Heliyon 10 (2024) e25687

Contents lists available at ScienceDirect

Heliyon

journal homepage: www.cell.com/heliyon

Research article

Climate shocks' impact on agricultural income and household food security in Bangladesh: An implication of the food insecurity experience scale

Md. Rashid Ahmed [a,b,*]

[a] Department of Social Sciences, Wageningen University & Research, the Netherlands
[b] Department of Agricultural Finance and Banking, Sylhet Agricultural University, Sylhet, 3100, Bangladesh

ARTICLE INFO

Keywords:
Agricultural income
Climate shocks
Floods
Excessive rain
Food security
Bangladesh

ABSTRACT

Floods and extreme rainfall are common climatic phenomena in Bangladesh, and farm households are more susceptible to such shocks. This paper assesses the impact of climate shocks on agricultural income and food security of farm households in Bangladesh using an extensive nationally representative dataset from the Bangladesh Integrated Household Survey 2018–19, including 5604 sample rural households in 64 districts. However, this research considered 24 districts, representing 2131 sample farm households, by developing an exogenous climate shock indicator based on data from the Yearbook of Agricultural Statistics of Bangladesh 2018. Empirical findings on the grounds of simultaneous quantile regression reveal that climate shocks substantially lower agricultural income in the study regions. However, the presence of prime-age women (15–49) in the home, the male-headed family, farmland, and livestock ownership of the household are the decisive factors that safeguard agricultural income. Applying the Food Insecurity Experience Scale (FIES), descriptive statistics disclose that most farm households suffer at various food insecurity levels (considerably moderate, noticeably mild, and tiny severe), while the rest are at the food security level. The key finding regarding ordered probit regression uncovers that climate shocks significantly increase household food insecurity (at different levels of FIES). In other words, cropland damage due to floods and extreme rainfall reduces the food security of farm households in the study districts. On the other hand, increased farm size and educated households are profoundly protected against food insecurity. This study, therefore, recommends that raising livestock can complement agricultural income, and enhancing education would ensure households' food security in the climate-exposed areas of Bangladesh.

1. Introduction

Bangladesh's economy initially relied on agriculture, covering about 70% of its land area [1]. The agriculture sector significantly contributes to the national economy, making up 11.61% of the GDP in 2022 [2]. However, agriculture is still the primary employment source, occupying nearly half of the workforce in Bangladesh [3].

Farmers are the core of the agricultural system, playing a vital role in sustainable production and food security [4]. Approximately 52% of rural people in Bangladesh are engaged in farming, followed by 19% and 3% in urban and city-corporation areas [5]. The

* Corresponding author. Department of Agricultural Finance and Banking, Sylhet Agricultural University, Sylhet, 3100, Bangladesh.
E-mail addresses: rashid.afb@sau.ac.bd, mrashid.ahmed.bd@gmail.com.

https://doi.org/10.1016/j.heliyon.2024.e25687
Received 26 November 2023; Received in revised form 25 January 2024; Accepted 31 January 2024
Available online 7 February 2024

agriculture sector accounts for nearly 41% of the total employed labor force, while the service and industry sectors are around 39% and 20%, respectively [5]. However, many people involved in agricultural activities experience a higher income loss than those in the industry and service sectors [6].

Bangladesh is one of the prominent climate-prone nations in the world and is currently experiencing different climatic shocks. Climate change is increasing the vulnerability of farming, particularly the country's crop sector, to heavy rainfall, floods, drought, storms, cyclones, and riverbank erosion [7,8]. Farmers frequently face excessive rain, floods, flash floods, and rapid hill stream water rushes in Bangladesh's northeast and northern regions, which affect significant land surfaces during wet monsoons. The magnitude of such events dramatically varies according to land levels due to the varying impacts of climate change on different regions [9].

Bangladesh is a relatively low-lying country, with about 60% of its land at an average elevation below 6 m above sea level, making it vulnerable to climatic shocks [10–12]. Notably, Bangladesh has five types of land levels based on the flooding depth: "Highland (above regular flood depth), Medium Highland (flooded nearly 90 cm deep), Medium Lowland (flooded between 90 and 180 cm deep), Lowland (flooded between 180 and 300 cm deep), and Very Lowland (flooded deeper than 300 cm)" [13]. Besides, the country has four monsoon seasons: "pre-monsoon, from March to May; monsoon, from June to September; post-monsoon, from October to November; and winter, from December to February" [14].

Climatic shocks severely restricted crop cultivation in Bangladesh during the Rabi and Kharif seasons[1] [7]. Especially floods and excessive rain, typically from early April to late May in the 'pre-monsoon' period, may hamper standing Rabi crops in the northeastern (mostly low-lying and wetland) regions. Also, monsoon floods from the end of June to the beginning of October, usually triggered by excessive rainfall and rising river water levels, may affect Kharif crops in the northern (mostly medium-highland and lowland) areas [13,15]. Thus, climate events can damage crop areas yearly or for some years. Over the decade, climate shocks have increased concerns about declining agricultural production in Bangladesh, impacting households' farm income and food security.

Agricultural income usually falls in flood-prone zones of Bangladesh during the flooding seasons [16]. Mottaleb et al. [17] observed that natural disasters greatly reduce farm income. For example, the 2017 flash flood affected the low-lying areas in Bangladesh, causing a massive income loss for rural farmers who relied on open water resources [6]. Besides, they suffer severe crop and fishery income losses due to flood shocks [6,18]. Such catastrophic climate incidents raise poverty in Mymensingh, while farm income drops in the Khulna, Barishal, and Rajshahi districts [19]. Thus, stable farm income is necessary to safeguard rural households in Bangladesh.

Farm income loss due to climate shocks can affect household food security by damaging crop production and reducing food access. For instance, Bangladesh experienced food insecurity due to the 2017 floods and heavy rainfall impact on household food consumption [20]. Based on the intensity, volume, and timing of floods, they pose an enormous threat to household food security [21]. During lean periods, farm households usually suffer food insecurity, especially in rural riverside regions with high flood frequencies, causing them to struggle to meet food requirements [22,23]. Thus, flood-damaged cultivated areas reduce crop production and increase household food insecurity [24]. Béné et al. [25] assessed that floods, river erosion, droughts, and salinity intrusion adversely impact household food security in rural Bangladesh. Smith and Frankenberger [26] noted that the sudden 2014 flood had a massive effect on household food security in northern Bangladesh. Moreover, Parvez et al. [20] revealed that around 62% of households in northeast Bangladesh faced food insecurity due to the 2017 flash flood.

Remarkably, in 2017, an unexpected flash flood and heavy rainfall damaged crops severely in the northeastern and northern areas of Bangladesh. This flash flood occurred at the end of March and beginning of April 2017 during the early monsoon flooding season [6,27]. Crops were also considerably destroyed in July and August of the same year because of monsoon floods [27]. Since 2017, floods or flash floods and extreme rain have drastically affected agricultural production; accordingly, they could reduce the income and food security of farm households.

Considering the severity of floods and excessive rain in 2017, the researcher intends to assess the effects of climate shocks on agricultural income and households' food security in Bangladesh. Hence, this study responds to the following questions: i. What effects do climate shocks have on agricultural income? ii. Do climate shocks affect the food security of farm households in Bangladesh?

