DROUGHT ASSESSMENT USING REMOTE SENSING AND GOOGLE EARTH ENGINE IN KALABURGI DISTRICT,NORTH-EASTERN DRY ZONE OF KARNATAKA

Abstract

Drought is a significant natural disaster exacerbated by global warming, leading to severe environmental, economic and societal impacts. As one of the most complex phenomena, drought requires advanced methods for effective monitoring and assessment. Remote sensing indices have proven effective in analyzing drought's geographical and temporal distribution. In this study, utilized the Google Earth Engine (GEE) platform, which provides cloud-based access to advanced computational resources for processing multi-temporal satellite data. GEE, a cloud-based solution, provides geospatial analysis and multi-temporal satellite data management. Its ability to handle large dataset efficiently makes it an indispensable tool for environmental studies. In this study, GEE was applied to create and execute customized scripts for drought assessment, thereby accelerating the procedure and minimizing the need for extensive data downloads and complex software operations.The study focused on the North Eastern Dry Zone of Karnataka, particularly Kalaburgi district, employing the Normalized Difference Vegetation Index (NDVI) and Vegetation Condition Index (VCI) derived from MODIS data. The analysis revealed severe drought conditions, particularly in 2001, with NDVI values as low as 0.07 at Afzalpur station and 0.06 at Chitapur station, indicating significant vegetation stress. The VCI analysis further supported these findings, with values as low as 0.05 at Afzalpur station and 0.03 at Chitapur station, highlighting the drought's intensity. This integrated approach provides a reliable evaluation of agricultural drought, essential for enhancing drought management and mitigation strategies in the region. The study covers data from all 5 stationsand specific results are discussed in detail.

Keywords: Drought, Google Earth Engine, MODIS, NDVI and VCI.

I. Introduction

In recent years, climate change has been a main cause of global warming, resulting to less rainfall and aggravating drought conditions. This has had a severe influence on

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agriculture, manifesting in reduced crop production, diminished cultivated areas, and less yields, notably in food crops. Understanding the extent and severity of drought is crucial for developing effective stratergies to mitigate its effects on agricultural sustainability.

Drought can occur over multiple timescales, often becoming evident dry seasons characterized by low precipitation and high temperature (Wilhite, 2000). These conditions frequently affect vast regions, promoting scientists to study the possibilities of remote sensing data for effective drought monitoring. Remote sensing technology offers a comprehensive perspective of the Earth’s surface, with the advantage of continuous, global imaging data that provides specific insights into different locations. This approach is particularly beneficial in region with spares meteorological station, where conventional monitoring is limited. Freely available. The use of remote sensing data to construct drought maps offers an overview of drought-prone areas, particularly in regions with inadequate meteorological stations. Additionally, freely available satellite imagery from sources like MODIS and Landsat has shown suitable for evaluating drought conditions.

Among the different drought indicators produced from remote sensing data, the Normalized Difference Vegetation Index (NDVI) paired with Land Surface Temperature (LST) has demonstrated a good connection, providing valuable insights for understanding agricultural drought (Sruthi et al., 2015). Several drought indices based on the NDVI-LST relationship, such as the Temperature-Vegetation Dryness Index (TVDI), Vegetation Health Index (VHI), and Water Supplying Vegetation Index (WSVI), have been successfully tested in multiple countries (Alshaikh, 2015; Schirmbeck et al., 2017; Sholihah et al., 2016). The vegetation condition index (VCI), derived from NDVI, and the temperature condition index (TCI), reflecting LST variations, are widely recognized for estimating drought severity. These indices have been employed in numerous studies, using data from MODIS and Landsat, to characterize drought intensity (Masitoh et al., 2019; Sreekesh et al., 2019).

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The advent of Google Earth Engine (GEE), a cloud-based geospatial platform, has revolutionized the processing of multi-temporal satellite data by providing access to high-performance computing resources (Gorelick et al., 2017). Since its introduction in 2010, GEE has been used for diverse applications, including vegetation mapping, land cover analysis, and flood monitoring (Mutanga et al., 2019; Midekisa et al., 2017; Sidhu et al., 2018; DeVries et al., 2020). Its vast repository of freely available satellite imagery and robust image processing capabilities make GEE an ideal tool for drought studies (Khan et al., 2019). The platform supports flexible geographic and temporal analyses and enables rapid drought assessments through global soil moisture data (Sazib et al., 2018). For example, Aksoy et al. (2019) used GEE to analyze drought conditions over two decades in Turkey, employing indices such as the Vegetation Health Index (VHI) and the Normalized Difference Drought Index (NDDI). Studies like these demonstrate the effectiveness of MODIS-derived indices and GEE's capability for large-scale drought assessments.

