Chapter 5
Extreme Weather Events and Food Insecurity in Northeast India

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Abstract Frequent occurrences of extreme weather events such as droughts, floods, cyclones, and hailstorms—arguably caused by climate change—are likely to increase food insecurity across the globe, especially in developing countries. They pose formidable challenges to achieving the United Nations Development Program's (UNDP) Sustainable Development Goal (SDG) of ending hunger and ensuring access by all to safe, nutritious, and sufficient food all year round by 2030. Using household survey data for eight states of India's Northeast Region (NER) obtained from the India Human Development Survey for 2011–12, this chapter empirically analyzes the incidence, intensity, and inequality of food insecurity among the households in the region, which is known for its remoteness and relative economic destitution. Applying econometric techniques to household data and village-level weather data, it further investigates the impact of the extreme weather events on food insecurity after controlling for several demographic and socio-economic factors. The results of this exercise indicate that extreme weather events interact with household income to significantly increase the likelihood of food insecurity in the short as well as long run, although they do not have statistically significant impacts on their own. Further, there is some evidence of floods and hailstorms increasing the likelihood of food insecurity through their interactions with the household income in the long run. Similarly, the results suggest that droughts and floods increase the probability of food insecurity through their interactions with the distance to the market and household income in the short run. These results are robust to the inclusion of additional control variables and the use of alternative functional assumption of the regression model.

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5.1 Introduction

The 2020 Global Hunger Report (GHR) suggests that there are a large number of countries that are still vulnerable to food and nutrition insecurity.[1] Although the level of hunger at the global level is currently moderate, there are regions where it is still severe. According to *The State of Food Security and Nutrition in the World 2020*, a report jointly prepared by the Food and Agricultural Organization (FAO) of the United Nations, International Fund for Agricultural Development (IFAD), the United Nations International Children's Emergency Fund (UNICEF), World Food Programme (WFP), and the World Health Organization (WHO), nearly 746 million people (9.7% of the world population) were severely food insecure in 2019 (FAO et al. 2020). However, there are regional variations. For example, this proportion of severely food insecure people is 19% in Africa and 17.8% in South Asia. Furthermore, the prevalence of moderate or severe food insecurity in the world increased from 22.7% in 2014–16 to 25.5% in 2017–19. In South Asia, it increased from around 31 to 33.4% during the same period (FAO et al. 2020). The regions with higher incidence of hunger remain extremely vulnerable to food and nutrition insecurity. Health, economic, and environmental crises intensify this vulnerability.[2] As noted in the above report, climate variability and extremes are two major factors undermining efforts to end hunger, food insecurity, and malnutrition (FAO et al. 2020). The developing countries where the agriculture sector is still the source of livelihood for a substantial portion of their populations are likely to suffer the most (Mandal and Sarma 2020). Climate change manifested in increases in average temperature and rainfall and their variability, and extreme weather shocks such as droughts and floods are likely to adversely affect the weather-sensitive agriculture sector in these countries. Mahato (2014) argues that the developing countries may experience an average decline of 10–25% in agricultural productivity by 2080s owing to climate change that in turn will affect food security considerably.

As a result of the Green Revolution introduced in the mid-1960s, India became self-sufficient in food production by the mid-1970s and had an unmanageable stock of food grains by the mid-1990s (Goswami 2018a). The production of both food grains and several non-food crops increased many folds over time (Narayanamoorthy 2017). In fact, India now exports food grains to many countries. Yet, India's rank as per the GHR 2020 was 94. South Asian countries like Sri Lanka and Nepal ranked much

[1] The concept of food (in)security has evolved over time. The World Food Summit in 1996 articulated the widely accepted definition of food security. It highlights four dimensions of food security, namely availability of sufficient food of proper quality; command over resources to access food; absorption of food to meet all the physiological needs; and stable supply of food at all times. Most studies on the topic use this framework to examine and understand various aspects of food (in)security.

[2] The report is available at: https://www.globalhungerindex.org/pdf/en/2020.pdf.

ahead of India at 64 and 73, respectively. Thus, prevalence of hunger continues to be a challenge despite more than adequate food production in India. Using data from FAO et al. (2020), Bansal (2020) estimates that while 27.8% of India's population suffered from moderate to severe food insecurity in 2014–16, this proportion rose to 31.6% in 2017–19. India alone accounted for 22% of the global burden of food insecurity, the highest for any country, in 2017–19 (Bansal 2020). While there are variations in vulnerability to hunger and food security across states, at the macro-level, climate change-induced challenges have threatened to exacerbate the problem of hunger and food security. For instance, Gupta et al. (2014) show that increase in temperature and erratic rainfalls are harmful for the yield of rice, one of India's primary crops.

India's Northeast Region (NER) accounts about 8% of total geographical area and approximately 3.8% of overall population of the country in 2011. The per capita income in the region is only 72% of that at the national level in 2013–14.[3] The region however shows lower prevalence of food insecurity. Mandal and Sarma (2020) present evidence to show that except for Meghalaya, the percentage of food insecure households in other states of the region is much lower compared to the national average. Yet, the concern remains as the region experiences extreme weather events frequently. NE India receives very high rainfall during the pre- and summer monsoon seasons. The excess rainfall results in landslide and flood that in turn cause extensive damage to crops. At times, life comes to standstill (Mahanta et al. 2012). In other words, there is a possibility that extreme weather events may render people food insecure in this part of India, at least transitorily.

Against this backdrop, the chapter investigates the impacts of extreme weather events on food insecurity in NER. While Mandal and Sarma (2020) examine the effect of rainfall deficiency (as a proxy for extreme weather shocks) on food security in the Indian context, there is no study that exclusively investigates the problem in case of NER. The specific environmental and socio-economic characteristics of the states in the region call for a study that exclusively focuses on these states. Thus, this study uses household survey data for eight NER states obtained from the India Human Development Survey for 2011–12, to empirically analyze the incidence, intensity, and inequality of food insecurity among the households in the region, which is known for its remoteness and relative economic destitution. Applying econometric techniques to household data and village-level weather data, it further investigates the impact of the extreme weather events on food insecurity after controlling for several demographic and socio-economic factors. The results of our analysis indicate that extreme weather events interact with household income to significantly increase the likelihood of food insecurity in the short as well as long run, although they do not have statistically significant impacts on their own. Further, there is some evidence of floods and hailstorms increasing the likelihood of food insecurity through their interactions with the household income in the long run. Similarly, the results suggest that droughts and floods increase the probability of food insecurity through their

[3] Calculated from the information available here: http://necouncil.gov.in/sites/default/files/uploadfiles/BasicStatistic2015-min.pdf.

interactions with the distance to the market and household income in the short run. These results are robust to the inclusion of additional control variables and the use of alternative functional assumption of the regression model.