Nevertheless, several previous studies examined the effects of climate change and natural catastrophes on agricultural production, farm income, food consumption, livelihood, and poverty [1,8,15–17,19,21,28–31], but empirical evidence on household food security remains negligible [23,25,26]. Notably, the effects of the 2017 devastating floods and excessive rain on farm households' income and food security are rare in the literature [6,20,32]. Most of these prior studies represented specific regions, not the overall aspects of Bangladesh.

Moreover, this research contributes to enhancing the national-level literature by addressing the exemplified gaps. Therefore, the study examines the climate shocks' impact on income and food security, representing 2131 sample farm households in 24 districts using the Bangladesh Integrated Household Survey (BIHS) 2018–19, a large national-level dataset [33]. In addition, this study generated an exogenous climate shock indicator based on data related to floods and excessive rain that occurred in 2017 from the 'Yearbook of Agricultural Statistics of Bangladesh (YBASB) 2018' [27]. As concerns, no empirical study has used BIHS 2018-19 datasets that reflect the recent information on rural households in Bangladesh and estimate the national-level climate shock effect on farm income and food security. Besides, the study would be pioneering in using the Food Insecurity Experience Scale (FIES) for measuring the severity of food insecurity, which would provide useful insights into Bangladesh's food security status concerning SDG 2. Moreover, the findings are crucial for interested researchers and policymakers to make effective policies regarding stable

[1] Rabi (November 15 to March 14) and Kharif (March 15 to November 14) are mainly two cropping seasons in Bangladesh. Common Rabi crops include winter vegetables, Boro rice, wheat, potatoes, mustard, pulses, etc. The Kharif season is separated into Kharif-I (March 15 to July 14) and Kharif-II (July 15 to November 14). Summer vegetables, Aus and Aman rice, jute, etc. are common Kharif crops [28].

agricultural income and ensure household food security to deal with devastating climate shock effects in the climate-vulnerable regions of Bangladesh.

This research paper is organized into four separate sections. Section 2 below describes the methodology, and Section 3 sequentially illustrates the results obtained and discusses the findings. Lastly, in Section 4, an exclusive conclusion and implications for policy are stated.

2. Materials and methods

2.1. Analytical framework for measuring households' food security status

"Food security exists when all people, at all times, have physical, social, and economic access to sufficient safe and nutritious food that meets their dietary needs and food preferences for an active and healthy life" [34]. Food security is a complex concept encompassing multiple dimensions and can be assessed through various measurements [24,35–40]. Several indicators have been developed to measure household food security [41–43]. However, FAO introduced a common scale for food security measurement called the "**Food Insecurity Experience Scale (FIES)**," which has been used by many experts in different countries worldwide [44–47]. Hence, this study used the FIES to determine farm household food security in Bangladesh.

FIES is a metric for measuring the severity of food insecurity based on individual experiences with food consumption [46]. The FAO conducted a project in 2014 called "Voices of Hungry," gathering FIES data from over 150 countries to assess the incidence of valid severity at various levels of food insecurity for developing a global standard [45,46]. The Rasch model, also called the one-parameter logistic model, was used to determine unobservable traits in FIES data based on individual dichotomous responses to the eight questions (8Qs) on accessing food [44,48,49], as listed in Table 1.

The individual responses can be classified at various levels of severity as **"food secure"** (for people who answer "no" to 8Qs) or **"food insecure"** (for people who answer "yes" to 8Qs). The raw score (0–8) is the sum of yes responses to the 8Qs, which is the main parameter for measuring the severity of food insecurity [44,48,49]. Thus, the 8Qs are in order, implying that as the scores increase, the level of food insecurity increases, indicating less to more severe incidents of food insecurity [43,47,50]. The individual was categorized as facing mild, moderate, and severe food insecurity [44,48,49,51]. Hence, food security status related to the FIES 8Qs (scale items) is classified into a total of four categories and can be defined below:

a Food Security

This category belongs to household respondents who answered "no" (zero) to all 8Qs regarding experiences of food insecurity for the past year.

b Mild Food Insecurity

This group goes to households that were **uncertain and worried** (Q1) about enough food consumption and a lack of inadequate food quality (Q2 & Q3) at a particular time of the past year due to financial or resource constraints.

c Moderate Food Insecurity

Households in this class suffered from **insufficient quantities of food**. They either ate less, skipped a meal, or ran out of food consumption over the past year due to financial or resource constraints regarding Q4, Q5, & Q6.

d Severe Food Insecurity

In this type of food insecurity, household members also suffer from **insufficient quantities of food**. However, they were **hungry or did not eat for an entire day** during the past year due to financial or resource constraints concerning Q7 and Q8.

The "yes" answers on food consumption are intended for food insecurity. Thus, the total of "yes" responses from all 8Qs was

Table 1
FIES eight questions for determining household food security.

"During the last year, was there a time when you or others in your household ……… … … … … … … … …. due to a shortage of money or other resources?"	
Q1.	"were **worried** you did not have enough food to eat"
Q2.	"were not able to have **healthy and nutritious** food"
Q3.	"ate only a **few kinds of foods"**
Q4.	**"ran out/did not have food"**
Q5.	**"ate less** than you thought you should"
Q6.	"had to **skip** a meal"
Q7.	"were **hungry** but did not eat"
Q8.	"went without eating for a **whole day"**

Source: Ballard et al. [44]; Brunelli and Viviani [48]; FAO [49]; IFPRI [33].

estimated to assess farm households' food security in this study. Considering the proposed model as illustrated in Section 2.5.2 for measuring food security status, a score of 7 and 8 determines "severe food insecurity," 4, 5, and 6 ascertain "moderate food insecurity," 1, 2, and 3 determine "mild food insecurity," and 0 stands for "food security." Finally, for comprehensive data analysis of the variable *"food insecurity,"* a score of 1 is assigned for "food security," 2, 3, and 4, respectively, for "mild food insecurity," "moderate food insecurity," and "severe food insecurity." Hence, "*food insecurity*" is an ordered variable.

Numerous studies [35,41,43,52–57] have used the FIES 8Qs and similar survey questions to measure household food security. Over the years, the FIES approach has shown promise in validating and realistically measuring food insecurity throughout the globe [53]. BIHS 2018–19 asked FIES 8Qs (Table 1) on food consumption in the last twelve months related to household food security in Bangladesh [33,58]. Since the BIHS 2018-19 dataset was used in this study, the researcher considered the FIES matrix to determine farm household food security. This particular scale would be useful in achieving the study's aim by assessing the various food insecurity levels that farm households suffer due to climate shocks. Besides, the FIES method would provide helpful insights to policymakers about the severity of food insecurity among farm households in Bangladesh.

Fig. 1 represents the four types of food security status that farm households experienced in the study areas. Overall, 43% of farm households were food secure, while the rest, 57%, suffered from different levels of food insecurity. Out of 57%, over 40% were mildly food insecure, a visible portion (roughly 13%) of families suffered from moderate food insecurity, and nearly 3% encountered severe food insecurity. The scenario was almost the same for the sample households with and without the Sunamganj & Rangpur districts.

2.2. Description of data

The study mainly used cross-sectional data from the BIHS 2018–19 round 3 survey conducted by the International Food Policy Research Institute (IFPRI) from November 2, 2018, to April 16, 2019. This survey gathered data referring to the last 12 months (December 1, 2017, to November 30, 2018) in all 64 districts of Bangladesh through in-person interviews with a structured questionnaire, following two-stage stratified random sampling [33].

