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ORIGINAL RESEARCH ARTICLE

Impacts of climate change and tropical cyclones on rice farming in coastal Bangladesh

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Abstract: The coastal agriculture sector is highly exposed to natural disasters, especially cyclones, severely affecting rice production and farmer livelihoods in Bangladesh. This study aimed to assess the impacts of Cyclones Amphan and Bulbul on rice production in the cyclone-prone districts of Khulna and Satkhira. The analysis focused on rice-producing farming households in these districts using primary data collected from 400 farmers (200 in each district) through structured interviews, focus group discussions, and key informant interviews. T-tests, Cobb Douglas production functions, and panel fixed effects regressions were applied to estimate production losses. The results showed that Cyclone Amphan reduced rice output by 38% in Khulna and 26% in Satkhira. Cyclone Bulbul caused losses of 45% in Khulna and 38% in Satkhira. Average production losses ranged 30 – 37% across both events. Panel regression results further showed that rice production decreased by 29%, 22%, and 26% in Khulna, Satkhira, and both regions combined, respectively, during the cyclone season compared to the pre-cyclone period. Farmers whose primary occupation was agriculture, and who had lower levels of education and smaller household sizes, experienced greater financial losses. These results offer evidence to inform targeted adaptation and disaster mitigation strategies for coastal farming communities.

Keywords: Disaster impact; Agricultural vulnerability; Amphan; Bulbul; Rice production; Cobb-Douglas model

1. Introduction

Bangladesh is highly vulnerable to tropical cyclones due to its geographical location. Its topography and position at the triangular-shaped head of the Bay of Bengal make it susceptible to frequent natural hazards, such as tropical cyclones and associated storm surges.[1] Besides, the low-lying coastal area, high population density, and lack of coastal flood defenses further heighten its vulnerability.[2] The tropical monsoon climate of the South Asian subcontinent and proximity to the equator also increases the country's exposure to cyclones.[3] Consequently, the southern coastal region has repeatedly experienced tropical cyclones, tidal surges, salinity intrusion, flash-flooding, and waterlogging over the years.[4,5] As the Bay of Bengal is a significant source of tropical storm formation,[6] the 580 km coastline of the country remains highly susceptible to cyclones along with other natural hazards.[7]

In recent years, tropical cyclones have caused significant economic loss and damage in Bangladesh. Besides, it has caused various forms of noneconomic damages, such as property damage and adverse impacts on agriculture and livelihoods.[8-14] Historical cyclone data reveal the recurring nature of these disasters and their devastating consequences on the populations and infrastructure.[15,16] The World Meteorological Organization estimated that tropical cyclones have led to an average of USD 78 million in damages and 50 casualties daily over the past 50 years in the country.[14] Moreover, storm surges and inundation have posed significant threats to lives and property in affected regions.[13,17]

Cyclones have had a negative impact on crop production in coastal Bangladesh, causing crop loss, soil salinity, waterlogging, damage to agricultural inputs, delayed planting, and reduced yields. Several studies have investigated the vulnerability of coastal agriculture to cyclones.[9,10,18] Recent changes in climatic variables—like rising temperatures, erratic rainfall, and increased cyclone intensity—have further exacerbated these challenges by reducing crop production and increasing food insecurity in the region.[19] In coastal areas, cyclones have affected millions of people, destroying homes and livelihoods, and triggering migration.[7] For instance, the economic damage from events like Cyclone Sidr in 2007 has severely impacted the agriculture, housing, and construction sectors.[14] The impact also extended to rural water supply, sanitation, and public health, underscoring the need to explore adaptation strategies.[20] Besides, cyclones like Sidr (2007) and Aila (2009) caused severe damage to coastal fisheries and fishing grounds, further impacting the agricultural economy.[21]

Super Cyclone Amphan, which struck coastal Bangladesh in May 2020, caused significant economic impacts. The cyclone led to widespread destruction of agricultural land, forests, and infrastructure, causing substantial income loss and heightened food insecurity among affected households.[16] The aftermath included the destruction of thousands of houses, embankment collapses, and extensive saltwater flooding of agricultural land, leading to the decimation of crops and livelihoods.[22] The cyclone also caused USD 130 million in damages, making it one of the costliest storms in the North Indian Ocean region.[23] Similarly, Cyclone Bulbul made landfall on the southwestern coast of Bangladesh on November 10, 2019, with storm surges of 1.0 – 1.5 m, inundating low-lying areas across 14 coastal districts.[24]

Given this context, the present study aims to analyze the impact of Cyclone Amphan and Bulbul on rice production in coastal Bangladesh. Specifically, we addressed the effects of these cyclones on rice production in the affected coastal regions. To the best of our knowledge, this is the first attempt to investigate the cyclone impacts on farm-level rice production in coastal Bangladesh.

2. Literature review

In recent years, there has been a noticeable increase in the occurrence and severity of disasters, especially cyclones, in different parts of the world. Several studies have documented the substantial challenges cyclones pose to vulnerable households in cyclone-prone areas.[25] For instance, households in coastal Bangladesh reported a rise in climate hazards, notably tropical cyclones, storm surges, and flash floods. These events caused significant economic damages, averaging USD 144 per household following Cyclone Aila.[26] Similarly, Kmoch *et al.*[27] outlined how existing vulnerabilities, agricultural difficulties, and cascading impacts of Cyclone Komen disproportionately affected lowland and upland communities in western Myanmar. The repercussions of cyclones extend beyond economic loss, impacting various aspects of household well-being. Subhani *et al.*[3] reported severe consequences of Cyclone Yaas (2021), including losses in income, housing, food consumption, and water, sanitation, and hygiene conditions among affected households in Bangladesh.

Shamsuzzoha *et al.*[28] used Landsat 8 operational land imager and thermal infrared sensor data, incorporating normalized difference vegetation index, soil-adjusted vegetation index, and soil moisture index-based change detection, combined through a weighted overlay and pixel-code sum method, to assess cyclone damage in coastal Bangladesh. Their findings showed that of 309.08 km² of agricultural land, only 2.50% remained undamaged, with 87.01% of damage occurring in transplanted Aman rice fields and 5.28% in winter vegetable fields. Hossain *et al.,*[29] using the Ricardian method, found that rising temperatures and rainfall positively impacted net crop income, especially in irrigated areas. Farukh *et al.*[30] analyzed the impact of 52 severe cyclones (1960 – 2010) on coastal agriculture using tropospheric instability indexes, general circulation model, and geographic information system, reporting major losses in Boro rice, Aus rice, and other crops, especially during the 1991 cyclone. Kabir *et al.*[18] used thematic analysis to study the impacts of Cyclones Sidr and Aila on coastal communities in Amtali (Barguna) and Koyra (Khulna), revealing severe effects on livelihoods, health, and vulnerable populations, with poor health increasing disease susceptibility. Huq *et al.*[31] applied participatory rural appraisal to examine climate change impacts on smallholder farmers in coastal Bangladesh. The impacts were categorized as first-order (increased vulnerability), second-order (shifts in agriculture and production), and third-order (decline in livelihood resources). Haque and Jahan[32] used input-output modeling to assess the economic impacts of Cyclone Sidr at the regional and national levels in Bangladesh. The study found that Chittagong experienced the highest productivity loss, while Barishal faced the greatest declines in income and employment, though the study lacked household-level analysis. Ahmed and McDonnell[33] showcased the extensive housing damage caused by cyclones like Harold in Vanuatu. Collectively, these findings underscore the disruptive potential of cyclones on households and livelihoods in vulnerable regions.

The aftermath of cyclones leads to immediate economic losses and long-term implications for households. Research has indicated that cyclones can decrease household income, increase health expenditures, disrupt educational investments, and exacerbate socioeconomic challenges in affected communities.[34,35] Subhani and Ahmad[36] indicated adverse socioeconomic impacts of cyclones on household assets, incomes, livelihood options, and food consumption among both migrant and non-migrant families in coastal Bangladesh. In addition to economic and social impacts, cyclones pose major health risks. Events such as Cyclones Sidr and Aila have been associated with heightened health complications among coastal populations.[37]

Cyclones are recognized as major natural disasters with detrimental effects on agricultural productivity. Rahman *et al.*[38] identified changes in climatic conditions, including increased cyclone frequency, as key contributors to reduced crop yields and livestock production in the southwestern coastal region. In cyclone-prone areas such as the Bay of Bengal, tropical cyclones have caused significant agricultural damage.[39] The vulnerability of agricultural systems in coastal zones is a critical factor contributing to severe farm-level losses in tropical countries.[40] Kunze[41] further revealed the negative impact of tropical cyclones on a range of economic sectors, including agriculture, hunting, forestry, fishing, trade, and tourism. Additionally, cyclones have been linked to the reductions in coastal land suitable for agriculture,[42] with low-lying villages being especially hard-hit and facing significant challenges in sustaining agriculture.[43]

Cyclones also significantly impact the income, expenditure, and welfare of farming households. Low-income farmers are particularly vulnerable due to their limited capacity to mitigate or adapt to such shocks.[44] Several studies have highlighted the multifaceted and cascading effect of cyclones on smallholder agricultural activities, underscoring the need for a comprehensive understanding of the challenges they face.[45] Hossain and Paul[21] explored the effectiveness of disaster mitigation measures in vulnerable regions like coastal Bangladesh, emphasizing the importance of understanding the underlying vulnerability factors and implementing strategies to enhance resilience. Household resilience in coastal areas is crucial for coping with cyclone impacts and requires adequate access to resources and proactive response mechanisms.[46] For instance, Hossain[16] found that Cyclone Amphan caused food insecurity, income loss, and psychological distress among adults in coastal Bangladesh.

