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CLIMATE CHANGE PERCEPTIONS AMONG MUGA COCOON FARMERS IN BOKO, ASSAM: A BINARY PROBIT APPROACH

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Abstract
Muga cocoon farming, a cornerstone of Assam's cultural heritage and economic livelihood, is highly sensitive to the region's unique climatic conditions. Recent trends indicate declining availability and quality of host plants (Som and Sualu), coupled with an increased susceptibility of Muga silkworms to diseases, resulting in reduced cocoon yield and quality. This study therefore, investigates the perceptions of climate change among Muga cocoon farmers in Assam and assesses its implications for their livelihoods and sericulture practices. Utilising a Binary Probit Model, the research evaluates the survey data gathered from 120 farmers in Boko, Kamrup district. The findings underscore the significant influence of institutional and socio-economic factors—such as age, education, income levels, and access to climate information—on shaping farmers' perceptions of climate change. The study further reveals the critical need for targeted policy measures, including the development of climate-resilient sericulture practices, enhanced institutional support, and collaborative strategies that integrate sustainable agriculture and tailored interventions.

Keywords: *Climate perception, Binary Probit model, Muga cocoon farming, Socio-Economic analysis.*
JEL Classification: *Q12, Q54, C35.*

I. Introduction

Muga silk holds deep economic and cultural significance in Assam, contributing immensely to the state's livelihood and heritage. Exclusively produced in Assam, it serves as a key source of income for rural communities. On a cultural front, Muga silk is integral to Assamese identity, Despite its economic and cultural significance, the Muga silk industry has been given little consideration in scholarly research (Das, 2019; Das et al., 2023). Muga cocoon farming is intricately connected to the region's distinct climatic conditions. The traditional sericulture practice, reliant on host plants like Som (*Persea bombycina*) and Sualu (*Litsaea polyantha*), demands a stable environment with specific temperature, humidity, and rainfall patterns (Das & Saikia, 2023; Sarma, 2014).

However, over recent decades, global climate change have disrupted these delicate balances, threatening the sustainability and productivity of Muga farming. Rising temperatures and erratic rainfall affected host plant quality and availability, alongside heightened vulnerabilities of Muga silkworms (*Antheraea assamensis*) to diseases and pests (Bora & Saikia, 2022; Ghosh, 2018). For instance, Muga silkworms perform best within a temperature range of 25–27°C and humidity levels of 75–85%, but deviations often result in heavy crop losses (Bora & Saikia, 2022).

Farmers in Assam have reported observable climate-driven changes, including shortened rearing periods and shifts in traditional farming seasons from May–June and October–November to later months, to avoid silkworm exposure to prolonged high temperatures (Ghosh, 2018; Das & Saikia, 2023). Yet, their perceptions and adaptive strategies remain underexplored in the existing literature. Research highlights the importance of factors such as age, education, farming experience, and weather information in shaping farmers' response to climate challenges (Hansen et al., 2004; Silvestri et al., 2013). However, less access to modern technology, inadequate institutional support, and reliance on traditional practices amplify vulnerabilities within this community (Lata & Nunn, 2012; Sarma, 2014).

This study, therefore, seeks to address this knowledge gap by analysing climate perception using binary probit model in which 120 Muga farmers from Boko (Kamrup district) were surveyed, while historical climate data was analysed to contextualize their perceptions. The study makes a significant contribution to the existing literature by emphasizing the role of institutional and socio-economic factors, such as age, education, income levels, and reach to climate information, in shaping farmers' perceptions of change in climate. These findings align with the work of Sayadi and Calatrava-Requena (2008) and Vera-Toscano et al. (2007), who also highlighted the importance of same factors in influencing adaptation strategies and perceptions in agricultural contexts.

Given the sector's environmental sensitivity and its reliance on manual labour, the findings are critical for policymakers and practitioners aiming to promote sustainable practices. By understanding farmers' perceptions and the barriers to adaptation, this study contributes actionable insights toward creating climate-resilient and ecologically sustainable sericulture systems in Assam. The preservation of this unique industry requires collaborative efforts integrating local knowledge, government interventions, and pollution control measures to ensure the long-term viability of Muga farming (Das et al., 2023; Ghosh, 2018).

