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Farmers Perceived Effectiveness of Agricultural Extension Services for Climate Smart Agricultural Practices: Insights from a Selected Coastal Area of Bangladesh

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Abstract: Coastal Bangladesh is highly vulnerable to climate change. Although Agricultural Extension Services (AESs) play a crucial role in promoting Climate Smart Agriculture (CSA) to enhance farmers' adaptive capacity, farmers' perceptions of their effectiveness remain poorly understood. This study employed a convergent parallel mixed-methods approach to assess farmers' perceptions of AES effectiveness in Koyra Upazila, Khulna District. Quantitative and qualitative data were collected concurrently from 9 March to 26 April 2025 using a semi-structured questionnaire survey administered to 190 farmers, complemented by focus group discussions (FGDs). The Perceived Effectiveness Index (PEI), one-way ANOVA, and multiple regression analysis were used to examine perceived effectiveness and its determinants. Findings reveal that 76.8% of farmers perceived AESs as moderately to highly effective in supporting CSA adoption. Introduction of stress-tolerant crop varieties (PEI = 678), stakeholder involvement in decision-making (PEI = 638), and climate-related training (PEI = 614) were rated most effective. Conversely, credit facilities (PEI = 280), ICT use (PEI = 292), and infrastructure support (PEI = 306) were perceived as least effective. ANOVA results show significant variation in perceived effectiveness by age and farming experience. Regression analysis (R^2 = 0.311) identified age, training, and CSA adoption as positive predictors, while climate impact perception, farm size, and adoption barriers negatively influenced perception. Despite moderate success, substantial gaps exist in service delivery, especially regarding financial support, value addition of agricultural products, infrastructure development, fair market access, and digital support. Enhancing AES effectiveness requires greater integration of localized training, farmer participation, and access to enabling resources.

Keywords: climate smart agriculture; agricultural extension services; coastal Bangladesh; perceived effectiveness; climate change adaptation

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1. Introduction

Agricultural productivity is increasingly constrained by the impacts of climate change, particularly in developing regions where food insecurity remains widespread (M. T. Islam & Nursey-Bray, 2017; Kundu et al., 2020). According to the Intergovernmental Panel on Climate Change (IPCC, 2023), climate change is already adversely affecting food production in many regions of the world, with negative impacts outweighing positive ones, especially in developing countries that are more vulnerable to climatic shocks. Moreover, it is projected that by 2050, the population of developing countries will increase by an additional 2.4 billion, particularly in South Asia and further intensifying the pressure on agricultural systems (Fróna et al., 2019).

Bangladesh is widely recognized as one of the most climate-vulnerable countries in the world due to its geographic location, low-lying topography, and high population density (Murshed et al., 2021). Among its most exposed regions are the coastal areas, which cover approximately 32% of the national landmass and are home to nearly 28% of the country's population (M. R. Islam, 2004). These coastal zones are increasingly affected by a range of climate-induced hazards, including tropical cyclones, storm surges, saline water intrusion, sea-level rise, and irregular rainfall patterns (Ahmed et al., 2021; Mitra et al., 2023). Agriculture and climate change have played a reciprocal relationship that is evident in Bangladesh. On one hand, key climatic variables-such as temperature, rainfall variability, humidity, and seasonal shifts-directly affect crop yields, planting calendars, and soil fertility (Bruinsma, 2003). On the other hand, agriculture itself is a significant contributor to greenhouse gas (GHG) emissions, mainly through methane emissions from rice paddies and livestock, and nitrous oxide from synthetic fertilizer use (MacDicken, 2015). This dual relationship underscores the urgency of adopting Climate-Smart Agriculture (CSA) practices that can simultaneously reduce emissions and strengthen farmers' adaptive capacity. At the same time, global evidence suggests that transforming food systems, expanding renewable energy, promoting sustainable production methods, and enhancing carbon sequestration are essential pathways to achieving carbon neutrality and long-term agricultural sustainability (Wang et al., 2021; 2023).

CSA practices refer to an integrated farming technique designed to increase agricultural productivity, enhance resilience to climate change, and reduce greenhouse gas emissions, thereby addressing food security challenges (Lou et al., 2024; Mnukwa et al., 2025). CSA adoption involves the use of technologies and practices that increase productivity and adaptive capacity (Abedin & Shaw, 2014) and aligns strongly with global carbon-neutrality goals, given that food systems and energy together contribute more than 90% of global emissions (Wang et al., 2021). The CSA approach encompasses practices such as improved crop management, sustainable farming methods, agroforestry, integrated pest management, organic pesticides/bio-fertilizer, balanced use of agrochemicals, rainwater harvesting, and the use of climate-resilient crop varieties, all aimed at improving soil health, water use efficiency, and carbon sequestration (Billah et al., 2025; Borychowski et al., 2022; Zheng et al., 2024). Advancing CSA adoption requires targeted efforts to bolster the adaptive and resilience capacities of stakeholders, thereby facilitating the transition to climate-resilient agricultural systems and contributing to national food security and sustainable development objectives (Abedin & Shaw, 2014; Billah et al., 2025; Ma & Rahut, 2024).

The Government of Bangladesh has implemented a range of policy initiatives and institutional reforms aimed at promoting CSA and improving the delivery of agricultural extension services (Nandi et al., 2024). Agricultural extension services (AESs) serve as a critical link between research institutions and farming communities, facilitating the dissemination of knowledge, technologies, and practices that promote sustainable and adaptive farming (Somanje et al., 2021). When effectively delivered, these services can play a transformative role in strengthening farmers' resilience, enhancing productivity, and ensuring long-term food security (Becerra-Encinales et al., 2024).

However, despite significant investments, several challenges persist within the country's extension system. These include limited outreach in remote and marginalized regions, insufficient farmer training, inadequate integration of indigenous knowledge, and administrative inefficiencies (Mamun-ur-Rashid et al., 2018). Scholars further note that many coastal smallholder and marginal farmers continue to face barriers such as limited access to timely agricultural information, weak technical support, financial constraints, labor shortages, insufficient modern farm knowledge, and poor access to quality inputs and markets (Billah et al., 2025; Lou et al., 2024). These constraints reduce their capacity to adopt CSA practices effectively and raise important questions regarding how effectively existing AESs address the differentiated needs of climate-exposed farming communities.

A critical gap also exists in understanding how farmers themselves perceive the effectiveness of extension services, particularly in climate-stressed coastal regions where local relevance and farmer engagement strongly determine service outcomes. Farmer perception plays a pivotal role in the adoption of extension-led innovations: when services are perceived as credible, accessible, and beneficial, uptake improves substantially (Somanje et al., 2021). From a theoretical perspective, farmers' perceptions can be understood through Expectation–Confirmation Theory (ECT), which posits that individuals evaluate services by comparing prior expectations with perceived performance after service use (He et al., 2023). Applying Expectation–Confirmation Theory to agricultural extension underscores why farmers' perceptions are central to the ultimate success or failure of extension interventions. According to ECT, positive evaluations emerge when perceived performance meets or exceeds expectations, whereas unmet expectations result in negative perceptions (Sackl et al., 2017). In the context of agricultural extension, even well-designed and policy-supported programs may fail to promote climate-smart agricultural practices if farmers perceive a mismatch between expected support and actual service delivery. Conversely, when farmers perceive extension services as effective and responsive, trust in extension agents increases, adoption of recommended CSA practices improves, and sustained engagement with extension systems is more likely (Wang et al., 2023). In this sense, perceived effectiveness functions as a key evaluative mechanism linking extension service provision to farmers' behavioral responses and adaptive outcomes.

