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Monitoring of agricultural and meteorological drought indices in Gujarat (India) using remote sensing and GIS

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ABSTRACT

India's agricultural productivity relies heavily on rainfall due to its agrarian nature. A lack of rainfall adversely affects the national economy. Effective drought planning and management require constant monitoring to understand its complex nature better. Droughts occur worldwide with varying severity, necessitating long-term vegetation analysis for regional agricultural drought monitoring. This study aims to analyze and monitor the spatial and temporal variations of agricultural and meteorological droughts in Gujarat, India a state particularly prone to drought, especially during failed or altered monsoon seasons. The study used the long-term Normalized Difference Vegetation Index (NDVI) from NOAA-AVHRR data to assess agricultural drought through the NDVI-based Vegetation Condition Index (VCI), a popular index for describing vegetation health, from 1986-2015. The VCI variations during the major crop-growing period of the Kharif season (June to September) were used to determine the spatial-temporal drought conditions in Gujarat. The standardized precipitation index (SPI) and the precipitation evapotranspiration index (SPEI) are commonly used indicators for drought monitoring; unlike SPI, SPEI also considers temperature. In this study, SPI and SPEI were calculated at 1-, 3-, 6-, and 12-month timescales for 33 districts of Gujarat from 1986 to 2015. Their performances in drought monitoring were compared and analyzed in terms of temporal and spatial variations, consistency, and applicability. The results show a wide variation in drought intensity among the state's districts. Observing the yearly variation of long-term agricultural drought helps identify the onset, duration, and spatial extent of drought in different districts. Strategies were developed to improve agricultural productivity in districts frequently prone to moderate to severe drought conditions during the analysis period. VCI values for normal and drought years were compared with SPI, SPEI, and the Rainfall Anomaly Index derived from meteorological data, revealing a good agreement among them. The correlation coefficient between maximum NDVI and mean seasonal rainfall ($r > 0.52$) confirms the usefulness of assessing agricultural drought. The results of SPI and SPEI show that: (1) as the timescale increases, the temporal variations in SPI and SPEI become more consistent, although slight differences in fluctuation value and continuity persist; (2) due to differences in time series, drought characteristics identified by SPI and SPEI vary significantly across different timescales, and with a longer timescale, the spatial distributions of drought in Gujarat change. Persistent drought in the state necessitates that the government takes appropriate preventive measures. By identifying high-risk zones based on agricultural drought intensity maps, action plans can be prioritized according to the severity of the drought.

Keywords: standardized precipitation index (SPI); standardized precipitation evapotranspiration index (SPEI); vegetation condition index (VCI); normalized difference vegetation index (NDVI); agricultural drought; meteorological drought; drought indices.

INTRODUCTION

Drought is widely regarded as the most complex but least understood disaster, affecting more people than any other. There is significant uncertainty about its characteristics within the scientific and policy communities, conducive to the absence of progress in drought development globally. Drought is a slow-onset, creeping natural hazard that is a normal part of the world's climate and has serious economic, social, and environmental consequences. Its onset, end, and severity are often difficult to predict. Drought risk arises from a region's vulnerability to natural disasters and the risk of extended water scarcity (Wilhite, 2000).

To mitigate the severe impacts of drought, nations and regions must enhance their understanding of the hazard and the factors influencing vulnerability. Drought-prone areas need to deepen their knowledge of drought climatology (the likelihood of drought at various intensities and durations) and develop a comprehensive, integrated drought information system. This system should encompass climate, soil, and water supply factors, including precipitation, temperature, soil moisture, snowpack, reservoir and lake levels, groundwater levels, and streamflow.

All drought-prone countries should develop national drought policies and preparedness plans that emphasize risk management rather than the traditional crisis management approach, which focuses on reactive emergency responses. Drought is broadly categorized as meteorological, hydrological, agricultural, or socioeconomic (Boken *et al.*, 2005; Lloyd-Hughes and Saunders, 2002). In India, agricultural droughts are further classified based on the timing of rainfall deficiency during a crop season: early, mid, and late-season droughts (Kumar *et al.*, 2009). Early-season droughts are associated with a delayed monsoon onset, leading to no or delayed crop sowing. Mid-season droughts occur due to breaks in the southwest monsoon, coinciding with the vegetative growth stage of crops. Late-season droughts coincide with the reproductive stage of crops, causing forced maturity. Understanding the relationships between different types of droughts is crucial for assessing their impacts.

Several drought indices have been developed over the last century, with new ones emerging as technological advances improve the quantification of drought impacts. Each index has its advantages and limitations (Lloyd-Hughes and Saunders, 2002; Morid *et al.*, 2006; Dhakar *et al.*, 2013; Vaani and Porchelvan, 2017). Typically, a drought index value is a single number that helps in making decisions about drought mitigation based on drought severity (http://drought.unl.edu/Planning/Monitoring/Comparison of DroughtIndices.aspx, accessed on 25/06/2020). Drought indices utilize various hydro-meteorological data, including rainfall, streamflow, reservoir storage, soil moisture, groundwater, and water supply indicators (WMO, 1975).

Based on these physical datasets, drought indicators are divided into three categories: meteorological, agricultural, and hydrological. Popular meteorological drought indicators include the Standardized Precipitation Index (SPI), Standardized Precipitation Evapotranspiration Index (SPEI), and Reconnaissance Drought Index (RDI). Vicente-Serrano *et al*. (2010) compared the performance of SPI, SPEI, and PDSI for global drought monitoring, finding SPI and SPEI to be more effective than PDSI for hydrological and agricultural drought monitoring.

In recent decades, several indices using remote sensing data have been developed, such as the Normalized Difference Vegetation Index (NDVI), Vegetation Condition Index (VCI), Enhanced Vegetation Index (EVI), and Temperature Condition Index (TCI). These indices are widely used for monitoring vegetation drought (Quiring and Ganesh, 2010; Dutta *et al.*, 2013; Kumar and Purushothaman, 2016; Bento *et al.*, 2018; Yulistya *et al.*, 2019). NDVI data, in particular, play a significant role in monitoring vegetation drought (Zhou *et al.*, 2009; Sona *et al.*, 2012; Dutta *et al.*, 2013; Aswathi *et al.*, 2018; Venkadesh *et al.*, 2019; Jimenez-Donaire *et al.*, 2020). These indices can be integrated with meteorological indices to provide valuable information when ground data is unavailable. However, frequent cloud cover during monsoon seasons can complicate the interpretation of vegetation cover from remote sensing images.

Geography and Area of Extent

The state of Gujarat, India, is situated on the west coast between latitudes 20°06′N and 24°42′N and longitudes 68°10′E and 74°28′E, encompassing an area of 196,000 km². Gujarat boasts the longest coastline (1,600 km) among India's mainland states. Despite its proximity to the Arabian Sea, much of Gujarat experiences an arid to semi-arid climate due to its closeness to the Great Indian Desert to the north. The environment in Gujarat is shaped by the interplay of topography, soil, vegetation, and climate. The topography features vast plains interspersed with occasional small hills.

Gujarat's climate is marked by significant spatial and temporal variations in monsoon rainfall. The southwest monsoon, which occurs from late June to the end of September, accounts for more than 90% of the annual rainfall. Despite the state's overall arid conditions, these monsoon rains play a critical role in supporting agriculture and replenishing water resources. However, the monsoon's arrival and intensity can be highly variable, leading to challenges in water management and agriculture.

The state also exhibits considerable variation in seasonal temperatures, except in coastal regions. The mean annual temperature ranges between 28°C and 33°C, while the mean summer temperature (April-June) is around 40°C. During heatwave events, the maximum temperature in many areas can soar to 48°C, posing significant health risks and affecting agricultural productivity. The interplay of these climatic factors with the state's diverse topography and soil types results in a complex and dynamic environmental landscape. Location map of study area Gujarat (India) given in Fig. 1.

Normalized Difference Vegetation Index (NDVI)

Numerous researchers have successfully utilized the NDVI in studies related to vegetation phenology, vegetation classification, and land cover mapping on the continent (Tucker et al., 1985). NDVI is also effective for drought classification, estimating crop growth conditions, and predicting crop yields (Kogan, 1987). The NDVI is based on the principle that the internal structure of healthy leaves reflects Near-Infrared (Ch2) radiation, while chlorophyll and other pigments absorb a large proportion of red visible (Ch1) radiation. In water-stressed, unhealthy vegetation, this function is reversed.

$$NDVI = (Ch_2 - Ch_1) / (Ch_2 + Ch_1) \quad (1)$$

The NDVI utilizes the near-infrared (Ch_2) and visible red (Ch_1) bands of the electromagnetic spectrum. NDVI values range from -1 to +1. Values below 0.1 are typical of areas with rock, sand, and snow cover, while values between 0.6 and 0.8 are common in tropical and temperate rainforests. NDVI is a popular index for the classification of agricultural drought, estimating soil moisture, and evaluating vegetation conditions. However, the utility of NDVI can be limited by various sources of error, such as atmospheric noise, satellite orbital drift, and sensor degradations (Kogan, 1995).

