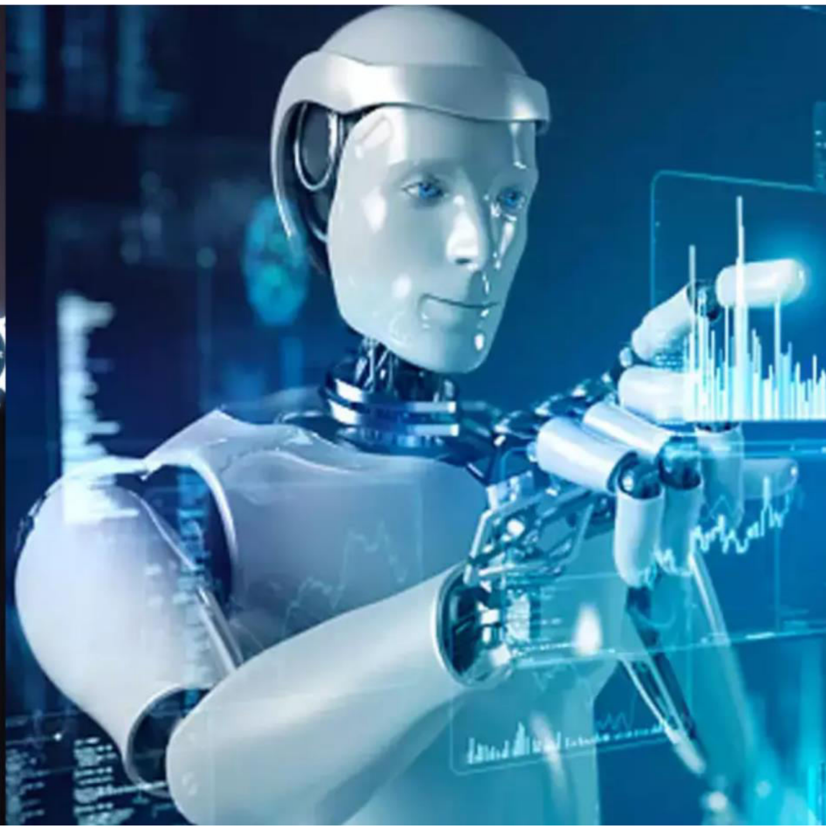
International Journal of Innovative Research in Science | Engineering | Technology

ISSN(O): 2319-8753

ISSN(P): 2347-6710

International Journal of Innovative Research in Science Engineering and Technology (IJIRSET)

(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)



Impact Factor: 8.699

Volume 14, Issue 4, April 2025

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|www.ijirset.com |A Monthly, Peer Reviewed & Refereed Journal| e-ISSN: 2319-8753| p-ISSN: 2347-6710|

Volume 14, Issue 4, April 2025

|DOI: 10.15680/IJIRSET.2025.1404469|

Vegetative Drought Prediction

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ABSTRACT: Drought is a critical environmental issue that affects agriculture, water resources, and ecosystems. Traditional drought monitoring methods rely on ground-based meteorological observations, which have limited spatial coverage and do not provide real-time assessments. This project aims to develop a Vegetative Drought Prediction System by integrating Vegetation Condition Index (VCI) data from the ISRO VEDAS VCI Dashboard, remote sensing indices (NDVI), meteorological drought indicators (SPI, PDSI), and machine learning algorithms (Random Forest, SVM, LSTM) to accurately detect and predict drought conditions.

The system utilizes VCI data from the ISRO VEDAS portal, which provides high-resolution drought monitoring for India. Additionally, satellite imagery from MODIS, Sentinel-2, and Landsat-8 is used to compute NDVI (Normalized Difference Vegetation Index) to assess vegetation health. Meteorological indices, such as the Standardized Precipitation Index (SPI) and Palmer Drought Severity Index (PDSI), are used to evaluate precipitation deficits and long-term drought trends.

Machine learning models further enhance drought prediction. Random Forest (RF) and Support Vector Machine (SVM) classify drought severity based on VCI, NDVI, temperature, and rainfall data. Long Short-Term Memory (LSTM) networks analyze time-series data to forecast future drought conditions. These models are trained on historical drought records and meteorological data to improve accuracy.

