The wide 95% confidence intervals observed on the high negative values of NDVI anomalies (> = 1) in **Figure 6** most likely reflect the very low number of observations at these values suggesting they are relatively rare events. No significant association between NDVI anomaly and wasting was found in 2007. As with stunting, actual NDVI values were not significantly associated with wasting in either year. Few control variables have significant associations with wasting in either year. There is a strong positive association between wasting and mother being underweight in both years. The odds of being wasted increased by 42.7% in 2007 and 54.7% in 2011 when the mother is underweight compared to children of women who have normal weight/overweight. Wasting is also significantly associated with the child's age in 2007 but not in 2011. Surprisingly, the effect in 2007 is negative, whereby the odds of being wasted deceases by 1.4% for every month increase in age.

In contrast to the stunting model, household wealth is not a determinant of wasting. In 2007, only children whose households belong to Q3 have significantly lower odds of being wasted compared to children belonging to Q1, the poorest quintile. In 2011, children belonging to Q5 (richest quintile) have a 49.5% reduction in the odds of being stunted compared to children belonging to the poorest quintile. There is also comparatively little variation in wasting according to region. In 2007, the likelihood of being wasted was 2.2 times higher in Sylhet division compared to Barisal division. In 2011, the odds of being wasted was 47.4% and 67.6% in Khulna and Rangpur divisions respectively compared to the Barisal Division.

5. Discussion and conclusions

The objective of this study was to explore the potential of NDVI as an indicator of climatic variability impacts on food availability to explain child nutrition outcomes in the Bangladesh part of the GBM delta. The NDVI anomalies for the specific growing season months of Aman and to a lesser extent Boro rice correspond with reported occurrences of significant climatic events such as the floods in 2004 and 2007. Therefore, the NDVI can be regarded as indicative of climatic variability and periods of low food production. This is an improvement on previous studies such as Shively et al., (2015) where NDVI was not able to observe climatic variability in Nepal. One reason for this may be the much higher spatial resolution of NDVI data used in this study (250 metre resolution) versus 5 kilometre spatial resolution used in the study by Shively et al. (2015). Other studies have used even lower spatial resolution, e.g. Johnson and Brown (2014) used NDVI data with a spatial resolution of 8 kilometre. The advantage of some of the lower resolution NDVI data however is that longer time-series exist to determine anomalies (i.e. more than 30 years compared

Table 2: Logistic regression results for stunting as odds ratios for 2007 and 2011 Demographic health surveys. DOI: https://doi.org/10.1525/elementa.153.t2

	DHS 2007		DHS 2011	
	OR	**Test stat**	**OR**	**Test stat**
Child				
Age	**1.024**	6.00**	**0.011**	3.05**
Birthorder				
1 (ref.category)	1.000		1.000	
2–3	0.901	–0.79	1.129	1.19
4–5	1.015	0.08	1.151	0.94
6+	0.883	–0.53	**1.686**	2.33*
Mother				
Normal/overweight (ref. category)	1.000		1.000	
Underweight	1.155	1.34	**1.477**	3.93**
Household Wealth				
Q1 (ref.category)	1.000		1.000	
Q2	0.909	–0.58	**0.681**	–2.9**
Q3	**0.543**	–3.91**	**0.605**	–3.49**
Q4	**0.482**	–4.44**	**0.485**	–4.72**
Q5(Richest)	**0.189**	–6.81**	**0.278**	–5.82**
Region				
Barisal (ref.category)	1.000		1.000	
Chittagong	1.016	0.09	0.869	–0.95
Dhaka	0.793	–1.17	0.962	–0.25
Khulna	**0.611**	–2.81**	**0.742**	–2.1*
Rajshahi	**0.599**	–3.23**	**0.569**	–3.17**
Rangpur[1]	1.099	0.21	**0.507**	–5.31**
Environment				
NDVI_Anomaly	**0.287**	–3.02**	0.975	–0.11
Constant	0.714	–1.62	0.788	–1.2

[1]Sylhet in 2007, Significance *$p < 0.05$ **$p < 0.01$.

to post-2000 data used in this study). Nevertheless, even the 250 metre resolution data used in this study is likely too coarse to capture paddy rice production at field scale as field sizes in Bangladesh are small. Furthermore, in contrast to some of the previously mentioned studies linking NDVI to nutritional outcomes which have mostly been carried out in arid or semi-arid environments, Bangladesh has a humid tropical climate with considerable cloud cover during the growing season which impedes the potential for NDVI retrieval (Xiao et al., 2006; Whitcraft et al., 2015). Another potential issue with the use of NDVI for estimating crop productivity is signal saturation, where the metric is not able to pick up on extremely high production (Gnyp et al., 2014; Yao et al., 2014).

