



The effect of the local environment on child nutritional outcomes: how does seasonality relate to wasting amongst children under 5 in south-west coastal Bangladesh?

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Abstract

The impact of short-term environmental changes on child nutritional status is not constant within populations. In many countries, the seasons are closely linked with many factors that are known to affect nutritional outcomes, such as food consumption, crop harvests, employment opportunities and illness. With extreme seasonal variation becoming more common, understanding how seasonality is related to child nutritional outcomes is vital. This study will explore spatial and temporal variation and determinants for acute malnutrition in a coastal river delta in south-west Bangladesh over the period of a year. Using a rural longitudinal survey, conducted in 2014–15 with 3 survey waves, wasting amongst children under 5 was studied. Spatial variation was analysed through ‘socio-ecological systems’, which capture interactions between ecosystems, livelihoods and populations. Wasting prevalence varied from 18.2% in the monsoon season to 8.7% post-major rice harvest (Aman). Seasons did not relate to wasting consistently over socio-ecological systems, with some systems showing greater variability over time, highlighting distinct seasonal dynamics in nutritional status. Wealthier socio-ecological systems had lower wasting generally, as expected, with greater livelihood diversification opportunities and strategies to smooth consumption. Nutrition interventions must consider seasonal peaks in acute malnutrition, as well as the environmental context when implementing programmes to maximise effectiveness. With increasing variability in seasonal changes, inequalities in the impact of season must be accounted for in health promotion activities. Furthermore, timing and season of survey implementation is an important factor to be accounted for in nutrition research, especially when comparing between two cross-sectional surveys.

Keywords Seasonality · Child nutrition · Wasting · Socio-ecological system

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Introduction—the importance of seasonality on malnutrition

Malnutrition is a key cause of morbidities and mortality for children under-5 in many low- and middle-income countries (Black et al., 2013). Inequalities in the prevalence of malnutrition and links to key socioeconomic determinants have been studied using cross-sectional data sources in different population groups (Hasan et al., 2018; Islam & Biswas, 2015; Pulok et al., 2016; Van Soesbergen et al., 2017). However, less attention has been given to shorter-term seasonal variations in nutritional status (Baye & Hirvonen, 2020; Devereux et al., 2012; Marshak et al., 2021). Firstly, understanding seasonality and short-term fluctuations in malnutrition is becoming increasingly important as seasons become ever more extreme and uncertain as a result of longer-term climatic changes (Devereux et al., 2012; FAO, 2018; IPCC, 2022; Marshak et al., 2021). Furthermore, the appreciation of understanding seasonal influences on under-5 malnutrition will help to address intra-year fluctuations in nutritional status and differentials in this fluctuation between individuals. Additionally, related interventions could also consider seasonality and optimal timing of implementation to maximise impact (Devereux et al., 2012; Vaitla et al., 2009). Finally, the comparison of malnutrition indicators over time needs to account for sampled measurements collected at different times of the year (Baye & Hirvonen, 2020; Marshak et al., 2021; Pullum, 2008).

Seasonality refers to cyclical patterns of climatic and hydrological variation that are associated with the changing of seasons (Devereux et al., 2012; Sullivan, 2013). Seasonal variation can drive poverty, hunger and poor health, constraining seasonal rural livelihoods and obtaining the 2030 Sustainable Development Goals (Chambers et al., 1981; Devereux et al., 2012; Marshak et al., 2021; Mohsena et al., 2018). Seasonal variation in temperature and rainfall can lead to variation in employment opportunities and therefore changes in income, agricultural outputs, food price and availability, health and disease prevalence and access to services (Devereux et al., 2012; Lázár et al., 2015; Zug, 2006). The effect of seasonality may vary for communities and households that are dependent on different livelihood strategies and income-generating activities (Adams et al., 2016b), leading to variations in malnutrition between and within communities (Mohsena et al., 2018).

Critical hunger periods coincide with pre-harvest periods when food supplies run low and prices are high (Chambers, 1982; Devereux et al., 2008; Raihan et al., 2018; Zug, 2006), linked to the stability of food security (Wheeler & Von Braun, 2013). Experiences of seasonality vary by location, wealth and poverty, occupation, gender, age, social status, access to resources and livelihood strategies (Chotard et al., 2010; Devereux et al., 2012). Access to drinking water and sanitation facilities can vary during the year, impacting the prevalence of infections (Chambers et al., 1981; Pullum, 2008). Limited income during agricultural low periods and the inability to transfer assets between the seasons can diminish the ability to cope with a shock, often resulting in debt accumulation (Khandker et al., 2011; Mohsena et al., 2018). Such setbacks can result in a downward spiral of poverty, food insecurity and poor health outcomes (Devereux et al., 2012).

Cross-sectional Demographic Health Survey (DHS) data is considered the gold standard for population prevalence of child nutritional status (Brown et al., 2014). However, cross-country and year comparisons of acute malnutrition prevalence are often made with DHS data as an annual estimate, without accounting for the survey month (Baye & Hirvonen, 2020). Documenting short-term changes in malnutrition is challenging given that surveys are not conducted at the same time of year (FAO, 2018; Marshak et al., 2021). Furthermore, the lack of longitudinal, high-frequency, observational studies on nutritional status means that it is difficult to explore both spatial and temporal dimensions of malnutrition prevalence in the same analysis (Randell, 2022; Sassi & Trital, 2021). This is particularly important where socio-economic characteristics and food security do not remain stable over time (Sassi & Trital, 2021).

This paper will explore acute undernutrition in a region of Bangladesh using wasting (weight-for-height) as an indicator, which is sensitive to short-term changes and fluctuations throughout the annual seasons (Brown et al., 1982; Egata et al., 2013). Previous studies found that the prevalence of under-5 wasting halved between repeated measurements 6 months apart, suggesting substantial seasonal variation of nutritional status (Baye & Hirvonen, 2020; Kinyoki et al., 2016). Child undernutrition is a multi-causal issue, with complex interactions between social, demographic, economic, biological and environmental factors (Black et al., 2008). The UNICEF (1998) conceptual framework for child malnutrition classifies determinants at the societal, household and individual levels, although temporal variation of determinants is not captured in the framework. Previous research using cross-sectional data in rural Bangladesh found the associations between acute nutritional outcomes and characteristics including gender, age, education, birth order, incidence of fever, acute respiratory infection and diarrhoea in the past 2 weeks varied widely, with little consistency between studies (Akhter & Haque, 2018; Alom et al., 2012; Chowdhury et al., 2016; Das et al., 2008; Hasan et al., 2018; Pulok et al., 2016; Rahman et al., 2020; Sultana et al., 2019; Van Soesbergen et al., 2017). A study on fragile environments and seasonal variation in poverty and malnutrition found that a child has increased odds of being wasted in the monsoon season compared to the harvest seasons (Mohsena et al., 2018), although this study was based on repeated cross-sectional data and did not collect data from the same child at different times during the year.

The unequal effects of seasonality

Short-term and regular changes in environmental conditions do not affect child nutritional status equally across population groups (Mohsena et al., 2018). Several factors are seen to be related to child malnutrition and differentials at the individual, household and community levels. These include spatial and temporal factors (Hasan et al., 2018; Mohsena et al., 2018; Van Soesbergen et al., 2017).

Inadequate calorie consumption and low diet diversity are key factors relating to child malnutrition (Pulok et al., 2016; Rah et al., 2010). In rural Bangladesh, those that consume seven or more food groups were found to have lower rates of undernutrition (Ahmed et al., 2018), although this study did not consider how diet varied

over a year. Previous studies found that diets and consumption vary between periods of food surplus and shortage (Abizari et al., 2017; Hirvonen et al., 2016; Savy et al., 2006). Gender inequality can often manifest in intra-household food allocation, with men consuming more than their required daily calories, and women often eating least and last (Ahmed et al., 2007; Alston & Akhter, 2016; HFSNA, 2009; HKI & BIGH, 2015; Kamal & Islam, 2010). This allocation is likely to change over different seasons. A study in rural Burkina Faso observed a 6% increase in the prevalence of underweight women between the beginning and end of the seasonal food shortage period (Savy et al., 2006), with a link observed generally between mother and child nutritional status. Adverse reproductive outcomes are reported to vary seasonally, such as insufficient weight gain during pregnancy, preterm birth and low birthweight, impacting child nutritional status (Strand et al., 2011). However, nutritional status of women remains more stable during the year compared to children under-5 (Mohsena et al., 2018).

Within households, children living with adults who have physical labour occupations are more likely to be wasted, compared to those with adults in service and business jobs (Alom et al., 2012; Das & Gulshan, 2017). The association of occupation status may relate to the size of income, but also the stability of income over time (Devereux et al., 2012). Livelihoods sensitive to seasonality can determine differentials in nutritional outcomes both seasonally and year-to-year (Ahmed et al., 2018; Chotard et al., 2010; HKI & BIGH, 2015; Raihan et al., 2018). Agricultural livelihoods have low and unstable incomes concentrated around planting and harvest periods (Khandker, 2012). Sensitivity to food prices and capacity to smooth income can influence seasonal poverty incidence and nutritional outcomes (BBS, 2017; Devereux et al., 2012; HFSNA, 2009).

Wealthier households are less likely to have monotonous diets and to be reliant on staple crops, whilst also having increased economic access to food and healthcare (FAO, 2018; Szabo et al., 2016). However, associations between wealth and wasting in rural contexts are weak and inconclusive (Deolalikar, 2005; Johnson & Brown, 2014; Van Soesbergen et al., 2017). Poor access to drinking water and sanitation facilities increases exposure to environmental contaminants and parasites, increasing waterborne illnesses (Cumming & Cairncross, 2016; FAO, 2018; NIPORT, 2020; WFP, 2012). The odds of being wasted are halved for those with a hygienic sanitation facility, compared to an unhygienic one (Das & Gulshan, 2017; Hong et al., 2006).

