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Spatio-Temporal Assessment of Agricultural Drought under Changing Climatic Conditions Using Geospatial Techniques: A Case Study of Prakasam District, Andhra Pradesh, India

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Abstract

Prakasam District in Andhra Pradesh is one of the most drought-prone areas in the state. Its semi-arid climate, dependence on rainfed farming, and falling groundwater levels lead to frequent agricultural droughts. In this study, we used remote sensing and GIS to track how drought changed over time, analyzing Landsat 8 and 9 OLI/TIRS images from 2015, 2020, and 2025. We generated five drought indicators-Normalized Difference Vegetation Index (NDVI), Land Surface Temperature (LST), Vegetation Condition Index (VCI), Temperature Condition Index (TCI), and Vegetation Health Index (VHI)-at a 30-meter resolution.

The results showed that thermal stress continued to rise, with the highest LST increasing from 38.72°C in 2015 to 41.30°C in 2025. Maximum NDVI values increased slightly from 0.47 to 0.52, indicating some local improvement in vegetation. However, VHI results showed that drought-affected areas increased in size. Mild drought areas increased from 110 km² in 2015 to 160 km² in 2025, and extreme drought became common by 2025. The negative link between NDVI and LST strengthened, from -0.62 to -0.79, indicating that vegetation had a growing effect on surface temperatures.

These findings show that more green vegetation does not always mean less drought risk if thermal stress is also rising. Using both vegetation and temperature indices together gives a better picture of agricultural drought than using just one index. This study is the first to use 30-meter Landsat data for remote sensing and GIS-based drought assessment in Prakasam District, and it offers a practical approach for drought monitoring and climate-resilient farming in semi-arid parts of peninsular India.

Keywords: Agricultural Drought, NDVI, LST, VCI, TCI, VHI, Prakasam District, Remote Sensing, Semi-Arid, Andhra Pradesh

1. Introduction

Drought is one of the most economically destructive and ecologically pervasive natural hazards, affecting all climatic regions but exerting the greatest impact on agriculture in arid and semi-arid environments (Wilhite and Glantz, 1985; Mishra and Singh, 2010) [75, 40]. Unlike rapid-onset disasters, drought develops gradually through meteorological, agricultural, hydrological, and socio-economic stages, making timely detection and mitigation challenging (Mishra and Singh, 2010; Satapathy *et al.*, 2024) [40, 57]. Its impacts include crop failure, livestock losses, water scarcity, land degradation, and reduced food security, disproportionately affecting smallholder farmers and rural communities (Godfray *et al.*, 2010; IPCC, 2023) [23, 27]. The IPCC Sixth Assessment Report highlights that anthropogenic climate change has intensified the global water cycle, increasing the frequency and severity of drought events (IPCC, 2021, 2023) [26, 27]. Rising temperatures and higher potential evapotranspiration further aggravate soil moisture deficits, even during years of near-normal rainfall (Chaubey *et al.*, 2023) [13]. Consequently, reliable agricultural drought monitoring has become a critical scientific and policy priority.

Satellite-derived vegetation and thermal indices have transformed agricultural drought monitoring. NDVI is widely used to assess vegetation condition but cannot distinguish natural sparse vegetation from drought stress (Rouse *et al.*, 1974; Pettorelli *et al.*, 2005; Xue and Su, 2017; Alahacoon and Edirisinghe, 2022; Kogan and Guo, 2016) [56, 51, 76, 5, 34]. To address this limitation, Kogan (1995) [30] developed VCI and TCI, whose integration as VHI

provides a reliable indicator of drought severity validated against crop, rainfall, and soil moisture data (Kogan, 1995, 2001; Kogan *et al.*, 2004; Aswathi *et al.*, 2018; Jiao *et al.*, 2017; Mohamed Adou *et al.*, 2024; Shastri *et al.*, 2025) [30, 32, 33, 6, 28, 42, 59].

The inverse NDVI-LST relationship is a sensitive indicator of vegetation thermal stress (Weng *et al.*, 2004; Sun and Kafatos, 2007; Barbosa *et al.*, 2006; Mondal *et al.*, 2020; Trisasongko *et al.*, 2025) [74, 65, 8, 43, 69]. The VCI-TCI-VHI framework has been widely applied worldwide, while GEE and 30 m Landsat imagery enable accurate district-level drought assessment (Massari *et al.*, 2023; Tadesse *et al.*, 2024; Satapathy *et al.*, 2024; Rahmati *et al.*, 2025; Dilshad *et al.*, 2025; Stefan *et al.*, 2025; Agarwal *et al.*, 2025; Subash *et al.*, 2025; Patel *et al.*, 2012; Dhawale, R. 2018, ÖZDEMİR, Y. 2026) [37, 66, 57, 52, 18, 62, 3, 63, 50, 15, 49].

India is highly drought-prone, with nearly two-thirds of its area vulnerable and agriculture heavily dependent on monsoon rainfall, making drought a major threat to food security and rural livelihoods (Aadhar and Mishra, 2024; Satapathy *et al.*, 2024; Mishra *et al.*, 2019; Chuphal *et al.*, 2024) [1, 57, 41, 14]. Rainfall variability has intensified drought across semi-arid India (Chaubey *et al.*, 2023; Tripathy *et al.*, 2026; Rao *et al.*, 2024; Samuel *et al.*, 2024). Although VCI-, TCI-, and VHI-based drought studies exist, Landsat-based multi-temporal, mandal-level assessments remain scarce in Andhra Pradesh (Aswathi *et al.*, 2018; Nag *et al.*, 2024; Agarwal *et al.*, 2025; Subash *et al.*, 2025; Shastri *et al.*, 2025) [6, 45, 3, 63, 59].

Andhra Pradesh is a drought-prone state where rainfed agriculture dominates, with Anantapur, Kadapa, Chittoor, Kurnool, and Prakasam accounting for nearly 70% of drought-induced crop losses (Journal of Current Research, 2021; RMSI, 2006; IFAD, 2016; APMAS, 2016). Remote sensing studies have identified Prakasam as one of the most vulnerable districts (Bhardwaj and Mishra, 2025; Murthy *et al.*, 2015; Kumar *et al.*, 2019) [9, 44, 35]. Despite high dependence on erratic rainfall and groundwater (IFAD, 2016; ICAR-CRIDA, 2014; RMSI, 2006; Deccan Chronicle, 2019, 2026), no Landsat-based integrated NDVI-LST-VCI-

TCI-VHI assessment exists for mandal-level agricultural drought in Prakasam District.

Objectives

1. To assess the spatiotemporal dynamics of agricultural drought in Prakasam District, Andhra Pradesh, using Landsat 8 and 9 OLI/TIRS imagery (2015, 2020, and 2025).
2. To evaluate vegetation condition, thermal stress, drought severity, and drought hotspots using NDVI, LST, VCI, TCI, and VHI derived from remote sensing and GIS techniques.
3. To provide a practical framework for drought monitoring and climate-resilient agricultural planning in semi-arid regions, with a specific focus on Prakasam District.

2. Study Area

The united Prakasam District is located in the tropical region of Andhra Pradesh, India, between 15°05'39" and 16°09'28" N latitude and 79°05'50" and 80°10'00" E longitude (Fig. 1). The district is characterized by diverse physiographic features, with the central part comprising extensive tracts of scrub vegetation, dry deciduous forests, rocky hills, and stony plains. The Markapur Revenue Division, formed following the administrative reorganization of Andhra Pradesh, represents a predominantly upland terrain. The united Prakasam district is bounded by Bapatla and Palnadu districts to the north, Nandyal district to the west,YSR Kadapa and SPSR Nellore districts to the south, and the Bay of Bengal to the east, with a coastline of approximately 50 km. Ongole serves as the district headquarters. Following the administrative reorganization of Andhra Pradesh on 4 April 2022, Prakasam District comprises three revenue divisions (Ongole, Kanigiri, and Markapur), 38 revenue mandals, one Municipal Corporation (Ongole), three municipalities (Markapur, Kanigiri, and Chimakurthy), three Nagar Panchayats (Giddalur, Podili, and Darsi), and 730 Gram Panchayats (Government of Andhra Pradesh, 2023).

