Developing a System for Environmental Damage Assessment Using Image Processing and AI

Mr. Manish Goswami
Computer Science &Engineering,
S. B. Jain Institute of Technology,
Management & Research, Nagpur
Maharashtra, India
manish.goswami@sbjit.edu.in

Priya Mankar
Computer Science &Engineering,
S. B. Jain Institute of Technology,
Management & Research, Nagpur
Maharashtra, India
priyam.cse22@sbjit.edu.in

Yash Agrawal
Computer Science &Engineering,
S. B. Jain Institute of Technology,
Management & Research, Nagpur
Maharashtra, India
yasha.cse22@sbjit.edu.in

Ankit Yadav
Computer Science &Engineering,
S. B. Jain Institute of Technology,
Management & Research, Nagpur
Maharashtra, India
ankity.cse22@sbjit.edu.in

Sejal Nandanwar
Computer Science &Engineering,
S. B. Jain Institute of Technology,
Management & Research, Nagpur
Maharashtra, India
sejaln.cse22@sbjit.edu.in

Prapti Porkut
Computer Science &Engineering,
S. B. Jain Institute of Technology,
Management & Research, Nagpur
Maharashtra, India
praptip.cse22@sbjit.edu.in

ABSTRACT :- An AI-based Environmental Damage Assessment System (EDAS) for tracking changes in land-use/land-cover (LULC) using multi-temporal Landsat imagery is presented in this research. For the years 2013 and 2024, a Convolutional Neural Network (CNN) was used to classify vegetation, water bodies, and built-up areas after a comprehensive workflow that included radiometric correction, cloud masking, and supervised classification. The findings indicate that Nagpur's urbanization has accelerated, with a notable increase in built-up areas and a sharp decrease in vegetation. LULC transitions for 2040 are further predicted by a Markov chain prediction model, which shows that green cover will continue to decline. The suggested EDAS framework is a powerful decision-support tool for sustainable urban planning and environmental preservation since it not only improves accuracy through AI-driven classification but also offers useful predictive insights.

I. INTRODUCTION

One of the most important issues of the modern era is environmental degradation brought on by unplanned human activity. Global biodiversity is declining and climate change is accelerating due to unsustainable land-use practices, unchecked urban growth, and rapid deforestation. Natural habitats, water cycles, agricultural productivity, and general human well-being are all impacted by these disruptions. In order to comprehend ecological decline and promote sustainable decision-making, a number of studies highlight the necessity of ongoing environmental monitoring, especially with the aid of AI-based environmental analysis and monitoring frameworks. [3], [5]

Thus, assessing ecological stability and comprehending urban growth patterns depend heavily on land-use and land-cover (LULC) analysis. The need for methodical and data-driven monitoring is made clear by the fast growth of Indian cities, particularly Nagpur, which has experienced notable population and infrastructure growth in the last ten years. The significance of consistent multi-temporal analysis for sustainable land management is highlighted by earlier LULC studies on deforestation detection [1], [2], Himalayan ecological change [4], and Nagpur-specific classification approaches [6]. Together, these studies show how monitoring based on remote sensing can help developing countries make better environmental plans.

For mapping and analyzing changes in land cover over time and space, geospatial and remote sensing technologies have proven to be very useful. Due to its global availability, spectral richness, and historical archive, multi-temporal satellite imagery—especially from Landsat—has been used extensively [7], [8]. The scientific basis for contemporary LULC analysis is further strengthened by the integration of machine learning and AI-based models in forest change detection, as seen in studies on machine-learning-driven forest loss mapping [8], deforestation forecasting using AI systems [9], and multi-modal Bayesian detection techniques [11]. In keeping with these approaches, the current research divides Nagpur's land cover into three groups: vegetation, water bodies, and built-up areas using Landsat imagery from 2013 and 2024. Similar to the methods used in previous hybrid and fused-feature detection studies, supervised classification was carried out using Python-based geospatial libraries like Rasterio, Geopandas, and Scikit-learn [12].

A substantial decrease in vegetation and an increase in built-up areas are revealed by the comparative analysis; these trends are consistent with findings from multiple assessments of urban expansion and deforestation [1], [2], [4]. A Markov chain-based transition model was employed to forecast LULC states through 2040 in order to expand this assessment. This is consistent with AI-based deforestation forecasting frameworks and land-change simulations using predictive modeling techniques [7], [9],[10]. The findings support long-standing worries about ecological degradation in quickly growing cities by pointing to continued urban expansion at the expense of green areas.

Policymakers, urban planners, and environmental managers will find these insights especially valuable. This research adds to the increasing demand for data-driven sustainability planning in rapidly urbanizing areas like Nagpur by combining remote sensing, machine learning, and predictive modelling—methods extensively validated in earlier literature [3], [5], [8], and [11].