Spatial variation in nutritional outcomes may be related to a wide variety of geographical characteristics (Johnson & Brown, 2014; Kandala et al., 2011; Mohsena et al., 2018). Access to infrastructure, such as transport, roads, electricity, healthcare and educational opportunities and food storage facilities, varies over space, but also over time, through the seasons (Devereux et al., 2012). For example, seasonal shocks and stressors may damage infrastructure, determining access during the year (Deolalikar, 2005; FAO, 2018; Mohsena et al., 2018; UNICEF, 2009). Vectors and water-borne diseases influence the utilisation of food, which can vary spatially, but this distribution is also determined by the seasonal climatic conditions (Kandala et al., 2011; Rahman & Ahmad, 2018). Some regions are considered ecologically unfavourable based on poor soil, land and water quality (Mohsena et al., 2018). Environmental quality can also vary by climatic seasons. Meanwhile, ecosystems in

Bangladesh can provide food sources, such as fish and shrimp collection, forest and mangrove products (Arnold et al., 2011), which can act as a safety net during pre-harvest periods (Sassi, 2019; Shimi et al., 2010; Zug, 2006). Exposure to flooding, storm surges and saline intrusion vary by proximity to the coast and rivers indirectly, impacting nutritional outcomes (Adams et al., 2018c; Mohsena et al., 2018; Rahman & Ahmad, 2018). For example, sea-level rise and saline intrusion can contaminate drinking and irrigation water sources and reduce crop yields (Béné et al., 2015). A larger area (and population) is impacted during dry seasons when river flows are lowest and saline water can travel further inland (Hossain et al., 2016; Shammi et al., 2019).

Previous studies about child malnutrition generally consider spatial inequalities based on administrative areas (Hasan et al., 2018; Sultana et al., 2019). Various studies have found differences in nutritional status based on spatial classifications of contextual factors and livelihood strategies that may capture unobserved place effects, such as social capital, market access and open access ecosystem services (Ahmed et al., 2018; Mohsena et al., 2018; Roba et al., 2016).

Unanticipated shocks, such as cyclones, flooding and economic crises, can cause increases in short-term malnutrition, especially wasting (Béné et al., 2015; FAO, 2018; Thorne-Lyman et al., 2010). For example, severe flooding can result in reduced harvest and food shortage, where crop production is disrupted and infrastructure is damaged (Béné et al., 2015; Mohsena et al., 2018). Monsoon season is also when the increased incidence of diarrhoea and malaria are observed (FAO, 2018; Ferro-Luzzi et al., 2002), which again can affect nutritional outcomes.

This study will explore under-5 child acute malnutrition using panel data. Data collected at three time points over the period of a year will be used to explore short-term seasonal variation in child wasting. This research will explore how changes in wasting are related to seasonality and their location, as well as studying whether potential explanatory factors also vary by time and space.

Data and method

The data for this research are taken from the survey entitled ‘Spatial and temporal dynamics of multidimensional well-being, livelihoods and ecosystem services in coastal Bangladesh’, collected as part of the ESPA-Deltas project (Adams et al., 2016a, b). The low-lying study area is located in the Ganges, Brahmaputra and Meghna coastal river delta in the Barisal and Khulna Divisions of south-west Bangladesh (see Fig. 1), which are particularly vulnerable to climate-related disasters and sea-level rise (Adams et al., 2016b). The survey sampled 1586 rural households, conducting 3 survey waves during June 2014, October–November 2014 and March 2015. The first survey wave coincided with the monsoon season, the second wave occurred during the pre-Aman rice harvest, and the final wave coincided with the pre-Boro (and post-Aman) rice harvests, in addition to being the end of the dry season (Mohsena et al., 2018). Over the 3 survey waves, attrition rates remained low, with 4.4% and 3.5% of those interviewed in the first wave unavailable in the second and third waves, respectively, due to migration or

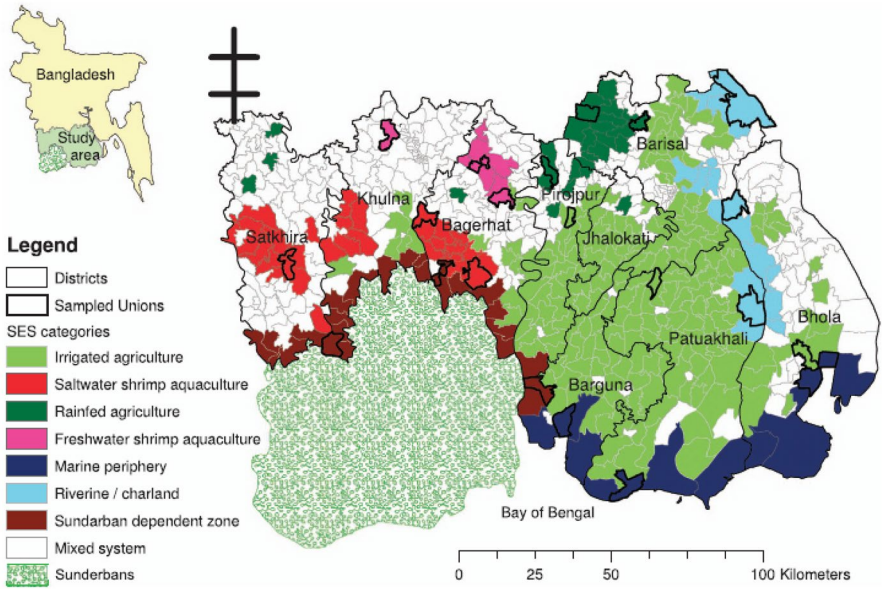


Fig. 1 Unions in the ESPA-Deltas study area, assigned to socio-ecological systems, with surveyed Unions highlighted in bold. Source: (Adams et al., 2016b) (Reproduced under the Creative Commons CC BY license)

unwillingness to participate. The nature of the ESPA-Deltas research relates to natural resource dependence, and therefore, only rural areas were sampled, which exhibit higher rates of under-5 undernutrition (NIPORT, 2020).

Bangladesh has the 7th largest within-country sub-regional inequalities of child acute malnutrition globally and hence is an appropriate place to conduct this study (FAO, 2018). Food insecurity is found to be higher for cyclone and flood-prone areas in the southern coastal area, especially in Khulna and Barisal divisions, which are the main study area of this research (WFP, 2012). On average, 70% of energy requirements in Bangladesh are obtained from rice (FAOSTAT, 2018), with hunger periods revolving around the rice harvests (Mohsena et al., 2018).

The original survey assigned each Union (administrative area) within the study area to one of seven ‘socio-ecological systems’ (SES) (Adams et al., 2018b). A SES is defined as ‘the amalgamation of physical, ecological, and social phenomena into a set of recognisable and distinct systems of interaction’ (Adams et al., 2018b, p. 406). The concept of SESs is operationalised by combining land-uses within livelihood systems that are thought to mediate ecosystem service and poverty dependence (Adams et al., 2016b). Three SESs were defined based on dominant land-use (e.g. farming of rice varieties), and 4 were assigned based on

proximity to a land feature (e.g. adjacent to mangroves, rivers or coasts). Previous research suggests that the prevalence of wasting varies between SESs (Ahmed et al., 2018). The wealth of each of the SES was previously calculated (see Ahmed et al. (2018)), and these classifications were used in this study. Table 1 summarises the characteristics of each SES, appearing in order of relative wealth. Figure 1 shows the spatial distribution of the 7 SESs, with sampled Unions highlighted in bold. A household may only belong to one SES. The socio-ecological location was explored to assess if it is related to the effect of seasonality on wasting, as well as exploring inequality between locations.

To select the households in the survey, multi-stage random sampling was employed. Three Unions were systematically randomly sampled from each SES to ensure all SESs were represented (21 Unions in total), with three sampling clusters per union randomly selected from each Union. After enumeration in each sampled cluster, approximately 25 households were sampled, with a set number from each wealth category chosen. Additional information about the methods used to define each SES and sample design can be found in Adams et al. (2016b, 2018b).

Table 1 Summary table characterising each socio-ecological system

Socio-ecological system	Characterisation
Sunderban (Mangrove) Dependent	<ul style="list-style-type: none"> • Open-access mangrove forest products • Insecure property rights • Pirates and bandits • Highly seasonal livelihoods (fishing and aquaculture)
Coastal Periphery (Marine)	<ul style="list-style-type: none"> • Offshore fisheries • Open-access resources • Unpredictability of fish catch • Loan system to buy boats and nets
Charland (Riverine)	<ul style="list-style-type: none"> • Small eroding islands • Insecure property rights • Threat of erosion • High population mobility
Saltwater Shrimp (Bagda)	<ul style="list-style-type: none"> • Shrimp farming in dry season (February–July) • Social breakdown • Absentee landlords • Salinisation
Rainfed Agriculture (Aman rice)	<ul style="list-style-type: none"> • Harvested in December–March • Private property rights • Sharecropping • High seasonality of income
Irrigated Agriculture (Boro rice)	<ul style="list-style-type: none"> • Harvested in late March to June • Private property rights • Sharecropping • Access to irrigation allowing multiple cropping seasons
Freshwater Prawn (Golda)	<ul style="list-style-type: none"> • Prawn farming in monsoon season and harvested between November and January • Private property rights dominate • High start-up costs require large loans • High land prices

Source: (Adams et al., 2016b, 2018b; Islam et al., 2005; Kazal et al., 2020)

Households were selected if both a male aged 18–54 and a female aged 15–49 were present (Adams et al., 2016b). A set of key household characteristics were surveyed. The survey also collected anthropometric measurements of the head of household, their spouse, and, if a child was present, the oldest child who was aged over 1 year, but under 5 years. Households without children, or with only one anthropometric measure, or evidence that a different child (different sex, or decreasing age) was measured between waves, were excluded from this study. The final sample size for each wave is shown in Table 2.

Outcome variable

This research will use wasting as the indicator for acute malnutrition. Wasting is a non-age-based measure reflecting short-term changes in nutritional status, which is often linked to nutrition and energy deficits, food insecurity or recurrent infections (Islam & Biswas, 2015). This will be assessed using the child's weight-for-height (WHZ). Following the WHO (2006) protocol, the weight/height ratio of an individual under-5 years is compared to the distribution of a healthy population and assigned a z-score using the 'Anthro' software package (WHO, 2010). A child is considered wasted if their z-score is below a cut-off of -2 z-scores, leading to a binary outcome of 1 for 'wasted' and 0 for 'not wasted'. The percentage of children classified as wasted in each wave is shown in Table 2. In order to assess if the results found using the dichotomous wasting outcome are robust to different specifications, the continuous WHZ has also been used (see Table 12, Appendix 3).

Explanatory factors

As this analysis aims to capture seasonal variation in nutritional outcomes, individual, household and geographic-level dependent variables were classified into time-varying, time-invariant and spatial groups.

Time-varying factors were identified based on existing literature about seasonal changes in rural households (Devereux et al., 2012; Lázár et al., 2015; Sassi & Trital, 2021). These variations over time are shown within the ESPA-Deltas survey, with the factors often taking different values in each survey wave. These include wealth, sanitation facility, source of drinking water, maternal and paternal occupation status, household diet diversity and food consumption score. The distribution of selected variables can be found in Appendix 1 (Table 7).

