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Monitoring Drought in Guntur with MODIS Data and the Google Earth Engine Platform

Pureti Siva Nagendram[1,*] and Penke Satyanarayana[2]

[1]*Department of Electronics and Communication Engineering, Koneru Lakshmaiah Education Foundation, Vaddeswaram, Guntur, Andhra Pradesh, India*
[2]*Department of Internet of Thinks, Koneru Lakshmaiah Education Foundation, Vaddeswaram, Guntur, Andhra Pradesh, India*

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Abstract

This evaluation explores the utility of specific methodologies, particularly Geographic Information System (GIS) and Remote Sensing (RS), in the near real-time assessment of drought conditions across regions. The investigation focuses on comparing Remote Sensing Derived Drought Indices (RSDIs) with the Standardized Precipitation Evapotranspiration Index (SPEI) for the period 2001–2023. The RSDIs, including Vegetation Condition Index (VCI), Temperature Condition Index (TCI), and Vegetation Health Index (VHI), are computed utilized MODIS data through Google Earth Engine (GEE) platform. To assess the efficacy of these indices, correlation analyses are conducted between VCI, TCI, VHI, and the Standardized Precipitation Index (SPI). Pearson correlation coefficients (CC) are employed to quantify the agreement between SPEI and RSDIs. Results indicate varying levels of agreement, with higher correlation observed between VCI and SPEI across different time scales (12, 9, 6, 3, and 1 month). Conversely, TCI demonstrates comparatively lower agreement with SPEI. Moderate correlation is noted between VCI and SPEI across different time scales. These findings suggest that VHI and SPEI exhibit stronger correlation, making them preferable for drought monitoring in regions with limited meteorological data Using the VCI, TCI, and SPEI, one can determine the drought in the Guntur district. The VCI geographical distribution maps show that the year of extreme drought conditions was observed in 2001, 2003, 2005, 2007, 2011, 2016, and 2019. However, conditions recovered in the subsequent years, with a relatively mild drought. Furthermore, the study reveals a persistent presence of drought across the study area throughout the analysed period. This research contributes to enhancing our comprehension of the interrelationships among Weather and remote sensing-based drought indices.

Keywords: estimate of the drought, Weather data, RSDI, standardized drought indices, Modis, GEE

1. Introduction

Due to its complex nature, drought is difficult to accurately monitor and assess at the outset, severity, frequency, persistence, and transmission, particularly in hyper-arid locations where data is scarce [1]. Drought is a common hydro meteorological occurrence that produces disasters and is the second leading source of social and economic instability, behind floods [2]. Based on the industries impacted, drought occurrences are divided into four groups [3] meteorological, hydrological, agricultural, and socioeconomic droughts. A long-term period of below-average precipitation in comparison to the mean rainfall in the area is indicative of a meteorological drought. Crop aridity occurs when earth wetness levels fall below what is necessary for plant maturation and enhancement [4]. A hydrological drought occurs when there is inadequate precipitation for a protracted time, resulting in a reduction in both surface and groundwater levels [5]. Socio-economic strain examines the impact of dry spell on hydrological resources, cultivation, and industry.

Droughts have been monitored and statistically described by several ways, including standardised and custom indices used in climate science, hydrology, and farming [6]. Previously, aridity observation relied on earth bound measures from stations , gauges, such the Palmer Drought Severity Index (PDSI), SPI, and SPEI work flow formation of the identifying the nature. Traditional drought monitoring relies on erroneous and limited in-situ precipitation records [7, 8]. The poor allocation of in situ meteorological centres and accompanying inconsistencies make it difficult to accurately estimate drought in Dry and extremely dry areas. Native barriers like hills and sand fields which include to the situation [9]. El Kenawy and McCabe [10] verified weaknesses in the weather centre network across the Kingdom of Saudi Arabia (KSA). Progress in RS and earth observation methods, such as the NASA Landsat series launched in 1972, have transformed drought monitoring [11]. Rising temperatures have sparked more interest and awareness of climate change. Geospatial experts believe remote sensing is vital for assessing ecosystem conditions and monitoring significant climate changes on both spatial and time-related dimensions [12].

