Beyond the risks to food availability – linking climatic hazard vulnerability with the food access of delta-dwelling households

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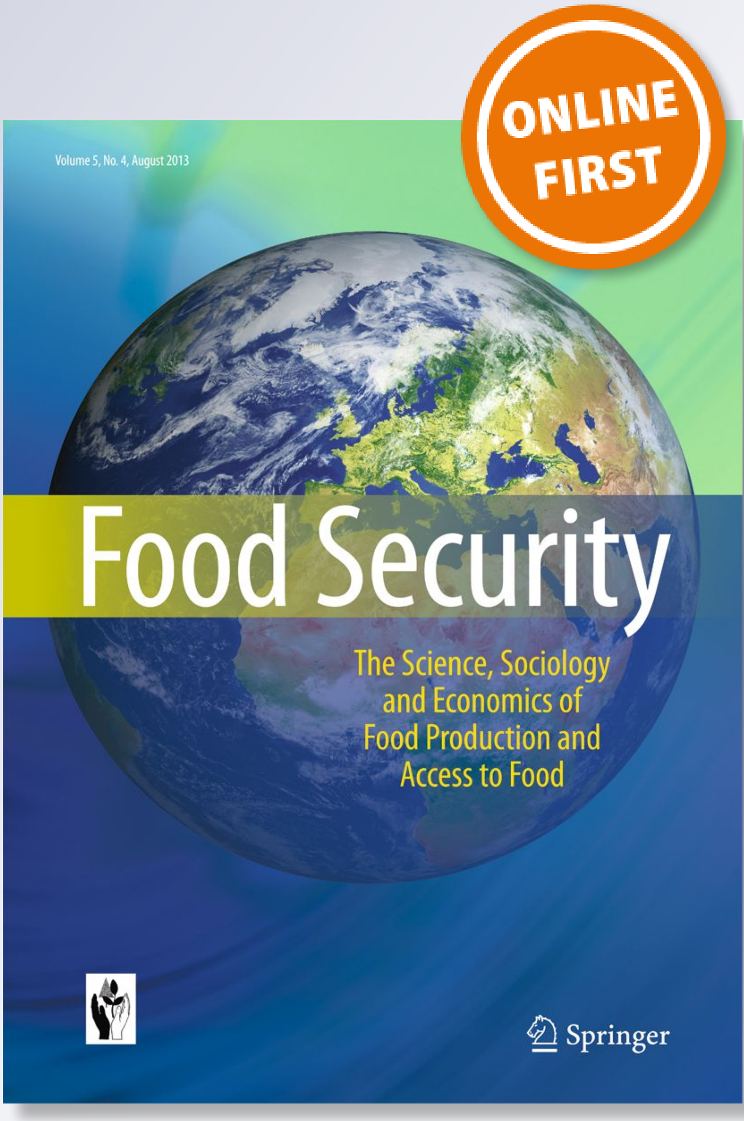

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ORIGINAL PAPER

Beyond the risks to food availability – linking climatic hazard vulnerability with the food access of delta-dwelling households

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Abstract
Although climate-driven hazards have been widely implicated as a key threat to food security in the delta regions of the developing world, the empirical basis of this assertion has centred predominantly on the *food availability* dimension of food security. Little is known if climatic hazards could affect the *food access* of delta-resident households and who is likely to be at risk and why. We explored these questions by using the data from a sample of households resident within the Ganges-Brahmaputra-Meghna (GBM) delta in Bangladesh. We used an index-based analytical approach by drawing on the vulnerability and food security literature. We computed separate vulnerability indices for flood, cyclone, and riverbank erosion and assessed their effects on household food access through regression modelling. All three vulnerability types demonstrated significant negative effects on food access; however, only flood vulnerability could significantly reduce a household's food access below an *acceptable* threshold. Households that were less dependent on natural resources for their livelihoods – including unskilled day labourers and grocery shop owners – were significantly more likely to have *unacceptable* level of food access due to floods. Adaptive capacity, measured as a function of household asset endowments, proved more important in explaining food access than the exposure-sensitivity to flood itself. Accordingly, we argue that improving food security in climatic hazard-prone areas of developing country deltas would require moving beyond agriculture or natural resources focus and promoting hazard-specific, all-inclusive and livelihood-focused asset-building interventions. We provide an example of a framework for such interventions and reflect on our analytical approach.

Keywords Climatic hazard · Vulnerability · Food security · Delta · Bangladesh

1 Introduction

Several recent reports on the state of food security in the world produced by UN institutions suggest that our target of achieving zero hunger and food security for all by the year 2030, as stated in the UN's Sustainable Development Goal number two,[1] continues to remain elusive. While, in 2014, the number of undernourished people was 795 million (216 million less than the nineties) (FAO et al. 2015), the figure increased to 815 million in 2016 and to 821 million in 2017 (FAO et al. 2018; FAO et al. 2017). Two main reasons for this rise in global hunger and food insecurity have been identified - one is violent conflicts (FAO et al. 2017) and the other is climate-driven hazards arising from climate variability and extremes (FAO et al. 2018). Our focus in this paper is on the latter, i.e. the links between climate-driven hazards and food security. This is an area about which there are significant knowledge gaps and the 2018 UN world food security report (FAO et al. 2018), which focused exclusively on climate change and food security, has called for further studies.

While this topic is global in scope, in this paper, we are primarily concerned with the deltaic regions in the developing

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[1] This target relates to the Goal#2 of the UN's Sustainable Development Goals. For details please visit: https://www.un.org/sustainabledevelopment/hunger/

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world – for example, the Ganges-Brahmaputra-Meghna (GBM) and the Mahanadi deltas in Asia as well as the Niger and Nile deltas in Africa. These regions not only have considerable prevalence of food insecurity, but also are widely identified as vulnerable to global climate change and associated hazards (Abdrabo et al. 2015; Arto et al. 2019; Dasgupta et al. 2009; FAO et al. 2018; FAO et al. 2017; Lauria et al. 2018; Nicholls et al. 2018). This vulnerability is linked to their unique physical characteristics (e.g. low elevation from sea level and high flood probabilities) and socio-demographic profiles (e.g. high population density, high prevalence of poverty, and commercial activities) (Alam 2012; Arto et al. 2019; van Driel et al. 2015; Ericson et al. 2006; IPCC 2007; Lauria et al. 2018; Nicholls et al. 2018; Wright et al. 2012). Consequently, developing world deltas are frequently affected by saline water intrusion, floods, riverbank and coastal erosions, underground water depletion, and storms and cyclones (Alam 2012; Arto et al. 2019; Dar et al. 2017; Masterson and Garabedian 2007; McElwee et al. 2017; Neumann et al. 2015; Nicholls et al. 2018; Rasul et al. 2012). Evidence provided in the 2018 UN world food security report (FAO et al. 2018) indicate that such hazards have increased significantly in the last 20 years, with others suggesting that they are likely to aggravate due to global climate change (Dasgupta et al. 2011; IPCC 2007; Nicholls et al. 2018; Woodruff et al. 2013).

The vulnerability of the deltas and its implications for food security have received widespread attention; however, the published research on this issue suffer from notable shortcomings in their focus on the 'human dimension' of climatic hazards and food security. The overwhelming focus has been on the vulnerabilities of the deltas (as physical or ecological entities), rather than on the vulnerabilities of the people living within the deltas. Likewise, concerning food security, the predominant focus has been on the risks to agricultural and fisheries production (usually at sectoral, national, regional, or landscape levels), that is, the *availability* dimension of food security (Abdrabo et al. 2015; Allison et al. 2009; Arto et al. 2019; Clarke et al. 2018; Dar et al. 2017; Hughes et al. 2012; Krishnamurthy et al. 2014; Lauria et al. 2018; Liersch et al. 2013; Rasul et al. 2012). In comparison, not many published research can be found on the ability of people to access foods, that is, the *access* dimension of food security. This deficiency has also been noticed by many authors (e.g. Esham et al. 2018; Keller et al. 2018; van Soesbergen et al. 2017). Such shortcomings are counterintuitive, since the term "food security", according to its commonly accepted definition, refers primarily to food access (FAO 1996). Food production or supply is certainly important for food security; however, the research of Nobel Laureate Amartya Sen (Sen 1981) suggests that hunger and famine, the most extreme manifestations of food insecurity, may occur even when foods are available, but people lack the ability to access those foods. This evidence challenged the erstwhile FAD (Food Availability Decline) view[2] of food insecurity prevalent in the late seventies. It also greatly influenced the redefinition, in the 1996 World Food Summit, of the very concept of "food security" from being a production issue to an access issue. Therefore, there is a need to move beyond national or regional level food availability analysis and focus on food access at the individual and household levels.

Although the 2018 UN world food security report (FAO et al. 2018) touch upon the access issue, the empirical evidence linking climatic hazards and household food access have largely been extrapolated based on the impacts of climatic hazards on agricultural production and trades and the consequent rise in food prices. It is also unclear who in the deltas is likely to be food insecure because of climatic hazards, and why. Although FAO et al. (2018) identifies that the most vulnerable are those whose livelihoods depend on agricultural and natural resources, it provides no direct evidence from the world's deltas.

Accordingly, in this paper we aim to investigate if climate-driven hazards could affect the food access of the households resident within low-lying deltaic zones and who is likely to be at risk and why. To achieve these aims, we use the data collected from a sample of households resident within the Ganges-Brahmaputra-Meghna (GBM) delta in Bangladesh. We apply an index-based analytical approach by drawing on insights from the vulnerability and food security literature. In section 2 we provide the analytical framework and then in section 3 describe the data source and research methods. In section 4, we present the results of the research and, in section 5, discuss those results and draw the study's main conclusions.

2 Analytical framework

The term "vulnerability" is defined and interpreted in different ways (Cutter et al. 2009; IPCC 2007; Nelson et al. 2010). Here, we refer to the widely-cited definition provided by the Intergovernmental Panel on Climate Change (IPCC) that defines vulnerability as "the degree to which an environmental or social system is susceptible to, and unable to cope with, adverse effects of climate change, including climate variability and extremes" (IPCC 2007: 883). According to the IPCC (2007), "vulnerability" (V) is a function of three variables – exposure (E), sensitivity (S), and adaptive capacity (AC). E refers to the exposure of a system to the hazards caused by

[2] In his writings Amartya Sen uses the terms "FAD view" or "FAD approach" to refer to the traditional and commonly-found approach to famine explanation in terms of a decline in food availability or supply. This term is now used by others within the development community to refer to the discourses or views that consider food insecurity solely or primarily as a problem of not having adequate food production or supply.

climate variability or extremes, S refers to the degree to which a system is affected by those hazards, and AC refers to the ability of the system to avoid the damages caused by those hazards. Many authors (Antwi-Agyei et al. 2012; Smit and Wandel 2006) however argue that, at the household level of analysis, it may be difficult to separate E from S. This argument is plausible, since a household cannot incur damage (S), unless E occurs first. Moreover, climatic hazards are macro level incidents (Dilley and Boudreau 2001) which makes it immensely difficult to precisely assess the E of individual households to a specific hazard. Studies therefore measure S or E as an integrated concept at household and even at higher level (Žurovec et al. 2017). Therefore, for household level analysis we could conceptualise V as a function of ES and AC.

The commonly identified climatic hazards which the deltas are exposed to include: sea level rise, tidal surges, floods, tropical cyclones, salinity of soils and water bodies, and riverbank and coastal erosions (Anthony et al. 2015; Das 2017; Duncan et al. 2017; IPCC 2007; McElwee et al. 2017; Neumann et al. 2015; Nguyen 2007; Nicholls et al. 2018; Yang et al. 2011). The harms that these hazards could inflict are well-documented. The key ones include: declining agricultural productivity, destruction of crops, loss of livestock, loss of lives, damage to assets and properties, damage to infrastructure, and disease outbreaks (AMS 1998; Bhattacharjee and Behera 2018; Das 2017; Dar et al. 2017; Duncan et al. 2017; Ericksen et al. 2011; IPCC 2007; Jutla et al. 2013; McElwee et al. 2017; Nguyen 2007; Nicholls et al. 2018).