3. Methods

3.1. Study area selection

This study was conducted in Shyamnagar and Koyra upazilas, located in the Satkhira and Khulna districts of Bangladesh, respectively. These regions were selected due to the severe impact they experienced from Cyclone Amphan in 2020 and Cyclone Bulbul in 2019. Shyamnagar is located in southwestern Satkhira between 21°40’ and 22°24’ N latitudes and 89°00’ and 89°19’ E longitudes. It spans an area of 1,968.24 km^2 and shares a border with the Sundarbans mangrove forest, making it highly vulnerable to cyclones and tidal surges. Koyra is situated between 22°12’ and 22°31’ N latitudes and 89°14’ and 89°29’ E longitudes, spanning 1,775.41 km^2 near the Bay of Bengal. The proximity to the coast and intricate network of rivers and canals further increases its vulnerability to cyclonic events and saline water intrusion.

Ten unions were selected from the two upazilas—five from each—based on the severity of damage caused by the cyclones (Figure 1). The selected unions in Shyamnagar were Bhurulia, Ishwaripur, Koikhali, Nurnagar, and Ramjannagar; in Koyra, they were Uttar Bedkashi, Dakshin Bedkashi, Koyra, Amadi, and Moharajpur. These unions were chosen due to their direct and significant exposure to the cyclones, making them suitable for analyzing the effects of cyclones on rice production.

For comparison, two control upazilas—Dumuria in Khulna and Kalaroa in Satkhira— were selected to represent cyclone-unaffected regions. The aim was to assess differences in rice productivity between cyclone-affected and unaffected areas. Five unions were randomly selected from each control upazila: Atlia, Dumuria, Raghunathpur, Rangpur, and Sahas from Dumuria; and Jogikhali, Sonabaria, Jalalabad, Deara, and Joynagar from Kalaroa (Figure 1).

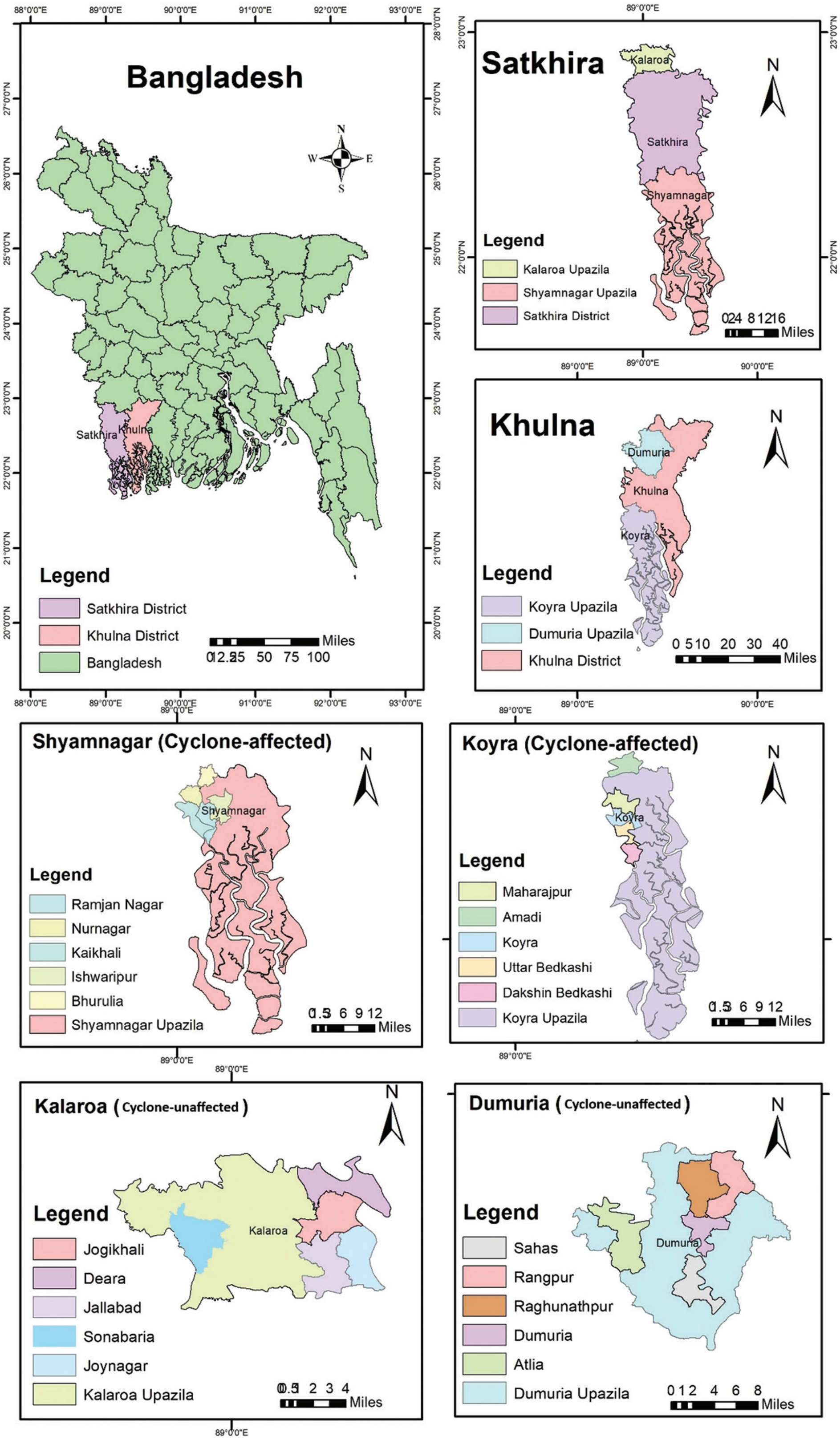

Figure 1. Maps of selected study locations in different unions of Bangladesh

3.2. Sampling and data technique

The sampling strategy targeted rice-producing farmers who were severely affected by the cyclones. A total of 400 cyclone-affected farmers were selected using a simple random sampling technique—200 each from five unions in Shyamnagar and Koyra upazilas. Similarly, 400 farmers were randomly selected from the ten unions in the control upazilas, Dumuria and Kalaroa. This selection ensured the inclusion of respondents with relevant experience and knowledge of agricultural practices and challenges in both cyclone-affected and unaffected regions.

Data were collected through face-to-face, in-depth interviews using a pre-tested semi-structured questionnaire designed to capture relevant information systematically. The interviews were further supplemented by focus group discussions. In addition, key informant interviews were conducted with local leaders, agricultural experts, and government officials. These interviews provided expert opinions and contextual information, offering critical insights that influence farmers' adaptation strategies. A case study approach was also employed to provide an in-depth analysis of the impacts and adaptive responses of the most affected unions. All data collection activities were performed between March and August 2023.

3.3. Empirical methods

3.3.1. Cobb-Douglas production function

The Cobb-Douglas production function is a widely used model in empirical research to analyze production efficiency. The general form of the function is expressed in Equation I.

$$Y_i = A \cdot X_{1i}^{\beta 1} \cdot X_{2i}^{\beta 2} \cdot \ldots \cdot X_{ki}^{\beta k} \cdot e^{\epsilon i} \quad \text{(I)}$$

where Y_i is the output of rice production for the i^{th} farmer; X_{1i}, X_{2i}., X_{ki} represents input variables (e.g., land, labor, seeds, fertilizers); β_1, β_2..., β_k are the output elasticities of the respective inputs; and ϵ_i is the error term.

To facilitate estimation, the function is transformed into a linear logarithmic form, as shown in Equation II.

$$InY_i = \beta_0 + \beta_1 \text{ In } X_{1i} + \beta_2 \text{ In } X_{2i} + \beta_3 \text{ In } X_{3i} + \beta_4 \text{ In } X_{4i} + \beta_5 \text{ In } X_{5i} + \gamma D_i + \varepsilon_I \quad \text{(II)}$$

where Y_i is the output measured in maunds (1 maund = 40 kg) of the i^{th} rice farmers; X_1 is the land size in acres (1 acre = 0.4047 hectares); X_2 is the human labor measured in man-days; X_3 is the quantity of rice seed used (kg); X_4 is the quantity of chemical fertilizer (kg); X_5 is the quantity of pesticide (kg); D is the cyclone dummy variable (1 = cyclone-affected farmers, 0 = non-affected farmers); γ captures the marginal effect of cyclone exposure on rice production; β_0, β_1,…, β_5 are the output elasticities of the respective inputs; and ε_i is the error term. The model assumes no perfect multicollinearity. Robust standard errors are applied to correct heteroskedasticity, and autocorrelation is assumed to be absent.