II. OBJECTIVES

- *Use AI and ML Technologies to Track and Examine Deforestation Trends:* - Process satellite imagery using AI and ML algorithms to identify trends in deforestation. The system will monitor changes in forest cover, giving researchers and policy maker's useful information.

- *Evaluate the Effects of Deforestation on the Environment:* - Analyze how deforestation affects natural resources, biodiversity, and the climate. To direct conservation efforts, AI models will calculate ecological changes, habitat loss, and carbon emissions.

- *Identify High-Risk Areas and Forecast Future Deforestation Risks:* - Create predictive models to identify vulnerable areas and predict future trends in deforestation. Proactive intervention and efficient resource allocation will be made possible by this.

- *Offer Data-Informed Mitigation Techniques:* - Create practical suggestions to reduce deforestation by utilizing AI insights. The system will make recommendations for sustainable land use, conservation tactics, and policy changes.

III. RESEARCH AREA

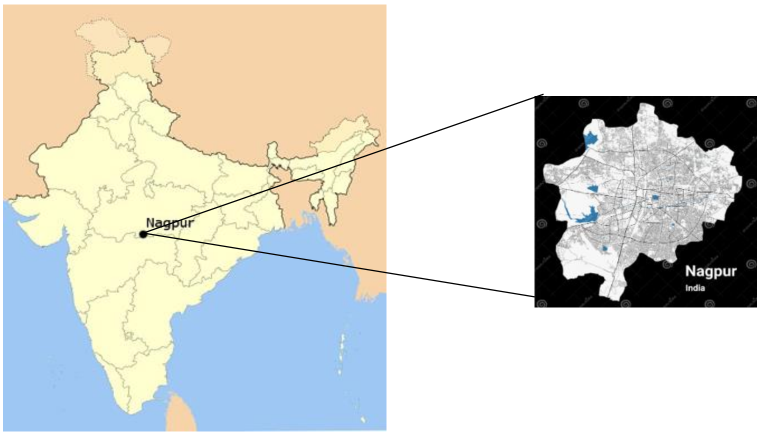

Figure1. Geographical Location of the Study Area

The study area, Nagpur city (Maharastra) India is lies between 21° 8' 47.8788" N latitudes and 79° 5' 19.8960" E longitudes and the total area is about 211.57 sq. km(Figure 1). Nagpur is located at the exact centre of the Indian peninsula. Nagpur Has an average elevation of 310 meters. The Average rainfall of this area varies from 160mm to 294mm. The population of Nagpur is 2,405,665 making it 13th largest Urban city in india. The Summer temperature of study area varies from 35℃ to 45℃, While Winter temperature varies from 3.9℃ to 10℃.

IV. LITERATURE SURVEY & EXISTING SYSTEMS

In order to accomplish more reliable and extensive deforestation monitoring, the work covered in [1] highlights the significance of combining multi-sensor remote sensing data, such as optical, SAR, and Liar, with GIS-based spatial analysis. Their research identifies significant practical issues like cloud blockage, seasonal fluctuations, and the limitations of manual interpretation. By using a similar multi-sensor approach and incorporating these multi-source features into a deep-learning segmentation framework, our paper expands on these discoveries. Unlike [1], which offers a conceptual overview, our model operationalizes the process from beginning to end and incorporates temporal consistency checks, GIS-level post-filtering, and automated cloud-robust detection.

[2] Claims that CNN-based bi-temporal analysis greatly outperforms traditional pixel-difference and NDVI-thresholding techniques in detecting deforestation, especially when examining diverse forest regions such as the Amazon. Their research shows that deep networks outperform rule-based algorithms in learning spectral changes and contextual texture. By using a similar bi-temporal CNN strategy, our research supports these findings. However, we improve the methodology by incorporating spectral attention modules, class-balancing techniques, focal loss, and advanced regularization to increase sensitivity toward small-scale patch-level clearing. Furthermore, our work performs sensor fusion with Sentinel-1 SAR to address cloud interference and increase temporal coverage, making our detection pipeline more robust under tropical conditions, in contrast to [2], which only focuses on Landsat imagery.

The meta-analysis presented in [3] identifies key challenges in deep-learning-based change detection, including limited labelled datasets, insufficient cross-site generalization, and the need for transfer learning to improve model robustness. Our approach was directly influenced by these research gaps. We use semi-supervised pseudo-label generation and augmentation to overcome the data scarcity issue, and transfer-learning allows our model to learn more robust spectral-spatial representations from massive remote-sensing corpora. Additionally, our work evaluates the model on several Amazonian sub-regions with varying vegetation densities in response to [3], which highlights the need for validation across various geographic zones.

