



IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Volume: 13 Issue: V Month of publication: May 2025

DOI: https://doi.org/10.22214/ijraset.2025.69944

www.ijraset.com

Call: 🕥 08813907089 🔰 E-mail ID: ijraset@gmail.com



Spatio-Temporal Analysis of Vegetation Health and Soil Characteristics across Rajasthan using NDVI Anomalies

Shrijit Chatterjee¹, Subha Dey², Prabir Kumar Mahatha³

Department of Computer Science and Engineering, Institute of Engineering and Management (IEM) Kolkata-91 www.iem.edu.in

Abstract: This study presents a comprehensive spatio-temporal analysis of vegetation health and soil patterns across Rajasthan, India, using NDVI (Normalized Difference Vegetation Index) anomalies derived from MODIS satellite data for the period 2020– 2025. The research leverages Google Earth Engine (GEE) to process and visualize NDVI trends, generate anomaly maps, and correlate vegetation dynamics with soil properties and rainfall variability. District-level time series charts highlight spatial differences in vegetation re- sponse, while Sentinel-2 imagery validates regional patterns with finer detail. A GEE-based dashboard facilitates interactive exploration of NDVI anomalies, vegetation-soil relationships, and seasonal variation across all 33 districts. The results reveal persistent vegetation stress in arid western districts and stronger recovery in eastern regions with clay-rich soils and higher rainfall. The integration of soil classification, land use, and climatic datasets supports improved understanding of ecological vulnerability in dryland systems. The study proposes scalable methods for environmental monitoring, with potential applications in drought assessment, land-use planning, and agricultural decision-making in arid and semi-arid regions.

Keywords: NDVI, MODIS, Rajasthan, anomaly detection, vegetation health, soil analysis, GEE dashboard

I. INTRODUCTION

The study of vegetation dynamics is essential for understanding ecosystem health, especially in regions vulnerable to climatic extremes. Rajasthan, India's largest state, is ecologically diverse—ranging from arid desert zones in the west to semi-arid and fertile regions in the east. NDVI is a critical remote sensing tool that quantifies vegetation health using reflectance in the red and near-infrared bands.

This study aims to analyze NDVI anomalies across Rajasthan using MODIS data in a multi-year framework (2020–2025) and develop an interactive dashboard for geospatial exploration. The integration of soil and vegetation types en-hances our understanding of how these factors affect regional NDVI patterns and responses to environmental stress

II. DATA AND METHODOLOGY

A. Study Area.

Rajasthan spans over 342,239 km² and comprises 33 districts with varying vegetation cover, rainfall patterns, soil prop- erties, and land-use types. The western districts (e.g., Jaisalmer, Barmer) are arid, while eastern districts (e.g., Jaipur, Alwar) are agriculturally active. This variety makes Rajasthan an ideal case study for spatio-temporal NDVI analysis.

B. Datasets

- MOD13Q1 NDVI (250m, 16-day composite)
- ESA WorldCover 2020 Land Use Classification
- FAO GAUL boundaries
- ISRIC SoilGrids (global gridded soil database)
- SRTM DEM (for topographic context)
- Rainfall datasets from CHIRPS and IMD (India Meteorological Department)
- Sentinel-2 imagery for finer spatial resolution in supplementary analysis



ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538 Volume 13 Issue V May 2025- Available at www.ijraset.com

- C. Methodology.
- Load MOD13Q1 dataset in GEE and spatially filter to Rajasthan
- Compute mean NDVI from 2020–2025
- Extract NDVI for the latest available date (2025)
- Calculate anomaly (Latest NDVI Mean NDVI)
- Use reduceRegions for district-wise aggregation
- Generate charts using ui.Chart and export CSVs
- Animate annual NDVI anomaly using GEE's video export feature
- Overlay vegetation and soil type classifications for each district
- Integrate climatic datasets to examine correlation between NDVI anomalies and rainfall patterns
- Validate vegetation classifications with Sentinel-2 imagery