3.3.2. Event study with panel fixed effects regression model

An event study approach, using a fixed effects panel regression, was used to estimate the impact of cyclones on rice production across the three periods: before, during, and after the cyclone. The purpose of the model is to capture the dynamic effects of cyclones on rice production over time. The model, modified to include lagged variables, is expressed in Equation III:

$$Y_{it} = \alpha_i + \delta_1 \text{D}_{duringt} + \delta_2 \text{D}_{aftert} + \beta X_{it} + \varepsilon_{it} \quad \text{(III)}$$

where Y_{it} is the rice output (maunds) for the i^{th} farmer at time t; αi is the farmer-specific fixed effect (e.g., education, soil quality, market access); D_{during} is the dummy variable = 1 during the cyclone, 0 otherwise; D_{after} is the dummy variable = 1 after the cyclone, 0 otherwise; D_{before} is the base period (omitted); X_{it} is the vector of control variables (e.g., land, labor, seed, fertilizer, pesticide); ε_{it} is the idiosyncratic error term (i.i.d). In order to adjust for heteroskedasticity and autocorrelation, clustered standard errors at the farmer level were used.[47]

3.3.3. Relative cyclone loss (RCL) model

RCL measures the proportion of a household's annual income lost due to cyclone-induced damage. It provides a normalized metric to compare impacts across households of varying income levels, with higher RCL values reflecting greater financial vulnerability.[48] Equation IV shows the formula for estimating RCL.

$$\text{RCL} = \frac{\text{Cyclone loss}}{\text{Annual average income}} \quad \text{(IV)}$$

To identify the determinants of RCL, a multiple linear regression model was estimated (Equation V). It normalizes the disaster loss, making it possible to compare the impact across households of varying economic scales.

$$RCL_i = \emptyset_0 + \emptyset_1 Z_{1i} + \emptyset_2 Z_{2i} + \emptyset_3 Z_{3i} + \emptyset_4 Z_{4i} + \emptyset_5 Z_{5i} + \varepsilon_i \quad \text{(V)}$$

where RCL_i is the relative cyclone loss of i[th] farmer (measured across rice, fish, vegetables, and other crops); Z_1 is the dummy variable for occupation (1 = Primary occupation is agriculture, 0 otherwise); Z_2 is the age of farmer (years); Z_3 is the gender of the farmer (1 = Male, 0 = Female); Z_4 is the years of schooling; Z_5 is the family size (number of members); $\emptyset_1,\ldots\ \emptyset_5$ are the coefficients representing the influence of each independent variable on RCL; and ε_i is the error term. The model assumes zero perfect multicollinearity. Robust standard errors were used to mitigate heteroskedasticity.

3.3.4. T-test for comparison of sociodemographic and production-specific variables

The t-test is a parametric statistical test used to compare the means of two independent groups. In this study, a t-test was employed to assess sociodemographic and production-specific differences between cyclone-affected and unaffected farmers. The variables analyzed include age, education, household size, household income and expenditure, farming experience, as well as production-specific variables such as output, land area, labor, seed, fertilizer, and pesticide use. The t-test operates under the null hypothesis H_0: $\mu_1=\mu_2$ (i.e., no significant difference between the means of the two groups) and the alternative hypothesis H_1: $\mu_1\neq\mu_2$. Equation VI shows the formula for calculating the test statistic:

$$t = \frac{\bar{X}_1 - \bar{X}_2}{\sqrt{\frac{s_1^2}{n_1} + \frac{s_2^2}{n_2}}} \quad \text{(VI)}$$

where, $\bar{X}_1$ and $\bar{X}_2$ are the sample means, s_1^2 and s_2^2 are the sample variances, n_1 and n_2 are the sample sizes of the two groups. The calculated t-statistic is compared to a critical value from the t-distribution at a specified significance level (e.g., α = 0.05). If the t-statistic exceeds the critical value, the null hypothesis is rejected, indicating a significant difference between the groups.

4. Results

4.1. Summary statistics of rice farmers

The sociodemographic characteristics and farm-specific variables of cyclone-affected farmers are presented in Table 1. The average age of farmers is 48 years, ranging from 20 to 80 years. The educational attainment averages approximately 6 years, ranging from no formal education to a postgraduate degree. The average household size is 4 members, with some households comprising up to 15 individuals. The number of earning family members, excluding the household head, ranges from 0 to 5. The respondents' average monthly earnings and expenditures are BDT 15,166 and BDT 14,412, respectively. On average, farmers report 21 years of experience in rice production.

Regarding production-specific statistics, the average rice yield is 35.71 maund (approximately 1428.4 kg). The output level ranges from 5 to 390 maunds, depending on the inputs used. On average, 1.216 acres of land was cultivated, involving around 15 man-days of labor, 40 kg of seed, 68 kg of chemical fertilizer, and 1 kg of pesticide. Regional-specific descriptive statistics for cyclone-affected districts (Khulna and Satkhira) are presented in Tables A1 and A2, respectively. The sociodemographic characteristics are generally similar for both districts, with minor differences in a few variables.

The mean differences in the sociodemographic variables of cyclone-affected and unaffected farmers are presented in Table A3. On average, unaffected farmers have significantly higher levels of educational qualifications and farming compared to affected farmers. On the other hand, the average family size and monthly expenditures are statistically higher for affected farmers compared to unaffected farmers. Unaffected farmers have statistically greater rice output and cultivated land size than treatment groups, while affected farmers apply statistically greater quantities of chemical fertilizers and pesticides.

4.2. Impact of Cyclone Amphan on rice production

4.2.1. Cobb-Douglas production function model

The impact of Cyclone Amphan on rice production was estimated using the Cobb-Douglas production function applied separately to farmers in Khulna (Model 1), Satkhira (Model 2), and both districts combined (Model 3). Regression results are presented in Table 2, using both log-transformed and standardized coefficients (mean = 0, standard deviation = 1). The standardized regression coefficients reflect the strength of the explanatory variables on the dependent variable.

In Model 1, land, labor, and seed variables show positive and statistically significant associations with rice output at a 1% level. Specifically, a 1% increase in land, labor, and seed led to 0.57%, 0.20%, and 0.25% increases in rice production, respectively. However,

Table 1. Descriptive statistics of the cyclone-affected rice farmers

Variable	Mean	SD	Min	Max
Sociodemographic variables				
Age (years)	48.95	12.81	20	80
Education (years of schooling)	6.24	3.84	0	18
Household size (number of members)	4.97	1.91	1	15
Earning members except the household head (number of members)	0.62	0.90	0	5
Household monthly income (BDT)	15166.25	9642.70	1000	85000
Household monthly expenditure (BDT)	14412.87	6777.22	600	50000
Farming experience (years)	21.96	12.20	2	50
Production-specific variables				
Output (maunds)	35.71	40.17	5	390
Land (acres)	1.216	0.96	0.331	6.612
Labor (man-days)	15.72	13.97	2	100
Seed (kg)	39.653	42.12	6	500
Chemical fertilizer (kg)	68.302	57.43	5	380
Pesticide (kg)	0.951	1.07	0.002	8

Notes: Total respondents=400.
Abbreviations: Max: Maximum; Min: Minimum; SD: Standard deviations.

Table 2. The impact of Cyclone Amphan on rice production (estimated using Cobb-Douglas production function model)

Variables	Model 1 (Khulna)	Model 2 (Satkhira)	Model 3 (Combined)
Land (acres)	0.576*** (0.137)	0.792*** (0.0596)	0.713*** (0.0703)
Labor (man-days)	0.202*** (0.0475)	0.176*** (0.0456)	0.188*** (0.0316)
Seed (kg)	0.258*** (0.0986)	0.0210 (0.0560)	0.113* (0.0582)
Chemical fertilizer (kg)	0.0423 (0.0731)	0.134*** (0.0459)	0.0807* (0.0421)
Pesticide (kg)	0.0412 (0.0298)	−0.0159 (0.00973)	0.00232 (0.0113)
Cyclone (affected=1)	−0.386*** (0.0625)	−0.267*** (0.0357)	−0.298*** (0.0256)
Constant	1.986*** (0.359)	2.559*** (0.163)	2.369*** (0.175)
Number of observations	400	400	800
R^2	0.856	0.875	0.847

Note: Regression coefficients are expressed in logarithmic form. Robust standard errors are reported in parentheses. The dependent variable is rice output measured in maund (1 maund=40 kg). $^{*}p<0.10$, $^{**}p<0.05$, $^{***}p<0.01$.

the cyclone dummy variable indicates that the rice production of affected farmers decreased by 38% compared with the unaffected farmers in Khulna, which is statistically significant at a 1% level.

In Model 2, the coefficients of land, labor, and chemical fertilizer are positively and significantly associated with rice production. A 1% increase in land, labor, and chemical fertilizer increases rice output by 0.79%, 0.17%, and 0.13%, respectively. The coefficient of the cyclone dummy indicates that affected farmers faced a 26% loss in rice production compared with the unaffected farmers in Satkhira.

Model 3 presents pooled results from both districts. Here, land, labor, seed, and fertilizer inputs all show positive and significant effects on rice production. On average, cyclone-affected farmers experienced a 30% reduction in rice output compared to unaffected farmers. The cyclone effect is more pronounced in Khulna (Model 1) than in Satkhira (Model 2), indicating a relatively greater impact in Khulna. The graphical representation of regression coefficients is provided in Figure A1, and standardized regression coefficients confirming the direction and magnitude of cyclone impact are shown in Table A4.

4.2.2. Event analysis using panel fixed effects regression

The dynamic impact of Cyclone Amphan on rice production was analyzed using the panel fixed effects regression techniques, as shown in Table 3. This analysis estimates the impact of the cyclone by comparing rice production levels before, during, and after the event while controlling for unobserved, time-invariant factors. In Model 1 (Khulna), the logarithmic coefficient for the *Dduring* dummy indicates that, during the cyclone season, farmers experienced a 30% reduction in rice production compared to the pre-cyclone season (p<0.001). In the post-cyclone period, the loss remained at 8% (p<0.001) relative to the pre-cyclone baseline.

