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Real-Time Drought Monitoring And Prediction Using Multispectral Remote Sensing And Machine Learning

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Abstract

This research examines real-time drought monitoring & prediction utilizing multispectral satellite data as well as machine learning algorithms. Multiple drought indicators, including NDVI, VCI, TCI, LST, Rainfall, & SPI-3, were used to evaluate vegetative health and identify drought conditions in the Beed and Maharashtra areas. The findings suggest that vegetative health was regularly poor between the years 2020 and 2023, with NDVI decreasing to 0.12, VCI and TCI falling below 40, through VHI reaching severe drought levels of 10-20, particularly between January and May. Conditions only improved during the monsoon season, when rainfall climbed to 20-30 mm, bringing NDVI to 0.25-0.35 and VHI to 60-70. A drought-prediction model was created utilizing 262 Beed data and 2,355 Maharashtra samples, using VHI as the goal variable. Beed's model has an average cross-validation score of $R^2 = 0.977 \pm 0.028$ *and outstanding overall accuracy (*$R^2 = 0.998$*, RMSE = 0.836). The Maharashtra model performed much better, with CV* $R^2 = 0.993 \pm 0.010$*, final* $R^2 = 0.999$*, & RMSE = 0.351. Feature significance analysis revealed that vegetation-based variables dominated prediction, with VCI (0.43-0.46) and NDVI (0.41-0.47) accounting for more than 90% of the model's predictive power. The temperature indicators (TCI = 0.03-0.05; LST = 0.03-0.06) had a little impact, whereas rainfall (~0.001) and SPI-3 (~0.000) provided nearly nothing. Overall, the data show that drought conditions in both locations are primarily caused by vegetative stress resulting from low rainfall along with rising land-surface temperatures. The combination of multispectral remote sensing with machine-learning models allows a highly accurate and dependable method for real-time drought assessment, delivering a strong tool for agricultural planning and climate risk management in drought-prone regions.*

Keywords: *Beed, Drought Monitoring, LST, Maharashtra, NDVI, Prediction, Rainfall, RMSE, SPI-3, TCI, VCI*

1. INTRODUCTION

In order to assess the severity, duration, and spatial extent of a drought, drought indices are quantitative measures that define and monitor drought conditions. They do this by condensing complex hydroclimatic data into a single numerical value. It is common knowledge that drought is a naturally occurring phenomenon brought on by a lack of precipitation and the ensuing hydrological imbalance. Drought has numerous detrimental effects and can occur in any climate[1].

The Standardized Precipitation Index (SPI) for precipitation deficits, the Palmer Drought Severity Index (PDSI) for regional water balance, the Standardized Precipitation-Evapotranspiration Index (SPEI) for evapotranspiration, and remote sensing indices like the Vegetation Condition Index (VCI) for vegetation health monitoring are examples of common types. Planning for agriculture, disaster preparedness, and the management of water resources all depend on these indices[2].

Drought is defined in a variety of ways, such as "a period of dry weather," "an unusually dry weather cycle that causes an extreme hydrogeological imbalance, with effects such as crop losses as well as lack of water for humans and livestock," and "a creeping situation of scarcity without a recovery of resources." Droughts can be classified in a variety of ways because we have different ways of identifying drought conditions in particular places and times. The most commonly used definition, meteorological drought, is linked to the extent of dryness and the duration of dry weather[3].

A precipitation deficit greater than 25% of the average in a particular region of the world is referred to as a drought. Severe drought occurs when the precipitation deficit surpasses 50% of the long-term average. It is crucial to remember that hydrological, ecological, and human-caused factors are not taken into account by the meteorological concept of drought. Hydrological drought conditions, which include low stream flow along with acute drying of ponds, lakes, reservoirs, as well as rivers, are brought on by a large loss of surface water. A period of inadequate soil moisture that severely stresses crops and lowers crop productivity is known as an agricultural drought. The phrase "ecological drought" describes a situation where decreased precipitation causes a natural or managed ecosystem's primary productivity to drastically decline over time. Socio-economic droughts, when combined with all other types of droughts, happen when precipitation is insufficient to support human activity[4].

Drought indices combine a number of environmental variables, including temperature, precipitation, soil moisture, and streamflow. This standardized value makes it simple to compare drought conditions over time and across different regions, offering a reliable method of tracking drought status[5]. When making decisions about reservoir operations, infrastructure design, and water allocation, indices offer a precise, numerical foundation. Using these indices for ongoing monitoring aids in the early identification and proactive execution of drought response plans. They make it possible to systematically monitor the availability of water and assist in controlling demand during dry spells, guaranteeing a steady supply. Crop selection and irrigation scheduling are guided by indicators of soil moisture as well as vegetation health[6]. The IMD reports that 258 districts in September 2023 and 220 districts in June–September 2023 fell into the deficient/large deficient rainfall categories. As of early 2024, 26% of India's land area was affected by drought, with 9% of that area experiencing extreme drought, according to Sphere India. Research has identified areas that are particularly affected by drought, such as the precarious state of Karnataka, vulnerable parts of Tamil Nadu, and the northwest as well as southern regions[7].

India's drought conditions vary significantly from year to year and by region. The use of multiple drought indicators for monitoring is validated by studies that consistently demonstrate strong correlations between various indices. The need for sophisticated, real-time data integration and also adaptive management techniques is highlighted by the rising frequency of serious drought incidents including the severe droughts in 2020 and 2021. Improving agricultural drought monitoring techniques is becoming more and more important since it has a big impact on crop yields and food security[8].

Impact of Drought:

The effects of drought are extensive and impact many different economic sectors and domains. The effects of drought are felt well beyond the boundaries of the regions that are experiencing the attacks of physical drought because water and farming supplies are essential to our ability to produce more products and services. Drought is the root cause of the nation's economic problems, which have both direct and indirect effects on the macro and microeconomic levels[9].

Food insecurity among the impoverished and vulnerable has increased as a result of decreased agricultural production. Depletion of water levels has resulted in increased wildlife mortality, migration of livestock and cattle, damage to the ecosystem from careless exploitation, an increase in fires, and other consequences. The following elements must be taken into account when evaluating the indirect impacts of drought: lower incomes for farmers as well as seed companies, higher prices for food and fodder, a decline in consumer spending and purchasing power, farm loan defaults, depressed sales of livestock in the agriculture sector, unrest in rural areas, and fewer job opportunities in agriculture these negative impulses have a substantial negative multiplier effect on society and the economy. The effects of drought fall into three categories: social, economic, and environmental[10].

The effects of drought are usually broad and all-encompassing, and it can be challenging to differentiate them from other causes. The fact that drought is consistently viewed as a "crisis condition" and a temporary issue is another factor exacerbating the issue. Individuals at the household level perceive drought as a significant phenomenon that is uncontrollable. The drought has an impact on agriculture and the economy at both the macro and micro levels across the nation. It can happen directly or indirectly, and depending on the location, the effect's type and strength change. The severity and intensity of the drought's impact and its consequences are influenced by a number of challenging factors, including economic conditions, agricultural sector patterns, irrigation operation, the availability of cereal reserves (both locally and international), conflicts within and between countries, and so forth[11].

The ability to grow and get food has a significant impact at the micro level, and this depends on a number of factors, including social structure, village as well as socioeconomic status, and endowments of domestic resources. On the other hand, the distinctive characteristics of each area would compare the precise and actual dimensions of each impact. As a direct result of water scarcity, droughts cause the loss of assets like crops, livestock, and productive capital. Livestock are also killed by droughts. The next time when there is a shortage of premium seeds, is when the aftereffect is felt. In parts of the impacted state or region that are experiencing severe drought, conditions such as famine are brought about[12]. Three broad categories can be used to classify the social, environmental, and economic consequences of drought:

Effects on the economy: Reduced productivity in the agricultural sector and associated sectors, especially dairy, poultry, farm animals, landscaping, as well as fishing, is referred to as agro-economic losses. The majority of sharecroppers, farmers, craftsmen, farm laborers, small agricultural enterprises, along with rural people as a whole who depend on agriculture are negatively impacted. All industries that depend on essential components from the primary industry suffer as a result of decreased supplies and rising prices in the primary industry. The economy experiences a dampening effect as a result of the supply chain disruption, which includes decreased consumer and industrial demand, a greater reliance on imports, as well as a decline in general market sentiment. Because there is less fresh water and clean drinking water available, drought also has a detrimental effect on the environment[13].

