Drought Prediction and its long and short run consequence on major crops in Purulia District, West Bengal: An ARDL Analysis

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Abstract

Insufficient rainfall or drought adversely affects agricultural yield, resulting in food insecurity. *The present study comprises two components. The major objectives are to analyse the frequency of droughts in the Purulia region over a 20-year period using the Normalised Rainfall Index (NRI) and to examine the short- and long-term correlations between rainfall and agricultural output. The study develops indices to monitor drought periods and employs time series econometrics to correlate them with agricultural output. It also conducts a comprehensive examination of prior research. This study organises secondary data on rainfall and rice output collected from 2001 to 2020. The research utilises a satellite data set provided by the California-based Centre for Hydrometeorology and Remote Sensing (CHRS) to collect rainfall information. The rice production data was sourced from the Purulia district's agricultural office and the district statistical handbook. According to the skewness-based NRI measurement, the study found that Purulia was undergoing a slight drought. The strong link between the underlying variables was determined by cointegration analysis and ARDL bounds testing. The results indicate that rainfall and other climatic factors positively influence the production of Aman rice in both the short and long timeframes. The study found that rice production is greatly affected by insufficient rainfall. Farmers and policy officials should explore using temperature-resistant crop varieties to prevent food scarcity.*

Keywords: *Drought, Rainfall, Aman rice, Normalised Rainfall Index, Autoregressive Distributed Lag Approach*

1.1 Introduction

Environmental challenges are the most urgent worry of the twenty-first century since it endangers livelihood security and sustainability [Xie et al. 2018]. Various studies have demonstrated that environmental concerns and climate change have a detrimental effect on agricultural production at national, international, and regional levels. Climate change adversely affects agricultural productivity and influences rainfall patterns, water quality, and availability of irrigation water [Aryal et al. 2019]. Droughts are the most expensive natural catastrophes globally and affect a bigger number of people compared to other types of disasters. Drought is a temporary deviation that mainly occurs in regions with low precipitation and varies based on dryness levels [NDMC, 2006]. Studies have identified four main types of droughts: meteorological, hydrological, agricultural, and socio-economic. Meteorological drought is due to a temporary lack of precipitation, hydrological drought is caused by insufficient water

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supply, agricultural drought results in declining soil moisture and crop failure, and socio-economic drought involves the failure of supply and demand for an economic good like water. Many research [Mishra,2012] has documented the characteristics and consequences of different droughts, whereas some research has also focused on evaluating and observing droughts. The agriculture industry is the most vulnerable to climate change, even if all big corporations are also vulnerable [Guntukula 2020]. The current study intends to identify the type of drought in the study area and its impact on agricultural productivity, specifically the principal crop, to assess long-term variability.

The production function approach is commonly used and involves analysing the relationship between crop output and environmental factors, such as climate variables, through empirical research [Mishra et al. 2013]. Disparities in food production impact farmers' income [Li et al. 2013;] and the accessibility of food [Burke 2010]. Resultantly price of food increases proves itself as a negative outcome of climate change. Nevertheless, the production function approach neglects the viewpoints of farmers about climate adaptation [Mishra and Sahu, 2014]. The hedonic approach is a strategy that evaluates rent based on physical, demographic, economic, and climatic aspects. Some study suggests a connection between climatic factors and agricultural productivity, and historical data could play a role. This method is commonly used on a global scale. An approach to identify the long-term relationship within a series is the autoregressive distributed lag (ARDL) bound test [Pesaran et al. 2001]. ARDL has been utilised in several studies to examine the correlation between climatic factors and agricultural production in both the short and long run. The study employed time series models to assess the magnitude and direction between rainfall and agricultural productivity [Acaravci & Ozturk, 2010].

1.2 *Background*

In the last several decades, research has demonstrated that the adverse effects of climate change on the agricultural industries of emerging countries have become more noticeable [Chandio et al. 2020]. Several factors, including the rapid decrease in arable land, the inconsistent climate conditions, and other events, hinder agricultural productivity. Nevertheless, these occurrences present a clear danger to food security. The countries' economic progress is bolstered by the coordination of agricultural and other industries [Ahmad et al. 2020]. Elevated temperatures impact the growth of both food and non-food crops, causing delays in maturation and reducing overall production and yield [Hatfield and Prueger 2015].

The Standardized Precipitation Index (SPI) has been utilized as a tool for monitoring and analyzing drought conditions. India is very susceptible to drought [Mishra and Singh, 2010], with the south-west monsoon providing 70–80% of the country's annual average rainfall from June to September. Severe droughts in the Indian region are mostly due to substantial decreases in rainfall, as reported in reference. Intra-seasonal rainfall variability is characterised by alternating wet and dry episodes of rainfall within the summer monsoon season [Gadgil and Joseph, 2003]. In 1987 and 1988, droughts in India led to a decrease of 36 million tonnes in food production, and the drought in 2002 caused a 1% decline in GDP [Gadgil et al., 2003].

In Purulia district, rainfall from the south-west monsoon between June and September adequately fulfils the water requirements for agriculture. Studies show that despite Purulia receiving an annual rainfall of 1331 mm, the western and south-western uplands of the area suffer from drought [Ghosh and Jana, 2017]. During summer season of Purulia, groundwater remains the only source of water supply, which is often found to be fluoride bearing because most of the surface water sources like tanks, streams etc. go dry [Bhattacharya & Chakrabarti, 2011]. Cultivation of more than one crop is generally impossible in most of the region of Purulia district due to lack of irrigational facility [Nag, 1998]. The drought conditions of Purulia district were tested by different established drought index like SPI for meteorological

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drought NVDI for vegetation health and agricultural drought [Tucker, 1979; Kogan, 1995; Rhee et al., 2010] and Standardized Water level Index (SWI) as an indicator of hydrological drought [Bhuiyan,2004]. Vegetation Condition Index or VCI has been frequently found as a suitable index for monitoring agricultural drought [Kogan, 1997]. Here this study tried to quantify the drought intensity through another index (Normalised Rainfall Index) by using the rainfall data of the region.