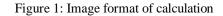
III. NDVI CALCULATION FORMULA AND PROCESS

A. NDVI Calculation Formula NDVI= (NIR-Red)/(NIR+Red) Where: NIR = Near-Infrared band reflectance Red = Red band reflectance

- B. NDVI Calculation Process.
- 1) Data Acquisition: Obtain multispectral or hyperspectral imagery containing the required NIR and Red bands. Common sources include satellite data (e.g., Landsat, Sentinel), aerial imagery, or UAV/drone data.
- Pre-processing: Ensure the imagery is calibrated and corrected for atmospheric effects if necessary. Convert the digital number (DN) or radiance values to reflectance values using calibration coefficients provided by the sensor or through atmospheric correction algorithms.
- *3) Extracting NIR and Red Bands:* For satellite imagery, extract the NIR band and the Red band from the multispectral dataset. Ensure that the NIR and Red bands are in the same spatial resolution and alignment.
- 4) *NDVI Calculation:* Calculate the NDVI for each pixel using the formula: $NDVI = NIR RedN \square \square R + RedNIR Red Apply the formula pixel-wise across the entire image to generate an NDVI image or map. The resulting NDVI values typically range from -1 to 1.$
- 5) *Interpretation and Visualization:* Visualize the NDVI image using a color scale, where higher NDVI values (closer to 1) represent healthy vegetation, and lower values (closer to -1 or 0) represent non-vegetated or stressed areas.

Use color enhancement techniques (false color composites) to enhance the visibility of vegetation, such as assigning high NDVI values to green colors.

```
Normalized Difference Vegetation Index (NDVI)
NDVI = (NIR - RED) / (NIR + RED)
Where:
- NIR = Surface reflectance in Near-Infrared Band
- RED = Surface reflectance in Red Band
For this study (MODIS MOD13Q1 data):
- NIR corresponds to Band 2 (841-876 nm)
- RED corresponds to Band 1 (620-670 nm)
Interpretation of NDVI Values:
- NDVI > 0.5 : Dense vegetation (forests, healthy crops)
- 0.2 < NDVI < 0.5 : Sparse vegetation (grasslands, shrubs)
- NDVI < 0.2 : Bare soil, urban areas, deserts
Project Application:
- Mean NDVI computed for 2020-2025
- Latest NDVI anomaly = Latest NDVI - Mean NDVI
- Positive Anomaly: Greener than normal
- Negative Anomaly: Vegetation stress due to drought or degradation
```





International Journal for Research in Applied Science & Engineering Technology (IJRASET) ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538

Volume 13 Issue V May 2025- Available at www.ijraset.com

IV. RESULTS

A. NDVI Distribution.

The spatial mean NDVI across 2020–2025 shows that eastern Rajasthan exhibits denser vegetation compared to the arid west. Figure 1 illustrates the mean NDVI distribution, while Figure 2 displays the NDVI as of 2025. These maps serve as baseline indicators of average vegetation density across seasons and years.



Figure 2: Mean NDVI Map of Rajasthan (2020-2025)

B. NDVI Anomaly Mapping.

The NDVI anomaly identifies stress zones in Barmer, Jaisalmer, and Bikaner, while Jaipur and Udaipur exhibit minor positive anomalies. An animated visualization helps track spatio-temporal vegetation variability. Significant NDVI drops are observed during years of low monsoon rainfall, revealing a strong vegetation-rainfall dependency. Additionally, dry spells in 2022 and 2024 caused considerable stress in western Rajasthan



Figure 3: Latest NDVI Snapshot for 2025

C. District Time Series Analysis

1) Time series plots offer temporal insights into vegetation recovery and stress cycles:

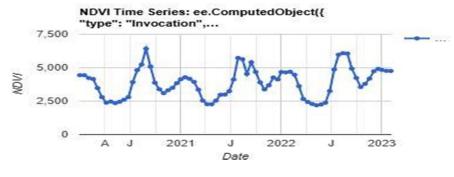
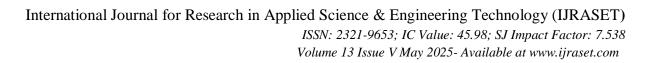
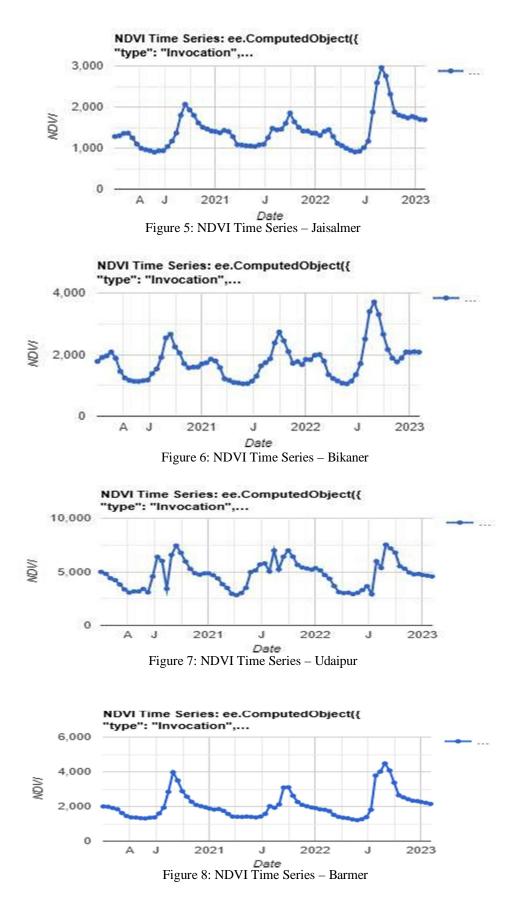


Figure 4: NDVI Time Series – Jaipur









D. Inter-District NDVI Comparison.

Figure 8, presents a bar chart comparing average NDVI values across districts. Jaipur, Udaipur, and Sirohi score higher, while Barmer, Jaisalmer, and Churu show the lowest NDVI values. Seasonal comparison reveals NDVI peaks during August-September, correlating with monsoon rainfall. Districts with irrigation support show smaller anomaly ranges. Sentinel-2 data validated these findings by offering better spatial detail in vegetated patches.

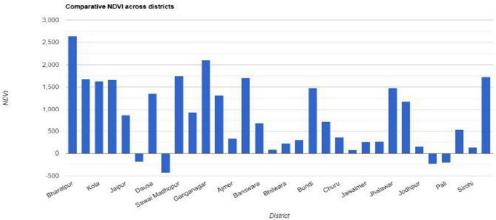


Figure 9: Average NDVI by District (2020–2025)

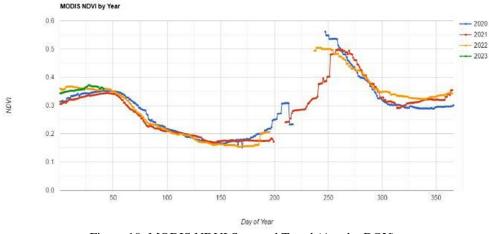


Figure 10: MODIS NDVI Seasonal Trend (Avg by DOY)

- E. Vegetation and Soil Classification Using ESA WorldCover and SoilGrids
- Eastern districts (Jaipur, Kota): Dominated by croplands, clayey soils
- Western districts (Jaisalmer, Barmer): Sparse vegetation, sandy soils
- Mount Abu (Sirohi): Forested highland with loamy soils
- Nagaur and Churu: Grasslands and scrub, mostly sandy loam soils

District	Dominant Vegetation Type						
Jaipur	Cropland						
Udaipur	Scrubland						
Barmer	Sparse vegetation						
Jaisalmer	Bare/Sparse Vegetation						
Sirohi	Forest						
Bikaner	Grassland						

