

Adapting to climate change: The case of saline-tolerant rice varieties in coastal Bangladesh

Shreya Kapoor

shr.kpr1995@gmail.com

Indian School of Business

Barun Deb Pal

International Food Policy Research Institute

Shahidur Rashid

International Food Policy Research Institute

Research Article

Keywords: climate change, salinity intrusion, adaptation, SDG, causal impact, coastal livelihoods, South Asia, Bangladesh

Posted Date: March 18th, 2026

DOI: <https://doi.org/10.21203/rs.3.rs-8838430/v1>

License:   This work is licensed under a Creative Commons Attribution 4.0 International License.

[Read Full License](#)

Additional Declarations: No competing interests reported.

Adapting to climate change: The case of saline-tolerant rice varieties in coastal Bangladesh

Abstract

Climate change-induced salinity intrusion increasingly threatens agricultural productivity and rural livelihoods in coastal South Asia. In Bangladesh's deltaic agro-ecosystems, rising soil salinity has severely undermined rice cultivation, intensifying concerns over food security and farm incomes. Adoption of saline-tolerant rice varieties is a promising climate adaptation strategy aligned directly with SDG 13 (Climate Action), and indirectly with SDG 1 (No Poverty), and SDG 2 (Zero Hunger), yet rigorous evidence on adoption drivers and welfare effects remains limited. Using farm-level survey data from coastal Bangladesh, this study examines the determinants of farmers' adoption of saline-tolerant rice varieties and the causal impacts of adoption on rice yields and net farm income. Adoption decisions are analysed using a logistic regression model, and treatment effects are estimated via causal impact techniques like PSM, CEM and ESR. Results indicate that adoption increases rice yields by approximately 1–2 tonnes per hectare, corresponding to an average net income gain of about US \$100 per hectare. These findings highlight the substantial productivity and income benefits of saline-tolerant technologies in salinity-affected areas and their potential contributions to climate resilience (SDG 13), food security (SDG 2), and poverty reduction (SDG 1), while supporting more sustainable agricultural practices. The study underscores the need for targeted policy interventions—especially improved seed dissemination, farmer awareness, and institutional support—to scale adoption and strengthen the resilience of coastal farming systems under climate change.

Keywords: climate change; salinity intrusion; adaptation; SDG; causal impact; coastal livelihoods; South Asia; Bangladesh

1 Introduction

Climate change is increasingly disrupting agricultural systems across the developing countries, where livelihoods, food security, and poverty alleviation remain tightly linked to farming systems. Rising temperatures, changing precipitation levels, rising sea-levels, and increasing frequency of extreme weather events erode agricultural productivity and increase income volatility in climate-sensitive agro-ecological zones (IPCC, 2007; Sikder and Xiaoying, 2014; Iqbal and Roy, 2015; Hossain et al., 2020; Rahman and Anik, 2020). The main challenges faced by the agriculture sector are adaptation of agricultural systems to climate change and mitigating its causes and effects, improving combinations of economic, social and environmental preferences, and increasing degree of food autonomy of the regions (Selbonne et al., 2022). Developing countries are more vulnerable to climate change as compared to developed nations and South Asia is world's most vulnerable region to climate change (Abeysekara et al., 2023). Bangladesh, a south Asian deltaic country faces challenges both from disasters as well as climate change and is ranked 7th most vulnerable country in the world (Germanwatch, 2021). As a low-lying deltaic nation, the country's food security and rural livelihoods are directly threatened by climate change. Several studies have shown the negative impacts of climate change (changes in temperature, precipitation levels, weather events like floods, cyclones, etc.) on agriculture in the country (Hossain et al., 2020; Rahman and Anik, 2020). One of the most consequential manifestations of climate change in Bangladesh is salinity intrusion into coastal soils and freshwater systems, driven by sea-level rise, storm surges, and altered river flows (Dasgupta et al., 2014).

Rice occupies a central position in Bangladesh's economy and food system. It contributes nearly half of agricultural value added, provides employment for close to half of the rural workforce, and supplies roughly two-thirds of daily caloric intake (BRRI, 2011; BER, 2019). Rice occupies almost 78% of the total cropped area in the country, with an annual production of 36.3 metric tonnes and an average import of 0.5 metric tonnes (BBS, 2018, 2019). Despite substantial gains in rice production over recent decades, climate change poses risks to rice production in the country (Jamal et al., 2022). Around 40 million people in Bangladesh remain severely food insecure and another 11 million suffer from acute hunger (World Food Programme, 2016). It has been estimated that overall rice production will fall by an average 7.4% every year over the time 2005-2050 (Yu et al., 2010). These risks are particularly pronounced in coastal divisions such as Khulna, Barisal, and Chittagong, which together account for roughly 30 - 35% of national rice production but experience the highest exposure to salinity stress (USDA, 2021). According to Ahsan and Bhuiyan (2010), around 1 million hectares of arable land in these regions are affected by salinity. These zones cover about 20% of the country and 30% of the cultivable land, and around 63% of the coastal cultivable lands have been impacted by some degree of salinity over the past 50 years. In response to this, Bangladesh Rice Research Institute (BRRI) and Bangladesh Institute of Nuclear Agriculture (BINA) have developed saline-tolerant rice varieties to sustain agricultural production in the affected regions. These varieties are developed through agronomic research and breeding programs, designed to withstand high salinity levels, allowing farmers to cultivate rice in previously unproductive and low-yielding farms and is widely viewed as one of the most promising agronomic adaptation strategies for coastal farming systems (Dam et al., 2019).

Saline-tolerant rice varieties represent a form of climate-smart agriculture that simultaneously strengthens adaptation to climate change, stabilizes food production in vulnerable regions, and protects farm incomes - thereby contributing directly and indirectly sustainable development goals - SDG 13 (Climate Action), SDG 2 (Food Security), and SDG 1 (Poverty Reduction). Studies have found that saline-tolerant rice varieties have the potential to improve crop yield, stabilize farmer's income, and enhance resilience to climate shocks (Islam, 2018; Haque et al., 2019; Sarker, 2024; Begum et al., 2024). There is vast empirical literature that illustrates that stress-tolerant crop varieties can generate substantial productivity and welfare gains in climate-affected regions. Evidence from Bangladesh and comparable regions also suggests that saline-tolerant rice varieties can increase crop yield and net farm income, thereby improving household food and income security in saline-prone areas (Hasan et al., 2018; Haque et al., 2019; Begum et al., 2024; Sarker, 2024). Despite the demonstrated agronomic potential of saline-tolerant rice varieties, adoption rates in Bangladesh's coastal regions remain modest. The gap between technological innovation and realized outcomes mirrors a broader pattern observed in the agricultural development literature, where high-return technologies diffuse slowly due to information frictions, liquidity constraints, weak input markets, and limited extension access (Feder and Umali, 1993; Croppenstedt et al., 2013; Ruzzante et al., 2021).

This study tries to address two interrelated questions that are central to the climate adaptation and agricultural development literatures. First, what socio-economic, institutional, and market factors determine farmers' adoption to saline-tolerant rice varieties in salinity-affected coastal Bangladesh? Second, what are the causal impacts of adoption on rice yields and net farm incomes. Addressing these questions is critical not only for understanding the effectiveness of varietal innovation as an adaptation strategy, but also for designing policies that translate proven technologies into large-scale development outcomes. Using nationally representative household and plot-level data from Bangladesh Integrated Household Survey (BIHS) 2015-16, we examine determinants of adoption using logistic regression framework and evaluate the causal impacts of adoption on crop yield and net farm income using three econometric approaches. This multi-method strategy allows us to address both observable and unobservable sources of selection bias and to assess the robustness of estimated impacts across identification strategies (Mendola, 2007; Iacus et al., 2011; Abdulai and Huffman, 2014). By providing rigorous empirical evidence on the role of climate-resilient rice varieties as an adaptation strategy, this study seeks to inform policymakers, agricultural researchers, and development practitioners about pathways to strengthen climate resilience in Bangladesh's rice-based farming systems. It also assesses the effectiveness and scalability of saline-tolerant rice varieties as a sustainable response to persistent agro-climatic stress. Lastly, this study also focusses on providing insights to support SDGs through improved rural livelihoods.

Following the introductory section, the rest of the paper is organized in the following manner: Section 2 describes sample data and the selected locations. Section 3 describes the econometric models used to analyse the impact of adoption of saline-tolerant seed varieties on the crop yield and net income of the farmers. Section 4 reports the key findings of the study, followed by the discussion in section 5. Section 6 concludes the study with summary and policy implications.

