Dhristhi - Robust Change Detection, Monitoring, and Alert System on User-defined AOI using Multi-Temporal Sentinel-2 Satellite Imagery

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Abstract: Unregulated and aggressive Land Use Land Cover (LULC) dynamics such as urban sprawl and informal deforestation require a monitoring system that is close to real time, accurate, and readily available. Currently available commercial and cloud-based systems often demand high levels of technical knowledge in geospatial and programming, posing a stumbling block to local practitioners and NGOs. We propose Dhristhi, an automated, end-to-end Web-GIS platform designed to overcome this expertise bottleneck. Dhristhi integrates a sophisticated hybrid methodology: it employs a pre-trained U-Net Deep Learning model for high-precision, pixel-wise semantic segmentation of multispectral imagery, followed by an Object-Based Post-Classification Comparison (OBC) approach to aggregate and validate changes into meaningful geographic regions. An important component of the framework is a Random Forest (RF) classifier with user defined dynamic thresholding mechanism & seasonal variation in values of spectral indices (NDVI, NDBI) to prevent false positive and improve change validation. This platform works on a fully automated, plug-and-play workflow, it automatically handles everything from data collection to pre-processing, so anyone can use the platform easily without having technical expertise. After any successful change detection system automatically sends alert and generates report in the user's dashboard. Dhristhi successfully demonstrates advanced geospatial intelligence, providing a robust, noise-resilient tool for environmental and civil governance. On a validation dataset covering forest-sprawled and urban regions, the proposed system achieves an overall change detection accuracy of 92.1%, with a Kappa coefficient of about 0.88 and mean IoU of about 0.89 for binary anthropogenic change detection.

Keywords: Geospatial change detection, Semantic segmentation, Object-Based machine learning, Random forest, Web-GIS, Time-series analysis

1. Introduction

Timely and accurate monitoring of land use/land cover (LULC) changes is important for global environmental management and the planning of environmental policy, and in fact, land cover is classified as an Essential Climate Variable (ECV) by the Global Climate Observing System (GCOS) (NRSC/ISRO, 2024). Unmanaged LULC changes, such as land use changes resulting from natural and anthropogenic activity and environmental degradation, result in large amounts of error in environmental monitoring, particularly if these changes are very small and challenging to distinguish in a coarser resolution image (10-30 m). A key challenging aspect in operational LULC monitoring is that many state-of-the-art monitoring systems lack practical operational compatibility. Platforms like Google Earth Engine (GEE) demand extensive coding skills (JavaScript or Python API scripting) and specialized remote sensing knowledge for complex tasks like data preparation and atmospheric correction (Gupta et al. 2019; Kuria et al. 2019). Similarly, archives like ISRO's Bhuvan, Bhoonidhi often require manual data ordering and specific knowledge (ISRO) of satellite sensors (e.g. LISS, AWiFS), rather than offering automated analysis for arbitrary user-defined areas of interest (AOIs). This technical expertise barrier prevents operational use by local governmental and non-governmental agencies. The proposed Dhristhi platform is designed to resolve this gap by offering a fully automated, end-to-end Web-GIS solution. The platform integrates a hybrid methodology that combines the high precision of Deep Learning with the spatial coherence of Object-Based analysis. Its core contribution is a "Plug-and-Play Web Interface" where users define an Area-of-Interest (AOI) on a map, and the system autonomously executes all complex backend processes including data fetching, segmentation, validation, and reporting without any scripting requirement.

Change Detection methodologies mainly help to detect or identify the difference in the surface of the Earth over time. Existing approaches can be classified into two categories: Pixel-Based Change Detection (PBCD) & Object Based Change Detection (OBCD). There are some popular PBCD methods such as the image differentiating process which is very simple but highly noise-sensitive & prone to errors for high-resolution satellite imagery. To overcome the limitation of PBCD, Object-Based Change Detection (OBCD) is introduced (Singh and Kumar, 2022; Pant et al. 2000), in which the image is segmented into meaningful objects before comparison. It improves detection accuracy by focusing only on the significant changes & reducing noise.