1.3 Objective of the Study

Developing nations are more susceptible to the impacts of climate change due to their constrained resources, limited ability to lessen unfavourable outcomes, and decreased adaptive capability [Aryal et al. 2019]. The research area is vulnerable to drought, however it is not considered severe, as indicated by multiple studies [Goswami A., 2018]. This study focuses on analyzing the impact of rainfall on the productivity of the main crops in the research area. Rainfall was the primary factor assessed to determine the presence of drought in the region from 2001 to 2020. The study observed the productivity of the main crop alongside the long-term correlation with rainfall. The project had two main objectives: first, to detect any drought patterns in the study area, and second, to establish the long-term connections between rainfall and main crop productivity. By identifying drought patterns, the research can pinpoint specific periods and conditions under which crop productivity is most vulnerable. Establishing long-term connections between rainfall and crop productivity helps to reveal trends and predict future scenarios, which is essential for developing sustainable agricultural practices.

2.1 Data

The study primarily focuses on two variables: rainfall and the productivity of the primary crops in the study area. Rainfall was the primary criteria used to identify the occurrence of drought in the region from 2001 to 2020. For the rainfall data, study collects the satellite data set provided by Centre for Hydrometeorology and Remote Sensing (CHRS) of California, United States of America. The main data set of precipitation is estimated from currently operational PERSIANN (Precipitation Estimation from Remotely Sensed Information using Artificial Neural Networks) system. The study will evaluate the productivity of the major crop (Aman rice) in the study area over the same period and analyse the long-term relationship between them. The study aims to analyse the drought pattern in the study area and examine the relationship between rainfall and productivity of the major crop in terms of long-term relations. Examine the long-term relationship by analysing its variability across time. The data of Aman rice production were obtained from District Statistical Handbook of Purulia (provided by the Bureau of Applied Economics office, West Bengal) and District Agricultural office of Purulia district.

2.2 Methods

The Normalised Rainfall Index (NRI) is used as a tool to monitor and analyse drought conditions. The study utilised 20 years of rainfall data from the district for drought estimation. Before the estimation of rainfall-based drought prediction, confirmation of normality of the rainfall data is the key requirement. The normality of rainfall data reassures us in accurately estimating droughts across the area and its blocks. This study will assess the normality of rainfall in the Purulia district from 2001 to 2020 using standardised coefficients of skewness and kurtosis given by Brazel and Balling (1986). Here, the standardized coefficients of skewness (z_1) and standardized coefficients of kurtosis (z_2) formula will be

$$z_1 = \frac{1}{\left({}^{6}/_{N}\right)^{1/2}}\left\{\frac{\frac{1}{N}\left[\sum_{j=1}^{N}(\bar{X}j-\bar{X})^3\right]}{\left[\frac{1}{N}\sum_{j=1}^{N}(\bar{X}j-\bar{X})^2\right]^{3/2}}\right\};\ z_2 = \frac{1}{\left({}^{24}/_{N}\right)^{1/2}}\left\{\frac{\frac{1}{N}\left[\sum_{j=1}^{N}(\bar{X}j-\bar{X})^4\right]}{\left[\frac{1}{N}\sum_{j=1}^{N}(\bar{X}j-\bar{X})^2\right]^{2}}-3\right\}$$

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Here, $\bar{X}^j$ is the average yearly rainfall for the j-th year and $\bar{X}$ is the average rainfall over the considering years and N is the total number of years. In order to test the null hypothesis that the individual temporal samples of rainfall came from a population with a normal (Gaussian) distribution we use above statistics. If the absolute value of standardized coefficients of skewness (z_1) or standardized coefficients of kurtosis (z_2) are greater than 1.96, there is a significant deviation from the normal curve is indicated at the 95% level.
To measure the intensities of drought for the district for different years' present study uses the Normalized Rainfall Index (NRI) [Türkes, 1996]. This measure is defined and used to depict different drought intensity periods [Table-1].

Table-1: Modified Classes of NRI Values

Index	**Character of Rainfall**
1.31 or more	Very wet (VW)
0.86 to 1.30	Moderately wet (MOW)
0.51 to 0.85	Mildly wet (MW)
0.50 to -0.50	Near normal (NN)
-0.51 to -0.85	Mild drought (MD)
-0.86 to -1.30	Moderate drought (MOD)
-1.31 or less	Severe drought (SD)

Source: Authors estimation, 2023

This index basically requires annual or seasonal rainfall and the standard deviation in order to indicate the deficit of water of any given period. The annual rainfall amount of j-th year $(\bar{X}^j)$ expressed in millimetres, long term mean $(\bar{X})$ and the standard deviation (X_{dev}) are used in calculating the NRI. The index for a given period is computed as

$$\mathrm{NRI}_{\mathrm{PURULIA}} = \frac{\bar{\mathrm{X}}^{\mathrm{j}} - \bar{\mathrm{X}}}{\mathrm{X}_{\mathrm{dev}}}$$

The study calculates the Normalised Rainfall Index (NRI) for the district annually from 2001 to 2020 and categorises each NRI value into distinct groups. The study utilised a modified form of the classification of normalised rainfall index for the classification. He categorised seven characteristics of rainfall based on NRI data in Table-1. Türkes characteristics categorise NRI values as wet, normal, and drought densities. Wet densities are determined by NRI values greater than or equal to 0.51, whereas drought densities are determined by NRI values less than or equal to -0.51. NRI values falling between 0.50 and -0.50 are classified as near normal (NN) years. The drought intensities are categorised into three classes: mild drought (MD), moderate drought (MOD), and severe drought (SD) based on the NRI values falling within the ranges of -0.51 to -0.85, -0.86 to -1.30, and -1.31 or below, respectively. The wetness densities are categorised into three classes: mild wet (MW), moderate wet (MOW), and very wet (VW) years based on the NRI values with positive sign. The study calculates absolute empirical probabilities to measure the rates of mild, moderate, and severe drought occurrences. Absolute empirical probabilities are determined by dividing the number of observed mild, moderate, and severe drought occurrences by the total number of potential occurrences. It can be formulated as