2 Data Description

The study relies on Bangladesh Integrated Household Survey (BIHS), 2015-16 conducted by International Food Policy Research Institute (IFPRI), the only nationally representative household survey in Bangladesh that collects detailed data on plot-level agricultural production and practices, dietary intake of individual households, anthropometric measurements, and women’s empowerment index. A community survey supplements the BIHS data to provide information on area-specific contextual factors. This unique integration of agronomic, socio-economic, and institutional variables makes BIHS well-suited for studying agricultural technology adoption and its welfare impacts. Covering 6,500 households across 325 primary sampling units, BIHS is representative of rural Bangladesh at national, divisional (seven divisions), and USAID Feed the Future (FTF) zone levels. For our study, plot-level crop information is matched with Bangladesh Agricultural Research Council (BARC) varietal features to identify saline-tolerant seed varieties like BRRI Dhan 61, BINA Dhan 10 etc. We select three salinity prone divisions of the country – Barisal, Chittagong, and Khulna for our study. Out of the 6500 farm households surveyed, about 60% are in these three divisions with Chittagong having the least while Khulna having the most, reflecting earlier findings on salinity patterns (Ahmed et al., 2016). From the full BIHS sample, we retain only rice-growing households located in these divisions. After cleaning for missing plot-level and household level information, the final analytical sample comprises of 3943 rice-growing farm households, out of which 1029 (26%) are adopters and remaining 2914 (74%) are non-adopters. This relatively large sample size allows for robust econometric analysis and reliable matching procedures. Table 1 shows the division-wise distribution of adopters and non-adopters of saline-tolerant seed varieties in the sample. Figure 1 below depicts the study location for this research.

Table 1: Sample frequency by administrative divisions affected by salinity

Administrative division	Adopters (N = 1029)	Non-adopters (N = 2914)	Total (N = 3943)
Barisal	210 (14.66)	1222 (85.33)	1432
Chittagong	199 (27.18)	533 (72.81)	732
Khulna	620 (34.85)	1159 (65.15)	1779
Total	1029 (26.10)	2914 (73.91)	3943

Source: Authors’ calculations based on BIHS, 2015.

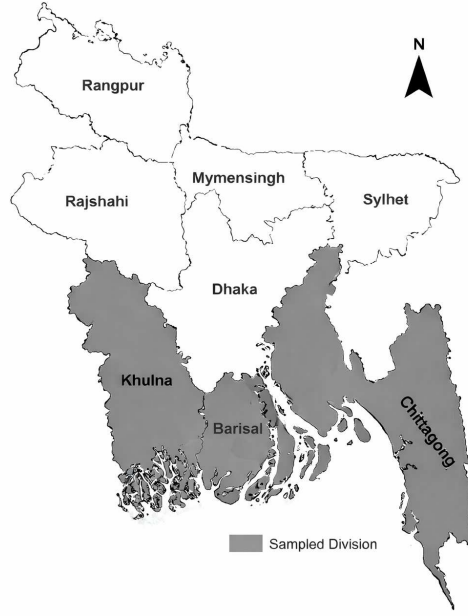
Note: Percent values in parentheses.

3 Empirical Framework

3.1 Determinants of adoption

Adoption studies of agricultural innovations have been carried out since 1970s, but these are mere correlational techniques to explain the adoption behaviour as a function of variables that are collected from farmer survey (Ruzzante et al., 2021). Understanding why farmers adopt climate-resilient technologies is central to designing effective adaptation policies. Adoption of agricultural technologies is influenced by

Figure 1: Study Location



Source: Authors' compilation

a combination of household socio-economics characteristics, asset endowments, institutional access, and information networks. In salinity-affected coastal Bangladesh, the decision to adopt saline-tolerant rice varieties is additionally shaped by farmers' exposure to environmental risk and access to input and extension systems. To empirically examine the determinants, we model the adoption decision using a binary logistic regression framework, consistent with technology adoption literature (Simtowe et al., 2016; Tufa et al., 2022). The adoption decision can be conceptualized as a utility-maximizing choice where a farmer adopts saline-tolerant seeds if the expected utility from adoption exceeds that of non-adoption. Let the latent utility of adoption for farmer i be denoted as:

$$A_i^* = X_i\beta + \epsilon_i \quad (1)$$

where X_i is a vector of observable household, farm, and institutional characteristics, β is a vector of coefficients to be estimated, and ϵ_i is the error term. Table 2 showcases the list of key explanatory variables used for analysis along with their rationale. The adoption decision is defined as:

$$A_i = \begin{cases} 1 & \text{if } A_i^* > 0 \\ 0 & \text{otherwise} \end{cases} \quad (2)$$

Hence, the probability of adoption can be expressed as:

$$P(A_i = 1 | X_i) = \frac{\exp(X_i\beta)}{1 + \exp(X_i\beta)} \quad (3)$$

Parameters are estimated using maximum likelihood estimation (MLE). Since logit coefficients are expressed in log-odds ratio, direct interpretation is not intuitive. Therefore, we report marginal effects which provide a much clear understanding of the measure of impact of explanatory variable. Marginal effect provides the change in probability of adoption associated with a unit change in explanatory variable, keeping other factors constant. The marginal effect is computed as:

$$\frac{\delta y}{\delta x} = \beta x_i \left[\frac{\exp(z)}{(1 + \exp(z))^2} \right] \quad (4)$$

Table 2: List of Explanatory variables and their rationale

Category	Variables	Rationale in salinity context
Demographic	Age, gender, household size	Experience, risk perception, labour availability
Human capital	Education	Information processing ability
Asset endowment	Landholding size, asset index	Capacity to bear risk and invest in new technology
Farm mechanization	Tractor, power tiller ownership	Complementarity with improved seed use
Financial inclusion	Bank account	Liquidity and credit access
Institutional access	Access to seed dealer, fertilizer dealer, pesticide dealer, agriculture office	Information and input availability
Policy linkage	Subsidy card	Exposure to government programs

Source: Authors' compilation.

3.2 Impact Evaluation

3.2.1 Propensity Score Matching (PSM)

Evaluating the causal impact of agricultural technology adoption on farm outcomes is challenging because adoption is not random in nature. Farmers self-select into adoption based on certain observable household, farm, and institutional characteristics, which may influence productivity and income outcomes, leading to biased estimates of the impact of adoption. Propensity Score Matching (PSM), a quasi-experimental impact evaluation approach is widely used to address the potential selection bias arising in observational data (Mendola, 2007; Ogotu et al., 2014; Malabayabas et al., 2023; Park and Ochieng, 2024). PSM creates a quasi-experimental setting that mimics the randomized control trials (Mendola, 2007).

PSM helps to construct a counterfactual framework by matching adopters of saline-tolerant seed varieties (treatment group) with non-adopters (control group) who exhibit similar observable features based on

their propensity scores. The propensity score is defined as the conditional probability of adopting saline-tolerant seed varieties given a vector of covariates, including demographic characteristics, landholding size, asset ownership, and access to extension and input markets (Rosenbaum and Rubin, 1985). These scores can be generated using different approaches like nearest neighbourhood, kernel density, radius caliper, and bootstrapping, each with trade-offs in bias and efficiency (Caliendo and Kopeinig, 2008). Balancing test is conducted to ensure covariates distribution between treatment and control groups are comparable. Standardized mean differences (bias) should be minimal, confirming that the matched control group serves as a credible counterfactual (Rosenbaum and Rubin, 1985). The PSM estimates don't account for selection of unobservable factors, therefore, it is accepted that such selection bias has minimum impact on the results (Kapoor and Kapoor, 2022). PSM helps us to generate the average treatment effect for the treatment group (ATT).

Let D_i be an indicator of whether the farmer adopts saline-tolerant seed varieties or not. The potential productivity outcome of being an adopter, represented by i , for each farmer is defined as D_i . The ATT is computed as:

$$\Delta_{ATT} = E(\Delta \mid D_i = 1) = E(\theta(1) \mid D_i = 1) - E(\theta(0) \mid D_i = 1) \quad (5)$$

where Δ_{ATT} denotes the average treatment effect on the treated (ATT), $E[\theta(1) \mid D_i = 1]$ is the expected outcome for adopter farmers, and $E[\theta(0) \mid D_i = 1]$ represents the counterfactual expected outcome that adopters would have obtained had they not adopted. Identification of the ATT using PSM relies on the Conditional Independence Assumption (Lechner, 1999) and the common support condition (Mendola, 2007). When these assumptions hold, the PSM estimator of the ATT is given by:

$$\Delta_{ATT}^{PSM} = E_{p(X) \mid D_i=1} [E\{\theta(1) \mid D_i = 1, p(X)\} - E\{\theta(0) \mid D_i = 1, p(X)\}] \quad (6)$$

3.2.2 Coarsened Exact Matching (CEM)

As a robustness check to the PSM estimates, we employ Coarsened Exact Matching (CEM), a matching method proposed by Iacus et al. (2011) within the monotonic imbalance bounding (MIB) framework. CEM works in sample distributions and requires no assumption about data generation process except for the usual ignorability assumptions. This approach assures that imbalance between the matched and unmatched groups will not be more than the ex-ante choice stated by the user. Empirical evidence has shown that CEM outperforms other matching tools by reducing imbalance, model dependence, estimated bias variance, and mean square error (Iacus et al., 2011). The procedure involves recoding variables so that similar values are grouped, applying exact matching to identify and drop unmatched units, and then restoring the original values for the retained matched data.