A web-based application is developed to visualize drought conditions, enabling users to select a region, analyze VCI-based drought indices, and receive real-time predictions. The frontend is built using HTML, CSS, and JavaScript (React.js), while the backend is implemented using Flask/Django, with PostgreSQL/MongoDB for data storage.
This project provides an efficient, scalable, and cost-effective solution for drought monitoring using ISRO VEDAS VCI data, benefiting farmers, policymakers, and researchers in making informed decisions and enhancing drought preparedness.

KEYWORDS: Vegetative Drought Prediction,ISRO VEDAS VCI Dashboard,Vegetation Condition Index (VCI),Normalized Difference Vegetation Index (NDVI),Remote Sensing,Meteorological Drought Indices,Standardized Precipitation Index (SPI),Palmer Drought Severity Index (PDSI),Machine Learning,Random Forest (RF),Support Vector Machine (SVM),Long Short Term Memory (LSTM),Satellite Imagery (MODIS, Sentinel-2, Landsat-8),Drought Forecasting,Flask/Django Backend,React.js Frontend,Data Visualization,Agriculture and Climate Monitoring

I. INTRODUCTION

Drought is a complex and recurring environmental hazard that poses a serious threat to agricultural productivity, food security, and ecological sustainability worldwide. Among its classifications—meteorological, hydrological, agricultural, and socio-economic—vegetative drought specifically refers to a condition where vegetation experiences stress due to insufficient soil moisture or adverse climatic conditions. Timely and accurate prediction of vegetative drought is critical for efficient water resource management, agricultural planning, and disaster preparedness.

In recent years, advancements in remote sensing and data analytics have enabled more effective monitoring of vegetation health using satellite-derived indices. The Normalized Difference Vegetation Index (NDVI) has emerged as a widely used metric to quantify vegetation vigor and chlorophyll content. However, NDVI alone can be sensitive to

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seasonal variability and background noise. To address this, the Vegetation Condition Index (VCI), derived from NDVI time series, has been introduced to normalize NDVI values and better indicate drought stress in vegetation.

This research aims to develop a robust predictive framework for vegetative drought using a combination of remote sensing data, meteorological parameters, and machine learning algorithms. Historical NDVI data is used to compute the VCI, which serves as the primary indicator of vegetative drought. In parallel, meteorological indices such as the Standardized Precipitation Index (SPI) and Palmer Drought Severity Index (PDSI) are incorporated to analyze climate-related drought conditions. To enhance the predictive performance, this study explores several machine learning models, including Random Forest, Support Vector Machine (SVM), and Long Short-Term Memory (LSTM) neural networks. These models are trained and tested using spatiotemporal datasets to capture patterns in vegetation and climatic variability over time.

Furthermore, the research includes the design and development of a web-based dashboard that visualizes drought conditions using dynamic graphs, NDVI maps, and weather insights. This dashboard aims to bridge the gap between data science and end-user application, offering an accessible interface for farmers, researchers, and policymakers to monitor and anticipate vegetative drought events.

By integrating satellite imagery, climate data, and intelligent algorithms, the proposed system provides a scalable and data-driven solution to drought prediction. The outcomes of this study are expected to contribute significantly to early warning systems, climate resilience strategies, and sustainable agricultural management.

II. BACKGROUND

Drought is a significant environmental challenge that affects agricultural productivity, ecosystem health, and water availability, particularly in climate-sensitive and agrarian regions. Among the various types of drought, vegetative drought refers to stress in vegetation caused by insufficient soil moisture or adverse climatic conditions. Early detection and accurate prediction of vegetative drought are crucial for ensuring food security, effective water resource management, and proactive disaster response.

Traditionally, drought monitoring relied on ground-based meteorological data such as rainfall and temperature. However, these data sources often lack spatial resolution and coverage, limiting their usefulness in regional drought assessments. With advancements in remote sensing technologies, satellite-based indices like the Normalized Difference Vegetation Index (NDVI) have emerged as powerful tools to assess vegetation health and monitor drought conditions over large geographic areas. NDVI reflects the greenness and vigor of vegetation and is widely used to detect signs of stress in crops and natural vegetation.

