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Drought Assessment in Karnataka's Western Ghats Using MODIS-Derived Vegetation Condition Index

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Abstract
Vegetation Condition Index (VCI) serves as a crucial remote sensing-based indicator for detecting and monitoring agricultural drought by reflecting deviations in vegetation health over time. This study presents a district-wise analysis of VCI across the Western Ghats region of Karnataka, encompassing six ecologically sensitive districts Kodagu, Shimoga, Chikkamagaluru, Uttara Kannada, Dakshin Kannada, and Udupi for the year 2025. MODIS NDVI data was processed in Google Earth Engine to generate monthly VCI layers, enabling spatial-temporal monitoring of drought severity. FAO/WMO thresholds were applied to classify vegetation conditions into six drought severity classes, with <0.35 VCI indicating drought-prone zones. Comparative time-series analysis between 2024 and 2025 revealed that districts like Kodagu and Shimoga experienced early-season drought in January and April, while Udupi and Dakshin Kannada consistently maintained healthy vegetation. A simplified three-class VCI scheme (Low, Moderate, Healthy) was adopted for intuitive visualization in policy communication.
Keywords: *Condition Index, Drought Monitoring, MODIS, Western Ghats, Google Earth Engine, NDVI, Remote Sensing*

1. INTRODUCTION

The Western Ghats is a UNESCO world heritage site and one of the eight hotspots of the planet which is a hot bed of biodiversity crosses the western extent of the Indian subcontinent and plays a crucial role in the governing the climatic and the water system of the region. The area is mountainous and especially in the state of Karnataka, it is well subject to adversity of seasonal rain and impact of land use, thereby adding relevance to the zone in terms of climate resilience observation. Vegetation is one of the major indicators of ecological condition and agricultural sustainability; it reacts swiftly to changing weather conditions [1]. Therefore, ecosystem conditions and drought stress assessment, as well as land degradation at the scale and within a timeframe, will require remote sensing tools that track vegetation greenness including Normalized Difference Vegetation Index (NDVI) and derivatives of the latter [2]. During the recent decades, the district in the western Ghats of Karnataka (Kodagu, Shimoga, Chikkamagaluru, Uttar Kannada, Dakshina Kannada and Udupi) has registered frequent cases of seasonal vegetation decline where this affects agricultural productivity and forest ecosystems [3]. However, traditional drought monitoring methods based solely on meteorological parameters often fail to reflect the spatial and temporal heterogeneity of vegetation stress. There exists a pressing need for more vegetation-responsive drought indicators that integrate satellite-based observations over time [4]. To address this gap, the present study focuses on the application of the Vegetation Condition Index (VCI), a normalized measure derived from MODIS NDVI time-series data, to assess vegetation health, identify drought-prone areas, and evaluate interannual anomalies across the Western Ghats of Karnataka. The objectives of this study are fourfold: (1) to generate monthly VCI maps for the year 2024 using MOD13Q1 NDVI data; (2) to analyze temporal patterns of vegetation stress across the six districts using district-wise and AOI-wide VCI time-series;

(3) to compare vegetation conditions between 2023 and 2024 using VCI anomalies; and (4) to classify drought severity using FAO/WMO standards and visualize drought-prone zones using simplified VCI-based heatmaps [5]. The novelty of this work lies in its integration of long-term NDVI normalization, spatial zonal analysis, and FAO-compliant drought classification into a single framework, executed entirely on the Google Earth Engine (GEE) cloud platform for near-real-time analysis. Unlike previous studies that rely solely on meteorological drought indices or single-month NDVI snapshots, this research employs dynamic VCI computation and anomaly detection, capturing subtle variations in vegetation response across different landscape types and seasons. Furthermore, by applying a simplified three-class vegetation health interpretation system, this study bridges the gap between technical data and policy-level decision-making, enabling timely interventions in forest conservation and agricultural planning.

