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Adoption of Climate-Smart Agriculture Among Rice Farmers in Bangladesh

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Abstract

Rice-based smallholder systems in southern Bangladesh face reinforcing pressures from climate variability and soil degradation driven by decades of input-intensive cultivation. This study examines Climate-Smart Agriculture (CSA) adoption among modern rice farmers in this region, with particular attention to joint adoption behavior and variation in adoption intensity. Rather than treating CSA as a discrete technological choice, this study conceptualizes it as a portfolio of interrelated practices such as crop diversification, agroforestry, integrated soil fertility management, small-scale irrigation, and integrated pest management, and estimates adoption decisions jointly using a multivariate probit (MVP) model. An adoption index complements the MVP estimates by capturing depth of engagement beyond binary indicators. The study found that CSA adoption is widespread but uneven. Most households adopt multiple practices. However, full portfolio adoption is rare. This is consistent with a gradual and selective adjustment process rather than systemic transition. MVP estimates confirm that decisions across practices are interdependent but not perfectly correlated. Determinants of CSA adoption differ significantly across practices. Human capital, farm size, access to credit and extension services, and market information impact adoption. But their effects are not uniform. Exposure to soil salinity and drought increases adoption of specific practices while leaving others largely unaffected. This indicates that agroecological context mediates the incentive structure rather than operating merely as background condition. Climate awareness alone does not sustain adaptation. Institutional support determines whether awareness translates into behavior change. These findings suggest that policy frameworks predicated on technology dissemination alone are unlikely to expand the adoption frontier. Effective intervention requires explicit attention to institutional capacity, localized environmental constraints, and heterogeneity in adoption intensity across households.

Keywords: *Adoption Intensity, Bangladesh, Climate-Smart Agriculture (CSA), Drivers of Climate Adaptation, Multivariate Probit Model, Portfolio-Based Technology Adoption*

Introduction

Agriculture remains a primary source of livelihood, food security, and rural employment across developing economies. In these economies production is typically organized around small-holder systems. Bangladesh exemplifies this structure. More than 80 percent of farmers operate on less than one hectare, yet the sector continues to contribute substantially to employment and national income (Tajuddin et al., 2017). Comparable patterns are observed across much of the Global South, where agriculture absorbs a large share of the labor force and plays a stabilizing role in poverty reduction and economic performance (ADB, 2000; ILO, 2024). This structural dependence heightens exposure to environmental stress. Smallholders must sustain productivity under conditions of land fragmentation, resource degradation, and increasing climatic variability. Climate smart agriculture (CSA) has therefore gained policy and analytical relevance as an approach that seeks to raise productivity while strengthening resilience and limiting environmental damage (Campbell et al., 2014; Lipper et al., 2014).

Rice based production systems lie at the center of this problem in Bangladesh. Rice dominates both cropping patterns and food consumption. The diffusion of high yielding varieties since the Green Revolution expanded output considerably. But these gains have relied on input intensive cultivation. Fertilizer use, pesticide application, mechanization, and groundwater extraction have increased yields while altering the ecological balance of production systems. Over time, these practices have contributed to declining soil quality, reduced fertility, depletion of groundwater resources, and increased environmental vulnerability (Kafiluddin and Islam, 2008). Similar tradeoffs between productivity and sustainability are documented in other developing regions characterized by intensive cereal cultivation (Arslan et al., 2015; Tsige et al., 2024). Conservation oriented approaches such as reduced tillage and integrated farming systems offer viable alternatives. However, their uptake remains constrained by production risk, uncertainty, and adjustment costs faced by farmers (Rahman et al., 2021).

Climatic stress further increase these structural pressures. Variability in temperature and rainfall, alongside recurrent floods, droughts, cyclones, salinity intrusion, and pest dynamics has increased the volatility of agricultural production and rural incomes (Islam et al., 2022; World Bank Group, 2021). Bangladesh is consistently identified among the most climate exposed countries in South Asia, with repeated shocks reinforcing production risk for smallholders (Kreft et al., 2017). Within this setting, CSA is better understood as a portfolio of interrelated practices rather than a discrete technological intervention. It considers strategies such as crop diversification, agroforestry, soil fertility management, water management, conservation agriculture, and the use of climate information services (Belay et al., 2017; Partey et al., 2018). The underlying rationale is that combinations of practices can jointly influence productivity, adaptive capacity, and environmental outcomes (De Pinto et al., 2017; FAO, 2022). Empirical evidence indicates that adoption decisions are shaped by education, farm size, asset endowments, access to credit, extension support, training, and market integration (Kassie et al., 2013; Khatri-Chhetri et al., 2017). Adoption is rarely isolated. Farmers tend to combine practices that suggest the presence of complementarities and joint decision-making processes (Kangogo et al., 2021).