$$P_i = \frac{N}{N_y}$$

Where P_i = Absolute probabilities of occurrence of a particular type of drought. N = Number of occurrences of a given category of drought (mild, moderate and severe droughts). N_y= Total number of possible occurrence (the period specified for the station). This study also calculates the average intervals of occurrences of different types of droughts which is called as drought recurrence intervals or return periods. Recurrence intervals are calculating by using the absolute probability values. If R_i is the recurrence intervals of drought, then the recurrence intervals will be derived by the inverse of the absolute probabilities of occurrence of a particular type of drought

$$R_i = \frac{1}{P_i}$$

To observe the short and long-run influences of rainfall on Aman crop in Purulia district, study uses autoregressive distributed lag (ARDL) approach [Pesaran and Shin, 1999 and Pesaran, Shin and Smith, 2001]. ARDL has certain advantages like that firstly, this is well-suited for simultaneously estimating short-run and long-run relationship [Pesaran et al. 2001]. Secondly, the flexibility of ARDL extends to accommodate different orders of integration for the variables. Studies observed that such accommodation is effective for independent variables in the model, whether they are of order $I(0), I(1)$, or mutually cointegrated [Frimpong and Oteng, 2006]. However, ARDL is not suitable when dealing with variables of order $I(2)$. Thirdly, ARDL approach is well-suited particularly in the situations with a small sample size [Haug, 2002]. When we associated to the Johansen and Juselius cointegration test, the ARDL test confirms more consistent estimates in the case of small samples. Fourthly, the ARDL test can manage the eventual phenomenon of endogeneity among variables and it is free of residual correlation. Fifthly, by developing error correction mechanism (ECM), ARDL integrates short run adjustments with the long-run equilibrium through short run adjustments can be integrated with the long-run equilibrium simple linear transformation without trailing the information about long-run [Ali et al., 2017]. Lastly, it employs the ordinary least squares (OLS) method to examine cointegration among variables [Duasa, 2007]. This study is carried out through several stages and following we have mentioned it.

2.2.1 Unit root test

Prior to implementing the statistical models, study conducted an exhaustive assessment of each dataset to ensure stationarity. A time series dataset achieves stationarity when both its mean and variance remain constant over time, and the covariance between two time periods is contingent solely upon the temporal gap rather than the specific time points considered. Failing to meet these criteria designates the process as nonstationary. To investigate whether a time series dataset is stationary, economists often use tests like the Augmented Dickey-Fuller (ADF) test, Phillips-Perron (PP) test, or Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test. The ADF and PP tests are primary tools, and the KPSS test, serving as a complement to the former two, provides additional insights into the stability characteristics of the data. In this study, the assessment of stationarity is performed using the ADF test and PP test. If a dataset was found to be non-stationary, a differencing process will be applied using the formula $\Delta Y_t = Y_t - Y_{t-1}$. This differencing procedure was repeated until the dataset achieved stationarity. The subsequent sections delve into the details of the stationarity testing process and the specific statistical models employed. In preparation for evaluating potential cointegration among rainfall and Aman rice production, a crucial preliminary step involved a thorough investigation into the order of integration for each individual series. This preliminary analysis aimed to discern whether the examined time series were stationary or non-stationary, laying the groundwork for subsequent cointegration assessments. To achieve this, two distinct unit root tests were employed: firstly, the ADF test, and secondly, the PP test. The ADF test scrutinizes the presence of a unit root, indicating non-stationarity, by estimating a regression equation. Similarly, the PP test, while akin to the ADF test, employs a different method to handle serial correlation in errors during its assessment of unit root existence. The general form of ADF test that is used to test the stationarity of a series is

$$\Delta X_t = \alpha + \alpha_t + \alpha X_{t-1} + \delta_i \sum_{i=1}^{\rho} \Delta X_{t-1} + \varepsilon_t$$

The presence of white noise errors, denoted by ε_t, is a fundamental aspect of the model. Additional lagged terms are incorporated to ensure the independence of errors. The ADF test operates on the hypotheses that underlie its assessment considering

Null Hypothesis (H_0): Y_t is either not integrated of order zero (0) or is nonstationary.

Alternative Hypothesis (H_1): Y_t is integrated of order zero (0) or is stationary.

The evaluation involves comparing the calculated ADF statistics with critical values from Fuller's table. If the test statistic is lower than the critical value, the null hypothesis (H_0) is not rejected, indicating that the series is nonstationary or not integrated of order zero. Additionally, the p value of the test can be compared to the significance level for making this determination. A variable is considered integrated of order zero if it is stationary without differencing, while being integrated of order one implies stationarity only after the first difference. The examination involved subjecting the variables to unit root tests in both their original level and first difference states. The order of integration encompasses a combination of $I\ (0)$ and $I\ (1)$.

2.2.2 Cointegration

In the initial phase, to test the objective of the study employs bound test with the primary aim to determine the existence of co-integration status of the series [Pesaran et al., 2001]. Cointegration refers to a situation where variables exhibit a stable long-term relationship through a linear combination that is stationary. When the variables under consideration show unit roots (indicating nonstationary) and are of the same order, the cointegrating relationship, or the tendency of these variables to move together in the long run, can be examined using several methods [Engle-Granger approach, 1987, Johansen-Juselius procedure, 1992, Autoregressive Distributed Lag (ARDL) approach]. Notably, the Engle-Granger approach and Johansen-Juselius procedure are suitable when the variables share the same order of integration, whereas the ARDL method is applicable when the variables have unequal orders of integration. In the context, the study uses ARDL methods due to the differing orders of integration among the variables. Subsequently, determining the integration order in variables involves assessing the equation to determine the existence of a long-term relationship between the variables. The outcome of the bound test and the reported F-statistics value will indicate the presence of long-term relationships among the variables. If the cumulative F-statistics value exceeds a critical threshold, as previously illustrated, it signifies rejecting the null hypothesis and endorsing alternative hypotheses that indicate long-term relationships among variables.