Table 2 Summary of seasonal indicators survey waves and outcome variable

Season	Sample period	Total N	% Wasting	95% CI
Monsoon (Wave 1)	June 2014	550	18.2	15.0–21.4
Pre-Aman (Wave 2)	October–November 2014	518	13.7	10.7–16.7
Pre-Boro (Wave 3)	March 2015	515	8.7	6.3–11.2

An indicator for each survey wave is included in the modelling as a time-varying variable as a proxy for seasonality, henceforth referred to as season indicator, to account for the corresponding survey months and harvest season.

A number of variables show little variability between waves and were therefore considered time-invariant. In these cases, the measurement in the first survey wave is used. These include the child's gender and age, maternal age, maternal BMI, maternal and paternal educational status and household size. The distribution of time-invariant variables is found in Appendix 1 (Table 8).

To prevent a substantial reduction in the sample size, for variables with a significant number of missing values (including occupation and education), a missing category was included in the analysis, but not included in preliminary exploratory chi2 associations. The high proportion of missing data on some variables is difficult to explain, with the survey reports not indicating why this is the case. An assumption was made that the adult male and female sampled are the parents of the child in this analysis and that these are the same individuals between survey waves. An asset-based index of household wealth was calculated (Filmer & Pritchett, 2001) for each corresponding survey wave, using individual observations from this rural survey data. Although sanitation facility and source of drinking water were included in the wealth index, they were also explored as underlying determinants of hygiene and sanitation. A full description and justification of data preparation for all considered variables, including food consumption and diet diversity, can be found in Appendix 2 (Table 9).

Statistical analysis

This analysis will explore variation in wasting status over three repeated measures. Each observation about wasting status is nested within individual children. This nesting needs to be considered when analysing the determinants of wasting over time, and hence binary logistic random effects regression will be utilised (Goldstein, 2011; Twisk, 2006). This analysis focuses on differences in nutritional outcomes across seasons and SESs. Fixed effects and random effects models were estimated using the panel data, and the Hausman test was conducted to assess which of the two modelling strategies was most effective. The Hausman test for an empty model indicated that a random effects model should be used ($p=0.050$). The fixed effects models can be found in Table 11 (Appendix 3).

The hierarchical data structure is as follows: the repeated wasting measures, considered level-1 (i), clustered within an individual child at level-2 (j). The final 2-level random effects (multi-level) model equation, including an interaction term (see Model 2, Table 6), is written as follows:

$$\text{logit}(y_{ij}) = \beta_0 + \beta_1(\text{season indicator})_{ij} * \beta_2(\text{socioecological system})_j + u_{0j} + e_{0ij}$$

The outcome variable (child wasting) is denoted as y_{ij} . β_0 is the intercept value, β_1 is a coefficient for the level-1 explanatory variable (seasonal indicator), and β_2 is a coefficient for a level-2 explanatory variable (socio-ecological system). The level-2 random error is denoted by u_j , and level-1 error is denoted by e_{0ij} .

A binary logistic random effects model was generated using quasi-likelihood estimation (Twisk, 2006), including the seasonal indicator (Model 1). Model 2 is the final model which has an interaction term for SES and the season indicator (Assaf et al., 2018), which does not include any additional time-varying variables to prevent introducing endogeneity when interpreting the coefficients of the seasonal indicators. Different groupings of SESs were investigated, such as ‘Agricultural’, ‘Aquaculture’ and ‘Fishing and Other’; however, this did not change the overall results of the analysis. Random slopes to allow the gradient as well as the intercept to vary at the level-2 were explored but were not found to be significant. Multilevel model assumptions were also checked, mainly at level-2, including normality of the random effect. These checks indicated the assumptions were adequately satisfied.

An additional model with demographic control variables (such as age and gender of child) was also estimated (Model 3), which is also presented in Table 10 (Appendix 3) to see how the addition of control variables affects the magnitude of the season indicator and SES interaction terms. Due to the small sample size, and lack of statistical power, a linear regression fixed and random effects model was also generated using WHZ as an outcome (Table 12, Appendix 3). The linear results are similar to the logistic model, regarding the size and direction of the explanatory variables.

Although time-varying variables are not included in the final model (Model 2) due to concerns of endogeneity, it is interesting to regress each variable individually with the season indicator as a predictor to explore likely factors that may be driving seasonal variation in wasting. Such models can be found in Appendix 4 (Tables 13–19).

The analysis was undertaken using STATA IC version 16, R and MLwiN 3.05.

Descriptive statistics

WHZ scores

Figure 2 illustrates an increase in the average WHZ score over time, suggesting an improvement in nutritional status, although observations generally cluster below 0, indicating poorer nutrition overall than the reference population. Table 2 shows a corresponding large reduction in the average prevalence of wasting over the seasons, with the peak during the monsoon season. In the monsoon season (wave 1), 18.2% of children are wasted, declining to 13.7% in the pre-Aman season (wave 2), and 8.7% in the pre-Boro (and post-Aman) season (wave 3). Using DHS data, the overall prevalence of wasting over the whole of rural Bangladesh in 2014 was 15.1%, while the prevalence was 13.5% in Khulna Division and 17.7% in Barisal Division. In the 2014 DHS, sampling occurred during June to November. In the ESPA-Deltas data, the first and second survey waves were conducted during a similar period, in June and October–November, respectively, coinciding with the beginning and end of the DHS data collection. The large variation in prevalence in the ESPA-Deltas survey over three waves over a year period has been observed in previous literature in other locations, such as in sub-Saharan Africa (Baye & Hirvonen, 2020; Egata et al., 2013). The temporal variation in this dataset, therefore, highlights the need to better understand short-term seasonal fluctuations in wasting prevalence.

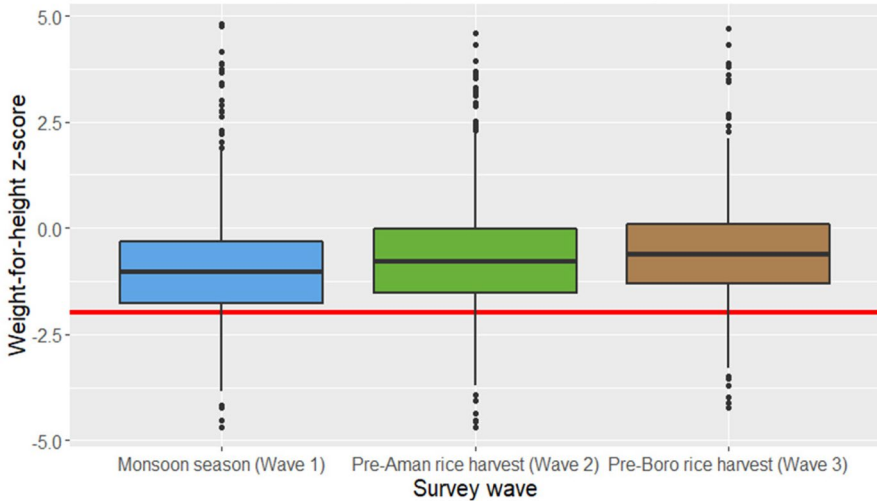


Fig. 2 Boxplot of continuous weight-for-height z-scores for each survey round, with reference line to illustrate the threshold for wasting (< -2 SDs)

Time-varying factors

If each survey wave is studied as a cross-section, only one significant relationship was seen between the explanatory variables and wasting. Table 3 shows that paternal occupation in the monsoon season was associated with wasting ($p=0.04$). Wasting is higher amongst children whose father is unskilled compared to skilled fathers. Across the seasons, there is greater variation in wasting for children with unskilled fathers. Wasting prevalence is highest in the poorest quintile and lowest in the richer quintile, declining over the seasons, although this does not show a significant relationship. To explore if the relationships between wasting and the expected explanatory variables are as expected, simple bivariate associations were estimated. In Table 3, variables that are seen to vary over the seasons are shown, while in Table 4, the variables that are expected to remain stable over time are shown.

Time-invariant factors

Using the responses from the first survey wave, Table 4 shows that none of the selected variables were associated with wasting in any of the survey waves. No marked differences between gender were observed in the monsoon season, although the disparity increases thereafter, with males observing higher levels of wasting. No discernible pattern is observed for wasting prevalence and variables including child age, maternal and paternal education. Wasting prevalence is higher as the maternal age category increases, although women aged under 20 also have a raised wasting prevalence between the pre-Aman and pre-Boro rice harvest seasons, in contrast to all other categories showing a decrease in wasting. Children with underweight

Table 3 Bivariate independent descriptive statistics: time-variant

Variable	Categories	Monsoon (Wave 1)					Pre-Aman (Wave 2)					Pre-Boro (Wave 3)				
		Total N	% Wasted	95% CI	Chi ²	Missing N	Total N	% Wasted	95% CI	Chi ²	Missing N	Total N	% Wasted	95% CI	Chi ²	Missing N
Wealth index	Poorest	110	22.7	15.4–30.1	0.19	0	102	13.7	2.9–24.6	0.65	0	100	11.0	2.7–19.3	0.37	0
	Poorer	110	20.9	15.5–26.3			105	14.3	7.0–21.5			102	10.8	3.7–17.9		
	Middle	110	19.1	10.9–27.3			106	17.0	7.3–26.6			106	9.4	3.1–15.8		
	Richer	110	10.9	5.7–16.2			104	9.6	4.1–15.1			103	3.9	0.0–7.9		
	Richest	110	17.3	11.6–22.9			101	13.9	8.8–19.0			104	8.7	2.2–15.1		
Sanitation facility	Private improve	383	17.5	14.3–20.7	0.57	0	365	13.9	10.0–17.7	0.41	19	397	8.3	5.0–11.6	0.86	21
	Shared improved	106	21.7	13.3–30.1			96	12.5	5.9–19.1			83	9.8	4.5–15.0		
Source of drinking water	Unimproved	61	16.4	8.8–24.0			70	14.5	6.1–22.9			49	10.4	1.3–19.5		
	Improved	466	17.8	14.5–21.1	0.60	0	437	13.1	9.9–16.3	0.31	19	462	7.8	4.8–10.8	0.11	21
	Unimproved	84	20.2	13.9–26.6			94	16.7	5.7–27.6			67	15.5	4.6–25.7		
Maternal occupation	Unskilled	254	19.3	15.1–23.5	0.76	217	218	16.1	10.2–21.9	0.28	211	231	8.2	4.1–12.3	0.53	187
	Skilled	79	17.7	10.1–25.3			89	11.2	3.2–19.3			97	6.2	2.2–10.2		
Paternal occupation	Unskilled	373	20.6	17.1–24.2	0.04	15	308	15.6	10.3–20.8	0.17	70	322	9.6	5.3–13.9	0.56	66
	Skilled	162	13.0	0.0–29.4			140	10.7	4.2–18.6			127	7.9	0.0–12.1		
Household diet diversity score	≤6	229	17.0	13.2–20.9	0.55	0	256	12.5	8.1–16.9	0.43	19	222	9.9	5.8–14.1	0.41	21
	7+	321	19.0	15.1–22.9			262	14.9	9.8–20.0			293	7.9	3.7–12.0		
Food consumption score	Poor	199	16.1	11.3–20.8	0.13	0	265	12.8	8.7–16.9	0.45	19	205	8.8	4.1–13.4	0.59	21
	Borderline	302	20.9	16.7–25.0			218	15.6	9.8–21.4			267	9.4	5.4–13.3		
	Acceptable	49	10.2	1.1–19.3			35	8.6	1.2–15.9			43	4.7	0.0–11.0		
Total		550	18.2	15.3–21.5	-	-	518	13.7	10.5–17.8	-	-	515	8.7	5.9–12.8	-	-