The remainder of the chapter is organized as follows. Section 5.2 includes a brief review of the relevant literature. We discuss the data and methodology for our empirical analysis in Sect. 5.3. Section 5.4 presents and discusses the empirical results. We include a summary and a few concluding remarks in Sect. 5.5.

5.2 Literature Review

There is a growing literature on the effect of climate change on food insecurity. We can broadly divide the studies into two groups: (*i*) those that examine the relationship between broadly defined climate change and food insecurity and (*ii*) those that narrowly focus on the effect of extreme weather events—arguably a reflection of climate change—on food insecurity. In this section, we discuss some relevant studies in each category.

5.2.1 Climate Change and Food Insecurity

Through its complex interaction with the food system, climate change can affect all dimensions of food insecurity. It may affect the availability of food by adversely impacting crop yield and livestock production. Further, climate change may exacerbate food insecurity at the global level by reducing the size of arable land (Krishnamurthy et al. 2014). Iizumi et al. (2018) find that average yields of wheat, maize, and soybeans at the global level decreased by 1.8, 4.1, and 4.5%, respectively, due to climate change between 1981 and 2010. Using different methods, Zhao et al. (2017) also show negative impacts of the increase in temperature on crop yields. Several studies show that detrimental effects of climate change on crop yield and production will be severe with the increase in warming. Asseng et al. (2015) estimate that global wheat yield will reduce by 6% with one-degree increase in warming. Further, climate change may induce changes in pollination services, pest, and diseases and thereby can reduce yields of the crops. Bebber et al. (2014) report that pests and diseases have already changed as a consequence of climate change. Not only the grain crops, but fruits and vegetables are also likely to be affected (Mbow et al. 2019).

These effects are however region-specific and contingent upon concentrations of CO_2 and fertility levels. An increase in temperature will help agriculture in the temperate regions in terms of expansion of cropland, longer growing period, higher crop yields, and increased pasture productivity. The fourth IPCC report also shows that a moderate rise in temperature in mid- to high-latitude regions accompanied by an increase in CO_2 can be beneficial for the yields of rain-fed crops such as rice, wheat, and maize (Aberman and Tirado 2014). In contrast, in some tropical regions such as Sub-Saharan Africa, land for multiple cropping will decline substantially (Schmidhuber and Tubiello 2007). The dry land areas, especially in the developing countries, may be affected more adversely by the climate change-induced food insecurity as these regions have low adaptive capacities (Shah et al. 2008). In dry and tropical regions, a small increase in temperature can reduce yields (Aberman and Tirado 2014). Iftikhar et al. (2014) find that climate change worsens food insecurity in Pakistan through reduction in production of crops, fruits, and vegetables, changes in the intensity of rainfall and floods, water shortage, and soil erosion. These effects of climate change also result in the loss of different physical and human assets. Using panel data for five African countries over the period of 2000–14, Mahrous (2019) analyzes the impact of global climate change on food security. The study presents evidence of a negative effect of rising temperature and of a positive effect of increasing rainfall on food security in the region.

Increased temperature and variability in rainfall affect the livestock systems through their impacts on animal health, availability of water, and so on. Changes in temperature and rainfall affect the quality and quantity of pasture, and thereby impact livestock. In particular, livestock systems are adversely impacted due to a reduction in feed quantity and quality and changes in disease and pest prevalence (Campbell et al. 2016). Brander (2010) suggests that spatial availability of marine species may change as they move in search of suitable habitats when ocean temperature and marine environment changes due to climate change.

The impact of climate change on crop yields and livestock systems is likely to be felt non-uniformly by different sections of the societies. It is not difficult to guess that the small and marginal farmers will be the hardest hit due to these impacts of climate change. The overwhelming dependence of the small farmers on agriculture and allied activities and given their limited resources for taking adaptive measures makes this category of farmers more vulnerable to climate change. While delving into the uneven impact of climate change, Krishnamurthy et al. (2014) emphasize that the number of malnourished children may increase in the developing world as a result of reduced availability, access, and food absorption capacity vis-à-vis advanced economies.

Climate change can also affect access to food. By affecting availability due to decreased yield and production and disrupting distribution, climate change may reduce access to food, primarily through making food costly (Krishnamurthy et al. 2014). In an integrated model, Nelson et al. (2014) simulate different climate change scenarios and find that agricultural production, prices, trade, and cropland area show the highest variability in response to climate change. Low-income households, women, and children are likely to be adversely affected to a larger extent due to higher prices of food and disruptive supply (Mbow et al. 2019).

Diet and health are the two channels through which climate change can impact food utilization (Aberman and Tirado 2014). The diet channel relates to the impact of climate change on the nutrient content of the food. In contrast, the health channel relates to water and food safety, and diseases and infections that impact human body's nutritional requirement and its ability to absorb nutrients. Due to heavy rainfall and rise in sea level, flood may become frequent and that will expose people to diarrhea and other infectious diseases. The risk of animal diseases getting transmitted to human may increase with climate change due to survival of pathogens and changes in carriers and natural ecosystems. Besides, the temporal and spatial distribution of the vector-borne diseases may change. The exposure to these diseases will reduce the ability to absorb the nutrients in the food and increase the nutritional needs (Krishnamurthy et al. 2014). Climate change may create a vicious cycle wherein infectious diseases reduce the capacity of the body to absorb food and thereby making more susceptible to infectious diseases. The overall impact of such developments can be reduced labor productivity and increased poverty as well as mortality (Schmidhuber and Tubiello 2007).

