



International Journal of Research in Agronomy

E-ISSN: 2618-0618
P-ISSN: 2618-060X
© Agronomy
NAAS Rating (2026): 5.20
www.agronomyjournals.com
2026; SP-9(5): 157-170
Received: 22-03-2026
Accepted: 24-04-2026

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Assessment of the drought in the semi-arid Marathwada region applying satellite data indices and Google Earth Engine algorithms

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DOI: <https://www.doi.org/10.33545/2618060X.2026.v9.i5Sb.5542>

Abstract

Drought is regarded as a natural disaster in the semi-arid Marathwada region, arising from high temperatures and inadequate, irregular rainfall. The economy, society, environment, and people's means of subsistence are all directly impacted by these circumstances. The launch of the cloud-based geospatial analysis platform GEE has simplified the process of obtaining high-performance computing resources for the online processing of multi-temporal MODIS satellite data. An analysis of drought conditions, including their severity, can be done on this platform, along with their spatial and temporal distribution. GEE changes the focus from the conventional method of software calculations and downloading large remote sensing imagery files through the drought indices of TCI and VCI to writing and executing scripts using appropriate indicators to evaluate drought. In the Marathwada semi-arid region of Maharashtra state, India, which is frequently affected by agricultural drought. For the current study, we gathered and evaluated MODIS (Terra/Aqua) images taken during the crop season from 2000 to 2022 (from June to September), spanning nearly twenty-two years. We discovered that the majority of the region's drought, which could be mild to severe, was concentrated in the west and occasionally in the east. Low to moderate NDVI values and high LST were the defining characteristics of this. These results are playable.

Keywords: Google earth engine, normalized difference vegetation index, land surface temperature, temperature condition index, vegetation condition index, marathwada

Introduction

Recently, the main cause of global warming and a reduced pattern of rainfall, which exacerbates drought, has been identified as climate change. This phenomenon reduces crop yields, especially for important food crops, and shrinks cultivated areas, all of which have a substantial impact on agriculture (Kumar *et al.*, 2022; Malhi *et al.*, 2021) ^[23, 21]. As a result, identifying the extent of drought has become a crucial initiative, serving as a vital program to assess the occurrence and severity of drought and its impact on agricultural development in Marathwada (Chandrasekara *et al.*, 2021; Pandey *et al.*, 2021) ^[31, 7]. Drought, typically characterized by deficits in precipitation and elevated temperatures, tends to be most pronounced during the dry season (Wilhite, 2000) ^[49]. Large areas are frequently affected by it. As such, scientists around the world have come to realize that indices generated from data from remote sensing can be used to efficiently track drought. Remote sensing technology provides a comprehensive view of the Earth's surface, which is the main justification for this recognition. Image data is continuously delivered over time, from all over the world, providing a technological advantage. Measurements limited to individual monitoring points are less effective in displaying results across various regions than this continuous coverage. In areas with insufficient number of weather stations, the use of remote sensing data to create maps of drought is particularly helpful. Additionally, the method offers a thorough spatial overview of drought-prone areas due to the availability of numerous free satellite images, including LANDSAT and MODIS, which are ideal for assessing drought conditions. A multitude of data and observations related to remote sensing have been amassed over the last ten years due to a notable increase in the quantity of earth observation satellites.

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The National Aeronautics and Space Administration (NASA) and the European Space Agency (ESA) have implemented commendable free data policies that guarantee the regular and free dissemination of observations from important satellites, including the Landsat series, MODIS, Sentinel-1, 2, and 3, among others, for the benefit of scientists and the general public (Pham-Duc, 2018) [34].

Supercomputer-powered cloud computing platforms have shown to be extremely effective tools for managing, processing, and analyzing the massive amount of remote sensing data collected by these satellites (Jackson *et al.*, 2010) [17]. This technological integration enables streamlined and effective handling of the massive datasets, contributing to advancements in scientific research and educational endeavors. Globally, numerous studies have been conducted to assess drought intensity by the Vegetation Health Index (VHI) is extensively employed for the examination and surveillance of global drought conditions through remote sensing observations. VHI relies on a linear combination of two indices: the Vegetation Condition Index (VCI), utilizing data from visible and near-infrared channels typically called as Normalized Difference Vegetation Index (NDVI), and the Thermal Condition Index (TCI), derived from information in thermal infrared channels. Usually top-of-atmosphere brightness temperature or land surface temperature (Bento *et al.*, 2018; Masitoh & Rusydi, 2019) [5, 24]. In Vietnam, this index has been successfully applied in research conducted (Du *et al.*, 2018; Nguyen & Chuc, 2018; Tran *et al.*, 2017) [10, 29, 47]. This underscores how the access to remote sensing data, providing extensive spatial coverage, has enabled scientists to investigate global drought patterns. Google Earth Engine (GEE) has found applications in various domains, including Land Cover/Land Use (LCLU) classification, hydrology, urban planning, natural disaster management, climate analyses, and image processing. There has been a noticeable surge in the publication of GEE-related research in recent years, and there is an anticipation that GEE will see increased adoption across diverse fields as more users leverage its capabilities to address significant challenges in big data processing (Gorelick *et al.*, 2017) [13]. Differentiating itself from competition, GEE provides a wide range of satellite imaging types, such as the MODIS, Sentinel-1, -2, -3, and -5P, Landsat series, Advanced Land Observing Satellite (ALOS), National Oceanic and Atmospheric Administration (NOAA), geophysical, meteorological, and climate datasets. Additionally, it offers pre-processed products like the NDVI and the Enhanced Vegetation Index (EVI) (Mutanga & Kumar, 2019; Qiu *et al.*, 2019) [36, 26]. Various methods exist for interacting with GEE, including the Code Editor, the Explorer, and the Client libraries. The Code Editor, a web-based Integrated Development Environment (IDE), is specifically designed for the Earth Engine Java Script Application Programming Interface (API). It accelerates the development and implementation of intricate geospatial operations. The Explorer, on the other hand, is a user-friendly web interface for browsing, visualizing data in the public catalog, and conducting basic analytics through the Earth Engine API. Additionally, the Client libraries enable users to create their own applications by offering wrapper functions in Python or Java Script. Notably, Temperature (LST) emerges as a prominent drought index derived from remote sensing data, showcasing a robust correlation (Anderson *et al.*, 2013; Neeti *et al.*, 2021) [28, 1]. This combination furnishes valuable insights for identifying agricultural drought, as noted by (Sruthi & Aslam, 2015) [42]. Building upon the relationship between NDVI and LST, various drought indices have been introduced, including the Temperature – Vegetation Dryness Index (TVDI), Vegetation Health Index (VHI), and Water Supplying Vegetation Index (WSVI), proving

successful in multiple countries (Arekhi *et al.*, 2020; Mehravar *et al.*, 2021; Sholihah *et al.*, 2016) [40, 25, 2]. Particularly, VHI has demonstrated superior capability and suitability in monitoring drought, as emphasized by (Bento *et al.*, 2018) [5]. VHI combines two essential indices: the VCI to measure changes in NDVI and the TCI to assess variations in LST over time. Due to its free accessibility, particularly significant for users in developing countries, and numerous advantages, GEE currently stands as the most popular cloud computing platform in the remote sensing community (Zhao *et al.*, 2022) [52]. It has evolved into a potent tool for analyzing earth and environmental processes, with an extensive body of research in earth sciences and the environment relying on this platform. GEE's capacity to handle huge volumes of satellite imagery and geospatial data has facilitated research on land cover changes, ecosystem health monitoring, disaster analysis, disease tracking, food security, and assessing the impacts of climate change on natural resources and human communities (Gorelick *et al.*, 2017) [13]. Earth and environmental science-related sectors have made substantial use of GEE (Roteta *et al.*, 2021) [39]. Applications include land studies (Raj & Sharma, 2022; Ravanelli *et al.*, 2018; Tamiminia *et al.*, 2020) [43, 38, 37]; hydrology (Fu *et al.*, 2022; Thakur *et al.*, 2020; Yousefi *et al.*, 2022) [51, 44, 11]; agriculture (Awad, 2021; Gumma *et al.*, 2022; Jin *et al.*, 2019) [18, 14, 4]; forestry (Nursaputra *et al.*, 2021; Praticò *et al.*, 2020; Xulu *et al.*, 2021) [50, 35, 30], monitoring for wetlands (Ashok *et al.*, 2021; Mahdianpari *et al.*, 2020) [22, 3]; and disaster analysis (Ghaffarian *et al.*, 2020; Peter *et al.*, 2020) [32, 12]. Furthermore, GEE has been instrumental in developing techniques for mapping and tracking carbon emissions, land use/cover, and other environmental indicators. These techniques have been essential in supplying critical information for policymaking and planning related to sustainable development. In Vietnam, the exploration of GEE is still in its early stages. Research endeavors have primarily focused on forest land monitoring (Nguyen & Chuc, 2018) [29], riverbank changes (Boothroyd *et al.*, 2021; Kim *et al.*, 2020) [19, 6], and flood monitoring (De Vries *et al.*, 2020) [9]. However, there is a noticeable gap in studies assessing drought using medium-resolution imagery like Landsat within the GEE framework in Vietnam. Hence, this study aims to fill this void by employing GEE to calculate satellite-based drought indices, including NDVI, LST, VCI, TCI, and VHI, utilizing algorithms and Landsat-8 at the local level. The assessment specifically targets drought conditions during the dry season in year 2019. The outcomes of this research are anticipated to furnish initial insights into drought hazards, serving as valuable information for local authorities and regional planners. In Vietnam, the research of GEE is still relatively new. The applications have focused on forest land monitoring (Du *et al.*, 2018) [10]. However, few studies evaluate drought using medium resolution imagery such as Landsat in GEE in various parts of world. Therefore, in this study, satellite-based drought indices of NDVI, LST, VCI, TCI, VHI are calculated in the GEE using algorithms and MODIS satellite data in the local level to assess drought conditions assessment in the crop season in the years 2000 – 2022. The results of the research may provide the initial information about drought hazards for authorities and regional planners.