2.2.3 ARDL Approach *to* Cointegration

With p exogenous variables the general form of ARDL (m, n) model can be written up as

$$y_t = \alpha_0 + \sum_{i=1}^{m} \alpha_i y_{t-1} + \sum_{j=1}^{p} \sum_{i=0}^{n} \beta_{ij} x_{jt-i} + \epsilon_t \ldots\ldots\ldots\ldots\ldots (1)$$

Where, $\epsilon_t \sim\ iid(0, \sigma^2)$

For only one lag of both independent and independent variables the simple ARDL $(1,1)$ model can be

$$y_t = \alpha_0 + \alpha_1 y_{t-1} + \beta_0 x_t + \beta_1 x_{t-1} + \epsilon_t \ldots\ldots\ldots\ldots (2)$$

Where, $\epsilon_t \sim\ iid(0, \sigma^2)\ and\ \alpha_1 < 1$

Estimation of the equation coefficients will provide the long-run effect and in long run it can be expected that $y_t = y_{t-1}$ *and* $x_t = x_{t-1}$ therefore the above equation is as

$$y_t = \alpha_0 + \alpha_1 y_t + \beta_0 x_t + \beta_1 x_t \dots\dots\dots (3)$$

$$(1-\alpha_1)y_t = \alpha_0 + (\beta_0 + \beta_1)x_t \dots\dots\dots\dots (4)$$

Therefore, the long run impact of y on any change in x can be given by

$$y^* = \frac{\beta_0 + \beta_1}{1-\alpha_1} \dots\dots\dots\dots\dots..(5)$$

To establish the relationship between the ARDL model and the Error Correction model (ECM), first subtract y_{t-1} from both sides of equation (2), and then include and subtract $\beta_0 x_{t-1}$on the right-hand side to achieve the desired form.

$$y_t - y_{t-1} = \alpha_0 + (\alpha_1 - 1)y_{t-1} + \beta_0(x_t + x_{t-1}) + (\beta_0 + \beta_1)x_{t-1} + \epsilon_t \dots (6)$$

Now subtracting $\beta_0 + \beta_1 = y^*(1-\alpha_1)$ from the equation (5) and replacing $\Delta y = y_t - y_{t-1}$ *and* $\Delta x = x_t - x_{t-1}$ into equation (6) it will be as follows

$$\Delta y = \alpha_0 + (\alpha_1 - 1)y_{t-1} + \beta_0 \Delta x + y^*(1-\alpha_1)x_{t-1} + \epsilon_t$$

$$\Delta y = \alpha_0 + (\alpha_1 - 1)(y_{t-1} - y^* x_{t-1}) + \beta_0 \Delta x + +\epsilon_t$$

Here equation (6) is the form of ECM for the above ARDL (1,1) model.

In our study we have to apply such application of ARDL and ECM. An ARDL model is performed here with two selected variables namely production of Aman rice and rainfall. To check the relationship among Aman rice production and rainfall the applied ARDL specification of the study is

$$P_t = \gamma_0 + \sum_{i=1}^{m} \alpha_i P_{t-i} + \sum_{i=1}^{n} \beta_i R_{t-i} + \epsilon_0$$

Here P represents Aman rice production, R represents rainfall, m and n are lag length of Aman rice production and rainfall respectively, ϵ_0 represents white noise error terms, α_0, β_0 are the drift components and γ_0 is the intercept component. The ECM of the relationship of two selected variables named production of Aman rice and rainfall can be written as

$$P_t = \gamma_0 + \sum_{i=1}^{m} \alpha_i P_{t-i} + \sum_{i=1}^{n} \beta_i R_{t-i} + ECM_{t-1} + \epsilon_0$$

Here $ECM_{t-1}$is the Error correction term for the above ARDL (m, n) model. The Cumulative Sum (CUSUM) and Cumulative Sum of Squares (CUSUMQ) diagnostic tests [Brown et al. 1975] are executed to demonstrate the stability of both long-run and short-run coefficients. Additionally, such test helps to identify the robustness of the bound test. The analysis is conducted on the residuals of the estimated model, providing insights into the stability of the parameters. If both tests yield results below the 5% significance level, indicating that the model is well-fitted, and the estimated parameters maintain stability throughout the study period.

3.1 Results and Discussion

Result section of the study is two folds in nature, firstly, the study estimates the result drought prediction of the district Purulia. Estimation of Skewness and Kurtosis for Purulia district over 2001-2020 is made [Table-2] with the adopted method [Brazel and Balling, 1986]. The computed values of skewness and kurtosis for the district are as follows.

$$z_1 = \frac{1}{0.5477}\left\{\frac{\frac{1}{20}\left[\sum_{j=1}^{20}(\bar{X}^j - \bar{X})^3\right]}{\left[\frac{1}{20}\sum_{j=1}^{20}(\bar{X}^j - \bar{X})^2\right]^{3/2}}\right\} = \frac{1}{0.5477}\left\{\frac{290635975.55}{52081961.27}\right\} = 0.51$$

$$z_2 = \frac{1}{1.0955}\left\{\frac{\frac{1}{N}\left[\sum_{j=1}^{N}\left(\bar{X}^j - \bar{X}\right)^4\right]}{\left[\frac{1}{N}\sum_{j=1}^{N}(\bar{X}^j - \bar{X})^2\right]^2} - 3\right\} = \frac{1}{1.0955}\left\{\frac{806545608666.82}{19449858240} - 3\right\} = -1.11$$

Since the absolute values of standardized coefficients of skewness ($z_1 = 0.51$) and the standardized coefficients of kurtosis ($z_2 = 1.11$) are less than 1.96, there is no significant deviation from the normal curve at 95% level of confidence. Hence the normality of rainfall is restored and no transformation is required to the rainfall series of Purulia district**.** The Normalised Rainfall Index (NRI) formula was applied to estimate NRI values for the Purulia district, resulting in values ranging from -1.27 to 2.16 over the period. From the distribution of these NRI values for the district during this period [Table-3] The study observes that the years 2005, 2009-11, 2013-14, and 2016 exhibits only moderate droughts were evident. Overall, for the entire 20-year period under consideration, the study found that the Purulia district experienced moderate drought conditions. The densities of moderate drought occurrences across these seven years varied from -0.9057 to -1.2676, with an average value of -1.0949.