After the coarsening of data, CEM creates a set of strata, say, $s \in S$, each with few coarsened values of

X. Consider a sample size of $n \leq N$, which contains units drawn from the population N . Let T_i denote a treatment variable given as:

$$Y_i = T_i Y_i(1) + (1 - T_i) Y_i(0) \quad (7)$$

where $Y_i(0)$ denotes the potential outcome for farmer i under non-adoption and $Y_i(1)$ denotes the potential outcome under adoption. To identify the causal impact of adoption, we assume ignorability, that is, conditional on observed covariates X , treatment assignment is independent of the potential outcomes, and all treated units receive a homogeneous treatment. Under this assumption, the individual causal effect is defined as:

$$TE_i = Y_i(1) - Y_i(0) \mid X \quad (8)$$

The estimate of the causal effects on the outcome variable is defined as:

$$SATT = \frac{1}{n_T} \sum_{i \in T} TE_i \quad (9)$$

where n_T denotes the total number of treated units in the original sample. This estimator is valid only when all treated units are successfully matched. When some treated observations fall outside the common support region, as in the present study, the estimand shifts from the Sample Average Treatment Effect on the Treated (SATT) to the Local Sample Average Treatment Effect on the Treated (LSATT), which is defined over the subset of matched treated units. The LSATT is given by:

$$LSATT = \frac{1}{m_t} \sum_{i \in T^m} TE_i \quad (10)$$

where m_T denotes the number of matched treated units and T^m represents the subset of matched treated units.

3.2.3 Endogenous Switching Regression (ESR)

The ESR framework jointly estimates a selection equation governing adoption decisions and separate outcome equations for adopters and non-adopters, allowing consistent estimation of treatment effects under endogenous self-selection (Heckman et al., 2001; Abdulai and Huffman, 2014; Alene et al., 2015). The decision of adoption is endogenous as farmers usually self-select based on both observable and unobservable features, therefore without controlling for this, the effects of adoption on outcome variables (yield and income) will be biased. Thus, ESR model helps to address the problem of endogeneity by estimating selection

and outcome equations simultaneously using full information and maximum likelihood estimation method (Ma and Abdulai, 2016; Manda et al., 2019; Eshetie et al., 2022; Kapoor and Kapoor, 2022; Nonvide, 2024).

Let the selection or adoption of saline-tolerant seed variety equation be defined as:

$$D_i = X_i\alpha + \delta_i, \quad D_i = \begin{cases} 1, & \text{if } D_i > 0, \\ 0, & \text{otherwise.} \end{cases} \quad (11)$$

where X_i is a vector of explanatory variables capturing the socio-economic and demographic characteristics of farmer i , including age, household size, landholding size, gender, asset index, access to seed, fertilizer, and pesticide dealers, and possession of a subsidy card, among others. The relationship between these explanatory variables and the latent utility of adoption can be written as:

$$Y_i = f(X_i) \quad (12)$$

The farmer will adopt saline-tolerant seed varieties $D_i = 1$ when latent utility from adoption is greater than zero, i.e.,

$$D_i = \begin{cases} 1, & \text{if } Y_i > 0, \\ 0, & \text{otherwise.} \end{cases} \quad (13)$$

Now, the outcome equation conditional on treatment can be stated as:

$$\begin{aligned} \text{Regime 1 (Adopters): } Y_{1i} &= X_{1i} + \mu_{1i} \quad \text{if } D_i = 1, \\ \text{Regime 2 (Non-adopters): } Y_{2i} &= X_{2i} + \mu_{2i} \quad \text{if } D_i = 0. \end{aligned} \quad (14)$$

where Y_{1i} and Y_{2i} denote the outcome variables for adopters and non-adopters, respectively, and the error terms (μ_{1i}, μ_{2i}) are assumed to follow a trivariate normal distribution with zero mean and covariance matrix.

If the estimated covariances between the selection equation error term (δ_i) and the outcome equation error terms (μ_{1i}, μ_{2i}) , denoted by ρ_1 and ρ_2 , are statistically significant, this indicates correlation between adoption decisions and outcome variables (Abdulai and Huffman, 2014). The statistical significance of these parameters provides evidence of endogenous switching and leads us to reject the null hypothesis of no sample selection bias. The resulting framework constitutes an Endogenous Switching Regression (ESR) model, which allows estimation of both the Average Treatment Effect on the Treated (ATT) and the Average Treatment Effect on the Untreated (ATU) (Maddala and Nelson, 1975). Identification of the ESR model relies on an instrumental variable (IV) that affects the adoption decision but does not directly influence the outcome variables. In this study, access to seed dealers is used as the instrument. In addition, we compute

household-level conditional expectations of outcome variables under actual and counterfactual adoption states, as presented below:

$$\begin{aligned}
E(Y_{1i} | D_i = 1) &= \frac{\sum D_i = 1 (X_{1i}\beta_1 + \sigma_{1n}\gamma_{1i})}{N_1} \\
E(Y_{2i} | D_i = 0) &= \frac{\sum D_i = 0 (X_{2i}\beta_2 + \sigma_{2n}\gamma_{2i})}{N_0} \\
E(Y_{1i} | D_i = 1) &= \frac{\sum D_i = 1 (X_{1i}\beta_2 + \sigma_{2n}\gamma_{1i})}{N_1} \\
E(Y_{2i} | D_i = 0) &= \frac{\sum D_i = 0 (X_{2i}\beta_1 + \sigma_{1n}\gamma_{2i})}{N_0}
\end{aligned} \tag{15}$$

where N_1 and N_0 denote the number of observations with $D_i = 1$ (adopters) and $D_i = 0$ (non-adopters), respectively. The above expressions are summarized in Table 3. Cases (a) and (c) correspond to observed outcomes, whereas cases (b) and (d) represent counterfactual outcomes.

Table 3: Decision stage treatment and heterogeneity effects

Transitional heterogeneity	Treatment	Control	Treatment effects
Treatment	$E(Y_{1i} D_i = 1)$	$E(Y_{2i} D_i = 1)$	TT
Control	$E(Y_{1i} D_i = 0)$	$E(Y_{2i} D_i = 0)$	TU
Heterogeneity effects	BH_1	BH_2	TH

Source: (Carter and Milon, 2005)

Following Heckman et al. (2001), the treatment effect on the treated (TT) is computed as the difference between cases (a) and (c), capturing the impact of adoption on outcome variables for actual adopters. Similarly, the treatment effect on the untreated (TU) is defined as the difference between cases (b) and (d), representing the expected impact if non-adopters were to adopt saline-tolerant seed varieties. In addition, we compute base heterogeneity effects to capture differences in outcomes arising from inherent characteristics rather than treatment status. Base heterogeneity for adopters is measured as the difference between cases (a) and (d), while base heterogeneity for non-adopters is measured as the difference between cases (c) and (b) (Carter and Milon, 2005). Finally, we calculate transitional heterogeneity (TH) as the difference between TT and TU. This measure indicates whether the impact of adoption is larger for actual adopters relative to non-adopters under the counterfactual adoption scenario.

4 Results

4.1 Descriptive Statistics

Table 4 presents the summary statistics of the key demographic, economic, institutional, and outcome variables for adopters and non-adopters of saline-tolerant seed varieties. The analytical sample consists of 3,943 rice-growing households, of which 1,029 (26%) are adopters and 2,914 (74%) are non-adopters. We find no statistical difference between adopters and non-adopters in terms of age and household size. Landholding size appears to have a significant difference (0.27 ha) between adopters (1.03 ha) and non-adopters (0.91 ha), statistically significant at 99% level of significance. This indicates that relatively larger farmers are more inclined to adopt saline-tolerant varieties, possibly due to greater ability to experiment and absorb risk. This is also clear from the statistical significant difference in asset index between adopters and non-adopters of saline-tolerant seed varieties at 99% level of significance. Ownership of farm assets like tractor and power tiller turn out to be greater for adopters as compared to non-adopters, with differences being 17% and 6%, respectively, each of them being statistically significant. Adopters (52%) are observed to have higher access to formal financial services through possession of bank accounts as compared to non-adopters (38%), difference being significant at 99% level of significance. Ownership of mobile phones is also higher for adopters as compared to non-adopters, difference between them being 4% statistically significant at 99% level of significance.

Role of extension services and input markets play an important role in facilitating adoption decisions. Access to fertilizer dealer is reported by 87% of the adopters and 85% of the non-adopters, difference (2%) being statistically significant at 90% level. Similarly, access to pesticide dealer is reported by 87% of the adopters and 79% of the non-adopters, and difference between them 8% is statistically significant at 99% level. Lastly, access to seed dealers is reported by 81% of the adopters and 64% of the non-adopters, and the net difference between them (17%) is significant at 99% level of significance. Adoption also translates into higher crop yield and farmer's income. Average yield across the sample is 4.16 tons per hectare, but adopters achieve 4.97 tons per ha compared to 3.87 tons per hectare for non-adopters, a significant difference of 1.09 tons per hectare at 99% level. Likewise, average net farm income is US \$249 per hectare, with adopters earning US \$307/ha versus US \$229 per hectare for non-adopters. The net difference of US \$77 per hectare is statistically significant at 1% level, implying adopters earn 23% more than non-adopters from rice cultivation.

