Impact of Climate Change on farmers Physical and mental well-being: An investigation from Rajshahi District in Bangladesh

Abstract

Climate change poses significant threats to agriculture and public health. The aim of this study is to explore the public health consequences of climate change, highlighting increased cases of heat stress, respiratory diseases, and vector-borne illnesses in response to climatic extremes. In this study we use Simple Random Sampling (SRS) technique to select our required sample from the Rajshahi district. The empirical result showed that the maximum number of farmers are male and their main occupation is agriculture farming. The frequency distribution presented that heat stress is the most common issue, reported by 31.5% of participants, followed by Water borne at 22%. The findings from the Chi-Square and logistic regression analyses indicated a significant relationship between climate change factors such as temperature, rainfall, and water scarcity and health issues like heat stress, respiratory problems, and waterborne diseases. These findings suggested that climate change poses significant risks to public health, particularly among vulnerable populations like farmers. Most of the climate-related health impacts were statistically significant, some variables, such as healthcare access, did not show significant relationship with health outcomes. The findings underscore the necessity of integrating climate adaptation strategies into health policies. This includes the establishment of early warning systems for extreme weather events and health risks, improving healthcare access in remote areas, and strengthening the capacity of healthcare workers to respond to climate-related health issues.

Key Words: Climate change, descriptive statistics, logistic regression and physical and mental health

1. Introduction

Climate change refers to the long-term alterations in temperature and weather patterns, primarily driven by human activities, such as the combustion of fossil fuels. According to recent studies (IPCC, 2023), the burning of fossil fuels like coal, oil, and gas significantly contributes to the accumulation of greenhouse gases in the atmosphere, particularly carbon dioxide (CO_2) and methane (CH_4). Farmers are among the most vulnerable groups affected by climate change, facing both physical and mental health challenges due to their direct exposure to environmental hazards. Rising temperatures contribute to heat stress, dehydration, and increased incidence of heat-related illnesses, especially during peak harvesting seasons. Vector-borne diseases such as malaria and dengue have become more common due to changing humidity and rainfall patterns (Atwoli et al 2021, WHO 2015). Salinity intrusion in drinking water is linked to hypertension, kidney diseases, and skin infections, particularly in coastal regions. Furthermore, crop failures, financial instability, and displacement caused by climate disasters significantly impact farmers' mental health, leading to stress, anxiety, and even suicidal tendencies. Mental health is also impacted by the disturbance of social capital, especially for women. Additionally, physical health problems like respiratory, gastrointestinal, and cardiovascular disorders are predicted to rise due to climate change, which may subsequently exacerbate mental health. It is also anticipated that mental health conditions like depression and cognitive decline may be exacerbated by nutritional deficits brought on by food shortages, especially in poorer nations. As a result, the effects of climate change on mental health are complex and have an impact on both individuals and communities. Influences on actual wellbeing and local prosperity might have indirect effects on psychological well-being. There is a connection between emotional and physical well-being. A decline in psychological wellness will occur shortly after a severe influence on an individual's actual wellbeing. Due to their susceptibility and worries about potential threats, they pose a threat to joyful prosperity. These are the social and local repercussions of large-scale ranching, conflicts linked to mobility, and changes that occur after a conflict or disaster.

Research indicates that the rate of self-destruction rises after environmental change, indicating a decline in emotional well-being. Farmers have nothing left over after this event, and at the start of the next season, they had to get a large sum to sell their goods, reduce their stock, and grow crops. These effects have led to an increase in grief, family badness, and self-destruction. Farmers frequently deal with issues related to their friends' and family members' mental health, such as disappointment, sadness, indignity, and captivity. Compared to other implications, such as social collaboration, media, and communication, some of the effects of mental correspondence are more comprehensive and progressive. Generally speaking, farmers will be farther away from social connections both inside and between networks. Networks are forced to migrate or relocate because to stress on limited resources. It deteriorates due to extreme weather events caused by environmental change. Health issues of Farmers i) Heat Stress, ii) Respiratory Problems, iii) Skin condition, iv) Waterborne disease, v) Vector borne disease, vi) Anxiety, vii) Mental health Issue and viii) Asthma (Baker et al. (2022), Wilson (2010), Levy et al (2018))

The primary cause of contemporary climate change is the increase in GHGs due to human activities. Pachauri et al. (2014) identify the burning of fossil fuels, industrial activities, and deforestation as key drivers. These activities increase the concentration of carbon dioxide in the atmosphere, which traps heat and leads to a warming effect known as the greenhouse effect. Hansen et al. (2017) further highlights the role of land-use changes, especially the conversion of forests to urban areas or agricultural land, which significantly contributes to the carbon footprint. Korasidis et al (2018) argues that while these natural processes influence short-term climate variability, the overwhelming scientific consensus is that human activity is the dominant force behind the rapid rise in global temperatures. Stern (2007) emphasizes the need for both global mitigation efforts to reduce emissions and local adaptation strategies to deal with the inevitable changes already underway. Raftery et al. (2017) used multiple models to predict possible climate outcomes, ranging from moderate warming to catastrophic temperature increases, depending on future human actions, particularly in terms of reducing emissions. The local climate has a significant impact on farming operations (Howden et al. 2007; Kalra et al. 2007). Global food yields are unavoidably impacted by climate fluctuation and change (Lobell et al. 2011; Ray et al. 2015). Adaptation is still a non-negotiable choice for farmers because mitigation efforts may be beyond their short-term capabilities (Gopalakrishnan et al. 2019). Therefore, farmers' primary worry now is converting to climate-resilient farming enterprises. By changing the selection of farm types in response to climate change, it is possible to modify the dominant patterns of a community's agricultural enterprises, or farming systems (Dixon et al. 2001, Etwire 2020). However, non-climatic factors like soil fertility, input costs, market prices, agricultural policy, and extension assistance also have an impact on agricultural practices in addition to climate