Remote sensing (RS) devices monitor several factors at the earth's surface, including plant health and water availability, providing contextual data for drought monitoring [13]. Satellite imagery (RS) and GIS enable monitoring and analysing changes in the globe over time RS and GIS approaches provide continuous data across wide areas, addressing data scarcity challenges in desert places such as Saudi Arabia [14].

GEE, a cloud-based service by Google, allows users to compute and visualize raw and processed geospatial data from satellite sources. Since its release in 2010, engine tool has been extensively utilized for hydro-meteorological

*E-mail address: satece@kluniversity.in
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purposes and has been particularly effective in applications such as vegetation mapping and monitoring [15]. With a significant amount of publicly accessible satellite images and integrated picture processing, tool has been nominated in numerous studies conducting examination of drought through temporal data . Researchers predominantly used the landsat satellite dataset with earth tool algorithms for drought monitoring through RSDIs. During this time, Pham and Tran investigated how droughts were distributed chronologically." by calculating various drought indices from Landsat (L) observation information using the earth infrastructure [16]. Benzougagh employed algorithm and a blend of L8 and S-2 data collection to survey drought in Morocco. These indicated that LDI offer significant spatial insights for assessing aridity status at regional and national scales [17]. The objective is to tackle facts technical matters in the Lith watershed, where the existing measures fail to capture climate variability. The correlation gap between the Standardized Precipitation Evapotranspiration Index (SPEI) and Rainfall Severity Drought Indices (RSDIs) was assessed using Pearson Correlation Coefficient (CC) metrics for the Guntur district from 2001 to 2023, as detailed in Table 2. The analysis revealed that the Vegetation Condition Index (VCI) and Vegetation Health Index (VHI) exhibited a strong correlation with SPEI, each achieving a CC of 0.89 during the study period. Additionally, TCI and VHI demonstrated a moderate correlation with each other, with a CC of 0.46. In contrast, the correlation between VCI and TCI was relatively weak, with a CC of 0.27. The correlation between SPEI and RSDIs across various temporal intervals (1, 3, 6, 9, and 12 months) indicated that SPEI-3 had a robust relationship with VCI, showing a CC of 0.60. Conversely, VCI showed a lower correlation with SPEI-1 (CC = 0.29) and a further reduction to 0.15 with SPEI-9. TCI demonstrated a weaker correlation with SPEI, with the highest CC of 0.19 observed between TCI and SPEI-1 and the lowest CC between TCI and SPEI-12. No additional objectives were identified in this context. Accordingly RST were used to address lack of data, and various remote sensing indices were computed using platform [18].

Throughout the years, numerous DI have emerged to gauge and calibrate desiccation in the land-based aspect of the hydro cycle. These validations split into three main types of drought. Characterized by extended periods of subpar precipitation, meteorological droughts are often measured using the SPI, based on the concept that dehydrations are evaluated compared to the mean environmental and its variability at a specific location [19]. These MD can progress into hydrological droughts, feature average water elevation or river current were typically assessed using storage basin, the SRI, or the Stream flow Index. Soil moisture deficiency characterizes agricultural droughts. Although only a few studies clearly define it, they concur that agricultural drought involves a deficit in soil moisture substantial to disrupt flora expansion, farming output, or Harvest production. Various other definitions are also present. These definitions also connect soil wetness content to the state of crop health. Because of link to farming production and irrigation, AD frequently becomes the central Concentration on drought surveillance and prognostication. In accordance with crop droughts have typically measured based on soil dampness in the zone region [20].

The widely used Palmer Drought Severity Index (PDSI), referenced in numerous studies calculates a basic water budget from monthly precipitation and potential evapotranspiration figures. It employs optimized parameters to ensure that comparable pdsi values result in similar effects on greenness and harvest yield, regardless of atmospheric variations. Terrestrial surface models developed for pan African -scale applications provide physics-based choice to PDSI, allowing incorporation of local soil and vegetation properties [21]. Utilizing accessible orbiter scrutiny of vegetation indices such as normalized difference vegetation index (NDVI), enhanced vegetation index (EVI), solar-induced chlorophyll fluorescence (SIF), fPAR, near-infrared reflectance of vegetation (NIRv), and other research has concentrated on employing these parameters to measure AD. Similarly, two separate indices have been developed for monitoring agricultural drought: one centred on soil moisture (SMDI) and the remaining deficits in ETDI. Otherwise have explored alternative combinations—such as precipitation, PET, and SM —to quantify agricultural drought [22]. The current understanding of agricultural droughts, as previously defined—a soil content shortfall sufficiently severe to hinder greenery —suggests that a single index cannot adequately capture either its cause (soil moisture deficit) or its effect. While both SM and VBI aim to quantify Farming dry spell, the relationship between SM and foliage exhibits significant Intricacy and unpredictability [23].