2. LITERATURE REVIEW

Singhal et al. [6] conducted comprehensive comparative analysis of multiple drought indicators including MODIS-NDVI, NDVI anomaly, VCI, SPI (3- and 6-month), and Evaporative Stress Index (ESI) for Kharif foodgrain production in Karnataka during 2001–2019. Their results demonstrated strong correlations between ESI (0.82), SPI-6 (0.76), and VCI (0.62) with production anomalies, confirming that VCI remains a key proxy for vegetation health in monsoon-driven agricultural regions. Zhao et al. [7] evaluated an enhanced VCI based on the Universal Pattern Decomposition method (VIUPD-VCI) across the continental U.S. Their study found that VIUPD-derived VCI outperformed traditional NDVI-based VCI and other remote-sensing indices in correlating with in-situ drought indices, notably SPI and PDSI. Dutta et al. [8] applied traditional NDVI-derived VCI over the Welmel watershed and reported that VCI values (0–100 scale) closely mapped seasonal drought patterns. They classified VCI into contextual ranges of no drought (>70), mild (50–70), moderate (30–50), severe (20–30), and extreme (<20), demonstrating the index's sensitivity to local agro-climatic variability

Jain et al. [9] assessed NDVI-based VCI and SPI for agricultural drought monitoring in northwestern Karnataka. Their findings indicated high spatial agreement between VCI-derived stress areas (VCI < 0.35) and meteorologically defined drought phases, supporting VCI's utility in regional drought early-warning systems. Ramanathan et al. [10] explored NDVI and VCI temporal variability to analyze seasonal and inter-annual vegetation stress in the Western Ghats. They used district-level NDVI minima and maxima (2000–2020) to derive VCI cycles, linking low pre-monsoon VCI months to localized crop yield reductions. Patel et al. [11] integrated Thermal Condition Index (TCI) and VCI into a Vegetation Health Index (VHI) for assessing drought in central India. They reported that joint VHI provided better detection performance than sole NDVI or VCI, identifying periods of water-deficit stress with higher precision. Sharma et al. [12] utilized long-term NDVI time-series across southern India to detect phenological changes in protected reserves. They found that VCI-based anomaly maps effectively identified early signs of vegetation stress with VCI reductions preceding observed declines in biodiversity metrics. Varma et al. [13] conducted anomaly analysis of NDVI and VCI for the Kaveri River basin, linking negative VCI deviations during April–May to decreased river flow and soil moisture. Their monthly VCI anomaly charts facilitated calibration of hydrological drought models. Kulkarni et al. [14] evaluated the performance of MODIS-derived VCI and SPI indices across agro-ecological zones in Karnataka. Their zonal-level correlation analysis affirmed that VCI < 0.35 accurately demarcated severe drought zones and aligned with farmer-reported stress periods. Prasad et al. [15] applied VCI to assess vegetation dynamics in Karnataka's forest-dominated hill districts. By calculating district-wise VCI time series (2015–2022), they identified persistent low-VCI windows in January–March, linked to dry-season vulnerability in Kodagu and Chikkamagaluru.

