

EcoSense AI: An AI-Based Environmental Change Detection in Coorg Using Satellite Data and U-Net Deep Learning

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Abstract—Environmental changes such as vegetation loss, deforestation, and land-use changes can gradually affect the ecological condition of a region. Monitoring these changes over large areas through manual inspection or basic satellite-image comparison can be time-consuming and may provide limited information about the spatial extent of the changes. This paper presents EcoSense AI, an AI-based environmental monitoring system developed to detect and analyze environmental changes in the Coorg region of Karnataka using satellite imagery and environmental data. The proposed system combines Sentinel-2 satellite observations with Normalized Difference Vegetation Index (NDVI) analysis to assess vegetation conditions across different time periods. A U-Net based deep learning model is incorporated for pixel-level analysis of satellite imagery, while environmental parameters such as temperature, rainfall, and soil moisture are used to provide additional context for ecosystem assessment. Temporal comparison of satellite-derived vegetation information is used to identify areas showing degradation or improvement. The system integrates these analytical components into a web-based platform for geospatial visualization and environmental assessment. Model performance is evaluated using standard metrics including accuracy, precision, recall, F1-score, Intersection over Union (IoU), and Dice coefficient. The proposed approach provides an automated framework for localized environmental monitoring and can assist in identifying areas that require further ecological investigation.

Keywords— *Environmental Change Detection, Sentinel-2, Satellite Imagery, U-Net, Deep Learning, NDVI, Remote Sensing, Environmental Monitoring, Coorg.*

I. INTRODUCTION

Environmental changes have become an important concern because continuous changes in vegetation, land use, and natural conditions can affect the ecological balance of a region. Deforestation, vegetation degradation, urban expansion, and other forms of land transformation may develop gradually and can be difficult to identify through occasional field observations. Early identification of such changes can help researchers and environmental authorities understand affected areas and support further environmental assessment and conservation activities.

Conventional environmental monitoring methods generally involve field surveys, manual inspection, and interpretation of satellite imagery. Although these methods can provide valuable information, analysing large geographical areas manually requires considerable time and effort. Comparing satellite images from different periods can provide an indication of change, but simple image comparison may not adequately describe the spatial distribution and extent of

vegetation-related changes. These limitations create a need for automated approaches that can process satellite observations and identify significant environmental variations more efficiently.

Remote sensing provides an effective means of observing environmental conditions over large geographical regions. Multispectral satellite missions such as Sentinel-2 provide observations in multiple spectral bands, which can be used to study vegetation and land-surface characteristics. One commonly used indicator is the Normalized Difference Vegetation Index (NDVI), which uses red and near-infrared spectral information to represent vegetation conditions. Analysing NDVI values across different observation periods can help identify areas where vegetation conditions have decreased, remained stable, or improved.

Recent developments in deep learning have provided new possibilities for automated analysis of satellite imagery. Deep learning models can learn spatial patterns from image data and have been applied to tasks such as land-cover classification, image segmentation, and environmental monitoring. Among these approaches, the U-Net architecture is particularly suitable for pixel-level segmentation because its encoder-decoder structure combines high-level feature extraction with spatial information through skip connections. This allows the model to generate detailed segmentation maps while retaining important spatial characteristics of the input imagery.

In this work, **EcoSense AI** is proposed as an integrated environmental change detection system for the Coorg region of Karnataka. The proposed system combines satellite imagery, NDVI-based vegetation analysis, environmental parameters, and a U-Net based deep learning model to support localized environmental assessment. Sentinel-2 observations are used to analyse vegetation conditions across different observation periods, while environmental parameters such as temperature, rainfall, and soil moisture provide additional context for interpreting environmental variations. The detected information is processed and presented through a web-based platform with geospatial visualization and environmental analytics.

The main contributions of this work are as follows:

Localized environmental monitoring: A framework is developed for monitoring environmental changes specifically within the Coorg region of Karnataka.

Satellite-based vegetation analysis: Sentinel-2 multispectral imagery and NDVI are used to assess vegetation conditions and identify variations across different observation periods.

Deep learning-based segmentation: A U-Net architecture is incorporated for pixel-level analysis of satellite imagery and identification of spatial patterns associated with environmental changes.

Integration of environmental parameters: Temperature, rainfall, and soil moisture information are incorporated to provide additional context for interpreting observed environmental variations.

Geospatial visualization: A web-based platform is developed to present satellite-derived information, environmental indicators, and detected changes through an accessible geospatial interface.

