Impact of Submergence-Tolerant Rice Varieties on Smallholders' Income and Expenditure: Farm-Level Evidence from Bangladesh

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Abstract

This study examines the adoption of submergence-tolerant (Sub1) rice varieties (BRRI dhan51, BRRI dhan52, BINA Dhan 11, and BINA Dhan 12), grown in the Aman season (July-November) in northwest Bangladesh, using data obtained from more than 1,100 farm households. The impacts of these varietal adoptions on profit from rice production and household consumption expenditure are also examined. Employing the endogenous switching regression model, this paper finds that the predicted probability of adopting Sub1 varieties is about 0.40, implying that 40% of the sampled farm households in northwest Bangladesh adopted Sub1 rice varieties. The main drivers of Sub1 adoption decisions are education, access to information, cropped area, migration, and access to electricity. This paper also finds that Sub1 rice varieties had a significant positive impact on adopters' farm profit and consumption expenditure compared with those of non-adopters. Therefore, we suggest implementing policies and developing institutional capacity that help increase the dissemination of Sub1 seeds and incentivize farmers to adopt Sub1 varieties in flood-prone areas in Bangladesh.

Key words: adoption, Bangladesh, endogenous switching regression, impact assessment, rice varieties, submergence-tolerant (Sub1).

JEL Classification: C34, D13, O12, Q12, Q16.

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1. Introduction

Bangladesh is one of the most climate-affected countries in the world. According to two recent reports, the global Climate Risk Index 2017 (Kreft et al., 2016) and the Climate Change Vulnerability Index 2017 (Maplecroft, 2016), Bangladesh was ranked in the top-10 countries most vulnerable to climate change in the world. Note that more than 200 extreme climatic events such as floods, cyclones, and storms hit Bangladesh during the last two decades, which cost on average 1% of the national gross domestic product (GDP) (Kreft et al., 2016). The most common climatic events in Bangladesh are floods, especially monsoon and flash floods (Dewan, 2015; Rahman and Zhang, 2016). Hydrological characteristics such as low-lying topography surrounded by a large network of rivers, high annual evapotranspiration (ca. 1,600 mm), and being situated at the head of the Bay of Bengal make the country highly vulnerable to floods (Figure 1). Floods sometimes (e.g., floods in 1998, 2007, and 2017) significantly affect the country's economy by damaging crops, fisheries, livestock, household assets, and infrastructure (Ahmed et al., 2000; Dewan et al., 2003; Majumder, 2013). In each year, on average, one-fifth of the total agricultural lands are affected by the floods (Figure 2), which cost approximately BDT 4.0 billion annually (USD 1 = BDT 79.0 in 2016), equivalent to 0.5% of the agricultural GDP (Bairagi and Bari, 2015).

Rice fields in many parts of the country are affected the most. Note that more than 2.5 million hectares (ha) of rice lands are prone to floods, of which around 1.0 million ha are highly flood prone (FAO, 2001; Gumma et al., 2012). On average, 4% of the total rice production is lost every year because of the floods (Paul and Rashid, 1993). Rice is the dominant cash crop and the staple food in Bangladesh, accounting for three-fourths of the total calorie intake, one-half of the agricultural GDP, and one-half of the rural employment. Shocks to the rice supply from floods could aggravate the country's food insecurity, rural unemployment, and poverty situation. Therefore, to minimize rice production loss due to floods, the government of Bangladesh has been giving high priority and accordingly investing resources to develop and disseminate flood-tolerant rice varieties. The Bangladesh Rice Research Institute (BRRI) and the Bangladesh Institute of Nuclear Agriculture (BINA), in collaboration with the International Rice Research Institute (IRRI), have already developed and promoted five Sub1 rice varieties, BRRI dhan51, BRRI dhan52, BRRI dhan79, BINA Dhan 11, and BINA Dhan 12, which are suitable for farming in the Aman season (July-November).[1]

The main attribute of Sub1 rice varieties is that they can survive at least 7-14 days under water (Mackill, et al., 2012; Rahman and Zhang, 2016)[2]. In addition, they yield 1-3 tons/ha more than traditional varieties and, most importantly, under normal conditions, they have no yield penalty (Sarkar et al., 2006, 2009; Neeraja et al., 2007; Dar et al., 2013). Field trials in India showed that Sub1 rice reduces yield variability and increases yield; as a result, socially disadvantaged groups are benefited (Dar et al., 2013). Other randomized trials in India by Emerick et al. (2015) found that adoption of this rice has a positive impact on productivity and much of this gain originates from crowding-in effects (e.g., modern inputs and cultivation practices). In India, at present, the adoption rate of the flood-resilient rice varieties is 3.5-4.5% (Yamano et al., 2016; Mohanty and Yamano, 2017), and has been increasing over the years. However, in Bangladesh, Sub1 adoption levels and its impact on smallholder farmers are unknown, even though Sub1 rice varieties were released six years ago, and this paper attempts to overcome this lack of knowledge. In addition,

[1] Three types of rice are grown in Bangladesh: Aus, Aman, and Boro. Aman rice is cultivated in one-half of the total rice areas (11.5 million ha), mainly under rainfed conditions, most of which are prone to monsoon and flash floods (Gumma et al., 2012).
[2] A detailed molecular characterization of Sub1 can be found in Bailey-Serres and Voesenek (2008) and Bailey-Serres et al. (2010)

knowledge from this study could be used in other rice producing countries (e.g., Nepal, Myanmar, Laos, and Cambodia) where submergence is a big threat to rice production.

The structure of this paper follows: Section 2 provides the foundation for building a model for assessing Sub1 adoption and its impact on outcome variables. Data collection procedures and insights from data including adoption rate and whether adopters are distinct appear in Section 3. Section 4 describes the results followed by drivers of Sub1 adoption, its impact, and economic ramifications of the scaling out of Sub1 in Bangladesh, whereas conclusions appear in the final section.

2. Theoretical and Empirical Framework

2.1 Technology adoption decision

The decision to adopt a new technology can be modeled in a random utility framework (de Janvry et al., 2010; Becerril and Abdulai, 2010; Asfaw et al., 2012). Let us assume that a representative farm household, i, maximizes its utility subject to budget constraints, information and credit access, the availability of the technology (here, Sub1 rice varieties), and other inputs. Farm household i will choose to adopt a Sub1 variety only if the utility gain from adopting (U_{iA}) is greater than the utility from not adopting (U_{iNA}) it ($U_i^* = U_{iA} - U_{iNA} > 0$). Because these two utilities are unobservable, it is impossible to observe the choices made by the i^{th} household. However, these utilities can be modeled as a function of observable elements in the latent variable model, which is expressed below:

$$U_i^* = \delta Z_i + e_i \text{ with } U_i = \begin{cases} 1, & \text{if } U_i^* > 0 \\ 0, & \text{otherwise} \end{cases} \qquad (1)$$

where U_i^* is the latent variable, indicating the likelihood of the i^{th} household's decision to adopt Sub1, which takes the value 1 if Sub1 is adopted and otherwise 0; Z is a vector of exogenous variables that explain adoption decisions; δ is a vector of parameters associated with Z to be estimated; and e is the random error term assumed to be independent and identically distributed.