. Table 1. Dominant	Vegetation	Classer	w District	(FCA	WorldCover)
. Lable L. Dominant	vegetation	Classes	by District	(L'D'L	wonucover)

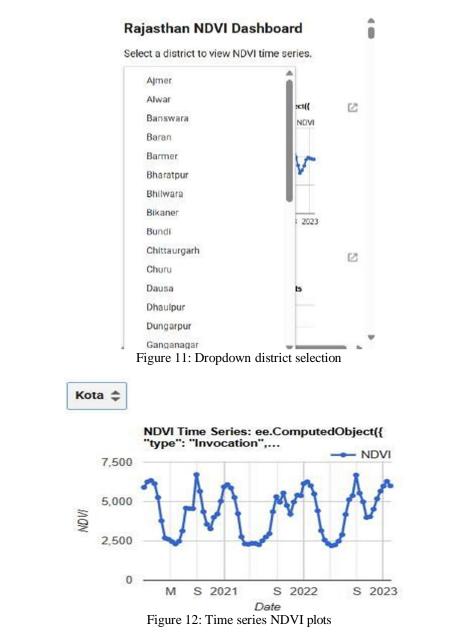


ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538 Volume 13 Issue V May 2025- Available at www.ijraset.com

Tuble 2. Son Types by District (Ibrate Sonemas)							
District	Dominant Vegetation Type						
Jaipur	Clay						
Udaipur	Clay Loam						
Barmer	Sandy						
Jaisalmer	Sandy						
Sirohi	Loam						
Bikaner	Sandy Loam						

F. Dashboard Implementation the GEE Dashboard Enables

The GEE dashboard received positive feedback during internal demonstrations. Users could dynamically explore charts, anomaly maps, and download CSVs. The inclusion of vegetation and soil data provided a holistic view for policy discussions, especially concerning drought vulnerability zones.



International Journal for Research in Applied Science & Engineering Technology (IJRASET) ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538 Volume 13 Issue V May 2025- Available at www.ijraset.com