Table 4 Bivariate independent descriptive statistics: time-invariant

Variable	Categories	Total N	Monsoon (Wave 1)				Pre-Aman (Wave 2)				Pre-Boro (Wave 3)			
			% Wasted	95% CI	Chi ²	p-value	% Wasted	95% CI	Chi ²	p-value	% Wasted	95% CI	Chi ²	p-value
Child gender	Male	283	18.0	13.2–22.9	0.92	15.0	9.9–20.1	0.38	10.2	6.0–14.3	0.24	0		
	Female	267	18.4	14.4–22.3		12.4	7.5–17.2		7.2	3.3–11.1		0		
Child age	1	103	16.5	9.9–23.1	0.96	12.4	5.4–19.3	0.62	6.2	2.2–10.2	0.30	0		
	2	149	18.8	11.7–25.9		11.2	6.7–15.6		9.4	5.0–13.7				
	3	164	18.9	11.4–26.4		16.2	9.2–23.3		11.8	6.2–17.5				
	4+	134	18.0	11.1–24.7		14.6	8.4–20.8		6.3	2.0–10.6				
Maternal age	< 20 years	29	10.3	16.9–30.4	0.52	7.4	0.0–16.8	0.55	8.7	0.0–19.8	0.72	0		
	20–29 years	338	18.3	12.2–20.0		13.5	8.8–18.2		8.0	4.3–11.6				
	≥ 30 years	183	19.1	6.3–27.0		15.1	9.3–20.9		10.1	4.7–15.5				
Maternal BMI	Underweight	148	23.7	16.9–30.8	0.13	14.9	8.2–21.6	0.88	9.6	3.9–15.4	0.15	0		
	Normal	342	16.1	12.2–20.0		13.4	8.6–18.2		9.6	5.5–13.6				
	Overweight	60	16.7	6.3–27.0		12.7	3.3–22.1		1.8	0.0–5.3				
Maternal education	No and pre-primary	145	20.7	13.9–27.5	0.80	11.0	2.6–19.3	0.62	11.7	4.9–18.5	0.41	62		
	Primary	175	17.2	11.2–23.3		16.2	9.8–22.5		6.8	2.0–11.6				
	Lower-secondary	115	17.4	11.4–23.4		13.8	7.0–20.5		9.5	4.9–14.1				
Upper-secondary and tertiary	54	14.8	3.1–26.5		12.2	2.2–22.3		5.8	0.0–11.9					

Table 4 (continued)

Variable	Categories	Total N	Monsoon (Wave 1)			Pre-Aman (Wave 2)			Pre-Boro (Wave 3)			Missing cases
			% Wasted	95% CI	Chi ² <i>p</i> -value	% Wasted	95% CI	Chi ² <i>p</i> -value	% Wasted	95% CI	Chi ² <i>p</i> -value	
Paternal education	No and pre- primary	171	14.6	9.4–19.8	0.17	11.1	6.2–16.1	0.50	5.2	1.0–9.3	0.19	136
	Primary	100	24.0	16.8–31.2		17.4	9.5–25.3		12.6	5.5–19.8		
	Lower- secondary	77	23.4	12.4–34.3		16.2	7.7–24.7		9.5	0.8–18.1		
Household size	Upper- secondary and tertiary	66	16.7	9.1–24.2		13.1	4.6–21.6		6.7	0.1–13.2		
	3 to 5	334	20.1	16.3–23.8	0.16	15.8	11.7–19.9	0.09	9.7	6.0–13.4	0.34	0
	6+	216	15.3	11.2–19.4		10.5	6.8–14.1		7.3	3.0–11.5		
Total		550	18.2	15.3–21.5	-	13.7	10.5–17.8	-	8.7	5.9–12.8	-	-

mothers have a higher prevalence of wasting compared to normal and overweight mothers. Interestingly, children in larger households (7+) have a lower prevalence of wasting compared to smaller households.

The tables indicate that there are only a few significant relationships within the data. This is due to the sample size and the resulting limited power. The percentage wasted within each group follows the patterns expected in general, although there are some relationships, such as paternal education, which do not show expected trends.

Socio-ecological variation

Although the prevalence of wasting declines over the seasons, Table 5 shows that this is not the case in all of the SESs, indicating that seasonality differs in its effect depending on location and socioeconomic characteristics. The prevalence of wasting within Sunderban (mangrove forest) Dependent and Saltwater Shrimp communities is higher in the pre-Aman harvest season than in the pre-Boro (and post-Aman) harvest season (albeit by a small amount). In all SES, the lowest prevalence is in the pre-Boro (and post-Aman harvest season). Some SESs note large declines in wasting prevalence over time, while others remain consistently high. The SES variable is significantly associated with wasting prevalence in the pre-Boro (and post-Aman) harvest season ($p=0.03$).

Model results

The final models are found in Table 6. Model 1 presents a random effects model including the season indicator, while Model 2 presents a season indicator and SES interaction. Given the small sample size of this dataset, few variables are found to be significant. Therefore, the results and discussion will mostly focus on the effect size of each factor in the model. Effect sizes in Table 6 are reported as odds ratios (OR), whereby an OR of less than one means that a category is associated with a decrease in the odds of the response occurring, compared to the reference category. Alternatively, an OR of more than one is associated with an increase in the odds of the response occurring.

Model 1 shows that the odds of a child being wasted are declining across each survey wave, aligning with the descriptive statistics. The greatest decline in the odds of being wasted occurs between the monsoon season and the pre-Aman harvest season. Model 2 presents the SES and season indicator interaction. Figure 3 shows that the predicted log-odds of a child being wasted is decreasing over time in most SESs, with negative log-odds indicating the outcome of wasting is less likely to happen, which mirrors the exploratory descriptive statistics shown in Table 5. Although Sunderban Dependent SESs observe a slight increase in the log-odds between the monsoon season and the pre-Aman harvest season.

The main finding from the model is that there is an interaction between the season indicator and the socio-ecological system, indicating that the effect of season on

Table 5 Bivariate independent descriptive statistics: spatial

Variable	Total N	Monsoon (Wave 1)			Pre-Aman (Wave 2)			Pre-Boro (Wave 3)		
		% Wasted	95% CI	Chi ² p-value	% Wasted	95% CI	Chi ² p-value	% Wasted	95% CI	Chi ² p-value
Sunderban Dependent	73	17.8	15.7–19.9	0.73	18.6	12.5–24.7	0.28	16.4	8.8–24.1	0.03
Costal Periphery	80	21.3	16.3–26.2		13.2	5.5–20.8		9.3	5.4–13.2	
Charland	107	14.0	6.9–21.1		8.7	2.3–15.2		2.0	0.0–4.7	
Saltwater Shrimp	66	21.2	14.1–28.4		21.7	7.5–35.9		11.1	1.5–20.7	
Rainfed Agriculture	96	18.8	10.4–27.1		14.0	6.1–21.8		12.1	4.1–20.1	
Irrigated Agriculture	70	14.3	7.2–21.4		12.1	8.8–15.5		6.0	2.3–9.7	
Freshwater Prawn	58	22.4	15.7–29.2		10.0	5.0–15.0		5.8	0.0–11.9	
Total	550	18.2	15.3–21.5	-	13.7	10.5–17.8	-	8.7	5.9–12.8	-

Table 6 Final random effects models

Variable	Category	Model 1: season indicator				Model 2: season indicator*SES interaction			
		OR	Wald <i>p</i> -value	95% confidence interval		OR	Wald <i>p</i> -value	95% confidence interval	
				LB	UB			LB	UB
Season indicator	Monsoon (1) (ref)								
	Pre-Aman (2)	0.54	0.01	0.35	0.83				
	Pre-Boro (3)	0.27	0.00	0.17	0.44				
Socio-ecological system	Sunderban Dependent (ref)								
	Coastal Periphery					1.63	0.50	0.39	6.81
	Charland					0.85	0.82	0.21	3.44
	Saltwater Shrimp					1.46	0.62	0.32	6.69
	Rainfed Agriculture					1.22	0.77	0.31	4.91
	Irrigated Agriculture					0.81	0.80	0.17	3.88
	Freshwater Prawn					1.85	0.43	0.40	8.56
Socio ecological system * Season (survey wave)	Sunderban Dependent * pre-Aman (2)					1.03	0.96	0.33	3.24
	Coastal Periphery (Marine) * pre-Aman (2)					0.57	0.48	0.12	2.68
	Charland (Riverine) * pre-Aman (2)					0.37	0.19	0.08	1.66
	Saltwater Shrimp (Bagada) * pre-Aman (2)					1.32	0.73	0.28	6.25
	Rainfed Agriculture (Aman) * pre-Aman (2)					0.68	0.60	0.16	2.87
	Irrigated Agriculture (Boro) * pre-Aman (2)					0.60	0.54	0.12	3.07

Table 6 (continued)

Variable	Category	Model 1: season indicator			Model 2: season indicator*SES interaction			
		OR	Wald <i>p</i> -value	95% confidence interval	OR	Wald <i>p</i> -value	95% confidence interval	
				LB UB			LB UB	
	Freshwater Prawn (Golda) * pre-Aman (2)				0.32	0.24	0.05	2.13
	Sunderban Dependent * pre-Boro (3)				0.83	0.93	0.02	39.06
	Coastal Periphery (Marine) * pre-Boro (3)				0.33	0.19	0.06	1.73
	Charland (Riverine) * pre-Boro (3)				0.06	0.01	0.01	0.45
	Saltwater Shrimp (Bagda) * pre-Boro (3)				0.33	0.20	0.06	1.81
	Rainfed Agriculture (Aman) * pre-Boro (3)				0.56	0.44	0.13	2.45
	Irrigated Agriculture (Boro) * pre-Boro (3)				0.16	0.06	0.02	1.09
	Freshwater Prawn (Golda) * pre-Boro (3)				0.24	0.16	0.03	1.79
CONST		0.13	<0.001	0.09	0.19	<0.001	0.04	0.32
Random part		Variance	Standard Deviation		Variance	Standard Deviation		
	Var(CONST)	7.31	2.70		7.60	2.76		

