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Smallholder adaptation to flood risks: Adoption and impact of Swarna-Sub1 in Eastern India

Prabhakaran T. Raghu[a,b], Prakashan Chellattan Veettil[a,*], Sukanya Das[b]

[a] Agri-Food Policy Platform, International Rice Research Institute (IRRI), NAS Complex, Pusa Campus, DPS Marg, New Delhi 110012, India
[b] Department of Policy Studies, TERI School of Advanced Studies, New Delhi, India

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ABSTRACT

Climate change and the consequent increase in the incidence of drought and flood will remain a major threat to smallholders. Hence, it is crucial to adopt an appropriate adaptation strategy to overcome this threat and increase farmers' income. Because seed is a primary input, the adoption of stress-tolerant rice varieties is a potential mitigation strategy to combat climate risks. In this context, the present study is carried out among paddy farmers in the flood-prone region of Eastern India to understand the adoption and impact of submergence-tolerant rice variety Swarna-Sub1 on yield and income. The study reveals that the adoption of Swarna-Sub1 varies significantly across eastern India. Education, primary occupation, credit, social group, cultivated land, and access to information on stress-tolerant rice varieties significantly influence the adoption decision. Endogenous switching regression estimates revealed that the expected paddy yield of Swarna-Sub1 adopters in an actual scenario and for non-adopters in a counterfactual scenario is significantly higher than for their counterparts. The average treatment effect confirms that the benefit of cultivating Swarna-Sub1 is much higher in submergence conditions than in normal conditions. An additional 19.0% and 48.2% of paddy yield and income is obtained respectively by cultivating Swarna-Sub1 in flooded conditions.

1. Introduction

The recurring incidence of flood and drought is the key reason of crop loss, seasonal earnings instability, and poverty among smallholder farmers (Arora et al., 2019; Mottaleb et al., 2015). Mainly, exposure to these stresses is high because of poor access to irrigation and flood control infrastructure in developing countries (Pingali et al., 2019). The impact of flood is more severe than that of drought. Flood not only affects crop production but also affects the livelihoods of people, affects livestock, damages household property, etc. (Douglas et al., 2008). It is projected that extreme climate events will increase, such as the timing of the onset of monsoon, intensity of rainfall, and frequency of flood (Khan et al., 2009). This will adversely affect agricultural production and food security in the regions where poverty and food insecurity are common (Mackill et al., 2012).

Flash flood distresses approximately 16% of the world's paddy area by frequent submergence (Dar et al., 2018). Majority of the rice farmers residing in rainfed areas of India are in absolute poverty (Veettil et al., 2021; Ismail et al., 2013). Still, large number of rural population in India depends on agriculture for its livelihood. India's agricultural sector contributed approximately 18% of the gross domestic product in 2018 and plays a vital role in the development of the country. A clear trend of increased paddy productivity has been witnessed in India over the years. At the same time, it is observed that the rice production environment is sensitive to climatic fluctuations (Duncan et al., 2017). Agriculture is predominantly vulnerable to floods, approximately 33% of the cultivable area is flood-prone in India (Ranuzzi and Srivastava, 2012).

The Green Revolution introduced high yielding varieties of rice and wheat to increase the food production and achieve self-sufficiency, accordingly it contributed to alleviating hunger and poverty in the irrigation areas (Nelson et al., 2019). However, the Green Revolution was not targeted to rain-fed areas prone to flood and drought, where the food insecurity and poverty is severe (Pingali, 2012). The adoption of stress-tolerant rice varieties (STRVs) could be one of the major risk adaptation strategies to overcome the challenges of low productivity in flood-prone areas, and to improve seasonal earnings for the marginal communities that predominantly depend on paddy cultivation for their livelihood (Veettil et al., 2021).

2. Flood and rice cultivation

In the midst of changing climate, flood is one of the major climate events that significantly restrain rice production in India. Most paddy varieties can withstand submergence for around a week and this results

* Corresponding author.
E-mail address: pc.veettil@irri.org (P.C. Veettil).

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in nearly 50% crop loss (Nguyen, 2012). But, if the paddy crop is submerged for 14 days, this will result in 100% crop loss (Ismail et al., 2013). Approximately 80% of the paddy-producing areas in Eastern India are rainfed, suffering from either excess rainfall leading to flood or a shortfall in rainfall leading to drought (Aryal et al., 2019). Approximately 27% of the paddy-producing areas in Odisha suffer from submergence of the crop, and 40% in Bihar and West Bengal (ibid).

Almost 30% of paddy area is prone to flash flood in India, with an average yield of only 0.5 to 0.8 t/ha in India (Bhowmick et al., 2014). Paddy is mainly cultivated in one (*kharif*) season in India, particularly in the states of Assam, Chhattisgarh, Jharkhand, and Odisha. Given the frequent flood incidence, some farmers keep their cultivable land fallow in the eastern part of the country (Singh et al., 2016). This leads to decreased income, food insecurity, and increased vulnerability for those depending primarily on farming (Somanathan and Somanathan, 2009). The frequent flood decreases farm income, that discourage farmers to test any newest technologies including the adoption of new varieties (Dar et al., 2017).

India is home for 86% of small and marginal farmers owning 47% of the total cultivable land. Approximately 67% of the rural population in India lives in severe poverty and mainly depends on agriculture (Bisht et al., 2020). The adverse impact is more on these farmers because of extreme climate events. Henceforth, innovative research has a high priority given the adverse consequences and susceptibility in agriculture brought about by climate stresses. A Hattori et al. (2009) study strongly suggests that the development of STRVs can enhance paddy production in flood-prone areas. For example, Scuba rice (flood-tolerant varieties) can withstand 17 days of full submergence and yield up to 3 t/ha under flash flood in Bangladesh (Dar et al., 2017; Singh et al., 2009). To increase the paddy yield under submergence conditions in India, a variety ‘Swarna-Sub1’ is developed by breeders at the International Rice Research Institute (IRRI) in 2009 (Veettil et al., 2021; Gregorio et al., 2013). This variety can withstand a submergence for 14 days, and under normal conditions, in comparison with other varieties, there are no significant differences in agronomic performance and grain yield (Neeraja et al., 2007; Sarkar et al., 2006). Under the National Food Security Mission (NFSM) of the Government of India, Swarna-Sub1 seed was distributed in its Eastern India programs during the year 2010 (Yamano et al., 2015). The present study analyzes farmers’ choice of Swarna-Sub1 as a coping strategy against flood risks.

3. Methods and materials

3.1. Study area

The present study was carried out in three eastern states of India: Assam, Odisha, and West Bengal. Rice is the primary crop in the study area, where the incidence of flood is a frequent and common phenomenon. Rice occupies around 55% of the gross cropped area in Assam (Phukan, 2016). On average, 40% of the total land in Assam is flood-prone, which is 9.4% of the flood-prone regions of the country (ibid). Flood in the early season mostly damages autumn rice, however flood occurring late in the season damages the standing winter paddy (Mandal, 2014).

Odisha is located in the eastern part of India. Drought and flood occur frequently in Odisha. The districts prone to frequent drought also encounter increasing number of floods (Ranuzzi and Srivastava, 2012). From 2001 to 2008, around 0.9 million hectares of rice area were affected by the flood and submergence (GoO, 2013). In West Bengal, 80% of the rainfall received during June to September (Laha et al., 2014). Approximately 10.5% of the gross rice cropped area is under flood-prone regions in West Bengal, and the lowest average paddy yield obtained in the region is 1.9 t/ha (Adhikari et al., 2011).

The study areas, Assam, Odisha and West Bengal contributes nearly 27.5% of the country’s total paddy area and production in the year 2015–2016 (Veettil et al., 2021). Approximately 30% of the total paddy area in the study region have experienced a flood in the 2015 *kharif* season (ibid). About, 88.2% of the total paddy area in Assam was affected by flood, followed by Odisha (27.0%) and West Bengal (5.0%).