In Model 2 (Satkhira), farmers experienced an average 23% decrease in production during the cyclone (p<0.001). However, the *Dafter* coefficient is statistically insignificant, suggesting a potential recovery in the following season.

Model 3, which aggregates data from both districts, reveals an overall 27% production loss during the cyclone and a 5% loss in the post-cyclone season, both statistically significant at the 1% level (p<0.001). These findings are visually presented in Figure A2, and the standardized coefficients in Table A5 further confirm the cyclone's adverse effect on rice production.

4.3. Determinants of Cyclone Amphan-induced relative financial loss

Several factors influenced the relative loss of farmers due to cyclone Amphan, as shown in Table 4. The analysis revealed that the relative financial loss from the cultivation of rice (Model 1), fish (Model 2), vegetables (Model 3), other crops (Model 4), and overall farming (Model 5) activities are positively dependent on occupation (p<0.001) of the farmers. Farmers solely reliant on agriculture were more financially vulnerable to the cyclone's impact. The relative financial loss was highest for rice cultivation, followed by fish cultivation. Other factors, such as age, were positively associated with the relative losses from farming activities, whereas household size and education were negatively associated with the relative losses. Aged farmers were less resilient in preventing loss from production activities, while having more family members or higher education qualifications led to reduced relative financial losses. Figure A3 illustrates the estimated regression coefficients from Models 1 to 5.

The region-specific regressions, provided in Table A6 (Khulna) and Table A7 (Shatkhira), offer additional insight. In Khulna, farmers primarily dependent on agriculture experienced no relative financial losses in rice, fish, and vegetable cultivation, and only minor losses in others. In contrast, similar farmers faced significant relative financial losses in Satkhira across rice, vegetables, other crops, and overall farming activities.

4.4. Impact of Cyclone Bulbul on rice production

4.4.1. Cobb-Douglas production function model

The impact of Cyclone Bulbul on rice production was estimated using Equation II, with results presented in Table 5. In Model 1 (Khulna), only labor input was

Table 3. The impact of Cyclone Amphan on rice production (estimated using panel fixed effects regression model)

Variables	Model 1 (Khulna)	Model 2 (Satkhira)	Model 3 (Combined)
Land (acres)	−0.103** (0.0491)	0.195*** (0.0474)	−0.0465 (0.0790)
Labor (man-days)	−0.208** (0.0801)	−0.00899 (0.0500)	−0.105** (0.0483)
Seed (kg)	0.153 (0.111)	−0.230*** (0.0544)	−0.106** (0.0525)
Chemical fertilizer (kg)	−0.0179 (0.0912)	0.141*** (0.0447)	0.168*** (0.0393)
Pesticide (kg)	0.0396 (0.0499)	0.0773 (0.0545)	0.0565 (0.0359)
D_{during}	−0.297*** (0.0251)	−0.225*** (0.0219)	−0.265*** (0.0172)
D_{after}	−0.0826*** (0.0214)	−0.0175 (0.0164)	−0.0503*** (0.0146)
Constant	3.495*** (0.508)	3.813*** (0.276)	3.460*** (0.250)
Number of farmers	200	200	400
R^2 (within)	0.406	0.599	0.445
R^2 (between)	0.350	0.321	0.119
Number of observations	600	600	1200

Note: Regression coefficients are expressed in logarithmic form. Robust standard errors clustered at the farmer level are reported in parentheses. The dependent variable is rice output measured in maund (1 maund=40 kg). D_{during} is the dummy variable=1 during the cyclone; D_{after} is the dummy variable=1 after the cyclone. *p<0.10, **p<0.05, ***p<0.01.

Table 4. Determinants of Cyclone Amphan-induced relative financial loss

Variables	Model 1 (loss from rice cultivation)	Model 2 (loss from fish cultivation)	Model 3 (loss from vegetable cultivation)	Model 4 (loss from other crop cultivation)	Model 5 (total loss)
Occupation (agriculture=1, otherwise=0)	0.0790*** (0.0266)	0.0504*** (0.0123)	0.00875*** (0.00326)	0.0242*** (0.00764)	0.161*** (0.0428)
Age (years)	0.00193*** (0.000647)	0.000873** (0.000386)	0.000175* (9.48e-05)	0.000294 (0.000191)	0.00360*** (0.00107)
Gender (male=1, female=0)	0.00232 (0.0237)	0.00539 (0.0123)	0.00196 (0.00520)	−0.00537 (0.00515)	−0.0213 (0.0338)
Education (years of schooling)	−0.00557 (0.00358)	−0.00334* (0.00181)	−0.000495 (0.000449)	−0.000532 (0.000920)	−0.00982* (0.00570)
Household size (number of members)	−0.0109*** (0.00366)	−0.00455*** (0.00162)	−0.000993 (0.000690)	−0.00301*** (0.000914)	−0.0199*** (0.00562)
Constant	0.0863** (0.0414)	0.0221 (0.0230)	0.00807 (0.00956)	0.0357*** (0.0118)	0.160** (0.0634)
Number of observations	400	400	400	400	400
R^2	0.068	0.102	0.039	0.052	0.095

Notes: Robust standard errors are reported in parentheses. *p<0.10, **p<0.05, ***p<0.01.

Table 5. The impact of Cyclone Bulbul on rice production (estimated using Cobb-Douglas production function model)

Variables	Model 1 (Khulna)	Model 2 (Satkhira)	Model 3 (Combined)
Land (acres)	0.126 (0.123)	0.374*** (0.0932)	0.192** (0.0863)
Labor (man-days)	0.189** (0.0847)	0.392*** (0.104)	0.240*** (0.0702)
Seed (kg)	−0.127 (0.0918)	−0.100 (0.108)	−0.0157 (0.0733)
Chemical fertilizer (kg)	−0.145 (0.0879)	0.165** (0.0785)	0.0940 (0.0603)
Pesticide (kg)	0.0190 (0.0483)	−0.0163 (0.0188)	−0.0397* (0.0206)
Cyclone (affected=1)	−0.450*** (0.111)	−0.377*** (0.0606)	−0.366*** (0.0570)
Constant	4.721*** (0.410)	2.381*** (0.221)	2.935*** (0.230)
Number of observations	400	400	800
R^2	0.113	0.492	0.203

Notes: Regression coefficients are expressed in logarithmic form. Robust standard errors are reported in parentheses. The dependent variable is rice output measured in maund (1 maund=40 kg). *p<0.10, **p<0.05, ***p<0.01.

positively associated (p<0.05) with rice production. In Model 2 (Satkhira), land, labor, and chemical fertilizer were positively and statistically significantly associated with rice production. Farmers in Khulna experienced a 45% reduction in rice production (p<0.001) compared with the unaffected farmers in the region. In Satkhira, the production loss was slightly, at 38% (p<0.001).

Aggregated results across both districts (Model 3) indicate an overall 37% reduction in rice production (p<0.001) among cyclone-affected farmers relative to the control group. Figure A4 provides the graphical presentation of these findings, while the estimated standardized regression coefficients are presented in Table A8.

4.4.2. Event analysis using panel fixed effects regression

The dynamic impact of Cyclone Bulbul on rice production was estimated using panel fixed effects regression, with coefficients presented in Table 6. After adjusting for time-invariant unobserved heterogeneity, the effects of inputs on production varied by region. In Khulna, chemical fertilizer had a negative effect on rice production, while other inputs were statistically

Table 6. The impact of Cyclone Bulbul on rice production (estimated using panel fixed effects regression model)

Variables	Model 1 (Khulna)	Model 2 (Satkhira)	Model 3 (Combined)
Land (acres)	−0.0125 (0.0383)	0.0468 (0.0423)	−0.0937*** (0.0301)
Labor (man-days)	0.179 (0.142)	−0.0431 (0.0487)	0.125** (0.0623)
Seed (kg)	0.0159 (0.0495)	0.0298 (0.0513)	−0.00214 (0.0355)
Chemical fertilizer (kg)	−0.188** (0.0785)	−0.0565 (0.0427)	−0.0107 (0.0314)
Pesticide (kg)	0.0305 (0.0393)	0.0862*** (0.0330)	0.0767*** (0.0272)
D_{during}	−0.491*** (0.0254)	−0.252*** (0.0302)	−0.429*** (0.0211)
D_{after}	0.0910*** (0.0290)	−0.0623*** (0.0163)	−0.0323** (0.0151)
Constant	4.574*** (0.753)	3.783*** (0.262)	3.687*** (0.250)
Number of farmers	200	200	400
R^2 (within)	0.660	0.555	0.570
R^2 (between)	0.001	0.176	0.093
Number of observations	600	600	1200

Notes: Regression coefficients are expressed in logarithmic form. Robust standard errors clustered at the farmer level are reported in parentheses. The dependent variable is rice output measured in maund (1 maund=40 kg). D_{during} is the dummy variable=1 during the cyclone; D_{after} is the dummy variable=1 after the cyclone. *p<0.10, **p<0.05, ***p<0.01.

insignificant. In contrast, the combined model for both districts found that land had a negative effect, while labor had a positive influence on rice output. The coefficient for the *Dduring* dummy variable was negative and highly significant across all models, indicating that cyclone-affected farmers experienced substantial production losses during the cyclone season: 49% in Khulna (p<0.001), 25% in Satkhira (p<0.001), and 43% overall (p<0.001) across both regions. Post-cyclone effects varied: rice production increased slightly in Khulna but declined marginally in Satkhira. The coefficients of Models 1, 2, and 3 are presented visually in Figure A5. The standardized regression coefficients are provided in Table A9, further confirming the adverse effects of Cyclone Bulbul during the event.