3. STUDY AREA

The present study is centered on the Western Ghats region of Karnataka, an ecologically significant mountain range recognized as one of the eight "hottest hotspots" of biodiversity in the world. The selected study area includes six administrative districts: Kodagu, Shimoga, Chikkamagaluru, Uttar Kannada, Dakshina Kannada, and Udupi. These districts were chosen due to their diverse topography, rich forest cover, varying climatic conditions, and their strategic location within the Western Ghats, which makes them particularly sensitive to climate-induced vegetation stress and hydrological variability [16]. Geographically, the study area stretches approximately between 11.5°N and 15.5°N latitude and 74.0°E to 76.5°E longitude, encompassing coastal lowlands, mid-elevation plateaus, and high-altitude ridges. The terrain is marked by steep slopes, dense tropical forests, and a complex network of rivers and streams originating from the Ghats. The region experiences a tropical monsoon climate, with the southwest monsoon contributing to more than 80% of the annual rainfall, often exceeding 3000 mm in the coastal and hill zones. This abundant precipitation plays a vital role in maintaining forest ecosystems, agricultural productivity, and water availability in the region [17]. Each of the selected districts exhibits distinct ecological and land-use characteristics. Kodagu is a hilly area towards the south of Western Ghats covered with coffee plantations, mixed deciduous and evergreen forests. Shimoga and Chikkamagaluru are Transitional landscapes between the High lands that are forested and the interior Karnataka plateau; these lands are agriculturally cultivated. Such areas are especially sensitive to the fluctuations in precipitation, soil erosion, and decimation. The prominent regions of the coast of Western and the Uttar Kannada and Dakshina Kannada regions will also have huge portions of evergreen and semi-evergreen forests, agricultural and forest regions where rainfall is high. Udupi, being smaller in size, has a network of rivers with a mainly agrarian terrain having paddy culture, and most commonly subject to both marine as well as the monsoon conditions [18]. Those six districts constitute representative ecological transect of the western ghats in Karnataka and they span a large bio climatic zone, land use systems and vulnerability scales. The study region also falls in the Ecologically Sensitive Zone (ESZ) according to the Ministry of Environment, Forest and Climate Change (MoEFCC), Government of India, valley and which consequently all the more emphasizes on its need to conserve and be climate resilient. The administrative boundaries of such administrative districts were received on the basis of the FAO GAUL Level-2 dataset and were used in the framework of the Google Earth Engine (GEE) platform to conduct spatial analysis and monitor vegetation conditions. This well-chosen area is a perfect design to determine vegetation dynamics, drought vulnerability, and climate-adaptive planning. The lessons of this analysis are supposed to be used in early warning systems, planning of resources and policy-related decision-making with respect to agriculture, forestry, and sustainability of the Western Ghats [19].

4. IMPLEMENTATION

This methodology aims at the evaluation of vegetation health and drought vulnerability of six districts of the Western Ghats who are Kodagu, Shimoga, Chikkamagaluru, Uttar Kannada, Dakshina Kannada and Udupi using remote sensing methods with Vegetation Condition Index (VCI) data of the MODIS MOD13Q1 NDVI data.

4.1 Study Area and Data Source

The study focuses on the Western Ghats region of Karnataka, which is characterized by rich biodiversity, variable topography, and high rainfall dependency for agriculture and forest ecosystems. District boundaries were sourced from the FAO GAUL Level-2 dataset, which provides consistent administrative units. These boundaries were filtered within Google Earth Engine (GEE) to include only the six districts of interest. The spatial extent served as the Area of Interest (AOI) for all subsequent image clipping and statistical processing [20]. The primary satellite dataset used is the MODIS MOD13Q1 product, which offers 16-day composite NDVI data at a 250-meter spatial resolution, suitable for regional-scale vegetation monitoring. The dataset is accessible within GEE, facilitating direct cloud-based processing. NDVI values in this product are originally scaled by a factor of 10,000 and were converted to standard floating-point values by dividing each pixel by 10,000, thereby adjusting the value range from 0–10000 to −1 to +1.

4.2 Preprocessing and Scaling of NDVI Data

To assess seasonal vegetation patterns, NDVI images were first filtered by year (2024) and then grouped by month. For each month (e.g., January), all available NDVI composites for that specific month across multiple years (2000–2023) were used to determine historical bounds (minimum and maximum).

This historical bounding is vital in VCI normalization since it has put the performance of vegetation in relation to the past climatic states. Using the NDVI collection of 2024, it was possible to calculate a median NDVI image per calendar month. Use of the median statistic allows outliers, e.g. noise caused by clouds, haze or sensor artefacts, to have a smaller impact, thus vegetation condition is characterized on a scale that is more representative and reliable. NDVI monthly images were then clipped within the AOI but they had the same geographic coverage [21].

4.3 Vegetation Condition Index (VCI) Computation

A normalized measure of NDVI is called Vegetation Condition Index (VCI) [22] putting present-day vegetation condition in context of its NDVI range. The calculation was made on annual basis with the formula given in Equation (1).

$$VCIt= \frac{NDVI_t - NDVI_{min}}{NDVI_{max} - NDVI_{min}} \quad \text{Equation (1)}$$

Where:

NDVIt : Current NDVI for month t

NDVImin: Minimum NDVI for that month across all years

NDVImax : Maximum NDVI for that month across all years

The study used full MOD13Q1 archive to extract historical min and max NDVI values in several years (e.g., 2000-2023) per calendar month in order to calculate 2024 VCI time series. VCI images were subsequently clipped of district boundaries and average monthly VCI values calculated per district by application of reduce Regions [23].