Although the effects of these ES indicators on household food access in deltas is yet to be empirically established we could expect a link according to Sen's (1981) theory of entitlement. According to Sen, people's ability to access food is mediated through four types of "entitlements" – production (growing food), trade (buying food), own labour (working for food), and inheritance and transfer (receiving foods donated by others). Intuitively, one could argue that the exposure to and damages from climatic hazards could undermine these entitlements. For instance, saline water intrusion and consequent decline in farm productivity may erode a delta-resident household's ability to produce its own foods, i.e. cause a decline in its "production-based entitlement". Disease and/or death of working age family members may reduce a household's ability to access foods through the sale of family labour (i.e. a failure in "labour-based entitlement"). It may also increase the household's burden of care, which, in turn, could affect its ability to buy foods (de Waal and Whiteside 2003). Likewise, loss of livestock could deplete household income and resources (FAO 2016; FAO et al. 2018), leading to a decline in both production and trade-based entitlements (since livestock are sometimes used as buffer during periods of crisis).

Insights from the climate vulnerability literature, however, suggest that the link between ES and food access may not be that straightforward. Humans are not merely the passive recipients of hazards, but they also can adjust to hazards, moderate potential damages, take advantage of opportunities, or cope with the consequences (Adger 1999; IPCC 2007; Vincent and Cull 2010; Vincent 2007). In the literature this is defined as Adaptive Capacity (AC). Accordingly, researchers analyse vulnerability to climatic hazards as V = ES-AC (e.g. Hughes et al. 2012; Piya et al. 2016). This suggests that ES may not have a direct effect on food access. Rather, the difference between ES-AC, i.e. vulnerability, will determine whether a household's food access will suffer from climatic hazards.

However, confusions are rife as to what exactly determines this AC (Vincent 2007). With insights from the Sustainable Livelihoods literature (Chambers and Conway 1992; DFID 1999), many researchers assess AC indirectly by using a household's possession of five types of assets or capitals – human, social, financial, natural, and physical – as proxy indicators (Adger and Kelly 1999; Antwi-Agyei et al. 2012; Piya et al. 2016; Wright et al. 2012). Assets, termed as "endowments", is also a central element in the theory of entitlement (Devereux 2001; Sen 1981). According to Sen, it is by converting their endowments into entitlements that households acquire food. By combining this premise with the asset-based conceptualisation of AC in the climate vulnerability literature, we could argue that the more a household possesses the five types of assets (endowments), the less vulnerable it will be to climatic hazards, and consequently, to the disruption of food access, and vice versa.

The roles of the five types of assets in enabling households to overcome climatic hazards are well-documented in the literature, including examples from developing country deltas (Table 1). In consideration of this evidence and the literature reviewed above, we conceptualise the links between ES, AC, V, and food access as in Fig. 1. Using this framework, we then investigate if there is an effect of ES and an effect of V on household food access and how these effects interact with various livelihood groups living in a delta zone.

3 Data and methods

3.1 Data source

The data for this study came from a household survey conducted in the Hatiya *Upazilla* (sub-district) of Noakhali District in the South-eastern part of Bangladeshi coasts. Hatiya is located within the Ganges-Brahmaputra-Meghna (GBM) delta – one of the world's largest deltas covering most of Bangladesh and the Indian state of West Bengal and some parts of China, Nepal, and Bhutan. The GBM delta is formed by the flows of the three major river systems – The Ganges, Brahmaputra, and Meghna. Within the GBM, Hatiya is

Table 1 Assets and their roles in enabling households to overcome climatic shocks and hazards

Assets	Roles
Physical capital	Physical assets – such as mobiles, TV, radio – indicate not only status and wealth, but also can help households to access weather information and early warning. Empirical studies in coastal Bangladesh (Wright et al. 2012) and Sri Lanka (Thathsarania and Gunaratneb 2018) found strong links between the ownership of these assets and AC. Ownership of permanent or structurally strong houses can provide securer shelter and thereby improve household AC and reduce climate-related vulnerabilities, as observed in Vietnam delta (Tran et al. 2017), Sri Lanka (Thathsarania and Gunaratneb (2018), and Nepal (Piya et al. 2016).
Social capital	Social capital in the forms of trust, reciprocity, group memberships, and networks can help households overcome climatic hazards by improving access to resources, information, institutional assistance, and collective action. Empirical evidence have been found in the coastal areas of Southeast Asia and the Caribbean (Adger 2003), Sri Lanka (Thathsarania and Gunaratneb 2018), Ethiopia (Demeke et al. 2011), Nepal (Piya et al. 2016), and coastal Bangladesh (Jordan 2015; Parvin and Shaw 2013).
Natural capital	Natural capital, such as lands and livestock, can help maintain productive activities (e.g. farming), generate income, and act as insurance in times of crisis. Amount of land ownership had a negative correlation with household vulnerability to climatic hazards in Vietnam delta (Tran et al. 2017). Household landholding size had positive effects on AC against floods in the Indian state of West Bengal (Bhattacharjee and Behera 2018) and in the Mahanadi delta of Odisha, India (Duncan et al. 2017). Livestock ownership improved AC and reduced household vulnerability to climatic shocks in Ethiopia (Demeke et al. 2011), Peru (Sietz et al. 2012), and Nepal (Piya, Joshi and Maharjan (2016).
Human capital	Higher education increases job opportunities (especially, off-farm employment); increases awareness of hazards and the ability to understand early warning signals; and thus, can enhance AC and reduce vulnerability. Low education can have the opposite effects. Empirical evidence have been found in Bangladesh (Collins 2014; Quader et al. 2017), Vietnam (Tran et al. 2017), Ethiopia (Demeke et al. 2011), Peru (Sietz et al. 2012), Nepal (Piya et al. (2016), and Sri Lanka (Thathsarania and Gunaratneb 2018). Dependency ratio (more children and elderly people compared to working age adults) can reduce households' ability to overcome climatic shocks, e.g. due to burden of care. Evidence comes from the Myanmar delta (Oo et al. 2018), and Nepal (Piya et al. 2016. Higher age can reduce physical abilities, thus reducing opportunities for employment and increasing the burden of care. Younger age can enhance the ability to work and to take quicker actions during hazards, and thus, can improve adaptive capacity and reduce vulnerability, as found in Sri Lanka (Thathsarania and Gunaratneb 2018) and the Indian state of West Bengal (Bhattacharjee and Behera 2018).
Financial capital	Income and savings can help households cope with climatic hazards, as found in Vietnam (Tran et al. 2017) and Nepal (Piya et al. 2016). Non-agricultural income can enable households to adapt and quickly recover from hazards impacts, as observed in Sri Lanka (Thathsarania and Gunaratneb 2018) and the Mahanadi delta (Duncan et al. 2017) and West Bengal (Bhattacharjee and Behera 2018) in India.

located at the eastern estuary of the Meghna river. It is formed by "deltaic lobes", which consist of a series of smaller, shallower channels that branched-off from the Meghna river while it emptied into the Bay of Bengal (Fig. 2). Thus, Hatiya looks like an island (and is sometime called as such locally). The island has an area of ca. 1507 Km^2, of which 20% is forest reserve and around 22% is riverine area (BBS 2011).

Hatiya has a population of 453,000 in around 91,000 households (BBS 2011). Agriculture contributes to over 65% of the income, while non-agricultural labour contributes to 5%, commerce 12%, service 4%, remittance 1%, and others 12% (Banglapedia 2015). The literacy rate in Hatiya is 34% which is significantly lower than the national average of 68%. Poverty, on the other hand, is much higher (64%) than the national average of 23% (BBS 2013; BBS 2017), with one earlier study finding over 50% being landless, two-thirds having a monthly household income of Taka 5,000 only (ca. US$60), and the vast proportion living in temporary houses with unhygienic hanging latrines (Parvin et al. 2008).

Like other low-lying areas within the GBM delta, Hatiya faces several climate-driven hazards, the most common ones being cyclones, floods, riverbank erosion, and salinity intrusion. The island is in a pathway that cyclones affecting Bangladesh commonly follow. Hatiya experienced disastrous cyclones in 1970, 1985, and 1991, leading to the death of about 130,000 people (Parvin et al. 2008). Successively, Hatiya and the adjoining islands were hit by cyclone *Sidr* in 2007 and cyclone *Aila* in 2009, with devastating effects on the houses, crops, household goods, livestock, and income sources of over 100,000 inhabitants in 25,000 households (Alam 2012). The risks are far from being over. In fact, due to rise in temperature, the intensity and frequency of cyclones have increased in Bangladesh, with 70 high intensity cyclones striking the coastal areas in the last 200 years. Of these, 40% were in the Noakhali and Chittagong zone (Minar et al. 2013).

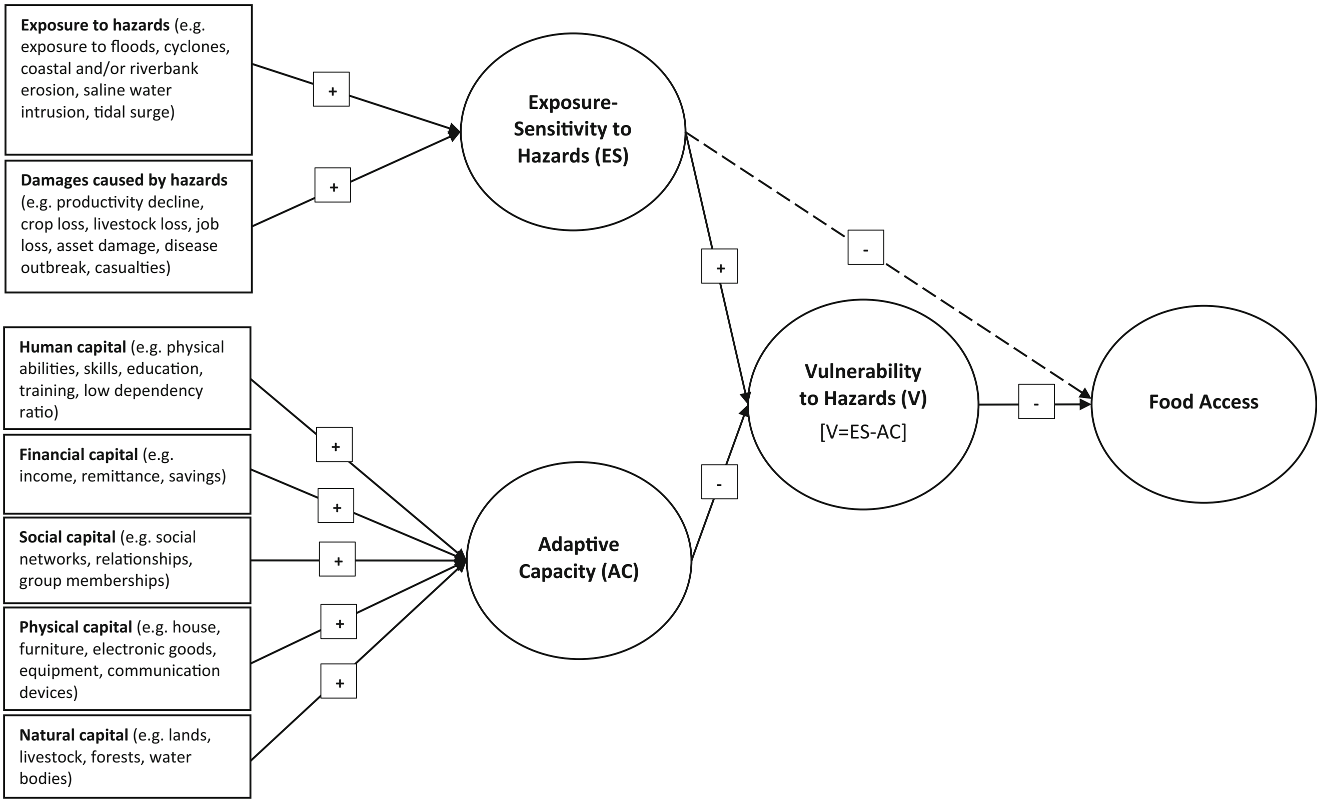


Fig. 1 Conceptual framework showing the links between exposure-sensitivity, adaptive capacity, climatic hazard vulnerability, and household food access (the arrows and the ± signs indicate expected direction of effects on the corresponding variables; the dashed line indicates a potential effect)

Another major climatic hazard facing Hatiya is floods. As in other parts of the GBM delta, this flooding can be: fluvial floods, tidal floods, fluvio-tidal floods, and storm surge floods (Haque and Nicholls 2018). In Hatiya (and adjacent regions) fluvial flooding occurs during the monsoon season (June–October) when the combined flow of the GBM rivers is drained into the Bay of Bengal through the lower Meghna or via the estuarine networks. Sometimes these flows breach or overtop the polders, causing floods (Haque and Nicholls 2018).