Findings from Bangladesh are consistent with this evidence. Studies found positive associations between the uptake of climate smart practices and improvements in food security and livelihood resilience. At the same time, adoption remains conditioned by household and institutional characteristics such as education, landholding size, livestock ownership, access to finance, and extension services (Abid et al., 2015; Saha et al., 2019). Context specific practices including agroforestry, floating agriculture, and sorjan farming further illustrate how local adaptation can enhance resilience in ecologically vulnerable settings (Kabir et al., 2022). Despite the expansion of this literature, several limitations persist. A large share of existing work isolates individual practices and models adoption as a binary outcome. This approach ignores interactions across practices and fails to capture variation in the adoption intensity. It also limits the analysis of complementarities that may be central to farmer decision making under risk. The present study addresses these gaps by examining the joint adoption of multiple climate smart practices among modern rice growing households in southern Bangladesh. A multivariate probit framework is employed to account for interdependent adoption decisions, alongside a CSA adoption index that captures adoption intensity. The empirical strategy integrates climate exposure and institutional conditions to identify the mechanisms shaping both the likelihood and extent of adoption.

Materials and Methods

Study Area

The empirical setting is the southern coastal belt of Bangladesh. In this region agricultural production operates under persistent exposure to climatic stressors. Salinity intrusion alters soil chemistry and constrains crop choice, cyclonic events damage standing crops and infrastructure, and tidal surges and irregular rainfall disrupt planting and harvesting cycles. These processes interact in ways that elevate production risk in rice-based systems, making the region a suitable context for examining the uptake of climate smart agriculture practices. Three southern districts were selected with the intention of capturing heterogeneity in both agroecological conditions and exposure intensity. The samples were collected Bagerhat, Pirojpur, and Barguna districts. Within these three districts, ten upazilas were included to ensure variation in local production environments. The selected upazilas (sub districts) are Bagerhat Sadar, Fakirhat, Mollahat, and Chitalmari in Bagerhat, Nazirpur, Nesarabad, and Pirojpur Sadar in Pirojpur, and Amtali, Barguna Sadar, and Bamna in Barguna. These upazilas share a strong dependence on agriculture as a primary livelihood source. However, they differ in their degree of climatic vulnerability and resource endowments. Such variation is necessary for identifying differential adoption behavior under changing environmental conditions. Primary data were obtained through a structured household survey that was designed to capture both production decisions and institutional access. A multistage sampling strategy was employed. Villages were first selected within each upazila, after which farm households were randomly drawn from village lists. The final sample consists of 497 households, distributed across Bagerhat with 171 observations, Pirojpur with 162 observations, and Barguna with 164 observations. The survey instrument collected detailed information on household demographics, farm characteristics, production practices, perceptions of climate variability, adoption of climate smart agriculture measures, and access to extension and financial services. Data collection was carried out between January and July 2025. Data collection spans both dry and early monsoon conditions which allows responses to reflect seasonal variation in farming decisions.

Analytical Techniques

The analysis quantifies the extent of climate smart agriculture adoption through an index that reflects engagement across multiple practices. This construction follows a portfolio perspective in which farmers combine different CSA practices to manage risk, rather than adopting a single technology in isolation. The index is therefore intended to capture the breadth of adoption rather than the intensity of any individual practice. Five practices that are prevalent in rice-based systems in southern Bangladesh are considered. These include crop diversification, agroforestry, integrated soil fertility management, small scale irrigation, and integrated pest management. Each practice is coded as a binary indicator that takes the value one when the household reports adoption and zero otherwise. This coding assumes that the primary distinction of interest lies in whether a practice is used, given that the survey design does not support consistent measurement of intensity across all practices. For each household, the index is calculated as the average of these binary indicators. The CSA adoption index for household i is defined as:

$$CSA\_Index_i = \frac{1}{K}\sum_{k=1}^{K} CSA_{ik} \quad (1)$$

where CSA_{ik}denotes the adoption status of CSA practice k by household i, and Krepresents the total number of CSA practices considered in the analysis ($K = 5$). This normalization facilitates comparison across households by placing all observations on a common scale. It also preserves the additive structure implied by the portfolio approach where each additional practice contributes incrementally to the index. The method is consistent with empirical strategies used in prior studies of multi practice agricultural technology adoption (Kassie et al. 2015 and Teklewold et al. 2013), and provides a efficient representation of overall engagement with CSA in the study area.

Multivariate Probit (MVP) Model

Decisions of the farmers to adopt CSA practices are discrete and often interdependent. While probit models are commonly used to analyze binary technology adoption decisions in agriculture (Ma and Rahut, 2024; Musafiri et al., 2022), CSA adoption typically involves multiple practices that are adopted jointly rather than independently. These practices are sometimes complementary, and sometimes they are substitutes. These practices are influenced by common socioeconomic, institutional, and climatic factors. Estimating separate probit models would ignore potential correlations across adoption decisions. Thus, this study employs a Multivariate Probit (MVP) model, which allows the joint estimation of multiple correlated adoption equations and accounts for interdependence among CSA practices (Moshi et al., 2016; Teklewold et al., 2013).

Suppose that farmer i faces j binary adoption decisions corresponding to different CSA practices. For each practice j $(j = 1,2, \ldots, J)$, there exists an unobserved latent variable Y_{ij}^* that reflects the net benefit associated with adoption:

$$Y_{ij}^* = X_i\beta_j + \varepsilon_{ij} \tag{2}$$

where X_i is a vector of explanatory variables capturing household demographic characteristics, farm and resource endowments, institutional access, and climate-related factors; β_j is a vector of parameters to be estimated for CSA practice j; and ε_{ij} is a stochastic error term. The observed adoption outcome is defined as:

$$Y_{ij} = \begin{cases} 1 & \text{if } Y_{ij}^* > 0 \\ 0 & \text{otherwise} \end{cases} \tag{3}$$

The error terms $(\varepsilon_{i1}, \varepsilon_{i2}, \ldots, \varepsilon_{iJ})$ are assumed to follow a multivariate normal distribution with zero mean and variance–covariance matrix Σ, where the off-diagonal elements capture correlations across adoption equations. Statistically significant correlations provide evidence of complementarities or trade-offs among CSA practices. This justifies the use of the MVP framework. In this study, five CSA practices such as crop diversification, agroforestry, integrated soil fertility management, small-scale irrigation, and integrated pest management are considered. Thus, the MVP system is specified as:

Yi1 = 1 if farmer i adopts crop diversification, 0 otherwise
Yi2 = 1 if farmer i adopts agroforestry, 0 otherwise
Yi3 = 1 if farmer i adopts soil fertility management, 0 otherwise
Yi4 = 1 if farmer i adopts small-scale irrigation, 0 otherwise
Yi5 = 1 if farmer i adopts integrated pest management, 0 otherwise

Each adoption decision is regressed on the same set of independent variables that allow consistent comparison of determinants across practices while capturing interdependence through the estimated error correlations. Estimation is carried out using simulated maximum likelihood techniques that are standard in multivariate discrete choice models. Location-specific heterogeneity is addressed through the inclusion of detailed agroecological, climatic, and institutional variables such as soil salinity exposure, irrigation conditions, drought experience, and access to extension and markets. These variables vary significantly across districts and capture much of the spatial variation affecting adoption decisions of the farmers. Given this rich set of controls and the study's primary focus on household-level behavioral and institutional determinants rather than district-level comparisons, explicit district fixed effects are not included in the baseline specification.

Description and Measurement of the Variables

The empirical specification distinguishes between adoption outcomes and a set of covariates that represent household characteristics, resource constraints, institutional linkages, and exposure to climatic conditions. Adoption is treated as a set of discrete choices rather than a single aggregated decision. Each outcome variable corresponds to the use of a specific climate smart agriculture practice and is coded as a binary indicator. A value of one denotes that the household reports using the practice during the reference period, while zero indicates non adoption. The practices considered include crop diversification, agroforestry, integrated soil fertility management, small scale irrigation, and integrated pest management. This formulation allows the analysis to capture joint decision making across practices while preserving variation at the level of individual technologies.

