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Climate Change Effects on Crop Area Dynamics in the Cachar District of Assam, India: An Empirical Study

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ABSTRACT

Climate change is a worldwide phenomenon that significantly impacts the area, production, and yield of crops. Changes in climate conditions have diverse effects on farming globally. For instance, an increase in temperature can make specific crops more vulnerable to pests. Similarly, a decrease in rainfall reduces water availability, affecting both irrigated and rainfed farming practices. This study aims to investigate climate change effects on crop area dynamics in the Cachar district of Assam, India, for a period spanning from 1981 to 2017. The time series ARDL (Autoregressive Distributed Lag) model is employed to analyze the relationship between climate factors and areas under different crops. As a pre-requisite condition for ARDL, the Augmented Dickey-Fuller (ADF) test is employed to check the order of integration of area under selected crops. The research reveals that the annual average temperature negatively affects the area dedicated to chickpeas, while annual average rainfall negatively impacts the areas allocated to rice and chickpeas. Conversely, annual average relative humidity has a significant positive impact on the area of these crops in the study region. Policymakers may consider strategies and policies for agriculture by encouraging the cultivation of crop varieties that are more resilient to climate change.

INTRODUCTION

Climate change encompasses any prolonged alteration in weather patterns stemming from either natural fluctuations or human actions (Lema & Majule 2009). According to the Intergovernmental Panel on Climate Change (IPCC) in their 2007 report, shifts in the average and/or variability of climate characteristics lasting multiple decades or beyond are key indicators of climate change.Top of Form Climate variability is the variation in weather mean states at each temporal and spatial scale, while climate change is the persistence of those variations, including their origin in natural physical processes and anthropogenic factors (Cardenas et al. 2006). There are two types of climate change variability: internal (caused by processes inside the climate system itself) and external (caused by natural and manmade external causes). Since the extratropical spatial structure of climate variability is highly reliant on the seasons, this variability is typically described in terms of "anomalies," where an anomaly is the difference between the instant state of the climate system and the climatology (Hurrell & Deser 2010).

Climate change can have a substantial impact on cropping patterns in different regions of the world. Changes in average temperature and pattern of rainfall can have a substantial impact on agricultural production and cropping patterns as agriculture depends on optimal temperature ranges and predictable rainfall patterns (Porter & Semenov 2005, Lobell et al. 2007, 2011). Relative humidity and wind speed may have detrimental effects on crops through dust concentration. Wind erosion is a severe land degradation process that can influence the agricultural production system (Santra et al. 2017, Csavina et al. 2014).

It is predicted by research that the amount of land that will be cultivated in Egypt's five agroclimatic zones will decrease due to increased water needs in 2030. The cultivated area in the current cropping pattern will also decrease by 13% in 2030 compared to its counterpart value in 2014-15 (Ouda & Zohry 2018). In the Satkhira district of Bangladesh, it is reported that crop production has significantly decreased due to the effects of climate change, and local farmers have modified their cropping patterns as a result (Islam et al. 2020). It has been revealed that climatic variables differently affect crop production in Assam's Cachar district (Ahmed & Saha 2021).

In the plains of Assam that have experienced flooding, it is observed that crop diversification significantly increases farm income (Mandal & Bezbaruah 2013). In China, climate change affects farmers' crop selections. Farmers favor maize and cotton over vegetables and potatoes when temperatures rise. Farmers choose wheat over rice, soybeans, oil crops, and vegetables when precipitation rises (Wang et al. 2010). It is revealed from farm-level survey data that farms with diversified cropping patterns were able to reap greater financial benefits from farming in Assam's plains (Mandal 2014). Farmers who use this strategy are found to be more successful when they have better irrigation and institutional credit facilities. A study based in the Jashore District of Bangladesh noted that climate change has a significant impact on cereal production and cultivation patterns. Farmers adjust their cropping practices over time in response (Shaibur et al. 2018). It is observed that rainfall significantly influences the cultivation area for maize, rapeseed, mustard, and potato in the Dima Hasao district of Assam (et al. 2022). The research found that, along with other driving forces, climate variability, and change are significant causes of changing agriculture and cropping patterns in Mizoram (Sati 2017).

