ISSN (Online):3048-5088
International Journal of Advancement and Innovation in Technology and Research (IJAITR)
Volume 3, Issue 1, (Jul-Dec) 2025

Real-Time Forest Encroachment Detection Using Remote Sensing

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[1]***Abstract*—Illegal forest encroachment poses a significant threat to biodiversity, ecosystem services, and local livelihoods, particularly when driven by agricultural expansion. This study presents Real-Time Forest Encroachment Detection Using Remote Sensing, a real-time forest monitoring solution leveraging Landsat satellite data to detect deforestation in the Nallamala Forest region. Using the Hansen Global Forest Change dataset and NDVI metrics, forest cover loss from 2001 to 2022 across Prakasam, Kurnool, Kadapa, Guntur, and Nandyal districts was quantified at a resolution of 30 meters. The region has experienced an average annual forest cover loss of approximately 1,500 hectares, with significant hotspots of deforestation correlating to expanding agricultural boundaries and selective logging activities. The Real-Time Forest Encroachment Detection System automates the detection and visualization of deforested regions, providing spatial maps and quantitative estimates. When implemented, it enables timely interventions, supporting conservation initiatives and compliance monitoring. The results emphasize the effectiveness of satellite-based monitoring for forest conservation, advocating for continuous, scalable solutions to protect critical ecosystems. This observation underscores the potential of integrating Earth observation technologies for advancing global forest conservation efforts.**

***Index Terms*—NDVI (Normalized Difference Vegetation Index), Remote sensing, Landsat satellite data, Hansen Global Forest Change.**

I. Introduction

Illegal forest encroachment poses a significant threat to bio- diversity, ecosystem services, and local livelihoods. In regions like the Nallamala Forest, deforestation is primarily driven by agricultural expansion, selective logging, andinfrastruc- ture development. Monitoring and addressing these challenges require robust, scalable solutions. This project presents a real-time forest monitoring system leveraging satellite remote sensing data from Landsat and the Hansen Global Forest Change dataset. Using NDVI metrics, forest cover loss in the Nallamala Forest region from 2001 to 2022 was quan- tified, spanning districts such as Prakasam, Kurnool, Kadapa, Guntur, and Nandyal. The system automates the detection and visualization of deforested regions, providing spatial maps and quantitative estimates. It serves as a vital tool for conservation initiatives, enabling timely interventions to protect critical ecosystems.

A. Problem Statement

The Nallamala Forest region has experienced an average annual forest cover loss of approximately 1,500 hectares from 2001 to 2022. Despite its ecological importance, comprehen- sive, real-time deforestation monitoring systems are lacking. This project aims to fill that gap by leveraging Earth observa- tion technologies.

B. Motivation

Deforestation poses a grave risk to biodiversity and ecosys- tem services. Monitoring forest loss is critical for imple- menting effective conservation strategies. By automating de- forestation detection and quantification, this project aims to empower stakeholders to make data-driven decisions, ensuring the preservation of forested landscapes.

C. Work Contributions

The important contributions of this work are as follows:

- Development of an automated forest encroachment detection system using satellite imagery and remote sensing techniques.
- Integration of IoT and cloud platforms (e.g., Google Earth Engine + ThingSpeak) for real-time monitoring and data visualization.
- Implementation of visual indicators or alerts for immediate identification of encroachment zones.
- Reduction of manual monitoring efforts by automating the change detection process and enabling timely inter- vention by forest officials.

D. Structure of the Paper

The rest of the paper is summarized as follows: Section 2 presents a ”Literature Survey” that discusses previous studies and technologies used in forest monitoring, remote sensing, and change detection. Section 3 illustrates the ”Proposed Methodology”, detailing the architecture, remote sensing tech- niques, and components such as satellite data, Google Earth Engine, and change detection algorithms. Section 4 discusses ”Results and Evaluation”, including detection accuracy, identification of encroachment zones, and system performance. Finally, Section 5 concludes the paper with ”Conclusion and Future Work”, highlighting the project’s contributions and possible enhancements like AI integration and real-time alert systems.