Material and Methodology

Study area location

The study region Marathwada which falls in semi-arid region situated in Maharashtra, a central part of India. The region is bounded by several administrative region like west to Vidarbha, east of Khandesh and its shares the boundary with Karnataka state and Telangana state of India (Fig. 1). It is located within the

Latitude $17^{\circ}35'N$ to $20^{\circ}30'N$ and Longitude $74^{\circ}00'$ to $79^{\circ}12'E$. It comprises of eight districts viz., Chhatrapati Sambhajnagar, Beed, Hingoli, Jalna, Latur, Nanded, Dharashiv and Parbhani: with a total geographical area of 64,823 km².

Marathwada region is situated at an altitude ranging from 300 – 650 m above mean sea level (msl) (Fig. 2); whereas the highest altitude peak Surpalnath (960m, msl) located in Chhatrapati Sambhajnagar district (GWM, *et al.*, 2019) ^[15].

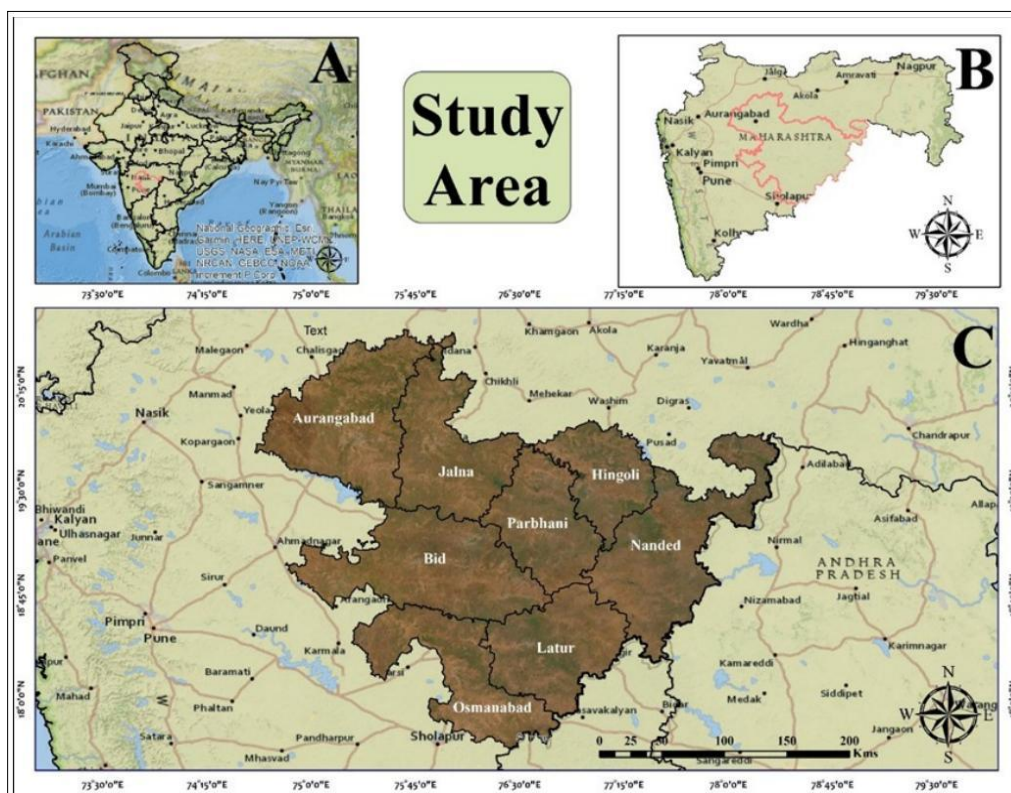


Fig 1: The study area representing the on the country as well as state boundary.

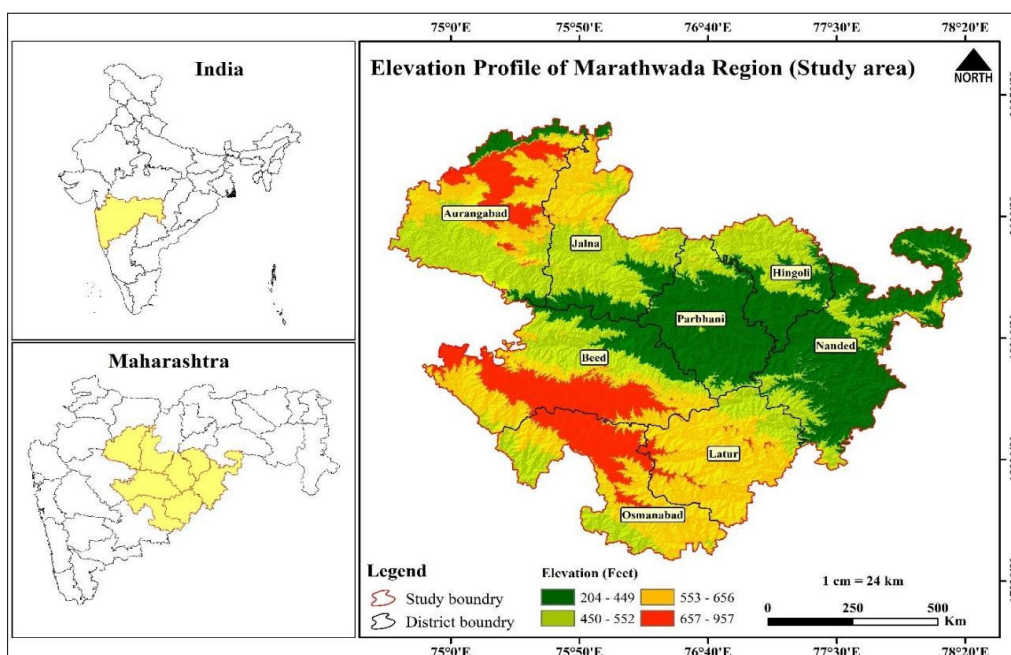


Fig 2: Digital Elevation Profile of Marathwada Region as a study region.

Agro-climatic zonation

The study region falls under three agro-climatic zones which are classified by; The zone I denotes Scarcity region, the zone II denoting Assured rainfall area and the zone III representing the moderate to moderately high rainfall zone (Fig. 3). Except western 1/2nd of Parbhani, south side of Nanded district and remaining part of Marathwada districts (Chhatrapati

Sambhajnagar district, Beed and Osmanabad districts) come under assured rainfall zone. Whereas moderate to high rainfall zone contains eastern part of Parbhani district and northern part of Nanded district. Scarcity zone of Marathwada are covers western trap of Beed and Chhatrapati Sambhajnagar districts, also Bhoom and Paranda talukas of (dharashiv) district.