In India, research using GEE is gaining traction. Applications have generally focused on forest land monitoring, riverbank alterations and flood monitoring. However, there has been minimal research on drought assessment utilizing data, such as MODIS, within the GEE framework in the North Eastern Dry Zone of Karnataka of Kalaburgi districts. Therefore, this work seeks to generate satellite-based drought indicators, including NDVI and VCI, utilizing GEE algorithms at a local level to assess drought conditions during the study period. The results are expected to provide critical insights into drought patterns, assisting policymakers and planners in implementing effective drought management and mitigation strategies.

II. Data collection and study area

2.1 Study area

This study focuses on the Kalaburgi district of Karnataka, which includes five key stations: Afzalpur, Chitapur, Jevargi, Kalaburgi and Sedam. Geographically, the region is situated between 17°00' to 17°33' N latitude and 76°21' to 77°17' E longitude(Fig. 1). Agriculture in this semi-arid zone is predominantly rainfed, with major crops including red gram, sorghum and bajra. The total agricultural area is substantial, and both *Kharif* (rainy season) and *Rabi* (dry season) crops are cultivated. Farming activities in the district are predominantly driven by monsoonal rains, with the prime cropping period occurring from June to October. Sowing normally begins with the onset of the southwest monsoon, while harvesting is done between November and January. Given its semi-arid nature, this region is particularly sensitive to agricultural droughts, highlighting the need for a comprehensive comprehension of drought patterns to design effective mitigation strategies.

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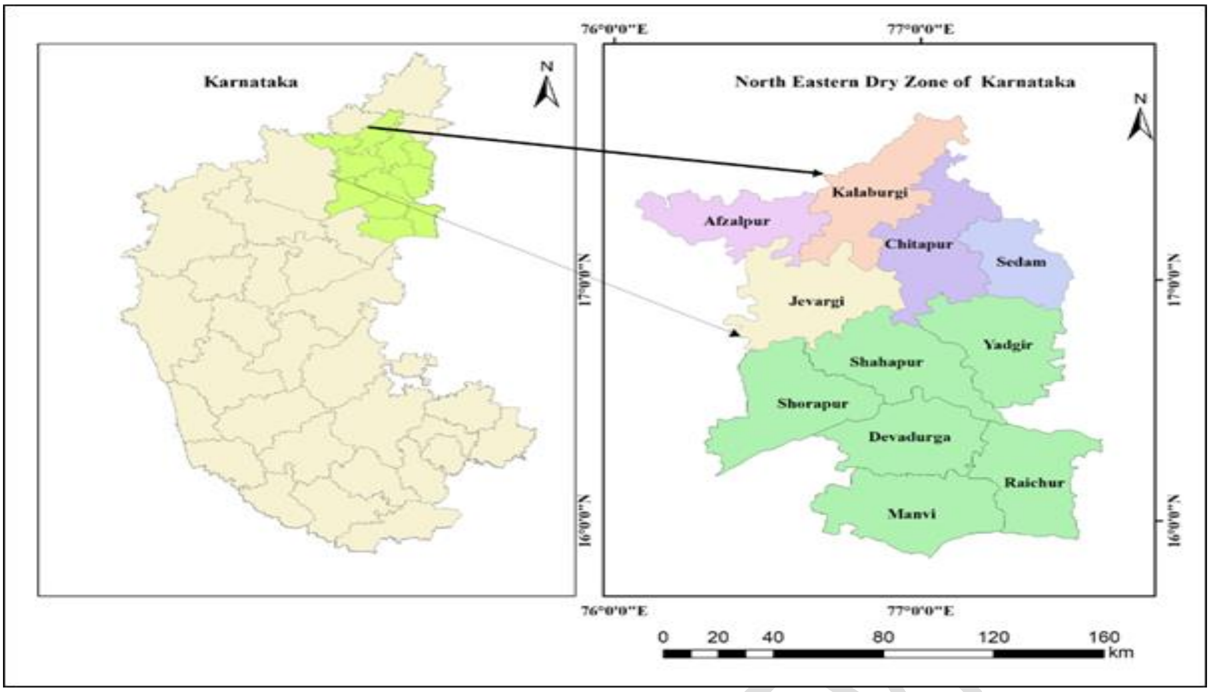

Fig. 1. Location of the study area

2.2 Data resources

Google Earth Engine (GEE) provides access to anextensiverepository of satellite data, hosted and maintained by Google. Each datasetis organized into an Image Collection, defined by a unique ID. These datasets can be accessed through the GEE Data Cata-log (https://earthengine.google.com/datasets/).