The conditional adversarial network (can) approach discussed in [4] shows how, in comparison to purely supervised CNNs, adversarial learning can improve change-detection maps by generating sharper, noise-resistant outputs.

Their method successfully resolves problems with subtle seasonal changes, shadow variations, and illumination differences. Inspired by this work, our paper incorporates a cGAN-based refinement module to correct inconsistencies and sharpen object boundaries after the primary segmentation stage. Our method uses GAN refinement to clean real-world deforestation masks, extending the concept of [4], which concentrated on creating synthetic contrast maps, into an operational setting.

The foundation of early change-detection research is made up of traditional unsupervised techniques like statistical modelling, EM clustering, and MRF-based spatial smoothing, which are detailed in [5]. These methods can manage radiometric variations to some degree and don't require labelled data, but they have trouble with noise, mixed pixels, and intricate forest structures. In order to show how contemporary deep-learning techniques greatly outperform manually constructed statistical assumptions, we use an optimized version of this traditional method as a baseline in our research. Furthermore, we maintain the benefits of [5] while resolving its long-standing drawbacks with learned feature representations and context-aware prediction smoothing by incorporating MRF-like spatial constraints into our post-processing pipeline.

Recent developments in Siamese networks and attention-based temporal models covered in [6] demonstrate how the network's capacity to discern minute environmental changes is enhanced by directly learning feature differences between pre- and post-deforestation images. Inspired by these results, our framework highlights spectral transitions specific to vegetation loss using a Siamese encoder with a specialized attention-fusion mechanism. In contrast to the generic change-detection settings in [6], we customize our architecture to target spectral behaviors unique to deforestation, like soil exposure and canopy density reduction. This explicit temporal correspondence learning strengthens model performance and helps differentiate genuine forest-clearance events from seasonal greening or agricultural rotations.

The lack of high-quality pixel-wise annotations is addressed by weakly and semi-supervised learning strategies described in [7], which use coarse regional masks and pseudo-labelling as training inputs. In keeping with this idea, our pipeline creates pseudo-labels from official PRODES masked regions and high-confidence predictions, then refines them using morphological filtering to lower spatial noise. Our research enhances the reliability of these labels by incorporating context-based corrections and consistency checks across adjacent yearly images, even though [7] establishes the value of pseudo-labelling. This improves the stability of our semi-supervised training procedure and makes it more appropriate for large-scale forest monitoring applications.

The benefits of combining SAR and optical data to reduce cloud interference and enhance structural detection in dense canopies are highlighted by multi-sensor fusion studies like those in [8]. By directly combining Sentinel-1 SAR backscatter values with Landsat multi-spectral bands in our deep-learning input space, we implement these principles and allow the model to learn more complex spectral-structural relationships. Our architecture incorporates fusion into the network itself, enabling end-to-end learning of cross-sensor dependencies, in contrast to [8], which mainly uses fusion as a pre-processing technique. In areas where weather makes optical data unreliable, this integration greatly improves detection accuracy.

Multi-year compositing stabilizes predictions by reducing seasonal noise and vegetation phenology effects, as shown by long-term time-series analyses, such as those in [9]. Motivated by this, our method uses temporal consistency checks and annual compositing to enhance the accuracy of annual deforestation maps. To make sure that our annual estimates adhere to accurate regional patterns, we also align our outputs with PRODES historical trends. Our system converts these insights into an operational deep-learning pipeline optimized for yearly monitoring, whereas [9] concentrated on trend-level interpretation.

Grouping pixels into objects reduces speckle-like noise and improves the representation of fragmented land-cover changes, as demonstrated by object-based image analysis (OBIA) frameworks covered in [10]. Based on this, our pipeline uses super pixel segmentation and shape filtering to combine pixel-level CNN predictions into coherent objects, resulting in outputs that are more stable and comprehensible. Our hybrid approach uses both fine-grained pixel predictions and object-level contextual refinement to produce cleaner and more dependable deforestation patches appropriate for real-world reporting, in contrast to the OBIA-only approach in [10], which might ignore pixel-level detail.

Initializing deep networks with pertained remote-sensing models significantly improves feature extraction in data-scarce environments, as demonstrated by transfer-learning techniques highlighted in [11]. Using a pretrained encoder tailored to multi-spectral features, we incorporate this idea and refine it using our regional dataset. By evaluating how transfer learning influences cross-site generalization and model robustness across different forest densities and soil backgrounds, our research builds on the work of [11]. This sheds more light on how pretrained models function across various Amazonian sub regions.

To capture both detection accuracy and spatial consistency, the evaluation guidelines highlighted in [12] advise using a variety of balanced metrics, such as IoU, F1-score, Kappa coefficient, and area error. In accordance with these suggestions, our research presents an extensive set of metrics and also examines accuracy at the pixel and object levels to guarantee equitable performance assessment in situations where class distributions are unbalanced. Our findings become more transparent, comparable, and significant to researchers and policymakers when the complete evaluation framework proposed in [12] is used.