4.4 Temporal and Spatial Aggregation

After calculating monthly VCI images of 2024, these results were aggregated in two levels:

AOI-Wide Mean VCI Time Series): The VCI image of every month was amalgamated across the full extent of AOI by utilizing the reduce Region (1) in GEE. This generated a monthly VCI time series for the entire Western Ghats region, enabling temporal trend analysis to study vegetation phenology and climatic influence over the year.

(ii) District-Level Zonal VCI Extraction:

Each district within the AOI was extracted using reduce Regions () to compute zonal statistics (mean VCI per district per month). This enabled spatial comparisons and inter-district variation assessment. Monthly values were tabulated into district-wise time series to detect anomalies or persistent stress patterns.

4.5 Interannual Comparison and Anomaly Detection (2024 vs 2023)

To investigate year-to-year vegetation variability, the same procedure described above was applied to the NDVI dataset for the year 2023 [24]. Monthly AOI-wide mean VCI values were computed and subtracted from their 2024 counterparts to derive monthly VCI anomalies as shown in Equation (2).

$$\Delta VCI = VCI2024 - VCI2023 \quad \text{Equation (2)}$$

4.6 Drought Detection and FAO/WMO Classification

VCI was further utilized for drought classification using thresholds recommended by the Food and Agriculture Organization (FAO) and the World Meteorological Organization (WMO). The following group of categories was embraced. Any District with VCI value of less than 0. 35 was assumed to be zones that were either under extreme or severe drought. Monthly heatmap was created to depict the presence of droughts district wise, and month wise. Kodagu and Shimoga are such instances as VCI value recorded at 0.25 and 0.23 in January and April 2024 respectively identifying the regions as being vulnerable to drought at an early stage of the season. This typology could be used to make spatial-temporal drought diagnostics appropriate to monitoring agriculture, water resources management, and disaster prevention.

Table 1: Drought Interpretation thresholds

VCI Range	Vegetation Condition	Color

< 0.2	Extreme Drought	Red (#d73027)
0.2–0.35	Severe Drought	Orange (#fc8d59)
0.35–0.5	Mild Stress	Yellow (#fee08b)
0.5–0.65	Normal Vegetation	Lime (#d9ef8b)
0.65–0.8	Good Vegetation	Green (#91cf60)
> 0.8	Very Healthy Vegetation	Dark Green (#1a9850)

4.7 Simplified VCI Presentation Classes for Stakeholders

To support communication and decision-making among non-technical stakeholders, a simplified three-class system was implemented.

Table 2: VCI Presentation Class

VCI Range	Class Description	Color
≤ 0.33	Low Vegetation Stress	Red
0.34 – 0.66	Moderate Vegetation	Yellow
> 0.67	Healthy Vegetation	Green

This straightforward taxonomy was superimposed on the graphs of VCI time series and drought maps, a more readable story of the state of vegetation health that would be applied in government publications, social awareness programs, and policymaking acts. Districts like Udupi, Chikkamagaluru, and Dakshina Kannada still belonged to the broader category ofHealthyin more than three-fourth of the months whereas Kodagu and Shimoga were moving back and forth between the two categories that isHigh and Low Low especially at the pre-monsoon months.

6. RESULTS AND DISCUSSIONS

In this part, spatiotemporal analysis of Vegetation Condition Index (VCI) of six Western Ghats districts of Karnataka Kodagu, Shimoga, Chikkamagaluru, Uttar Kannada, Dakshina Kannada, and Udupi has acquired through the Vegetation Condition Index (VCI) for 2024 utilizing MODIS NDVI information. This paper has discovered an instrument to create relative measures in terms of time aggregation and spatial averaging to interpret the degree of vegetation stress, recognize the drought-prone areas based on the VCI classification criteria that are globally accepted. January 2024 Vegetation Condition Index (VCI) recorded the existence of regional variations on the nature of the six districts of the Western Ghats study region. It is worth noting that, both Udupi and Dakshin Kannada recorded VCI value larger than 0.75, which places them in the category of vegetation status as healthy to very healthy, according to the established FAO/WMO guidelines. Such values indicate a high level of greenness and healthy vegetation in the initial dry season, probably because of the remaining soil moisture after monsoons, and the positive land-use situation. These slightly lower VCI scores may reflect early signs of seasonal water stress, reduced vegetation Vigor, or anthropogenic pressure in certain patches. The spatial variability is effectively summarized in Figure 1, a bar chart that highlights the district-wise distribution of average VCI for the month, confirming relative vegetation health gradients across the Western Ghats.