This study used data regarding the *"Household Questionnaire"* of BIHS 2018–19 on household identification, composition, education, employment, land owned, agriculture production, livestock & poultry, fish or shrimp production & inputs, and food security. Household attributes are determined by the total family size, women (ranging in age from 15 to 49 years), gender, age, and education of the household head. Farm sizes are estimated based on households' current land holdings or under-operation. Besides, livestock ownership is ascertained as animal assets the household possesses. Agricultural income is determined by computing income from crops, livestock, fisheries, and related farming activities. In addition, household food security was measured using FIES eight questions concerning food consumption in the past year, as mentioned in Table 1.

Notably, the response and explanatory variables (Table 2) used in this study were generated from the BIHS 2018-19 dataset, except for the climate shock indicator. An exogenous climate shock variable was developed using relevant data in the Yearbook of Agricultural Statistics of Bangladesh (YBASB) 2018 [27], as clarified in Section 2.3 below.

2.3. Construction and measurement of climate shocks indicator

Climate shock indicators in BIHS 2018–19 were dummies and mostly omitted. Thus, to overcome the potential endogeneity problem, this study generated an exogenous climate shock variable from the YBASB 2018 [27]. How this variable is constructed is clarified below.

The Yearbook of Agricultural Statistics is based on annual or periodic sample surveys, and data are taken in the fiscal year (FY), counting from July 1 of the ongoing year to June 30 of the following year. YBASB 2018 reported data on crop areas damaged due to floods and excessive rain in March & April of FY2016-17 and July & August of FY2017-18. Specifically, FY 2016-17 started on July 1, 2016, and ended on June 30, 2017, indicating that cropland was damaged in March and April 2017 due to pre-monsoon floods. On the other hand, FY2017-18 started on July 1, 2017, and ended on June 30, 2018, meaning that cropland was damaged in July and August 2017 due to monsoon floods. It is found that both Rabi and Kharif crops were ruined in a total of 24 districts in the calendar year 2017, which is the reference year for the climate shock variable in this study. This suggests that in other districts, cropland was not damaged by floods and excessive rain this year. The YBASB 2018 is the national agricultural statistic that reported crop damage in 24 districts of Bangladesh in 2017, indicating valid data. Hence, these 24 districts are considered in this study, as displayed in Figs. 2 and 3.

Initially, I calculated the estimated cultivated (i.e., harvested areas) and non-estimated cultivated cropland (i.e., damaged areas). The damaged crop areas were cultivated but not harvested due to floods and excessive rain. Thus, *total cultivated cropland* was computed by aggregating *estimated* and *non-estimated cultivated crop areas.* Afterward, *the percentage of cropland damaged* over the *total cultivated cropland* was determined in each of the 24 districts, as stated in Fig. 2. Thus, the "percentage of cropland damaged" is the climate shock indicator measured at the district level. Overall, climate shocks affected about 13% of Bangladesh's crop areas in 2017, while Sunamganj (nearly 70%) and Rangpur (around 44%) districts experienced the most tremendous damage.

The susceptibility of households to climate shocks may vary across different regions in Bangladesh. Sylhet, Dhaka, and Rangpur divisions[2] are prone to flooding and rainfall [21], whereas Sunamganj and Rangpur are two districts[3] of Sylhet and Rangpur divisions, respectively. Sunamganj is located in the *Haor*-based northeastern part of the country. *Haor* is a wetland that is unique in its features in

[2] Division is the first administrative unit in Bangladesh.

[3] District is the second administrative unit in Bangladesh.

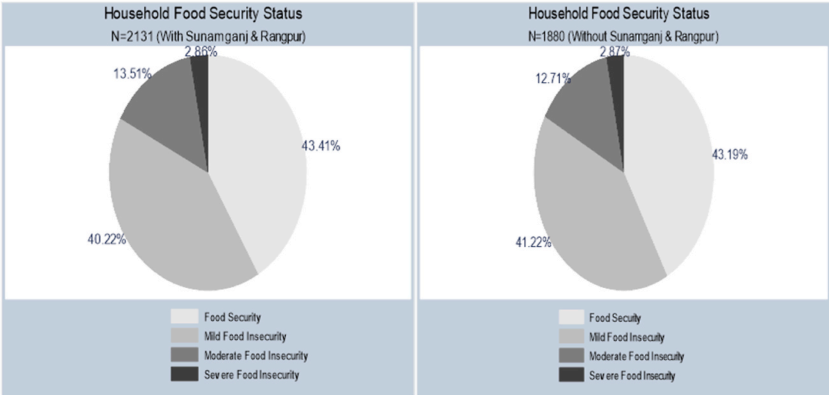

Fig. 1. Percentage distribution of farm households' food security status.
Note: The author generated Fig. 1 by estimating the percentage distribution of food security among farm households based on the relevant data in BIHS 2018–19 [33].
Source: Author Estimation

Table 2
Descriptive statistics of variables.

Variables	Description	N = 2131		N = 1880	
		Mean	Std. Dev.	Mean	Std. Dev.
Explanatory Variables					
Household size	Number of total members in the family	4.33	1.78	4.27	1.70
Women aged 15–49	Total number of women in the household aged 15–49 years	1.18	0.70	1.18	0.71
Gender of the Head *(1 = Male)*	Gender of the household head	0.86	0.35	0.86	0.35
Age of the Head	Age of the household head (years)	46.63	13.21	46.61	13.16
Education of the Head	Education of the household head				
(1 =) No Schooling		0.48	0.50	0.49	0.50
(1 =) Primary		0.27	0.44	0.27	0.44
(1 =) Secondary & Over		0.25	0.43	0.25	0.43
Farm size	Farm size of the household (acre)	1.11	1.50	1.03	1.31
Livestock ownership *(1 = Yes)*	Household livestock ownership	0.91	0.29	0.91	0.29
Percentage of cropland damaged	Percentage of cropland damaged over total cultivated crops area due to flood and excessive rain	13.87	18.61	7.83	7.79
Outcome Variables					
Agricultural income	Annual farm income of the household In Bangladesh Taka (BDT)	148,107	596,577	149,068	629,587
Food insecurity	Food security status of farm household				
(1=) Food security		0.43	0.50	0.43	0.50
(2=) Mild food insecurity		0.40	0.49	0.41	0.49
(3=) Moderate food insecurity		0.14	0.34	0.13	0.33
(4=) Severe food insecurity		0.03	0.17	0.03	0.17

Notes: Based on BIHS 2018–19 [33] & YBASB 2018 [27], the author computed the descriptive statistics for respective variables as in Table 2; N = 2131 & N = 1880 indicate sample households with & without Sunamganj and Rangpur districts, respectively.
Source: Author Estimation

the low-lying floodplain areas of northeast Bangladesh [31,59]. This region has around 400 *haors* (wetlands), most of them in the Sunamganj district [32]. Over the monsoon season, *Haor* areas are often submerged under floods or flash floods resulting from excessive rainfall and upstream flows from neighboring Indian hills, which remarkably affect crops and property [31,32,59]. *Haor* families in the Sunamganj district are more vulnerable to the adverse impacts of such climatic events, particularly in accessing food, water, and healthcare [31]. Thus, the 2017 flash flood affected over 39% of households and around 102,436 ha of standing croplands in the Sunamganj district of Bangladesh [32].