The Cachar district of Assam falls under the Barak Valley agro-climatic zone of Assam. The crops grown in the region are essential for local food supply and the entire state. Therefore, it is imperative to acknowledge that agriculture serves not only as a driving force for economic prosperity but also holds a substantial position in the holistic advancement of the region.

This research examines the impact of climate variables on crop area dynamics under major crops in the Cachar district of Assam. Rice, wheat, maize, rapeseed and mustard, chickpea, pigeon pea, pulses, sesamum, safflower, castor, linseed, soybean, sugarcane, potatoes, onion, etc., are the principal crops of the district, according to statistics from the "International Crop Research Institute for Semi-Arid Tropics (ICRISAT)". For this study, rice, wheat, maize, rapeseed and mustard, chickpea, pigeon pea, pulses, and sesame are chosen which are the major crops in the district.

MATERIALS AND METHODS

Data Sources

Data on annual average temperature maximum (°C), temperature minimum (°C), relative humidity (%), wind speed (m/s), at 2 meters above the earth's surface, and total rainfall (mm), were collected from the freely accessible NASA's "Prediction of Worldwide Energy Resources (POWER) project (https://power.larc.nasa.gov/data-access-viewer/)" for the period 1981-2017 (Accessed on 10th December 2021). On the other hand, Data on the area (in 000 hectares) of rice, wheat, maize, rapeseed and mustard, sesame, chickpea, pigeon pea, and pulses at the district level were collected from the online portal of ICRISAT from 1981 to 2017 (As district level agricultural data are available up to 2017 only).

Methodology

The relationship between climatic factors and area under different agricultural crops has been investigated using the time series ARDL (Autoregressive Distributed Lag) model. Charemza and Deadman (1992) introduced the ARDL test, which was then developed by Pesaran and Shin (1999) and Pesaran et al. (2001). In certain circumstances the strategy is more beneficial than other ways. First, the ARDL technique may be employed even when independent variables have distinct integration orders. Here according to the results of the unit root test, certain variables are stationary at level, while others are stationary at their first difference in this study (Table 1). This indicates that the integration order is mixed with both I (0) and I (1). ARDL model is hence appropriate for our investigation. Second, compared to other procedures, it provides more reliable findings for small samples. Third, since the ARDL test lacks residual correlation, it can handle potential endogeneity across variables (Marques et al. 2016). Fourth, short-run corrections may be merged with the long-run equilibrium by deriving the error correction mechanism (ECM) using a straightforward linear transformation without using the knowledge about long-run equilibrium in ARDL (Ali & Erenstein 2017). Through the automated lag selection option in Eviews12, the Akaike information criterion (AIC) is employed to establish the optimal lags for the variables.

To investigate the association of selected climate variables, i.e., average temperature, rainfall, relative humidity, and wind speed, with area under crops in the Cachar district of Assam throughout the period 1981-2017, the following model is specified:

$$CA_t = f\,(Avgtemp_t, Rain_t, RH_t, WS_t) \qquad \ldots(1)$$

Where CA_t indicates the area under a specific crop (in 000 hectares) over time. $Avgtemp_t$ indicates average temperature (°C), which is measured as the gap between the annual average maximum and minimum temperature, $Rain_t$ is the average annual rainfall (mm), which is calculated from the monthly total rainfall; RH_t represents the average annual Relative Humidity (%) and WS_t stands average annual Wind Speed (m/s) over time. Equation (1) can also be written as:

$$CA_t = \beta_0 + \beta_1 Avgtemp_t + \beta_2 Rain_t + \beta_3 RH_t + \beta_4 WS_t + \mu_t \qquad \ldots(2)$$

