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Climate risk perceptions and perceived yield loss increases agricultural technology adoption in the polder areas of Bangladesh

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ABSTRACT

The effects of climate change are likely to increase the frequency of flood, drought, and salinity events in the coastal areas of Bangladesh, posing many challenges for agrarian communities. Sustainable intensification in the form of improved agricultural management practices and new technologies may help farmers cope with stress and adapt to changing conditions. In this study, we explore how climate change perceptions of agricultural risk affect adaptation to climate change through technology adoption in a unique landscape: the polders of Bangladesh. In 2016, a survey was conducted in 1003 households living on these artificial, leveed islands facing the Bay of Bengal. We analyzed the responses from polder residents to construct a climate risk index which quantifies climate risk perception in this highly vulnerable agrarian landscape. We analyzed how polder demographics influence their perceptions about climatic change using seemingly unrelated regression (SUR). Further, by using three bivariate probit regression models, we estimated how the perception of climate risk drives the differential adoption of new agricultural technologies. Our findings show that farmers perceive polder agriculture as highly vulnerable to four environmental change factors: flooding, drought, salinity, and pest infestation. The SUR model suggests that farmer demographics, community group memberships, and access to different inputs and services strongly influence climatic risk perceptions. Findings also suggest that polder farmers with higher risk perceptions have a higher propensity to adopt both chemical and mechanical adaptation strategies. Cost, however, limits the ability of farmers to adopt improved technologies, suggesting an opportunity for institution-led approaches.

1. Introduction

The sustainable intensification of agriculture is essential for fostering economic development and feeding growing populations in low-income countries such as Bangladesh. The Bangladesh economy, along with a mostly agrarian population, is largely dependent on agricultural production to sustain livelihoods. Nevertheless, farmers earn very little from their efforts. The agriculture sector only contributes 14.23% to the country's gross domestic product (GDP) (Bagchi et al., 2019), with an average farm size of approximately 0.24 ha (0.60 acres) (Rapsomanikis 2015). Despite small landholdings, agriculture in Bangladesh occupies more than 9.5 million hectares, representing approximately 65% of the land area in the country (Hasan et al., 2013). Deltaic Bangladesh is exposed to sea-level rise and extreme weather events according to the

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IPCC's Fifth Assessment Report (AR5) (Hijioka et al., 2014). Increasingly frequent high temperatures and rainfall events generate seasonal flooding, drought, and salinity intrusion in coastal areas, all of which negatively impact agricultural production and livelihoods (Nahar et al., 2018; Yadav et al., 2020; Assefa et al., 2021). Several studies have shown that riverine topography, limited income, less adaptive capacity, high population density, and weak infrastructure are important factors making Bangladesh vulnerable to the increasingly frequent impacts of climate change (Mirza et al., 2003; Mottaleb et al., 2016; Panday 2017). Climate change adaptation in Bangladesh hinges on improving agricultural resilience and livelihoods through better management practices and new improved technologies. Understanding farm-level climate risk perceptions and adaptation strategies are crucial for improving the adaptive capacity of such vulnerable communities (O'Brien et al., 2007; Conway et al., 2019; Hasan and Kumar 2020).

The polder areas are a unique landscape of coastal Bangladesh that are some of the world's most vulnerable regions to climate change (Dasgupta et al., 2018; Hasan and Kumar 2020). As a result of compounding environmental hazards, the morphology of the coast is continually altered, in some cases, making the land entirely uninhabitable (Auerbach et al., 2015). The impact of sea-level rise, coupled with salinity intrusion and frequent flooding, severely affects coastal agriculture, biodiversity, and human livelihoods (Mondal et al., 2001; Dasgupta et al., 2018; Das et al., 2020; Assefa et al., 2021). The coastal area has long battled environmental problems associated with flooding and salinity (Auerbach et al., 2015; Yadav et al., 2020; Assefa et al., 2021).

To defend and protect the coastal zone and its economy, the Government of Bangladesh undertook a massive coastal embankment project (Thompson and Sultana 1996). The 139 polders were constructed with covering 1.2 million hectares of land to house the agriculture, infrastructure, and economy of 8 million climate-vulnerable people of the southern coastal zone (Thompson and Sultana 1996; Gain et al., 2017; Yadav et al., 2020). The earthen embankments were made to a height of 6 m above sea level around the perimeter of arable lands reclaimed from the Ganges River delta (Thompson and Sultana 1996; Gain et al., 2017). Polders are constructed in such a way that natural tidal water cannot flow into, and flood farmed areas under normal conditions. However, to facilitate drainage from agricultural land and for seasonal replenishment of river sediment vital for polder agriculture, sluice gates were constructed permitting tidal river water to flow in and out of the polder ecosystem (Mondal et al., 2001; Das et al., 2020; Assefa et al., 2021; Yadav et al., 2020). In general, the sluice gates remain closed during the dry season due to high river salinity (Dasgupta et al., 2018).

Despite their beginnings, the polders have largely missed out on the adoption of improved agricultural technologies. Recent literature in agricultural development proposes sustainable agricultural intensification as an effective mechanism for improving livelihoods and eliminating poverty (Tilman et al., 2011; Weltin et al., 2018; Ahmed et al., 2021b). A recent global assessment showed significant increases in sustainable agricultural intensification practices in terms of land area and number of farms and approaching a tipping point where it could be transformational (Pretty et al., 2018). Sustainable agricultural systems must also embrace a changing climate. Vulnerability, therefore, has been a key point of investigation within the literature (Cutter 1996; Hasan et al., 2021; Jakariya et al., 2020; O'Brien et al., 2007; Mahmood et al., 2020; Mechler and Bouwer 2015). In the face of adverse climatic uncertainties, adopting improved agricultural technologies can help achieve sustainable economic development (Evenson and Gollin 2003; Gollin 2010; Yadav et al., 2020; Ahmed et al., 2021b, a; Assefa et al., 2021). Understanding perceptions of climate risks is critical for determining research gaps and future directions (Hoque et al., 2019). The use of participatory approaches to gain perspectives and insights into critical issues such as climate change perceptions and climate vulnerability will help improve outcomes (Middendorf et al., 2020).

Therefore, the major aim of this study was to analyze how climate risk perceptions informed farmers' adoption of new technologies. We conducted our study in three polders of the Khulna District of southwest Bangladesh (Fig. 1), the most climate-vulnerable region of the country (Auerbach et al., 2015; Assefa et al., 2021). We investigate how the differential perception of crop yield loss to different climate change factors might influence the adoption of improved agricultural technologies for sustainable intensification in the polders of southwest Bangladesh. In addition, we tried to ascertain what socio-economic characteristics are associated with perceiving the risk of climate change and its impacts. Furthermore, our study adds to the greater discussion on how socio-economic factors and perceptions of climate impacts drive the adoption of technology for agricultural intensification.

2. Methodology

2.1. Data and variables

A survey was conducted from randomly selected households living in polders 28/1, 28/2 and 30 to capture farmers' perceptions about climate change risk, perceived yield loss due to climatic events, adaptation strategies, and overall socio-economic conditions. To streamline the data, we used extreme value deletion to eliminate 22 outliers, leaving 1003 household responses as our study sample. There were 523, 169, and 311 respondents in polders 28/1, 28/2, and 30, respectively. The 2016 household survey was conducted by the International Water Management Institute (IWMI) and the International Rice Research Institute (IRRI) using a structured questionnaire. This was pretested before data collection.