change (Bhatta et al. 2016). When soil conditions are unfavorable or input costs are higher than the market price of a given crop's production, farmers may decide to switch farming operations. As a result, both climatic and non-climatic causes contribute to changes in farming systems. According to Lobell et al. (2021), for every 1°C rise in temperature, global wheat yields decline by approximately 6%, while maize yields decrease by about 7%. These temperature increases not only reduce crop productivity but also alter growing seasons, affecting harvest cycles and food security. Furthermore, changing rainfall patterns have intensified droughts in some regions while causing flooding in others, leading to increased crop failure rates (FAO, 2020).
From the above study we found that the impact of climate change on the farmer's health is rare in case of Rajshahi district. The introduction and related literature study is given in section 1, section 2 presents the methodology, section 3 presents the result and discussion and finally section 4 presents the conclusion.

2. Methodology

2.1 Study Area and Sampling Strategy

Randomly selected Poba Upazila from Rajshahi district is chosen for study area. The study used simple random sampling technique to select participants from a list of eligible veterans residing in Poba. This method ensures that each individual has an equal chance of being included, providing a representative sample of the veteran population. Determining the appropriate sample size is crucial to ensuring the reliability and generalizability of research findings. Since the total population size of farmers in Poba Upazila is unknown, Cochran's formula is commonly used for sample size estimation:

$$N_0 = \frac{z^2(1-p)p}{e^2}$$

Where N_0 is the required sample size, z is the standard normal value at the desired confidence level, p is the proportion of population and e is the margin of error.

Using a 95% confidence level and a 5% margin of error, the formula gives a required sample size of approximately 385. However, considering resource availability, time constraints, and logistical feasibility, a final sample size of 350 farmers was chosen. This still ensures high statistical power while being manageable for data collection and analysis.

2.2 Statistical Analysis Methods

In this study, we employed statistical software tools, specifically SPSS and R Programming, to perform comprehensive data analysis. These tools facilitated the execution of various statistical methods, including descriptive statistics, frequency analysis, and graphical data visualization.

2.3 Crosstabulation Analysis

Crosstabulation (or contingency table analysis) is a method used to examine relationships between two or more categorical variables by displaying their frequency distribution in a tabular format. In SPSS or other statistical tools, crosstabs help to analyze patterns, associations, and potential interactions between variables. Crosstabulation presents the joint frequency distribution of two categorical variables in a contingency table.

Chi-Square Test for Independence: To test whether the row and column variables are independent, we use the Chi-square statistic:

$$\chi^2 = \sum\sum\frac{(O_{ij} - E_{ij})^2}{E_{ij}} \sim \chi^2_{(r-1)(c-1)}$$

O_{ij} is the observed and E_{ij} is the expected frequency.

2.4 Binary Logistic Regression Modeling

Binary Logistic Regression is a statistical method used to model the relationship between a binary dependent variable (with two outcomes, e.g., Yes/No, 0/1) and one or more independent variables. Unlike linear regression, it predicts the probability of an event occurring rather than a continuous outcome. The binary logistic regression model is

$$Y = logit(p) = \ln\left(\frac{p}{1-p}\right) = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_k X_k + \varepsilon_j$$

Where, Y be the binary outcome variable (farmers' general health issues). X_1 X_2 X_3 ………… X_K be the independent variables representing climate change factors and ε error term.

Now test the following hypothesis:

H_0: β_j=0 or OR=1, where, j = 1, 2, 3.

H_1: H_0 is not true.

Where, OR (odds ratio) = $e^{\beta j} = e^0 = 1$

If the regression coefficient is positive, non-reference case (group) is more likely to get Yes for outcome variable; on the other hand, if regression coefficient is negative, non-reference case (group) is less likely to get Yes for outcome variable. The OR is useful for comparing non-reference group to reference getting time (how many time) more or less to get Yes case.

3. Result and Discussion

3.1 Frequency Distribution

A frequency distribution is a statistical representation that displays the number of observations within a given interval. The representation of a frequency distribution can be graphical or tabular. The frequency distribution of farmers by sex is given in table 1.

Table 1: Frequency Distribution of the Farmers by Sex

	Frequency	**Percent**	**Valid Percent**	**Cumulative Percent**
Female	38	10.9	10.9	10.9
Male	312	89.1	89.1	100.0
Total	350	100.0	100.0	

Table 1 presents the frequency distribution of respondents based on the sex of the farmers. The table reveals that out of 350 farmers, 312 (89.1%) are male, while 38 (10.9%) are female. This indicates that the majority of farmers in the dataset are male, suggesting a higher participation of males in farming compared to females. The frequency distribution of the farmers by occupation is given in figure 1.