Dhristhi uses the Object-Based Post- Classification & Comparison method. For a user-defined AOI (Area of Interest) images from two-time point (T_{Latest} & $T_{Baseline}$) are fetched automatically from GEE (Google Earth Engine) then independently classified & compared. Once significant change is detected, Dhristhi alerts the user.

2. Methodology

The Dhristhi platform uses a multi-stage automated process to achieve high accuracy change detection & validation for seasonal changes, regional noise. The multi-stage process is discussed below:

2.1 Data Acquisition and Pre-Processing

Once any user defines their Area of Interest (AOI) on the Dhristhi platform, the system automatically fetches Sentinel-2 Multi-temporal imagery (in 5 days' loop) from Google Earth Engine (GEE) API for better comparison. Once data is collected it goes for cloud and Shadow masking then Deep Learning Ingestion Preparation. Spectral indices (NDVI, NDBI, NDWI) are computed after segmentation and are used during the validation stage rather than during initial pre-processing, as index-based features are evaluated at the object level to support noise-resilient change validation rather than pixel-level classification.

- **Cloud and Shadow Masking:** Before further process and comparison we need to mask the cloud and shadow to obtain cloud free clear image for comparison. In Dhristhi, system automatically removes cloud cover, flying objects, etc. using COPERNICUS/S2_CLOUD_PROBABILITY dataset (s2cloudless) and custom shadow masking. This helps to overcome the noise due to atmospheric conditions reducing false positives.
- **Deep Learning Ingestion Preparation:** System fetches large size satellite tiles, but this cannot be used directly for Deep Learning inference. These tiles are divided into fixed-sized patches (eg. 256 x 256px) and converted into Numpy Array, creating input for the U-Net. Patch extraction is used strictly for computational feasibility during deep learning inference and does not alter the pixel-wise nature of the semantic segmentation output, as predictions from individual patches are reconstructed to generate continuous land-cover maps for the entire AOI.

2.2 Deep Learning Segmentation and Object-Based Comparison

The change detection pipeline begins with high-precision, pixel-level semantic mapping, followed by spatial validation.

- **Semantic Segmentation (U-Net):** The masked image is segmented semantically using a U-Net Model pre-trained on annotated multispectral LULC samples and implemented using PyTorch (Amin et al. 2025).
- **Object-Based Comparison:** Post classification comparison between two segmented images of different time point detects the changes. The classification scheme used in the proposed system is presented in Table 1.
- Changed pixels are then grouped into spatially contiguous objects to identify meaningful changes within the AOI.

2.2.1. Training and Validation Dataset

Sentinel-2 Level-2A multispectral imagery from the Copernicus Open Access Hub was used to train and validate the Random Forest and U-Net modules using Google Earth Engine. Representative Areas of Interest (AOIs) were chosen from among India's agricultural, urban, forested, and water-dominated landscapes. NRSC/ISRO LULC reference datasets and manual visual interpretation of high-resolution imagery were combined to create ground truth labels (NRSC/ISRO, 2024). The dataset was divided into training, validation, and testing subsets to support model development and performance evaluation.

Table 1: Core LULC Classification Scheme

Class ID	Land Cover Class	Anthropogenic Change Relevance
1	Buildings	Urbanization/Encroachment
2	Roads	Infrastructure Development
3	Water	Water Body Shrinkage/Expansion
4	Forest/Vegetation	Deforestation/Reforestation
5	Bare Land/Other	Land Reclamation/Clearing

2.3 Adaptive Noise Mitigation and Validation

To remove false positives and to get high accuracy, the system must be robust enough to differentiate between false positives and true positives. For that, the Random Forest platform is used for feature Engineering and Dynamic Thresholding to reduce false detection and retain significant changes only.