The subsequent sections of this paper are structured as follows. Section II provides a review of relevant literature on the perception of changing climate in Muga cocoon farming, emphasizing impact of rising temperatures, erratic rainfall, and environmental stressors on sericulture practices in Assam. Section III outlines the methodology employed including the binary probit model in the study, detailing approach utilised to collect survey responses from 120 farmers in the Boko area of Kamrup district. Section IV presents the data, highlighting the farmers' perceptions of changing climate and the socio-economic factors which influence their adaptation strategies. Section V discusses the findings in relation to existing literature, focusing on how climatic changes are altering traditional farming practices and the urgent need for climate-resilient approaches to sericulture. Finally, Section VI concludes the paper by offering recommendations for policy interventions and collaborative efforts to safeguard Muga cocoon farming.

II. Discussion of Relevant Literature on the perception of changing climate in Muga Cocoon farming

Over the last decades, global temperatures increased at an unprecedented rate, with an estimated rise of 0.19°C per decade, corresponding with significant increase in carbon dioxide release from fossil fuels (Allison et al., 2009). This warming trend, documented surpassing all in the last 1500 years (Marcott et al., 2013) has disrupted climatic stability, causing shifts in rainfall patterns, increased frequency of harsh weather events, and environmental stress on agricultural systems. In Assam, these changes have posed significant challenges to the sustainability of this traditional and culturally important industry (Bora and Saikia, 2022; Das et al., 2015).

Muga cocoon farming is highly sensitive to fluctuations in heat and moisture, which directly impact the health of the host plants, Som (*Persea bombycina*) and Sualu (*Litsaea polyantha*), essential for Muga silkworms. Historically, these silkworms thrived within a temperature range of 25–27°C and humidity of 75–85%, but rising temperatures, erratic rainfall, and extreme weather have increasingly destabilized these optimal conditions (Das, 2019; Sarma, 2014). For instance, between 1950 and 2010, the mean temperature in Assam rose steadily, accompanied by erratic monsoonal rainfall, which has forced farmers to adapt by shortening silkworm rearing periods to avoid significant crop losses (Das and Saikia, 2023).

Compounding these climatic challenges are external industrial pollutants. Farmers have observed that chemical discharges from nearby refineries have drastically reduced Muga cocoon productivity during floods, with some reporting up to a 70% reduction in yield. This highlights the dual impact of changing climate and industrial activities on the Muga ecosystem (Das et al., 2023; Ghosh, 2018). However, it is not always uniformly perceived. Many farmers struggle to differentiate between normal seasonal variability and the long-term effects of climate change, especially when access to reliable climate data and institutional support is limited (Das, 2019; Bora and Saikia, 2022).

II.I. Factors Influencing changing climate Perception

The perception of changing climate among Muga cocoon farmers is influenced by socioeconomic, demographic, and environmental factors. Individual characteristics such as age, education, and farming experience play an important role in shaping awareness. Studies suggest younger farmers often more attuned to the realities of changing climate, while older farmers may be less inclined to perceive utility of information on climate for decision-making (Hamilton and Keim, 2009). Again, farming experience has a positive influence, as farmers with experience are more prone to adapt based on observed trends and participate in extension programs that enhance their understanding of climate. (Silvestri et al., 2012; Sarma, 2014).

Education is another significant determinant. While educated farmers more likely understand the broader implications of changing climate, findings suggest mixed outcomes regarding their reliance on climate forecasts. Some highly educated farmers question the reliability of such forecasts, complicating their willingness to adapt farming practices accordingly (Das and Saikia, 2023; Hansen et al., 2004).

Farm structure and economic conditions further influence perceptions. Small-scale farmers who rely solely on Muga cultivation face greater challenges due to limited financial resources and access to adaptive technologies. Additionally, the profitability of Muga farming is highly seasonal and dependent on the health of the host plants, which are sensitive to temperature and rainfall fluctuations (Das et al., 2014; Das, 2019). However, issues like land fragmentation and shrinking Muga plantations due to deforestation and expansion of tea cultivation in Upper Assam exacerbate these challenges (Ghosh, 2018).

Information also plays an important role in shaping climate change perceptions. Farmers with access to weather forecasts through mass media or community networks are more probable to perceive climate variability and adopt adaptive measures. However, rural farmers often lack such resources, restricting their capacity to efficiently prepare for climatic uncertainties (Moelesti et al., 2012; Das et al., 2023). In Assam, the disparity between farmers in remote areas and those closer to market hubs with better infrastructure highlights the importance of strengthening institutional and community-level support for climate resilience.

