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FACTORS AFFECTING FARMERS' USE OF CLIMATE-SMART AGRICULTURAL PRACTICES

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ABSTRACT
The main objective of this study was to determine farmers' extent of use of climate-smart agricultural practices and identify the most influential factors affecting the use of these practices. The study was conducted in Gangachara Upazila of Rangpur district in Bangladesh. Data were collected using a structured questionnaire from one hundred thirty-three (133) farmers from May 2023 to July 2023. The use of ten selected climate-smart agricultural (CSA) practices by the farmers was measured by a 4-point rating scale using the following responses: 'Not at all', 'Rarely', 'Occasionally', and 'Frequently', with corresponding weights of 0, 1, 2, and 3. In addition to descriptive statistical analyses, correlation analysis and multiple linear and stepwise regression analyses were performed to determine the most influential factors. The majority (55.6%) of the farmers used climate-smart agricultural (CSA) practices moderately. The top three CSA practices used by the farmers were 'crop rotation' (SUI=0.516), 'organic composting' (SUI=0.415), and 'cover cropping' (SUI=0.309). The least used practice was 'using intelligent technologies (GPS, sensors, drones, etc.)' (SUI=0.092). Farmers' educational qualifications, annual income, access to information sources, and risk orientation were the most significant factors in explaining farmers' use of climate-smart agricultural practices. However, farmers' educational qualification contributed about 61.1% of the variance in explaining the dependent variable. Strategies should include targeted educational campaigns, training programs, tailored financial subsidies, and robust extension services to enhance the utilisation of CSA practices.

Keywords: Climate-smart, CSA, greenhouse, food security, vulnerability,

INTRODUCTION
Climate-smart agriculture (CSA) refers to a collection of agricultural practices and innovations that have the dual benefit of increasing productivity while improving the system's ability to withstand and recover from climate-related challenges (World Bank 2024). According to FAO, 'agriculture that sustainably increases productivity, enhances resilience (adaptation), reduces or removes green house gases mitigation where possible, and enhances achievement of national food security and development goals is termed as climate-smart agriculture (FAO 2013).

Adopting CSA methods is crucial in addressing the interconnected challenges of climate change and food security (Lipper *et al*. 2014).

Implementing CSA practices is significant in Bangladesh due to the nation's susceptibility to climate change impacts. Bangladesh, as identified by the Global Climate Risk Index, is the nation most susceptible to climate change's impacts. Presently and in the decades to come, the nation is anticipated to experience adverse consequences stemming from sea level rise and saline intrusion, elevated mean temperatures (estimated to rise by 1.7ºC by 2050), increased precipitation variability, and extreme weather severity (Harmeling 2011). Each of these factors will significantly influence the nation's agricultural output. Prolonged occurrences of natural catastrophes, including floods, cyclones, and droughts, present substantial obstacles to advancing agriculture, food security, and rural livelihoods (Sarmin and Hasan 2020). Therefore, it is critical to advocate for CSA practices to establish sustainable agricultural systems in Bangladesh which will be resilient to the consequences of climate change. Nevertheless, the degree to which these practices will be implemented and adopted, differs significantly and is contingent upon many factors.

The adoption rates of CSA practices are impacted by social factors such as community norms and peer networks. The educational credentials of farmers are also crucial, given that improved comprehension and application of innovative agricultural methods are commonly associated with more advanced levels of education (Reimers and Klasen 2013). In addition, the capability of farmers to invest in CSA technologies is substantially essential as it is impacted by economic factors, such as access to financial resources and annual income (Akter *et al.* 2022). Moreover, access to information sources such as extension services, agricultural training programs, and digital tools is also vital in disseminating knowledge regarding the advantages and technologies of CSA practices (Li *et al.* 2023).

The lack and scarcity of resources, including land, labour, finances, and competition for water, biomass, income, and agricultural inputs, impede the implementation of CSA practices (Sarmin and Hasan 2019). Access to markets, the absence of markets, and market information are also essential for farmers to embrace CSA practices (Sardar *et al.* 2021). The adoption of CSA practices is further influenced by risk orientation, which may be defined as the propensity to accept innovations involving some degree of risk (Kangogo *et al.* 2021). The desire of farmers to switch from traditional practices can also be influenced by technological factors such as the availability of modern instruments such global positioning systems (GPS), sensors, and climate-resilient crop varieties, as well as the perceived utility of these new tools (Abiri *et al.* 2023).