2.3.1. Feature Engineering and Index Calculation

A supervised Random Forest (RF) model (Maithani, 2014) is used as a final validation module due to its robustness in classifying land disturbances and separating seasonal noise from real events. The model is trained using a feature set that includes the magnitude and direction of change in spectral indices (NDVI, NDBI, NDWI), alongside contextual variables such as the Land Cover Class at T_1, the specific Season of acquisition, and the Region ID.

2.3.2. Dynamic Thresholding Mechanism

Changes in the Earth's surface can be due to the seasonal changes, for example, in times of rain, when forest area increases naturally but in summer it reduces, which are not due to anthropogenic activity. We need to identify seasonal changes to get genuine anthropogenic changes. For that, the system uses the Dynamic Thresholding Method. Seasonal variations are handled automatically by the Random Forest validation module using contextual features, which learns a decision boundary of a feature vector, incorporating season-of-acquisition and region-specific historical spectral behaviour as its input features, and giving a confidence score as output.
Let **F** denote the contextual feature vector associated with each detected object, F = {ΔNDVI, ΔNDBI, ΔNDWI, Season, RegionID, LandCoverClass}.

The Random Forest classifier learns a non-linear decision function RF(F) that outputs a confidence score P(change) ∈ [0,1]. A detected object is labelled as a true anthropogenic change if:

RF(F) ≥ τ, where τ is a user-defined sensitivity threshold controlling the trade-off between detection sensitivity and false-positive suppression.

Instead of using a global fixed threshold, the Random Forest classifier labels true changes when objects exceed a user-adjustable threshold. Table 2. illustrates how the contextual features are used by the Random Forest model to achieve noise-resilient validation.

2.4 Predictive Monitoring and Time-Series Analysis

In addition to retrospective change detection, Dhristhi has predictive aspect as well from time-series analysis and chart visualisation, as remote sensing and GIS techniques are widely used for environmental monitoring and spatial analysis (Simoonga et al. 2009). Time series spectral indices (NDVI, NDBI) are accumulated, and the Autoregressive Integrated Moving Average (ARIMA) technique is used to operate as a complementary analytical layer, taking into account historical values of the time series to predict future trend behaviour, which provides stakeholders with an essential forecast perspective of its possible long-term evolution. However, if we are looking for real operational predictive intelligence in the future, we would need innovations with longer time-span deep learning models along with it.

3. System Architecture

The Dhristhi system architecture consists of several layers. The Client Layer interacts with end-user and administrator providing map-based visualization and reports. The Data Fetching & Pre-Processing layer fetches the data from GEE & pre-process it for further operation. Once Patch Preparation is done in the Image Segmentation Layer, data goes for post comparison. Once Comparison is done, the Accuracy module performs seasonal filtering & Dynamic Thresholding. After that if any significant change is detected then the system updates the user. All the layers combined provide a fully automated interface to the user. Web-GIS platforms have been widely used for geospatial applications and environmental monitoring (Gupta et al. 2019). Figure 1. illustrates the overall architecture of the proposed Dhristhi system. Figure 2. depicts the complete operational workflow of the system.

3.1 The Client Layer and User Interaction

The client layer is made with React.js & Tailwind CSS, which provides a fast and responsive user experience. The UI is designed in this way so that user without prior expertise in remote sensing or other related technical things can use the application easily. Users can Select AOI in the live map made with leaflet.js. They can manage AOI & see the change detection report in the dashboard.

3.2 API and Control Layer

This is the backend layer made with Node.js & Express.js to handle APIs & control the system. It receives AOI inputs according to which the system fetches images & sends for pre-processing. User authentication & authorization is achieved by JWT-based authentication and Bcrypt-based password hashing. This layer is responsible for sending alert to the user when change is detected, via Twilio for SMS alerts & smtplib for email notification.