4.2 Determinants of adoption - logistic regression

Table 5 reports the logistic regression estimates of the key determinants of adoption of saline-tolerant seed varieties in saline-prone divisions of Bangladesh. We also present marginal effects alongside the logit coefficients to aid interpretation, focussing the discussion only on statistically significant covariates. The results show that farmer age has a positive and statistically significant effect on adoption. A unit increase in age raises the probability of adoption by 2.4%, consistent with the finding is consistent with evidence

Table 4: Descriptive statistics of key variables

Variables	Sample size (N = 3943)	Adopters (N = 1029)	Non-adopters (N = 2914)	Difference in mean (t-test)
Age (number)	48.20	48.42	48.12	0.29
Household size (number)	4.57	4.62	4.55	0.07
Landholding size (ha)	0.83	1.03	0.76	0.27***
Asset index	0.44	0.45	0.44	0.01***
Gender (male = 1, female = 0)	0.92	0.93	0.91	0.02**
Education				
Illiterate	0.42	0.42	0.42	0.01
Primary and below	0.24	0.21	0.25	-0.04*
Middle and secondary	0.30	0.28	0.30	-0.02
Higher-secondary and above	0.04	0.09	0.03	0.06***
Subsidy card (yes = 1, no = 0)	0.26	0.20	0.28	-0.08***
Tractor (yes = 1, no = 0)	0.19	0.32	0.15	0.17***
Power tiller (yes = 1, no = 0)	0.80	0.76	0.82	-0.06***
Land (irrigated = 1, rainfed = 0)	0.35	0.43	0.32	0.11***
Fertilizer dealer (yes = 1, no = 0)	0.85	0.87	0.85	0.02*
Pesticide dealer (yes = 1, no = 0)	0.81	0.87	0.79	0.08***
Seed dealer (yes = 1, no = 0)	0.68	0.81	0.64	0.17***
Urea shop (yes = 1, no = 0)	0.08	0.02	0.11	-0.09***
Agriculture office (yes = 1, no = 0)	0.17	0.18	0.16	0.02
Bank account (yes = 1, no = 0)	0.41	0.52	0.38	0.14***
Mobile (yes = 1, no = 0)	0.89	0.93	0.89	0.04***
Yield (tons/ha)	4.16	4.97	3.87	1.09***
Net income (US \$/ha)	249.54	307.01	229.24	77.77***

Source: Authors' calculation based on BIHS survey, 2015–16;

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

from Bangladesh and Ghana where experience plays a central role in agricultural technology uptake (Begum et al., 2024; Zakaria et al., 2021). We can also observe that females are more likely (12.3%) to adopt saline-tolerant seed varieties as compared to their male counterparts. Ownership of farm machinery such as tractors and power tillers significantly increases the likelihood of adoption by 15.3% and 5%, respectively. These assets proxy for capital endowments and reflect household's capacity to bear risk and experiment with new technologies. This aligns with broader evidence that farm assets and capital intensity facilitate agricultural technology adoption (Feder and Umali, 1993; Croppenstedt et al., 2013; Ma and Abdulai, 2016; Kumar et al., 2021; Hussain and Maharjan, 2025; Banik et al., 2026).

Asset index, capturing household wealth emerges as strong determinant, raising the probability of adoption by 31.4% which confirms that liquidity and wealth constraints remain a crucial barrier to adoption of seed varieties (Hasan et al., 2018; Saha et al., 2019). Financial inclusion, indicated through possession of bank account, increases the probability of adoption by 9%, supporting evidence from Vietnam and other developing countries (Ho et al., 2022). Access to seed dealers has the largest marginal effect, raising the probability of adoption by 25%, consistent with the findings from Nepal and Bangladesh that emphasized the role of input market access in adoption (Ghimire et al., 2015; Saha et al., 2019). Similarly, access to agricultural offices raises the likelihood of adoption by 7%, highlighting the importance of extension services and institutional support for disseminating information about new seed varieties (Wossen et al., 2017; Varshney et al., 2022). Interestingly, education doesn't exhibit statistically significant impact on adoption which appears to be counter-intuitive to the given general literature on technology adoption.

Overall, the results indicate that adoption of saline-tolerant seed varieties in coastal Bangladesh is shaped primarily by asset ownership, financial access, accessibility to input markets, extension service, and gender dynamics instead of formal education. These findings align with the broader literature emphasizing that agricultural technology adoption among smallholders is driven by socio-economic capacity and institutional environment as much as by expected agronomic returns (Feder and Umali, 1993; Croppenstedt et al., 2013; Ruzzante et al., 2021; Tufa et al., 2022).

4.3 Causal Impact - crop yield and net income

This section evaluates the causal impact of adopting saline-tolerant rice seed varieties on two key outcome variables: rice yield (tons/ha) and net farm income (USD/ha). Since the adoption is not random and farmers self-select the adoption of these varieties based on certain observable and unobservable characteristics, we employ three complementary econometric approaches - propensity score matching (PSM), coarsened exact matching (CEM) and endogenous switching regression (ESR) to ensure robust estimation and address the issue of selection bias through different identification strategies.

Table 6 presents the result from PSM approach using the nearest neighbourhood matching approach. PSM constructs a counterfactual group of non-adopters that are similar to adopters in terms of socio-economic, demographic, and institutional factors. The balancing test confirms that covariate differences between

Table 5: Logit estimates

Variables	Logit coefficient (Adopter = 1, non-adopter = 0)	Marginal effect (dy/dx)
Age	0.157*** (0.023)	0.024*** (0.004)
Gender (female = 1, male = 0)	0.798*** (0.189)	0.123*** (0.029)
Education (Base: Illiterate)		
Middle and secondary	-0.087 (0.118)	-0.014 (0.018)
Higher secondary and above	0.223 (0.181)	0.035 (0.028)
Asset index	2.034*** (0.653)	0.314*** (0.101)
Tractor (yes = 1, no = 0)	0.992*** (0.118)	0.153*** (0.017)
Power tiller (yes = 1, no = 0)	0.322*** (0.128)	0.050*** (0.020)
Bank account (yes = 1, no = 0)	0.583*** (0.096)	0.090*** (0.015)
Seed dealer (yes = 1, no = 0)	1.674*** (0.199)	0.259*** (0.030)
Agriculture office (yes = 1, no = 0)	0.444*** (0.133)	0.069*** (0.020)
Observations	3943	3943

Source: Authors' calculation based on BIHS survey, 2015–16.

Robust standard errors in parentheses; *** $p < 0.01$.

treatment and control groups are reduced substantially after matching and common support condition is also satisfied. PSM estimates indicate that adopters of saline-tolerant seed varieties achieve higher crop yield and net income of 1.25 tonnes per ha and USD\$ 95 per hectare, respectively. The results are statistically significant at 1% level of significance and confirm with earlier findings from Bangladesh (Islam, 2018; Haque et al., 2019; Salam and Sarker, 2023). Table A1 gives a detailed result on balancing test of covariates before and after matching. The assumption of common support is also satisfied as shown in Figure A1 where the distribution of propensity scores for treated and untreated households show considerable overlapping.

Table 6: PSM estimates

Outcome variable	ATT	Standard error
Yield (tons/ha)	1.25***	0.19
Net income (US \$/ha)	95.85***	28.25

Notes: Authors' estimates.

*** $p < 0.01$.

Table 7 presents the results obtained using CEM approach which pre-processes data by coarsening covariates and ensuring exact matches within strata. CEM is known to reduce model dependence and imbalance more effectively as compared to traditional matching approaches (Blackwell et al., 2009; Iacus et al., 2011). CEM results show that adopters experience 0.92 tonnes per hectare higher rice yield as compared to non-adopters of saline-tolerant seed varieties. Moreover, adopters of saline-tolerant seed varieties achieve a higher net income of US \$102 per hectare in comparison to non-adopters. The coefficients are statistically significant at 99% level of significance. The findings align with the results obtained by Pal et al. (2021) and Kumar et al. (2020, 2021). Table A2 provides a detailed output for CEM results for the outcome variables.

Table 7: CEM estimates

Outcome variable	ATT	Standard error
Yield (tons/ha)	0.92***	0.11
Net income (US \$/ha)	102.02***	29.64

Notes: Authors' estimates.

*** $p < 0.01$.

Table 8 presents results obtained using ESR method that jointly models the adoption decision and outcome equations, correcting for both observable and unobservable selection biases (Abdulai and Huffman, 2014; Manda et al., 2019; Kapoor and Kapoor, 2022). Results portray that adopters achieve a higher crop yield of 4.86 tonnes per hectare as compared to 4.01 tonnes per hectare of non-adopters, signifying productivity gains of equal to 0.85 tonner per hectare (TT) from adoption of saline-tolerant seed varieties. More strikingly, ESR counterfactual estimates show that non-adopters currently have a crop yield of 3.62 tonnes per hectare but would have achieved an average yield of 6.03 tonnes per hectare, if they would have adopted saline-tolerant seed varieties, implying treatment effect on untreated (TU) of 2.41 tonnes per hectare. This large TU indicates that non-adopters stand to gain even more from adoption than current adopters. The heterogeneity effect (TH) of 1.56 tons/ha confirms that productivity gains from adoption are higher for non-adopters under the counterfactual scenario. A similar pattern emerges for net income of the farmers. Adopters earn an average

income of US \$531.87 per hectare as compared to US \$407.75 for non-adopters. Hence, the treatment effect on treated (TT) is calculated to be US \$124.12 per hectare. On the other hand, average income of non-adopters is calculated to be US \$352.76 but would eventually rise to US\$478.71 per hectare, if they adopt saline-tolernat seed varieties, signifying TU to be US\$125.95 per hectare. All ESR estimates are statistically significant at the 99% level and align with results from studies in India, Nepal, and Nigeria (Manda et al., 2019; Kumar et al., 2020; Pal et al., 2021; Malabayabas et al., 2023). Regime-wise equations for both outcome variables - yield and net income are presented in Table A3 and Table A4, respectively.