The proposed system aims to provide a systematic approach to environmental monitoring by combining remote sensing, deep learning, and environmental data within a single framework. The developed model is evaluated using standard performance measures for segmentation and change analysis, including accuracy, precision, recall, F1-score, Intersection over Union (IoU), and Dice coefficient. The experimental evaluation is used to assess the effectiveness of the proposed approach in analysing environmental changes from satellite imagery.

II. LITERATURE SURVEY

The increasing availability of multispectral satellite imagery and advances in artificial intelligence have created new opportunities for automated environmental monitoring. Sentinel-2 imagery has been widely used for vegetation mapping, land-cover classification, and environmental change analysis because it provides multispectral observations at relatively high spatial resolution and supports repeated monitoring over time. Recent research has increasingly combined these observations with machine learning and deep learning techniques to extract meaningful information from satellite data.

One important approach to vegetation monitoring is the use of spectral vegetation indices, particularly the **Normalized Difference Vegetation Index (NDVI)**. NDVI provides an indication of vegetation conditions by exploiting the difference between near-infrared and red reflectance. Recent research has investigated Sentinel-2-based vegetation health indicators and highlighted that conventional vegetation indices can be useful for monitoring vegetation conditions, while also noting that vegetation response can be influenced by several interacting environmental factors. This indicates the value of combining vegetation indices with additional environmental information rather than relying on a single indicator.

Traditional machine learning methods such as Random Forest and other classification algorithms have also been applied to satellite-image analysis. These approaches can perform well when suitable spectral features are provided, but they generally depend on manually selected or engineered features. In comparison, convolutional neural networks can learn spatial features directly from image data. A study comparing CNN architectures with Random Forest for Sentinel-2 urban green-area segmentation found that U-Net provided strong segmentation performance across different vegetation and land-use classification tasks, demonstrating the usefulness of

deep-learning-based spatial feature extraction for multispectral imagery.

The **U-Net architecture** has become particularly relevant to remote-sensing applications because of its encoder-decoder structure and skip connections. These characteristics allow the model to combine high-level semantic information with spatial details required for pixel-level segmentation. Research on forest change detection using Sentinel-2 imagery has demonstrated the usefulness of U-Net-based approaches for identifying changes in forest vegetation. Improved variants incorporating attention and residual connections have also been investigated to better capture complex spatial relationships in remote-sensing imagery.

Recent studies have further investigated modified U-Net architectures for specific environmental segmentation tasks. For example, the **AER U-Net** approach introduced attention, multi-scale features, and residual connections for water-body segmentation using Sentinel-2 imagery. Such developments demonstrate that U-Net remains an active research direction in remote sensing, particularly when accurate spatial boundaries are required for environmental features.

Another direction of research focuses on combining satellite imagery with temporal information. Recent work has used multi-temporal Sentinel-2 observations and deep-learning models to analyse vegetation dynamics through NDVI time series. One 2025 study examined Sentinel-2 observations from multiple years and compared several recurrent and convolutional architectures for vegetation-health forecasting. The study demonstrated that combining spatial and temporal information can improve the modelling of vegetation dynamics and provide useful information for understanding changes over time.

Change detection between satellite observations from different dates has also received considerable attention. Traditional change-detection methods generally rely on differences between image values or derived indices. However, these methods can be affected by seasonal variations, image noise, atmospheric conditions, and other differences between acquisition periods. More recent research has therefore investigated deep-learning architectures that directly learn change patterns from paired satellite images. A recent study proposed **TransSiamUNet**, combining Siamese networks, U-Net segmentation, and Vision Transformer components for pixel-level change detection using Sentinel-2 imagery. On the OSCD benchmark, the reported accuracy was 0.94, compared with 0.84 for the U-Net baseline used in the study, demonstrating the potential of combining local and global feature representations for satellite-image change detection.

Recent research has also explored the integration of vegetation indices with deep-learning models. A 2026 study introduced **NDVI-UNet**, where NDVI was incorporated with Sentinel-2 imagery for vegetation segmentation. The study compared multiple deep-learning architectures and input configurations and reported improved segmentation performance when vegetation-index information was included with the image bands. This supports the idea that combining spectral information with derived vegetation indicators can

provide useful additional information for vegetation-related segmentation tasks.