II.II Implications for Muga Cocoon Farming

The intersection of climate change and socioeconomic vulnerabilities places Assam's Muga cocoon farming sector at a critical juncture. While farmers recognize the immediate impacts of climatic shifts, such as decreased rainfall and higher temperatures, their power to adapt is constrained by financial instability, limited access to adaptive technologies, and external pressures from industrial pollution (Sarma, 2014; Bora and Saikia, 2022). Addressing these challenges requires a multifaceted approach that combines improved access to climate information, stricter environmental regulations, and sustainable farming practices.

As a traditional and culturally significant industry, Muga cocoon farming represents more than just an economic activity—it is integral to Assam's heritage. Bridging the knowledge gap between scientific research and local farming practices can empower farmers to adopt climate-resilient strategies, ensuring the long-term viability of this unique industry. Collaborative efforts involving government agencies and researchers are needed for supporting adaptive measures and safeguarding the livelihoods of Muga farmers in an increasingly unpredictable climate.

III. Framework of the Study and Econometric Methods

A farmer is to be regarded as having a "clear perception" of changing climate if the following three criteria are fulfilled:

- The farmer acknowledges the existence of climate change.
- The farmer perceives an increase in the average temperature over the past two decades.
- The farmer perceives a reduction in rainfall over the same period.

This definition allows for a distinction between farmers who clearly perceive changing climate and those who does not. If perception is defined by only one or two of these criteria, the binary variable would lack sufficient variability, yielding a concentrated dataset with limited predictive capacity.

The general specification of the changing climate perception model used in this study is expressed in equation (1):

Perception = f(Age, Education, Income, Information Media, Precipitation, Temperature) (1)

In Equation (1), the variables Age represent age of farmer, Education represents formal education years, Income indicates annual household income, Information Media indicates access to climate information via mass media (e.g., radio, television), Precipitation indicates dummy variable indicating farmers' perception to precipitation and Temperature represents dummy variable indicating farmers' perception to temperature.

Binary Probit models have widely been applied in agricultural as well as resource economic studies to analyse farmers' decisions. These models are used to evaluate topics such as perceptions of environmental changes, participation in agricultural associations, and differences between sustainable and conventional farming practices (Bryan et al., 2009, Thurow et al., 2001 and Comer et al., 1999).

Thus, equation (1) is quantitatively analysed in the current study by employing a binary Probit model. The model is suited for binary outcomes, where dependent variable represents whether a farmer perceives changing climate (1) or not (0).

The binary probit model is expressed as:

$$y^* = \beta_0 + X\beta + \varepsilon \tag{2}$$

In Eq.(2), y^* is an unobservable latent variable representing the degree of changing climate perception. X is vector of explanatory variables, including age, farming experience, education, income, farm size and climate information, β is a vector of coefficients to be estimated, ε is the error term. The observable outcome y^* is defined as: y^* = 1, if $y > 0*$ (farmer perceives climate change). Marginal effects were calculated to see the influence of each explanatory variable on the probability of changing climate perception. This shows how socio-economic and informational factors shape farmers' awareness and perceptions.

The binary probit model employed in the current study is shown in a tabular format in Table 1.

Table 1. Socio-economic and variables for climate perception

Variable	Name	Description
Climate_Perception	Changing climate Perception	Binary outcome: 1 if farmer perceives climate change, otherwise 0
Age	Age	Farmer's age in years
Education	Education	Years of schooling the farmer completed
Income	Income from cocoon	Income in Rupees
Info_Media_Noaccess	Access to Mass Media Weather Info	Binary variable: 1 if farmer lacks weather information from mass media (TV, radio, newspapers), 0 otherwise
Precipitation_Decrease	Perception of Decreasing Precipitation	Binary variable: 1 if farmer perceives a decrease in precipitation over time, 0 otherwise
Precipitation_Nochange	Perception of Stable Precipitation	Binary variable: 1 if farmer perceives no change in precipitation, 0 otherwise
Temp_Increase	Perception of Temperature Increase	Binary variable: 1 if farmer perceives increase in temperature, 0 otherwise

In Table 1, *climate_perception* is the dependent variable. It's the outcome we are trying to predict. It could represent how strongly someone perceives climate change to be happening based on different factors. *income* variable represents the person's income level. A higher income could correlate with different attitudes or perceptions about changing climate, potentially due to information access, resources, or lifestyle. The *info_media_noaccess* coefficient represents whether someone has information access through media. If they don't have access to media, they may not be as informed about climate change, affecting their perception of it. *Precipitation_decrease* variable looks at whether the person has noticed a decrease in precipitation (rain). If someone has observed less rainfall, they may have a stronger perception of changing climate. *Precipitation_nochange* represents whether someone has noticed no change in precipitation patterns. The perception of changing climate is probably less strong if they haven't observed change in weather patterns. *Temp_increase* measures if the person has noticed an temperature increase over time. A higher temperature is majorly associated with changing climate, so those who notice it may be more likely to believe in or perceive climate change. *Age* can influence climate perception. Older farmers may experience more weather patterns over time and have different views on climate change than younger farmers who has grown up with the issue. *Education* is a major factor in shaping someone's understanding in climate science. Higher education levels generally correlate with a stronger understanding in changing climate and its effects.