Table 1
Sample used in the analysis.

State	Villages	Households
Assam	155	1544
Odisha	160	1600
West Bengal	160	1600
Total	475	4744

Source: Household survey, 2016.

According to the Ministry of Agriculture and Farmers’ Welfare, Government of India, an average paddy yield in West Bengal is 2.74 t/ha, which is above the national average of 2.30 t/ha. The paddy yield in the states of Assam and Odisha is very low at 1.91 t/ha and 1.37 t/ha, respectively. However, average yield in the flood-prone areas is much lower than the state average. Hence, it is important to address this low productivity in the states where extreme climate events are common to make progress for the livelihood of the farmers and enhance production to feed the increasing population.

3.2. Data and sampling

Flood-prone districts were identified with the help of the remote-sensing crop monitoring team at the International Rice Research Institute. From the identified flood-prone regions, 160 villages each in three states were selected randomly (a total of 480 villages). This included 155 villages[1] from 19 districts in Assam, 160 villages from 13 districts in Odisha, and 160 villages from 9 districts of West Bengal. Using the farmers list from a census survey,[2] 10 rice-farming households from each village were randomly selected for a detailed survey, adding up to a total of 4750 households.

A detailed household survey was implemented immediately after harvesting the paddy crop of the 2015 *kharif* season. The data collection was carried out from December 2015 to March 2016. The sample used in the analysis is shown in Table 1.

3.3. Information on sampled households

The socioeconomic characteristics of Swarna-Sub1 adopters and non-adopters are presented in Table A.1. On average, 96% of the households are male-headed, with an average size of five members. Average age of the head is 50 years, mostly married, and having 27 years of experience in rice cultivation (Veettil et al., 2021). Two-thirds of the household heads are literate with primary and secondary school education. We observed that the proportion of non-adopters in the non-literate group is higher than that of adopters, but lower in the high education group (college graduate). The contribution of household income from farming is 43% for the adopter group and 32% for the non-adopter group, indicating a high dependence on agriculture by adopters. After farming, non-agricultural labor and self-employment are the major livelihood options, for which the involvement and contribution to household income are higher in the non-adopter group.

Adopters and non-adopters differ significantly in terms of social structure (caste composition)[3], land ownership, and cultivation behav-

[1] During the household survey, 5 sample villages are flooded and there was no connectivity for a longer period. Due to logistic reasons, these villages were dropped from the survey.

[2] Before the farm household survey, a census of all selected villages in the study region was conducted (17866 households in Assam, 30719 households in Odisha, and 44455 households in West Bengal).

[3] In India, a caste system is a closed social stratification and occupational transmission through generations, an individual status in society is based on the

ior. Adopters are dominated by backward caste groups (other backward caste 45% and scheduled caste 18%) whereas non-adopters mostly belonged to the forward caste (46%). This can be attributed to the fact that majority of marginal land is owned by the backward caste groups and comparatively higher flood-prone area is observed amongst them. Moreover, the social welfare schemes in India have a specific target on marginal people, and thus backward caste groups are more likely to be benefited in the programs. Adopters possess more land (31%) and cultivate more area (35%) than non-adopters. Further, adopters cultivate three rice varieties, which is one more than non-adopters. We also observed that a higher exposure of non-adopters to flood than adopters clearly showed the need for a detailed investigation of STRV adoption behavior in the region.

4. Empirical procedure

4.1. Stochastic frontier model

To estimate the adoption of STRV on production efficiency, we test whether adoption of Swarna-Sub1 significantly improves the technical efficiency of agricultural production using a frontier production function. The Cobb–Douglas stochastic frontier model is widely used in agricultural studies to measure technical efficiency (Radhakrishnan and Das, 2019; Islam et al., 2016; Rajendran, 2014; Baten and Hossain, 2014). Technical efficiency denotes the ability to produce an optimal output with minimum input use under certain production technology (Farrell, 1957). The stochastic frontier model is specified as

$$LnY_1 = \beta_0 + \beta_1 LnX_1 + \ldots + \beta_8 LnX_8 + \beta_9 X_9 + \beta_{10} X_{10} + V_i - u_i \tag{1}$$

where Ln is the natural log, Y = paddy yield (t/ha); β_1 to β_8 are the regression coefficients of the input (paddy area, seed, chemical fertilizer, pesticide, irrigation, male labor, female labor, and machinery) variables used in model 1; β_9 to β_{10} are the regression coefficients of the non-input (Swarna-Sub1 cultivation and rice plot experienced submergence) variables used in model 2 along with input variables (see Table 3); V_i is the noise term in the production (random term normally distributed) and u_i is a non-negative technical in-efficiency of the i$^{\text{th}}$ farmers. The summary statistics of the variables are shown in Table A.2.

Following Islam et al. (2016) and Coelli et al. (2005), the technical efficiency score for the i^{th} paddy farm (TE_i) is calculated as the ratio of observed output to the corresponding frontier output, which is specified as

$$TE_i = \exp(-u_i) \tag{2}$$

where TE_i is the technical efficiency of the paddy farm (0 < TE < 1). When $u_i = 0$, the i^{th} paddy farm lies on the frontier is technically efficient. If $u_i > 0$, the i^{th} paddy farm lies below the frontier is technically inefficient.

4.2. Endogenous switching regression

The decision on whether to adopt or not to adopt climate smart variety, Swarna-Sub1 by the farm household is based on the perceived net benefit that s/he can achieve. Under a random utility theory, a decision on the adoption of Swarna-Sub1 will take place if the net benefit is positive (Veettil et al., 2021; Bidzakin et al., 2019; Abdulai and Huffman, 2014; Asfaw and Shiferaw, 2010). The selection equation for Swarna-Sub1 adoption is specified as

$$SS1_i^* = \psi W_i + \epsilon_i \; with \; SS1_i = \begin{cases} 1 \; if \; SS1_i^* > 1 \\ 0 \; Otherwise \end{cases} \tag{3}$$

The adoption of Swarna-Sub1 takes value equals to one and non-adoption takes value equals to zero. Where $SS1_i^*$ is the unobservable variable for Swarna-Sub1 adoption, $SS1_i$ is the observable counterpart. W_i are the vector of explanatory variables affect the Swarna-Sub1 adoption, ϵ_i is an error term with mean (0) and variance (σ_ϵ^2).

The decision to adopt or not to adopt Swarna-Sub1 is influence by the outcome variable, paddy yield in the study. To address the unobservable selection bias, endogenous switching regression is used to estimate the outcome variable of two regimes (Bidzakin et al., 2019; Tesfaye and Tirivayi, 2018; Abdulai and Huffman, 2014; Asfaw and Shiferaw, 2010). That is, Swarna-Sub1 adopters in Regime 1 and non-adopters in Regime 2 as follows

$$Regime\ 1: \; Y_{1i} = W_{1i}\phi_1 + \epsilon_{1i} \; if \; SS1_i = 1 \tag{4}$$

$$Regime\ 2: \; Y_{2i} = W_{2i}\phi_2 + \epsilon_{2i} \; if \; SS1_i = 0 \tag{5}$$

Where Y_{1i} and Y_{2i} represents the paddy yield of Swarna-Sub1 adopters and non-adopters; Similarly ϕ are vectors of explanatory variables to be estimated and assumed to be weakly exogenous. The error terms are assumed to have a trivariate normal distribution, with zero mean and non-singular covariance matrix (Bidzakin et al., 2019; Tesfaye and Tirivayi, 2018; Abdulai and Huffman, 2014; Asfaw and Shiferaw, 2010).