Impacts on the environment: Reduced water levels on land, ponds, lakes, surface reservoirs, river and stream flows, springs, loss of forest cover, wildlife migration, an increase in human-animal conflicts, as well as mental stress on biodiversity have all been linked to climate change. Salinity may be impacted by decreased flow rate and the disappearance of wetlands. Increased rates of groundwater depletion and decreased supply have the potential to harm aquifers and adversely affect water quality (such as acidity, pH, dissolved oxygen, and turbidity), which could eventually lead to a decline in soil biological productivity[14].

Social effects: Due to the migration of people from drought-affected areas, the increase in school dropout rates, the rise in poverty and debt, land alienation as well as food insecurity, the decreasing value of livestock resources, as well as social exclusion among some of the most economically disadvantaged populations, rural society has experienced widespread social disruption. In certain situations, scarcity can worsen tensions and lead to the depletion of social capital[14].

In India, modern technologies are used to monitor and forecast agricultural drought in real-time by analyzing vegetation health (e.g., NDVI), soil moisture, land surface temperature, as well as rainfall. These technologies include satellite-based remote sensing and sophisticated drought indices combined with machine learning. In order to create timely, high-resolution maps of drought severity for better resource management and food security, data from sources such as the Copernicus satellites along with the MODIS tool are incorporated into Composite Drought Indices (CDIs) and assessed using deep learning models[12].

Remote Sensing Technologies

Optical Sensors to calculate indices such as the Normalized Difference Vegetation Index (NDVI), which evaluates the health of the vegetation, analyze the radiation reflected from the Earth's surface in different spectral bands. Sensors for heat Calculate Land Surface Temperature (LST), which indicates soil moisture levels, by detecting the heat released from the Earth's surface. Sensors for microwaves to determine the soil moisture content a crucial component of drought severity use radar and radiometers. Sentinel-1 (SAR) and Sentinel-2 (Multispectral) High-resolution radar (SAR) as well as multispectral data from the EU's Copernicus program are used to map changes in vegetation stress, soil moisture, and land cover. NASA's Terra and Aqua satellites' Moderate Resolution Imaging Spectroradiometer [MODIS] provide daily to eight-day composites of Land Surface Temperature (LST) as well as other information essential for monitoring drought[10].

Drought Indices

The vigor and health of vegetation are measured by the Normalized Difference Vegetation Index [NDVI]. The NDVI is used to calculate the Vegetation Condition Index [VCI], which evaluates plant health in comparison to past data. Composite indices are created by combining the Temperature-based Vegetation Condition Index [TCI] with the VCI and NDVI. Drought monitoring is aided by the Soil Moisture Deficit Index [SMDI], which is frequently utilized as a model response variable in deep learning models. In order to provide a more thorough understanding of drought conditions, Composite Drought Indices (CDIs) indices combine several data sources and parameters using sophisticated weighting techniques[15]. The Combined Drought Indicator (CDI) and the Integrated Drought Monitoring Index (IDMI) are two examples.

Monitoring and Prediction Techniques

Fusion of Data a completer and more precise overview of drought conditions can be obtained by combining data from multiple remote sensing sources, such as optical, thermal, and microwave. Models of Deep Learning large amounts of remote sensing data are processed, complex relationships are learned, and discriminative features are extracted from the data using methods such as Multi-Layer Perceptron Neural Networks (DLMLPNN) alongside other deep forward neural networks. Analysis of Time Series understanding drought trends, severity, and long-term effects on ecosystems is made easier by analyzing long-term remote sensing data. The NADAMS project of the National Remote Sensing Centre (NRSC) in India uses remote sensing to monitor agricultural drought severity at the state, district, as well as sub-district levels in almost real-time. Earth Engine on Google for applications such as drought monitoring using MODIS along with additional satellite data collections, this cloud-based platform enables the processing and analysis of enormous volumes of satellite data[8].

Although there may be differences in the characteristics of the variables of interest for instance, low quantile is of interest for drought prediction while high quantile accuracy is of interest for flood prediction the techniques used in this study for drought prediction based on specific drought indicators may be applied directly to predict other risks related to hydroclimatic variables, including flood forecasting. By monitoring precipitation, the environment, land surface temperature, soil moisture, evaporation, and total water storage, among other things, remote sensing products already enable the observation of drought from a variety of angles[13].

Several indices, including the Vegetation Health Index (VHI), Temperature Vegetation Dryness Index (TVDI), and Short-wave Infrared Dryness Index (VSDI), were used in this study to track agricultural drought. The moisture state of vegetation (VCI) as well as thermal condition of vegetation (TCI) serve as the foundation for VHI. TCI is based on LST, while VCI is based on the NDVI. Two additional indices, TVDI and VSDI, were calculated using the LST and NDVI as well as the difference between a moisture reference band (blue) and moisture-sensitive bands (SWIR and red)[10].

2. LITERATURE REVIEW

Over the past few decades, researchers have explored the use of multispectral imagery and various drought indices, such as the Normalized Difference Vegetation Index (NDVI), Vegetation Health Index (VHI), and Standardized Precipitation Index (SPI), to assess drought severity and spatial distribution. Recent advances emphasize the integration of band combinations and spectral indices to improve the early detection of drought conditions, enabling near real-time monitoring and decision-making. Furthermore, the characterization of spatial drought patterns through geospatial analysis provides deeper insights into drought progression and regional vulnerability. This growing body of literature highlights the need for developing novel frameworks that combine multispectral data, spectral indices, and spatial analytics to enhance early prediction and effective drought management.

Hao Chen, et.al. [2025] results show that IMLDI has a higher spatial and temporal consistency with standardized precipitation evapotranspiration index, can better reflect the real-world observed drought-affected cropland areas and gross primary production, and can also well describe the evolutions of 2009/2010 and 2019 drought events in the eastern parts of China, indicating higher drought monitoring performance of IMLDI. Besides, IMLDI-based agricultural drought risk analysis shows that the Huang-Hai Region and Yunnan, Guizhou, and Guangxi Provinces have a high risk to suffer from severe agricultural droughts. Overall, IMLDI has a great potential to use as a new integrated remote sensing drought index for agricultural drought monitoring.

Neha Andure, et.al. [2024] explores the application of remote sensing, utilizing drought indexes, for effective monitoring and assessment of drought variables. The increasing availability of multispectral images, driven by rapid advancements in remote sensing technology, broadens the scope of this field. Droughts, as natural disasters, exert profound impacts on environmental factors such as agriculture, vegetation, human populations, wildlife, and local economies. Optical remote sensing technology emerges as a crucial tool in addressing these challenges, providing valuable insights into diverse land characteristics, and contributing to advancements in agricultural management and vegetation analysis. This study reviews and discusses various types of drought indexes based on multispectral data, utilizing different freely available satellite multispectral datasets such as Sentinel-2 data, Landsat, and MODIS.

Narayan Tatyaba Narbat, et.al. [2024] reviews about the current status of drought in India especially Maharashtra and offers suggestions to manage the drought in future. Drought has a gradual impact on the country's economy, but it has a long-term impact. Drought is one of the most serious dangers to people's livelihoods and socioeconomic development among natural catastrophes. It occurs less frequently than other dangers, but when it does, it typically impacts a large area for months or years at a time. India is split into 36 sub-divisions based on weather. The nation is split into 127 agro-climatic zones for agricultural planning and development, based on temperature, rainfall quantity, soil, and cropping pattern. Drought is a common occurrence in India's climate, and it is typically defined by its regional extent, intensity, and duration. It has a gradual beginning, unlike other natural catastrophes, but increases in strength with deadly consequences.