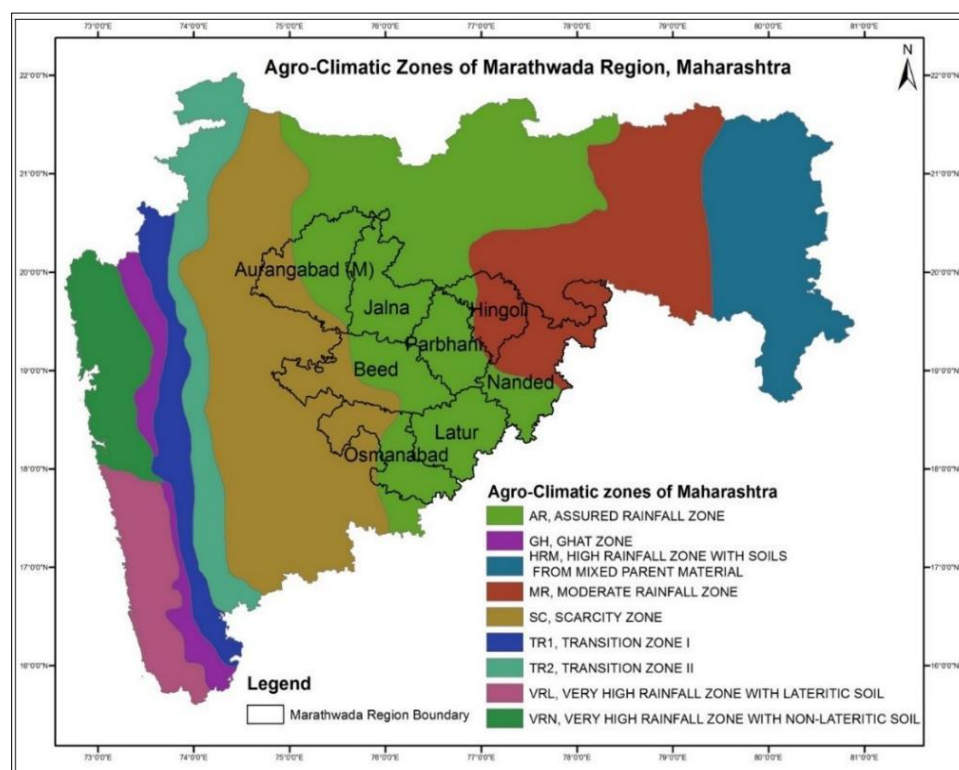


Fig 3: Agro-climatic zone profile of Marathwada region as study area.

Hydrology

The study region majorly comes under three river basins

Godavari, Purna, Penganga and some part is ruled by Krishna river basin. The entry of the Godavari River in Marathwada region through Chhatrapati Sambhajnagar district, flows on its southern boundary, untying it from Beed district. It passes through the Jalna, Parbhani and Nanded districts to enter the Telangana State (CWC & NRSC, 2014) [8]. The Marathwada comes under semi-arid tropic zones where weather is generally dry and moderately extreme. Marathwada region receives an annual rainfall of 600 - 900 mm (IMD, 2022) [16]. The annual average rainfall is not uniform in all districts of Marathwada region. The rainy season lies in between mid of June to September end. The average day temperature ranges between 27.70 to 38°C and average temperature during the night drops down between 26.90 to 20.00°C. Extremely low range relative humidity lies between 35 to 50% in majority part of annual whereas highest about 85% during monsoon season (IMD, 2022) [16].

In recent years, the drought situation in Marathwada has become increasingly complex. Particularly, the dry and cropping season of 2016 marked the most severe recorded drought in the region. The prolonged and intense drought, coupled with scorching temperatures, led to the desiccation of hundreds of hectares of crops and vegetation. The combination of hot weather, dry spell and scanty or unseasonal rainfall resulted in the declining the livelihood of the region. Numerous communities faced challenges in practicing agriculture due to water scarcity, and many households experienced a shortage of water resources.

Data Acquisition

Earth Engine offers an extensive array of data from satellites hosted by Google. Each available data source on GEE is organized into Image Collections, identified by a unique ID. To explore the available data on GEE, users can refer to the GEE catalog via the website <https://earthengine.google.com/datasets/>. One noteworthy addition to GEE's data sources is MODIS imagery, incorporated following the satellite's launch in 2000. MODIS operates on a 16-day repeat cycle and provides imagery

with spatial resolutions 250 meters for multiband with global spatial extent.

Table 1: The characteristics of data used and their sources used in study.

Characteristic	NDVI Description	LST Description
Collection	Terra / Aqua MODIS	Terra / Aqua MODIS
DOI	MOD13A2.006	MYD13Q1.006
File Size	~8.59 MB	~92.96 MB
Temporal Resolution	Multi-Day	Multi-Day
Temporal Extent	Year 2000 to Present	2002 to 2023
Spatial Extent	Global	Global
Geographic Dimensions	1200. x 1200 km	1200.x 1200 km

All MODIS, including Terra, Aqua for NDVI and LST, are readily accessible on GEE. Table 1 describes the MODIS data in this study. All MODIS images which were covered entirely all district of Marathwada, were retrieved from the year 2000 - 2022. Data have the highest radiometric and positional quality and are recommended for all time-series analysis United States Geological Survey (USGS). Top of Atmosphere (TOA) data were converted from raw digital numbers of values using the calibration coefficients from the image metadata. MODIS data were chosen for spatial processing analysis to compute LST and NDVI and further use to calculate the VCI & TCI.

Intervention of Google Earth Engine (gee)

The GEE is accessible through a web-based JavaScript Application Programming Interface (API) known as the Code Editor. The GEE platform comprises three main components: (1) Earth Engine Explorer, (2) EE Code Editor, and (3) EE Time-lapse. The Earth Engine Explorer, depicted in Fig. 4, functions as a data viewer platform that allows users to access the vast datasets available through the EE Data Catalog. This catalog serves as a repository for millions of publicly available datasets, encompassing a wide array of data sources such as Landsat-4, -5, -7, and -8, MODIS, Sentinel-1, -2, -3, and -5P imagery, along with

diverse atmospheric, meteorological, and vector datasets. The EE Code Editor, also illustrated in Fig. 4, is specifically designed for processing extensive datasets using the JavaScript programming language and for creating applications within the Earth Engine environment. This component includes key elements such as the Code editor, Map, Layer manager, Geometry tools, and various tabs like Script, Doc, Assets, Inspector, Console, and Tasks. Overall, GEE provides a comprehensive and user-friendly environment for accessing, processing, and analyzing geospatial data, making it a powerful tool for researchers and developers in the field of remote sensing and geospatial analysis. The Google

Earth Engine (GEE) platform incorporates the use of Moderate Resolution Imaging Spectrometer (MODIS) images. MODIS, renowned for its substantial potential in Near Real-Time (NRT) mapping of the Earth's surface, operates at both national and global scales. Acquiring images in 36 spectral bands, MODIS provides spatial resolutions ranging from 250 meters to 1 kilometer. The MODIS time series is accessible in the GEE Data Catalog, spanning from the year 2000 to the present. This extensive temporal coverage enables users to conduct thorough temporal analyses on a global scale.

