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From Pixels to Patrols: Integrating Remote Sensing Alerts with Field Verification in Forest Protection

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Abstract

Forest landscapes in India face continuous pressures from encroachment, deforestation, grazing, and unregulated land-use expansion. Traditional patrol-driven monitoring often detects disturbances late due to limited staff capacity and vast spatial extents. This study presents a near real-time "Pixels to Patrols" workflow that converts satellite-derived land cover changes into actionable forest alerts and integrates ranger feedback to refine detection. Using Google Earth Engine (GEE) and Dynamic World V1 composites, significant pixel-level class probability changes are identified through a systematic before–after comparison. These detections are vectorised into alert polygons, enriched with spectral, spatial, terrain, and temporal attributes, and assigned to field staff for verification. Verification outcomes then serve as ground-truth labels for a machine learning feedback loop, enabling continuous model improvement. This operational framework demonstrates how remote sensing, GIS, and AI can be integrated into daily forest governance.

Keywords

Remote sensing; Google Earth Engine; Dynamic World; AI feedback; forest governance; patrol monitoring.

1. Introduction

Forests in India provide vital ecological services but are continuously threatened by agricultural encroachment, tree removal, understory clearing, illegal grazing, and gradual land-use shifts. These changes often begin subtly—one felled tree, a freshly ploughed patch, a small path opened through a compartment. Detecting such early signals is essential for timely intervention, yet conventional patrols are constrained by manpower and terrain.

Recent advances in satellite imagery and cloud computing support near real-time forest monitoring at actionable resolutions. Sentinel-2 provides frequent 10 m multispectral coverage; Dynamic World (DW) adds per-pixel class probabilities; Google Earth Engine (GEE) enables server-side image processing at scale. Yet these datasets must be operationally integrated with beat-level responsibilities and patrol cycles.

The "Pixels to Patrols" system bridges this gap by converting detected land-cover changes into structured alert polygons, assigning them to beat guards, and feeding their verification back into an AI model. This section presents the full methodology, results, and implications for adaptive forest management.

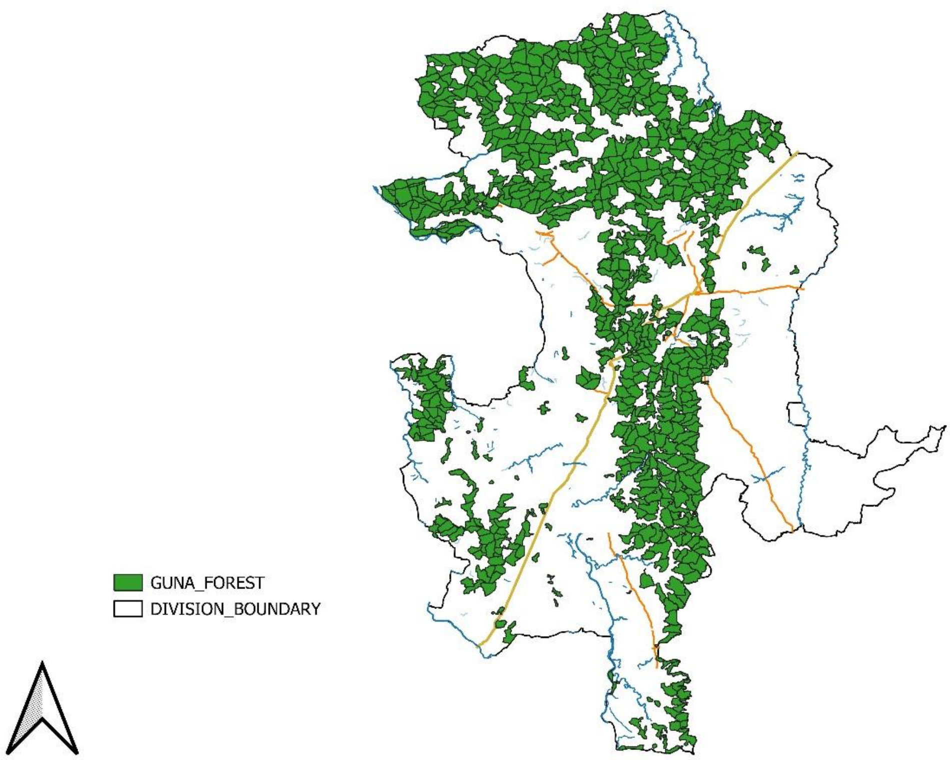
2. Materials and Methods

This section describes the complete workflow, including data sources, change detection logic, operational processing, field verification, and integration of ranger feedback into AI learning.