Pranav B. Mistry, et.al. [2023] analyze the vegetation stress in the Vadodara district with the calculation of NDVI, NDWI, MNDWI, WRI, NDBI and NDSI indices values. The results of NDVI values shows agricultural fields more susceptible to drought. Similarly, decreasing trend was observed in NDWI index which is 22.12% to 19.3% from 2013 to 2018.The built-up index (NDBI) is increasing by 1.85% in last 5 years. The Water ratio index is also showing decreasing trend in study area by 22.35% to 14.29%. The intercomparisons of NDVI and all other indices with rainfall data provides very useful information for agricultural drought monitoring and early warning system for the farmers. The findings of this research will be of interest to local agriculture authorities, like plantation and meteorology departments to understand drier areas in the state to evaluate water deficits severity and cloud seeding points during drought.

Niranga Alahacoon, et.al. [2022] review on drought indices used in monitoring meteorological, agricultural, hydrological, and socio-economic drought. Drought indices have been introduced as an important approach to quantitative and qualitative calculations of drought's severity and impact. There were 111 drought indices reviewed in this study, which fall into two categories: traditional (location-specific/model) and remote sensing (RS). Out of 111 indices, 44 belong to the traditional indices and 67 belong to the RS section. This study shows that meteorological drought monitoring has the highest number (22) of traditional indices, about 20% overall, while the lowest (7) agricultural drought monitoring is 6.3%. The specialty is that when considering remote sensing-based drought indices, 90% are used for agricultural drought monitoring and 10% for hydrological and meteorological drought monitoring. However, the study found that advances in satellite technology have accelerated the design of new drought indices and that replacing traditional location-specific data with satellite observation makes it easier to calculate more spatial distribution and resolution.

Lixin Wang, et.al. [2021] conclude that leveraging multi-sensor remote sensing provides unique benefits for regional to global drought studies, particularly in: revealing the complex drought impact mechanisms on various ecosystem components; providing continuous long-term drought related information at large scales; presenting real-time drought information with high spatiotemporal resolution; providing multiple lines of evidence of drought monitoring to improve modeling and prediction robustness; and improving the accuracy of drought monitoring and assessment efforts. Author specifically highlights that more mechanism-oriented drought studies that leverage a combination of sensors and techniques (e.g., optical, microwave, hyperspectral, LiDAR, and constellations) across a range of spatiotemporal scales are needed in order to progress and advance our understanding, characterization and description of drought in the future.

Foyez Ahmed Prodhan, et.al. [2021] show that the DFNN model outperformed the other two models for SMDI prediction. Furthermore, the results indicated that DFNN captured the drought pattern with high spatial variability across three penology stages. Additionally, the DFNN model showed good stability with its cross-validated data in the training phase, and the estimated SMDI had high correlation coefficient R2 ranges from 0.57~0.90, 0.52~0.94, and 0.49~0.82 during the start of the season (SOS), length of the season (LOS), and end of the season (EOS) respectively. The comparison between inter-annual variability of estimated SMDI and in-situ SPEI (standardized precipitation evapotranspiration index) showed that the estimated SMDI was almost similar to in-situ SPEI. The DFNN model provides comprehensive drought information by producing a consistent spatial distribution of SMDI which establishes the applicability of the DFNN model for drought monitoring.

N. Chattopadhyay, et.al. [2020] an effort has been made to monitor agricultural drought based on exploitation of new data, methodologies and metrics that would aid the experts to make best judgments of regional-scale drought conditions through CDI using geospatial technology. The present study has been carried out for three consecutive years of 2014, 2015 and 2016 in five states (Andhra Pradesh, Chhattisgarh, Haryana, Maharashtra and Telangana) in India at district level for southwest monsoon season when rainfed kharif crops are grown extensively across the above-mentioned states in India. CDI gives a synthetic and synoptic overview of the drought situations using a calibration scheme derived from various individual indices as it has been developed to combine the strength of various indices.

Willibroad Gabila Buma, et.al. [2019] results obtained present a coherent spatial distribution of VTCI values estimated using LST and NDVI. Most areas during the study period experienced mild drought conditions, though severe cases were often seen around the northern part of the lake. With limited in-situ data in this area, this study presents how VTCI estimations can be developed for drought monitoring using satellite observations. This further shows the usefulness of remote sensing to improve the information about areas that are difficult to access or with poor availability of conventional meteorological data.

Abhilash Maryada, et.al. [2018] use the precipitation and NDVI from Satellite data to monitor the drought. A comparative study on precipitation for the year 2015 to precipitation anomalies change from 2001 to 2010 and NDVI for the year 2015 to NDVI anomalies change from 2001 to 2010 is done to access the amount of drought. Drought is a natural disaster that occurs throughout the world affecting the water, social, environmental and economical parts of the society. Monitoring the drought is a tough task as it includes different spatial-temporal dimensions. Satellite-based remote sensing has been broadly utilized over the recent years for national to worldwide scale on numerous natural checking exercises, including drought because of the availability of continuous monitoring across wide areas that reflect both atmospheric and land surface characteristics.

Table 1 Comparative Table for Previous Reviews

Author & Year	**Focus of Study**	**Methods / Data Used**	**Key Findings**	**Significance**
Hao Chen et al. (2025)	Development of IMLDI for drought monitoring in China	Integrated remote sensing drought index compared with SPEI	IMLDI showed high spatial-temporal consistency, reflected real-world drought impacts, and effectively captured 2009/10 & 2019 drought events	Demonstrated IMLDI's potential as a new robust index for agricultural drought monitoring
Neha Andure et al. (2024)	Remote sensing applications in drought monitoring	Multispectral images (Sentinel-2, Landsat, MODIS) and drought indices	Optical remote sensing provided insights into agriculture, vegetation, and environmental impacts	Showed how freely available datasets can advance drought monitoring and agricultural management
Narayan Tatyaba Narbat et al. (2024)	Status and management of drought in India (esp. Maharashtra)	Review of drought occurrence and agro-climatic zones	Drought has long-term economic and social impacts; occurs gradually but affects large regions	Suggested strategies for managing future droughts in India
Pranav B. Mistry et al. (2023)	Vegetation stress and drought analysis in Vadodara, India	NDVI, NDWI, MNDWI, WRI, NDBI, NDSI indices with rainfall data	NDVI showed agricultural fields' vulnerability; NDWI decreased; NDBI increased	Useful for local authorities to assess drought severity and plan mitigation
Niranga Alahacoon et al. (2022)	Review of drought indices across categories	111 drought indices (44	90% of RS indices used for agricultural drought; satellite data	Highlighted the shift from traditional to

		traditional, 67 RS-based)	improved spatial monitoring	remote sensing indices for broader applicability
Lixin Wang et al. (2021)	Multi-sensor approaches for drought monitoring	Optical, microwave, hyperspectral, LiDAR data	Multi-sensor integration improves real-time monitoring, spatiotemporal coverage, and mechanism understanding	Stressed need for mechanism-oriented, multi-sensor drought studies
Foyez Ahmed Prodhan et al. (2021)	DFNN model for SMDI prediction	Deep Feedforward Neural Network with SPEI validation	DFNN showed high correlation (R^2 up to 0.94) and stability across crop stages	Demonstrated AI-based models' effectiveness for consistent drought monitoring
N. Chattopadhyay et al. (2020)	Agricultural drought monitoring in India	Composite Drought Index (CDI) using geospatial data (2014–2016)	CDI synthesized multiple indices, enabling regional-scale monitoring	Helped improve district-level drought assessment in multiple Indian states
Willibroad Gabila Buma et al. (2019)	VTCI-based drought monitoring near Lake Chad	LST and NDVI via satellite	VTCI captured spatial drought patterns; severe drought in northern areas	Showed RS utility in data-scarce regions for drought monitoring
Abhilash Maryada et al. (2018)	Drought monitoring with precipitation and NDVI	Satellite-based precipitation anomalies and NDVI (2001–2010 vs 2015)	Drought severity measured across temporal scales; RS enabled continuous monitoring	Reinforced role of RS in large-scale drought assessment

RESEARCH GAP

Despite major breakthroughs in drought monitoring, numerous gaps remain that restrict the accuracy, timeliness, overall geographical applicability of present systems. The majority of conventional drought evaluations rely mostly on rainfall-related or weather indices, which are inaccurate in places with little ground-station data, such semi-arid districts of Maharashtra, and fail to capture the early reaction of plants to moisture stress. Many earlier studies similarly rely on single-index techniques, missing a thorough integration of multiple spectral vegetation, temperature, as well as hydrological information. Additionally, while remote sensing has shown promise, there are currently few studies that validate model performance using real plant conditions, and its integration with machine-learning models for vegetation-health-based drought prediction is still restricted. Existing research generally misses the comparative importance of multiple environmental factors on drought, creating confusion regarding which indicators are most helpful for prediction. Additionally, there is minimal work on district-level, real-time drought prediction systems that may help targeted agriculture management. In order to fill these gaps, our research combines many drought indicators with cutting-edge machine learning to create a reliable, highly accurate VHI prediction system specifically designed for drought-prone areas.