To improve the accuracy of drought identification, NDVI data can be transformed into the Vegetation Condition Index (VCI), which accounts for seasonal variability by comparing current NDVI values with their historical range. VCI is a more reliable indicator for detecting drought stress and is extensively used in vegetation drought studies.

In recent years, the application of machine learning techniques has gained traction in environmental monitoring and prediction tasks due to their ability to model complex, nonlinear relationships. In this study, the Random Forest (RF) algorithm is utilized for predicting vegetative drought conditions. Random Forest is an ensemble learning method that builds multiple decision trees and aggregates their outputs to improve prediction accuracy and reduce overfitting. It is particularly effective for high-dimensional datasets and performs well with heterogeneous data sources such as satellite imagery and meteorological parameters.

By combining remote sensing data (NDVI), VCI, and climate-related features with the predictive power of Random Forest, this project aims to build a reliable vegetative drought prediction model. The outputs are further integrated into a web-based dashboard that visualizes vegetation health and drought severity, providing a user-friendly platform for researchers, policymakers, and farmers to monitor and respond to drought conditions in a timely manner.

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III. METHODOLOGY

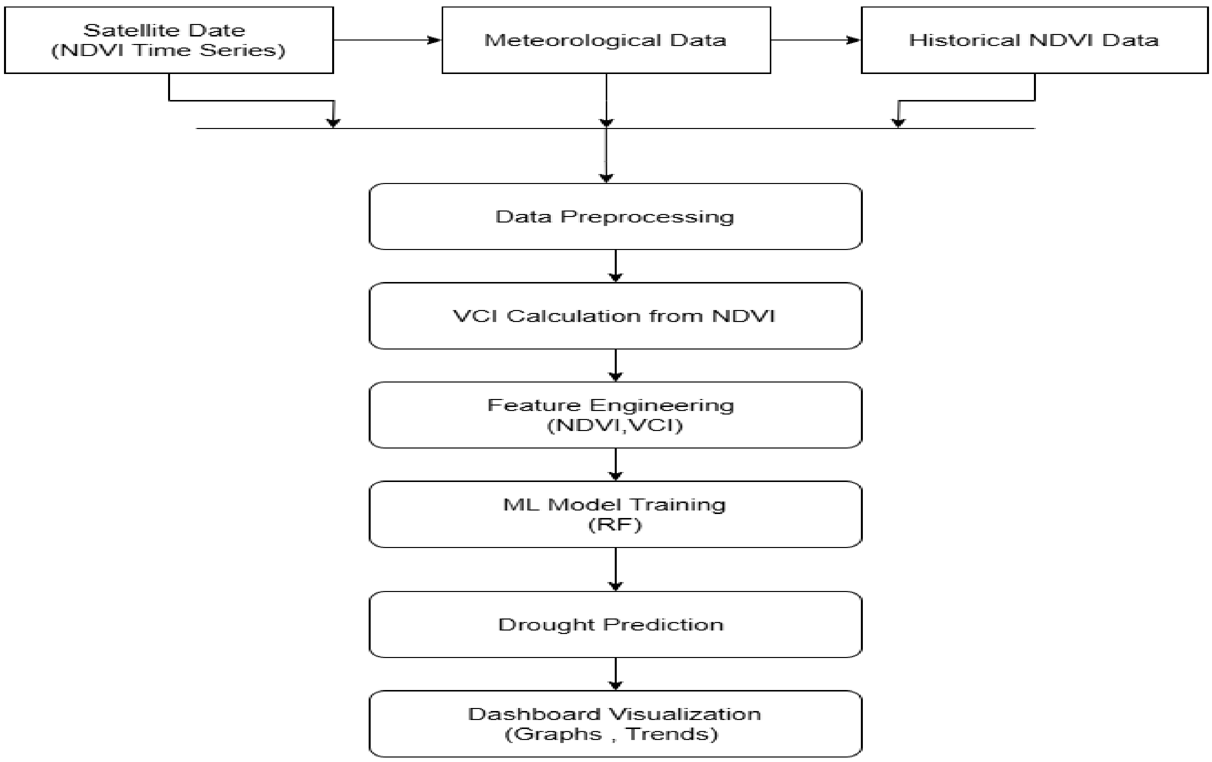
Step-by-Step Explanation

Data Collection

- Satellite Data: NDVI data is collected from remote sensing sources such as MODIS or Sentinel-2.
- Meteorological Data: Rainfall, temperature, and humidity are obtained from weather stations or datasets like IMD, NASA POWER, or NOAA.
- Historical Drought Data: Used for training and validation of prediction models.