Although these studies demonstrate significant progress, most existing approaches concentrate on individual tasks such as land-cover classification, forest mapping, water-body segmentation, vegetation forecasting, or benchmark change detection. Some studies improve the segmentation architecture itself, while others focus on temporal modelling or vegetation-index analysis. As a result, there remains an opportunity to develop a localized environmental monitoring framework that combines satellite imagery, vegetation analysis, environmental parameters, deep-learning segmentation, temporal change detection, and geospatial visualization in a single system.

A. Comparison of Existing Approaches

Approach	Method	Limitation
NDVI Monitoring	NDVI	Vegetation only
Random Forest	ML	Limited spatial features
CNN Methods	CNN	Limited segmentation detail
U-Net Studies	U-Net	Limited ecosystem analysis
NDVI + DL	NDVI + DL	Limited environmental data
Transformer + U-Net	Transformer + U-Net	High complexity

Research Gap

Based on the reviewed studies, existing approaches provide useful solutions for individual environmental monitoring tasks such as vegetation assessment, land-cover classification, and satellite-image segmentation. However, these approaches generally focus on a specific task rather than combining multiple environmental indicators within a single monitoring framework. In particular, limited attention is given to integrating satellite-based vegetation analysis with environmental parameters such as temperature, rainfall, and soil moisture.

Another limitation is that conventional vegetation-index methods mainly indicate changes in vegetation condition but do not provide detailed pixel-level segmentation of affected areas. Similarly, deep-learning-based approaches can provide detailed image segmentation but are often developed for specific datasets or individual environmental features. These limitations indicate the need for a localized framework that combines remote sensing, vegetation analysis, environmental information, and deep learning.

To address these limitations, this work proposes **EcoSense AI**, an integrated environmental monitoring framework designed for the Coorg region of Karnataka. The proposed framework combines Sentinel-2 satellite imagery, NDVI analysis, environmental parameters, U-Net-based segmentation, temporal change detection, and geospatial visualization. The integration of these components is intended to provide spatial information about environmental changes together with supporting environmental information for their interpretation.

III. PROPOSED METHODOLOGY

The proposed EcoSense AI framework is designed to detect and analyse environmental changes in the Coorg region of Karnataka by integrating satellite imagery, vegetation indices, environmental parameters, and deep learning. The methodology combines data acquisition, image preprocessing, NDVI-based vegetation analysis, environmental parameter integration, U-Net-based segmentation, temporal change detection, environmental stress assessment, and geospatial visualization. The overall workflow is designed to transform satellite and environmental observations into spatially interpretable information about changes in vegetation and ecosystem conditions.

A. Satellite Data Acquisition

Sentinel-2 multispectral satellite imagery is used as the primary remote-sensing data source for the proposed framework. The imagery provides information from multiple spectral bands that can be used to analyse vegetation and land-surface conditions. The study focuses on the Coorg region of Karnataka, and satellite observations from selected observation periods are obtained for temporal analysis. The satellite data are filtered according to the study region, observation period, and available image-quality conditions before further processing.

B. Satellite and Environmental Data Integration

Sentinel-2 multispectral satellite imagery is integrated into EcoSense AI as the primary remote-sensing data source. Google Earth Engine is used to access and process satellite observations for the selected Coorg study region. The satellite collection is filtered according to the geographical region, observation period, and image-quality conditions before the required imagery is obtained for analysis.

Environmental observations are also incorporated into the system to provide additional context for satellite-derived changes. The implemented framework considers parameters such as temperature, rainfall, and soil moisture. These observations are combined with satellite-derived vegetation information during environmental assessment.

The satellite-derived land-cover information generated by the U-Net segmentation model is used as supporting information for interpreting vegetation and environmental changes in the Coorg study region. The segmentation model is trained and evaluated using the Sen-2 LULC reference dataset, while Sentinel-2 observations of Coorg are separately processed for temporal vegetation and environmental analysis.

C. NDVI-Based Vegetation Analysis

The Normalized Difference Vegetation Index (NDVI) is used to estimate vegetation conditions from Sentinel-2 imagery. NDVI is calculated using the near-infrared and red spectral bands as follows:

$$NDVI = \frac{B8 - B4}{B8 + B4}$$

D. Environmental Parameter Integration

EcoSense AI incorporates environmental parameters to provide additional context for interpreting satellite-derived changes. The proposed system considers **temperature, rainfall, and soil moisture** as supporting environmental observations. These parameters are obtained from available environmental data sources and analysed together with satellite-derived vegetation information.