3. RESEARCH METHODOLOGY

The study employed a remote sensing and geospatial analysis approach to develop a framework for near real-time drought monitoring. Multispectral satellite imagery from open-source platforms such as NASA, ESA, and ISRO was used, with radiometric and atmospheric corrections applied to ensure accuracy. Key indices such as NDVI, VCI, TCI, VHI, and TVDI were derived to analyze vegetation health, soil moisture, and land surface temperature. The study also identified and tested optimal multispectral band combinations for early drought prediction. Ground-based measurements, including soil moisture and land surface temperature, were collected at selected sites to validate satellite-derived results. Data analysis was carried out using specialized software, which enabled integration of spectral indices with spatial drought characterization. The results were compared with meteorological datasets to assess consistency and reliability. Finally, spatial and temporal drought patterns were modeled to provide insights for early warning systems and agricultural risk management.

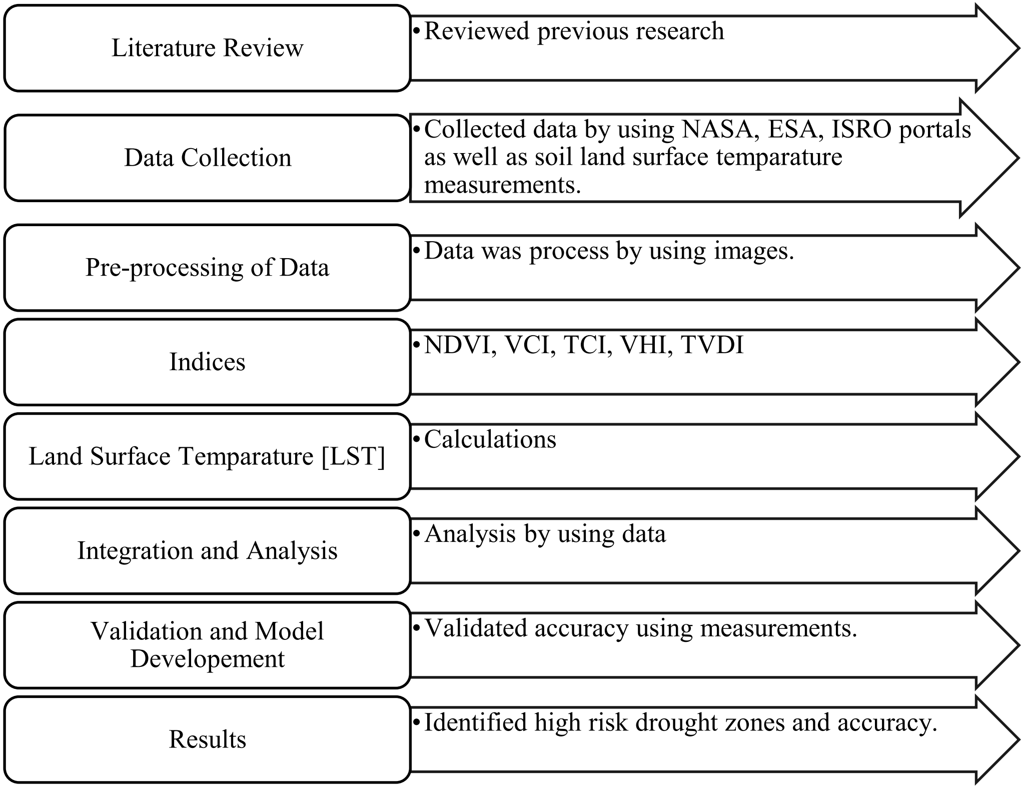


Figure 1 Methodology Flowchart

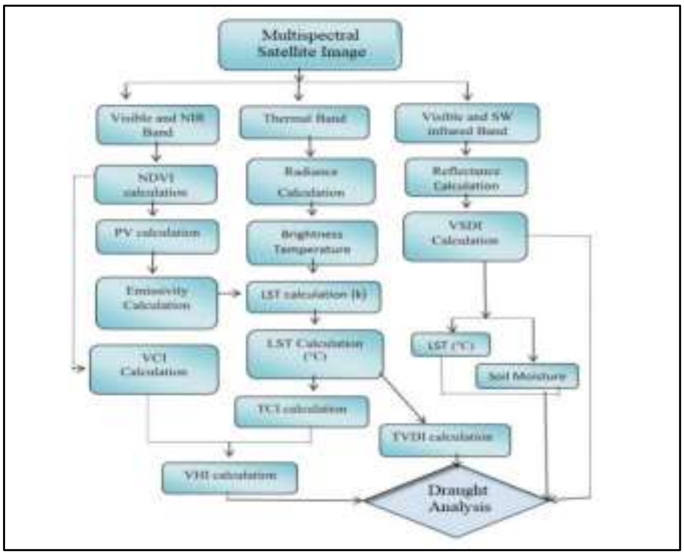


Figure 2 Multispectral Satellite Image - Data Processing Steps

Data Processing Steps:

1. **Multispectral satellite image**

Sensors that record data in the visible, NIR, SWIR, as well as thermal bands are used to create multispectral satellite images. Temperature, soil moisture, vegetation, along with land surface conditions are all revealed by these various bands. All calculations related to drought are based on this raw data.

2. **NDVI Calculations**

Visible with near-infrared reflectance measurements are used to calculate the NDVI, which measures the greenness of vegetation. Healthy vegetation is indicated by higher NDVI values, whereas sparse or stressed vegetation is indicated by lower values. This is an initial step toward comprehending how plants are affected by drought.

3. Proportion of Vegetation [PV] Calculation

To determine how much vegetation covers a given area, PV is computed from NDVI. It assists in transforming NDVI into a format that is helpful for analysis pertaining to temperature. The data is ready for the emissivity calculation in this step.

4. Emissivity Calculation

The efficiency with which the land surface emits thermal radiation is known as emissivity. It comes from PV and is necessary for precise estimation of the land surface temperature. Temperature readings could be off if emissivity correction isn't applied.

5. VCI Calculation

To assess vegetation stress, VCI compared current NDVI readings to previous NDVI ranges. High VCI values indicate healthy vegetation, while low VCI values suggest drought-like conditions. In order to identify vegetation-based drought, this index is crucial.

6. Radiance Calculation

Thermal band values recorded by the satellite are used to calculate radiance. It stands for the energy released by the surface of the Earth. The brightness temperature is calculated using this radiance.

7. Brightness Temperature Calculation

Thermal energy from the ground is indicated by brightness temperature, which is calculated from radiance. It is an intermediary step rather than the actual temperature of the land surface. The value helps in the conversion of thermal data into temperature units that can be used.

8. LST Calculation

Land Surface Temperature, or LST, is first determined in Kelvin and then converted to degrees Celsius. The land surface's heating patterns, which have a significant impact on the intensity of drought, are revealed by LST. High LST typically indicates dry soil and stressed vegetation.