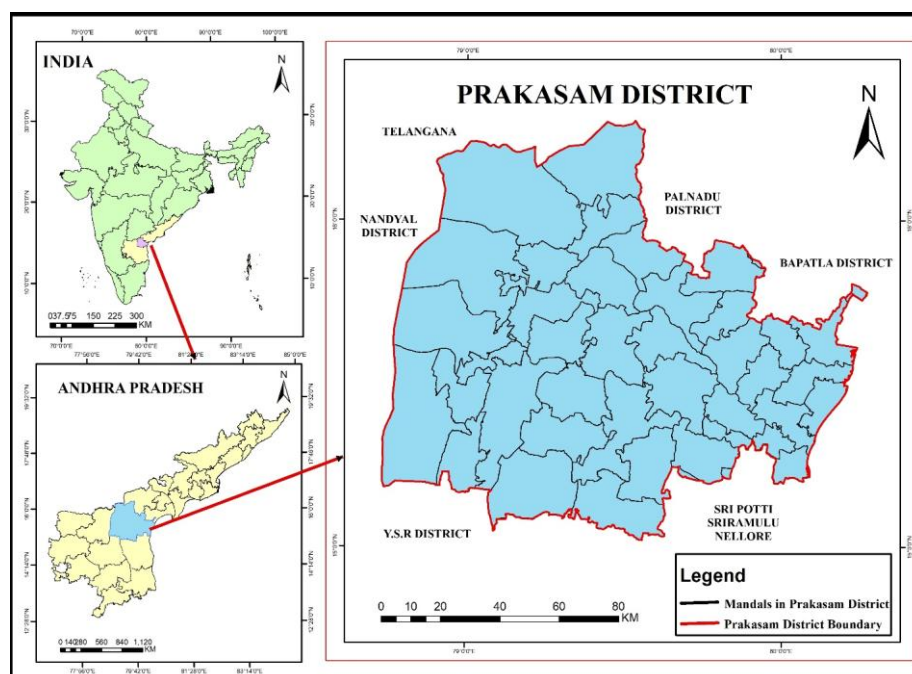


Fig 1: Location within Land use of the Prakasam district

Prakasam District extends from the Eastern Ghats in the west to the Bay of Bengal coastal plains in the east. The central region is characterized by rocky hills, scrub forests, and stony plains, while the eastern coastal plains consist of fertile alluvial soils with better irrigation potential. Geologically, the district is underlain mainly by Precambrian granite-gneiss complexes, together with quartzites, sandstones, and shales of the Cuddapah and Kurnool Supergroups, which influence groundwater occurrence and landforms (Subba Rao, 2018; Upadhyay *et al.*, 2006; Reddy and Murthy, 2014) [64, 71, 55]. The district has a 50 km coastline extending across Naguluppapadu, Ongole, Kothapatnam, Tangutur, and Singarayakonda mandals, with prominent beaches at Kothapatnam and Pakala (Government of Andhra Pradesh, 2023).

Surface drainage is dominated by the Gundlakamma, Musi, and Paleru rivers, with support from smaller rivers and seasonal streams. The Gundlakamma River is the major river system. It supports irrigation through the Gundlakamma Reservoir, Thippayapalem Reservoir, Cumbum Tank, and other irrigation projects, and supplies drinking water to Ongole (Directorate of Economics and Statistics, 2023) [19]. The climate is tropical semi-arid, with moderate coastal conditions and hotter inland uplands. The district records an average maximum temperature of 36.9°C and a minimum of 22.2°C. Rainfall is bimodal, receiving

366.2 mm from the Southwest Monsoon and 384.7 mm from the Northeast Monsoon. Delayed monsoon onset, prolonged dry spells, and high rainfall variability frequently result in agricultural drought (Directorate of Economics and Statistics, 2023; RMSI, 2006).

Agriculture is the principal livelihood, with cropping patterns determined by soil and water availability. Tobacco, cotton, and chili dominate black cotton soils, paddy is concentrated in irrigated coastal areas, and pulses and millets are cultivated under rainfed conditions (Directorate of Economics and Statistics, 2023; ICAR-CRIDA, 2014) [19, 25]. The predominance of rainfed agriculture, coupled with variable rainfall and groundwater stress, makes Prakasam District highly suitable for multi-temporal remote sensing-based agricultural drought assessment.

3. Data and Methodology

The methodological framework adopted in this study integrates satellite data acquisition and preprocessing, derivation of five remote sensing indices, drought severity classification, and statistical correlation analysis, structured to enable consistent inter-annual comparison across the three benchmark years (Fig. 2). Each stage follows established radiometric and biophysical conventions widely validated in the agricultural drought monitoring literature, as detailed below.

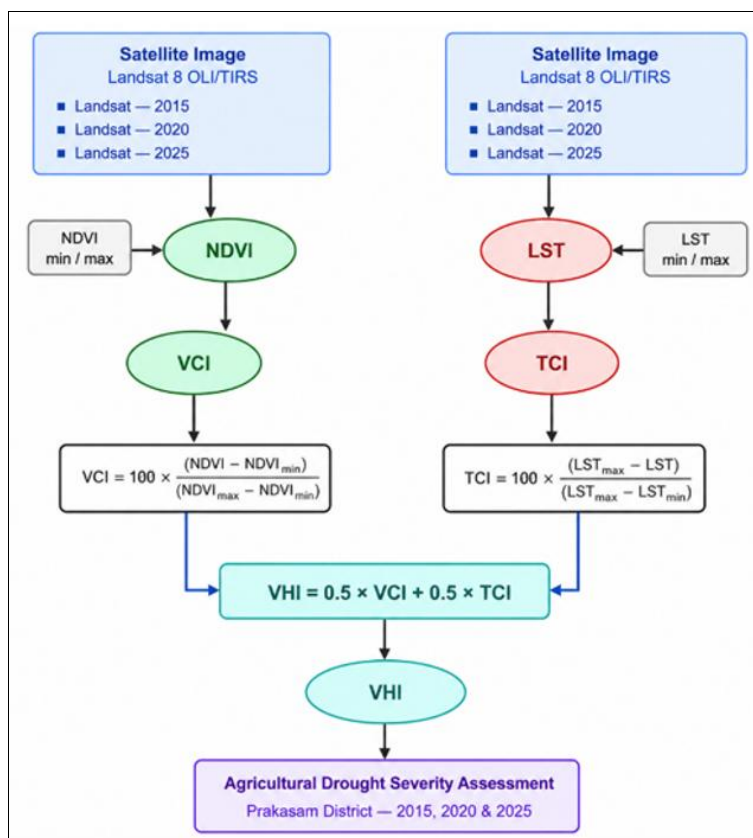


Fig 2: Flowchart diagram of VHI calculation and drought classification.

3.1 Satellite Data Acquisition and Selection Criteria

Three Landsat scenes with less than 10% cloud cover were obtained from the USGS EarthExplorer portal as the primary data source. Landsat 8 OLI/TIRS imagery was used for 2015 and 2020, and Landsat 9 OLI/TIRS imagery for 2025. Both sensors provide 30 m multispectral and thermal infrared data, with the thermal infrared data resampled from

100 m to 30 m to ensure consistency across the three study years (USGS, 2023) [73]. All scenes were acquired as Collection 2 Level-1 products after screening for cloud cover, scan-line artifacts, and sensor anomalies. Image acquisition dates were selected during the post-monsoon to early pre-monsoon period to minimize cloud contamination while capturing vegetation and thermal conditions

representative of cumulative agricultural drought stress (Patel *et al.*, 2012; Mohamed Adou *et al.*, 2024; Adam *et*

al., 2026) [50, 42, 2].

Table 1: Satellite data used in this study

1	Landsat 8 OLI/TIRS	15 December 2015	NDVI, LST, VCI, TCI	< 10%	30 m	USGS EarthExplorer
2	Landsat 9 OLI/TIRS	22 November 2020	NDVI, LST, VCI, TCI	< 10%	30 m	USGS EarthExplorer
3	Landsat 9 OLI/TIRS	18 May 2025	NDVI, LST, VCI, TCI	< 10%	30 m	USGS EarthExplorer

3.2 Image Preprocessing

All Landsat scenes underwent a standardized preprocessing workflow before index derivation. Radiometric calibration converted digital numbers (DN) to top-of-atmosphere (TOA) reflectance for OLI bands and TOA brightness temperature for the TIRS band using scene-specific metadata coefficients (USGS, 2023) [73]. Atmospheric correction was performed using the Land Surface Reflectance Code (LaSRC) within the USGS Collection 2 processing chain, which uses MODIS-derived water vapor, ozone, aerosol optical thickness, and elevation data to remove atmospheric scattering and absorption effects (USGS, 2022, 2023) [72, 73]. Geometric accuracy was verified using the Level-1 Precision and Terrain (L1TP) standard, ensuring sub-pixel co-registration across all scenes and minimizing spurious temporal changes due to image misalignment (USGS, 2023) [73].