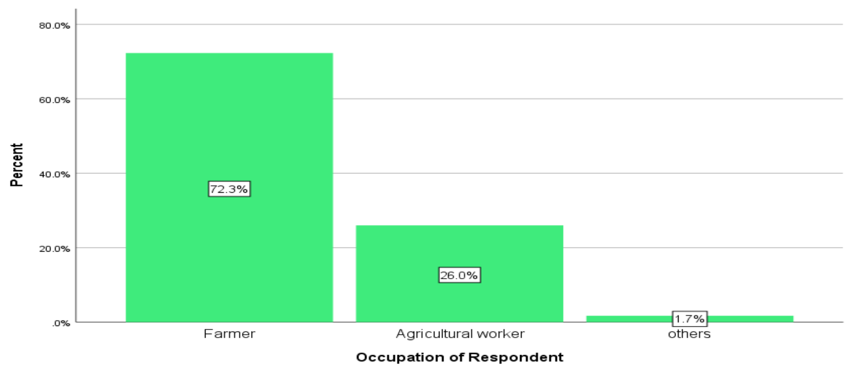


Figure 1: Bar chart of the occupation of the farmers

Figure 1 presents the bar diagram of the occupation of the farmers. The figure showed that out of 350 respondents, 253 (72.3%) are farmers, while 91 (26%) are agricultural workers. Additionally, a small proportion of respondents, 6(1.7%), belong to other occupations. This table indicates that the majority of respondents are either farmers or agricultural workers, with only a few engaged in other professions. The frequency distribution of years of farming practice is given in table 2.

Table 2: Frequency distribution of Years in Farming

	Frequency	**Percent**	**Valid Percent**	**Cumulative Percent**
less 5	25	7.1	7.1	7.1
5-10	105	30.0	30.0	37.1
eleven-20	141	40.3	40.3	77.4
more 20	79	22.6	22.6	100.0
Total	350	100.0	100.0	

Table 2 showed that crop farming is dominant, with 60% of farmers having 11-20 years of experience. Livestock farming is more common among those with less than 5 and 5-10 years of experience (around 35% each), indicating it attracts early and mid-level farmers. Mixed farming is preferred by the most experienced, with nearly 40% having over 20 years of experience. Overall, mid-experienced farmers favor crop farming, livestock farming is popular among early-stage farmers, and mixed farming is preferred by highly experienced farmers. The frequency distribution of the observation of climate change is given in figure 2.

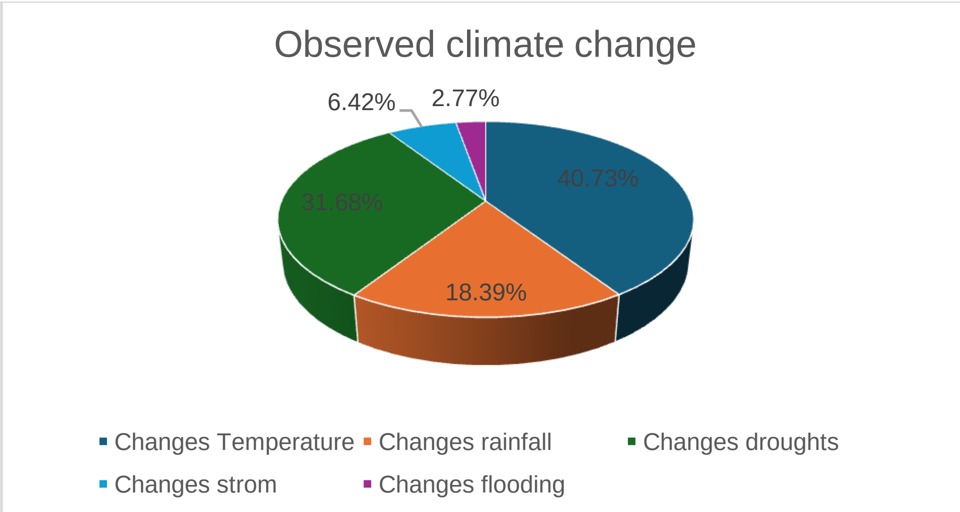


Figure 2: Pie chart of the respondent observed Climate Change Observations

The most frequent observed climate changes were temperature, rainfall changes and droughts with 40.73% ,18.39% and 31.66% of cases reporting these changes, respectively. Storm and flooding were less common. The frequency distribution of the health condition reported is given in table 3.

Table 3: Frequency distribution of Health condition reported.

	Responses Frequency	Percent
Heat stress	246	31.5%
Respiratory problem	156	20%
Skin condition	146	18.7%
Water borne	172	22%
Vector borne	61	7.8%
Total	781	100%

Dichotomy group tabulated at value 1.

Table 3 shows the frequency distribution of health conditions reported by individuals. Heat stress is the most common issue, reported by 31.5% of participants, followed by Water borne at 22%. Respiratory problems were less frequent, reported by 20%, while skin condition and vector-borne diseases were the least common, with 18.7% and 7.8% reporting them, respectively. The frequency distribution of the respondent anxiety level is given in figure 3.

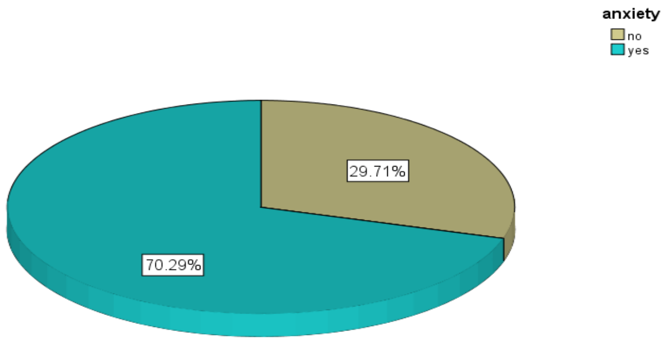


Figure 3: Pie chart of the respondent anxiety level

The data reveals that a significant proportion (70.3%) of respondents experience anxiety, while only 29.7% (figure 3) do not. This suggests that anxiety is a prevalent concern among the surveyed individuals, potentially influenced by various stressors in their environment or lifestyle. The slope chart for stress or anxiety due to farming challenges is reported in figure 4.