4.2.1. Treatment effects

Subsequently, after estimating the endogenous switching regression model, conditional expectation of paddy yield can be obtained from different scenarios (Tesfaye and Tirivayi, 2018; Asfaw and Shiferaw, 2010) as follows

Swarna-Sub1 adopters:

$$E(y_{1i}|SS1_i = 1) = W_{1i}\phi_1 + \sigma_1 p_1 Z_{1i}\,. \tag{6}$$

Swarna-Sub1 non-adopters:

$$E(y_{2i}|SS1_i = 0) = W_{2i}\,\phi_2 + \sigma_2 p_2 Z_{2i} \tag{7}$$

Swarna-Sub1 adopters, had they made a decision not to adopt (counterfactual):

$$E(y_{2i}|SS1_i = 1) = W_{1i}\,\phi_2 + \sigma_2 p_2 Z_{1i} \tag{8}$$

Swarna-Sub1 non-adopters, had they made a decision to adopt (counterfactual):

$$E(y_{1i}|SS1_i = 0) = W_{2i}\,\phi_1 + \sigma_1 p_1 Z_{2i} \tag{9}$$

Where, p_1 is the correlation coefficient between ϵ_1 and ϵ, p_2 between ϵ_2 and ϵ, $Z_{1i} = f(\psi W_i)/F(\psi W_i)$ and $Z_{2i} = f(\psi W_i)/[1 - F(\psi W_i)]$. From Table 2, (i) and (ii) represent observed paddy yield of Swarna-Sub1 adopters and non-adopters; (iii) and (iv) represent counterfactual paddy yield of Swarna-Sub1 adopters and non-adopters.

Following Heckman et al. (2001) and Di Falco et al. (2011), the following treatment effect is estimated

Table 2
Conditional expectations, treatment, and heterogeneity effects.

Swarna-Sub1	Decision stage		Treatment effect
	To adopt	Not to adopt	
Adopters	(i) $E(Y_{1i} / SS1_i = 1)$	(iii) $E(Y_{2i} / SS1_i = 1)$	TT
Non-adopters	(iv) $E(Y_{1i} / SS1_i = 0)$	(ii) $E(Y_{2i} / SS1_i = 0)$	TU
Heterogeneity effects	BH_1	BH_0	TH

Note: Y_{1i} = paddy yield of the household decision to adopt Swarna-Sub1 and Y_{2i} = paddy yield of the household decision to not adopt Swarna-Sub1.

caste into which s/he is born (Debnath et al., 2015). A caste system in India holds a characteristic such as occupational specialization, purity scale, hierarchy, commensality and ascription (Freitas, 2006). For administrative purpose, caste is categories into four groups (low to high status), (i) scheduled tribes is a list of marginalized tribal communities, (ii) scheduled castes is a listing of formerly untouchable and lowest ranked group, (iii) other backward castes is a collection of low to middle-ranking castes and communities, and (iv) everyone else is clubbed into a residual category called “general/forward”, which is used as a proxy for upper-castes.

Treatment effect on the treated (TT) is calculated as the deviation among observed paddy yield of Swarna-Sub1 adopter and its counterfactual scenario (deviation between i and iii in Table 2) as follows

$$TT = E(y_{1i}|SS1_i = 1) - E(y_{2i}|SS1_i = 1) = W_{1i}(\phi_1 - \phi_2) + (\sigma_1 p_1 - \sigma_2 p_2) Z_{1i} \tag{10}$$

Treatment effect on the untreated (TU) is calculated as the deviation among observed paddy yield of Swarna-Sub1 non-adopters and its counterfactual scenario (deviation between ii and iv in Table 2) as follows

$$TU = E(y_{1i}|SS1_i = 0) - E(y_{2i}|SS1_i = 0) = W_{2i}(\phi_1 - \phi_2) + (\sigma_1 p_1 - \sigma_2 p_2) Z_{2i} \tag{11}$$

4.2.2. Heterogeneity effects

The effect of base heterogeneity for the household decision to adopt Swarna-Sub1 (BH1) is a deviation between i and iv in Table 2 as follows

$$BH1 = E(y_{1i}|SS1_i = 1) - E(y_{1i}|SS1_i = 0) = (W_{1i} - W_{2i})\phi_{1i} + \sigma_1 p_1 (Z_{1i} - Z_{2i}). \tag{12}$$

The effect of base heterogeneity for the household decision not to adopt Swarna-Sub1 (BH2) is a deviation between iii and ii in Table 2 as follows

$$BH2 = E(y_{2i}|SS1_i = 1) - E(y_{2i}|SS1_i = 0) = (W_{1i} - W_{2i})\phi_{2i} + \sigma_2 p_2 (Z_{1i} - Z_{2i}). \tag{13}$$

Transitional heterogeneity (TH) is the deviation between the treatment effect of the treated (TT) and the treatment effect of the untreated (TH) is shown in Table 2.

5. Results and discussion

The results section is categorized into two sub-sections. *First* is Swarna-Sub1 adoption and technical efficiency of paddy cultivation. *Second* is the impact of Swarna-Sub1 on its yield and income.

5.1. Swarna-Sub1 adoption and technical efficiency

5.1.1. Swarna-Sub1 adoption

Figure 1 reveals that the adoption of Swarna-Sub1 varies significantly across the study area. The adoption rate is higher in Odisha, with 16.7% of the sampled households cultivating the variety during the 2015 *kharif* season. A total of 4.2% of the household cultivated it in West Bengal and the adoption rate was negligible in Assam. Every alternative adopter reported the reason for selecting Swarna-Sub1 as mainly its characteristic of submergence tolerance and one-third reported the reason as good crop yield.

5.1.2. Technical efficiency of paddy cultivation

Technical efficiency is estimated using the Cobb–Douglas stochastic frontier production function for major paddy varieties cultivated in the study area. The estimates of stochastic frontier production are presented in Table 3 and the ordinary least squares (OLS) estimates are presented in Table A.3. The dependent variable used is paddy yield (production per hectare). We used Swarna-Sub1 cultivation (takes the value equals to 1 if the plot is cultivated under Swarna-Sub1, and 0 otherwise) and paddy plot submerged (takes the value equals to 1 if the plot had experienced submergence during the season, and 0 otherwise) as explanatory variables along with regular production inputs.

The γ-parameter estimates (which explain the variation of output from the frontier attributed to technical inefficiency) are 0.87 (model 1) and 0.90 (model 2), implying the presence of inefficiency in the production function. Paddy area and quantity of seed used are not statistically significant. The elasticity of the mean value of paddy yield for chemical fertilizer is significant in model 1 of the frontier estimation; however, the coefficient of chemical fertilizer applied is much lower (by 0.016). In other words, holding other variables constant, a 1% increase in a unit of chemical fertilizer would increase paddy yield by 0.016%. Pesticide application positively and significantly influences paddy yield in both models with a lower coefficient, likewise for irrigation and machinery variables in model 2. Similarly, Swarna-Sub1 cultivation positively and significantly influences paddy yield; for example, the adoption of Swarna-Sub1 increases paddy yield by 9.1%. When the paddy plots experienced submergence, yield decreased by 7.3% vis-à-vis paddy cultivated in normal conditions. The distribution of individual technical efficiency of both models is presented in Fig. B.1.

5.2. Impact of Swarna-Sub1

5.2.1. Swarna-Sub1 adoption and paddy yield

The impact of Swarna-Sub1 adoption on yield is estimated using endogenous switching regression (ESR), which controls for unobservable selection bias (Ahmed and Mesfin, 2017). The full information maximum likelihood estimates of the ESR model are presented in Table 4. Column two reports the coefficients of selection for Swarna-Sub1 adoption and column four and six reports the outcome equations (paddy yield (t/ha) for Swarna-Sub1 adopters and non-adopters, respectively). Results from maximum likelihood estimates of the ESR model show that the estimated coefficient of correlation between the Swarna-Sub1 adoption equation and paddy yield function (ρ_i) is negative and significant. Both observed and unobserved factors influence the Swarna-Sub1 adoption decision and paddy yield outcomes provided adoption decision. The model explains the self-selection followed in the Swarna-Sub1 adoption. The presence of heterogeneity is witnessed between paddy yield of Swarna-Sub1 adopters and non-adopters.