Table 8: ESR estimates

Outcome variable	Adopters	Non-adopters	Treatment effect
Yield (tons/ha)			
Adopters	4.86	4.01	TT = 0.85***
Non-adopters	6.03	3.62	TU = 2.41***
Heterogeneity effect	BH ₁ = -1.17***	BH ₂ = 0.39***	TH = -1.56***
Net income (US \$/ha)			
Adopters	531.87	407.75	TT = 124.12***
Non-adopters	478.71	352.76	TU = 125.95***
Heterogeneity effect	BH ₁ = 52.29***	BH ₂ = 53.99***	TH = -1.83***

Source: Authors' calculation based on BIHS survey, 2015–16; *** $p < 0.01$.

5 Discussion

Salinity intrusion is one of the most extreme environmental factors limiting agricultural productivity, especially in low-lying developing countries where coastal ecosystems and agricultural systems are closely connected with each other (Nicholls et al., 2007). Coastal regions are vulnerable to tidal inundation and sea-level rise, accelerating the movement of saline water into agricultural soil and freshwater aquifers (Dasgupta et al., 2014). In Bangladesh, this process has progressively degraded the quality of cultivable land in coastal districts, constraining rice production and threatening the food security and livelihoods of households dependent on these fragile agro-ecosystems. Estimates suggest that around 63% of Bangladesh's coastal zone has already been affected by some degrees of salinity over the past 50 years (SRDI, 2012). Moreover, out of 8.1 million hectares of arable land in the country, 1.02 million hectares lie in 19 coastal districts and are severely affected by salinity intrusion (SRDI, 2012). In response to this growing challenge, the development of rice varieties with salt-tolerance traits has been identified as one of the most promising and practical adaptation strategies to sustain agricultural production under increasing salinity stress (Dam et al., 2019). The Bangladesh Rice Research Institute (BRRI) has developed different saline-tolerant rice seed varieties to support farmers in the coastal belt to sustain their livelihoods. Despite the multiple benefits of saline-tolerant seed varieties, adoption remain low in Bangladesh. Without large-scale uptake, the intended goals of food security, income stability, and climate resilience can't be achieved. Improvements in agricultural productivity through new technologies occur through an integrated approach considering farmer's

characteristics, institutional support, and input delivery systems (Asfaw et al., 2012; Teklewood et al., 2013; Aryal et al., 2015; Ghimire et al., 2015). This study sets out not only to merely test whether saline-tolerant rice varieties improve outcomes, but also to understand why demonstrably high-return climate adaptation technology diffuses slowly in salinity affected coastal belt of Bangladesh along with proposing some policy recommendation to increase its adoption.

Using a nationally representative sample, Bangladesh Integrated Household Survey (BIHS) 2015-16, we examine the key drivers of adoption of saline-tolerant seed varieties, and evaluate its impact on crop yield and farmer's net income. We use a logistic model to assess how household characteristics influence adoption decisions. Various results are in conformity with theory and earlier evidences, but some may appear to be counter-intuitive. Asset holdings and ownership of agricultural equipments like tractors and power tillers significantly influence likelihood of adoption. However, education levels show no significant effect, contradictory to the present literatures (Varshney et al., 2022). Moreover, Table 4 reveals that around 42% of the farmers are illiterate in both the categories (adopters and non-adopters), with no significant differences across middle and secondary education levels, implying homogeneity in education attainments (Pal, et al., 2024).

Unlike earlier studies like Lunduka et al. (2019) and Mwalongo et al. (2020) which suggested male headed households are more likely to adopt saline-tolerant seed varieties due to their greater risk taking appetite, but this study finds that female-headed households exhibit a higher likelihood of adoption. This reflects evolving rural dynamics in Bangladesh economy, where sustained efforts by NGOs such as Grameen Bank and BARC have strengthened women's empowerment, access to credit, and extension services (Amin et al., 1998). Moreover, it is also evident from the results that accessibility to extension services emerges as a significant driver of adoption.

Next, by using three complementary causal frameworks PSM, CEM, and ESR, correcting for selection bias and unobserved heterogeneity, we try to evaluate the impact of adoption of saline-tolerant seed varieties on crop yield and farmer's net income. Results from PSM and CEM indicate significant and positive impacts on crop yield and net income. PSM shows that adopters achieve 1.25 tons/ha higher yield and USD 95.85/ha more income than non-adopters, while CEM estimates yield and income gains to be 0.92 tons/ha and USD 102.02/ha, respectively as compared to non-adopters. The close similarity of these estimates suggests robustness, though the small differences in them could be due to the sensitivity of results arising out of choice of matching technique. CEM often results in better balance due to lower standardized mean differences across the covariates. However, the assumption of selection bias remains a limitation in both these methods, as unobserved cofounders may still influence the estimated treatment effects. Thus, this underscores the importance of complementing these approaches with models like ESR that explicitly accounts for endogeneity. Also, the ESR results highlight the potential heterogeneous treatment effects, showing the adopters and non-adopters would have different outcomes under counterfactual scenarios. The ESR estimates indicate that non-adopters have an average yield of 3.62 tons per hectare which would increase to 6.03 tons per hectare if they had adopted saline-tolerant seed varieties. The net treatment effect of adoption on the non-adopters (TU) is calculated to be 2.41 tons per hectare. Conclusively, the net impact

of adoption of saline-tolerant seed varieties is computed to be 1.56 tons per hectare, which is statistically significant, reinforcing productivity gains of adoption. Additionally, the heterogeneity effect of net income is smaller but is statistically significant. This could be due to inherent differences in skills and human capital (managerial skills) and experience in rice farming which suggests qualitative differences between adopters and non-adopters in the sample are not huge.

The empirical results of this study allow the role of saline-tolerant seed varieties to be interpreted not merely as an agronomic innovation, but also as a multi-dimensional climate adaptation strategy connected directly/indirectly with SDGs, particularly SDG 13 (climate action), SDG 2 (zero hunger), and SDG 1 (no poverty). In a country where rice supplies two-thirds of calorie intake and coastal divisions contribute nearly one-third of national production, such gains are not merely agronomic improvements but critical to maintaining food system resilience and preventing income shocks that can trigger poverty and climate-induced migration. However, the low adoption rate (26%) reveals that the barrier to achieving these SDG gains is not technological feasibility but institutional, informational, and behavioural constraints—such as weak seed delivery systems, limited extension outreach, liquidity constraints at sowing time, and lingering distrust from earlier varietal failures. Therefore, realizing the full SDG potential of saline-tolerant varieties requires policy attention not on further varietal development but on strengthening last-mile input markets, extension credibility, and low-cost behavioural interventions that can accelerate technology diffusion and translate proven climate-smart innovations into large-scale development outcomes.

6 Conclusion

Bangladesh is one of the most climate-vulnerable countries globally, and its coastal rice system faces acute risks from climate-induced salinity intrusion (World Bank, 2022). Salinity stress threatens farm productivity and rural livelihoods, amplifying poverty and contributing to distress migration. A major policy response has been sustained public investment in developing saline-tolerant rice varieties; yet adoption has remained low. Using the 2015-16 Bangladesh Integrated Household Survey (BIHS) conducted by the International Food Policy Research Institute (IFPRI), a nationally and division-representative survey with detailed information on agricultural practices, this study documents adoption levels, identifies their correlates, and estimates the productivity and welfare impacts of adopting saline-tolerant varieties. We find that adoption remains low (26%), but adopters realize meaningful gains: yields increase by about 0.85-1.25 tons per hectare and net income rises by roughly US \$100-125 per hectare. Counterfactual estimates suggest that non-adopters could gain substantially up to 2.4 tons per hectare in yields and about US \$126 per hectare in net income, if adoption constraints were relaxed.

Determinants of adoption point to the central role of market access and service delivery, particularly access to agricultural extension, proximity to seed dealers, and access to complementary farm implements. These findings imply that profitability alone is not sufficient for diffusion when farmers face information frictions, liquidity and credit constraints, and thin input markets. Hence, from a policy perspective, the relevant question

is not only to improve varietal performance, but also to design institutions and delivery systems that enable the farmers to adopt the climate-smart intervention. Rather than relying on broad input subsidies—whose effectiveness and environmental consequences have been widely debated (UNEP, 2021; Laborde et al., 2022) — a more cost-effective approach may combine strengthened extension and seed delivery systems with innovative institutional arrangements and behavioural interventions. Drawing on nudge-based policy design, small and timely changes to choice architecture (e.g., ensuring availability of quality seed at the right time, simplifying purchase and delivery, or leveraging trusted local intermediaries) may increase adoption without large subsidies (Thaler and Sunstein, 2008). Evidence from input adoption in other contexts suggests that timing and liquidity-sensitive delivery mechanisms can generate large behavioural responses (Duflo et al., 2011).

