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# Rainfall analysis of Halia river basin and comparison of agricultural drought using remote sensing indices

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**Abstract**
Halia basin in the semi-arid region of Telangana experiences prolonged dry spells resulting in yield reduction/ crop failure in most of the years. Therefore, studying the variability in rainfall and monitoring the drought is very important for this basin. Rainfall variability significantly impacts agricultural productivity, especially in rainfed regions. This study analyzed historical rainfall patterns in the Halia Basin in Nalgonda district of Telangana state over 73 years (1951-2023) using Weather Cock software. The analysis examined rainfall trends on a weekly, monthly, seasonal, annual, and decadal basis for Halia. The annual rainfall ranged from 318 mm to 1,541 mm, with 26 to 63 rainy days per year. The highest annual rainfall of 1,541 mm and *kharif* season rainfall of1,233 mm occurred in 1988, distributed over 60 rainy days. The region experienced two severe meteorological droughts in 1984 and 1999 and 11 moderate drought years, with rainy days ranging from 33 to 44. Decadal rainfall analysis revealed considerable seasonal variability. Out of 73 years, agricultural droughts occurred in 34 years, lasting for 6 to 12 weeks during the *kharif* season. Normalized Difference Drought Index (NDDI) data, analyzed at eight-day intervals, showed strong correlations between reduced precipitation and increased drought severity. In 2014, distinct drought phases in June, August, and late September-October coincided with critical crop growth stages. Satellite imagery from June 9 and June 19, 2014, highlighted moderate to extreme drought conditions. This study demonstrated the effectiveness of integrating long-term weather data with remote sensing for comprehensive drought assessment. The findings highlight NDDI's potential for agricultural drought monitoring and provide valuable insights for water resource management and sustainable farming practices. The consolidated 73-year hydro-meteorological dataset generated by this work also establishes a baseline for predictive drought-risk modelling and climate-smart agricultural advisories in semi-arid river basins.

**Keywords:** Annual and decadal rainfall analysis, Agricultural drought, NDVI, NDWI, NDDI

## 1. Introduction

Rainfall is a critical component of the hydrological cycle, influencing water resources, agriculture, and ecosystem sustainability. The temporal and spatial variability of rainfall significantly impacts agricultural productivity, particularly in regions dependent on rain-fed farming. Analyzing historical rainfall trends is essential for understanding long-term climatic patterns, assessing drought risks, and developing strategies for sustainable water management with the rainfall pattern prevalent in the region [4].

Numerous studies have been conducted to develop region-specific agricultural and crop planning strategies by examining daily, weekly, monthly, seasonal, and annual rainfall data. Stern and Coe analyzed daily rainfall data to aid in crop planning for semi-arid and tropical regions [18]. Similarly, Panigrahi and Sharda, and Das [14, 16] conducted comparable studies on rainfall patterns for crop planning in coastal areas, semi-arid zones, dry farming regions, sub-humid areas, and the Himalayan foothills. Ganchaudhuri [7] analyzed daily rainfall for a suitable risk-proof crop which can be best suitable for *kharif* and *rabi* seasons for two districts, Unakoti and West Tripura of Tripura.

Drought is a highly complex and severe environmental condition that affects all living organisms [21] It is defined as a significant shortage of water resources compared to typical levels, often leading to substantial agricultural losses along with environmental problems like erosion and soil loss. The severity of a drought is determined by factors such as its duration, geographic extent, timing, and intensity [12, 13]. It refers to a significant decline in water availability compared to usual levels, often resulting in major agricultural damage. The intensity of a drought is determined by its duration, geographic spread, timing, and severity. Therefore, its effects are analyzed based on specific requirements and circumstances. Agricultural droughts are of two types. *Kharif* drought means at least four consecutive weeks receiving less than half of the normal rainfall during the *kharif* season, and *rabi* drought means six consecutive weeks during the *rabi* season receiving less than half of the normal rainfall. Agricultural drought can also be analyzed through various spatial indices like Simple Ratio Water Index (SRWI), Normalized Difference Water Index (NDWI), Normalized Difference Drought Index (NDDI), Land Surface Water Index (LSWI), Vegetation Condition Index (VCI), etc.