4.5. Determinants of Cyclone Bulbul-induced relative financial loss

The determinants of the relative financial loss of cyclone Bulbul-affected farmers were estimated using Equation V, with results shown in Table 7. Among several sociodemographic variables, the primary occupation of the farmer emerged as a critical factor influencing financial loss across all farming activities—rice, fish, vegetables, other crops, and overall farming. Specifically, farmers who relied exclusively on agriculture as their main occupation suffered significantly higher relative losses in all farming activities except fish. These findings highlight a crucial aspect of cyclone risk management: Monocentric livelihood dependence increases vulnerability to natural disasters. Graphical representations of the regression results are provided in Figure A6. To account for geographical variation, the same models were estimated separately for Khulna and Satkhira. Results are reported in Tables A10 and A11, which indicate that farmers in Satkhira experienced greater relative financial loss compared to those in Khulna.

5. Discussion

This study examined the impact of Cyclones Amphan and Bulbul on rice production in the coastal areas of Khulna and Satkhira, Bangladesh. Cyclone Amphan led to a significant reduction in rice yield, with an average production loss of 38% in Khulna and 26% in Satkhira. Cyclone Bulbul, though slightly less intense, similarly diminished productivity by approximately 45% in Khulna and 38% in Satkhira. These findings are consistent with prior research indicating that climate-induced disasters disproportionately affect agricultural outputs in vulnerable coastal regions, where soil salinity, waterlogging, and direct crop damage intensify the effects of climatic shocks.[5,11]

The application of the Cobb-Douglas production function model and fixed effects panel regression underscores the multidimensionality of cyclone impacts on agriculture. Results show that key agricultural inputs, including land, labor, and chemical fertilizers, contributed positively to productivity. However, their

Table 7. Determinants of Cyclone Bulbul-induced relative financial loss

Variables	Model 1 (loss from rice cultivation)	Model 2 (loss from fish cultivation)	Model 3 (loss from vegetable cultivation)	Model 4 (loss from other crop cultivation)	Model 5 (total loss)
Occupation (agriculture=1, otherwise=0)	0.112** (0.0444)	0.00851 (0.0176)	0.0264** (0.0116)	0.0394*** (0.0133)	0.167** (0.0682)
Age (years)	0.00378*** (0.00113)	0.00115** (0.000564)	0.000235 (0.000216)	−0.000161 (0.000326)	0.00491*** (0.00182)
Gender (male=1, female=0)	−0.0272 (0.0306)	−0.0285*** (0.00830)	−0.00824 (0.00549)	−0.00919 (0.00966)	−0.0791** (0.0382)
Education (years of schooling)	0.00313 (0.00666)	0.00172 (0.00187)	−0.00163 (0.00113)	−0.00417*** (0.00158)	0.00328 (0.00963)
Household size (number of members)	−0.0212*** (0.00675)	0.00146 (0.00677)	−0.00227*** (0.000752)	−0.00169 (0.00147)	−0.0249** (0.0122)
Constant	0.0910 (0.0719)	0.0102 (0.0475)	0.0299*** (0.00768)	0.0717*** (0.0203)	0.210* (0.108)
Number of observations	400	400	400	400	400
R^2	0.051	0.014	0.029	0.046	0.044

Note: Robust standard errors are reported in parentheses. *p<0.10, **p<0.05, ***p<0.01.

effects were substantially undermined during cyclone seasons. These findings suggest that the input-output relationship becomes unstable under extreme weather conditions, a pattern consistent with prior studies that note how climatic shocks disrupt otherwise predictable production dynamics.[42] A notable finding is the financial vulnerability of households reliant solely on agriculture. Such households reported higher relative financial losses, especially in rice cultivation. This supports earlier research, including that of Blanc and colleagues, who emphasize the importance of income diversification in enhancing rural resilience to environmental shocks.[44] Furthermore, the negative correlation between household size and financial losses suggests that larger households may mitigate economic risks through collective labor contributions or diversified income sources, as noted in the broader disaster resilience literature.[46] Post-cyclone effects also reveal lingering impacts, as seen in the sustained reduction in rice output beyond the cyclone periods. These may be attributed to persistent soil salinity and structural crop damage, which inhibits full recovery within a single agricultural cycle—a phenomenon well-documented in studies of salinity-affected coastal agriculture.[17,37]

This study contributes to the broader discourse on climate change adaptation, highlighting the critical need for tailored intervention strategies that address both the immediate and residual impacts of cyclones. Enhancing community resilience through diversified income sources, improved agricultural practices for salt-tolerant crop varieties, and reinforced physical defenses against storm surges could mitigate future risks.[33] Moreover, adaptive strategies at the household level, such as savings or access to credit, may play a role in financial resilience. Households with varied income sources exhibited better post-disaster outcomes.[3] The study also offers a practical and evidence-based framework for assessing disaster impacts on agriculture in other coastal regions with similar exposure to climate risks.

While the study provides valuable insights, certain limitations must be acknowledged. While the study adapts the Cobb-Douglas model to assess cyclone impacts under specific conditions, the model may not fully capture the complexity of post-cyclone effects, such as prolonged soil salinity, structural crop damage, and household-level adaptive strategies. The panel data are limited to three time points within a single agricultural season, limiting the analysis of long-term effects. Finally, the exclusive focus on rice production, while appropriate for this study, does not allow generalization to other crops or sectors.

6. Conclusion

This study makes an important contribution to the quantification of cyclone-induced agricultural damage by estimating the impact of Cyclones Amphan and Bulbul on rice production in the coastal districts of Khulna and Satkhira in Bangladesh. Using a unique dataset collected from cyclone-affected farmers and applying both the Cobb–Douglas production function and panel fixed effects regression, this study measures production losses across multiple time periods and compares affected and unaffected farmers. This methodological approach provides a more detailed and time-sensitive understanding of the impact of cyclones on rice farming compared to earlier studies based on single time points or aggregated data. The findings show that farmers affected by the cyclones suffered significant production losses, with reductions in rice output reaching up to 49% during the cyclone season. Specifically, Cyclone Amphan caused a 38% rice production loss in Khulna and a 26% loss in Satkhira, with an average reduction of 30% across both districts. Additionally, Cyclone Bulbul led to a 45% production loss in Khulna and a 38% loss in Satkhira, resulting in an average loss of 37% for both regions. Farmers who depend entirely on agriculture, had lower levels of education, or lived in smaller households were more likely to experience higher financial losses. To mitigate these losses, targeted interventions are needed at both the household and policy levels. Promoting livelihood diversification beyond agriculture can reduce dependence on single-crop income sources and enhance resilience to climate shocks. Investments in agricultural extension services, early warning systems, and the development of climate-resilient rice varieties can improve farmers' preparedness and recovery capacity. Future research should consider extending the time frame and incorporating other farming systems and occupational groups to enhance the general relevance of the findings and better inform climate adaptation policies aimed at safeguarding food security and rural livelihoods in disaster-prone regions.

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The author declares no competing interests.

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Availability of data

The data underlying this study are not available due to confidentiality or privacy restrictions.

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Appendix

Table A1. Descriptive statistics of farmers in Khulna

Variables	Mean	SD	Min	Max
Sociodemographic variables				
Age (years)	50.45	12.478	20	80
Education (years of schooling)	6.795	3.695	0	16
Household size (number of members)	5.05	1.936	1	15
Earning members except household head (number of members)	0.805	1.021	0	5
Household monthly income (BDT)	17392.5	7988.194	3000	45000
Household monthly expenditure (BDT)	15910	6407.392	3000	30000
Farming experience (years)	22.715	11.508	4	50
Production-specific variables				
Output (maund)	33.37	41.012	5	390
Land (acres)	1.207	0.954	0.331	6.612
Labor (man-days)	15.59	13.789	2	100
Seed (kg)	41.145	48.139	7	500
Chemical fertilizer (kg)	70.545	52.972	14	380
Pesticide (kg)	1.11	1.249	0.1	7

Note: Total respondents=200.
Abbreviations: Max: Maximum; Min: Minimum; SD: Standard deviation.

Table A2. Descriptive statistics of farmers in Satkhira

Variables	Mean	SD	Min	Max
Sociodemographic variables				
Age (years)	47.46	13.004	23	78
Education (years of schooling)	5.695	3.915	0	18
Household size (number of members)	4.895	1.895	2	12
Earning members except household head (number of members)	0.445	0.721	0	3
Household monthly income (BDT)	12940	10614.009	1000	85000
Household monthly expenditure (BDT)	12915.75	6821.464	600	50000
Farming experience (years)	21.22	12.857	2	50
Production-specific variables				
Output (maund)	38.05	39.281	8	280
Land (acres)	1.225	0.983	0.331	6.612
Labor (man-days)	15.85	14.199	4	100
Seed (kg)	38.16	35.15	6	220
Chemical fertilizer (kg)	66.06	61.624	5	350
Pesticide (kg)	0.792	0.837	0.002	8

Note: Total respondents=200.
Abbreviations: Max: Maximum; Min: Minimum; SD: Standard deviation.