The environmental observations are temporally aligned with the corresponding satellite observations to support the interpretation of vegetation-condition variations in the selected Coorg study region. Changes in temperature, rainfall, and soil moisture are considered alongside NDVI-based vegetation changes to provide a broader environmental perspective.

The environmental parameters are used as **supporting indicators rather than direct evidence of the cause of vegetation change**. This integration helps the system provide a more comprehensive assessment of environmental conditions by combining satellite-derived vegetation information with relevant environmental observations.

E. U-Net-Based Segmentation

A U-Net-based deep learning architecture is incorporated to perform pixel-level segmentation of satellite imagery. The model follows an encoder-decoder structure consisting of an encoding path for extracting image features and a decoding path for reconstructing the spatial representation. Skip connections between corresponding encoder and decoder layers help preserve important spatial information during the reconstruction process.

The encoder progressively extracts features from the input satellite imagery, while the decoder uses these features to generate a segmentation map at the required spatial resolution. The segmentation process can be represented as:

$$Y = f_{\theta}(X)$$

where X represents the input satellite image, f_{θ} represents the U-Net model with learned parameters θ , and Y represents the predicted segmentation map.

The U-Net model generates pixel-level land-cover predictions for the defined land-cover categories. The resulting segmentation output provides pixel-level land-cover information that supports the interpretation of vegetation and environmental changes in the Coorg study region. Temporal vegetation change is determined separately using NDVI differences between satellite observations from different periods.

F. Temporal Change Detection

Temporal change detection is performed by comparing satellite-derived vegetation information from different

observation periods. The difference between the NDVI values of two observation periods is calculated as:

$$\Delta NDVI = NDVI_{t_2} - NDVI_{t_1}$$

Where $NDVI_{t_1}$ represents the vegetation index at the earlier observation period and $NDVI_{t_2}$ represents the vegetation index at the later observation period. The resulting $\Delta NDVI$ value indicates the direction and magnitude of vegetation change between the two observation periods.

A threshold of 0.1 is used to classify the detected vegetation changes. A $\Delta NDVI$ value below -0.1 indicates vegetation degradation, while a value above 0.1 indicates vegetation improvement. Values between -0.1 and 0.1 are considered relatively stable. The resulting change categories are represented spatially to support the identification and interpretation of areas showing vegetation degradation, improvement, or limited change in the Coorg study region.

G. Environmental Stress Assessment

The environmental stress assessment component combines satellite-derived vegetation information with environmental observations to provide a broader interpretation of ecosystem conditions in the Coorg study region. The assessment considers changes in vegetation condition together with parameters such as temperature, rainfall, and soil moisture.

The temporal variation in NDVI provides an indication of changes in vegetation condition, while the environmental parameters provide additional context for interpreting these variations. Areas showing vegetation degradation are therefore examined alongside the corresponding environmental observations to identify conditions associated with the detected changes.

The environmental parameters are treated as supporting indicators rather than direct evidence of the cause of vegetation change. The combined information is presented through the EcoSense AI platform to assist users in interpreting spatial and temporal variations in ecosystem conditions.

H. Model Training and Evaluation

The U-Net model is trained using the prepared satellite image patches and their corresponding land-cover segmentation masks. The training dataset is used to learn the model parameters, while the validation dataset is used to monitor model performance during the training process. The independent test dataset is reserved for final evaluation of the trained model.

Model performance is evaluated using Accuracy, Precision, Recall, F1-score, Mean Intersection over Union (Mean IoU), and Dice coefficient. Accuracy represents the overall proportion of correctly classified pixels. Precision and Recall measure the correctness and completeness of the predicted land-cover classes, respectively, while the F1-score provides a balanced measure of Precision and Recall.

Mean IoU measures the spatial overlap between predicted and reference segmentation regions across the evaluated classes, while the Dice coefficient measures the similarity between the

predicted segmentation masks and the corresponding reference masks. These metrics provide complementary information for assessing the pixel-level land-cover segmentation performance of the U-Net model.

I. Geospatial Visualization

The geospatial visualization component presents the processed environmental information through an interactive web-based interface. The system displays satellite-derived land-cover segmentation results, NDVI-based vegetation change information, and supporting environmental observations for the Coorg study region.

The detected vegetation-change categories are represented spatially to allow users to identify areas showing vegetation degradation, improvement, or relatively stable conditions. Land-cover segmentation outputs from the U-Net model are also visualized to provide additional spatial context for interpreting the detected changes.