The Halia basin, an agriculturally important region, has experienced fluctuations in rainfall patterns that directly affect soil moisture levels and crop growth. This study aims to analyze long-term rainfall trends in the Halia basin, agricultural drought during crop season, and comparison of agricultural drought with remote sensing-based drought indices NDDI. The findings will contribute to better drought assessment, early warning systems, and sustainable agricultural planning in the region. Studying the rainfall patterns of a region is essential for designing effective cropping systems, selecting appropriate cropping patterns [15], and planning drainage and water harvesting structures [11], and week-by-week rainfall analysis gives more valuable data in crop planning [17].

## 2. Materials and Methods

### Study area

Halia basin, situated in Nalgonda district of Telangana state, geographically, it lies between 16° 37 19" to 17° 17 21" N latitudes and 78° 34 23" to 79° 29 20" E longitudes. The average annual rainfall of the basin ranges from 700 to 800 mm. The region experiences a semi-arid to dry sub-humid climate, with annual rainfall predominantly influenced by the southwest monsoon. Rainfall variability in the basin has a direct impact on agricultural productivity as the area is highly dependent on seasonal precipitation for crop growth. Major crops grown in the region include paddy, maize, pulses, and cotton, which are sensitive to fluctuations in rainfall and drought conditions.

## 3. Methodology

### Rainfall Analysis

WEATHER COCK software which was developed by CRIDA, Hyderabad for weather data analysis is used to analyze the rainfall pattern of long term rainfall data for the study region. Data was collected from the India Meteorological Department (IMD) for the period of 73 years from 1951 to 2023, and is used. Weather Cock contain 26 number of modules which are related to agro climatic parameters out of few modules were used in this study for weather data analysis like weekly, monthly, seasonal, annual rainfall, number of rain events, meteorological and agricultural drought. Based on the rainfall trends of seven decades of the region and decadal rainfall analysis aids in planning the critical irrigation to protect the crop and to conserve water and soil during heavy rain events. Satellite data is used to show the impact of drought spatially during prolonged drought, moderate drought period, and normal year.

### Remote Sensing Indices

The Normalized Difference Drought Index (NDDI) is an index used for monitoring drought conditions. It is derived by combining the Normalized Difference Vegetation Index (NDVI) and the Normalized Difference Water Index (NDWI). NDDI is calculated as the ratio of the difference between NDVI and NDWI to their sum [20], providing insights into drought severity. The NDDI values are handled on a scale between −1 and 1, where negative values indicate the presence of water, while positive values close to 1 indicate more intense drought conditions [1, 6].

$$NDDI = \frac{NDVI - NDWI}{NDVI + NDWI}$$

The concept of NDVI was given by Deering [3]. Normalized difference vegetation index (NDVI) is the normalized reflectance difference between the two spectral bands, i.e., near-infrared (NIR) and visible red bands is used mainly for monitoring vegetation of the earth's surface. NDVI is one of the well-known vegetation indices and is used to monitor and analyze drought occurrence and vegetation health [6]. Drought is assessed further by using a GIS tool for the study area, and the NDVI values range from -1 to +1, where -1 is a severe drought condition and +1 is no drought condition, Alternatively shows vegetation and the ratio is expressed in an equation

$$NDVI = \frac{\rho NIR - \rho RED}{\rho NIR + \rho RED}$$

Whereas NIR and RED represent reflectance in the near-infrared and red bands. The MODIS Terra MOD09A1 Version 6 product offers an estimation of surface spectral reflectance for Bands 1 through 7 of the Terra MODIS sensor, with corrections applied for atmospheric influences such as gases, aerosols, and Rayleigh scattering. This dataset includes seven reflectance bands at a 500-meter resolution, along with two quality assessment layers and four observation bands. Each pixel value is selected from multiple observations captured over an 8-day period, with the selection criteria considering factors like cloud cover and solar zenith angle.

NDWI is calculated by the subtraction of green and near-infrared bands, then dividing by the sum of the green and near-infrared bands [8]. NDWI was derived using the following equation.

$$NDWI = \frac{\rho NIR - \rho SWIR}{\rho NIR + \rho SWIR}$$

ρNIR is the near infrared channel (841-876 nm), and ρSWIR = one of the middle infrared channels (2,105-2,155 nm) measured by the MODIS sensor.