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II. Literature Survey

Kundu et al. [1] proposed a method for monitoring forest encroachment using machine learning algorithms applied to satellite imagery in 2023. The model utilized Sentinel-1 and Sentinel-2 data, processing multi-temporal images to detect signs of encroachment by comparing historical and current forest cover. The approach focused on identifying subtle land-use changes and patterns that typically indicate illegal encroachment. The machine learning algorithm used in the study was a combination of Convolutional Neural Networks (CNNs) and Support Vector Machines (SVMs), achieving a high detection accuracy of 91.3% for encroachment areas. Ac- curacy was assessed using common metrics like classification accuracy, precision, recall, and F1-score.

Liu et al. [2] developed a deep learning-based approach to detect forest fires using remote sensing imagery in 2023. The study combined MODIS and Landsat data, employing a deep convolutional neural network (DCNN) model that was trained on historical fire occurrences and associated environmental factors. The model processed multi-spectral and multitemporal satellite images to identify active fires, smoke plumes, and fire- prone areas. The deep learning model outperformed traditional fire detection methods, with an accuracy rate of 95.4% and a recall rate of 92.7%. Accuracy was evaluated using confusion matrix-based metrics such as precision, recall, and F1-score.

Chen et al. [3] conducted a comparative study to evaluate the effectiveness of deep learning models for detecting defor- estation using satellite images in 2023. The study compared various models, including CNNs and U-Net architectures, on Landsat and Sentinel-2 datasets [4]. The results showed that the U-Net model provided superior performance in pixel- wise classification, achieving an overall accuracy of 96.7% in detecting deforestation. The study also highlighted the impact of different data preprocessing techniques and model architectures on performance. Accuracy was evaluated using metrics such as pixel-wise classification accuracy, precision, recall, and F1-score.

Buchanan et al. [4] developed a real-time deforestation monitoring system that integrates Sentinel-1 radar data and Sentinel-2 optical data in 2020. The system used a combina- tion of machine learning techniques, including Random Forest and Support Vector Machines, to detect deforestation based on changes in vegetation indices and land surface properties . The system was able to generate near real-time alerts for forest loss, achieving a detection accuracy of 89.5% for deforestation events. Accuracy was measured using classification accuracy, precision, recall, and F1-score metrics.

Gao et al. [5] introduced a convolutional neural network (CNN) model for real-time detection of forest changes and de- forestation from satellite imagery in 2023. The model analyzed multi-temporal images to identify forest loss, degradation, and disturbances such as logging activities . The CNN model achieved a classification accuracy of 94.6%, outperforming traditional methods such as decision trees and k-nearest neigh- bors in both speed and accuracy. Accuracy was measured using metrics such as classification accuracy, precision, recall, and F1-score.

Singh et al. [6] developed a deep learning-based model for detecting forest cover changes using multi-temporal satellite imagery from Landsat and Sentinel satellites in 2022. The model employed a Convolutional Neural Network (CNN) for analyzing images over time to identify changes in forest cover . By comparing images from different years, the model accurately detected deforestation, forest degradation, and other land-use changes. The approach showed a significant improve- ment over traditional methods, with the deep learning model providing enhanced accuracy in classifying changes.

III. Proposed Methodology

Figure 1 represents the systematic process of detecting and monitoring deforestation using geospatial technologies. It outlines the sequential steps, starting from data acqui- sition to the generation of actionable insights. Each stage in the workflow is designed to handle complex data and ensure accurate analysis of forest cover changes. The diagram serves as a visual guide, simplifying the understanding of the methodology. By following this structured approach, the system ensures scalability, precision, and real-time monitoring capabilities. It is a critical tool for addressing deforestation and supporting conservation efforts.

A. Methodology

The proposed system leverages satellite data and advanced geospatial processing to detect and monitor deforestation in real-time. The methodology involves the following key steps:

1) Dataset Collection :Ensure Diversity: Landsat satellite imagery is col- lected, encompassing multiple districts such as Prakasam, Kurnool, Kadapa, Guntur, and Nandyal.