The Complication became recognized as early as the late nineteenth century when it was mentioned that a drought intricate impacting outcome influenced by several factors [24]. While aggregate indices have been suggested a solution navigate the complex relationship between SM and VY, it remains debated whether a single normalized index can effectively quantify agricultural drought and its impacts across diverse climate gradients. At scales ranging from small to continental, distinct soil moisture regimes influenced by both water and energy constraints can be identified, often described by a bilinear relationship between soil moisture and the evaporative ratio [25]. Beyond the critical moisture content threshold in soil, which represents an absolute value of SM, both transpiration and plant function remain unaffected by precipitation deficiency. In humid climates, periods of meteorological drought can paradoxically increase incoming solar radiation, potentially boosting evapotranspiration and resulting in despite relatively dry weather, there are positive anomalies in vegetation indices compared to typical conditions [26].

Various drought indices, such as the Normalised Difference Vegetation Index (NDVI), Temperature Condition Index (TCI), Vegetation Condition Index (VCI) [27], and VHI , have been proposed evaluated using remote sensing and GIS.TCI, VCI, and VHI are sometimes referred to greenness metrics are represent the flora status in a given region, categorise focused distinct dehydration, frequently used in DMI [28]. CCI is commonly employed to determine vegetation varies from considerably bad better situations [29]. TCI identifies flora stress caused by extreme hot and excess wetness [30]. The Role of TCI and VCI in Formulating the Vegetation Health Index (VHI) [31].

Due to limited data availability and minimal application of Remote Sensing (RS), Geographic Information Systems (GIS), and Google Earth Engine (GEE) in drought assessment for the Guntur district, this study seeks to achieve the following objectives: (1) To determine the spatial extent of drought in the Guntur district using MODIS satellite datasets spanning from 2001 to 2023. (2) To utilize MODIS data to extract precipitation, temperature, Land Surface Temperature (LST), and Normalized Difference Vegetation Index (NDVI), and subsequently compute the Standardized Precipitation Evapotranspiration Index (SPEI) for 1, 3, 6, 9, and 12-month periods. This will facilitate the characterization of spatiotemporal drought patterns using SPEI, Vegetation Condition Index (VCI), Temperature Condition Index (TCI), and Vegetation Health Index (VHI) within the GEE platform. (3) To evaluate the efficacy of various drought indices, particularly comparing the SPEI with Rainfall Severity Drought Index (RSDI), by calculating the Pearson correlation coefficient (CC). The results of this study will aid urban planners and environmental scientists in devising strategies and policies to alleviate drought conditions in the Guntur district and similar regions worldwide

2. Study area

As seen in Figure 1, the study focuses on the Guntur district of Andhra Pradesh, India. It is bordered by the Bay of Bengal to the southeast, Bapatla District to the south, Palnadu District to the west, NTR District to the northwest, and Krishna District to the northeast. It covers an area of approximately 2,443 Square km² (943 mi²) and is located between 16.314209° N latitude and 80.435028° E longitude, namely at 16° 18' 51.1524" N and 80° 26' 6.1008" E. The Environmental in this area is tropical, with an average annual temperature of 28.5°C (83.3°F) and an average annual rainfall of 905 mm (36 in). Using sensing and GIS tools, the study focuses on drought monitoring in the coastal area. This region has a variety of droughts, including severe, moderate, and average droughts.

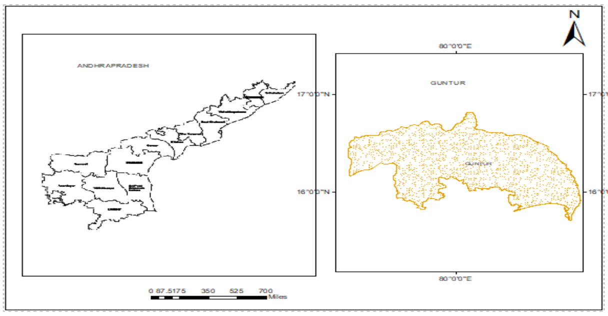

Fig. 1. location of the Area

3. Methodology

The approach adopted in this analysis is segmented into: (i) satellite data retrieval, (ii) drought monitoring using RSDI (VCI, TCI, and VHI) , Sequential and geospatial analyses of the metrics using GEE (iii) Correlation Analyses Figure 2 illustrates the procedure for this investigation.

