IJBPAS, January, Special Issue, 2022, 11(1): 815-841

ISSN: 2277–4998

International Journal of Biology, Pharmacy and Allied Sciences (IJBPAS)

'A Bridge Between Laboratory and Reader'

www.ijbpas.com

RAINFALL VARIABILITY AND ITS IMPACT ON CROP CALENDAR OF RAIN-FED RICE CULTIVATION IN EAST COAST OF INDIA: A STUDY OF PURBA MEDINIPUR COASTAL AREA, WEST BENGAL, INDIA

PANJA S[1*] AND MUKHOPADHYAY S[2]

1: Department of Geography, Asutosh College, University of Calcutta, Kolkata, West Bengal, India

2: Department of Geography, Asutosh College, Kolkata, West Bengal, India

[*]**Corresponding Author: Sumit Panja; E Mail: sumitpanja17@gmail.com**

Received 10th June 2021; Revised 11th July 2021; Accepted 20th Aug. 2021; Available online 15th Jan. 2022

https://doi.org/10.31032/IJBPAS/2022/11.1.1070

ABSTRACT

The crop calendar of a particular region is extensively dependent on rainfall. And the onset of the rainy season plays a vital role to maintain it. Thus the rainfall variability can hamper the crop calendar vividly, and affect the whole agricultural system, including yield and production. The condition might become more difficult for the developing countries, where a huge number of small and marginal farmers are solely dependent on agriculture for their livelihood. Since more than 60% of India's total agricultural land is rain-fed, a large proportion of it is used to cultivate rice therefore, and rainfall variability has a direct impact on the Indian agricultural system especially on rice farming. Limited irrigation facility, and exposure to extreme climatic events (e.g. cyclones) makes agriculture of the coastal zones as one of the most vulnerable areas to rainfall variability. The current study intends to find out the impact of rainfall variability on the crop calendar of Rain-fed rice cultivation in the Purba Medinipur coastal area, a part of the east coast of India. The study analysed the rainfall data of a long term period, and identified the years with very high to extreme rainfall anomaly for the period of 2010-2020 by applying Rainfall Anomaly Index. And examined the crop calendars of those particular years, then compared with a normal year's crop calendar. To analyse the crop calendar, some vegetation indices have been calculated for the growing season and heading season by using

MODIS data. The result of the study depicted that the value of vegetation indices of the rainfall variability years are low to very low in most of the areas in the growing season, but it becomes high to very high in the heading season. On the other hand, normal years achieved the maximum values of vegetation indices in most of the areas in just the growing season. Hence the result has a clear indication of modification of crop calendar according to the onset of the rainy season to cope up with the rainfall variability as stated in the farmers' perception data.

Keywords: Crop calendar, Rain-fed rice cultivation, farmers' perception, rainfall variability

INTRODUCTION

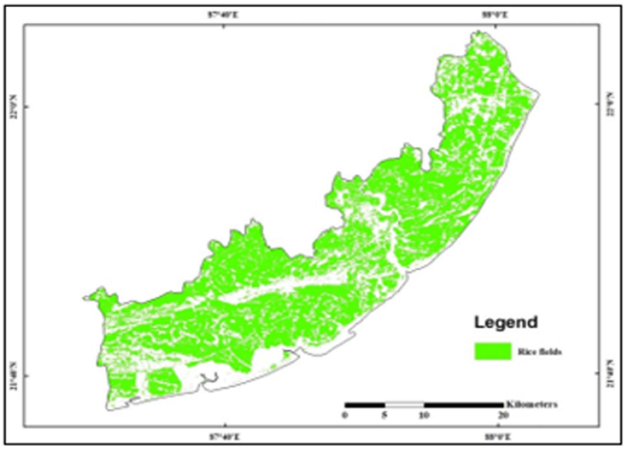
In the 6th assessment report 2021, IPCC has mentioned that internal variability of rainfall (seasonal, yearly and decadal) will increase significantly, which will instigate the agricultural and ecological drought in some of the parts of the world. Several studies have already revealed that rainfall variability (i.e., anomalies and internal variability) is a leading and recurring challenge for the agricultural sector (FAO, 2015; Lesk *et al*., 2016), and it is more prominent in a warmer climate (Hawkins & Sutton, 2011; Pendergrass *et al*., 2017). Variations in daily, monthly, seasonal, yearly or even decadal rainfall have a significant negative impact on crop production and food security especially, for developing countries (Kinda & Badolo, 2019; Rahman *et al*., 2017). In India, where 60% of total agricultural land is directly dependent on monsoon rainfall for agriculture, will face more difficulty, since the variability of availability of monsoon rainfall is increasing in the scenario of climate change (Mall *et al*., 2006; Kulkarni, 2012; Loo *et al*., 2015). The situation will worsen in the coastal area, being the most vulnerable to climate change and climate change-induced phenomenon (IPCC, 2007). Several studies (Geethalakshmi *et al*., 2016; Gopalakrishnan *et al*., 2019) has stated that coastal areas of India will face more strains since, its scope of groundwater and canal irrigation is very lower, due to intrusion of saline water in groundwater, and unavailability of freshwater.

The impact of rainfall variability on crop production, and yield has been examined extensively in various studies (Kyei-Mensah *et al*., 2019; Lesk *et al*., 2016; Oscar Kisaka *et al*., 2015; Sadiq A.A., 2020; Shortridge, 2019) but, there are fewer studies (Fiwa *et al*., 2014; Kengni *et al*., 2019) attempted to examine the changes in crop calendar due to rainfall variability. Although, variation in a crop calendar could distress the production system of a particular crop as well as for the other crops in the same cropping years. However, modification of the crop calendar could be an effective adaptation strategy for the farmers against climate variability (Truong An, 2020; Yegbemey *et al*., 2014). Thus the present study aims to assess the impact of seasonal and yearly rainfall variability (anomaly) on the crop calendar of Rain-fed (rain-fed) rice cultivation and examine the farmers' adaptive response to the rainfall variability. Previously, fewer studies have stated that Spatio-temporal changes in rainfall patterns are creating difficulty to maintain the traditional cropping cycle (Alam *et al*., 2011) moreover, the decreasing trend of rainfall and rainy days during the sowing season is seriously impeding the production system of rice (Atedhor, 2019). Hence, this paper has identified the years with severe rainfall variability (anomaly) of the last decade (2010-2020) by applying Rainfall Anomaly Index, and analysed its crop calendar to identify the changes during the variability.

To analyse the crop calendar, Moderate Resolution Imaging Spectroradiometer (MODIS) data has been used, which is very much effective to detect temporal changes (M. Boschetti *et al*., 2009; Kirana *et al*., 2020; Li *et al*., 2014; Patel & Oza, 2014). Previously, several studies have successfully monitored the crop calendar and crop health of rice by using MODIS data (M. Boschetti *et al*., 2009; Raghavendra & Mohammed Aslam, 2017; Semedi, 2012; Zhang *et al*., 2015) with the help of different vegetation indices. Therefore, the study has calculated Normalized Difference Vegetation Index (NDVI), Enhanced Vegetation Index (EVI), and Optimized Soil-Adjusted Vegetation Index (OSAVI) to study the crop calendar. Vegetation Condition Index (VCI) has also been calculated to detect the water stress on crops due to rainfall shortage. Finally, the crop calendar of detected rainfall variability years is compared with a normal year to identify the changes.

2. Study area:

The study has been done in the coastal part of Purba Medinipur district of West Bengal covering six coastal administrative blocks (Figure 1). The study area is located in between 21°36ˈ39″ and 22° 05ˈ33″ North, and 87° 29ˈ01″and 87° 58ˈ39″East. The study area has a geographical coverage of 1078.08 Sq. Km, out of which rain-fed Rain-fed paddy (Aman Paddy) occupies 68.47% of the area (Figure 2). The climate of the area is tropical in nature. The average temperature varies from 25.50°C to 38.60°C with an average rainfall of 1,752.6 mm, and the area is occasionally affected by cyclones. The area belongs to the "coastal saline" agro-climatic zone.



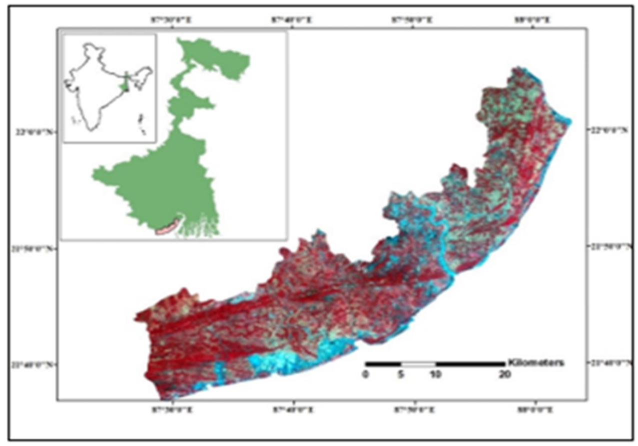


Figure 1: Distribution of rice farms. **Figure 2: Study Area**

3. MATERIALS AND METHODS:

3.1. Materials:

3.1.1. Perception data

The household survey was conducted with a questionnaire to collect the primary data regarding farmers' perception of the anomaly of rainfall and how it is affecting their agricultural practices especially Rain-fed paddy cultivation. The questionnaire was focused to generate information about the anomaly of different rainfall parameters like the onset of the rainy season, amount of rainfall, the pattern of rainfall etc. in this area and to know whether the farmers are modifying their crop calendar for these variabilities or not. A total of 232 households were surveyed randomly to collect those perception data. Six focused group discussions were also carried out in randomly selected villages to cross-check the information collected from the household survey.

3.1.2. Rainfall data:

Daily rainfall data has been downloaded from the online portal of NASA (https://power.larc.nasa.gov/) for a period of 1990-2020. The study considered examining the rainfall variability of June to mid of the July, which is the initial month of monsoon, and sowing period of Rain-fed paddy is very much dependent on the rainfall of this month.