2.1 Study Area

The workflow was piloted in the Guna Forest Division of Madhya Pradesh. The region consists of dry deciduous forest interspersed with agriculture, forming a mosaic where encroachment pressures are spatially concentrated. Administrative units—Range, Beat, and Compartment structure forest governance and form the basis for assigning alerts.

FIGURE 1: Study Area Map



2.2 Data Sources

2.2.1 Dynamic World V1

Near real-time 10-m land cover probabilities for: Trees, Crops, Grass, Shrub/Scrub, Bare, Built-up, Water.

2.2.2 Sentinel-2 Surface Reflectance

Used for vegetation indices (NDVI, SAVI, MSAVI, EVI, NDWI, EWI).

2.2.3 DEM/SRTM

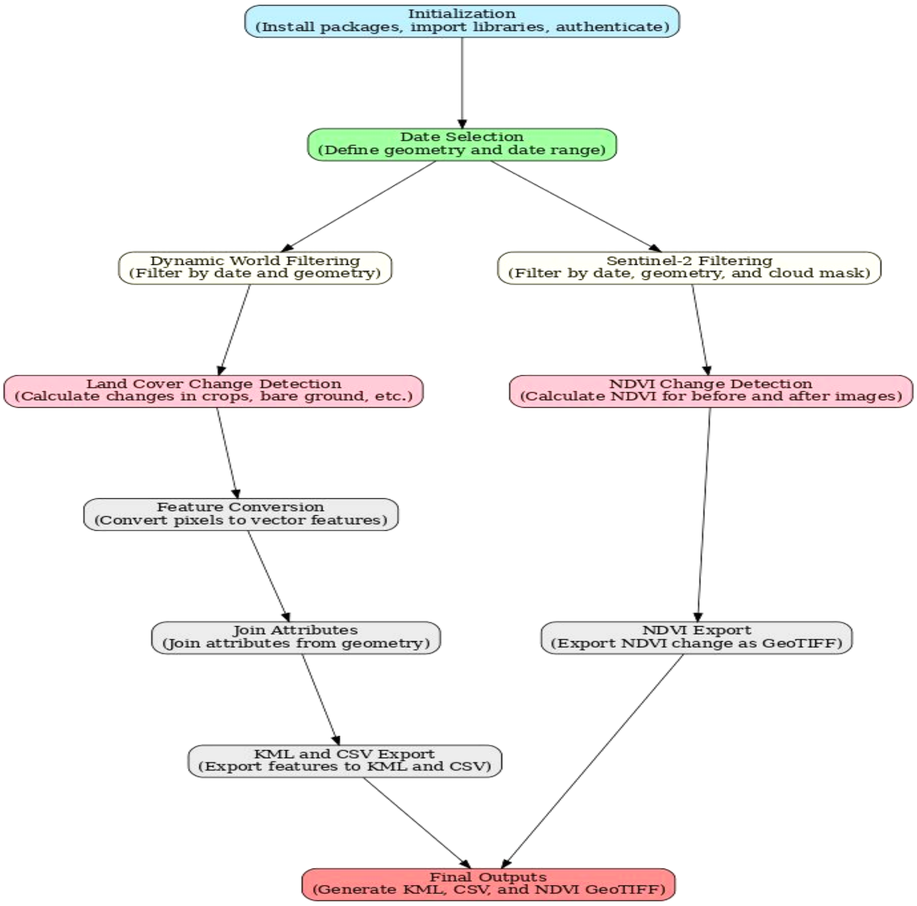
Provides elevation, slope, aspect, and roughness.

2.2.4 Forest Administrative Boundaries

Range → Beat → Compartment shapes.

2.2.5 Field Verification Metadata

GPS photos, notes, and classification from beat staff.



2.3 System Architecture

This step defines the high-level flow from satellite images to beat-level action.