Besides the aforementioned factors, there might be a multitude of factors that might affect the use of CSA practices among farmers. It is critical to comprehend these factors to advance sustainable agriculture and alleviate the detrimental consequences of climate change in Bangladesh.

Therefore, this study was undertaken keeping in mind the following objectives: i) to determine farmers’ extent of use of climate-smart agricultural (CSA) practices, and ii) to identify the most influential factors affecting the use of climate-smart agricultural (CSA) practices among farmers.

MATERIALS AND METHODS

Study area, population and sample

The study was conducted in Rangpur district. Gangachara Upazila of the Rangpur district was selected purposively for data collection out of eight Upazilas in this district. This Upazila is situated at coordinates 25.8500°N and 89.2167°E. This upazila is highly susceptible to river erosions, which have contributed to the destruction of several historical structures and devastating impacts on agricultural productivity. This Upazila was purposively chosen for data collection because of its high susceptibility to harsh climatic conditions.

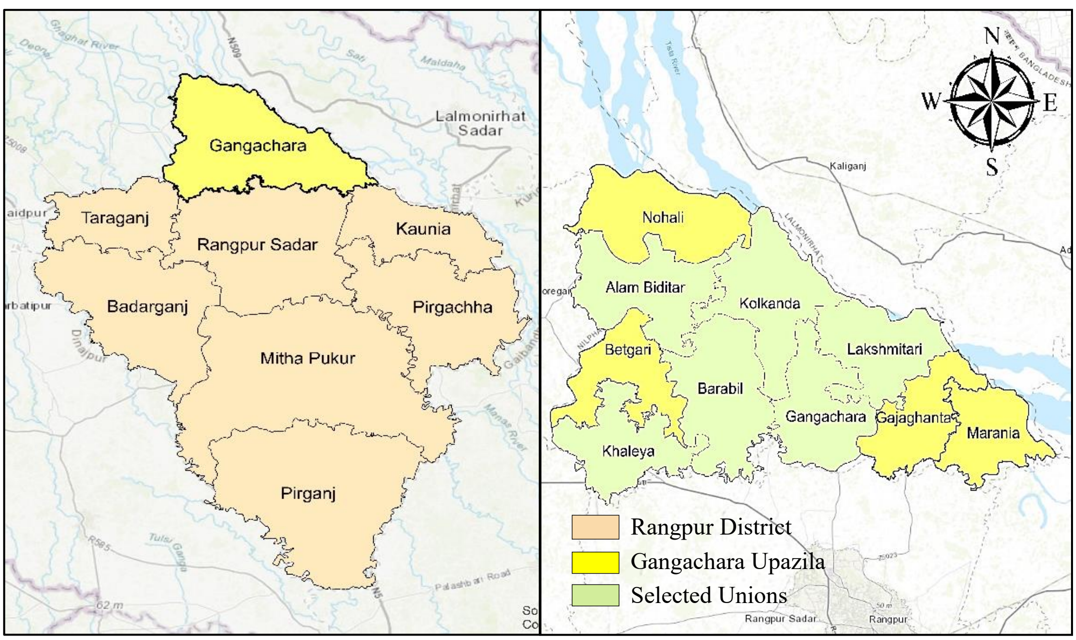

Figure 1. Maps of Rangpur District showing Gangachara Upazila and its selected Unions

Following a multi-stage random sampling procedure, six out of 10 unions of this Upazila were selected. An updated list of 3026 farmers of these unions was collected from Upazila Agriculture Office. One hundred thirty-three (133) farmers from this population were finally selected as samples for data collection following Cochran’s sample size calculating formula (Cochran 1977). The Cochran formula is:

$$n_0 = \frac{Z^2 pq}{e^2}$$

Where, n_0 is Cochran’s sample size recommendation.