The questionnaire was categorized broadly into ten sections: demographic identification, land use, cropping patterns, risk perceptions,

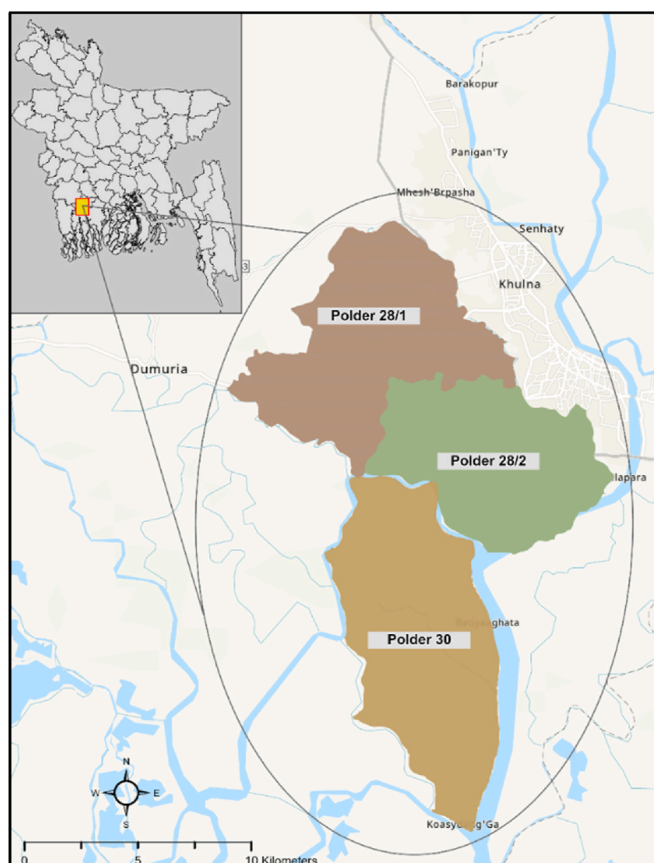

Fig. 1. Study polders in southwest coastal Bangladesh.

water management systems, migration, gender, farm incomes and livelihoods, and assets. In the identification and land sections, respondents were asked about general socio-economic, demographic, and land-related questions. In the technology adoption section, respondents answered either 'yes' or 'no' to the question whether they had adopted chemical fertilizers, pesticides and power tillers in agriculture. The respondents were also asked about the area under traditional variety (TV) and high yielding varieties (HYV) of rice in the polder zone. In the risk perception section, respondents were asked about their perceived climatic risk and perceived yield loss in both *aman* (June–December) and *rabi* (January–May) crops from various climatic events, including flooding, drought, salinity, and insect infestation. The respondents provided their perception of the frequency of climatic events and estimated their lost crop yield as a percentage for each type of climatic event. In the water management and community participation section, respondents were asked about their active participation in several community groups (water management groups, agriculture groups, income generation groups, local development groups, and credit union groups). The respondents indicated their membership in each with either 'yes' or 'no'. In the farm income and food security section, respondents were asked about their annual income and the agriculture or non-agriculture (i.e., store-bought) source of their household diet.

2.2. Conceptual framework

The conceptual framework (Fig. 2) on farmer perceptions of climatic events and associated adaptation was modified from Nguyen et al. (2016) and Pasqui and di Giuseppe (2019). Farmers witness extreme climatic events such as floods from coastal storm surge events and local rainfall, salinity intrusion from seawater following drying inland rivers during non-monsoonal time periods, drought from weak monsoons, and insect infestations due to warming and humidifying climatic conditions. All these factors jeopardize crop yields, livelihoods, and farming systems in the polder zone. Due to climatic variability, farming households may adopt new technologies as an adaptation strategy to hedge against threatening climate impacts. Conceptually, farmers perceive different types of agricultural risk associated with climatic change. They quantify the impact of each climatic risk for their production system by estimating perceived yield losses, and farmers may discuss their perceived knowledge and experience with their family members and neighbors, perhaps talk with their local ag-extension staff, take part in different membership groups, and subsequently weigh the opportunity cost of adopting new technologies. After evaluating and considering different scenarios and inputs, farmers may adopt technologies perceived to outpace the impacts of climatic change in their farming or crop management system. In contrast, if the adoption of new technologies is not perceived to outpace climatic impacts, farmers prefer to stay with their current farming or crop management system.

2.3. Analytical framework for linking perceptions of climate risk and yield losses with technology adoption

We examined cross-sectional data from farmer surveys to understand different aspects of the determinants of agricultural technology adoption based on climate change hazard rankings, climatic risk perception, and perceived yield losses. For our analysis, we converted the frequency of flood, drought, salinity, and insect infestation separately as binary categorical variables to identify perceived climatic risk. We investigated how a set of explanatory variables such as demographics, socio-economic status, farm characteristics, and climatic knowledge may influence farmers to adopt technology. In order to further measure adaptive capacity, we analyzed what types of farmers perceive climate change (Williams et al., 2016). For this analysis, we used farmers' characteristics, membership in community support groups, and access to different services, among other control variables. We reviewed several literatures and selected our regressors based on local context and nature of the survey data (Sarker et al., 2013; Uddin et al. 2014, 2017; Mottaleb et al., 2016; Aryal et al., 2020; Islam et al., 2020a; Ahmed et al., 2021a).

2.3.1. Climate change risk perception index

The climate change risk perception index can be used to rank farmers' perceptions of local climatic hazards (Ahmed et al., 2021a). For this study, we adopted an index for ranking climatic hazards in polder areas (Eq. (1)). The frequency of the five year's (2011–2015) climatic hazards were classified into 4 major categories, namely "High Occurrence", "Medium Occurrence", "Low Occurrence" and "No Occurrence." We assigned values to respective risk categories based on the frequency the farmers faced particular hazards. High occurrence was defined as four or more hazards over five years, medium as two to three hazards, low occurrence as one hazard in five years and no occurrence if no hazards were reported by survey households in the last five years. We summed these to create a cumulative perception score (Ahmed et al., 2021a). The Climate Change Risk Perception Score (CCRPS) is calculated as:

$$CCRPS = CCRPS_n*0 + CCRPS_l*1 + CCRP_m*2 + CCRP_h*3 \quad (1)$$

where $CCRPS_n$ is the number of respondents having no occurrence risk perception, $CCRPS_l$ is the number of respondents having a low occurrence risk perception, $CCRPS_m$ is the number of respondents having a medium occurrence risk perception, and $CCRPS_h$ is the number of respondents having a high perception of risk occurrence.

Since there were a total of 1003 respondents, the Climate Change Risk Perception Score (CCRPS) for any given climatic event could range from 0 to 3009, where 0 indicates a minimum level of perceived hazard occurrence and 3009 indicates a maximum level of perceived hazard occurrence. We converted the CCRPS to a standardized index for further interpretation of the results. The Standardized Climate Change Risk Perception Index (SCCRPI) transforms the CCRPS into percentages (Eq. (2)). The index is calculated as:

$$SCCRPI = \frac{Total\ CCRPS\ value\ for\ each\ climatic\ hazards}{Maximum\ level\ of\ perceived\ hazard\ occurrence} * 100 \quad (2)$$

where, the *Total CCRPS Value* was calculated by multiplying respective occurrence risk perception values with total occurrence frequency against four climatic events (Eq. (1); note 0 or no occurrence is counted as one of the four climatic event scenarios), and the *maximum level of perceived hazard occurrence* value was calculated by dividing by the total respondents in each category. The SCCRPI provides a means to understand and classify climate change occurrence risk perception (Ahmed et al., 2021a). The SCCRPI value can range from 0 to 100, where 0 indicates a minimum level of risk perceived and 100 indicates a maximum level of risk perceived by polder respondents.

2.3.2. Seemingly unrelated regression (SUR) of farmer perceptions of climate change risk

The seemingly unrelated regression (SUR) model is a special form of a linear regression model that consists of several regression equations (Zellner 1962). Each equation is independent in nature and can be estimated separately. Hence, it is termed "seemingly unrelated" regression. Importantly, one of the special features of this model is that the error terms are assumed to be correlated across all equations. The SUR model could be estimated using an ordinary least squares (OLS) method; however, OLS estimates generally are not as efficient as the SUR method, which notably amounts to feasible generalized least squares (FGLS) with a specific form of the variance-covariance matrix.