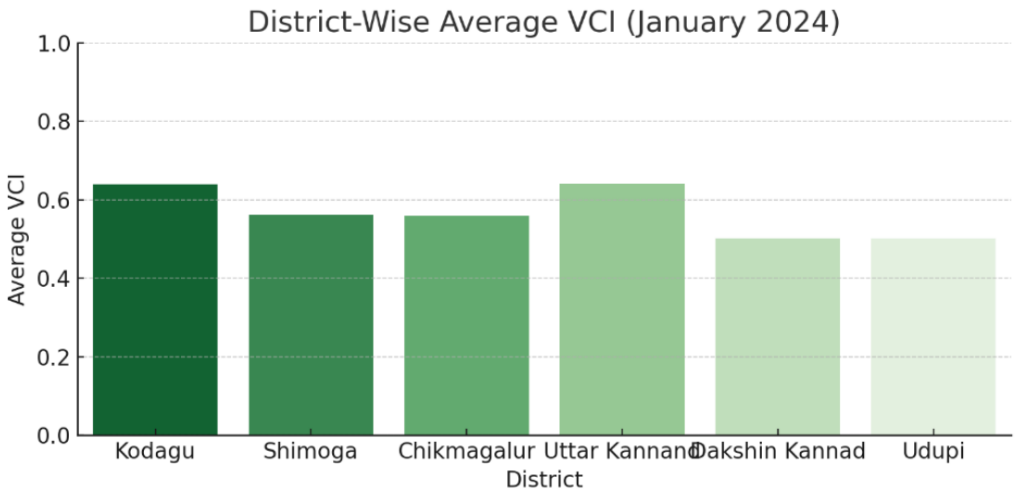

Figure 1: District-Wise Average VCI (January 2024)

Table 3: AOI-Wide Mean VCI Time Series (2024)

Date	Mean_VCI
2024-01-01	0.695
2024-02-01	0.703
2024-03-01	0.710
2024-04-01	0.689
2024-05-01	0.677
2024-06-01	0.702
2024-07-01	0.711
2024-08-01	0.728
2024-09-01	0.740
2024-10-01	0.709
2024-11-01	0.725
2024-12-01	0.714