On the other hand, the Rangpur district is located in northern Bangladesh, south of the Himalayan Mountains. During the summer monsoon season, enormous amounts of moisture from southwesterly winds cause excessive rain to the south of the Himalayan Mountains and Rangpur [60]. Thus, in 2017, monsoon rainfall and upstream floods also considerably affected crop areas in Rangpur due to flattened land levels.

The above discussion clarifies that climate shocks hugely affected crop production in northeast and northern Bangladesh in 2017.

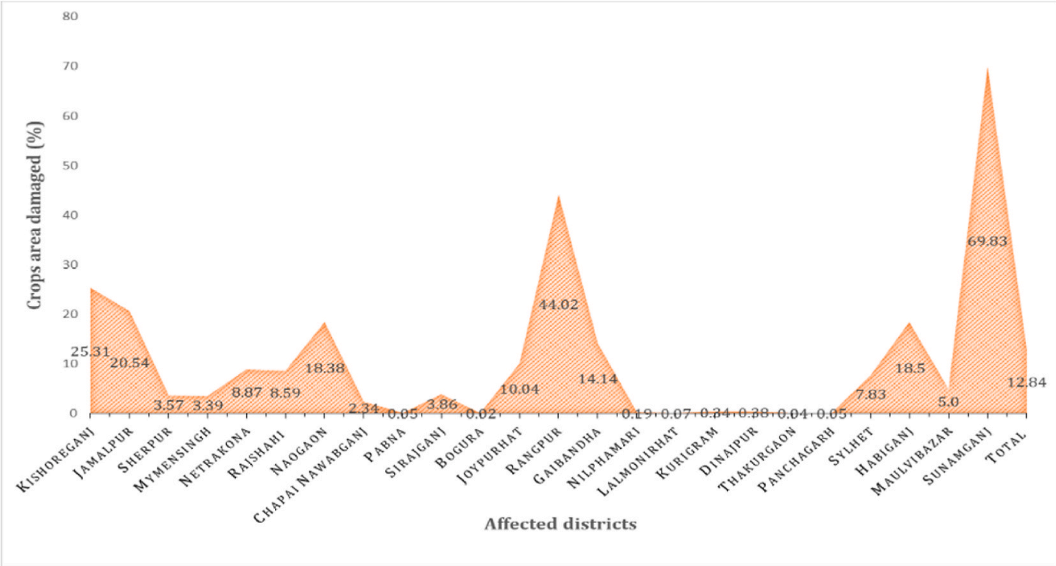

Fig. 2. Percentage of cropland damaged over total cultivated cropland.
Note: The author generated Fig. 2 by estimating the percentage of crop area damaged due to floods and excessive rain over total cultivated cropland based on the relevant data in YBASB 2018 [27].
Source: Author Estimation

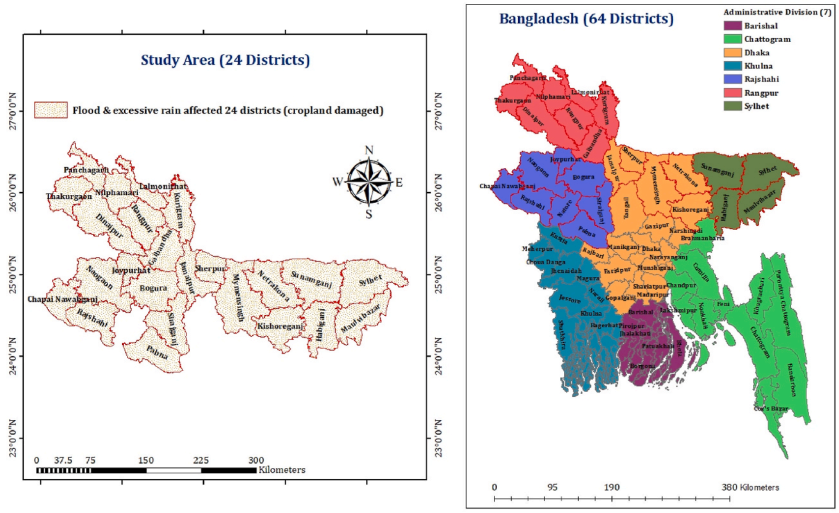

Fig. 3. Study area (left) and Bangladesh (right) map.
Note: The author generated (using ArcGIS), the Bangladesh map (right) and the study area map (left) as in Fig. 3, where cropland is damaged due to floods and excessive rain.
Source: Author Creation

Hence, the exceptional results of cropland damage found for the Sunamganj and Rangpur districts, as exhibited in Fig. 2, are thought to be reliable. Therefore, this study assumes that cropland damaged by floods and extreme rain negatively affects agricultural income in the study districts, and thus, Hypothesis 1 is developed regarding Research Question 1 as follows:

Hypothesis 1. Climate shocks decrease agricultural income

In addition, cropland damage could unexpectedly affect households' food security. Thus, it is assumed that climate shocks increase farm households' food insecurity (lower food security), and Hypothesis 2 is developed concerning Research Question 2 as follows:

Hypothesis 2. Climate shocks increase the food insecurity of farm households

2.4. Study area and sample

BIHS 2018–19 covered 5604 rural households, selecting 325 villages in "Dhaka, Chattogram (Chittagong), Rajshahi, Khulna, Barishal, Sylhet, and Rangpur," which are seven administrative divisions of Bangladesh that cover 64 districts [33]. Hence, BIHS 2018–19 is a national-level dataset that represents all 64 districts of the country. However, this study considered 24 districts, as shown in Fig. 3, based on climate shock data in the YBASB 2018, as clarified in Section 2.3.

Moreover, this research is intended for households that have agricultural income. Thus, households not involved in farming (i.e., agricultural income is zero) were excluded from the BIHS 2018-19 datasets, and a sample of 2131 farm households was found. Nevertheless, as observed in Fig. 2 in Section 2.3, the percentage of cropland damage in the Sunamganj and Rangpur districts shows extreme values. Both are exceptional compared to other districts and seem to be outliers that would affect the results. Hence, excluding the Sunamganj and Rangpur districts, the total sample size in this study is 1880.

2.5. Data analyses

2.5.1. Quantile regression

This study used the quantile regression approach to assess the climate shocks' impact on agricultural income concerning Hypothesis 1. Koenker and Bassett [61] pioneered the quantile regression technique that allows us to analyze the asymmetrical and non-linear effects of conditional factors on the dependent variable. In other words, it measures the effects of independent variables at various quantiles (such as 25th, 50th, 75th, etc.) in the conditional distribution of the response variable [61,62]. Following Duasa and Zainal [63], Eide and Showalter [62], Koenker and Bassett [61], and Uematsu et al. [64], I formulated the quantile regression as specified in Eq. (1).

$$\boldsymbol{I}_{ij} = \boldsymbol{\gamma} + \boldsymbol{Z}_j\boldsymbol{\alpha}_{\theta} + \boldsymbol{X}^{'}_{ij}\boldsymbol{\beta}_{\theta} + \boldsymbol{\mu}_{\theta ij};\ 0 < \ \theta \ < 1\ldots\ldots\ldots\ldots\ldots \quad (1)$$

$$Quant_{\theta}\left(\boldsymbol{I}_{ij}\middle|\boldsymbol{Z}_j + X_{ij}\right) = \boldsymbol{Z}_j\boldsymbol{\alpha}_{\theta} + X_{ij}\boldsymbol{\beta}_{\theta}$$

where I_{ij} is the agricultural income (natural log value) for household i in district j; Z_j is the percentage of cropland damaged (natural log value) for district j. X'_{ij} is the vector of other independent (control) variables for the ith household in district j; α & β are coefficients associated with the respective explanatory variables. $Quant_{\theta}(I_{ij}|Z_j + X_{ij})$ expresses the θth quantile of the response variable (I) conditional on explanatory variables (Z and X), while the disturbance term μ_{ij} indicates zero conditional distribution, i.e., $Quant_{\theta}(\mu_{\theta ij}\big|Z_j + X_{ij}) = 0$.