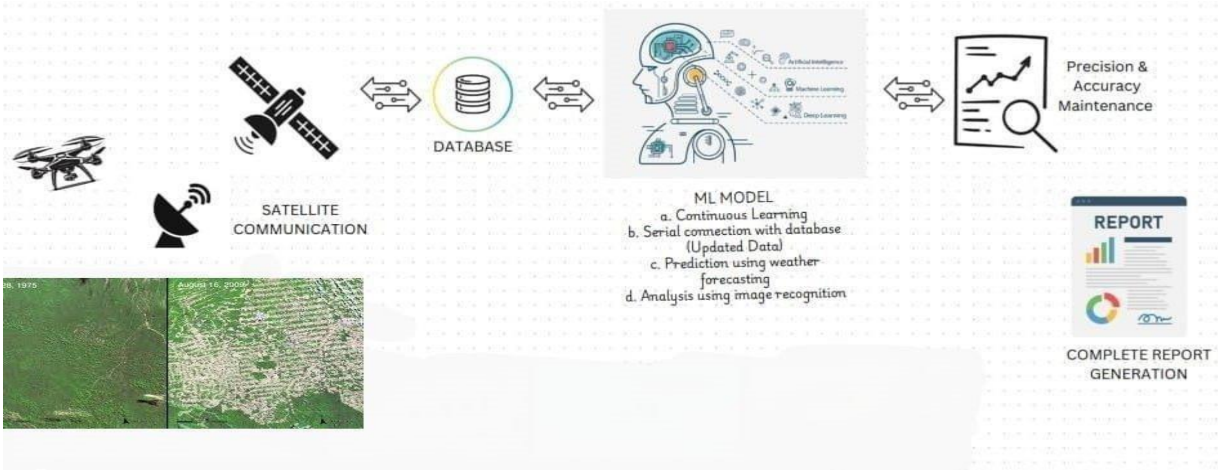

Figure2. System Architecture of the Environmental Damage Assessment Using Image Processing

V.METHODOLOGY

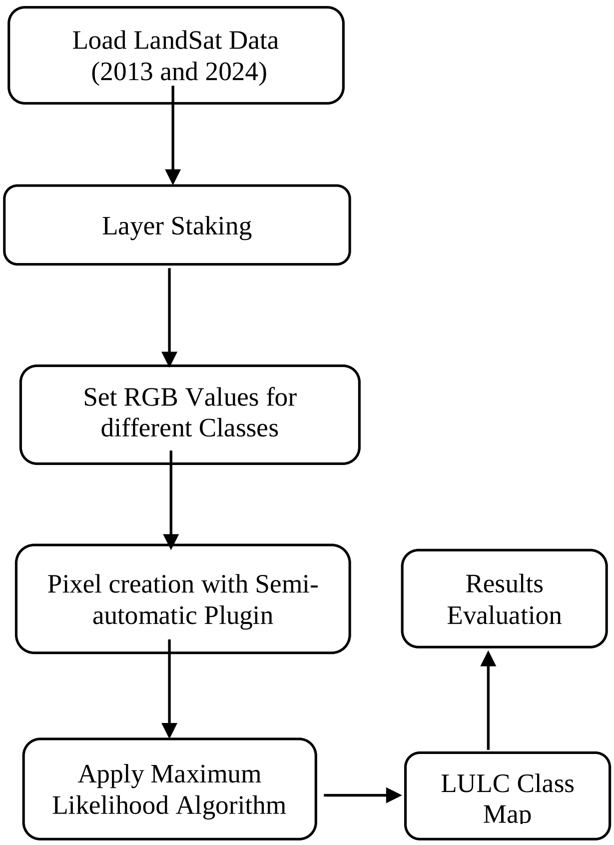

Figure 3. Flowchart of the Environmental Damage Assessment Using Image Processing

VI. MODULE DESCRIPTION

The Environmental Damage Assessment System (EDAS) is designed as a modular and scalable framework that integrates geospatial pre-processing, machine-learning-based classification, and predictive modelling.

The workflow is organized into eight functional modules, each responsible for a specific stage of the LULC analysis pipeline. This modular design ensures systematic processing of multi-temporal satellite imagery and supports reliable environmental monitoring.

1. Data Acquisition Module

The First module is responsible for collecting multi-temporal and multispectral satellite imagery required for LULC change analysis. Landsat datasets for the years 2013 and 2024 were obtained from USGS Earth Explorer and Google Earth Engine (GEE) in TIF format.