The regression estimates of the adoption model reported that Swarna-Sub1 adopters are significantly more highly educated than non-adopters, that is, the likelihood of an educated farmer adopting Swarna-Sub1 is more than for a non-literate farmer. Highly educated farmers process information about new technologies more quickly and effectively than non-literate farmers (Foster and Rosenzweig, 2010). When the household head's primary occupation is farming, the likelihood of adopting Swarna-Sub1 is higher. High-income farmers are found to be high in risk taking and mostly enjoying multiple income sources, or more fertile lands, showing less appetite for variety Swarna-Sub1. Adoption is higher for those who have taken out a loan; naturally, one would expect to avoid risks in this context. Consistent with other studies (Emerick et al., 2016), people belonging to backward castes (OBCs and SCs) are more likely to adopt Swarna-Sub1. Cultivated land area is positively and significantly affecting the adoption of Swarna-Sub1. Large farmers usually test the new variety on a small portion of their land. Households having access to information on STRVs were more likely to adopt Swarna-Sub1, *ceteris paribus*. Similarly, when the farmers are informed about the characteristics and benefits of STRVs, their choice of Swarna-Sub1 increases significantly.

The productivity of paddy is significantly higher in male-headed households than in female-headed ones irrespective of Swarna-Sub1 adoption. In developing countries, female farmers are constrained in access to inputs, information, and markets. Among non-adopters, productivity is high when farmers are educated, but yield effects are also observed through higher adoption of Swarna-Sub1 by educated farmers. The positive and significant yield effects of livestock rearing among Swarna-Sub1 adopters indicate the need for a farming system-based climate-resilient approach. Similarly, a livelihood-based approach shows positive effects on climate resilience irrespective of Swarna-Sub1 adoption. Self-employment in the household positively influences the productivity of paddy. The productivity of farmers belonging to the forward caste is significantly higher than for other castes in both adopter and non-adopter categories. As paddy cultivated land increases, the yield of adopters and non-adopters decreases. This suggests that small farms are more efficient and productive than large

Table 3
Cobb–Douglas stochastic frontier production function (half-normal distribution).

Ln yield (t/ha)	Model 1		Model 2	
	Coefficient	Std. err.	Coefficient	Std. err.
Ln area (ha)	−0.0026	0.0211	−0.0063	0.0200
Ln seed (kg/ha)	−0.0011	0.0103	−0.0033	0.0096
Ln chemical fertilizer (kg/ha)	0.0158***	0.0036	0.0037	0.0035
Ln pesticide (L/ha)	0.0493***	0.0085	0.0450***	0.0080
Ln irrigation (number)	0.0100	0.0068	0.0152**	0.0064
Ln labor used (man-day/ha)				
Male labor	0.0026	0.0033	0.0005	0.0032
Female labor	0.0020	0.0025	0.0022	0.0024
Ln machine use (hours/ha)	−0.0031	0.0056	0.0130**	0.0054
Swarna-Sub1 cultivation	–	–	0.0909***	0.0121
Paddy plot submerged	–	–	−0.0732***	0.0085
Constant	1.6823***	0.0470	1.7432***	0.0443
lnsig2v	−4.3957***	0.0891	−4.7101***	0.0990
lnsig2u	−2.5206***	0.0595	−2.4607***	0.0530
Sigma_v	0.1110	0.0049	0.0949	0.0047
Sigma_u	0.2836	0.0084	0.2922	0.0077
Sigma2	0.0927	0.0042	0.0944	0.0041
Lambda	2.5538	0.0121	3.0794	0.0111
γ = (Sigma2^2)/Lambda	0.8671	0.9046		
Likelihood-ratio test sigma_ u = 0: Chibar2(01)	180.00	230.00		
Prob >= Chibar2	***	***		

Note: *, **, ***: statistically significant at 10%, 5%, and 1% levels of significance, respectively.

Table 4
Endogenous switching regression for Swarna-Sub1 adoption and its impact on yield (t/ha).

Variables	Swarna-Sub1 adoption		Paddy yield (t/ha)			
			Adopters		Non-adopters	
	Coefficient	Std. err.	Coefficient	Std. err.	Coefficient	Std. err.
Household head variables						
Male = 1	−0.2797	0.1830	0.6898*	0.3530	0.3386***	0.1244
Age (years)	0.0033	0.0030	−0.0059	0.0054	−0.0009	0.0023
Rice cultivation (years)	−0.0090***	0.0034	0.0083	0.0058	0.0001	0.0027
Education status (dummy variable)						
Non-literate	Reference variable					
Primary (up to class 8)	0.4607***	0.1113	−0.2117	0.2413	0.1892***	0.0666
Secondary (class 9–12)	0.5556***	0.1164	−0.1323	0.2519	0.0593	0.0739
Graduate & above	0.7803***	0.1471	−0.2416	0.2949	0.1435	0.1171
Primary occupation (dummy variable)						
Non-agricultural labor	Reference variable					
Agriculture	0.3843***	0.1293	0.2525	0.2302	0.2413**	0.1029
Agricultural labor	0.0791	0.1836	0.4089	0.3208	0.2957**	0.1404
Livestock rearing	0.2088	0.2983	1.2627**	0.5294	0.2605	0.2360
Salaried	−0.9439***	0.2560	0.4875	0.5169	0.0773	0.1373
Self-employment	−0.2309	0.1455	0.7086**	0.2785	0.2060**	0.1028
Other occupation	−0.5899***	0.2263	1.1300**	0.4795	0.2094	0.1357
Household-level variables						
Annual income (000 INR)	−0.0010***	0.0003	0.0007	0.0005	0.0010***	0.0003
Loan taken = 1	0.2723***	0.0967	−0.0938	0.2094	−0.2689***	0.0707
Social group (caste) (dummy variable)						
Forward caste	Reference variable					
Other backward caste	0.3254***	0.0608	−0.1232	0.1058	−0.2516***	0.0498
Scheduled caste	0.1422*	0.0765	−0.2773**	0.1364	−0.2522***	0.0586
Scheduled tribe	−0.8371***	0.2363	0.1594	0.5492	−0.2583***	0.1003
Farm-level information						
Cultivated land in *kharif* 2015 (ha)	0.2246***	0.0338	−0.2043***	0.0636	−0.1789***	0.0303
Access to STRV information	1.1240***	0.0547	–			
CONSTANT	−2.3617***	0.2705	3.8885***	0.6141	3.1403***	0.1904
σ_i			0.1448 (0.0322)***		0.1881 (0.0130)***	
ρ_i			−0.2720 (0.1021)***		−0.2112 (0.0752)***	
Number of observations	3995					
Log-likelihood	−7796.39					
LR test of independent equation Chi^2 (1)	14.33***					

Note: *, **, ***: statistically significant at 10%, 5%, and 1% levels of significance, respectively.