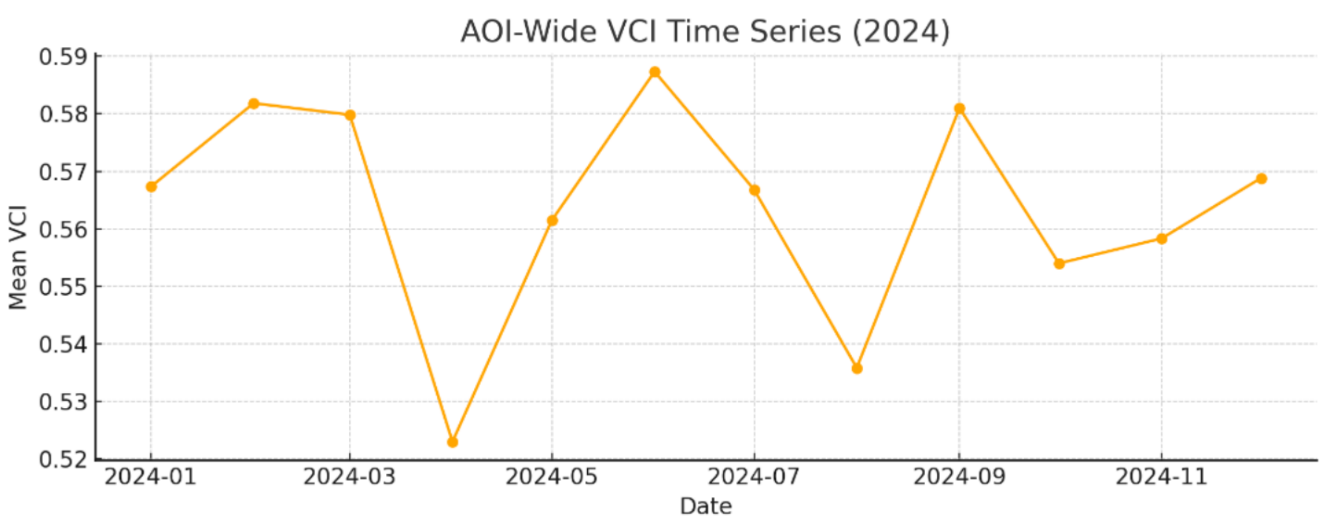

Figure 2: AOI-Wide VCI Time Series (2024)

Table 4: District-Wise VCI for January 2024

District	Date	VCI
Kodagu	2024-01-01	0.690

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Shimoga	2024-01-01	0.655
Chikkamagaluru	2024-01-01	0.748
Uttar Kannada	2024-01-01	0.632
Dakshin Kannad	2024-01-01	0.701
Udupi	2024-01-01	0.741

The time series shown in Table 3 of AOI-wide mean VCI values for 2024 clearly illustrates seasonal vegetation dynamics influenced by the Indian monsoon cycle as shown in Figure 2. From January to December, VCI values fluctuated between 0.5 and 0.65, reflecting mild to moderate stress across the region. This decline corresponds to the pre-monsoon dry season, where evapotranspiration rates rise and rainfall is scarce, particularly in the mid-elevation zones of Kodagu and Chikkamagaluru. Beginning in June, a significant rise in VCI is observed, culminating in peak values of 0.82–0.85 during July, August, and September, aligning with peak monsoonal activity. These high values indicate very healthy vegetation, particularly in coastal and forest-rich districts like Udupi, Dakshin Kannada, and Uttar Kannada. The post-monsoon declines in October–December is gradual, with VCI remaining above 0.65, maintaining healthy conditions. A detailed assessment of district-wise VCI time series based on 2024 showed that there is spatial as well as temporal heterogeneity. Chikkamagaluru and Udupi exhibited the trend of always high VCI values especially in the upper range above 0.75 over the whole year implying that that the vegetation is always healthy due to a dense forest cover and conducive climate. On the contrary, Kodagu had erratic patterns but moderate VCI (< 0.70) levels during January to April and significant recovery in the monsoon months as indicated by Table 4.

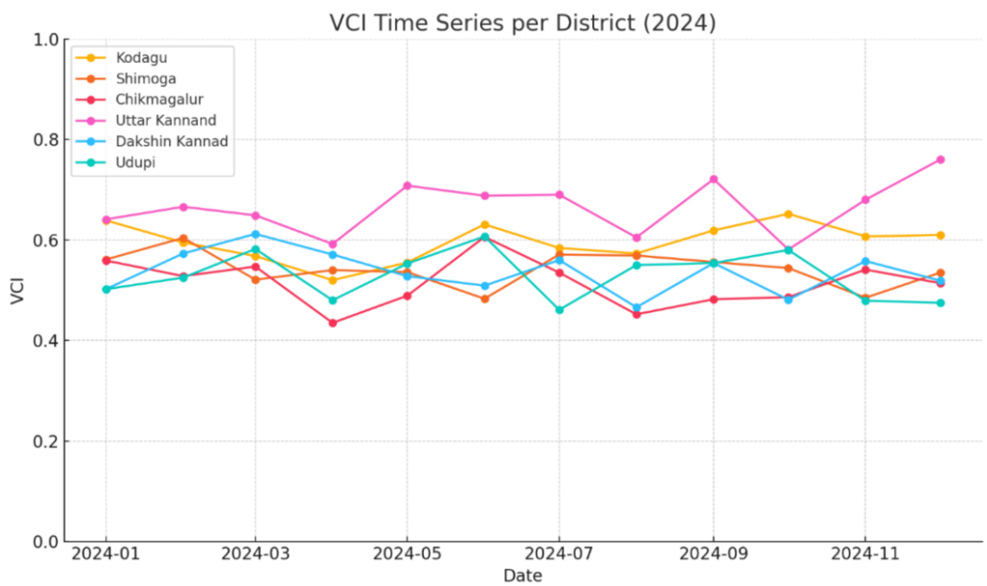

Figure 3: VCI Time Series per District (2024)