9. TCI Calculation

TCI measures the impact of heat stress on vegetation using LST values. Poor conditions are indicated by lower TCI values at higher temperatures. By capturing the temperature element of drought, it enhances VCI.

10.Reflectance Calculation

To determine how the land surface reflects sunlight, reflectance is calculated using visible and SWIR bands. Depending on the amount of moisture and vegetation present, different surfaces reflect energy in different ways. These numbers aid in the computation of indices pertaining to vegetation and soil.

11.VSDI Calculation

Reflectance data is used by VSDI (Vegetation Supply Demand Index) to estimate vegetation moisture demand. It makes it easier to distinguish between areas that are already under stress and those that need more water. Lower values suggest that a drought may be developing.

12.Soil Moisture Calculation

LST and reflective characteristics from SWIR bands are used to estimate soil moisture. In general, warmer surfaces retain less moisture, indicating dry conditions. This helps in comprehending soil dryness that extends beyond surface vegetation.

13.TVDI Calculation

To determine the degree of drought, TVDI is computed using LST as well as vegetation conditions. It shows the connection between vegetation cover and temperature. Stronger drought intensity is indicated by higher TVDI values.

14.VHI Calculation

VHI is an indicator of overall vegetation health that combines VCI and TCI. It shows how plants are affected by both temperature and moisture stress. A common method for identifying agricultural drought is VHI.

15.Final Drought Analysis

To determine the severity of the drought, all drought indices NDVI, VCI, TCI, LST, VSDI, soil moisture, TVDI, and VHI are combined. A more realistic and accurate awareness of drought conditions is provided by this combined approach. The final product helps in real-time drought monitoring and prediction.

Study Area: Maharashtra and Beed Region

Maharashtra, one of the biggest and most agriculturally important states in India, sees regular climate fluctuation and periodic conditions of drought, making it an attractive site for drought monitoring studies. In Maharashtra, the Beed district located in the drought-prone Marathwada region has been chosen as the focus research area owing to its history of severe and recurring droughts, high dependency on monsoon rainfall, and vulnerability in agricultural production. The region's climatic awareness, along with its socio-economic dependence on rain-fed agricultural, offers a good setting to assess and verify contemporary multispectral technologies for remote sensing including drought indices. Studying Maharashtra and especially Beed offers real-time evaluation of vegetation stress, soil moisture deficiencies, & drought advancement, hence aiding the development of reliable drought monitoring as well as prediction systems.

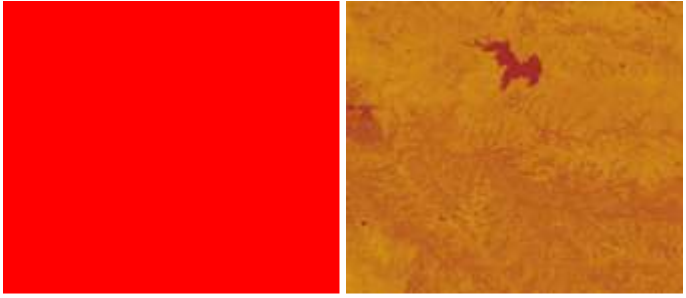


Figure 3 Satellite Images for Beed Region

The Beed region is shown in the satellite image above, which has been employed in our research for environmental analysis as well as drought monitoring. Multispectral remote sensing data is utilized to make the picture, which employs color-coded intensity values to accentuate surface details. The region's changes in plant cover, soil moisture, as well as land surface features are depicted by the varying tones of yellow and orange. Drought-prone zones may be recognized by checking for areas with less vegetation activity or increased thermal intensity, which are depicted by the darker red patches. We were able to measure vegetative stress, detect geographical patterns, & acquire knowledge regarding seasonal environmental developments in the Beed region owing to these processed satellite pictures. It supplied the foundation for producing indices that were employed throughout the study, such as NDVI, VCI, TCI, LST, & various other drought-related parameters.

Formulas used for calculating the results are given below:

NDVI [Normalized Difference Vegetation Index]

One of the most used multispectral indicators for tracking drought is the NDVI. It uses the difference between the Near-Infrared (NIR) & Red spectral bands collected using satellite sensors. Healthy vegetation has strong NIR & low red reflectance, resulting in NDVI values near to +1. The NDVI is a useful real-time drought indicator since it decreases as plant reflectance patterns shift due to drought stress.

$$\text{NDVI} = \frac{\text{NIR}-\text{RED}}{\text{NIR}+\text{RED}} \quad [1]$$

NIR: Reflectance in the Near-infrared band [Healthy vegetation strongly reflects NIR]

RED: Reflectance in the Red band [Vegetation absorbs red light for photosynthesis]

VCI [Vegetation Condition Index]

VCI is used to assess vegetation health compared to its historical range. It makes it simpler to assess drought severity across various locations and seasons by normalizing current NDVI readings according to their long-term low and maximum. A level of moderate to extreme drought is indicated by a VCI of less than 40%. VCI between 40–60% suggests typical vegetation conditions. Healthy vegetation is indicated by a VCI > 60%. VCI is often used for real-time drought monitoring which helps in the early detection of drought stress.

$$\text{VCI} = \frac{\text{NDVI}-\text{NDVImin}}{\text{NDVImax}-\text{NDVImin}} \text{ x } 100 \quad [2]$$

NDVI: Current NDVI value,
NDVImin: Minimum historical NDVI for the same period,
NDVImax: Maximum historical NDVI for the same period,

TCI [Temperature Condition Index]

TCI assesses how present temperature conditions relate to past extremes. Because plant gets stressed at higher temperatures during drought, TCI aids in detecting heat-related drought severity. Low TCI (<40%)

leads to high temperature stress and possible drought. High TCI (> 60%) indicates normal or healthy temperature conditions. TCI is often paired with VCI to form the Vegetation Health Index (VHI), which is beneficial for real-time drought detection & severity assessment.

$$\text{TCI} = \frac{\text{LSTmax} - \text{LST}}{\text{LSTmax} - \text{LSTmin}} \times 100 \quad [3]$$

LST: Current Land Surface Temperature,
LSTmax: Maximum historical LST for the same period,
LSTmin: Minimum historical LST for the same period,

VHI [Vegetation Health Index]

VHI combines vegetation greenness (VCI) and temperature stress (TCI) to provide a complete indicator of drought severity. The VCI identifies moisture-related vegetative stress. TCI detects heat-related stress. VHI provides a more complete view of drought conditions than either indicator alone. VHI < 40% indicates moderately to extreme drought. VHI > 60% indicates normal vegetation health. VHI is extensively utilized for real-time drought evaluation, early detection of agricultural stress, including regional drought mapping.

$$\text{VHI} = \alpha \times \text{VCI} + (1 - \alpha) \times \text{TCI} \quad [4]$$

VCI: Vegetation Condition Index,
TCI: Temperature Condition Index,
α: Weighting factor (commonly 0.5),

TVDI [Temperature-Vegetation Drought Index]

TVDI measures soil moisture stress by comparing land surface temperature (LST) to vegetation greenness (NDVI). In the NDVI-LST space: The wet edge is associated with low LST as well as high NDVI (moist soil, healthy vegetation). The dry edge is associated with high LST along with low NDVI (dry soil, stressed vegetation). TVDI readings vary from 0 (wet, no drought) to 1 (very dry, significant drought stress), making it very useful for real-time drought detection, particularly in semi-arid environments.

$$\text{TVDI} = \frac{\text{LST} - \text{LSTmin (NDVI)}}{\text{LSTmax (NDVI)} - \text{LSTmin(NDVI)}} \quad [5]$$

LST: Current Land Surface Temperature,
LSTmin (NDVI): Minimum LST for a given NDVI (the wet edge),
LSTmax (NDVI): Maximum LST for a given NDVI (the dry edge),