These findings have direct/indirect implications for SDGs. Adoption of saline-tolerant rice varieties directly contributes to SDG 13 (Climate Action) by enhancing farm productivity under climate-vulnerable coastal systems. The increased crop yield strengthens food availability and production resilience to climate change, supporting SDG 2 (Zero Hunger). Moreover, higher farm incomes contribute to SDG 1 (No Poverty) by reducing income volatility and securing smallholder farmers against climate-related shocks. More importantly, these SDG-linked benefits arise not from expanded input use or costly farm intensifications, but from varietal innovations that helps to improve productivity with ecological constraints. Overall, saline-tolerant rice varieties offer a high-return and scalable adaptation option for coastal Bangladesh and unlocking their full potential requires shifting policy attention from technological development toward institutional design and delivery mechanisms that translate innovation into widespread adoption.

Acknowledgements

This work was undertaken as part of the CGIAR Science Program on Policy and Innovation. This program combines state-of-the-art analytics, innovative use of data, and close engagement with national, regional and global partners to offer better insights into alternative transformation pathways that can inform choices and sharpen decision-making today, leading to more productive, sustainable and inclusive food, land and water systems in the future. We would like to thank all funders who supported this research through their contributions to the CGIAR Trust Fund for the Science Program on Policy and Innovation. We also thank the Bangladesh Integrated Households Survey (BIHS) team led by the IFPRI-Bangladesh office for making this large database available online and extending support to help us understand the sampling strategy and primary data. Without their support, this study would not have been possible.

Funding: This study has been supported by the Consultative Group on International Agricultural Research (CGIAR) through the CGIAR Trust Fund for the Science Program on Policy and Innovation.

Competing Interests

The authors declare no potential conflicts of interest with respect to research, authorship, and/or publication of this study.

References

- Abdulai, A. and Huffman, W. (2014). The adoption and impact of soil and water conservation technology: An endogenous switching regression approach. *Land Economics*, 90(1):26–43.
- Abeysekara, W. C., Siriwardana, M., and Meng, S. (2023). Economic consequences of climate change impacts on the agricultural sector of south asia: A case study of sri lanka. *Economic Analysis and Policy*, 77:435–450.
- Ahmed, A., Tauseef, S., and Ghostlaw, J. (2016). IFPRI’s bangladesh integrated household survey (bihs) second round dataset now available. International Food Policy Research Institute (IFPRI). Please verify authors and publication type (blog post/data release) and add full publication details.
- Ahsan, M. and Bhuiyan, M. R. (2010). Soil and water salinity, their management in relation to climate change in coastal areas of bangladesh. *Khulna University Studies*, Special Issue:31–42.
- Alene, A. D. et al. (2015). The effectiveness of crop improvement programmes from the perspectives of varietal output and adoption: Cassava, cowpea, soybean and yam in sub-saharan africa and maize in west and central africa. In *Crop Improvement, Adoption and Impact of Improved Varieties in Food Crops in Sub-Saharan Africa*, pages 74–122. Please add editors, publisher, and place of publication.
- Amin, R., Becker, S., and Bayes, A. (1998). Ngo-promoted microcredit programs and women’s empowerment in rural bangladesh: Quantitative and qualitative evidence. *The Journal of Developing Areas*, 32(2):221–236.
- Aryal, J. P., Mehrotra, M. B., Jat, M. L., and Sindhu, H. S. (2015). Impact of laser land levelling in rice-wheat systems of the north-western indo-gangetic plains of india. *Food Security*, 7:725–738.
- Asfaw, S., Shiferaw, B., Simtowe, F., and Lipper, L. (2012). Impact of modern agricultural technologies on smallholder welfare: Evidence from tanzania and ethiopia. *Food Policy*, 37(3):283–295.
- Banik, B., Jahan, H., Ahmed, M. R., Nandi, R., Jackson, T., and Jannat, A. (2026). Determinants of modern agricultural machinery adoption in northern bangladesh: A multivariate probit analysis. *Sustainable Futures*, 11:101615.
- BBS (2018). 45 years agricultural statistics of major crops (aus, aman, boro, jute, potato & wheat).
- BBS (2019). Yearbook of agricultural statistics 2019.

- Begum, M. E. A. et al. (2024). Farmers' choices and factors driving adoption of climate change adaptation strategies in saline coastal areas of bangladesh. *African Journal of Science, Technology, Innovation and Development*, 16(1):113–127.
- BER (2019). Bangladesh economic review 2019.
- Blackwell, M., Iacus, S., King, G., and Porro, G. (2009). cem: Coarsened exact matching in stata. *The Stata Journal*, 9(4):524–546.
- BRRI (2011). Bangladesh rice knowledge bank.
- Caliendo, M. and Kopeinig, S. (2008). Some practical guidance for the implementation of propensity score matching. *Journal of Economic Surveys*, 22:31–72.
- Carter, D. W. and Milon, J. W. (2005). Price knowledge in household demand for utility services. *Land Economics*, 81(2):265–283.
- Croppenstedt, A., Goldstein, M., and Rosas, N. (2013). Gender and agriculture: Inefficiencies, segregation, and low productivity traps. *The World Bank Research Observer*, 28(1):79–109.
- Dam, T. H., Amjath-Babu, T. S., Bellingrath-Kimura, S., and Zander, P. (2019). The impact of salinity on paddy production and possible varietal portfolio transition: A vietnamese case study. *Paddy and Water Environment*, 17:771–782.
- Dasgupta, S., Hossain, M. I., Huq, M., and Wheeler, D. (2014). Climate change, soil salinity, and the economics of high-yield rice production in coastal bangladesh. Please add report series/number if applicable.
- Duflo, E., Kremer, M., and Robinson, J. (2011). Nudging farmers to use fertilizer: Theory and experimental evidence from kenya. *American Economic Review*, 101(6):2350–2390.
- Eshetie, A. M. et al. (2022). Nexus of cash crop production using improved varieties and household food security. *The European Journal of Development Research*, 34:1803–1830.
- Feder, G. and Umali, D. L. (1993). The adoption of agricultural innovations: A review. *Technological Forecasting and Social Change*, 43(3-4):215–239.
- Germanwatch (2021). Global climate risk index 2021.
- Ghimire, R., Huang, W.-C., and Shrestha, R. B. (2015). Factors affecting adoption of improved rice varieties among rural farm households in central nepal. *Rice Science*, 22(1):35–43.
- Haque, M. R., Sultana, R., Rahman, M. H., and Hasan, A. K. (2019). Impact of adopting salt tolerant rice varieties in the coastal areas of bangladesh. *Fundamental and Applied Agriculture*, 4(2):823–828.
- Hasan, M. K., Desiere, S., D'Haese, M., and Kumar, L. (2018). Impact of climate-smart agriculture adoption on the food security of coastal farmers in bangladesh. *Food Security*, 10:1073–1088.