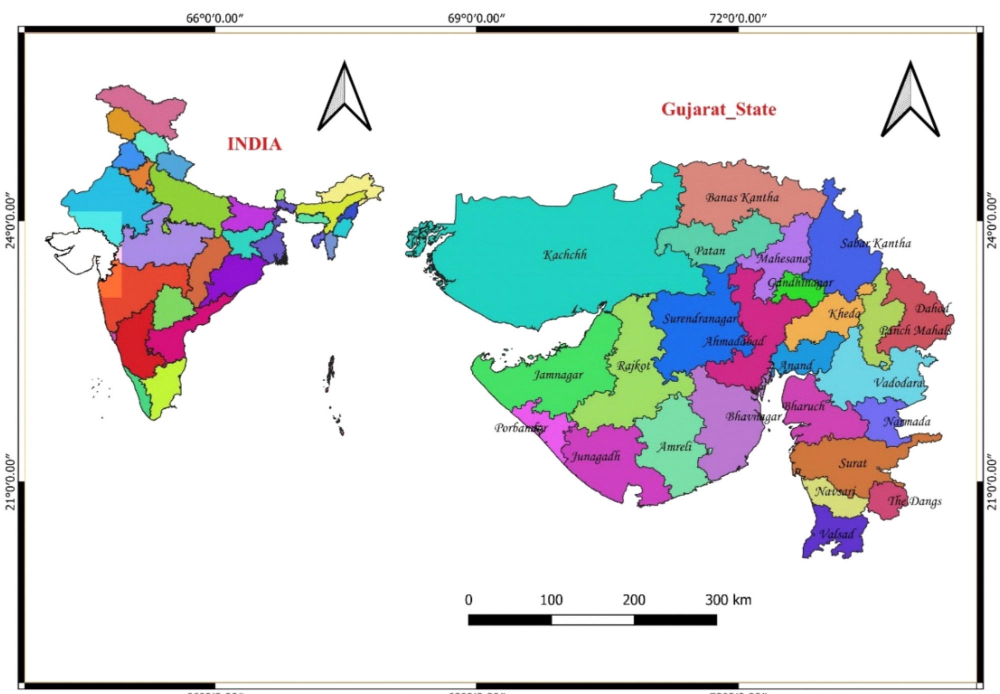


Fig. 1. Location map of study area Gujarat (India)

Vegetation Condition Index (VCI)

The following VCI equation was applied to the final NDVI database:

$$VCI = (NDVI_i - NDVI_{min}) / (NDVI_{max} - NDVI_{min}) * 100 \quad (2)$$

Here, $NDVI_{max}$ and $NDVI_{min}$ represent the maximum and minimum NDVI of each pixel calculated for each month and j represents the index of the current month. The VCI value is expressed as a percentage ranging from 1 to 100. A value between 50% and 100% indicates that the vegetation is in good condition, while a value between 35% and 50% suggests that the vegetation is experiencing drought. Values below 35% indicate severe drought conditions. This index normalizes NDVI and separates the long-term ecological signal from the short-term climate signal, making it a more effective indicator for monitoring water stress conditions than NDVI. Drought severity classification range of Vegetation Condition Index (Table 1).

Table 1. Drought severity classification range of Vegetation Condition Index

VCI Range	Dryness level
0-20	Extreme drought
20-40	Severe drought
40-60	Moderate drought
60-80	Light drought
80-100	Very light

NDVI Anomaly Index

The severity of drought (or, conversely, the extent of wetness) can be defined by the deviation of NDVI values from their long-term mean (Bandyopadhyay and Saha, 2016). The following formula is used for the calculation of the anomaly index:

$$NAI = NDVI_i - NDVI_{mean,\, m} \quad (3)$$

Where NDVIi is the NDVI value for a month I and $NDVI_{mean}$, m is the average of mean monthly NDVI values of 30 years from 1986 to 2015 for (June to October) month of a particular year. When the NDVI Anomaly is negative, it indicates below-normal vegetation condition/health, signifying a drought situation. The severity of the drought is proportional to the magnitude of this negative departure. In general, NDVI deviation from the long-term mean is more than just a drought indicator, as the long-term NDVI value reflects the conditions of healthy vegetation under normal circumstances. However, its limitations include not accounting for the standard deviation, which can lead to mis-interpretation when vegetation condition variability is very high in a given year. The values range from -100% to +100% departure from normal.

Rainfall Anomaly

Rainfall anomaly has to be computed from (1986-to 2015 years) for the growing season June-October to indicate meteorological drought. Rainfall anomaly has been computed as:

$$RFA_i = [(RF_i - RF_\mu)] / (RF_\mu)*100 \quad (4)$$

Where I is the rainfall anomaly for an ith year; RF_i is seasonal rainfall for the ith year and RF_μ is the mean seasonal rainfall.

Meteorological drought, as defined by the Indian Meteorological Department (IMD), occurs when seasonal rainfall in an area is less than 75% of its long-term average. It is further classified based on the extent of rainfall deficiency: mild drought when rainfall is 25% below normal, moderate drought when rainfall is 50% below normal, and severe drought when rainfall is 75% below normal. This classification follows the criteria established by the IMD.

Standardized Precipitation Index (SPI)

Recognizing that a precipitation deficit affects reservoir storage, soil moisture, groundwater, snowpack, and streamflow in varying ways led to the development of the Standardized Precipitation Index (SPI) by McKee *et al.* (1993). The SPI has since gained widespread acceptance and is recommended by the World Meteorological Organization as the primary index for monitoring meteorological droughts.

$$SPI_{ij}\, H \approx X_{ij} - \mu_{ij} / \sigma_{ij} \quad (5)$$

where SPI_{ij} is the SPI of the i^{th} month at the j^{th} time-scale, X_{ij} is the precipitation total for the i^{th} month at the j^{th} time-scale, $\mu_{ij,}$ and σ_{ij} are long-term mean and standard deviation associated with an i^{th} month at the j^{th} time-scale. Since precipitation data is often not normally distributed, the SPI addresses this issue by fitting the data to a suitable gamma distribution and then transforming it into a normal or Gaussian distribution. The SPI is subsequently calculated according to the method outlined in Eq. (5).

Standardized Precipitation Evapotranspiration Index (SPEI)

The Standardized Precipitation Evapotranspiration Index (SPEI) was proposed by Vicente-Serrano et al. (2010) to merge the sensitivity of the PDSI to changes in evaporation demand with the multi-time scale property of the SPI. They emphasized that SPEI is particularly suited for detecting and monitoring the effects of global warming on drought conditions. It represents a simple climatic water balance, calculated as the weekly or monthly difference between cumulative precipitation and potential evapotranspiration. It is mathematically expressed as follows:

$$D_i = P_i - PET_i \quad (6)$$

The calculated 'D' values are aggregated at different time scales as:

$$D_n^k = \sum_{i=0}^{k=1} (P_{n-i} - PET_{n-i}) \quad (7)$$

Where k (months) is the timescale of the aggregation and n is the calculation month. SPEI is calculated similarly to SPI. However, a three-parameter distribution is needed to standardize D-series as D-values can have negative values. Globally, the three-parameter log-logistic distribution was found to be a better fit for SPEI at all-time scales using the Kolmogorov-Smirnov test (Vicente-Serrano *et al.,* 2010). The drought severity classification based on SPEI values is similar to the SPI classification and it can be defined at multiple scales.

RESULTS AND DISCUSSION

Evaluation of Relationship of Maximum NDVI with Seasonal Rainfall

The relationship between maximum NDVI and seasonal rainfall indicates a consistent increase in NDVI as rainfall increases. Maximum NDVI values are used because they are assumed to represent the peak greenness during the period. According to studies by Li *et al*. (2004), Kassa (1993), and Senamaw *et al*. (2021), NDVI measures the magnitude of greenness over time and quantitatively reflects the land's capacity to support photosynthesis and primary production. From Fig. 2, it can be observed that NDVI linearly increases from 0.1 to 0.5 as seasonal rainfall rises from 300mm to 1000mm. However, NDVI saturates once seasonal rainfall exceeds the 1000mm threshold, showing no significant increase even with additional rainfall. While average NDVI and seasonal rainfall fairly represent the growing season, Fig. 2 reveals that NDVI achieves a higher value at its maximum but is lower on average. The correlation is higher with average NDVI than with maximum NDVI. This increase in R^2 due to data averaging might be accredited to a significant decrease in observations rather than the removal of outliers. Therefore, averaging NDVI values to account for inter-annual variations might reduce the accuracy of NDVI measurements, potentially distorting the true condition of vegetation during the growing season.