Spectral bands such as Red, Green, Blue, Near-Infrared (NIR), and Short-Wave Infrared (SWIR) were specifically selected due to their high sensitivity to vegetation health, water content, and urban surfaces. Metadata files accompanying each scene were extracted for radiometric, atmospheric, and geometric corrections.

2. QGIS-Based Preprocessing Module

This module performs spatial preprocessing and prepares imagery for classification. The QGIS environment was used due to its strong geospatial capabilities and plugin ecosystem. Key preprocessing steps include:

- Band Stacking: Combining individual spectral bands into a multispectral composite.

- RGB Composition: Visual interpretation using standard and false-color band combinations.
- Semi-Automatic Classification Plugin (SCP):
  - ROI creation
  - Pixel extraction
  - Training mask generation
- Cloud Masking: Removal of cloud-contaminated pixels.
- Radiometric Correction: Adjustment of sensor-related illumination variations.
- Geo-referencing: Ensuring accurate spatial alignment with ground coordinates.

It Outputs Cleaned, composite images and class-specific masks for model training.

3. Image Processing Module

Python-based geospatial computation was used to automate preprocessing and feature extraction. Libraries including Rasterio**,** Geopandas**,** Numpy**,** Scikit-Learn**, and** Matplotlib handled raster operations and statistical processing. Steps in this module are as follows :

- Band extraction and merging
- Normalization of pixel values using min–max normalization:

$$X_{\text{norm}} = \frac{X - X_{\min}}{X_{\max} - X_{\min}}$$

- Mask generation for training vegetation, water, and built-up classes
- Feature extraction from multispectral bands
- Maximum Likelihood Classification (MLC) based on Bayesian probability:

$$P(\omega_i|x) = \frac{1}{(2\pi)^{n/2}\,|\Sigma_i|^{1/2}}\, e^{-\frac{1}{2}(x-\mu_i)^T \Sigma_i^{-1}(x-\mu_i)}$$

After the processing we get pixel-level feature matrices and normalized training data.

4. Classification Module (MLC + CNN)*:* This module performs supervised land-cover classification using two complementary approaches:

a) Maximum Likelihood Classifier (MLC)*:* Used for statistically driven classification based on class probability distributions.

b) Convolutional Neural Network (CNN): Used for spatial-context-aware classification with improved accuracy.The CNN uses a softmax activation function for class prediction:

$$P(\text{class}_i) = \frac{e^{z_i}}{\sum_j e^{z_j}}$$

The classification focuses on three major LULC categories ***Vegetation, Built-up areas, Water bodies*** and Classified LULC maps for 2013 and 2024.

5. Accuracy Assessment Module

Accuracy Assessment module evaluates the reliability of the classification using ground-truth data and confusion-matrix-based metrics which include Accuray, Precision, Recall and F1 Score.

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}$$

$$\text{Precision} = \frac{TP}{TP + FP}$$

$$\text{Recall} = \frac{TP}{TP + FN}$$

$$F_1 = \frac{2PR}{P + R}$$

Confusion matrices help identify class-wise misclassification patterns, while cross-validation ensures robustness across different datasets.

6. Change Detection Module

This Module examines the classified LULC maps of 2013 and 2024 to identify how land-cover patterns have changed over time. The system detects three major transitions—vegetation loss**,** built-up expansion**,** and changes in water bodies—by performing a pixel-wise comparison between the two years.

A transition matrix is generated to show how many pixels shifted from one class to another, and these pixel counts are converted **to** area values (sq. km) for quantitative assessment. Change detection maps are then produced to visually highlight regions experiencing major environmental changes.

7. Prediction Module (Markov Chain Model)*:*
Future land-cover conditions for the year **2040** are forecasted using a Markov Chain–based transition model.

$$S_{t+1} = S_t \cdot T$$

Where:

- St= present land-cover distribution
- T= transition probability matrix

The predicted output highlights zones at high risk of vegetation loss and urban encroachment.

8. Results and Visualization: This Module presents the final outcomes of the LULC analysis in visual and statistical form. RGB composites for 2013 and 2024 offer a natural-color view of the study area, helping identify broad surface patterns before classification. The classified maps for both years clearly highlight vegetation, built-up land, and water bodies, making spatial changes easy to observe.

Bar charts compare the land-cover areas between 2013 and 2024, showing a strong increase in urban regions and noticeable shifts in forest and barren areas. Pie charts further summarize the percentage distribution of each land-cover class, illustrating the overall decline in vegetation and expansion of built-up areas over the decade.

VII. IMPLEMENTATION

The practical implementation of EDAS integrates QGIS preprocessing with a Python-based classification and visualization pipeline. The Python pipeline automates band stacking, training-sample extraction, model training, tiled classification, post-processing, area computation, prediction and plotting. Key implementation details and parameter choices are listed below to ensure reproducibility

1. Environment & Libraries

- **Python 3.x** in Colab.
- Primary libraries: rasterio, numpy, geopandas, scikit-learn (RandomForest), matplotlib, tqdm.
- Outputs written to GeoTIFF and PNG files for later inspection and integration into QGIS.