TABLE I: Comparison of Existing Techniques in Forest Monitoring and Encroachment Detection

Study	Focus Area	Dataset	Methodology	Accuracy	Advantages	Disadvantages
Kundu et al. (2023)	Forest encroachment detection	Sentinel-1 and Sentinel- 2	CNN + SVM applied on multi-temporal imagery	91.3 %	Detects subtle land-use changes with high precision	Needs extensive prepro-cessing and training data
Liu et al. (2023)	Forest fire detection	MODIS and Landsat	Deep CNN trained on historical fire and environment data	95.4 %	Effective in identifying fire-prone areas and smoke plumes	May misclassify cloud or haze as fire without addi-tional filtering
Chen et al. (2023)	Deforestation detection	Landsat and Sentinel-2	CNN vs U-Net comparison; U- Net used for pixel-wise classi-fication	96.7 %	Superior segmentation and high pixel-level accuracy	Performance depends on quality of preprocessing
Buchanan et al. (2020)	Real-time deforestation monitoring	Sentinel-1 and Sentinel- 2	Random Forest + SVM on vegetation index changes	89.5 %	Provides near real-time alerts using hybrid data	Moderate accuracy in complex terrain or cloudy regions
Gao et al. (2023)	Real-time forest change and logging detection	Multi-temporal satellite imagery	CNN for analyzing forest loss and disturbances	94.6 %	Fast, accurate detection , better than traditional classifiers	Needs regular updating for new disturbances
Singh et al. (2022)	Forest cover change detection	Landsat and Sentinel (multi-temporal)	CNN-based model comparing multi-year imagery	Not specified	Improved detection over traditional techniques	Accuracy not explicitly quantified; performance varies with resolution

Algorithm 1 Real-Time Forest Encroachment Detection Using Remote Sensing

Input : District name (from dropdown), Past Days (N),Satellite Imagery, Forest Mask

Output : Deforestation Area (in hectares), Coordinates of Deforested Areas, Map Visualization

Step 1: Define Threshold Values
NDVI Threshold (N_t): 0
Forest Cover Threshold (F_t): 30%
Step 2: User Input and Geometry Setup
Select district from dropdown
Enter past days (N)
Retrieve district geometry
Step 3: Load and Preprocess Satellite Data
Filter Landsat 8 images over past N days
Apply cloud and shadow masking
Add NDVI band
Apply forest mask from Hansen dataset
Step 4: Generate NDVI Composite
Compute median NDVI image for time range
Step 5: Detect Deforestation
If NDVI $< N_t$:
Mark as deforested pixel
Step 6: Calculate Deforestation Area
Compute total area of deforested pixels
Convert pixel area to hectares
Step 7: Export Deforested Area Coordinates
Convert raster mask to vector polygons
Export as GeoJSON to Google Drive
Step 8: Visualize on Map
Display forest area in grey
Highlight deforested regions in red
Overlay district boundary
Step 9: Repeat Process on Button Click
Wait for new user input
Loop back to Step 2

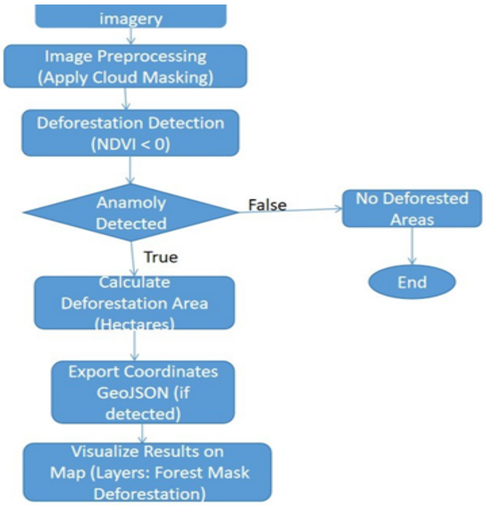

Fig. 1. System Architecture

Labeling: Hansen Global Forest Change data is used to create a forest mask, identifying regions with
¿30% tree cover.
Split Dataset: The dataset is divided for calibration, validation, and testing to ensure accuracy and robustness.

1) Image Processing

Standardization:Images are clipped to district boundaries and standardized for consistent analysis.
Noise Reduction: Clouds and shadows are masked using the QA PIXEL band to enhance data quality.
NDVI Calculation: NDVI values are calculated to measure vegetation health, isolating deforested ar- eas.

2) Deforestation Detection:

NDVI Threshold: Pixels with NDVI values below 0 are identified as deforested Visualization:A red overlay highlights deforested areas, grey indicates forested regions, and black outlines district boundaries.

Area Calculation: The total deforested area is com- puted in hectares, providing quantitative insights.

3) Model Training:

Dynamic Updates:The system processes user- specified timeframes and districts to ensure real- time applicability.