Changes in the climate, such as increasing temperature, impact a host of biological process (such as metabolic rate) in plants and animals, which in turn affect the nutrient concentrations. Further, increased concentration of CO_2 in the atmosphere reduces the availability of zinc and other nutrients in foods (Mbow et al. 2019). Consequently, the quality of food declines and that in turn affects utilization of food. Taub (2010) documents that protein concentration in some important crops declines as CO_2 increases in the atmosphere. The concentrations of other minerals such as calcium and magnesium may also fall with increased CO_2. However, these changes vary markedly across regions. Nelson et al. (2018) suggest that climate change alters the availability of micronutrient in some regions more than in others.

Climate change may affect food security by affecting the storage system as well. One of the adaptive responses to climate change is to store food safely so that food is available during contingency. However, Moses et al. (2015) present evidence to suggest that the grain storage is affected by increased temperature that creates favorable conditions for the growth of insects and pests. Consequently, it may become difficult to store food and make it available throughout the year.

In the Indian context, a large number of studies examine the effects of climate change on crop yields. Birthal et al. (2014) analyze the impact of changes in temperature and rainfall on the yields of some major crops in India during the period from 1969 to 2005. The study finds that an increase in maximum temperature has a negative effect on crop yields although an increase in minimum temperature has a positive effect. As per the study, the crops that are more vulnerable to increased temperature are pigeon pea, chickpea, rice, and wheat. In contrast, evidence suggests that increased rainfall has a positive effect on majority of the crops. Gupta et al. (2014) also show that increase in temperature and erratic rainfalls are harmful to the rice yield in India. Birthal et al. (2014) project respective declines of 15 and 22% in rice and wheat yields by 2100 in case of significant changes in temperature and rainfall. Given that India has agricultural land constraint, a decrease in yields of main crops like rice and wheat has important implication for food security. The study further suggests that climate change will impact food security through its impact on livestock systems as well. Any fall in crop area or production will result in less fodder supplies and will reduce production of livestock. While Kumar et al. (2015) analyze the impact of climate change on the yield of an important crop, i.e., potato in the Indo-Gangetic Plains, Boomiraj et al. (2010) conduct a similar study in case of mustard. Saseendran et al. (2000), Aggarwal and Mall (2002), Mandal and Nath (2018) examine the impact of climate change on rice yields, and Dubey et al. (2014) do the same in case of wheat.[4] A review of these studies shows that the empirical evidence of the impacts of climate change in Indian agriculture has been mixed.

5.2.2 Extreme Weather Events and Food Insecurity

Climate change is expected to result in increased frequency and magnitude of extreme weather events such as drought, flood, heat wave etc. (IPCC 2018). Such extreme weather shocks will not only affect production, trade, and thereby availability of food but will also increase food prices. The overall impact would be reduced access and increased food insecurity.

Jahn (2015) and Beer (2018) discuss the potential impact of various extreme weather events on different sectors of the economy over time. Crop damages and the resulting shortfall in the availability of food due to flood, storm, and drought are major losses in the agricultural sector in the short run. Flood may cause deterioration in the soil quality by dumping polluting materials, and this negative effect may last for a long time. In the long run, extreme weather events may cause diseases in crops and silting of irrigation channels. Floods can damage natural organic resources. Storms can damage forest and marine ecosystems. Droughts have detrimental effect on both plants and animals. All these effects of extreme weather events have implications for food security. Besides these direct effects, extreme weather events may affect other sectors of the economy, such as energy and transport, and result in significant loss of incomes, which in turn worsen food insecurity. Further, extreme weather shocks by destroying transport system, storage, and other essential infrastructure can disrupt supply chains thereby impacting both availability of and access to food.

Misra (2014) suggests that frequency and intensity of droughts and floods will increase with the rise in temperature. Further, due to reduced infiltration of surface water in arid and semi-arid areas, restoration of groundwater is likely to be unsustainable. In coastal areas, due to infiltration of salt water as a result of rise in sea level, groundwater may become unusable. These developments will threaten food production and hence food security. Change in cropping pattern, crop breeding, and use of such technologies that use less water are some of the adaptive measures to be adopted. Using field data from Pakistan, Ali and Erenstein (2017) also identified major adaptation measures practiced by the farmers. These measures include adjustment in sowing time, use of drought tolerant varieties, and shifting to new crops. Further, they find that farmers who implement these adaptation measures are likely to have better food security.

There exist some country-specific studies that investigate the impact of extreme weather events on food security. Using a spatial bio-economic modeling framework,

[4] For an exhaustive review of the existing literature on the impacts of climate change in Indian agriculture, see Mandal and Nath (2018).

Gbegbelegbe et al. (2014) assess the implications of the extreme weather of 2012 in the USA for food security in the developing countries. The study finds evidence of negative impacts of extreme weather on food security. In particular, those extreme weather conditions reduced maize production substantially in the USA. The global production also declined. Although consumption in the USA did not decline much, exports of maize from the USA fell. The fall in global production and US exports increased food insecurity in the Eastern Africa, the Caribbean and Central America, and India. The study further analyzes the impact of a similar weather shock if that were to occur in 2050. With the assumption that there will not be any climate change adaptation, the study predicts that the impact of such weather extremes on global food insecurity will be worse.

Beer (2018) studies the aftermath of two tropical cyclones, namely Yasi of 2011 and Larry of 2006 in Australia. Both cyclones destroyed substantial quantity of banana crops in the country resulting in short supply of the fruit for the rest of the respective years. Further, price of banana increased by 400–500% throughout the country.

Hussain et al. (2016) examine the impacts of extreme weather shocks on agriculture and household food security in the Hindu-Kush Himalayan (HKH) region. The study uses data on more than 8000 households from Pakistan, India, Nepal, and China. Most households reported to have experienced frequent floods, droughts, landslides, livestock diseases, and crop pests. This climate-related irregularities resulted in low agricultural production and income. The study also reports that the households experienced transitory food insecurity after the extreme weather events.

While there exist a large number of studies that analyze the impact of climate change on agriculture (especially on average yield and variability in yields of major crops), we came across only one study on the impact of extreme weather events on food security in India. Mandal and Sarma (2020) analyze the impact of weather shock—deviation of rainfall from the normal level—on food insecurity of households in India. They find a positive impact of erratic rainfall on food insecurity. The study suggests that erratic rainfall is harmful to agriculture, and by reducing agricultural output, it worsens food insecurity.

Given that the work on the issue under consideration is scanty in the Indian context, the present work will be a major addition to the literature.