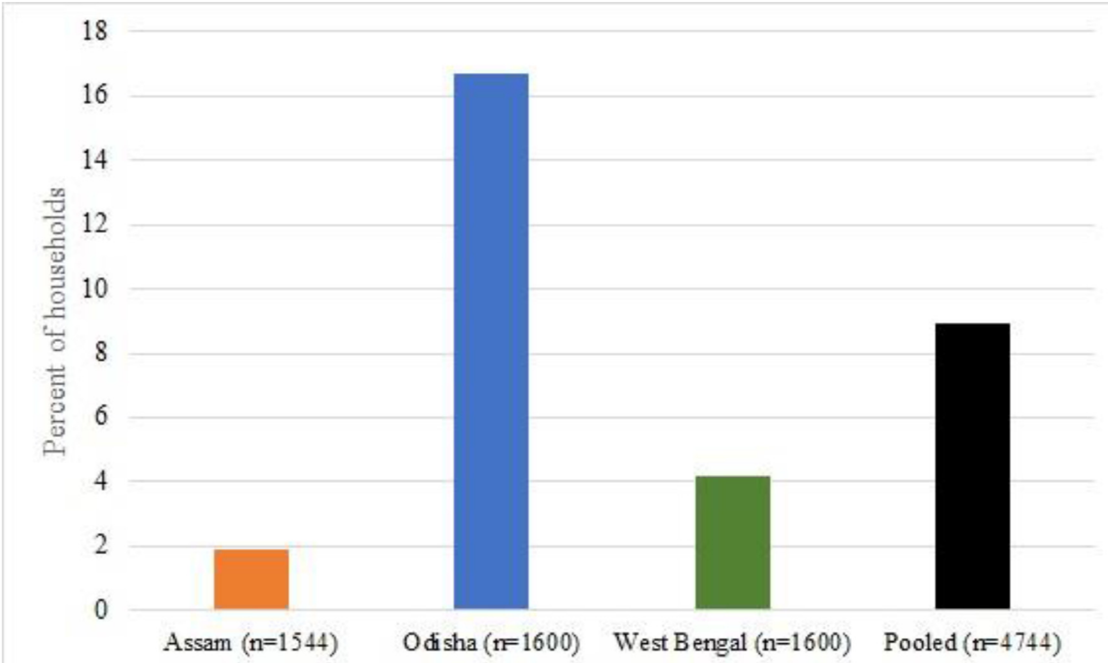

Fig. 1. Swarna-Sub1 adoption in the study area
Source: Household survey, 2016.

Table 5
Average expected paddy yield (t/ha) for Swarna-Sub1 adopters and non-adopters.

Swarna-Sub1	Decision stage		Treatment effect
	To adopt	Not to adopt	
Adopters	3.81	2.94	TT = 0.87 (0.01)***
Non-adopters	4.37	3.34	TU = −1.03 (0.01)***
Heterogeneity effects	BH_1 = −0.56	BH_0 = −0.40	TH = 1.90

*** Note: statistically significant at 1% level of significance using the independent *t*-test between adopting and not adopting, respectively, for Swarna-Sub1 adopters and non-adopters; the number in parentheses is the standard error.

farms. In the context of low mechanization and modernization of agriculture, smallholders are observed to manage farm better, as they are able to utilize the inputs effectively given that agriculture is labor intensive (due to low mechanization) and family labor has high intrinsic motivation for higher economic return. The result is also in accordance with the Chand et al. (2011), small farms motivated to obtain more yield by practicing intensive input use and adopting new technologies.

The estimated impact of Swarna-Sub1 on paddy yield under observed and counterfactual scenarios is shown in Table 5. The observed mean paddy yield of Swarna-Sub1 adopters is 3.81 t/ha and that of non-adopters is 3.34 t/ha. The average treatment effect on treated (Swarna-Sub1 adopters) and untreated (non-adopters) is 0.87 t/ha and −1.03 t/ha, respectively. Both values are significant and indicate that had the adopters not adopted Swarna-Sub1, the yield effect would have been 0.87 t/ha lower than what they obtained now. Similarly, had the non-adopters decided to adopt Swarna-Sub1, they would have received an additional yield of 1.03 t/ha.

Base heterogeneity is computed to see the effect of unobservable characteristics on yield obtained by the Swarna-Sub1 adopters and non-adopters irrespective of making decision to adopt it. The effect of base heterogeneity for households that make decision to adopt Swarna-Sub1 is 0.56 t/ha and for the households that did not adopt Swarna-Sub1 it is 0.40 t/ha. This negative base heterogeneity effect implies that the paddy yield of Swarna-Sub1 non-adopters is higher, probably attributed to unobservable characteristics.

5.2.2. Impact of Swarna-Sub1: average treatment effect

Average treatment effect (ATE) is estimated after controlling for potential counterfactuals using the propensity score matching approach is presented in Table 6. The outcome variables are paddy yield, net income, and technical efficiency estimates of model 1 (from Table 3). The outcome variables were compared between Swarna-Sub1 adopters and non-adopters under submergence and normal conditions.

It is evident from Table 6 that Swarna-Sub1 produces an additional 19% yield compared with other varieties under submergence conditions. Under normal conditions, there is no significant difference in yield between Swarna-Sub1 and other varieties.

From Table A.4., it is noted that there is no significant difference in the total cost of cultivation between Swarna-Sub1 and other varieties. The seed cost of other paddy varieties is significantly higher than for Swarna-Sub1, mainly because the seed price of some major varieties is higher. It is also observed that a significant difference exists in the quantity of seed applied. The labor cost of Swarna-Sub1 is significantly higher than for other inputs. Swarna-Sub1 tolerates flood more than other varieties under submergence conditions and more labor is involved in harvest and post-harvest activities.

Income from Swarna-Sub1 cultivation is higher in both normal and submergence conditions. However, the benefit is two times higher in submergence conditions. For instance, Swarna-Sub1 adopters earn an additional net income of 48.3% and 22.5% in submergence and normal conditions, respectively. The technical efficiency of the frontier production estimates also shows that the technical efficiency of Swarna-Sub1 adopters is higher than for other varieties by 5.7% in submergence conditions and by 6.8% in normal conditions.

Table 6
ATE estimates for plots cultivated under Swarna-Sub1 and other major paddy varieties for yield, income, and technical efficiency.

	Condition	Potential outcome mean (other varieties)	Swarna-Sub1 *vs* other varieties			
			Nearest-neighbor matching	Radius matching	Kernel matching	Stratification matching
Paddy yield (t/ha)	Submergence	2.77 (0.05)***	0.32 (0.23)	0.53 (0.18)***	0.60 (0.18)***	0.66 (0.20)***
	Normal	3.33 (0.05)***	0.32 (0.19)*	0.25 (0.15)*	0.22 (0.17)	0.18 (0.18)
	Pooled	3.05 (0.04)***	0.51 (0.15)***	0.39 (0.12)***	0.39 (0.12)***	0.39 (0.12)***
Net income (INR/ha)	Submergence	13,952 (576)***	4313 (2761)	6545 (2024)***	7712 (2094)***	8357 (1975)***
	Normal	18,997 (588)***	5147 (1993)***	4431 (2112)**	4054 (1799)**	3430 (1805)*
	Pooled	16,359 (415)***	6978 (1749)***	5660 (1429)***	5653 (1381)***	5719 (1447)***
Technical efficiency	Submergence	0.7531 (0.0052)***	0.035 (0.022)	0.046 (0.014) ***	0.045 (0.013) ***	0.045 (0.014) ***
	Normal	0.7443 (0.0046)***	0.031 (0.016)*	0.060 (0.011)***	0.057 (0.011)***	0.054 (0.011)***
	Pooled	0.7684 (0.0035)***	0.021 (0.013)	0.058 (0.008)***	0.056 (0.009)***	0.054 (0.009)***

Note: *, **, ***: statistically significant at 10%, 5%, and 1% levels of significance, respectively. Other varieties refer to all major varieties cultivated in the study area.

6. Conclusions

The present study captured the adoption status and performance of Swarna-Sub1 in the flood-prone areas of Eastern India. Endogenous switching regression was used to assess the impact by controlling for the role of selection bias in adoption decisions and paddy yield. The estimate revealed that paddy yield was significantly higher for Swarna-Sub1 adopters in the actual scenario and for non-adopters in the counterfactual scenario of adoption.