Our regression results suggest that negative NDVI anomalies for the growing period of Aman and Boro rice can explain a higher probability of stunting and wasting in the GBM delta for the 2007 and 2011 survey data respectively. However, for both stunting and wasting models, no significant associations were found for the actual NDVI values and for the NDVI anomaly values for the 2007 wasting model and the 2011 stunting model. Such inconsistent findings have been reported in similar studies (e.g. Curtis and Hossain, 1998; Johnson and Brown, 2014; Shively et al., 2015) and these could be due to a number of reasons. One reason for the lack of association with some of our dependent variables could be related to our analysis focusing on two rice varieties only. While rice is the dominant crop in Bangladesh, there are other sources of food available which may be more resilient to specific climatic events. In addition, the Aus rice crop, while contributing only around 6.3% in 2013 (Bangladesh Bureau of Statistics, 2016) to the annual rice

Table 3: Logistic regression results for wasting as odds ratios for 2007 and 2011 Demographic health surveys. DOI: https://doi.org/10.1525/elementa.153.t3

	DHS 2007		DHS 2011	
	OR	**Test stat**	**OR**	**Test stat**
Child				
Age	**0.986**	–3.17**	1.003	0.83
Birth order				
1 (ref.category)	1.000		1.000	
2–3	1.017	0.11	1.13	0.84
4–5	1.135	0.61	**1.772**	3.29**
6+	0.67	–1.31	1.065	0.28
Mother				
Normal/overweight (ref. category)	1.000		1.000	
Underweight	**1.421**	2.49**	**1.547**	3.39**
Household SES				
Q1 (ref.category)	1.000		1.000	
Q2	0.899	–0.6	0.928	–0.38
Q3	**0.692**	–2.12*	1.075	0.42
Q4	0.829	–0.91	0.791	–1.22
Q5(Richest)	0.607	–1.61	**0.505**	–1.99*
Region				
Barisal (ref.category)	1.000		1.000	
Chittagong	0.995	–0.03	0.975	–0.13
Dhaka	0.862	–0.62	1.287	1.22
Khulna	1.227	1.01	**1.474**	1.96*
Rajshahi	0.778	–0.97	1.453	1.47
Rangpur[1]	**2.22**	3.52**	**1.676**	2.75**
Environment				
NDVI_Anomaly	0.949	–0.19	**0.504**	–2.51*
Constant	0.375	–3.61	0.123	–8.21

[1]Sylhet in 2007, Significance *p < 0.05 **p < 0.01.

production has a different harvest season which may be less affected in years where Boro and Aman rice have seen very low yields and may thus have contributed more to food security in those years. Indeed, Aus rice had some of the highest reported yields in 2006–2007 (2.44 ton/ha for modern varieties) when Boro rice yields were relatively low.

Furthermore, since wasting is a short term indicator pointing to recent events, the wasting model is based on the mean of the most recent growing season for Boro and Aman rice in relation to the interview date. For our study, this means that our wasting model only takes into account NDVI and NDVI anomalies for Boro and Aman growing seasons for the years 2006–2007 and 2010–2011 for the 2007 and 2011 surveys respectively. Therefore, mean anomalies are based on a limited number of observations which can explain the high uncertainty associated with predicted probabilities of wasting observed for high negative NDVI anomalies (**Figure 6**). In 2006 a negative NDVI anomaly exists for Boro rice but the following Aman rice shows a positive anomaly (**Figure 3c**). A similar (but reversed) pattern exists for 2007 and again for 2010, a negative Boro rice anomaly is followed by a positive Aman rice anomaly. The balance between productions of the two rice varieties may be able to explain why the wasting model was able to explain wasting for the 2011 survey year but not for 2007. Being able to utilise the different rice varieties throughout the year however will contribute towards households being able to achieve food and nutrition security.

Household socio-economic status in particular was found to be a key determinant for stunting for both