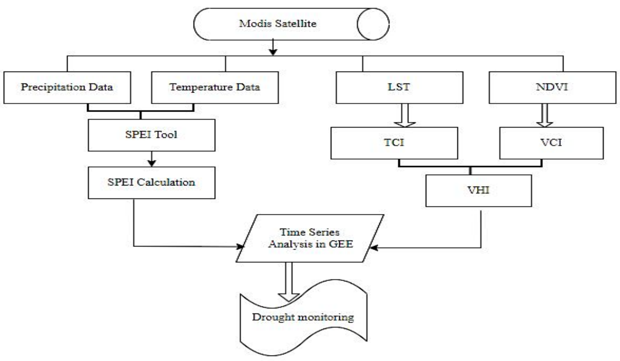

Fig. 2. Analysis of work flow of Drought Monitoring

This study uses MODIS satellite data to track vegetation conditions and assess agricultural dryness from 2001 to 2023. Precipitation data is obtained from the CHIRPS pentad data for the relevant years. MOD11A2 provides data on land surface temperature (LST), whereas MOD13Q1 provides data on normalised difference vegetation index (NDVI), both at various geographical resolutions. Maximum NDVI and LST products are developed to account for a variety of parameters such as solar elevation angle, observation angle, orbit drift, clouds and shadows. Temperature data is obtained using LST, and the Vegetation Condition Index (VCI) is produced using NDVI, representing crop health throughout the research period. The SPEI (Standardised Precipitation Evapotranspiration Index) tool is used to calculate SPEI values for 1st, 3rd, 6th, 9th, and 12th months. Time series analysis is performed on the Google Earth Engine (GEE) platform to monitor trends over time, and relationships between SPEI and drought indicators are investigated. Finally, the research assesses drought conditions in the Guntur area.

3.1 Standard Precipitation Evapotranspiration Index (SPEI)

For monitoring drought conditions, the most extensively used drought index is the standard precipitation index, which created McKee et al, spatial resolution of 0.5◦ lat/lon, and temporal coverage from January 1901 to December 2011 by use of the Climate Research Unit (CRU TS3.2). It combines temperature and precipitation information to give a complete picture of the amount of moisture present in a certain area. The Standardized Precipitation Index (SPEI) is based on the standardized precipitation index (SPI), but it takes evapotranspiration as a factor to adjust for the impact of temperature on drought conditions. Understanding and managing drought risk is made possible by the SPEI, which is a useful tool for comparing drought severity across climatic zones and regions due to its standardization of results. Meteorologists, climatologists, hydrologists, and policymakers frequently use it to quantify drought severity, track drought patterns, and guide choices on water management. The SPI has been calculated using monthly temperature and precipitation data for the years 2001–2023. Software that uses observed monthly data to automatically calculate the SPI value in order to identify historical droughts at time span of 1, 3, 6, 9, and 12 months.

Each state allows for the estimation of SPEI at several time frames, including 1, 3, 6, 9 and 12 months. The monthly temperature and precipitation are used to compute SPEI-1. By changing the average of the three months' worth of temperature and precipitation data, SPEI-3 is computed. The residual 6-, 9- and 12-month indices may be computed in a similar manner. While SPEI-3 and SPEI-6 are often to track annual fluctuations in drought, SPEI-1 is helpful for examining temporary fluctuations in drought occurrence and intensity , while SPEI-12 is helpful for examining yearly trend in drought. The parameter, which contrasts actual rainfall with the volume of water wastage via transpiration and volatilization during a specific time period, can be used to determine assessing drought severity using the numeric values of SPEI, it segmented were various types according to McKee, as illustrated in Table 1.

Table 1. Classification of drought severity using SPEI values.