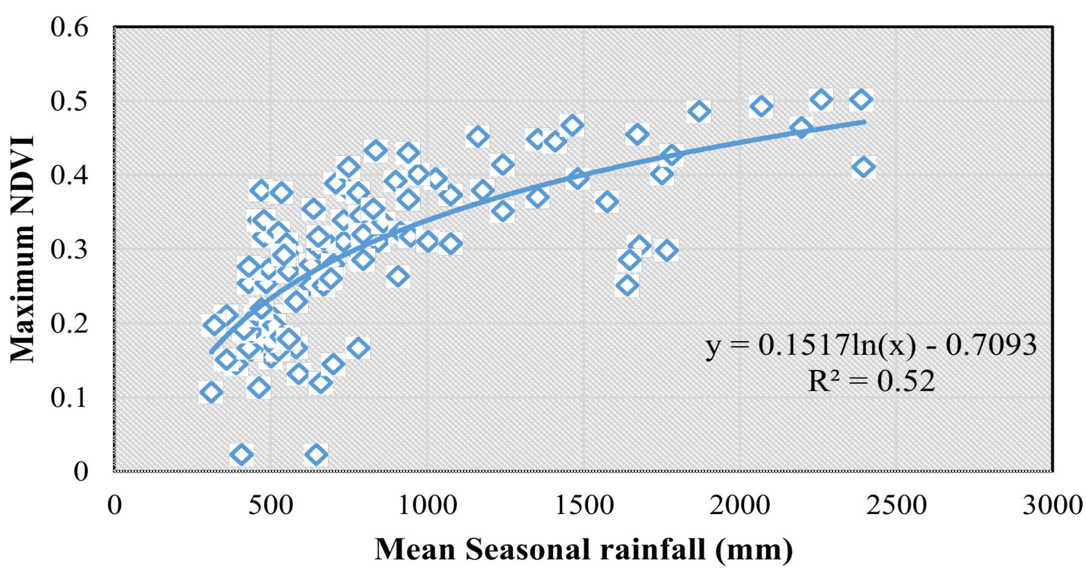


Fig. 2. Relationship between mean seasonal rainfall and maximum NDVI

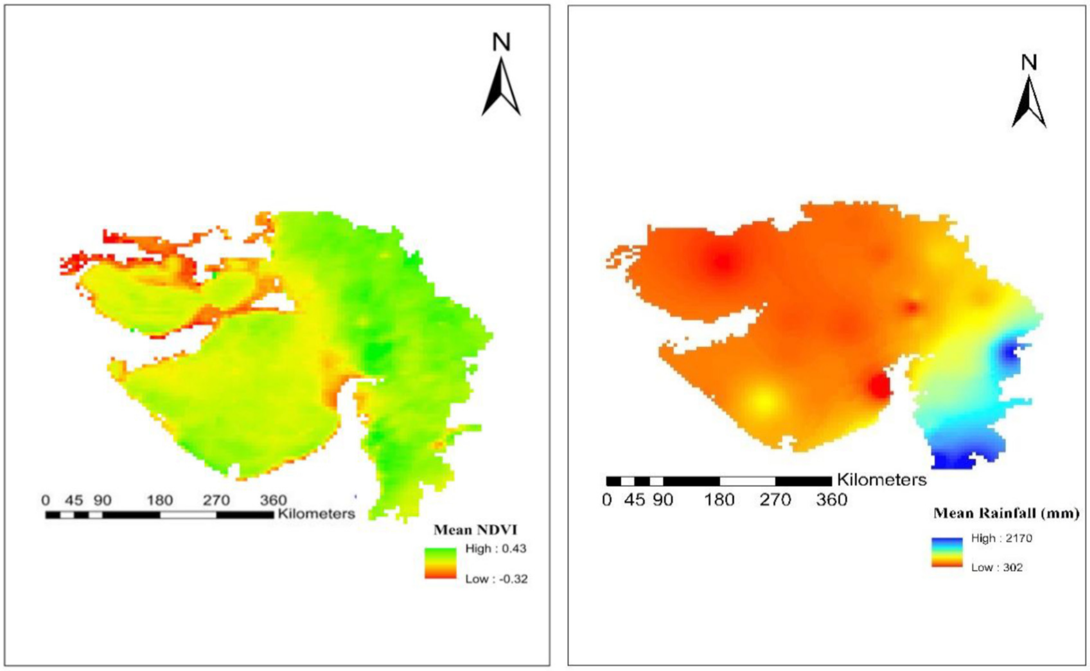


Fig. 3. Average rainfall and Average NDVI (1986-2015)

The seasonal patterns of rainfall and NDVI are illustrated in Fig. 3, which shows that the western part of Gujarat receives low rainfall, averaging 300 mm for the entire season, resulting in low NDVI values of around -0.3. Conversely, central and southern Gujarat experience significantly higher rainfall, exceeding 2500 mm, leading to higher NDVI values (Chopra, 2006; Shukla *et al.*, 2007; Murad and Islam, 2011; Kundu and Dutta, 2011).

Rainfall is vital for plant growth, with seasonal growth in many ecosystems, especially grasslands and croplands, aligning closely with the rainy season. During droughts, these ecosystems exhibit minimal or no vegetation growth, while abundant rainfall prompts a surge in greenery. The rainfall graph displays total annual rainfall in millimeters, while vegetation is represented by an index of greenness, which is influenced by factors such as plant diversity, leafiness, and overall health. Areas with dense foliage and vigorous growth appear dark green, indicating a high greenness index (Davenport and Nicholson, 1993; Islam and Mamun, 2015). Fig. 4 depicts the temporal patterns of NDVI and rainfall from 1986 to 2015. The graph highlights that years with low rainfall correspond to low NDVI values, with notable dips in 1986 and 1987 reflecting drought

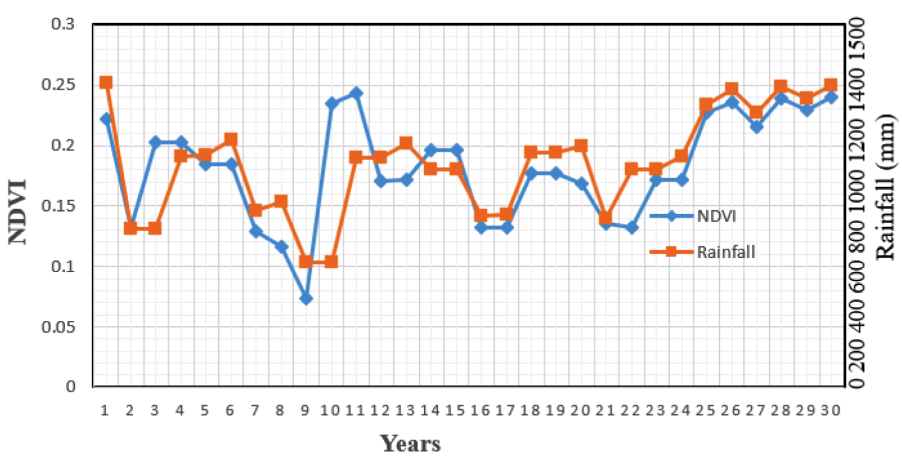


Fig. 4. Temporal trends of NDVI and Rainfall (1986-2015)

conditions and reduced NDVI (Rimkus *et al*., 2017; Pei *et al*., 2019).

Spatial Pattern of NDVI and Rainfall Anomaly

Fig. 5 illustrates the spatial patterns of NDVI and rainfall anomalies during the 1987 drought and the 1997 wet year. In 1987, Gujarat experienced negative NDVI and rainfall anomalies across the entire state. In contrast, 1997, a particularly wet year, showed positive anomalies for both rainfall and NDVI (Chopra, 2006; Hasan Murad, 2010; Nanzad *et al*., 2019). This demonstrates the important influence of precipitation on vegetation conditions: abundant rainfall leads to positive vegetation responses, resulting in higher NDVI values, whereas limited rainfall results in lower NDVI values.

Spatial Pattern of Drought Years of SPI and VCI

Fig. 6 presents SPI and VCI-based maps of meteorological and agricultural drought intensity from 1986 to 2015. Bandyopadhyay and Saha (2016) noted that Gujarat faced some of its worst droughts in the late 20th century, particularly in 1986, 1987, 1990, 1991, 1993, 1995, 1998, 1999, 2000, 2001, 2002, and 2009. This study's drought analysis, starting from 1986, does not cover the severity of droughts in 1987, 1999, and 2001. Nonetheless, Fig. 6 highlights severe drought conditions in 1986 and shows similar intensity in 1990, 1998, 2000, 2001, 2002, and 2009, with many districts in extreme to severe drought categories.

The severity of drought during the monsoon season varies monthly, as shown in the drought maps for major drought years. This variability reflects changes in the monsoon onset and uneven vegetation conditions across years. For example, in 1997, Gujarat generally experienced normal conditions, but drought conditions worsened to moderate to severe levels by July, August, and September. This pattern suggests that an early monsoon onset can result in crop failures due to inaccurate predictions.