The research used all variables in their natural logarithmic forms to reduce multicollinearity and instability in the time series data. Equation (2) is transformed using the natural logarithm to get the log-linear model shown below:

$$LnCAt = \beta_0 + \beta_1 LnAvgtemp_t + \beta_2 LnRain_t + \beta_3 LnRH_t + \beta_4 LnWS_t + \mu_t \quad \ldots(3)$$

The ARDL approach consists of two phases. According to Pesaran et al. (2001), the first step is to determine the long-run cointegrating relationship using either the Wald-coefficient test or F-statistics. There are two different types of critical values: lower and upper bounds. Lower-level critical values are assigned to the I (0) variables, whereas higher-level critical values are assigned to the I (1) variables. If the estimated value of the F-Statistic exceeds the upper bounds, the null hypothesis of no co-integration among the variables is rejected, indicating the presence of a long-run cointegration relationship among the variables regardless of their integration order. We cannot reject the null hypothesis if the calculated F-statistic value is less than the lower limit of the critical value, indicating the absence of a long-run equilibrium connection. Without knowing the underlying regressors' order of integration, a clear conclusion cannot be drawn when the estimated F-statistic is between lower and upper-level bounds. The ARDL bounds-testing model for this work is represented mathematically as follows:

$$\Delta\, LnCAt = \beta_0 + \beta_1 \sum_{i=1}^{n} \Delta\, LnCA_{t-i} + \beta_2 \sum_{i=1}^{n} \Delta\, LnAvgtempt_{t-i} + \beta_3 \sum_{i=1}^{n} \Delta\, LnRain_{t-i} + \beta_4 \sum_{i=1}^{n} \Delta\, LnRH_{t-i} + \beta_5 \sum_{i=1}^{n} \Delta\, LnWS_{t-i} + \gamma_1 LnCA_{t-1} + \gamma_2\, LnAvgtemp_{t-1} + \gamma_3 LnRain_{t-1} + \gamma_4 LnRH_{t-1} + \gamma_5 LnWS_{t-1} + \varepsilon_t \quad \ldots(4)$$

In this equation, Δ stands for change, β_0 For the intercept, n for the lag order. β_i, $_{i=1,..5,}$ represent the short-run effects on crop production of changes in lagged differences of crop area, average temperature, rainfall, relative humidity, and wind speed (all calculated at natural logarithmic values), respectively. Similarly, γ_i, $_{i=1,\ldots 5,}$ represents long-run effects of changes in lagged differences of the same explanatory variables on LnCA. $\mathcal{E}_t$ is an error term representing unobserved factors that affect crop production (LnCA) but are not included in the model. Pesaran et al. (2001) suggest testing the hypotheses as follows:

The null hypothesis H_0: $\gamma_1 = \gamma_2 = \gamma_3 = \gamma_4 = \gamma_5 = 0$, means the absence of cointegration, which indicates no relationship between crop production with climate variables in the long run. Acceptance of H_0 implies we cannot reject the absence of cointegration against the alternative hypothesis H_1: $\gamma 1 \neq \gamma 2 \neq \gamma 3 \neq \gamma 4 \neq \gamma 5 \neq 0$, implying the existence of a long-run relationship between climate variables and crop variables (output of selected crops). Rejection of the null hypothesis would indicate the existence of a long-run relationship.

The Error Correction Model (ECM), based on the ARDL approach, is used to examine the short-term connections between the variables, as shown in Equation (5).

$$\Delta\, LnCAt = \gamma_0 + \gamma_1 \sum_{i=1}^{n} \Delta\, LnCAt_{t-i} + \gamma_2 \sum_{i=1}^{n} \Delta\, LnAvgtemp_{t-i} + \gamma_3 \sum_{i=1}^{n} \Delta\, LnRain_{t-i} + \gamma_4 \sum_{i=1}^{n} \Delta\, LnRH_{t-i} + \gamma_5 \sum_{i=1}^{n} \Delta\, LnWS_{t-i} + \gamma_6 ECM_{t-1} + \varepsilon_t \quad \ldots(5)$$

Where the ECM (-1) term is a lagged value of the residual of the model in which the long-term relationship is obtained, ECM (-1) is the speed of adjustment parameter, which is expected to be negative.