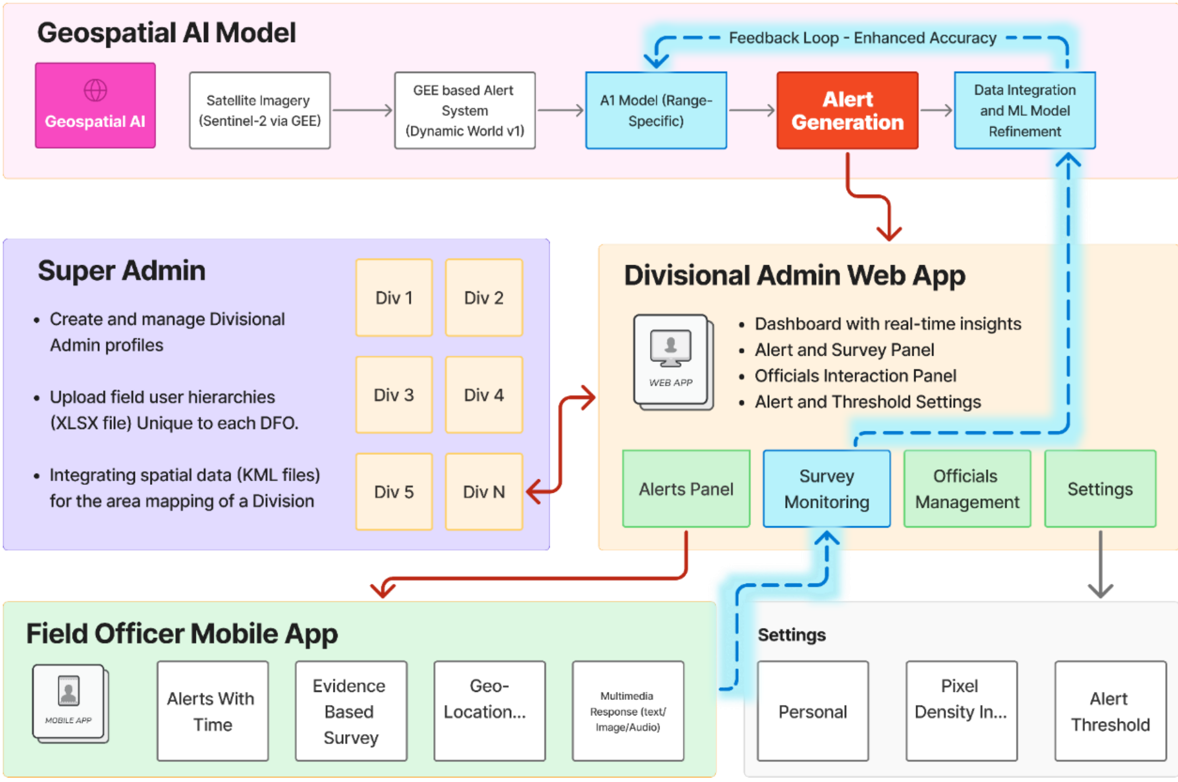


FIGURE 2: "Pixels-to-Patrols System Architecture"

Figure 2. System architecture connecting satellite data, GEE processing, alert generation, dashboard visualization, and field verification.

2.4 Temporal Image Selection and Compositing

Three most recent cloud-free DW images are identified for the AOI. Composites are computed as:

- **Before composite:** median of (Image_latest-2, Image_latest-3)
- **After composite:** median of (Image_latest, Image_latest-1)

This stabilizes temporal noise while preserving recent changes.

2.5 Change Detection Logic

For each class, probability difference is computed:

- Δ = After – Before for non-tree classes
- Δ = Before – After for Trees (detect loss)

Class	Threshold	Change Direction
Crops	0.20	After - Before
Bare	0.50	After - Before
Shrub/Scrub	0.50	After - Before
Built-up	0.50	After - Before
Grass	0.50	After - Before
Trees	0.20	Before - After

TABLE 1: Thresholds & Logic

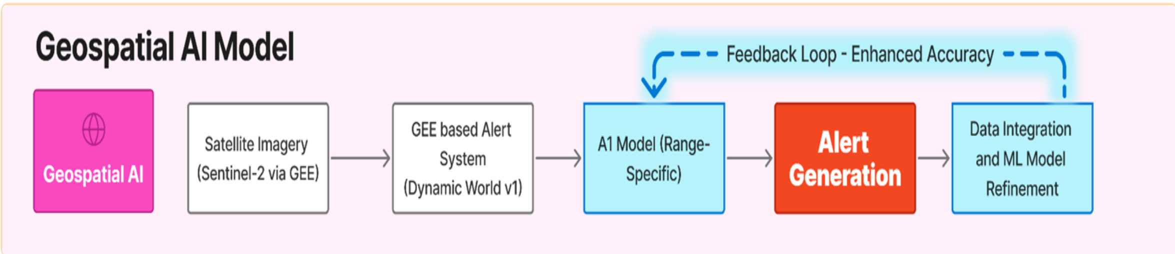
These thresholds can be varied by the DFO to sensitise according to his need. for example, since guna has problem of high illegal felling and encroachments so we have decreased for that class.