G. Display of Vegetation and soil Information

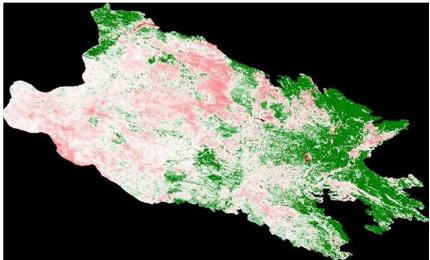


Figure 13: Animated NDVI anomaly across years

K 🔋 District_NDVI_Anomaly_Export.csv			Open with 👻						Œ	🖨 🕹	: 👌 sł	• ener			
asteminies	ADMC_CODE	ADM0_	NANE	ADM1_CODE	ADW1_NAME	ADW2_00DE	ADM2_NAWE	DISP_AREA	EXP2_YEAR	STATUS	STR2_YEAR	Shape_Area	Shape_Leng	mean	.geo
000100000000000000000000000000000000000		t15 bdia		15	06 Rejestron	17838	8-aabur	NO	3	00) Member State	1990	0.4652717477	6.173566258	2638.124366	(Type" Pol
0001000000000000	0	115 India		15	i06 Rajashan	17844	Draulour	NO	3	100 Member State	1950	0.274339432	3,592473893	1682.041255	(Type": "Po
0001000000000000	2	115 India		1:	ice Rajashan	17853	Kota	NO	>	000 Member State	1991	0.4926133602	6.107466172	1614.574259	(1)00"."Fo)
0001000000000000000		115 hda		15	ice Rejection	70236	Вальо	NO	.3	00 Member State	1991	0.4101398175	5.70737256	1665 463043	(Type) Poly
0001000000000000		115 India		15	i06 Rejestrari	17847	Jaipur	NO	3	000 Member State	1996	1.022298598	7.26567352	869.2721227	(Type": Fo)
000100000000000000000000000000000000000		115 India		10	ice Rajashon	17610	Uzapar	NO	3	00 Member State	1996	1,13140984	7,871570345	-185.6149031	("spe": "Po)
0001000000000000		115 India		15	ice Rajashan	70237	Dause	NO	3	100 Member State	1956	0.3260372295	4.321984912	1360.541809	(Type" 'Po)
000100000000000000000000000000000000000		115 India		10	ice Rajashan	70240	Rajsonant	NO	3	100 Member State	1956	0.4112725454	5.257091913	433.7820528	("spa": "Pot
0001000000000000	2	115 hda		11	26 Rejestren	17856	Sawa Machopur	NO	3	00 Nember State	1997	0.4217442209	4.755900837	1748.116529	(Type": "Pol;
0001000000000000		115 India		15	06 Rajashon	70219	Kinul	NO	3	100 Member State	1997	0.4692745552	4.568023057	\$16.6733006	(Type": "Pol)
000100000000000		115 hda		10	ice Rejestran	17646	Garganapar	NO	3	000 Member State	1998	1.040776564	0.576085857	2103.690101	(Type": Po)
000100000000000000000000000000000000000		115 India		15	ice Rejestren	70238	Hanumangam	NO		000 Member State	1958	0.8201049415	7.156515652	1318.383848	(Type" Poly
0001000000000000	0	115 India		15	ice Rajashan	17834	Amer	NO	3	100 Member State	1000	0.7612029083	7.23556665	340.8790729	(Type") Web
000100000000000000000000000000000000000	>	115 India		1	C6 Rajastran	17835	A war	NO		00 Member State	1000	0.7576973692	7.583410859	1711.768335	(Type": "Poly
000100000000000000000000000000000000000	,	115 India		15	ice Rejestren	17836	Sinwara	NO	3	00 Member State	1000	0.4458261565	3,642668422	684,2983826	(type" Pay
0001000000000000	0	115 India		15	06 Rajashan	17637	Same	NO	3	100 Member State	1000	2.551769979	9.74367742	87.8622198	Type": "Poly
000100000000000000000000000000000000000	0	115 hdia		15	66 Rajashan	17839	Bhitwitti	NO	3	000 Member State	1010	0.936017678	6,668916811	227.1742535	(Type": Pot
0001000000000000		115 hda		15	ice Rejestran	17840	S kansr	NO	3	00 Nember State	1000	2.475846208	9,993547547	305.1136205	(Type": Po)
00010000000000000		115 Inda		15	06 Rajastran	17841	Bindi	NO	,	00 Member State	1000	0.5003254578	4.113960612	1450.410263	(Type": Foly
0001000000000000	5	115 India		16	ice Rajashan	17642	Chitteurgart	NO	3	100 Member State	1000	0.94555562138	11.06703258	711.3583712	

Figure 14: CSV download functionality for analysts

The dashboard includes a list of all districts, each linking to their respective NDVI anomaly time series and classifi- cation metadata. Upon clicking a district, users can explore vegetation-soil interactions and observe NDVI stress trends interactively. This feature is supported by Earth Engine UI panels and dynamic charting. Additional integration with user-uploaded shapefiles or CSVs allows for custom region analysis. Future versions aim to include real-time alerts and climate projections.

V. DISCUSSION

A. NDVI Interpretation and Vegetation Response:

NDVI (Normalized Difference Vegetation Index) is a crucial tool for assessing vegetation health, density, and phenol- ogy based on red and near-infrared reflectance. High NDVI values typically indicate healthy, photosynthetically active vegetation, while low values reflect sparse or stressed vegetation, bare soil, or urban areas.

NDVI values vary seasonally, capturing phenological events such as leaf emergence, growth peaks, and senescence. These variations help monitor vegetation dynamics and land-use changes over time. Additionally, different land cover types exhibit unique NDVI patterns, aiding in classification and mapping.