The study utilized the data from MOD09A1 for comparing the agricultural drought period analyzed using weather cock with satellite data ie., NDDI indices for two different periods ie., prolonged drought year, moderate drought year during *kharif* season. Estimating NDDI was performed utilizing evaluated NDVI and NDWI tiles, separated into six distinct drought classes. The MODIS Terra MOD09A1 Version 6 product offers an estimation of surface spectral reflectance for Bands 1 through 7 of the Terra MODIS sensor. The data with spatial resolution at a 500-meter captured over an 8-day period of temporal resolution, with the selection criteria considering factors like cloud cover, were used for the study.

## 4. Results

### Rainfall trend over the Halia basin

The long-term rainfall analysis of the Haliabasin over a 73-year period (1951-2023) reveals significant inter-annual variability in precipitation patterns. The mean annual rainfall of 791.42 mm, with a standard deviation of 216.75 mm, indicates considerable fluctuations in rainfall distribution across the years. The coefficient of variation (CV%) of 27.39% suggests a moderate level of variability, which may impact water availability and agricultural productivity in the region.

The relationship between the number of rainfall events and annual rainfall over a 73-year period was analyzed using linear regression. The results indicate a strong positive correlation ($r = 0.86$, $p < 0.001$), demonstrating that an increase in rainfall events is associated with higher annual rainfall. The regression analysis yielded a significant model ($R^2 = 0.731$, $p < 0.001$), explaining 73.1% of the variation in annual rainfall based on the number of rainfall events. The regression equation suggests that each additional rainfall event contributes approximately 16.49 mm to the total annual rainfall. The scatter plot, accompanied by a regression line and confidence interval, illustrates the consistency of this relationship, with most data points closely following the trend line. The confidence interval highlights the range within which the true regression line is likely to fall, reinforcing the reliability of the model. These findings underscore the crucial role of rainfall frequency in determining annual precipitation levels and have implications for hydrological modeling, climate variability studies and water resource management.

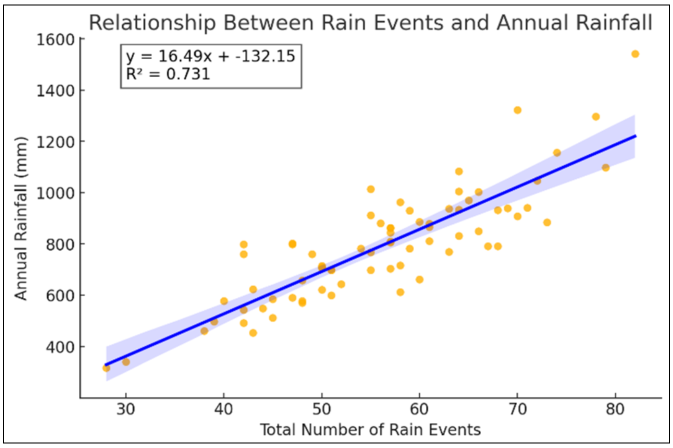


**Fig 1:** Graph showing the relationship between rainfall events and annual rainfall

The frequency of extreme events, assessed using percentile-based thresholds (e.g., 90th percentile for wet years and 10th percentile for dry years), indicates increasing rainfall variability, necessitating improved water resource management strategies. The 90th percentile of annual rainfall is 1013.1 mm, identifying the threshold for wet years, while the 10th percentile is 543.98 mm, marking the threshold for dry years. Years exceeding the 90th percentile indicate extreme wet conditions (during the years 1961,981,1995,1998, 2010, 2013, and 2020), leading to potential flood risks and excessive soil moisture, which can adversely affect certain crops and infrastructure. The pattern of rainfall in these years suggests periodic high rainfall events occurring roughly every decade, which aligns with climate variability trends. Such high rainfall years can be beneficial for seasonal agriculture, particularly for water-intensive crops like rice and sugarcane, as they ensure adequate soil moisture and replenishment of groundwater. However, excessive rainfall can also lead to waterlogging, soil erosion, and flooding, which negatively impact crop yields and infrastructure. To mitigate these losses, proper drainage systems, rainwater harvesting, and the ad-option of flood-resistant crop varieties are recommended. Additionally, staggered sowing and the use of raised bed planting techniques can help reduce the risk of crop damage due to excessive rainfall [19].