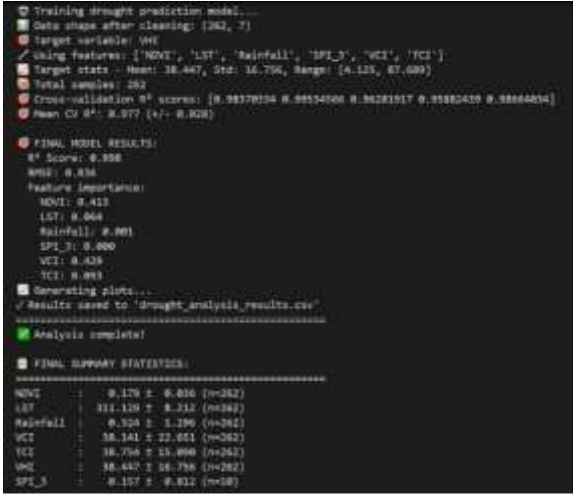
4. ANALYSIS AND RESULTS

Drought monitoring & prediction are growing more crucial due to increased climatic variability and harsh weather events. Modern technical breakthroughs including multiple-spectral remote sensing, vegetation indices, with machine-learning models now enable real-time monitoring of drought severity with great precision. It is feasible to evaluate vegetation health, identify early warning signs, and anticipate drought conditions more accurately than with conventional approaches by combining satellite-derived indicators like NDVI, VCI, TCI, LST, Rainfall, & SPI-3 with predictive modeling tools. The findings reported in this work indicate how remote sensing datasets, statistical summaries, drought indices, features significance analysis, and actual-versus-predicted comparisons significantly increase real-time drought evaluation. These results demonstrate that integrating multispectral satellite images with sophisticated analytical tools provides a potent and current method to understanding and forecasting drought dynamics in sensitive locations.

The drought study for Beed reveals that from early 2020 to early 2023, the area commonly suffered poor vegetation health, high land surface temperatures, as well as minimal rainfall, particularly during the dry months. NDVI readings were largely low, indicating limited vegetative growth, while LST values continued continuously high, showing heat stress in crops. VCI, TCI, and VHI readings were frequently below 40 between January–May in numerous years, which implies moderate to severe drought conditions. Rainfall was nearly nonexistent for lengthy periods, and this led to diminishing vegetation health. Additionally, SPI levels sometimes fell below zero, indicating a meteorological dryness. During the monsoon season (June–October), conditions improved, with NDVI rising and VHI rising beyond 60–70, a sign of vegetation regrowth. Overall, the data demonstrates recurring seasonal dryness, significant heat stress before monsoon, with apparent reduction only after rainfall events.

Following data cleaning, 262 samples were used to train the drought prediction model using VHI as the goal & six input features: NDVI, LST, Rainfall, SPI-3, VCI, & TCI. The target VHI values showed significant variation in vegetation health conditions, with a mean of 38.447, a standard deviation of 16.756, and a range of 4.125 to 87.689. Cross-validation performance was high, with R² values ranging from 0.958 to 0.995, generating an average CV R² of 0.977 ± 0.028, showing consistent model behavior over folds.

With a low RMSE of 0.836 and an amazing R² score of 0.998 on the whole dataset, the final model demonstrated that the predictions identical the actual VHI values. Feature significance values reveal that vegetation-related variables dominate the prediction: VCI provides the most at 0.429, then follows NDVI at 0.413. Temperature-based indicators have a minimal contribution, with TCI providing 0.029 and LST contributing 0.064, while Rainfall (0.001) & SPI-3 (0.000) have almost little effect on model choices. This shows that vegetative health measures alone explain virtually all VHI variance for this dataset.



```
Training drought prediction model...
Data shape after cleaning: (262, 7)
Target variable: VHI
/ Using features: ['NDVI', 'LST', 'Rainfall', 'SPI_3', 'VCI', 'TCI']
Target stats - Mean: 38.447, Std: 16.756, Range: [4.125, 87.689]
Total samples: 262
Cross-validation R² scores: [0.98370134 0.99534506 0.96281917 0.95882439 0.98864034]
Mean CV R²: 0.977 (+/- 0.028)

FINAL MODEL RESULTS:
  R² Score: 0.998
  RMSE: 0.836
  Feature importance:
    NDVI: 0.413
    LST: 0.064
    Rainfall: 0.001
    SPI_3: 0.000
    VCI: 0.429
    TCI: 0.093
Generating plots...
✓ Results saved to 'drought_analysis_results.csv'
============================================================
✅ Analysis complete!

FINAL SUMMARY STATISTICS:
============================================================
NDVI      :    0.179 ±  0.036 (n=262)
LST       :  311.139 ±  8.212 (n=262)
Rainfall  :    0.324 ±  1.296 (n=262)
VCI       :   38.141 ± 22.651 (n=262)
TCI       :   38.754 ± 15.090 (n=262)
VHI       :   38.447 ± 16.756 (n=262)
SPI_3     :    0.157 ±  0.812 (n=10)
```

Figure 4 Model Training and Summary Results

The last overall statistics represent the atmospheric conditions throughout the analysis period. NDVI was 0.179 ± 0.036, LST averaged 311.139 ± 8.012, and rainfall remained low at 0.324 ± 1.296. VCI and TCI exhibited means of 38.754 ± 15.695 and 18.747 ± 4.191, respectively. The large range of vegetative health states is compatible with the desired VHI, which averaged 38.447 ± 16.756. SPI-3, available only for 10 samples, has a mean of 0.157 ± 0.812. Overall, the findings reveal that the model represents vegetation-based drought dynamics remarkably well, with vegetation indices contributing virtually all predicted accuracy.

The Vegetation Health Index (VHI) serves as the goal variable for the real-time drought prediction system. VHI is a composite drought index that combines temperature & vegetation conditions generated from multiple-spectral satellite data. As an early indication of plant stress, VHI indicates vegetation deterioration under moisture deficiency, excessive heat, and protracted dry spells. By adopting VHI as the dependent variable, the research harnesses remote sensing technologies to concentrate on the health of vegetation, therefore allowing reliable monitoring and forecast of agricultural drought conditions throughout semi-arid areas.

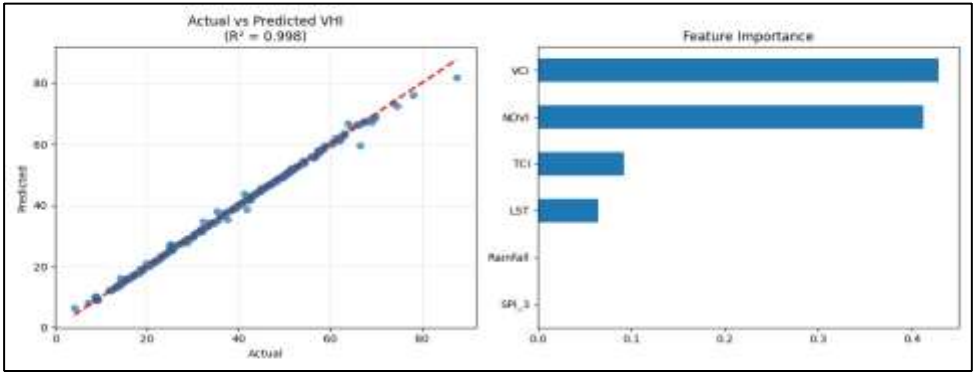


Figure 5 Actual VHI & Predicted VHI

The comparison indicates that the model estimates VHI fairly correctly across every value ranges. When the actual VHI is about 10, the model predicts 9–11, suggesting a very close match. For values that are moderate like 20 & 40, the predictions remain within 1–2 points, suggesting high agreement. At larger values such as 60, the model continues to perform well with predictions around 60–63. The model only slightly overestimates by one to three points for very high values close to 80; otherwise, the prediction accuracy is consistently strong. According to the feature significance study, vegetation condition has the greatest impact on drought severity, with VCI (0.43) & NDVI (0.40) being the two most significant factors in predicting VHI. TCI (0.10) & LST (0.07) have lesser but nonetheless important impacts. Meanwhile, Rainfall and SPI-3 exhibit very negligible relevance (~0.00) in the model, showing they have limited effect on forecasting VHI compared to vegetation-based indices.