2. Input & Configuration

- **Input bands**: separate TIF files per band for 2013 and 2024 (B2–B7). Paths configured at script top.
- **Training raster**: single-class label raster used to extract ROIs (resource for supervised learning).
- **Class mapping**: water class intentionally excluded; final classes used are water bodies (2), vegetation (3) and build-up area (4) .
- **Output paths**: classified rasters saved to data/classified_2013.tif & data/classified_2024.tif.

3. Preprocessing & Band Stacking

- Bands are read with rasterio.open() and stacked into a 3D array (bands × height × width). No-data values replaced with NaN for safe handling.
- Image profile (CRS, transform, dtype) copied from first band and updated for stacked output.

4. Training Sample Extraction

- The training label raster is resampled to match the stacked image grid using rasterio.warp.reproject(..., Resampling.nearest).
- Pixel-wise features (n_bands features per pixel) are reshaped into X (samples × features) and labels y.
- Invalid pixels (background 0, water 1, NaN values) are filtered out.
- To limit memory usage, samples are optionally downsampled (`max_samples=10000`) with random selection; the script prints class distributions for transparency.

5. Classifier & Training

- **Classifier**: RandomForestClassifier(n_estimators=100, max_depth=15, random_state=42, n_jobs=1).
- Training uses the prepared X_train, y_train arrays; model fit executed with clf.fit(X,y).
- The choice of RF provides a robust, fast ensemble baseline suitable for multispectral pixel classification.

6.Tiled Classification

- The full raster is classified in tiles to control memory: tile_size=512 (rows × cols). For each tile, feature vectors are predicted and reassembled into a full-class map.
- Output is saved as uint8 GeoTIFF with nodata=0. This approach enables processing large images on limited RAM.

7. Post-processing: Cropping & Masking

- After classification, a tight **bounding box crop** is computed around non-zero pixels to remove large background margins (function crop_bounding_box).
- Water-class pixels (class 2) are masked out when computing area and when plotting, as specified by the workflow.

8. Area Computation & Statistics

- Area per class computed from pixel counts: pixel_area = 30 × 30 = 900 m². Area in km² = (count × 900) / 1e6.
- The script computes class-wise area and percent of the cropped region (total area of non-excluded classes). Totals and percentages printed in a formatted table.

10. Visualization

- Built-in plotting utilities produce:
  - Side-by-side LULC comparison image
  - Area comparison bar chart
  - Projected trend bar chart
  - Area difference chart showing absolute km² gains/losses
- Colors and legends are explicitly set for reproducible styling (Water Bodies= Blue, vegetation = green, Build-up area = orange).

VIII. RESULTS AND ANALYSIS

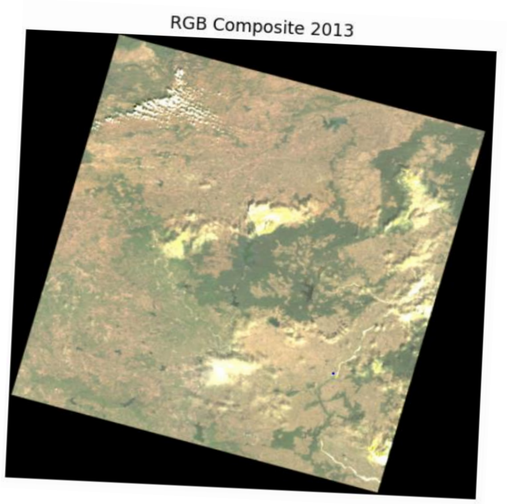

Figure 4. RGB Composite Image (2013)

"This fig shows the 2013 RGB composite generated from Landsat satellite data, converted into TIFF format to retain the spatial and spectral detail required for reliable land-cover interpretation."

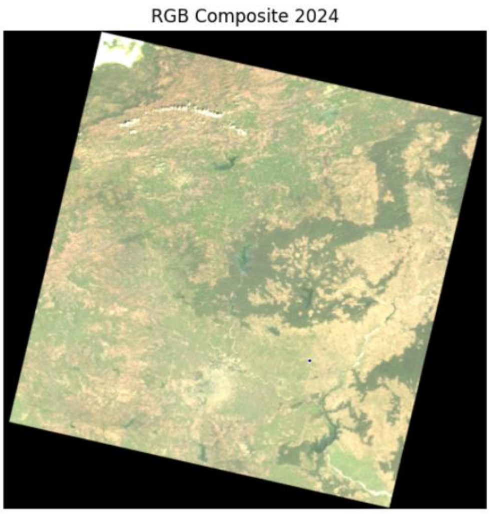

Figure 5. RGB Composite Image (2024)

"The figure illustrates the 2024 RGB composite image, processed in TIFF format to preserve high-quality spectral information, enabling precise detection of land-cover changes and recent environmental variations."