SPEI	Divisions
>2	Saturated condition
1.50 to 1.99	Severely wet

1.00 to1.49	Fairly wet
−0.99 to 0.99	Nearly Normal
−1.49 to −1.0	Moderately drought
−1.99 to −1.5	Severe drought

3.2 Vegetation Condition Index :

NDVI has long been a valuable tool for monitoring vegetation, but its applicability across different ecosystems is limited. To overcome this, the Vegetation Condition Index (VCI) has emerged as a more comprehensive measure, capturing the combined effects of rainfall, soil moisture, weather, and agricultural practices on vegetation health. Particularly in regions like AP with diverse topography and ecosystems, VCI is essential for comparing weather impacts across areas with varying resources. Unlike NDVI, VCI excels in capturing dynamic rainfall patterns, especially in geographically diverse regions. Throughout the cultivation period, VCI is a reliable indicator of plant health and moisture stress, though it loses effectiveness outside this period. Its global adoption underscores its significance, as it sensitively detects stressors like insect infestations, diseases, and nutrient deficiencies. For the calculation of the Vegetation Condition Index (VCI), MODIS satellite data from 2001 to 2023 for the Guntur district was utilized within the Google Earth Engine (GEE) platform. Initially, the shapefile of the study area was imported into GEE. The workflow involved loading the MODIS NDVI dataset, followed by scaling the NDVI values to their original range. The target year and month were specified to filter the NDVI dataset accordingly. Subsequently, the maximum and minimum NDVI values for the selected month across all years were calculated and visualized. The NDVI for the specified year and month was then filtered and displayed. The VCI was computed using these NDVI values. To automate this process, a function was defined to calculate the VCI for all images in the dataset, which was then applied to generate a comprehensive VCI image collection for the entire period. VCI values, ranging from 1 to 100%, categorize vegetation conditions from extremely low to high, with values between 50 and 100% indicating ideal conditions and values nearing zero representing severe dry seasons. For each annually and seasonal NDVI image, VCI will be processed from 2001 to 2023 using the GEE platform .The following expression demonstrates the calculation of VCI [21]:

$$VCI = \frac{NDVIcurrent - NDVImin}{NDVImax - NDVImin} X\ 100 \quad (1)$$

4. Results

4.1 Assessment of the SPEI Indices

In Guntur district's (GD) drought severity and conditions from 2001 to 2023 have been comprehensively analysed using both geographical and temporal scales. This analysis employs the Standardized Precipitation-Evapotranspiration Index (SPEI) across multiple timescales—1, 3, 6, 9, and 12 months—as well as remote sensing drought Indices (RSDIs), including the Vegetation Condition Index (VCI), Temperature Condition Index (TCI), and Vegetation Health Index (VHI).The findings, illustrated in the accompanying figure 3, show that the SPEI-6, SPEI-9, and SPEI-12 indices are particularly effective in identifying moderate drought events. These indices provide a more nuanced detection of drought conditions compared to the SPEI-1 and SPEI-3 indices, which generally reflect nearly normal conditions. This suggests that longer timescale indices are more sensitive and reliable for monitoring drought severity in this region. Furthermore, the time sequence analysis for the period indicates that drought events in 2001 and 2002 were characterized by normal to moderate severity. This detailed temporal analysis helps in understanding the patterns and frequency of drought occurrences over the 22-year period, providing valuable insights for water resource management and agricultural planning in the GD.

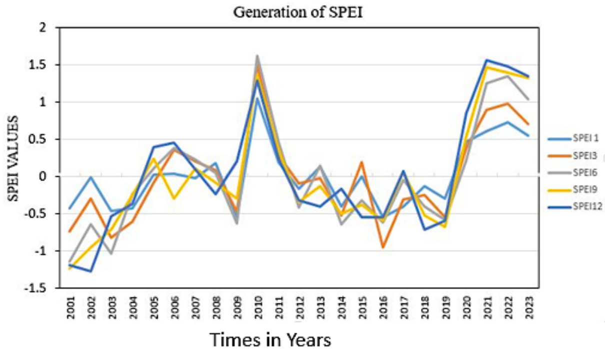

Fig. 3. SPEI graph

4.2 VCI

The Vegetation Condition Index (VCI) for Guntur district, which is calculated from the Normalised Difference Vegetation Index (NDVI), is shown in Figures 4 and 5 for the years 2001 to 2023. Extreme drought conditions were recorded in 2001, 2003, 2005, 2007, 2011, 2016, and 2019, according to the VCI geographical distribution maps (Figure 4). On the other hand, the years 2004, 2006, 2008, 2009, 2012, 2013, 2014, 2015, 2018, 2022, and 2023 saw wetter circumstances with comparatively medium drought. It's also important to note that some parts of the Guntur district are experiencing a comparatively greater level of drought.