3.1.3. Remote Sensing data:

A set of terra MODIS data has been downloaded from the Earth Data portal of NASA (https://search.earthdata.nasa.gov). The data sets are 16 days composite of Terra MODIS Vegetation Indices (MOD13Q1). These data sets contain the reflectance of band 1 (Red) and band 2 (NIR) with a spatial resolution of 250m. For the present study, we have downloaded MOD13Q1-h26v06 tile for the ordinal dates of 241(last week of August), and 273 (last week of September) to represent growing and heading stages of Rain-fed paddy for the selected rainfall variability years.

Table 1: Assigned modalities for different statements regarding rainfall variability:

Statements	Assigned modalities
Delay in onset of monsoon has been increased.	1= Strongly disagree, 2= Disagree, 3= No change, 4=Agree, 5= Strongly agree.
Number of rainy days during monsoon period has been decreased.	1= Strongly disagree, 2= Disagree, 3= No change, 4=Agree, 5= Strongly agree.
Erratic rainfall events have been increased.	1= Strongly disagree, 2= Disagree, 3= No change, 4=Agree, 5= Strongly agree.
Dry spell has been increased.	1= Strongly disagree, 2= Disagree, 3= No change, 4=Agree, 5= Strongly agree.
Rainy season has become shorter.	1= Strongly disagree, 2= Disagree, 3= No change, 4=Agree, 5= Strongly agree.
Total amount of rainfall has been decreased.	1= Strongly disagree, 2= Disagree, 3= No change, 4=Agree, 5= Strongly agree.
Practicing to change crop calendar during rainfall anomaly year.	1= Strongly disagree, 2= Disagree, 3= No change, 4=Agree, 5= Strongly agree.

3.2. Methods:

3.2.1. Rainfall Anomaly Index (RAI):

Rainfall Anomaly Index has been calculated to identify the years with rainfall anomaly and its magnitude. Rainfall Anomaly Index was developed by van Rooy (1965) and in this study we applied it in depicting periods of dryness and wetness in the area. The Index has been calculated for a period of 1990-2020. The positive and negative RAI indices are computed by using the mean of ten extremes. The formula for calculating positive RAI (for positive anomalies) is given below-

$$RAI = 3 \times \frac{P - \bar{P}}{\bar{M} - \bar{P}}$$

The formula for calculating negative RAI is-

$$RAI = -3 \times \frac{P - \bar{P}}{\bar{m} - \bar{P}}$$

Where, P is the actual rainfall, $\bar{P}$ is the mean precipitation of the period, $\bar{M}$ is the mean of 10 highest precipitation for the period, and $\bar{m}$ is the mean of 10 lowest precipitation. The arbitrary threshold values of +3 and -3 have, respectively, been assigned to the mean of the ten most extreme positive and negative anomalies.

3.2.2 Rainfall Variability Analysis:

Rainfall variability analysis has been done by calculating range of rainfall, Inter-Quartile Range (IQR), standard deviation and variance on the basis of daily rainfall data for the sowing season of

Rain-fed rice (June to mid of July). A box and Whisker plot also prepared to show the variability of daily rainfall. The analysis has been done for the selected years with rainfall anomaly.

3.2.3. Perception data analysis:

The responses of the perception-based statements are converted to a Likert scale by assigning values (1 to 5) on the basis of the strength of agreement (Frondel *et al.*, 2017; Mase *et al*., 2017). After assigning the values mean, median, mode, and standard deviation are calculated. The details of the questions are given below (Table 1).

3.2.4. Vegetation Indices:

3.2.4.1. NDVI:

Normalized Difference Vegetation Index represents the reflectance characteristics of the Red and Infra-Red band of the electromagnetic spectrum and helps to identify the area with vegetation. This index also helps to monitor vegetation health. The NDVI is calculated by using the following equation-

$$NDVI = \frac{NIR - Red}{NIR + Red}$$

Downloaded MODIS Vegetation Indices data has been reclassified on the basis of reference values of the known crop calendar of the particular crop (Rain-fed paddy). The NDVI values are reclassified as very low (<1), low (0.1-0.3), moderate (0.3-0.4), high (0.4-0.5), and very high (>0.5) categories (Ozyavuz *et al*., 2015).

3.2.4.2. EVI:

Enhanced Vegetation Index is used in this study because of its high sensitivity to canopy greenness and resistance to cloud haze (Rossi *et al*., 2013; Zhang *et al*., 2015). EVI can be calculated from the following equation-

$$EVI = \frac{Gx\ (NIR - Red)}{(NIR + C1\ x - Cx\ Blue + L)}$$

where Red/NIR/Blue are atmospherically corrected surface reflectance values for MODIS Bands 1, 2 and 3, respectively; L is a canopy background adjustment; C1 and C2 are coefficients of aerosol resistance term; and G is the gain factor. In the MODIS EVI product, these coefficient values are L=1, C1=6, C2= 7.5 and G=2.5 (Raghavendra & Aslam, 2017).

3.2.4.3. OSAVI:

Optimized Soil-Adjusted Vegetation Index (OSAVI) is not dependent on soil line and ignores the influence of soil background. This index can be expressed as:

$$OSAVI = \frac{NIR - Red}{Red + NIR + X}$$

where X is coefficient of Scattering from Arbitrarily Inclined Leaves (SAIL), which is 0.16 in this data (Xue & Su, 2017).

3.2.4.4. VCI:

Vegetation Condition Index (VCI) measures the percentage of NDVI in respect to maximum recorded variation of NDVI values of a particular pixel (Dutta *et al*., 2015; Liu & Kogan, 1996). It can be calculated from following expression-

$$VCI = \frac{(NDVI_{j} - NDVI_{\min})}{(NDVI_{\max} - NDVI_{\min})}$$

Where $NDVI_j$ = NDVI value of the particular period, $NDVI_{max}$ = maximum value of NDVI of the j period, $NDVI_{min}$ = minimum value of NDVI of the j period.

Anomaly in rainfall may significantly affect the vegetation condition and potential agricultural drought zones could be effectively identified through VCI mapping (Dutta *et al*., 2015).

4. RESULT:

4.1. Understanding Farmers' Perception regarding Rainfall anomaly:

Farmers' perceptions are represented in Figure 3. A total of 232 households have been surveyed for the study. Among the six statements regarding rainfall anomaly, 'delay in onset of monsoon' has the highest mean value (4.65), with a standard deviation of 0.699 which means most of the farmers (74%) are strongly agree with the statement. Other two statements with more than 4.00 mean value (agreed with the statement) is 'decrease of the number of rainy days (83%) and 'increase of dry spells' (93%) with a standard deviation of 0.901 and 0.652 respectively (Table 2). Farmers also agreed with the remaining statements e.g. Increase in erratic rainfall, shorter rainy season, and decrease in the amount of total rainfall with a convincing mean value and standard deviation. Farmers' responses towards crop calendar change are clearly depicting that farmers are changing their crop calendar depending on the rainfall anomaly. Most of the farmers agree with the statement that they are changing their crop calendar in a year with rainfall anomaly. The statement has a mean value of 3.76 and a standard deviation of 0.869.

Table 2: Descriptive Statistics of Farmers' Perception

	Delay in onset of monsoon has been increased.	Number of rainy days during monsoon period has been decreased.	Erratic rainfall events has been increased.	Dry spell has been increased.	Rainy season has become shorter.	Total amount of rainfall has been decreased.	Practicing to change crop calendar during rainfall anomaly year.
Mean	4.65	4.29	3.89	4.21	3.5	3.8	3.76
Median	5	5	4	4	4	4	4
Mode	5	5	4	4	4	5	4
Std. Deviation	0.699	0.901	1.022	0.652	0.921	1.284	0.869

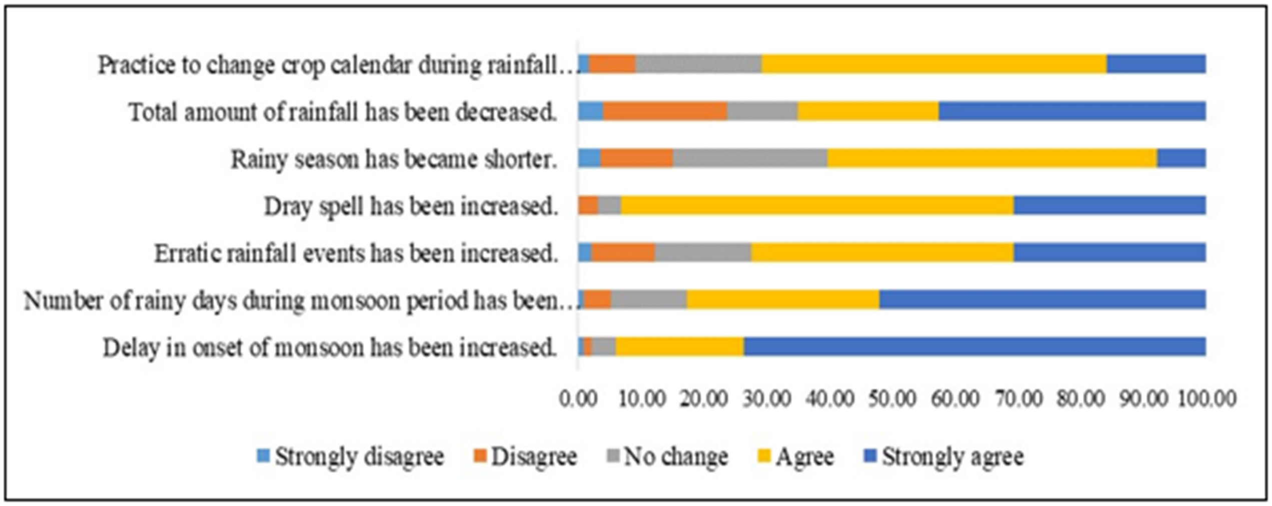


Figure 3: Farmer's Perception

4.2. Identification of rainfall variability years by applying Rainfall Anomaly Index:

A table has been prepared depending on values of Rainfall Anomaly Index of the period 1990-2020, depicting the dryness and wetness of each years (Table 3). Since, previous studies has confirmed, negative rainfall anomaly (dryness) and delay in onset of monsoon has the maximum effect on rice farming than, the positive anomaly (wetness) and advance onset of monsoon (Shrivastava & Chaudhary, 2020; Zaveri *et al*., 2020), thus we only considered the years with negative rainfall anomaly index. From the table, the years with extreme dryness (RAI value <-3), and extreme wetness (RAI value >3) of last decade (2010-2020) are identified and selected to anaylyse the changes in crop calendar of those years. According to farmers, beginning of transplantation season of rice depends on availability of rainfall of early monsoon (June to mid-July), therefore the RAI has been calculated based on daily rainfall of 1st June to 15th July. From the RAI, a total of 4 individual years of the time period 2010-2020 (Figure 4) are selected for the study. Among the years, two years with 'Extreme dryness' (2010 and 2012), and one year with 'Very dryness' (2011) are selected. A years with near normal rainfall situation (RAI value -0.49 to 0.49) has also been select to monitor the normal crop calendar of the area.