The linear Ordinary Least Square (OLS) regression specifies the relationship between a set of independent variables (x) and the outcome variable (y) based on the conditional mean function, $E(y_i|x_i)$. In contrast, the quantile regression extends such a relationship at different points (quantiles) in the conditional distribution of the outcome variable, $Q_{\theta i}(y_i|x_i)$ [61,62].

In this study, the density (kernel and normal) distribution of the outcome variable (log values of agricultural income) is presented in Fig. 4. It indicates that farm income is skewed and deviates from the normal distribution. In that case, a single conditional mean distribution in the OLS regression does not provide a complete picture of a group distribution, but estimating such distributions at multiple quantiles does [65]. Besides, compared to the OLS approach, when confronted with deviations from normality, the quantile regression is less susceptible to outliers and provides a more efficient and robust estimate [66]. Previous studies [62,64,67,68] used the

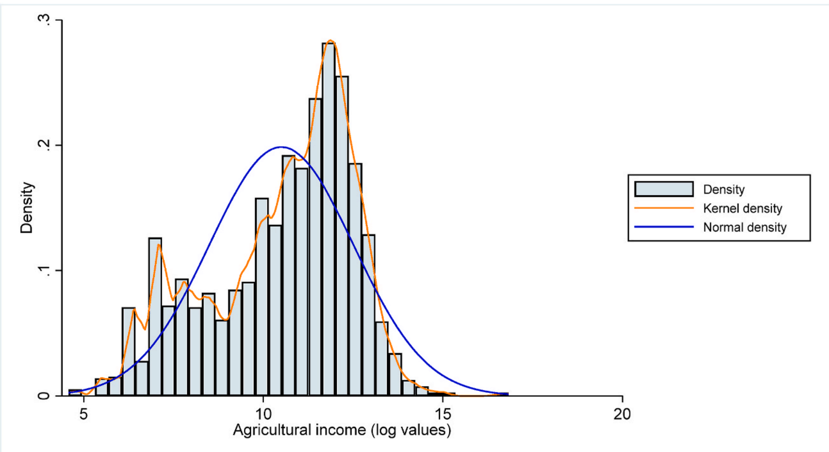

Fig. 4. Density distribution of agricultural income (log values).
Note: The author generated Fig. 4 by estimating the density distribution of agricultural income based on the data in BIHS 2018–19 [33].
Source: Author Estimation

quantile regression approach to determine household off-farm and farm income. Hence, this study employed the simultaneous quantile regression (SQREG) to ascertain a comprehensive association between climate shock and other explanatory (control) variables over the agricultural income at the 25th, 50th, and 75th quantiles.

2.5.2. Order probit regression

In Section 2.1, I discussed that this study used the FAO's FIES matrix to measure farm households' food security, and it is an ordered variable. For analyzing ordered response data, the ordered probit regression approach is the most popular model [41,67]. Thus, this study used the ordered probit regression to test Hypothesis 2 specified in Eq. (2), following Allee et al. [43], Burris and Wiley [54], Davidson and MacKinnon [67], Magaña-Lemus et al. [35], Mutisya et al. [57], and Nkegbe et al. [41]. Hence, climate shocks' impact on farm households' food security is analyzed, where food insecurity is assumed to have an inherent unobserved (latent) variable (Y*), as given below:

$$Y^*_{ij} = \gamma + Z_j\alpha + X^{'}_{ij}\beta + \varepsilon_{ij}\ldots\ldots\ldots\ldots\ldots \tag{2}$$

where Y^* is *Food insecurity,* an ordered response variable that estimates the four categories of household food security as coded below:

$$Y^* = \begin{cases} 1 = \textit{Food Security if } Y^* \le \gamma_1 \\ 2 = \textit{Mild Food Insecurity if } \gamma_1 < Y^* \le \gamma_2 \\ 3 = \textit{Moderate Food Insecurity if } \gamma_2 < Y^* \le \gamma_3 \\ 4 = \textit{Severe Food Insecurity if } \gamma_3 < Y^* \end{cases}$$

The ordered Y^*_{ij} (*Food insecurity)* determines the severity level of food insecurity for the farm household i in district j; γ indicates the cut-off point for each level of food security; Z_j is the climate shock variable (percentage of cropland damaged) for district j; X'_{ij} stands for the vector of explanatory (control) variables for the ith household in district j.

In both Eq. (1) and Eq. 2 I used the same set of explanatory variables. Regardless of the key independent variable (percentage of cropland damaged), I considered some socioeconomic attributes to control the other associated factors on agricultural income and household food security status. Control explanatory variables include household size, women aged 15–49, gender, age and education of the household head, farm size, and livestock ownership of the household.

Usually, more family members (larger household size) may positively influence agricultural income but negatively affect food security, and vice-versa. In addition, women aged 15–49 are the household's economically active primary age group. They could enhance agricultural income and household food security by directly or indirectly participating in farming activities. In Bangladesh, men are predominately household heads and decision-makers. Thus, male-headed households (gender) may have positive effects on farm income and food security. Besides, the elder household head seems to have more working experience. Hence, the age of the household head may positively impact agricultural income and food security. Nevertheless, old household heads may face health issues and require healthier food, leading to high expenses and a potential decline in food security and their involvement in farming. However, educated household heads tend to have more skills and knowledge to enhance farm income and ensure household food security.

Moreover, possessing more land allows households to use more land for agricultural activities, leading to higher production, which in turn raises farm income and household food security. Farm households owing livestock assets may increase domestic consumption of eggs, meat, milk, and milk products. Thus, livestock ownership may positively increase farm income and household food security, and vice-versa.

Notably, the selection of explanatory variables is based on insights derived from related literature and the real-life perspective in the study region. Therefore, this study generated all control explanatory variables from the BIHS 2018-19 dataset [33], while the climate shock indicator was from the YBASB 2018 report [27], as explained in Section 2.3. Moreover, the details of the variables used in this study are presented in Table 2.

2.6. Multicollinearity test

Multicollinearity among the continuous independent variables used in Eq. (1) and Eq. (2) was detected by checking the variance inflation factor (VIF). If VIF>10, the variable is highly collinear [68–70]. This study found VIF values below 2, conferring no severe multicollinearity between continuous explanatory variables, as presented in Table A1. Besides, the contingency coefficient was also computed to test whether multicollinearity exists among the discrete explanatory variables, following Mirkin [71] and Harris & Treloar [72]. The rule for the contingency coefficient is that its value should be between 0 and 1, and the higher the value, the stronger the association between dummy variables [73]. Thus, the contingency coefficient between the dummy independent variables is seen much below 1, ensuring no visible multicollinearity (Table A2).