For this investigation, we employed data from the Moderate Resolution Imaging Spectroradiometer (MODIS), specifically the MOD13Q1 product. The MOD13Q1 dataset is part of the MODIS Collection and is an Image Collection within GEE, identifiable by the ID MODIS/061/MOD13Q1. This package gives a 16-day composite of the Normalized Difference Vegetation Index (NDVI) with a spatial resolution of 250 m. The MOD13Q1 product also includes Quality Assurance (QA) information, allowing for the selection of high-quality pixels and ensuring the reliability of the NDVI data used for this research.

The selected MODIS NDVI data for this study covers the entire region of interest for the year 2000-2022, allowing for a comprehensive investigation of vegetation conditions and drought assessment. The data were processed and analyzed directly on the GEE platform, employing the cloud-based capabilities to quickly handle big datasets and execute geographical analyses. By integrating the MODIS NDVI product in GEE, this study was able to efficiently monitor and assess drought conditions at a regional scale, offering useful information for drought management and mitigation methods.

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Google Earth Engine

Google Earth Engine (GEE) is a cloud-based platform built for large-scale environmental data analysis, accessible via a web-based JavaScript Application Program Interface (API) called the Code Editor. The Code Editor is structured into several components: a central panel where users write and edit JavaScript code, a bottom panel that visually displays the map with layers added by the script, and a left panel that houses various tabs including the Scripts tab for saved scripts and code examples, the Docs tab for method documentation, and the Assets tab for managing uploaded data assets. GEE enables many actions, including calling methods attached to objects, executing pre-built algorithms, using Code Editor-specific functions, and setting custom rules. This versatility, paired with a comprehensive library of operations, makes GEE a strong tool for geographic data processing and analysis. The ability to distribute scripts via encoded URLs further promotes collaboration and reproducibility, which is particularly helpful for completing complicated environmental assessments, such as the drought analysis in this work (https://developers.google.com/earth-engine).

III. Methodology

Use of satellite-based indices are very popular for characterizing the agricultural drought. In the present study, agricultural drought was characterized by using two types of remote sensing-based indices *i.e.* Normalized Difference Vegetation Index (NDVI) and Vegetation Condition Index (VCI) which measures the greenness of vegetation in the vegetation canopies.

Utilizing the Google Earth Engine (GEE) platform, we constructed algorithms and functions to develop and execute scripts for computing essential drought assessment indices, notably the Normalized Difference Vegetation Index (NDVI) and Vegetation Condition Index (VCI). The NDVI was produced from the red and near-infrared bands (Band-1 and Band-2, respectively) of the MODIS satellite data, whereas the VCI was calculated based on the NDVI values over time. These indexes gave vital insights into the geographical and temporal patterns of drought, enabling a detailed assessment of drought conditions across the study area (Fig. 2).

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3.1 The analysis of GEE for drought assessment

The processing for generating the NDVI and VCI index for drought assessment. Our processing workflow consists of some steps using coding by the JavaScript (JS) API:

1. Loading input data

   Load the collections of MODIS/006/MOD13Q1: using function ee. Image ();

   Load the study area with shapefile format: the component files of your shapefile (.shp, .shx, .dbf, prj, etc.)