The performance of Swarna-Sub1 and other major paddy varieties was compared between normal and submergence plot conditions using average treatment effects. Compared to plots cultivated under normal conditions, paddy yield and net income obtained in submergence conditions were significantly higher for Swarna-Sub1 adopters. This shows that Swarna-Sub1 has potential for impact at scale to mitigate possible crop loss in flood-prone environments.

The adoption of Swarna-Sub1 varied significantly across the study area; low adoption was witnessed in Assam and West Bengal. However, the frequency and intensity of flood were higher in Assam. Henceforth, we recommend effective seed dissemination and promoting the variety in flood-prone regions. Information access play a key role in the decision on Swarna-Sub1 adoption, which highlights the importance of information flow and awareness about the variety. Further, this technology is found to be socially inclusive and can easily integrate with climate-smart farming systems. Therefore, a targeted scaling in flood-prone areas will have a substantial impact on the food security of small farmers living in those fragile environments.

We observed education playing a key role in adoption of climate resilient Swarna-Sub1. Inclusion of a curriculum on stress-tolerant rice varieties in agricultural extension and farmer schools is recommended. For instance, training material that International Rice Research Institute (IRRI) developed for quality seed and grain production of flood-tolerant rice varieties is readily available for such purposes. Further, social networks and media can be effectively utilized to generate social awareness about the new varieties. In short to medium term, information flow and convergence between different stakeholders (both public and private sector) as well as involving local institutions such gram panchayat is central in educating smallholders and faster dissemination of technologies. Hence, farmer schools of local institutions such as NGOs, local governments, agricultural department, seed dealers, etc. could be used to bring awareness about new climate resilient varieties among farmers. Seed dealer significantly influences the farmers' decision on modern rice variety purchase (Bannor et al., 2020). Thus, agricultural and climate policies needed to take account of importance of farmer education and involvement of local institutions in bringing resilience among smallholders.

Declaration of Competing Interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests

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Appendix

Table A1
Information on sampled households.

	Swarna-Sub1		Pooled ($n = 4744$)
	Adopters (8.9%)	Non-adopters (91.1%)	
Household head information			
Males (%)	98.1	95.5**	95.7
Currently married (%)	94.0	92.0	92.2
Age (years)	50.9 (12.5)	50.4 (12.9)	50.4 (12.9)
Rice cultivation (years)	25.9 (12.4)	27.8 (12.5) **	27.2 (12.5)
Household size (number)	5.1 (1.9)	4.9 (2.2) *	4.9 (2.1)
Educational status (%)			
Non-literate	8.8	22.1**	21.2
Primary (up to class 8)	42.6	42.7	42.7
Secondary (class 9–12)	37.6	30.4**	30.9
Graduate & above	11.0	4.8**	5.2
Primary occupation (%)			
Agriculture	80.9	61.2***	62.5
Agricultural labor	4.1	5.7	5.6
Non-agricultural labor	5.0	11.5***	11.1
Salaried	1.6	4.5**	4.3
Self-employment	5.6	10.6***	10.2
Others	2.8	6.5**	6.3
Household-level information			
Primary income source (%)			
Agriculture	42.9	32.3***	33.0
Agricultural labor	7.5	8.5	8.4
Non-agricultural labor	14.4	24.3***	23.6
Salaried	7.2	9.4	9.3
Self-employment	15.0	15.7	15.6
Others	12.8	9.9	10.1
Social group (caste) (%)			
Forward caste	36.1	45.6***	45.0
Other backward caste	44.8	26.2***	27.5
Scheduled caste	18.2	20.5	20.4
Scheduled tribe	0.9	7.6***	7.1
Farm-level information			
Landholding owned (ha)	0.98 (1.13)	0.68 (0.81) ***	0.70 (0.83)
Cultivated land in *kharif* 2015 (ha)	1.19 (0.83)	0.77 (0.73) ***	0.80 (0.74)
Rice area in *kharif* 2015 (ha)	1.17 (0.78)	0.70 (0.68) ***	0.80 (0.69)
Rice varieties cultivated in *kharif* 2015 (number)	2.8 (1.1)	1.8 (1.1) ***	1.9 (1.1)
Flood-affected area in *kharif* 2015 (%)	37.9	68.8***	66.7

Source: Household survey, 2016.

Note: *, **, *** statistically significant at 10%, 5%, and 1% levels of significance, respectively, using the Wilcoxon-Mann-Whitney test (for binary variables) and independent *t*-test (for continuous variables) between Swarna-Sub1 adopters and non-adopters; numbers in parentheses are the standard deviation.

Table A2
Descriptive statistics of variables used in stochastic frontier production function.

	Mean	Std. Dev.
Rice yield (t/ha)	3.90	0.97
Area (ha)	0.44	0.37
Seed (kg/ha)	58.88	19.65
Chemical fertilizer (kg/ha)	105.47	37.25
Pesticide (L/ha)	1.49	1.42
Irrigation (number/ha)	1.17	2.80
Male labor (man-days/ha)	27.37	16.25
Female labor (man-days/ha)	17.90	18.57
Machinery (hours/ha)	15.84	13.90
Swarna-Sub1 cultivation (dummy = 1)	12%	
Flood-affected area (dummy = 1)	49%	

Table A3
Cobb–Douglas stochastic frontier production function (OLS).

Ln yield (t/ha)	Model 1		Model 2	
	Coefficient	Std. Err.	Coefficient	Std. Err.
Ln area (ha)	0.0201	0.0241	0.0228	0.0237
Ln seed (kg/ha)	0.0111	0.0116	0.0120	0.0114
Ln chemical fertilizer (kg/ha)	0.0201***	0.0041	0.0116***	0.0042
Ln pesticide (L/ha)	0.0627***	0.0095	0.0591***	0.0093
Ln irrigation (number)	0.0017	0.0076	0.0046	0.0075
Ln labor used (m-day/ha)				
Male labor	0.0048	0.0037	0.0029	0.0037
Female labor	0.0050*	0.0027	0.0056**	0.0027
Ln machine use (hours/ha)	−0.0079	0.0061	0.0037	0.0062
Swarna-Sub1 adoption	–	0.0928***	0.0138	
Paddy plot submerged	–	−0.0545***	0.0097	
Constant	1.3761***	0.0511	1.4014***	0.0507
R^2	0.0652	0.0988		

Note: *, **, ***: statistically significant at 10%, 5%, and 1% levels of significance, respectively.

Table A4
Economics of production.

	Swarna-Sub1			Other varieties		
	Submergence (n = 123)	Normal (n = 206)	Pooled (n = 329)	Submergence (n = 1214)	Normal (n = 1118)	Pooled (n = 2332)
Area (ha)	0.47 (0.39)	0.39** (0.30)	0.42 (0.34)	0.44 (0.37)	0.46†† (0.42)	0.45 (0.39)
Yield (t/ha)	3.29 (1.91)	3.54 (2.19)	3.45 (2.09)	2.77††† (1.69)	3.33*** (1.65)	3.04††† (1.69)
Cost of production (INR/ha)						
Seed	1074 (551)	967* (340)	1007 (433)	1527††† (854)	1164$^{***, \dagger\dagger\dagger}$ (588)	1364††† (768)
Chemical fertilizer	1460 (718)	1545 (437)	1513 (559)	1352 (880)	1548*** (512)	1446 (734)
Pesticide	702 (812)	708 (677)	705 (729)	698 (877)	807$^{***, \dagger}$ (787)	751 (837)
Labor	10,156 (4935)	10,604 (4163)	10,437 (4465)	8671††† (5471)	9820$^{***, \dagger\dagger}$ (4963)	9222††† (5264)
Machinery	4370 (1955)	4510 (1819)	4458 (1869)	4525 (2062)	4477 (1764)	4502 (1925)
Other cost	260 (1010)	975*** (1909)	708 (1666)	612†† (1657)	878*** (1626)	739 (1647)
Total cost	*18,022 (5328)*	*19,309** (5163)*	*18,828 (5254)*	*17,385 (6997)*	*18,694*** (5694)*	*18,024†† (6435)*
Revenue (INR/ha)						
Gross revenue	38,349 (22,727)	42,337 (27,306)	40,846 (25,727)	31,337††† (19,512)	37,691$^{***, \dagger\dagger\dagger}$ (19,805)	34,383††† (19,904)
Net revenue	20,327 (21,072)	23,028 (26,984)	22,018 (24,939)	13,952††† (20,253)	18,997$^{***, \dagger\dagger\dagger}$ (19,415)	16,359††† (20,014)