Table 3: Categories of Rainfall Anomaly Index, 1990-2020

Categories	Values	Years
Extremely wet	≥3.00	1991, 2001, 2007, 2015
Very wet	2.00 to 2.99	1990, 2006
Moderately wet	1.00 to 1.99	2016, 1994, 2008
Slightly wet	0.50 to 0.99	2004, 2018, 2017
Near normal	-0.49 to 0.49	1999, 2020
Slightly dry	-0.99 to -0.50	2019, 2013
Moderately dry	-1.99 to -1.00	2000, 2002, 1995, 2014
Very dry	-2.99 to -2.00	2011, 1997, 1998, 2005, 2009,
Extremely dry	≤ -3	2010, 1993, 2012, 1992, 1996, 2003

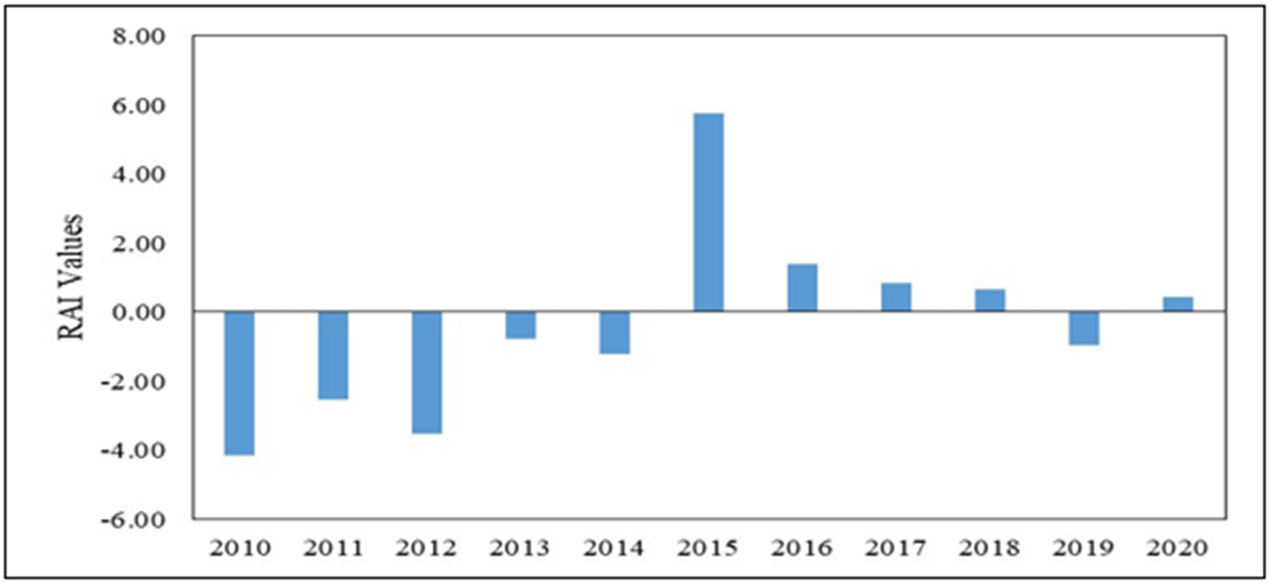


Figure 4: Rainfall Anomaly Index, 1990-2020

4.3. Analysis of statistical parameters of rainfall variability for the selected years:

The figure 4 is showing the variability of daily rainfall for the selected rainfall anomaly years. Variability of rainfall is maximum in the year 2011 (Figure 5) among all the selected years with a standard deviation and variance of15.46 and 239.8 respectively. Though the year 2010 is the driest year according to RAI value but it has the lowest variability with a standard deviation of 5.66 and variance is 32.04 (table 4).

Table 4: Statistical parameters of rainfall variability

	2010	2011	2012	2020
Range	24.23	99.42	33.34	28.7
Inter Quartile Range	7.01	10.94	8.56	11.13
Standard Deviation	5.66	15.46	7.46	6.77
Variance	32.04	239.08	55.63	45.87

4.4. Vegetation Indices:

4.4.1. Vegetation Indices of last week of August:

4.4.1.1. NDVI:

A set of NDVI has been calculated on the basis of selected normal rainfall year (2020) and rainfall anomaly years (2010, 2011, and 2012). On the basis of the known crop calendar for Rain-fed paddy, transplantation of the crop has been done between May-June (DRD) in this area, so NDVI has been calculated for the last week of August (27th and 28th) considering a minimum of 60 days after the transplantation of the crop (Patel & Oza, 2014). The values of NDVI is categorized into 5 classes, very low, low, moderate, high, and very high (Figure 6). Generally heading stage of medium-duration rice variety occurs after 70-75 days of transplantation (Murthy *et al*., 1998) thus, it is expected that the value of NDVI for the last week of August will represent a high to very high category. In the normal year (2020), maximum areas are showing very high NDVI values. The category very high NDVI is covering an area of 88.56% in the year 2020 (Table 5). On the other hand in the negative rainfall anomaly years, only 43.91% and 43.40% and of the total area has achieved the high NDVI categories in 2011 and 2012, which are quite less than the normal year. Though in 2010 a total area of 57.81% has achieved the maximum category of NDVI. From the figure 4, a visual difference is clear between normal years and rainfall anomaly years. Since, the onset and amount of rainfall for the year 2020 was normal, hence the sowing season was unchanged which is showing a high value of NDVI in the maximum of the area. For the years 2010, 2011, and 2012, the rainfall anomaly affected the sowing season, which is clearly visible in the NDVI values of those years.

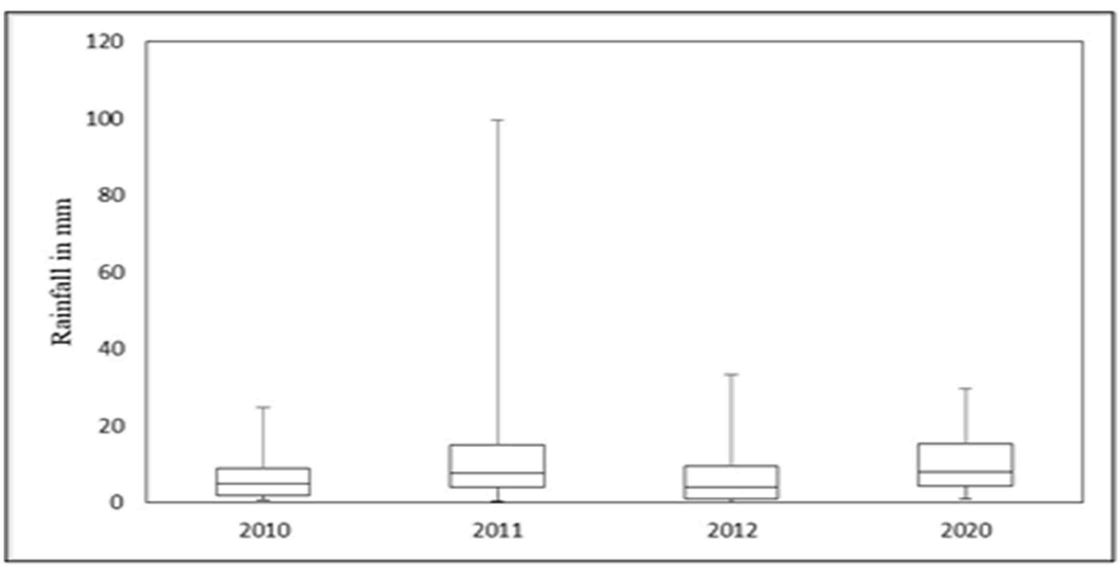


Figure 5: Whisker plot showing the variability of daily rainfall for June to mid-July