2.2 Impact assessment of technology adoption

The impact of Sub1 adoption on farm profit and household expenditure in Bangladesh can be modeled in a linear function as specified below:

$$Y_i = \beta X_i + \gamma U_i + \varepsilon_i \qquad (2)$$

where Y is the outcome variable, in our case profit from rice cultivation and household consumption expenditure; X is a vector of explanatory variables; β are vectors of parameters associated with U to be estimated; U is defined before; γ is the parameter that defines the impact of the adoption of Sub1 rice on outcome variables; and ε is an error term.

One can estimate these steps independently/separately (equations 1-2), for example, employing a single econometric technique such as probit, double hurdle, correlated random effects, and other fixed effects models.[3] Nonetheless, the estimated parameters are inefficient if the problem of self-selection issues and non-random allocation of subjects to treatment and control groups arise, which are the most common cases with observational data; therefore, γ needs to be correctly estimated (Faltermeier and Abdulai, 2009). In experimental trials, this problem is addressed by randomly assigning adoption to treatment and control status to two groups, which guarantees that the outcome variables observed on the control group without adoption are representative of what would have occurred without adoption. However, in non-experimental trials (observational studies), impact assessment of technology adoption on outcome variables (e.g., farm profit) is non-trivial because the outcome variables for adopters are unobservable if they had not adopted

[3] Langyintuo and Mungoma (2008), Mason et al. (2013).

(or the reverse). Farm households could themselves choose to adopt given the information they have; as a result, adopters and non-adopters are unlikely to be systematically different (Amare et al., 2012). Therefore, following Khonje et al. (2015), this paper uses endogenous switching regression that is able to capture selection bias and the endogeneity problem as well as being able to provide results under different counterfactual states of adoption decision.[4]

Endogenous switching regression

Using endogenous switching regression (ESR), this study estimates the average treatment effect of the treated (ATT) to assess the impacts of Sub1 rice varieties on outcome variables, farm profit, and consumption expenditure. The ATT calculates the mean difference in outcomes of adopters with and without a technology adoption. The ESR framework works as follows: (i) the decision to adopt Sub1 is estimated with a probit model (equation 1), and (ii) the relationship between the outcome variables and a vector of exogenous variables conditional on the adoption decision is estimated with a selectivity corrected OLS (ordinary least squares) model.

Mathematically, it can be expressed as:

Regime 1: (adopters): $y_{1i} = \alpha_1 x_{1i} + \mu_{1i}$ if $U = 1$ (3.1)

Regime 2: (non-adopters): $y_{2i} = \alpha_2 x_{2i} + \mu_{2i}$ if $U = 0$ (3.2)

where the subscripts $_1$ and $_2$ represent regime 1 and regime 2, respectively; α_1 and α_2 are the coefficients associated with a set of explanatory variables, x, to be estimated; and μ_1 and μ_2 are the random error terms. The ESR model needs to be identified through a set of instrumental

[4] For assessment of technology adoption, PSM (propensity score matching) and ESR are the two methods that are most widely used. However, PSM has some disadvantages that ESR does not have; for example, even though, like ESR, PSM is able to correct selection bias, it ignores unobserved characteristics affecting the adoption process and assumes characteristics to be the same for both adopters and non-adopters.

variables that are important to include in the adoption model (equation 1) in addition to those automatically generated by the non-linearity of the selection model of adoption (Shiferaw et al. 2014). This study uses three instruments: had information on Sub1 rice varieties (yes = 1), whether households are members of any organization (yes = 1), and access to electricity (yes = 1). Note that the first two instruments jointly define access to information on technology adoption. The validity or admissibility of these instruments was tested using a simple falsification test following Di Falco et al. (2011). This test suggests that an instrument is valid if it affects the technology adoption but does not affect the outcome variables. Based on the results, we find that the instruments are valid, as they are jointly significantly correlated with the adoption decision but insignificantly correlated with the outcome variables.

Equations 1 and 3 can be estimated using OLS, but the parameters are likely to be biased because the error terms (e and μ) are not normally distributed (Shiferaw et al., 2014). The error terms are assumed to be a trivariate normal distribution with mean vector zero and the following covariance matrix:

$$\Omega = cov(e, \mu_1, \mu_2) = \begin{bmatrix} \sigma_e^2 & \sigma_{e1} & \sigma_{e2} \\ \sigma_{e1} & \sigma_1^2 & . \\ \sigma_{e2} & . & \sigma_2^2 \end{bmatrix} \qquad (4)$$

where $\sigma_e^2 = var(e) = 1$, $\sigma_1^2 = var(\mu_1)$, $\sigma_2^2 = var(\mu_2)$, $\sigma_{e1} = cov(e, \mu_1)$, and $\sigma_{e2} = cov(e, \mu_2)$. The covariance between μ_1 and μ_2 is undefined (.) because y_1 and y_2 cannot be observed simultaneously. Since e_i is correlated with μ_1 and μ_2, the mean values of μ_1 and μ_2 conditional on the sample selection are non-zero (Lokshin and Sajaia, 2004; Asfaw et al., 2012), expressed as:

$$E(\mu_{1i}|U=1)=\sigma_{e1}\frac{\phi(\delta Z_i)}{1-\Phi(\delta Z_i)}\equiv\sigma_{e1}\lambda_1 \qquad (5)$$

$$E(\mu_{2i}|U=0)=\sigma_{e2}\frac{\phi(\delta Z_i)}{1-\Phi(\delta Z_i)}\equiv\sigma_{e2}\lambda_2 \qquad (6)$$

where ϕ and Φ are the standard normal probability density and cumulative density functions, respectively; and $\lambda_1$and λ_2 are the inverse Mills ratio, which is estimated from the selection equation and is to be included in equations 3.1 and 3.2 for correcting selection bias.