For this study, Confidence level = 95%, e (the margin of error) = 5%, p (proportion of the population) = 10%, $q = (1 - p) = (1 - 0.1) = 0.9$, the Z-value for 95% confidence level is 1.96.
Thus,

$$n_0 = \frac{Z^2pq}{e^2} = \frac{1.96^2 \times 0.1 \times 0.9}{0.05^2} = 138.3$$

Thus, the sample size for this study is

$$n = \frac{n_0}{1 + \frac{(n_0 - 1)}{N}}$$

Here, n is the new adjusted sample size, and N is the population size, and here it is 3026.

$$\boldsymbol{n} = \frac{\boldsymbol{n_0}}{1+\frac{(\boldsymbol{n_0}-1)}{\boldsymbol{N}}} = \frac{\mathbf{138.3}}{\mathbf{1+0.0435}} \cong \mathbf{133}$$

Thus, the final sample size for this study was 133. In addition, a reserve list of 15 farmers was made to use in case the original sampled farmers were unavailable for interviews. The detailed population and sample distribution are shown in Table 1.

Table 1. Distribution of the population and sample

Unions	Population	Sample farmers	Reserve list
Alambiditar	499	22	2
Kolkanda	415	20	2
Lakshmitari	581	28	3
Khaleya	589	24	3
Gangachara	387	16	3
Barabil	555	22	2
Total=	3026	133	15

Measurement of variables

The questionnaire for data collection was designed by incorporating nine independent variables and one dependent variable. The measurement techniques of the independent variables are presented in Table 2.

Table 2. Measurement techniques of different independent variables

Variables	Measuring techniques (Scale/Score)	Possible score (Observed score)	Mean (SD)
Age	Number of years since the birth	- (18-62)	35.65 (8.84)
Educational qualification	Year of schooling (1 = Each year of completion 0.5 = Can sign name only 0 = Cannot read and write)	- (0-16)	6.71 (4.23)
Family size	Number of members in the family	- (1-10)	4.29 (1.75)

Variables	Measuring techniques (Scale/Score)	Possible score (Observed score)	Mean (SD)
Farm size	Hectare	- (0.22-4.34)	1.01 (0.86)
Farming experience	Number of years	- (1-28)	10.38 (6.86)
Annual income	Thousand BDT	- (5-166)	52.92 (37.78)
Access to information sources	The score was computed based on a respondent's extent of access to 12 selected information sources (Frequently = 3, Occasionally = 2, Rarely = 1, Not at all = 0)	0-36 (8-28)	19.72 (5.99)
Risk orientation	A total of eight statements. Likert-type scale (Likert 1932) was used for scoring (For positive statements: Strongly agree = 4, Agree = 3, Disagree = 2, Strongly disagree = 1, Reverse for the negative ones**)**	8-32 (8-32)	23.50 (6.63)
Knowledge of climate change and climate risk management	Ten questions of different weights in two dimensions (climate change and climate risk management)	0-24 (6-22)	16.32 (4.02)

SD= Standard Deviation

The dependent variable of the study was the use of climate-smart agricultural (CSA) practices. Ten widely used CSA practices were selected to develop this variable and subsequently evaluated using a 4-point rating scale. Each practice was assessed using the following responses: 'Not at all', 'Rarely', 'Occasionally', and 'Frequently', with corresponding weights of 0, 1, 2, and 3. Therefore, the possible score of this variable can vary between 0 and 30. In addition, the Use Index (UI) was calculated for each of the participants. The ranking of each practice was determined based on the UI score collected from the respondents. The calculation was performed using the subsequent formula:

$$UI = (Upf \times 3) + (Upo \times 2) + (Upr \times 1) + (Upn \times 0)$$

Where,

UI = Use Index

Upf = Percentage of farmers responding 'frequently'

Upo = Percentage of farmers responding 'occasionally'

Upr = Percentage of farmers responding 'rarely'

Upn = Percentage of farmers responding 'not at all'

The UI score of the practices could range from 0 to 399 (as the highest possible score of an item was 3, and the number of farmers was 133). Again, the Standardized Use Index (SUI) of each item was measured using the following formula as used by Moonmoon (2022). The rank order was made based on the descending order of SUI to compare among items.

$$SUI = \frac{\text{UI of the item}}{\text{Highest possible UI (i.e. 399)}} \times 100$$

A respondent's SUI could range from 0 to 100, where 0 indicates no use of the practice, and 100 indicates the greatest extent of use of the practice.