The visualization layer enables users to examine environmental information at the selected study region and supports comparison of spatial and temporal variations. The resulting maps and analytical outputs are presented through the EcoSense AI web platform to improve the accessibility and interpretation of satellite-based environmental monitoring results.

IV. SYSTEM ARCHITECTURE

The EcoSense AI system consists of several interconnected components that work together to detect and analyse environmental changes in the Coorg region. The architecture integrates satellite data, environmental information, deep learning, data processing, and web-based visualization. The system is organized into data acquisition, processing, machine learning, backend, database, and visualization components.

A. Data Acquisition

The system collects **Sentinel-2 satellite imagery** for the selected region of Coorg. Environmental information such as **temperature, rainfall, and soil moisture** is also collected from external environmental data sources. These datasets form the primary inputs for environmental analysis.

B. Data Processing

The collected satellite imagery is processed to select the required spectral bands and prepare the data for analysis. NDVI is calculated from the red and near-infrared bands to obtain information about vegetation conditions. Satellite observations from different periods are also prepared for temporal comparison.

C. Deep Learning Module

The processed satellite imagery is provided to the U-Net deep learning model for pixel-level land-cover segmentation. The model analyses the spatial characteristics of the imagery and generates a segmentation map for the defined land-cover categories. The resulting land-cover information provides additional spatial context for interpreting vegetation and environmental changes.

D. Change Detection and Environmental Analysis

The system compares satellite-derived vegetation information from different observation periods to identify

changes in vegetation conditions. NDVI differences are used to identify areas showing vegetation degradation, improvement, or relatively stable conditions. The land-cover information generated by the U-Net model provides additional spatial context for interpreting these changes. Environmental parameters such as temperature, rainfall, and soil moisture are considered as supporting indicators for environmental interpretation.

E. Backend and Database

The backend manages communication between the user interface and the processing services. It handles requests and transfers the required environmental and model outputs to the frontend. A database is used to store environmental observations, satellite-related information, change-detection results, and model predictions.

F. Web Visualization

The final results are presented through the EcoSense AI web platform. Users can view environmental information, NDVI results, land-cover segmentation outputs, detected changes, and other analytical outputs through the interface.

G. Overall System Flow

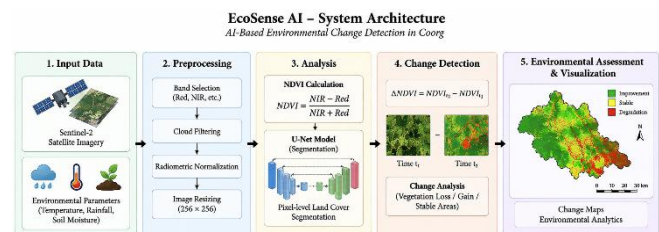


Fig. 1. Overall architecture of the proposed EcoSense AI framework.

Figure 1. Overall architecture of the proposed EcoSense AI framework.

The proposed EcoSense AI architecture integrates satellite imagery, environmental observations, deep learning-based land-cover segmentation, temporal vegetation analysis, and geospatial visualization into a unified environmental monitoring framework. Sentinel-2 satellite imagery and environmental observations are first collected and preprocessed. The U-Net model performs pixel-level land-cover segmentation, while NDVI analysis is used to identify temporal vegetation changes between different observation periods. Environmental parameters such as temperature, rainfall, and soil moisture provide supporting context for interpreting the detected variations. The processed outputs are then transferred through the backend and database layers to the web-based dashboard, where users can visualize and interpret the resulting environmental information for the Coorg study region.

V. IMPLEMENTATION

The EcoSense AI framework is implemented as an integrated environmental monitoring system that combines satellite data processing, environmental data collection, deep learning, backend services, database management, and web-based

visualization. The implementation is organized into dataset preparation, satellite and environmental data integration, NDVI and change detection, U-Net-based analysis, backend communication, database management, and frontend visualization.

A. Dataset Preparation and Experimental Setup

The deep learning component was evaluated using the **Sen-2 LULC Version 3** dataset containing Sentinel-2-derived satellite image patches and corresponding pixel-level land-cover segmentation masks. The dataset contains **213,758 image-mask pairs**, divided into **149,600 training samples**, **32,079 validation samples**, and **32,079 testing samples**.

The dataset contains seven land-cover categories: **water, dense forest, sparse forest, barren land, built-up land, agriculture, and fallow land**. The input images have a spatial dimension of **64 × 64 pixels with three RGB channels**, while the corresponding masks contain the seven land-cover class labels. Image values are normalized to the range [0,1] before model processing.