The above-specified ESR framework can be applied to calculate the ATT and ATU (average treatment effect of the untreated) by comparing the expected values of the outcomes of adopters and non-adopters in actual and counterfactual scenarios.[5] The ATT and ATU are calculated as:

Adopters with Sub1 adoption (observed in the sample)

$$E(y_{1i}|U=1;x)=\alpha_1 x_{1i}+\sigma_{e1}\lambda_{1i} \qquad (7.1)$$

Non-adopters without Sub1 adoption (observed in the sample)

$$E(y_{2i}|U=0;x)=\alpha_2 x_{2i}+\sigma_{e2}\lambda_{2i} \qquad (7.2)$$

Sub1 adopters had they chosen not to adopt (counterfactual)

$$E(y_{2i}|U=1;x)=\alpha_2 x_{1i}+\sigma_{e2}\lambda_{1i} \qquad (7.3)$$

Sub1 non-adopters had they chosen to adopt (counterfactual)

$$E(y_{1i}|U=1;x)=\alpha_1 x_{2i}+\sigma_{e1}\lambda_{2i} \qquad (7.4)$$

The ATT is computed, differentiating between 7.1 and 7.3, as:

$$ATT=(y_{1i}|U=1;x)-(y_{2i}|U=1;x),$$

$$=\ x_{1i}(\alpha_1-\alpha_2)+\lambda_{1i}(\sigma_{e1}-\sigma_{e2}) \qquad (8)$$

[5] Many studies followed similar notations, but here Lokshin and Sajaia (2004), Di Falco et al. (2011), Shiferaw et al. (2014), and Khonje et al. (2015) are referred to.

The ATU is computed, differentiating between 7.4 and 7.3, as:

$$ATU = (y_{1i}|U = 0; x) - (y_{2i}|U = 0; x),$$

$$= x_{2i}(\alpha_1 - \alpha_2) + \lambda_{2i}(\sigma_{e1} - \sigma_{e2}) \qquad (9)$$

The first terms of equations 8 and 9 capture whether adopters (or non-adopters) had characteristics similar to those of non-adopters (or adopters), whereas the second terms capture the differences in unobserved variables.

3. Survey Data

3.1 Sampling method

The data for this study came from a household survey of 1,625 sample rice farmers conducted in 2016. This was a baseline survey conducted by the International Rice Research Institute (IRRI), Dhaka Office, for the Stress-Tolerant Rice for Africa and South Asia (STRASA) project. The survey was conducted in the same STRASA project districts (Lalmonirhat, Kurigram, Rangpur, Gaibandha, Jamalpur, and Sherpur) in northwest Bangladesh (Figure 3). The northwest region was targeted because (a) it is a major rice-growing region of the country. The sampled six districts together account for around 12% of the country's total rice production (Table 1), and (b) it is a highly flood-prone region (Figure 1).

We used a multi-stage stratified random sampling technique to select the sampling unit. In the first stage, each district was divided into two sub-districts based on flood-prone and non-flood-prone strata, making 12 sampled sub-districts in total. In the second stage, a list of flood-prone Unions was selected based on the 2015 flood information. Then, we randomly selected five Unions from each sub-district, making 60 sampled Unions in total. In the third stage, one village per Union was randomly selected, except in Darshana Union of Rangpur Sadar in Rangpur

District, where five villages were selected because of the large size of the Union, making 65 sampled villages in total. In the final stage, we conducted a census of the 65 villages and prepared a list of rice farm households from the census information. Finally, we randomly selected 25 rice farmers from each sampled village, making 1,625 farm households in total (Table 2).

These farm households were interviewed using a semi-structured questionnaire, which contains different modules pertaining to the farm and household characteristics of rice farmers, cultivation of rice varieties, flood characteristics, adoption of Sub1 rice varieties, cost of production, income and expenditure, and access to information. This survey questionnaire was developed after several iterations of discussion and pre-testing and conducting face-to-face interviews of respondents using computer-assisted personal interview (CAPI) software Surveybe.[6] The primary respondent was the household head, but, if the household head was not available, information was collected from another knowledgeable member of the household. The survey was conducted soon after the Aman rice harvest season (March to June 2016).

3.2. Data visualization

3.2.1 Adoption of Sub1 rice varieties

Because of some missing information and outliers, the following analysis is based on 1,134 samples, comprising 449 Sub1 adopters and 685 non-adopters. A farmer is to be called an adopter if any of these four rice varieties, BRRI dhan51, BRRI dhan52, BINA Dhan 11, and BINA Dhan 12, are adopted. Adoption can be measured in terms of the percentage of sample households adopting (probability of adoption) and the share of area cultivated under Sub1 rice varieties (adoption intensity). The results (in Figure 4) reveal that around one-third of the

[6] Details can be found at http://surveybe.com/.

sampled farmers adopted these rice varieties in 2015 (the survey year), which is used as the selection variable in our econometric analysis. Regarding adoption intensity, one-fifth of the total Aman areas were found to be cultivated with Sub1 rice varieties, which is lower than the probability of adoption because famers might adopt both Sub1 and other available rice varieties (e.g., Swarna) to maximize their utility.

3.2.2 Are adopters really distinct?

Table 3 reports the means of selected variables by adoption category (adopters = 1 and non-adopters = 0). The results reveal that adopters are indeed distinct in terms of accessing human capital. For example, the level of the household head's education is significantly higher for adopters than for non-adopters, but both groups actually had a low level of education (2.4 vs 2.1 years). Education is theorized to have a positive impact on the adoption of new technology (Huffman, 2001), as it helps one to be the first mover (leader), because education helps adopters to better understand the importance of adopting a new technology. The level of farming experience is also significantly higher (five years) for adopters than for non-adopters. Farming experience may or may not affect technology adoption significantly because it is hypothesized to have an inverted-U relationship with technology adoption, implying that, at the early stages of adoption, farming experience is useful, but not in the later stages (Ainembabazi and Mugisha, 2014).

In terms of access to social capital, adopters are also distinct: for example, having a Pucca house,[7] accessing electricity and a sanitary toilet, and having migrated family members. Table 3 reveals that adopters own more Pucca houses than non-adopters. They also accessed more

[7] Houses (dwellings) that are made of bricks and are designed to be solid and permanent.

electricity and sanitary toilets. Table 3 also reveals that the numbers of migrated family members (internal and external) are significantly higher for adopters than for non-adopters. Migration is expected to have a positive effect on technology adoption because it could help sustain household income flows and provide financial liquidity so that household decision makers are able to solve their credit constraints to investing in agricultural technologies.

Adopters also owned more agricultural land than non-adopters (3.76 vs 2.83 acres). The decision to adopt a new or improved agricultural technology could depend on the amount of land that farmers are able to allocate for that technology. Because adoption could involve high risks and uncertainties, if farmers own enough land, they can only allocate more land to such technology or become the first adopter.

3.2.3 Do Sub1 varieties require fewer inputs and yield more?

Table 4 presents a detailed rice production budget by adoption category, which shows that adopters of Sub1 rice varieties used significantly less TSP (triple superphosphate) and pesticides on their fields. In other words, adopters had to spend significantly less money for fertilizer and pesticides to produce rice. In terms of yield, adopters obtained significantly higher productivity (around 300 kg per ha) than non-adopters (Figure 5), although adopters received a lower market price per unit of paddy than non-adopters. However, the net benefits (profit) for adopters were significantly higher than for non-adopters (BDT 5,000 per ha). Thus, we conclude that Sub1 rice varieties require on average less fertilizer but yield more; consequently, farmers can obtain more profit from adopting them.