In this study, we used the SUR model to analyze the types of farmers likely to perceive climatic change in the study polders (Gbetibouo 2009; Eskander and Barbier 2016; Acharya 2018; Ojo and Baiyegunhi 2020; Parvez and Chowdhury 2020). We used perceived flood, drought, salinity, and insect infestation from climate change as the dependent variables. Additionally, we selected farmer socio-economic

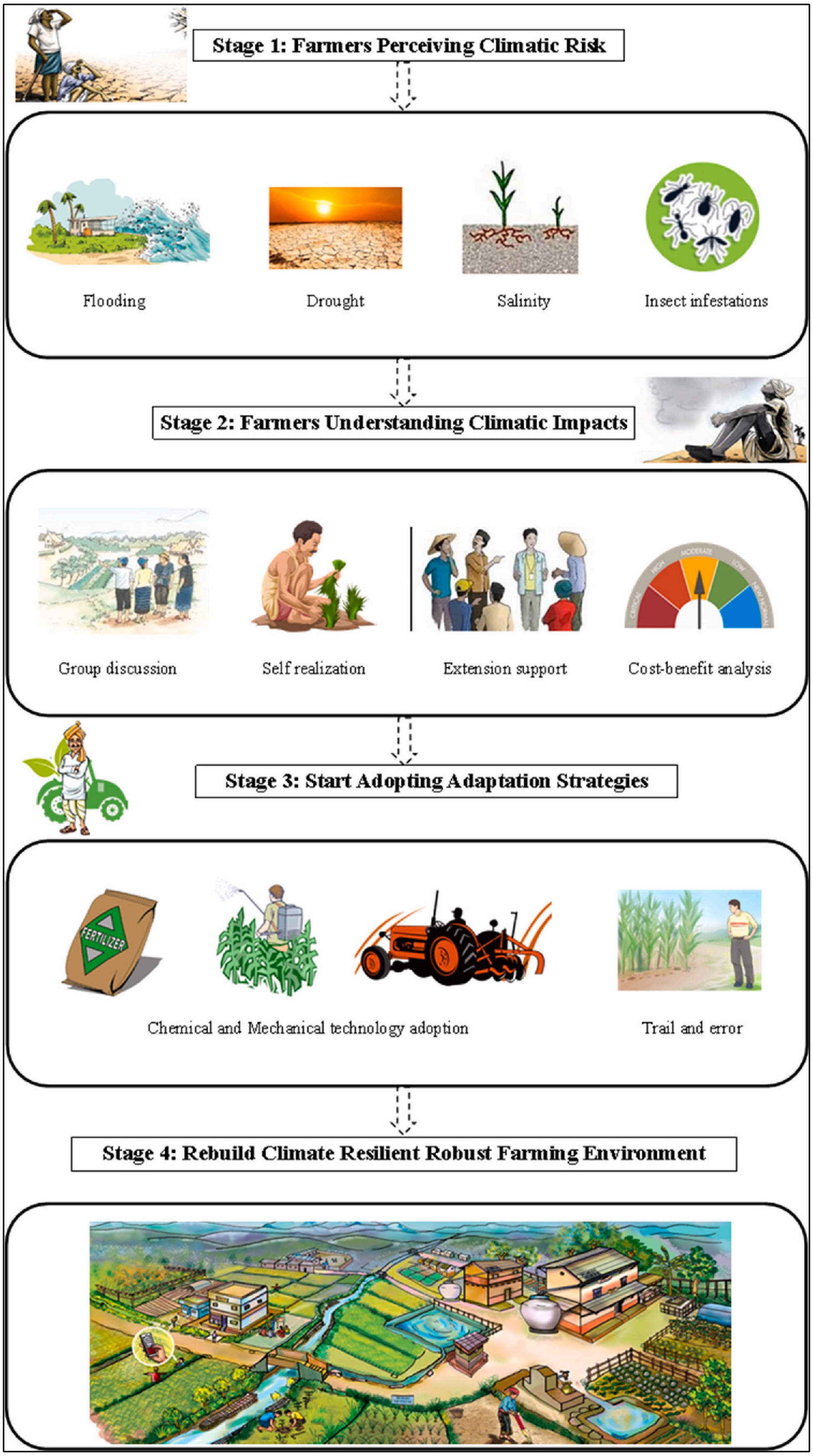

Fig. 2. Conceptual framework for climate risk perceptions and agricultural adaptation (Adapted and modified from Nguyen et al., 2016 and Pasqui and di Giuseppe, 2019).

Note: Stage 1 pictures derived from https://bit.ly/3kajKjG; https://bit.ly/3iYFEHd; https://bit.ly/37V3r4j; https://bit.ly/3mieMUO; https://bit.ly/3D4Bd5s; Stage 2 pictures derived from https://bit.ly/3AXzEo6; https://bit.ly/2Wbsc9N; https://bit.ly/3ghf0ra; https://bit.ly/3sv0jpk; https://bit.ly/3y3c6fV; Stage 3 and 4 pictures derived from https://bit.ly/2WchkII; https://bit.ly/3j3rp41; https://bit.ly/3misSWc; https://bit.ly/3xZrSIr; https://bit.ly/3ggCrkx; https://bit.ly/2W8IkcG.

characteristics, group membership, and access to different services, as the hypothesized variables of influence. The four types of climate change impact categories with associated explanatory variables were estimated separately, but their error terms are likely to be correlated (hence we chose the SUR model). The four perceived climatic change impacts were modeled in the analysis based on the following equations:

$$A_{i1} = Z_i\delta_{i1} + \theta_{i1} \tag{3}$$

$$A_{i2} = Z_i\delta_{i2} + \theta_{i2} \tag{4}$$

$$A_{i3} = Z_i\delta_{i3} + \theta_{i3} \tag{5}$$

$$A_{i4} = Z_i\delta_{i4} + \theta_{i4} \tag{6}$$

where, A_{i1-4} are the binary variables which only take a value of 1, if a farmer perceives climatic change, and zero (0) otherwise; Z_i represents a vector of predictors of associated variables; δ_{i1-4} are coefficients to be estimated; and θ_{i1-4} are random error terms.

After matrix transformation of Eqs. (3)–(6), and for the i^{th} observation, we can form the $M\,x\,M$ covariance matrix as follows:

$$\begin{vmatrix} A_1 \\ A_2 \\ \dots \\ A_M \end{vmatrix} = \begin{bmatrix} Z_1 & 0 & 0 \\ 0 & Z_2 & 0 \\ 0 & 0 & Z_M \end{bmatrix} \begin{vmatrix} \delta_1 \\ \delta_2 \\ \dots \\ \delta_M \end{vmatrix} + \begin{vmatrix} \theta_1 \\ \theta_2 \\ \dots \\ \theta_M \end{vmatrix} = Z\alpha + e \tag{7}$$

In this matrix of equations, the coefficients were estimated using the Feasible Generalized Least Squares (FGLS) method for a SUR model.

2.3.3. Probit regression of factors affecting adoption of agricultural technologies

In this study, Binominal Probit Regression (BPR) was used to analyze the relationship between the polder farmers' adoption of technology and characteristics of socioeconomic, climatic risk perception, or farm-level characteristics (Kazianga and Masters 2002; Thuo et al., 2014). We measured three adaptation strategies: fertilizer adoption, pesticide adoption and power tiller adoption as our dependent variables. In the survey questionnaire, there were a total of five adaptation categories, but we only selected three adaptation strategies because we did not get adequate responses for the other two categories. Fertilizer adoption is important for the farmers who expect fertilizer improves crop yield through adoption of HYVs to outpace the impacts of climatic hazards. There are HYVs that are tolerant to salinity and stagnant flooding and in contrast TVs are very sensitive to those climatic hazards. Similarly, pesticide adoption may be viewed as an effective adaptation to climatic influences on pest populations. Lastly, power tillers alleviate labor burdens and improve the efficiency and speed with which fields can be prepared, which might offset increasing alternative labor needs (e.g., dealing with flooding, pest management and more) due to climate change impacts (Mottaleb et al., 2016).