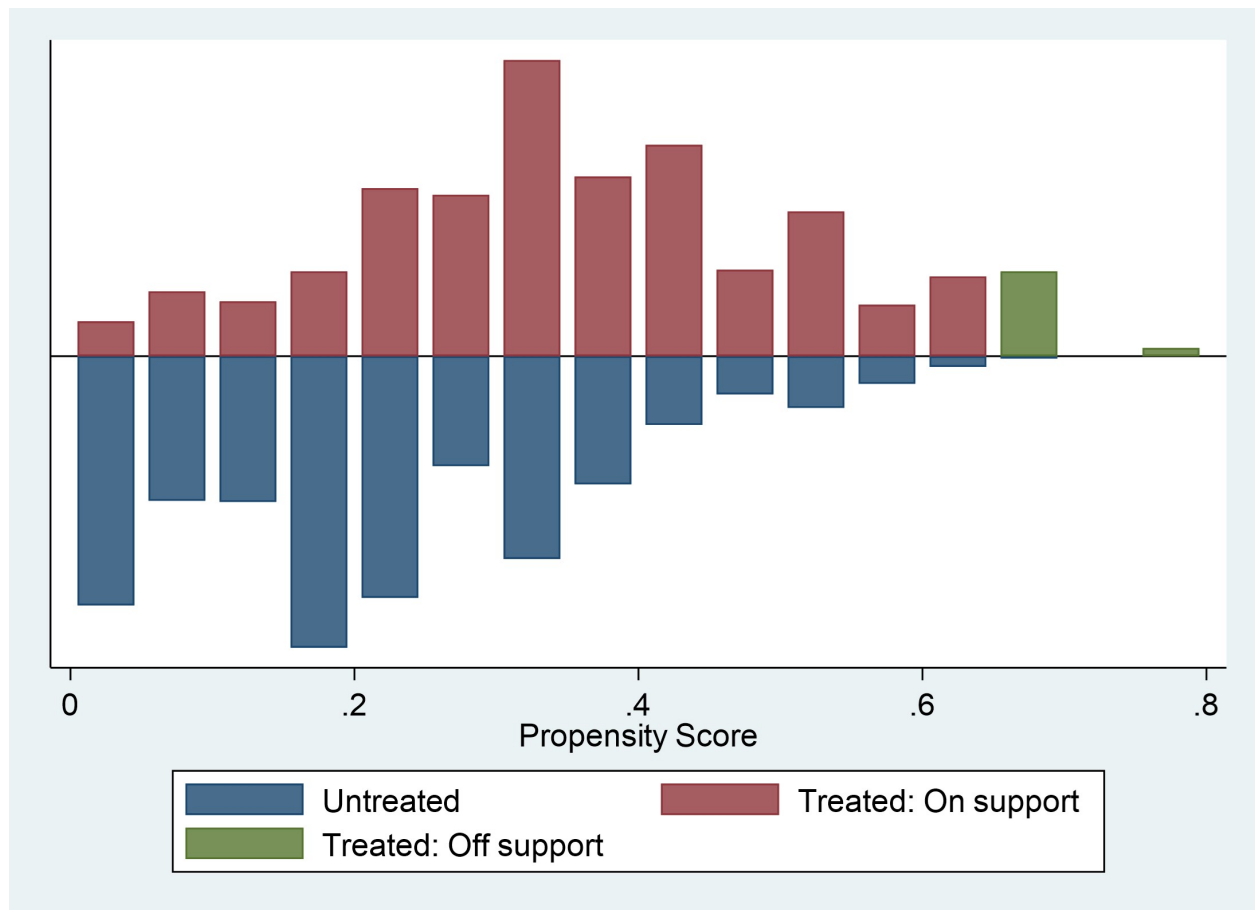
- Heckman, J. J., Tobias, J. L., and Vytlačil, E. (2001). Four parameters of interest in the evaluation of social programs. *Southern Economic Journal*, 68(2):210–223.
- Ho, T. D., Kuwornu, J. K., and Tsusaka, T. W. (2022). Factors influencing smallholder rice farmers' vulnerability to climate change and variability in the mekong delta region of vietnam. *The European Journal of Development Research*, 34:272–302.
- Hossain, M. S. et al. (2020). Climate change impacts on farmland value in bangladesh. *Ecological Indicators*, 112:106181.
- Hussain, N. and Maharjan, K. L. (2025). Impact of on-farm demonstrations on technology adoption, yield, and profitability among small farmers of wheat in pakistan—an experimental study. *Agriculture*, 15(2):214.
- Iacus, S. M., King, G., and Porro, G. (2011). *Causal Inference Without Balance Checking: Coarsened Exact Matching*. Oxford University Press. Please verify edition and place of publication.
- IPCC (2007). Climate change 2007: Synthesis report.
- Iqbal, K. and Roy, P. K. (2015). Climate change, agriculture and migration: Evidence from bangladesh. *Climate Change Economics*, 6(2):1550006.
- Islam, A. (2018). Impact of improved rice varieties adoption on farmers' wellbeing (livelihood) in rural bangladesh. *Bangladesh Journal of Agricultural Economics*, 38(1-2):35–54. Please verify journal title and issue formatting.
- Jamal, M. R., Kristiansen, P., Kabir, M. J., and de Bruyn, L. L. (2022). Cropping systems intensification and diversification: Risk, vulnerability and adaptation in southwest coastal bangladesh. *International Journal of Sustainable Development & World Ecology*, 29(8):677–694.
- Kapoor, S. and Kapoor, S. (2022). Effectiveness of non-farm diversification on rural household income: Evidence and policy implications from india. *International Journal of Development Issues*, 21(1):1–23.
- Kumar, A. et al. (2020). Adoption and diffusion of improved technologies and production practices in agriculture: Insights from donor-led interventions in nepal. *Land Use Policy*, 95:104621.
- Kumar, A., Tripathi, G., and Joshi, P. K. (2021). Adoption and impact of modern varieties of paddy in india: Evidence from a nationally representative field survey. *Journal of Agribusiness in Developing and Emerging Economies*, 11(3):255–279.
- Laborde, D. et al. (2022). Repurposing agricultural policies and support. Technical report, World Bank Group. Please verify full title/subtitle and report series information.
- Lechner, M. (1999). Earnings and employment effects of continuous off-the-job training in east germany after unification. *Journal of Business & Economic Statistics*, 17(1):74–90.
- Lunduka, R., Fisher, M., Snapp, S., and Fisher, E. (2019). Adoption and impact of drought-tolerant maize varieties on farm productivity and welfare in malawi. *Climate and Development*, 11(6):502–515.

- Ma, W. and Abdulai, A. (2016). Does cooperative membership improve household welfare? evidence from apple farmers in china. *Food Policy*, 58:94–102.
- Maddala, G. S. and Nelson, F. D. (1975). Specification errors in limited dependent variable models. Technical report, National Bureau of Economic Research. Please add report number if available.
- Malabayabas, M. L., Mishra, A. K., and Pede, V. O. (2023). Joint decision-making, technology adoption and food security: Evidence from rice varieties in eastern india. *World Development*, 171:106367.
- Manda, J. et al. (2019). The poverty impacts of improved cowpea varieties in nigeria: A counterfactual analysis. *World Development*, 122:261–271.
- Mendola, M. (2007). Agricultural technology adoption and poverty reduction: A propensity-score matching analysis for rural bangladesh. *Food Policy*, 32:372–393.
- Mwalongo, S., Mlozi, M. R., Tumbo, S. D., and Rwegasira, G. M. (2020). Factors influencing farmers' preferences and adoption of improved groundnut varieties in tanzania. *Agronomy*, 10(9):1271.
- Nicholls, R. J. et al. (2007). Coastal systems and low-lying areas. In *Climate Change 2007: Impacts, Adaptation and Vulnerability*. Please add editors, publisher, and page range (listed as 315–356 in source list).
- Nonvide, G. M. (2024). Impact of irrigation on food and nutrition security among rice farmers in benin. *The European Journal of Development Research*, 36:1343–1371.
- Ogutu, S. O., Okello, J. J., and Otieno, D. J. (2014). Impact of information and communication technology-based market information services on smallholder farm input use and productivity: The case of ghana. *World Development*, 64:311–321.
- Pal, B. D. et al. (2021). Adoption of climate-smart agriculture technology in drought-prone area of india: Implications on farmers' livelihoods. *Journal of Agribusiness in Developing and Emerging Economies*, 15(5):824–848.
- Park, B. and Ochieng, H. K. (2024). The impacts of rural development project on resilience to climatic disasters: The case of bangladesh. *World Development*, 180:106631.
- Rahman, S. and Anik, A. R. (2020). Productivity and efficiency impact of climate change and agroecology on bangladesh agriculture. *Land Use Policy*, 94:104507.
- Rosenbaum, P. R. and Rubin, D. B. (1985). Constructing a control group using multivariate matched sampling methods that incorporate the propensity score. *The American Statistician*, 29(1):33–38.
- Ruzzante, S., Labarta, R., and Bilton, A. (2021). Adoption of agricultural technology in developing world: A meta-analysis of the empirical literature. *World Development*, 146:105599.
- Saha, M. K. et al. (2019). Factors affecting adoption of climate-smart agricultural practices by coastal farmers in bangladesh. *American Journal of Environment and Sustainable Development*, 4(4):113–121.

- Salam, M. A. and Sarker, M. N. I. (2023). Impact of hybrid variety adoption on the performance of rice farms in bangladesh: A propensity score matching approach. *World Development Sustainability*, 2:100042.
- Sarker, J. R. (2024). *An Economic Analysis of the Impact of Practicing Climate Smart Agriculture by Rice Producers in Bangladesh*. PhD thesis, CQ University. Please verify thesis type and location.
- Selbonne, S. et al. (2022). Designing scenarios for upscaling climate smart agriculture on a small tropical island. *Agricultural Systems*, 199:103401. Please verify article number/page range.
- Sikder, R. and Xiaoying, J. (2014). Climate change impact and agriculture in bangladesh. *Journal of Environment and Earth Science*, 4(1):35–40.
- Simtowe, F., Asfaw, S., and Abate, T. (2016). Determinants of agricultural technology adoption under partial population awareness: The case of pigeonpea in malawi. *Agriculture and Food Economics*, 4:7. Please verify article number/page range.
- SRDI (2012). Soil resource development institute.
- Teklewood, H., Kassie, M., and Shiferaw, B. (2013). Adoption of multiple sustainable agricultural practices in rural ethiopia. *Journal of Agricultural Economics*, 64(3):597–623.
- Thaler, R. H. and Sunstein, C. R. (2008). *Nudge: Improving Decisions About Health, Wealth, and Happiness*. Yale University Press, New Haven, CT.
- Tufa, A. H. et al. (2022). Gender differences in technology adoption and agricultural productivity: Evidence from malawi. *World Development*, 159:106027.
- UNEP (2021). Annual report 2021. Technical report, United Nations Environment Programme.
- USDA (2021). Rice explorer. Accessed via USDA FAS.
- Varshney, D. et al. (2022). Examining the transfer of knowledge and training to smallholders in india: Direct and spillover effects of agricultural advisory services in an emerging economy. *World Development*, 160:106067.
- World Bank (2022). Bangladesh: Country climate and development report. Technical report, World Bank. Please verify report subtitle/series information as needed.
- World Food Programme (2016). Strategic review of food security and nutrition in bangladesh. Please verify publisher/institution details.
- Wossen, T., Abdoulaye, T., Alene, A., and Haile, M. (2017). Impacts of extension access and cooperative membership on technology adoption and household welfare. *Journal of Rural Studies*, 54:223–233.
- Yu, W. H. et al. (2010). *Climate Change Risk and Food Security in Bangladesh*. EarthScan, London.

Appendix

Figure A1: Common support



Source: Authors' compilation.