RESULTS AND DISCUSSION

Unit Root Test Results

A pre-requisite condition for the ARDL test is to check the stationarity and the integration order of the study variables. The Augmented Dickey-Fuller (ADF) test is employed to test the order of integration of climate variables, area, and yield of selected crops. As stated in Table 1, the stationarity test is applied by taking a natural log to each variable in

Table 1: Unit root test results for area under selected crops.

Variables	ADF Unit Root Test		Order of Integration
	Level	First Difference	
LnRA	-5.859167* (-3.540328)	-----	I (0)
LnWA	-3.402381 (-3.540328)	-4.685868* (-3.557759)	I (1)
LnMA	-3.824312* (-3.540328)	------	I (0)
LnRMA	-4.231782* (-3.540328)	------	I (0)
LnSA	-0.118247 (-3.557759)	-9.478349* (-.3.544284)	I (1)
LnCPA	-4.477421* (-3.552973)	------	I (0)
LnPPA	-2.803248 (-3.540328)	-7.685080* (-3.544284)	I (1)
LnPULSEA	-4.651485* (-3.540328)	-------	I (0)
LnAvgtemp	-4.503726* (-3.540328)	-	I (0)
LnRain	-4.227482* (-3.540328)	-	I (0)
LnRH	-4.492685* (-3.540328)	-	I (0)
LnWS	-6.493417* (-3.540328)	-	I (0)

Note: t-statistic of intercept and trend model, values in the parentheses are critical values. *Indicates statistically significant at a 5 % level of significance.

level and first difference forms. The integration order is shown as a combination of I (0) and I (1) for crop area. Area under rice, maize, rapeseed and mustard, chickpea, and pulse are stationary at levels [I(0)] whereas area under wheat, sesame, and pigeon pea are stationary at their first order differences [I(1)] and climate variables are integrated at [I(0)].

LnRA, LnWA, LnMA, LnRMA, LnSA, LnCPA, LnPPA, and LnPULSEA denote the natural log value of area (000 hectares) under rice, wheat, maize, rapeseed and mustard, sesamum(sesame), chickpea, pigeon pea, and pulse production, respectively. LnAvgtemp, LnRain, LnRH, and LnWS are natural log values of average temperature (^{0}C), rainfall (mm), relative humidity (%), and wind speed (m/s), respectively.

Results of the Cointegration Test

The results of the ARDL bound test for crop area and averages of climate variables are presented in Table 2. It is observed that areas under three crops, namely rice, chickpea, and pulse, are showing long-run association with the averages of climate variables, i.e., average temperature, rainfall, relative humidity, and wind speed.

Annual Averages of Climate Variables and Crop Area

Long-run ARDL estimates: Table 3 presents long-run ARDL coefficients of annual averages of climate variables, i.e., average temperature, rainfall, relative humidity, and wind speed with crop area as suggested by ARDL F-bound test results in Table 2. It is found that areas under three crops, namely rice, chickpea, and pulse, show long-run association with climate variables. Results indicate that area under rice is negatively and significantly affected by rainfall whereas it is positively and significantly impacted by relative humidity. The coefficient of rainfall implies that an increase of 1 percent in rainfall will reduce the area under rice production by 0.35 percent, whereas an increase of 1 percent in relative humidity will lead to a growth of 0.98 percent in the rice area. The area under chickpea production is negatively and significantly associated with average temperature and rainfall but positively and significantly influenced by relative humidity. A 1 percent increase in the average temperature and rainfall decreases chickpea production by 7.03 percent and 3.46 percent, respectively. However, an increase in relative humidity by 1 percent will enhance chickpea production by 10.09 percent. Though pulse area is showing long-run cointegration with climate variables as suggested by the

Table 2: Result of cointegration test for crop area with averages of climate variables.