Although a substantial body of research in Bangladesh has explored CSA adoption, adaptation strategies, and farmers' perceptions of climate risks (Filho et al., 2022; Mnukwa et al., 2025), far less attention has been devoted to understanding how farmers evaluate the effectiveness of AESs in facilitating CSA, particularly in climate-exposed coastal regions. Existing studies tend to focus on policy frameworks or generalized service delivery performance (Vincent & Balasubramani, 2021), often overlooking farmers' differentiated assessments of specific extension service components such as training, credit facilitation, ICT-based advisory support, infrastructure assistance, and market access. This gap limits the ability of policymakers and extension agencies to develop demand-driven, context-sensitive extension strategies that respond to farmers' lived experiences.

This study fills that gap by focusing on a highly climate-vulnerable coastal region to generate new insights into how smallholder farmers evaluate the effectiveness of AESs in supporting CSA adoption. Specifically, the study aims to explore farmers' perceptions of the effectiveness of AESs in promoting climate-resilient agriculture in a coastal district of Bangladesh. Specifically. It seeks to (i) identify perceived climate change impacts and adopted CSA practices; (ii) assess overall AES effectiveness as perceived by farmers; (iii) examine demographic and socio-economic variations to perceived effectiveness; and (iv) investigate the determinants that contribute to farmers' perceptions of the effectiveness of AESs.

This study makes several significant contributions. It advances a farmer-centered evaluative perspective by positioning farmers as active assessors of extension service effectiveness rather than passive recipients of extension interventions, grounded in Expectation–Confirmation Theory. It also employs a convergent parallel mixed-methods approach that integrates a Perceived Effectiveness Index (PEI), inferential statistical analysis, and qualitative insights from focus group discussions to provide a robust assessment of extension performance. Empirically, by focusing on a highly climate-exposed coastal context, the study generates context-specific evidence on how climate stress intensity, adoption barriers, and farm characteristics shape farmers' evaluations of extension services. The findings offer actionable insights for policymakers and extension organizations by identifying both effective service domains and critical gaps, thereby informing the design of more inclusive, responsive, and climate-adaptive agricultural extension systems for vulnerable coastal regions.

2. Materials and Methods

2.1. Study Area

The study was conducted in Koyra Upazila of Khulna District (Figure 1), which is located in the southwestern part of Bangladesh. Koyra Upazila is situated in close proximity to the Bay of Bengal. This area faces significant agricultural vulnerability due to climate change (Iqbal & Aziz, 2022). Fluctuating temperature, rainfall, and humidity, along with hot and humid rainy seasons (Chowdhury et al., 2020), negatively impact the agricultural settings in this region. Multiple environmental hazards, including cyclones, flooding, storm surges, waterlogging, and soil salinity, also affect crop production in this region (Biswas et al., 2024; Iqbal & Aziz, 2022).

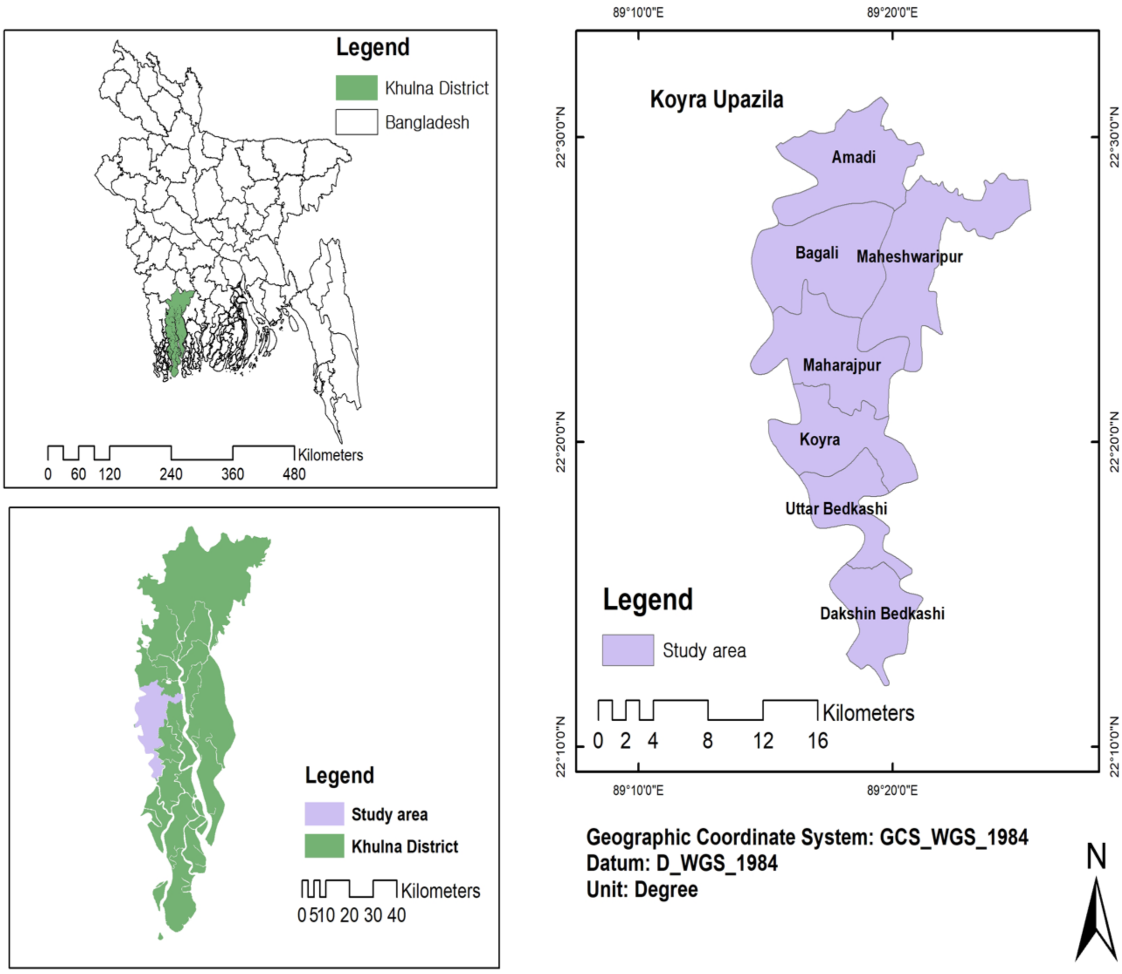

Figure 1. Geographical location of the study area.

Beyond environmental stressors, the socio-economic conditions of coastal communities also heighten their exposure to climate risks. Limited access to resources, weak market infrastructure, and constrained livelihood opportunities increase their overall vulnerability (Kundu et al., 2020). The economy of Koyra Upazila is predominantly agrarian, with a large share of the population dependent on crop farming, aquaculture, and fishing for income and subsistence (Kundu et al., 2020; Mamun et al., 2024). Household incomes tend to be low, and many families frequently face seasonal food insecurity due to climate-driven uncertainties in agricultural production (Mamun et al., 2024). Low levels of education and limited technical knowledge further restrict farmers' ability to adopt modern agricultural practices and to fully benefit from agricultural extension services (M. K. Islam & Farjana, 2024).