The study used technology adoption Y_i as a binary dependent variable with a value of $Y = 1$ if a farmer adopted a technology in the farming system, $Y = 0$, otherwise. Following Amemiya (1981), the farmers' probability of adopting technology can be specified as:

$$p = Pr\,Pr\,[X] = F(X'\beta) \tag{8}$$

where, p is the probability, Y is binary dependent, X' is the vector of independent variables and β is the vector of unknown parameters.

The farmers' intent to adopt agricultural technology can be modeled using a random utility framework (Lancaster 1972; Adesina and Zinnah 1993; Greene 2002). We hypothesize that a farmer is more likely to adopt an agricultural technology if the farmer perceives climatic risk and yield loss. We can assume that a rational farmer, i, seeks to maximize their utility or expected benefits by choosing a set of available technologies. In this study, we assume that the farmer i decides to use j technologies (here, any technology adoption) when the perceived benefit of adoption is greater than the utility than not adopting the technology. As these utilities are very difficult to observe, we can model these as a function of observable elements in the latent variable probit or selection model (Muthén 2012). $A_i^* = Z_i\alpha + e_i$ with

$$A_i^* = \begin{cases} 1, \; if\; A_i^* > 0 \\ 0, \; otherwise \end{cases} \tag{9}$$

where, A_i^* is the latent variable that captures the expected benefits or the likelihood of the i^{th} farmer's intention to adopt technology versus not adopting. In other words, farmer i will choose to adopt a technology ($A_i = 1$, otherwise 0) in response to perceived climatic risk and yield losses; the vector Z represents exogenous variables that affect the expected benefits of technology adoption; α is a vector of parameters to be estimated for respective variables in Z; e is the error term.

The marginal effects of predictor variables on the likelihood to adopt different technologies are calculated as:

$$\frac{\partial P_i}{\partial Z_i} = \varphi(z'\alpha)\alpha_{i,} i = 1, 2, 3, \dots, n \tag{10}$$

where, P_i is the likelihood of event i which increases the adoption of each technology. $\varphi(.)$ is the standard normal density distribution function where z' represents exogenous variables and α is a vector of parameters.

The parameter estimates of the binomial probit model give the likelihood of the outcomes' occurrence. It cannot be quantified or interpreted, but the marginal effect can be calculated for each adoption model, which gives quantification of the influence of the independent variables.

2.3.4. Description of model variables and diagnosis

Table 1 provides an overview of the means, standard deviations, range of the model variables. Fig. 3 shows the Pearson correlation matrix among model variables. We can see both positive and negative correlations between model variables with different levels of significance.

Econometric analysis is often associated with heteroskedasticity and multicollinearity problems. Multicollinearity among model variables can lead to imperfect parameter estimates. To check the potential multicollinearity among model variables, we calculated the Variance Inflation Factor (VIF) for each independent variable and are presented in appendix (Table A1) and Pearson correlation matrix (Fig. 3). According to Hair et al. (2010), VIF value of 10 or more is considered problematic during any regression analysis. In our analysis, we have VIF values ranging from 1.0 to 1.8, well under the threshold value of 10. Regarding correlation thresholds, a value below $r < 0.7$ is considered optimal for model estimation (Dormann et al., 2013). From the correlation matrix, we find that all model parameter correlation values are less than the threshold, with the highest value 0.63. To address the possibility of heteroskedasticity in our models, we estimated standard errors that are heteroskedasticity robust.

3. Results and discussion

3.1. Socio-economic profile

Table 2 provides an overview of the socio-demographic characteristics of the respondents. Most of study household respondents were headed by males (96.41%), the typical social norm for Bangladesh. About 50% of household heads fell within the old age group (>50 years), followed by 33.70% in the middle age group (36–50 years) and 16.35% in the young age group (≤35 years). The mean age of the respondents was 52 years. Education is an important variable in evaluating development status of a county or region. From our results, we can see that almost 88% of the respondents were literate and only 12% illiterate. This suggests that basic education is not only proximal to our study area, but

Table 1
Descriptive statistics of model variables.

Variable name	Description	Mean	SD	Min	Max
Gender of household head (hhgend)	1 if household head is male, 0 otherwise (female)	0.96	0.19	0	1
Age of household head (hhage)	HH head age in years	52	14	15	99
Household size (hsize)	Total number of household members	4.90	2.10	1	13
Education of household head (hhedu)	1 if household head is literate, 0 otherwise	0.88	0.33	0	1
Farm type (ftype)	1 if farm is owned by household, 0 otherwise	0.85	0.35	0	1
Membership credit group (mcg)	1 if farmer has membership, 0 otherwise	0.96	0.21	0	1
Membership income generation group (migg)	1 if farmer has membership, 0 otherwise	0.87	0.34	0	1
Membership local development group (mldg)	1 if farmer has membership, 0 otherwise	0.58	0.49	0	1
Membership agriculture group (mag)	1 if farmer has membership, 0 otherwise	0.55	0.50	0	1
Membership water group (mwg)	1 if farmer has membership, 0 otherwise	0.23	0.42	0	1
Insect risk perception (irisk)	1 if farmer perceive insect risk, 0 otherwise	0.95	0.22	0	1
Flood risk perception (frisk)	1 if farmer perceive flood risk, 0 otherwise	0.94	0.24	0	1
Drought risk perception (drisk)	1 if farmer perceive drought risk, 0 otherwise	0.70	0.46	0	1
Salinity risk perception (srisk)	1 if farmer perceive salinity risk, 0 otherwise	0.53	0.50	0	1
Flood yield loss (fylos)	Perceived yield loss by flood (%)	29.0	27.0	0	100
Insectinfestation yield loss (iylos)	Perceived yield loss by insect-pest (%)	19.0	16.0	0	100
Drought yield loss (dylos)	Perceived yield loss by drought (%)	11.0	22.0	0	100
Salinity yield loss (sylos)	Perceived yield loss by salinity (%)	5.30	13.0	0	100
Fertilizer adoption (feradop)	1 if farmer adopt fertilizer, 0 otherwise	0.93	0.26	0	1
Power tiller adoption (powadop)	1 if farmer adopt power tiller, 0 otherwise	0.90	0.30	0	1
Pesticide adoption (pesadop)	1 if farmer adopt pesticides, 0 otherwise	0.89	0.31	0	1
Household annual income (haincom)	Total annual income of the household (USD)	760.0	587.0	0.0	3009.0
Agricultural farmland (agland)	Total cultivable farming land (ha)	0.55	0.49	0.0	3.70
Crops submerge (cropsub)	1 if crop submerged by flood, 0 otherwise	0.21	0.40	0	1
Food shortage (foodshor)	1 if food insecure for 12 months, 0 otherwise	0.23	0.42	0	1
Per capita rice consumption (pcriceconw)	Household's weekly rice consumption (kg/person)	3.10	1.50	0.0	13.0
Female's decision in technology adoption (womadopdec)	1 if considered, 0 otherwise	0.58	0.49	0	1
Wealth index[a] (wealthidx)	Equal wealth quintiles (1–5)	3.10	0.96	1	5

Note: Most of the variables' mean and standard deviations are reported here for dummy equals 1.
[a] Wealth index is constructed based on household's ownership of selected assets and generated using principal component analysis. This places individuals on a continuous scale based on the scores of the first principal component. The scale is then ranked, and further subdivided into 5 equal wealth quintiles. Quintile 1 represents the poorest 20% (See for details: https://docs.wfp.org/api/documents/WFP-0000022418/download/).

accessible and effective (Hossain et al., 2018; Islam et al., 2020b).