Conversely, years falling below the 10th percentile represent dry conditions (during the years 1952, 1965, 1972, 1984, 1986, 1999, 2002 and 2011), the occurrence of these low-rainfall years suggests periodic drought-like conditions, typically appearing every one to two decades, aligning with broader climate cycles such as El Nino events, which are known to suppress monsoon activity in the region. Such dry years pose significant challenges for rainfed agriculture, leading to soil moisture deficits, reduced groundwater recharge, and lower crop yields, especially for water-dependent crops like rice and maize.

### Decadal rainfall analysis

The long-term analysis of decadal rainfall trends reveals significant variations across different seasons. The North East (Oct-Dec) monsoon shows an increasing trend from 1954 to 2003, peaking at 187.1 mm (2004-2013) before declining to 104.4 mm (2014-2023), suggesting possible shifts in seasonal rainfall patterns, potentially due to changes in atmospheric circulation and regional climatic variability. The South West (June-Sept) monsoon, the primary contributor to annual rainfall, exhibits a steady increase from 500.7 mm (1964-73) to 686.5 mm (2014-2023), indicating a strengthening monsoon, which may be linked to increased sea surface temperatures and monsoonal wind intensity. Similarly, Summer (Mar-May) rainfall has risen from 41.7 mm (1954-63) to 74.8 mm (2014-2023), highlighting a shift in pre-monsoon precipitation patterns, possibly influenced by changes in convective activity and land surface temperatures. Winter (Jan-Feb) rainfall remains relatively low, fluctuating between 8.6 mm and 20.3 mm, without a clear long-term trend, which may be attributed to the limited influence of global warming on winter precipitation in the region.

Statistical insights indicate high variability in seasonal rainfall, with the South West monsoon showing the most consistent increasing trend, while the North East monsoon exhibits higher inter-decadal fluctuations. The decline in North East monsoon rainfall in recent years aligns with global observations of weakened post-monsoon circulation and shifting moisture availability. These findings correlate with broader climate change indicators, such as rising global temperatures, changes in oceanic circulation (e.g., El Nino-Southern Oscillation - ENSO), and regional deforestation impacts, all of which can influence rainfall distribution. The increasing trend in summer rainfall may also be associated with higher evaporation rates and localized convective storms due to rising surface temperatures.

These variations emphasize the need for adaptive water resource management, improved monsoon forecasting, and climate-resilient agricultural planning. Further research integrating climate models, remote sensing data, and hydrological assessments can provide deeper insights into the underlying drivers of these trends and their long-term implications.