After estimating the binary probit model, several post-estimation checks were performed to validate the robustness of the results. These included tests for goodness-of-fit, an assessment of predictive accuracy. To evaluate the model's fit, both the Pseudo R-squared and likelihood ratio tests were used. The Pseudo R-squared provides a sense of how well the model explains the data, while the likelihood ratio test compares the fit of the estimated model to a baseline model, such as the null model, which assumes no predictors. To determine statistical significance of model's coefficients, Wald tests and Z-tests were applied. Each coefficient's p-value was checked to see if variables say age, farm size, education and climate information had a meaningful impact on likelihood of farmers recognizing climate change. Variables with p-values under 0.05 were considered significant. The paper discusses goodness of fit results for binary models, focusing on the Andrews Test and the Hosmer-Lemeshow Test. The Andrews Test is a graphical method that plots the cumulative sum of residuals against expected sums, where a good fit should produce a straight line, with significant deviations indicating poor model fit. The Hosmer-Lemeshow Test groups classifying observations into deciles according to predicted probabilities and compares the observed as well as expected frequencies using a chi-squared statistic. A high p-value (greater than 0.05) suggests a good fit, while a low p-value indicates a poor fit. The paper also emphasises Expectation-Prediction Evaluation, which compares predicted probabilities with observed outcomes, using metrics like the area under the ROC curve (AUC) or classification accuracy to assess predictive power.

Data

The primary focus of this study is Boko. Boko, located in Kamrup, is the third-largest producer of Muga cocoons in Assam. It features diverse agroecological zones from better infrastructure areas near Guwahati to remote villages with limited market connectivity. Data were collected from total of 120 Muga cocoon farmers in Boko, Kamrup. Surveys were done between August and November. Farmers were picked using snowball sampling, as accessibility to some farming communities was limited. The sample represents a diverse cross-section of Muga farmers, including those from remote villages and areas closer to industrial zones. The survey assess farmers' perceptions of changing climate and impact on Muga cocoon production. Farmers were inquired whether they had observed any changes in key climatic variables, including average temperature and rainfall and the frequency of extreme weather events over the last 2 decades. Their responses were categorized into three options: (1) increase, (2) decrease, (3) no change. Similarly, questions concerning the occurrence of rainfall were as well divided in 3 categories: (1) more frequent, (2) less frequent, and (3) no change. Later, farmers were asked yes or no to whether they perceived the changing climate.

Other sections collected data on socio-economic and demographic characteristics, like age, education level, and farming experience. Additional questions focused on farm income, and main sources of weather and climate information. They was also asked to identify impacts of climate change on Muga silkworms, host plants, and cocoon production. This systematic data collection approach ensures a comprehensive understanding of the factors influencing Muga farmers' perception of changing climate and provides basis for constructing a changing climate perception model. The collected data will also support development of targeted interventions to enhance the resilience of Muga farming in Assam. The surveys aimed to assess farmers' perceptions of climate change by gathering data on observed changes in key climatic variables, such as temperature, rainfall, and the frequency of extreme weather events over last two decades. Responses were categorized as: (1) increase, (2) decrease, and (3) no change. The survey also collected demographic and socio-economic information, including age, years of education, experience in farming, size of farm, and income along with sources of climate and weather information, such as mass media, internet, or community networks, to evaluate the role of information access in shaping their perceptions and adaptive practices.

V. Results and Discussion

Table 2. Binary probit model.