Data collection and statistical analysis

A comprehensive questionnaire was developed, incorporating a combination of open-ended and closed-ended questions and appropriate rating scales. The interview schedule was pre-tested with 13 farmers (excluding those included in the study sample) in the study area. Before finalizing the questionnaire, necessary modifications and revisions were made depending on the pre-test results. The interviews were performed individually with the respondents at their respective homes/farms from May 2023 to July 2023. This study utilized descriptive statistics, including frequency, percentage, mean, standard deviation, indices, and rank order, and inferential statistical analyses such as correlation and multiple linear regression (both enter and stepwise methods). The data was analysed using the Statistical Packages for the Social Sciences (SPSS) version 25.

RESULTS AND DISCUSSION

Socio-demographic profile of the farmers

The mean age of the farmers was 35 years, with the majority (60.2%) falling into the young age category. The respondents had an average educational qualification score of 6.71. Approximately 50% of the respondents possessed a secondary level of education, while 22.6% of the farmers were illiterate, and only 9% had attained a higher secondary level of education. Approximately 83.5% of the farmers had a small-sized family, while the majority (58.6%) had only 10 years of farming experience. Nearly 70% of the farmers possessed small farms, and no landless or marginal farmers were present in the study area. Most respondents, specifically 58.6%, reported an annual income below BDT 50000. Nevertheless, a significant majority (55.6%) of the farmers had a strong inclination towards various risks. Furthermore, approximately 60% of them had medium access to different information sources and possessed a sufficient understanding of climate change and climate risk management.

The overall extent of use of climate-smart agricultural (CSA) practices

Climate-smart agricultural practices aim to efficiently enhance agricultural productivity and revenues while adapting and fortifying resilience to climate change. In the study area, the average extent of farmers' use of climate-smart agricultural practices was 9.97, with a standard deviation of 7.60. The distribution of farmers according to their extent of use is presented in Figure 2. The majority (55.6%) of the farmers used climate-smart agricultural (CSA) practices moderately, followed by 33.1% using minimally and only 11.3% extensively. Therefore, the findings imply that a substantial majority (88.7%) of the farmers use climate-smart agricultural practices to a minimal or moderate degree. This suggests that although a subset of farmers has initiated using these sustainable practices, their overall implementation remains restricted. A mere percentage of farmers completely incorporate these practices into their farming operations, indicating that substantial potential exists for enhancing and expanding the adoption of climate-smart practices within the farming community. This underscores the necessity for enhanced resources, education, and support to promote the widespread and concentrated implementation of these practices.

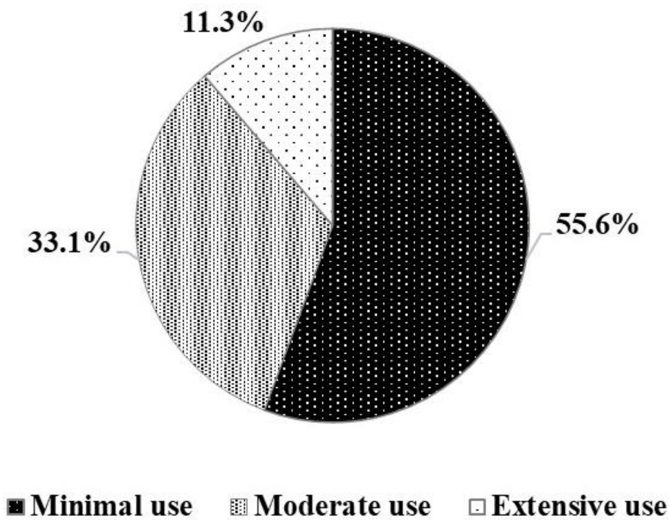

Figure 2. Extent of use of climate-smart agricultural practices

Extent of use of individual climate-smart agricultural (CSA) practices

Figure 3 and Table 3 depict the extent of use by the farmers for each climate-smart agricultural practice. Among the ten practices, the top three practices used by the farmers were 'crop rotation' (SUI=0.516), 'organic composting' (SUI=0.415), and 'cover cropping' (SUI=0.309). On the other hand, the least used practices include 'using intelligent technologies (GPS, sensors, drones, etc.)' (SUI=0.092), 'rainwater harvesting' (SUI=0.145), and 'integrated pest management (IPM)' (SUI=0.156).