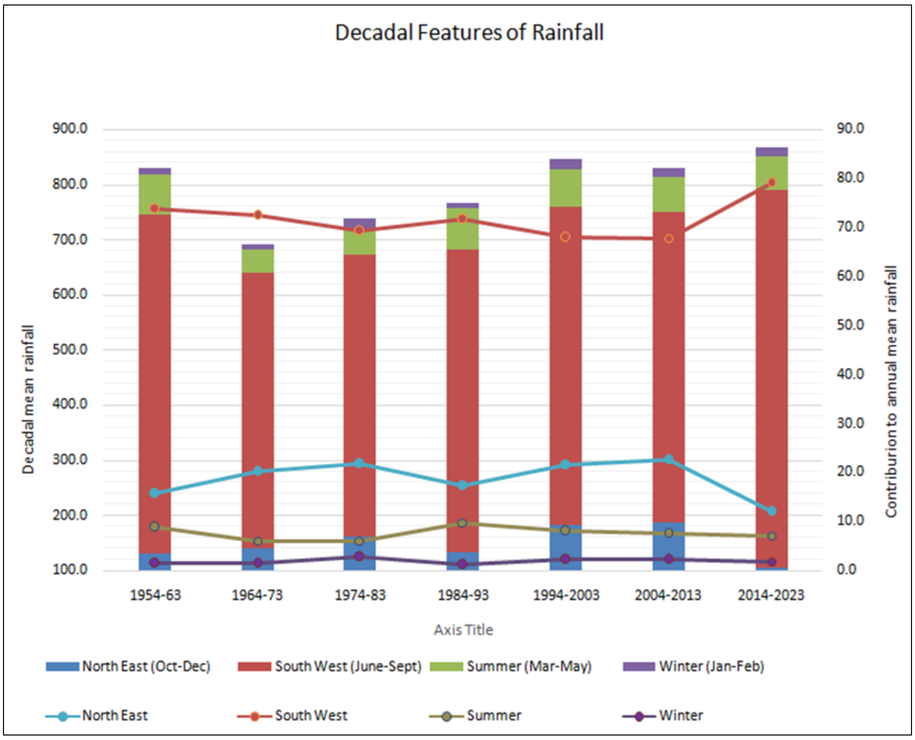


**Fig 2:** Graph showing the seasonal decadal rainfall pattern and contribution to annual rainfall

**Table 1**: Decadal features of rainfall events

| Year | 2.5<25mm | 25<50mm | 50<75mm | 75<100mm | ≥ 100 mm | Avg. Decadal RF |
|---|---|---|---|---|---|---|
| 1954-63 | 422 | 132 | 32 | 12 | 8 | 830.84 |
| 1964-73 | 379 | 90 | 26 | 12 | 6 | 691.32 |
| 1974-83 | 399 | 124 | 26 | 8 | 2 | 738.17 |
| 1984-93 | 365 | 132 | 18 | 14 | 12 | 766.95 |
| 1994-2003 | 359 | 158 | 30 | 14 | 8 | 847.63 |
| 2004-2013 | 368 | 148 | 30 | 6 | 8 | 831.46 |
| 2014-2023 | 356 | 166 | 36 | 12 | 6 | 868.76 |
| Mean | | | | | | 796.4 |
| SD(mm) | | | | | | 65 |
| CV(%) | | | | | | 8 |

**Table 2:** Decadal seasonal rainfall analysis

| Season | | 1954-63 | 1964-73 | 1974-83 | 1984-93 | 1994-03 | 2004-13 | 2014-23 |
|---|---|---|---|---|---|---|---|---|
| Decadal annual rainfall | | 830.8 | 691.3 | 738.2 | 767.0 | 847.6 | 831.5 | 868.8 |
| North East (Oct-Dec) | Mean | 131.2 | 139.1 | 161.4 | 133.0 | 183.2 | 187.1 | 104.4 |
| | Contribution | 15.8 | 20.1 | 21.9 | 17.3 | 21.6 | 22.5 | 12.0 |
| | SD(mm) | 103.4 | 89.7 | 89.0 | 138.5 | 115.9 | 164.7 | 78.2 |
| | CV(%) | 78.8 | 64.5 | 55.2 | 104.2 | 63.2 | 88.1 | 74.9 |
| South West (June-Sept) | Mean | 613.8 | 500.7 | 511.6 | 550.6 | 576.6 | 564.2 | 686.5 |
| | Contribution | 73.9 | 72.4 | 69.3 | 71.8 | 68.0 | 67.9 | 79.0 |
| | SD(mm) | 77.7 | 118.0 | 140.7 | 230.3 | 293.3 | 139.2 | 183.5 |
| | CV(%) | 12.7 | 23.6 | 27.5 | 41.8 | 50.9 | 24.7 | 26.7 |
| Summer (Mar-May) | Mean | 73.9 | 41.7 | 45.0 | 74.8 | 68.9 | 62.0 | 61.7 |
| | Contribution | 8.9 | 6.0 | 6.1 | 9.7 | 8.1 | 7.5 | 7.1 |
| | SD(mm) | 50.8 | 41.0 | 55.3 | 85.0 | 51.6 | 50.6 | 31.6 |
| | CV(%) | 68.7 | 98.2 | 123.0 | 113.7 | 74.9 | 81.7 | 51.3 |
| Winter | Mean | 11.9 | 9.8 | 20.3 | 8.6 | 19.0 | 18.2 | 16.2 |
| | Contribution | 1.4 | 1.4 | 2.7 | 1.1 | 2.2 | 2.2 | 1.9 |
| | SD(mm) | 20.2 | 18.3 | 44.7 | 17.1 | 25.0 | 23.2 | 29.8 |
| | CV(%) | 169.7 | 187.1 | 220.4 | 197.5 | 131.4 | 127.9 | 183.3 |