2.6 Pixel Highlighting and Cluster Formation

Binary masks are produced using Δ thresholds, then smoothed to fill gaps. Small noisy detections (<10 pixels) are discarded.

FIGURE 4: Change Detection Workflow

(Flowchart: Before → After → Δ → Threshold → Mask → Cleaned Mask.)



2.7 Vectorisation and Enrichment

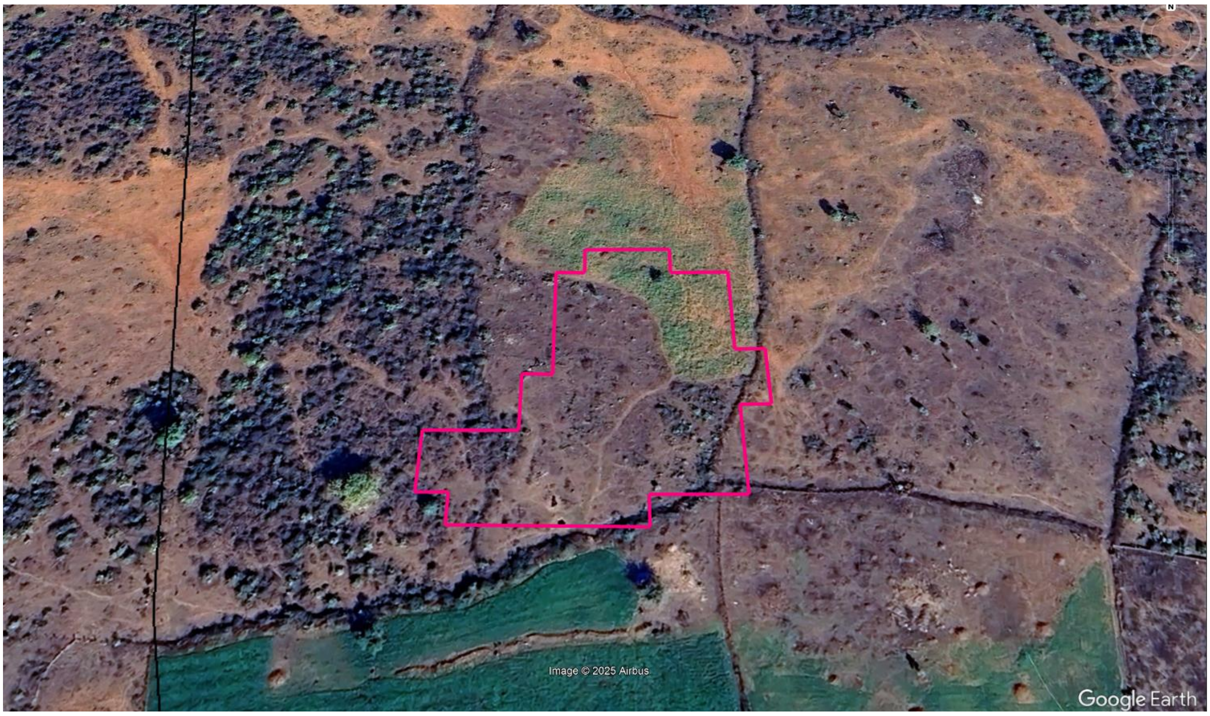
Pixels are converted to polygons. Each polygon receives:

- ΔTrees, ΔCrops, ΔBare, etc.
- NDVI_before/after
- Slope, elevation
- Area, perimeter, compactness
- Distance from road/village/forest boundary
- Range/Beat/NEW_NO_ attribution
- Detection date