Table A3. Comparison between control and cyclone-affected farmers

Variables	Control farmers (*n*=400)		Cyclone-affected farmers (*n*=400)		Mean difference	*t*
	Mean	SE	Mean	SE		
Sociodemographic variables						
Age (years)	48.73	0.49	48.95	0.64	−0.22	−0.27
Education (years of schooling)	8.96	0.15	6.24	0.19	2.72	11.10***
Household size (number of members)	4.71	0.06	4.97	0.09	−0.26	−2.20**
Earning member except household head (number of members)	0.52	0.03	0.62	0.04	−0.09	−1.63
Household monthly income (BDT)	14459.5	413.25	15316.25	521.29	−856.75	−1.28
Household monthly expenditure (BDT)	12527.75	293.97	14437.88	344.46	−1910.12	−4.21***
Farming experience (years)	23.61	0.49	21.96	0.61	1.65	2.09**
Production-specific variables						
Output (maund)	49.84	2.48	35.71	2.01	14.13	4.42***
Land (acres)	1.50	0.07	1.21	0.04	0.29	3.32***
Labor (man-days)	14.18	0.68	15.72	0.69	−1.53	−1.57
Seed (kg)	43.15	2.27	39.65	2.10	3.50	1.12
Chemical fertilizer (kg)	60.98	3.34	68.30	2.87	−7.31	−1.65*
Pesticide (kg)	0.51	0.03	0.95	0.05	−0.43	−7.10***

Note: *t>1.64, **t>1.96, ***t>2.58.
Abbreviation: SE: Standard error.

Table A4. The impact of Cyclone Amphan on rice production (standardized coefficients of Cobb–Douglas production function model)

Variables	Model 1 (Khulna)	Model 2 (Satkhira)	Model 3 (Combined)
Land (acres)	0.369*** (0.104)	0.832*** (0.0721)	0.472*** (0.0797)
Labor (man-days)	0.397*** (0.0977)	0.262*** (0.0633)	0.368*** (0.0602)
Seed (kg)	0.0913 (0.0621)	0.00658 (0.115)	0.0398 (0.0390)
Chemical fertilizer (kg)	0.0915*** (0.0289)	0.0379 (0.0913)	0.112*** (0.0346)
Pesticide (kg)	0.0150 (0.0136)	0.0142 (0.0139)	0.0113 (0.0129)
Cyclone (affected=1)	0.230*** (0.0340)	0.250*** (0.0309)	0.256*** (0.0282)
Constant	0.0495** (0.0226)	0.218*** (0.0326)	0.128*** (0.0192)
Number of observations	400	400	800
R^2	0.917	0.917	0.900

Notes: Regression coefficients are expressed in standardized coefficients. Robust standard errors are reported in parentheses. The dependent variable is rice output measured in maund (1 maund=40 kg). *p<0.10, **p<0.05, ***p<0.01.

Table A5. The impact of Cyclone Amphan on rice production (standardized coefficients of panel fixed effects regression model)

Variables	Model 1 (Khulna)	Model 2 (Satkhira)	Model 3 (Combined)
Land (acres)	−0.0182*** (0.00592)	0.362 (0.307)	−0.0102 (0.0207)
Labor (man-days)	−0.129 (0.125)	−0.162* (0.0880)	−0.137* (0.0728)
Seed (kg)	−0.0550 (0.0924)	0.120 (0.0908)	−0.0221 (0.0695)
Chemical fertilizer (kg)	0.0607 (0.139)	−0.157*** (0.0548)	−0.0666 (0.0508)
Pesticide (kg)	−0.0112 (0.0323)	0.00360 (0.100)	−0.00250 (0.0255)
D_{during}	−0.203*** (0.0218)	−0.149*** (0.0285)	−0.175*** (0.0160)
D_{after}	−0.0425 (0.0262)	0.0653*** (0.0202)	0.0118 (0.0170)
Constant	0.0235 (0.0147)	0.0803*** (0.0247)	0.0542*** (0.00949)
Number of farmers	200	200	400
R^2 (within)	0.260	0.405	0.299
R^2 (between)	0.762	0.625	0.886
Number of observations	600	600	1,200

Notes: Regression coefficients are expressed in standardized coefficients. Robust standard errors clustered at the farmer level are reported in parentheses. The dependent variable is rice output measured in maund (1 maund=40 kg). D_{during} is the dummy variable=1 during the cyclone; D_{after} is the dummy variable=1 after the cyclone. *p<0.10, **p<0.05, ***p<0.01.

Table A6. Cyclone Amphan-induced relative financial loss in Khulna

Variables	Model 1 (loss from rice cultivation)	Model 2 (loss from fish cultivation)	Model 3 (loss from vegetable cultivation)	Model 4 (loss from other crop cultivation)	Model 5 (total loss)
Occupation (agriculture=1, otherwise=0)	0.00173 (0.0176)	0.00935 (0.00606)	0.00138 (0.00257)	0.0120** (0.00554)	0.0211 (0.0268)
Age (years)	0.00128** (0.000506)	0.000739*** (0.000207)	0.000156* (8.39e-05)	0.000522*** (0.000187)	0.00285*** (0.000840)
Gender (male=1, female=0)	0.00744 (0.0318)	0.0234 (0.0146)	0.00928 (0.00999)	0.0199 (0.0129)	0.0585 (0.0541)
Education (years of schooling)	0.00554** (0.00229)	0.000319 (0.000907)	−5.87e-05 (0.000274)	0.000675 (0.000592)	0.00532 (0.00341)
Household size (number of members)	−0.00689** (0.00340)	−0.00213* (0.00125)	−0.000969** (0.000483)	−0.00140 (0.00119)	−0.0114** (0.00539)
Constant	0.0150 (0.0476)	−0.0270 (0.0210)	−0.00138 (0.0112)	−0.0182 (0.0200)	−0.0263 (0.0827)
Number of observations	200	200	200	200	200
R^2	0.056	0.068	0.034	0.090	0.064

Notes: Robust standard errors are reported in parentheses. *p<0.10, **p<0.05, ***p<0.01.

Table A7. Cyclone Amphan-induced relative financial loss in Satkhira

Variables	Model 1 (loss from rice cultivation)	Model 2 (loss from fish cultivation)	Model 3 (loss from vegetable cultivation)	Model 4 (loss from other crop cultivation)	Model 5 (total loss)
Occupation (agriculture=1, otherwise=0)	0.109*** (0.0375)	0.0705*** (0.0177)	0.0125*** (0.00480)	0.0317*** (0.0115)	0.230*** (0.0607)
Age (years)	0.00301** (0.00122)	0.00122 (0.000775)	0.000210 (0.000179)	0.000139 (0.000377)	0.00488** (0.00204)
Gender (male=1, female=0)	−0.0190 (0.0299)	−0.000693 (0.0157)	0.000133 (0.00552)	−0.00966 (0.00634)	−0.0518 (0.0429)
Education (years of schooling)	−0.0119** (0.00556)	−0.00482 (0.00309)	−0.000642 (0.000780)	−0.00115 (0.00154)	−0.0178* (0.00908)
Household size (number of members)	−0.0158** (0.00715)	−0.00770** (0.00332)	−0.00107 (0.00142)	−0.00438*** (0.00166)	−0.0299*** (0.0110)
Constant	0.130** (0.0569)	0.0391 (0.0356)	0.00986 (0.0135)	0.0584*** (0.0161)	0.234*** (0.0882)
Number of observations	200	200	200	200	200
R^2	0.110	0.128	0.047	0.056	0.134

Notes: Robust standard errors are reported in parentheses. *p<0.10, **p<0.05, ***p<0.01.

Table A8. The impact of Cyclone Bulbul on rice production (standardized coefficients of Cobb-Douglas production function model)

Variables	Model 1 (Khulna)	Model 2 (Satkhira)	Model 3 (Combined)
Land (acres)	0.0160 (0.0226)	0.116** (0.0456)	0.0614*** (0.0214)
Labor (man-days)	0.000770 (0.0394)	0.437*** (0.0812)	0.0462 (0.0333)
Seed (kg)	0.697*** (0.0644)	0.331*** (0.0591)	0.649*** (0.0495)
Chemical fertilizer (kg)	0.217** (0.107)	0.191*** (0.0508)	0.241*** (0.0840)
Pesticide (kg)	−0.00892 (0.0128)	0.00172 (0.0183)	−0.0168 (0.0111)
Cyclone (affected=1)	−0.503*** (0.0633)	−0.302*** (0.0275)	−0.373*** (0.0337)
Constant	0.348*** (0.0419)	0.108*** (0.0268)	0.187*** (0.0266)
Number of observations	400	400	800
R^2	0.754	0.888	0.783

Notes: Regression coefficients are expressed in standardized coefficients. Robust standard errors are reported in parentheses. The dependent variable is rice output measured in maund (1 maund=40 kg). *p<0.10, **p<0.05, ***p<0.01.