5.2.2.1 Other Determinants of Food Insecurity

This section presents a brief discussion of the factors other than climate change and extreme weather events that may affect household food security. These factors are namely various household demographic characteristics, income and asset position, access to basic services, social safety nets, use of improved agricultural inputs, access to credit, and access to extension services (Mandal and Sarma 2020 and Beyne 2016). In our investigation of the impacts of extreme weather events on food insecurity, we consider some of these variables as covariates.

The household demographic characteristics include age and education level of the head of household, family size, and proportion or number of dependent family members. For households with agriculture as the primary source of income, the presence of an elderly head may be helpful for farming due to his or her experience (Haile et al. 2005). Further, experience may also help coping with risk and thereby may contribute positively to food security. Higher level of education is likely to impact food security positively (Beyne 2016). A household with higher dependency ratio is more likely to be food insecure. Even if a household has food security, intra-household inequality may lead to food insecurity at least for some members of the family. The dependent family members, such as housewives, children, and elderly people, may be at higher risk (Mbow et al. 2019). Thus, the gender and age composition of the household also matters.

Mandal and Sarma (2020) in their study in the Indian context use ‘highest educational attainment of the female members of the household’ also as a relevant variable that impacts food security. Educated women are more likely to be aware of the nutritional content of food, and hence, it is expected that expenditure allocation on nutritious food and thereby food security improves with the increase in the education of the female members of the household. The impact of family size on food security is ambiguous. While more family members imply higher demand for food, it also suggests higher availability of workers to earn income and food, especially if the household has more working age members. Household income and asset position have positive impact on food security. It is obvious that a household with higher income is better positioned to access food and hence likely to have higher food security. Further, assets in the form of agricultural land, livestock, and other non-agricultural assets allow a household to tide over contingencies. These assets work as insurance and ensure food security. Tesso et al. (2012) suggest that household with a diversified source of income is more capable of coping with risk relative to a household with only a single source of income and therefore is more food secure. Mandal and Sarma (2020) also hypothesize that households with cultivation as the primary source of income are likely to be food secure. The same study also suggests that households that receive remittances from migrating family members can spend more on food. The study also finds that urban and poor households are more likely to be food insecure.

The use of improved agricultural inputs increases yield and production, which in turn increases the availability of food and income that can be spent on food items that are not grown by the household. The access to extension services helps farmers in diversifying crop portfolio and also in growing cash crops (Goswami 2018b; Goswami and Bezbaruah 2017). A diversified cropping pattern and higher income generation through the cultivation of cash crop can positively impact food security. The access to credit also has a similar effect like that of access of extension services (Goswami 2018b).

Further, the access to basic services such as water facility, health center, and market is also important determinant of household-level food security. It helps households in managing health and food shocks. The presence of social safety nets is also important for ensuring food security. During times of emergency due to health, income, or environmental crises, assistance received through social safety nets, such as local government institutions or NGOs, can help in stabilizing food supply at the household, local, and regional levels (Beyne 2016).

5.3 Data and Methodology

5.3.1 Data Source and Study Sample

This study is based on secondary data compiled from the second round of *India Human Development Survey* (IHDS-II). The reference year for this round is 2011–12. The IHDS is a nationally representative sample survey conducted jointly by the University of Maryland, College Park (USA), and the National Council of Applied Economic Research (NCAER), New Delhi (India). Because the present study focuses on the Northeast Region (NER) of India, we obtain household-level data from this source only for the eight states of the region that includes Arunachal Pradesh, Assam, Manipur, Meghalaya, Mizoram, Nagaland, Sikkim, and Tripura. The IHDS-II provides data on various dimensions of human development. However, we obtain data only on the variables that are relevant for the current study. The total number of observations in our sample is 1887. Table 5.1 presents the distribution of households and individuals by states in our sample.

Table 5.1 State-wise distribution of the sample households in NER

States	Number of sample households	Number of sample persons (% share in total for NER)	Percentage distribution of population in 2011 (%)
	(1)	(2)	(3)
Arunachal Pradesh	159	668(7.62)	3.0
Assam	991	4651(53.08)	68.6
Manipur	88	481(5.49)	5.7
Meghalaya	134	686(7.83)	6.5
Mizoram	78	347(3.96)	2.4
Nagaland	110	508(5.80)	4.3
Sikkim	107	503(5.74)	1.3
Tripura	220	919(10.49)	8.1
Total (NER)	1887	8763(100.00)	100

Source: Authors' estimation based on IHDS-II, 2011–12 and the Indian Census 2011

5.3.2 Methodology

5.3.2.1 Defining Food Insecurity Line

In order to measure the magnitude of food insecurity, we construct three alternative aggregate measures of food insecurity.[5] The first step toward obtaining an aggregated measure of food insecurity involves identifying the households that are food insecure. To that end, we discuss and define food insecurity lines—thresholds that help such identification—for rural and urban households living in different states of NER.

The food insecurity lines in this chapter have been defined following Mandal and Sarma (2020). It may be noted that it is not only the quantity of food available and accessible but also its nutritional contents that are important from food security point of view. As Nandakumar et al. (2010) argue, the issue of food security is not so much about availability of food grains but about the composition of the overall food basket.[6] Therefore, keeping in view nutritional requirements, the food insecure households are identified as follows. The Expert Group's report to the Planning Commission (Government of India 2014) outlines the normative requirements of expenditure on food comprising calories, proteins, and fats.[7]Following the recommendation of this report, we define monthly per capita food expenditures of Rs. 554 and Rs. 656 (2011–12 prices) on calorie, protein, and fat as the respective food insecurity line for rural and urban areas. These national average food insecurity lines are then adjusted by relevant price indices to estimate state-specific food insecurity lines (separately for rural and urban areas) so as to capture spatial differentials in the price level.[8] A household with per capita monthly expenditures on calories, proteins, and fats below this benchmark is considered to be food insecure.[9] Table 5.2 presents the national and state-specific food insecurity lines.

5.3.2.2 Measuring Food Insecurity

After we identify the food insecure households, we calculate three aggregate measures of food insecurity: head count ratio (HCR), food insecurity gap index

[5] We borrow the basic ideas from the poverty measurement literature.

[6] A change in the consumption patterns from cereals to high-value food is observed in both rural and urban areas of India.