Spatial Pattern of Drought Years of RAI and NAI

Fig. 7 represent spatial Pattern of Drought Years of RAI and NAI. The Rainfall Anomaly Index (RAI) is effective in detecting rainfall deviations. Research shows a strong link between vegetation growth and rainfall. Analysis of the RAI from 1986 to 2015 identified severe rainfall deficits and drought stress in 1986, 1987, 1990, 1991, 1993, 1995, 1998, 1999, 2000, 2001, 2002, and 2009, with RAI values falling below -3. Conversely, extreme wet conditions were noted in 1988, 1993, 1997, 2003, 2011, and 2013, with RAI values above 3. These findings align with SPI results on severe drought and normal conditions in 2003 and 2013, respectively. Previous studies

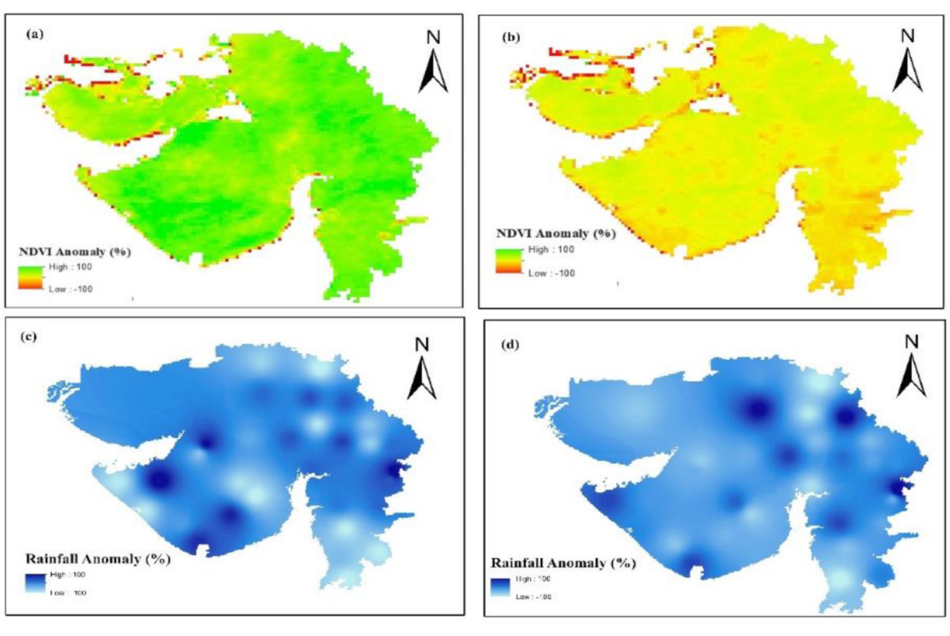
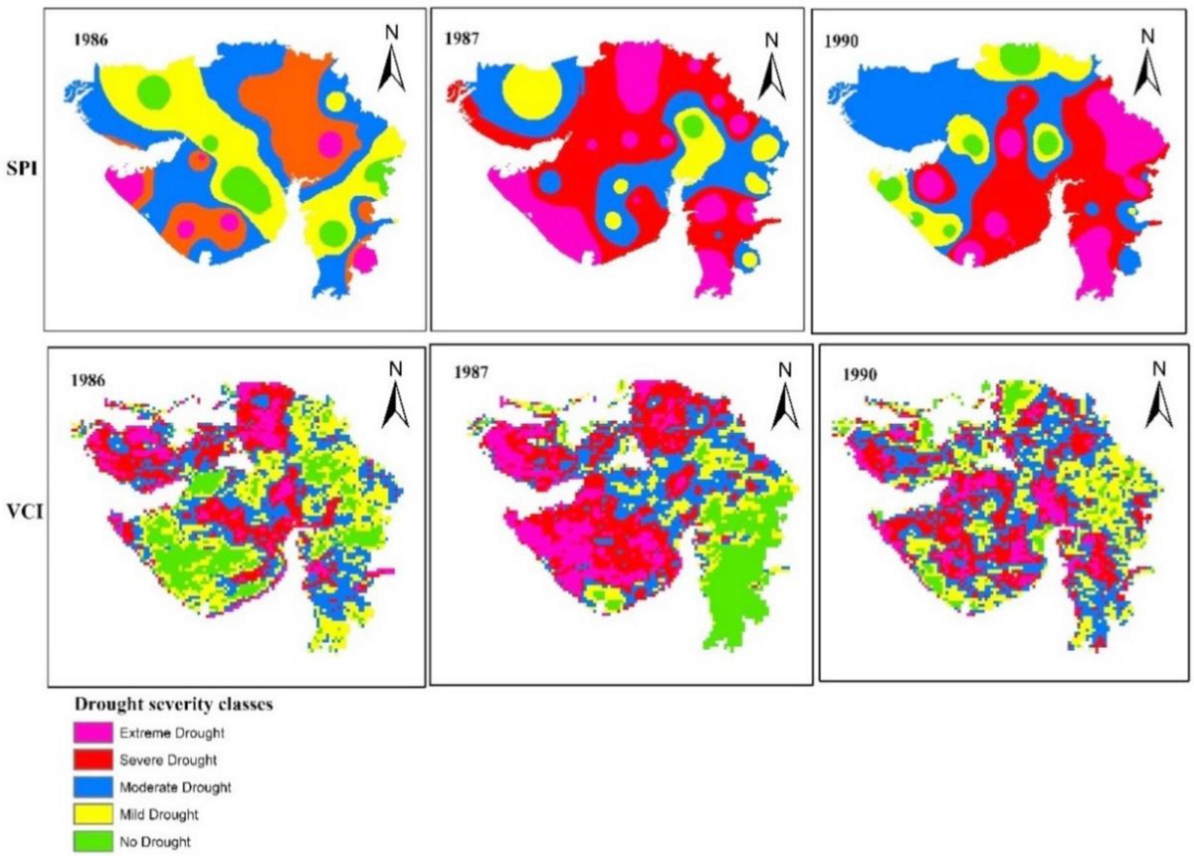