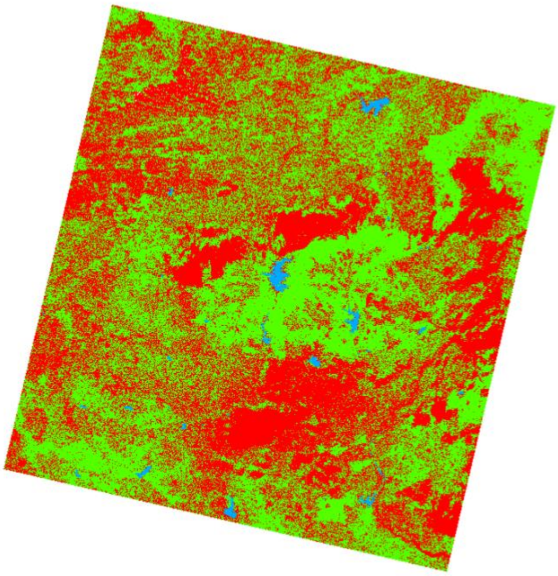

Figure 6. Traning Image of (2013)

"The above figure represents the classified land-cover map, where each pixel is assigned to a specific class such as vegetation, built-up area, or water body. This processed output highlights spatial distribution patterns and enables detailed assessment of environmental changes within the study region."

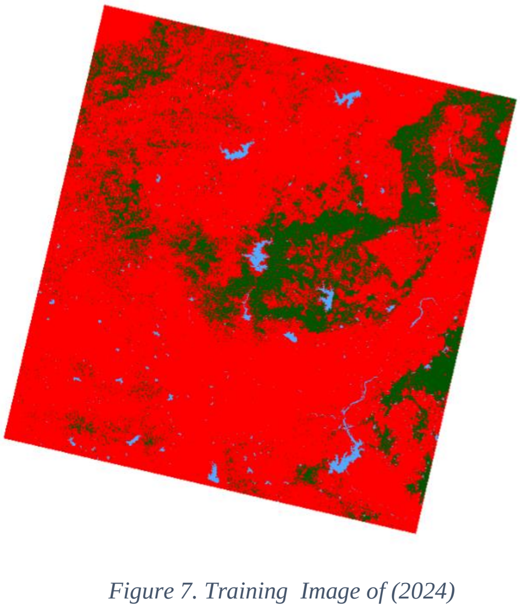

Figure 7. Training Image of (2024)

"The above figure displays the classified land-cover map for the 2024 dataset, where distinct colors represent vegetation, built-up regions, and water bodies. This refined output highlights the current spatial distribution of land classes and serves as a basis for comparing recent environmental changes with earlier years."