Note: *, **, *** statistically significant at 10%, 5%, and 1% levels of significance using the independent t-test between submergence and normal conditions, respectively, for Swarna-Sub1 and other varieties. †, ††, ††† statistically significant at 10%, 5%, and 1% levels between Swarna-Sub1 and other varieties, respectively, for submergence conditions, normal conditions, and pooled. Numbers in parentheses are the standard deviation.

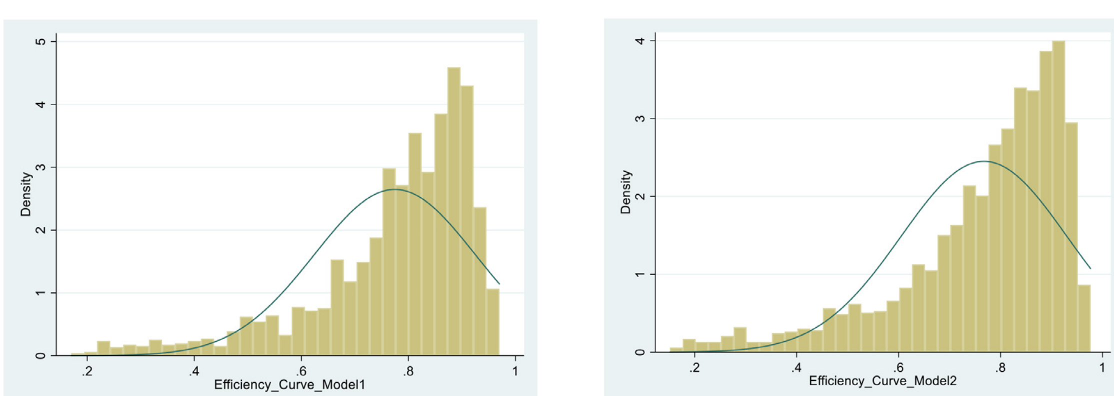

Fig. B1. Distribution of individual technical efficiency.

References

Abdulai, A., Huffman, W., 2014. The adoption and impact of soil and water conservation technology: an endogenous switching regression application. Land Econ. 90, 26–43. www.jstor.org/s/24243729.

Adhikari, B., Bag, M.K., Bhowmick, M.K., Kundu, C., 2011. Status Paper on rice in West Bengal. Rice Knowledge Management Portal (RKMP), Directorate of Rice Research, Hyderabad. [available at https://www.researchgate.net/publication/255742981_Status_Paper_on_Rice_in_West_Bengal (accessed 11 June 2021)].

Ahmed, M.H., Mesfin, H.M., 2017. The impact of agricultural cooperatives membership on the wellbeing of smallholder farmers: empirical evidence from eastern Ethiopia. Agric. Food Econ. 5, 1–20. doi:10.1186/s40100-017-0075-z.

Arora, A., Bansal, S., Ward, P.S., 2019. Do farmers value rice varieties tolerant to droughts and floods? Evidence from a discrete choice experiment in Odisha, India. Water Resour. Econ. 25, 27–41. doi:10.1016/j.wre.2018.03.001.

Aryal, J.P., Sapkota, T.B., Khurana, R., Khatri-Chhetri, A., Rahut, D.B., Jat, M.L., 2019. Climate change and agriculture in South Asia: adaptation options in smallholder production systems. Environ. Dev. Sustain. 22, 5045–5075. doi:10.1007/s10668-019-00414-4.

Asfaw, S., Shiferaw, B., 2010. Agricultural technology adoption and rural poverty: application of an endogenous switching regression for selected East African countries. In: Proceedings of the AAAE Third Conference/AEASA 48th Conference. Cape Town, South Africa. African Association of Agricultural Economists (AAAE). September 19-23, 201097049.

Bannor, R.K., Kumar, G.A.K., Oppong-Kyeremeh, H., Wongnaa, C.A., 2020. Adoption and impact of modern rice varieties on poverty in Eastern India. Rice Sci. 27, 56–66. doi:10.1016/j.rsci.2019.12.006.

Baten, M.A., Hossain, I., 2014. Stochastic frontier model with distributional assumptions for rice production technical efficiency. J. Agric. Sci. Technol. 16, 481–496.

Bhowmick, M.K., Dhara, M.C., Singh, S., Dar, M.H., Singh, U.S., 2014. Improved management options for submergence-tolerant (Sub1) rice genotype in flood-prone rainfed lowlands of West Bengal. Am. J. Plant Sci. 5, 14–23. doi:10.4236/ajps.2014.51003.

Bidzakin, J.K., Fialor, S.C., Awunyo-Vitor, D., Yahaya, I., 2019. Impact of contract farming on rice farm performance: endogenous switching regression. Cogent Econ. Financ. 7 (1), 1618229. doi:10.1080/23322039.2019.1618229.

Bisht, I.S., Rana, J.C., Ahlawat, S.P., 2020. The future of smallholder farming in India: some sustainability considerations. Sustainability 12, 3751. doi:10.3390/su12093751.

Chand, R., Prasanna, P.L., Singh, A., 2011. Farm size and productivity: understanding the strengths of smallholders and improving their livelihoods. Econ. Political Wkly. 5–11. https://www.jstor.org/stable/23018813.

Coelli, T.J., Rao, D.S.P., O'Donnell, C.J., Battese, G.E., 2005. An Introduction to Efficiency and Productivity Analysis, 2nd ed. Springer, New York.

Dar, M.H., et al., 2018. No yield penalty under favorable conditions paving the way for the successful adoption of flood tolerant rice. Sci. Rep. 8, 9245. doi:10.1038/s41598-018-27648-y.

Dar, M.H., Chakravorty, R., Waza, S.A., Sharma, M., Zaidi, N.W., Singh, A.N., Singh, U.S., Ismail, A.M., 2017. Transforming rice cultivation in flood prone coastal Odisha to ensure food and economic security. Food Secur. 9, 711–722. doi:10.1007/s12571-017-0696-9.

Debnath, S., Jain, T., Singh, M., 2015. Social Networks and Health Insurance Utilization. International Growth Centre, London https://www.isid.ac.in/~epu/acegd2015/papers/TarunJain.pdf.

Di Falco, S., Veronesi, M., Yesuf, M., 2011. Does adaptation to climate change provide food security? A micro-perspective from Ethiopia. Am. J. Agric. Econ. 93, 829–846. doi:10.1093/ajae/aar006.

Douglas, I., Alam, K., Maghenda, M., Mcdonnell, Y., Mclean, L., Campbell, J., 2008. Unjust waters: climate change, flooding, and the urban poor in Africa. Environ. Urban. 20, 187–205. doi:10.1177/0956247808089156.

Duncan, J.M.A., Dash, J., Tompkins, E.L., 2017. Observing adaptive capacity in Indian rice production systems. AIMS Agric. Food 2, 165–182. doi:10.3934/agrfood.2017.2.165.