Lower and upper bounds reflect the level of certainty of the odds ratio; a larger interval between the LB and UB reflects a greater level of uncertainty
 OR odds ratio, CI confidence interval, UB upper bound, LB lower bound

wasting varies by SES. Figure 3 shows that the effect of seasonality on the log-odds of wasting is not consistent over time between different SESs. In nearly all SESs, the likelihood of a child being wasted is highest in the monsoon season and lowest in the pre-Boro (and simultaneously post-Aman) rice harvest periods. Figure 3 shows the predicted log-odds of wasting is generally lowest in the wealthier SESs (Irrigated Agriculture and Freshwater Prawn). The smallest change over time (and consistently high predicted log-odds of a child being wasted) is seen in the poorest SES, Sunderban Dependent. Meanwhile, Charland Riverine SESs have some of the lowest predicted log-odds of wasting compared to other SESs in each season. Children in the Saltwater Shrimp SES have relatively higher predicted log-odds of wasting in the monsoon season and pre-Aman harvest season and observe a large drop in the pre-Boro (and post-Aman) harvest season, suggesting a sudden improvement in nutritional status. Conversely, the log-odds of child wasting in the Rainfed Agriculture, Freshwater Prawn and Coastal Periphery SESs are high in the monsoon season and then drop in the following seasons. Irrigated Agriculture has comparatively lower predicted log-odds in the monsoon season compared to other SESs, declining slightly in the pre-Aman rice harvest season, and a far lower predicted log-odds in the pre-Boro (and post-Aman) rice harvest season. This indicates the complexity of the relationship between season and nutrition and demonstrates that the socio-economic system is related to resilience from seasonal effects on nutritional status.

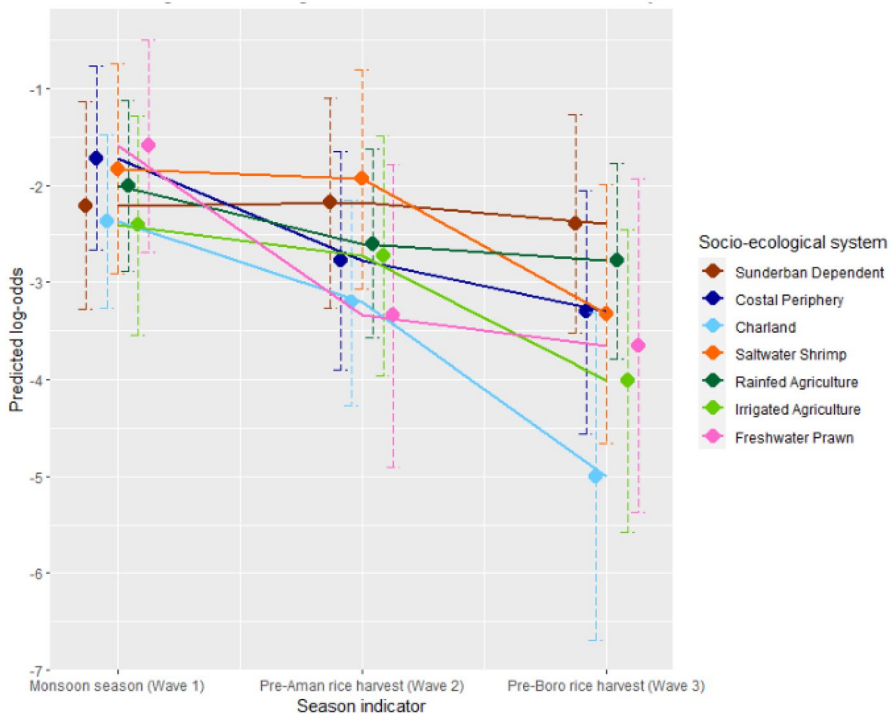


Fig. 3 Predicted log-odds of a child being wasted for each season. Each colour indicates a given socio-ecological system. Dashed lines indicate 95% confidence intervals for each SES. Measurements were taken once in each season. Note: point and interval estimates are staggered for clarity only

Model 3 (Table 10, Appendix 3) has included demographic (time-invariant) control variables so that the coefficients for the season indicator and SES can be compared, to assess if this changes the magnitude of key variables. Once demographic variables have been accounted for, the magnitude of the odds of wasting becomes slightly lower in all SESs and seasons compared to Model 2, while p -values remain broadly similar. The only demographic variable that is significantly associated with an increase in the odds of wasting in Model 3 is fathers with primary education ($p=0.01$).

In order to explore key hypothesised drivers of seasonal variation in undernutrition that vary across space and time, random effect models (binary and multinomial models were required) were also estimated with time-varying characteristics (found in Table 4) as the outcome variable and including a seasonal indicator as a predictor. These models can be found in Tables 13 to 19 in Appendix 4. Results suggest that each time-varying variable such as maternal and paternal occupation, dietary diversity and food consumption, does vary seasonally, following a similar pattern to the outcome of wasting, although few variables show statistical significance in the relationships examined. The variation seen supports the hypothesis that time-varying factors are, at least partly, driving changes in nutritional outcomes, although a formal test of how these factors may lead to wasting has not been conducted.

Tables 14 and 15 show a similar pattern, with the odds of having an unimproved drinking water source or sanitation facility are lowest in the pre-Boro (and post-Aman) rice harvest season compared to the monsoon season and those with improved facilities. This indicates that infection risks due to poor water and sanitation facilities are lowest in the pre-Boro (and post-Aman) harvest, when nutritional status is best.

Table 16 shows that the odds of mothers having a skilled occupation are highest during the monsoon season, with consistently lower odds in the pre-Aman and pre-Boro seasons compared to those with unskilled occupations. Conversely, Table 17 shows that fathers have the highest odds of having a skilled occupation in the pre-Aman harvest season, before decreasing in the pre-Boro rice harvest, compared to fathers with unskilled occupations. These results contradict the hypothesis that a parent having a higher-skilled job is associated with better nutritional status for their child through the seasons.

Table 18 shows the odds of having a diet diversity score below 7 in the past 24 hours are highest in the monsoon season compared to those with a diet diversity score of 7 or above, suggesting that diet diversity is lower during the monsoon season, when nutritional status is at its worst. Conversely, Table 19 shows the odds of having an acceptable food consumption score in the past 7 days are lowest in the pre-Aman rice harvest season, compared to the monsoon season and those with a poor food consumption score. The pre-Aman rice harvest is when nutritional status begins to improve; therefore, it is surprising that food consumption scores are least likely to be acceptable during this season.

Discussion

This research examined spatial and temporal variation in nutritional status of children under-5 in the coastal river delta region of south-west rural Bangladesh, using a longitudinal dataset from the 'ESPA-Deltas' project. The analysis considered

how seasons and SESs are associated with the anthropometric indicator of wasting (weight-for-height). This study indicates the importance of the consideration of seasonal variation in several ways. Firstly, the results show large variability between seasons in most locations, indicating that seasonality is an important determinant of wasting. Caution is therefore needed when interpreting analyses about wasting in large-scale national surveys (such as DHS) that do not account for seasonality or survey month (Baye & Hirvonen, 2020; Marshak et al., 2021), especially when comparing wasting prevalence between different surveys when those surveys are conducted at different times of the year. Secondly, the contribution of SES as a variable in statistical analysis to capture previously unobserved place and spatial effects of nutritional status is valuable, such as social capital and access to ecosystem services. The effect of SES on wasting prevalence is not significant by itself, but the importance of SES is seen through the interaction between seasonality and different SESs. This gives insight to understand distinct seasonal dynamics of nutritional status in different socio-ecological contexts (Assaf et al., 2018). It is possible that different factors by location may buffer individuals from changes in nutritional status through the seasons. These findings highlight the need for high-frequency longitudinal data on nutritional status to explore short-term changes in more depth.

With increasing seasonal variation in climatic conditions due to human-driven environmental changes that are observed globally (FAO, 2018), these results contribute to the evidence that the effects will not be felt evenly across population groups. This study has taken a small spatial area and has shown that there are different effects of season on child wasting prevalence over a single year even within this small area. This is related to the type of socio-ecological system which the child is living within. Some systems seem to have a greater ability to cope with these seasonal variations than others, with lower peaks of wasting during the monsoon season. The reasons for this are likely to be multifaceted, and further exploration to understand the resilience of each system to seasonal effects is needed.

The interaction of SES and seasonality in this research suggest that wasting may also be influenced through a pathway that relates to the stability of food security and income stability in each SES, highlighting the interdependent role of livelihoods and place in understanding nutrition over time. Although the effect of the interaction between these factors on nutritional status is small, the variation between SESs is of interest while demonstrating the effect of season on wasting overall.

The results of this study found that the odds of wasting are consistently lower across all SESs in the pre-Aman and pre-Boro rice harvest seasons (except in the poorest SES, Sunderban Dependent), compared to the monsoon season. Previous literature also finds that the likelihood of under-5 child wasting is also highest in monsoon season in rural Bangladesh (Mohsena et al., 2018). The monsoon season is when a peak in rainfall is associated with an increase in waterborne diseases, when access to a safe water supply and healthcare facilities may be limited (Mohsena et al., 2018; Sullivan, 2013). The secondary analysis found in Appendix 4 also finds that the odds of having unimproved drinking water and sanitation facilities are higher in the monsoon season compared to the pre-Boro harvest season, supporting this hypothesis.

There seem to be several contributing factors as to why the likelihood of wasting is highest in the Sunderban Dependent SES throughout each season. Firstly, it is the poorest SES and is noted as having particularly poor transport infrastructure, leaving communities isolated from nutrition intervention programmes and health care facilities (Pakrashi, 2016). Sunderban Dependent SESs are characterised by highly seasonal livelihoods, and corresponding variation in incomes, alongside insecure property rights (Adams et al., 2016b, 2018b). High levels of landlessness may therefore prevent livelihood diversification and coping strategies for households to produce fish, crops and livestock from homesteads as a safety net, particularly in hunger periods (Ahmed & Waibel, 2019; Lázár et al., 2015). Additionally, freshwater is limited in the dry seasons (during the pre-Boro season) (Adams et al., 2018b), which may lead to consumption of lower-quality water sources, which may be associated with an increase in infections and diarrhoeal diseases, explaining why the log-odds of a child being wasted in the pre-Boro season remain far higher compared to other SESs.