Table 2: Dynamic Thresholding Mechanism for Noise-Resilient Change Validation

Change Event Type	Spectral Index Analyzed	Contextual Features Applied	Dynamic Threshold Determination (RF Model Output)
Deforestation	NDVI	Region ID, Season (Monsoon vs. Dry)	High threshold required if change is detected during peak green season (Monsoon), as even minor natural variance could be filtered out as noise.
Urban Encroachment	NDBI	Land Cover Class (= Forest/Land), Proximity to Roads.	Threshold is optimized to ignore small, transient spectral shifts, focusing instead on high-magnitude changes that are spatially coherent (OBCD) and indicative of permanent construction.
Water Body Shrinkage	NDWI	Season (Summer vs. Winter), Region ID	Lower threshold may be acceptable during known drought/dry seasons, whereas a higher threshold is required outside of expected seasonal variation to minimize false alerts.
General LULC Change	All Indices	User Sensitivity (Low, Medium, High).	The sensitivity input scales the required change magnitude, aligning the model's assigned numeric threshold with the user's operational requirement.

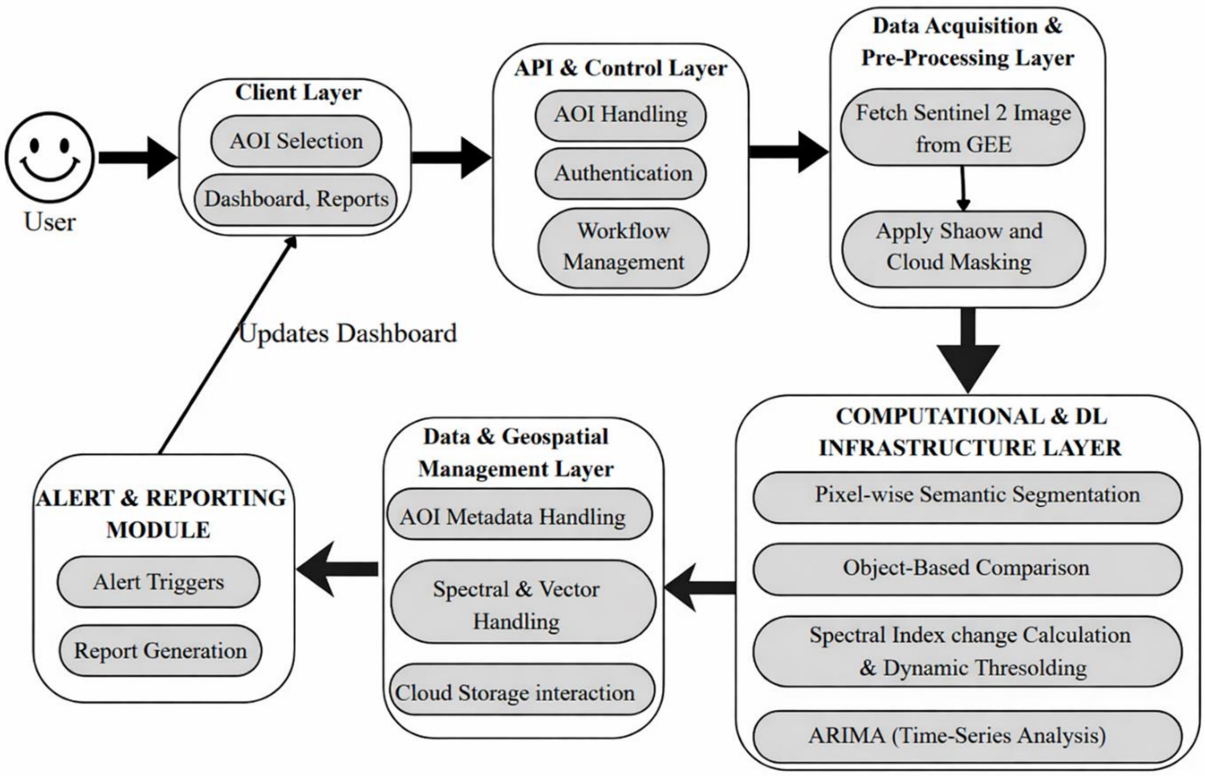

Figure 1: System Architecture

3.3 Data and Geospatial Management Layer

This layer is responsible for data management. Here a hybrid approach is taken for efficient data management. The system combines PostgreSQL database with PostGIS to store data like spectral indices & geospatial information. This combination can efficiently handle geometric data. Other assets like segmented patches, GeoTIFF outputs & generated reports are stored at Cloudinary, which reducing load on the primary database.