4. Results and Discussion

4.1 Driving factors of Sub1 adoption

The parameters estimated from the endogenous switching regression model (equations 1 and 3) are presented in Table 5. The first column of Table 5 presents the estimated parameters of the probit model for Sub1 adoption. The results show that 10 out of 16 variables are found to be the significant driving factors of Sub1 adoption in northwest Bangladesh. These are education, share of non-farm income, migration, access to Sub1 information, membership, electricity, and four location variables. All these drivers are significantly and positively associated with the adoption of Sub1, except for share of non-farm income.

The findings indicate that the coefficient for education dummy (if the household head had at least one year of schooling equals 1 and 0 otherwise) is significantly and positively associated with the adoption of Sub1. This suggests that educated heads are more likely to adopt Sub1 than their counterparts, which is consistent with the fact that educated heads are likely to be well aware of the benefits of new agricultural technologies, such as Sub1 rice varieties.

The findings further indicate that access to information can play an important role in adopting Sub1. Access to information is defined by two variables: whether the household head had information on Sub1 rice varieties (yes = 1) and whether any household members in a family had membership in any formal and informal organizations (yes = 1). It is assumed that household members are likely to be more and better informed about agricultural technologies through different organizations, which are assumed to be a source of information. Both the dummy variables are found to be statistically significant and positively correlated with the adoption decision on Sub1 rice varieties. This suggests that the likelihood of adopting agricultural technologies, such as Sub1, is more for the farm households that had access to information than for those that did not. However, note that the survey results reveal that one-third of the sampled smallholders did not receive any information regarding Sub1 adoption. Moreover, smallholders who received Sub1 information were informed most of the time by friends and family members. Here, this suggests that a trusted partner such as family and friends (e.g., extension agents, input dealers, seed company workers) is important for the scale-out of a new technology.

Column 1 of Table 5 reveals that the coefficient of the migration dummy variable, whether any family members migrated for employment (yes = 1), is significant at the 10% level and positively associated with the adoption decision. This indicates that smallholders are more likely to adopt Sub1 rice if a member of their household works outside the home and sends a remittance. Remittance income is assumed to be a flow of additional income in a household that can overcome household credit constraints. Therefore, smallholders are more likely to invest in a risky business such as adopting Sub1 rice varieties. Column 1 of Table 5 also reveals that smallholders who had more income from non-farm (off-farm) activities are more likely to adopt Sub1 rice than their counterparts.

Finally, location variables were included in the regression to control for regional heterogeneities. Recall that data were collected from six districts, so five dummy variables were used, for which Lalmonirhat District is the base location variable. The results in column 1 of Table 5 reveal that the probability of adoption of Sub1 is significantly different for four districts (Kurigram, Jamalpur, Sherpur, and Gaibandha) than for Lalmonirhat District. This is consistent with the higher adoption rates for these districts (78%, 70%, 42%, and 36%, respectively) compared with Lalmonirhat (26%).

4.2 Drivers of farm profit and consumption expenditure

The determinants of profit from rice cultivation and per capita consumption expenditure are presented in columns 2-3 and columns 4-5 of Table 5, respectively. First, the findings from the profit function indicate that two variables are statistically significantly and negatively associated with both adopters' and non-adopters' profit function. These variables are index of production cost and flood-damaged plot. The index (the former one) is constructed with the relevant cost items (e.g., seed, fertilizer, irrigation, and labor), (see rows 9-14 of Table 5), using principal component analysis, which defines the intensity of costs to produce rice. The coefficients related to this index are -2.62 for adopters and -2.17 for non-adopters and are found to be statistically significant at the 1% and 5% levels, respectively. This implies that, with more costs associated with rice production, the less profit smallholders would obtain, which is consistent with economic theory. The latter one, damaged plot, is defined as a dummy variable that takes the value 1 if rice plots are flood-prone plots and otherwise 0. The coefficients related to this variable are negatively and significantly correlated with farm profit for both adopters and non-adopters. This implies that flood-damaged plots are unlikely to yield more than plots that were not affected.

Second, with regard to consumption expenditure function, education dummy variable and log of cropped areas are positively and significantly associated with per capita consumption. This implies that per capita consumption increases with increased education and the more cropped areas the households have. Finally, the results show that both profit and consumption are found to be geographically significantly different.

4.3 Impact of adopting Sub1 rice varieties

Table 6 presents the treatment effects of Sub1 adoption on predicted farm profit per ha and per capita consumption expenditure. The findings suggest that the average treatment effects on the treated (ATT) and untreated (ATU) are statistically significant from zero for both outcome variables. These indicate that adopters would lose profit and spend less had they not adopted Sub1. The average increase in profit from rice production for adopters (ATT) was estimated to be about BDT 20,700 (USD 262, USD 1 = BDT 79 in 2016) per hectare, implying that adopters would have lost BDT 20,700 per hectare had they not adopted Sub1 varieties. In contrast, the average increase in profit from rice production by non-adopters (ATU) is estimated to be about BDT 11,700 (USD 112) per hectare. This implies that non-adopters could have gained BDT 11,700 per hectare had they adopted Sub1 varieties. The findings further suggest that the average increase in annual per capita consumption expenditure for adopters (ATT) is about BDT 2,000 (USD 25), implying that adopters would have spent BDT 610 less annually on a per capita basis had they not adopted Sub-1 varieties. In contrast, the average increase in annual per capita consumption for non-adopters (ATU) is about BDT 7,560 (USD 96), meaning that non-adopters could spend BDT 7,560 more if they adopted Sub1 varieties. Therefore, we conclude that the adoption of Sub1 rice varieties had a great impact on adopters' income and consumption expenditure compared with those of non-adopters in northwest Bangladesh.

5.0 Economic Ramifications

Rice is not only the staple food for more than 165 million Bangladeshi; it is also an important economic, social, cultural, and political commodity in the country. During the last decades, Bangladesh has made tremendous progress in rice production, which is largely driven by yield growth. Current rice (milled) production is about 34 million tons (mt); but, assuming that 80% is available for consumption, the actual rice supply for human consumption is 27 mt.[8] On the demand side, supposing annual consumption of 152 kg per capita (BBS, 2011), the total demand for rice is 25 mt per year. Therefore, given the current scenarios, a mere 2 mt of rice surplus per year is expected. However, if any natural calamities destroy the rice sector partially (10% of total rice production is lost), the country will experience a rice deficit. For example, a severe flood in 2017 caused a large increase in milled rice imports, amounting to 2.41 mt, compared with only 0.06 mt of rice imports in 2016. The severe floods of 2017 also caused about a 40% increase in rice price as compared to the previous year. Because rice accounts for one-third of the total food expenditure for the poor, an increase in rice prices directly affects food and nutrition security as well as the incidence and severity of poverty. Therefore, this evidence indicates that flood is a major risk to food security and poverty in Bangladesh. To mitigate this risk, short-, medium-, and long-term policies are required. An important one could be the large-scale dissemination and adoption of Sub1 rice varieties, which is expected to have a significant impact in Bangladesh, as this study found that the adoption of Sub1 rice is a profitable as well as welfare-improving technology.