Emerick, K., de Janvry, A., Sadoulet, E., Dar, M.H., 2016. Technological innovations, downside risk, and the modernization of agriculture. Am. Econ. Rev. 106, 1537–1561. doi:10.1257/AER.20150474.

Farrell, M.J., 1957. The measurement of productive efficiency. J. R. Stat. Soc. 120, 253–281. doi:10.2307/2343100.

Foster, A.D., Rosenzweig, M.R., 2010. Microeconomics of technology adoption. Annu. Rev. Econ. 2 (1), 395–424. doi:10.1146/annurev.economics.102308.124433.

Freitas, K., 2006. The Indian Caste System as a Means of Contract Enforcement. Nortwestern University unpublished manuscript https://web.stanford.edu/~avner/Greif_228_2007/Freitas,%20Kripa.%202006.%20The%20Indian%20Caste%20System.pdf .

Government of Odisha (GoO), 2013. Agriculture Department, Disaster Management Plan for Odisha. Government of Odisha (GoO) http://agriodisha.nic.in/http_public/pdf/DMP.pdf.

Gregorio, G.B., Islam, M.R., Vergara, G.V., Thirumeni, S., 2013. Recent advances in rice science to design salinity and other abiotic stress tolerant rice varieties. SABRAO J. Breed. Genet. 45, 31–41.

Hattori, Y., Nagai, K., Furukawa, S., Song, X.J., Kawano, R., Sakakibara, H., Wu, J., Matsumoto, T., Yoshimura, A., Kitano, H., Matsuoka, M., 2009. The ethylene response factors SNORKEL1 and SNORKEL2 allow rice to adapt to deep water. Nature 46, 1026–1030. doi:10.1038/nature08258.

Heckman, J.J., Tobias, J.L., Vytlacil, E.J., 2001. Four parameters of interest in the evaluation of social programs. South. Econ. J. 68, 210–233. doi:10.2307/1061591.

Islam, G.M.N., Tai, S.Y., Kusairi, M.N., 2016. A stochastic frontier analysis of technical efficiency of fish cage culture in Peninsular Malaysia. Springerplus 5, 1–11. doi:10.1186/s40064-016-2775-3.

Ismail, A.M., Singh, U.S., Singh, S., Dar, M.H., Mackill, D.J., 2013. The contribution of submergence-tolerant (Sub1) rice varieties to food security in flood-prone rainfed areas in Asia. Field Crop Res. 152, 83–93. doi:10.1016/j.fcr.2013.01.007.

Khan, S.A., Kumar, S., Hussain, M.Z., Kalra, N., 2009. Climate change, climate variability, and Indian agriculture: impacts, vulnerability and adaptation strategies. In: Singh, S.N. (Ed.), Climate Change and Crops. Environmental Science and Engineering. Springer-Verlag, Berlin, Heidelberg, pp. 19–38.

Laha, A.K., Chatterjee, S., Bera, K., 2014. Flood hazard cause assessment and their mitigation option using geo-informatics technology. IJSRP 4, 1–7. http://www.ijsrp.org/research-paper-0814/ijsrp-p3235.pdf.

Mackill, D.J., Ismail, A.M., Singh, U.S., Labios, R.V., Paris, T.R., 2012. Development and rapid adoption of submergence-tolerant (Sub1) rice varieties. Adv. Agron. 115, 303–356. doi:10.1016/B978-0-12-394276-0.00006-8.

Mandal, R., 2014. Flood, cropping pattern choice and returns in agriculture: a study of Assam plains, India. Econ. Anal. Policy 44, 333–344. doi:10.1016/j.eap.2014.08.001.

Mottaleb, K.A., Gumma, M.K., Mishra, A.K., Mohanty, S., 2015. Quantifying production losses due to drought and submergence of rainfed rice at the household level using remotely sensed MODIS data. Agric. Syst. 137, 227–235. doi:10.1016/j.agsy.2014.08.014.

Neeraja, C.N., Maghirang-Rodriguez, R., Pamplona, A., Heuer, S., Collard, B.C., Septiningsih, E.M., Vergara, G., Sanchez, D., Xu, K., Ismail, A.M., Mackill, D.J., 2007. A marker-assisted backcross approach for developing submergence-tolerant rice cultivars. Theor. Appl. Genet. 115, 767–776. doi:10.1007/s00122-007-0607-0.

Nelson, A.R.L.E., Ravichandran, K., Antony, U., 2019. The impact of the green revolution on indigenous crops of India. J. Ethn. Foods 6, 8. doi:10.1186/s42779-019-0011-9.

Nguyen, N.V., 2012. Global Climate Change and Rice Food Security. International Rice Commission, FAO http://www.fao.org/forestry/15526-03ecb62366f779d1ed45287e698a44d2e.pdf.

Phukan, K., 2016. Impacts of flood in economy of Assam, India and the changing cropping practice. South Asian J. Multidiscip. Stud. 3, 64–75.

Pingali, P.L., 2012. Green revolution: impacts, limits, and the path ahead. PNAS 109, 12302–12308. www.pnas.org/cgi/doi/10.1073/pnas.0912953109.

Pingali, P., Aiyar, A., Abraham, M., Rahman, A., 2019. Transforming Food Systems For a Rising India. Palgrave Studies in Agricultural Economics and Food Policy, Switzerland https://www.palgrave.com/gp/book/9783030144081.

Radhakrishnan, K., Das, S., 2019. Application of stochastic frontier production function in sugarcane industry-treated wastewater reuse in agriculture: case study of a coastal district in Tamil Nadu, India. J. Econ. Theory Pract. 18, 185–200 10.1177/0976747918825019.

Rajendran, S., 2014. Technical efficiency of fruit and vegetable producers in Tamil Nadu, India: a stochastic frontier approach. Asian J. Agric. Dev. 11, 77–93.

Ranuzzi, A., Srivastava, R., 2012. Impact of Climate Change On Agriculture and Food Security. Indian Council for Research on International Economic Relations, New Delhi, India ICRIER Policy Series No. 16 http://icrier.org/pdf/Policy_Series_No_16.pdf .

Sarkar, R.K., Reddy, J.N., Sharma, S.G., Ismail, A.M., 2006. Physiological basis of submergence tolerance in rice and implications for crop improvement. Curr. Sci. 91, 899–906. https://www.jstor.org/stable/24094287.

Singh, D., Singh, B., Mishra, S., Singh, A.K., Sharma, T.R., Singh, N.K., 2016. Allelic diversity for salt stress-responsive candidate genes among India rice landraces. Indian J. Biotechnol. 15, 25–33 http://nopr.niscair.res.in/bitstream/123456789/34475/2/IJBT%2015%281%29%2025-33.pdf.

Singh, S., Mackill, D., Ismail, A., 2009. Responses of Sub1 rice introgression lines to submergence in the field: yield and grain quality. Field Crop Res. 113, 12–23. doi:10.1016/j.fcr.2009.04.003.

Somanathan, E., Somanathan, R., 2009. Climate change: challenges facing India's poor. Econ. Political Wkly. 44, 51–58. https://www.jstor.org/stable/25663391.

Tesfaye, W., Tirivayi, N., 2018. The impact of postharvest storage innovations on food security and welfare in Ethiopia. Food Policy 75, 52–67. doi:10.1016/j.foodpol.2018.01.004.

Veettil, P.C., Raghu, P.T., Ashok, A., 2021. Information quality, adoption of climate-smart varieties and their economic impact in flood-risk areas. Environ. Dev. Econ. 26, 45–68. doi:10.1017/S1355770X20000212.

Yamano, T., Rajendran, S., Malabayabas, M.L., 2015. Farmers' self-perception toward agricultural technology adoption: evidence on adoption of submergence-tolerant rice in Eastern India. J. Soc. Econ. Dev. 17, 260–274. doi:10.1007/s40847-015-0008-1.