Table-2: Skewness & Kurtosis of Rainfall of the District Purulia

$\bar{X}$	$\frac{1}{20}\sum_{j=1}^{N}(\bar{X}^j - \bar{X})^2$	$\frac{1}{20}\sum_{j=1}^{N}(\bar{X}^j - \bar{X})^3$	$\frac{1}{20}\sum_{j=1}^{N}(\bar{X}^j - \bar{X})^4$	$\left[\frac{1}{N}\sum_{j=1}^{N}(\bar{X}^j - X)^2\right]^{3/2}$	$\left[\frac{1}{20}\sum_{j=1}^{20}(\bar{X}^j - \bar{X})^2\right]^2$
1832.73	2789254.97	290635975.55	806545608666.82	52081961.27	19449858240

Source: Authors estimation, 2023

To determine the frequency of mild, moderate, and severe droughts, the probability of each kind occurring are calculated for every block within the Purulia area. Subsequently, the recurrence intervals of Purulia district are also calculated and presented in Table-4.
Probability values vary across different blocks for various forms of drought. The study shows that there is a 35 percent probability of experiencing any sort of drought in the Purulia district, with an average recurrence period of about 2.86 years. During the study period, only moderate drought was present in the Purulia district, with no occurrences of mild or severe drought. For the years 2010 and 2011, the NRI value of -1.27 was near the severe drought criterion of less than -1.30.

Table-3: NRI of the District Purulia

YEAR(j)	$\bar{X}^j$	**NRI**	**RAINFALL CHARACTER**
2001	2019.1	0.49	**NN**
2002	2132.05	0.78	**MW**
2003	2189.85	0.93	**MOW**
2004	2016.6	0.48	**NN**
2005	1485.7	**-0.91**	**MOD**
2006	2153.91	0.84	**MW**
2007	2243.62	1.07	**MOW**
2008	1675.86	-0.41	**NN**
2009	1433.67	**-1.04**	**MOD**
2010	1347.07	**-1.27**	**MOD**
2011	1347.07	**-1.27**	**MOD**
2012	1650.17	-0.48	**NN**
2013	1443.49	-1.02	**MOD**
2014	1374.03	-1.2	**MOD**
2015	1888.58	0.15	**NN**
2016	1461.5	**-0.97**	**MOD**
2017	2259.07	1.11	**MOW**

2018	1808.02	-0.06	**NN**
2019	2658.8	2.16	**VW**
2020	2066.48	0.61	**MW**
$(\bar{X})$	**1832.73**		
(X_{dev})	**383.15**		

Source: Authors estimation, 2023

Table-4: ***Recurrence intervals of Purulia district***

DISTRICT	***MILD DROUGHT***		***MODERATE DROUGHT***		***SEVERE DROUGHT***	
	Probability	Recurrence Interval	Probability	Recurrence Interval	Probability	Recurrence Interval
PURULIA	0	0	0.35	2.857142857	0	0

Source: Authors estimation, 2023

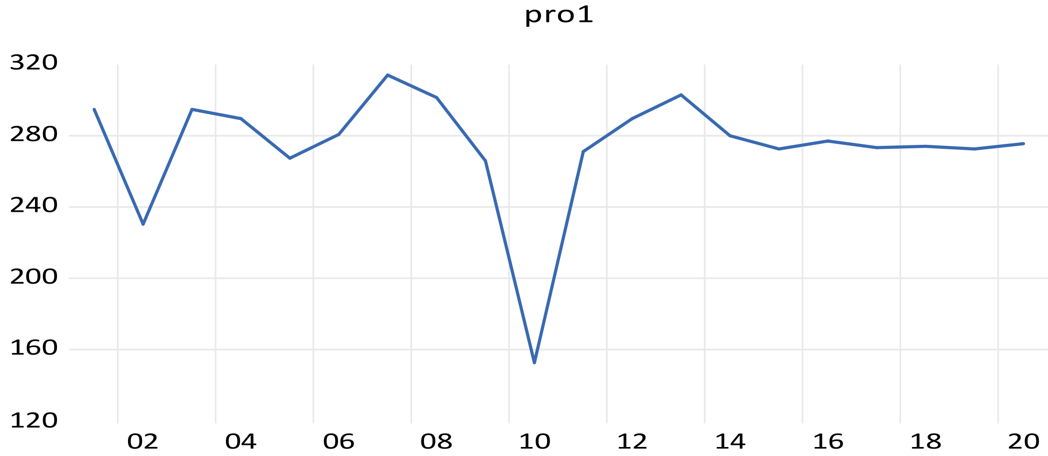
The study used annual data on Aman rice production and rainfall in Purulia district, and it is comprehensive in scope. The study commences by presenting a time series diagram of chosen variables. Next, the variables are checked for stationarity, followed by the application of ARDL and ECM techniques to evaluate short and long-term associations. Finally, several necessary diagnostic tests are conducted to meet the study's requirements. Figure-1 displays a time series plot of Aman rice output in Purulia district from 2001 to 2020, indicating stationarity. The ADF test at a 5% significance level indicated that Aman rice production in Purulia district from 2001 to 2020 is stationary, as it showed the absence of a unit root (non-stationarity) [Table-5].

Table-5: ADF & PP Unit Root Test on Aman Rice Production & Rainfall on Purulia, 2001-2020

		ADF-Unit Root Test		P-P -Unit Root Test		Order of Integration
variables		level	First Difference	level	First Difference	
Production of Aman rice	Intercept	-3.900 (0.008)	-	-4.01 (0.006)	-	I(0)
	Intercept + trend	-3.78 (0.041)	-	-3.84 (0.03)	-	I(0)
	None	-0.45 (0.50)	-	-0.37 (0.53)	-	
Rainfall	Intercept	-2.90 (0.06)	-7.42 (0.00)	-2.92 (0.06)	-7.63 (0.00)	I(1)
	Intercept + trend	-1.03 (0.90)	-7.73 (0.00)	-2.80 (0.21)	-17.02 (0.00)	I(1)
	None	-0.02 (0.66)	-7.75 (0.00)	-0.30 (0.56)	-7.78 (0.00)	I(1)