Environmental disturbances like droughts, heat stress, or deforestation often result in noticeable NDVI declines, mak- ing the index a valuable indicator for stress detection and landscape monitoring.



ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538 Volume 13 Issue V May 2025- Available at www.ijraset.com

B. Implications for Drought Monitoring and Land Management:

This study highlights NDVI anomalies as early indicators of ecological stress, particularly when combined with soil and rainfall datasets. The integration supports proactive drought management, afforestation planning, and crop insurance schemes. Local-level anomaly detection enhances decision-making for sustainable land use and resource allocation.

This research demonstrates a scalable methodology for detecting vegetation anomalies using NDVI and GEE. The dash- board facilitates data-driven decision-making for ecologists, planners, and farmers. Future work includes incorporating Sentinel-2 data, rainfall datasets, and higher-resolution soil profiles for enriched analysis. Additional features like pre- dictive vegetation modeling and crop yield forecasting are also proposed. Expansion toward dynamic drought forecasting models and land degradation assessment is underway.

VI. CONCLUTION

This study comprehensively demonstrates the effectiveness of the Normalized Difference Vegetation Index (NDVI) as a robust and scalable tool for assessing vegetation health, detecting drought-induced stress, and analyzing land-use dy- namics across ecologically diverse regions such as Rajasthan. By integrating NDVI anomalies with auxiliary datasets such as soil texture (from ISRIC SoilGrids) and rainfall variability (from CHIRPS and IMD records), this project suc- cessfully mapped patterns of ecological vulnerability, resilience, and land degradation over a six-year period (2020–2025).

The analysis highlighted notable spatial gradients — from the sparsely vegetated and drought-prone districts of western Rajasthan, like Barmer and Jaisalmer, to the greener, agriculturally dominant eastern regions like Jaipur and Udaipur. Seasonal NDVI time series and multi-year anomaly mapping offered insights into the effects of monsoon variability, soil moisture retention capacity, and land management practices. These findings are particularly critical for drought early warning systems, agro-ecological planning, and sustainable resource allocation in semi-arid and arid zones.

A significant achievement of the project was the development of an interactive, district-wise dashboard built using Google Earth Engine (GEE). This dashboard empowers users—including policymakers, researchers, and land manag- ers—to dynamically explore NDVI anomalies, track vegetation trends, assess soil-vegetation relationships, and down- load custom CSV reports. The integration of real-time visualization capabilities with backend geospatial computation makes the dashboard a valuable decision-support tool for operational monitoring. Despite its success, the study acknowledges several limitations. The moderate spatial resolution of MODIS imagery (250 meters) occasionally masks finer-scale land cover variability, especially in heterogeneous agricultural landscapes. Cloud contamination, particularly during the monsoon months, poses challenges for generating seamless NDVI composites. Moreover, global soil datasets, while valuable, may not always capture localized anthropogenic impacts such as soil salinity increase, land degradation, or changing irrigation practices. Future improvements could involve the fusion of MODIS data with higher-resolution Sentinel-2 NDVI products and the incorporation of near-real-time ground-truth data for validation.

Nevertheless, NDVI remains an indispensable tool in the field of remote sensing for environmental monitoring, precision agriculture, biodiversity conservation, and land-use management. Its simplicity, proven effectiveness, and compatibility with cloud computing platforms like GEE ensure its continued relevance in addressing 21st-century ecological and cli- matic challenges.

The results of this research underline the immense potential of integrating Earth observation data with cloud-based ana- lytics to enhance resilience, ensure sustainable resource management, and foster proactive environmental stewardship at regional and local scales.