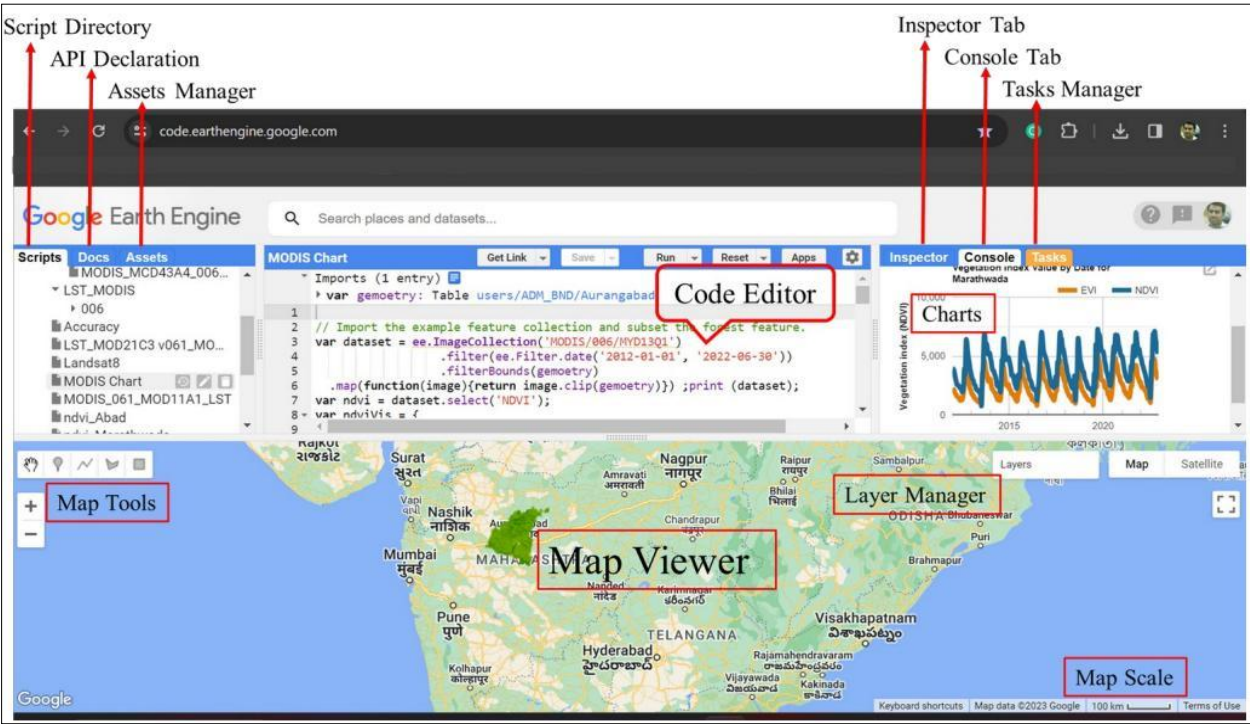


Fig 4: Pictorial representation of components of the Earth Engine

Methodology for Data Processing

The methodology employed aims to assess drought conditions through the computation of various remote sensing indices.

Leveraging the capabilities of the GEE platform, we utilized algorithms and functions to script and execute calculations for indices mentioned in section 1: NDVI, LST, VCI, and TCI.

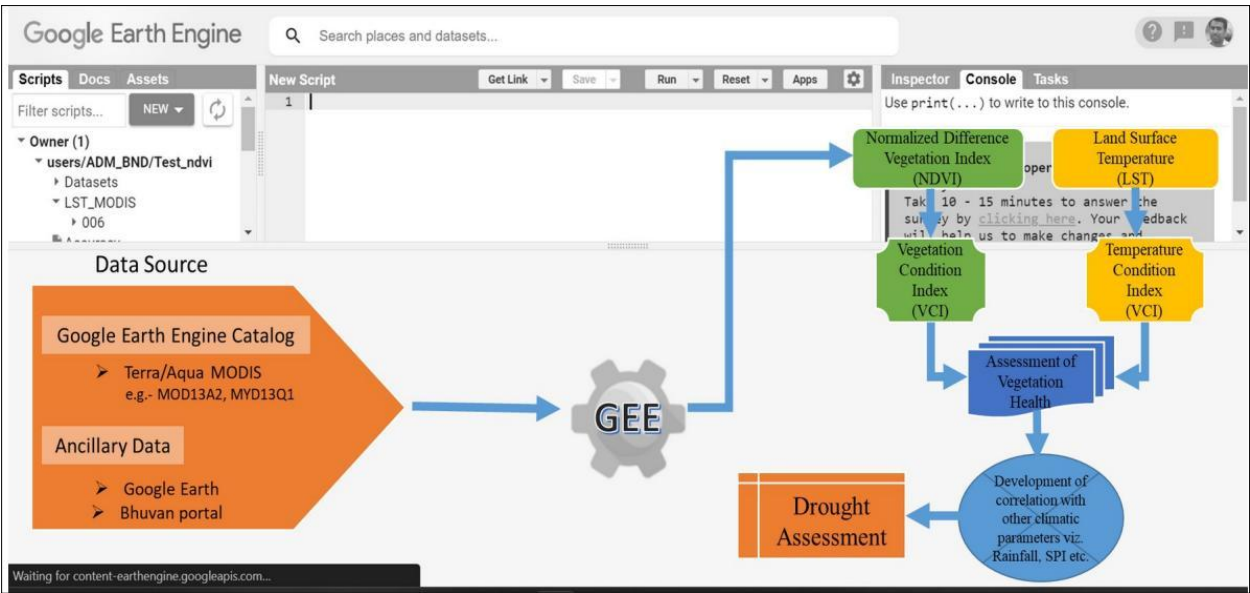


Fig 5: Flow-chart of methodological approaches to drought assessment.

Table 2: List of equation and formula for analyze the different indices.

Equation	Formula	References
Computation of NDVI	$NDVI = \frac{(NIR - RED)}{(NIR + RED)}$	(Prasad Srinivasa Thenkabail & Gamage, 2004; Wang & Tenhunen, 2004) [45, 46, 48].
Computation of VCI	$VCI = \frac{NDVIa - NDVIMIN}{NDVIMAX - NDVIMIN} * 100$	(Naumann <i>et al.</i> , 2014; Singh <i>et al.</i> , 2003; Prasad Srinivasa Thenkabail & Gamage, 2004) [27, 41, 45, 46]
Computation of TCI	$TCIj = \frac{(LSTmax - LSTj)}{(LSTmax - LSTmin)} * 100$	(Kogan, 1995; Prasad S Thenkabail <i>et al.</i> , 2004) [20, 45, 46].

The four drought indices presented in Table 2 were computed over the time span from year 2000 to 2022. Each index was derived in accordance with the drought scale and subsequently mapped to evaluate the intensity and condition of drought in the Marathwada region. Fig. 5 delineates the processing chain employed for generating the Vegetation Condition/Health Index for drought assessment. The processing workflow is executed through coding using the JavaScript (JS) API and involves the following steps:

Loading input data

- Load the collections of Landsat 8 Top of Atmosphere (TOA) and Surface Reflectance (SR) using the function `ee.Image()`;
- Load the study area in shapefile format using Table Upload in the Assets tab.

Filtering images

- Filter images based on the specified date range and the region of interest using filter Date () and filter Bounds ()

Clipping images

- Clip images to match the boundary of the study area using the clip (geometry) function.

Ndvi calculation

Compute the Normalized Difference Vegetation Index (NDVI) using the existing image processing function in GEE with the formula normalized Difference (band Names).

Computation of Lst, Ndvi, Tci, and Vci

Calculate Land Surface Temperature (LST), NDVI, Temperature Condition Index (TCI), and Vegetation Condition Index (VCI) by creating expressions using operators such as Add, Subtract, Multiply, and Divide with the expression () function.

These steps collectively form a comprehensive workflow for processing and analyzing satellite imagery to derive key indices for drought assessment in the Semi-arid Marathwada region. The utilization of GEE's functionalities through JavaScript coding enables an efficient and customizable approach to remote sensing data analysis. The evaluation of drought in the Marathwada region involves deriving the vegetation condition through key indicators, namely the VCI and TCI. This process requires the generation of the NDVI and LST. These indices are crucial components in assessing drought, and their data are compared or correlated with other climatic parameters. The entire process of

calculating and mapping these drought assessment indices, including NDVI and LST, has been conducted using the GEE. GEE serves as a powerful platform for efficiently processing, deriving, and visualizing remote sensing data, enabling a comprehensive analysis of drought conditions in the Marathwada region.

Results

Temporal trends in NDVI and rainfall throughout the seasons and agricultural drought

Analyzing NDVI trends and rainfall patterns across all eight districts of the Marathwada study area from the year 2000 to 2022, as discussed by (Pettorelli *et al.*, 2005) [33], reveals a discernible correlation between NDVI and rainfall. The provided Fig. 6 illustrates that there is a noticeable increase in NDVI corresponding to higher rainfall levels. Upon closer examination of the data, it becomes evident that as rainfall exceeds the average of 669.6 mm, NDVI experiences a corresponding elevation, reaching its peak within the range of 0.42 to 0.7. A distinctive trend becomes apparent around the average rainfall threshold, with the table displaying both maximum and minimum NDVI values (Table 3). This observation underscores the interconnectedness between NDVI and rainfall in the Marathwada region, highlighting the influence of precipitation on vegetation dynamics. The seasonal pattern of rainfall and NDVI can also be analyzed for the years 2000, 2003, 2007, 2008, 2014, 2015, 2016, 2018, 2021 & 2022 (Fig. 6) which shows that the North and Southwestern part of Marathwada districts is a low rainfall area where rainfall for the entire season and the corresponding NDVI values is also low. Whereas if one moves towards the Hingoli and Nanded comparatively high rainfall areas can be identified where rainfall shoots up to 2223.20 mm and above thereby giving high NDVI values. The results of the GEE for NDVI assessment presented in Fig. 7.