Agricultural extension services (AESs) in the upazila are primarily delivered by the Department of Agricultural Extension (DAE), which provides farmers with information, training, and technical guidance at the local level. The Government of Bangladesh has undertaken several projects in the region focusing on climate change adaptation through infrastructure development, early warning systems, and the dissemination of climate-resilient agricultural technologies. Notably, from 2021 to 2025, the DAE has been implementing the project titled "Adaptation to Climate Change through Climate-Smart Technologies in Khulna Agriculture Region", aimed at minimizing climate-related impacts and reducing the agricultural sector's contribution to climate change in the region (Nandi et al., 2024). The study area is therefore highly suitable for examining farmers' perceptions of the effectiveness of AESs in promoting climate-smart agriculture under conditions of high climatic stress and institutional intervention.

2.2. Sampling and Data Collection

The study population consisted of 353 registered farmers listed by the local agricultural extension office in Koyra Upazila, all of whom had continuously received extension services during the previous two years under the project "Adaptation to Climate Change through Climate-Smart

Technologies in the Khulna Agricultural Region." The required sample size of 190 farmers was determined using Yamane's (1967) formula:

$$n = \frac{N}{1 + N(\delta)^2} \tag{1}$$

where n denotes the sample size, N represents the total population, and $\delta = 0.05$ denotes the acceptable level of sampling precision (5% margin of error)

A stratified random sampling technique was employed, where each of the seven unions of Koyra Upazila was treated as a distinct stratum. To ensure proportional representation from all seven unions of the upazila, the number of respondents from each union was calculated according to its share of the total registered farming population. The final distribution was as follows: Amadi (34 of 66), Bagali (24 of 41), Koyra (28 of 50), Maharajpur (23 of 48), Maheshwarpur (27 of 49), Uttar Bedkashi (27 of 48), and Dakshin Bedkashi (27 of 51). This proportional allocation strategy preserved population representativeness (N = 353) and minimized sampling bias by capturing farmers from diverse socio-economic backgrounds and geographically distinct areas.

Although the sample consists of project-registered farmers who were actively engaged with agricultural extension services, the age distribution and farm-size composition of the sampled farmers closely reflect the dominant characteristics of smallholder farmers in Koyra Upazila, where agriculture is predominantly small-scale and largely practiced by middle-aged and older farmers. Therefore, the findings can be reasonably extrapolated to the broader population of smallholder farmers receiving AESs in the coastal area of Bangladesh.

A convergent parallel mixed-method design was employed to examine farmers' perceived effectiveness of AESs in promoting CSA practices in coastal Bangladesh. Quantitative and qualitative data were collected simultaneously from 9 March 2025 to 26 April 2025 through a semi-structured questionnaire and focus group discussions (FGDs), respectively. Four FGDs were conducted, each involving seven farmers, who were included from the survey sample. To capture diverse viewpoints, participants were selected to reflect variations in age and farming experience. Prior to data collection, the research objectives were clearly explained to all participants to ensure informed and voluntary participation.

2.3. Variable Definition, Measurement, and Instrument Validation

The study employed well-defined operational definitions and measures for all variables, utilizing established scales and context-specific indicators to ensure consistency and analytical rigor (Table 1). It included socio-demographic and farm-related variables (e.g., age, education, income, farming experience, and farm size) as well as perceptual and behavioral variables (e.g., adoption of CSA practices, perceived climate change impacts, farming barriers, and perceived effectiveness of AESs). These variables are essential because they capture the key socio-economic and perceptual factors that influence farmers' decision-making, adaptive behavior, and overall evaluation of extension services.

Table 1. Operational definitions and measurement approaches of study variables.

List of variables	Definition	Measurement
Age	Age of respondents	Assign 1 for each year
Farming experience	Total number of years the respondent has been engaged in agricultural activities.	Assign 1 for each year of experience
Income	Annual household income derived from agricultural sources.	Assign 1 for each Bangladeshi taka (1$ = 117.65 BDT)
Education	Formal education level attained by the respondent	Can't read and write=0; Primary = 1 up to class 5 Secondary = 2 (class 6–10); Higher Secondary = 3 (class 11–12); Graduate = 4
Use of information sources	Frequency of using agricultural information sources	3–4 time/week = 4; 2–3 time/15 days = 3; Once/ month = 2; Don't use = 1
Climate change impact on agriculture	Perception of how climate change affects their agriculture productivity	Strongly Agree = 5; Agree = 4; Undecided = 3; Disagree = 2; Strongly Disagree = 1
Training	Number of days the respondent participated in CSA-related training	Assign 1 for each day of training experience
Farm size	Respondent's total cultivated land area	Assign 1 for each hectare (1 hectare = 247.128 decimal)
Farming practice barriers	Perceived level of barriers that limit adoption of CSA practices	High = 4; Moderate = 3; Low = 2; Not at all = 1.
Adoption of CSA practices	Degree to which respondents adopt CSA practices	Always = 5; Frequently = 4; Occasionally = 3; Rarely = 2; Do not Use = 1
Perceived effectiveness of AESs	Perception of AES effectiveness in promoting CSA practices	Highly Effective = 4; Moderately Effective = 3; Low Effective = 2; Not Effective = 1

Note: AES refers to the agricultural extension services.

The survey instrument was designed by integrating insights from existing empirical research with contextual knowledge obtained through field consultations involving experienced farmers and local extension officers. This mixed approach ensured that the instrument was both theoretically grounded and contextually relevant to the realities of coastal agriculture in Bangladesh. We began by identifying 10 key climate change impacts on agriculture, focusing on how coastal farming systems are affected by changing weather patterns, salinity, flooding, and other climate-related challenges.

Following this, we outlined 14 CSA practices that coastal farmers currently apply to cope with these climate challenges. The internal consistency of the adopted CSA practices was satisfactory, with Cronbach's alpha values of 0.74, indicating acceptable reliability of these practices. These practices included a range of adaptive and mitigation techniques tailored to local conditions, offering insight into how farmers are responding on the ground. To explore the barriers in adapting to climate change, five categories of barriers were included: social, economic, technological, organizational, and personal. The barrier items were adopted from previous studies, which reported a Cronbach's alpha of 0.79, further supporting the reliability of this construct (Biswas et al., 2024).

In addition, we incorporated 15 AESs based on the National Agricultural Extension Policy 2020 and National Agricultural Policy 2018 (Ministry of Agriculture, 2018; 2020). These services included, among others, training on climate change adaptation, dissemination of stress-tolerant crop varieties, farm management advisory support, facilitation of access to quality inputs and credit, ICT-based information services, support for infrastructure development, and assistance with market access and value addition. Each item was measured using a 4-point Likert-type scale, where responses were coded as: Highly Effective (4), Moderately Effective (3), Low Effective (2), and Not Effective (1). The PEI score was calculated by summing the weighted frequencies of responses across these four categories, with higher scores indicating higher perceived effectiveness (Anzum et al., 2023). To ensure the questionnaire was contextually appropriate, clear, and relevant, it was reviewed and validated by a panel of regional extension officers. Their feedback helped refine the wording and focus of the questions, enhancing the instrument's accuracy and local relevance. Finally, we tested the internal consistency of the AES effectiveness scale, which showed good reliability, as indicated by a Cronbach's alpha coefficient of 0.81.