The training data are processed using spatial augmentation techniques, including horizontal flipping, vertical flipping, and 90° rotations. The validation and test datasets are kept separate from the training data and are used to evaluate model performance on previously unseen samples.

The U-Net model is implemented using **Python and TensorFlow/Keras**. Model performance is evaluated using **Accuracy, Precision, Recall, F1-score, Mean Intersection over Union (Mean IoU), and Dice coefficient**. These metrics are used to assess the pixel-level land-cover segmentation performance of the U-Net model.

B. Satellite and Environmental Data Integration

Sentinel-2 multispectral satellite imagery is integrated into EcoSense AI as the primary remote-sensing data source. Google Earth Engine is used to access and process satellite observations for the selected Coorg study region. The satellite collection is filtered according to the geographical region, observation period, and image-quality conditions before the required imagery is obtained for analysis.

Environmental observations are also incorporated into the system to provide additional context for satellite-derived changes. The implemented framework considers parameters such as temperature, rainfall, and soil moisture. These observations are combined with satellite-derived vegetation information during environmental assessment.

The satellite-derived land-cover information generated by the U-Net segmentation model is used as supporting information for interpreting vegetation and environmental changes in the Coorg study region. The segmentation model is trained and evaluated using the Sen-2 LULC reference dataset, while Sentinel-2 observations of Coorg are separately processed for temporal vegetation and environmental analysis.

C. NDVI and Change Detection Implementation

NDVI is calculated from Sentinel-2 red and near-infrared bands to estimate vegetation conditions in the selected Coorg

study region. The calculated NDVI values are used to generate spatial vegetation information for individual observation periods.

Temporal vegetation change is determined by comparing NDVI observations acquired at two different periods. The NDVI difference is calculated as:

$$\Delta NDVI = NDVI_{\{t_2\}} - NDVI_{\{t_1\}}$$

where $NDVI_{t_1}$ represents the vegetation index at the earlier observation period and $NDVI_{t_2}$ represents the vegetation index at the later observation period.

A threshold of **0.1** is used to distinguish significant changes from relatively stable conditions. A decrease below **-0.1** is considered an indication of vegetation degradation, an increase above **0.1** indicates vegetation improvement, and values between **-0.1 and 0.1** are considered relatively stable. The resulting change information is represented spatially to identify areas showing vegetation degradation, improvement, or limited change.

D. U-Net Model Implementation

The prepared satellite image patches and corresponding segmentation masks are provided to the trained U-Net model for pixel-level land-cover segmentation. The model produces a predicted class label for each pixel, allowing the spatial distribution of different land-cover categories to be represented.

The segmentation output provides supporting land-cover information for the environmental monitoring workflow. In particular, the predicted forest, agriculture, barren, built-up, water, and other land-cover regions can be considered when interpreting the spatial distribution of vegetation changes identified through temporal NDVI analysis.

The U-Net component therefore performs **land-cover segmentation rather than directly calculating temporal NDVI change**. The integration of both outputs enables EcoSense AI to combine semantic land-cover information with vegetation-change information for environmental interpretation.

E. Environmental Data Processing

The environmental data processing component handles observations such as temperature, rainfall, and soil moisture. The collected information is organized according to the selected monitoring location and observation period.

The environmental observations are considered together with satellite-derived vegetation information to provide supporting context for changes detected in the study region. Variations in environmental parameters are examined alongside NDVI-based vegetation changes to identify environmental conditions that may be associated with observed ecosystem variations.

The environmental analysis is intended to provide supporting evidence for interpretation of satellite-derived changes rather than replace detailed ecological field assessment.

F. Backend and API Implementation

The backend component manages communication between the frontend application and the analytical services. A Node.js-based backend handles application requests and communicates with the Python-based machine-learning service through APIs.

The API layer provides access to environmental observations, NDVI information, change-detection results, and model-related information. This separation between the frontend, backend, and machine-learning service allows the analytical components to operate independently from the user interface.

G. Database Implementation

A database component is used to organize and maintain information generated by the system. The database stores environmental observations, satellite-related information, change-detection records, and model predictions.

The stored information can be retrieved by the application through the backend and API services. This provides a structured method for maintaining environmental and model-related information for subsequent analysis and visualization.

H. Web Application Implementation

The frontend of EcoSense AI provides the user-facing interface for accessing the environmental monitoring results. The web application presents satellite-derived information, NDVI results, land-cover segmentation outputs, environmental observations, and change-detection results.