Table 3: Status of Normalized difference vegetation index (NDVI) of Marathwada (for the 2000 - 2022)

Districts	NDVI-Max	NDVI-Min
Chhatrapati Sambhajnagar	0.69	0.13
Beed	0.65	0.12
Hingoli	0.70	0.14
Jalna	0.70	0.13
Latur	0.68	0.11
Nanded	0.71	0.14
Osmanabad	0.92	0.12
Parbhani	0.70	0.12

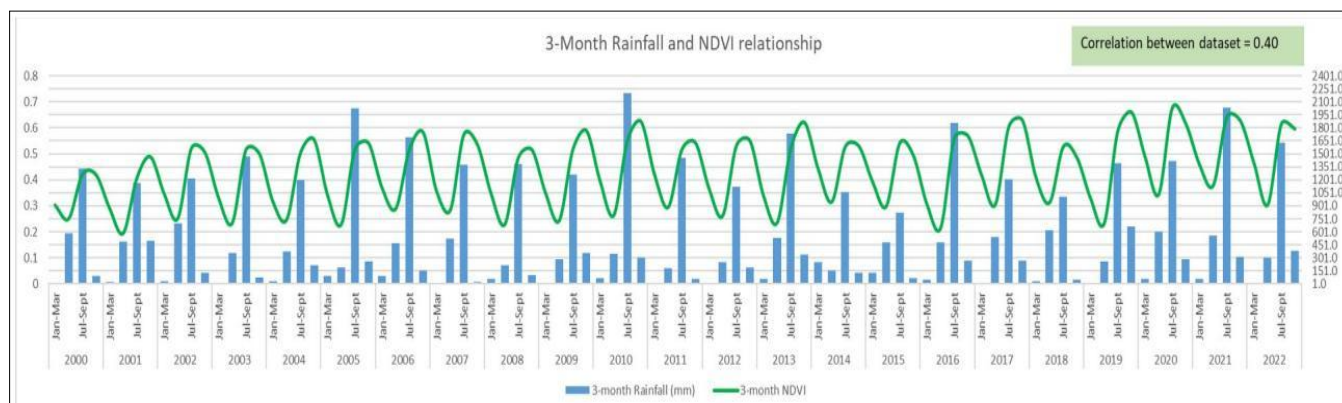


Fig 6: NDVI and Rainfall pattern relationship understanding.

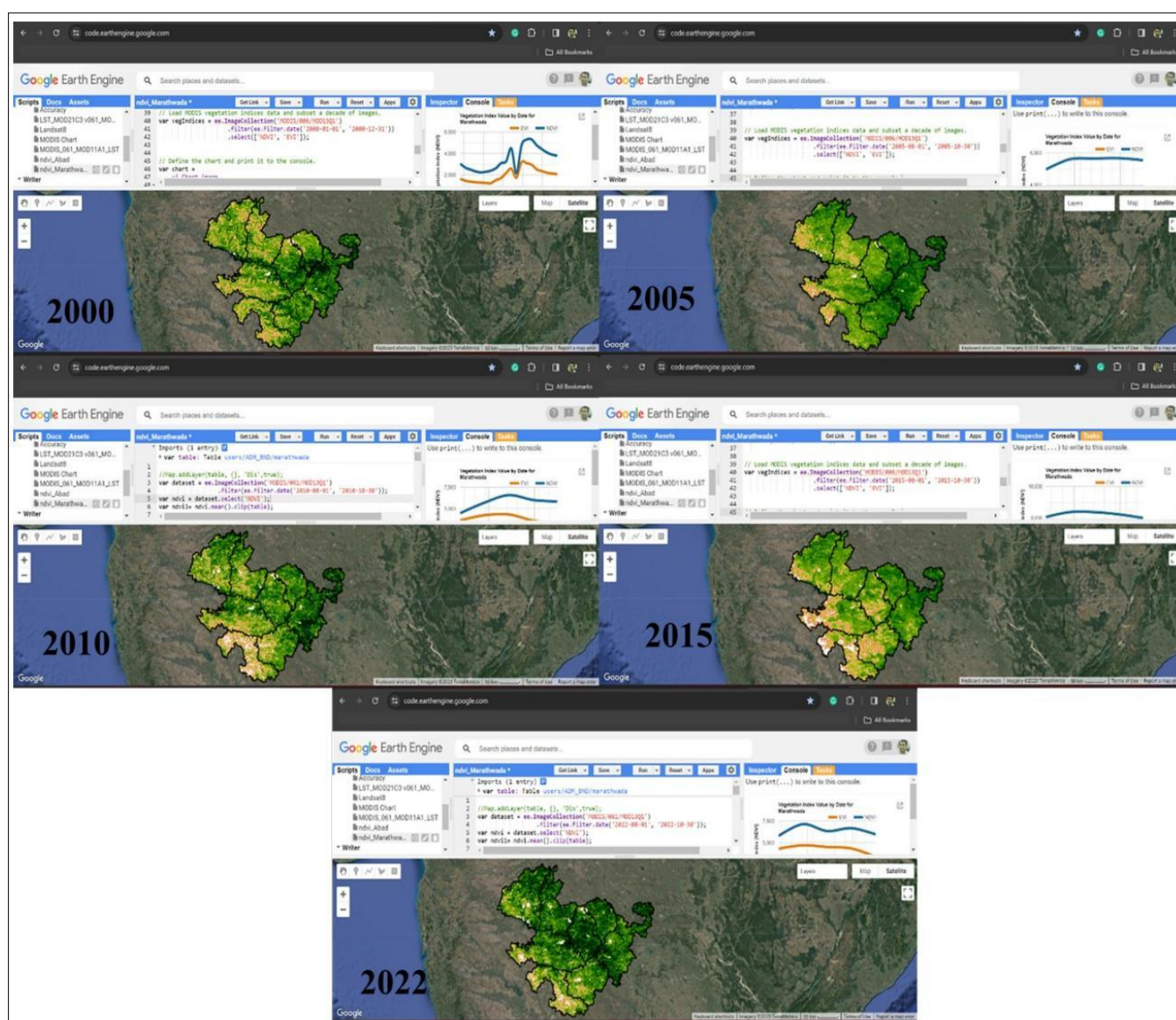


Fig 7: Temporal spatial behavior of NDVI using GEE for year 2000, 2005, 2010, 2015 & 2022 (August – Oct)

Temporal Trends in LST throughout the Seasons and Agricultural Drought

The NDVI value are lower in western and north region of the Marathwada during the assessment year of the 2000 where the respective LST shows the higher. An assessment year of 2010 and

2022 NDVI values are shows the good vegetation values as compared to other years shown in the Fig. 7 & Fig. 8 This comparison and handling of the 22 years as data (2000 – 2022) possible due to intervention of GEE technology.