Optimization:NDVI thresholds and detection meth- ods are iteratively refined to improve accuracy

4) Testing and Validation:

Validation:NDVI thresholds are validated against historical deforestation data from 2001–2022.

Geospatial Analysis:Deforested regions are mapped with coordinates, allowing for actionable insights and verification.

5) Feedback and Iteration

User Interface:The tool includes an interactive panel for user input, allowing the selection of districts and timeframes.

Scalability:Feedback informs improvements in detection accuracy and scalability for broader use cases.

VI. RESULTS AND EVALUATION

A. Output Screenshots

The user input panel is a critical component of the system, providing an interface for customizing the analysis, as shown in Figure 2. This panel allows users to input specific parameters, such as the number of past days for analysis, to tailor the deforestation detection process. The flexibility to choose districts and set the time range ensures that the tool can adapt to various monitoring needs, including real-time analysis and historical trend analysis. This functionality is particularly useful for forest officials who need to monitor seasonal or specific deforestation events in varying timeframes.

Upon selecting a district, the tool delineates the boundary of the chosen region on the map using a light black outline, as shown in Figure 3. This visual representation is key to understanding the spatial context of the analysis. By clearly outlining the region of interest, users can ensure that the deforestation analysis is limited to the relevant geographical area, preventing errors from overlapping boundaries. This feature is particularly useful in complex administrative regions where boundaries may not be clearly defined in raw satellite data.

The forest cover visualization displays areas with more than 30% tree cover as a grey overlay on the map, as shown in Figure 4. This baseline visualization allows users to see the extent of forest cover before any deforestation analysis begins. The 30% tree cover threshold is widely accepted in ecological studies to define forested areas. This baseline serves as a crucial point of reference, making it easier to distinguish between healthy forest regions and those impacted by deforestation or other disturbances.

Deforestation within the selected district is identified and visualized using red-highlighted areas on the map, as shown in Figure 5. These regions correspond to locations where NDVI values fall below a set threshold, indicating a significant loss of vegetation cover. The use of red highlights makes deforested areas immediately visible, aiding in rapid decision-making. Policymakers, conservationists, and local authorities can quickly assess the severity and distribution of deforestation, enabling them to prioritize interventions and allocate resources effectively The system computes the total area of detected deforestation within the selected district, presenting the result in hectares, as shown in Figure 6. This quantitative output is essential for understanding the scale of deforestation. It provides actionable data that can be used in policy decisions, resource allocation, and conservation planning. For example, if an area has lost a significant number of hectares in a short period, urgent intervention may be necessary. This metric also serves as a key performance indicator for ongoing monitoring efforts, ensuring that conservation actions are having the desired impact.