VII. FUTURE WORK

The scope of NDVI applications continues to expand with advancements in technology and analytics. Key directions for future work include:

- 1) Higher-Resolution Analysis: Incorporating Sentinel-2 NDVI (10 m) for finer spatial detail and localized planning.
- 2) Field Validation: Conducting ground surveys and drone-based imaging to validate remote sensing outputs.
- 3) Machine Learning Integration: Applying AI and ML algorithms for improved vegetation classification and anom- aly detection.
- 4) Multi-Sensor Fusion: Combining optical, thermal, and radar datasets for a holistic view of ecosystem dynamics.
- 5) *Public Dashboard Deployment:* Hosting the GEE dashboard on open platforms with user access tracking for broader utility.
- 6) Socio-Economic Integration: Linking NDVI trends with socio-economic indicators for policy formulation.
- 7) Climate Resilience Monitoring: Using NDVI to study vegetation response to climate change and support adapta- tion strategies.
- 8) Community Participation: Promoting citizen science approaches to enhance local monitoring and validation ef- forts.



ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538 Volume 13 Issue V May 2025- Available at www.ijraset.com

VIII. ACKNOWLEDGMENT

We would like to express our deepest gratitude towards Prof. Pinaki Karmakar, our devoted supervisor, whose guidance and encouragement have been the driving force behind carrying our research forward. His inspiration and leadership have been the driving force behind making this project feasible and enhancing our academic life to a great extent. Our path has been wisely and foresightedly led by Prof. Karmakar's precious ideas and suggestions for our professional life.

We would also like to express our profound gratitude to Prof. Moutushi Singh for always encouraging us to proceed without a series of obstacles we encountered along the way of the course. We would also like to thank all the technical, non-technical, and office personnel in our department for extending their support where needed. We would also like to thank all our depart-mental colleagues for ensuring a welcoming working environment to complete our project work.

We would also like to thank our director, Prof. Satyajit Chakraborti, for offering us such a great platform to build our scholarly lives. We also have a very special position in our hearts for our Principal, Prof. Arun Kumar Bar, because he has inspired us throughout.

REFERENCES

- [1] Tucker, C.J. (1979). Red and photographic infrared linear combinations for monitoring vegetation. Remote Sensing of Environment, 8(2), 127–150.
- [2] Huete, A., et al. (2002). Overview of the radiometric and biophysical performance of the MODIS vegetation indices. Remote Sensing of Environment, 83(1–2), 195–213.
- [3] ESA WorldCover 10m 2020 v100. https://esa-worldcover.org
- [4] Hengl, T., et al. (2017). SoilGrids250m: Global gridded soil information. Geoderma, 324, 126–137.
- [5] CHIRPS Rainfall Dataset. Climate Hazards Centerhttps://www.chc.ucsb.edu/data/chirps
- [6] Roy, D.P., et al. (2014). Landsat-8: Science and product vision for terrestrial global change research. Remote Sensing of Environment, 145, 154–172.
- [7] Jain, M., et al. (2016). The importance of satellite data in global agricultural monitoring. Nature Food, 2(4), 200–206.
- [8] Didan, K. (2015). MOD13Q1 MODIS/Terra Vegetation Indices. NASA.
- [9] ESA WorldCover 2020. European Space Agency.
- [10] Gorelick, N. et al. (2017). Google Earth Engine: Planetary-scale geospatial analysis. Remote Sensing of Environment.
- [11] FAO GAUL. Global Administrative Unit Layers.
- [12] ISRIC SoilGrids (2018). International Soil Reference and Information Centre.
- [13] Google Earth Engine Documentation. (2024). https://developers.google.com/earth-engine/
- [14] ISRO Bhuvan Data Repository. (2024). https://bhuvan.nrsc.gov.in
- [15] Funk, C., Peterson, P., Landsfeld, M. et al. (2015). CHIRPS: A new precipitation dataset for climate monitoring. Scientific Data.
- [16] Sentinel-2 Mission Guide. Copernicus ESA. https://sentinel.esa.int/web/sentinel/missions/sentinel-2











45.98



IMPACT FACTOR: 7.129







INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Call : 08813907089 🕓 (24*7 Support on Whatsapp)