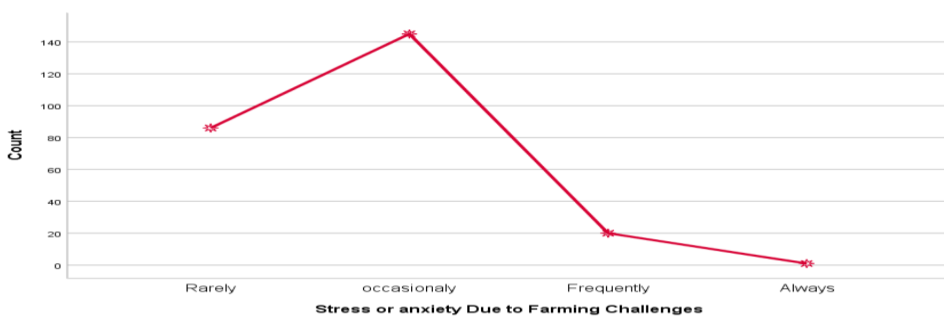


Figure 4: Slope chart for stress or anxiety due to farming challenges

The graph 4 represents the majority of respondents (41.4%) experience stress or anxiety occasionally due to farming challenges, making it the most common response. This is followed by 24.6% who rarely feel stress, indicating that a significant portion of farmers do not face frequent stress. A smaller percentage (5.7%) experience stress frequently, while only 0.3% report feeling stress always. This suggests that while farming challenges do cause stress, it is generally not persistent or overwhelming for most farmers.

The bubble chart (figure 5) illustrates the impact of financial losses on mental health challenges, with the x-axis representing financial losses and the y-axis depicting anxiety, depression, and sleep disturbances. Bubble size indicates frequency, with larger bubbles signifying higher prevalence. The findings suggest that financial losses are associated with increased cases of depression (47), sleep disturbances (35), and anxiety (24), while individuals without financial losses report fewer mental health issues (40 cases). This suggests a potential link between financial distress and worsening mental health.

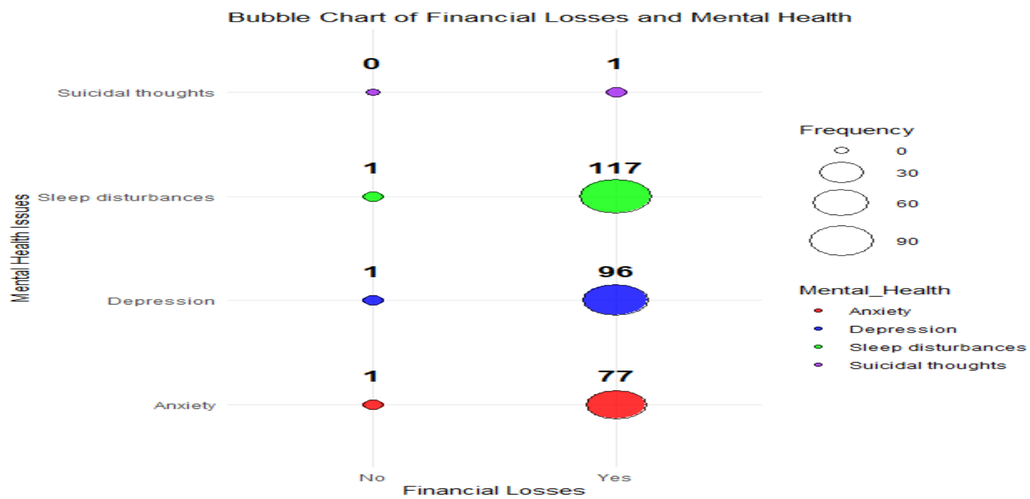


Figure 5: Bubble chart of financial losses and mental health

Figure 6, the Venn diagram illustrates the distribution of 293 observations across three health protection factors: Hydration, Equipment, and Medicine. Among these, 60 observations (20.48%) fall exclusively under Hydration, 9 (3.07%) under Equipment, and 13 (4.44%) under Medicine. Additionally, 78 observations (26.62%) are shared between Hydration and Equipment, 41 (13.99%) between Hydration and Medicine, and 10 (3.41%) between Equipment and Medicine. Notably, 82 observations (27.99%) are common to all three categories. This distribution highlights both the distinct and overlapping contributions of these health protection factors, emphasizing the extent to which individuals benefit from multiple protective measures.