3. Results and discussion

Using STATA (16), descriptive and empirical results are analyzed and discussed accordingly for both sample households of 2131 (with Sunamganj & Rangpur districts) and 1880 (without Sunamganj & Rangpur districts).

3.1. Farm households' characteristics

The socioeconomic indicators and food security status for both sample households are stated in Table 2. The average farm household size is about 4.3, considerably larger than the national average family size of 4.06 in Bangladesh [74]. In addition, the average number of women aged 15 to 49 in the household is more than one. Household heads are likely to be male in most farm families, who are around 47 years old. Nearly half of farm households have the probability of no formal education, while the rest half tend to have primary, secondary, or higher school education. Besides, the mean farm size is above 1 acre of land, conferring that most households possess marginal land (0.50–1.49 acres), although 91% of families own livestock. Unexpectedly, on average, over 13% of the crop area was damaged due to floods and excessive rain for the sample with Sunamganj & Rangpur districts, while the magnitude of destruction was below 8% without these districts.

Moreover, the household annual mean agricultural income was BDT 148107 and 149,068, equivalent to nearly $1363 and $1372 (1 $ = BDT 108.63) [75], respectively, for the sample with and without Sunamganj & Rangpur districts. In both sample households, the food security status remained almost the same. Overall, most farm households (57%) are likely to suffer from distinct levels of food insecurity (considerably moderate food insecurity, noticeably mild food insecurity, and tiny severe food insecurity), while the rest are food secure (43%).

3.2. Impact of climate shocks on agricultural income

Table 3 illustrates the simultaneous quantile regression (SQREG) output by estimating Eq. (1) (Hypothesis 1) at the 25th (Q25), 50th (Q50), and 75th (Q75) quantiles. It also estimates the OLS regression coefficients to compare with SQREG in the left column of different quantiles. As noticed, the coefficient magnitude of several explanatory variables differs significantly across the quantiles and OLS regression. The key explanatory variable, the climate shock indicator, significantly and negatively impacts farm revenue at all quantiles and in linear regression. At the 25th quantile, agricultural income was reduced by almost 8%, including Sunamganj & Rangpur districts, while it was more than double (nearly 17%), excluding Sunamganj & Rangpur, with a 1% increase in the fraction of cropland damaged due to floods and excessive rain. Similarly, at the 50th and 75th quantiles, this effect was more than 3% and 1% higher for the second group of sample farm households than the first group.

On the other hand, in OLS regression, climate shocks' effect on farm revenue was 8.5%, slightly higher compared to all quantiles, with Sunamganj & Rangpur districts. However, without these districts, agricultural income declined by 12% in OLS regression, about 5% lower than the 25th quantile but 1% and 4% higher than the 50th and 75th quantiles, respectively. Thus, the result clarifies that croplands were affected by floods and excessive rain in study districts, leading to a substantial loss of farm income for households. This finding relates to the current empirical study of Dey et al. [6] and Parvez et al. [20], as they found massive losses in fisheries and crop income because of climate shocks. Hossain et al. [10] also illustrated that floods trigger devastating effects on people's income in the climate-vulnerable area of Bangladesh, in line with this study.

Table 3
Quantile and OLS regression results for Hypothesis 1.

Explanatory Variables	N = 2131 (With Sunamganj & Rangpur)				N = 1880 (Without Sunamganj & Rangpur)			
	OLS (Coefficient at mean)	SQREG (Coefficient at Quantiles)			OLS (Coefficient at mean)	SQREG (Coefficient at Quantiles)		
		Q25	Q50	Q75		Q25	Q50	Q75
(Ln) Percentage of cropland damaged	−0.085***	−0.076**	−0.082***	−0.072***	−0.120***	−0.166***	−0.113***	−0.083***
	(0.017)	(0.032)	(0.022)	(0.013)	(0.019)	(0.045)	(0.025)	(0.015)
Household size	−0.033	−0.06	−0.059**	−0.048*	−0.033	−0.015	−0.080***	−0.04
	(0.027)	(0.058)	(0.028)	(0.028)	(0.031)	(0.053)	(0.027)	(0.038)
Women aged 15–49	0.180***	0.233	0.176**	0.149***	0.196***	0.129	0.218**	0.162***
	(0.068)	(0.15)	(0.086)	(0.054)	(0.072)	(0.124)	(0.085)	(0.055)
Gender of the Head	1.242***	1.708***	1.776***	1.090***	1.208***	1.473***	1.777***	1.055***
(1 = Male)	(0.119)	(0.217)	(0.186)	(0.128)	(0.126)	(0.249)	(0.247)	(0.178)
(Ln) Age of the Head	0.269*	0.667**	−0.071	0.007	0.175	0.525**	−0.012	0.026
	(0.161)	(0.336)	(0.213)	(0.125)	(0.173)	(0.266)	(0.206)	(0.142)
Education of the Head								
(1 =) Primary	0.068	0.24	−0.02	−0.012	0.056	0.157	−0.051	−0.003
	(0.094)	(0.191)	(0.122)	(0.078)	(0.101)	(0.191)	(0.113)	(0.085)
(1 =) Secondary & Over	0.091	0.232	0.03	−0.011	0.029	0.08	−0.03	0.034
	(0.103)	(0.235)	(0.107)	(0.077)	(0.108)	(0.26)	(0.127)	(0.085)
Farm size	0.517***	0.630***	0.619***	0.480***	0.659***	0.828***	0.727***	0.553***
	(0.054)	(0.077)	(0.05)	(0.037)	(0.063)	(0.076)	(0.046)	(0.041)
Livestock ownership	0.386***	0.235	0.667***	0.603***	0.417***	0.163	0.746***	0.516***
(1 = Yes)	(0.120)	(0.182)	(0.178)	(0.123)	(0.132)	(0.213)	(0.166)	(0.157)
Constant	7.489***	4.516***	8.517***	9.916***	7.689***	5.080***	8.123***	9.799***
	(0.625)	(1.24)	(0.894)	(0.507)	(0.675)	(1.023)	(0.838)	(0.575)

Notes: Dependent Variable: (Ln) **Agricultural Income**; ***p < .1; **p < .05; ***p < .01**; Values in the parentheses stand for Robust and Bootstrap Standard Errors in the OLS and SQREG models, respectively.

Table 4
Order Probit regression results for Hypothesis 2.