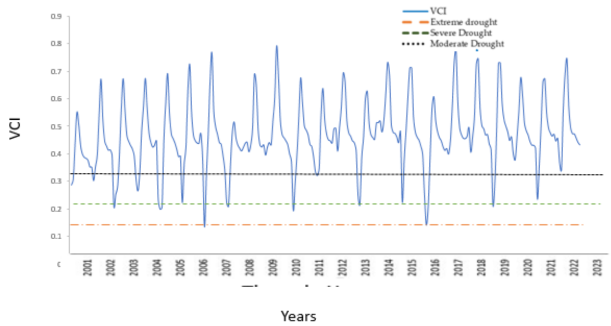

Fig. 4. Visualizing the VCI time line in GD derived from GEE data.

The analysis period's mean VCI values vary from 0.1 to 0.8, as demonstrated by the sequential data of VCI acquired using the earth engine (Figure 5). The Guntur district recorded minimal VCI values (severe and extreme drought phases) in the first ten years, 2001, 2003, 2011, and 2022, as reflected in the VCI chronological plot. In the same way, the following years show the lowest VCI values for the second decade: 2002, 2007,2010,2013,2015, and 2019. Put differently, the VCI time series shows that the years 2004, 2006, 2010, 2016, 2015, and 2018 were marked by a severe drought .As which shown in figure4 the results which indicates the VCI map using modis satellite which are acquired in google earth engine, by using vegetation condition indicates by using the colour combination which the red colour which indicates the more drought is occurred in that particular year and that area more over the research which identified the which area drought is to be occurred.

4.3 Correlation between SPEI, VCI, TCI, and VHI

The relationship between the SPEI and RSDIs is assessed through the Pearson Correlation Coefficient (CC) metrics was evaluated for Guntur district of 2001 to 2023 which were represented in Table 2. The indices VCI and VHI demonstrated a strong correlation with SPEI, each showing a CC value of 0.89 during the study period. Additionally, TCI and VHI exhibited a reasonable correlation with each other, with a CC worth of 0.46. However, the association among VCI and TCI was notably lower, with a CC value of 0.27.