2. Filter images by date range and the region of interest: using filter Date () and filter Bounds ().

3. Clip images according to the boundary of the study area: using the clip (geometry).

4. NDVI was calculated with the existing image processing function in GEE: Normalized Difference (Band names).

5. VCI were computed by creating expression () with operators as Add, Subtract, Multiply, Divide.

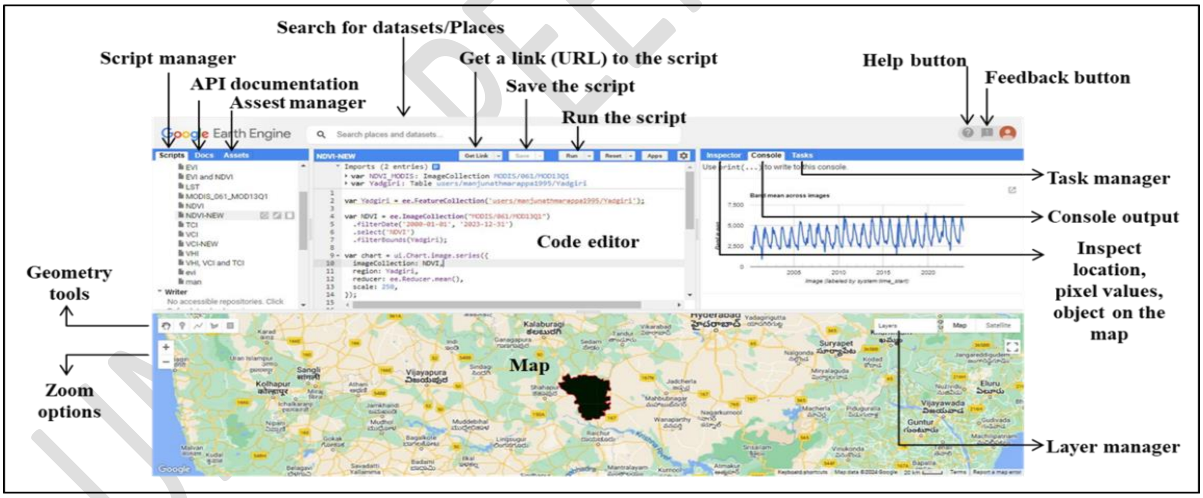

Fig. 2. Diagram of components of the Earth Engine

3.2 Formulae for calculating NDVI and VCI

NDVI estimates vegetation by measuring the difference between near-infrared (which vegetation strongly reflects) and red light (which vegetation absorbs). The range of NDVI ranges from −1 to +1. Higher NDVI values imply healthy and thick vegetation, while lower

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values signal sparse or stressed vegetation. The NDVI is determined using the following formula (Tucker, 1979):

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

Where, NIR = Reflectance in the near-infrared band, RED = Reflectance in the red band

VCI (Vegetation Condition Index) is produced from NDVI readings and represents the relative condition of vegetation in a specific area compared to its historical range. VCI is calculated as follows:

$$\mathrm{VIC} = \frac{\mathrm{NDVI} - \mathrm{NDVI}_{\mathrm{min}}}{\mathrm{NDVI}_{\mathrm{max}} - \mathrm{NDVI}_{\mathrm{min}}} \times 100$$

Where, the NDVI is the value for the pixel and month, and NDVImin and NDVImax are the minimum and maximum values of the NDVI over the whole period, respectively, for the considered pixel and month.Band 1 of MOD13Q1 (MODIS product) gives NDVI imageries which were used to compute VCI by following equation.In this study, NDVI and VCI was calculated on a monthly. The NDVI and VCI threshold ranges that were used to define drought conditions are presented in Table 1 and 2, ranging from extreme wet to extreme drought.

Table 1. Drought classification based on NDVI index (Lalmuanzuala *et al.*, 2023)

Drought classes	**NDVI values**
Extreme drought	< 0.00
Severe drought	0.00 - 0.20
Moderate drought	0.20 - 0.40
Good Condition	0.40 - 0.60
Very Good Condition	> 0.60

Table 2. Drought classification based on VCI index (Xie and Fan, 2021)

Drought classes	**VCI values**
Normal	0.40 -1.00

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Mild drought	0.30 - 0.40
Moderate drought	0.20 - 0.30
Severe drought	0.10 - 0.20
Extreme drought	0.0 - 0.10

IV. Results and Discussions

Agricultural drought analysis using NDVI and VCI provides valuable impact of drought on vegetation and crop health. These indicators are collected from satellite images, presenting a comprehensive perspective on how drought affects crop growth over time. This study explores the regional and temporal variability in agricultural drought, providing insights into vegetation stress and production fluctuations. The study focuses on identifying severe drought events and their implications for regional agricultural sustainability.