4.3.1 Scaling out of Sub1 adoption

The survey data reveal that, in the study areas, one-half of the sampled households experienced floods during 2010-2015, and most of them experienced two flash floods. Rice fields were submerged on average 15 days in a severe flood event, and around 40% of total rice production was lost because of these floods. However, recall that approximately one-third of the sampled households adopted Sub1 rice varieties, which is significantly low given the suitability of Sub1

[8] Seed, animal feed, and wastage are the rest.

varieties for surviving under flood conditions. If Sub1 rice varieties had been adopted widely, a significant portion of this production loss could have been averted. In addition, as before, the results of this study show that non-adopters could benefit if they adopted flood-resistant rice varieties. Now, the question is why the adoption rate (area under Sub1 cultivation) and the intensity of adoption (% of households adopting Sub1) are still low. One of the important reasons could be the lack of access to information on new technology. The survey results reveal that one-half of the non-adopters did not receive any information with regard to Sub1, and their sources of information are neighborhood farmers and relatives. Concerning this, training on information dissemination to farmers could have helped increase Sub1 adoption. However, farmers' lack of trust in the new technology could have been an important obstacle to adoption. In this regard, information dissemination through different mass media as well as through different trusted partners (e.g., government extension specialists) could have increased adoption. Finally, the lack of Sub1 seeds and grain quality could be other major constraints to a larger adoption of Sub1 varieties. IRRI can play an important role in this, for example, developing farmer-preferred traits along with flood-resistant traits. Therefore, we suggest implementing policies that can solve the above-mentioned problems and developing institutional capacity that can help increase the dissemination of Sub1 seeds and incentivize farmers to adopt Sub1 rice in flood-prone areas in Bangladesh.

6. Conclusions

This paper investigated the driving factors for the adoption of submergence-tolerant (Sub1) rice varieties and their impact on smallholders' profit from rice production and consumption expenditure in northwest Bangladesh. To obtain these objectives, endogenous switching regression, comprising probit and selectivity corrected OLS models, is used with household survey data obtained from more than 1,100 rice farmers. The findings indicate that the predicted probability of adopting Sub1 varieties is about 0.40, which implies that 40% of the sampled farm households in northwest Bangladesh adopted Sub1 rice varieties. The main drivers of the Sub1 adoption decision are education and access to information (whether smallholders had Sub1 information and membership in an organization). The adoption of Sub1 varieties was also affected by whether the household head had more cropped areas, at least one migrated family member working outside the home, and access to electricity. The findings also indicate that the adoption of Sub1 rice varieties led to a significant gain in farm profit and consumption expenditure for adopters. For non-adopters, they would have also gained from the adoption of Sub1 rice varieties if they had adopted those varieties. This evidence suggests that Sub1 is a potential as well as emerging technology, especially for flood-prone areas. Nonetheless, adoption rates in the study areas are still low. Access to information on Sub1 rice varieties, lack of trust in the new technology, lack of Sub1 seeds, and farmer-disfavored grain quality are the potential constraints to the scaling out of Sub1 adoption. Therefore, we suggest implementing policies that can overcome these constraints and developing institutional capacity that can help increase the dissemination of Sub1 rice varieties and can help farmers to adopt Sub1 rice varieties in flood-prone areas in Bangladesh, through which this is expected to have a greater impact on the country’s food security as well as poverty.

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Table 1. Rice area and production in the study areas

Districts	Rice area (1,000 ha)		Rice production (1,000 tons)	
	Aman	Total	Aman	Total
Bangladesh	5,530	11,416	19,785	52,066
Study districts				
Lalmonirhat	78	128	317	624
Kurigram	104	206	367	994
Rangpur	157	294	653	1,566
Gaibandha	126	250	483	1,205
Jamalpur	84	216	321	1,079
Sherpur	83	178	258	799
Sub-total	632	1,272	2,400	6,268
Share of study districts in Bangladesh (%)	11.4	11.1	12.10	12.0

Source: Bangladesh Bureau of Statistics (BBS) (www.bbs.gov.bd/)and Ministry of Disaster Management and Relief (www.modmr.gov.bd/), the government of Bangladesh.

Table 2. Distribution of the sample households

District	Number of Upazilas	Number of Unions	Total sampled farmers	Number of households used in the analysis [§]		
				Adopters	Non-adopters	Total
Gaibandha	2	5	250	16	29	45
Jamalpur	2	7	250	160	67	227
Kurigram	2	10	375	89	25	114
Lalmonirhat	2	7	250	59	170	229
Rangpur	2	15	250	40	276	316
Sherpur	2	10	250	85	118	203
Total	12	54	1,625	449	685	1,134

Notes: [§] 491 samples were excluded from the analysis because of missing information on yield, area, and other data; missing pre-identified respondents; and outliers.

Table 3. Mean differences of sociodemographic profiles of the sample households by adoption category

Variables	Definition	Adopters	Non-adopters	Mean difference
Individual characteristics				
Sex	1 = yes if household head is male, and otherwise 0	0.99	0.98	-0.338
Age	Household head's age in years	46.36	46.04	-0.009
Married	1 = yes if household head is married, and otherwise 0	0.96	0.95	-0.005
Household size	Total members in a family	4.95	4.96	0.007
Religion	1 = yes if household head practices Hindu religion	0.13	0.12	-0.005
Human capital				
Education	Number of schooling years	2.39	2.08	-0.314***
Occupation	1 = yes if household head's occupation is farming, and otherwise 0. Note that non-farming includes salaried employed, non-agricultural labor, self-employed, trade and business, housewife, and others.	0.94	0.83	-0.115***
Farming experience	Farming experience in years	22.30	17.54	-4.778***
Social capital				
Pucca house structure	1 = yes if household head's family resided in a dwelling that is made of bricks, and otherwise 0	0.29	0.23	-0.05**
Electricity	Access to electricity (1 = yes)	0.77	0.68	-0.08***
Sanitary toilet	Access to sanitary toilet (1 = yes)	0.98	0.95	-0.02**
Phone	Access to mobile phone (1 = yes)	0.98	0.97	-0.01
Migration	1 = yes if any members of the household had migrated within and outside the country for employment	0.19	0.11	-0.08***
Membership	1 = yes if any members of the household are members of any formal or informal organizations	0.26	0.22	-0.04
Land assets, income, and consumption				
Agricultural land	Total land and water bodies that are owned and rented (decimals)	223.07	181.03	-42.04***
Rice area †	Paddy cultivated area in cropping year 2015-16 (May 2015 to April 2016) (decimals)	376.97	283.01	-94.43***
Share of non-farm income	Income earned by a household from non-farming sources, for example, salaried employment, non-agricultural labor, and trade and business (%)	118.37	118.37	0.09***
Annual expenditure	Annual household expenditure (1,000 BDT)	127.13	109.67	-17.59***
Per capita expenditure	Annual expenditure/household size (1,000 BDT/year)	28.23	23.52	-4.74***
Share of food expenditure	Share of total expenditure spent on food consumption by a household in a year (%)	34.10	33.67	-0.38