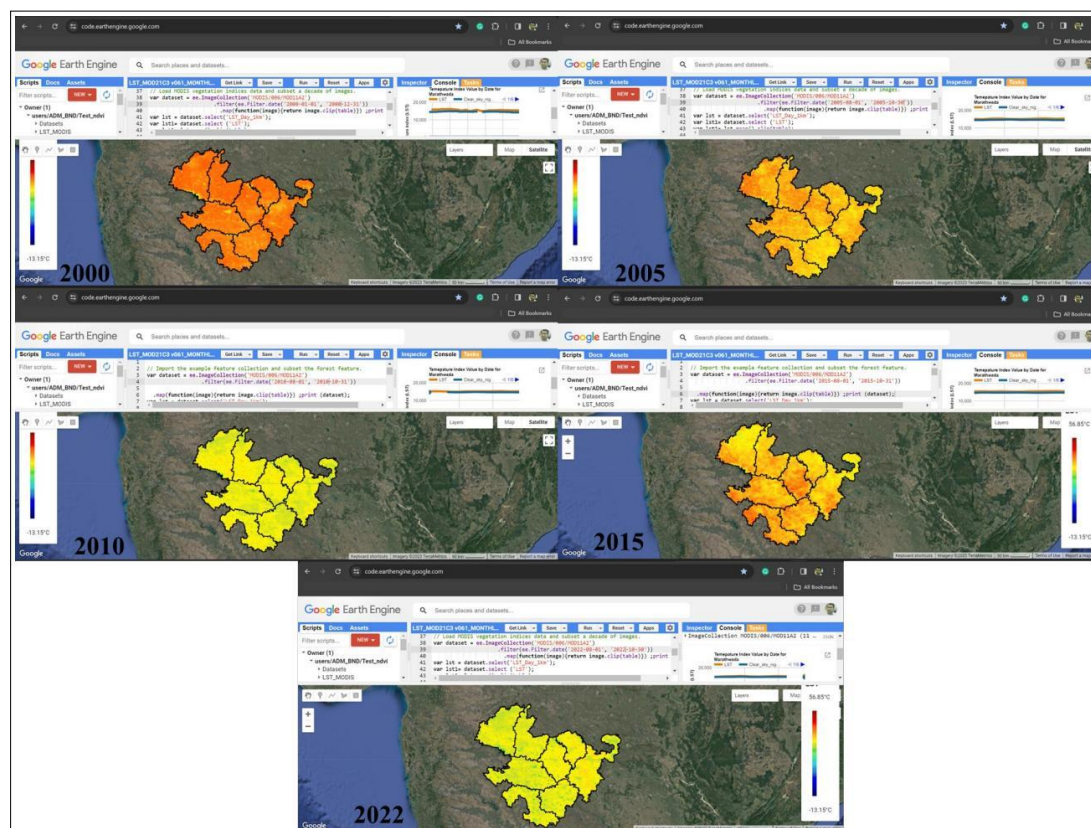


Fig 8: Temporal spatial behavior of LST using GEE for year 2000, 2005, 2010, 2015 & 2022 (August – Oct).

Assessment of the correlation between LST and NDVI

One prominent observation is the inverse relationship between these two parameters. When the temperature is higher, the NDVI value tends to be lower, indicating a decrease in vegetation density. This decrease is primarily attributed to reduced soil moisture resulting from inadequate or untimely rainfall, combined with elevated temperatures, which exacerbate agricultural drought conditions. An analysis of the years reveals that NDVI values are lower during the hotter months of April and

May, whereas September and November exhibit higher vegetation density. A quantitative assessment of this relationship between LST and NDVI is made by calculating their correlation, revealing a strong negative correlation with a coefficient of -0.78 for the years 2000 to 2022, as depicted in Fig. 9; which possible by utilization of the GEE to derive the spatial as well as the charts of LST and NDVI timescale and export into *.csv. These all-possible coding in the GEE platform.

Table 4: Correlation between LST & NDVI

Year	Jan-Mar	Apr-Jun	Jul-Sep	Oct-Dec
2000	-0.99	-0.98	1.00	0.98
2001	-1.00	0.99	-0.14	0.76
2002	-0.99	0.42	-0.35	0.95
2003	-0.99	0.58	-0.56	0.89
2004	-1.00	-1.00	-0.75	1.00
2005	-0.99	0.78	-0.98	0.76
2006	-1.00	-0.97	-0.68	0.98
2007	-0.96	-0.98	-0.85	0.97
2008	-0.97	0.96	-1.00	1.00
2009	-0.98	1.00	-0.29	0.99
2010	-0.98	-0.83	-0.06	0.99
2011	-0.98	0.45	-0.34	0.68
2012	-1.00	0.69	-0.70	0.99
2013	-0.97	0.89	0.96	0.81
2014	-0.86	0.42	-1.00	0.84
2015	-0.99	-0.95	-0.98	0.99
2016	-0.93	0.99	-0.85	0.59
2017	-0.99	-0.98	-0.95	0.51
2018	-0.98	-0.95	0.26	0.97
2019	-0.98	0.96	-0.97	0.91
2020	-1.00	-0.91	-0.90	0.69
2021	-1.00	-0.99	-0.55	0.89
2022	-0.98	0.86	0.99	-0.90

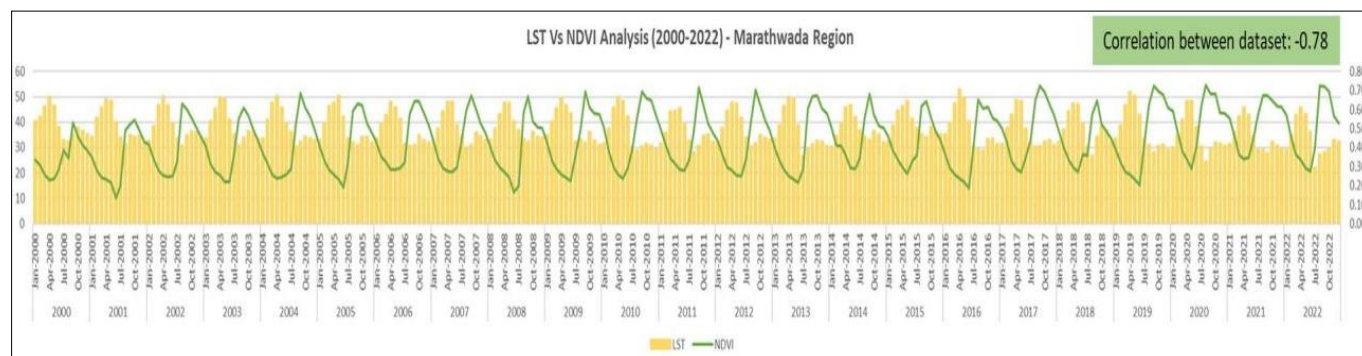


Fig 9: LST and NDVI assessment plotting of Marathwada (2000 to 2022)

Also, for understanding of correlation between LST and NDVI, calculated the 3 – month correlation (Jan-Mar, Apr-Jun, Jul-Aug

& Oct-Dec) shows in below Table 4 and Fig. 10.

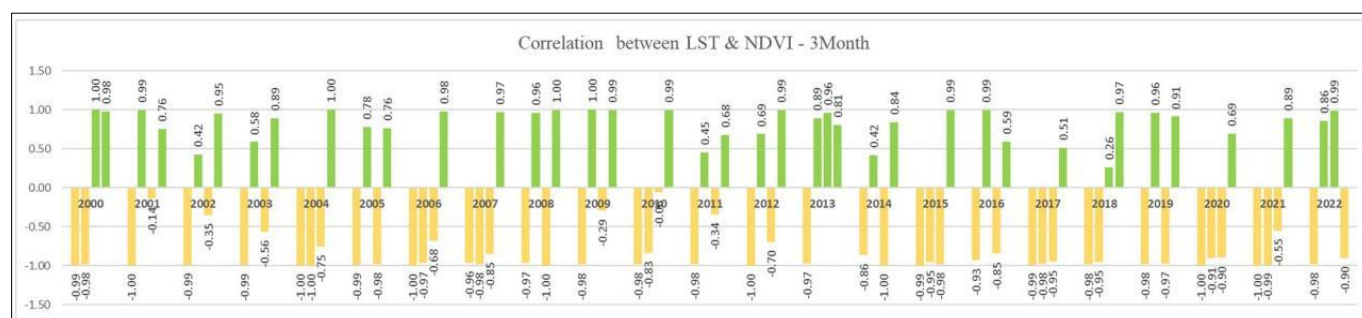


Fig 10: Extracted correlation analysis between LST & NDVI.

Spatial and Temporal Trends in Tci-vci and Drought Intensity

Temperature condition Index (TCI) and Vegetation Condition Index (VCI) map was generated using LST and NDVI; are classified into different drought classes (Zhao, S., Cong, D., He, K. *et al.* 2017) [52] as shown in Table 5

Table 5: The classification scheme of TCI and VCI adopted for study.

Classification Scheme	
Drought Classes	TCI & VCI (%)
Extreme Drought	00 to 10
Severe Drought	10 to 19.9
Moderate Drought	20 to 29.9
Mild Drought	30 to 39.9
No Drought	40 to 49.9
No Drought	50 to 59.9
No Drought	60 to 69.9
No Drought	70 to 79.9
No Drought	80 to 89.9
No Drought	90 to 100

The Table 5 of TCI and VCI based drought classes and Fig. 11 depict the monthly temporal changes in the TCI & VCI across the Marathwada region for specific years. Fig. 11 (A1 and A2),

focusing on the year 2000, demonstrates the monthly fluctuations in the VCI and TCI across the Marathwada region. It is evident that the entire study area encountered water stress conditions from June through a portion of August. Furthermore, during June and August, mild to moderate drought conditions were observed, particularly during the kharif crop season. Fig. 11 (B1 & B2) of drought assessment year 2005 demonstrate as per B1 that; during month of June & July (Kharif crop season) experiences the Extreme and moderate drought and TCI depict the mild drought condition from July to December (Kharif crop season). Fig. 11 C1, C2 & D1, D2 show the water stress conditions in the months of June and July for the years 2010, 2015, resulting in severe and moderate drought conditions in June and mild drought conditions in July for both years. However, in the subsequent year, 2022, as seen in Fig. 11 E1 and E2, June showed severe drought conditions, and July exhibited mild drought conditions, indicating the return of water stress conditions and TCI shows favorable temperature condition. As discussed above the result comes from the analysis of MODIS satellite data using GEE platform for NDVI and LST; further calculate the VCI and TCI for the analysis of drought condition in the

Marathwada region, the spatial distribution of the VCI values which help to understand the extent of the drought condition in the different part of the Marathwada.