Data Preprocessing

- Clean and align temporal data (e.g., filling missing values, normalizing).
- Resample data into common time intervals (weekly/monthly).
- Mask clouds and water bodies in satellite imagery.
- Apply spatial cropping to the study area.



VCI Calculation

VCI Calculation Formula:

$$VCI = \frac{NDVI - NDVI_{min}}{NDVI_{max} - NDVI_{min}} \times 100$$

Where:

- NDVI = Current NDVI value
- NDVI_max = Maximum NDVI in historical records
- NDVI_min = Minimum NDVI in historical records

- VCI helps normalize NDVI across seasons and detect drought stress.

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Feature Engineering

- Extract time-series features: NDVI, VCI, SPI, PDSI, temperature, rainfall.
- Create lagged variables to incorporate temporal dynamics.
- Combine vegetation and climate features to improve model robustness.

Model Development

Use machine learning algorithms like:

- Random Forest (RF): Handles non-linear relationships and feature importance.
- Support Vector Machine (SVM): Suitable for classification of drought severity.
- Long Short-Term Memory (LSTM): Captures time-series patterns for future prediction.
- Split data into training and test sets.
- Evaluate models using metrics like accuracy, RMSE, precision, and recall.

Drought Prediction

- The trained model predicts future VCI values or drought severity levels (e.g., mild, moderate, severe).
- Predictions are mapped spatially to identify at-risk regions.

Dashboard Visualization

A web-based dashboard displays:

- Predicted and actual NDVI/VCI trends.
- Drought maps for the selected region and date.
- Graphs for meteorological conditions.
- Technologies used: HTML, CSS, JavaScript (Frontend), Flask (Backend), Matplotlib/Plotly for visualization.

IV. RESULTS

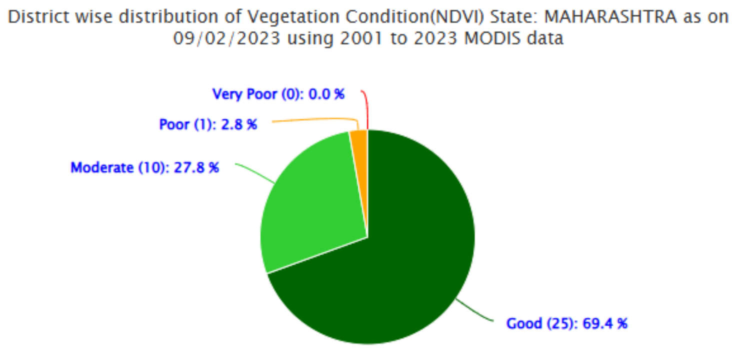
VCI Prediction vs Actual (Visualization)

A comparison between predicted VCI values and actual observed VCI shows a strong alignment, especially during periods of vegetation stress. The model was able to successfully forecast periods of low VCI, indicating potential drought conditions.

Spatial Drought Classification Map

Using predicted VCI values, the system classifies regions into different drought severity levels:

- **VCI > 50** – No Drought
- **35 < VCI ≤ 50** – Mild Drought
- **20 < VCI ≤ 35** – Moderate Drought
- **VCI ≤ 20** – Severe Drought