Fig. 5. Spatial pattern of NDVI anomaly and rainfall anomaly (a) & (c) 1987 and (b) & (d) 1997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Severe Drought
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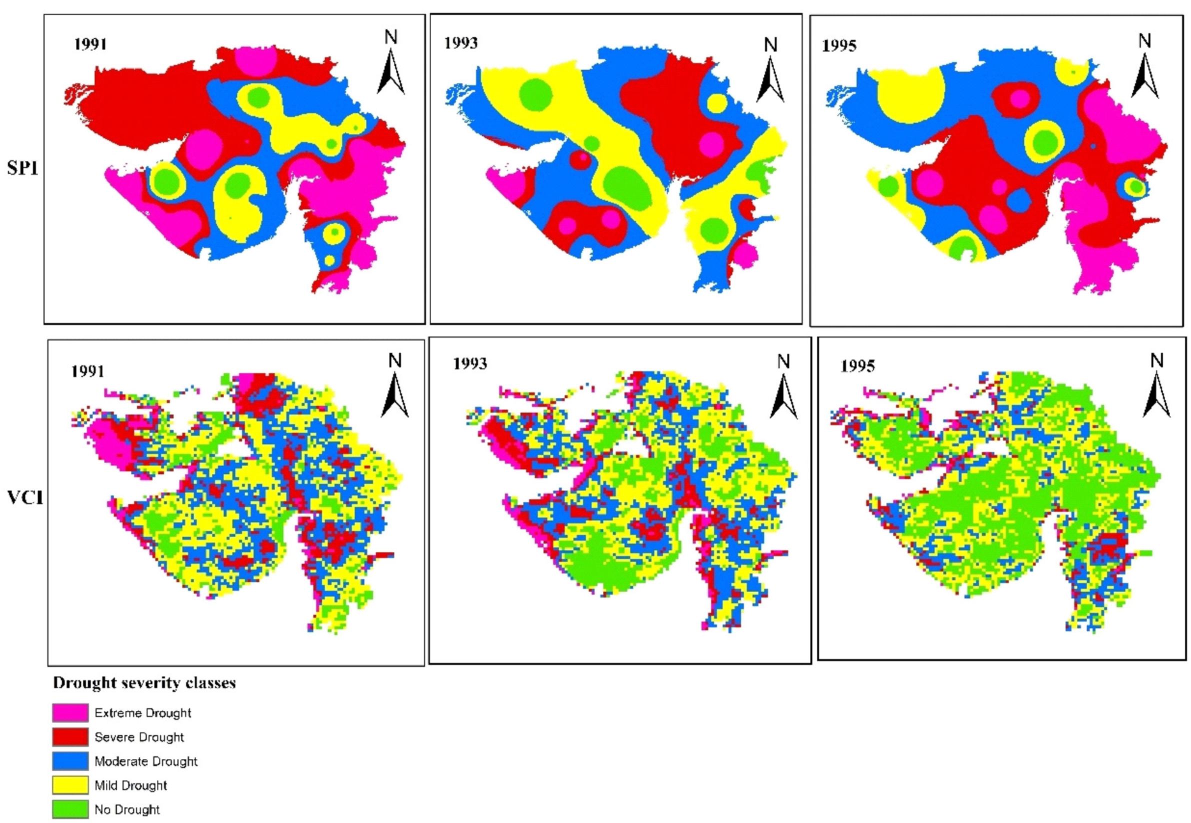
Mild Drought
No Drought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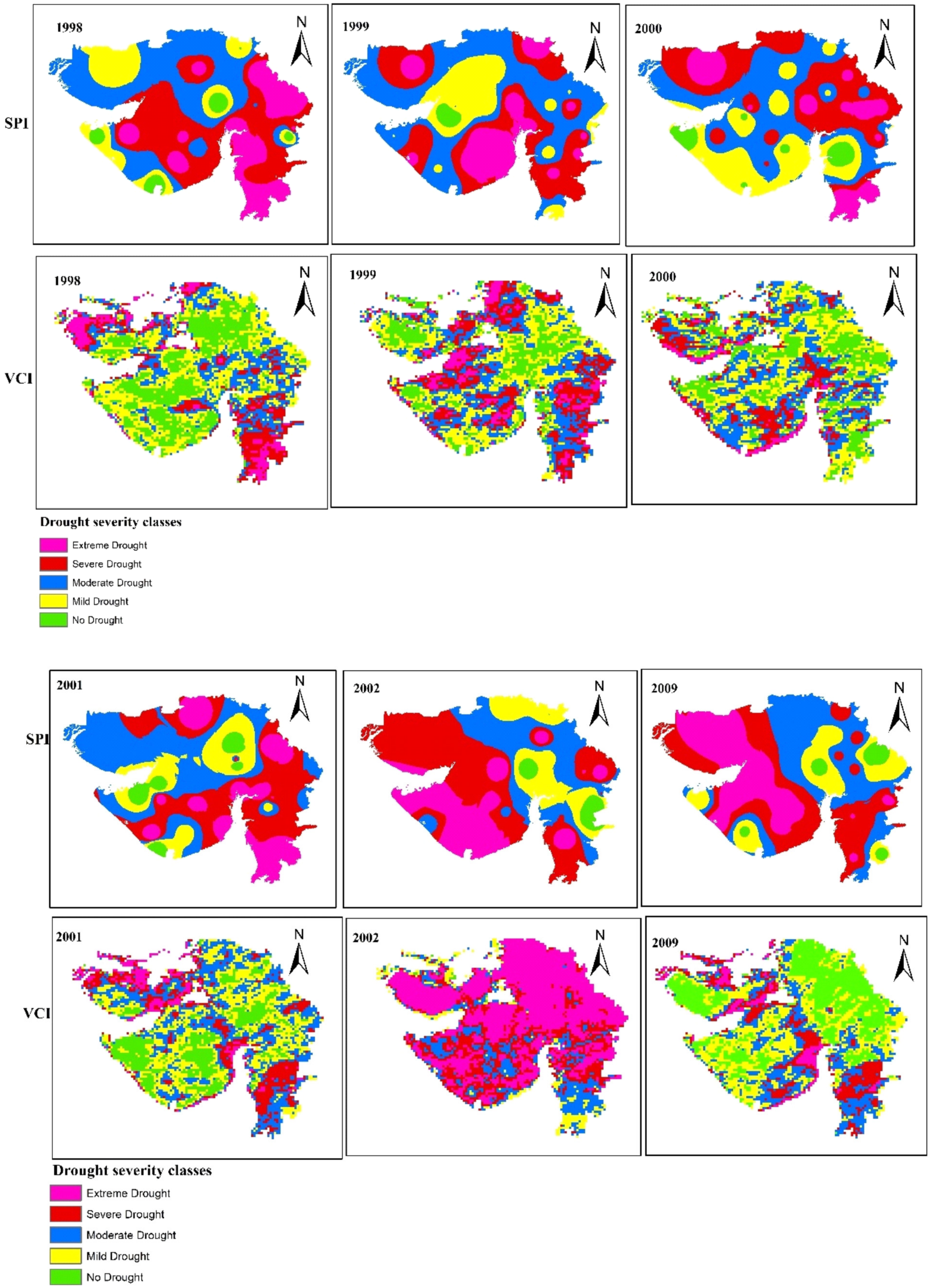
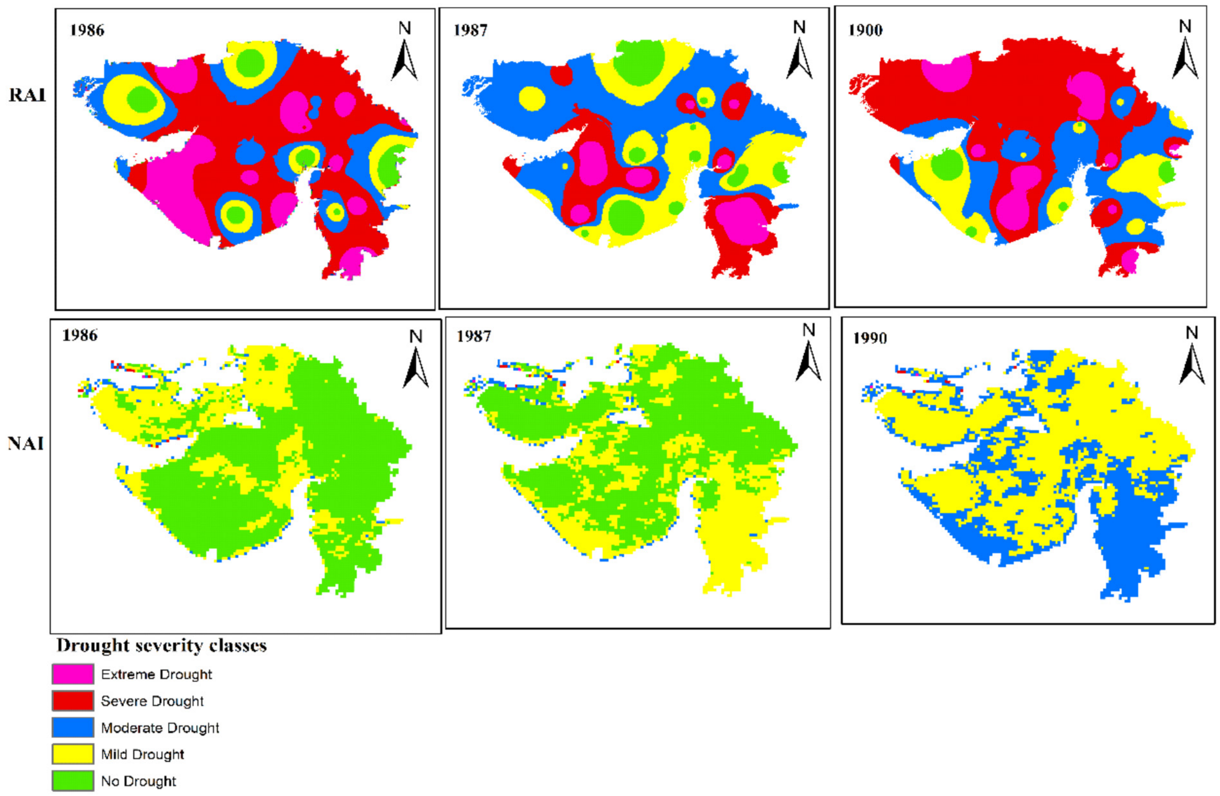