3.3 Index Derivation

3.3.1 Normalised Difference Vegetation Index (NDVI)

The Normalised Difference Vegetation Index (NDVI) was derived from the red (Band 4) and near-infrared (Band 5) bands of Landsat 8 OLI using the method of Rouse *et al.* (1974) [56]:

$$\text{NDVI} = (\text{NIR} - \text{Red}) / (\text{NIR} + \text{Red}) \dots (1)$$

NDVI values range from -1 to +1, where lower values indicate water bodies, bare land, or built-up areas, while higher values represent healthy and dense vegetation (Rouse *et al.*, 1974; Pettorelli *et al.*, 2005) [56, 51]. Owing to its sensitivity to vegetation condition and climatic variability, NDVI was used as the primary vegetation indicator for drought assessment (Kogan, 1995) [30].

3.3.2 Land Surface Temperature (LST)

Land Surface Temperature (LST) was estimated from Landsat 8 Thermal Infrared Sensor (Band 10) using the mono-window algorithm (Avdan and Jovanovska, 2016) [7]. Spectral radiance ($L\lambda$) was first calculated from the digital number (DN):

$$L\lambda = \text{ML} \times \text{Qcal} + \text{AL} \dots (2)$$

Brightness temperature (BT, in °C) was then derived using the band-specific thermal calibration constants K1 and K2 (USGS, 2023; Avdan and Jovanovska, 2016) [73, 7]:

$$\text{BT} = [\text{K2} / \ln(\text{K1} / L\lambda + 1)] - 273.15 \dots (3)$$

The proportion of vegetation (PV) was computed from NDVI as an intermediate step toward emissivity estimation:

$$\text{PV} = [(\text{NDVI} - \text{NDVI}_{\min}) / (\text{NDVI}_{\max} - \text{NDVI}_{\min})]^2 \dots (4)$$

Land surface emissivity (E) was estimated from PV following the empirical linear relationship of Avdan and Jovanovska (2016) [7]:

$$E = 0.004 \times \text{PV} + 0.986 \dots (5)$$

Finally, LST was calculated by correcting BT for surface emissivity using the Planck-function-derived expression:

$$\text{LST} = \text{BT} / [1 + (\lambda \times \text{BT} / \rho) \times \ln(E)] \dots (6)$$

where λ is the central wavelength of Landsat 8 Band 10 (10.9 μm), and ρ is the second radiation constant (1.438 $\times 10^{-2}$ m) (Mikhaylov *et al.*, 2020) [38]. The derived LST was used to assess surface thermal conditions and vegetation stress associated with agricultural drought (Avdan and Jovanovska, 2016) [7].

3.3.3 Vegetation Condition Index (VCI)

The Vegetation Condition Index (VCI) was computed following the method proposed by Kogan (1995) [30], which normalises the current NDVI value using the historical minimum and maximum NDVI recorded for each pixel. This approach minimises the influence of differences in vegetation type and highlights the effect of climatic variability on vegetation condition.

$$\text{VCI} = 100 \times (\text{NDVI} - \text{NDVI}_{\min}) / (\text{NDVI}_{\max} - \text{NDVI}_{\min}) \dots (7)$$

VCI values range from 0 to 100, where lower values indicate severe vegetation stress associated with drought, while higher values represent favorable vegetation conditions. Owing to its ability to capture drought-induced vegetation stress, VCI has been widely used for agricultural drought assessment and monitoring (Kogan, 1995, 1997; Kogan *et al.*, 2004) [30, 31, 33].

3.3.4 Temperature Condition Index (TCI)

The Temperature Condition Index (TCI) was calculated following Kogan (1995) [30] by normalising the land surface temperature (LST) with respect to its historical maximum and minimum values for each pixel. The inverse relationship ensures that higher surface temperatures correspond to lower TCI values, indicating greater thermal stress (Aswathi *et al.*, 2018) [6].

$$\text{TCI} = 100 \times (\text{LST}_{\max} - \text{LST}) / (\text{LST}_{\max} - \text{LST}_{\min}) \dots (8)$$

TCI values range from 0 to 100, where lower values indicate severe thermal stress and higher values represent favorable temperature conditions. As vegetation experiences moisture stress, reduced evapotranspiration increases surface temperatures, leading to lower TCI values. Therefore, TCI is widely used to assess thermal stress and monitor agricultural drought (Kogan, 1995; Weng *et al.*, 2004; Jiao *et al.*, 2017)

[30, 74, 28].

3.3.5 Vegetation Health Index (VHI) and Drought Classification

The Vegetation Health Index (VHI) combines vegetation condition (VCI) and thermal condition (TCI) to assess the combined effects of moisture deficiency and heat stress on vegetation (Kogan, 2001) [32].

$$VHI = \alpha \times VCI + (1 - \alpha) \times TCI \dots (9)$$

Table 2: VHI-based drought severity classification (after Kogan, 2001) [32]

0-10	Extreme Drought (EXD)	Severe vegetation stress; critical water deficit
10-20	Severe Drought (SED)	Significant reduction in vegetation health
20-30	Moderate Drought (MOD)	Moderate stress; below-normal vegetation condition
30-40	Mild Drought (MID)	Slight stress; near-normal conditions
> 40	No Drought (NOD)	Normal or favourable vegetation conditions

For each benchmark year, the minimum and maximum NDVI and LST values from the district-clipped Landsat images were used to normalise VCI and TCI. Although the original method recommends multi-year pixel-based normalisation (Kogan, 1995) [30], this study adopted a single-date scene-based approach, which is widely used in drought studies (Aswathi *et al.*, 2018; Nag *et al.*, 2024) [6, 45]. This approach captures spatial drought variability and enables comparison among the benchmark years.

3.4 Statistical Analysis

Pearson's product-moment correlation coefficient (r) was used to evaluate the relationship between NDVI and LST for each benchmark year. Paired pixel values were extracted using a systematic sampling grid across the study area to minimise the influence of spatial autocorrelation (Sun and Kafatos, 2007) [65]. The coefficient of determination (R^2) and adjusted R^2 were also calculated to quantify the variation in LST explained by NDVI and to compare the strength of their relationship across the benchmark years. Statistical significance was evaluated at $p < 0.01$ using standard regression and raster analysis techniques.

3.5 Drought Category Extent Mapping

Following computation of VHI for each benchmark year, the continuous VHI raster was reclassified into five drought-severity categories, as shown in Table 2. The spatial extent (km^2) of each drought category was then calculated using zonal area statistics, allowing direct comparison of drought

where $\alpha = 0.5$, giving equal weight to both VCI and TCI, as recommended by Kogan (2001) and Bhuiyan *et al.* (2006) [10]. VHI values range from 0 to 100, with lower values indicating severe drought conditions and higher values representing healthy vegetation. Owing to its ability to integrate vegetation and thermal stress, VHI has been widely used for agricultural drought monitoring and drought severity assessment (Kogan, 2001; Singh *et al.*, 2003; Bhuiyan *et al.*, 2006) [32, 61, 10]. Drought severity was classified into five categories following the standard classification proposed by Kogan (2001) (Table 2).

conditions across 2015, 2020, and 2025. Compared with average VHI values, area-based analysis provides a more meaningful assessment of the spatial extent of drought and is widely adopted in agricultural drought monitoring and resource planning (Bhuiyan *et al.*, 2006; Satapathy *et al.*, 2024) [10, 57].

4. Analysis and Results

4.1 Normalised Difference Vegetation Index (NDVI)

NDVI maps revealed a gradual but spatially uneven improvement in vegetation cover across Prakasam District during the study period (Fig. 3). In 2015, the central and interior mandals were dominated by bare land and sparse vegetation. Similar conditions persisted in 2020, whereas by 2025 the northern and western mandals showed increased shrub and healthy vegetation, indicating improved vegetation conditions, possibly due to favorable rainfall and better land management (Pettorelli *et al.*, 2005; Xue and Su, 2017) [51, 76].

NDVI values ranged from approximately -0.20 to $+0.57$, with the maximum increasing from 0.47 in 2015 to 0.52 in 2025 (Table 4). These values are characteristic of semi-arid, rainfed landscapes and indicate localized vegetation recovery, whereas persistent negative values represent water bodies and barren surfaces (Bhuiyan *et al.*, 2006; Nag *et al.*, 2024) [10, 45]. However, NDVI alone cannot fully assess drought conditions because it does not account for climatic variability or thermal stress (Kogan and Guo, 2016) [34].