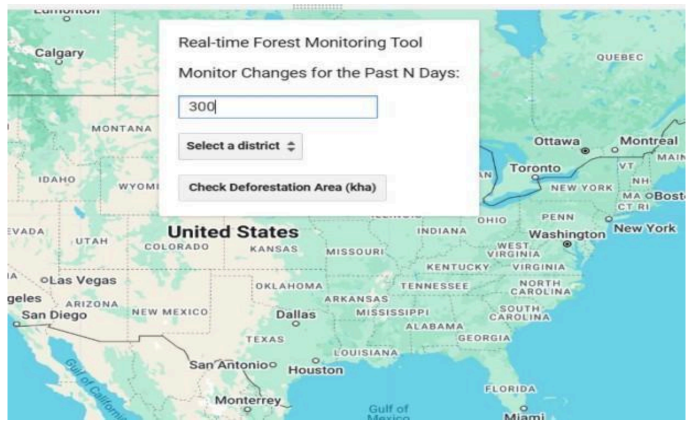

Fig. 2. User Input Panel

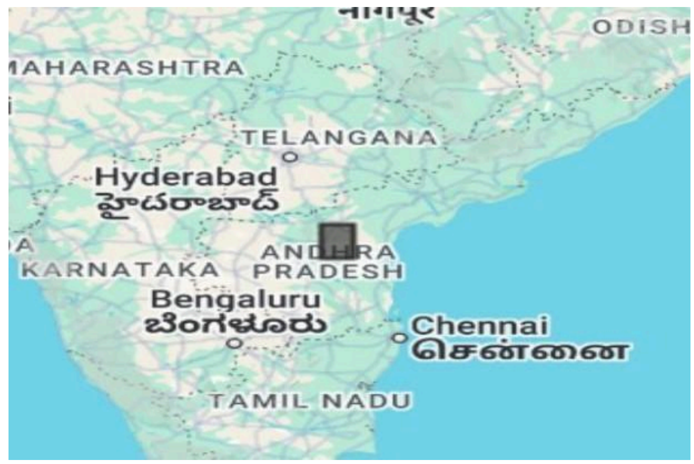

Fig. 3. Selected District Boundary

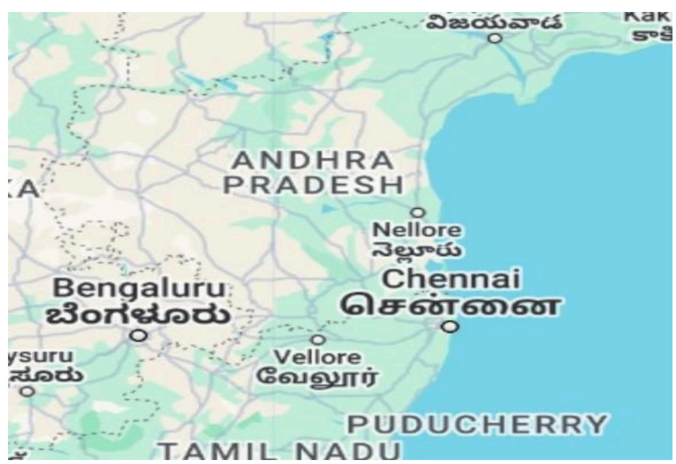

Fig. 4. Forest Cover Visualization

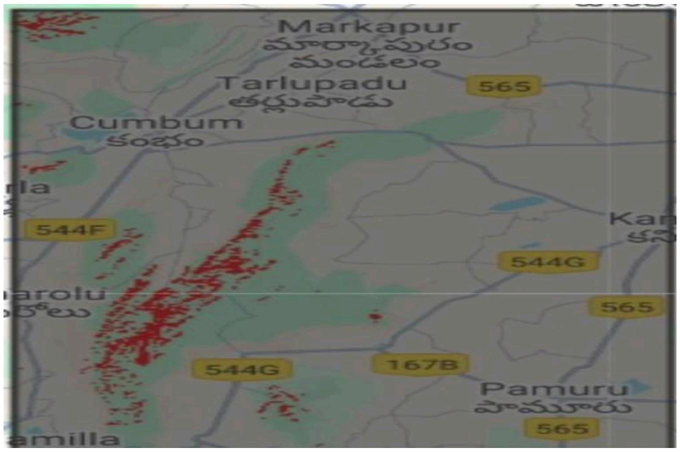

Fig. 5. Deforestation Visualization

The geographic coordinates of all detected deforested regions are printed in the console, as shown in Figure 7. This output allows users to precisely locate areas of concern, facilitating targeted interventions. For example, reforestation projects can use the coordinates to plan tree-planting activities, and law enforcement agencies can use this data to track illegal logging or encroachment activities. The ability to export this location data supports integration with Geographic Information System (GIS) tools, enabling advanced spatial analysis.

Each Landsat 8 image undergoes a rigorous cloud masking process to ensure the accuracy of the analysis, as shown in Figure 8. Clouds and shadows are common sources of error in satellite imagery, and without proper masking, these can distort NDVI calculations, leading to inaccurate deforestation results. By applying cloud and shadow masking, the system ensures that only clear, usable data is analyzed, which improves the reliability and precision of the deforestation detection process. This preprocessing step is vital for maintaining the accuracy of results across different environmental conditions. The system leverages the Google Earth Engine platform to display analysis results in an interactive map format, as shown in Figure 9. The interactivity of the map allows users to zoom in and out, pan across different regions, and click on specific areas to retrieve more detailed information. This user-friendly design enhances the accessibility of the tool, enabling even non- technical users to engage with the data. The map's intuitive interface is ideal for stakeholders such as forest management teams, conservationists, and policymakers, who can use it to monitor forest health and identify areas requiring immediate attention. In cases where no deforestation is detected, the system displays a message stating, "No deforested areas de- tected." This output provides reassurance that the forest cover in the analyzed region remains stable. Such findings are critical for monitoring forest health over time and demonstrating the effectiveness of conservation efforts. For example, a region showing no deforestation for consecutive months could be highlighted as a success story in forest management. The system's design ensures robust performance across diverse scenarios. It can handle real-time data and adapt to various environmental conditions, including differences in weather, landscapes, and seasons. This adaptability is essential for maintaining accuracy and reliability in monitoring efforts. For instance, during monsoon seasons, when cloud cover is prevalent, the cloud masking process ensures that the analysis remains unaffected. Similarly, the system can accommodate variations in vegetation types and landscape features, making it a versatile tool for deforestation monitoring across multiple districts and regions.