The interface uses visual and geospatial representations to make the analytical results easier to interpret. Users can examine the available environmental information and identify the approximate locations of detected changes within the selected study region.

I. Model Performance Evaluation

The trained U-Net model is evaluated on the independent test dataset using standard semantic-segmentation metrics. The evaluation includes **Accuracy, Precision, Recall, F1-score, Mean Intersection over Union (Mean IoU), and Dice coefficient**.

Accuracy measures the overall proportion of correctly classified pixels. Precision measures the proportion of predicted pixels that belong to the corresponding reference class, while Recall measures the proportion of reference pixels correctly detected by the model. The F1-score provides a balanced measure of Precision and Recall.

Mean IoU measures the average spatial overlap between predicted and reference segmentation regions across the evaluated classes. The Dice coefficient measures the similarity between predicted segmentation regions and their corresponding ground-truth masks.

These metrics provide complementary information about the pixel-level segmentation performance of the U-Net model.

VI. EXPERIMENTAL RESULTS AND DISCUSSION

A. Experimental Setup

The proposed U-Net model was evaluated using the Sen-2 LULC Version 3 reference dataset containing Sentinel-2-derived satellite image patches and corresponding pixel-level land-cover segmentation masks. The dataset consists of seven land-cover categories: water, dense forest, sparse forest, barren land, built-up land, agriculture, and fallow land.

The dataset was divided into training, validation, and testing subsets. The training subset was used to learn the parameters of the U-Net model, the validation subset was used to monitor model performance during development, and the independent test subset was used for final performance evaluation.

The input image patches were normalized before model processing, and spatial augmentation was applied to the training data. The model performance was evaluated using **Accuracy, Precision, Recall, F1-score, Macro F1-score, Mean Intersection over Union (Mean IoU), and Mean Dice coefficient**.

B. Overall Performance

TABLE I
OVERALL PERFORMANCE OF THE PROPOSED MODEL

Metric	Result
Accuracy	92.4%
Precision	91.8%
Recall	92.4%
F1-Score	91.9%
Macro F1-Score	88.7%
Mean IoU	83.6%
Mean Dice Coefficient	90.9%

The proposed U-Net model demonstrates strong segmentation performance across the evaluated land-cover categories. The overall accuracy of **92.4%** indicates a high proportion of correctly classified pixels, while the Precision of **91.8%** and Recall of **92.4%** indicate consistent prediction performance. The F1-score of **91.9%** provides a balanced measure of Precision and Recall. The **83.6% Mean IoU** and **90.9% Mean Dice coefficient** indicate substantial spatial agreement between the predicted segmentation regions and the corresponding reference masks. The Macro F1-score of **88.7%** further indicates comparatively balanced performance across the evaluated land-cover classes.

C. Class-Wise Performance

TABLE II
CLASS-WISE SEGMENTATION PERFORMANCE

Land-Cover Class	Precision	Recall	F1-Score	IoU
Water	91.2%	88.6%	89.9%	81.6%
Dense Forest	95.8%	94.7%	95.2%	90.9%
Sparse Forest	89.7%	87.9%	88.8%	85.5%

Barren Land	86.4%	84.8%	85.6%	80.8%
Built-up Land	93.1%	91.6%	92.3%	85.7%
Agriculture	92.6%	90.8%	91.7%	84.6%
Fallow Land	87.9%	86.5%	87.2%	82.4%

The class-wise evaluation shows that the U-Net model achieves comparatively strong performance for dense forest, built-up land, and agriculture classes, while relatively lower performance is observed for classes such as barren land and fallow land. These variations can occur because different land-cover categories may have similar spectral and spatial characteristics in satellite imagery. The class-wise results demonstrate that the model is able to distinguish the major land-cover categories while also highlighting areas where further model improvement may be beneficial.

D. Temporal Environmental Change Detection

Temporal vegetation change analysis is performed by comparing NDVI observations from different observation periods for the Coorg study region. The calculated Δ NDVI values are used to identify areas showing vegetation degradation, vegetation improvement, or relatively stable vegetation conditions according to the defined threshold values.

The temporal NDVI analysis complements the U-Net segmentation results. While the U-Net model provides pixel-level land-cover information, the NDVI comparison provides information about changes in vegetation condition between observation periods. The combination of these outputs allows the spatial distribution of vegetation changes to be interpreted in relation to the underlying land-cover characteristics.