The main occupation of the respondents in our study area was agriculture. 85% of respondents were directly involved with agriculture for their livelihood, followed by day laborer (5%), service (4%), business (3%) and other (3%) professions. Though about 15% of the respondents' primary occupations were not agriculture, they were still indirectly involved with agricultural operations in the study polders. Approximately half of the study households (48%) belonged to the medium-income group (USD 601–1000 per year), while 32% and 20% were under low (up to USD 600) and high (> USD 1000) income groups, respectively. The mean annual income was about 760 USD per year. In addition, more than 85% households have small farm sizes (<1.01 ha) followed by 12.36% medium (1.01–3.03 ha) and only 0.20% large (>3.03 ha) farm, respectively. The mean farm size in the study area was 0.55 ha, almost double than the national average of 0.24 ha (Rapsomanikis 2015). On the other hand, 85% of the study households owned farmland and about 15% leased land for cultivation which includes shared cropland.

3.2. Standardized climate change risk perception index of polder farmers

The unique geographical location of the coastal Bangladesh makes it particularly vulnerable to flood, salinity intrusion and drought (Mondal et al., 2001; Auerbach et al., 2015; Yadav et al., 2020). In order to effectively plan for disaster risk reduction for polder areas, we need to better understand how local people perceive climatic risk (Dasgupta et al., 2014; Shameem et al., 2015). Disaster perceptions and potential adaptation strategies are important for effectively creating policies as well as providing practitioners key insights into farmer behavior.

We analyzed polder inhabitant's climate risk perceptions for four key climatic hazards using a standardized index (Eqs. (1) and (2)). First, the climate change perception score was calculated using frequency analysis, and then converted to a standardized index. Based on the highest score, we ranked the perceived climate risks (Table 3). Farmers ranked insect infestation highest among risks, followed by flood, drought, and salinity. It was surprising that salinity ranked lowest compared to other climatic hazards given how much attention has been focused on this in the literature for polders near our study area, although polders in our study are notably medium saline not highly saline like others (Shameem et al., 2015; Dasgupta et al., 2018; Chen and Mueller 2018). The results of our study indicate that salinity continues to be one of the chief hazards for increasing agricultural productivity in the medium-saline coastal zone of Bangladesh. Nevertheless, from the SCCRPI risk ranking, we conclude that polder people consider insect infestation and flooding as the primary climatic hazards in their region. Drought and salinity were considered less frequent climatic hazards in our study area. However, due to low land elevation, high rainfall, poor management of sluice gates despite the proximity of tidal river channels, the polder

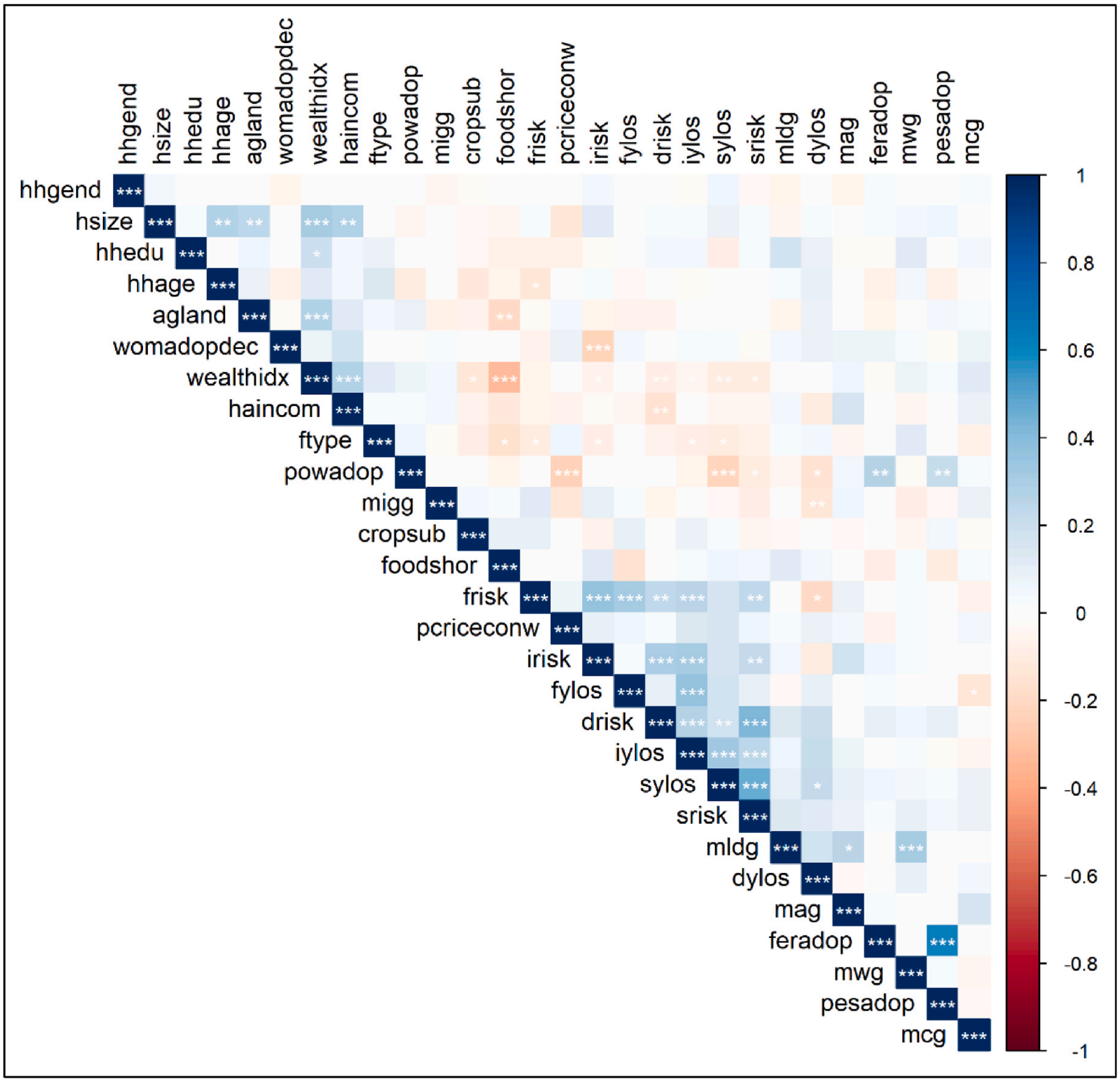

Fig. 3. Pearson correlation matrix of model variables.

areas are frequently affected by flooding and water stagnation. In addition, polder areas have been frequently affected by devastating storms and tidal surges, which bring their own kind of persistent flooding—e.g., major cyclones Sidr in 2007, Aila in 2009, Mohasen in 2013, and Amphan in 2020 (Auerbach et al., 2015; Dasgupta et al., 2014). Insect infestation may be increasing due to the adaptation of a mono-cropped rice regime in an increasingly more humid environment. Similar findings were observed in our study and others in literature (Uddin et al., 2014; Morshed et al., 2020).

3.3. *Types of farmers and factors affecting perceived climatic risk in polder areas*

It is important to know which factors affect farmers' perceptions of climate variability and then which ones determine new technology adoption (Slegers 2008). Therefore, we extended our analysis of farmers' perceived climatic risk ranking for polder areas using SUR methods in order to understand and identify factors and types of farmers aware of local climate change. We specifically analyze four climatic events as we assume that these four perception categories are likely to be correlated. Their combined results as a system are presented in Table 4. From the underlying assumption of the SUR model, we know that the model's residuals are assumed to be correlated across all four equations. For better understanding, we calculated the correlations of the residuals for each of the four equations in the SUR model in the appendix (Table A2).