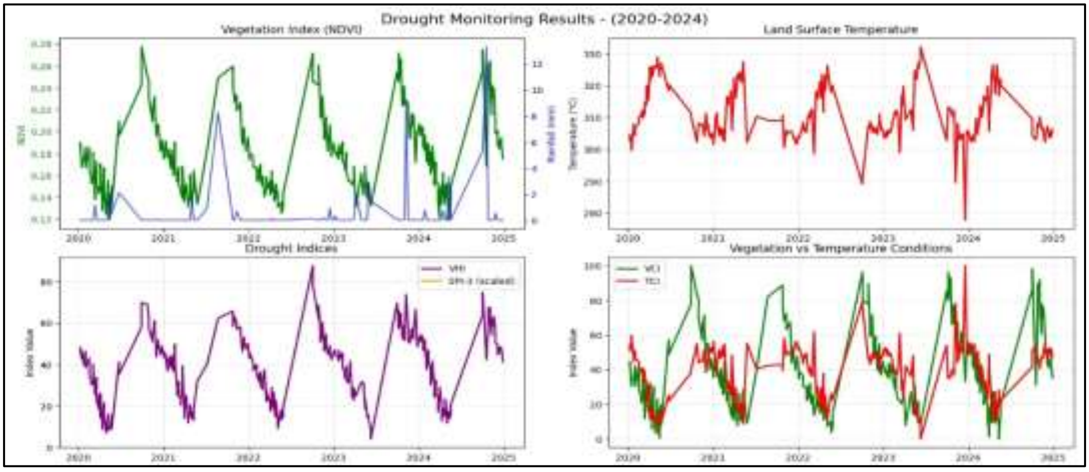


Figure 6 Drought Monitoring Results-[2020-2024]

The vegetation & drought indicators exhibit considerable seasonal activity from 2020 to 2024, following cycles of temperature and precipitation. NDVI ranges from ~0.12 during dry times and ~0.27–0.28 at peak greenness, generally after rainfall surges. For particularly of the year, rainfall is very low, with sporadic maxima of 10–13 mm that provide a brief rebound of vegetation. Land Surface Temperature (LST) fluctuates greatly, often falling between 280°C and 330°C (scaled brightness temperature); lower vegetation conditions are frequently associated with higher temperatures.

The drought-related indexes exhibit comparable seasonality. VHI varies from severe-drought levels of ~10–20 to healthy vegetation levels of ~70–85, with significant peaks in mid-2021, early 2023, and late 2024. SPI-3 (scaled in the figure) reflects similar cycles, with negative or near-zero values during dry months & positive peaks during occasional rainy episodes. While the temperature condition index TCI normally ranges from ~15–25 under heat stress and up to ~60–70 during cooler times, the vegetation condition index VCI fluctuates from ~5–15 during drought periods to ~90–100 during wet/green circumstances. The comparison between VCI and TCI demonstrates that poor vegetative health generally corresponds with high temperatures observed mainly in mid-2020, late-2022, & mid-2024.

Overall, the figures reveal that vegetation health throughout these five years is primarily driven by brief rainfall bursts and modulated by temperature fluctuations, with drought conditions returning practically each year when both rainfall & vegetation indices decline concurrently.

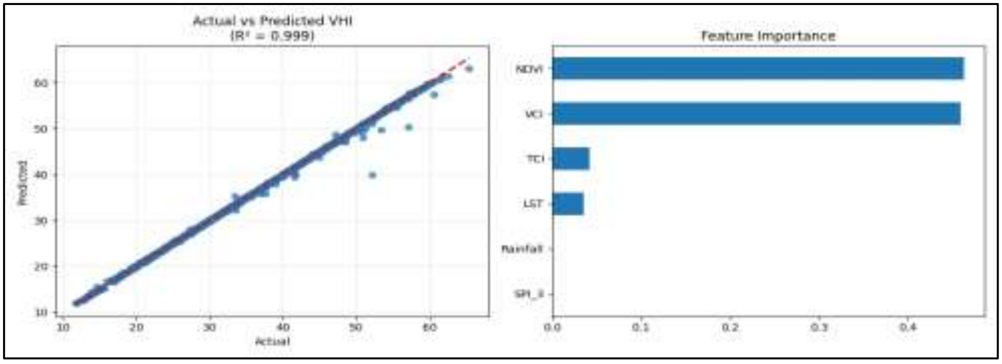
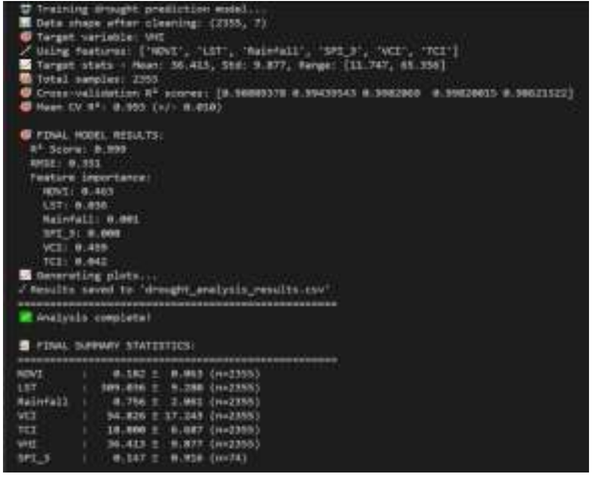


Figure 7 Actual VHI & Predicted VHI

The model displays unusually good performance in predicting the Vegetation Health Index (VHI), as indicated by the near-perfect alignment between actual and anticipated values. Most locations lay directly on the 1:1 red dashed line, with very tiny variations. The model explains 99.9% of the variance in VHI, according to the R2 value of 0.999. Across the dataset, real VHI runs from roughly 12 to 65, whereas projected values match closely for example, actual VHI values around 15, 25, 35, 45, and 60 all have matching forecasts within 1–2 units of the genuine values. Minor under- or over-estimation emerges at 50–55, when a few projected values fall just below the optimum line, but the total accuracy remains quite good.

The feature significance plot demonstrates that NDVI & VCI are clearly the most powerful contributors to VHI predictions, both with importance values of roughly 0.46–0.47, together taking into consideration more than 90% of the model's decision power. TCI contributes just approximately 0.05, and LST even less at around 0.03, suggesting a tiny secondary function. Rainfall and SPI-3 have near-zero relevance, indicating that in this dataset they have no meaningful prognostic value for VHI. Overall, the model depends nearly exclusively on vegetation-based indicators, which corresponds well with how VHI is formed and with the significant correlations seen in the findings.

The drought analysis for Maharashtra shows that vegetation gets stressed when NDVI drops below 0.10 and VHI falls to around 20–30, which typically develops throughout months with very low rainfall (0–2 mm) as well as hight land surface temperatures of 300–320 K (27–47°C), while conditions improve throughout the monsoon when rainfall rises to 20–30 mm, causing NDVI to increase to 0.25–0.35 as well as VHI to rise above 50, resulting in healthier vegetation along with reduced drought.



```
Training drought prediction model...
Data shape after cleaning: (2355, 7)
Target variable: VHI
✓ Using features: ['NDVI', 'LST', 'Rainfall', 'SPI_3', 'VCI', 'TCI']
Target stats - Mean: 36.413, Std: 9.877, Range: [11.747, 65.356]
Total samples: 2355
Cross-validation R² scores: [illegible]
Mean CV R²: 0.993 (+/- 0.010)

FINAL MODEL RESULTS:
  R² Score: 0.999
  RMSE: 0.351
  Feature importance:
    NDVI: 0.463
    LST: 0.036
    Rainfall: 0.001
    SPI_3: 0.000
    VCI: 0.459
    TCI: 0.042
Generating plots...
✓ Results saved to 'drought_analysis_results.csv'
============================================================
Analysis complete!

FINAL SUMMARY STATISTICS:
============================================================
NDVI       :    0.182 ±  0.063 (n=2355)
LST        :  309.036 ±  9.280 (n=2355)
Rainfall   :    0.756 ±  2.061 (n=2355)
VCI        :   54.826 ± 17.243 (n=2355)
TCI        :   18.000 ±  6.978 (n=2355)
VHI        :   36.413 ±  9.877 (n=2355)
SPI_3      :    0.147 ±  0.916 (n=74)
```

Figure 8 Model Training and Summary Results

The drought prediction model was trained using 2,355 cleaned samples & six input characteristics (NDVI, LST, Rainfall, SPI-3, VCI, and TCI), with VHI serving as the goal variable. The target's mean value was 36.413, with a standard deviation of 9.877 and a range of 11.747 to 65.356. Cross-validation demonstrated high performance, with R² values ranging from 0.986 to 0.998 and an average CV R² of 0.993 ± 0.010, showing great consistency across folds. The model earned an impressive R² score of 0.999 on the whole dataset and a low RMSE of 0.351, indicating very accurate predictions.