Notes: Computed by authors based on the 2016 Household Survey Data, International Rice Research Institute (IRRI). ***, **, and * are 1%, 5%, and 10% level of significance, respectively. BDT denotes Bangladesh Taka.

† Plot areas that were under Aman, Aus, and Boro cultivation were summed up. Note that rice area is greater than agricultural land because one plot could be used for single, double, or triple cropping purposes.

Table 4. Comparison of production costs and revenues by adoption category

Items	Unit	Adopters	Non-adopters	Mean difference
Quantity of inputs used				
Seed	kg/ha	47.37	46.08	-1.28
Urea	kg/ha	149.76	146.01	-3.75
TSP	kg/ha	67.20	74.57	7.37*
MoP	kg/ha	60.61	60.06	-0.55
Pesticides	No.	1.01	1.21	0.20***
Labor	Person-days/ha	72.28	75.94	3.65
Production costs and returns				
Seed	BDT/ha	2,167.77	2,014.15	-153.62
Fertilizer	BDT/ha	5,359.24	5,726.62	367.38**
Pesticides	BDT/ha	1,223.61	1,443.85	220.24**
Irrigation	BDT/ha	2,425.45	2,364.72	-60.73
Machinery	BDT/ha	6,935.12	6,540.03	-395.08***
Cost of hired labor	BDT/ha	21,578.05	21,914.02	335.96
Total variable cost (TVC)	BDT/ha	39,698.24	40,003.39	314.15
Yield	kg/ha	3,803.20	3,518.48	-284.71***
Price of paddy	BDT/kg	13.80	14.64	0.84***
Total revenue (TR)	BDT/ha	52,808.00	48,953.20	-3,900.0***
Profit	BDT/ha	13,118.75	8,949.80	-4,200.0***
Ratio of revenue to cost	TR/TVC	1.52	1.44	-0.08

Notes: Computed by authors based on the 2016 Household Survey Data, International Rice Research Institute (IRRI). BDT = Bangladesh Taka. USD 1 = BDT 80. ha = hectares, kg = kilograms. ***, **, and * are 1%, 5%, and 10% significance level, respectively.

Table 5. Parameters estimated from endogenous switching regression

Variables	Sub1 cultivation (1/0)	Profit from rice cultivation		Per capita consumption expenditure	
		Adopters	Non-adopters	Adopters	Non-adopters
Household head's education (yes = 1)	0.19*	0.08	0.78	7.07***	3.30**
	(0.11)	(2.93)	(2.31)	(2.35)	(1.60)
Household head's farming experience (years)	-0.0001	0.08	0.05	-0.14**	-0.13**
	(0.00)	(0.09)	(0.08)	(0.07)	(0.05)
Log of cropped areas (decimals)	0.0001	-0.005	0.011*	0.032***	0.05***
	(0.00)	(0.01)	(0.01)	(0.01)	(0.00)
Share of non-farm income (%)	-1.24***	-7.0	3.57	5.19	2.80
	(0.35)	(10.83)	(4.48)	(8.39)	(3.09)
Index of production cost	0.06	-4.36***	-2.62***	-2.17**	0.35
	(0.05)	(1.25)	(0.99)	(1.03)	(0.69)
Pucca house (yes = 1)	-0.02	-3.53	-2.95	3.30	3.61**
	(0.11)	(2.63)	(2.50)	(2.17)	(1.75)
Migration (yes = 1)	0.24*	2.65	1.76	10.41***	1.03
	(0.13)	(2.94)	(3.22)	(2.39)	(2.26)
Flood-damaged plot (yes = 1)$^{\perp}$	-0.11	-15.64***	-10.90***	0.93	-0.15
	(0.16)	(3.79)	(3.20)	(3.14)	(2.24)
Had information on Sub1 rice varieties (yes = 1)‡	2.31***				
	(0.29)				
Member in any organization (yes = 1)‡	0.37**				
	(0.15)				
Access to electricity (yes = 1)‡	0.39***				
	(0.11)				
Location 1 (= 1 if district is Kurigram)$^{+}$	1.22***	-10.34*	-17.28***	-5.76	7.99*
	(0.18)	(5.55)	(6.66)	(3.79)	(4.20)
Location 2 (= 1 if district is Rangpur)$^{+}$	0.04	2.263	-9.88***	-1.41	-1.02
	(0.19)	(5.30)	(2.86)	(4.32)	(1.99)
Location 3 (= 1 if district is Gaibandha)$^{+}$	1.38***	-2.72	-25.83***	-6.53	-1.85
	(0.30)	(8.27)	(5.32)	(6.39)	(3.71)
Location 4 (= 1 if district is Jamalpur)$^{+}$	1.28***	-9.85*	-23.63***	4.03	2.26
	(0.18)	(5.45)	(4.50)	(3.70)	(2.86)
Location 5 (= 1 if district is Sherpur)$^{+}$	0.41**	-1.20	-4.20	7.63**	9.01***
	(0.17)	(4.19)	(3.30)	(3.42)	(2.23)
Constant	-3.12***	35.97***	19.98***	15.68***	11.20***
	(0.38)	(9.08)	(4.73)	(6.07)	(3.28)
Sigma		23.32***	25.51***	18.71***	17.53***
Rho		-0.13	-0.398***	-0.158*	-0.09*
Wald chi-squared		43.67***		-0.097***	
LR test of independent equation		4.62**		2.05	
Observations		1134		1134	

Notes: Computed by authors based on the 2016 Household Survey Data, International Rice Research Institute (IRRI). SE stands for standard error. ***, **, and * denote 1%, 5%, and 10% levels of significance, respectively.

$^{\perp}$ No damaged plot is the base case for severely and partially damaged plots.

$^{+}$ Lalmonirhat is the base case of location variable.