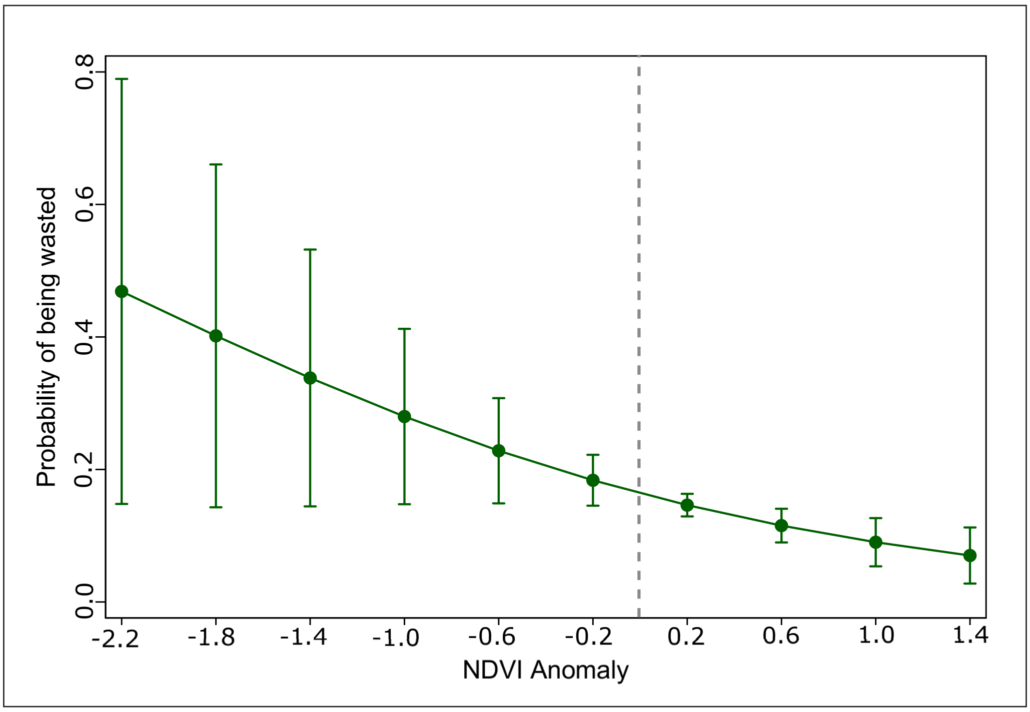

Figure 6: Predicted probabilities of being wasted. The predicted probabilities of being wasted according to NDVI anomaly with 95% confidence interval for the 2011 BDHS survey year. Dashed grey line represents the transition from negative to positive NDVI anomaly. DOI: https://doi.org/10.1525/elementa.153.f6

survey years with children in wealthier households having significantly reduced odds of stunting. Therefore, households in the lowest income brackets are likely to experience a further reduction in their access to food in low production years. Analysis of secondary data from the 2011 BDHS survey by Szabo et al., (2016a) for the south–west coast of Bangladesh confirms that households in the highest wealth bracket are considerably less likely to suffer from food insecurity when compared to the poorest households. In general, subsistence-oriented households will be more at risk from climatic variability and extreme events since they are more dependent on local production of food for their own consumption with immediate consequences for nutrition. This highlights the necessity for spatially explicit measures of environmental variables and nutrition outcomes, particularly in areas where environmental impacts can be localised such as the GBM delta.

Even though our study has shown significant findings on the relation between NDVI anomalies and stunting and wasting in children, there are still many uncertainties surrounding the use of remotely sensed data to assess the link between climatic variability, food production and child nutrition outcomes that need to be explored further. On the one hand, there are known limitations to the use of NDVI in measuring crop productivity, particularly in areas affected by extensive cloud cover such as Bangladesh which may explain the lack of association in some of our results. In addition, NDVI signal saturation may result in not accounting for higher than average yields. However, since our study is focused on lower than average food production this should not affect our conclusions.

There are also difficulties in identifying different crops and distinguishing between rain-fed and irrigated agriculture using NDVI. Improved remote sensing data (e.g. higher resolution) and metrics, calibrated with observational data would allow for better assessments. On the other hand, the link between food production and child nutrition outcomes is not always clear. Households may have access to alternative sources of income and food through market access or food crops not identified by the NDVI. Irrigation structures can also buffer water resources for agriculture, ameliorating impacts of droughts and floods. These factors can displace impacts of climate variability on food production spatially and temporally. Obtaining additional information related to this through the household surveys would greatly improve the potential for using remote sensing data to predict child nutritional outcomes.

Despite having access to geo-referenced household survey data for Bangladesh, our analysis highlighted the difficulty with analysing the impacts of climatic variability on nutritional outcomes for specific geographical areas like the GBM delta. It was not possible to assess the full extent of the delta as the BDHS survey data are only available at national scales and cannot easily be merged between countries due to differences in survey years and in some cases survey design. However, since at least two thirds of the GBM delta falls within Bangladesh, our results are representative for the whole delta. Nevertheless, harmonisation and spatial disaggregation of datasets beyond national borders should be a focus of future research in order to analyse impacts for different aggregation levels and units of analysis. This is particularly critical for climate change hotspots, such as river delta's (Szabo et al., 2016b), as disaggregated data would allow for addressing the specific challenges and vulnerabilities that deltaic systems are subject to. Monitoring at the delta scale would allow for tailor-made policies to improve targets against specific Sustainable Development Goals and targets (Szabo et al., 2015; Szabo et al., 2016b).

Data Accessibility Statement

The data for the 2007 and 2011 Bangladesh Demographic Health Surveys are publicly available from the DHS Program at: http://dhsprogram.com/ The NDVI data at 250 metre spatial resolution (MOD13Q1 NDVI) is available from the Oak Ridge National Laboratory Distributed Active Archive Center (ORNL DAAC) at: https://daac.ornl.gov/.

Supplemental Files

The supplemental files for this article can be found as follows:

- **Table S1.** Description of the sample used in the analysis of stunting (children aged 6–59 months) for 2007 and 2011. DOI: https://doi.org/10.1525/elementa.153.s1
- **Table S2.** Description of the sample used in the analysis of wasting (children aged 6–59 months) for 2007 and 2011. DOI: https://doi.org/10.1525/elementa.153.s2

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Competing interests

The views expressed in this work are those of the authors and do not necessarily represent those of the Save The children UK.

Author contributions

- Contributed to conception and design: AvS, KN, ZS, NB, ZM
- Acquisition of data: AvS, KN
- Analysis and interpretation of data: AvS, KN
- Drafting and/or revised the article: AvS, KN, ZS, NB, ZM
- Approved the submitted version for publication: AvS

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