Adams et al. (2018a) found that SESs, such as Sunderban Dependent, are increasing the quantity of fishing during hunger periods as a coping strategy. Increasing fish production (sustainably) and consumption will increase protein intake and diet diversity (Adams et al., 2018a). This may explain why, compared to other SES, the log-odds of being wasted in the Sunderban Dependent SES is not highest in the monsoon season. Increasing diversity of food sources as a coping strategy also aligns with the secondary analysis (in Appendix 4), showing that the odds of an 'acceptable' food consumption scores were higher in the monsoon season. Survey documentation found that an oil spill occurred in the Sunderban Dependent SESs between survey waves 2 and 3. This may partly explain why wasting prevalence remains consistently high in Sunderban Dependent SESs in waves 2 and 3 (Adams et al., 2016a).

The log-odds of wasting is often lower in SESs that are involved in fishing and aquaculture (including Coastal Periphery, Charland, Saltwater Shrimp and Freshwater Prawn), suggesting that better access to diverse foods and protein sources, such as fish and crustaceans, improves nutritional outcomes during the year, aligning with Ahmed et al. (2018), in addition to higher incomes. These SESs are often located nearby waterways and rivers, which also provide an open-access source of food and nutrition during periods of pre-rice harvest (Adams et al., 2018b).

Freshwater prawns are generally harvested at the end of the monsoon season, which may explain the sudden drop in the log-odds of wasting in the pre-Aman season (Kazal et al., 2020). Saltwater shrimps are generally farmed during the dry season when salinity is high (coinciding with the pre-Boro rice harvest) (Islam et al., 2005) and harvested at the beginning of the monsoon season. However, this does not explain why the predicted log-odds of wasting is much higher in the monsoon season compared to the pre-Boro rice harvest. Fisherfolk generally fish in nearby rivers in the monsoon season, and offshore during the dry season (Adams et al., 2018b). Hilsa fish are collected during the summer (during March, in the pre-Boro season) when they are most profitable, which may explain the reduction in the log-odds of wasting in the pre-Boro season. Saltwater Shrimp SESs are also characterised as being remote from health services and markets, in addition to being exposed to storm surges and cyclones (Adams et al., 2018a, b, c). This may be attributed to the high

predicted log-odds of wasting in the monsoon and pre-Aman rice harvest seasons when the risk of storm surges and cyclones are highest.

Results show the log-odds of wasting in the monsoon season is lowest for Irrigated Agriculture SESs, coinciding with when the Boro harvest occurs, although the log-odds of wasting is higher during the pre-Aman and pre-Boro rice harvest seasons, relative to other SESs. Boro rice is grown in the dry season (hence must be irrigated) and is harvested from late March to June (Adams et al., 2018a). Irrigation of agriculture can act as a buffer for some seasonal effects relating to rainfall and crop production (Cooper et al., 2019), and therefore perhaps also changes in child nutritional status.

The SESs defined in this study area are dependent on those employed in the agriculture, livestock, aquaculture and fishing occupations. Policies to improve nutritional outcomes for those employed in low-skilled, seasonally unstable occupations should aim to stabilise income security and consumption throughout the year, especially during pre-harvest hunger periods when individuals may not be in employment. This could promote smooth consumption and food supply throughout the year (FAO, 2018; Khandker, 2012). Once demographic control variables have been accounted for, few additional variables were significantly associated with wasting, and existing variables remained the same. This suggests that protective factors that mitigate seasonal variation in wasting were not captured in the survey data, such as access to credit and health care facilities or intervention programmes.

Seasonal feeding programmes, particularly prior to the monsoon season, could attempt to combat temporal fluctuations in food and nutrition security and peaks in wasting prevalence (Sullivan, 2013; WFP, 2012), while targeted feeding programmes in poorly performing SESs could reduce spatial inequalities (WFP, 2012). Households in rural Bangladesh often take out loans and credit as a coping strategy, when seasonal poverty is often highest, reducing the ability to accumulate assets for the following year (Adams et al., 2018b; Béné et al., 2015; Devereux et al., 2008; Mohsena et al., 2018; Pitt & Khandker, 2002). Previous research has found that the greatest effects of credit on household consumption are found during the lean seasons in rural Bangladesh, to smooth seasonal patterns of consumption (Pitt & Khandker, 2002). Seasonal social protection systems could make households more resilient to fluctuations in income and food and nutrition insecurity throughout the seasons, although dependent on the credit provider (Chowdhury et al., 2016; Feed the Future, 2018; Mohsena et al., 2018; Raihan et al., 2018; Schaafsma et al., 2021; Sullivan, 2013).

Subsistence production can promote food stability and self-sufficiency throughout the seasons which can improve nutrition and food security (Nath, 2015). Crop diversification allows non-rice foods to be grown in fallow periods, generating employment and diversifying food supplies for households (Ahmed et al., 2018; Mostofa et al., 2010; Rahman et al., 2009; Raihan et al., 2018). Provision of loans to purchase fishing equipment or resources for shrimp and prawn production may also assist in diversifying diets. Diversification of income, especially incomes that are not tied to agriculture or seasonal variation, may also assist in smoothing consumption and economic access to food (Khandker, 2012; Pitt & Khandker, 2002). This is widely acknowledged in the literature relating to

seasonal migration to urban and peri-urban areas (Cattaneo, 2018; Kartiki, 2011; Mohsena et al., 2018).

This study has provided new insights for the analysis of nutritional status and seasonality; however, several limitations are noted. A small sample size meant the model lacked statistical power, but effect sizes still prove interesting. The results of this analysis are generalisable for rural areas within Khulna Division and Barisal Division, where the sampling took place. This data and therefore the analysis and results are not statistically representative at the national level. However, we believe that this indicates that there are differences over seasons in wasting in all rural areas of Bangladesh, but the magnitude and importance of this is not able to be assessed. The similar wasting prevalence observed in the ESPA-Deltas dataset during the corresponding months that the 2014 DHS survey was conducted also indicates that the DHS survey is likely to be affected by seasonality in months when sampling did not occur. Previous DHSs in Bangladesh do not occur at the same time of the year, for example, the 2014 survey was conducted from June to November, but the 2017/18 survey was conducted between October 2017 and March 2018. The wasting estimate in 2017/8 is 8.4% compared to 14.3% in 2014. It is unclear if this is due to a rapid improvement in the nutritional status of children under-5, or because the most recent survey was conducted during the dry season, when you would expect estimates to be lower (as seen in the pre-Boro harvest season). Given the large variation observed in this longitudinal study, it highlights the large seasonal variations that must be accounted for in cross-sectional data that is sampled over many months, such as DHS.

This study was conducted over one seasonal cycle, which limits the potential of this analysis to draw wider conclusions about seasonality. This paper presents evidence of intra-annual variation; however, it is not clear if variation is driven by seasonality or by other unmeasured time-varying effects, such as political events, conflict, extreme events and changes to policy. According to the survey documentation, no extreme climatic events were recorded during (or prior to) the survey implementation period that may have influenced the observed decline in wasting prevalence over time (Adams et al., 2016a). Chowdhury (2022) presents evidence that the El Nino/La Nina events in 2014–2015 were not extreme. An extreme El Nino event was observed in 2015–2016; however, the final survey wave was conducted in March, prior to the monsoon season, suggesting that the survey should not be impacted (Chowdhury, 2022). No major cyclones occurred during 2014 and 2015 in the study area (Hossain & Mullick, 2020).

Current conceptual frameworks about malnutrition do not account for a seasonal or temporal dimension. This research reflects a greater need for further surveillance or monitoring programmes at multiple points in the year, over multiple years to understand temporal variation in nutritional outcomes with reliable data (Alom et al., 2012), particularly to understand causal pathways between such large seasonal fluctuations in wasting prevalence. Furthermore, the inclusion of environmental conditions and spatial contexts can prove insightful for understanding inequalities and variation in seasonal acute malnutrition.

This research has highlighted that an individual's nutritional status can vary greatly during the changing seasons, with variability differing by household and

place of residence. As seasonal climatic conditions become increasingly extreme and uncertain, intra-year variation in malnutrition is likely to increase, particularly for communities whose livelihoods depend on the changing seasons. Evidence for long-term effects of climate change (such as increasing temperatures) on health is emerging; however, this research reinforces that understanding short-term, cyclical effects is currently neglected, but remains crucial for meeting the 2030 Sustainable Development Goals.

Appendix 1

Table 7 Univariate statistics: time-variant variables

Variable	Category	Monsoon (Wave 1)		Pre-Aman (Wave 2)		Pre-Boro (Wave 3)	
		Total N	%	Total N	%	Total N	%
Wealth index	1	110	20.0	110	20.0	110	20.0
	2	110	20.0	110	20.0	110	20.0
	3	110	20.0	110	20.0	110	20.0
	4	110	20.0	110	20.0	110	20.0
	5	110	20.0	110	20.0	110	20.0
Sanitation facility	Private improved	383	69.6	365	66.4	397	72.2
	Shared improved	106	19.2	96	17.5	83	15.1
	Unimproved	61	11.1	70	12.7	49	8.9
	Missing	0	0.0	19	3.4	21	3.8
Source of drinking water	Improved	466	84.7	437	79.5	462	84.0
	Unimproved	84	15.3	94	17.1	67	12.2
	Missing	0	0.0	19	3.4	21	3.8
Maternal occupation	Unskilled	254	46.2	221	40.2	233	42.4
	Skilled	79	14.4	93	16.9	98	17.8
	Missing	217	39.5	236	42.9	219	39.8
Paternal occupation	Unskilled	373	67.8	314	57.1	330	60.0
	Skilled	162	29.5	144	26.2	131	23.8
	Missing	15	2.7	92	16.7	89	16.2
Household diet diversity score	≤ 6	229	41.0	262	47.6	230	41.8
	7+	321	58.4	269	48.9	299	54.4
	Missing	0	0.0	19	3.4	21	3.8
Food consumption score	Poor	199	36.2	271	49.3	212	38.6
	Borderline	302	54.9	222	40.4	273	49.6
	Acceptable	49	8.9	38	6.9	44	8.0
	Missing	0	0.0	19	3.4	21	3.8
Total		550	100.0	550	100.0	550	100.0