The results from the perceived change in insect infestation model suggest that farmers' household size ($p < 0.01$), income generation group membership ($p < 0.1$), agriculture group membership ($p < 0.01$), % yield loss by insect infestation ($p < 0.01$) and per capita rice consumption ($p < 0.1$) have a statistically significant positive association with their perception about change in insect infestation. Farmer's household size, income generation group membership, agriculture group membership, % yield loss by insect infestation and per capita rice consumption increases the probability of perceived insect infestation risk. With increasing household size, it is highly likely that farmers will perceive a yield loss due to an insect infestation. Large families are more prominent in their communities and tend to gather more news from the outside world, which increases family members' knowledge about community perception. However, other studies have shown that household size was negatively and significantly associated with farmer's climate change perception (Ehiakpor et al., 2016; Ndambiri et al., 2014). In Ehiakpor and Ndambiri's contexts, small farming households were *more* likely to perceive climate variability. In contrast, farmers who

Table 2
Demographics and socio-economic characteristics of the polder respondents.

Characteristic	Scoring system	Categories	Respondents N	(%)	Mean	SD
Gender HH head	Code	Male (1)	967	96.41	0.96	0.19
		Female (2)	36	3.59		
Age of HH head	Years	Young (≤35)	164	16.35	52	14
		Middle (36–50)	338	33.70		
		Old (>51)	501	49.95		
Education HH head	Code	Literate (1)	879	87.64	0.88	0.33
		Illiterate (0)	124	12.36		
Family size	Number	Small (up to 4)	516	51.45	4.90	1.52
		Medium (5–6)	324	32.30		
		Large (>6)	163	16.25		
Primary Occupation HH head	Code	Agriculture (1)	856	85.34	1.98	1.64
		Service (2)	36	3.59		
		Business (3)	28	2.79		
		Day labor (4)	55	5.48		
		Others (5)	28	2.79		
Annual Family Income	USD	Low (up to USD 600)	471	31.95	759.62	463.72
		Medium (USD 601–1000)	711	48.24		
		High (>USD 1000)	292	19.81		
Farm size	Hectare	Small farm (<1.01 ha)	877	87.44	0.55	0.36
		Medium farm (1.01–3.03 ha)	124	12.36		
		Large farm (>3.03 ha)	2	0.20		
Farm types	Code	Owned (1)	855	85.24	0.85	0.25
		Leased (0)	148	14.76		

belong to any income generation and agricultural group are highly likely to notice changes in insect infestation in their fields. With income generation and agricultural group membership, farmers can learn about a changing climate's impact on pest proliferation, aligned with findings of Gbetibouo (2009). Complicating this shared perception, % yield loss by drought ($p < 0.01$), household's annual income ($p < 0.05$), crop submergence ($p < 0.05$) and female's decision in technology adoption ($p < 0.01$) all have a significant negative association with perceived change in insect infestation.

The results from the perceived changes in flooding model show a statistically significant positive association of farmer's flood risk perception between agriculture group membership ($p < 0.05$), % yield loss by flood ($p < 0.01$) and % yield loss by insect infestation ($p < 0.01$). This suggests that with increasing agriculture group membership, % yield loss by flood and insect infestation, farmers may be highly likely to perceive changes in flood risk. With agricultural group membership, farmers may interact with their local farming community and agricultural experts and trade experiences about flooding impacts. Similar findings arose from two separate studies done by Maddison (2007) and Deressa et al. (2011), both noting that farmers' access to information through various group membership is likely to enhance climatic change perception. We also find a positive association between farmer's flood risk perception and % yield loss by insect infestation. It might be that yield loss is a fundamental problem in agricultural production systems and may not be easily disaggregated across perceived floods and insect infestations. Moreover, flooding may create an environment more ideal for insect infestations. When farmers experience yield loss, they may perceive various factors responsible for that loss and in this case, they might identify insect infestation as the primary reason. However, we find a significant negative association between household head age ($p < 0.05$), % yield loss by drought ($p < 0.01$), and household's annual income ($p < 0.05$) with their perception about change in flooding events.

We see slightly different results from the perceived change in drought model. Farmer's local development group membership ($p < 0.05$), % yield loss by drought ($p < 0.01$) and % yield loss by insect infestation ($p < 0.01$) has a statistically significant positive association with their perception about change in drought risk. As group membership increases and as farmers perceive % yield loss by drought and insect infestation, farmers are highly likely to identify changes in drought risk in their community. Agricultural and climatic related knowledge can be disseminated and discussed easily through local development groups. Being part of any local development group, farmers can learn about drought and other associated impacts. According to Nhemachena and Hassan (2007) and Tesso et al. (2012), access to different types of extension services and receiving training from local development groups often gives farmers a greater perception of climatic change. As with the perceived flood risk model, we see a statistically significant positive association between farmer's drought risk perception and % perceived yield loss by insect infestation. This likely means that farmers experiencing yield loss have a challenging time disaggregating impacts across different factors. However, we found a statistically significant negative association between drought risk perceptions and household annual income ($p < 0.01$). As household income rises, droughts recede as a threat. However, we expect to see a positive relationship between these two variables. Semenza et al. (2008) found that household income positively and significantly influenced the perception of climate change.

Results in Table 4 shows that credit group membership ($p < 0.01$), local development group membership ($p < 0.05$), % yield loss by salinity ($p < 0.01$) and % yield loss by insect infestation ($p < 0.05$) have a significant and positive association with salinity risk perceptions. Farmers who are involved with credit and local development groups, perceived % yield loss by salinity and insect infestation, are likely to perceive an increase in salinity risk. Other studies (Nhemachena and Hassan 2007; Maddison 2007; Gbetibouo 2009) have shown similar findings that different types of development group memberships positively and significantly influence the perception of climate change. Importantly, we find that greater household wealth has negative implications on perceptions of all four major climate risks.

3.4. Adoption of improved agricultural technologies as an adaptation strategy

Table 5 illustrate both a binomial probit and the marginal effects of independent variables for three adaptation models. The results from the fertilizer adoption model show that five variables, i.e., age of household head, perceived change in insect infestation, food shortage, per capita rice consumption and female's decision-making in technology adoption have a significant influence on fertilizer adoption. Among those, age of

Table 3
Results of SCCRPI analysis about farmers' perception of agricultural risks from climatic change.

Climatic hazards	High Occurrence	Medium Occurrence	Low Occurrence	No Occurrence	CCRPS	SCCRPI	Rank
Insect Infestation	336	316	205	44	1845	61.32	1st
Flood	181	485	177	55	1690	56.16	2nd
Drought	39	230	191	199	768	25.52	3rd
Salinity	90	105	116	276	596	19.81	4th

Table 4
Results of SUR analysis about farmers' perception about climatic risk.