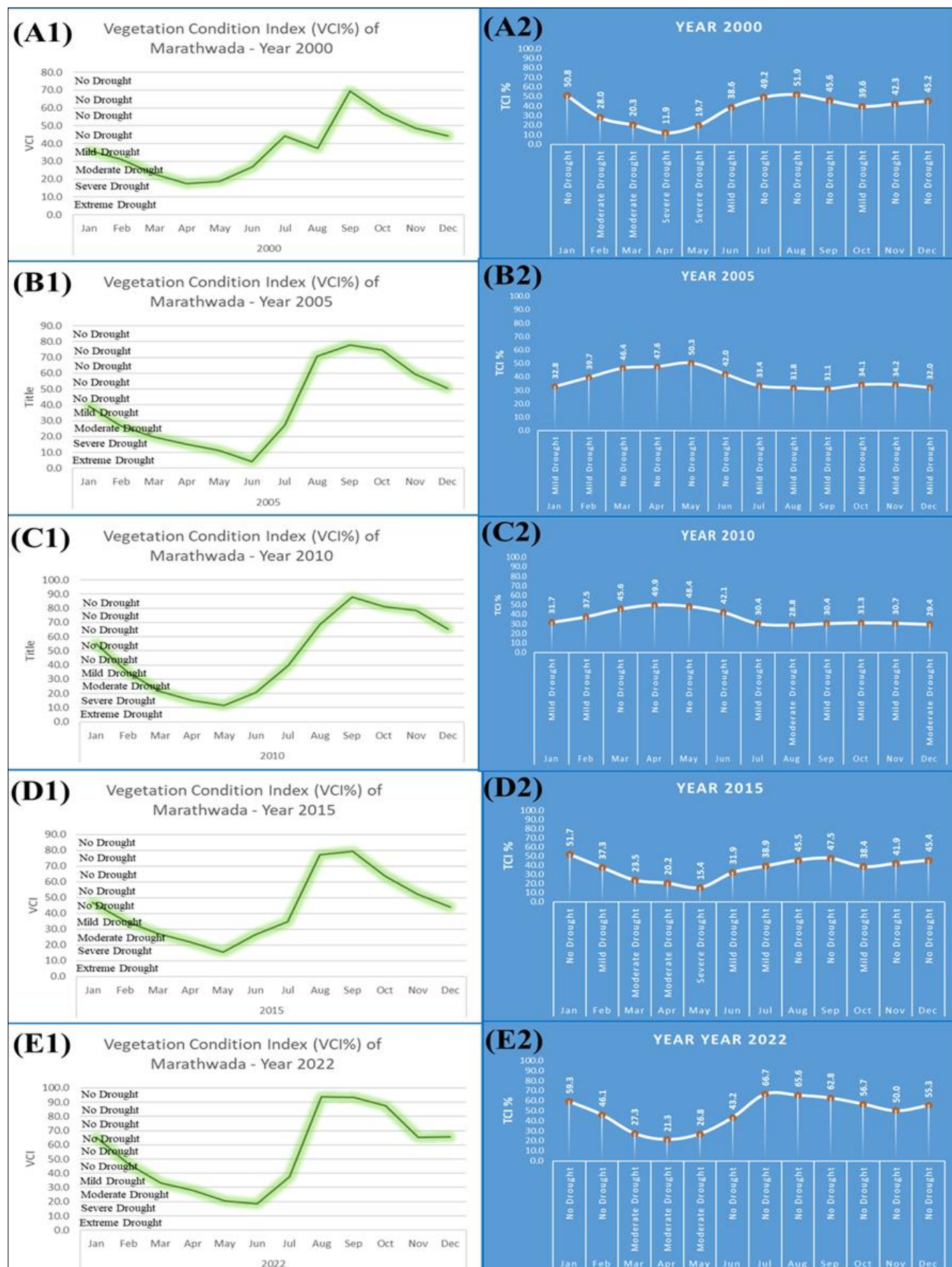


Fig 11 Vegetation Condition Index (VCI) and Temperature condition Index (TCI) of study region of selective years (Year 2000- A1 & A2; Year 2005- B1 & B2; Year 2010- C1 & C2; Year 2015- D1 & D2 & Year 2022- E1 & E2)

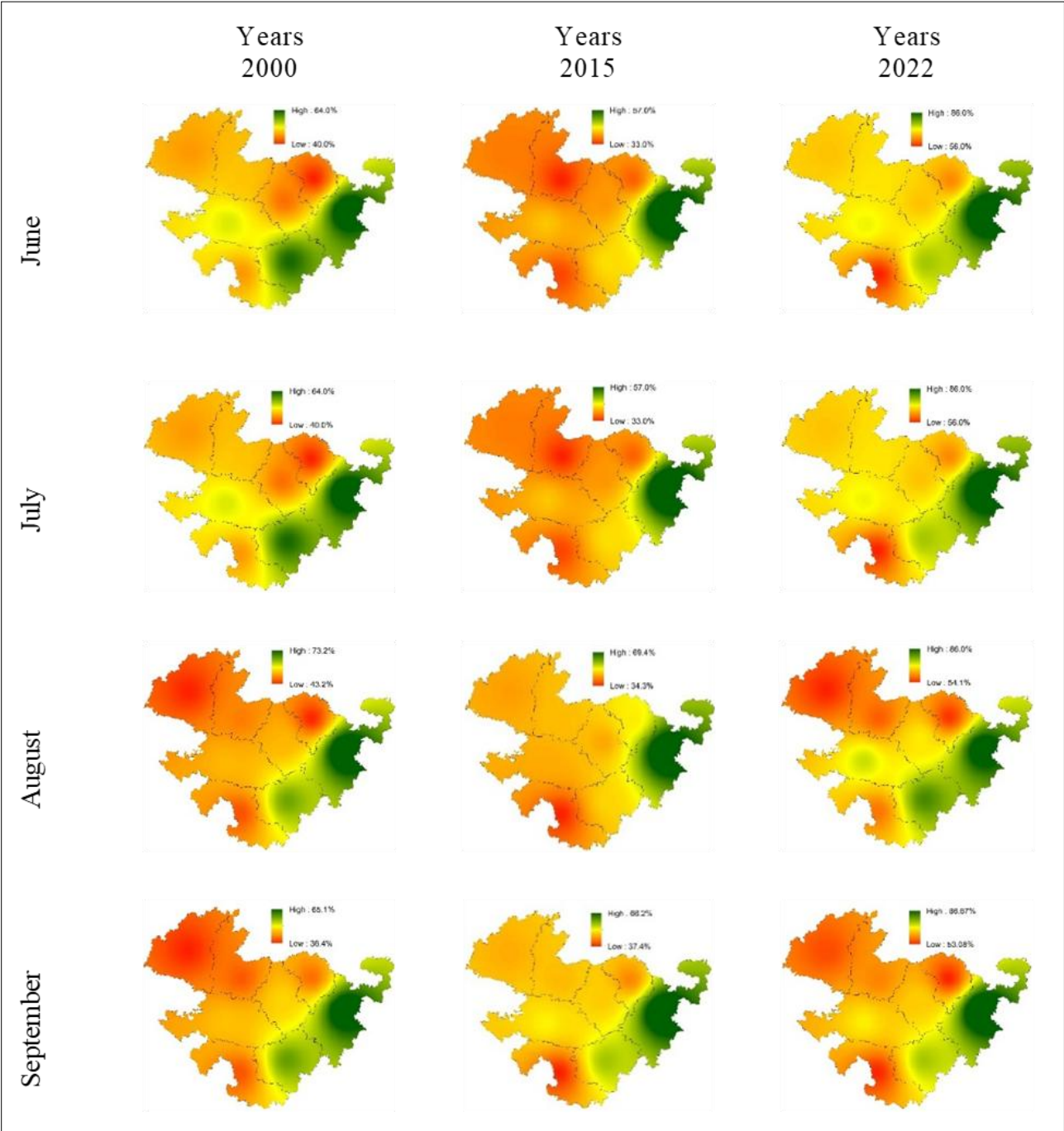
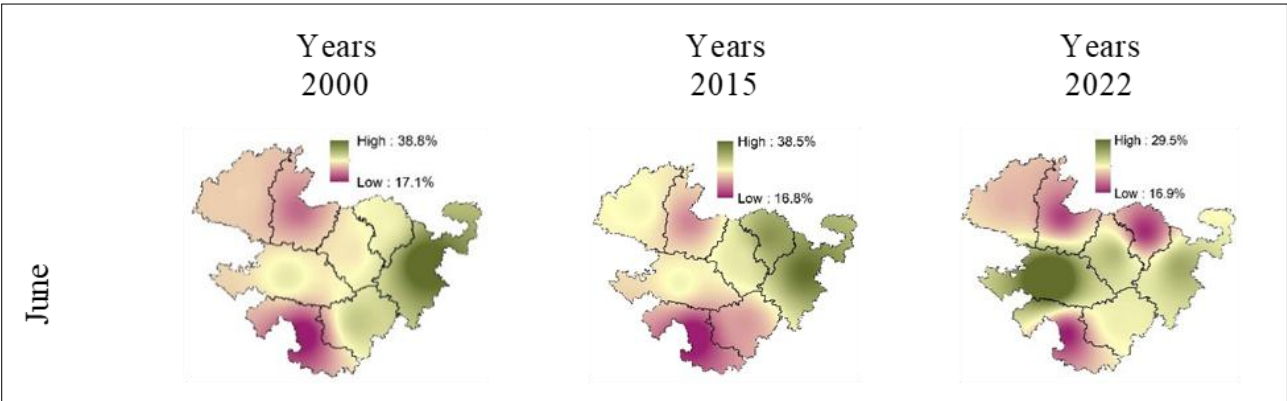