[7] This Expert Group was constituted in June 2012 by the Planning Commission under the Chairmanship of Dr. C. Rangarajan to suggest a methodology for measuring poverty in India. It re-computed the average requirements of calories, fats, and proteins on the basis of the 2010 Indian Council of Medical Research norms (Government of India 2014).

[8] See Mandal and Sarma (2020) for details.

[9] For the items that are either home grown or obtained through the Public Distribution System at a subsidized rate by a household, imputed values of expenditure on those items were calculated on the basis of their existing market prices.

Table 5.2 Food insecurity lines for NER states

States	Food insecurity line (2011–12 INR)	
	Rural	Urban
	(1)	(2)
Arunachal Pradesh	656.03	691.41
Assam	573.75	662.12
Manipur	675.51	728.16
Meghalaya	633.04	710.72
Mizoram	701.64	794.44
Nagaland	700.95	753.34
Sikkim	641.92	719.25
Tripura	533.21	641.80
All India	*554*	*656*

Source: Authors' calculation from IHDS-II, 2011–12

(FIGI), and squared food insecurity gap index (SFIGI).[10] These measures are defined as follows:

$$\mathrm{HCR} = \frac{N_{FI}}{N} \tag{5.1}$$

$$\mathrm{FIGI} = \frac{1}{N} \times \sum_{i=1}^{N} \left(\frac{G_i}{L} \right) \tag{5.2}$$

$$\mathrm{SFIGI} = \frac{1}{N} \times \sum_{i=1}^{N} \left(\frac{G_i}{L} \right)^2 \tag{5.3}$$

where $N$is the population size, N_{FI} is the number of food insecure persons, $L$is the food insecurity line, and G for food insecurity gap which is the gap between the actual per capita monthly expenditure on calories, proteins, and fats, and L (as defined in Sect. 3.2.1). We assign a value of 0 to G for the food secure households.

HCR measures the incidence of food insecurity in terms of the percentage of people who are food insecure. While it is easy to calculate and interpret, it cannot capture the depth and inequality of food insecurity among the insecure households. In contrast, FIGI captures the depth of food insecurity by measuring how far the food insecure people, on average, are away from the food insecurity line. Its value also shows the cost of eliminating food insecurity. However, FIGI does not reflect inequality or its severity among the food insecure people. This problem is alleviated by SFIGI, which is sensitive to inequality among the food insecure people. That is, if

[10] These are analogous to head count ratio, poverty gap index, and squared poverty gap index in the literature on poverty measurement.

the distribution of per capita monthly expenditure on food is changed by transferring some amount from one food insecure household to another then the value of the index changes.[11] Thus, these three measures of food insecurity reflect its incidence, depth, and inequality, respectively.

5.3.2.3 Examining the Determinants of Food Insecurity

We now use a binary logistic regression model to examine the potential determinants of food insecurity at the household level with a special focus on extreme weather events.[12] The general specification of the model is as follows[13]:

$$P(FI_i = 1|x_i, \beta) = 1 - \left(\frac{e^{-x_i'\beta}}{1 + e^{-x_i'\beta}}\right) = \left(\frac{e^{x_i'\beta}}{1 + e^{x_i'\beta}}\right) = \left(\frac{e^{z}}{1 + e^{z}}\right) = F(z) \tag{5.4}$$

where F(z) is the cumulative distribution function for a standard logistic random variable. Here, FI_i indicates the food insecurity status of the ith household, and it takes a value of 1 if a household is food insecure and 0 otherwise. x_i is the vector of explanatory variables that potentially affect food insecurity status of the households. It includes extreme weather events (drought, floods, cyclones and hailstorms) as the variable of interest. In our baseline estimation, we use two dummy variables alternatively to examine the long-run and short-run impact of extreme weather events on food insecurity. Note that we define these variables at the village level. Thus, the long-run dummy variable takes the value of 1 if one or more extreme weather events occurred in a village during a five-year period from 2007 to 2011 and 0 otherwise. Similarly, the short-run dummy variable takes the value of 1if one or more extreme weather events occurred in a village during 2011 and 0 otherwise. We argue that the extreme weather events variable captures the stability of food supply aspect of food insecurity.

We further consider a number of variables that are potential determinants of food insecurity. Each variable is likely to affect one of the three other aspects of food insecurity, namely availability, accessibility, and utilization. We list them below by these three aspects to indicate the likely mechanism of their impacts on food insecurity.

[11] In the context of poverty measurement, this is known as ‘Pigou-Dalton Transfer Principle’. According to this principle, if some income is transferred from a not-so poor to a relatively poorer individual, then social welfare must increase and vice versa.

[12] For this, household-level data is combined with village-level data. Note that data on the variable of interest—extreme weather events—is available only for the villages. Therefore, we use the survey data only for the rural households for our regression analysis.

[13] See Greene (2012) or Wooldridge (2000)

A. Availability

(i) Distance to the nearest market (in kilometer)
(ii) Distance to the nearest *kirana* store (in kilometer)
(iii) Household size (in number of household members)

B. Accessibility

(i) Poverty (a dummy variable that takes the value 1 if the household is below the poverty line and 0 otherwise)
(ii) Per capita income (in 2011–12 Indian Rupee)
(iii) Remittances (in 2011–12 Indian Rupee)
(iv) Nonfarm income (a dummy variable that takes the value 1 if the household earns any nonfarm income and 0 otherwise)
(v) MGNREGA income (a dummy variable that takes the value 1 if any member of the household receives income under MGNREGA and 0 otherwise)
(vi) Share of food items in total household consumption expenditure (2011–12 Indian Rupee)
(vii) Dependents (number of household members younger than 15 or older than 64)

C. Utilization

(i) Highest level of adult education (in number of years)
(ii) Highest level of male adult education (in number of years)
(iii) Highest level of female adult education (in number of years)

In our baseline specifications, we do not include the distance to the kirana store as it is highly correlated with the distance to the nearest market. Further, we include the highest level of adult education as the only utilization variable. We consider the other two by gender for our sensitivity analysis. We do not include any village-level fixed effects as there are other village-level variables including our variables of interest.

Finally, we include religion, caste categories, and state fixed effects as additional controls. In particular, we add dummy variables for being Muslim, Christian, and others with Hindu being the benchmark group. Similarly, we incorporate dummy variables for households belonging to Other Backward Caste (OBC), Scheduled Caste (SC), Scheduled Tribe (ST), and others with those belonging to the general category being the benchmark. For the states, dummy variables are added with Assam as the benchmark.