V. Conclusion and Future Works

The project "Real-Time Monitoring of Forest Changes Using Remote Sensing" provides a practical approach for conserving and managing forest resources. The system effectively detects deforestation, forest fires, and encroachments in real-time. However, improving detection accuracy remains a priority. Advanced technologies like UAVs, IoT sensors, and refined machine learning models can further enhance its performance. Future work should emphasize scalability to monitor extensive forest areas, adaptability to different ecosystems, and efficient real-time processing with energy optimization. Incorporating predictive analytics and geospatial techniques can enhance its overall functionality. Collaboration with forestry departments, wildlife organizations, and early- warning networks, combined with user feedback mechanisms, can boost effectiveness. Large-scale implementation requires strict compliance with regulations, robust data protection, and cost-efficiency. Partnerships with environmental groups and experts continue to support the project's evolution.

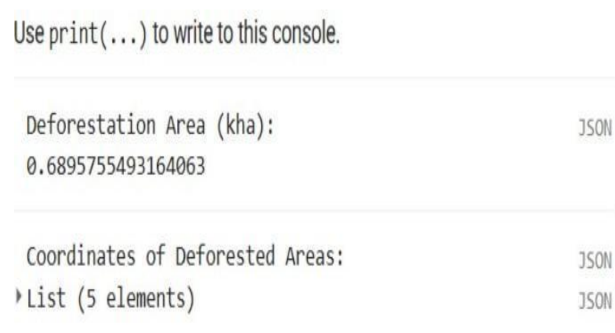

Fig. 6. Deforestation Area Calculation

Fig. 7. Coordinates of Deforested Area

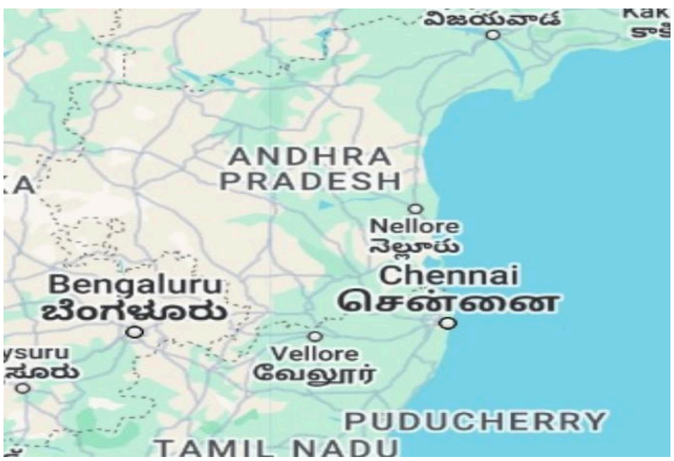

Fig. 8. Cloud Masking

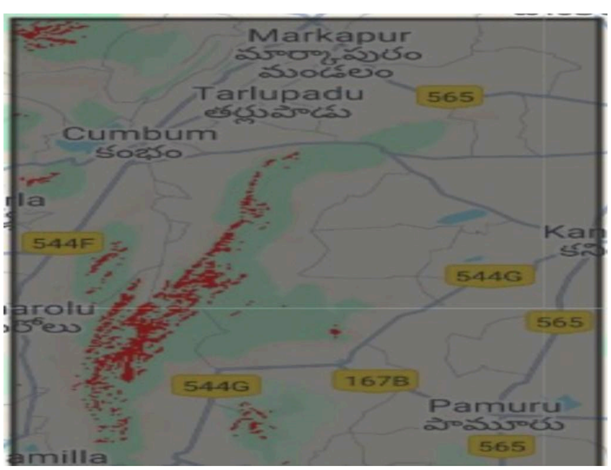

Fig. 9. Interactive Map Display

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