In the Halia Basin, the *kharif* season typically extends from June to October, coinciding with the monsoon rains. This period is crucial for rainfed crops like paddy, jowar, groundnut, chillies,etc, which heavily rely on consistent rainfall for germination and growth [2]. On the other hand, the *rabi* season spans from November to April, depending on residual soil moisture and irrigation sources. The analysis of agricultural drought weeks indicates that droughts occur across various crop growth stages, affecting both *kharif* and *rabi* production. Early-season drought (weeks 22-27, June-July) hampers *kharif* sowing and seed germination, while mid-season drought (weeks 28-36, August-September) impacts flowering and grain formation, leading to yield reductions. Late-season drought (weeks 37-42, October-November) can delay harvesting and soil moisture recharge, subsequently affecting *rabi* sowing and winter crop establishment.

Prolonged droughts, characterized by extended dry spells affecting multiple crop growth stages, were observed in 1965, 1994, 2002, and 2014, where drought weeks extended beyond six weeks, impacting both *kharif* and early *rabi* crops. These years pose challenges, leading to crop failures, soil moisture depletion, and groundwater stress. Moderate droughts during *kharif*, typically lasting 3-5 weeks, were recorded in 1962, 1971, 1990, 1999, 2006, and 2018. Out of 73 73-year of study period, 8 years ie, 1959,1960, 1965, 1967, 1988, 1989, 2011, and 2018, recorded 6 to 7 weeks of drought periods. While these droughts causeyield reductions and delayed crop development, their impacts will be relatively less severe, especially when supplemented with irrigation or improved soil moisture conservation techniques. The variability in drought intensity highlights the need for climate-resilient agricultural strategies, such as drought-resistant crop varieties, water conservation techniques, and efficient irrigation systems, to mitigate the adverse effects of dry spells on both *kharif* and *rabi* farming systems.

**Table 3:** Showing agricultural drought period during *kharif* and *rabi*

| Year | Drought week (*kharif*) | Year | Drought week (*kharif*) | Year | Drought week (*rabi*) |
|---|---|---|---|---|---|
| 1951 | 36-39 | 1990 | 28-31 | 1959 | 41 - 46 |
| 1960 | 30-34 | 1991 | 33-36 | 1960 | 41 - 46 |
| 1962 | 28-31 | 1992 | 23-26 | 1965 | 40 - 46 |
| | 38-41 | 1993 | 31-34 | 1967 | 41 - 46 |
| 1965 | 22-27 | 1994 | 22-26 | 1988 | 40 - 46 |
| | 39-42 | | 36-39 | 1989 | 40 - 45 |
| 1966 | 23-28 | 1997 | 39-42 | 2011 | 40 - 46 |
| 1967 | 31-34 | 1999 | 25-28 | 2018 | 40 - 46 |
| 1968 | 31-35 | | 30-33 | | |
| 1969 | 22-25 | 2000 | 35-40 | | |
| | 37-40 | 2001 | 25-30 | | |
| 1971 | 28-32 | 2002 | 26-31 | | |
| 1972 | 28-33 | | 35-40 | | |
| 1974 | 25-29 | 2004 | 32-36 | | |
| 1976 | 37-41 | 2005 | 22-25 | | |
| 1979 | 26-30 | 2006 | 26-29 | | |
| | 32-36 | 2009 | 27-32 | | |
| 1980 | 38-41 | 2011 | 38-42 | | |
| 1984 | 32-40 | 2014 | 22-25 | | |
| 1987 | 35-39 | | 31-34 | | |
| | | | 39-42 | | |