2.4. Data Analysis

We have used descriptive statistics (mean, standard deviation, frequency, and percentage) to describe respondents' characteristics and key variables (Table 2).

Table 2. Descriptive statistical analysis of study variables.

List of variables	Categories	Frequency	Percent (%)	Mean	SD
Age	Young (18–37)	54	28.4	46.51	13.64
	Middle aged (38–57)	91	47.9		
	Old aged (above 57)	45	23.7		
Farming experience	2–16 years	63	33.2	24.25	14.51
	17–31 years	75	39.4		
	32–46 years	38	20.0		
	Above 47 years	14	7.4		
Income	20000–213000 BDT	181	95.3	94136.84	73001.43
	214000–406000 BDT	7	3.1		
	Above 406000 BDT	2	1.6		
Education	Illiterate	31	16.3	6.85	4.4
	Primary	49	25.8		
	Secondary	81	42.6		
	Higher secondary	15	7.9		
	Graduate/Diploma	14	7.4		
Use of information sources	Low (10–15)	132	69.5		
	Medium (16–20)	52	27.3		
	High (above 20)	6	3.2		
Climate change impact on agriculture	Low impact (35–38)	9	4.7	43.78	3.08
	Medium impact (39–44)	82	43.2		
	High impact (above 44)	99	52.1		
Training	No training	96	50.5	3.72	11.07
	1–30 days	91	47.9		
	31–60 days	1	0.5		
	Above 60 days	2	1.1		
Farm size	0.12–0.84 Hectare	171	90	0.48	0.37
	0.85–1.56 hectare	13	6.8		
	Above 1.56 hectare	6	3.2		
Farming practice barriers	Low barrier (31–44)	7	3.7	55.45	6.66
	Medium barrier (45–58)	129	67.9		
	High barrier (above 58)	54	28.4		
Adoption of CSA practices	Low adoption (17–28)	28	14.7	35.61	7.09
	Medium adoption (29–40)	109	57.4		
	High adoption (above 40)	53	27.9		
Perceived effectiveness of AESs	Low effectiveness (18–28)	44	23.2		
	Moderate effectiveness (29–39)	78	41.0		
	High effectiveness (above 39)	68	35.8		

To assess farmers' perceptions of the effectiveness of AESs, we analyzed the Perceived Effectiveness Index (PEI) by using the following equation that was cited from the previous research articles (Anzum et al., 2023; Debnath & Biswas, 2022).

Perceived Effectiveness Index (PEI): $PEI_h \times 4 + PEI_m \times 3 + PEI_l \times 2 + PEI_n \times 1$ (2)

Where, PEIh, PEIm, PEIl, and PEIn represent the frequencies of respondents who reported the high, moderate, low, and not effectiveness of AES for CSA practices, respectively. The weights (4, 3, 2, and 1) reflect the relative intensity of perceived effectiveness, with higher values indicating stronger perceived effectiveness of agricultural extension services.

One-way ANOVA was performed to test whether the mean perceived effectiveness of AESs differed significantly across groups categorized by age and years of farming experience. According to Levene's Test for Homogeneity, the assumption of equal variances was met for the age groups; therefore, the Tukey HSD post hoc test was employed. In contrast, the assumption was violated for the farming experience groups, indicating unequal variances and group sizes; hence, the Games-Howell post hoc test was applied for those comparisons. Furthermore, a multiple regression analysis was performed to determine the extent to which selected predictor variables explain the perceived effectiveness of AESs in promoting CSA practices in coastal Bangladesh. The regression model used is as follows:

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \ldots + \beta_k X_k + \varepsilon \tag{3}$$

Where: Y denotes the perceived effectiveness of agricultural extension services, β_0 is the intercept, $\beta_1, \beta_2, \ldots, \beta_k$ are the regression coefficients for the predictor variables $X_1, X_2, \ldots, X_k$ and ε is the error term.

All statistical analyses were performed using IBM SPSS Statistics, Version 24.0. After analyzing the quantitative data, we integrated the qualitative insights from focus group discussions (FGDs) to contextualize and enrich the interpretation of related findings, thereby illustrating the actual conditions in the research area.

3. Result and Discussion

3.1. Descriptive Characteristics of Respondents

The descriptive statistical analysis (Table 2) indicated that the majority (48%) of the respondents were middle-aged (38–57 years), with an average age of 46.51 years. The majority possessed 17–31 years of farming experience, averaging 24.25 years, making them well-suited to assess agricultural extension policies. The findings revealed that 95.3% of the respondents had a low annual income (20000–213,000 BDT or 170–1810$), suggesting potential challenges in adopting new agricultural technologies without external financial assistance. A substantial portion of the farmers (42.6%) had attained secondary-level education (6–10 years of schooling), while 16.3% were illiterate, which could affect their ability to access and use technical agricultural information. Furthermore, 69.5% of respondents had limited access to agricultural sources, with minimal engagement with government extension agents.

In terms of the perceived impact of climate change on agriculture, more than half of the farmers (52.1%) reported a high level of impact. This highlights widespread vulnerability to climate variability and extreme weather events. Access to training was also limited; 50.5% of respondents reported receiving no training, with an average of just 3.72 days. This reveals a considerable need for enhanced capacity-building support. The majority (90%) of farmers operated on small farms between 0.12 and 0.84 hectares, with an average landholding of 0.48 hectares, suggesting significant land constraints.

Regarding farming barriers, a total of 96.3% of farmers encountered medium to high-level barriers, with a mean barrier score of 55.45. These include challenges related to technology access, financial resources, institutional support, and personal limitations. Despite these challenges, 57.4% of farmers reported medium-level adoption of CSA practices and 27.9% showed high adoption, reflecting moderate implementation of climate-smart techniques. As for perceptions of AESs, 41% of farmers found it somewhat effective, 35.8% thought it was highly effective, and 23.2% did not see it as very effective. These findings suggest that while the extension system is generally recognized as relevant, there is substantial scope for improving its reach, responsiveness, and impact.

3.2. Perceived Impact of Climate Change on Agriculture

Our study found that increased soil salinity (mean 4.85), altered weather patterns (mean 4.78), reduced fresh water resources (mean 4.74), poor harvest (mean 4.71), poor vegetative growth in plants (mean 4.65), and declined soil moisture retention capacity (mean 4.55) were the most perceived climate change impacts by the farmers (Figure 2). These factors directly impinge on agricultural productivity, exacerbating livelihood vulnerabilities and underscoring the urgent need for CSA practices.