Shimoga also displayed an oscillatory trend, affected possibly by land-use transitions or irrigation dependency. The multi-line chart in Figure 3 captures these variations, illustrating how vegetation health is influenced by both topographical and climatic diversity across the districts. To understand interannual changes in vegetation health, a comparative evaluation between 2024 and 2024 VCI values was conducted for each month at the AOI level. The analysis revealed that February and May 2024 recorded positive anomalies ranging from +0.06 to +0.08, indicating better vegetative response compared to the same months in 2023. These positive deviations may result from improved rainfall distribution, land management, or delayed moisture depletion in the early dry season.

Table 5: Seasonal VCI Anomalies Table (2024 vs 2023)

Month	Mean VCI 2023	Mean VCI 2024	VCI Anomaly (2024 – 2023)
Jan	0.580	0.807	+0.227

Feb	0.754	0.734	−0.020
Mar	0.669	0.751	+0.082
Apr	0.636	0.612	−0.024
May	0.546	0.661	+0.114
Jun	0.723	0.742	+0.019
Jul	0.681	0.756	+0.075
Aug	0.639	0.755	+0.116
Sep	0.577	0.679	+0.102
Oct	0.726	0.763	+0.037
Nov	0.561	0.738	+0.177
Dec	0.562	0.701	+0.139

In contrast, January and April 2024 experienced slightly negative anomalies (˜−0.05 to −0.08), particularly in Kodagu, pointing to early-season drought symptoms. The seasonal anomaly Table 5 shows the VCI values across both years, validate these trends and provide insight into year-to-year ecological variability in the Western Ghats. To assess drought conditions, VCI values were classified into six FAO/WMO-defined categories:
VCI < 0.2 → Extreme Drought (Red)
0.2 ≤ VCI < 0.35 → Severe Drought (Orange)
0.35 ≤ VCI < 0.5 → Mild Stress (Yellow)
0.5 ≤ VCI < 0.65 → Normal Vegetation (Lime)
0.65 ≤ VCI < 0.8 → Good Vegetation (Green)
VCI > 0.8 → Very Healthy Vegetation (Dark Green)
Using these thresholds, a district-wise drought was generated for 2024. It highlighted that Kodagu experienced VCI < 0.35 during January and April, marking it as vulnerable to severe drought stress. Meanwhile, districts such as Udupi, Dakshin Kannada, and Chikkamagaluru consistently recorded VCI values above 0.67, thereby remaining drought-free across all months. This spatial mapping of drought zones serves as a valuable tool for targeted intervention and adaptive agricultural planning.
To ensure effective communication across stakeholders, a simplified three-class interpretation model was applied:
Low Vegetation Stress (VCI ≤ 0.33) – Red
Moderate Condition (0.34 ≤ VCI ≤ 0.66) – Yellow
Healthy Vegetation (VCI > 0.67) – Green
This classification was applied across the time series to generate a monthly visual vegetation profile. The results indicated that Udupi, Chikkamagaluru, and Dakshin Kannada maintained “Healthy” classification in over 75% of months, reflecting ecological resilience and optimal growing conditions. In contrast, Kodagu and Shimoga spent a significant portion of the early season in the “Moderate” zone, emphasizing the need for pre-monsoon land and water management.