Characteristic	Perceived change in insect infestation	Perceived change in flood	Perceived change in drought	Perceived change in salinity
Gender of household head	0.03 (0.05)	−0.02 (0.05)	−0.01 (0.11)	−0.12 (0.11)
Age of household head	−0.00 (0.00)	**−0.00**** (0.00)	−0.00 (0.00)	−0.00 (0.00)
Household size	**0.01***** (0.00)	0.01 (0.01)	0.01 (0.01)	0.01 (0.01)
Education of household head	0.02 (0.03)	−0.02 (0.03)	0.04 (0.06)	0.07 (0.06)
Farm type	−0.03 (0.03)	−0.03 (0.03)	−0.04 (0.05)	−0.03 (0.05)
Membership credit group	0.03 (0.04)	−0.02 (0.05)	0.11 (0.08)	**0.22***** (0.08)
Membership income generation group	**0.05*** (0.03)	0.04 (0.03)	−0.09 (0.06)	−0.09 (0.06)
Membership local development group	0.02 (0.02)	−0.00 (0.02)	**0.08**** (0.04)	**0.08**** (0.04)
Membership agriculture group	**0.07***** (0.02)	**0.04**** (0.02)	0.00 (0.04)	0.04 (0.04)
Membership water group	0.01 (0.02)	0.02 (0.03)	−0.01 (0.05)	0.04 (0.05)
% Yield loss by flood	0.00 (0.00)	**0.00***** (0.00)	−0.00 (0.00)	−0.00 (0.00)
% Yield loss by drought	**−0.00***** (0.00)	**−0.00***** (0.00)	**0.00***** (0.00)	−0.00 (0.00)
% Yield loss by salinity	0.00 (0.00)	0.00 (0.00)	−0.00 (0.00)	**0.01***** (0.00)
% Yield loss by insect infestation	**0.00***** (0.00)	**0.00***** (0.00)	**0.00***** (0.00)	**0.00**** (0.00)
Fertilizer adoption	0.04 (0.05)	−0.02 (0.05)	−0.01 (0.10)	−0.14 (0.10)
Power tiller adoption	−0.00 (0.03)	−0.01 (0.04)	−0.01 (0.07)	−0.06 (0.07)
Pesticide adoption	−0.01 (0.04)	0.01 (0.04)	0.09 (0.08)	0.10 (0.09)
Household annual income	**−0.00**** (0.00)	**−0.00**** (0.00)	**−0.00***** (0.00)	**−0.00**** (0.00)
Agricultural farmland	−0.02 (0.02)	0.00 (0.02)	−0.06 (0.04)	−0.01 (0.04)
Crops submerge	**−0.04**** (0.02)	0.02 (0.02)	−0.00 (0.04)	**−0.08*** (0.04)
Food shortage	0.04 (0.02)	0.00 (0.03)	−0.03 (0.05)	0.02 (0.05)
Per capita rice consumption	**0.01*** (0.01)	0.01 (0.01)	−0.01 (0.01)	−0.01 (0.01)
Female's decision in technology adoption	**−0.07***** (0.02)	−0.02 (0.02)	0.00 (0.04)	−0.02 (0.04)
Wealth index	−0.01 (0.01)	−0.00 (0.01)	−0.02 (0.02)	−0.03 (0.02)
Intercept	**0.75***** (0.10)	**0.96***** (0.11)	**0.70***** (0.20)	**0.59***** (0.20)
Number of observations	901	898	659	587
Pseudo R^2	0.18	0.15	0.12	0.24
Wald chi-square	120.9	106.3	20.3	11.1
Probability (p)	0.00	0.00	0.00	0.02
OLS-R^2	0.18			
McElroy-R^2	0.42			

All continuous predictors are mean-centered and scaled by 1 standard deviation. Standard errors are heteroskedasticity robust. ***$p < 0.01$; **$p < 0.05$; *$p < 0.1$.

household head ($p < 0.05$), food shortage ($p < 0.05$) and per capita rice consumption ($p < 0.1$) have a significant, negative relationship with fertilizer adoption. Perceived change in insect infestation risk ($p < 0.1$) and female's decision-making in technology adoption ($p < 0.1$) have a significant positive relationship with adoption of fertilizer. However, the marginal effects show that four predictor variables, age of household head, food shortage, per capita rice consumption and female's decision-making in technology adoption were significant. Except for female's decision-making in technology adoption, all three predictor variables have a negative relationship with fertilizer adoption. This suggests that engaging women in the decision-making process could substantially improve technology adoption. An increase in the age of the head of household lowers the probability of fertilizer adoption ($p < 0.05$). Older farmers may be more risk-averse than younger farmers and hence follow traditional methods. According to Haider et al. (2018), older age reduces the likelihood of fertilizer adoption. Several other adaptation studies found that a farmer's age has a negative association with adaptation strategies (Islam et al., 2020a; Uddin et al., 2014; Gbetibouo 2009).

From the pesticide adoption model, we can see that out of twenty-five predictor variables, three predictor variables, i.e., age of household head, perceived change in drought and food shortage significantly influence pesticide adoption. Two predictor variables, specifically age of household head ($p < 0.05$) and food shortage ($p < 0.05$) have a negative relationship with pesticide adoption. In contrast, perceived change in drought risk ($p < 0.05$) has a positive relationship with pesticide adoption. From the pesticide marginal effects model the same is true except for crop submergence. The same three predictor variables and crop submergence were found to influence the adoption of pesticides. From the marginal effects of pesticide adoption, results show that age of household head and food shortage decrease the probability of pesticides adoption ($p < 0.05$). As food shortage increases, farmers potentially buy food rather than pesticide. Hence arises a negative association. In contrast, perceived change in drought risk and crop submergence increases the probability of pesticides adoption by 6% ($p < 0.05$) and 4% ($p < 0.05$), respectively. Drought and flooding have widely been considered the riskiest climatic hazards in south-western Bangladesh (Abedin et al., 2012).

Lastly, we turn to the power tiller adoption model. Seven variables, specifically age of household head, farm type, perceived change in drought, % yield loss by drought, % yield loss by salinity, composition of farmland, and per capita rice consumption had a significant influence on power tiller adoption. Among those seven variables, four variables had a negative effect on power tiller adoption: age of household head ($p < 0.05$), % yield loss by drought ($p < 0.05$), % yield loss by salinity ($p < 0.05$) and per capita rice consumption ($p < 0.01$). Farm type ($p < 0.1$), perceived change in drought ($p < 0.1$) and farmland ($p < 0.05$) have a significant positive relationship with power tiller adoption. However, from the marginal effects, five out of seven variables, i.e., age of household head, % yield loss by drought, % yield loss by salinity, agricultural farmland and per capita rice consumption were significant. Except for the farmland variable, all four variables had a negative relationship with power tiller adoption. From the results, we see that age of household head decreases the probability of power tiller adoption ($p < 0.01$), % yield loss by drought decreases the probability of power tiller adoption ($p < 0.05$), % yield loss by salinity decreases the probability of power tiller adoption ($p < 0.05$) and per capita rice consumption decreases the probability of power tiller adoption ($p < 0.01$). In contrast, greater expanses of agricultural farmland increase the probability of power tiller adoption by 5% ($p < 0.05$). Indeed, farmers with greater landholdings have easier access to the capital markets necessary for debt-financed capital goods. Similar findings were found in previous studies (Abid et al., 2016; Ali and Erenstein 2017).

While this study sheds light on how climate change risk perceptions may affect the propensity to adopt agricultural technologies, more research is needed to understand how additional support from NGO's and governments increases adoption rates. For example, a number of

Table 5
Results of probit estimation and marginal effects of the determinants of technology adoption.