Tidal flooding occurs when the high tides overtop the estuary banks and/or breach the polders. The east of the lower Meghna estuary within which Hatiya is located is particularly vulnerable to tidal flooding as the tidal range is the greatest at this point (Haque and Nicholls 2018). Once overtopped, the flood water inside the polders cannot drain out due to confined sedimentation, causing waterlogging. For example, in August 2013, at least 10 villages in Hatiya were inundated when tidal water breached protective dykes (Star Country Desk 2013). Waterlogging, however, also occurs due to flooding from internal canals and "drainage congestion due to unplanned road networks and confined sedimentation" (Haque and Nicholls 2018: 153).

Fluvio-tidal flooding occurs due to the combined effects of fluvial flows (during monsoon) and high tides. The primary cause of storm surge flooding is tropical cyclones in which high wind speed leads to storm surges, resulting in inundation from the sea and rivers or estuaries. However, a high-intensity cyclone does not always cause major flooding. The risk increases when the cyclone occurs during high tides, rather than low tides (Haque and Nicholls 2018).

Hatiya faces flood risks also because it is situated only 10 m above the mean sea level, with about 25% area being below three meters. This low elevation increases its vulnerability to sea level rise experiencing the coastal zone in Bangladesh (Islam et al. 2016; Shamsuddoha and Chowdhury 2007; Siddiqui 2014). The floods can be severe, with a depth as high as 1.83 m (Siddiqui 2014) and are often accompanied by saline water intrusion. Such floods (and water logging) cause long-lasting damages to agricultural lands, contaminate drinking water, lead to disease outbreaks and damage the already poor infrastructure in Hatiya (Alam 2012; BBS 2013; Parvin and Shaw 2013; Siddiqui 2014).

Furthermore, the northern part of Hatiya has been facing severe riverbank erosion (Parvin et al. 2008; Parvin and Shaw 2013; Siddiqui 2014). Between 1973 and 2016, Hatiya lost an area of over $90km^2$ due to erosion (Hassan et al. 2017). This hazard often damages protective embankments, making Hatiya more vulnerable to tidal flooding and saline water intrusion (Siddiqui 2014).

Due to such disaster-proneness, a mangrove afforestation programme, several flood camps and over a hundred cyclone shelters have been established in Hatiya (BBS 2013; Parvin et al. 2008). Moreover, many NGOs operating in Hatiya

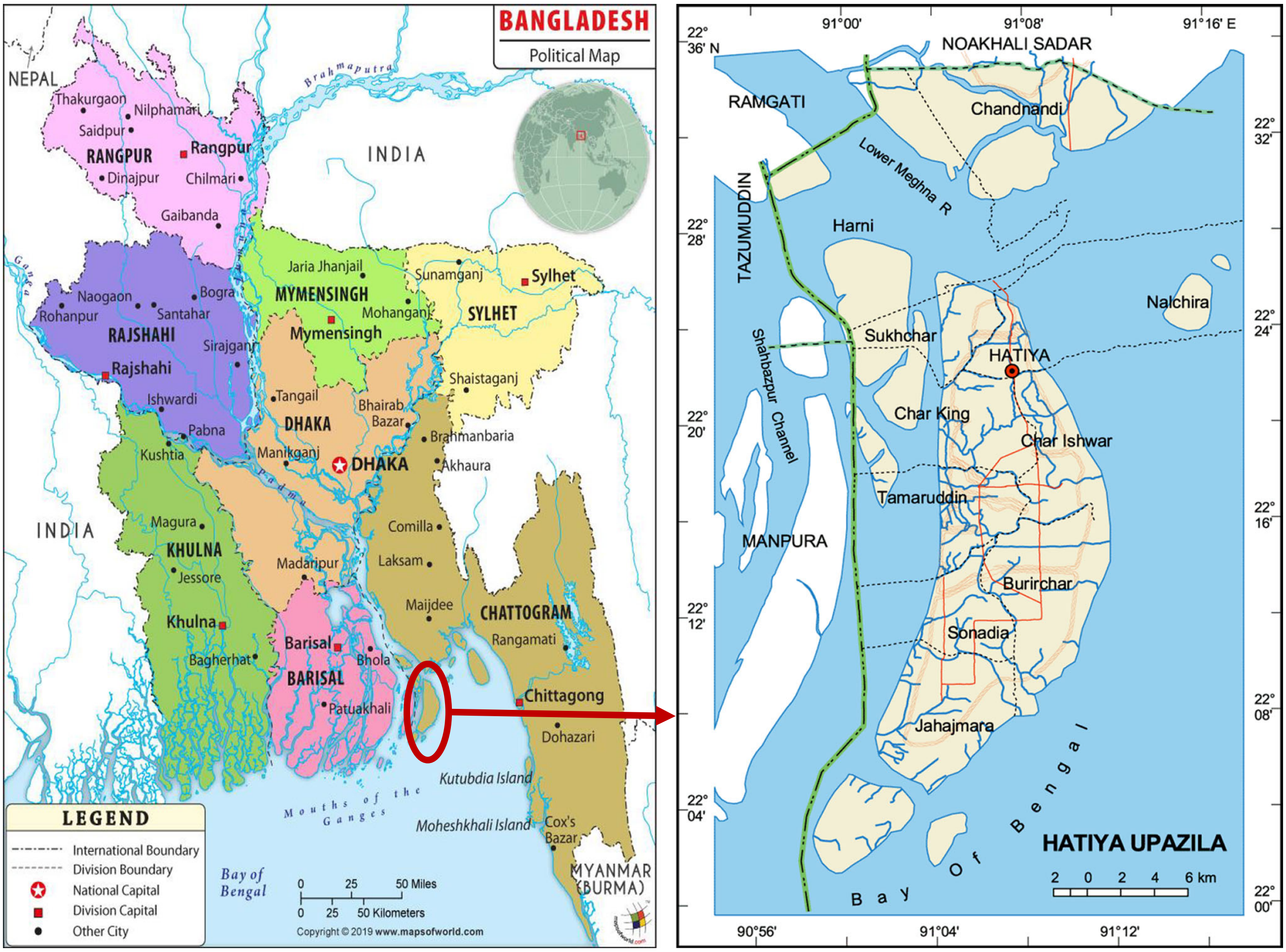


Fig. 2 Maps showing Bangladesh (left) and the study area Hatiya (right) (source: left – Maps of World, https://www.mapsofworld.com/bangladesh/bangladesh-political-map.html; right – Prime Minister's Office Library, Dhaka, Government of the People's Republic of Bangladesh, http://lib.pmo.gov.bd/maps/images/noakhali/Hatiya.gif)

provide a range of services, including micro-credit, awareness raising, drinking water purification, installation of sanitary latrines, disaster information, construction of safe houses, and relief (Alam 2012; Parvin et al. 2008).

The above features make Hatiya particularly suitable to achieve the aims of this study. Not only is it highly vulnerable to climate-driven hazards, but also has a high incidence of poverty and food insecurity, including starvation (substantial reduction in meal numbers or not eating at all in a day) to cope with the impacts of climatic hazards (Parvin, Takahashi and Shaw 2008).

Data for this study were collected during May–June 2018. A cluster sampling technique was used. At the initial stage, eight *Unions*[3] out of eleven were randomly selected. Then, households from each of these *Unions* were randomly selected, totalling a sample size of 421 households (Table 2).

A structured questionnaire was used for data collection. It included questions about whether or not the households were exposed to cyclones, floods (tidal/monsoon or seasonal/storm-surge), and riverbank erosion in the last five years, and if yes, whether or not they experienced as a consequence of their exposure to each of these hazards: (i) loss of life, (ii) loss of crops, (iii) loss of livestock, (iv) disease attack, (v) damage to house and/or household goods, and (vi) other damages. The questionnaire also included questions about the demographic characteristics of the households, their food access, and the five types of assets – physical, financial, social, natural, and human capital (Table 3).

The questionnaire was translated from English to *Bangla*[4] and pilot-tested before final administration. The data were collected by the co-author of this paper (assisted by two research assistants) through face-to-face interviews with a member within each of the selected households. Nearly 46% (192) of the interviewees were household heads (main income

[3] A *Union* is the lowest administrative unit at the local government level in Bangladesh

[4] Native language of Bangladesh

Table 2 Distribution of the sample used in this study

Name of Union	Number of households	% of the total sample
Burirchar	49	11.6
Char Ishwar	54	12.8
Tamaruddin	47	11.2
Jahajmara	50	11.9
Char king	53	12.6
Harni	59	14.0
Chandnandi	57	13.5
Nijhum Dwip	52	12.4
Total	421	100.0

earner, almost all of them being males), about 42% (175) the spouses of the heads, 10% (43) the adult sons and daughters of the household heads, and the rest (2.6%) the other members (e.g. the parents of the household heads living in the same household).

The study was conducted with strict adherence to ethical guidelines. A formal ethical approval was obtained from the authors' affiliated institutions. Informed consents were obtained from the elected Chairperson of the local government in Hatiya and the households before conducting the interviews. Throughout the study anonymity and confidentiality of the participants were strictly maintained.

3.2 Measurement and analysis

3.2.1 Measuring food access

As many as nine proxy indicators for assessing household food access have been identified, each having unique advantages and limitations (Leroy et al. 2015). We used the Food Consumption Score (FCS) proxy indicator developed and championed by the World Food Programme (WFP 2008). The FCS is one of the methodologically robust and most commonly-used tools for measuring household food access (Leroy et al. 2015; WFP 2008). The FCS was computed as a composite score based on dietary diversity, food frequency, and relative nutritional importance of eight food groups. The questionnaire included location-specific food items for those groups. A seven days recall period was used, as per the WFP (2008) guideline. The respondents were first asked about the number of days each of the listed food items was consumed within the household. Consumption frequencies of the food items were then multiplied by the corresponding food group weights as suggested by WFP (2008). The values were then summed up to obtain the FCS for each household as per eq. 1.

$$FCS = 2^*x_{staple} + 3^*x_{pulse} + 1^*x_{veg} + 1^*x_{fruit} + 4^*x_{animal} + 4^*x_{dairy} + 0.5^*x_{sugar} + 0.5^*x_{oil} \quad (1)$$

Where, x represents the number of days each food item was consumed within a week.

The summated FCS scores were then categorised as: poor (scores up to 28), borderline (scores 28.5 to 42) and acceptable (scores ≥42.5) consumptions (WFP 2008). These higher cut-off points were used, since the sampled households and the people in Bangladesh, in general, consume sugar and oil almost every day. Poor and borderline consumption categories together were considered as "unacceptable" food access.