Fig. 6. Important drought years from 1986 to 2015 are represented by two indices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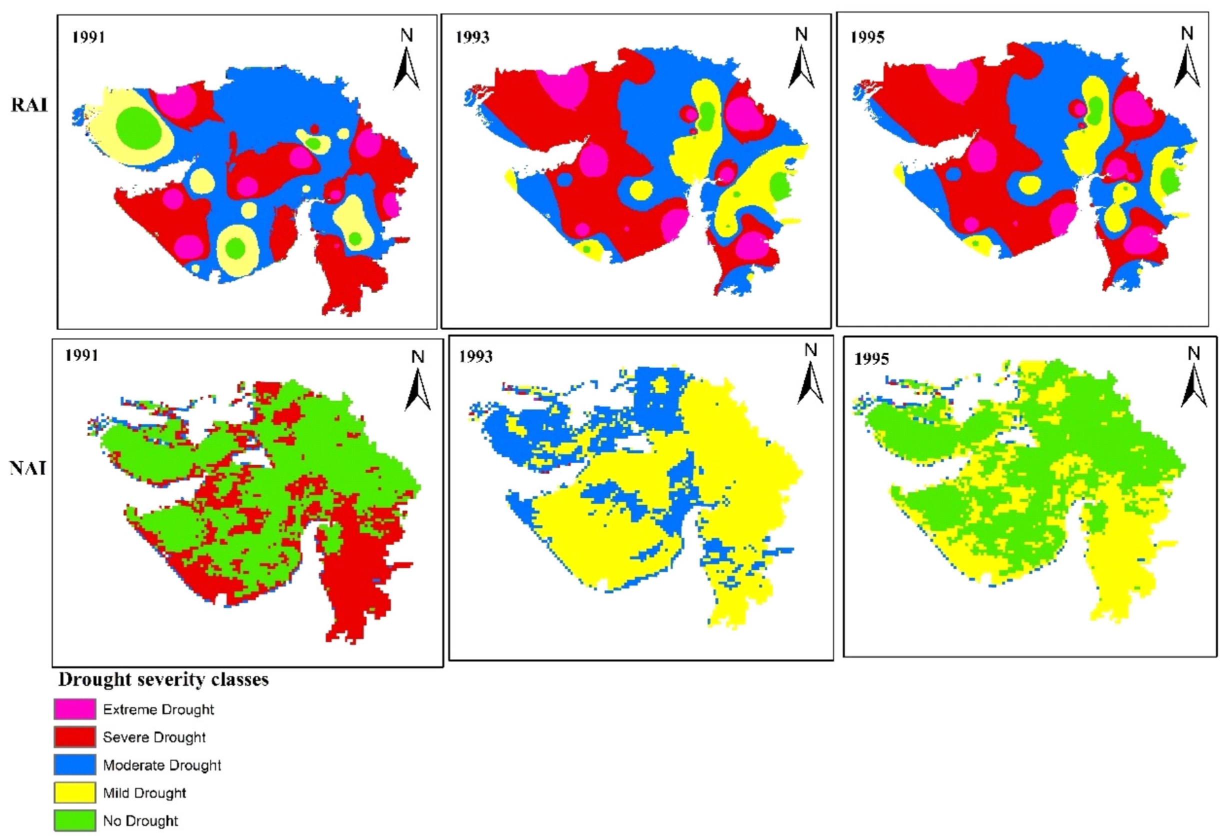
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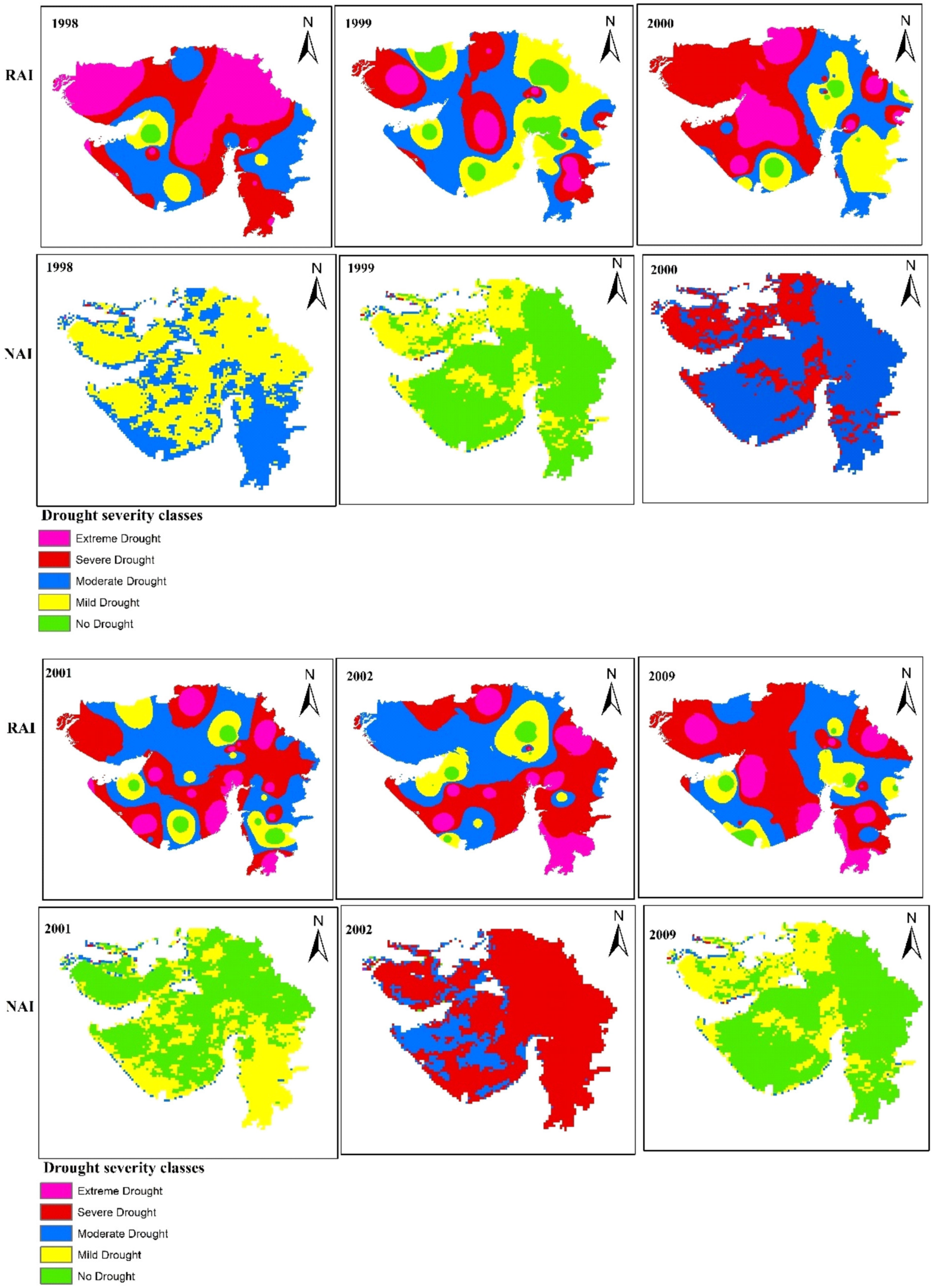


Fig. 7. Important drought years from 1986 to 2015 are represented by two indices

support severe droughts during these years in Gujarat (Patel and Yadav, 2015; Bandyopadhyay and Saha, 2016; Thomas *et al*., 2016; Nanzad *et al*., 2019).

Similarly, the Normalized Anomaly Index (NAI) developed by Anyamba and Tucker (2012) uses +100 to indicate normal drought conditions and -100 for severe drought (Nightingale and Phinn, 2003; Dubey *et al*., 2012; Bandyopadhyay and Saha, 2016; Vaani and Porchelvan, 2017; Nanzad *et al*., 2019). Lower NAI values in 1986, 1987, 1990, 1991, 1993, 1995, 1998, 1999, 2000, 2001, 2002, and 2009 reflected severe rainfall deficits and agricultural drought stress, while positive NAI values above +100 indicated extreme wet conditions in 1988, 1993, 1997, 2003, 2011, and 2013. NAI results were consistent with NDVI findings on severe drought and normal conditions in 2003 and 2013.

Analyze the SPI and SPEI Indices

To analyze SPI and SPEI, monthly meteorological data from 33 districts in Gujarat spanning 1986 to 2015 were used. The study employed time series analysis to assess drought characteristics, identifying droughts when SPI or SPEI values fell below 0 (Table 2). Key drought characteristics include frequency, duration, and intensity. Frequency is determined by dividing the number of drought months by the total number of months in the period, while duration is the average length of all drought events.

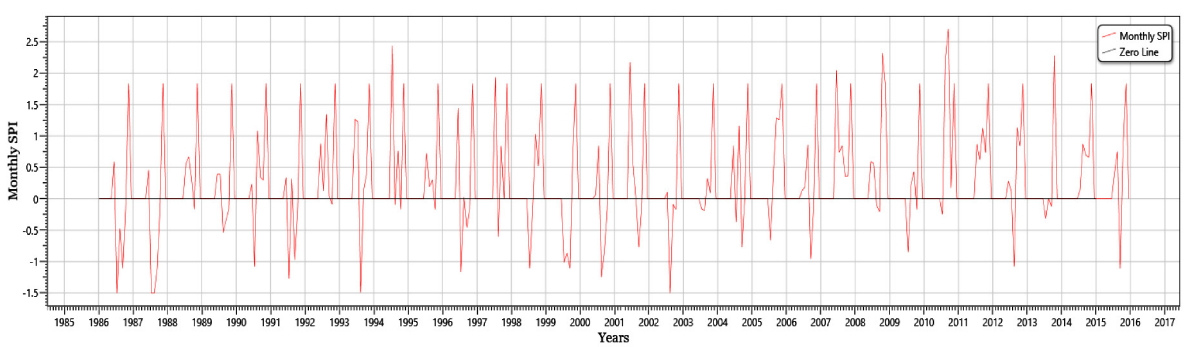
Over the past 30 years, drought frequency and intensity have increased, with clearer trends over longer timescales (Fig. 8). Short-term climate changes caused SPI and SPEI to fluctuate around 0, reflecting variations in water balance. Longer