Fig 12: Spatial distribution of TCI over the study region during Kharif crop season (For the years 2000, 2015 & 2022).



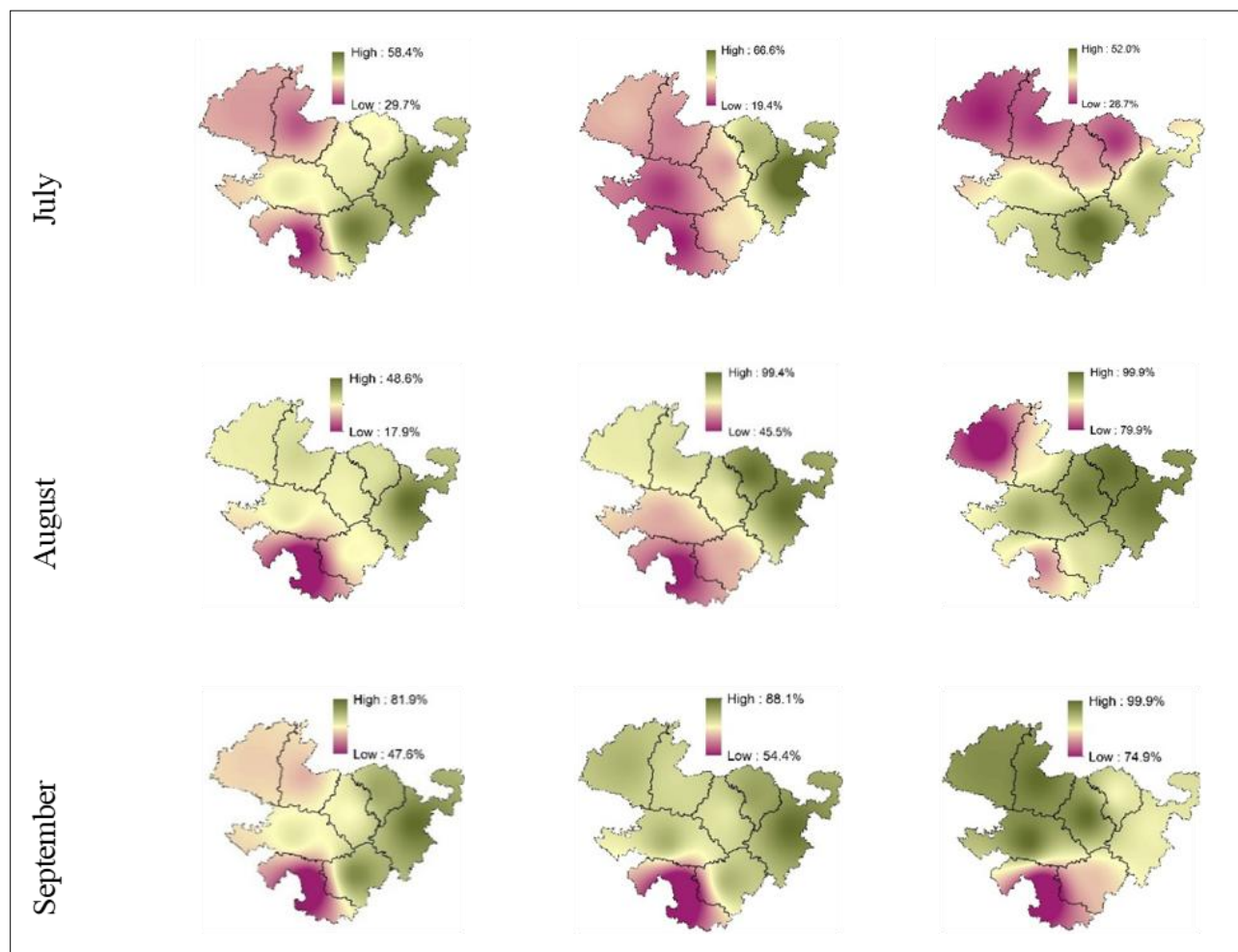


Fig 13: Spatial distribution of VCI over the study region during Kharif crop season (For the years 2000, 2015 & 2022).

In the above & of TCI and VCI spatial behavior in the kharif crop season (major crop season of region) of Marathwada from June – September 2000, 2015 & 2022 the selected sample years depicted that the relative low value of TCI % and VCI % (refer Table 5) shows the drought condition particularly in 2015 are worst during the kharif season as compare to 2000 and 2022.

Conclusion

This study utilized satellite-based indices to assess drought conditions in the semi-arid region of Marathwada, relying on the GEE and custom algorithms/scripts for the analysis and calculation of the VCI and TCI as drought indicators using the NDVI and LST. The assessment results indicate that from year 2000 to 2022, valuable preliminary information regarding the spatial distribution of mild, moderate, and severe drought in the Marathwada was swiftly provided. This underscores the potential of GEE as a powerful tool for monitoring drought conditions. While the developed GEE methodology contributes to the assessment and monitoring of drought in Marathwada, it is essential to acknowledge certain limitations. The method depends on the careful selection of suitable satellite images for the study area, and the exclusion of optical satellite images with substantial cloud cover could lead to the loss of critical drought information during those periods. To address this limitation, a potential solution is to incorporate different types of satellite imagery in GEE, such as MODIS, and integrate parameters indicative of drought conditions, such as water stress and rainfall. GEE emerges as a valuable tool for geospatial data analysis, particularly within the remote sensing community. Offering a free

cloud-based service eliminates the need to download and manage data locally. Built upon Google's cloud computing infrastructure, GEE automates and parallelizes computations on Google GPUs, facilitating the processing of vast amounts of remote sensing data on large geographical scales and over long temporal coverages. The platform supports regional, national, continental, and global-scale applications. Moreover, GEE provides a user-friendly environment where researchers can easily upload, share, and access datasets, scripts, and models through GPUs. On-the-fly generation of maps and products occurs when users execute code, eliminating the need for installing thirdparty software packages like ENVI and ERDAS. Overall, the automated and comprehensive features of GEE make it a robust and accessible tool for diverse geospatial analyses.

Acknowledgment

I acknowledge the support of the Department of Environmental Science, Dr. Babasaheb Ambedkar Marathwada University, during data analysis and express my sincere appreciation to the farmers of the Marathwada region.

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