Explanatory Variables	N = 2131 (With Sunamganj & Rangpur)					N = 1880 (Without Sunamganj & Rangpur)				
	Coefficient	Marginal Effects				Coefficient	Marginal Effects			
		Food security	Mild food insecurity	Moderate food insecurity	Severe food insecurity		Food security	Mild food insecurity	Moderate food insecurity	Severe food insecurity
(Ln) Percentage of cropland damaged	0.039*** (0.011)	−0.014*** (0.004)	0.005*** (0.001)	0.007*** (0.002)	0.002*** (0.001)	0.036*** (0.012)	−0.013*** (0.004)	0.005*** (0.002)	0.006*** (0.002)	0.002*** (0.001)
Household size	0.017 (0.019)	−0.006 (0.007)	0.002 (0.002)	0.003 (0.003)	0.001 (0.001)	0.031 (0.020)	−0.011 (0.007)	0.004 (0.003)	0.005 (0.003)	0.002 (0.001)
Women aged 15-49	−0.047 (0.047)	0.017 (0.017)	−0.006 (0.006)	−0.008 (0.008)	−0.003 (0.003)	−0.047 (0.049)	0.017 (0.018)	−0.007 (0.007)	−0.008 (0.008)	−0.003 (0.003)
Gender of the Head *(1 =) Male*	−0.109 (0.076)	0.040 (0.028)	−0.014 (0.010)	−0.019 (0.013)	−0.007 (0.005)	−0.100 (0.082)	0.036 (0.030)	−0.014 (0.011)	−0.016 (0.014)	−0.006 (0.005)
(Ln) Age of the Head	0.004 (0.095)	−0.001 (0.034)	0.0005 (0.012)	0.001 (0.016)	0.0002 (0.006)	0.146 (0.100)	−0.053 (0.036)	0.020 (0.014)	0.024 (0.016)	0.009 (0.006)
Education of the Head										
(1 =) Primary	−0.160*** (0.060)	0.059*** (0.022)	−0.018** (0.007)	−0.029*** (0.011)	−0.011*** (0.004)	−0.114* (0.064)	0.042* (0.024)	−0.014* (0.008)	−0.020* (0.011)	−0.008* (0.004)
(1 =) Secondary & Over	−0.532*** (0.065)	0.200*** (0.024)	−0.088*** (0.013)	−0.086*** (0.010)	−0.026*** (0.004)	−0.469*** (0.069)	0.177*** (0.026)	−0.081*** (0.014)	−0.073*** (0.011)	−0.023*** (0.003)
Farm size	−0.245*** (0.030)	0.089*** (0.010)	−0.032*** (0.004)	−0.042*** (0.006)	−0.015*** (0.002)	−0.257*** (0.033)	0.094*** (0.012)	−0.036*** (0.005)	−0.042*** (0.006)	−0.020*** (0.003)
Livestock ownership *(1 =) Yes*	0.080 (0.086)	−0.029 (0.032)	0.011 (0.013)	0.013 (0.014)	0.005 (0.005)	0.079 (0.094)	−0.029 (0.035)	0.012 (0.015)	0.013 (0.015)	0.005 (0.005)
Cut 1	−0.548 (0.370)					0.068 (0.394)				
Cut 2	0.686 (0.370)					1.334 (0.395)				
Cut 3	1.659 (0.374)					2.269 (0.400)				
Wald chi2	*183.29*					*144.70*				
Prob > chi2	*0.000*					*0.000*				
Pseudo R2	*0.054*					*0.050*				

Notes: Response variable: **Food insecurity** (1 = Food security, 2 = Mild food insecurity, 3 = Moderate food insecurity, 4 = Severe food insecurity); ***p < .1; **p < .05; ***p < .01**; Robust Standard Error is stated in the parentheses.

Regarding control variables, household size exerts negative coefficients but does not significantly influence agricultural income at Q25 (lower quantile) and OLS regression. A similar effect is seen at Q75 (higher quantile) but is weakly significant for the first sample household group. Although, at Q50 (medium quantile), farm income significantly drops by around 6% and 8% with an additional member, respectively, with and without Sunamganj & Rangpur. Thus, the lower farm income could be caused by a larger household size [63]. This is because a household with more members could be involved in non-farm earnings rather than farming. Besides, more family members consume more instead of selling farm produce, reducing farm income. This result resonates with the finding of Hussain et al. [76], who found that household size significantly lessens agricultural income.

In contrast, the presence of prime-age women (aged 15 to 49) in the household considerably increases agricultural income in both regressions, although the effect is insignificant at the 25th quantile. Farm income increases by approximately 18% at the 50th quantile and OLS regression for the first sample group, while this figure rises to around 22% and 20%, respectively, for the second group. However, at the 75th quantile, the effect was minimally lower than the OLS regression. Thus, prime-age women in Bangladesh could substantially contribute to farm profits through their direct and indirect involvement in agricultural activities.

Besides, the gender of the head in farm households plays a crucial role in boosting agricultural income in Bangladesh. Male-headed households generate higher farm revenue at all quantiles and OLS regression compared to women, and the effect is more profound at Q50. The key reason could be that farm families in Bangladesh are male-dominated and directly participate in agricultural activities. Hence, male members could supply more labor in farm production and significantly skew income compared to women. Abokyi et al. [77] confirmed that the male household member considerably increased farm income than their female counterpart in light of this study's result.

The household head's age is significant at a 10% level in OLS regression for the first sample group, which is significant at a 5% level at Q25 for both sample groups. This effect is much higher at this quantile, indicating that the increased age of the household head dramatically increases agricultural income. At other quantiles, age does not influence farm income. Household heads could gain more experience as they grow older, which can improve agricultural production and, in turn, raise farm income. Nevertheless, this could be tempered if they are much older and become inactive. Duasa and Zainul [63] observed a similar effect that is supported by this study.

Surprisingly, the education levels of household heads lack a meaningful association with agricultural income at SQREG and OLS regression. Educational attainment could decline their involvement in farm activities, and educated households could tend to diversify farm income to non-agricultural incomes [78].

On the other hand, farm size immensely increases agricultural revenue at every quantile and the mean, though the magnitude is much higher in SQREG compared to the OLS regression. Farm income was boosted at the lower quantile by about 63% and 83% with a 1-acre farm size increase, respectively, including and excluding Sunamganj & Rangpur districts, followed by medium and higher quantiles. Thus, a larger farm brings higher farm revenue. Likewise, in this study, Hussain et al. [76] ascertained that more farmland induced more agricultural income in Bangladesh. Mishra and Moss [79] and Uematsu et al. [64] found a similar link between farm size and farm profit.

Moreover, household livestock ownership substantially raises farm income compared to those not owning at the 50th and 75th quantiles and OLS regression. However, the effect of having livestock was relatively higher in SQREG for the second sample group than in the first group. Possessing livestock grows farm income by nearly 67% and 75% at the 50th quantile, respectively, with and without Sunamganj & Rangpur districts. This figure accounted for 39% and 42% in the case of OLS regression. It could be that by selling livestock assets, farm households earn higher profits. Rahman [80] revealed that farm income is significantly higher for households with livestock resources, which is consistent with this study's outcome. Thus, household livestock assets are of paramount importance in raising agricultural income in Bangladesh.

Lastly, this study accepted Hypothesis 1 since the climate shock coefficient is negative and significantly different from zero across the quantiles for both sample farm households. Therefore, in the study districts of Bangladesh, climate shocks noticeably decrease agricultural income.

3.3. Impact of climate shocks on farm households' food security

Table 4 reports the order probit regression results (Eq. (2)) with coefficients and marginal effects to assess whether climate shocks increase farm household food insecurity (Hypothesis 2). However, interpreting order probit regression coefficients does not directly clarify independent variables' effects [35,41]. Thus, this study interprets the findings based on the marginal effects of each level of food security using the FIES. Besides, the Wald test shows that homoscedasticity is rejected since it significantly differs from zero, implying that heteroscedasticity is detected for each output level. Moreover, three cut-off points for the four food security levels fulfill the conditions of cut1<cut2<cut3, i.e., each level is in order.

The marginal effects of climate shocks are negative and significant for the food security category. Farm households are less likely to be food secure by 1.4% and 1.3% points with increased climate shocks, respectively, for the samples with and without Sunamganj & Rangpur districts. On the other hand, households are 0.5% points more likely to be mildly food insecure, while moderate food insecurity goes up slightly more. However, floods and excessive rain have a small positive effect (0.2% points) on households' likelihood of severe food insecurity.