The explanatory variables are organized to reflect distinct but interrelated channels through which adoption decisions are formed. Household demographic characteristics enter the model to account for differences in human capital and decision-making capacity. Age of the household head is measured in completed years and proxies farming experience as well as exposure to past climatic events. Gender is introduced as a binary indicator to capture potential differences in access to resources and information. Education is measured in years of formal schooling and reflects the ability to process technical information and respond to extension advice. Farm and resource endowments represent the material constraints under which production decisions are made. Farm size is measured in cultivated land area and captures scale effects in technology adoption. Land tenure is included as a categorical variable distinguishing owned and non-owned plots. Livestock ownership is measured in number of animals and serves as an indicator of asset diversification and liquidity. Asset holdings are proxied through an index constructed from durable goods owned by the household, reflecting overall economic capacity. Institutional access variables are intended to capture the role of information flows and financial support. Access to extension services is recorded as a binary indicator based on whether the household had contact with extension agents during the reference period. Participation in training programs is similarly coded and reflects exposure to formal knowledge dissemination. Credit access is measured as a binary variable indicating whether the household obtained agricultural credit. Membership in farmer organizations is included to capture collective action and information exchange mechanisms. Climate related variables are introduced to account for both objective exposure and subjective interpretation of environmental change. Exposure to climate shocks is measured through reported experience of events such as floods, cyclones, or salinity intrusion within a defined time frame. Perceptions of climate change are captured through survey responses on changes in temperature, rainfall patterns, and frequency of extreme events. These variables enter the model to reflect how observed and perceived risks shape the incentives to adopt climate responsive practices.The definition and measurement of each variable are summarized in Table 1, which provides the operational coding used in the estimation.

Multicollinearity Diagnosis

Multicollinearity among explanatory variables was assessed using variance inflation factors (VIF). As shown in Table 2, all VIF values are below the commonly accepted threshold of 10, indicating that multicollinearity is not a concern in the regression model (Gujarati, 2004).

Results and Discussion

Descriptive Statistics

Table 1 summarizes the variables used in the empirical analysis and provides an overview of the sample structure. Adoption rates for the five CSA practices fall within a relatively narrow range (62.4 percent to 69.0 percent). Integrated pest management and integrated soil fertility management record the highest uptake at 69.0 percent and 68.8 percent, respectively. Agroforestry follows at 63.5 percent, while crop diversification and small-scale irrigation each stand at 62.4 percent. The clustering of adoption rates within this interval suggests that no single practice dominates choices of the farmers. This is consistent with a setting where multiple practices are considered jointly under similar constraints.

Household characteristics reflect a smallholder production environment. The average age of the household head is 41.9 years, with 7.8 years of formal education and 24.5 years of farming experience. These figures indicate that most respondents combine moderate schooling with substantial exposure to agricultural production. The average household comprises 5.8 members, of whom approximately 1.92 are economically active. Male headed households account for 92 percent of the sample, and 82 percent report farming as the primary occupation. This reinforces the dominance of agriculture in household income generation. Resource endowments show variation across households. Mean landholding is 125.9 decimals, while the average value of household assets is BDT 227983. Livestock ownership is reported by 59 percent of households, indicating the presence of mixed farming systems in a significant share of the sample. Such variation in asset portfolios is relevant for understanding differences in adoption capacity, as both land and non-land assets shape investment decisions. Exposure to production risk is substantial. Most of the respondents report experiencing soil salinity, with 65 percent indicating direct exposure. Crop failure is reported by 69 percent of households, while pest and drought shocks are noted by 51 percent and 53 percent, respectively. These figures point to a production environment characterized by recurrent climatic and biological stress. Access to institutional services remains uneven. Credit is available to 58 percent of households, extension services reach 62 percent, and 69 percent report access to market information. The average distance to markets is 2.2 kilometres that suggests physical access constraints are present but not prohibitive for most households.

CSA Adoption Intensity

Table 3 presents the distribution of the normalized adoption index that captures the number of CSA practices adopted by each household. The distribution is skewed toward multiple practice adoption. Only 0.60 percent of households report no adoption, while 4.43 percent adopt a single practice and 16.70 percent adopt two practices. These categories represent a relatively small share of the sample.