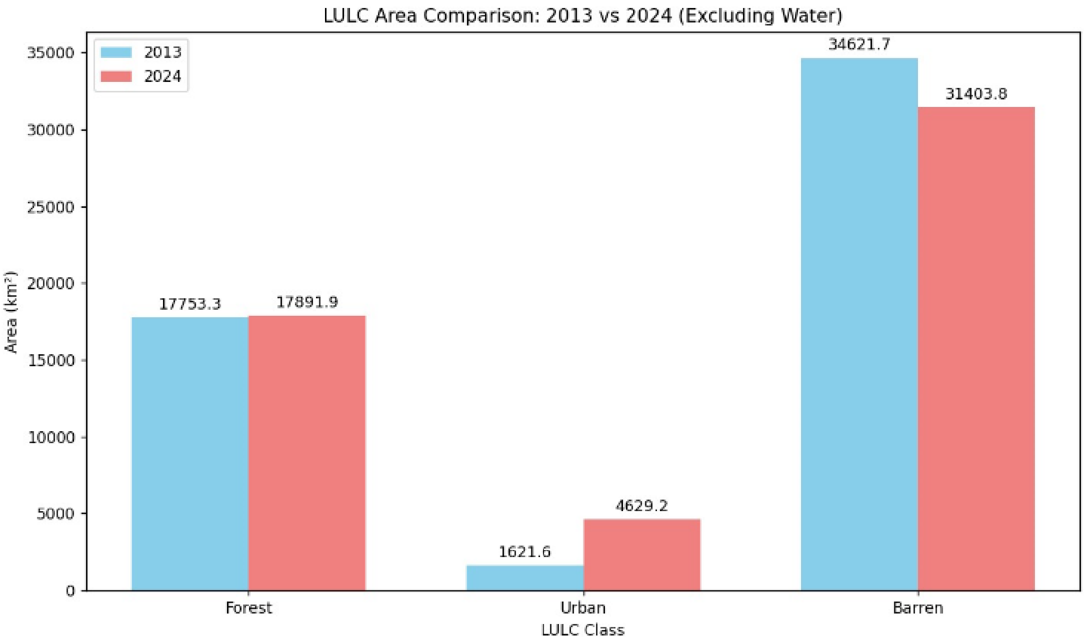

Figure 8. LCLU Area Comparison : 2013 Vs 2024

"The bar chart compares the LULC areas for Forest, Urban, and Barren classes between 2013 and 2024. The visualization highlights a notable increase in urban land and slight changes in forest and barren categories, providing a clear quantitative view of land-cover shifts over the decade"

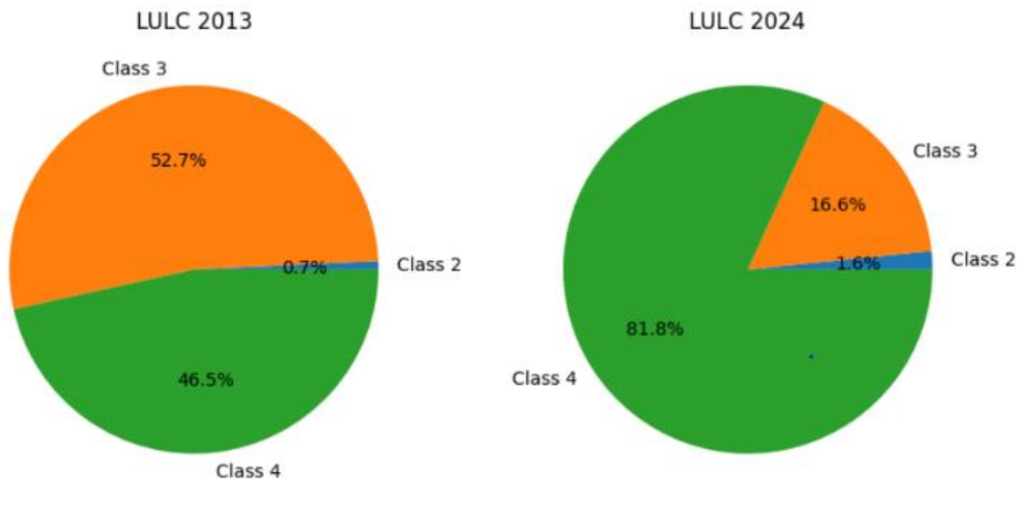

Figure 9. Analysis of 2013 And 2024

"The Pie chart presents the LULC percentage distribution for 2013 and 2024 using comparative pie charts. Each chart illustrates the proportion of vegetation (Class 3), water bodies (Class 2), and built-up areas (Class 4), clearly showing a major rise in built-up land and a sharp decline in vegetation over the decade."

IX. CONCLUSION

The study region's landscape has undergone a substantial transformation, as evidenced by the analysis of LULC changes between 2013 and 2024. Together, the classified maps, statistical summaries, and visualizations show a significant decrease in vegetated areas and an increase in barren or non-vegetated surfaces. Class 3 vegetation made up 52.7% of the total area in 2013, but by 2024, it had drastically decreased to just 16.6%, a significant 36.1 percentage point decrease.

The built-up/barren category (Class 4) increased by 35.3 percentage points from 46.5% to 81.8% during the same period, which is a clear indication of increased urban development and land degradation. . In comparison to other categories, water bodies (Class 2) only slightly increased from 0.7% to 1.6%, indicating little hydrological variation.

Overall, the findings show that, in just ten years, vegetated land gave way to arid and urbanized surfaces in a swift and alarming manner. This pattern highlights the pressing need for sustainable land-management techniques as well as growing anthropogenic pressure and environmental stress. The study effectively illustrates how machine learning-driven classification, GIS-based processing, and remote sensing can provide trustworthy insights into long-term spatial change, providing important direction for future research on regional land-use dynamics as well as policy makers and environmental planners.

X.FUTURE SCOPE

- LULC classification and boundary detection accuracy can be increased by using sophisticated deep-learning models like U-Net or ResNet.
- Google Earth Engine automation for real-time monitoring that produces quick alerts for changes in land use and deforestation.
- To better understand the factors influencing changes in land cover, additional datasets such as rainfall, temperature, soil moisture, and population growth are integrated.
- Sentinel, SAR, and LiDAR multi-sensor data fusion to produce more accurate and dependable mapping, particularly in cloud-prone regions.
- creation of an interactive dashboard that makes it simple for environmental organizations and legislators to see LULC trends, risk areas, and forecasts.

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