Characteristic	Fertilizer Adoption		Pesticides Adoption		Power tiller Adoption	
	Probit	Marginal effects	Probit	Marginal effects	Probit	Marginal effects
Gender of household head	0.34	0.03	0.09	0.01	0.16	0.02
	(0.56)	(0.06)	(0.55)	(0.07)	(0.62)	(0.07)
Age of household head	**−0.02****	**−0.00****	**−0.02****	**−0.00****	**−0.02****	**−0.00*****
	(0.01)	(0.00)	(0.01)	(0.00)	(0.01)	(0.00)
Household size	0.06	0.00	0.08	0.01	−0.06	−0.01
	(0.06)	(0.00)	(0.06)	(0.01)	(0.05)	(0.00)
Education of household head	−0.23	−0.01	−0.19	−0.02	−0.10	−0.01
	(0.38)	(0.02)	(0.30)	(0.03)	(0.31)	(0.02)
Farm type	0.11	0.01	−0.12	−0.01	**0.50***	0.06
	(0.34)	(0.02)	(0.28)	(0.03)	(0.26)	(0.04)
Membership credit group	−0.02	−0.00	−0.41	−0.04	0.60	0.08
	(0.51)	(0.03)	(0.50)	(0.03)	(0.39)	(0.07)
Membership income generation group	−0.14	−0.01	−0.15	−0.02	−0.33	−0.02
	(0.43)	(0.02)	(0.38)	(0.04)	(0.38)	(0.02)
Membership local development group	−0.04	−0.00	−0.00	−0.00	−0.12	−0.01
	(0.25)	(0.01)	(0.21)	(0.02)	(0.23)	(0.02)
Membership agriculture group	0.05	0.00	−0.05	−0.01	0.32	0.03
	(0.24)	(0.01)	(0.20)	(0.02)	(0.22)	(0.02)
Membership water group	−0.01	0.00	0.21	0.02	0.05	0.00
	(0.28)	(0.02)	(0.25)	(0.02)	(0.26)	(0.02)
Perceived change in insect infestation	**0.75***	0.08	0.12	0.01	0.10	0.01
	(0.42)	(0.07)	(0.38)	(0.05)	(0.46)	(0.05)
Perceived change in flood	−0.37	−0.02	−0.10	−0.01	−0.49	−0.03
	(0.41)	(0.01)	(0.33)	(0.03)	(0.44)	(0.02)
Perceived change in drought	0.43	0.03	**0.51****	**0.06****	**0.43***	0.04
	(0.29)	(0.02)	(0.22)	(0.03)	(0.25)	(0.02)
Perceived change in salinity	−0.28	−0.02	−0.01	−0.00	−0.32	−0.03
	(0.31)	(0.02)	(0.24)	(0.03)	(0.26)	(0.03)
% Yield loss by flood	0.00	0.00	−0.00	−0.00	0.01	0.00
	(0.01)	(0.00)	(0.00)	(0.00)	(0.01)	(0.00)
% Yield loss by drought	−0.00	−0.00	0.00	0.00	**−0.01****	**−0.00****
	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
% Yield loss by salinity	0.03	0.00	0.00	0.00	**−0.01****	**−0.00****
	(0.02)	(0.00)	(0.01)	(0.00)	(0.01)	(0.00)
% Yield loss by insect infestation	−0.01	−0.00	−0.01	−0.00	0.00	0.00
	(0.01)	(0.00)	(0.01)	(0.00)	(0.01)	(0.00)
Household annual income	0.00	0.00	0.00	0.00	−0.00	−0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Agricultural farmland	−0.27	−0.02	0.02	0.00	**0.55****	**0.05****
	(0.21)	(0.01)	(0.21)	(0.02)	(0.27)	(0.02)
Crops submerge	0.02	0.00	0.42	**0.04****	0.12	0.01
	(0.28)	(0.02)	(0.26)	(0.02)	(0.26)	(0.02)
Food shortage	**−0.71****	**−0.06***	**−0.57****	**−0.09****	−0.01	−0.00
	(0.29)	(0.04)	(0.24)	(0.04)	(0.25)	(0.02)
Per capita rice consumption	**−0.14***	**−0.01***	0.00	−0.00	**−0.22*****	**−0.02*****
	(0.08)	(0.00)	(0.07)	(0.01)	(0.05)	(0.01)
Female's decision in technology adoption	**0.45***	**0.03***	−0.15	−0.02	0.16	0.01
	(0.24)	(0.02)	(0.20)	(0.02)	(0.21)	(0.02)
Wealth index	−0.12	−0.01	0.05	0.01	0.10	0.01
	(0.14)	(0.01)	(0.11)	(0.01)	(0.12)	(0.01)
Constant	**2.66****		**2.47****		**2.25****	
	(1.21)		(1.04)		(1.02)	
Observations	474					
Log Likelihood	−78.02		−116.53		−98.14	
AIC	208.04		285.06		248.29	
Pseudo R^2	0.18		0.13		0.29	
Wald chi-square	28.01		26.69		58.50	
Probability (p)	0.31		0.37		0.00	

Note: All continuous predictors are mean-centered and scaled by 1 standard deviation. Standard errors are heteroskedasticity robust. ***$p < 0.01$; **$p < 0.05$; *$p < 0.1$.

NGO's provide donations and technical assistance to farmers, and government subsidies assist with capital barriers to adoption. In some cases, support is more indirect in the form of infrastructure construction or farmer training programs. In future studies, more information should be collected on these factors that may also support technology adoption among farmers. Although we were limited by the data available in the questionnaire, our results provide new insights into climate change risk perceptions and technology in the polders of Bangladesh.

4. Conclusions

The agrarian communities in the polders of coastal Bangladesh face tremendous challenges in adapting to climate change. With high levels of poverty, farmers must find ways to increase and diversify agricultural production to meet food security needs and improve livelihoods. In this study, we examined farmer perceptions of climate change impacts on agriculture and further investigated the impacts of these perceptions on technology adoption. Results from this study provide relevant information for policymakers and development practitioners working toward climate change adaptation and resilience in the polders. Our findings suggest that polder farmers experience substantial agricultural losses from climate change events, and that the perception of climate change risk influences their adoption of technology. Additionally, we show that farmers belonging to community groups have a higher propensity to adopt sustainable intensification practices, which suggests farmer networks play a strong role in adaptation. Overall, the results of this study are important for practitioners in agricultural development and for funding agencies leveraging opportunities to support and improve sustainable intensification in the polder region of Bangladesh. Moreover, the analysis may be repeated or used in support of projects in other agriculture-dependent regions that are highly vulnerable to climate change. Given many people in the polders rely on agricultural production for their livelihoods, a deeper understanding of how farmers threatened by climate change make adaptation decisions as presented in this study is essential for policymakers, international donors, and other stakeholders involved in the development of the coastal zone.

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Available upon request through Harvard Dataverse.

Code availability

Available upon request of the author.

Ethics approval

Not applicable.

Consent to participate

Not applicable.

Consent for publication

The authors give the publisher the permission to publish the work.

Credit author statement

Zobaer Ahmed: Conceptualization, Formal analysis, Investigation, Methodology, Writing. Aaron M. Shew: Conceptualization, Formal analysis, Investigation, Methodology, Writing. Manoranjan K. Mondal: Project administration, Data curation, Investigation, Writing. Sudhir Yadav: Funding acquisition, Data curation, Writing. S.V. Krishna Jagadish: Funding acquisition, Data curation, Writing. P.V. Vara Prasad: Funding acquisition, Data curation, Writing. Marie-Charlotte Buisson: Data curation, Investigation, Writing. Mahanambrota Das: Data curation, Writing. Mustafa Bakuluzzaman: Data curation, Writing.

Conflicts of interest

The authors declare no competing interests.

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Appendix

Table A.1
Variance Inflation Factor (VIF) value of model variables

Variable name	VIF value
Gender of household head	1.0
Age of household head	1.2
Household size	1.4
Education of household head	1.1
Farm type	1.1
Membership credit group	1.1
Membership income generation group	1.1
Membership local development group	1.3
Membership agriculture group	1.2
Membership water group	1.2
Insect risk perception	1.6
Flood risk perception	1.5
Drought risk perception	1.5
Salinity risk perception	1.6
Flood yield loss	1.4
Insect infestation yield loss	1.5
Drought yield loss	1.4
Salinity yield loss	1.5
Fertilizer adoption	1.8
Power tiller adoption	1.3
Pesticide adoption	1.8
Household annual income	1.3
Agricultural farmland	1.2
Crops submerge	1.1
Food shortage	1.3

(*continued on next page*)

Table A.1 (*continued*)

Variable name	VIF value
Per capita rice consumption	1.2
Female's decision in technology adoption	1.2
Wealth index	1.5

Table A.2
The correlations of the SUR model residuals

Characteristic	Perceived change in insect infestation	Perceived change in flood	Perceived change in drought	Perceived change in salinity
Perceived change in insect infestation	1.000	0.296	0.287	0.149
Perceived change in flood	0.296	1.000	0.241	0.200
Perceived change in drought	0.287	0.241	1.000	0.386
Perceived change in salinity	0.149	0.200	0.386	1.000

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