4.1 Historical drought analysis and characterization

The NDVI analysis across the study area shows significant variations in vegetation health over different years, (Fig. 3). At Afzalpur station exhibited critical drought stress during 2001, with NDVI values of 0.07 (June), 0.16 (July), 0.19 (August) and 0.33 (September),indicating prolonged drought impact. Similarly, in 2009, severe drought conditions occurred with NDVI results of 0.23 in June, 0.14 in July and 0.20 in September. At Chitapur station, severe drought conditions in 2001 were reflected by NDVI values of 0.06, 0.17 and 0.32 for June, Julyand September, respectively. The year 2000 also were having severe drought, with NDVI readings of 0.18 (June), 0.31 (July)and 0.17 (August) (Fig.4).

At Jawargi station, severe drought conditions occurred in 2001, with NDVI values of 0.06, 0.18 and 0.17 for June through August, respectively. Moderate drought conditions were also recorded in 2000 and 2013 (Fig.5). Kalaburgi station followed a similar pattern, with NDVI values of 0.09 (June), 0.17 (July) and 0.30 (August) during 2001, highlighting the pervasive drought stress in the region. Severe drought conditions were also recorded in 2000, with NDVI readings of 0.19 (June), 0.34 (July) and 0.18 (August) (Fig. 6).Moderate drought conditions persisted at Sedam station during 2000 and 2001, with NDVI values were 0.22 (June), 0.37 (July)and 0.23 (August) and 0.11 (June), 0.23 (July) and 0.36 (August) in 2001 (Fig. 7). Mild and moderate drought events were consistently recorded across all stations

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during the study period, with recent trends observed in 2016 and 2020, emphasizing the recurrent nature of drought in the region.

The NDVI analysis clearly demonstrates significant vegetative stress during severe drought years across several sites. For instance, at Afzalpur station, NDVI values were exceptionally low in 2001, with 0.07 in June and 0.33 in September. Similarly, Chitapur station recorded NDVI values of 0.06 in June and 0.32 in August during the same year, reinforcing the severity of drought. Jawargi station experienced severe drought in 2001, with NDVI values of 0.06 in June and 0.17 in August. Kalaburgi station exhibited a similar pattern, with NDVI values of 0.09 in June and 0.30 in August, further highlighting the vulnerability of vegetation to prolonged drought conditions. These findings align with established research by Kogan (1995), Tucker et al. (2005) and Jean et al. (2021), validating the use of NDVI as a reliable drought indicator.

The VCI (Vegetation Condition Index) analysis highlights the severity of vegetative stress across various locations, correlating strongly with NDVI patterns. At Afzalpur station in 2001, severe drought conditions were evident, with VCI values of 0.05 in June, 0.17 in July, 0.20 in August and 0.39 in September (Fig. 3). Similarly, at Chitapur station, severe droughts in 2001 were indicated by VCI values of 0.03 in June, 0.16 in July and 0.36 in August. The year 2000 also had severe drought at Chitapur, with VCI values of 0.16 (June), 0.31 (July), and 0.16 (August) (Fig.4).

Severe drought were also recorded at Javargi station in 2001, with VCI values of 0.04 in June, 0.18 in July, and 0.15 in August. Additional drought events were observed in 2000 and 2013 (Fig.5). At Kalaburgi station, severe drought in 2001 were evidenced by VCI values of 0.06 (June), 0.17 (July) and 0.35 (August) (Fig.6).At Sedam station, moderate drought was indicated in 2001 by VCI values of 0.08 (June), 0.24 (July) and 0.39 (August) (Fig.7). Mild drought conditions were also noted at Sedam in subsequent years such as 2009, 2011, and 2013,demonstrated persistent drought stress during the study period.

The VCI analysis further emphasizes the impact of sever drought years on vegetation health across the study area for instance, at Afzalpur station in 2001, VCI values ranged from 0.005 in June to 0.39 in September, demonstrating prolonged vegetation stress. Similarly, Chitapur station recorded extreme and mild drought in 2001, with values as low as 0.03 in June and 0.36 in August. Kalaburgi station also experienced significant stress in 2001, with values of 0.06 in June and 0.035 in August, highlighting the widespread nature of drought

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during this period. These findings underscore the reliability of VCI as a complementary tool to NDVI assessing drought severity and its impact on vegetation. The results align with established research by Kogan (1995), Tucker et al. (2005) and Jean et al. (2021), validating the use of satellite-based indices in drought monitoring. The strong correlation between VCI and NDVI reinforces the applicability of these indices for regional drought assessment and long-term agricultural planning.