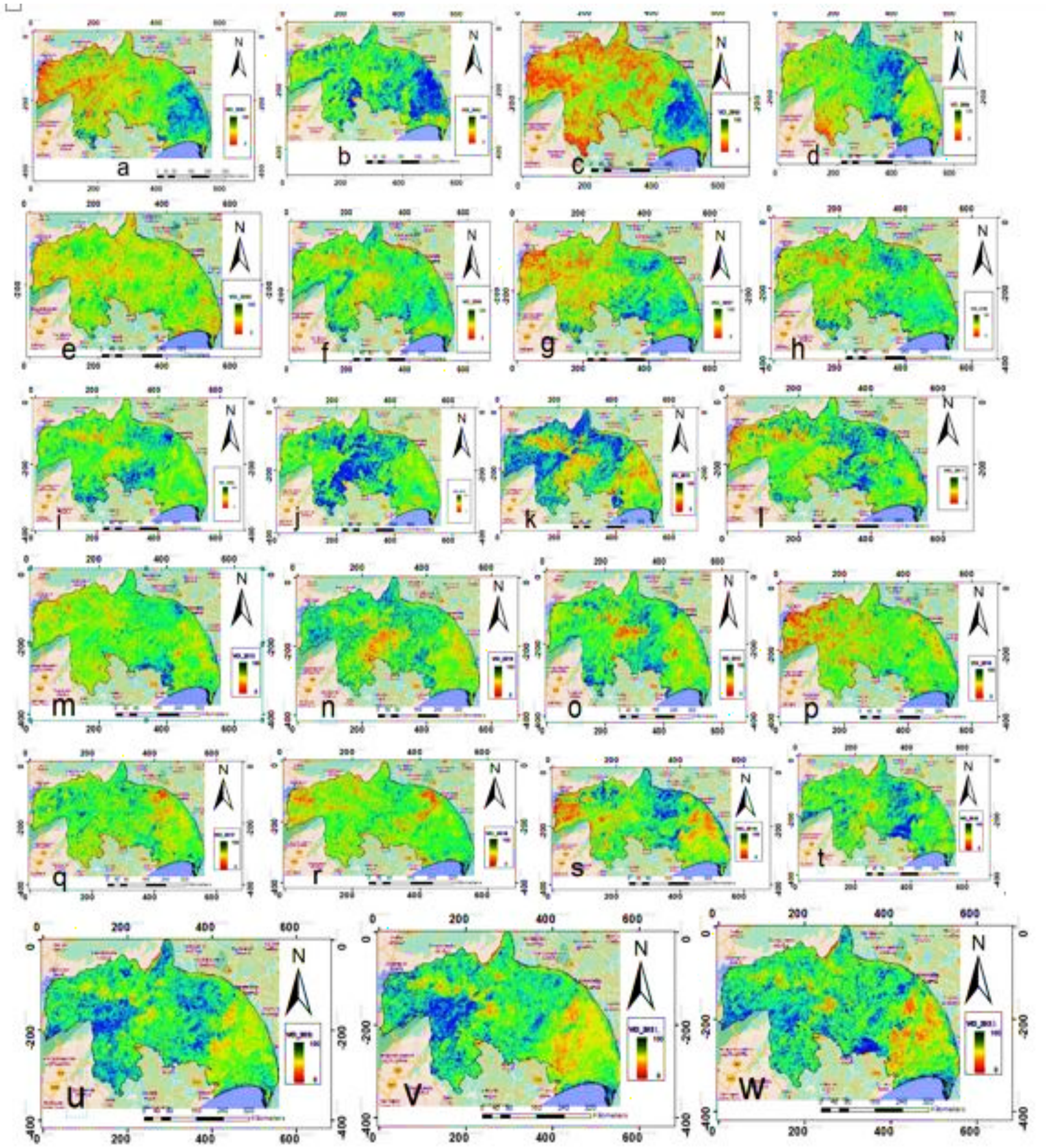

Fig. 5. (a–w) Spatial allocation of VCI in Guntur extracted from Modis Space station span of 2001–2023.

Table 2. GEE-Based Linkage table of RS AND MD Indices

	TCI	VCI	VHI	SPEI-1	SPEI-3	SPEI-6	SPEI-9	SPEI-12
TCI	1.000000	0.27700	0.460880	0.19	0.18	0.12	0.13	0.07
VCI	0.27700	1.000000	0.892479	0.29	0.60	0.16	0.15	0.24
VHI	0.460880	0.892479	1.000000	0.22	0.24	0.25	0.26	0.27

Further analysis extended the investigation of the link amid SPEI and RSDIs over different temporal intervals (1, 3, 6, 9, and 12 months). The Outcome, shown in Table 2, indicate that SPEI-3 had strong Connection to VCI, where CC value of 0.60. VCI also exhibits a lower correlation with SPEI-1 (CC = 0.29), which significantly drops 0.15 with SPEI-9. Conversely, TCI shows a lower interrelation with SPEI, with the highest and lowest CC values found between VCI/SPEI-3 and TCI/SPEI-12, respectively. The greatest coherence for TCI, with a CC of 0.19 is intervening TCI and SPEI-1, Sequentially, TCI and SPEI-3.Table 2 reveals that the Connection between VHI/VCI/TCI and SPEI. Elevates including longer SPEI time frames. The Determinations for VHI, TCI, and VCI use yearly records yet plant growth is influenced by the soaked or dry environments of both the current area of yearly and the previous years of greenery expansion. Consequently, the crop growth patterns and health indicator are attentively linked to wet or dry conditions over extended period of time. Therefore, VHI, TCI, and VCI, which are closely related to metrics, frequently show a greater association with SPEI over a longer period of time.