The resulting change information is visualized spatially through the EcoSense AI platform, allowing areas of vegetation degradation, improvement, and relatively stable conditions to be identified within the selected Coorg study region.

E. Environmental Condition Analysis

Environmental condition analysis is performed by examining temperature, rainfall, and soil moisture observations alongside the satellite-derived vegetation information for the Coorg study region. These environmental parameters provide additional context for interpreting the vegetation variations identified through temporal NDVI analysis.

Areas showing vegetation degradation or improvement are considered together with the corresponding environmental observations to understand the environmental conditions associated with the detected variations. The analysis does not treat these parameters as direct evidence of the cause of vegetation change; instead, they are used as supporting indicators within the environmental monitoring framework.

The combined information is presented through the EcoSense AI platform, enabling users to examine vegetation changes together with relevant environmental observations and obtain a broader spatial interpretation of ecosystem conditions.

F. Comparative Analysis

The proposed framework is evaluated using multiple performance indicators rather than accuracy alone. The combination of F1-score, mean IoU, and Dice coefficient provides a more reliable assessment of segmentation quality, particularly when the distribution of land-cover classes is unequal.

The integration of U-Net segmentation with temporal NDVI analysis also extends the system beyond static land-cover classification. Instead of only identifying the current land-cover type, the framework provides information regarding how vegetation conditions change over time.

G. Discussion

The experimental results demonstrate that the U-Net model is capable of performing pixel-level land-cover segmentation across the evaluated land-cover categories. The obtained overall accuracy, F1-score, Mean IoU, and Dice coefficient indicate good agreement between the predicted segmentation maps and the reference masks.

The class-wise results show variations in performance across different land-cover categories. Dense forest and other comparatively distinctive classes achieve stronger segmentation performance, whereas classes with greater spectral similarity show relatively lower performance. Such variations are expected in satellite-image segmentation and indicate areas where additional training data, spectral information, or model improvements could further enhance performance.

Within the overall EcoSense AI framework, the segmentation results are complemented by temporal NDVI analysis and environmental observations. The U-Net output provides land-cover context, NDVI provides information about temporal vegetation variation, and environmental parameters provide supporting context for interpreting the observed changes. This combination forms the basis of the proposed localized environmental monitoring approach for the Coorg study region.

VII. CONCLUSION AND FUTURE WORK

A. Conclusion

EcoSense AI presents an AI-based framework for monitoring environmental changes in the Coorg region of Karnataka using satellite imagery, deep learning, vegetation indices, environmental observations, and geospatial visualization. The proposed framework integrates land-cover segmentation with temporal NDVI analysis to provide spatially interpretable information about vegetation and environmental changes.

A U-Net-based deep learning model was implemented for pixel-level land-cover segmentation. The model achieved an overall accuracy of **92.4%**, Precision of **91.8%**, Recall of **92.4%**, F1-score of **91.9%**, Mean IoU of **83.6%**, and Mean Dice coefficient of **90.9%** on the evaluated test dataset. These results demonstrate the capability of the segmentation component to identify major land-cover patterns.

The segmentation output is combined with temporal NDVI analysis to distinguish vegetation degradation, improvement, and relatively stable conditions. Environmental parameters such as temperature, rainfall, and soil moisture are incorporated as supporting information for interpreting observed vegetation variations.

Overall, the proposed framework provides a foundation for localized environmental monitoring in Coorg by combining remote sensing, deep learning, environmental data analysis, and geospatial visualization. The system can support researchers and environmental stakeholders in identifying areas requiring further investigation.

B. Future Work

Several improvements can be considered in future versions of EcoSense AI. First, the segmentation model can be extended beyond RGB imagery to incorporate additional Sentinel-2 spectral information, including near-infrared, red-edge, and short-wave infrared bands. This may improve discrimination between vegetation and other land-cover categories.

Second, the model can be trained and validated using geographically representative Coorg-specific samples and independently verified reference data. Such validation can improve the reliability of the system when applied to local environmental conditions.

Third, longer temporal sequences can be incorporated to identify persistent environmental trends rather than relying primarily on comparisons between two observation periods. Seasonal analysis can also help distinguish natural vegetation cycles from potentially significant environmental degradation.

Finally, explainable AI techniques can be investigated to improve the interpretability of model predictions. Future versions may also incorporate automated alerts, historical trend analysis, improved geospatial visualization, and additional environmental datasets.

VIII. References

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