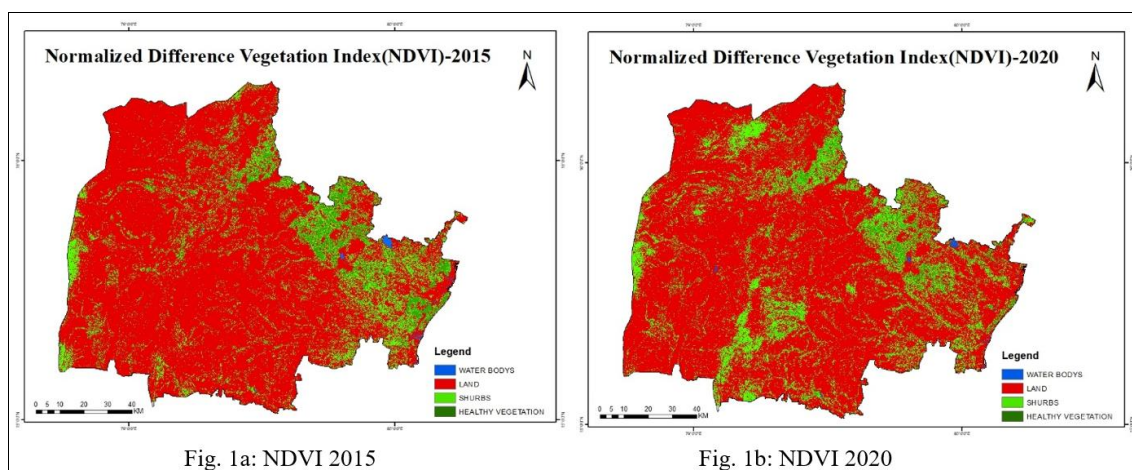


Fig. 1a: NDVI 2015

Fig. 1b: NDVI 2020

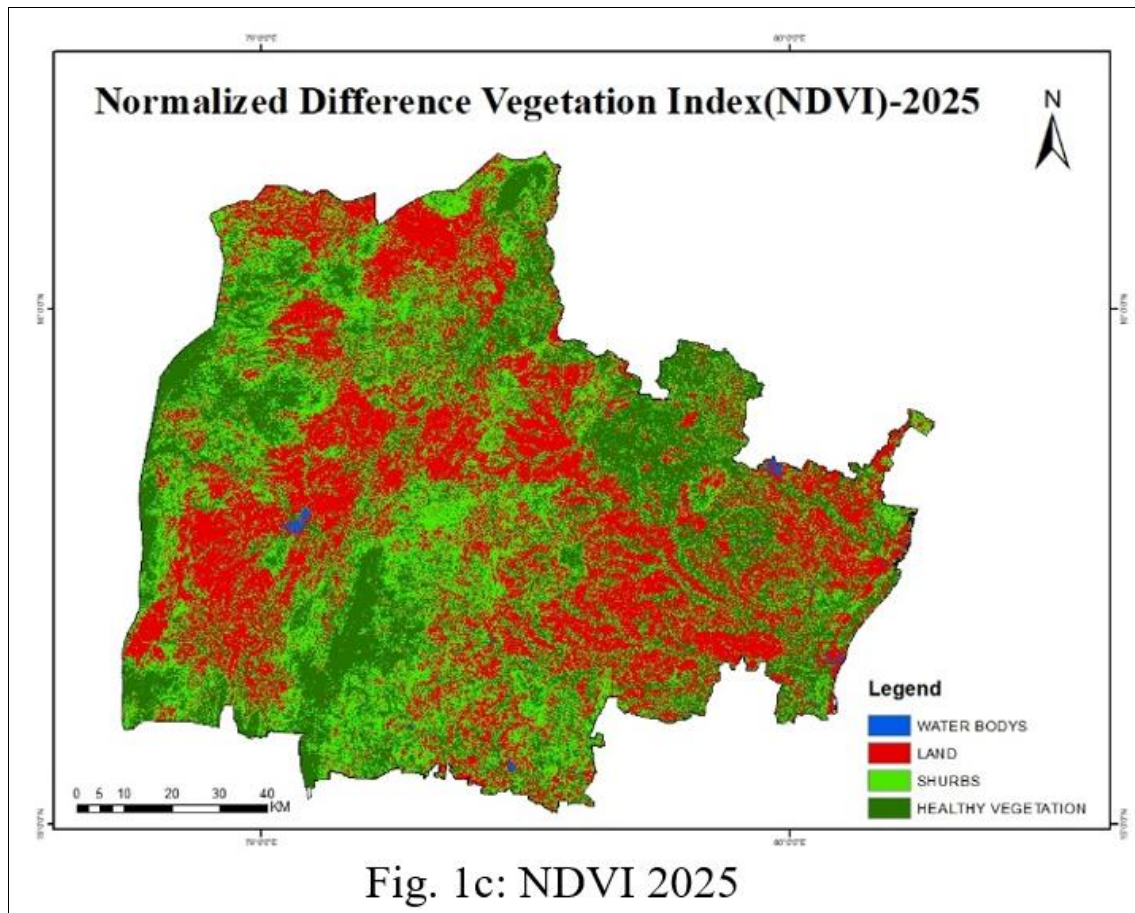


Fig. 1c: NDVI 2025

Fig 3: Spatial distribution of NDVI in Prakasam District for 2015, 2020, and 2025.

4.2 Land Surface Temperature (LST)

LST maps showed a gradual increase in surface temperature across Prakasam District during the study period (Fig. 4). Surface temperatures ranged from 22.45-38.72°C in 2015, increased to 40.15°C in 2020, and reached a maximum of 41.30°C in 2025. Higher temperatures became more prominent in the central and south-eastern mandals. In contrast, relatively lower temperatures in the northern

mandals during 2025 coincided with improved vegetation cover observed in the NDVI analysis. Built-up areas and barren land consistently recorded the highest LST values. In contrast, vegetated areas and water bodies remained cooler due to vegetation and evapotranspiration, consistent with findings from other semi-arid and tropical regions (Weng *et al.*, 2004; Sun and Kafatos, 2007; Mondal *et al.*, 2020) [74, 65, 43].