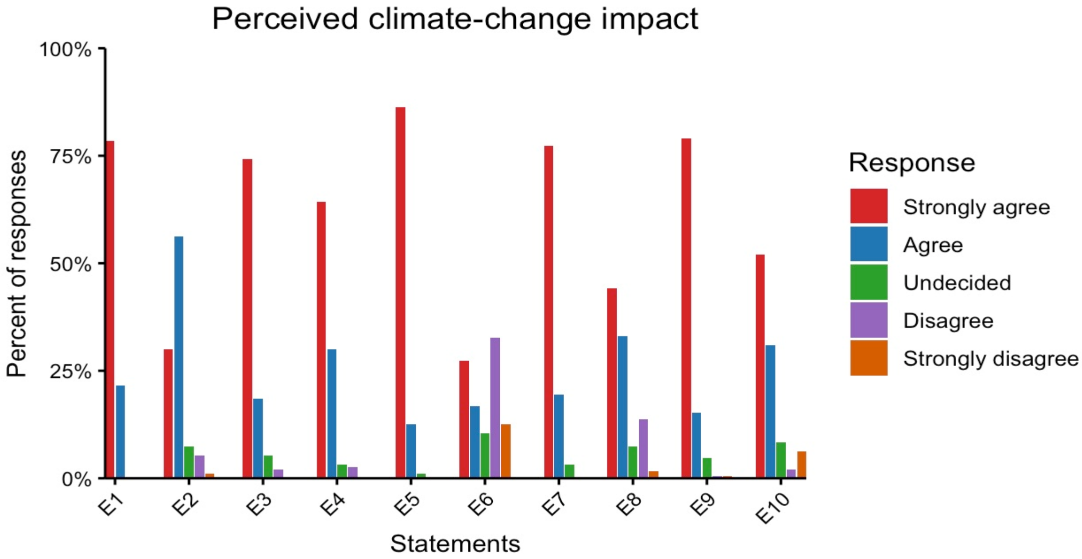

Figure 2. Farmers' perceptions regarding the impact of climate change on agriculture.
Note: E1: Change in weather pattern; E2: Change in farming schedule; E3: Poor vegetative growth in plants; E4: Declining soil moisture retention capacity E5: Increasing soil salinity in dry season; E6: Extinction of local crop varieties; E7: Reducing fresh water resources; E8: Tidal flood intrusion and waterlogging; E9: Poor harvest: E10: Unpredictable pest and disease outbreaks.

Soil salinity, in particular, severely compromises soil fertility by causing nutrient imbalances and ion toxicities, primarily due to elevated levels of sodium (Na^+) and chloride ($Cl^−$), which disrupt plant metabolic functions, induce oxidative stress, and result in seedling mortality and reduced crop quality (Rahman et al., 2023). Additionally, changes in temperature and rainfall patterns impose significant stress on coastal farming systems by affecting germination rates and vegetative growth, pest and disease dynamics, and increasing the risk of tidal water intrusion and prolonged waterlogging (Biswas et al., 2024; Iqbal & Aziz, 2022).

These climatic challenges have also forced farmers to alter the cropping schedule and, in some cases, abandon traditional local varieties altogether. Despite these hardships, a previous study has reported that adopting CSA practices can offer economic and environmental benefits. Helping farmers sustain livelihoods in the face of climate change (Arfanuzzaman et al., 2016). This underscores the critical importance of promoting and scaling up CSA solutions tailored to the specific challenges of coastal agricultural communities.

3.3. Adoption of Climate Smart Agriculture Practices

The study revealed that coastal farmers have adopted a range of CSA practices, though adoption levels varied across the 14 practices assessed (Figure 3). The most widely used practices included stress-tolerant rice varieties, homestead farming, intercropping, organic farming, the sorjon method, stress-tolerant vegetables and fruits, soil and water conservation, and low external input use. Empirical evidence shows that CSA practices can increase crop productivity by 10.5% and farm profitability by 29.4%, while improving resource efficiency and environmental sustainability (Farah et al., 2025). Conversely, practices such as agricultural waste recycling, mixed cropping, dyke cropping, AWD irrigation, rainwater harvesting, and adjusted cropping schedules showed lower adoption, primarily due to limited resources, inadequate extension support, low awareness, and perceived high costs (Arfanuzzaman et al., 2016).

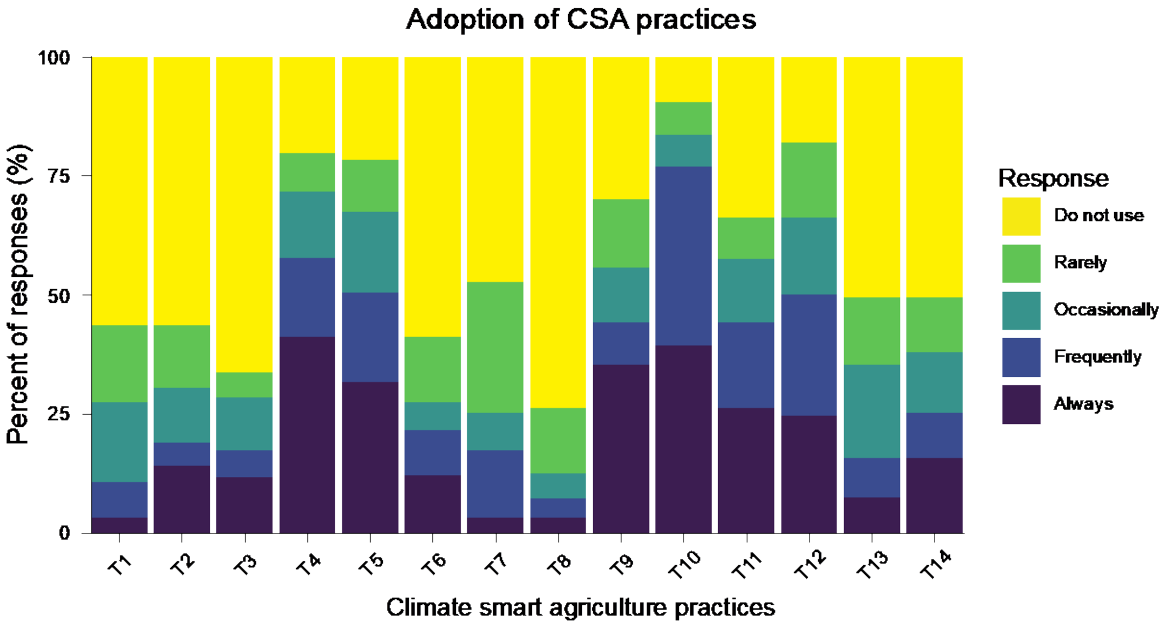

Figure 3. Farmers' perceptions regarding the adoption of CSA practices.
Note: T1: mixed cropping; T2: change in cropping schedule; T3: dyke cropping; T4: homestead farming; T5: intercropping; T6: rainwater harvesting; T7: alternate wetting and drying (AWD) irrigation; T8: recycling of agricultural waste; T9: sorjon method; T10: stress-tolerant rice varieties; T11: stress-tolerant vegetables and fruits; T12: organic farming; T13: use of low external inputs; and T14 = soil and water conservation.

Adoption of stress-tolerant rice varieties (saline, drought, short-duration, and submergence-tolerant types) has become essential for maintaining yields under harsh climatic conditions (Roy et al., 2019). Such adaptation is crucial for smallholder farmers, as resilience-building directly supports livelihood sustainability (Billah et al., 2025). Current adopters of stress-tolerant varieties experience a 41-percentage point reduction in multidimensional poverty compared to non-adopters (M. K. Islam & Farjana, 2024). Yield gains average 1.1 tons/ha (28%), increasing from 3.87 to 4.97 tons/ha, while net farm income rises from US$229/ha to US$307/ha, reflecting an income gain of about US$78/ha (23%; Pal et al., 2024). FGDs also confirmed that "stress tolerant crop varieties enable coastal farmers to minimize crop damage during flash floods in the rainy season and reduce irrigation demand for boro rice in the winter season."