3.4 Computational and Deep Learning Infrastructure

This is the core layer that performs the comparison to detect the changes. Once multi-temporal Sentinel-2 is collected from GEE API as per the Area of Interest (AOI), cloud and shadow masking is done here. After cloud and shadow masking, pixel-wise semantic segmentation is done by the U-Net model (Guimarães et al. 2025), producing dense land-cover labels at the pixel level through patch-wise inference and full-scene reconstruction. Spectral indices are subsequently computed and combined with segmentation outputs for Random Forest–based validation. The resulting segmented maps and their associated spectral index features are fed to the Random Forest Classifier. Two temporal datasets are compared to detect changes. ARIMA model is utilised for time series analysis & historic trend analysis, after which Rasterio is used to generate GIS compatible outputs & PDFkit to handle the automated generation of reports.

3.5 Operational Pipeline Flow

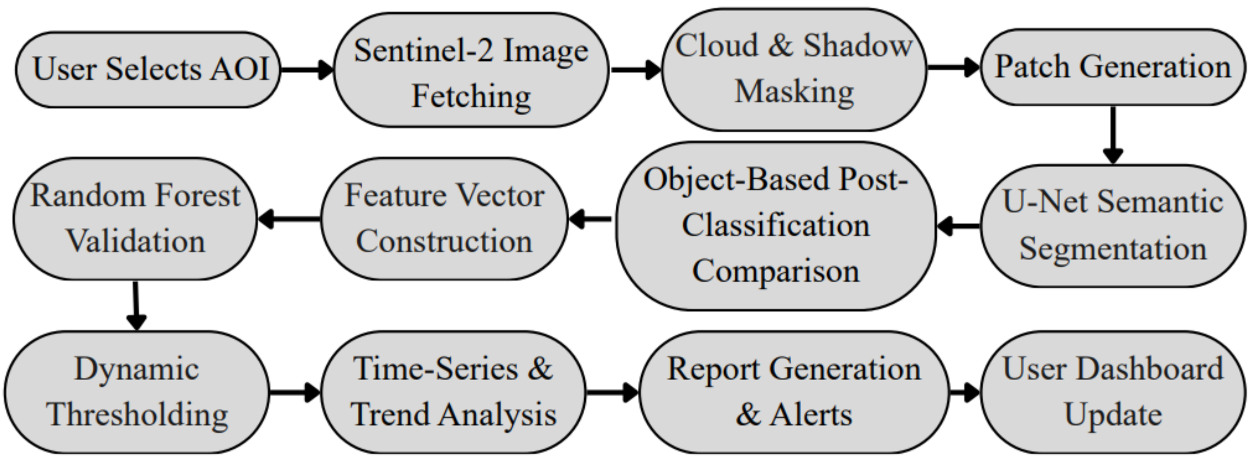

Figure 2: Process Flow Diagram

4. Results & Discussion

As aforesaid, the Dhristhi platform is designed as a multi-stage change detection platform to deliver highly reliable change detection, where accuracy is progressively refined from pixel-level segmentation to object-level validation. The reported final system performance of 92.1% overall accuracy and a mean IoU of 0.89 is achieved by mitigating the inherent weaknesses of purely pixel-based or index-threshold-based approaches through contextual and object-based validation.