Source: Authors estimation, 2023

Figure-1: Time series plot of Aman Production in Purulia, 2001 to 2020

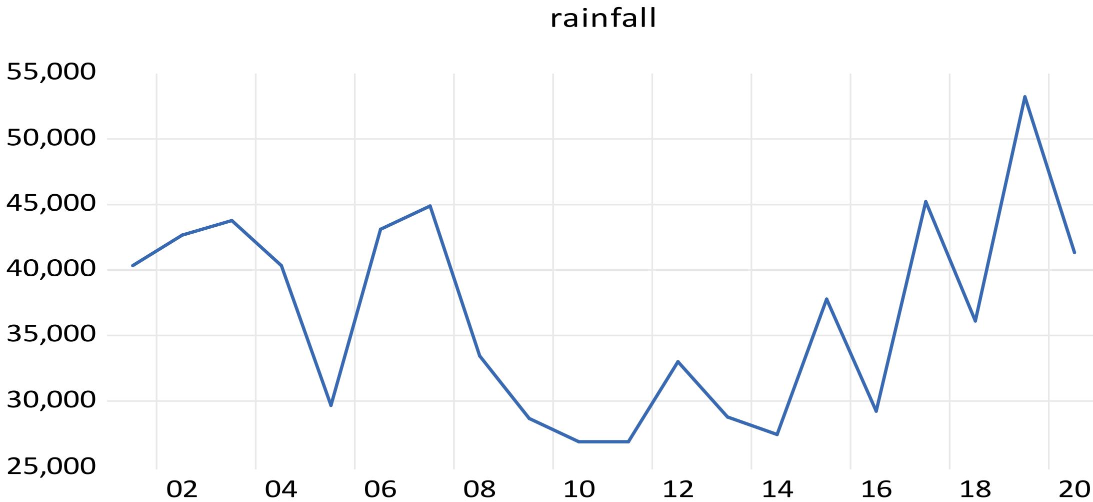


Source: Authors estimation, 2023

A time series graph of rainfall in Purulia district from 2001 to 2020 shows a non-stationary trend. The Augmented Dickey-Fuller (ADF) test at a 5% significance level confirmed the presence of a unit root, indicating that the rainfall in Purulia district was non-stationary during the period 2001-2020. The critical values for the rainfall variable suggest that the variables are non-stationary according to Table-5. This is consistent with the rainfall diagram shown in Figure-2, which demonstrates a non-constant mean and variance over time for rainfall in Purulia district from 2001 to 2020. The study attempts to overcome this issue by transforming the data by the application of ordinary differencing, as shown in Figure-3.

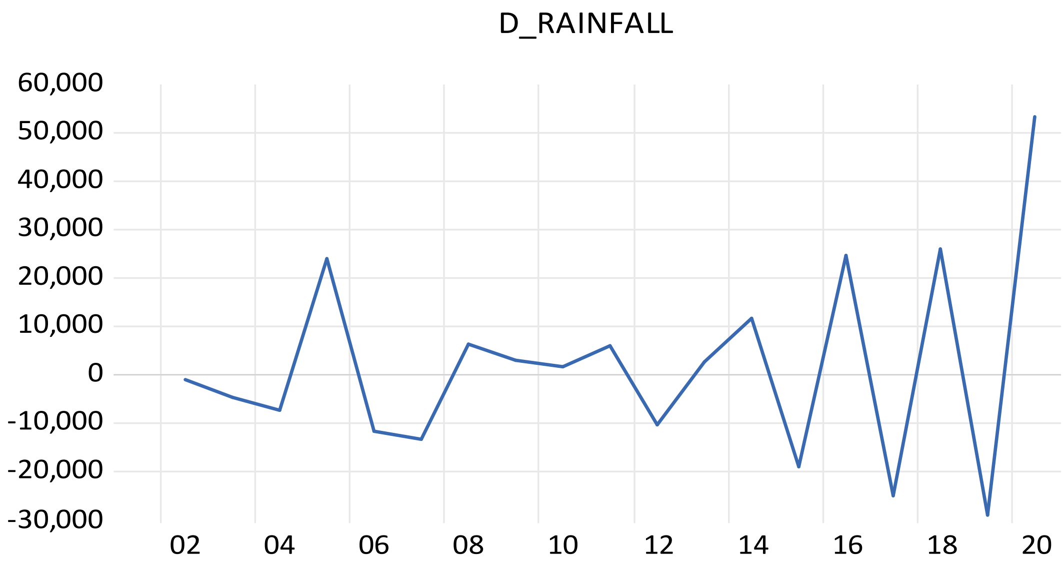
The plot of differenced values shows that the mean and variance remain constant for the first difference of rainfall (Δ rainfall). ADF tests, with p-values below 0.05 in Table-5, validate the stationarity of the variable post the initial difference. This suggests that the rainfall in Purulia district follows an integrated order of one [I(1)] after the first difference. The results indicate that Aman rice output is stationary at the initial level, but rainfall becomes stationary when analysed in its first difference.

Figure-2: Time series plot of Rainfall in Purulia, 2001 to 2020



Source: Authors estimation, 2023

Figure-3: Ordinary Differencing Time series plot of Rainfall in Purulia, 2001 to 2020



Source: Authors estimation, 2023

The plot of differenced values shows that the mean and variance remain constant for the first difference of rainfall (Δ rainfall). ADF tests, with p-values below 0.05 in Table-5, validate the stationarity of the variable post the initial difference. This suggests that the rainfall in Purulia district follows an integrated order of one [I(1)] after the first difference. The results indicate that Aman rice output is stationary at the initial level, but rainfall becomes stationary when analysed in its first difference.

The ARDL [Pesaran et al., 2001] is appropriate for cointegration analysis, regardless of the stationarity properties of the regressors. The results show that Aman rice production is integrated of order zero (I(0)), whereas rainfall is integrated of order one (I(1)) according to Table-5.Hence, the ARDL model is suitable for this scenario. The ARDL model is built utilising rainfall data from the research area as independent variables to analyse their combined influence on Aman rice production. The ARDL model estimates the link between Aman rice production and rainfall, as shown in Table-6.