F-Bound Test	Null Hypothesis: No long-term cointegration	
Model for Estimation		**F-Statistics**
F_{LNRA} (LNRA/ LNAVGTEMP, LNRAIN, LNRH, LNWS)	ARDL (1 ,0, 4, 1, 4)	**9.7047 ***
F_{LNWA} ((LNWA/ LNAVGTEMP, LNRAIN, LNRH, LNWS)	ARDL (1, 1, 2, 3, 0)	3.2564
F_{LNMA} ((LNMA/ LNAVGTEMP, LNRAIN, LNRH, LNWS)	ARDL (4, 4, 4, 0, 4)	2.2400
F_{LNRMA} ((LNRMA/ LNAVGTEMP, LNRAIN, LNRH, LNWS)	ARDL (4, 4, 4, 3, 3)	0.8428
F_{LNSA} ((LNSA/ LNAVGTEMP, LNRAIN, LNRH, LNWS)	ARDL (4, 4, 3, 4, 0)	3.0739
F_{LNCPA} ((LNCPA/ LNAVGTEMP, LNRAIN, LNRH, LNWS)	ARDL (4, 1, 1, 1, 1)	**8.1688***
F_{LNPPA} ((LNPPA/ LNAVGTEMP, LNRAIN, LNRH, LNWS)	ARDL (3, 3, 2, 3, 3)	1.6487
$F_{LNPULSEA}$ ((LNPULSEA/ LNAVGTEMP, LNRAIN, LNRH, LNWS)	ARDL (1, 4, 0, 2, 4)	**4.2222***
Critical Value of Bounds		
Significance	Lower Bound (I0)	Upper Bound (I1)
10%	2.20	3.09
5%	2.56	3.49
1%	3.29	4.37

Note: * signifies rejection of the null hypothesis at a 5% significance level.

Table 3: Crop area and averages of climate variables in the long run.

Crop Area	Average Temperature	Rainfall	Relative Humidity	Wind Speed
Rice	-0.2574 (0.1661)	-0.3552* (0.0120)	0.9825* (0.0331)	-0.0412 (0.8931)
Chickpea	-7.0319* (0.0048)	-3.4673* (0.0042)	10.0953* (0.0098)	0.9739 (0.5592)
Pulse	17.211 (0.2914)	-1.7236 (0.4960)	33.8279 (0.1151)	29.1303 (0.1799)

Source: Authors' own calculation using Eviews12. Note: * denotes significance level at 5 percent. The values in the parentheses are p-values.

ARDL bound test, any statistically significant relationship is not detected between these variables.

Short-run ARDL estimates: he results of short-run ARDL coefficients of annual averages of climate variables with crop area and coefficients of error terms are presented in Table 4. The important outcome of the short-run dynamics is the calculation of the coefficient of ECM (-1), which is the speed of adjustment parameter in the long run, and it is likely to possess a negative value. ECM (-1) value of less than 1 implies monotonically convergence whereas ECM (-1) value of greater than 1 implies oscillatory convergence towards long-run equilibrium.

It is observed that short-run estimated results are different from the long-run estimates in terms of magnitudes and signs. However, the error correction coefficients of all the crops are negative and highly significant, indicating that any short-run disequilibrium is corrected back to the long-run equilibrium at certain rates through an error correction mechanism that works within the system. The coefficient of ECM (-1) is -1.1984 for rice area, which means the error correction process swings around the long-term value in a dampening manner (Narayan & Smyth 2006). After finishing the processes, the convergence to the equilibrium path will be at a rapid rate. This means an oscillatory convergence occurs for rice areas as producers adjust their cultivation and harvesting activities in response to changing climate variables in the long run.

The coefficient of error correction for areas under wheat, maize, rapeseed and mustard, sesame, chickpea, pigeon pea, and pulse are presented in the last column of Table 4, implying around 53 percent, 72 percent, 2 percent, 43 percent, 65 percent, 7 percent and 61 percent any disequilibrium in the short run is corrected within one year.