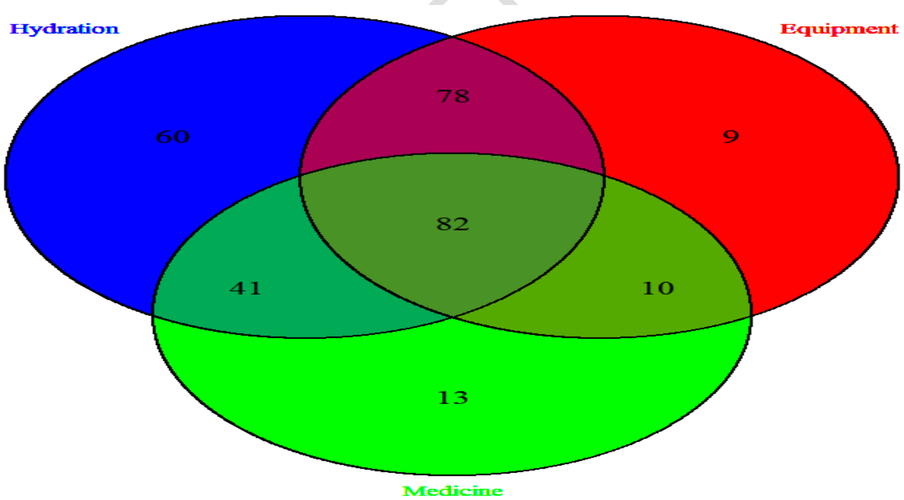


Figure 6: Venn Diagram of Health Protection Factor

The slope chart illustrates the distribution of healthcare facility accessibility among individuals with and without access to healthcare, highlighting differences in accessibility levels.

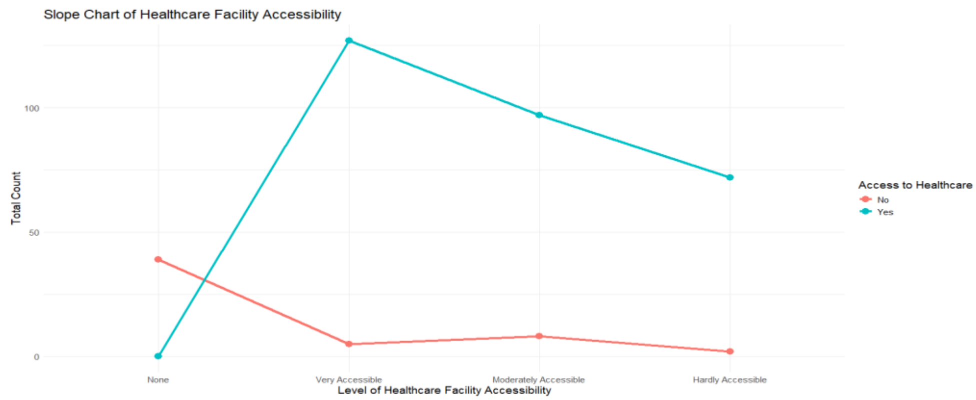


Figure 7: Frequency Distribution of Healthcare Facility Accessibility.

Among individuals without access to healthcare (n = 54), the majority reported "None" (39, 72.2%), followed by "Moderately Accessible" (8, 14.8%), while "Very Accessible" (5, 9.3%) and "Hardly Accessible" (2, 3.7%) were the least reported categories. Conversely, among individuals with access to healthcare (n = 296**)**, the distribution shows a marked shift. The majority reported "Very Accessible" (127, 42.9%**)** and "Moderately Accessible" (97, 32.8%), while "Hardly Accessible" (72, 24.3%) still accounted for a significant proportion. Notably, no respondents in this group reported having "None" accessibility. This comparison underscores a clear disparity in healthcare facility accessibility, with individuals lacking healthcare access experiencing significantly lower levels of facility accessibility.

3.2 Cross Tabulation

Cross Tabulation Analysis of the Relationship Between Health, Climate Change, and Livelihood Factors Among Farmers in Rajshahi.

Association between health issues and climate change exposure

H_0: There is no association between health issues and climate change exposure.

H_1: H_0 is not true

Table 4: Association Between Health Issues and Climate Change Exposure

Health Issues and Climate Change								
Variable		Health Issues Related to Climate Change		Total	Pearson Chi-Square		Likelihood Ratio	
		Yes	No		Value	p value	Value	p value
Climate Change	Yes	282	17	299	175.8797	0.000	133.3355	0.000
	No	10	41	51				
Total		292	58	350				
0 cells (0.0%) have expected count less than 5. The minimum expected count is 8.45.								

Table 4 presents the association between health issues related to climate change and climate change exposure. The value of the Chi-Square is observed to be 175.87, with a p-value of 0.000

(>0.05). Therefore, the null hypothesis may be rejected (accepted) at the 5% level of significance. It can be concluded that there is a significant association between health issues related to climate change and climate change exposure.

Association Between food insecurity and health issues

H_0: There is no association between food insecurity and health issues

H_1: H_0 is not true

Table 5: Association between food insecurity and health issues

Pearson Chi-Square		Likelihood Ratio	
Value	p value	Value	p value
138.287	**0.000**	180.216	0.000

Table 5 presents the association between reduced food availability and the health impacts of food insecurity. The value of the Chi-Square is observed to be 138.287, with a p-value of 0.000 (<0.05). Therefore, the null hypothesis is rejected at the 5% level of significance. It can be concluded that there is a significant association between reduced food availability and health impacts of food insecurity.

Association between financial losses and mental health

H_0: There is no association between financial losses and mental health

H_1: H_0 is not true

Table 6: Association between financial losses and mental health

Financial losses and impact mental health.								
Variable		Financial losses		Total	Pearson Chi-Square		Likelihood Ratio	
		Yes	No		Value	p value	Value	p value
Financial Loss Affecting Mental Health	None	1	55	56	321.42	0.000	270.91	0.000
	Anxiety	77	1	78				
	Depression	96	1	97				
	Sleep Disturbance	117	1	118				
	Suicidal thoughts	1	0	1				
Total		292	58	350				

Table 6 presents the association between financial losses and financial loss affecting mental health. The value of the Chi-Square is observed to be 321.42, with a p-value of 0.000 (<0.05). Therefore, the null hypothesis is rejected at the 5% level of significance. It can be concluded that there is a significant association between financial losses and financial loss affecting mental health.