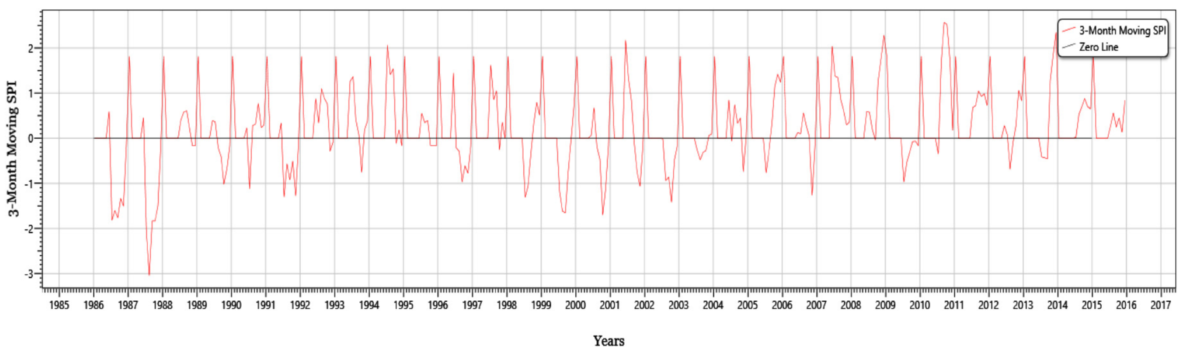
Table 2. Drought Severity Classification

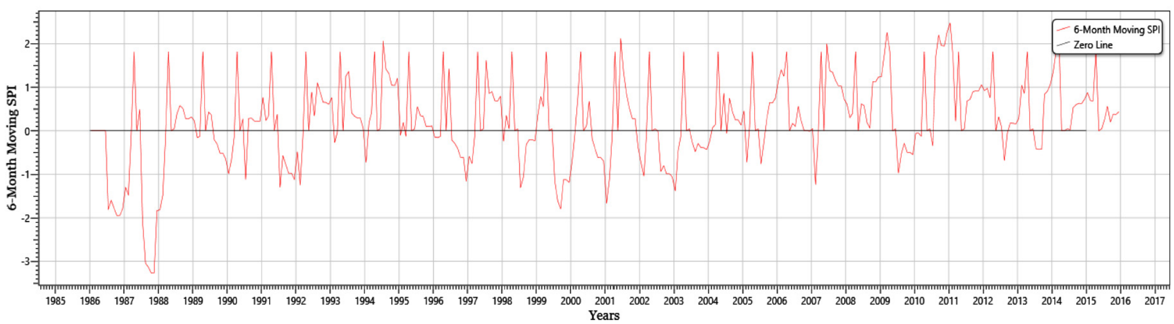
Class	Values of SPI and SPEI
Extremely Wet (EW)	≥2
Severe Wet (SW)	1.5 to 1.99
Moderately Wet (MW)	1 to 1.49
Normal (N)	0.99 to 0.99
Moderately Dry (MD)	-1 to -1.49
Severely Dry (SD)	-1.5 to -1.99
Extremely Dry (ED)	≤2

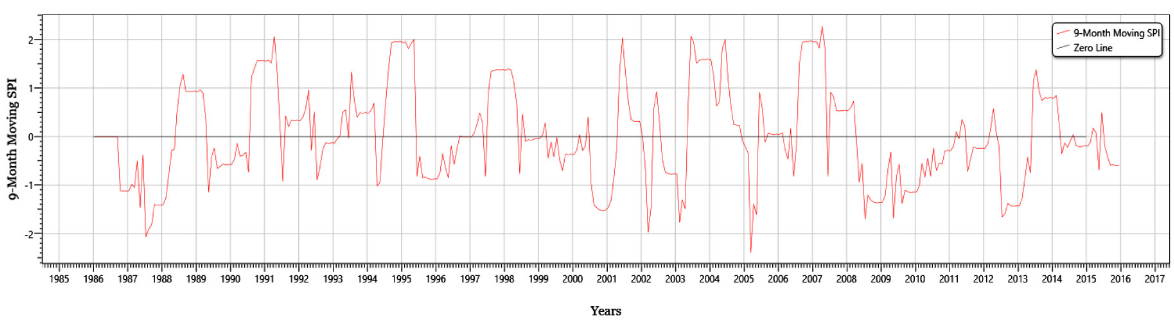
timescales revealed more pronounced variations, with reduced volatility and clearer interannual and interdecadal trends, indicating long-term drought characteristics. While SPI and SPEI trends were similar, differences in fluctuation and continuity highlighted varying drought frequencies and intensities. Recent years have shown a widening gap between SPI and SPEI.

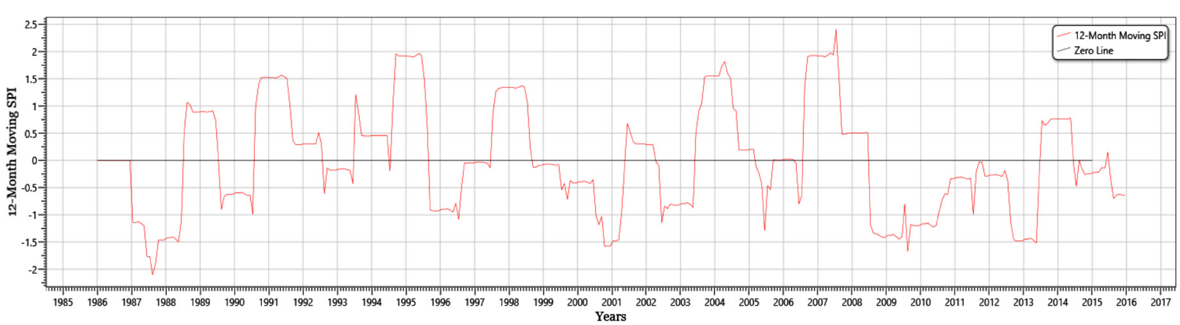
Fig. 8 shows differences in drought characteristics between SPI and SPEI over the 30-year period, with noticeable changes in dryness and wetness after 1987. Drought conditions were less severe in 1990, 1991, 1993, 1995, 1998, 1999, 2000, 2001, 2002, and 2009 (Fig. 8). Although SPI and SPEI generally reflected similar drought trends, there were minor differences, particularly at 1-, 3-, and 6-month scales. Before 1999, SPI indicated more frequent droughts from June to October, whereas SPEI showed fewer. After 1996, both indices reported similar dryness and wetness monthly, though SPI often indicated more severe drought conditions. SPEI occasionally showed higher drought levels than SPI, possibly due to rising temperatures. Annual variations were consistent across 1-, 3-, 6-, and 12-month timescales for both indices.




3-Month Moving SPI
Zero Line
3-Month Moving SPI
Years


6-Month Moving SPI
Zero Line
6-Month Moving SPI
Years


9-Month Moving SPI
Zero Line
9-Month Moving SPI
Years


12-Month Moving SPI
Zero Line
12-Month Moving SPI
Years

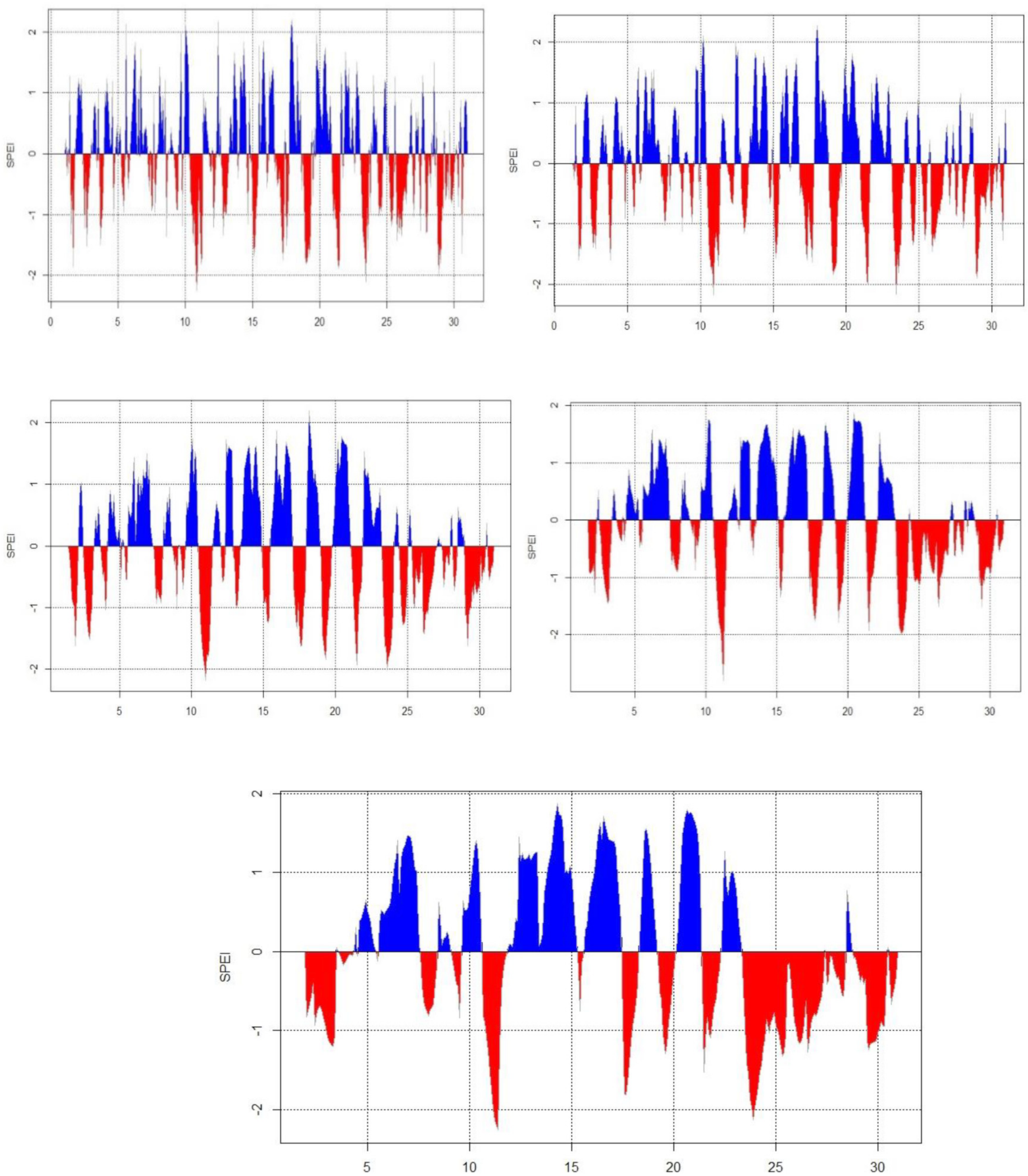


Fig. 8. Monthly variations in the SPI and SPEI at 1-, 3-, 6-, and 12-month timescales of Gujarat during 1986-2015