3.2.2 Measuring exposure-sensitivity (ES), adaptive capacity (AC), and vulnerability (V)

We used an index based method to measure the ES, AC, and V variables. At first, we created separate indices for ES and AC, and then used these to calculate V (Hahn et al. 2009; Piya et al. 2016). The ES and V indices were for flood, cyclone, and riverbank erosion each. The indicators of these indices were identified from the literature (Table 1) and validated through local consultations in the study area. The indicators, their hypothesised relationships with the corresponding index variables, and their literature sources are provided in Table 3. In the original questionnaire, some variables (e.g. education, income) were measured as ordinal-categorical which were later coded as dummy variables as per guidelines in the literature (Córdova 2008; Filmer and Pritchett 2001; WFP 2017). Some indicator variables with very low (<5%) or very high (>95%) frequency counts in the data were excluded from analysis (WFP 2017).

After exploratory analyses, all the ES and AC indicators were standardised. Weights for each of the indicators were then calculated. Some studies use an equal weighting method, but due to its arbitrariness it may lead to over- or under-weighting of indicators (Piya et al. 2016). Another method, based on expert judgements, may suffer from subjectivity and lack of agreement among experts (Piya et al. 2016). We, therefore, used a popular method based on Principal Component Analysis (PCA). After the seminal work of Filmer and Pritchett (2001), this weighting method is now widely used, not only by researchers (e.g. Piya et al. 2016), but also international programmes like the World Food Programme (WFP 2017), Latin American Public Opinion Project (LAPOP) (Córdova 2008), and the Demographic and Health Surveys (DHS) programme. In the PCA, the indicator loadings on the first principal component (PC1) were taken as the weights of the indicators. Based on these, ES index scores for each of the hazards and for AC were created using eq. 2 (Córdova 2008; Filmer and Pritchett 2001; Piya et al. 2016; WFP 2017).

$$I_j = \sum_{i=1}^{k} \alpha_i \left[\frac{x_{ij} - \overline{x}_i}{s_i} \right] \quad (2)$$

Table 3 Indicator variables and their hypothesised relationships with the corresponding index variables

Index variables	Indicators and measurement	Hypothesised relationships*
Exposure-Sensitivity	Household exposed to flood/cyclone/riverbank erosion in the last five years (0, 1)	+
	Faced loss of life (0, 1)	+
	Faced loss of crops (0, 1)	+
	Faced loss of livestock (0, 1)	+
	Faced disease attack (0, 1)	+
	Faced damages to house and/or household goods (0, 1)	+
	Faced other damages (0, 1)	+
Adaptive Capacity		
Human capital	Education of head secondary & above (0, 1)	+
	Education of spouse secondary & above (0, 1)	+
	Age of head up to 64 years (0, 1)	+
	Child dependency ratio (continuous)	–
Financial capital	Head income per month above TK 15,000 (0, 1)	+
	Spouse has monthly income (0, 1)	+
	Remittance (US$ per month)**	+
Social capital	Member of a professional association (0, 1)	+
	Member of a cultural/sports association (0, 1)	+
	Member of a religious group/association (0, 1)	+
	Member of an NGO group/association (0, 1)	+
Physical capital	Has two/more house (0, 1)	+
	Has bicycle/rickshaw (0, 1)	+
	Has motorbike (0, 1)	+
	Has TV (0, 1)	+
	Has radio (0, 1)	+
	Has two/more mobile phone (0, 1)	+
	Has smartphone (0, 1)	+
Natural capital	Tropical Livestock Unit (scale score)***	+
	Area of farmland (acres)	+
	Area of homestead (including ponds) (acres)	+

*The hypothesised relationships are based on a review of the literature cited in Table 1

**Converted from local currency (Bangladeshi Taka) @ 1 US$ = TK. 84 as of Nov 2018

***Tropical Livestock Unit (TLU) = $(no.\ of\ cows * 0.7) + (no.\ of\ buffaloes * 0.7) + (no.\ of\ goats * 0.1) + (no.\ of\ ducks * 0.01) + (no.\ of\ chicken * 0.01)$

Where,

I_j Index score of the j^{th} household ($j = 1, 2, \ldots\ldots, n$)
α_i weight (loading) for the i^{th} indicator ($i = 1, 2, \ldots\ldots, k$) from the first principal component
x_{ij} value of the i^{th} indicator for the jth household
$\overline{x}_i$ mean of the i^{th} indicator
s_i standard deviation of the i^{th} indicator

The construction of the AC index followed a two-step process (Piya, Joshi and Maharjan 2016). In the first step, index scores for each of the five capitals – human, financial, social, physical, and natural – were calculated using eq. 2. The resultant five index variables were then used in the second step to calculate the AC index score using the same equation.

Afterwards, the hazard vulnerability index was computed using eq. 3 (Hughes et al. 2012; Piya, Joshi and Maharjan 2016).

$$V_j = ESI_j - ACI_j \tag{3}$$

Where,

V_j Vulnerability index score of the j^{th} household ($j = 1, 2, \ldots\ldots\ldots, n$) for the corresponding hazard (i.e. flood or cyclone or riverbank erosion)
ESI_j Exposure-Sensitivity index score of the j^{th} household for the corresponding hazard
ACI_j Adaptive Capacity index score of the j^{th} household

For each household, separate vulnerability index scores for each of the three hazards – flood, cyclone, and riverbank erosion – were created.

To identify patterns in the data, exploratory analyses of the ES and AC variables were performed before moving on to confirmatory analyses through regression modelling.

3.2.3 Estimating the effects of exposure-sensitivity (ES) and vulnerability (V) on food access

To test the effects of the ES and the V variables on household food access we used a generalised linear regression model (GLiM) in SPSS Statistics version 25. We chose a GLiM as this procedure does not require the dependent variable to have a normal distribution and the data to be transformed (Agriesti

2007). The GLiM also offers the flexibility to model various kinds of distribution, including binomial. Our FCS data displayed a non-normal distribution (Fig. 3) and we wanted to model the binary outcome of the FCS (i.e. *unacceptable* and *acceptable* food access). Hence, the GLiM procedure was appropriate for us. The GLiM can be expressed as in eq. 4.

$$E(FCS) = g(\mu) = \beta_0 + \sum \beta_i x_i \qquad (4)$$

Where,

$E(FCS)$ Expected values (means) of the Food Consumption Score (FCS) variable

$g(\mu)$ the link function (*Identity*) of *FCS* which in this case is the same as $E(FCS)$ (i.e. no transformation is made in the dependent variable FCS)

x_i the ES index variables for flood, cyclone, and riverbank erosion (to test the effects of ES on food access) or the V index variables for flood, cyclone, and riverbank erosion (to test the effects of V on food access)

β_0 intercept of the model

β_i regression coefficients

Afterwards, we categorised the FCS scores into a binary variable – "unacceptable access" (FCS scores ≤42) (coded 1) and "acceptable access" (FCS scores ≥42.5) (coded 0) – and fitted the variable into a binary logistic regression model (eq. 5) in order to estimate the likelihood of a household having *unacceptable* food access. For this as well, we used the GLiM procedure in SPSS version 25.

$$\ln\left(\frac{p}{1-p}\right) = \beta_0 + \sum \beta_i x_i \qquad (5)$$

Where,

p the probability that the FCS variable takes the value of 1 (i.e. *unacceptable* access)

$\frac{p}{1-p}$ the odds of a household falling within the *unacceptable* access category

$\ln\left(\frac{p}{1-p}\right)$ the log link (*Logit*) of the FCS variable

We then estimated the odds of a household becoming food insecure from eq. 6.

$$\frac{p}{1-p} = e^{\beta_0 + \sum \beta_i x_i} \qquad (6)$$

Then, to identify which occupation groups in Hatiya were likely to be affected, we estimated the "interaction effects" between the statistically significant vulnerability variable(s) in eq. 5 and the "main occupation of household head" variable (having seven categories – unskilled labourer, farmer, fisherman, office employee, boatman, driver, and grocer). The odds of each of these occupation groups to have *unacceptable* food access were then calculated from eq. 6.

4 Results

4.1 Food access

The aggregate Food Consumption Scores ranged from 25.00 to 105.50, with a mean of 53.97 and standard deviation of 15.90. The distribution of the scores was non-normal (Fig. 3). According to WFP's (2008) suggested cut-off points, only 1.9% of the households had *poor* consumption (scores up to 28), nearly 24% had *borderline* consumption (scores 28.5 to 42), and over 74% had *acceptable* consumption (scores ≥42.5) (Fig. 4). The *poor* and *borderline* categories combined,

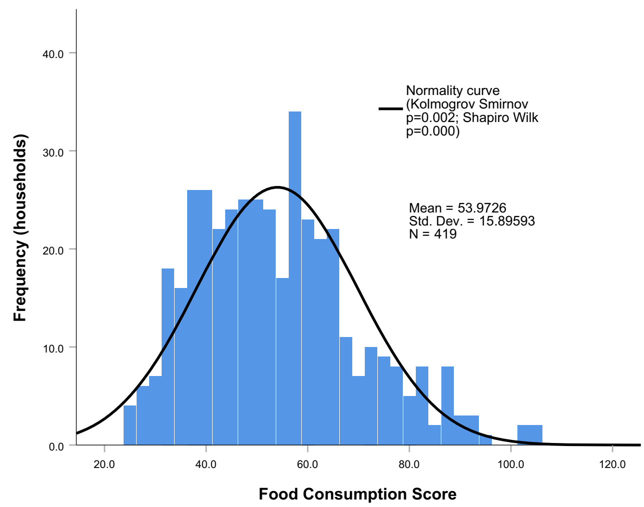


Fig. 3 Food Consumption Scores (FCSs) of the sample households in Hatiya

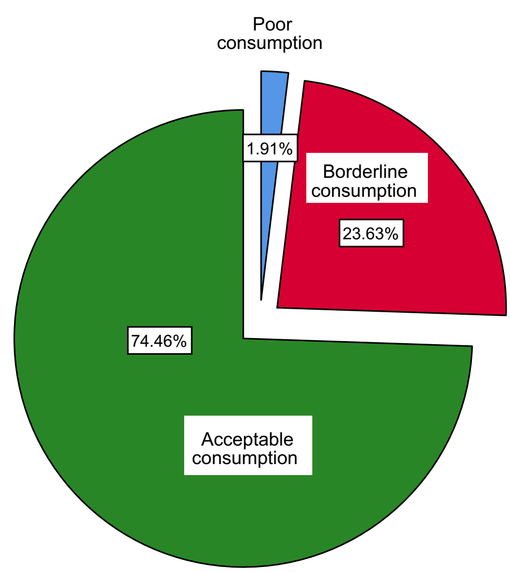


Fig. 4 FCS categories of the sample households in Hatiya

Table 4 Food access according to household head's main occupation

Household head's main occupation	Acceptable food access	Unacceptable food access	Total
Unskilled	69 (16.5)	28 (6.7)	97 (23.2)
Farming	82 (19.6)	29 (6.9)	111 (26.5)
Fishing	71 (16.9)	16 (3.8)	87 (20.8)
Office job	21 (5.0)	6 (1.4)	27 (6.4)
Boatman	27 (6.4)	7 (1.7)	34 (8.1)
Driver	17 (4.1)	12 (2.9)	29 (6.9)
Grocer	25 (6.0)	9 (2.1)	34 (8.1)
Total	312 (74.46%)	107 (25.54%)	419 (100%)

Figures within parentheses represent percentages of the total sample (419 households; 2 missing values)

slightly over 25% of the households in Hatiya had *unacceptable* food access.

The distribution of the households within the *acceptable* and *unacceptable* categories according to the "household head's main occupation" is shown in Table 4. The sample includes proportional representation of both the food access categories within each of the occupation types. However, over 70% the sample consists of the unskilled, farming, and fishing categories.