Table 8 Univariate statistics: time-invariant variables

Variable	Category	Total N	%
Child gender	Male	283	51.5
	Female	267	48.6
Child age	1	103	18.7
	2	149	27.1
	3	164	29.8
	4+	134	24.4
Maternal age	< 20 years	29	5.3
	20–29 years	338	61.5
	≥ 30 years	183	33.3
Maternal BMI	Underweight	148	26.9
	Normal	342	62.2
	Overweight	60	10.9
Maternal education	No and pre-primary	145	26.4
	Primary	174	31.6
	Lower-secondary	115	20.9
	Upper-secondary and tertiary	54	9.8
	Missing	62	11.3
Paternal education	No and pre-primary	171	31.1
	Primary	100	18.2
	Lower-secondary	77	14.0
	Upper-secondary and tertiary	66	12.0
	Missing	136	24.7
Household size	3 to 5	334	60.7
	6+	216	39.3
Socio-ecological system	Sunderban Dependent	73	13.3
	Costal Periphery	80	14.6
	Charland	107	19.5
	Saltwater Shrimp	66	12.0
	Rainfed Agriculture	96	17.5
	Irrigated Agriculture	70	12.7
	Freshwater Prawn	58	10.6
Total		550	100.0

Appendix 2

Table 9 Data preparation for independent variables

Variable	Preparation of data
Time-variant variables	
Household wealth index	<p>Similar to the DHS wealth index construction, principal component analysis (PCA) was used, based on household assets (Rutstein, 2015)</p> <p>A full list of variables included in the index:</p> <ul style="list-style-type: none"> • Household size • Land area • Number of Livestock and Poultry (cow, goat, sheep, buffalo, chicken, duck) • Sanitation Facility (also separated into shared and private facilities) • Drinking water supply • Main material of the floor • Main material of the walls • Main material of the roof • Type of cooking fuel used in the recall months of the survey • Does household have electricity? • Asset ownership: Television • Asset ownership: Radio • Asset ownership: Mobile phone • Asset ownership: Landline phone • Asset ownership: Refrigerator • Asset ownership: Tractor • Asset ownership: Car • Asset ownership: Motorcycle • Asset ownership: Bicycle • Asset ownership: Rickshaw/van • Asset ownership: Bull or Ox driven cart • Asset ownership: Engine driven boat <p>Missing values were replaced with the response from the next (or previous) wave, rather than being imputed from the mode value</p> <p>A new variable was generated for each response of a categorical question, with either a 0 or 1. PCA was then carried out, and the first principal component was used to generate a score for each household, which was assigned into quintiles</p>
Sanitation facility	<p>Similar to the DHS groupings, cases were divided into improved and unimproved facilities, and improved were separated into private and shared facilities. Unimproved could not be separated further as the sample size was too small</p>
Source of drinking water	<p>Drinking water was combined into fewer categories to ensure sample sizes larger than 30. Categories included 'improved' and 'unimproved'</p>

Table 9 (continued)

Variable	Preparation of data
Time-variant variables	
Maternal occupation status	<p>Ideally, employment status (currently working or not) would act as a filter before defining occupation. However, results find that no mothers were employed in wave 2 or 3, so maternal employment status will not be used. Caution must be taken given that it is not clear if the women are currently employed or not based on occupation status alone</p> <p>Occupations were mostly distributed in agriculture, livestock, aquaculture and fishing, which were combined with other unskilled occupations. Traditional, medical, business, service and other occupations were combined into a skilled category. A full list of all occupations included in each category is found on the UK Data service ReShare</p> <p>A missing category will also be included in the multi-level/random effects analysis when occupation was not recorded</p>
Paternal occupation status	<p>For consistency, the same categorisations were used for both maternal and paternal occupation status</p>
Household dietary diversity score: 24-hour recall	<p>Household diet diversity score (HHDDS) is a proxy for nutritional intake, indicating the ability to access food in the past 24 hours (Kennedy et al., 2011). The more diverse, the higher the score, which is often associated with energy and protein sufficiency (Swindale & Bilinsky, 2006). This measure hopes to capture dietary diversity and intake</p> <p>HHDDS consists of quick, standardised, simple questions, although not culture or population-specific (Kennedy et al., 2011; Swindale & Bilinsky, 2006). Ideally, this measure is collected at the individual level; however, in this analysis, it is only available at the household level, which assumes an even intra-household distribution of food (INDDX, 2018). The indicator is based on recall in 24 h, which is a recent, short reference period that minimises recall error. The respondent is the main earner, who is generally male, and may not be aware of the household dietary patterns</p> <p>Twelve food groups are included in this indicator, with a score ranging from 0 to 12. There is not a universally recognised cut-off point, so the mean, mode and median of 7 is chosen. < 7 is considered a 'low' diet diversity and ≥ 7 is 'adequate'</p>

Table 9 (continued)

Variable	Preparation of data
Time-variant variables	
Household food consumption score: 7-day recall	<p>The food consumption score (FCS) is an aggregation of <i>usual</i> household diet diversity over a 7-day period. A value of 1 is assigned to each food that was consumed, and 0 if not consumed. The score is totalled and weighted based on each food group. A household is categorised as poor, borderline or acceptable as a proxy for calorie availability and nutritional intake. A full method is outlined at INDDEx (2018)</p> <p>The index used in this research does not include oil and sugar as separate categories, but as the smallest weighting was assigned to these categories, it is not a major concern (INDDEx, 2018). A limitation is that it is hard to determine at what point small amounts of a food consumed should be included or not (Lovon & Mathiassen, 2014)</p> <p>FCS and HHDDS are highly correlated and used interchangeably, both were included in the preliminary regression analysis simultaneously and separately, but collinearity did not affect the results</p>
Season indicator	To capture the potential for variation in seasonality and harvest seasons, the survey wave is included as a seasonal indicator
Time-invariant variables	
Child gender	No recoding took place
Child age	Children aged 4 and 5 have been combined to ensure an appropriate sample size, as 13 children were sampled over 5 years
Maternal age	Maternal age ranges between 15 and 51. Age is positively skewed, with clear signs of age heaping. The variable has been grouped into 3 categories: '< 20', '20–29', and '≥ 30' (Akhter & Haque, 2018; Hossain & Khan, 2018). This hopes to separate some of the heaping effect
Maternal nutritional status	Maternal BMI is widely used as a reflection of maternal nutritional status (Ahmed et al., 2018). Maternal BMI will be grouped into 3 categories: 'underweight' (< 18.5 kg/m ²), 'normal' (18.5–25.00 kg/m ²) and 'overweight' (> 25 kg/m ²) (Hasan et al., 2017; Rahman et al., 2009)

Table 9 (continued)**Time-invariant variables****Maternal education status**

The household roster asks, 'What is the highest grade passed?' with responses ranging from 0 to 12 (No education through to Upper Secondary), and then 16 (Degree) and 18 (Masters or higher). Previous research generally classifies education categorically by 'No education', 'Primary education', 'Secondary education' and 'Tertiary education' (Akhter & Haque, 2018; Alom et al., 2012; Kamal, 2011). However, because of the low education levels of the study population, and to ensure a sample size above 30, the highest education level has been coded as 'No and pre-primary education', 'Primary education', 'Lower secondary education' and 'Upper secondary and tertiary education'. As there is a high number of missing cases, a 'missing' category will be included in the multi-level/random effects analysis

Paternal education status

For consistency and to ensure a reasonable sample size, the same categorisations were used for both maternal and paternal education status

Household size

Households range from 3 to 13 persons (to qualify for the survey, all households have at least one male and female and must have a child). This household size is for de jure household members only

The variable was recoded into categories defined as: '3–5' and '6+' household members

Spatial variables**Socio-ecological system**

No further data manipulation has been done to the SESs, although it should be noted that cases are evenly distributed across SES before cases were excluded; however, the distribution becomes unbalanced, with household counts ranging between 46 and 96. The SES categories are ordered based on mean raw wealth scores calculated in Ahmed et al. (2018), from relative poorest being Sunderban Dependent to relative wealthiest being freshwater prawn

Appendix 3

Table 10 Final random effects models

Variable	Category	Model 1: season indicator			Model 2: season indicator*SES interaction			Model 3: season indicator*SES interaction and demographic control variables		
		OR	Wald p-value	95% confidence interval LB UB	OR	Wald p-value	95% confidence interval LB UB	OR	Wald p-value	95% confidence interval LB UB
Season indicator	Monsoon (1) (ref)									
	Pre-Anan (2)	0.54	0.01	0.35 0.83						
	Pre-Boro (3)	0.27	<0.001	0.17 0.44						
Socio-ecological system	Sunderban Dependent (ref)									
	Coastal Periphery				1.63	0.50	0.39 6.81	1.54	0.56	0.36 6.55
	Charland				0.85	0.82	0.21 3.44	0.85	0.82	0.21 3.48
	Saltwater Shrimp				1.46	0.62	0.32 6.69	1.31	0.73	0.28 6.13
	Rainfed Agriculture				1.22	0.77	0.31 4.91	1.18	0.82	0.29 4.79
	Irrigated Agriculture				0.81	0.80	0.17 3.88	0.65	0.60	0.13 3.17
	Freshwater Prawn				1.85	0.43	0.40 8.56	1.51	0.60	0.32 7.16
Socio ecological system* Season (survey wave)	Sunderban Dependent * pre-Anan (2)				1.03	0.96	0.33 3.24	0.93	0.90	0.29 2.99
	Coastal Periphery (Marine) * pre-Anan (2)				0.57	0.48	0.12 2.68	0.55	0.46	0.11 2.65
	Charland (Riverine) * pre-Anan (2)				0.37	0.19	0.08 1.66	0.37	0.19	0.08 1.66
	Saltwater Shrimp (Bagdia) * pre-Anan (2)				1.32	0.73	0.28 6.25	1.18	0.83	0.24 5.76

Table 10 (continued)