Results of Table 3 reveal that an overwhelming majority (75.2%) of farmers practice crop rotation occasionally and frequently. More than half of the respondents use organic composting occasionally or frequently. A similar trend was observed for cover cropping. However, an overwhelming 82.7% of the farmers did not at all prefer to use intelligent technologies such as GPS, sensors, drones, etc. The same goes for using climate-resilient varieties and integrated pest management (IPM). These findings reveal farmers' inclination towards traditional practices rather than more sophisticated technology-driven practices.

Table 3. Extent of use of individual CSA practices

Practices	Percentage				SUI
	Not at all	Rarely	Occasionally	Frequently	
Crop rotation	14.3	10.5	30.1	45.1	0.516
No-till farming	46.6	23.3	19.5	10.5	0.235
Cover cropping	36.1	24.8	18.8	20.3	0.309
Using climate-resilient varieties	74.4	5.3	8.3	12.0	0.145
Rainwater harvesting	63.9	14.3	6.8	15.0	0.183
Alternate wetting and drying	55.6	16.5	13.5	14.3	0.217
Crop diversification	57.9	7.5	19.5	15.0	0.229
Organic composting	22.6	18	30.8	28.6	0.415
Using intelligent technologies (GPS, sensors, drones etc.)	82.7	4.5	6.0	6.8	0.092
Integrated pest management (IPM)	72.2	5.3	10.5	12.0	0.156

SUI= Standardized Use Index

The findings depict a gap at a time when farming communities worldwide are increasingly adopting sophisticated farming techniques. In order to address this disparity, it is critical to implement focused educational and training initiatives that illustrate the advantages and user-friendliness of cutting-edge agricultural technologies. Extension services should prioritize practical demonstrations, case studies of achievement, and cost-benefit evaluations to illustrate how these technologies can effectively augment efficiency and sustainability. Furthermore, implementing financial incentives or subsidies to promote adopting climate-resilient practices and intelligent technologies could reduce entry barriers and stimulate farmers to adopt these practices more. This strategy may result in a more effective and proportionate application of both conventional and contemporary agricultural practices, thereby enhancing the overall resilience and output of farms.