Table A9. The impact of Cyclone Bulbul on rice production (standardized coefficients of panel fixed effects regression model)

Variables	Model 1 (Khulna)	Model 2 (Satkhira)	Model 3 (Combined)
Land (acres)	0.0952 (0.0734)	0.155*** (0.0552)	-0.116* (0.0635)
Labor (man-days)	0.260 (0.201)	−0.351*** (0.0783)	0.180 (0.178)
Seed (kg)	0.0483 (0.0650)	−0.117** (0.0543)	−0.0143 (0.0483)
Chemical fertilizer (kg)	0.0214 (0.0339)	0.0666*** (0.0149)	0.0595*** (0.0202)
Pesticide (kg)	−0.00420 (0.0281)	−0.0124 (0.0826)	0.0241 (0.0338)
D_{during}	−0.499*** (0.0415)	−0.0525*** (0.0174)	−0.359*** (0.0309)
D_{after}	0.0395* (0.0237)	0.0122 (0.0121)	−0.00930 (0.0204)
Constant	0.343*** (0.0431)	−0.274*** (0.0224)	0.123*** (0.0130)
Number of farmers	200	200	400
R^2 (within)	0.427	0.455	0.330
R^2 (between)	0.575	0.783	0.094
Number of observations	600	600	1,200

Notes: Regression coefficients are expressed in standardized coefficients. Robust standard errors clustered at the farmer level are reported in parentheses. The dependent variable is rice output measured in maund (1 maund=40 kg). D_{during} is the dummy variable=1 during the cyclone; D_{after} is the dummy variable=1 after the cyclone. *p<0.10, **p<0.05, ***p<0.01.

Table A10. Cyclone Bulbul-induced relative financial loss in Khulna

Variables	Model 1 (loss from rice cultivation)	Model 2 (loss from fish cultivation)	Model 3 (loss from vegetable cultivation)	Model 4 (loss from other crop cultivation)	Model 5 (total loss)
Occupation (agriculture=1, otherwise=0)	0.124** (0.0513)	−0.000588 (0.0428)	0.00902* (0.00533)	0.0104 (0.00767)	0.135* (0.0811)
Age (years)	0.00243* (0.00145)	0.00179 (0.00111)	9.66e-05 (0.000121)	−0.000370 (0.000433)	0.00399* (0.00237)
Gender (male=1, female=0)	−0.0210 (0.125)	−0.0551** (0.0266)	−0.0126*** (0.00429)	−0.0187*** (0.00644)	−0.128 (0.145)
Education (years of schooling)	0.0141** (0.00628)	0.00530* (0.00286)	−0.000141 (0.000425)	−0.00197 (0.00159)	0.0233** (0.00934)
Household size (number of members)	−0.0168** (0.00818)	0.00843 (0.0128)	−0.00181** (0.000810)	0.000325 (0.00158)	−0.0156 (0.0186)
Constant	0.0869 (0.156)	−0.0414 (0.113)	0.0283** (0.0124)	0.0629* (0.0331)	0.186 (0.222)
Number of observations	200	200	200	200	200
R^2	0.103	0.028	0.039	0.015	0.075

Notes: Robust standard errors are reported in parentheses. *p<0.10, **p<0.05, ***p<0.01.

Table A11. Cyclone Bulbul-induced relative financial loss in Satkhira

Variables	Model 1 (loss from rice cultivation)	Model 2 (loss from fish cultivation)	Model 3 (loss from vegetable cultivation)	Model 4 (loss from other crop cultivation)	Model 5 (total loss)
Occupation (agriculture=1, otherwise=0)	0.126** (0.0607)	0.0353*** (0.0123)	0.0339** (0.0165)	0.0494*** (0.0188)	0.246*** (0.0901)
Age (years)	0.00382** (0.00179)	0.000148 (0.000428)	0.000477 (0.000454)	0.000396 (0.000566)	0.00325 (0.00284)
Gender (male=1, female=0)	−0.0397 (0.0345)	−0.0109* (0.00625)	−0.00959 (0.00820)	−0.00980 (0.0117)	−0.0712 (0.0498)
Education (years of schooling)	−0.0108 (0.00959)	−0.00234 (0.00162)	−0.00212 (0.00175)	−0.00420* (0.00234)	−0.0212 (0.0138)
Household size (number of members)	−0.0222** (0.0103)	−0.00487*** (0.00175)	−0.00323** (0.00149)	−0.00507** (0.00232)	−0.0286** (0.0144)
Constant	0.146* (0.0796)	0.0697*** (0.0171)	0.0297*** (0.0105)	0.0706*** (0.0209)	0.345*** (0.115)
Number of observations	200	200	200	200	200
R^2	0.060	0.067	0.031	0.053	0.070

Notes: Robust standard errors are reported in parentheses. *p<0.10, **p<0.05, ***p<0.01.

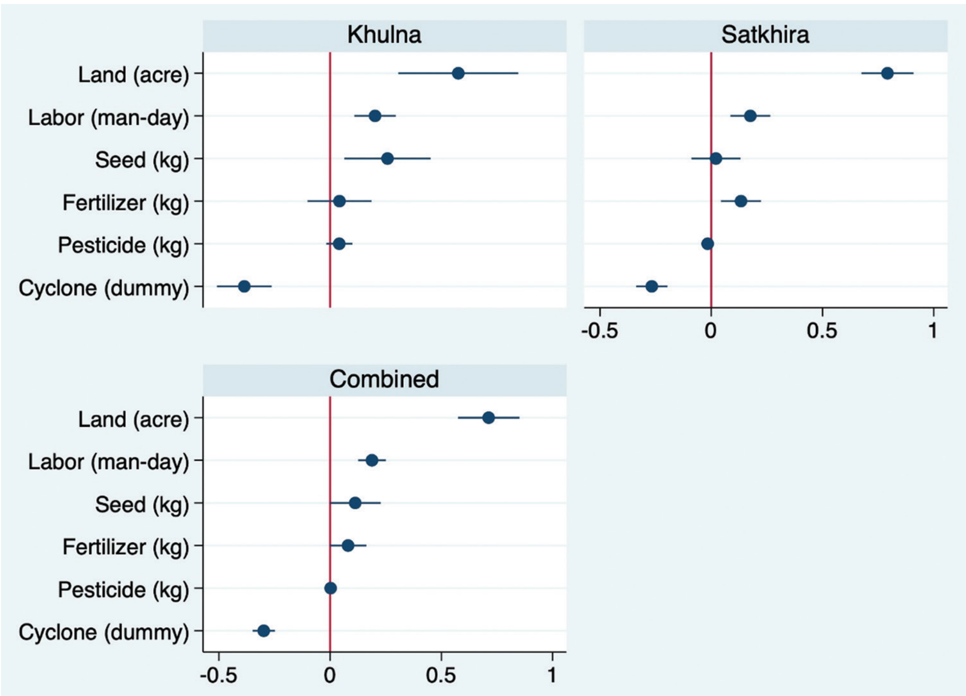

Figure A1. The impact of Cyclone Amphan on rice production (Cobb-Douglas production function model). Regression coefficients are expressed in logarithmic forms. 95% confidence intervals are shown for each point estimate. The dependent variable is rice output measured in maund (1 maund=40 kg).

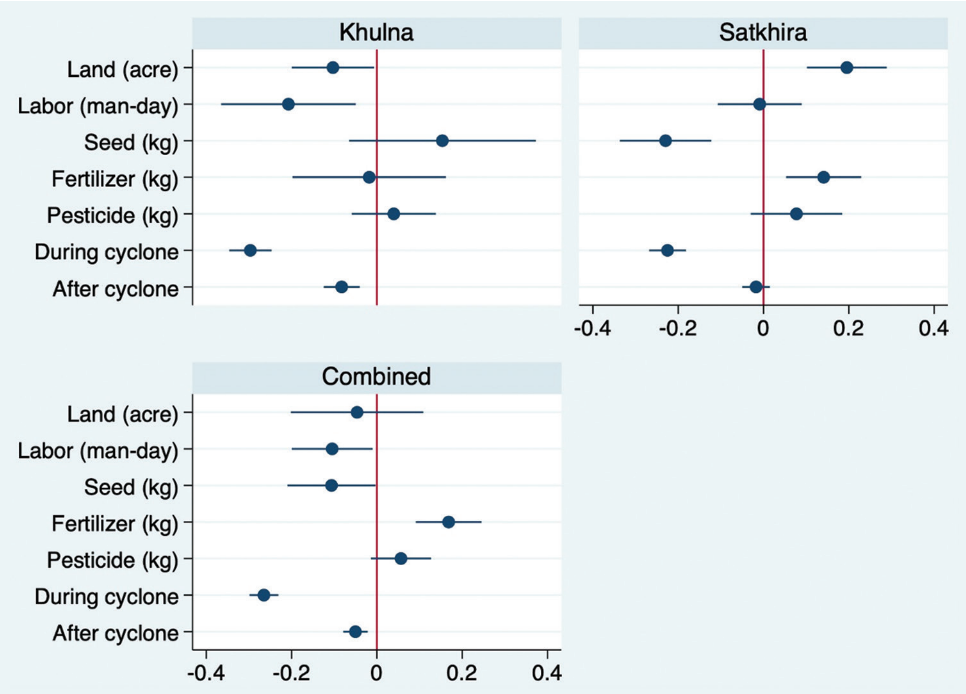

Figure A2. The impact of Cyclone Amphan on rice production (panel fixed effects regression model). Regression coefficients are expressed in logarithmic coefficients. 95% confidence intervals are shown for each point estimate. The dependent variable is rice output measured in maund (1 maund=40 kg).