Thus, climate shocks increased household food insecurity in the study regions. To put it another way, a fraction of cropland damage caused by floods and excessive rain significantly reduces the food security of farm households in Bangladesh. Evidently, this result relates to Pacetti [24], who examined that farmland destroyed by floods in Bangladesh caused crop loss and significantly declined household food security. A similar finding by Béné et al. [25] showed that climate shocks (floods, droughts, river erosion, and salinity) diminish households' food security in rural Bangladesh. The finding also aligns with Alam et al. [23] and Smith and Frankenberger

[26].

Total household size shows the likelihood of food security insignificantly decreasing (or food insecurity rising) with increased household members. Farm families could have more members but fewer earning people; hence, there could be a lack of sufficient food consumption, and they would suffer from food insecurity. In contrast, women aged 15 to 49, compared to total household size, had an insignificant opposite effect on food security. In addition, the gender and age of the family head do not significantly affect the food security status of households.

However, education plays a profound role in ensuring household food security in the climate-vulnerable regions of Bangladesh. Primary-educated households are more likely to be food secure by around 6% and 4% points, respectively, for the sample with and without Sunamganj & Rangpur districts compared to households with no formal education. Remarkably, households with secondary or higher school education increase the likelihood of food security by about one-fifth (roughly 20% and 18% for the first and second sample groups, respectively) compared to those households without school education. This finding is consistent with the recent empirical study of Parvez et al. [20], who revealed that households with secondary or higher schooling are 30% less susceptible to food insecurity in flood-affected northeastern Bangladesh. Hence, educated households are less likely to be food insecure.

Moreover, farm size is also a key determinant of increasing household food security. Increased farm size significantly increases the probability of food security level (around 9% points), while it declines for all food insecurity levels, revealing that using more farmland lowers food insecurity. Hence, more farmlands could expand food production, which ensures that farm households are more likely to be food-secured. The findings of Parvez et al. [20] and Raihan et al. [81] depict that owning agricultural land is significantly associated with household food security in Bangladesh, in accordance with this study. Nevertheless, households that own livestock do not significantly affect the likelihood of food security status compared to households without livestock.

Finally, this study accepted Hypothesis 2 since climate shocks have a significant negative effect on the food security level but are positive for each level of food insecurity. Therefore, it is concluded that climate shocks (floods and excessive rainfall) decrease household food security. Alternatively, climate shocks increase the food insecurity of farm households in the study districts of Bangladesh.

4. Conclusion and policy recommendations

Most rural households in Bangladesh still depend on the farming sector despite its vulnerability to climate shocks. This research explores the effects of climate shocks on agricultural income and food security for farm households in 24 districts of Bangladesh. The key findings based on the simultaneous quantile regression ascertain that climate shocks considerably reduce household agricultural income. Put another way, floods and excessive rain substantially decline the income of farm households in the study areas of Bangladesh. On the other hand, the presence of prime-age women (aged 15 to 49) in the home, the male-headed family, farmland, and livestock ownership of the household are the decisive factors that safeguard agricultural income. On the grounds of the Food Insecurity Experience Scale (FIES), descriptive statistics confer that most farm households suffer at different food insecurity levels (considerably moderate, noticeably mild, and tiny severe), while the rest are at the food security level. The crucial finding concerning ordered probit regression reveals that climate shocks significantly increase household food insecurity (at different levels of FIES). In other words, floods and excessive rain decrease the farm households' food security in the study regions of Bangladesh. Even though increased farmland and educated households are profoundly protected against food insecurity.

However, the study might be limited to a specific part. This study primarily used the BIHS 2018-19 data, but the district-level data on the cropland damaged by floods and heavy rain from the YBASB 2018. Because in the BIHS 2018-19 dataset, climate shock indicators were dummies and mostly omitted. Thus, an exogenous climate shock variable was generated from the YBASB 2018 to overcome the potential endogeneity issues. Hence, measuring household food security using an exogenous climate shock indicator might surprise readers.

Despite the limitations, this study recommends a couple of policies based on its key findings. Raising livestock assets could provide a stable income source against climate shocks, as livestock owned by households notably increases agricultural income. Policy initiatives focused on livestock could benefit from this finding. The state-owned agricultural and commercial banks might expand their credit facilities to promote raising and purchasing livestock assets in Bangladesh's climate-vulnerable regions. Moreover, the finding illustrates that educated households are more food secure than households with no formal education. Thus, investing in education can ensure the food security of farm households. This finding could aid in the development of education-oriented policy interventions. The government could widen opportunities to enhance education levels among farm households in the climate-prone regions of the country. Further research should be conducted on developing climate shock resilience, focusing on livestock-oriented income generation, expanding education levels, and targeting climate-vulnerable farm households in Bangladesh.

Funding

This research received no grants from public, commercial, or non-profit organizations.

Data availability statement

The BIHS 2018–2019 data associated with this study has been deposited at the International Food Policy Research Institute (IFPRI). 2020. Bangladesh Integrated Household Survey (BIHS) 2018–2019. Washington, DC: IFPRI [dataset]. https://doi.org/10.7910/DVN/NXKLZJ. Harvard Dataverse. Version 2.

The YBASB 2018 data associated with this study is the government's annual report on national agricultural statistics, available at the Bangladesh Bureau of Statistics (BBS). 2019. Yearbook of Agricultural Statistics 2018. Dhaka. https://bbs.gov.bd/site/page/3e838eb6-30a2-4709-be85-40484b0c16c6/Yearbook-of-Agricultural-Statistics.

Ethical statement

As the author mainly used the BIHS 2018–19 round 3 datasets conducted by the IFPRI [33], fulfilling all the required consents, he did not require participant consent. However, the author consented to the IFPRI's ethical terms and conditions for data use.

CRediT authorship contribution statement

Md. Rashid Ahmed: Writing – review & editing, Writing – original draft, Software, Resources, Methodology, Investigation, Formal analysis, Data curation, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgement

This paper is the author's original research work and is an outcome of his MSc Thesis (unpublished), carried out under the supervision of **Dr. Janneke Pieters**, Chair Group of Development Economics, Department of Social Sciences, Wageningen University & Research, the Netherlands. The author greatly thanks Dr. Janneke Peters for her unwavering assistance and direction. He also deeply appreciates the IFPRI and BBS for providing him with their datasets.

Appendices.

Table A1
VIF for independent (continuous) variables

Continuous Variables	N = 2131 (With Sunamganj & Rangpur)	N = 1880 (Without Sunamganj & Rangpur)
(Ln) Percentage of cropland damaged	1.03	1.02
Household size	1.59	1.58
Women aged 15–49	1.55	1.57
(Ln) Age of the Head	1.03	1.03
Farm size	1.08	1.06

Source: Author Estimation

Table A2
Contingency coefficient for independent (dummy) variables

Dummy Variables	Gender of the Head	Education of the Head	Livestock ownership
N = 2131 (with Sunamganj & Rangpur)			
Gender of the Head	1		
Education of the Head	0.021	1	
Livestock ownership	0.038	0.027	1
N = 1880 (without Sunamganj & Rangpur)			
Gender of the Head	1		
Education of the Head	0.020	1	
Livestock ownership	0.047	0.024	1

Source: Author Estimation

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