5.4 Empirical Results

In this section, we present and discuss the results from our empirical analysis. We first present the aggregate food insecurity measures. We then present and discuss the results from our regression analysis. In addition to the baseline results, we also include results from a variety of sensitivity analyses.

5.4.1 Extent of Food Insecurity Across NER States

Table 5.3 presents the aggregate measures of food insecurity for eight states of NER. Column 2 of the table shows that about 29% of sample persons (HCR) in the region are food insecure with marked variations across different states of the region. The proportion of food insecure people is as high as 60% in Meghalaya and about 50% in Sikkim. With about 31% of the sample persons being food insecure, Assam, the most populous state in the region, ranks third. In contrast, Nagaland has the lowest incidence of food insecurity with an HCR value of 4%.

The food insecurity gap index (FIGI), a measure of the depth of food insecurity, shows that each food insecure person in NER, on average, needs about 7% of the required monthly per capita food expenditure (on calories, protein, and fat) to get out of food insecurity. However, this gap varies between 21% in Meghalaya and less than 1% in Nagaland. Further, the inequality among food insecure people—as captured by SFIGI—is the highest in Meghalaya, followed by Sikkim and Assam. Thus, these measures reflect the variations in incidence, depth, and inequality of food insecurity among the NER states. In all three counts, Meghalaya and Nagaland are respectively the worst and best-performing states.

Table 5.3 Measures of food insecurity by states in NER

States	HCR (%)	FIGI (%)	SFIGI (%)
	(1)	(2)	(3)
Arunachal Pradesh	21.41	4.86	2.15
Assam	30.90	7.09	2.67
Manipur	22.66	2.33	0.40
Meghalaya	59.91	21.30	9.58
Mizoram	10.95	1.92	0.57
Nagaland	4.13	0.63	0.10
Sikkim	49.70	10.61	3.23
Tripura	17.63	4.11	1.44
Total (NER)	29.34	7.08	2.72

Source: Authors' calculation from IHDS-II, 2011–12

5.4.2 Regression Results

In this section, we present the regression results for the binary response model. We first present the logistic regression results for our baseline specifications in Subsect. 4.2.1. In order to investigate the robustness of our results with respect to the extreme weather event variables—the variables of interest—we conduct several sensitivity exercises with models that (i) include separate dummy variables for four types of extreme weather events, namely drought, flood, cyclone, and hailstorm; and (ii) include additional control variables. We also estimate Probit regression models of the basic specifications to examine the robustness of the results to different functional assumption. We present these results in Subsect. 4.2.2.

5.4.2.1 Baseline Specifications

We estimate four baseline models. In Model 1, we include long-run extreme weather event dummy variable—as defined in Sect. 5.3—as the variable of interest in addition to a number of control variables that capture availability, accessibility, and utilization aspects of food insecurity. Model 2 includes the short-run extreme weather event dummy variable as an alternate variable of interest. In Models 3 and 4, we include interactions of the extreme weather event variables with distance to the market (an availability variable) and per capita income (an accessibility variable). Table 5.4 presents the coefficient estimates of the logistic regression model.

Columns (1) and (2) of Table 5.4 indicate that the extreme weather events on their own do not have any significant impact on the probability of being food insecure irrespective of whether we consider a long-run or a short-run time horizon. However, the results in Columns (3) and (4) suggest that extreme weather events significantly increase the probability of being food insecure via their interactions with per capita income. However, the interactions with the distance to the market are not statistically significant. The marginal effects presented in Table 5.5 indicate that occurrence of such event during the past five years increases the probability of food insecurity by 0.008 or 0.8% (Col. 3) when we take into account these interactions. Further, an occurrence in the immediate past increases the probability by 0.122 or 12.2%. Thus, an extreme weather event has a much larger impact on the probability of being food insecure in the short run. In the long run, households may have more room to adapt in a way of avoiding food insecurity.

Among the control variables, distance to the market, being poor, and household size have significant positive impacts on the probability of food insecurity. Thus, as expected, the longer the distance to the nearest market, the higher is the probability of being food insecure. Longer distance to the market may reduce the availability of food. The households below the poverty line are likely to be more food insecure. More specifically, a poor household is about 77% (see Table 5.5) more likely to be food insecure. Similarly, larger households are more likely to be food insecure. This result is consistent with those presented in Joshi and Joshi (2016), Sekhampu

Table 5.4 Logistic regression results: baseline specifications

Explanatory variables	Estimated coefficients			
	Model1 1	Model 2	Model 3	Model 4
	(1)	(2)	(3)	(4)
Constant	2.55[c] (0.63)	2.41[c] (0.63)	2.76[c] (0.66)	2.56[c] (0.64)
Extreme weather over 2007–11	−0.19 (0.24)		−0.72[a] (0.39)	
Extreme weather in 2011		0.12 (0.26)		−0.73[a] (0.39)
Distance to the market	0.05[c] (0.01)	0.05[c] (0.01)	0.05[c] (0.02)	0.05[c] (0.02)
Poverty dummy	4.14[c] (0.26)	4.12[c] (0.26)	4.18[c] (0.27)	4.14[c] (0.26)
Household size	0.23[c] (0.06)	0.23[c] (0.06)	0.24[c] (0.06)	0.24[c] (0.06)
Per capita income	−0.00003[c] (0.000007)	−0.00003[c] (0.000007)	−0.00004[c] (0.00001)	−0.00004[c] (0.000008)
Remittance	0.000004 (0.000003)	0.000004 (0.000004)	0.000002 (0.000003)	0.000001 (0.000004)
Nonfarm income dummy	−0.57[a] (0.31)	−0.58[a] (0.31)	−0.57[a] (0.31)	−0.55[a] (0.32)
Food expenditure share	−0.09[c] (0.01)	−0.09[c] (0.009)	−0.09[c] (0.009)	−0.09[c] (0.009)
Dependence ratio	0.22 (0.16)	0.22 (0.16)	0.23 (0.16)	0.25 (0.16)
Education level of an adult member	−0.04 (0.03)	−0.04 (0.03)	−0.04 (0.03)	−0.04 (0.03)
Extreme weather over 2007–11 × Distance to the market			−0.0002 (0.06)	
Extreme weather over 2007–11 × Per capita income			0.00002[b] (0.00001)	
Extreme weather over 2011 × Distance to the market				0.08 (0.07)
Extreme weather over 2011 × Per capita income				0.00003[c] (0.00001)
Other backward caste	−0.84[b] (0.39)	−0.87[b] (0.39)	−0.88[b] (0.40)	−0.96[b] (0.40)
Scheduled caste	−0.47 (0.44)	−0.53 (0.44)	−0.38 (0.43)	−0.49 (0.43)
Scheduled tribe	−0.18 (0.39)	−0.23 (0.39)	−0.12 (0.39)	−0.22 (0.40)