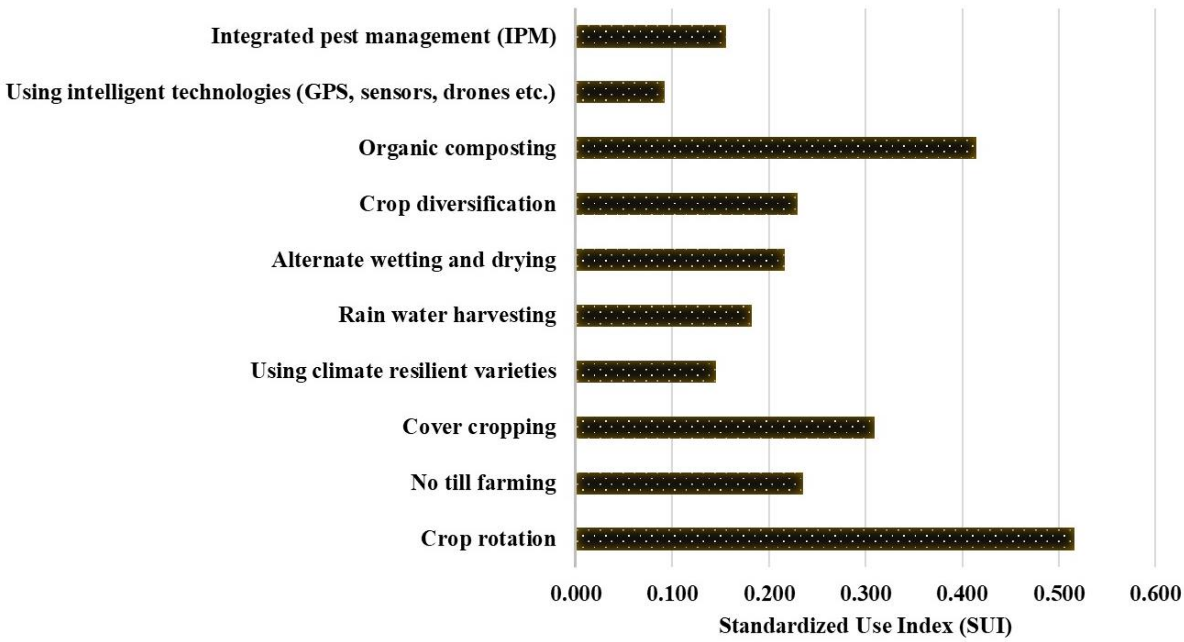

Figure 3. Extent of use of individual CSA practices

The relationships between the independent variables and farmers' use of CSA practices

Pearson's product-moment correlation test was performed to determine the correlation between the nine independent and dependent variables. Based on the results, a significant positive correlation was found between farmers' age (r= 0.511, p<0.01), educational qualification (r= 0.781, p<0.01), family size (r= 0.218, p<0.05), farming experience (r= 0.422, p<0.01), annual income (r= 0.431, p<0.01), access to information sources (r= 0.541, p<0.01), risk orientation (r= 0.538, p<0.01), knowledge of climate change and climate risk management (r= 0.487, p<0.01), and farmers' use of climate-smart agricultural practices. The findings suggest significant positive relationships exist between different characteristics of the farmers and their use of climate-smart farming practices. More precisely, older farmers with better educational credentials are more inclined to embrace these practices. Larger family sizes also exhibit a favorable association. Likewise, increased farming expertise and better yearly earnings correlate with higher use of these practices. Information access and a proactive attitude towards risk are important roles (Hasan *et al*. 2020). Furthermore, an enhanced comprehension of climate change and risk management is directly linked to a higher implementation rate of climate-smart practices. These findings emphasize the factors that might impact farmers' choices to use sustainable climate-smart agricultural practices.

Factors affecting farmers use of CSA practices

A multiple regression analysis was performed using enter and stepwise techniques to identify the factors determining farmers' use of climate-smart agricultural practices (Tables 4 and 5). The eight important independent variables identified from the correlation analysis were entered into the multiple regression analysis. The model employed for multiple linear regression demonstrates that the multiple correlation coefficient (multiple R) between all the variables and the dependent variable is 0.858. In addition, the coefficient of determination (R^2) was 0.736, and the adjusted R^2 was 0.719, suggesting that 71.9% of the variation in the dependent variable can be explained by the relevant independent variables employed in this study. The F-test yielded a significant result of 43.122 at a significance level of $p<0.001$. This indicates that the multiple regression model effectively predicts the dependent variable in this investigation. Therefore, this regression model is an ideal fit.

Table 4. Result of multiple regression analysis

Variables entered	B	SE	β	t-value
(Constant)	-5.043	1.989		-2.535
Age	-0.131	0.085	-0.169	-1.541
Educational qualification	1.163	0.099	0.648	11.762^{***}
Family size	0.136	0.237	0.031	0.576
Farming experience	0.113	0.099	0.102	1.138
Annual income	0.042	0.010	0.211	4.106^{***}
Access to information sources	0.247	0.085	0.195	2.901^{**}
Risk orientation	0.227	0.085	0.198	2.671^{**}
Knowledge of climate change and climate risk management	-0.143	0.128	-0.076	-1.117
R=0.858, R^2=0.736, Adjusted R^2=0.719, F=43.122, $p<0.001$				

Note: B= Unstandardized coefficients, SE= Standard Error, β= Standardized coefficients, *** = Significant at 0.1% level of significance, ** = Significant at 1% level of significance

According to the significance of the t-values of the independent variables presented in Table 4, four independent variables were identified: educational qualification, annual income, access to information sources, and risk orientation. These four variables were included in the stepwise multiple regression analysis. The results of stepwise regression analysis will depict the unique contribution of the concerned independent variables in predicting farmers' use of climate-smart agricultural practices.