It is noted from the results that the area under chickpeas is negatively affected by annual average temperature because chickpeas are generally cool-season crops and sensitive to high temperatures (Dixit 2022). High temperatures can lead to stress during critical growth stages, affecting the yield and cultivation areas of chickpeas. Average rainfall negatively affects the area under rice and chickpeas. Rice cultivation is often associated with flooded fields, especially in lowland rice systems. Excessive rainfall beyond what is suitable for rice cultivation can lead to waterlogging and flooding, negatively affecting rice areas (Ismail et al. 2012). Chickpea is generally cultivated as a rainfed crop, relying on natural rainfall rather than irrigation. However, too much rainfall can be detrimental to chickpea cultivation, as chickpea plants may not tolerate waterlogged conditions well. Average relative humidity positively affects rice and chickpea areas as higher humidity levels can create an environment less conducive to the development and spread of certain plant diseases, contributing to healthier crop areas. Therefore, areas of selected crops are affected by climate variables, depending upon the nature of the crops.

CONCLUSIONS

The primary goal of this paper was to investigate the impact of climate change on crop area dynamics for selected crops in the Cachar district of Assam. For this purpose, the Autoregressive distributed lag (ARDL) bound test technique

Table 4: Crop Area and Averages of Climate Variables in the Short Run.

Crop Area	Average Temperature	Rainfall	Relative Humidity	Wind Speed	Coefficient of ECM (-1)
Rice	------	-0.0192 (0.6839)	0.4179 (0.1379)	0.1964 (0.1245)	-1.1984* (0.0000)
Wheat	0.7210 (0.6143)	-2.2308* (0.0099)	5.2317 (0.1972)	-----	-0.5314* (0.0001)
Maize	-1.5882 (0.1920)	-0.6806* (0.0678)	-----	-3.1635* (0.0053)	-0.7277* (0.0009)
Rapeseed and Mustard	-3.0958* (0.0255)	-2.0030* (0.0012)	7.0495* (0.0056)	0.1635 (0.8455)	-0.0223* (0.0203)
Sesame	-0.5228 (0.1212)	-0.7624* (0.0005)	4.4278* (0.0001)	------	-0.4369* (0.0002)
Chickpea	-1.2884* (0.0491)	-1.3397* (0.000)	1.5032 (0.3490)	-1.8644* (0.0058)	-0.6523* (0.0000)
Pigeon	-3.8973* (0.0000)	-0.7967* (0.0064)	1.6236 (0.2293)	-0.9545 (0.1334)	-0.0751* (0.0025)
Pulse	-0.8765 (0.6853)	-------	-0.3454 (0.9355)	2.8830 (0.2260)	-0.6197* (0.0000)

Source: Authors' own calculation using Eviews12. Note: * indicates significance levels of 5%. The values in the parentheses are p-values.

was employed by taking the natural log of all variables. The results indicate that annual average temperature has statistically significant negative effects on the chickpea area. Annual average rainfall negatively affects areas under rice and chickpeas, while annual average relative humidity affects them positively. Wind speed has no significant effects on crop area under the selected crops. In the short run, coefficients of error correction for both area and yield of selected crops are negative and significant at a 5 percent level of significance, implying that any short-run disequilibrium is corrected back to the long-run value through an error correction mechanism.

Thus, it is concluded that the effects of climate variables on the area under different crops vary among the selected crops, i.e., for some crops, the impact of a specific climate variable is negative, whereas, for some other crops, the impact of the same climate variable may be positive depending upon the nature of the crops. Policymakers may consider strategies and policies for agriculture by encouraging the cultivation of crop varieties that are more resilient to climate change.

Based on available secondary data, the study is confined to examining the impacts of climate variables on crop area dynamics in the Cachar district of Assam using a time series ARDL approach. There are future scopes to study the effects of climate change in other districts of the region using different methods where data are available. Policymakers may develop policies for agriculture by encouraging the cultivation of crop varieties that are more resilient to climate change effects.

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