REFERENCES

Anyamba, A., and Tucker, C.J. (2005). Analysis of Sahelian vegetation dynamics using NOAA-AVHRR NDVI data from 1981-2003. *Journal of Arid Environments, 27*(10), 2071-2075.

Aswathi, P.V., Nikam, B.R., Chouksey, A., and Aggarwal, S.P. (2018). Assessment and monitoring of agricultural droughts in Maharashtra using meteorological and remote sensing-based indices. *Remote Sensing and Spatial Information Sciences, 4*(5), 253-264.

Bandyopadhyay, N., and Saha, A.K. (2016). Comparative analysis of four drought indices using geospatial data in Gujarat, India. *Arabian Journal of Geosciences, 9*(5), 341. https://doi.org/10.1007/s12517-016-2378-x.

Bento, V.A., Gouveia, C.M., Camara, C.C., and Trigo, I.F. (2018). A climatological assessment of drought impact on vegetation health index. *Agricultural and Forest Meteorology, 259*(09), 286-295.

Boken, V.K., Cracknell, A.P., and Heathcote, R.L. (2005). *Monitoring and predicting agricultural drought*. Oxford University Press, 472 pp.

Chopra, P. (2006). Drought risk assessment using remote sensing and GIS: A case study of Gujarat. *67 pp.* https://doi.org/10.2741/3594.

Davenport, M.L., and Nicholson, S.E. (1993). On the relation between rainfall and the Normalized Difference Vegetation Index for diverse vegetation types in East Africa. *International Journal of Remote Sensing, 14*(12), 2369-2389.

Dhakar, R., Sehgal, V.K., and Pradhan, S. (2013). Study on inter-seasonal and intra-seasonal relationships of meteorological and agricultural drought indices in the Rajasthan State of India. *Journal of Arid Environments, 97*(4), 108-119.

Dubey, S.K., Pranuthi, G., and Tripathi, S.K. (2012). Relationship between NDVI and rainfall relationship over India. *International Journal of Water Resources and Environmental Sciences, 1*(4), 102-108. https://doi.org/10.5829/idosi.ijwres.2012.1.4.11117.

Dutta, D., Kundu, A., and Patel, N.R. (2013). Predicting agricultural drought in eastern Rajasthan of India using NDVI and standardized precipitation index. *Geocarto International, 28*(3), 192-209. https://doi.org/10.1175/2009JCLI2909.

Islam, M.M., and Mamun, M.I. (2015). Variations of NDVI and its association with rainfall and evapotranspiration over Bangladesh. *Rajshahi University Journal of Science and Engineering, 43*, 21-28. https://doi.org/10.3329/rujse.v43i0.26160.

Jimenez-Donaire, M.P., Tarquis, A., and Giraldez, J.V. (2020). Evaluation of a combined drought indicator and its potential for agricultural drought prediction in Southern Spain. *Natural Hazards and Earth System Sciences, 20*(1), 21-33.

Kumar, M., Desai, V.R., and Manekar, V. (2009). An examination of relationships between vegetation and rainfall using maximum value composite AVHRR-NDVI data. *Journal of Atmosphere, 27*(2), 93-101.

Kumar, S.C., and Purushothaman, B.M. (2016). Assessment of agriculture drought in Uthangarai Taluk, Krishnagiri district using remote sensing and GIS techniques. *International Journal of Science and Research, 5*(4), 95-98.

Kundu, A., and Dutta, D. (2011). Monitoring desertification risk through climate change and human interference using remote sensing and GIS. *International Journal of Geomatics and Geosciences, 2*(1), 21-33.

Lloyd-Hughes, B., and Saunders, M.A. (2002). A drought climatology for Europe. *International Journal of Climatology, 22*(13), 1571-1592.

Morid, S., Smakhtin, V., and Moghaddasi, M. (2006). Comparison of seven meteorological indices for drought monitoring in Iran. *International Journal of Climatology, 26*(7), 971-985.

Murad, H., and Islam, A.K.M.S. (2011). Drought assessment using remote sensing and GIS in the north-west region of Bangladesh. *3rd International Conference on Water and Flood Management*, 861-877.

Nanzad, L., Zhang, J., Tuvdendorj, B., Nabil, M., Zhang, S., and Bai, Y. (2019). NDVI anomaly for drought monitoring and its correlation with climate factors over Mongolia from 2000 to 2016. *Journal of Arid Environments, 164*(5), 69-77.

Nightingale, J.M., and Phinn, S.R. (2003). Assessment of relationships between precipitation environments of South Australia. *Australian Geographical Studies, 41*(7), 180-195.

Pei, Z., Fang, S., Yang, W., Wang, L., Wu, M., and Zhang, Q. (2019). The relationship between NDVI and climate factors at different monthly time scales: A case study of grasslands in Inner Mongolia, China (1982-2015). *Sustainability (Switzerland), 11*(24).

Pei, Z., Fang, S., Wang, L., and Yang, W. (2020). Comparative analysis of drought indicated by the SPI and SPEI at various timescales in Inner Mongolia, China. *Water, 12*(7), 1925. https://doi.org/10.3390/w12071925.

Quiring, S.M., and Ganesh, S. (2010). Evaluating the utility of the vegetation condition index (VCI) for monitoring meteorological drought in Texas. *Agricultural and Forest Meteorology, 150*, 330-339.

Rimkus, E., Stonevicius, E., Kilpys, J., Maciulytë, V., and Valiukas, D. (2017). Drought identification in the eastern Baltic region using NDVI. *Earth System Dynamics, 6*(3), 627-637. https://doi.org/10.5194/esd-2017-5.

Senamaw, A., Addisu, S., and Suryabhagavan, K.V. (2021). Mapping the spatial and temporal variation of agricultural and meteorological drought using geospatial techniques, Ethiopia. *Environmental Systems Research, 15*(10), 1-17.

Shukla, V., Patel, N., Tolpekin, V., and Dadhwal, V. (2007). Modelling spatio-temporal pattern of drought using three-dimensional Markov Random Field. *Journal of South Asia Disaster Studies, 2*(1), 107-128.

Sona, N.T., Chen, C.F., Chen, C.R., Chang, L.Y., and Minh, V.Q. (2012). Monitoring agricultural drought in the Lower Mekong Basin using MODIS NDVI and land surface temperature data. *International Journal of Applied Earth Observation and Geoinformation, 18*(1), 417-427.

Vaani, N., and Porchelvan, P. (2017). GIS-based agricultural drought assessment for the state of Tamil Nadu, India using vegetation condition index (VCI). *International Journal of Civil Engineering and Technology, 8*(5), 1185-1194.

Venkadesh, S., Pazhanivelan, S., Ragunath, K.P., Kumaraperumal, R., Panneerselvam, S., and Sathy,

R. (2019). Assessment of agricultural drought using MODIS NDVI-based vegetation status for different agro-climatic zones of Tamil Nadu. *International Journal of Current Microbiology and Applied Sciences, 8*(5), 2204-2212. https://doi.org/10.20546/ijcmas.2019.805.260.

Vicente-Serrano, S.M., Begueria, S., and Lopez-Moreno, J.I. (2010). A multiscalar drought index sensitive to global warming: The standardized precipitation evapotranspiration index. *Journal of Climate, 23*(7), 1696-1718.

Yulistya, V.D., Wibowo, A., and Kusratmoko, E. (2019). Assessment of agricultural drought in paddy field area using Vegetation Condition Index (VCI) in Sukaresmi District, Cianjur Regency. *IOP Conference Series: Earth and Environmental Science, 311*(1), 012020.

Zhou, X., Guan, H., Xie, H., and Wilson, J.L. (2009). Analysis and optimization of NDVI definitions and areal fraction models in remote sensing of vegetation. *International Journal of Remote Sensing, 30*(3), 721-751.