Table-6: Results of ARDL Bounds Test

F-Bounds Test		Null Hypothesis: No levels relationship		
Test Statistic	Value	Signif.	I(0)	I(1)
			Asymptotic: n=1000	
F-statistic	44.40412	10%	5.59	6.26
k	1	5%	6.56	7.3
		2.5%	7.46	8.27
		1%	8.74	9.63

Source: Authors estimation, 2023

The study examines linkages and effects in both the short and long term. Prior to examining the relationships between variables in the long and short term, it is essential to utilise the ARDL bound test [Pesaran et al., 2001] to verify cointegration. If the F value is less than 0, we fail to reject the null hypothesis, indicating the absence of a long-run link and the non-existence of cointegration. If the F value exceeds I (1), we reject the null hypothesis and infer the presence of a long-run link and cointegration. An inconclusive test occurs when the F value falls within the range of I (0) and I (1). The ARDL bound test for cointegration shows a calculated F statistic of 44.404, which exceeds the crucial value of 9.63 at a 1% significance level [Table-6]. This suggests that the null hypothesis of no cointegrating relationship may be rejected, demonstrating that Aman rice production is cointegrated with Rainfall, implying a long-term link.

3.1.1 Short and long run estimation of parameters

After verifying the existence of both long and short-term associations between variables using the ARDL bound test, this study then analyses the parameters of the variables in both the short and long term. Aman rice, a major staple food crop in Purulia, is greatly impacted by many climate change effects. The empirical research on climatic factors is mostly concerned with long-term relationships, as shown in Table-7. An analysis of the long-term link between Aman rice output and rainfall suggests that rainfall has a statistically significant ($p = 0.005$) negative influence on Aman rice production, demonstrating the enduring impact of rainfall on Aman rice yields. Some studies also added that unstable rain pattern due to climate change poses a serious threat to agricultural production and food security and alterations in the frequency of rainfall can result in a decline in agricultural production. Some studies observe that heavy rainfall acts as a major constraint for rice productivity [Kakumanu et al., 2019]. Present study observes a significant impact of the area under rice cultivation on rice production at a 1% significance level in the long run. The long run form is observed as follows.

$$EC = Production - (-0.0008 \times Rainfall - 11.1967 \times trend)$$

where EC is the error correction term and it is the residual from long run equation. Short run coefficients and ECM estimates are computed and presented [Table-8]. The ARDL (1,4) indicates a lag of one for the dependent variable (Aman rice production) and a lag of four for the independent variable (rainfall). The error correction coefficient of -1.73 (p-value = 0.000) and found significant, suggesting a high speed of convergence to equilibrium. The evidence of cointegration is further affirmed by the values of the error correction term (ECM_{t-1}), which bear a significant level and negative sign. The negative sign indicates the direction of adjustment and swiftness or speed toward equilibrium. This result indicates that rainfall and its three times lag have significant short-term effect on production of Aman rice.

Table-7: Long run associations Test

Variable	Coefficient	Std. Error	t-Statistic	Prob.
RAINFALL	-0.002177	0.000569	-3.828514	0.0050

EC = PRO1 - (-0.0022*RAINFALL)

Source: Authors estimation, 2023

3.1.2 Diagnostic tests

Various diagnostic tests have been conducted by the study to identify errors in the model [Table-8]. The calculated values of R-square and adjusted R-square exceed .90, indicating that the model is a good fit. The R-square value of the ARDL model is 0.94, indicating a high reasonable fit. F statistic is also significant (p = 0.00) also indicates a food fitted model with an absence of autocorrelation supported by Durbin Watson value is 2.37, which proves that it is free from serial correlation. The Breusch-Pagan-Godfrey test for heteroscedasticity yields a chi-square value of 0.46 (p-value = 0.99) and we can't able to reject the null hypothesis of homoscedasticity [Table-9].

Table-8: Results of ECM Estimates

ECM Regression
Case 5: Unrestricted Constant and Unrestricted Trend

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	730.4893	73.93143	9.880633	0.0000
@TREND	-10.97193	1.530283	-7.169868	0.0001
D(RAINFALL)	0.003134	0.000586	5.351236	0.0007
D(RAINFALL(-1))	0.010573	0.001100	9.608329	0.0000
D(RAINFALL(-2))	0.010175	0.001250	8.137160	0.0000
D(RAINFALL(-3))	0.005981	0.001035	5.778154	0.0004
CointEq(-1)*	-1.737308	0.173810	-9.995462	0.0000

R-squared	0.942991	Mean dependent var	-0.912988
Adjusted R-squared	0.904985	S.D. dependent var	45.41379
S.E. of regression	13.99858	Akaike info criterion	8.415425
Sum squared resid	1763.643	Schwarz criterion	8.753433
Log likelihood	-60.32340	Hannan-Quinn criter.	8.432734
F-statistic	24.81160	Durbin-Watson stat	2.370749
Prob(F-statistic)	0.000041		

Source: Authors estimation, 2023

Table-9: Results of Breusch-Pagan-Godfrey Test

Heteroskedasticity Test: Breusch-Pagan-Godfrey
Null hypothesis: Homoskedasticity

F-statistic	0.462473	Prob. F(7,8)	0.8371
Obs*R-squared	4.609377	Prob. Chi-Square(7)	0.7075
Scaled explained SS	0.716453	Prob. Chi-Square(7)	0.9982

Source: Authors estimation, 2023

The Breusch-Godfrey Serial Correlation Lagrange multiplier test for serial correlation has a value of 0.696 (p-value = 0.22) indicating the absence of serial correlation [Table-10]. The results of the projected Ramsey reset test (χ^2 Ramsey reset) also suggest that the functional form of the estimated model is correct [Table-11]. Similarly, the anticipated outcomes of χ^2Arch and χ^2 B-G indicate the absence of heteroscedasticity issues in the model [Table-12]. Null hypothesis of Jarque-Bera test for normality is that the residuals are found normally distributed [Figure-4]. As the p-value is greater than 0.05, we unable to reject null hypothesis which means that residuals are normally distributed. Hence, the computed scores from the Jarque-Bera test (χ^2 normality) and serial correlation test (χ^2 SC) imply that the existing model is normal and does not exhibit serial correlation.