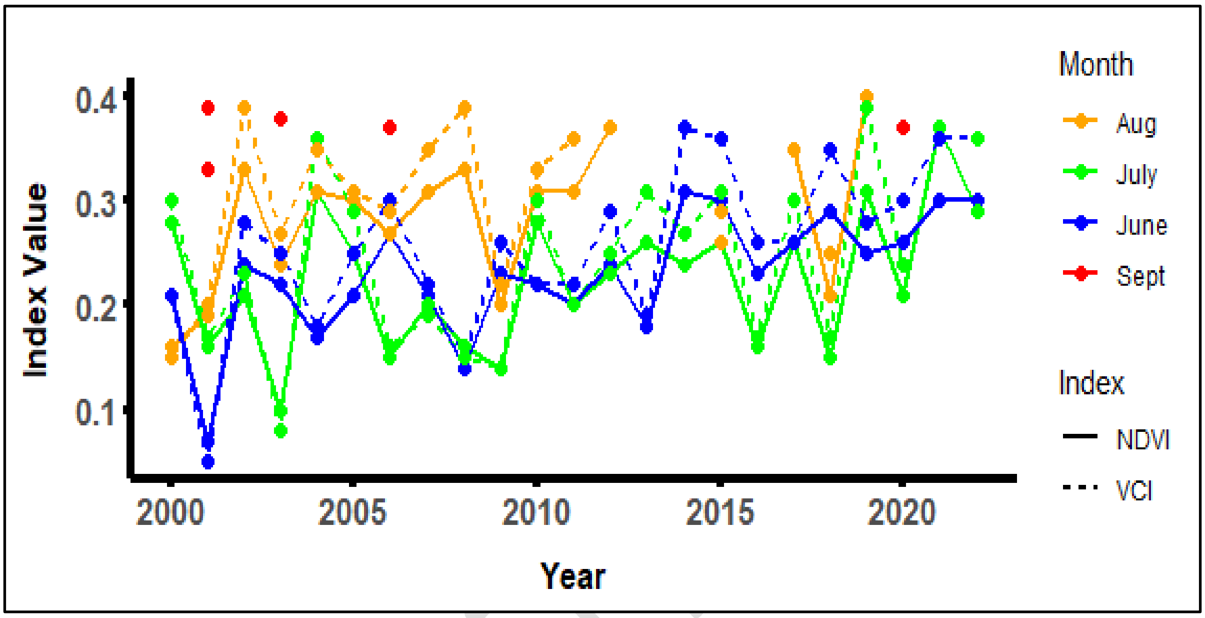

Fig 3. Agricultural drought events as per NDVI and VCI at Afzalpur station

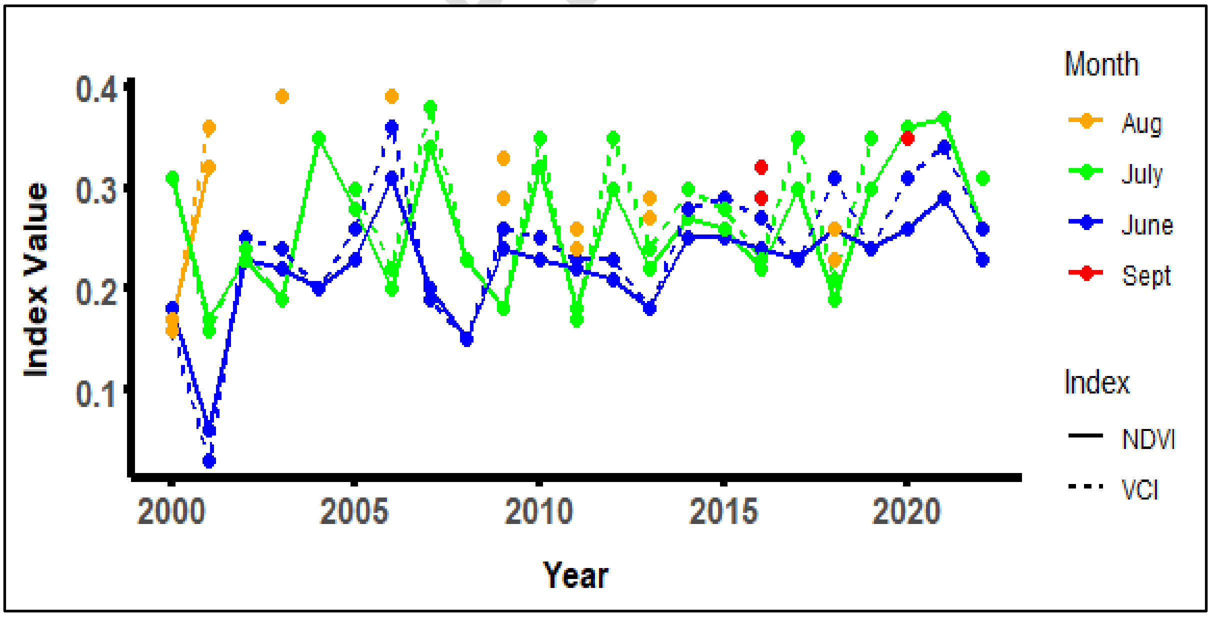

Fig 4. Agricultural drought events as per NDVI and VCI at Chitapur station

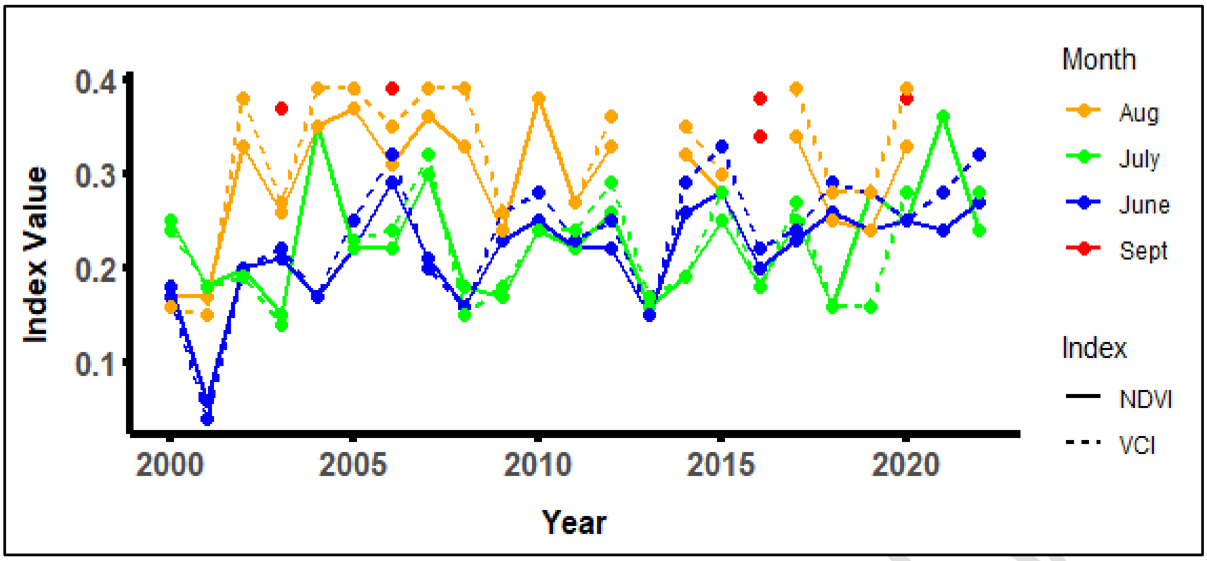

Fig 5. Agricultural drought events as per NDVI and VCI at Jawargistation

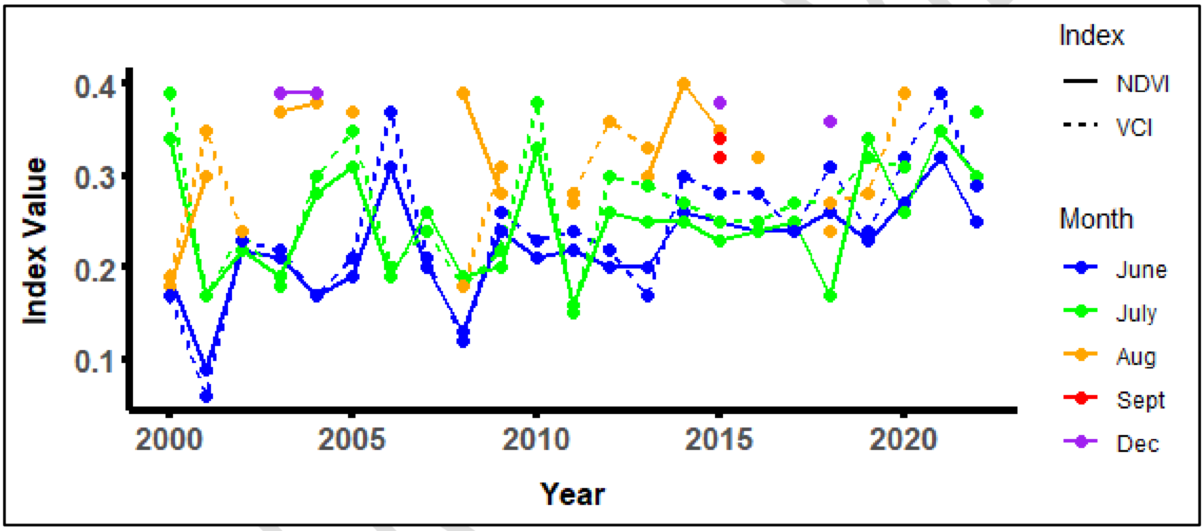

Fig 6. Agricultural drought events as per NDVI and VCI at Kalaburgistation

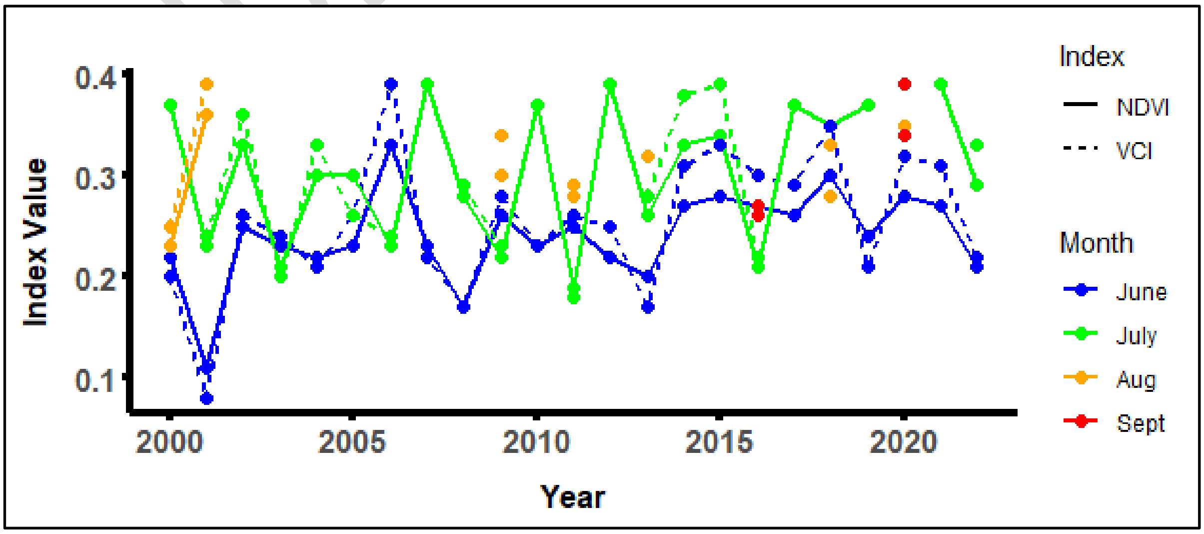

Fig 7. Agricultural drought events as per NDVI and VCI at Sedamstation

V. Conclusion

This study provides a detailed assessment of drought severity and its impact on vegetation health in the Kalaburgi district of North-Eastern Dry Zone of Karnataka, Utilizing NDVI and VCI within the Google Earth Engine (GEE) platform,the analysis reveals significant variability in drought conditions.Severe to moderate droughts during critical years adversely affected vegetation, while other years exhibited moderate and mild drought conditions. The strong correlation between NDVI and VCI confirms their effectiveness in monitoring vegetative stress due to drought. These indices offer valuable spatial and temporal insights, serving as effective tools for assessing agricultural drought impacts. The study highlights the importance of integrating remote sensing-based indices with advanced geospatial tools like GEE for efficient drought monitoring and mitigation strategies. This approach enhances drought resilience and supports sustainable agricultural practices, ensuring preparedness against climate variability in drought-prone regions.

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