* week numbers are as per IMD standard week

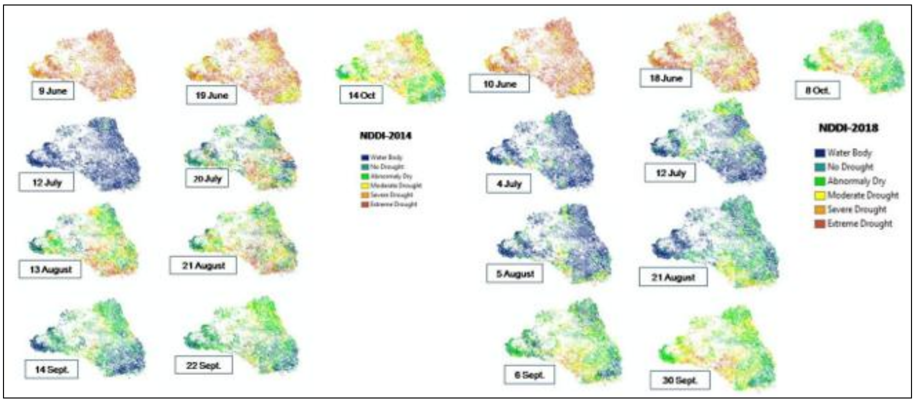


**Fig 3:** Spatio-temporal patterns of NDDI for the *kharif* season over the study area during the years 2014 and 2018

The time-series MODIS NDDI data, derived using NDVI and NDWI, were analyzed for the years 2014 and 2018 to assess drought stress conditions in agricultural fields during the crop-growing season. The year 2014 experienced a prolonged drought lasting 12 weeks, while 2018 had a comparatively shorter drought period of 4 weeks. These variations in drought severity are examined to understand their impact on vegetation health. NDVI and NDWI data, captured at 8-day intervals, were used to compute NDDI for selected dates, as illustrated in Fig. 3, to highlight changes in drought conditions. The analysis, conducted using the Weathercock software, reveals that in 2014, the Halia Basin experienced drought for 4 weeks in June, another 4 weeks in August, and 4 weeks from late week of September to October, coinciding with the crop's reproductive and harvesting stages. Images captured on June 9 and 19, 2014, clearly depict moderate to extreme drought conditions across the basin. NDDI image on 12$^{th}$ July 2014 shows a major part as blue as the basin received nearly 98mm rainfall in 3 consecutive days from 6$^{th}$ to 8$^{th}$July. Similarly, the images on the 20$^{th}$ of July 2014, along with the 13$^{th}$ and 21$^{st}$ of August 2014, highlight the persistent drought conditions affecting vegetation health, as indicated by increased NDDI values. The prolonged moisture stress during these critical growth stages likely had a significant impact on crop yield. In contrast, the year 2018, despite experiencing a shorter drought period of four weeks (last week of September to the 3$^{rd}$ week of October), exhibited a relatively lower intensity of drought stress, as evident from the NDVI and NDWI trends. The analysis of NDDI variations for selected dates in 2014, particularly during the peak drought phase, shows the moisture stress in vegetation compared to 2018.

It is evident that the NDDI can monitor the vegetation stress, but to completely rely on this updated land cover data and some *insitu* measurements are required, like temperature, precipitation, soil moisture, stream flow,etc, [9].These findings underscore the variability in drought severity and its potential implications for crop productivity. The integration of MODIS-derived indices with weather data offers a valuable approach to monitoring and assessing drought impact, aiding in better water resource management and agricultural planning.

## 5. Conclusion

The analysis of long-term rainfall trends in the Halia Basin reveals significant fluctuations in precipitation patterns, impacting agricultural productivity and water availability. The study highlights the increasing variability of seasonal rainfall, with notable shifts in the South West and North East monsoons over the decades. It is observed that there are periodic high rainfall events occurring roughly every decade. The occurrence of extreme wet and dry years necessitates improved irrigation planning, soil moisture conservation, and adaptive cropping strategies. The integration of remote sensing indices, such as NDDI, enhances drought assessment by providing spatial insights into agricultural stress during drought periods. Findings indicate that during the 2014 *kharif* season, experience drought conditions at various crop growth stages, and during 2018, drought coinciding with reproductive and harvesting stages, increased vulnerability of rain-fed agriculture. Implementing sustainable water management practices, drought-resistant crop varieties, and efficient irrigation systems can mitigate the adverse effects of climate variability. Further research incorporating advanced climate models and high-resolution satellite data will aid in refining drought prediction and enhancing regional agricultural resilience.

**Future scope**

Future studies should integrate large scale soil-moisture data recording and validation with high-resolution microwave/SAR remote-sensing products and machine-learning to develop field-level drought early-warning system.