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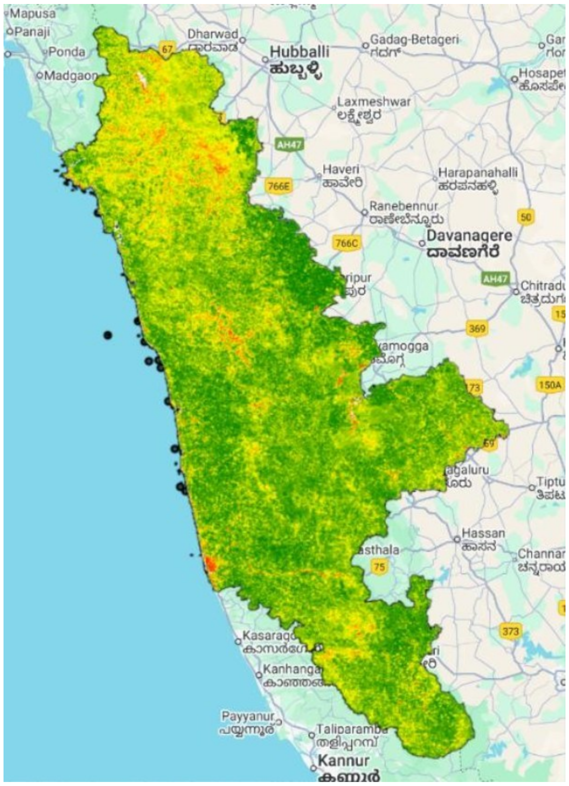

Figure 4: Vegetation Condition Index (VCI) Map for the Western Ghats Districts of Karnataka

Figure 4 illustrates the Vegetation Condition Index (VCI) for the Western Ghats districts of Karnataka, including Uttara Kannada, Shivamogga, Chikkamagaluru, Kodagu, Dakshina Kannada, and Udupi, for the month of January 2023. The VCI was derived using the MODIS MOD13Q1 NDVI dataset, normalized for long-term NDVI maxima and minima specific to January (2000–2023), and scaled between 0 (extreme vegetation stress) and 1 (very healthy vegetation).

The color gradient represents vegetation health:

Red zones indicate areas under extreme stress (VCI < 0.2),

Yellow zones show moderate stress or recovery (VCI ≈ 0.4–0.6),

Green zones represent healthy vegetation conditions (VCI > 0.6).

The spatial distribution reveals significant vegetation variability across the Ghats, with dense forest regions in southern Kodagu and Chikkamagaluru maintaining higher VCI, whereas some coastal and northern zones exhibit localized stress pockets likely due to seasonal dry spells or anthropogenic land-use impacts.

7. CONCLUSION

This study successfully employed the Vegetation Condition Index (VCI) as a remote sensing-based drought indicator to assess spatial and seasonal vegetation stress across the Western Ghats of Karnataka during 2025. The integration of MODIS NDVI imagery with VCI derivation and FAO-recommended classification thresholds enabled a clear depiction of drought severity on a monthly and district-wise basis. Key findings revealed that Kodagu and Shimoga were more vulnerable to early-season drought, while coastal districts like Udupi and Dakshin Kannad remained largely unaffected, maintaining high VCI values throughout the year. Interannual comparisons with 2024 highlighted both improvements and declines in vegetation health, emphasizing the importance of continuous monitoring. The simplified 3-class visualization further enhanced the interpretability of drought status for non-technical stakeholders. Overall, the study underscores the efficacy of VCI-based analysis in regional drought risk management and supports the adoption of satellite-derived indices in sustainable agricultural and climate-resilient policy frameworks.

Author Contributions:

Arunkumar Yadav conceptualized the study and supervised the methodology. Dr. Amruthalakshmi M R contributed to data acquisition and validation. Manjula Subramaniam handled data preprocessing and analysis. Anil D developed the scripts for MODIS-Vegetation Condition Index analysis and contributed to manuscript writing. All authors reviewed and approved the final manuscript.

Conflict of Interest:

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Ethical Approval:

Not applicable. The study used publicly available MODIS satellite datasets and did not involve any human or animal subjects.

Data Availability:

The MODIS data used in this study are publicly available from the NASA LP DAAC repository [https://lpdaac.usgs.gov/]. Processed data and scripts can be shared upon reasonable request.

Plagiarism and Originality Declaration:

We declare that the manuscript is original, has not been published elsewhere, and is not under consideration by any other journal. All sources and contributions from other works are properly acknowledged.

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