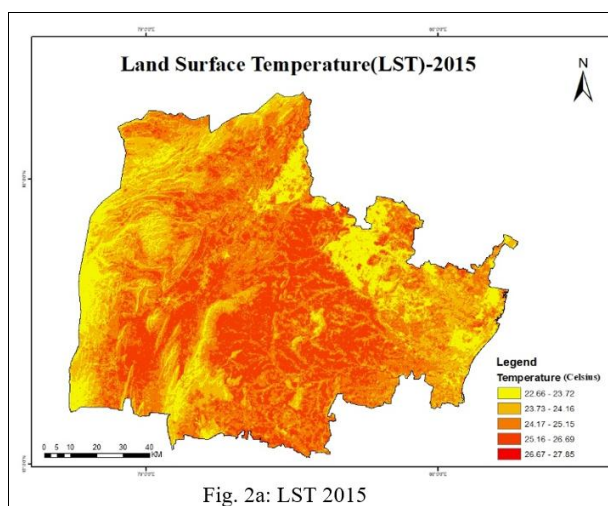


Fig. 2a: LST 2015

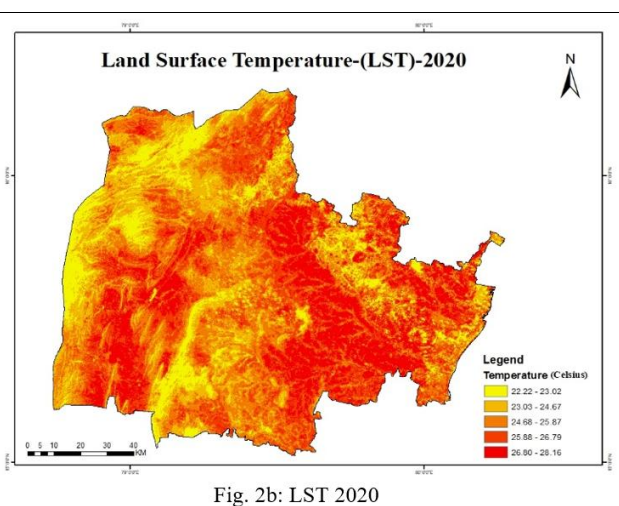


Fig. 2b: LST 2020

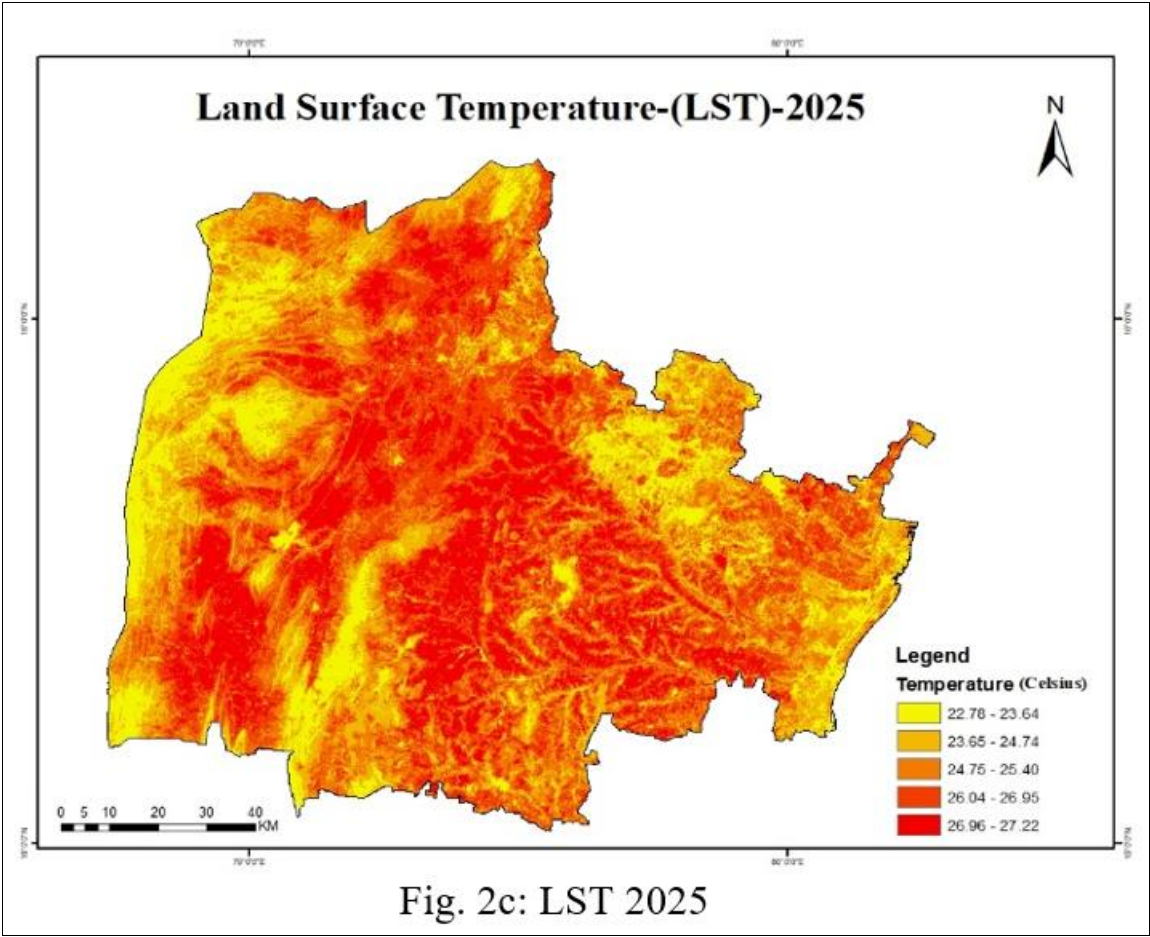
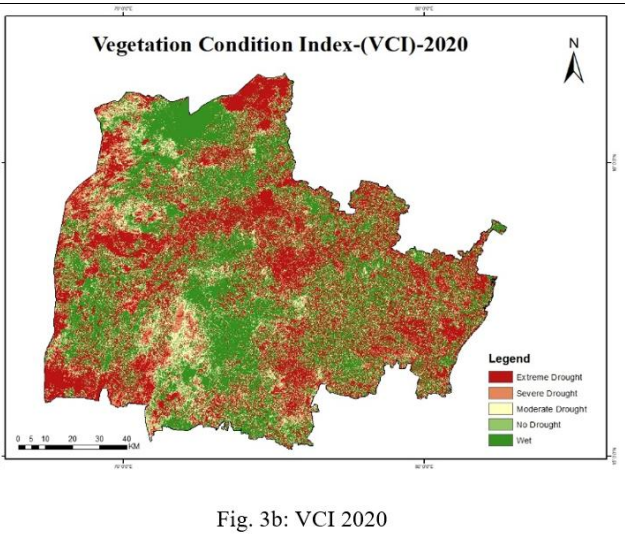
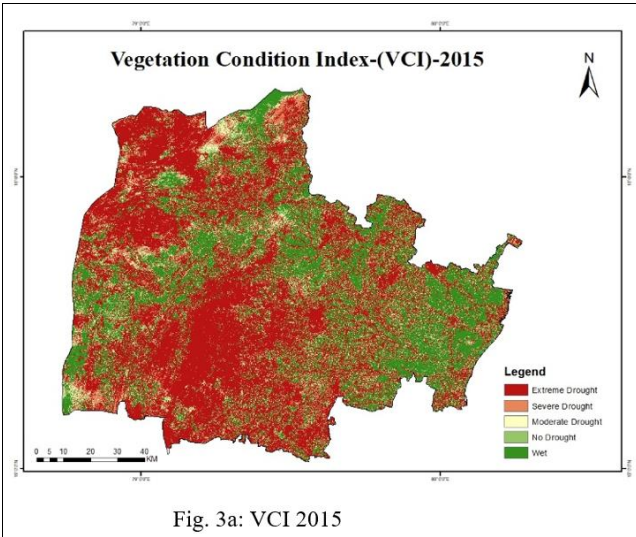


Fig 4: Spatial distribution of Land Surface Temperature (LST) in Prakasam District for 2015, 2020, and 2025

4.3 Vegetation Condition Index (VCI)

VCI maps showed considerable spatial variation in vegetation condition across the three benchmark years (Fig. 5). In 2015, the district experienced a mix of extreme drought and no-drought conditions, with higher VCI values mainly in the eastern coastal and southern mandals. A similar pattern was observed in 2020, although the areas with higher VCI shifted slightly northward. By 2025, VCI

indicated an overall improvement in vegetation condition across most of the district, consistent with rising NDVI values. However, low VCI values persisted in parts of the north-central and eastern mandals, indicating localized drought stress. These spatial variations reflect differences in rainfall, land use, and vegetation condition, consistent with earlier studies from semi-arid regions of India (Murthy *et al.*, 2015; Nag *et al.*, 2024) [44, 45].