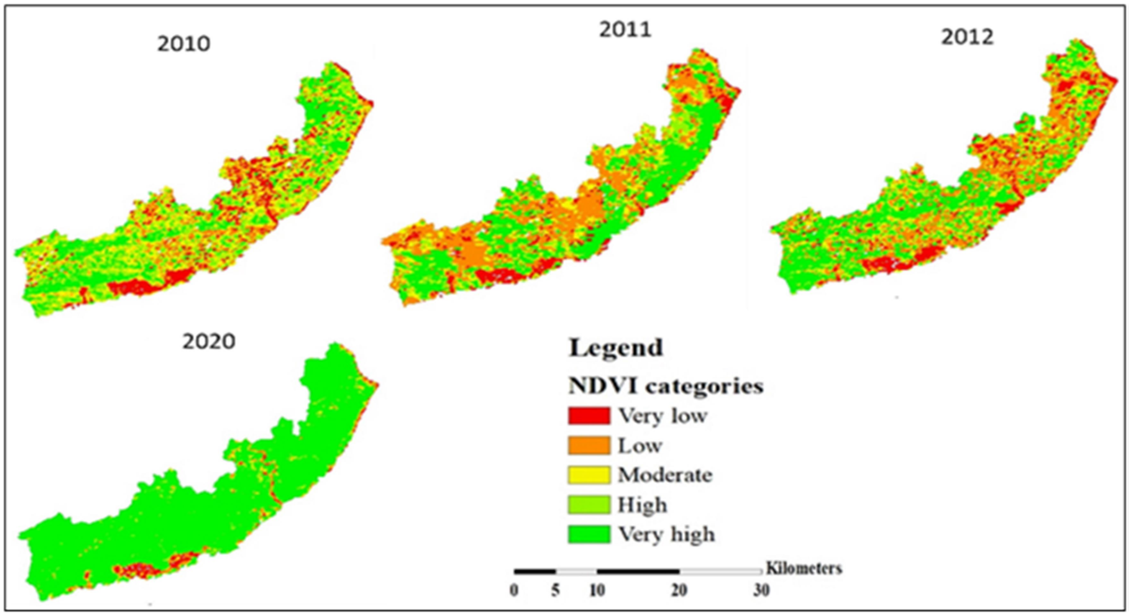


Figure 6: NDVI of last week of august

4.4.1.2. EVI:

EVI is depicting the scenario more clearly than NDVI as it is more responsive to leaf area than chlorophyll. Maximum EVI value for paddy can be observed in-between 55-65 days after plantation (Semedi, 2012). In the normal year, most of the areas are covers with moderate to very high EVI categories (Figure 7). In 2020 a total of 82.93% of area represents the same categories (Table 5).

In the extreme dry years, the majority of the area covered by low to very low EVI value which is clearly visible in the Figure 6, overall 50% to 60% area of all the rainfall anomaly years including positive anomaly year has low to very low EVI coverage.

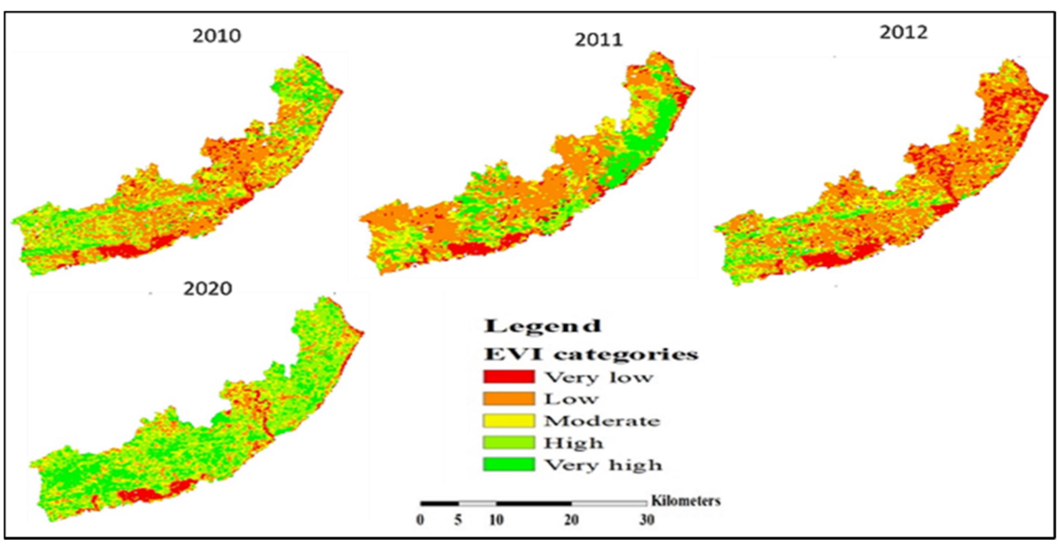


Figure 7: EVI of last week of August

4.3.1.3. OSAVI:

OSAVI is very much useful to detect above-ground biomass and leaf area by ignoring soil background (Xue & Su, 2017). In the OSAVI maps, a clear spatial change is noticeable for both normal and rainfall anomaly years (Figure 8). In the normal year 2020, an area of 91.91% showed high to very high category (Table 5). In contrast, the rainfall anomaly years are showing high spatial variation among the categories. In the year 2012, 40.56% of the area showed a low to very low category when 45% area is showing high to very high category. In the case of 2010 and 2011, 60% to 90% of the area belongs to the high to very high category.

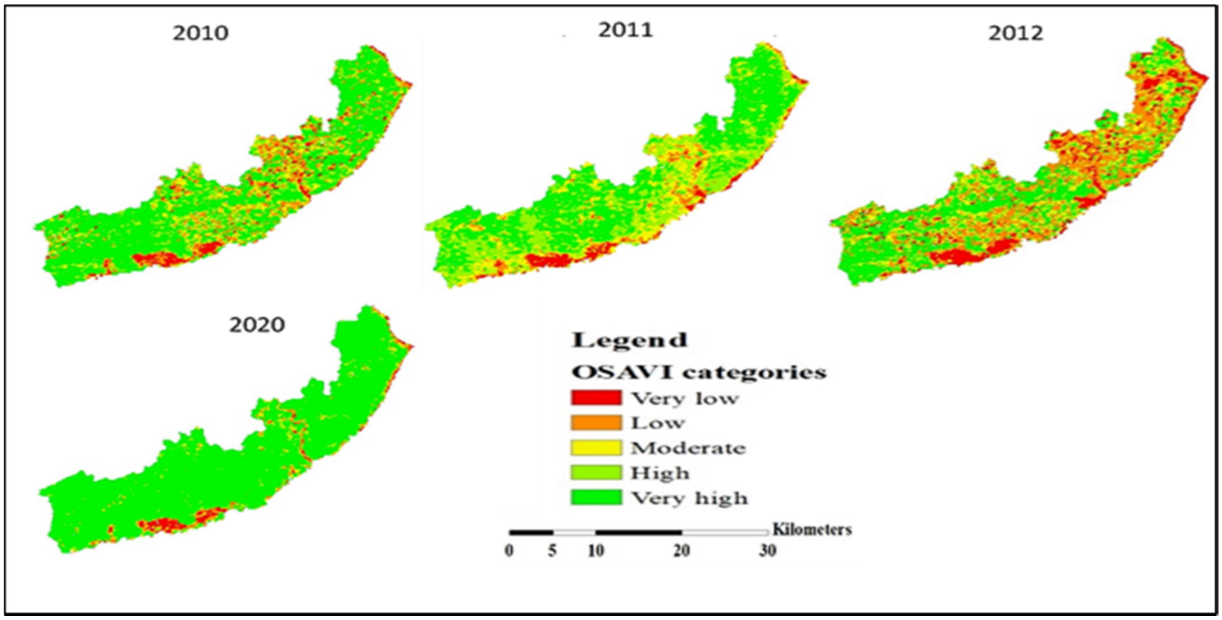


Figure 8: OSAVI of last week of August

4.4.1.4. VCI: Vegetation Condition Index (VCI) is applicable to monitor drought conditions. Low VCI signifies the low green vegetation or bad condition of vegetation and by considering some threshold value potential drought area can be delineated (Liu & Kogan, 1996). The last week of August is showing that 2020 having maximum area 95.62% with no drought condition (Table 5). An extreme drought condition occurred in 2012 with an area of 54.25%. In 2011 also a significant water stress can be visible where 47.47% area belongs to the high to extreme drought category whereas 2010 has a low drought affected region as compared to other dry years. (Figure 9).

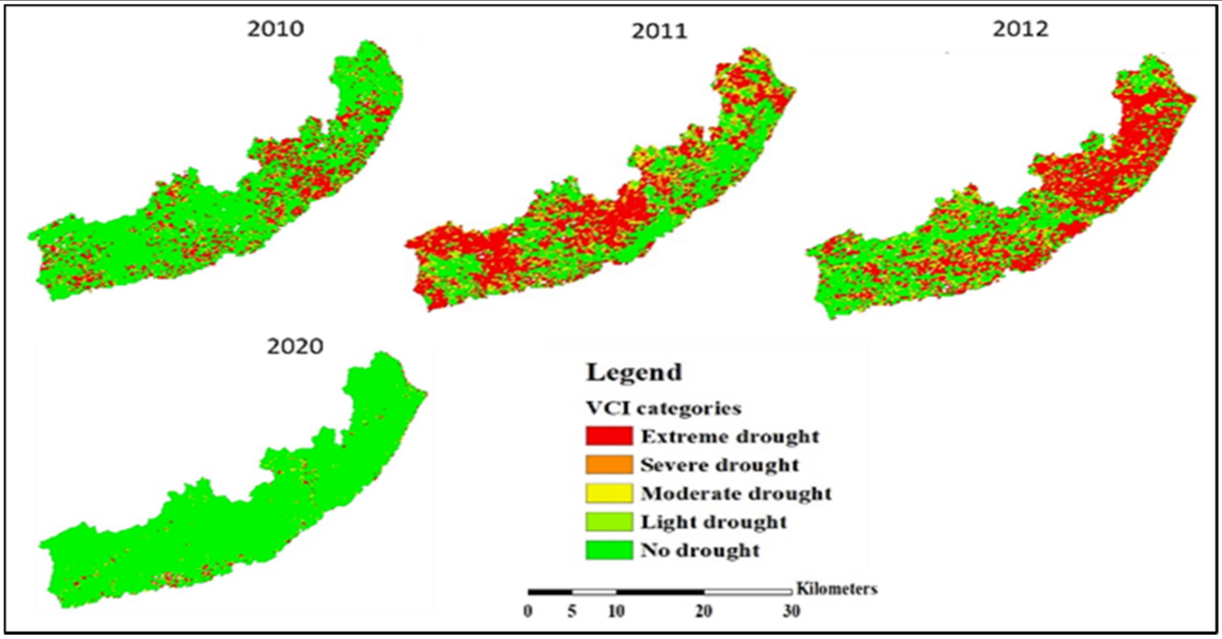


Figure 9: VCI of last week of August

Table 5: Category wise percentage of area share in different vegetation indices, last week of August.