Table 1. Description of the Variables

Variables	Description of the variables	Measurement / Type	Mean	SD	Min	Max
Dependent variables						
Crop diversification	Adoption of crop diversification by the household	Dummy, 1= yes, 0= otherwise	0.624	0.51	0	1
Agroforestry	Adoption of agroforestry by the household	Dummy, 1= yes, 0= otherwise	0.635	0.43	0	1
Integrated soil fertility management	Adoption of integrated soil fertility management by the household	Dummy, 1= yes, 0= otherwise	0.688	0.42	0	1
Small-scale irrigation	Adoption of small-scale irrigation by the household	Dummy, 1= yes, 0= otherwise	0.624	0.41	0	1
Integrated pest management	Adoption of integrated pest management by the household	Dummy, 1= yes, 0= otherwise	0.690	0.49	0	1
Independent Variables						
Demographic and human capital variables						
Age	Age of the household head (years)	Continuous	41.9	8.9	23	87
Gender	Gender of the household head	Dummy, 1= yes, 0= otherwise	0.92	0.298	0	1
Education of the household head	Education of the household head (years)	Continuous	7.8	2.54	0	16
Farming experience	Farming experience of the household head (years)	Continuous	24.5	7.6	0	51
Family size	No. of members in the family	Discrete	5.8	1.9	4	11
Working family members	No. of household members actively engaged in income-generating activities	Discrete	1.92	0.591	1	6
Main occupation	Main occupation of the household head	Dummy, 1= yes, 0= otherwise	0.82	0.312	0	1
Farm characteristics and assets						
Total agricultural land	Total agricultural land of the household (decimal)	Continuous	125.92	46.998	40	320
Total asset value	Total value of the assets owned by the household (BDT)	Continuous	227982.9	121886.3	25000	605000
Livestock ownership	Livestock ownership of the household	Dummy, 1= yes, 0= otherwise	0.59	0.41	0	1
Soil fertility perception	Subjective assessment of the household whether the soil on their agricultural land is fertile.	Dummy, 1= yes, 0= otherwise	0.61	0.49	0	1
Soil salinity perception	Subjective assessment of the household whether their agricultural land is affected by soil salinity	Dummy, 1= yes, 0= otherwise	0.65	0.48	0	1
Irrigation frequency	No. of times irrigation was applied to crops during the previous cropping season	Discrete	9.2	1.9	2	12
Prior crop failure	Whether the household experienced a crop failure in the most previous cropping season	Dummy, 1= yes, 0= otherwise	0.69	0.45	0	1
Subsidy beneficiary	Whether the household received any form of agricultural subsidy in the previous cropping season	Dummy, 1= yes, 0= otherwise	0.62	0.42	0	1
Market access	Proxy variable representing the distance (in kilometers) from the household to nearest agricultural market	Continuous	2.2	1.5	0	8
Access to credit	Whether the household had access to credit in the previous cropping season	Dummy, 1= yes, 0= otherwise	0.58	0.48	0	1
Climate and risk related variables						
Pest experience	Whether the household experienced a pest infestation affecting their crops in the previous cropping season	Dummy, 1= yes, 0= otherwise	0.51	0.43	0	1
Drought experience	Whether the household experienced a drought in the previous cropping season	Dummy, 1= yes, 0= otherwise	0.53	0.59	0	1
Perception of climate change	Subjective assessment of the household on whether they observed noticeable changes in climate patterns such as rainfall irregularity, rising temperatures, or extreme weather events over recent years.	Dummy, 1= yes, 0= otherwise	0.62	0.47	0	1
Institutional and infrastructure access						
Access to extension services	Whether the household received agricultural advice or support from government or Non-Governmental Organization extension officers in the last cropping season	Dummy, 1= yes, 0= otherwise	0.62	0.47	0	1
Access to market information	Whether the household received any timely and relevant market information through any medium such as mobile phone, television, radio, extension agents, or community networks.	Dummy, 1= yes, 0= otherwise	0.69	0.47	0	1