FIGURE 5: Example Alert CSV

B	C	D	E	F	G	H	I	J	K	L	M	N
Imagery_Dates	Compartm	Source	bare_chan	built_chan	count	crops_cha	grass_char	label	pixelCount	shrub_and	trees_char	.geo
2025-10-20 to 2025-11-01	186	Trees	0.002989	0.001087	136	0.005024	0.125462	1	136	0.095879	0.214764	{"geodesic":false,"type":"Polygon","coordinates":[[[76.31880041364107,21.4188906453
2025-10-20 to 2025-11-01	186	Trees	0.001149	0.005877	68	0.007875	0.130352	1	68	0.076271	0.212319	{"geodesic":false,"type":"Polygon","coordinates":[[[76.31862075058424,21.4218550858
2025-10-20 to 2025-11-01	194	Trees	0.009995	0.008405	133	0.008648	0.114387	1	133	0.078849	0.221344	{"geodesic":false,"type":"Polygon","coordinates":[[[76.32248350630596,21.4365874564
2025-10-20 to 2025-11-01	193	Trees	0.027141	0.005475	90	0.005871	0.037198	1	90	0.041798	0.227565	{"geodesic":false,"type":"Polygon","coordinates":[[[76.32859205023797,21.4208669390
2025-10-20 to 2025-11-01	193	Trees	0.019929	0.009331	701	0.001511	0.120897	1	701	0.080803	0.240385	{"geodesic":false,"type":"Polygon","coordinates":[[[76.32868188176639,21.4301195864
2025-10-20 to 2025-11-01	194	Trees	0.015196	0.006414	6166	0.006689	0.131898	1	6166	0.072749	0.248854	{"geodesic":false,"type":"Polygon","coordinates":[[[76.3317361537324,21.446918082239
2025-10-20 to 2025-11-01	193	Trees	0.007338	0.004032	3410	0.007148	0.119845	1	3410	0.097407	0.243932	{"geodesic":false,"type":"Polygon","coordinates":[[[76.33164632220398,21.4279636297
2025-10-20 to 2025-11-01	193	Trees	0.007388	0.005366	111	0.003025	0.107241	1	111	0.089734	0.220347	{"geodesic":false,"type":"Polygon","coordinates":[[[76.33209547984605,21.4233822217

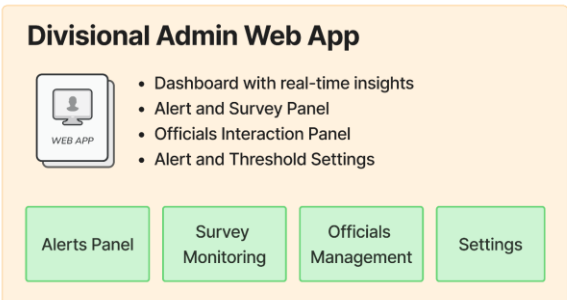
FIGURE 5: Example Alert Polygon

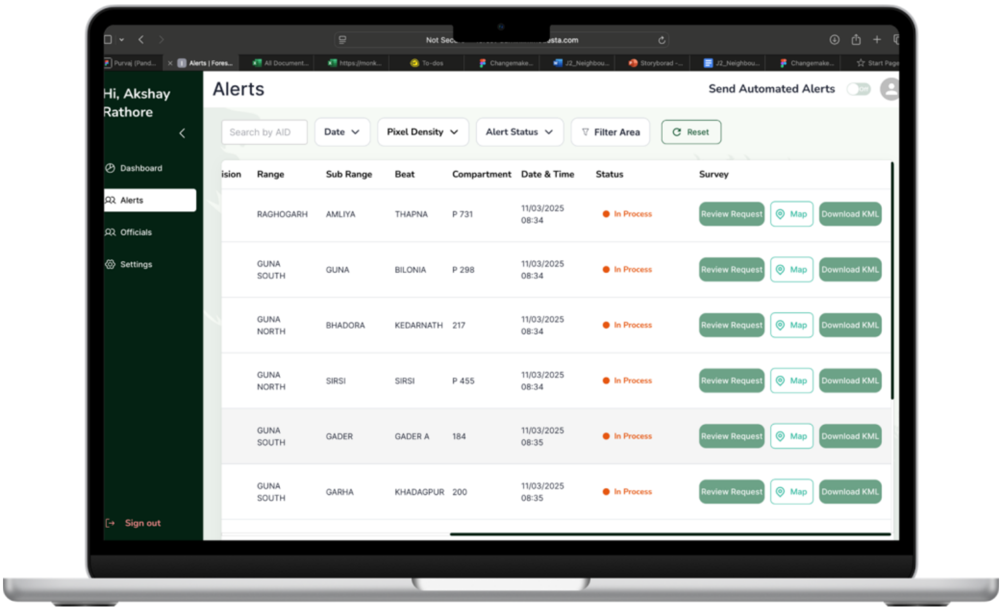


2.8 Integration with Field Operations

Alert polygons are uploaded to dashboard → assigned to beat staff → verified using GPS and photos.