Vegetation Indices	Years	Category wise Area in Percentage				
		Very low	Low	Moderate	High	Very high
NDVI	2010	4.44	13.1	10.18	14.46	57.81
	2011	7.89	34.28	13.85	12.29	31.69
	2012	10.46	31.53	14.61	14.8	28.6
	2020	2.03	3.08	2.41	3.92	88.56
EVI	2010	8.03	41.62	23.21	18.31	8.83
	2011	8.01	46.41	17.99	12.84	14.75
	2012	16.11	55.58	17.34	7.5	3.47
	2020	4.42	12.65	18.05	42.36	22.52
OSAVI	2010	4.47	13.07	10.13	14.55	57.78
	2011	3.51	6.47	14.53	32.92	42.58
	2012	10.52	30.04	14.16	14.44	30.84
	2020	2.32	3.33	2.43	3.89	88.02
VCI	2010	18.29	3.05	3.4	3.77	71.5
	2011	38.71	8.76	8.28	7.37	36.87
	2012	54.25	6.29	6.21	6.2	27.04
	2020	2.21	0.52	0.68	0.98	95.62

4.4.2. Vegetation Indices of last week of September:

4.4.2.1. NDVI:

As per the crop calendar, the end of September represents the heading stage of Rain-fed paddy, thus hypothetically the crop fields will show the higher NDVI values. Here also the normal year is having very high NDVI value for most of the area. In the rainfall anomaly years, the condition has improved a lot, as more than 90% of the area (Table 6) has reached maximum NDVI values in both of the years which indicates that late in the sowing season caused. The areas which were representing low or moderate NDVI values are not achieved in the high NDVI category (Figure 10). Late sowing and late transplantation can cause such results.

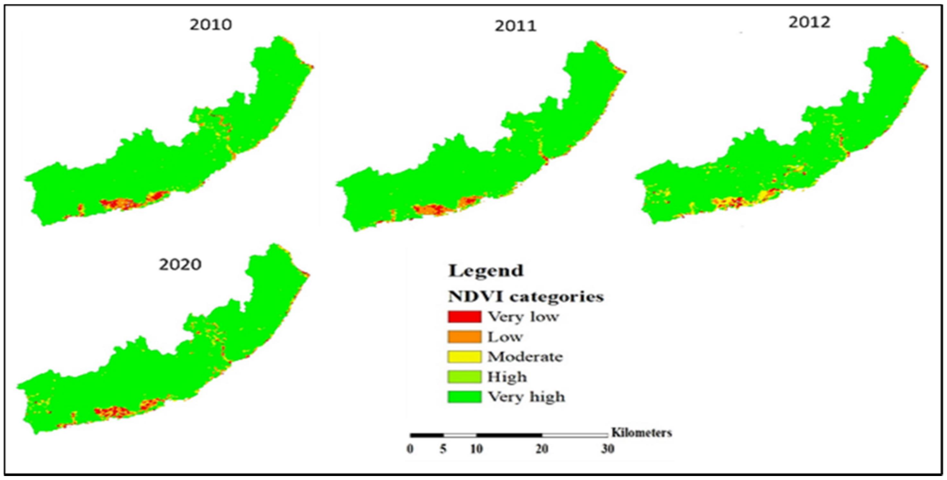


Figure 10: NDVI of last week of September

4.4.2.2. EVI:

At the end of September, the crop of rainfall anomaly years is achieved in better condition (Figure 11). In the years 2010, 2011, and 2012 majorities of the area (more than 70%) have achieved high to very high category. On the contrary in the normal year more than 80% areas are showing the high to very high category.

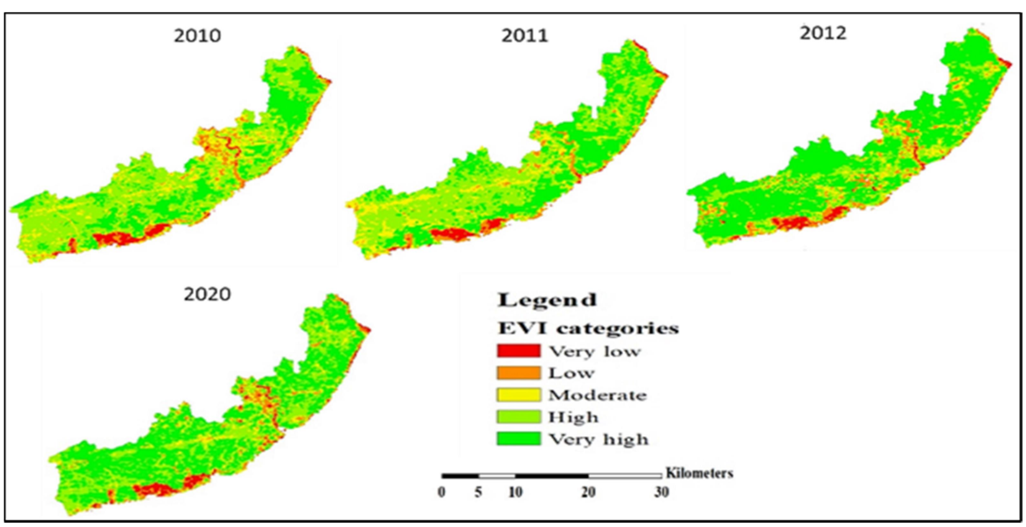


Figure11: EVI of last week of September

4.3.2.3. OSAVI:

In the last week of September all the years including normal and rainfall anomaly years are achieved in the high to very high category except

2011 (Figure 12). In 2010, 2012, and 2020 minimum 90% of areas are sharing the high to very high category of OSAVI (Table 6).

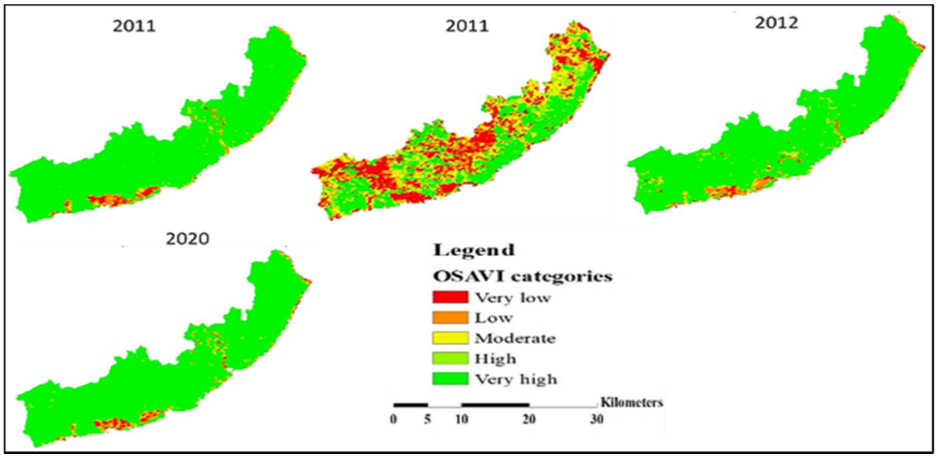


Figure 13: VCI of last week of September

4.4.2.4. VCI:

In the last week of September the condition has improved for the rainfall anomaly years (Figure 13). More than 60% of the area has achieved no drought conditions for the rainfall anomaly years except 2011 where the area under no drought condition is 55.10% (Table 6). For the normal year, the share of area under no drought category has reduced by 9.56%. Due to shortage of rainfall in June, an agricultural drought occurred for the year 2012 and 2020 but the severity has decreased as the rainfall after June becomes normal.

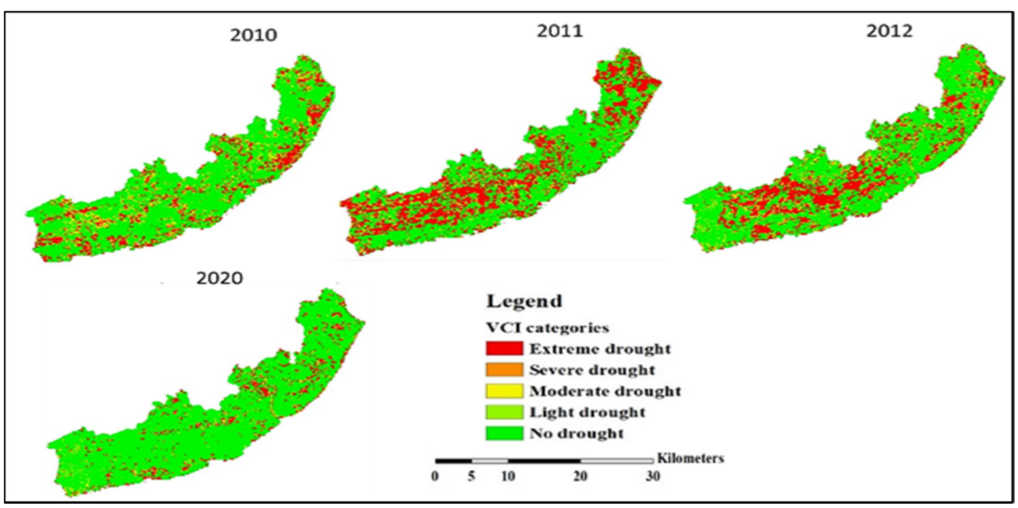


Figure 12: OSAVI of last week of September

Table 6: Category wise percentage of area share in different vegetation indices, last week of September