SD: Standard deviation

Table 2. Collinearity Statistics

Variables	*VIF*	*1/VIF*
Age	1.5	0.667
Gender	1.6	0.625
Education of the household head	1.2	0.833
Farming experience	1.7	0.588
Family size	1.9	0.526
Working family members	1.6	0.625
Main occupation	1.3	0.769
Total agricultural land	1.2	0.833
Total asset value	1.5	0.667
Livestock ownership	1.6	0.625
Soil fertility perception	1.6	0.625
Soil salinity perception	1.5	0.667
Irrigation frequency	1.5	0.667
Prior crop failure	1.6	0.625
Subsidy beneficiary	1.5	0.667
Market access	1.9	0.526
Access to credit	1.4	0.714
Pest experience	1.7	0.588
Drought experience	1.4	0.714
Perception of climate change	1.5	0.667
Access to extension services	1.5	0.667
Access to market information	1.5	0.667
Mean VIF	1.53	

Source: Field Survey, 2025.

Table 3. Distribution of the Normalized CSA Adoption Index

CSA Adoption Index (Normalized)	*Frequency*	*Percentage (%)*	*Cumulative Percentage (%)*
0.0	3	0.60	0.60
0.2	22	4.43	5.03
0.4	83	16.70	21.73
0.6	184	37.02	58.75
0.8	167	33.60	92.35
1.0	38	7.65	100.00
Total	497	100.00	

Note: The CSA adoption index is calculated as the proportion of five CSA practices adopted by each household, where each practice is binary-coded (1 = adopted, 0 = not adopted). The index ranges from 0 (no adoption) to 1 (full adoption of all practices).

The majority of households adopt three or more practices. Adoption of three practices accounts for 37.02 percent of the sample, and 33.60 percent adopt four practices. These two groups together comprise more than seventy percent of all households. 7.65 percent of the households adopt all five practices considered in the index. The concentration of observations in the upper range of the distribution indicates that farmers tend to combine practices rather than rely on isolated interventions. This pattern is consistent with a production setting in which different practices address distinct but related constraints.

Correlation Analysis of the Dependent Variable

Table 4 reports pairwise correlations among the adoption decisions for the five practices. The estimated coefficients are modest in magnitude, but they are not negligible. This pattern indicates that CSA adoption choices are neither fully independent nor strongly synchronized. Certain relationships are positive. Crop diversification exhibits a positive association with integrated soil fertility management, with a correlation coefficient of 0.16. Other relationships are negative. Crop diversification is negatively correlated with small scale irrigation at negative 0.27. Integrated soil fertility management shows a negative correlation with small scale irrigation at negative 0.29, and small-scale irrigation is negatively associated with integrated pest management at negative 0.18. These negative correlations suggest that some practices may compete for resources or reflect trade-offs in management strategies.

The presence of statistically significant correlations across several pairs of adoption decisions implies interdependence in farmers' choices. The magnitude of these correlations remains limited, which indicates that the interdependence is partial rather than deterministic. This empirical pattern supports a modeling approach that allows for correlated error structures across adoption equations, as implemented in the MVP framework.

Table 4. Correlation Coefficients for Multivariate Probit Regression Equations

Variables	Crop Diversification	Agroforestry	Integrated Soil Fertility Management	Small-scale Irrigation	Integrated Pest Management
Crop Diversification	1	0.07	0.16	-0.27	0.06
Agroforestry	0.07	1	0.01	-0.14	-0.002
Integrated Soil Fertility Management	*0.16	0.03	1	**-0.29	-0.003
Small-scale Irrigation	*-0.27	-0.14	*-0.29	1	*-0.18
Integrated Pest Management	0.06	-0.002	-0.003	**-0.18	1

Note: ***, ** and * represent statistically significant at 1%, 5%, and 10%, respectively.