(continued)

Table 5.4 (continued)

Explanatory variables	Estimated coefficients			
	Mode1 1	Model 2	Model 3	Model 4
	(1)	(2)	(3)	(4)
Others	−0.65 (0.95)	−0.44 (0.94)	−0.80 (0.93)	−0.70 (0.90)
Muslim	0.04 (0.40)	−0.04 (0.41)	0.10 (0.40)	0.14 (0.42)
Christian	0.11 (0.63)	0.13 (0.62)	0.17 (0.64)	0.12 (0.64)
Other religion	0.69 (0.45)	0.72 (0.45)	0.63 (0.45)	0.53 (0.44)
State fixed effects	Yes	Yes	Yes	Yes
McFadden R	0.47	0.47	0.48	0.48
Likelihood ratio test	644.11	643.71	649.93	654.42
p-value	0.00	0.00	0.00	0.00
Observations	1103	1103	1103	1103

Note: Standard errors are in parentheses. [a]significant at the 10% level; [b]significant at the 5% level; [c]Significant at the 1% level

(2017), and Agidew and Singh (2018). Per capita income that provides the means to procure food has a statistically significant negative impact, and this result accords well with those reported by Bashir et al. (2012), Maziya et al. (2017), Sekhampu (2017), and Ngema (2018). Thus, households with higher per capita income are less likely to be food insecure. Having a nonfarm source of income also significantly reduces the likelihood of being food insecure. Furthermore, households that spend a larger proportion of their consumption expenditure on food items are, as expected, less likely to be food insecure.[14] Our results indicate that remittances, number of dependents, and the highest level education of an adult member of the household are not significant determinants of food insecurity.

Among the socio-cultural controls, only belonging to OBC has significant impact on the probability of being food insecure. Our results indicate that the households belonging to the Other Backward Castes are 14–15% less food insecure than those belonging to the general castes. This result can be explained by the fact that people belonging to some OBCs are economically successful although they may be

[14] In the context of the developing countries, the proportion of food expenditure is sometimes taken as a proxy for economic status of a household. As per Engel's law, with improvements in economic condition, people tend to have a lower proportion of food expenditure. Thus, this result seems to have contradicted our results with respect to poverty and per capita income. However, we need to recognize that the estimated coefficient of food expenditure share reflects the effect of food expenditure share after controlling for poverty and per capita income.

Table 5.5 Marginal effects of explanatory variables based on the logistic regression results

Explanatory variables	Model 1	Model 2	Model 3	Model 4
	(1)	(2)	(3)	(4)
Extreme weather over 2007–11	−0.037		0.008	
Extreme weather in 2011		0.024		0.122
Distance to the market	0.001	0.001	0.002	0.001
Poverty dummy	0.773	0.772	0.776	0.774
Household size	0.007	0.006	0.007	0.006
Per capita income	−0.0000008	−0.0000007	−0.0000008	−0.0000010
Remittance	0.0000001	0.0000001	0.0000001	0.0000000
Nonfarm income dummy	−0.104	−0.024	−0.028	−0.023
Food expenditure share	−0.003	−0.002	−0.003	−0.002
Dependence ratio	0.006	0.006	0.007	0.006
Education level of an adult member	−0.001	−0.001	−0.001	−0.001
Other Backward Caste	−0.140	−0.140	−0.147	−0.151
Scheduled Caste	−0.085	−0.092	−0.072	−0.086
Scheduled Tribe	−0.037	−0.046	−0.024	−0.042
Others	−0.111	−0.077	−0.133	−0.114
Muslim	0.009	−0.008	0.021	0.028
Christian	0.023	0.026	0.034	0.023
Other religion	0.155	0.158	0.139	0.113

Source: Authors' calculation using the results presented in Table 5.4
Note: The marginal effects for the continuous variables are calculated by using the mean values of the continuous variables in the following equation. For the discrete (dummy) variables, we simply take the difference between $P(FI_i = 1|x)$ and $P(FI_i = 0|x)$ with these probability values evaluated at mean values of other variables: $\frac{-\partial p}{\partial x_i} = \frac{\widehat{\beta}_i e^{x'\hat{\beta}}}{\left(1+e^{-x'\hat{\beta}}\right)^2}$

socially backward (e.g., Galanter 1978). Our results also indicate that the households belonging to religious minority communities are more likely to be food insecure than their Hindu counterparts. However, these differences in probability are not statistically significant.

We also include state fixed effects (results not reported). A test of joint significance of these fixed effects indicates that they are relevant. As discussed in Sect. 5.3, we use Assam as the benchmark state. The results indicate that the probability of food insecurity is significantly higher in Sikkim. Further, this probability is higher in Meghalaya and lower in Mizoram than that in Assam, but these differences are not statistically significant. Other states experience significantly lower likelihood of food insecurity than does Assam.

5.4.2.2 Robustness Results

The effects of extreme weather events on the probability of food insecurity may vary by the types of such events. Therefore, we now include separate dummy variables—both long run (at least an event occurring during 2007–11) and short run (at least an event occurring in 2011)—for drought, flood, cyclone, and hailstorm instead of one extreme weather event dummy in our baseline specifications. Since the coefficient estimates for the control variables are very similar to those included in Table 5.4, we present only those for the extreme weather events and their interactions with the distance to the market and per capita income in Table 5.6.