Vegetation Indices	Years	Last week of September				
		Very low	Low	Moderate	High	Very high
NDVI	2010	1.41	2.74	1.63	1.97	92.26
	2011	0.99	3.33	1.15	2.33	92.19
	2012	0.88	3.37	2.09	2.7	90.96
	2020	1.31	2.62	1.58	1.82	92.67
EVI	2010	3.02	7.14	16.31	48.52	25.01
	2011	2.56	5.84	13.97	45.41	32.22
	2012	2.41	8.12	9.67	20.83	58.97
	2020	3.19	6.96	8.92	34.08	46.86
OSAVI	2010	1.45	2.74	1.63	1.96	92.22
	2011	22.46	12.72	21.89	11.52	31.4
	2012	0.97	3.44	2.17	2.79	90.63
	2020	1.54	2.86	1.71	1.88	92.01
VCI	2010	14.86	4.7	5.93	7.23	67.28
	2011	32.17	3.89	4.12	4.72	55.1
	2012	24.56	4.18	4.75	6.03	60.48
	2020	8.99	1.26	1.73	1.96	86.06

5. DISCUSSION:

The study has analysed farmers' perception and found that most of the farmers are sad about the increasing trend of rainfall variability in recent days, but the analysis of rainfall data is showing some disparity between farmers' perception and actual condition. From the RAI, we have found that in the last five years, sever anomaly of rainfall has not occurred, although farmers' responded that anomaly has increased in recent years. These findings from the analysis of perception data are relatable with the findings of the other studies (Abid *et al*., 2019; Negash and Eshetu, 2016; Ovuka & Lindqvist, 2000), and confirm that farmers perceptions are more biased with the extreme events, rather than the regular events. However, most of the farmers responded that they are modifying the crop calendar as an adaptive measure against rainfall variability, and the study has established the perception using remote sensing data. Previously, a study (Sawano *et al*., 2008) mentioned that, availability of water is the key factor which controls the transplantation process of rice, and delayed rainfall may affect the transplantation process. This study has come up with the result that farmers are delaying the plantation process by 15-30 days in extreme dry years (RAI $\leq$ 3) depending on availability of rainfall.

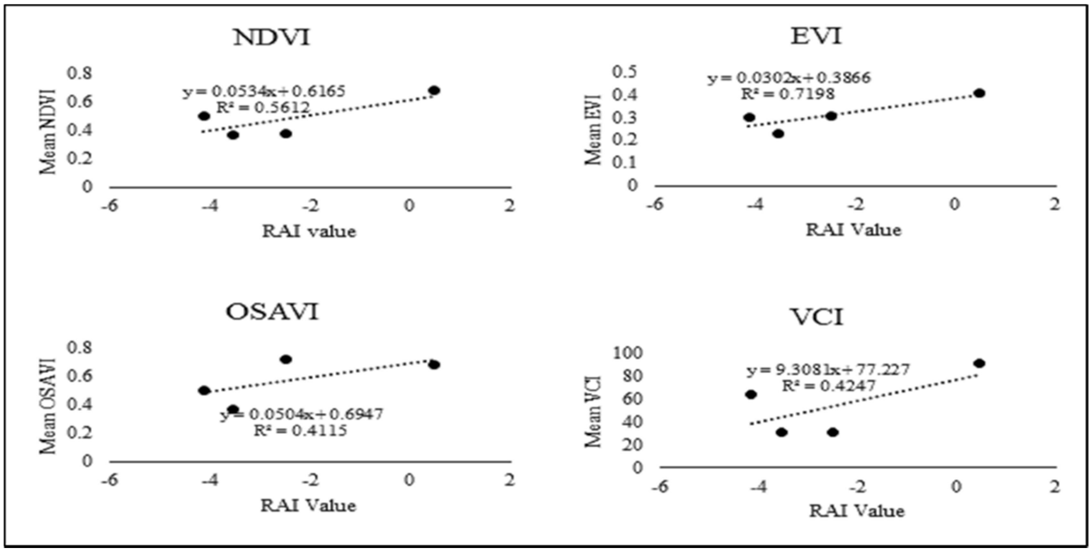


Figure 14: Correlation between RAI and Vegetation Indices

To observe this modification of the crop calendar, the study has been successfully applied different vegetation indices, and established a correlation between RAI and vegetation indices (Figure 15) Although, the result of some vegetation indices which are used in this study may not always depict the actual result, since the different vegetation indices have different sensitivity with the leaf area and the soil background. In some cases, the effect of the background could play a vital role in the result and, slope-based vegetation indices (NDVI, EVI) often fail to eliminate the effect of soil background (Silleos *et al*., 2006), here distance-based vegetation indices (OSAVI) may give a better result by minimizing soil reflectance. But in the case of rice, distance-based vegetation indices are not a good option for analysis of the growing stage. Because rice has a low leaf area coverage in the growing stage and OSAVI is less sensitive to low leaf area. Hence, EVI and OSAVI are more appropriate to study the rice crop in its mature stage. Whereas, NDVI is suitable to study the rice crop all over the season (Raghavendra & Aslam, 2017). In this study, OSAVI maps are showing little different results (high values) in the growing seasons (last week of August) of the years with rainfall anomaly due to this low sensitivity to low leaf area. But the other indices especially the NDVI maps are indicating the modification of the crop calendar during the rainfall anomaly period. In the case of negative rainfall anomaly years (2010, 2011, 2012), an acute water stress is causing the high VCI values (Dutta *et al*., 2015) in the last week of August, which decreased in the last week of

September, since the rainfall availability was increased in September. Although some parts of the study area are still having high water stress even in the last week of September especially, in the year 2011 and 2012, this could happen due to shortage of rainfall in the mid of the crop calendar (Atedhor, 2019). The study has found that 2011 has experienced a shrinkage in daily rainfall between 23rd July to 4th, and also August 19th to second week of September (Figure 15). The year 2012 has also come across from the same situation, here from 19th September to the last of the, daily rainfall was very nominal. This incidence in both of the years (2011 and 2012), are reflected in the VCI of the last week of September.

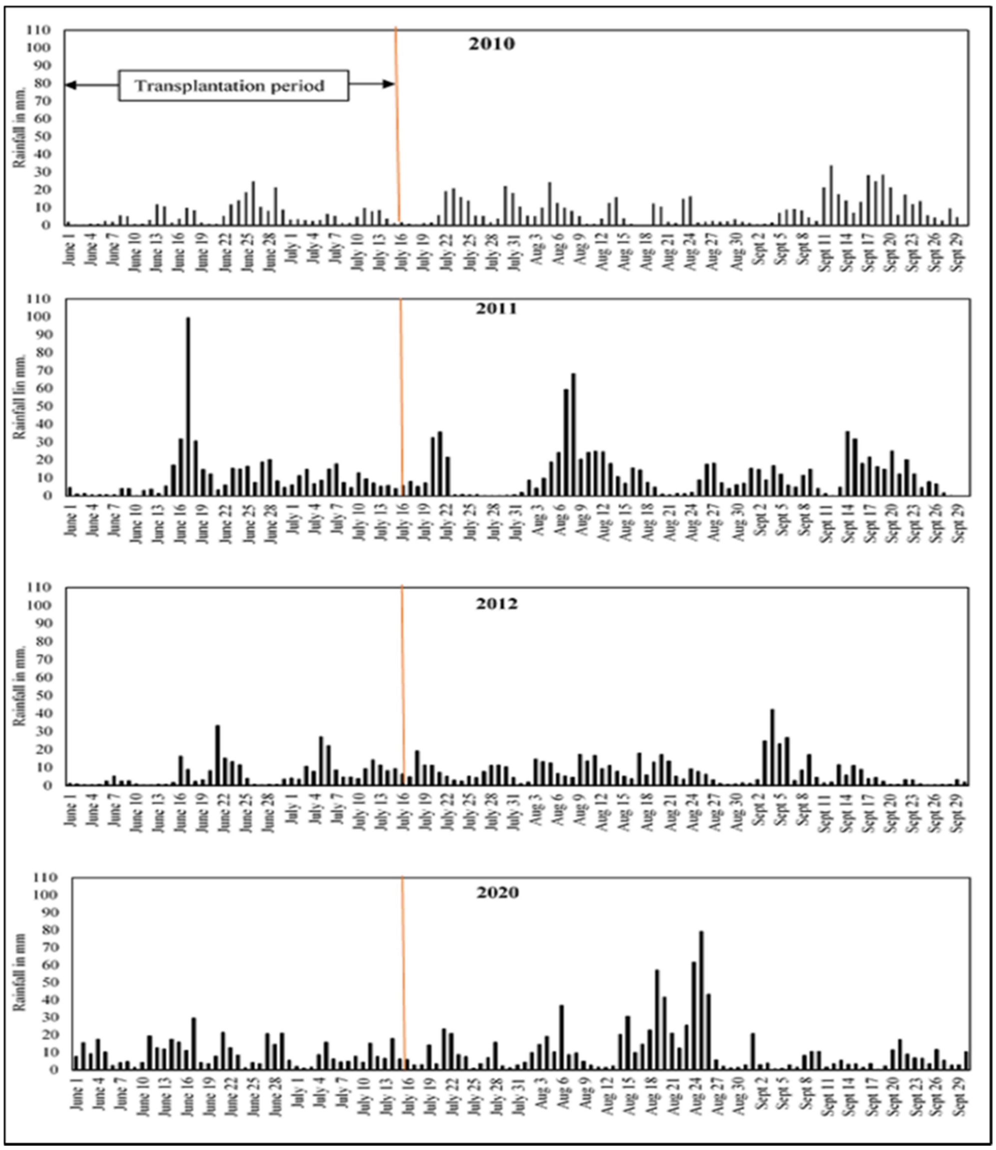


Figure 15: Distribution of daily rainfall of selected years

This result shows farmers are trying to modify their crop calendar, in accordance to availability of rainfall. Although the study has not examined whether the adaptation strategy is fruitful or not in this area in terms of production and yield, this is definitely a limitation of our study. Since the study site is a coastal area, any kind of unscientific practice could hamper the fragile ecosystem and distress the livelihood of thousands of farmers. Hence, the study is important to the policy makers to closely observe modification of crop calendar practiced by the farmers on the basis of their empirical knowledge, and need to provide proper information to get better results. It is also very important to conduct further detailed studies including not only physical aspects, but also socio-economic parameters for better understanding.