Table 5. Results of Multivariate Probit Regression Model

Independent variables	CSA Practices (dependent variables)									
	Crop diversification		Agroforestry		Integrated soil fertility management		Small-scale irrigation		Integrated pest management	
	CE	ME	CE	ME	CE	ME	CE	ME	CE	ME
Demographic and human capital variables										
Age (years)	0.002	0.005	0.004	0.002	-0.005	-0.001	-0.006	-0.001	-0.007	-0.001
Gender (1= male; 0 = female)	0.579	0.217	0.105	0.052	0.361	0.083	0.178	0.068	0.499	0.188
Education of the household head (years)	0.015	0.014	0.027**	0.025**	0.014**	0.012**	0.013*	0.035*	0.022*	0.080*
Farming experience (years)	**0.004	**0.002	0.006	0.009	0.003	0.001	0.005	0.003	-0.003	-0.004
Family size (no. of members)	0.021	0.008	0.109	0.025	0.074*	0.036*	0.170	0.041	-0.016	-0.005
Working family members	0.011	0.004	0.069	0.041	0.091*	0.041*	0.065	0.012	0.176	0.061
Main occupation (1 = agriculture, 0 = business)	0.003	0.009	0.142*	0.078*	0.091	0.029	-0.899	-0.087	-0.044	-0.002
Farm characteristics and assets										
Total agricultural land (decimal)	0.051*	0.056*	0.032**	0.043**	*0.012	*0.015	0.023**	0.023**	0.003	0.005
Total asset value (BDT)	0.007	0.006	*0.003	*0.005	-0.003	-0.002	0.005	-0.003	0.001	0.003
Livestock ownership (1= yes, 0 = no)	0.076	0.075	0.213*	0.053*	0.185*	0.072*	-0.230	-0.074	0.031	-0.032
Soil fertility perception (1=yes, 0 = no)	0.877	0.065	-0.023	-0.021	-0.054	-0.034	0.031	0.013	-0.069	-0.045
Soil salinity perception (1=yes, 0=no)	-0.555*	-0.043*	0.989***	0.188***	0.176	0.076	0.510	0.188	-0.421***	-0.170***
Irrigation frequency (no.)	0.081*	0.031*	0.091*	0.005*	0.031	0.003	-0.004	0.002	*0.053	*0.021
Prior crop failure (1=yes, 0=no)	0.213	0.067	-0.087	-0.086	*0.250	*0.072	**0.213	**0.053	-0.065	-0.018
Independent variables	CSA Practices (dependent variables)									
	Crop diversification		Agroforestry		Integrated soil fertility management		Small-scale irrigation		Integrated pest management	
	CE	ME	CE	ME	CE	ME	CE	ME	CE	ME
Subsidy beneficiary (1=yes, 0=no)	-0.024	-0.015	0.250*	0.069*	0.035	0.025	0.650	0.155	0.058	0.060
Market access (km)	0.017	0.005	0.035	0.004	0.005	0.002	-0.069*	-0.018*	0.019	0.007
Access to credit (1=yes, 0=no)	0.057**	0.014**	**0.004	**0.001	0.244*	0.01*	0.366***	0.058***	0.254*	0.067*
Climate and risk related variables										
Pest experience (1=yes, 0=no)	-0.041	-0.014	-0.240	-0.058	-0.074	-0.024	-0.312	-0.075	**0.061	**0.007
Drought experience (1=yes, 0=no)	0.048*	0.014*	0.257	0.061	0.133	0.051	0.021***	0.002***	0.071	0.031
Perception of climate change (1=yes, 0=no)	**0.016	**0.004	0.134	0.052	0.247*	0.079*	0.511***	0.360***	0.137**	0.049**
Institutional and infrastructure access										
Access to extension services (1=yes, 0=no)	0.104	0.045	0.052*	0.014*	0.105**	0.044**	0.357***	0.204***	0.360***	0.204***
Access to market information (1=yes, 0=no)	-0.004	-0.001	*0.157	*0.073	0.333*	0.094*	0.467***	0.145***	0.466***	0.144***
Constant	-0.21**		-0.31**		-0.03		**0.05		-0.06*	

Wald chi2 = 200.311; Log pseudolikelihood= -1503.447; Prob > chi2 = 0.000; Number of observations = 497.
CE=Coefficients; ME= Marginal effects
Note: ***, ** and * represent statistically significant at 1%, 5%, and 10%, respectively.

Results of MVP Model

Table 5 presents the estimates from the MVP model for the adoption of five CSA practices. The joint significance of the model is confirmed by the Wald statistic of 200.31 with a probability value below 0.01. This indicates that the set of explanatory variables, taken together, has substantial explanatory power in accounting for observed adoption patterns across practices.