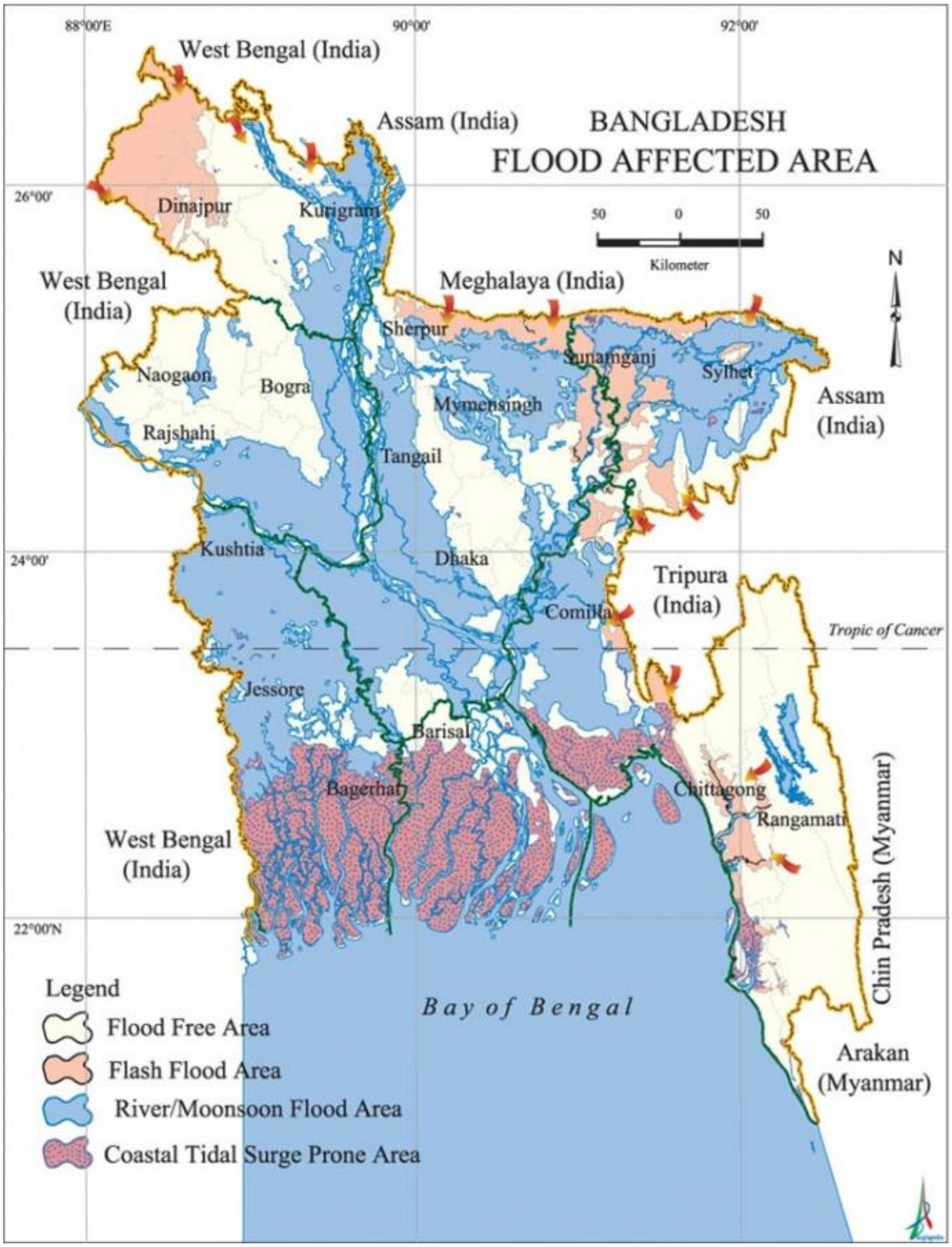
‡ Instrumental variables through which the selection model is identified.

Table 6. Impact of adoption of Sub1 varieties on crop income and consumption expenditure, parameter estimates from the ESR

Outcome variables	Treatment effects	Decision rule		Treatment effects
		To adopt	Not to adopt	
Profit from rice cultivation (1,000 BDT/ha)	Farm households that adopted (ATT)	13.11	-7.58	20.70*** [68.97]
	Farm households that did not adopt (ATU)	20.62	8.89	11.72*** [38.90]
Per capita consumption expenditure (1,000 BDT/year)	Farm households that adopted (ATT)	28.26	26.34	1.91 [5.06]
	Farm households that did not adopt (ATU)	31.09	23.52	7.56*** [20.48]

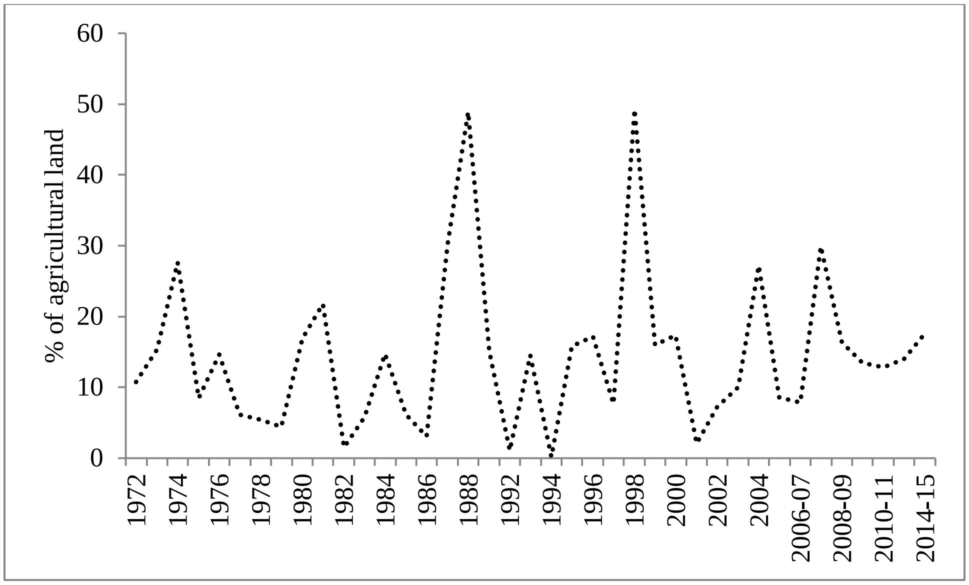
Notes: Computed by authors based on the 2016 Household Survey Data, International Rice Research Institute (IRRI). Values within [] are absolute values of t-statistics; *** denotes 1% level of significance.