6. CONCLUSION:

Recent IPCC reports (2007, 2012, and 2021) have confirmed that extreme climatic events will significantly increase in the coming decades, which will affect the agricultural sector most. The study has showed, how the extreme rainfall variability is affecting the crop calendar of rice, and forcing farmers to delay the crop calendar. Since the farmers are practicing this adaptation strategy without having proper knowledge, they might not get the proper sustainable result. Although study of climate change linking agriculture is widely popular all over the world among researchers, even so, local level study is very much important. The negative impact of rainfall variability on crop production and yield is well established globally (Frankl *et al*., 2013; Kinda & Badolo, 2019; Rahman *et al*., 2017), thus it is important to study the different component of a whole agricultural system (i.e. crop calendar) in detail.

Another important aspect of our study is the study area. Since the coastal area is very much vulnerable to the climate change induced phenomena (IPCC, 2007), thus it is essential to study this area with more emphasis. Being a part of a developing country, the east coast of India has a high population dependency on agriculture, especially on rice farming. Furthermore the study area is prone to tropical cyclones, which makes the agriculture of the area more at a risk. Our field survey has confirmed that there are some lacuna among the farmers' empirical knowledge and proper scientific information. Thus timely information sharing and proper training are recommended.

Conflict of Interest:

The authors declare that there is no conflict of interest.

REFERENCES:

[1] Abid, M., Scheffran, J., Schneider, U. A., & Elahi, E. (2019). Farmer Perceptions of Climate Change, Observed Trends and Adaptation of Agriculture in Pakistan. Environmental Management, 63(1), 110–123. https://doi.org/10.1007/s00267-018-1113-7

[2] Alam, M., Ekhwan, M., Siwar, C., Talib, B., Fssk, E. S., Bangi, U. K. M., Alam, M., & Ekhwan, M. (2011). Rainfall Variation and Changing Pattern of Agricultural Cycle : A Study on Paddy Farming in Malaysia Institute for Environment and Development (LESTARI), School of Economics , Faculty of Economics and Business , Corresponding Author : Md . Mahmudul Alam. American Journal of Environmental Sciences, 7(1), 82–89.

[3] Anderson, R., Bayer, P. E., & Edwards, D. (2020). Climate change and the need for agricultural adaptation. Current Opinion in Plant Biology, 56, 197–202. https://doi.org/10.1016/j.pbi.2019.12.006

[4] Atedhor, G. O. (2019). Rainfall variability and drought during the sowing season and mid-season of rice in the Sudano-Sahelian Region of Nigeria. Journal of the Cameroon Academy of Sciences, 15(1), 39. https://doi.org/10.4314/jcas.v15i1.4

[5] Bala, S. K., & Islam, A. S. (2009). Correlation between potato yield and MODIS-derived vegetation indices. In International Journal of Remote Sensing (Vol. 30, Issue 10, pp. 2491–2507). https://doi.org/10.1080/01431160802552744

[6] Banerjee, S., Samanta, S., & Chakraborti, P. K. (2018). Impact of Climate Change on Coastal Agro-Ecosystems. In E. Lichtfouse (Ed.), Sustainable Agriculture Reviews 33 (pp. 115–133). Springer International Publishing. https://doi.org/10.1007/978-3-319-99076-7_4

[7] Boschetti, M., Stroppiana, D., Brivio, P. A., & Bocchi, S. (2009). Multi-year monitoring of rice crop phenology through time series analysis of MODIS images. International Journal of Remote Sensing, 30(18), 4643–4662. https://doi.org/10.1080/01431160802632249

[8] Boschetti, Mirco, Busetto, L., Manfron, G., Laborte, A., Asilo, S., Pazhanivelan, S., & Nelson, A. (2017). PhenoRice: A method for automatic extraction of spatio-temporal information on rice crops using satellite data time series. Remote Sensing of Environment, 194, 347–365. https://doi.org/10.1016/j.rse.2017.03.029

[9] Dhanya, P., & Ramachandran, A. (2016). Farmers' perceptions of climate change and the proposed agriculture adaptation strategies in a semi arid region of south India. Journal of Integrative Environmental Sciences, 13(1), 1–18. https://doi.org/10.1080/1943815X.2015.1062031

[10] Dutta, D., Kundu, A., Patel, N. R., Saha, S. K., & Siddiqui, A. R. (2015). Assessment of agricultural drought in Rajasthan (India) using remote sensing derived Vegetation Condition Index (VCI) and Standardized Precipitation Index (SPI). Egyptian Journal of Remote Sensing and Space Science, 18(1), 53–63. https://doi.org/10.1016/j.ejrs.2015.03.006

[11] FAO. (2015). Impact of natural hazards and disasters on agriculture and food security and nutrition. FAO Report, May, 16. http://www.fao.org/3/a-i4434e.pdf

[12] Fiwa, L., Vanuytrecht, E., Wiyo, K. A., & Raes, D. (2014). Effect of rainfall variability on the length of the crop growing period over the past three decades in central Malawi. Climate Research, 62(1), 45–58. doi: 10.3354/cr01263

[13] Frankl, A., Jacob, M., Haile, M., Poesen, J., Deckers, J., & Nyssen, J. (2013). The effect of rainfall on spatio-temporal variability in cropping systems and duration of crop cover in the Northern Ethiopian Highlands. Soil Use and Management, 29(3), 374–383. https://doi.org/10.1111/sum.12041

[14] Frondel, M., Simora, M., & Sommer, S. (2017). Risk Perception of Climate Change: Empirical Evidence for Germany. Ecological Economics, 137, 173–183. https://doi.org/10.1016/j.ecolecon.2017.02.019

[15] Geethalakshmi, V., Manikandan, N., Sumathi, S., Bhuvaneswari, K., Gowtham, R. and Pannerselvam, S. (2016). Impact of Climate Change on Coastal Agriculture. International Journal of Economic Plants, 3(3), 97–97. http://www.indianjournals.com/ijor.aspx?target=ijor:ijep1&volume=3&issue=3&article=003

[16] Gopalakrishnan, T., Hasan, M. K., Haque, A. T. M. S., Jayasinghe, S. L., & Kumar, L. (2019). Sustainability of coastal agriculture under climate change. Sustainability (Switzerland), 11(24), 1–24. https://doi.org/10.3390/su11247200

[17] Haboudane, D., Miller, J. R., Tremblay, N., Zarco-Tejada, P. J., & Dextraze, L. (2002). Integrated narrow-band vegetation indices for prediction of crop chlorophyll content for application to precision agriculture. Remote Sensing of Environment, 81(2–3), 416–426. https://doi.org/10.1016/S0034-4257(02)00018-4

[18] Hazra, S. (2012). Climate Change Adaptation in Coastal Region of West Bengal. In Climate Change Policy Paper II. http://awsassets.wwfindia.org/downloads/climate_change_adaptation_in_coastal_region_of_west_bengal.pdf

[19] Hawkins, E., & Sutton, R. (2011). The potential to narrow uncertainty in projections of regional precipitation change. Climate Dynamics, 37(1), 407–418. https://doi.org/10.1007/s00382-010-0810-6

[20] Iglesias, A., Quiroga, S., Moneo, M., & Garrote, L. (2012). From climate change impacts to the development of adaptation strategies: Challenges for agriculture in Europe. Climatic Change, 112(1), 143–168. https://doi.org/10.1007/s10584-011-0344-x

[21] IPCC, 2007: Climate Change 2007: Impacts, Adaptation and Vulnerability. Contribution of Working Group II to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change, M.L. Parry, O.F. Canziani, J.P. Palutikof, P.J. van der Linden and C.E. Hanson, Eds., Cambridge University Press, Cambridge, UK, 976pp.

[22] IPCC, 2012: Summary for Policymakers. In: Managing the Risks of Extreme Events and Disasters to Advance Climate Change Adaptation [Field, C.B., V. Barros, T.F. Stocker, D. Qin, D.J. Dokken, K.L. Ebi, M.D. Mastrandrea, K.J. Mach, G.-K. Plattner, S.K. Allen, M. Tignor, and P.M. Midgley (eds.)]. A Special Report of Working Groups I and II of the Intergovernmental Panel on Climate Change. Cambridge University Press, Cambridge, UK, and New York, NY, USA, pp. 1-19

[23] IPCC, 2021: Summary for Policymakers. In: Climate Change 2021: The Physical Science Basis. Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change [Masson-Delmotte, V.,

P. Zhai, A. Pirani, S. L. Connors, C. Péan, S. Berger, N. Caud, Y. Chen, L. Goldfarb, M. I. Gomis, M. Huang, K. Leitzell, E. Lonnoy, J.B.R. Matthews, T. K. Maycock, T. Waterfield, O. Yelekçi, R. Yu and B. Zhou (eds.)]. Cambridge University Press. In Press.