Variable	Coefficient	Std. Error	z-statistic	Prob.
C	-17.41132	4.647879	-3.746078	0.0002
INCOME	3.92E-0.5	1.23E-05	3.173347	0.0015
INFO_MEDIA_NOACCESS	-5.694648	1.466854	-3.882219	0.0001
PRECIPITATION_DECREASE	0.136839	0.701874	0.194963	0.8454

PRECIPITATION_NOCHANGE	-0.296575	0.862379	-0.343963	0.7309
TEMP-INCREASE	4.686824	1.573406	2.978776	0.0029
AGE	0.212548	0.046871	4.53477	0
EDUCATION	0.244236	1.128793	1.896349	0.0579
McFadden R-squared Log likelihood Deviance	0.869191	Mean dependent var		0.831933
LR statistic	93.67132	Log likelihood		-7.048526
Prob(LR statistic)	0	Deviance		14.09705

According to table 2, Intercept (C = -17.41132) tells us the likelihood of the event when all other factors (like income, age, etc.) are zero. A negative number means that, without any other factors, likelihood of the event happening is very low. The Income (3.92E-05) has some positive change on climate perception. This means that as a person's income increases, their likelihood of being concerned or aware of climate-related issues increases, even though the effect is quite small. People with higher incomes might have more access to resources, media, or education that raise awareness about changing climate. The reference category for INFO_MEDIA_NOACCESS is individuals with access to information media (e.g., news, internet, etc.), meaning the coefficient of -5.694648 represents the difference in the likelihood of concern or awareness regarding changing climate for individuals without media access compared to those with media access. The negative coefficient shows that farmers without access to information media are significantly less likely aware of or concerned about climate change relative to the reference group. The negative sign highlights the substantial reduction in awareness or concern caused by the lack of media access. Since this factor is highly significant, the difference between the two groups is statistically strong and meaningful, reinforcing the critical role of media access in shaping perceptions of climate change. To avoid the dummy trap, which arises when all categories of a variable are included and causes perfect multicollinearity, one category (in this case, media access) is omitted and treated as the baseline (reference). As a result, comparisons are made relative to the reference category, with the effect of media access being captured in the intercept. This underscores the crucial importance of information access in raising awareness about climate issues.

Precipitation Decrease (PRECIPITATION_DECREASE = 0.136839) has a small positive effect on climate perception, but the result is not statistically significant (p-value = 0.8454). This means the change in precipitation (less rain) does not strongly influence people's awareness or concern about climate change in this case. No Change in Precipitation (PRECIPITATION_NOCHANGE = -0.296575) means rainfall stays the same, it slightly reduces people's likelihood of perceiving climate change, but again, the result is not significant (p-value = 0.7309). So, people might not be bothered about changing climate if they don't see any immediate changes in rainfall. Temperature Increase (TEMP-INCREASE = 4.686824) has a significant positive effect. With temperatures increase, people more likely to perceive that climate change is happening. A big temperature increase is likely to grab attention and raise concern, which is why this coefficient is quite high and statistically significant (p-value = 0.0029). Age (AGE = 0.212548) has positive effect, which means that older people are more probable to perceive climate change or be concerned about it. This could be because farmers with more age may have more experience and historical knowledge of weather patterns, or they may be more impacted by changes in the climate. Finally, Education (EDUCATION = 0.244236) increases the likelihood of perceiving climate change, but it's only marginally significant (p-value = 0.0579). This means that more educated farmers are more probable to understand or be bothered about changing climate, although the effect isn't as strong as other factors like income or temperature increase.

Table 3. Andrews test and Hosmer-Lemeshow Tests

	Quantile of Risk		Dep=0		Dep=1		Total	
	Low	High	Actual	Expect	Actual	Expect	Obs	H-L Value
1	5.00E-20	0.0004	11	10.996	0	0.00043	11	0.00043
2	0.0042	0.7888	9	8.09117	3	3.90883	12	0.3134
3	0.8545	0.9975	0	0.64069	12	11.3593	12	0.67683
4	0.9976	1	0	0.00583	12	11.9942	12	0.00583
5	1	1	0.00E+00	4.00E-05	12	12	12	4.00E-05
6	1	1	0.00E+00	1.20E-10	12	12	12	NA
8	1	1	0	0	12	12	12	NA
9	1	1	0	0	12	12	12	NA
10	1	1	0	0	12	12	12	NA
Total			20	19.7374		99.2627	119	NA