Figure 1. Map of flood-affected areas in Bangladesh



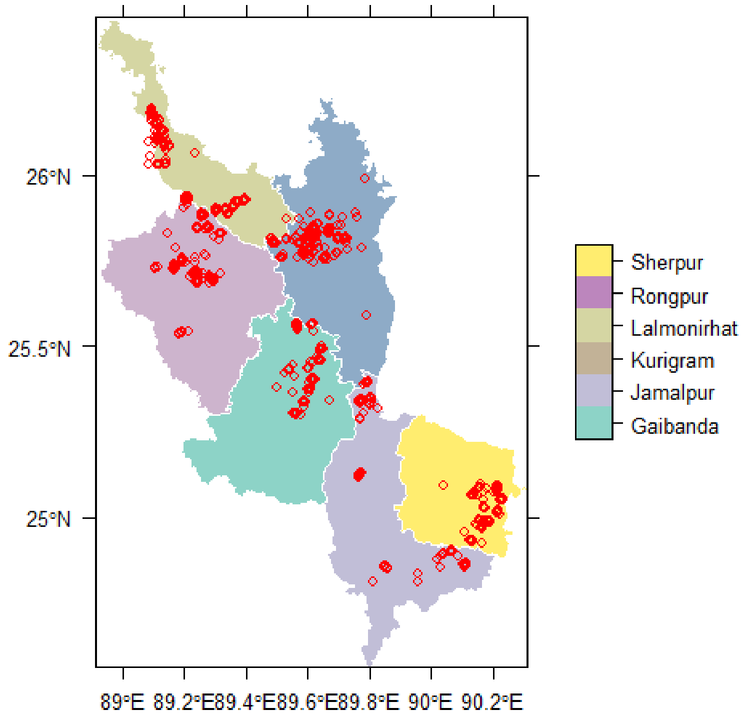
Source: Adopted from http://en.banglapedia.org/index.php?title=Natural_Hazard (accessed May 16, 2018).

Figure 2. Flood-affected agricultural land in Bangladesh: 1972-2015



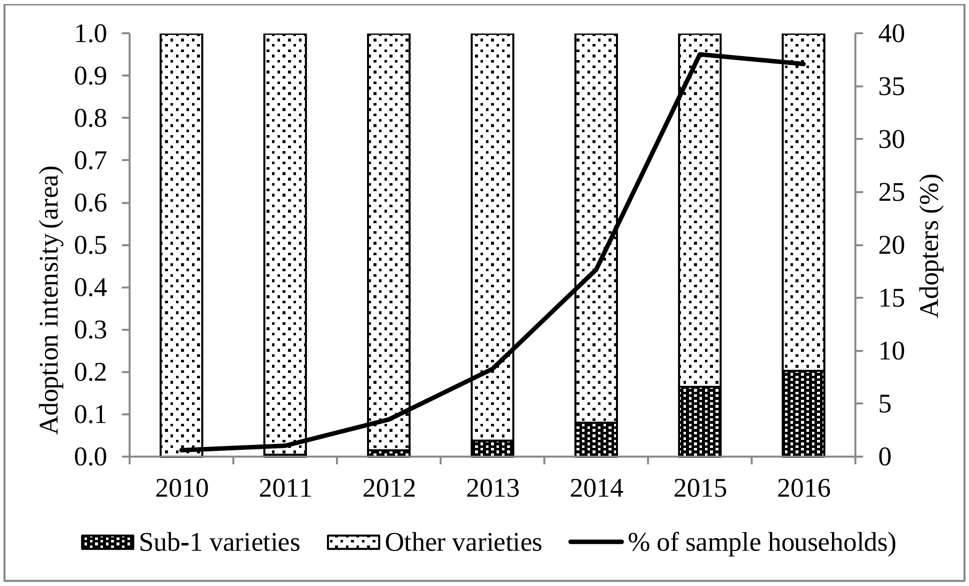
Source: Different issues of Statistical Yearbook published by the Bangladesh Bureau of Statistics, the government of Bangladesh.

Figure 3. Map of the study villages in Bangladesh



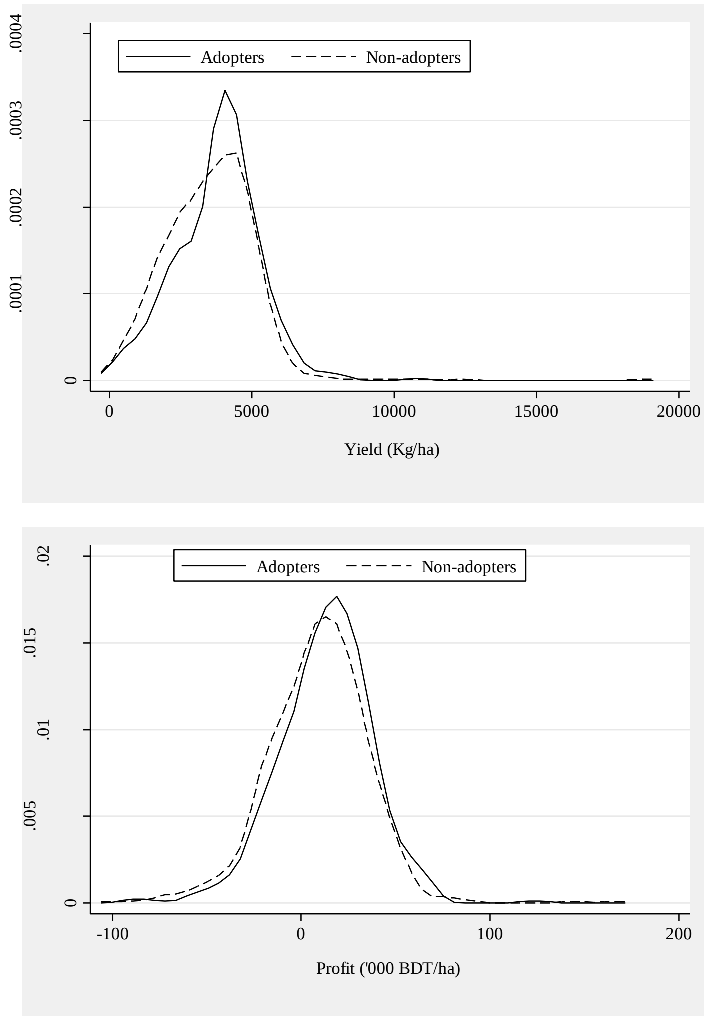
Source: Prepared by authors based on the Household Survey Data (2016), International Rice Research Institute (IRRI).

Figure 4. Adoption rate of Sub1 varieties and intensity of adoption



Notes: Computed by authors based on the Household Survey Data (2016), International Rice Research Institute (IRRI); the data for 2016 are based on farmers' predictions.

Figure 5. Kernel density of plot-level yield (upper panel) and profit (lower panel) by adoption category



Notes: Computed by authors based on the Household Survey Data (2016), International Rice Research Institute (IRRI).