Human capital emerges as a consistent determinant of adoption behavior. Years of schooling of the household head are positively associated with several practices. The marginal effects indicate statistically significant increases in the probability of adopting agroforestry at 0.025, integrated soil fertility management at 0.012, small scale irrigation at 0.035, and integrated pest management at 0.080. These estimates point to a mechanism in which education enhances the capacity to interpret technical information and manage practices that require coordination of inputs and timing. Farm size shows a strong influence on CSA adoption decisions. Larger landholdings increase the likelihood of adopting crop diversification with a marginal effect of 0.056, agroforestry at 0.043, integrated soil fertility management at 0.015, and small-scale irrigation at 0.023. The pattern is consistent with a relaxation of scale related constraints. Households with more land can allocate plots across different uses and absorb potential short-term risks associated with new practices. Livestock ownership shows a positive association with agroforestry and integrated soil fertility management, with marginal effects of 0.053 and 0.072, respectively. This relationship reflects complementarities within mixed farming systems. Perceptions of environmental conditions shape adoption choices in a differentiated manner. Soil salinity increases the probability of adopting agroforestry with a marginal effect of 0.188, while it reduces the likelihood of crop diversification at negative 0.043 and integrated pest management at negative 0.170. These responses indicate that the household adjust their strategies in relation to specific stressors rather than adopting practices uniformly. The direction of the effects suggests that some practices are perceived as more suitable for coping with salinity than others. Institutional access plays a significant role. Credit availability raises the probability of adopting crop diversification at 0.014, integrated soil fertility management at 0.010, small scale irrigation at 0.058, and integrated pest management at 0.067. Access to extension services and market information shows particularly strong effects. The estimated marginal effects for extension are 0.204 for small scale irrigation and 0.204 for integrated pest management, while the corresponding effects for market information are 0.145 and 0.144. These magnitudes indicate that information and advisory support reduce uncertainty and facilitate the adoption of practices that require technical knowledge and coordination. Climate related experiences and perceptions further contribute to observed behavior. Exposure to drought increases the probability of adopting crop diversification at 0.014 and small scale irrigation at 0.002. Perception of climate change shows a stronger association with adoption, increasing the likelihood of integrated soil fertility management at 0.079, small scale irrigation at 0.360, and integrated pest management at 0.049.

Conclusion

This study investigates the adoption of CSA practices among modern rice farmers in the southern coastal region of Bangladesh, with attention to both the determinants of adoption and the extent to which practices are combined. The empirical strategy integrates MVP framework with an adoption index. This allows the analysis to reflect interdependent decision making across practices rather than treating adoption as a series of isolated choices. The results indicate that farmers adjust their production strategies in response to a combination of resource constraints, institutional access, and exposure to climatic stress. CSA adoption is not uniform. It reflects differences in capacity, information, and perceived risk.

Several implications follow directly from these findings. Strengthening extension services and improving the availability of climate related information would alter the informational environment in which farmers operate. The estimated effects indicate that access to such services reduces uncertainty and increases the likelihood of adopting practices that require technical coordination. Financial constraints also shape adoption decisions. Improved access to credit can ease liquidity limitations and enable households to undertake investments that are otherwise deferred, particularly in practices with upfront costs. Human capital plays a consistent role across several adoption outcomes. Education and training influence the ability to interpret information and implement management intensive practices. Policies that expand training opportunities and improve the quality of agricultural education would therefore have direct effects on adoption behavior. At the same time, heterogeneity in resource endowments implies uneven capacity to adopt. Households with limited land or assets face tighter constraints that restrict their ability to experiment with multiple practices. Targeted interventions that address these constraints are necessary if adoption is to extend beyond better resourced farmers. The evidence also points to the importance of aligning CSA with broader development strategies. Adoption decisions are shaped by both immediate production considerations and longer-term expectations about environmental change. Integrating climate responsive practices into rural development planning would reinforce their role in sustaining productivity under increasing climatic variability.

Declarations

Ethical Approval

The study protocol was approved by the relevant authority of the authors' university, and all survey procedures followed standard ethical guidelines. Participation was voluntary, informed consent was obtained from all respondents, and all data were kept anonymous and confidential.

Author Contribution Statement

Ehsanur Rauf Prince conducted all aspects of the study and wrote the entire manuscript.

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Conflict of Interest

The author declares no conflict of interest.

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