Feature significance values show that the model is nearly completely dependent on vegetation-based indicators: NDVI contributes 0.463 and VCI provides 0.459, accounting for more than 92% of predictive power. Secondary contributions come from LST (0.036) & TCI (0.042), whereas Rainfall (0.001) and SPI-3 (0.000) show very minimal effect, indicating that they do not contribute further predictive data for VHI in this dataset.

The summary data indicate uniform & accurate environment conditions in which NDVI averaged 0.182 ± 0.063, LST averaged 309.036 ± 9.280, rainfall was minimal at 0.756 ± 2.061, VCI averaged 54.826 ± 17.243, TCI averaged 18.000 ± 6.978, & VHI averaged 36.413 ± 9.877. With just 74 samples, SPI-3 has a mean of 0.147 ± 0.916. Overall, the findings show that vegetation condition indicators are the primary drivers of VHI, while the model represents these associations with near-perfect precision.

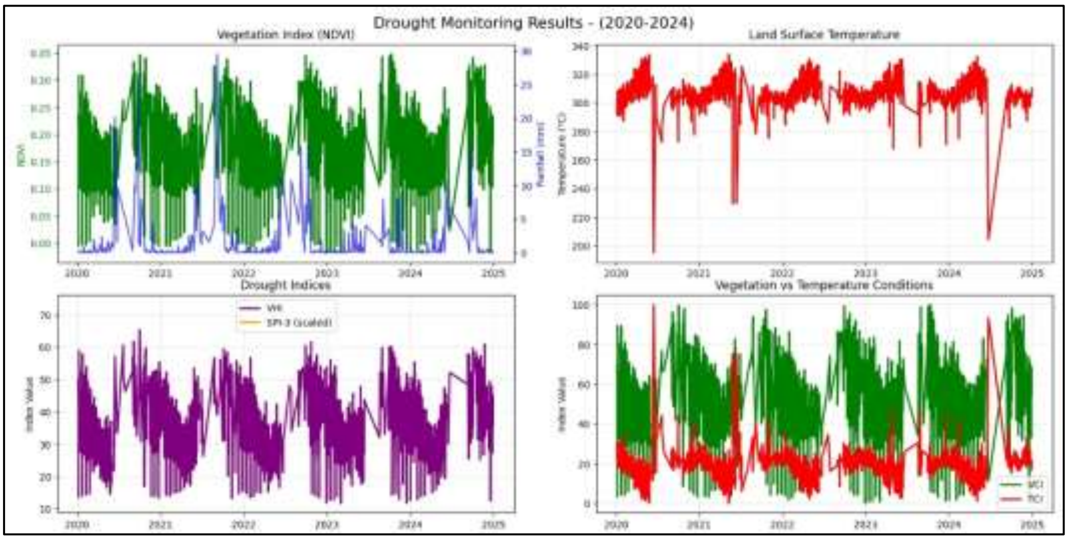


Figure 9 Drought Monitoring Results-[2020-2024]

The drought monitoring data from 2020 to 2024 reveals significant seasonal change in vegetation, temperature, and drought indices. NDVI readings range from 0.00 to 0.35, with maxima of 0.30-0.35 during greener times and dramatic drops to near zero during dry seasons. Rainfall is relatively sporadic, often about 0 mm, although rare bursts of 20-30 mm coincide with short-lived spikes in NDVI. Land Surface Temperature stays continuously high throughout the timeframe, ranging from 290°C to 330°C, with occasional decreases to 200-230°C during rare anomalous occurrences in 2020, 2022, and 2024.
Drought indexes exhibit similar cyclic patterns. VHI fluctuates from severe drought levels of 10-20 during the driest months to better vegetation conditions of 50-65 during wetter or cooler seasons, with considerable decreases happening on an annual basis. Despite being scaled for presentation, the SPI-3 index suggests episodic dry periods, with the majority of values remaining around drought-like conditions, indicating inadequate long-term moisture availability.
The vegetation & temperature status indexes also indicate seasonal stress. VCI fluctuates considerably from near zero (extremely poor vegetation conditions) to beyond 90-100 during peak greenness, but TCI normally ranges from 10 to 30, suggesting regular heat-related stress. Periods of low VCI are often associated with high temperatures exceeding 310-320°C, as seen in 2021, 2023, & 2024. Therefore, all of the patterns indicate repeated yearly drought cycles caused by little rainfall, high temperatures, & related variations in vegetation health.

5. DISCUSSION AND CONCLUSION

The study indicates how multispectral remote sensing data can track and forecast drought conditions nearly instantly when paired with contemporary drought indicators & machine-learning models. Vegetation stress and seasonal changes in the environment were clearly understood through the use of indices like NDVI, VCI, TCI, LST, SPI-3, and rainfall. The analysis showed that the Beed district experienced recurrent pre-monsoon dryness characterized by low rainfall, high temperatures, and weak vegetation, which was carried out by growth during the monsoon season. Because plants react quickly to heat and moisture stress, vegetation-based indicators are the best predictors of drought severity, as demonstrated by the model's exceptionally high R2 of 0.998 and low RMSE. The predictions were largely unaffected by rainfall and SPI-3, indicating that vegetation conditions take time to change due to weather. A multispectral data-driven method is dependable, particularly in semi-arid regions where soil data are rare, as evidenced by the model's consistent performance across validation folds. Overall, the study shows that an efficient system for real-time drought monitoring & prediction can be created by combining satellite data, sophisticated drought indices, and machine learning. Due to their high sensitivity to temperature and moisture stress, vegetation indicators like NDVI, VCI, and TCI is useful for evaluating agricultural drought. The system was able to produce realistic forecasts and accurately capture changes in vegetation health by using VHI as the target variable. The high predictive accuracy demonstrates how early warning systems, drought mitigation techniques, and agricultural planning can all benefit from remote sensing-based drought monitoring. This method allows for widespread, routine monitoring while overcoming the constraints of limited meteorological data. In the end, the study shows how combining machine learning and remote sensing can improve risk-informed decision-making in vulnerable areas and increase drought resilience.

6. FUTURE SCOPE

Future research should concentrate on improving drought forecast accuracy by adding other remote sensing factors such soil moisture from microwave sensors, evaporated moisture products, including groundwater abnormalities from GRACE satellite data. Expanding the model to incorporate multi-sensor data fusion methods and long-term climatic variables may improve the identification of early-onset droughts including long-duration water stress. The system may further be improved by using higher-resolution satellite datasets, such as Sentinel-1 SAR, Sentinel-2 MSI, or forthcoming hyperspectral missions, to better capture localized agricultural stress. Implementing spatial deep learning models, such as LSTM or CNN-LSTM hybrids, might improve the ability to capture time-dependent drought patterns. Additional study may aim at extending the framework across different agro-climatic zones to create a regionally operational drought early-warning system. Finally, connecting drought prediction results with mobile-based advice systems might assist farmers with timely suggestions on irrigation, crop selection, as well as risk management, thereby improving the practical effect of remote sensing-based drought monitoring.

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