4.1 Performance Evaluation

The experiments were conducted on multiple AOIs representing diverse environments, like forested areas, urban expansion areas and water bodies. Reference change maps were created for quantitative assessment by manually interpreting validated LULC datasets and high-resolution imagery. Intersection-over-Union (IoU), Kappa Coefficient, and Overall Accuracy were calculated independently for (i) pixel-wise semantic segmentation outputs and (ii) binary change/no-change maps generated following object-based validation. Evaluation metrics included Overall Accuracy, Kappa Coefficient and Intersection-over-Union (IoU). Qualitative assessment revealed high precision in distinguishing true anthropogenic changes from seasonal vegetation shifts. The integrated RF thresholding significantly reduced false positives especially in agricultural zones prone to cyclical variations. The important point to be noted here is that the Random Forest metrics are computed on change/no change validation masks, while the U-Net metrics refer to the pixel-wise semantic segmentation performance. Since there is a significant class imbalance in change detection by nature (unchanged areas predominate), supplementary metrics like Kappa and IoU were employed in addition to overall accuracy to guarantee accurate performance interpretation. The quantitative performance comparison of the system is shown in Table 3.

Table 3: Efficiency Tabulation of System Utilizing Different Metrics

Metric	U-Net Segmentation	RF Change Validation	Combined System
Overall Accuracy (%)	91.7	87.8	92.1
Kappa Coefficient	0.83	0.81	0.88
IoU (Mean)	0.85	0.79	0.89

4.2 Comparison with Existing Platforms

Unlike Google Earth Engine (GEE) which requires coding and manual threshold tuning, Dhristhi provides a fully automated & object-validated change detection platform suitable for users with less expertise. A comparison between the proposed system and existing platforms is presented in Table 4.

Table 4: Comparison between Dhristi and Existing Platforms

Feature	Dhristi	GEE
Coding requirement	No	Yes(JavaScript/Python)
Object-based validation	Yes	User-implemented
Seasonal noise filtering	Automated (with help of RF)	Manual
Immediate user alerts	Yes	No
AOI-based automation	Yes	Partial

4.3 Performance Validation and Interpretation

The effectiveness of the proposed Dhristhi platform is derived from its multi-stage validation strategy, where change detection accuracy is refined from pixel-level segmentation to object-level and contextual validation. While the U-Net model produces accurate pixel-wise land cover maps, such outputs remain sensitive to seasonal spectral variability and atmospheric effects. The Object-Based Post-Classification Comparison (OBCD) stage aggregates spatially contiguous changed pixels into meaningful geographic objects, reducing isolated misclassifications and improving spatial coherence. This object-level representation significantly suppresses noise commonly observed in purely pixel-based approaches. In the final validation stage, the Random Forest classifier incorporates spectral change magnitudes together with contextual features such as season of acquisition and region-specific characteristics. This enables effective separation of true anthropogenic changes from natural or cyclical variations, particularly in agricultural and vegetated regions. Given the inherent class imbalance between changed and unchanged areas, complementary metrics such as Kappa coefficient and Intersection-over-Union (IoU) are reported alongside overall accuracy to ensure reliable performance assessment. The results confirm that the combined framework achieves stable and noise-resilient change detection through the integration of deep learning, object-based analysis, and contextual validation.

5. Conclusions

Dhristhi is the first integrated approach to implement automated geospatial change detection. Through integration of U-Net top-down deep learning that is precision driven, object-based analysis spatially coherence driven, noise robustness of a contextualized Random Forest validation module the system scales on increased reliability to differentiate between true anthropogenic change and spectral seasonal variation. By removing the need for operators to understand end-to-end automated web interfaces and by delivering actionable in addition to immediate alerts as well as GIS-friendly reports, Dhristhi effectively demonstrates advanced geospatial intelligence capabilities, making it available anywhere and anytime the civil and environmental agencies want.

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