4.2 Exposure-sensitivity (ES)

The descriptive statistics of the ES index variables along with the weights of their corresponding indicators obtained through Principal Component Analyses (PCA) are provided in Table 5. As hypothesised (Table 3), all the indicators loaded positively on the ES indices. Within each ES category, exposure to the hazard itself had the highest loadings. Concerning damages, livestock loss had the highest weights within the flood index, followed by disease attack, and damage to houses/household goods. Within the cyclone index, damage to houses/household goods had the highest weight, the second and third highest being livestock loss and crop loss, respectively. Damage to houses/household goods had the highest weights within the riverbank ES, followed by livestock and crop losses. Across the three ES types, damage to houses/household goods and livestock loss were the common, high-impact damages. Crop loss was not strongly associated with floods and caused mostly by riverbank erosion and cyclones. Disease attacks contributed highly to flood ES. Loss of life did not come out as a significant indicator in any of the three ESs.

Table 5 Descriptive statistics and weights (loadings) of the Exposure-Sensitivity indicators

ES Indicators	Flood				Cyclone				Riverbank erosion			
	Min-Max	Mean	S.D.	Weight	Min-Max	Mean	S.D.	Weight	Min-Max	Mean	S.D.	Weight
Household exposed to the said hazard within the last five years (0, 1)[a]	–	0.86	0.345	0.858	–	0.39	0.487	0.907	–	0.70	0.459	0.921
Faced loss of life (0, 1)	–	0.16	0.364	NE[b]	–	0.00	0.000	NE[b]	–	0.045[b]	0.208	NE[b]
Faced loss of crops (0, 1)	–	0.42	0.493	0.447	–	0.14	0.345	0.679	–	0.44	0.497	0.708
Faced disease attack (0, 1)	–	0.60	0.490	0.747	–	0.09	0.291	0.647	–	0.28	0.451	0.568
Faced loss of livestock (0, 1)	–	0.71	0.454	0.789	–	0.23	0.422	0.844	–	0.48	0.500	0.787
Faced damage to house/household goods (0, 1)	–	0.71	0.453	0.729	–	0.35	0.479	0.875	–	0.68	0.468	0.890
Faced other damages (0, 1)	–	0.02	0.128	NE	–	0.01	0.084	NE	–	0.01	0.097	NE
ES Indices	Min − 5.81 Max 2.45	0.0076	2.6484	–	Min − 2.30 Max 7.58	0.0052	3.1808	–	Min − 4.43 Max 3.73	−0.0035	3.0813	–

[a] In the survey the respondents were also asked about the number of each events and the duration to which their household was exposed to each, but only a few of them could answer those questions

[b] Not Estimated (NE): excluded from PCA and index construction since these indicators have <5% occurrence for some or all of the hazards (e.g. see guidance in Córdova 2008; and WFP 2017)

For flood ES, Eigenvalue of the first principal component (PC1) = 2.647; variance explained by PC1 = 52.936

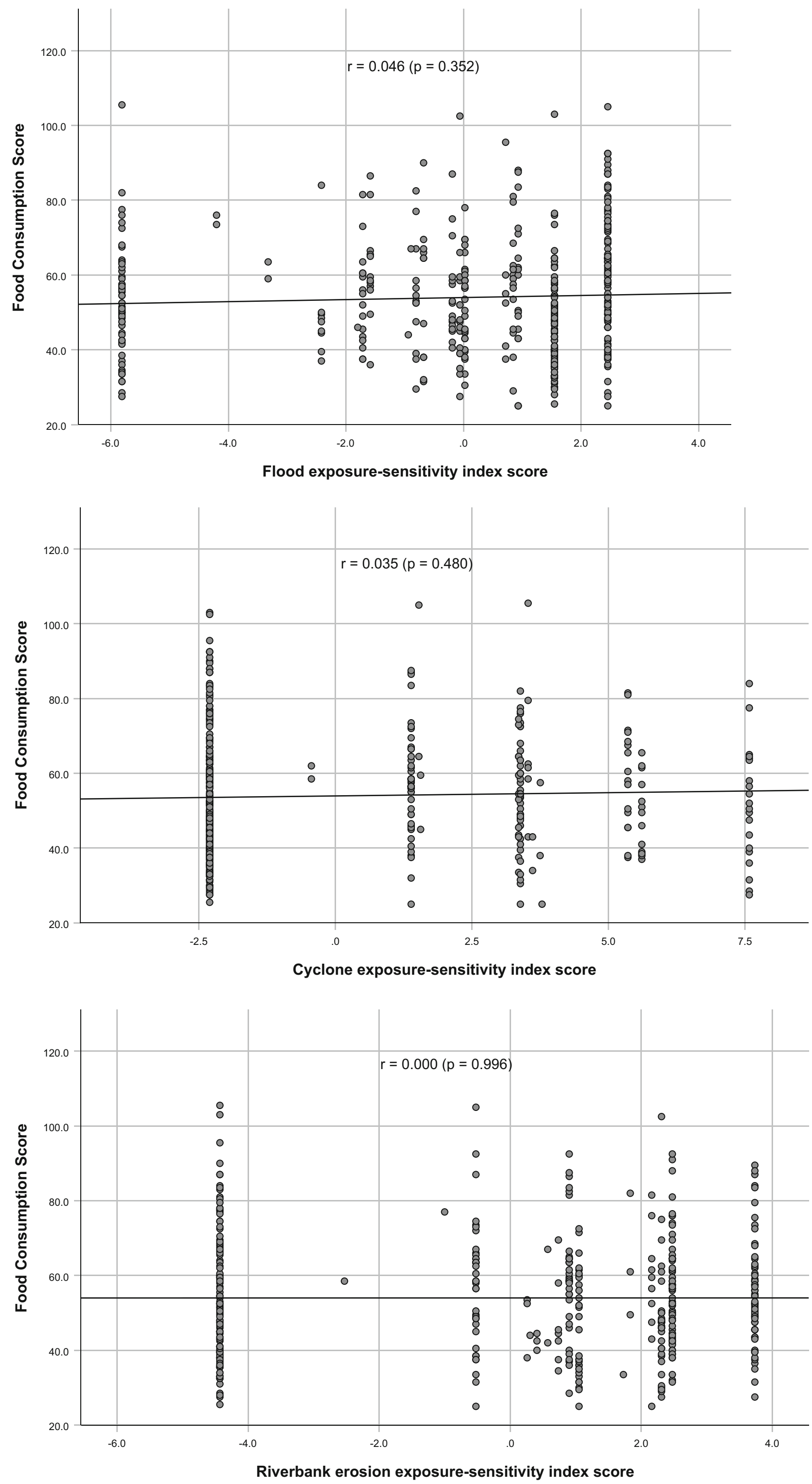
For cyclone ES, Eigenvalue of PC1 = 3.180; variance explained by PC1 = 63.610

For riverbank erosion ES, Eigenvalue of PC1 = 3.081; variance explained by PC1 = 61.623

Exploratory analysis of the ES index scores did not reveal statistically significant correlations with the Food Consumption Scores (FCSs) (Fig. 5).

By treating the FCS as a binary variable – *unacceptable* access and *acceptable* access – and disaggregating the ES scores between these two categories we found that the households within the former were affected more by floods, whilst those in the later by riverbank erosion and cyclone (Fig. 6). This suggested a possible link between flood ES and *unacceptable* food access in Hatiya.

Fig. 5 Scatterplots showing the spread and correlations of the ES index variables with the FCSs



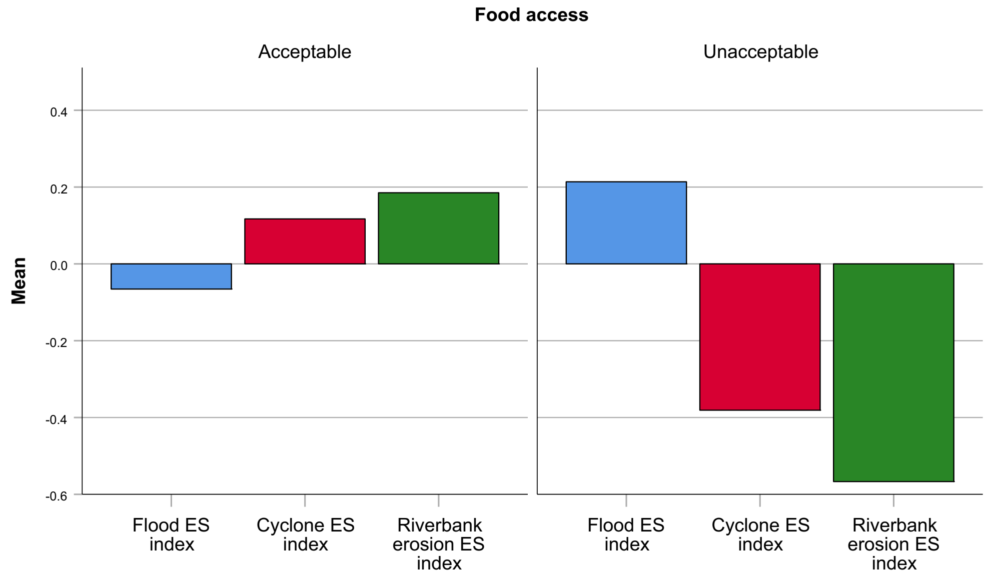


Fig. 6 Mean ES index scores within *acceptable* and *unacceptable* food access categories

By disaggregating the ES indices and food access categories according to the household heads' main occupation, we found that flood ES was the highest amongst the grocer within the *unacceptable* category (Fig. 7). Another group, driver within the *unacceptable* category, also had a higher flood ES compared to its counterpart in the *acceptable* category and so was the case of the unskilled. It suggested that flood ES might have a connection with *unacceptable* food access among the grocers, drivers, and unskilled labourers. However, the results did not show a clear pattern, since some groups, such as office employee and boatman, had higher flood ES within the *acceptable* category (Fig. 7).

4.3 Adaptive capacity (AC)

The AC index was constructed in two steps. First, index scores for the five capitals – human, financial, social, physical, and natural – were created. Second, these five indices were then aggregated to create the AC index. The descriptive statistics of these indices, along with the weights of their corresponding indicators, are provided in Table 6.

Within the human capital (HC) index, the highest weightings (0.802 and 0.801) were for the education (secondary and above) of household heads and spouses. Unexpectedly, however, child dependency ratio had a very small (0.052), but positive loading on HC.

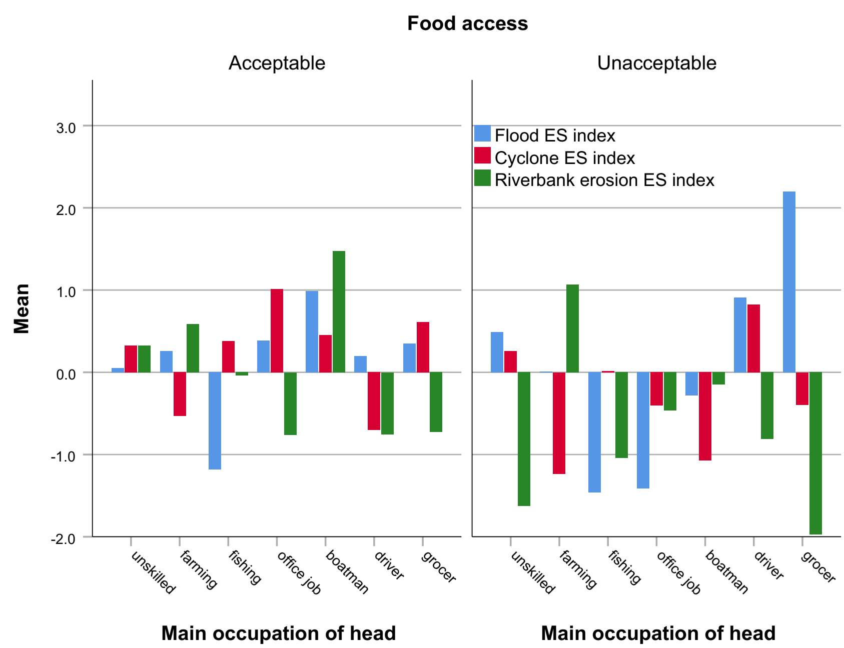


Fig. 7 Mean ES index scores of occupation groups within the *unacceptable* and *acceptable* categories