4.4 TCI

The Temperature Condition Index (TCI) is utilized as a measure to gauge the influence of temperature on vegetation health, often within the context of agricultural monitoring and environmental studies. It is part of a broader system of indices, VCI and the VHI, which help in evaluating vegetation stress due to climatic conditions. The tci posits that droughts decrease soil moisture and elevate land surface thermal stress, resulting in higher land surface temperatures (LST) during aridity span compared to conditions. Elevated LST during crop growth seasons indicates Adverse or arid conditions, while lower LS temperatures suggest predominantly advantageous conditions. TCI correlates with vegetation's sensitivity to adverse temperature changes. TCI measures the deviation of the current temperature from the optimum temperature conditions for vegetation growth. High TCI values indicate favourable temperature conditions for vegetation, whereas low TCI values suggest adverse temperature conditions, such as extreme heat or cold. The following expression demonstrates the calculation of TCI [20]:

$$TCI= \frac{T_{max}-T}{T_{max}-T_{min}} \times 100 \qquad (2)$$

Where t= Existing temperature, T_{max} =Maximum temperature observed over a specific period (usually a growing season or year, T_{min} =Minimum temperature observed over the same period

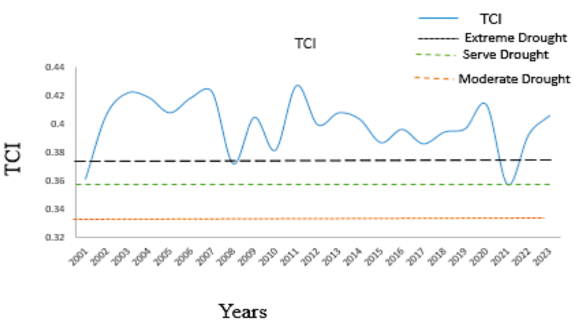

Fig. 6. Analyses of TCI in GD

Figures 6 show the time frames of TCI in the GD encompassing a span of 2001–2023 taken Modis data and earth platform, correspondingly. TCI is derived from temperature and represents an amalgamation of various factors such as vegetation, precipitation, topography, elevation, soil, and meteorological conditions. , along with thresholds for different drought conditions (Extreme Drought, Severe Drought, and Moderate Drought). Across various years, the mean TCI values exhibit variability 0.32 to 0.50 in the study area. Monitoring such trends helps in understanding the impact of temperature on growth and planning for agricultural and environmental management accordingly.

5. Conclusion

The study emphasizes the significance of RS approaches are for monitoring and assessing drought conditions in a variety of locations in near real time, this assessment provides of drought conditions in the Guntur district of Andhra Pradesh, India, for the years 2001–2023, by contrasting Standardised Precipitation Evapotranspiration Index (SPEI) with Remote Sensing Derived Drought Indices (RSDIs) like the Vegetation Condition Index (VCI). The TCI values, ranging from 0.32 to 0.50, reflected fluctuating thermal stress on vegetation, underscoring the region's vulnerability to extreme temperature conditions. The strong correlation between VCI and short-term Standardized Precipitation Evapotranspiration Index (SPEI) intervals suggests that vegetation responds quickly to changes in moisture availability, making these indices valuable for real-time drought monitoring. However, the study's reliance on MODIS satellite data, with its moderate spatial resolution, and the absence of ground-based meteorological validation, are limitations that may affect the precision of the findings. Despite these constraints, the research demonstrates the potential of remote sensing technologies in enhancing drought monitoring and management in regions like Guntur, where agriculture is heavily dependent on climatic conditions. This methodology aligns with global drought assessment standards, using remote sensing technologies and indices like VCI and TCI, known for their effectiveness in monitoring large areas over extended periods. This approach is scalable and applicable to other drought-prone regions globally. However, its effectiveness could be enhanced by integrating higher-resolution satellite imagery and ground-based data for improved accuracy. This study's methodology contributes to global efforts in developing resilient agricultural practices and improving drought mitigation. Refining these methods will provide policymakers and resource managers with essential tools to protect food security and water resources in vulnerable regions. Red implies greater drought, while green shows that the vegetation is in excellent condition. The correlation between SPEIs month intervals and RSDIs showed strong agreement for VCI/SPEI-3 and VCI/SPEI-1, with average CC values of 0.60 and 0.29 consecutively. A lower correlation was noted among SPEI and VHI, having maximum CC value of 0.27 approximated within VHI and SPEI-12, and 0.22 between VHI and SPEI-1. Additionally, a moderate correlation was noted in TCI and SPEI. The results support the wider use of these innovative tools in regions of the world that are vulnerable to drought, since this will enable more robust and flexible responses to drought conditions.

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