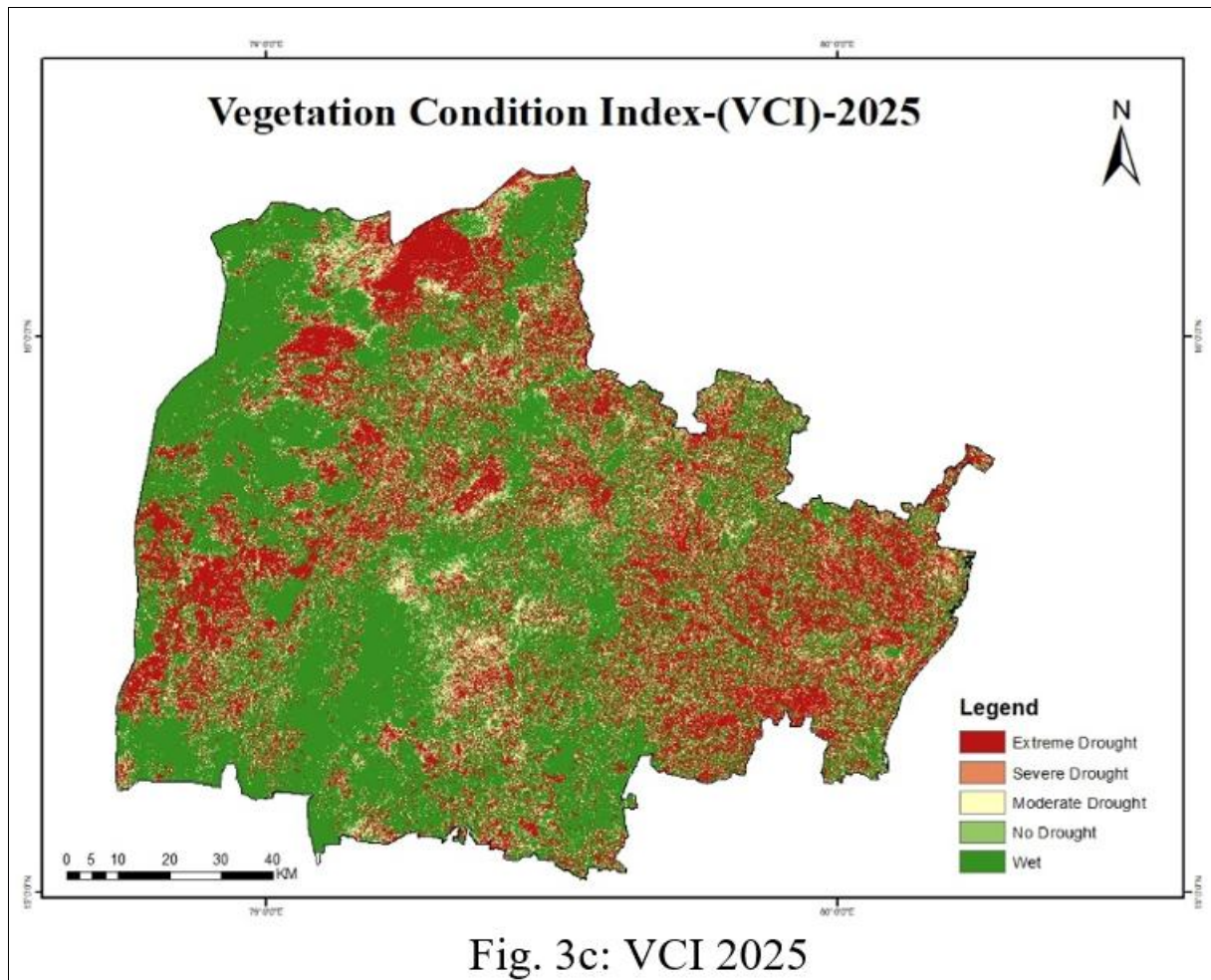
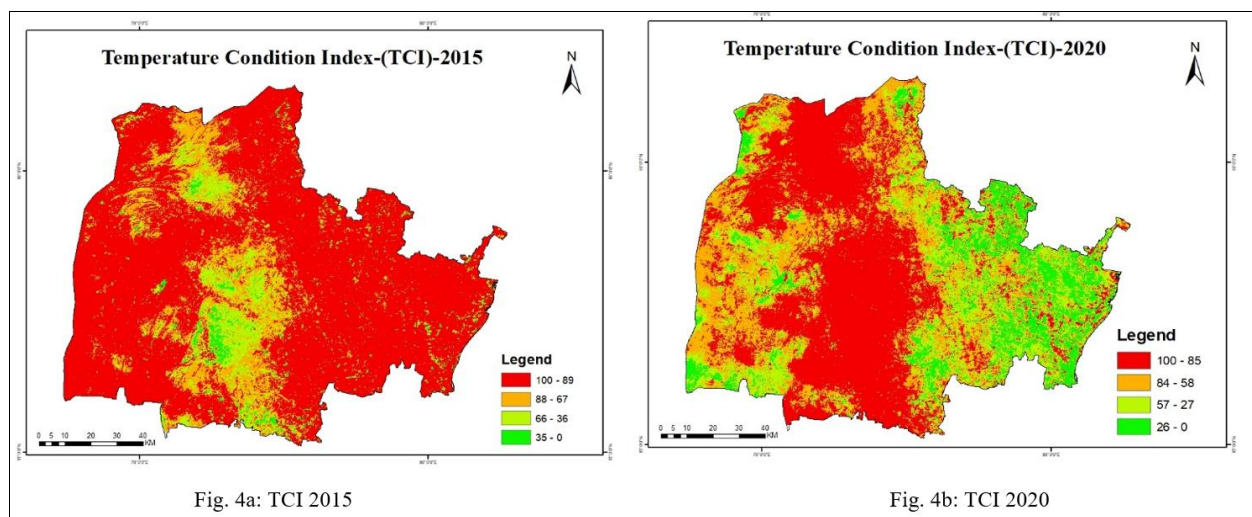


Fig 5: Spatial distribution of Vegetation Condition Index (VCI) in Prakasam District for 2015, 2020, and 2025.

4.4 Temperature Condition Index (TCI)

TCI maps showed considerable year-to-year variation in thermal stress across Prakasam District (Fig. 6). In 2015, high TCI values (89-100) were observed across most parts of the district, indicating relatively low thermal stress. In 2020, moderate spatial variation was evident, with intermediate TCI values (26-57) mainly in the eastern and

southern mandals. By 2025, TCI values declined to 0-10 across much of the district, indicating increased thermal stress due to higher surface temperatures. The marked interannual variation highlights the sensitivity of TCI to thermal conditions at the time of image acquisition, a limitation discussed in Section 5 (Bhuiyan *et al.*, 2006) ^[10].



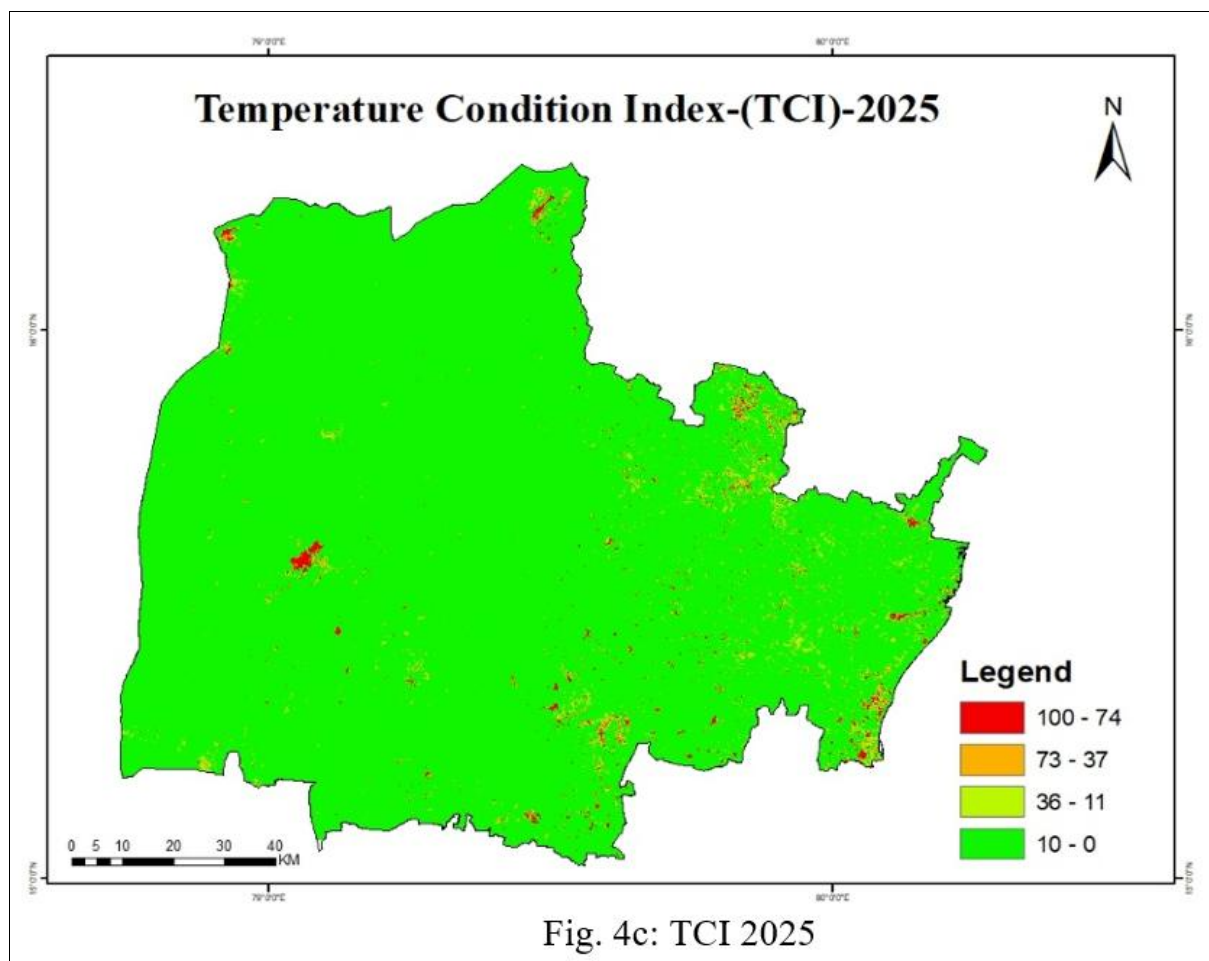


Fig. 4c: TCI 2025

Fig 6: Spatial distribution of Temperature Condition Index (TCI) in Prakasam District for 2015, 2020, and 2025.

4.5 Drought Assessment Using the Vegetation Health Index (VHI)

The Vegetation Health Index (VHI), which combines VCI and TCI, was used to assess the spatial pattern of agricultural drought across Prakasam District (Fig. 7). In 2015, the district showed a mix of moderate to severe drought, with isolated pockets of extreme drought in the river valleys and degraded uplands. By 2020, drought stress intensified, with larger areas falling under the severe and extreme drought categories, particularly in the inland

mandals. In 2025, extreme drought became the dominant class across most of the district despite improved NDVI. This contrast is mainly due to the very low TCI values in 2025, which lowered the overall VHI even in areas with moderate to good vegetation condition.