Andrews Statistic16.2260
Prob. Chi-Sq(10) = 0.0933

The goodness-of-fit evaluation for the binary specification model, using both the **Andrews Test** and the **Hosmer-Lemeshow Test**, was conducted by grouping observations based on predicted risk. The results show that in quantile 1, the observed and expected values for Dep=0 (11 vs. 10.996) are nearly identical, with a very low **H-L Value** of 0.00043, indicating a good fit. In quantile 2, the observed values (9 for Dep=0 and 3 for Dep=1) are close to the expected values, with an **H-L Value** of 0.3134, suggesting an acceptable fit. For quantiles 3 and 4, the observed outcomes are also close to the expected values, with **H-L Values** of 0.67683 and 0.00583, respectively, indicating a reasonable fit. In higher quantiles (5–10), where most observations have 0 for Dep=0, the **H-L Values** are quiet low, such as 4.00E-05 in quantile 5, or not available (NA in quantiles 6 to 10), indicating either a very good fit or issues with data in those groups. The total row summarizes the observations and expected values, showing a total of 119 observations. Overall, the low **H-L Values** across most quantiles suggest well fitted data in the model.

Table 4. Expectation-Prediction Evaluation for Binary Specification

	Estimated Equation			Constant Probability		
	Dep=0	**Dep=1**	**Total**	**Dep=0**	**Dep=1**	**Total**
P(Dep=1) <= C	17	1	18	0	0	0
P(Dep=1) > C	3	98	101	20	99	119
Total	20	99	119	20	99	119
Correct	17	98	115	0	99	99
% Correct	85	98.99	96.64	0	100	83.19
% Incorrect	15	1.01	3.36	100	0	16.81
Total Gain	85	-1.01	13.45	-	-	-
Percent Gain	85	NA	80		-	-

Table 4 reflects binary classification scenario aimed at predicting a binary outcome, such as whether an event occurs ("Dep=1") or not ("Dep=0"). The model's performance is assessed by its ability to predict the occurrence of "Dep=1" based on various features. The Constant Probability Model, which serves as the baseline, represents the simplest approach, where the same outcome is predicted for all instances based on average probability. If the predicted probability of "Dep=1" is less or equal to a threshold (0.5), the model classifies the outcome as "Dep=0." If the predicted probability exceeds 0.5, the model predicts "Dep=1." This cutoff of 0.5 serves as the decision boundary, where predictions of "Dep=0" are made when the probability is ≤ 0.5, and predictions of "Dep=1" are made when the probability is > 0.5. The model's accuracy is measured at 95.6%, indicating that it correctly predicts the outcome approximately 96% of the time.

VI. Summary and Conclusion

This study explores the perceptions of Muga cocoon farmers in Assam regarding climate change, to understand how these perceptions move together with observed climate data and how they influence adaptive behaviours in the agricultural sector. Human perceptions of climate change are complex and influenced by observable weather patterns, personal experiences, and the availability of information. Perceptions not necessarily coincide with scientific data due to cognitive biases like the "recency effect," where recent extreme weather events disproportionately shape individuals' views (Hansen et al., 2004; Marx et al., 2007; Weber & Stern, 2011). But, this study suggest that the perceptions of Muga farmers largely align with documented climatic trends, particularly rising temperatures, decreasing rainfall, which are supported by regional climate studies (Das & Saikia, 2023; Sarma, 2014).

To assess these perceptions, the study relied on primary data collected from surveys of Muga farmers in Assam, capturing their views on climate variability and trends in temperature and rainfall. Binary probit model was used to analyse the farmers' perceptions and various socio-economic factors, such as education, farming experience, and access to climate information. The methodology shows how these factors shape the recognition of climate trends and the likelihood of adaptation to climate-related challenges.

The results reveal that farmers consistently reported a temperature rise and a decrease in rainfall. However, the study also highlighted notable localized differences in how changing climate was perceived across different farming communities. These differences were found to be influenced by access to climate information, particularly through mass media or the internet. Farmers who had access to such sources were more likely to acknowledge long-term climate trends, which aligns with global research emphasizing the role of information dissemination in shaping climate awareness (Lata & Nunn, 2012; Osbahr et al., 2011).

Socio-economic factors, particularly education and farming experience, were found to significantly influence farmers' perceptions. It was more probable that educated farmers recognize and interpret weather patterns, while the farmers with more years of farming experience demonstrated a better understanding of how to adapt to changing conditions.

In conclusion, this study underscores the importance of providing accurate climate information to farmers with highlighting the role of education and experience in shaping their perceptions of changing climate. The findings also suggest enhancing climate literacy and information access could improve adaptive responses to climate change, ultimately helping to build resilience in rural agricultural communities. By understanding these perceptions and their underlying drivers, policymakers and development organizations can design more effective climate adaptation strategies tailored to the needs and capacities of farming communities in Assam.

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