Association among increased temperature and anxiety, heat stress, respiratory problems and Skin conditions

Anxiety

H_0: There is no association between increased temperature and anxiety

H_1: H_0 is not true

Heat stress

H_0: There is no association between increased temperature and heat stress

H_1: H_0 is not true

Respiratory problems

H_0: There is no association between increased temperature and Respiratory problems

H_1: H_0 is not true

Skin problems

H_0: There is no association between increased temperature and Skin problems

H_1: H_0 is not true

Table 7: Association between increased temperatures and anxiety, heat stress, respiratory problems and Skin conditions

		Value	P value
Anxiety	Pearson Chi-Square	18.789	0.000
	Likelihood Ratio	17.604	0.000
	N of Valid Cases	350	
Heat stress	Pearson Chi-Square	91.588	0.000
	Likelihood Ratio	85.367	0.000
	N of Valid Cases	350	
Respiratory problem	Pearson Chi-Square	36.676	0.000
	Likelihood Ratio	41.1140	0.000
	N of Valid Cases	350	
Skin problem	Pearson Chi-Square	11.5685	0.001
	Likelihood Ratio	12.1921	0.000
	N of Valid Cases	350	

Table 7 presents the association between increased temperatures and anxiety among farmers. The Chi-Square test value is 18.789, with a p-value of 0.000 (<0.05), indicating statistical significance. Therefore, the null hypothesis is rejected at the 5% level of significance. It can be concluded that there is a significant association between increased temperatures and anxiety among farmers, suggesting that those who experience temperature changes are more likely to report anxiety.

The association between increased temperatures and heat stress among farmers. The Pearson Chi-Square value is 91.588, with a p-value of 0.00 (< 0.05), indicating a statistically significant association between increased temperatures and heat stress at the 5% significance level. This suggests that farmers who experienced increased temperatures were more likely to report heat stress compared to those who did not.

The chi-square test was conducted to examine the association between increased temperatures and respiratory problems among farmers. The observed chi-square value is 36.676with a p-value of 0.000(>0.05). This suggests that there is a statistically significant relationship between increased temperatures and the occurrence of respiratory problems among the farmers at the 5% significance level.

The chi-square test was conducted to examine the association between increased temperatures and Skin condition among farmers. The observed chi-square value is 11.5685 with a p-value of 0.000 (>0.05). This suggests that there is a statistically significant relationship between increased temperatures and the occurrence of Skin condition among the farmers at the 5% significance level. The slope graph from figure 8 compares the frequency of health issues (Anxiety, Heat Stress, and Respiratory Problems) with respect to Temperature Increase (Changes_Temp: 0 vs. 1) and Response Type (Yes/No). It shows that heat stress and anxiety increase with rising temperatures, while respiratory problems decrease. This suggests a strong association between temperature rise and anxiety, whereas respiratory issues may be influenced by other factors. The "No" responses follow an opposite trend, with fewer reports of heat stress and anxiety when temperatures do not increase.

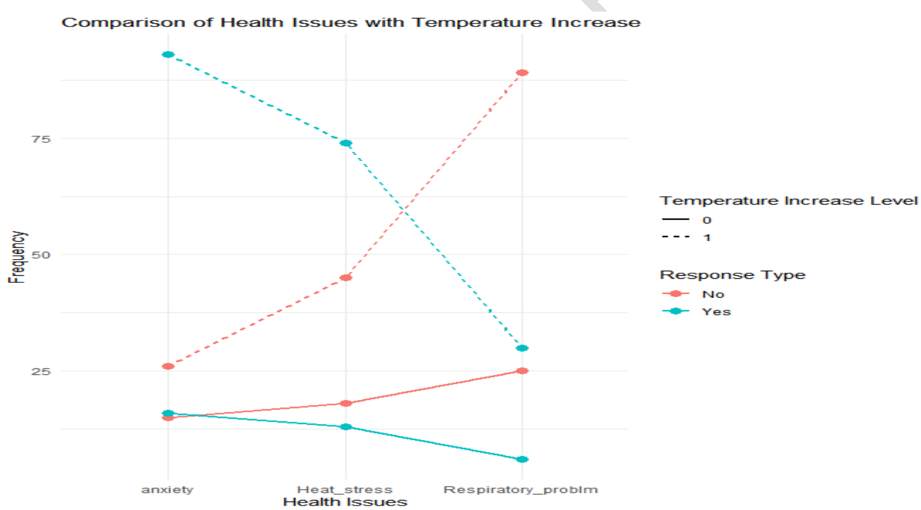


Figure 8: Slope graph for health issues with temperature increases

Association among irregular rainfall and anxiety, heat stress, respiratory problems and Skin conditions

Anxiety

H_0: There is no association between irregular rain fall and anxiety

H_1: H_0 is not true

Waterborne diseases

H_0: There is no association between irregular rain fall and anxiety and Waterborne diseases

H_1: H_0 is not true

Vector-borne diseases

H_0: There is no association between increased temperature and vector-borne diseases

H_1: H_0 is not true

Skin problems

H_0: There is no association between increased temperature and respiratory problems

H_1: H_0 is not true

Table 8: Association among irregular rainfall and anxiety, Waterborne diseases, Vector-borne and respiratory problems