The observed drought pattern is consistent with VHI-based assessments reported from other semi-arid regions of India, indicating that the drought conditions in Prakasam District follow a broader regional trend (Bhuiyan *et al.*, 2006; Gatha Cognition, 2024) ^[10, 21].

Table 3: Observed VCI, TCI, and VHI spatial extents by drought category for Prakasam District (2015, 2020, and 2025)

EXD	26	30	45	55	40	35	48	4	45
SED	34	48	50	28	52	30	22	3	30
MOD	63	47	55	38	28	30	44	8	45
MID	65	20	110	45	20	150	42	10	160
NOD	30	5	30	25	7	35	18	4	35

Note: EXD = Extreme Drought; SED = Severe Drought; MOD = Moderate Drought; MID = Mild Drought; NOD = No Drought. Left y-axis: index values; Right y-axis: VHI-derived spatial extent (km²).

The category-wise area presented in Table 3 highlights two consistent trends during the study period. The area under mild drought (MID) increased steadily from 110 km² in 2015 to 150 km² in 2020 and 160 km² in 2025, making it the largest drought category throughout the study period. In

contrast, the no-drought (NOD) category remained nearly stable at 30-35 km², indicating that drought-free conditions occupied only a small, consistent portion of the district despite interannual variations in the other drought categories.

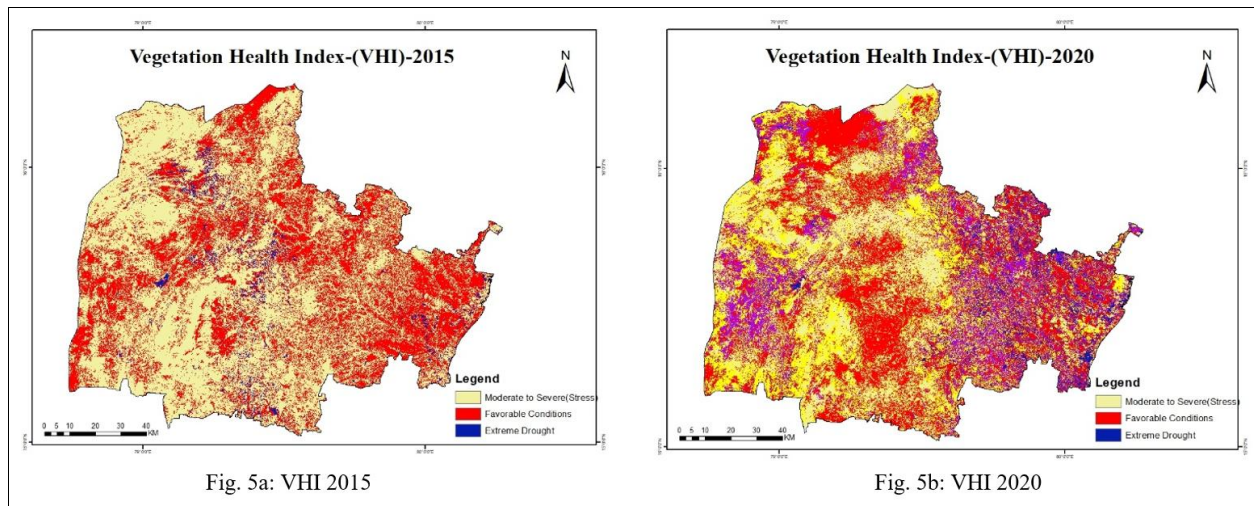


Fig. 5a: VHI 2015

Fig. 5b: VHI 2020

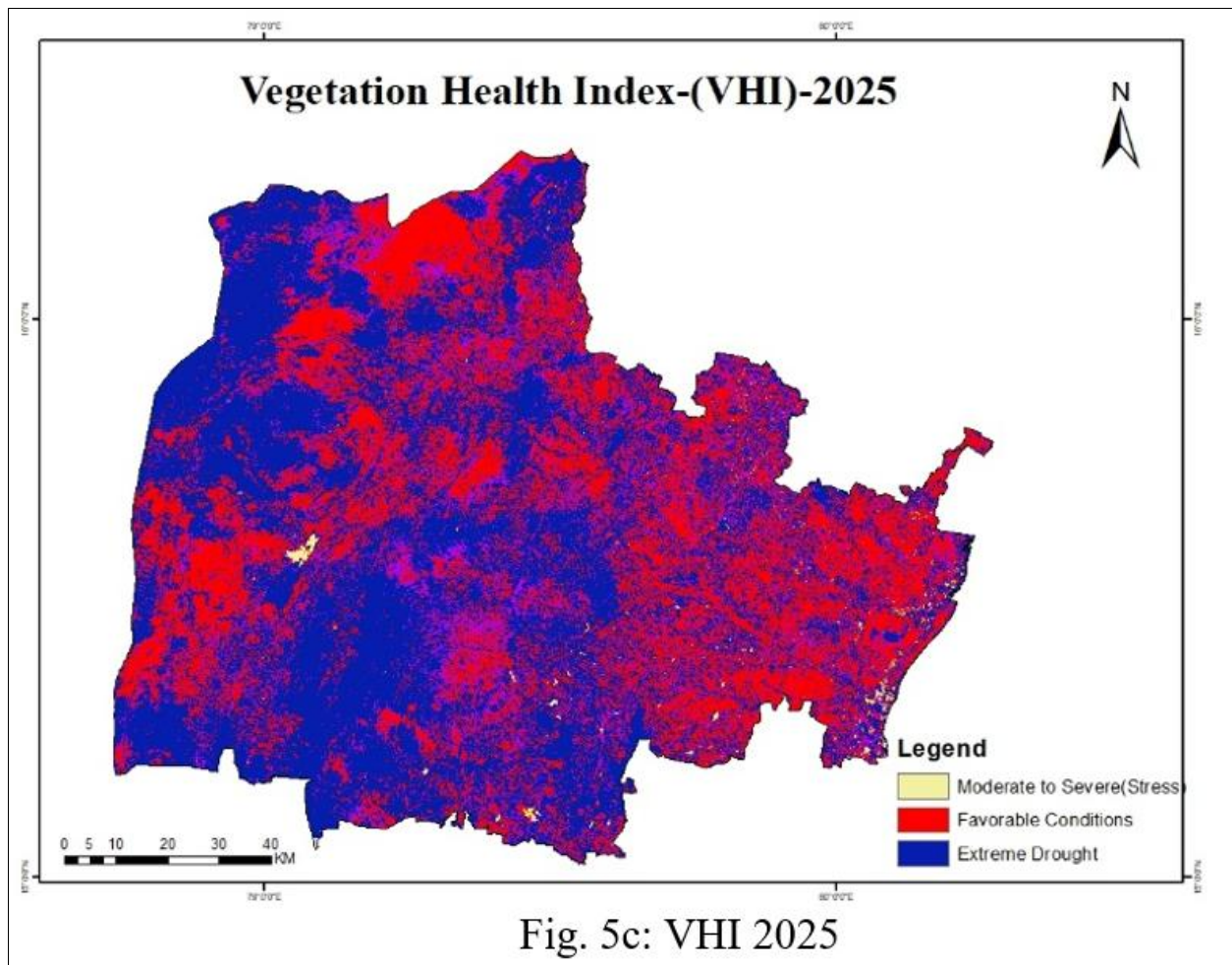


Fig. 5c: VHI 2025

Fig 7: Spatial distribution of Vegetation Health Index (VHI) in Prakasam District for 2015, 2020, and 2025.

4.6 LST-NDVI Correlation Analysis

The relationship between LST and NDVI was analysed for each benchmark year to evaluate the influence of vegetation cover on surface temperature (Fig. 8; Table 4). In 2015, NDVI ranged from -0.09 to 0.47 and LST from 22.45°C to 38.72°C , showing a moderate negative correlation ($r = -0.62$; $R^2 = 0.38$). The relationship became stronger in 2020 ($r = -0.71$; $R^2 = 0.50$) and further strengthened in 2025 ($r = -0.79$; $R^2 = 0.62$), indicating an increasing cooling effect of vegetation on land surface temperature.

The strengthening negative correlation over the study period is consistent with findings from other semi-arid and tropical regions (Sun and Kafatos, 2007; Mondal *et al.*, 2020; Trisasongko *et al.*, 2025) [65, 43, 69]. Across all three years, built-up areas and bare land recorded the highest LST, whereas vegetated areas and water bodies consistently showed lower temperatures, highlighting the important role of vegetation in regulating surface thermal conditions (Weng *et al.*, 2004; Sun and Kafatos, 2007) [74, 65].