Table 5. Results of stepwise multiple regression analyses

Predictors	B	SE	β	t	Adjusted R^2	Model Summary
(Constant)	-7.087	1.409		-5.028^{***}		
Educational qualification	1.116	0.094	0.622	11.914^{***}	0.608	ΔR^2=0.611 F=205.34^{***}

Predictors	B	SE	β	t	Adjusted R^2	Model Summary
Annual income	0.041	0.010	0.204	4.068***	0.678	ΔR^2=0.072 F=139.76***
Access to information sources	0.190	0.075	0.150	2.541**	0.710	ΔR^2=0.034 F=108.49***
Risk orientation	0.155	0.066	0.135	2.334**	0.719	ΔR^2=0.012 F=85.54***

Note: ΔR^2= R^2 Change (% contribution), B= Unstandardized coefficients, SE= Standard Error, β= Standardized coefficients, *** = Significant at 0.1% level of significance, ** = Significant at 1% level of significance

According to the results of stepwise regression analysis, farmers' educational qualification was the most significant contributor to explaining farmers' use of climate-smart agricultural (CSA) practices, contributing about 61.1% of the variance. Farmers' annual income, access to information sources, and risk orientation contributed a total of 11.8%.

The analysis highlights that the educational qualifications of farmers have a substantial influence on the use of climate-smart agricultural practices. Similar findings were reported by Zilberman (2018). According to their findings, educated farmers are more open to adopting the CSA practices and utilising the latest technological innovations. Given that just 50% of the participants in the study area have finished secondary education and a significant proportion (22.6%) are illiterate, it is clear that there is an urgent need to enhance educational opportunities for farmers. This may involve adult educational campaigns and training programs explicitly focusing on climate-smart practices.

Moreover, economic factors such as annual income contributed 7.2% to explaining the dependent variable. A positive inclination between economic solvency and the use of CSA practices was found in the study of Tecklewold (2023). According to them, farmers with more economic solvency will have better purchasing power for agricultural inputs such as seeds, pieces of machinery, and plant protection equipment. It is important to mention that a substantial percentage of farmers in the study area have an annual income of less than BDT 50,000, which limits their capacity to financially support the adoption and use of CSA practices. Strategies could involve providing enhanced financial literacy and tailored financial products and subsidies to incentivize the use of climate-smart practices.

Access to extension sources and risk orientation contributed about 4.6% to explaining the dependent variable, and the association between these variables was positive. Similar results were obtained by Jha *et al.* (2023). According to their findings, farmers with greater risk orientation backed up with adequate information will be willing to try out smart practices despite having associated risks. Notably, 55.6% of the farmers in the study area are willing to undertake risks, although about 60% possess a considerable degree of access to information. In order to encourage the use of climate-smart practices, it is crucial to provide targeted support addressing short and long-term risks and information gaps. This could be backed up with robust extension services enhancing the accessibility and dependability of agricultural information so that farmers are aware of the risks and can manage them.

CONCLUSIONS

In conclusion, a significant proportion of farmers employ climate-smart agricultural practices to a minimal or moderate extent. This illustrates the criticality of providing increased resources, education, and support to facilitate their widespread utilisation. The research underscores a deficiency in implementing advanced farming technologies. Educational qualification, annual income, access to information sources, and risk orientation are all influential factors in determining the extent to which climate-smart agricultural practices are used. Farmers' educational qualifications significantly influence climate-smart agricultural practices use, accounting for 61.1% of variability, highlighting the need for increased educational opportunities for farmers. Many agricultural workers have a low income, constraining their financial means to endorse implementing the CSA practices. Risk orientation and access to extension resources are additional factors that influence implementing climate-smart practices. Notwithstanding the potential hazards involved, farmers with sufficient information and a heightened risk propensity are more inclined to experiment with smart practices. Support should be tailored to address informational gaps and short-term and long-term risks to promote adopting climate-smart agricultural practices. This should be supplemented with extension services that effectively improve the availability and reliability of agricultural data.

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