		Value	P value
Anxiety	Pearson Chi-Square	5.070	0.024
	Likelihood Ratio	4.808	0.028
	N of Valid Cases	350	0.000
Waterborne diseases	Pearson Chi-Square	40.630	0.000
	Likelihood Ratio	46.331	
	N of Valid Cases	350	
Vector-borne diseases	Pearson Chi-Square	4.455	0.0347
	Likelihood Ratio	5.278	0.021
	N of Valid Cases	350	
respiratory problems	Pearson Chi-Square	28.93	.000
	Likelihood Ratio	33.106	.000
	N of Valid Cases	350	

From Table 8 we found that there is a significant association between changes in rainfall and anxiety. The Pearson Chi-Square value is 5.070552, with 1 degree of freedom, and an asymptotic significance (p-value) of 0.024. Since this p-value is less than the commonly used significance level of 0.05, we reject the null hypothesis. The analysis suggests that changes in rainfall appear to have a significant impact on the anxiety levels of the participants in the study.

The Chi-Square test value 40.639316, with a p-value of 0.000 (>0.05), indicating statistically significance. Therefore, the null hypothesis is rejected at the 5% level of significance. It can be concluded that there is a significant association between irregular rainfall and waterborne diseases among farmers, suggesting that those who experience irregular rainfall are necessarily more likely to report waterborne diseases.

The Chi-Square test results indicate a significant association between irregular rainfall and vector-borne disease (χ^2 = 4.455, p = 0.0347). Since the p-value is much greater than 0.05, we reject the null hypothesis, suggesting that irregular rainfall significantly influence the occurrence of vector-borne diseases in this dataset.

The results of the Chi-Square test indicate that there is no significant association between changes in rainfall and respiratory problems. The Pearson Chi-Square value is 28.93, with 1 degree of freedom, and an asymptotic significance (p-value) of 0.00. Since this p-value is less than the commonly used significance level of 0.05, we reject the null hypothesis. The analysis suggests that changes in rainfall appear to have a significant impact on the respiratory problems of the participants in the study.

3.3 Logistic Regression

The estimated result from binary logistic regression is reported in table 9.

Table 9: Classification Table in Step 0 for Binary Logistic Regression

Classification Table					
Variable			Predicted		Percentage Correct
			Health Issues Related to Climate Change		
			No	Yes	
Observed	Health Issues Related to Climate Change	No	0	58	.0
		Yes	0	292	100.0
Overall Percentage					83.4

Table 9 represents the classification table where no independent variables are included in the model. If all independent variables are zero, then the accuracy of the model is **83.4%.**

Table 10: Variables in the Equation for Binary Logistic Regression

Variables in the Equation							
Step 0		B	S.E.	Wald	df	Sig.	Exp(B)
	Constant	1.6163	0.1437	126.41	1	0.000	5.034

In **Table 10**, the intercept (B = 1.616) represents the log-odds of experiencing health issues related to climate change when no predictors are included. The p-value (0.000) indicates statistical significance ($p < 0.05$). The odds ratio (Exp(B) = 5.0344) suggests that, in the absence of predictors, farmers are 5.0344 times more likely to experience health issues than not.

Table 11: Model Summary for Binary Logistic Regression Assessing the Effect of Climate Change Factors on Farmers' General Health Issues

Model Summary			
Step 1	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
	174.217	0.3298	0.5566

In **Table 11** (Model Summary**)**, the -2 Log Likelihood (174.217) indicates the goodness of fit, with lower values suggesting a better model. The Cox & Snell R^2 **(**0.329**)** and Nagelkerke R^2

(0.556) represent the proportion of variance explained by the model, with Nagelkerke R^2 suggesting the model explains about 55% of the variation in health issues related to climate change.

Table 12: Hosmer and Lemeshow Goodness-of-Fit Test for Binary Logistic Regression

Hosmer and Lemeshow Test			
Step	Chi-square	df	Sig.
1	16.4819	5	0.00559

The Hosmer and Lemeshow Test evaluates the goodness of fit for a logistic regression model. It checks whether the observed data match the expected probabilities predicted by the model. The p-value (Sig.) 0.731 (>0.05) indicates there is no significant difference between the observed and expected values. That means, our selected model fitted good.

Table 13: Predicted Probabilities for Binary Logistic Regression

Predicted					
			Health Issues Related to Climate Change		
	Observed		no	yes	Percentage Correct
Step-1	Health Issues Related to Climate Change	no	38	20	65.5
		yes	9	283	96.9
	Overall Percentage				91.7

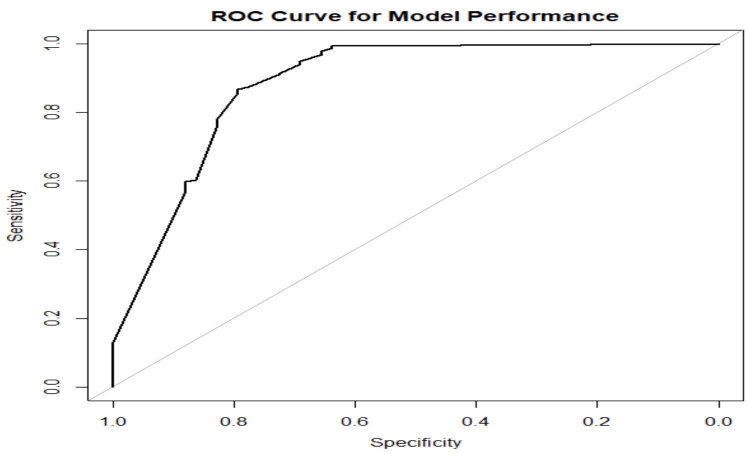
Table 14: Variables in the Equation for Binary Logistic Regression