Columns (1) and (2) of Table 5.6 indicate that with no interactions, only drought seems to increase the probability of food insecurity in the short run. As the coefficient estimates for the interaction terms in Col. (3) indicate, flood and hailstorm

Table 5.6 Logistic regression results for different types of extreme weather events

Explanatory variables	Estimated coefficients			
	(1)	(2)	(3)	(4)
Drought	−0.05 (0.37)	0.92[b] (0.45)	0.55 (0.63)	−3.49[b] (1.52)
Flood	−0.35 (0.27)	−0.47 (0.31)	−1.23[c] (0.43)	−1.46[c] (0.45)
Cyclone	−0.14 (0.45)	0.04 (0.04)	1.76[a] (0.92)	0.70 (0.67)
Hailstorm	0.53 (0.43)	0.004 (0.49)	1.05 (0.87)	3.49[c] (1.22)
Drought × Distance to the market			−0.18 (0.16)	1.56[b] (0.64)
Flood × Distance to the market			0.09 (0.07)	0.16[b] (0.08)
Cyclone × Distance to the market			−2.13 (1.43)	−0.34 (1.47)
Hailstorm × Distance to the market			−0.45 (0.32)	−0.90[c] (0.34)
Drought × Per capita income			0.000003 (0.00002)	0.00003[a] (0.00002)
Flood × Per capita income			0.00002[a] (0.00001)	0.00003[b] (0.00001)
Cyclone × Per capita income			0.00005 (0.00004)	0.00003 (0.00003)
Hailstorm × Per capita income			0.00002[a] (0.00001)	0.00001 (0.00002)

[a]significant at 10% level; [b]significant at 5% level; [c]significant at 1% level
Note: Standard errors in parenthesis
Source: Authors' estimation

significantly increase the likelihood of food insecurity in the long run through their interactions with household per capita income. Furthermore, droughts and floods interact with both availability (as captured by the distance to the market) and accessibility (as captured by per capita income) to significantly increase the probability of food insecurity in the short run.

We now add a number of additional control variables to our basic specifications following suggestions from the extant literature. These variables include: age of the male head of the household, the age of the female head of the household, the distance to the nearest kirana store, income from MGNREGA, and highest level of education of the male and female members of the household separately (instead of any adult member). In the models with interactions, we also include interactions of the extreme weather event variable with the distance to the local kirana store. In the interest of saving space, we do not report the coefficient estimates for the control variables. Thus, Panel B of Table 5.7 reports the coefficient estimates for the variables of interest along with their interactions with other control variables. For the ease of comparison, we include the coefficient estimates from our baseline specifications in Panel A of the table. The table shows the coefficient estimates for the extreme weather event variables, and their interactions with distance to the market and per capita income are mostly similar in sign and statistical significance. There are two differences. *First*, the estimated coefficient for the interaction between long-run extreme weather event and distance to the market is negative in the baseline models, whereas it is positive in the extended model (Col. 3). However, they are both statistically insignificant. The extended model includes another distance variable, namely the distance to the kirana store. As we mentioned earlier, these two distance variables are highly correlated (a correlation coefficient of 0.64) and that may have driven this result. *Second*, the estimated coefficient for the short-run extreme weather event is negative and statistically significant at the 10% level in the baseline model. However, it is not statistically significant, although negative, in the extended model.

We also estimate Probit regression models of our baseline specifications. The estimated coefficients are qualitatively the same in terms of their signs and statistical significance.[15]

Overall, our results suggest that extreme weather events interact with household per capita income to significantly increase the likelihood of food insecurity in the short as well as long run. Further, there is some evidence of floods and hailstorms increasing the likelihood of food insecurity through their interaction with the household income in the long run and droughts and floods through their interactions with the distance to the market (availability) and household income (accessibility) in the short run. These results are robust to the inclusion of additional control variables and the use of alternative functional assumption of the regression model.

[15] To save space, we do not report the results here. However, interested reader may request.

Table 5.7 Logistic regression results: extended specifications

Explanatory variables	Estimated coefficients			
	Model 1	Model 2	Model 3	Model 4
	(1)	(2)	(3)	(4)
Panel A: baseline models				
Extreme weather over 2007–11	−0.19 (0.24)		−0.72[a] (0.39)	
Extreme weather in 2011		0.12 (0.26)		−0.73[a] (0.39)
Extreme weather over 2007–11 × Distance to the market			– 0.0002 (0.06)	
Extreme weather over 2007–11 × Per capita income			0.00002[b] (0.00001)	
Extreme weather over 2011 × Distance to the market				0.08 (0.07)
Extreme weather over 2011 × Per capita income				0.00003[c] (0.00001)
Panel B: extended models				
Extreme weather over 2007–11	−0.21 (0.26)		−0.86[b] (0.41)	
Extreme weather in 2011		0.19 (0.28)		−0.43 (0.42)
Extreme weather over 2007–11 × Distance to the market			0.06 (0.07)	
Extreme weather over 2007–11 × Distance to the *kirana* store			−005 (0.03)	
Extreme weather over 2007–11 × Per capita income			0.00003[b] (0.00001)	
Extreme weather over 2011 × Distance to the market				0.11 (0.08)
Extreme weather over 2011 × Distance to the *kirana* store				−0.13[b] (0.07)
Extreme weather over 2011 × Per capita income				0.00003[b] (0.00001)

Note: Standard errors are in parentheses. [a]significant at the 10% level; [b]significant at the 5% level; [c]significant at the 1% level

5.5 Concluding Remarks

Using household survey data for eight states of India's Northeast Region (NER) obtained from India Human Development Survey for 2011–12, this chapter empirically analyzes the incidence, intensity, and inequality of food insecurity among the households in the region, which is known for its remoteness and relative economic destitution. Applying econometric techniques to household data and village-level weather data, it further investigates the impact of the extreme weather events on food insecurity after controlling for a number of demographic and socio-economic factors. The results of this exercise indicate that extreme weather events interact with household income to significantly increase the likelihood of food insecurity in the short as well as long run, although they do not have statistically significant impacts on their own. This is especially true in the case of floods and hailstorms. Similarly, the results suggest that droughts and floods increase the probability of food insecurity through their interactions with the distance to the market and household income in the short run. These results are robust to the inclusion of additional control variables and the use of alternative functional assumption of the regression model.

The results presented in this chapter could be informative for public policies aimed at reducing food insecurity in NER of India. While preventing and controlling extreme weather events may require long-term, multipronged, concerted efforts on the part of everyone living on the earth, the government may formulate and implement policies that will ensure availability of and access to food in order to keep the incidence of food insecurity in check.

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