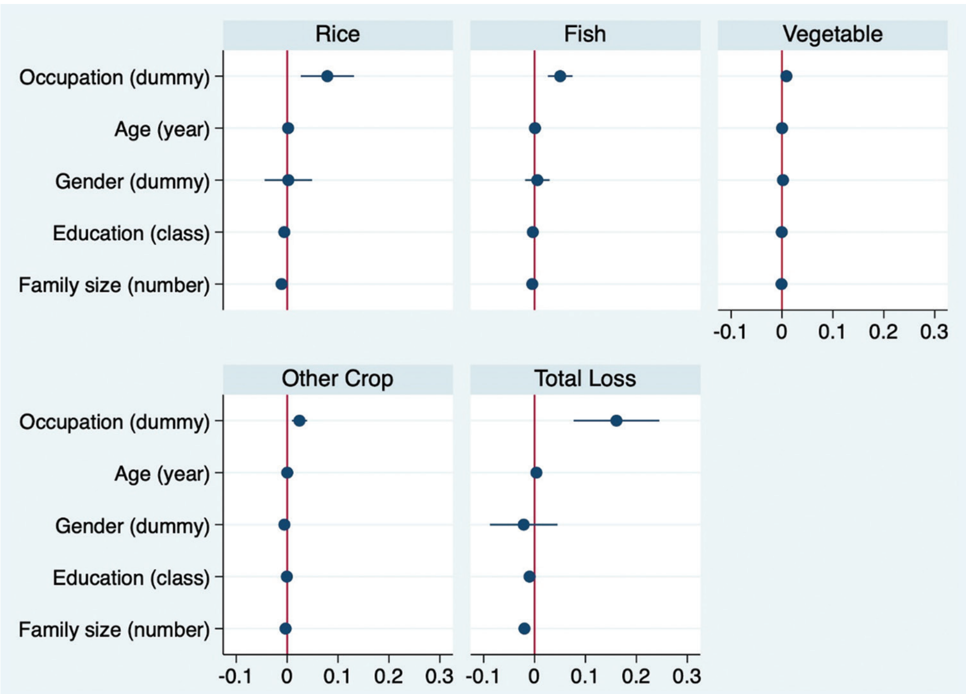

Figure A3. Determinants of Cyclone Amphan-induced relative financial loss. 95% confidence intervals are shown for each point estimate.

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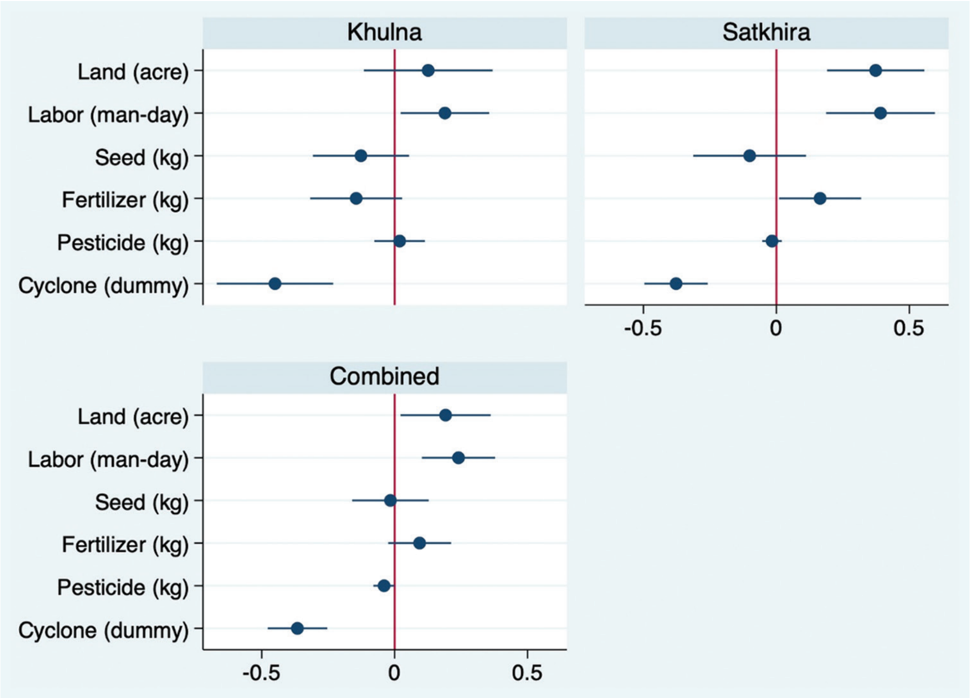

Figure A4. The impact of Cyclone Bulbul on rice production (Cobb-Douglas production function model). Regression coefficients are expressed in logarithmic forms. 95% confidence intervals are shown for each point estimate. The dependent variable is rice output measured in maund (1 maund=40 kg).

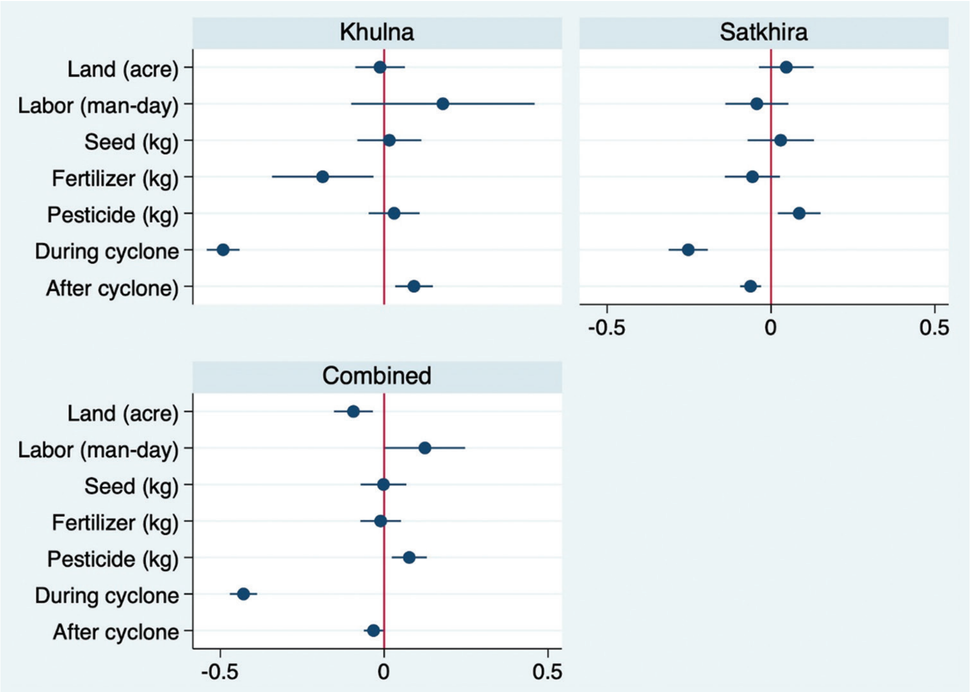

Figure A5. The impact of Cyclone Bulbul on rice production (panel fixed effects regression model). Regression coefficients are expressed in logarithmic forms. 95% confidence intervals are shown for each point estimate. The dependent variable is rice output measured in maund (1 maund=40 kg).

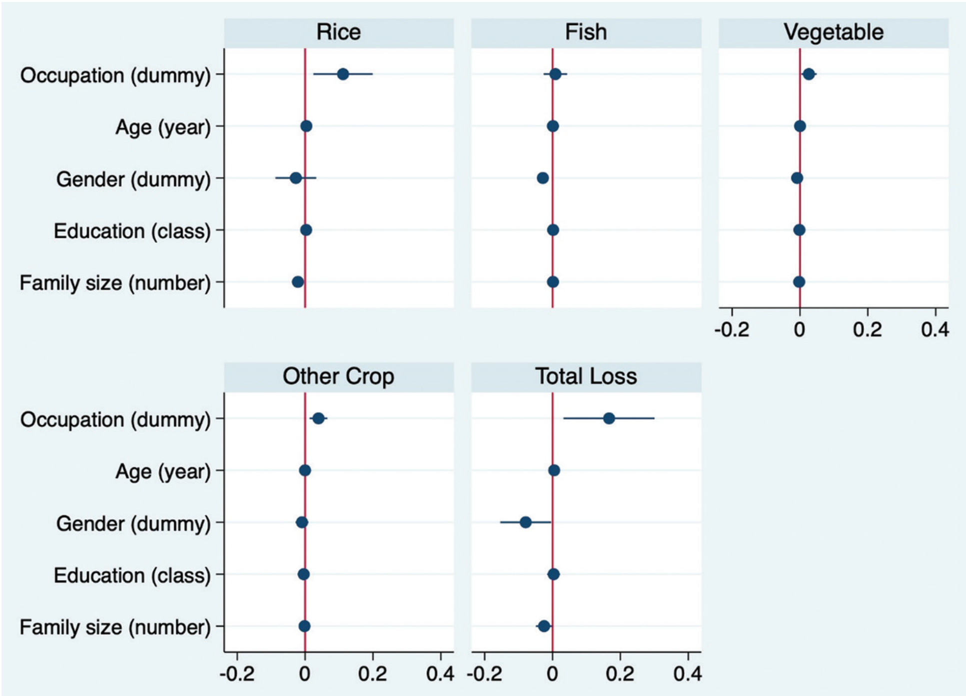

Figure A6. Determinants of Cyclone Bulbul-induced relative financial loss. 95% confidence intervals are shown for each point estimate.