Homestead vegetable farming, particularly using elevated "tower system" during flood and tidal water intrusion in the rainy season, has proven effective in enhancing food security (Biswas et al., 2024). Organic farming and sorjon methods were also widely adopted, helping reduce soil salinity and mitigate climate impacts (Ruba et al., 2024). Farmers noted that "homestead vegetable cultivation and organic practices reduced input costs while increasing dietary diversity, contributing to household food security." Vermicomposting is increasingly used as a low-cost organic fertilizer, reducing dependence on synthetic inputs.

The sorjon method integrates horticulture on raised beds with fish culture in ditches, optimizing resource use and strengthening farm profitability. Farmers also cultivate stress-tolerant fruits (e.g., watermelon) and apply mulching for high-value vegetables such as capsicum, brinjal, and tomato. Intercropping—such as maize or sugarcane with lentil, chickpea, or vegetables—was widely practiced for resource efficiency and risk reduction. As one farmer noted, "We plant lentils and vegetables between maize or sugarcane rows so that if one crop fails due to salinity or heavy rain, the other still gives us some income." Another added, "Intercropping helps us use the land better—we get more yield from the same field and can harvest at different times, which gives us cash flow throughout the year." Prior studies confirm its benefits in enhancing productivity and income diversification in saline regions (Ali et al., 2021).

Although less common, a few farmers have adopted harvesting rainwater by digging small ponds and utilizing this conserved water for irrigation during dry spells, which enhances water availability for crop production and reduces reliance on erratic rainfall (Sarker et al., 2024). Farmers participating in FGDs mentioned that "A few farmers dug small ponds near their fields to store rainwater. During the dry season, we use this water for irrigation-it saves our crops when rainfall is delayed. However, constructing a new pond is very expensive for small-scale farmers; we need more support or collective efforts on a cooperative basis." Many of the farmers who established such ponds also used the surrounding embankments for dyke farming—cultivating creeping vegetables and fruits—which further contributed to food production in these flood-prone zones.

3.4. Perceived Effectiveness of Agricultural Extension Services

The Perceived Effectiveness Index (PEI) was used to evaluate farmers' insights on 15 key extension service areas related to agricultural extension policy (Table 3). The findings reveal that farmers viewed several extension services as highly effective, especially the introduction of stress-tolerant crop varieties, stakeholder participation in agricultural decision-making, and training on climate change adaptation (Table 3). CSA promotion campaigns, provision of quality seeds, fertilizers, and pesticides, support for cooperative farming systems, and health and food safety programs were also regarded as valuable areas of extension support. FGDs confirmed that extension organizations played a key role in introducing salt-tolerant and short-duration rice varieties (e.g., BRRI dhan 61, 67, 97, 75, 87), as well as alternative crops such as sunflower, maize, watermelon, and various vegetables, helping farmers diversify and reduce salinity-related risks (Kundu et al., 2020). As one farmer noted, "When the extension officer showed us how to use the new rice variety in the field, I felt more confident to try it myself." This highlights the importance of institutional support and credibility, which are central to motivating technology adoption. Support from extension organizations not only facilitates the effective dissemination of CSA practices but also builds farmers' confidence in adopting innovative practices.

Table 3. Farmers' perceived effectiveness index (PEI) of AESs (N = 190).

Agricultural extension services	HE	ME	LE	NE	PEI	Mean	Rank
Introduction of stress-tolerant crops and varieties	55 (71.6%)	66 (11.6%)	58 (15.3%)	3 (1.6%)	678	3.53	1st
Stakeholder involvement in local agricultural decision-making	468 (61.6%)	99 (17.4%)	62 (16.3%)	9 (4.7%)	638	3.36	2nd
Training to cope with climate change impacts.	448 (58.9%)	108 (18.9%)	32 (8.4%)	26 (13.7%)	614	3.23	3rd
Promotion for climate-smart agricultural practices	216 (28.4%)	276 (48.4%)	30 (7.9%)	29 (15.3%)	551	2.9	4th
Access to quality seeds, fertilizers, and pesticides.	120 (15.8%)	225 (39.5%)	126 (33.2%)	22 (11.6%)	493	2.59	5th
Subsidies to support farmers.	240 (31.6%)	108 (18.9%)	40 (10.5%)	74 (38.9)	462	2.43	6th
Promotion of cooperative farming systems	152 (20%)	126 (22.1%)	118 (31.1%)	51 (26.8%)	447	2.35	7th
Health and food safety initiatives	132 (17.4%)	117 (20.5%)	128 (33.7%)	54 (28.4%)	431	2.26	8th
Advisory support to farmers	124 (16.3%)	147 (25.8%)	66 (17.4%)	77 (40.5%)	414	2.18	9th
Assistance for the adoption of modern agricultural machinery	16 (2.1%)	84 (14.7%)	160 (42.1%)	78 (41.1%)	338	1.78	10th
Initiatives for Fair Market Access	48 (6.3%)	105 (18.4%)	82 (21.6%)	102 (53.7%)	337	1.77	11th
Facilitation in infrastructure development	12 (1.6%)	72 (12.6%)	118 (31.1%)	104 (54.7%)	306	1.61	12th
Use of ICTs in agricultural extension	104 (13.7%)	15 (2.6%)	28 (7.4%)	145 (76.3%)	292	1.54	13th
Value addition of agricultural products	0 (0%)	66 (11.6%)	94 (24.7%)	121 (63.7%)	281	1.48	14th
Credit facility or financial assistance	24 (3.2%)	51 (8.9%)	76 (20.0%)	129 (67.9%)	280	1.47	15th

Note: HE = Highly Effective = 4; ME = Moderately Effective = 3; LE = Low Effective = 2; NE =Not Effective = 1; and PEI= Perceived effectiveness index.

Farmers emphasized that participation in decision-making and cooperative learning strengthened their ability to adopt climate-resilient practices (Abid et al., 2016). "Communal learning and shared experiences significantly enhance our capacity to implement new methods," they stated. This collaborative approach, supported by extension services, fosters social capital and enhances community resilience against the impacts of climate change. Training initiatives were also considered highly beneficial, though farmers stressed the need for field-level follow-up: "Training helped us understand new practices, but we need more follow-up in our own land." This finding indicates that the effectiveness of training interventions is maximized when theoretical instruction is complemented by continuous, practice-oriented support through on-farm guidance.

The localization training should move beyond generic capacity-building toward context-specific and problem-oriented approaches. In coastal areas such as Koyra Upazila, training programs should explicitly address site-specific challenges, including salinity intrusion, soil and water conservation, reduction of agriculture's contribution to climate change, and climate-risk-based cropping decisions.

Delivering such training through on-farm demonstrations, farmer field schools, and systematic post-training field-level follow-up can enhance the practical relevance of extension messages and support the effective adoption of climate-smart agricultural practices.

However, some extension service areas, such as credit access, value addition, ICT use, infrastructure facilitation, and market access, were perceived as less effective. Smallholder farmers often face difficulty accessing credit due to a lack of collateral, complex application procedures, and high interest rates, which limit their ability to invest in new technologies (Herliana et al., 2018). As several farmers explained during the FGDs: "We want to take loans, but the process is too complex, and without collateral we are not eligible." Given the very low perceived effectiveness of credit services, stronger coordination between AESs and microfinance institutions is needed. The development of green credit schemes tailored to CSA, along with simplified subsidy application and disbursement through local extension offices, could reduce administrative barriers and enhance smallholders' financial access, thereby supporting wider adoption of CSA in coastal regions.