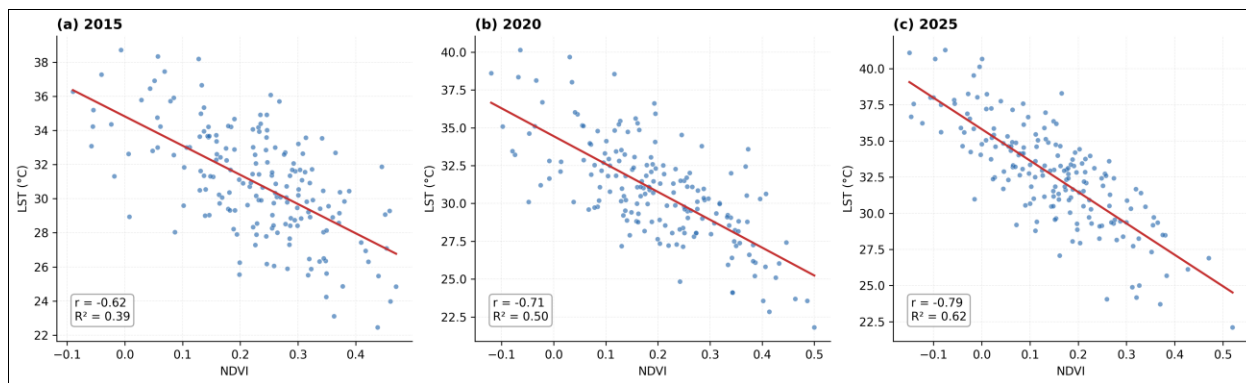


Fig 8: Correlation graphs of LST and NDVI for Prakasam District: (a)2015, (b)2020 & (c)2025

Table 4: Maximum and minimum values of LST and NDVI by acquisition date

Landsat 8 OLI/TIRS	15 Dec 2015	38.72	22.45	0.47	-0.09	-0.62	0.38
Landsat 9 OLI/TIRS	22 Nov 2020	40.15	21.80	0.50	-0.12	-0.71	0.50
Landsat 9 OLI/TIRS	18 May 2025	41.30	22.10	0.52	-0.15	-0.79	0.62

5. Discussion

The multi-indicator remote sensing analysis presented here reveals a complex and, at first glance, counterintuitive drought trajectory for Prakasam District over the 2015-2025 decade. The co-occurrence of improving NDVI values and expanding extreme drought, as classified by VHI, warrants careful interpretation, situated in relation to the global, national, and regional literature reviewed in Section 1.

5.1 Reconciling Vegetation Greening with Expanding Drought Severity

The IPCC AR6 reports that vegetation greening can occur alongside increasing moisture and thermal stress when rising temperatures outweigh the benefits of increased rainfall (IPCC, 2021, 2023) [26, 27]. A similar pattern was observed in Prakasam District. Between 2015 and 2025, NDVI improved in the northern and western mandals, likely due to favorable rainfall and the implementation of soil and water conservation measures under MGNREGS and the Andhra Pradesh Drought Mitigation Project (APMAS, 2016; IFAD, 2016). However, this localized vegetation recovery did not substantially reduce the district's overall drought vulnerability, consistent with findings from other drought-prone regions of India (Murthy *et al.*, 2015; Rao *et al.*, 2024) [44, 53].

The strengthening negative correlation between NDVI and LST ($r = -0.62$ to -0.79) further supports this observation. Vegetation improvement was mainly confined to intervention-supported mandals, whereas the interior and eastern parts of the district remained thermally stressed with sparse vegetation. These findings indicate that although vegetation condition improved in some areas, drought stress continued across much of the district, highlighting the uneven spatial impact of drought mitigation measures (Weng *et al.*, 2004; Sun and Kafatos, 2007; Trisasongko *et al.*, 2025) [74, 65, 69].

5.2 The Role of Acquisition Timing in the 2025 VHI Signal

The widespread extreme drought, as indicated by VHI in 2025, was strongly influenced by the very low TCI values derived from the Landsat image acquired on 18 May 2025, during the peak pre-monsoon period, when thermal stress is generally highest over peninsular India (Directorate of

Economics and Statistics, 2023) [19]. Nevertheless, the increase in maximum LST from 38.72°C in 2015 to 41.30°C in 2025 suggests a genuine intensification of drought conditions, consistent with CMIP6 projections and the IPCC Sixth Assessment Report (IPCC, 2021; Chuphal *et al.*, 2024) [26, 14].

The large interannual variation in TCI is mainly due to the use of scene-based normalization rather than the multi-year, pixel-wise approach proposed by Kogan (1995) [30]. Therefore, although the 2025 VHI indicates intensified thermal drought stress, its magnitude relative to 2015 and 2020 should be interpreted with caution and verified using longer time-series, rainfall, or soil moisture data (Bhuiyan *et al.*, 2006; Singh *et al.*, 2003) [10, 61].

5.3 Consistency with Drought Patterns Across Peninsular and Semi-Arid India

The drought pattern observed in Prakasam District is consistent with the increasing agricultural drought reported across semi-arid India. The expansion of the mild drought category from 110 km² in 2015 to 160 km² in 2025 aligns with the projected increases in drought frequency and severity for peninsular India (Aadhar and Mishra, 2024; Chuphal *et al.*, 2024) [1, 14]. Similarly, the predominance of moderate to extreme drought identified through VHI is comparable with findings from the Bhima Basin and the Bundelkhand Plateau (Gatha Cognition, 2024; ScienceDirect, 2026), suggesting that the observed drought pattern reflects a broader regional trend.

Compared with earlier studies in Andhra Pradesh, which mainly relied on rainfall-based or composite drought indices (Murthy *et al.*, 2015; Kumar *et al.*, 2019) [44, 35], the present study integrates 30 m Landsat-derived NDVI, LST, VCI, TCI, and VHI to provide a detailed mandal-level assessment of agricultural drought. This approach improves the spatial representation of drought conditions and provides useful information for drought monitoring and regional planning.

5.4 Implications for Drought Policy and Adaptation

The findings highlight the need for drought monitoring systems to integrate multiple remote sensing indices rather than relying on NDVI or LST alone, as vegetation and thermal responses may differ under changing climatic conditions. The use of multi-date imagery and long-term

TCI normalization would further improve the reliability of inter-annual drought assessment (Kogan, 1995; Bhuiyan *et al.*, 2006) [30, 10].

The persistence of drought despite localized vegetation improvement emphasizes the need to promote drought-tolerant, short-duration crops, expand drip and sprinkler irrigation, and strengthen extension and credit support for farmers (Aher and Yadav, 2021; Nair and Thomas, 2022; Samuel *et al.*, 2024). Expanding soil and water conservation measures in the interior and eastern mandals, together with the use of longer satellite time series and seasonal climate forecasts, would further enhance drought monitoring and climate resilience (Aadhar and Mishra, 2024; Chuphal *et al.*, 2024) [1, 14].

6. Conclusion

This study demonstrated the usefulness of an integrated remote sensing approach using NDVI, LST, VCI, TCI, and VHI derived from Landsat 8/9 imagery to assess the spatio-temporal dynamics of agricultural drought in Prakasam District, Andhra Pradesh, during 2015, 2020, and 2025.

The results revealed a clear increase in thermal stress, with maximum LST rising from 38.72°C in 2015 to 41.30°C in 2025. Although maximum NDVI increased slightly from 0.47 to 0.52, indicating localized vegetation improvement, the negative relationship between NDVI and LST strengthened ($r = -0.62$ to -0.79), reflecting an increasing influence of vegetation on surface temperature. Despite this improvement in vegetation, VHI indicated an overall increase in drought severity, with the mild drought category expanding from 110 km² in 2015 to 160 km² in 2025, while no-drought conditions remained limited to 30-35 km².

The findings indicate that localized vegetation recovery alone is insufficient to reduce district-level drought vulnerability when thermal stress continues to intensify. Therefore, integrating vegetation- and temperature-based indices provides a more reliable assessment of agricultural drought than using NDVI alone.

This study provides the first Landsat-based, multi-temporal assessment of agricultural drought at 30 m resolution in Prakasam District. It offers a practical framework applicable to other drought-prone regions in semi-arid India. The results highlight the need to promote drought-tolerant crops, expand micro-irrigation, strengthen soil and water conservation measures, and incorporate long-term satellite, rainfall, soil moisture, and crop yield data to improve drought monitoring and climate-resilient agricultural planning.

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