[24] Jain, S. K., Keshri, R., Goswami, A., & Sarkar, A. (2010). Application of meteorological and vegetation indices for evaluation of drought impact: A case study for Rajasthan, India. Natural Hazards, 54(3), 643–656. https://doi.org/10.1007/s11069-009-9493-x

[25] Kengni, L., Mboussop, A. N., Njueya Kopa, A., Tankou, C. M., Tematio, P., & Ndam Ngoupayou, J. R. (2019). Rainfall variability on the southern slope of the Bambouto mountain (West-Cameroon) and impact on the crop cultivation calendar. Journal of African Earth Sciences, 154, 164–171. https://doi.org/10.1016/j.jafrearsci.2019.03.020

[26] Kinda, S. R., & Badolo, F. (2019). Does rainfall variability matter for food security in developing countries ? Cogent Economics & Finance, 7(1). https://doi.org/10.1080/23322039.2019.1640098

[27] Kirana, A. P., Ririd, A., Ariyanto, R., Amalia, E. L., & Bhawiyuga, A. (2020). Spatiotemporal Pattern Distribution of Drought Area using MODIS Vegetation Health Index. Case Study: Paddy Field in East Java, Indonesia. IOP Conference Series: Earth and Environmental Science, 528(1). https://doi.org/10.1088/1755-1315/528/1/012056

[28] Kulkarni, A. (2012). Weakening of Indian summer monsoon rainfall in warming environment. Theoretical and Applied Climatology, 109(3–4), 447–459. https://doi.org/10.1007/s00704-012-0591-4

[29] Kyei-Mensah, C., Kyerematen, R., & Adu-Acheampong, S. (2019). Impact of Rainfall Variability on Crop Production within the Worobong Ecological Area of Fanteakwa District, Ghana. Advances in Agriculture, 2019, 1–7. https://doi.org/10.1155/2019/7930127

[30] Lesk, C., Rowhani, P., & Ramankutty, N. (2016). Influence of extreme weather disasters on global crop production. Nature, 529(7584), 84–87. https://doi.org/10.1038/nature16467

[31] Li, L., Friedl, M. A., Xin, Q., Gray, J., Pan, Y., & Frolking, S. (2014). Mapping crop cycles in China using MODIS-EVI time series. Remote Sensing, 6(3), 2473–2493. https://doi.org/10.3390/rs6032473

[32] Liu, W. T., & Kogan, F. N. (1996). Monitoring regional drought using the vegetation condition index. International Journal of Remote Sensing, 17(14), 2761–2782. https://doi.org/10.1080/01431169608949106

[33] Loo, Y. Y., Billa, L., & Singh, A. (2015). Effect of climate change on seasonal monsoon in Asia and its impact on the anomaly of monsoon rainfall in Southeast Asia. Geoscience Frontiers, 6(6), 817–823. https://doi.org/10.1016/j.gsf.2014.02.009

[34] Mall, R. K., Singh, R., Gupta, A., Srinivasan, G., & Rathore, L. S. (2006). Impact of climate change on Indian agriculture: A review. Climatic Change, 78(2–4), 445–478. https://doi.org/10.1007/s10584-005-9042-x

[35] Mase, A. S., Gramig, B. M., & Prokopy, L. S. (2017). Climate change beliefs, risk perceptions, and adaptation behavior among Midwestern U.S. crop farmers. Climate Risk Management, 15, 8–17. https://doi.org/10.1016/j.crm.2016.11.004

[36] Murthy, C. S., Raju, P. V., Jonna, S., Hakeem, K. A., & Thiruvengadachari, S. (1998). Satellite derived crop calendar for canal operation schedule in Bhadra project command area, India. International Journal of Remote Sensing, 19(15), 2865–2876. https://doi.org/10.1080/014311698214316

[37] Nandargi, S. S., & Barman, K. (2018). Evaluation of Climate Change Impact on Rainfall Variation in West Bengal. Acta Scientific Agriculture, 2(7), 74–82.

[38] Negash and Eshetu. (2016). Analysis of Rainfall Variability and Farmers ' Perception towards it in Agrarian Community of Southern Ethiopia. Journal of Environment and Earth Science, 6(4), 99–107.

[39] Oscar Kisaka, M., Mucheru-Muna, M., Ngetich, F., Mugwe, J., Mugendi, D., & Mairura, F. (2015). Seasonal rainfall variability and drought characterization: Case of Eastern Arid Region, Kenya. Climate Change Management, 53–71. https://doi.org/10.1007/978-3-319-13000-2_5

[40] Ovuka, M., & Lindqvist, S. (2000).

Rainfall variability in Murang'a district, Kenya: Meteorological data and farmers' perception. Geografiska Annaler, Series A: Physical Geography, 82(1), 107–119. https://doi.org/10.1111/j.0435-3676.2000.00116.x

[41] Ozyavuz, M., Bilgili, B. C., & Salici, A. (2015). Determination of vegetation changes with NDVI method. Journal of Environmental Protection and Ecology, 16(1), 264–273.

[42] Pal, S., Mazumdar, D., & Chakraborty, P. K. (2015). District-wise trend analysis of rainfall pattern in last century (1901-2000) over Gangetic region in West Bengal, India. Journal of Applied and Natural Science, 7(2), 750–757. https://doi.org/10.31018/jans.v7i2.678

[43] Patel, J. H., & Oza, M. P. (2014). Deriving crop calendar using NDVI time-series. ISPRS - International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences, XL–8(December), 869–873. https://doi.org/10.5194/isprsarchives-XL-8-869-2014

[44] Pendergrass, A. G., Knutti, R., Lehner, F., Deser, C., & Sanderson, B. M. (2017). Precipitation variability increases in a warmer climate. Scientific Reports, 7(1), 1–9. https://doi.org/10.1038/s41598-017-17966-y

[45] Raghavendra, B. R., & Mohammed Aslam, M. A. (2017). Sensitivity of vegetation indices of MODIS data for the monitoring of rice crops in Raichur district, Karnataka, India. Egyptian Journal of Remote Sensing and Space Science, 20(2), 187–195. https://doi.org/10.1016/j.ejrs.2016.06.005

[46] Rahman, M. A., Kang, S. C., Nagabhatla, N., & Macnee, R. (2017). Impacts of temperature and rainfall variation on rice productivity in major ecosystems of Bangladesh. Agriculture and Food Security, 6(1), 1–11. https://doi.org/10.1186/s40066-017-0089-5

[47] Rossi, E., Rogan, J., & Schneider, L. (2013). Mapping forest damage in northern Nicaragua after Hurricane Felix (2007) using MODIS enhanced vegetation index data. GIScience and Remote Sensing, 50(4), 385–399. https://doi.org/10.1080/15481603.2013.820066

[48] Sadiq A.A., S. M. U. and M. U. B. (2020). An Estimation f Rainfall

Anomaly Index And Its Impact on Crop Production in Yola and Environs. African Journal of Environment and Natural Science Research, 3(4), 35–53.

[49] Sawano, S., Hasegawa, T., Goto, S., Konghakote, P., Polthanee, A., Ishigooka, Y., Kuwagata, T., & Toritani, H. (2008). Modeling the dependence of the crop calendar for rain-fed rice on precipitation in Northeast Thailand. Paddy and Water Environment, 6(1), 83–90. https://doi.org/10.1007/s10333-007-0102-x

[50] Semedi, J. M. (2012). Rice Crop Spatial Distribution and Production Estimation Using (Issue July 2012) [Bogor Agricultural University]. https://doi.org/10.13140/RG.2.2.20109.03047

[51] Shakeel A. Khan, Sanjeev Kumar, M. Z. H. and N. K. 2. . (2009). Climate Change, Climate Anomaly and Indian Agriculture: Impacts Vulnerability and Adaptation Strategies. Book, January, 32. https://doi.org/10.1007/978-3-540-88246-6

[52] Shortridge, J. (2019). Observed trends in daily rainfall variability result in more severe climate change impacts to agriculture. Climatic Change, 157(3–4), 429–444. https://doi.org/10.1007/s10584-019-02555-x

[53] Shrivastava, D., & Chaudhary, S. J. (2020). Effect of monsoon onset and withdrawal on rice production in Chhattisgarh. International Journal of Chemical Studies, 8(6), 418–423. https://doi.org/10.22271/chemi.2020.v8.i6f.10807

[54] Silleos, N. G., Alexandridis, T. K., Gitas, I. Z., & Perakis, K. (2006). Vegetation indices: Advances made in biomass estimation and vegetation monitoring in the last 30 years. Geocarto International, 21(4), 21–28. https://doi.org/10.1080/10106040608542399

[55] Status Paper - 02. (n.d.). Retrieved May 10, 2021, from http://drdpat.bih.nic.in/Status Paper - 02.htm

[56] Truong An, D. (2020). Shifting crop planting calendar as a climate change adaptation solution for rice cultivation region in the Long Xuyen Quadrilateral of Vietnam. Chilean Journal of Agricultural Research, 80(4), 468–477. https://doi.org/10.4067/S0718-58392020000400468

[57] Vinutha, H. P., Poornima, B., & Sagar, B. M. (2018). Detection of outliers using interquartile range technique from intrusion dataset. In Advances in Intelligent Systems and Computing (Vol. 701). Springer Singapore. https://doi.org/10.1007/978-981-10-7563-6_53

[58] Xue, J., & Su, B. (2017). Significant remote sensing vegetation indices: A review of developments and applications. Journal of Sensors, 2017. https://doi.org/10.1155/2017/1353691

[59] Yegbemey, R. N., Kabir, H., Awoye, O. H. R., Yabi, J. A., & Paraïso, A. A. (2014). Managing the agricultural calendar as coping mechanism to climate anomaly : A case study of maize farming in northern Benin, West Africa. Climate Risk Management, 3(September), 13–23. https://doi.org/10.1016/j.crm.2014.04.001

[60] Zaveri, E., Russ, J., & Damania, R. (2020). Rainfall anomalies are a significant driver of cropland expansion. Proceedings of the National Academy of Sciences of the United States of America, 117(19), 10225–10233. https://doi.org/10.1073/pnas.1910719117

[61] Zhang, G., Xiao, X., Dong, J., Kou, W., Jin, C., Qin, Y., Zhou, Y., Wang, J., Menarguez, M. A., & Biradar, C. (2015). Mapping paddy rice planting areas through time series analysis of MODIS land surface temperature and vegetation index data. ISPRS Journal of Photogrammetry and Remote Sensing, 106, 157–171. https://doi.org/10.1016/j.isprsjprs.2015.05.011