Similarly, the low perceived effectiveness of ICT-based extension services suggests the need for more context-appropriate digital strategies. Rather than relying solely on complex mobile applications, AESs could prioritize the development of local-language, data-based agricultural advisory platforms, combined with strengthening extension personnel's capacity to use social media groups (e.g., WhatsApp, Facebook Messenger) to disseminate timely weather alerts, pest warnings, and crop-specific recommendations. Such hybrid digital approaches may improve information accessibility among farmers with limited digital literacy.

Although climate projects installed mini ponds, poly net houses, and machinery (Nandi et al., 2024), their long-term effectiveness depends on continued technical support, as infrastructure alone is insufficient without follow-up. Moreover, although value addition of agricultural products, such as processing, packaging, branding, and improved market access, can significantly increase profitability (Mbukanma et al., 2025), their practice remains underdeveloped due to limited technical skills, inadequate extension guidance, lack of facilities, and poor linkage to profitable markets. Overall, strengthening weak AES areas, particularly in financial services, value chain development, ICT integration, market access, and infrastructure maintenance, is essential for improving CSA adoption and enhancing resilience in coastal farming systems.

3.5. Perceived Effectiveness of AESs by Age Group

The one-way ANOVA analysis revealed a statistically significant difference among the groups ($F = 7.017$, $p = 0.001$), indicating that age significantly influences farmers' perceptions of extension policy support effectiveness (Table 4). Descriptive statistics showed that younger farmers reported the lowest mean perception score ($M = 31.56$, $SD = 7.54$), while the older age group showed the highest mean score ($M = 36.96$, $SD = 6.87$). This trend suggests that perceptions of AESs' effectiveness tend to increase with age.

Table 4. One-way ANOVA results showing differences in perceived effectiveness of AESs by age group

Dependent Variable	Age Group	Descriptive statistics			ANOVA results		
		N	**Mean**	**SD**	**df**	**F value**	***p* value**
Perceived Effectiveness of AESs	Young (18 – 37)	54	31.56	7.54	2, 187	7.017	0.001***
	Middle aged (38 – 57)	91	35.03	7.53			
	Old aged (above 57)	45	36.96	6.87			

*** represents less than 1% significance level.

Additionally, the Tukey HSD post hoc test (Table 5) identified significant differences between the young and middle-aged groups (mean difference = −3.48, $p = 0.018$) and the young and old-aged groups (mean difference = −5.40, $p = 0.001$), both statistically significant at the 5% and 1% levels, respectively. However, no significant difference was observed between the middle-aged and old-aged groups (mean difference = −1.92, $p = 0.328$). These findings suggest that older farmers are generally more likely to perceive agricultural extension policies as effective compared to younger farmers, possibly due to greater experience, more prolonged engagement with extension services, or higher levels of trust in institutional support mechanisms.

Table 5. Tukey HSD post hoc test comparing respondent groups based on age.

Group Comparison	Mean Difference (I–J)	Std. Error	*p*-value	95% Confidence Interval
Young aged vs Middle aged	−3.48**	1.27	0.018	−6.47, −0.48
Young aged vs Old aged	−5.40***	1.49	0.001	−8.92, −1.88
Middle aged vs Old aged	−1.92	1.35	0.328	−5.10, 1.26

Note: Group sizes' variances were assumed equal based on Levene's test ($p = 0.789$). The dependent variable in this model was the perceived effectiveness of AESs.
*** represents less than 1% significance level; ** represents less than 5% significance level.

3.6. Perceived Effectiveness of AESs by Farming Experience

The analysis of ANOVA presented in Table 6 demonstrates a significant difference in farmers' perceptions of AESs effectiveness based on their years of farming experience ($F = 7.152$, $p < 0.001$). Descriptive statistics show that farmers with 32–46 years of experience reported the highest perception of extension policy effectiveness (M = 38.86, SD = 5.74), whereas those with 2–16 years (M = 32.16) and above 46 years (M = 32.07) reported lower scores. Furthermore, the Games-Howell post hoc test (Table 7) also revealed statistically significant differences between the groups 2–16 years vs. 32–46 years ($p < 0.001$), 17–31 years vs. 32–46 years ($p = 0.012$), and 32–46 years vs. above 46 years ($p = 0.040$). These results suggest that farmers with 32–46 years of experience are more likely to recognize extension policy interventions as effective. This pattern may reflect the optimal combination of accumulated practical knowledge, openness to innovation, and active engagement with extension services among farmers in this experience group.

Table 6. One-way ANOVA results showing differences in perceived effectiveness of AESs by farming experience.

Dependent Variable	Farming Experience	Descriptive statistics			ANOVA results		
		N	Mean	SD	df	F value	*p* value
Perceived Effectiveness of Agricultural Extension Services	2 – 16 years	63	32.16	6.69	3, 185	7.152	$p < 0.001$***
	17 – 31 years	75	34.68	8.23			
	32 – 46 years	38	38.86	5.74			
	Above 46 years	14	32.07	7.93			

*** represents less than 1% significance level.

Table 7. Games-Howell post hoc test comparing respondent groups based on Farming experience.

Group Comparison	Mean Difference (I-J)	Std. Error	*p* value	95% Confidence Iterval
2–16 Years vs 17–31 Years	−2.52	1.27	0.199	−5.82, 0.78
2–16 Years vs 32–46 Years	−6.71***	1.27	0.000	−10.02, −3.39
2–16 Years vs above 46 Years	0.09	2.28	1.000	−6.38, 6.56
17–31 Years vs 32–46 Years	−4.18***	1.34	0.012	−7.69, −0.68
17–31 Years vs above 46 Years	2.61	2.32	0.680	−3.93, 9.15
32–46 Years vs above 46 Years	6.79**	2.32	0.040	0.25, 13.33

Note: Levene's test indicated a violation of the homogeneity of variance assumption ($p = 0.016$); therefore, equal variances were not assumed, and the Games–Howell post hoc test was applied. The dependent variable in this model was the perceived effectiveness of AESs.
*** represents significance at the 1% level; ** represents significance at the 5% level.

3.7. Determinants of Farmers' Perceived Effectiveness of Agricultural Services (AESs)

The results of a multiple linear regression analysis (Table 8) identified significant predictors contributing to farmers' perceptions of the effectiveness of AESs. The overall model was statistically significant ($F = 8.071$, $p < 0.001$) and accounted for approximately 31.1% of the variance in the perceived AES effectiveness ($R^2 = 0.311$), with a standard error of 6.497, indicating a good model fit.

Table 8. Determinants of farmers' perceived effectiveness of AESs.