Table 6 Descriptive statistics of the Adaptive Capacity indicator variables

Variables	Min-Max	Mean	S.D.	Weight
Human capital	Min − 1.89 Max 3.91	.0052	1.39898	0.506
Education of head secondary & above (0, 1)		0.16	0.366	0.801
Education spouse secondary & above (0, 1)		0.15	0.361	0.802
Age of head up to 64 years (0, 1)		0.92	0.273	0.334
Child dependency ratio (continuous)		97.09	60.966	0.052
Financial capital	Min − .47 Max 2.76	−.2043	.80382	0.630
Head monthly income above TK 15,000 (0, 1)		0.09	0.287	0.799
Spouse has monthly income (0, 1)		0.045	0.190	0.070
Remittance (US$ per month; conversion 1 US$ = TK. 84 as of Nov 2018)		28.85	112.413	0.806
Social capital	Min − 1.18 Max 4.56	.0117	1.43241	0.625
Member of a professional association (0, 1)		0.19	0.395	0.740
Member of a cultural/sports association (0, 1)		0.12	0.329	0.769
Member of a religious group/association (0, 1)		0.32	0.467	0.478
Member of an NGO group/association (0, 1)		0.43	0.495	0.249
Physical capital	Min − 2.00 Max 9.21	.0073	2.09427	0.790
Has two or more house (0, 1)		0.06	0.246	0.476
Has bicycle/rickshaw (0, 1)		0.19	0.395	0.527
Has motorbike (0, 1)		0.07	0.254	0.517
Has TV (0, 1)		0.07	0.250	0.654
Has radio (0, 1)		0.65	0.479	0.250
Has two or more mobile phone (0, 1)		0.49	0.501	0.575
Has smartphone (0, 1)		0.25	0.436	0.709
Natural capital	Min − 1.38 Max 13.88	.0011	1.65914	0.653
Tropical Livestock Unit (scale score)		1.366	1.664	0.690
Area of farmland (acres)		0.093	0.243	0.855
Area of homestead (including ponds) (acres)		0.085	0.106	0.671
Adaptive Capacity	Min − 2.66 Max 8.97	.0000	2.09373	–

Human capital: Eigenvalue of the first principal component (PC1) = 1.399; total variance explained by PC1 = 34.980% (age of spouse was excluded from analysis as >98% were up to 64 years)

Financial capital: Eigenvalue PC1 = 1.293; total variance explained by PC1 = 43.101%

Social capital: Eigenvalue PC1 = 1.428; total variance explained by PC1 = 35.709%

Physical capital: Eigenvalue PC1 2.096; total variance explained by PC1 = 29.936% (excluded: no mobile, one mobile, brick house, sanitary latrine, tube well, easy bike)

Natural capital: Eigenvalue PC1 = 1.658; total variance explained by PC1 = 55.252%

Adaptive capacity: PC1 Eigenvalue = 2.093; variance explained by PC1 = 41.868%

Child dependency ratio = total number of children (<15 years old) in the household divided by the total number of working age adults in the household multiplied by 100. Child dependency ratio was preferred over a dependency ratio as we did not have data on the number of members ≥65 years of age

Remittance had the highest weighting (0.806) in the financial capital (FC) index, the second highest (0.799) being head's monthly income of TK. >15,000. About 5% households had income from spouses, but this indicator had a very low (0.07) contribution to the FC index.

Over 40% households had NGO memberships, but this indicator had the lowest weighting (0.249) to the social capital (SC) index. Membership in religious groups had the second lowest weight (0.478). Very few were members of professional and cultural/sports

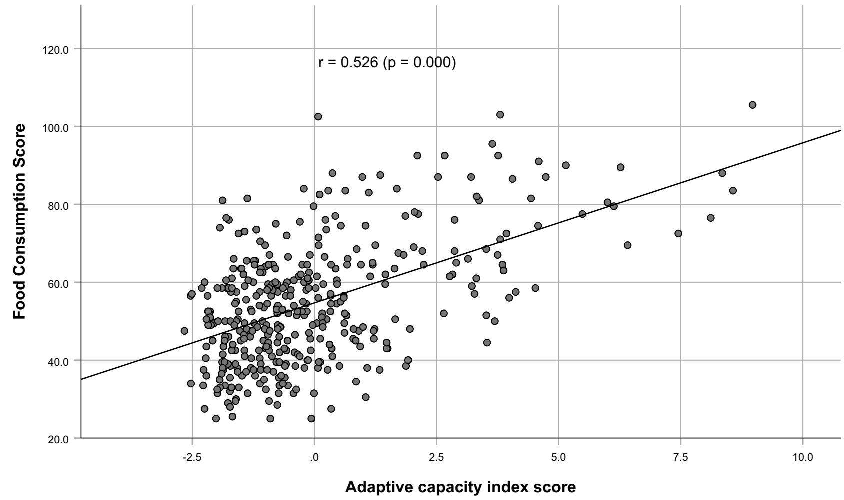


Fig. 8 Scatterplot showing the spread of AC and its correlation with the FCSs

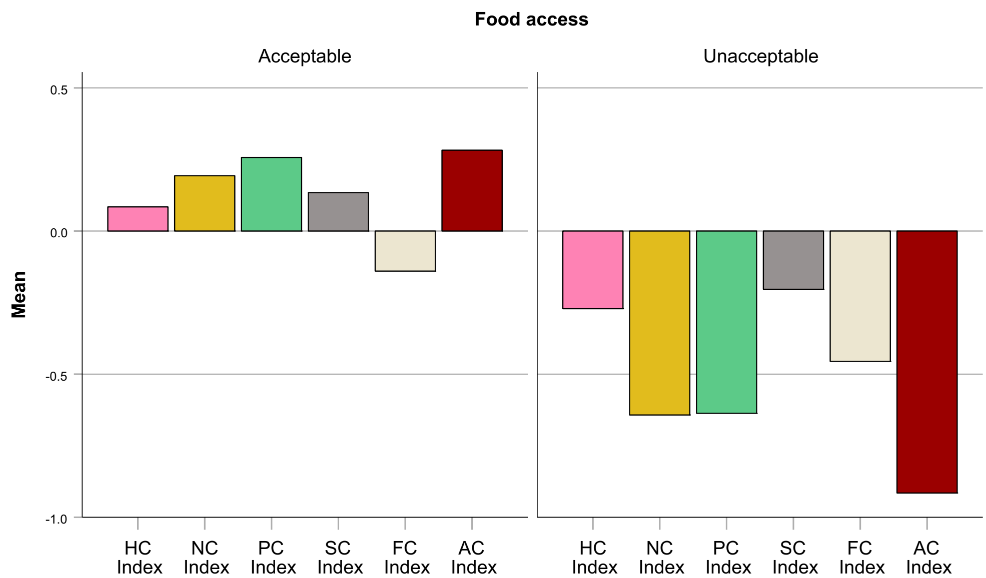


Fig. 9 Mean of the assets and AC indices within the *unacceptable* and *acceptable* categories (HC=Human Capital; NC=Natural Capital; PC=Physical Capital; SC=Social Capital; FC=Financial Capital; AC = Adaptive Capacity)

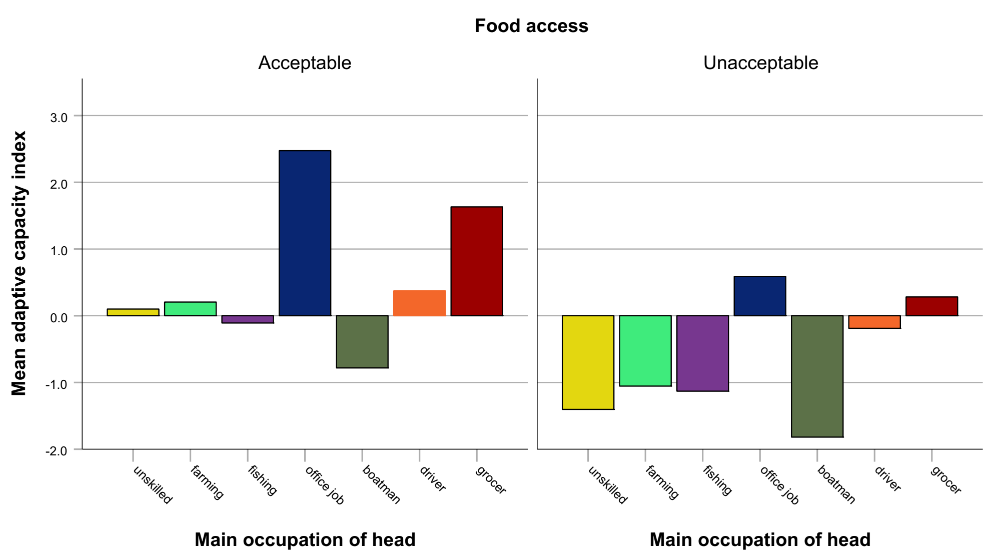


Fig. 10 Mean AC index scores of occupation groups within the *unacceptable* and *acceptable* categories

associations, with the latter contributing the most (0.769) to the SC index.

Only 6% of the households had two or more houses, but it had the second lowest weight (0.476) within the physical capital (PC) index. The ownership of motorbike and TV was also very low, with the latter having the second highest weight (0.654). A quarter of the households had smartphones and this indicator had the highest loading (0.709) on the PC index. The lowest weight (0.250) was for radio ownership.

Around 65% of the sampled households had no farmlands at all. Within the rest, land ownership ranged from 0.01 acre to 2.8 acres only. This indicator had the highest loading (0.855) on the Natural Capital (NC) index, followed by livestock and homesteads.

As expected, all the asset indices had positive contributions to the AC index, with the highest coming from the PC index and the lowest from the HC index (Table 6). The weightings for the other indices were very similar.

Exploratory analyses revealed a strong positive correlation between the Food Consumption Scores (FCSs) and the AC of the sampled households (Fig. 8).

Disaggregated analysis of the five asset indices and the AC index between the *unacceptable* and *acceptable* food access categories are shown in Fig. 9. All the asset indices, and thus the AC index, were considerably lower within the *unacceptable* category.

Further disaggregated analysis of the AC scores according to head's main occupation is shown in Fig. 10. Unskilled, farmer, and fisher groups had very low AC, but those within the *acceptable* category, especially unskilled and farmer groups, looked slightly better-off. Boatman had the least AC of all the occupation groups, but those within the *unacceptable* category had lower AC than those in the *acceptable* category. Drivers within the *unacceptable* category had less AC. The grocer group within the *acceptable* category showed significantly higher AC than those within the *unacceptable* category. The picture was the same for the office job holders.