Table-10: Results of Breusch-Godfrey Serial Correlation Test

Breusch-Godfrey Serial Correlation LM Test:
Null hypothesis: No serial correlation at up to 2 lags

F-statistic	0.696526	Prob. F(2,6)	0.5345
Obs*R-squared	3.014835	Prob. Chi-Square(2)	0.2215

Source: Authors estimation, 2023

Table-11: Results of Ramsey RESET Test

Ramsey RESET Test
Equation: UNTITLED
Omitted Variables: Squares of fitted values
Specification: PRO1 PRO1(-1) RAINFALL RAINFALL(-1) RAINFALL(-2) RAINFALL(-3) RAINFALL(-4) C @TREND

	Value	df	Probability
t-statistic	4.910114	7	0.0017
F-statistic	24.10922	(1, 7)	0.0017
Likelihood ratio	23.86550	1	0.0000

F-test summary:

	Sum of Sq.	df	Mean Squares
Test SSR	3622.763	1	3622.763
Restricted SSR	4674.615	8	584.3269
Unrestricted SSR	1051.852	7	150.2646

LR test summary:

	Value
Restricted LogL	-68.12152
Unrestricted LogL	-56.18877

Source: Authors estimation, 2023

Table-12: Results of Heteroskedasticity Test

Heteroskedasticity Test: ARCH

F-statistic	0.029587	Prob. F(1,13)	0.8661
Obs*R-squared	0.034061	Prob. Chi-Square(1)	0.8536

Source: Authors estimation, 2023

3.1.3 Stability checking

This study uses the Cumulative Sum (CUSUM) and Cumulative Sum of Squares (CUSUMSQ) tests to evaluate the stability of short-term and long-term coefficients in response to structural changes impacting all variables caused by single or many breaks [Brown et al., 1975]. The CUSUM and CUSUMSQ trends in Aman rice production show statistical significance at the 5% level across time, confirming the stability and strong fit of the ARDL model. The results of the CUSUM and CUSUMSQ tests are presented in Figure-5. The blue line falls between the red lines on both sides, indicating the lack of an issue with recursive residual in the mean term. This outcome confirms that adding another variable sensitive to the structural breach is unnecessary.

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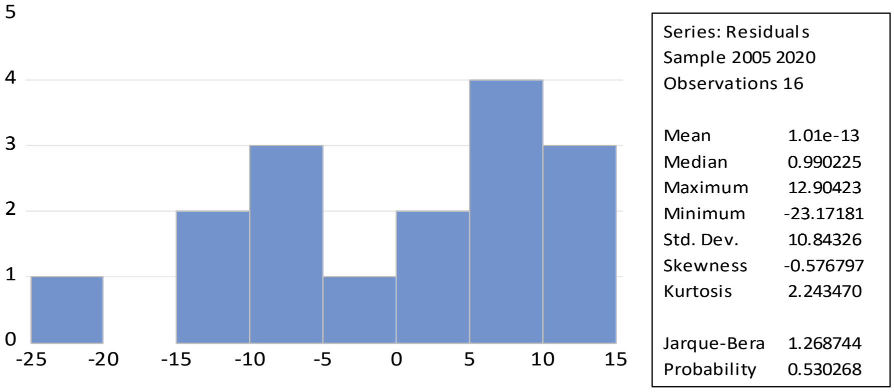
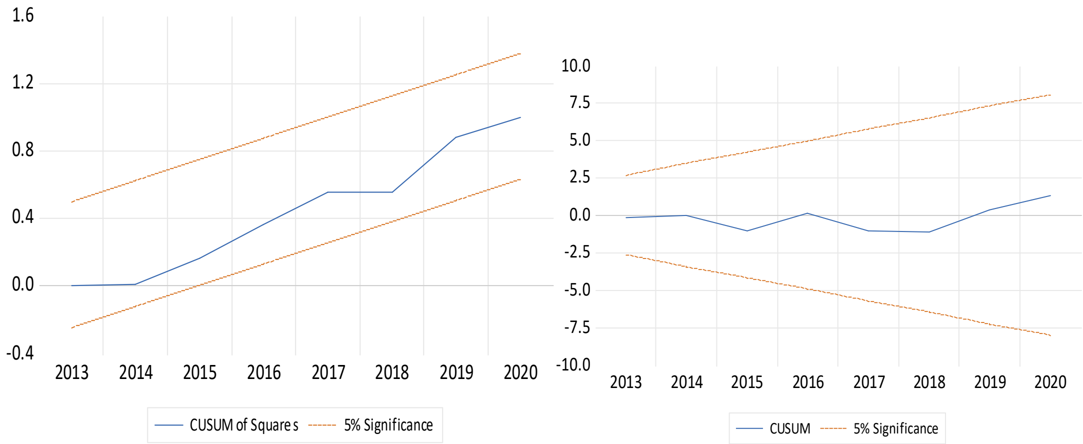
Figure-4: Jarque-Bera Test of Normality



Source: Authors estimation, 2023

Figure-5: Results of CUSUM & CUSUMSQ Test



Source: Authors estimation, 2023

4.1 Conclusion

The study identified the presence of low and moderate levels of drought in the district of Purulia from 2001 to 2020, significantly impacting the production of the main Aman crops during this period. Using annual time-series data, the study examined the short and long-term effects of climatic and non-climatic factors, particularly rainfall, on Aman rice production in Purulia. The ARDL bounds testing method and cointegration analysis established a strong long-term association among the variables, revealing that rainfall positively affected Aman rice production both in the short and long run. In Purulia, farming households have limited awareness of climate change, highlighting the need for increased consciousness among farming communities. Extension workers and policymakers should distribute the latest information on climate change to these communities. This model provides a strong outline for future research, allowing for the analysis of similar relationships in different regions or with different crops, thus enhancing the generalizability of the findings. The methodological approach used in this study serves as a template for examining long-term associations in agricultural research. The findings highlight the importance of improving climate change literacy and adaptive capacity among farmers. Future research can develop targeted intervention strategies and integrate socio-economic variables with localized climate data to refine predictive models and formulate effective agricultural policies and practices resilient to climate variability and change.

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