Prediction	β(Unstandard-ized)	β (Standard-ized)	Std. Error	t-value	*p* value	VIF
(Intercept)	47.969***		9.173	5.229	<0.001	
Age	0.148	0.264**	0.065	2.286	0.023	3.469
Farming Experience	0.001	0.002	0.059	0.015	0.988	3.280
Income	0.022	0.212*	0.011	1.948	0.053	3.068
Education	0.079	0.045	0.117	0.669	0.504	1.197
Information Source	0.297	0.113	0.19	1.565	0.119	1.353
Climate Change Impact	−0.500	−0.202***	0.162	−3.092	0.002	1.110
Training	0.123	0.179***	0.044	2.779	0.006	1.072
Farm Size	−4.647	−0.223**	2.089	−2.224	0.027	2.606
Barrier	−0.201	−0.176***	0.073	−2.766	0.006	1.050
Adoption to CSA	0.214	0.199***	0.069	3.09	0.002	1.082
$R^2 = 0.311$, Adj. $R^2 = 0.272$, $F(10, 179) = 8.071$, $p < 0.001$, SE = 6.497						

*** represents less than 1% significance level; ** represents less than 5% significance level; * represents less than 10% significance level.

Among the explanatory variables, age (β = 0.264), training (β = 0.179), and adoption of CSA practices (β = 0.199) were positively associated with farmers' perceptions of AES effectiveness. Older farmers reported higher AES effectiveness, suggesting that accumulated knowledge and long-term farming experience strengthen adaptive capacity and improve understanding of extension recommendations (M. S. Kabir et al., 2024). This also reflects their longstanding engagement with extension agents, greater familiarity with advisory services, and increased trust built through repeated interactions (Somanje et al., 2021). Training significantly reduced uncertainty and enhanced farmers' self-efficacy, thereby improving their perceived ease of applying extension advice (Masha et al., 2024). Adoption of CSA practices further reinforced perceptions of AES's usefulness, as farmers who actively implemented CSA practices were better able to observe the tangible benefits of extension guidance in enhancing productivity, resilience, and decision-making (M. K. Islam & Farjana, 2024). When farmers perceive extension services as offering practical, context-appropriate, and easily integrated CSA solutions, adoption increases, leading to stronger positive evaluations of AES effectiveness (M. K. Islam & Farjana, 2024; Omotoso & Omotayo, 2024). Well-designed training programs and targeted promotion of CSA practices can therefore strengthen farmers' perceptions of extension services, which is essential for sustained engagement and broader adoption of climate-resilient agricultural practices (Akpan & Agulu, 2019).

In contrast, perceived climate change impacts (β = −0.202), farm size (β = −0.223), and barriers to adoption (β = −0.176) were inversely related to perceived effectiveness of AESs. Farmers experiencing greater climate stress, such as salinity intrusion, water scarcity, or extreme weather events, may view existing extension support as insufficient for addressing their specific challenges (M. J. Kabir et al., 2017). This finding suggests that external environmental pressures can overwhelm institutional capacity (Barron et al., 2021). Larger farm sizes might reduce reliance on extension services due to economies of scale, as these farmers often have better access to resources, technology, and private advisory services, lessening their dependence on public extension support (Jamil et al., 2021). Additionally, barriers to adoption, such as a lack of initial investment, poor embankment infrastructure, and low crop prices, could diminish the perceived effectiveness of extension efforts by creating obstacles to implement CSA practices (Billah et al., 2025).

Although the model explains a meaningful share of variation in perceived AES effectiveness, approximately 69% of the variance remains unexplained. This unexplained component likely reflects institutional and social factors not captured in the present analysis, such as the technical competence and communication skills of extension personnel, the quality of farmer–extension agent relationships, levels of social capital and peer influence, and the role of local power structures in shaping access to extension services (Billah et al., 2025).

It is also important to emphasize that this study assesses perceived effectiveness rather than the actual effectiveness of agricultural extension services. Perceived effectiveness reflects farmers' subjective evaluations based on their experiences, expectations, and interactions with extension services (Somanje et al., 2021), whereas actual effectiveness would require objective indicators such as yield gains, income changes, or measurable improvements in adaptive capacity (Knook et al., 2018). Although perceived and actual effectiveness may not always align, perceived effectiveness remains a critical determinant of farmers' trust, adoption behavior, and sustained engagement with extension programs (Turyahikayo & Kamagara, 2016).

Overall, these findings highlight the complex interplay of individual, institutional, and environmental factors shaping farmers' evaluations of AESs and underscore the need for more adaptive, context-sensitive extension approaches to promote CSA in vulnerable coastal regions.

4. Limitations of the Study

Despite its valuable insights, this study is subject to several methodological limitations. The use of self-reported data may introduce potential subjective bias, as responses depend on individual perceptions and recall accuracy. Furthermore, while the relatively small sample size (190) was adequate for this exploratory study, it may limit the generalizability of the findings to the broader coastal regions of Bangladesh, necessitating caution when extrapolating these results (Aryal et al., 2020). Therefore, the findings should be interpreted as indicative rather than universally conclusive. Although the study employed descriptive statistics, ANOVA, and regression analysis to identify the determinants of perceived AES effectiveness, the use of more advanced analytical techniques such as Structural Equation Modeling (SEM) or Multilevel Modeling (MLM) was not applied due to methodological considerations related to sample size and research objectives. Future studies could expand the sampling frame to include non-registered farmers and larger samples across multiple coastal districts to increase statistical power and enhance the generalizability of findings. The geographical scope of the study, confined to a single Upazila, also restricts a comprehensive understanding of regional variations in agricultural extension service delivery and farmer engagement across Bangladesh's diverse coastal zones.

5. Conclusion

This study provides an in-depth assessment of farmers' perceptions of the effectiveness of agricultural extension services (AESs) in promoting Climate-Smart Agriculture (CSA) practices among smallholder farmers in coastal Bangladesh. Although 76.8% of respondents reported moderate to high levels of perceived effectiveness, the findings reveal a combination of notable strengths and persistent gaps within the extension system. Effective interventions such as the dissemination of stress-tolerant crop varieties, participatory decision-making processes, and targeted capacity-building programs were strongly associated with increased CSA adoption and more positive views of AESs.

However, farmers also identified significant shortcomings, particularly related to insufficient access to credit, limited value-chain support, inadequate ICT-based services, and weak agricultural infrastructure—issues that were especially pronounced among marginalized and resource-poor households. Perceptions of effectiveness varied significantly by age and farming experience, with older and more experienced farmers expressing more favorable assessments, while greater climate vulnerability, smaller farm size, and higher levels of adoption barriers contributed to more negative perceptions. These findings underscore that a uniform extension approach is unlikely to meet the diverse needs of coastal farmers; instead, a more inclusive, demand-driven, and context-responsive AES model is needed.

Strengthening extension services requires targeted, evidence-based, and institutionally coordinated interventions. Priority actions include developing CSA-oriented green credit products through collaboration between extension agencies and microfinance institutions, simplifying subsidy access via decentralized extension offices, and expanding low-cost, local-language digital advisory services supported by trained extension personnel. In addition, enhancing field-level follow-up, market linkages, and infrastructure support is essential for sustaining CSA adoption. Future research should employ longitudinal designs to examine changes in farmers' perceptions over time and conduct comparative studies across different agro-ecological zones to improve the generalizability of findings.

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Abbreviations

The following abbreviations are used in this manuscript:

AES	Agricultural Extension Service
AWD	Alternate Wetting and Drying
CSA	Climate Smart Agriculture
DAE	Department of Agricultural Extension
ECT	Expectation Confirmation Theory
FGD	Focus Group Discussion
ICT	Information and Communication Technology
PEI	Perceived Effectiveness Index

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