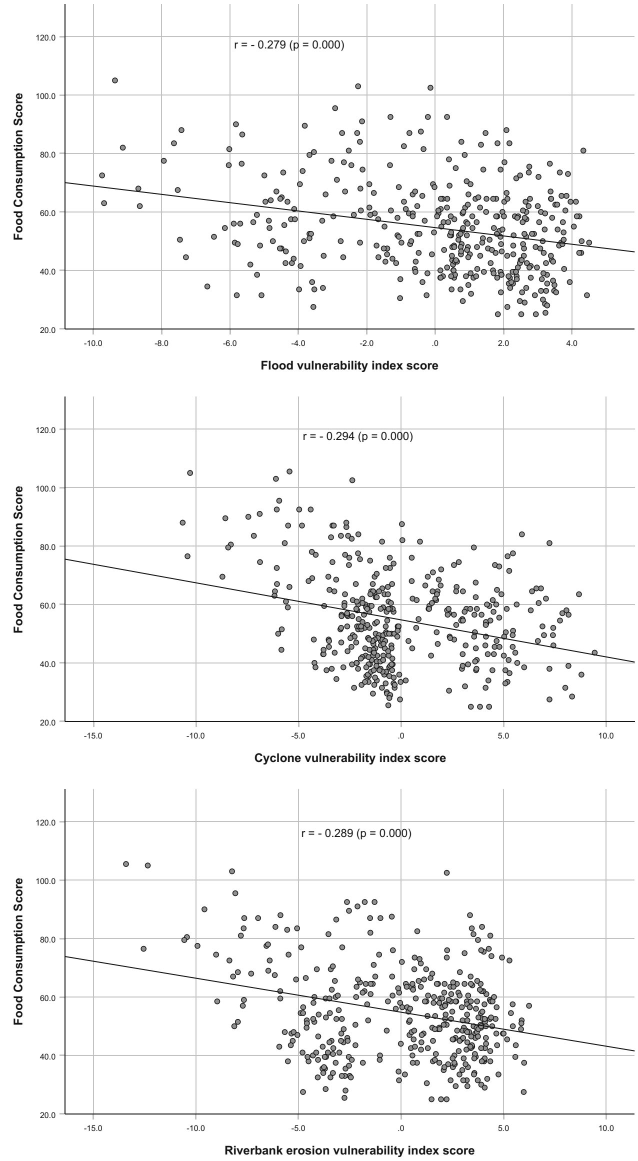


Fig. 11 Scatterplots showing the spread of the vulnerability index scores and their correlations with the FCSs

4.4 Vulnerability

The spread of the vulnerability index scores vis-à-vis the Food Consumption Scores (FCSs) are shown in Fig. 11. A higher score indicates a higher vulnerability of a household, and vice versa. Since the vulnerability scores were created by deducting the AC scores from the ES scores, a positive vulnerability score would indicate that the household concerned had insufficient AC to address their ES to a hazard. All the three vulnerability indices showed strong negative correlations with the FCSs.

Disaggregation of the vulnerability scores between the *unacceptable* and *acceptable* categories revealed that the households within the former category had considerably higher vulnerabilities to all the three hazards compared to the households within the latter category (Fig. 12). The variation in flood vulnerability was the highest, followed by the variations in cyclone and riverbank erosion vulnerabilities. This finding indicated that, whilst, all the vulnerabilities might have links with *unacceptable* food access, flood vulnerability might have the strongest link.

Further disaggregation according to occupation groups revealed clear distinction between the *acceptable* and *unacceptable* categories (Fig. 13). Grocers within the *unacceptable* category showed higher flood vulnerability scores than those within the *acceptable* category. The same was found for the driver, farmer, and unskilled groups. It was likely, therefore, that flood vulnerability would have a link with *unacceptable* food access within these groups.

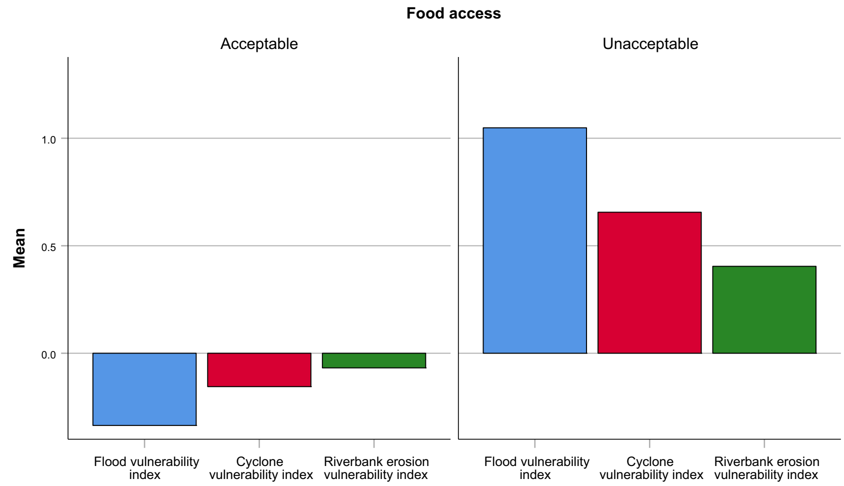


Fig. 12 Mean vulnerability index scores within the *acceptable* and *unacceptable* categories

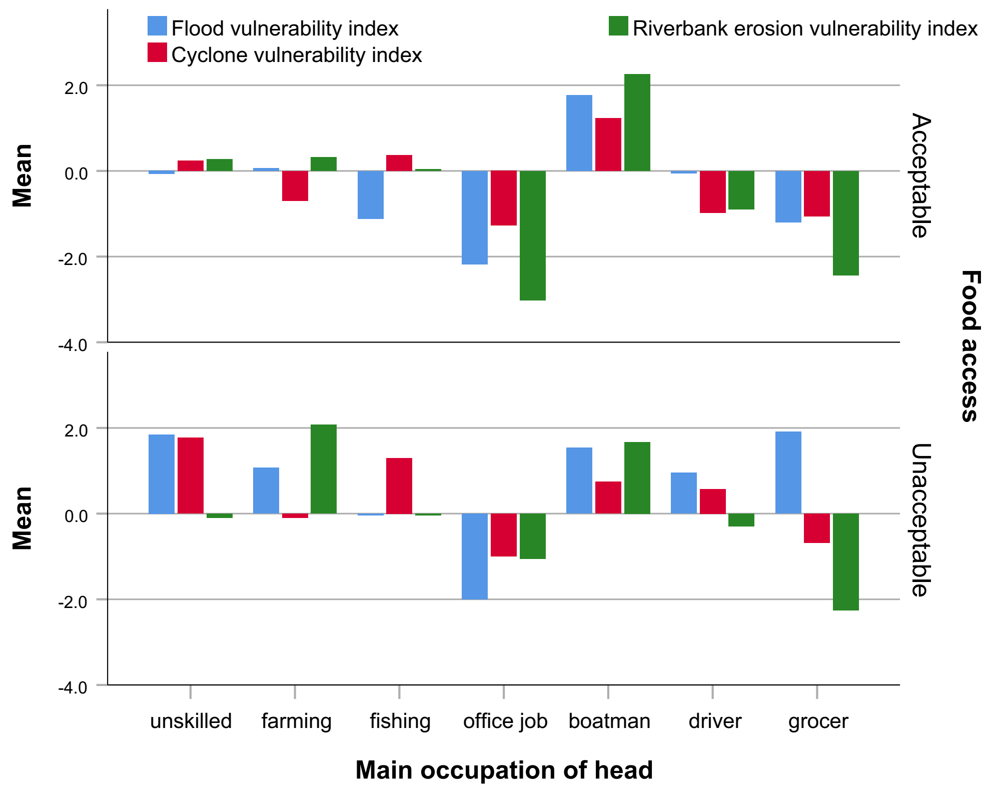


Fig. 13 Mean vulnerability index scores of occupation groups within the *acceptable* and *unacceptable* categories

4.5 Effects of exposure-sensitivity (ES) and vulnerability on food access

To confirm if ES had an effect on household food access, we fitted all the three ES variables into a generalised linear regression model (eq. 4) by taking the Food Consumption Scores (FCSs) as the dependent variable. The results (Table 7) confirmed that none of the ES variables had any significant effect on food access. The non-significant omnibus test statistic indicated that the model with the explanatory ES variables included was not a significant improvement over the baseline model. Therefore, we did not proceed to further analyses by disaggregating the FCS into a binary variable.

The results of the generalised regression model with the vulnerability indices included as explanatory variables indicated that all the variables had significant negative effects on food access (Table 8). The significant ($p \leq 0.001$) omnibus test statistics suggested that the model was plausible.

To confirm if the vulnerability variables could push a household below the *acceptable* threshold of food consumption (as per WFP 2008), we ran a binary logistic regression (equations 5and 6) by treating the FCS as a binary variable

Table 7 Effects of the ES variables on the household Food Consumption Scores

Parameter	Coeff. (B)	Std. Error	Wald	Sig.
(Intercept)	53.975	.7773	4822.469	.000
ES_{fl}	.278	.3030	.842	.359
ES_{cycl}	.160	.2478	.419	.518
ES_{re}	.069	.2613	.070	.791

Model: Genearlised linear regression model with *Identity* link function; Estimation: Maximum Likelihood

Omnibus Test: Likelihood Ratio Chi-sq. 1.312 ($p = 0.726$)

For missing values listwise deletion was used ($N = 417$ in the model)

ES_{fl}, ES_{cycl}, and ES_{re} refer to the exposure-sensitivity to flood, cyclone and river erosion, respectively

Table 8 Effects of the vulnerability variables on the household Food Consumption Scores

Parameter	Coeff. (B)	Std. Error	Wald	Sig.
(Intercept)	54.769	.7374	5516.861	.000
V_{fl}	−1.026	.2504	16.782	**.000**
V_{cycl}	−.740	.2179	11.529	**.001**
V_{re}	−.803	.1960	16.783	**.000**

Model: Genearlised linear regression model with *Identity* link function; Estimation: Maximum Likelihood

Omnibus Test: Likelihood Ratio Chi-sq. 71.795 ($p = 0.000$)

For missing values listwise deletion was used ($N = 398$ in the model)

V_{fl}, V_{cycl}, and V_{re} refer to the vulnerability to flood, cyclone, and river-bank erosion, respectively

(FCS ≤42.0 = *unacceptable* food access and FCS ≥42.5 = *acceptable* food access). In this model we treated *unacceptable* as the response (coded as 1.0) and the *acceptable* as the reference category (coded as 0.0).

The results (Table 9) indicated that flood vulnerability was the only variable having a significant effect. The odds ratios (exponential of Beta) suggested that, given the other vulnerability variables constant, the odds of a household with a flood vulnerability score of 1.0 to fall within the *unacceptable* category would be around 1.17 times (or 17%) higher than that of a household with a zero flood vulnerability score (as per eq. 6). The significant ($p \leq 0.01$) omnibus test statistics indicated that the model was plausible.

Table 9 Effects of the vulnerability variables on the likelihood of a household having an *unacceptable* level of food access

Parameter	Coeff. (B)	Std. Error	Wald	Sig.	Exp(B)
(Intercept)	−1.275	.1294	97.095	0.000	.279
V_{fl}	.159	.0501	10.022	**0.002**	1.172
V_{cycl}	.019	.0368	.275	0.600	1.019
V_{re}	.009	.0347	.064	0.800	1.009

Model: Genearlised linear regression model with *Logit* link function; Estimation: Hybrid

Omnibus Test: Likelihood Ratio Chi-sq. 15.210 ($p = 0.002$)

For missing values listwise deletion was used (N = 398 in the model)

Table 10 Interaction effects of flood vulnerability and household head's occupation on the odds of a household having *unacceptable* food access

Parameter	B	Std. Error	Wald	Sig.	Exp(B)
(Intercept)	−1.321	.1398	89.250	.000	.267
Unskilled * V_{fl}	.251	.0971	6.690	**.010**	1.285
Farmer * V_{fl}	.182	.0960	3.605	.059	1.200
Fisherman * V_{fl}	.111	.0901	1.504	.220	1.117
Office * V_{fl}	.075	.1827	.167	.683	1.078
Boatman * V_{fl}	−.138	.1667	.685	.408	.871
Driver * V_{fl}	.279	.2007	1.933	.164	1.322
Grocer * V_{fl}	.543	.2302	5.557	**.018**	1.720

Model: Genearlised linear regression model with *Logit* link function; Estimation: Hybrid

Omnibus Test: Likelihood Ratio Chi-sq. 89.250 ($p = 0.000$)

For missing values listwise deletion was used ($N = 398$ in the model)

To identify which occupational groups were likely to have *unacceptable* food access due to floods, we estimated the interaction effects of flood vulnerability and the household heads' main occupation. The results (Table 10) indicated that grocers and unskilled labourers were significantly more likely to be affected. Of this, grocers appeared to be the worst affected in terms of the corresponding odds ratio.

5 Discussion and conclusions

In this research we aimed to investigate if climatic hazards could affect the food access of households resident in hazard-prone areas of developing country deltas and who was likely to be at risk and why. To achieve these aims we applied an analytical framework (section 2) consisting of four constructs: exposure-sensitivity (ES), adaptive capacity (AC), vulnerability (V), and food access (measured as Food Consumption Scores). Accordingly, we explored, using data from a hazard-prone delta zone in Bangladesh, if there was an effect of ES on food access, an effect of V (ES-AC) on food access, and an effect on food access of the interactions between V and households heads' main occupation.