Variable	Category	Model 1: season indicator				Model 2: season indicator*SES interaction				Model 3: season indicator*SES interaction and demographic control variables			
		OR	Wald p-value	95% confidence interval	OR	Wald p-value	95% confidence interval	OR	Wald p-value	95% confidence interval	OR	Wald p-value	95% confidence interval
	Rainfed Agriculture (Aman) * pre-Aman (2)				0.68	0.60	0.16	2.87	0.61	0.50	0.14	2.62	
	Irrigated Agriculture (Boro) * pre-Aman (2)				0.60	0.54	0.12	3.07	0.49	0.41	0.09	2.60	
	Freshwater Prawn (Golda) * pre-Aman (2)				0.32	0.24	0.05	2.13	0.26	0.16	0.04	1.75	
	Sunderban Dependent * pre-Boro (3)				0.83	0.93	0.02	39.06	0.71	0.58	0.21	2.39	
	Coastal Periphery (Marine) * pre-Boro (3)				0.33	0.19	0.06	1.73	0.30	0.15	0.06	1.57	
	Charland (Riverine) * pre-Boro (3)				0.06	0.01	0.01	0.45	0.06	0.01	0.01	0.45	
	Saltwater Shrimp (Bagda)* pre-Boro (3)				0.33	0.20	0.06	1.81	0.27	0.14	0.05	1.56	
	Rainfed Agriculture (Aman) * pre-Boro (3)				0.56	0.44	0.13	2.45	0.49	0.35	0.11	2.17	
	Irrigated Agriculture (Boro)* pre-Boro (3)				0.16	0.06	0.02	1.09	0.13	0.04	0.02	0.88	
	Freshwater Prawn (Golda) * pre-Boro (3)				0.24	0.16	0.03	1.79	0.18	0.10	0.02	1.41	
Child gender	Male (ref)												
	Female								0.96	0.90	0.49	1.86	

Table 11 Fixed effects models

Variable	Category	Model 4: season indicator				Model 5: season indicator*SES interaction			
		OR	Wald p-value	95% confidence interval		OR	Wald p-value	95% confidence interval	
				LB	UB			LB	UB
Season indicator	Monsoon (1) (ref)								
	Pre-Aman (2)	0.71	0.05	0.51	1.00				
	Pre-Boro (3)	0.43	<0.001	0.30	0.63				
Socio-ecological system	Sunderban Dependent * monsoon (1) (ref)								
	Costal Periphery (Marine) * monsoon (1)					1.25	0.59	0.56	2.78
	Charland (Riverine) * monsoon (1)					0.75	0.49	0.33	1.69
	Saltwater Shrimp (Bagda) * monsoon (1)					1.24	0.61	0.54	2.88
	Rainfed Agriculture (Aman) * monsoon (1)					1.07	0.88	0.48	2.34
	Irrigated Agriculture (Boro) * monsoon (1)					0.77	0.57	0.31	1.89
	Freshwater Prawn (Golda) * monsoon (1)					1.33	0.51	0.56	3.15
	Socio ecological system * Season indicator	Sunderban Dependent * pre-Aman (2)					1.05	0.91	0.45
	Coastal Periphery (Marine) * pre-Aman (2)					0.70	0.43	0.29	1.71
	Charland (Riverine) * pre-Aman (2)					0.44	0.08	0.18	1.10
	Saltwater Shrimp (Bagda)* pre-Aman (2)					1.28	0.58	0.54	3.01
	Rainfed Agriculture (Aman) * pre-Aman (2)					0.75	0.50	0.32	1.73
	Irrigated Agriculture (Boro)* pre-Aman (2)					0.64	0.35	0.25	1.65
	Freshwater Prawn (Golda) * pre-Aman (2)					0.51	0.23	0.17	1.54
	Sunderban Dependent * pre-Boro (3)					0.91	0.83	0.38	2.19

Table 11 (continued)

Variable	Category	Model 4: season indicator			Model 5: season indicator*SES interaction				
		OR	Wald <i>p</i> -value	95% confidence interval		OR	Wald <i>p</i> -value	95% confidence interval	
				LB	UB			LB	UB
	Coastal Periphery (Marine) * pre-Boro (3)					0.48	0.14	0.18	1.27
	Charland (Riverine) * pre-Boro (3)					0.09	<0.01	0.02	0.43
	Saltwater Shrimp (Bagda)* pre-Boro (3)					0.58	0.28	0.21	1.55
	Rainfed Agriculture (Aman) * pre-Boro (3)					0.63	0.31	0.27	1.51
	Irrigated Agriculture (Boro)* pre-Boro (3)					0.29	0.04	0.09	0.95
	Freshwater Prawn (Golda) * pre-Boro (3)					0.28	0.06	0.08	1.05
CONST						0.22	<0.001	0.12	0.39

For Approval

Table 12 (continued)

Variable	Category	Model 6: season indicator					Model 7: season indicator*SES interaction				
		Estimate	SE	p-value	LB	UB	Estimate	SE	p-value	LB	UB
Socio ecological system * Season indicator	Sunderban Dependent * pre-Aman (2)						0.19	0.12	0.11	-0.04	0.41
	Coastal Periphery (Marine) * pre-Aman (2)						0.10	0.21	0.63	-0.32	0.52
	Charland (Riverine) * pre-Aman (2)						0.60	0.20	<0.01	0.20	0.99
	Saltwater Shrimp (Bagda) * pre-Aman (2)						0.26	0.23	0.26	-0.19	0.70
	Rainfed Agriculture (Aman) * pre-Aman (2)						0.38	0.21	0.06	-0.02	0.78
	Irrigated Agriculture (Boro) * pre-Aman (2)						0.36	0.22	0.11	-0.08	0.79
	Freshwater Prawn (Golda) * pre-Aman (2)						0.68	0.24	<0.01	0.22	1.15
	Sunderban Dependent * pre-Boro (3)						0.36	0.12	<0.01	0.13	0.59
	Coastal Periphery (Marine) * pre-Boro (3)						0.37	0.21	0.08	-0.05	0.80
	Charland (Riverine) * pre-Boro (3)						0.76	0.20	<0.001	0.37	1.16
	Saltwater Shrimp (Bagda) * pre-Boro (3)						0.31	0.23	0.17	-0.13	0.75
	Rainfed Agriculture (Aman) * pre-Boro (3)						0.44	0.21	0.03	0.04	0.85
	Irrigated Agriculture (Boro) * pre-Boro (3)						0.54	0.22	0.02	0.10	0.97
	Freshwater Prawn (Golda) * pre-Boro (3)						0.77	0.23	<0.01	0.30	1.23
	CONST						-0.94	0.06		-1.05	-0.83
										-1.36	-0.75

Appendix 4

Table 13 Model 8. Random effect multinomial regression—Wealth index ~ Season indicator (2 level) (ref= poorest)

Variable	Category	Poorer			Middle			Rich			Richer						
		OR	Wald <i>p</i> -value	95% confidence interval	OR	Wald <i>p</i> -value	95% confidence interval	OR	Wald <i>p</i> -value	95% confidence interval	OR	Wald <i>p</i> -value	95% confidence interval				
		LB	UB	LB	UB	LB	UB	LB	UB	LB	UB	LB	UB				
Season indicator	Monsoon (1) (ref)																
	Pre-Aman (2)	1.01	0.95	0.75	1.36	1.04	0.80	0.77	1.40	1.04	0.80	0.77	1.40	1.02	0.90	0.76	1.37
	Pre-Boro (3)	1.02	0.90	0.76	1.38	1.07	0.66	0.79	1.44	1.06	0.71	0.79	1.43	1.04	0.80	0.77	1.40
	CONST	1.00	1.00	0.81	1.23	1.00	1.00	0.81	1.23	1.00	1.00	0.81	1.23	1.00	1.00	0.81	1.23

Table 14 Model 9, Random effect multinomial regression—Sanitation facility~Season indicator (2 level) (ref=private improved facility)

Variable	Category	Shared Improved			Unimproved				
		OR	Wald <i>p</i> -value	95% confidence interval		OR	Wald <i>p</i> -value	95% confidence interval	
				LB	UB			LB	UB
Season indicator	Monsoon (1) (ref)								
	Pre-Aman (2)	0.95	0.74	0.70	1.29	1.20	0.32	0.84	1.73
	Pre-Boro (3)	0.76	0.08	0.55	1.04	0.77	0.20	0.52	1.15
	CONST	0.28	<0.001	0.22	0.34	0.16	<0.001	0.12	0.21

Table 15 Model 10, Random effect binary logistic regression Drinking water source~Season indicator (2 level) (ref=improved drinking water)

Variable	Category	OR	Wald <i>p</i> -value	95% confidence interval	
				LB	UB
Season indicator	Monsoon (1) (ref)				
	Pre-Aman (2)	1.18	0.32	0.85	1.63
	Pre-Boro (3)	0.82	0.25	0.58	1.15
	CONST	0.18	<0.001	0.13	0.24

Table 16 Model 11, Random effect multinomial regression—Maternal occupation~Season indicator (2 level) (ref=unskilled)

Variable	Category	Skilled			Missing				
		OR	Wald <i>p</i> -value	95% confidence interval		OR	Wald <i>p</i> -value	95% confidence interval	
				LB	UB			LB	UB
Season indicator	Monsoon (1) (ref)								
	Pre-Aman (2)	0.42	<0.001	0.34	0.53	0.98	0.84	0.83	1.17
	Pre-Boro (3)	0.42	<0.001	0.34	0.52	0.85	0.07	0.71	1.01
	CONST	0.21	<0.001	0.14	0.32	0.63	<0.001	0.47	0.83

Table 17 Model 12, Random effect multinomial regression—Paternal occupation~Season indicator (2 level) (ref = unskilled)

Variable	Category	Skilled				Missing			
		OR	Wald <i>p</i> -value	95% confidence interval		OR	Wald <i>p</i> -value	95% confidence interval	
				LB	UB			LB	UB
Season indicator	Monsoon (1) (ref)								
	Pre-Aman (2)	1.06	0.68	0.81	1.38	5.78	<0.001	3.28	10.21
	Pre-Boro (3)	0.91	0.52	0.70	1.20	5.12	<0.001	2.90	9.06
	CONST	0.43	<0.001	0.36	0.52	0.04	<0.001	0.02	0.07

Table 18 Model 13, Random effect binary logistic regression Household diet diversity score~Season indicator (2 level) (ref = 7 or more foods consumed)

Variable	Category	OR	Wald <i>p</i> -value	95% confidence interval	
				LB	UB
Season indicator	Monsoon (1) (ref)				
	Pre-Aman (2)	0.73	0.01	0.57	0.93
	Pre-Boro (3)	0.93	0.54	0.73	1.18
	CONST	1.40	<0.001	1.17	1.68

Table 19 Model 14, Random effect multinomial regression Food consumption score~Season indicator (2 level) (ref = poor)

Variable	Category	Borderline				Acceptable			
		OR	Wald <i>p</i> -value	95% confidence interval		OR	Wald <i>p</i> -value	95% confidence interval	
				LB	UB			LB	UB
Season indicator	Monsoon (1) (ref)								
	Pre-Aman (2)	0.54	<0.001	0.42	0.69	0.57	0.01	0.37	0.88
	Pre-Boro (3)	0.85	0.18	0.67	1.08	0.84	0.43	0.55	1.29
	CONST	1.52	<0.001	1.28	1.80	0.25	<0.001	0.18	0.33

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Declarations

Competing interests The authors declare no competing interests.

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