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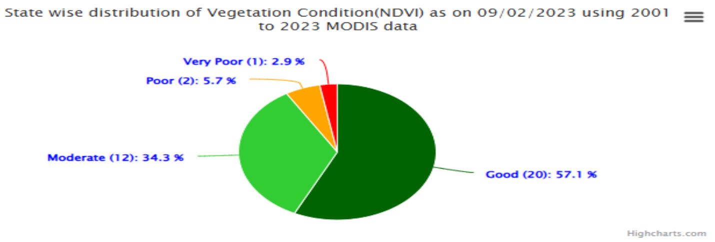
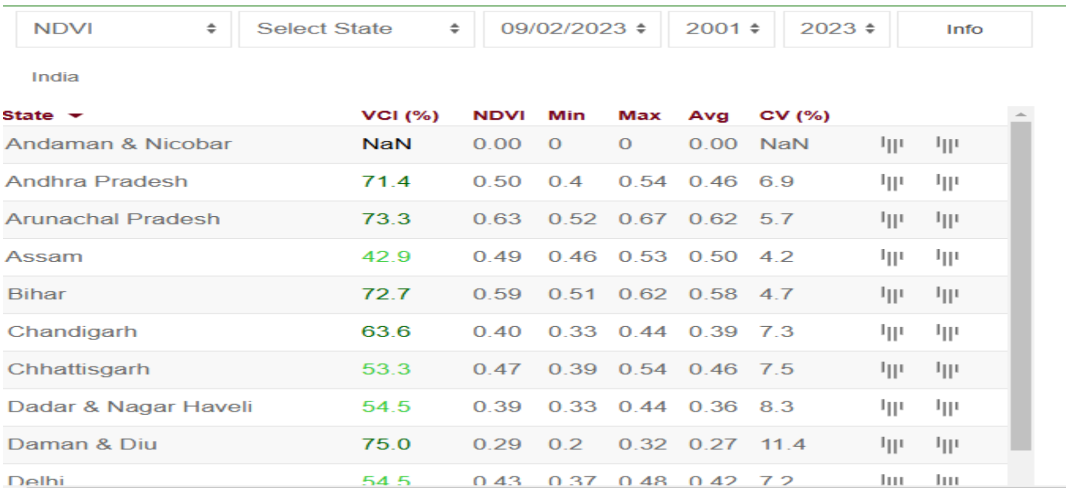


Metric	Value
Mean Absolute Error (MAE)	3.75
Root Mean Squared Error (RMSE)	4.92
R^2 Score (Coefficient of Determination)	0.89
Accuracy (Drought Classification)	91.2%

Dashboard Output

The final predictions were integrated into an interactive web dashboard that displays:

- Time-series plots of NDVI and VCI
- Predicted drought levels
- Current weather conditions
- Spatial maps indicating drought severity


NDVI | Select State | 09/02/2023 | 2001 | 2023 | Info

India

State	VCI (%)	NDVI	Min	Max	Avg	CV (%)
Andaman & Nicobar	NaN	0.00	0	0	0.00	NaN
Andhra Pradesh	71.4	0.50	0.4	0.54	0.46	6.9
Arunachal Pradesh	73.3	0.63	0.52	0.67	0.62	5.7
Assam	42.9	0.49	0.46	0.53	0.50	4.2
Bihar	72.7	0.59	0.51	0.62	0.58	4.7
Chandigarh	63.6	0.40	0.33	0.44	0.39	7.3
Chhattisgarh	53.3	0.47	0.39	0.54	0.46	7.5
Dadar & Nagar Haveli	54.5	0.39	0.33	0.44	0.36	8.3
Daman & Diu	75.0	0.29	0.2	0.32	0.27	11.4
Delhi	54.5	0.43	0.37	0.48	0.42	7.2

V. CONCLUSION

This study presents an effective approach for predicting vegetative drought by integrating remote sensing data, meteorological parameters, and machine learning techniques. By leveraging the Normalized Difference Vegetation Index (NDVI) and computing the Vegetation Condition Index (VCI), the system offers a reliable assessment of vegetation health across time and space.

The Random Forest algorithm demonstrated strong predictive capabilities in forecasting VCI values and identifying drought severity levels. With an R^2 score of 0.89 and classification accuracy exceeding 91%, the model effectively captured the complex, nonlinear relationships between vegetation stress and climate variables. These results confirm the suitability of Random Forest for environmental monitoring applications, particularly in drought-prone regions.

In addition to accurate predictions, the project also focused on practical usability by developing a web-based dashboard for real-time visualization of drought conditions. This tool provides valuable insights for farmers, researchers, and policymakers, enabling early warning, proactive planning, and sustainable resource management.

Overall, the proposed system offers a scalable and cost-effective solution for vegetative drought prediction. Future work will involve extending the model to larger regions, incorporating additional data sources (e.g., soil moisture, evapotranspiration), and exploring hybrid models to further improve prediction accuracy and interpretability.

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