Variables in the Equation									
								95% C.I. for EXP(B)	
		B	S.E.	Wald	df	Sig.	Exp(B)	Lower	Upper
Step 1	Changes_Temperature(1)	-1.105	.500	4.891	1	.027	.331	.124	.882
	Changes_rainfall(1)	-1.722	.516	11.118	1	.001	.179	.065	.492
	Changes_droughts(1)	-.852	.446	3.648	1	.056	.427	.178	1.023
	Changes_strom(1)	-.850	1.093	.604	1	.437	.428	.050	3.641
	Changes_flooding(1)	-19.618	8105.370	.000	1	.998	.000	.000	.
	Water Scarcity(1)	-1.407	.473	8.847	1	.003	.245	.097	.619
	Constant	24.032	8105.370	.000	1	.998	27340324734		

Table 14 showed that, none of the independent variables (predictors) or their subcategories were statistically significant (all p-values > 0.05)

This measures the model's ability to correctly predict the outcome. The higher the AUC (closer to 1), the better the model is at distinguishing between different outcomes. An AUC of 0.88 is excellent, meaning the model does a great job of predicting the results.

This value helps us determine how well our model fits the data while considering its complexity. A lower BIC value indicates a better model. In this case, the model is a good fit, but we would compare it with other models to be sure.



The closer the ROC curve is to the top-left corner, the better the model's performance, as this point represents perfect classification with no false positives or false negatives. Since an AUC of 0.88 is quite high, it suggests that the model is performing excellently in predicting the outcome, demonstrating strong discriminatory power between the positive and negative classes.

The analysis reveals that several climate change factors are associated with health outcomes, with varying degrees of statistical significance. Changes in temperature, rainfall, and water scarcity were consistently significant across multiple models, suggesting that they have a strong impact on health issues such as heat stress, respiratory problems, and waterborne diseases.

The results from the Chi-Square and logistic regression tests presented in the tables reveal a complex relationship between various climate change factors and their impact on public health, especially among farmers. In Table 4, a Chi-Square value of 175.87 (p-value = 0.000) indicates a significant association between health issues related to climate change and climate change exposure. This suggests that as climate change intensifies, the likelihood of experiencing health-related issues increases, providing strong evidence to reject the null hypothesis. Similarly, in Table 5, the association between reduced food availability and the health impacts of food insecurity shows a significant Chi-Square value of 138.287 (p-value = 0.000), again rejecting the null hypothesis and confirming that food security plays a significant role in the health outcomes of those affected by climate change. The associations between financial losses and mental health impacts and between increased temperatures and anxiety also show strong statistical significance, further reinforcing the evidence of climate change having broad and severe impacts on mental well-being.

On the other hand, the association between healthcare access and climate change's effects on public health was found to be statistically insignificant (p-value = 0.986), indicating that healthcare access does not modify the relationship between climate change and public health outcomes, at least in this sample. While some results indicate no significant impact, such as the association between prolonged droughts and anxiety, most of the findings strongly point to a connection between climate-related events and increased health risks. For instance, the Chi-Square test results for temperature changes, irregular rainfall, and their effects on health outcomes like respiratory issues and skin conditions are statistically significant, indicating that these factors directly influence the prevalence of these conditions.

The logistic regression analyses further confirm these findings, with significant predictors of health outcomes including temperature changes, rainfall variations, and water scarcity. In the binary logistic regression model for general health issues, variables like temperature and rainfall changes significantly predict the likelihood of health problems, particularly heat stress and respiratory issues, with odds ratios highlighting the increased likelihood of these outcomes as climate factors worsen. In the multinomial logistic regression model, the results indicate that financial losses have a profound impact on mental health outcomes like anxiety, depression, and sleep disturbances, demonstrating that financial instability caused by climate-related events significantly worsens the mental health of affected individuals. The findings emphasize the multidimensional nature of the effects of climate change, spanning both physical and mental health concerns, and highlight the need for targeted interventions to mitigate these effects on vulnerable populations, such as farmers.

4. Conclusion and Recommendation

This study investigates the impact of climate changes on public health especially in the Rajshahi District of Bangladesh, focusing on the yields of Aman and Boro rice and the health outcomes of climate-related factors.

The study examined the impacts of climate change on public health, with a particular focus on the health of farmers in the region. The findings from the Chi-Square and logistic regression analyses indicate a significant relationship between climate change factors—such as temperature, rainfall, and water scarcity—and health issues like heat stress, respiratory problems, and waterborne diseases. These findings suggest that climate change is not only a threat to food security and agricultural productivity but also poses significant risks to public health, particularly among vulnerable populations like farmers. The analysis also reveals the role of food insecurity and financial instability in exacerbating mental health problems, such as anxiety and depression. However, while most of the climate-related health impacts were statistically significant, some variables, such as healthcare access, did not show a statistically significant relationship with health outcomes. This suggests that while healthcare access is important, its direct role in modifying the effects of climate change on health may be limited in this specific context.

Continuous monitoring of climate variables and their effects on agriculture and public health is vital. The future of vulnerable regions like Rajshahi District relies on collective action. Collaboration between agricultural, public health, and environmental sectors is essential to mitigate the impacts of climate change. With significant investment in human and financial resources, and a commitment to long-term, integrated planning, we can safeguard food security, protect public health, and build a sustainable future for vulnerable communities.

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