**Conflict of Interest**

The authors have no conflicts of interest.

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**References**

1. Aksoy S, Sertel E. Comparison of drought monitoring indices derived from MODIS and CHIRPS data using Google Earth Engine. In: 9th Global Conference on Global Warming (GCGW-2021); 2021 Aug 1-4; Croatia.
2. Anuradha T, Kamraju M, Vani M, Manisha P. Impact of climate change on agricultural productivity: a case study of Nalgonda district, Telangana. Int J Res Manag Soc Sci. 2017;5(3)(IV):70-76.
3. Deering DW. Rangeland reflectance characteristics measured by aircraft and spacecraft sensors. College Station (TX): Texas A&M University; 1978.
4. Deka RL, Nath KK. Rainfall analysis for rainfed crop planning in the Upper Brahmaputra Valley Zone of Assam. J Agrometeorol. 2000;2(1):47-53.
5. Dobri RV, Sfica L, Amihaesei VA, Apostol L, Ţimpu S. Drought extent and severity on arable lands in Romania derived from normalized difference drought index (2001-2020). Remote Sens. 2021;13(8):1478.
6. Fan X, Liu Y, Tao J, Wang Y, Zhou H. MODIS detection of vegetation changes and investigation of causal factors in Poyang Lake basin, China (2001-2015). Ecol Indic. 2018;91:511-522.
7. Ganchaudhuri S, Sarmah K, Roy L, Goswami J. Rainfall probability analysis for crop planning of Unakoti and West Tripura districts, India. Int J Environ Clim Change. 2022;12(11):2520-2529.
8. Gao BC, Coetz AFH. Retrieval of equivalent water thickness and information related to biochemical components of vegetation canopies for AVIRIS data. Remote Sens Environ. 1995;52:155-162.
9. Gulacsi A, Kovacs F. Drought monitoring of forest vegetation using MODIS-based normalized difference drought index in Hungary. Hung Geogr Bull. 2018;67(1):29-42.
10. Hashemzadeh Ghalhari M, Vafakhah M, Damavandi AA. Agricultural drought assessment using vegetation indices derived from MODIS time series in Tehran Province. Arab J Geosci. 2022;15(5).
11. Kar G. Rainfall probability analysis for sustainable production strategies in coastal Orissa. J Agrometeorol. 2002;4(2):181-185.
12. Lesk C, Rowhani P, Ramankutty N. Influence of extreme weather disasters on global crop production. Nature. 2016;529:84-87.
13. Mishra D, Goswami S, Matin S, Sarup J. Analyzing the extent of drought in Rajasthan, India using vegetation condition index and standardized precipitation index. Model Earth Syst Environ. 2022;8:601-610.
14. Panigrahi B. Probability analysis of short duration rainfall for crop planning in coastal Orissa. Indian J Soil Conserv. 1998;26(2):178-182.
15. Ray CR, Senapati PC, Lal R. Rainfall analysis for crop planning at Gopalpur, Orissa. J Agric Eng I.S.A.E. 1980;17:384.
16. Sharda VN, Das PK. Modelling weekly rainfall data for crop planning in a sub-humid climate of India. Agric Water Manag. 2005;76(2):120-138.
17. Sharma HC, Chauhan HS, Ram S. Probability analysis of rainfall for crop planning. J Agric Eng. 1979;16(3):89-94.
18. Stern RD, Coe R. The use of rainfall models in agricultural planning. Agric Meteorol. 1982;26(1):35-50.
19. Tang L, Shaikh IA, Tunio A, Junejo AR, Hao L, Dahri J, *et al*. Effect of raised flat bed and ridge planting on wheat crop growth and yield under varying soil moisture depletions. Agronomy. 2024;14(7):1404.
20. Xie F, Fan H. Deriving drought indices from MODIS vegetation indices (NDVI/EVI) and land surface temperature (LST): is data reconstruction necessary? Int J Appl Earth Obs Geoinf. 2021;101:102352.
21. Zeng J, Zhang R, Qu Y, Bento VA, Zhou T, Lin Y, *et al*. Improving the drought monitoring capability of VHI at the global scale via ensemble indices for various vegetation types (2001-2018). Weather Clim Extremes. 2022;35:100412.