Our regression analysis confirmed that ES did not have a direct effect on food access (Table 7). Unlike ES, however, we found significant negative effects of all the three V indices – flood, cyclone, and riverbank erosion – on food access (Table 8). This confirmed that, rather than ES alone, it was the combined effects of both the ES and AC that hampered food access.

However, by considering food access as a binary variable – *unacceptable* and *acceptable* – we found that flood vulnerability was the only variable that could reduce a household's food access below an *acceptable* level (Table 9). These findings indicate that some hazards can be more significant than the others, and therefore, vulnerability analyses and interventions aimed at improving household food access in deltas need to be location- and hazard-specific, rather than general (Vincent 2007).

Disaggregated analyses of ES and AC can help explain why flood had such an effect. The households within the *acceptable* category had considerably lower flood ES (Fig. 6), but much higher AC (Fig. 9). In contrast, the households within the *unacceptable* category had higher flood ES (Fig. 6), but significantly lower AC (Fig. 9). The combined effects of these two variables, therefore, made the households within the *unacceptable* category significantly vulnerable to floods. Moreover, unlike cyclone and riverbank erosion, the damages inflicted by floods can be long-lasting. The ES indicators within the flood index (Table 5) suggest that in the current study area such damage occurred mainly through the loss of livestock (highest weight), disease attacks (second highest weight) and damage to houses/household goods (third highest weight). Disease attack is particularly noteworthy. As shown in Table 5, across the three hazards, disease attack had the highest weight in the flood ES and the lowest in the riverbank ES. Diseases can have very long-lasting consequences on a household, such as increased financial stress due to burden of care and reduced supply of labour due to illness and death. This, in turn, could worsen a household's ability to access food (de Waal and Whiteside 2003). These findings indicate the need for food security interventions in deltas to move beyond agricultural focus and adopt such measures as protecting livestock and houses as well as preventing disease outbreaks following a hazard.

Regarding livelihood groups, our finding contradicts the broad generalisation in the recent UN reports (FAO et al. 2018; FAO 2016) that climatic hazards would particularly affect the food security of 'natural-resource-based' livelihoods. The effects of flood vulnerability on the farmer- and fishermen-headed households in our study were not significant (Table 10). In contrast, floods significantly affected the food access of two non-natural-resource-based livelihoods, including small grocers and unskilled labourers (e.g. day labourers and rickshaw pullers). Such observations raise the need to make food security interventions in developing country deltas 'all-inclusive' by considering all livelihood groups. Such a requirement is rarely specified in the current literature on climate and food security, including the recent state of the world's food security reports (FAO et al. 2018; FAO 2016).

Disaggregated analyses shed light as to why the grocers and unskilled labourers were more likely to have *unacceptable* food access. In this case as well, a combined effect of ES and AC can be seen. The grocers within the *unacceptable* category had much higher flood ES (Fig. 7), but much lower AC (Fig. 10) compared to the grocers within the *acceptable* category. The same pattern can be observed for the unskilled.

Whilst, both ES and AC were found important in explaining household food access, AC appeared to be more important. Exploratory analyses showed that none of the ES variables was correlated with the Food Consumption Scores (Fig. 5). Unlike ES however, AC had a strong positive correlation (Fig. 8). Moreover, the ES scores did not show a clear pattern of variation between the *acceptable* and *unacceptable* categories. For example, the households within the *acceptable* category had higher ES to riverbank erosion and cyclones (Fig. 6). Similarly, flood ES was higher among the office job holders and boatmen within the *acceptable* category (Fig. 7). However, what was common among all the households within the *unacceptable* category was that they had much lower AC scores compared to those in the *acceptable* category (Figs. 9 and 10). Higher AC therefore explained why some households, e.g. within the office job holder group, managed to maintain an *acceptable* level of food consumption despite having higher ES. Since, AC is conceptualised in this research and the wider literature (see the references in Table 1) as a function of assets, it can be inferred that efforts towards improving food access in hazard-prone deltas would require more emphasis on building household assets, alongside preventing hazard exposure and damages.

Our study provides two important lessons for such an asset-building approach. First, it shows that, all the five types of assets considered in this study are important for AC, although their relative importance may vary. For instance, although physical capital had the highest contribution to the AC index, the other assets including social, financial, natural, and human capitals were almost equally important (Table 6). Therefore, the said asset-building approach needs to be holistic by going beyond traditional income-generation or cash support measures and include such less-recognised measures as improving vulnerable peoples' organisational capacity and literacy.

Second, within each asset type, the emphasis on specific assets may vary (Table 6). Within the physical capital index, the possession of smart phones and multiple houses had the highest weights. Not only are these manifestations of a household's wealth and status (which can help them access other forms of capital), but also are crucial for climate-related AC (Table 1). Smart phones, for instance, can help people access hazard early waring information, sometimes live through Internet connections. TV (the indicator with the second highest weight within physical capital) can also enhance access to such information. More mobile phones (third highest weight within physical capital) can mean more household members being able to access weather and early warning information.

Within financial capital, the highest weighting was for remittance (Table 6). Some households in our sample had members working overseas, especially in the Middle-Eastern countries. This study shows the importance of the money they send back home. The next highest weighting was for the head's monthly income of TK. >15,000. Improving the financial capital of vulnerable households, therefore, would require promoting high-income and off-farm jobs, as found in other studies (see Table 1).

Similarly, membership of cultural/sports and professional organisations was quite important within the social capital index (Table 6). Membership in NGO groups, however, had the least contribution, probably because NGOs operating in the region mostly provide micro-finance services, the impacts of which was found minimal in a previous study (Jordan 2015). Improving vulnerable households' social capital, therefore, would require greater emphasis on supporting and strengthening local institutions.

For natural capital, ownership of farmlands had the highest weight (Table 6), the importance of which is widely recognised in the literature (see Table 1), implying the need for land distribution interventions to support the landless. Additionally, the secondary and above level education of household heads and spouses had the highest effects on human capital, indicating the need for promoting higher education in deltaic areas.

By pulling together all these findings, we can develop a holistic, livelihood-oriented, and asset-based framework of interventions for improving food access in climatic hazard-prone areas of developing country deltas. An example of how such an intervention may look like is provided in Fig. 14, by taking the current study area as a case. This framework illustrates that an intervention that aims to improve food security in developing country deltas solely by addressing the risks to agricultural (fisheries) production is bound to be inadequate.

Some limitations of this study provide lessons for further studies. We could analyse the effects of hazard vulnerability on household Food Consumption Scores (FCSs) only. Although FCS is a well-tested and methodologically robust proxy indicator of food access, it is criticised as being weaker in capturing the *quality* dimension of food access (e.g. micronutrient adequacy) (Leroy et al. 2015). Therefore, it may be useful to test our models for other food access indicators (Leroy et al. 2015).

Additionally, we had to drop several important indicators – such as the ownership of brick houses, sanitary latrine, tube well; and female-headed households – as there was inadequate data variability on these indicators for PCA to be effective. A larger sample covering wider regions would have helped overcome this problem. Moreover, there are other indicator variables of interest, e.g. income diversification, household savings, and proportion of income coming from natural-resource-based occupations (e.g. agriculture and fisheries). Likewise, we could only include in our analyses the indicators of 'linking' social capital, although 'bridging' and 'bonding' social capital may be important as well (Jordan 2015; Vincent 2007). Due to data limitations, we could not verify the effects of institutional and policy factors on hazard vulnerability and food access. Relevant indicators – such as free or subsidised input distributions, public works programs, and

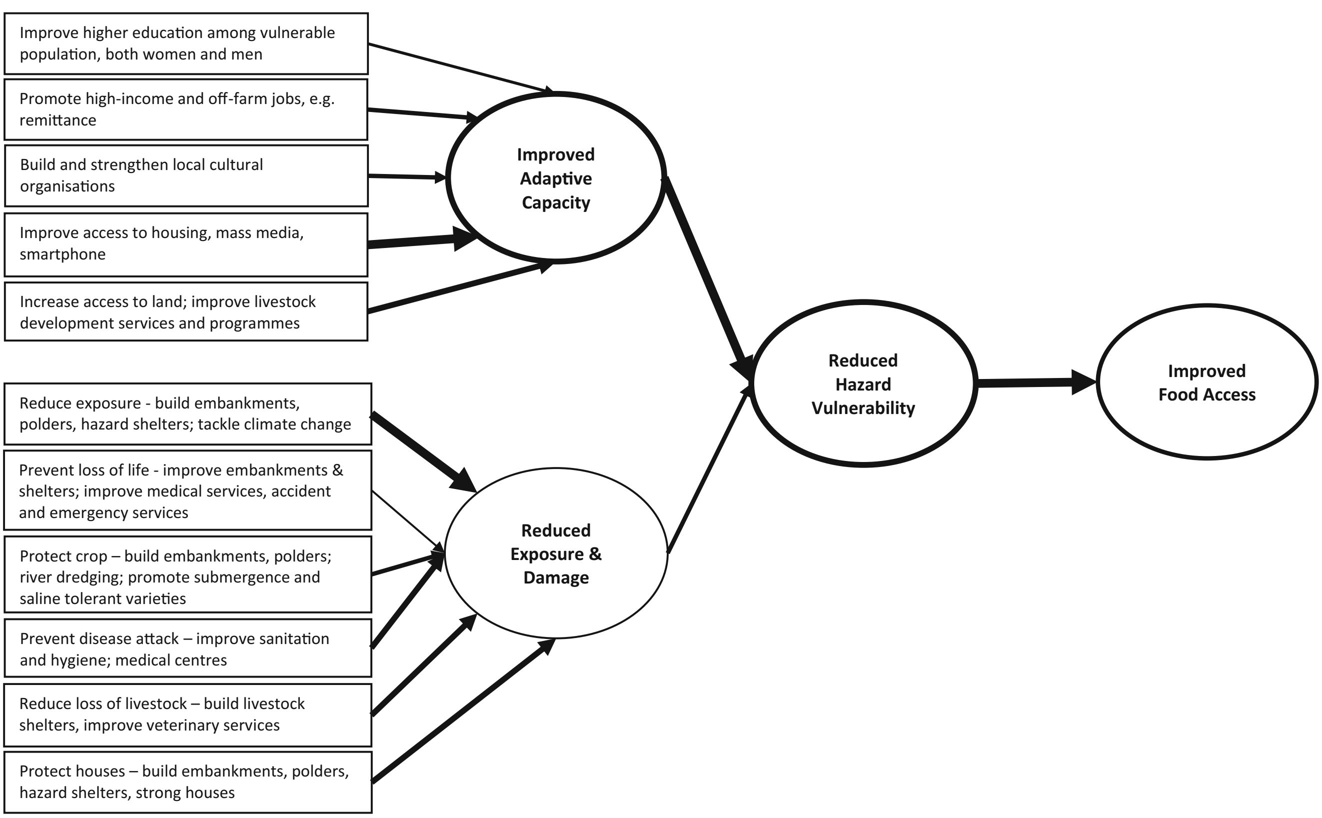


Fig. 14 An example of a holistic framework for improving household food access in climatic hazard-prone deltas (note: thicker lines indicate higher importance and urgency)

grain reserve management or food pricing policies (Devereux 2007) – may be worth investigating. In addition, in any adaptive system having a human component, learning is an important factor. Therefore, further studies could consider this indicator.

Because of the cross-sectional nature of this research, it provides only a snapshot in time. Such an approach has limitations, e.g. it cannot explain "chronic" (persistent, long-lasting) and "seasonal" food insecurities as well as the shifts in livelihood assets over time due to hazard impacts. Future studies could use a longitudinal or historical approach combining time series or panel data.

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Compliance with ethical standards

Conflict of interest The authors declare that they have no conflict of interest.

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