Table A1: T-test quality of means before and after matching

Variable	Matched	Treated	Control	% Bias	% Red. Bias	t	p>t
Age	U	48.42	48.12	2.3	-421.6	0.61	0.54
	M	48.96	47.43	12.0		2.83	0.01
Household size	U	4.62	4.55	4.2	-44.8	1.14	0.254
	M	4.54	4.44	6.0		1.40	0.16
Asset index	U	0.45	0.44	13.3	38.9	3.43	0.01
	M	0.45	0.45	-8.1		-1.96	0.05
Education (Base: Illiterate)							
Primary and below	U	0.22	0.25	-8.2	10.7	-2.24	0.03
	M	0.22	0.25	-7.3		-1.61	0.11
Middle and secondary	U	0.28	0.30	-4.6	-199.9	-1.26	0.21
	M	0.29	0.24	13.8		3.13	0.02
Higher secondary and above	U	0.08	0.03	26.2	4.6	8.29	0.01
	M	0.04	0.10	-25.0		-5.01	0.01
Subsidy card (Yes=1)	U	0.19	0.28	-19.9	91.5	-5.33	0.01
	M	0.16	0.16	1.7		0.43	0.66
Tractor (Yes=1)	U	0.67	0.85	-41.1	50.9	-12.1	0.01
	M	0.71	0.79	-20.2		-4.36	0.01
Power tiller (Yes=1)	U	0.24	0.18	14.1	-71.0	3.99	0.01
	M	0.26	0.16	24.1		5.41	0.01
Land (Irrigated=1)	U	0.57	0.68	-22.4	75.1	-6.25	0.01
	M	0.56	0.59	-5.6		-1.19	0.23
Gender (Female=1)	U	0.06	0.08	-7.8	-73.9	-2.10	0.04
	M	0.07	0.03	13.6		3.62	0.01
Pesticide dealer (Yes=1)	U	0.13	0.21	-20.6	93.3	-5.44	0.01
	M	0.13	0.14	-1.4		-0.33	0.74
Fertilizer dealer (Yes=1)	U	0.13	0.15	-7.0	-17.8	-1.91	0.06
	M	0.13	0.11	8.3		1.98	0.05
Seed dealer (Yes=1)	U	0.19	0.36	-39.4	78.6	-10.4	0.01
	M	0.19	0.16	8.4		2.14	0.03
Urea shop (Yes=1)	U	0.98	0.89	37.9	93.2	9.05	0.01
	M	0.98	0.99	-2.6		-1.10	0.27
Bank (Yes=1)	U	0.48	0.62	-28.3	51.3	-7.86	0.01
	M	0.51	0.44	13.8		3.00	0.01
Agriculture office (Yes=1)	U	0.82	0.84	-4.5	-84.9	-1.26	0.21
	M	0.85	0.82	8.4		1.90	0.06
Mobile (Yes=1)	U	0.93	0.89	14.3	60.2	3.78	0.01
	M	0.92	0.94	-5.7		-1.45	0.15

Source: Authors' estimation.

Table A2: CEM estimates – Yield and Net Income

Variables	Yield (tons/ha)	Net income (US \$/ha)
Salinity tolerant seed adoption (Yes=1)	3.613*** (0.410)	5,101.033*** (1,481.872)
Age	-0.074*** (0.020)	-32.674 (90.551)
Household size	0.135 (0.194)	-1,440.871** (617.674)
Subsidy card (Yes=1)	-1.085 (0.688)	4,916.998* (2,853.118)
Asset index	2.218 (3.091)	7,266.011 (10,915.952)
Education (Base: Illiterate)		
Primary and below	0.042 (0.560)	-13,738.593*** (1,713.908)
Middle and secondary	0.662 (0.631)	-15,438.823*** (1,897.009)
Tractor (Yes=1)	1.331*** (0.476)	5,832.157*** (1,904.115)
Power tiller (Yes=1)	2.102** (0.983)	20,900.466*** (3,243.401)
Land (Irrigated=1)	6.872*** (0.526)	6,261.518*** (2,234.452)
Bank (Yes=1)	-0.671 (0.518)	5,778.246*** (1,815.832)
Agriculture office (Yes=1)	-4.186*** (0.673)	-1,565.596 (5,926.746)
Mobile (Yes=1)	-2.029 (1.279)	5,921.006*** (2,228.178)
Constant	15.041*** (2.202)	-4,988.827 (8,270.707)
Observations	898	898
R-squared	0.435	0.242

Source: Authors' estimations based on BIHS survey, 2015–16.

Robust standard errors in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A3: ESR estimates – Yield (tons/ha)

Variables	Treatment = 1	Control = 0	Saline adoption
Log age	-1.800** (0.894)	-0.538 (0.690)	11.656*** (2.305)
Log household size	0.206 (0.162)	-2.030*** (0.166)	-1.264** (0.498)
Log age square	0.193* (0.117)	0.072 (0.091)	-1.455*** (0.306)
Log household size square	-0.058 (0.056)	0.704*** (0.058)	0.515*** (0.171)
Gender (Female=1)	-0.128*** (0.041)	0.076** (0.032)	0.421*** (0.103)
Subsidy card (Yes=1)	0.009 (0.022)	-0.077*** (0.019)	-0.318*** (0.061)
Asset index	0.014 (0.165)	-0.924*** (0.132)	1.635*** (0.404)
Education (Base: Illiterate)			
Primary and below	0.083*** (0.023)	-0.101*** (0.020)	0.132** (0.066)
Middle and secondary	-0.032 (0.020)	0.126*** (0.022)	-0.010 (0.062)
Higher secondary and above	-0.241*** (0.041)	-0.199*** (0.050)	0.258** (0.120)
Tractor (Yes=1)	-0.026 (0.024)	-0.296*** (0.032)	0.532*** (0.064)
Power tiller (Yes=1)	0.205*** (0.025)	-0.238*** (0.026)	-0.286*** (0.066)
Land (Irrigated=1)	0.274*** (0.019)	0.358*** (0.021)	0.027 (0.057)
Pesticide dealer (Yes=1)	-0.085** (0.035)	0.224*** (0.037)	0.096 (0.113)
Fertilizer dealer (Yes=1)	0.008 (0.040)	-0.117*** (0.040)	-0.777*** (0.127)
Urea shop (Yes=1)	0.135* (0.071)	-0.117*** (0.032)	-0.901*** (0.129)
Bank (Yes=1)	-0.013 (0.020)	0.104*** (0.020)	0.376*** (0.055)
Agriculture office (Yes=1)	-0.020 (0.024)	-0.021 (0.025)	0.305*** (0.069)
Mobile (Yes=1)	0.067* (0.036)	0.070** (0.030)	0.193** (0.093)
Seed dealer (Yes=1)			0.910*** (0.087)
Constant	6.792*** (1.734)	5.260*** (1.277)	-24.437*** (4.298)
Observations	3,943	3,943	3,943

Source: BIHS survey, 2015–16.

Standard errors in parentheses; ** $p < 0.01$, *** $p < 0.05$, * $p < 0.1$.

Table A4: ESR estimates – Net income (US \$/ha)

Variables	Treatment = 1	Control = 0	Saline adoption
Log age	1.110 (5.579)	-3.979 (4.018)	15.245 (10.378)
Log age square	-0.139 (0.643)	0.489 (0.532)	-1.948 (1.383)
Log household size	-6.633*** (1.987)	-0.691** (0.341)	-0.925 (1.997)
Log household size square	2.187*** (0.683)	0.207 (0.172)	0.339 (0.774)
Gender (Female=1)	0.777 (0.684)	-0.333** (0.140)	0.168 (0.250)
Subsidy card (Yes=1)	-0.024 (0.095)	-0.166 (0.183)	-0.280** (0.138)
Asset index	-0.402 (2.107)	0.790 (0.614)	1.020 (2.568)
Education (Base: Illiterate)			
Primary and below	0.238 (0.219)	-0.320*** (0.074)	0.062 (0.188)
Middle and secondary	0.166 (0.257)	-0.031 (0.143)	0.013 (0.205)
Higher secondary and above	0.828 (0.518)	0.066 (0.065)	0.539 (0.637)
Tractor (Yes=1)	-0.200 (0.243)	0.558** (0.226)	0.578** (0.234)
Power tiller (Yes=1)	-0.113 (0.195)	0.448*** (0.093)	-0.116 (0.514)
Land (Irrigated=1)	0.252*** (0.030)	0.099 (0.090)	0.249 (0.261)
Pesticide dealer (Yes=1)	0.941*** (0.209)	0.075 (0.178)	0.106 (0.366)
Fertilizer dealer (Yes=1)	-0.091 (0.325)	0.260 (0.306)	-0.709 (0.845)
Urea shop (Yes=1)	0.703 (0.518)	-0.044 (0.200)	-1.043** (0.493)
Bank (Yes=1)	0.109 (0.205)	0.050 (0.031)	0.279*** (0.102)
Agriculture office (Yes=1)	0.183 (0.131)	0.134 (0.165)	0.262 (0.229)
Mobile (Yes=1)	-0.638 (0.436)	-0.237** (0.094)	0.173 (0.123)
Seed dealer (Yes=1)			0.913** (0.449)
Constant	11.708 (12.683)	17.316** (7.746)	-30.559 (18.747)
Observations	3,943	3,943	3,943

Source: BIHS survey, 2015–16.

Standard errors in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.