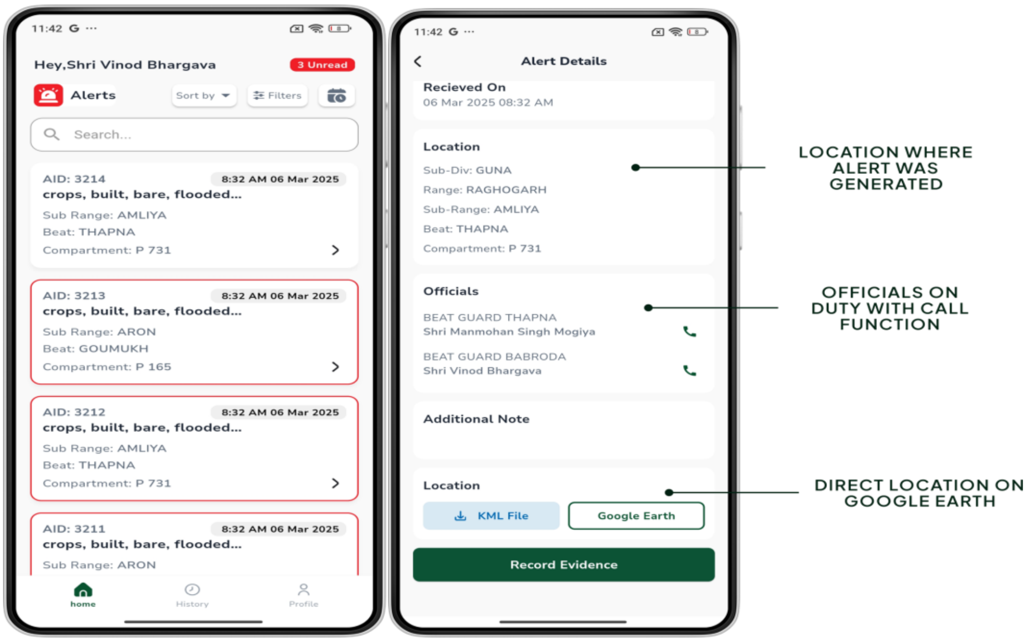
FIGURE 6: Dashboard Screenshot





2.9 FIELD APP

- Login securely using registered mobile number.
- View alerts assigned to him along with their time of generation.
- Respond to alerts by submitting up to 4 images and a voice note.
- Include GPS data with time and distance to alert location in the submissions.



2.10 Enriched Alert CSV

The enriched CSV contains 40+ variables across spectral, probability, terrain, spatial, temporal, and administrative dimensions. These include:

A. Spectral & Probability Features

- trees_before, trees_after
- crops_before, crops_after
- Δtrees, Δcrops, Δbare, etc.
- Sentinel-2 reflectance bands
- NDVI
- SAVI
- MSAVI
- NDWI
- EVI
- EWI

- **B. Terrain Features**

- Elevation
- Slope
- Roughness
- Aspect

C. Spatial Context

- Distance to forest boundary
- Pixel cluster size
- Area
- Compactness
- Perimeter

D. Temporal Context

- DOY (Day of Year)
- Time gap between before/after images

E. Environmental Features

- Rainfall anomaly
- LST (Land Surface Temperature) anomaly
- Soil moisture (if added later)

- **F. Administrative Attributes**

- Range

- Beat
- Compartment

2.11 AI Feedback Integration

Staff verification becomes training data.
Dependent Variable (Y)
1 = True Positive
0 = False Positive / Natural
Independent Variables (X)
All enriched attributes produced in Section 2.9.

Δtrees	Δcrops	NDVI_before	NDVI_after	slope	pixelCount		…	label(Y)
0.24	0.05	0.61	0.23	2.4	86		…	1
0.05	0.02	0.48	0.45	6.8	22		…	0
...	...	...	...	...	...		…	...

- **TABLE 3: Dependent vs Independent Variables**

Where: X = All enriched features Y = Verified field label (1 or 0)

Category	Examples	Role
Dependent Variable (Y)	Verified field label (1=True, 0=False)	Output
Land Cover Changes	ΔTrees, ΔCrops, ΔBare	Independent
Spectral Indices	NDVI, SAVI, EVI, NDWI	Independent
Sentinel-2 Bands	Red, NIR, SWIR1, SWIR2	Independent
Terrain Features	Slope, Elevation, Roughness	Independent
Spatial Metrics	pixel Count, Area, Perimeter	Independent
Contextual Variables	Distance to road/village, DOY	Independent
Administrative Fields	Range, Beat, NEW_NO_	Independent

2.12 Machine Learning Feedback Loop

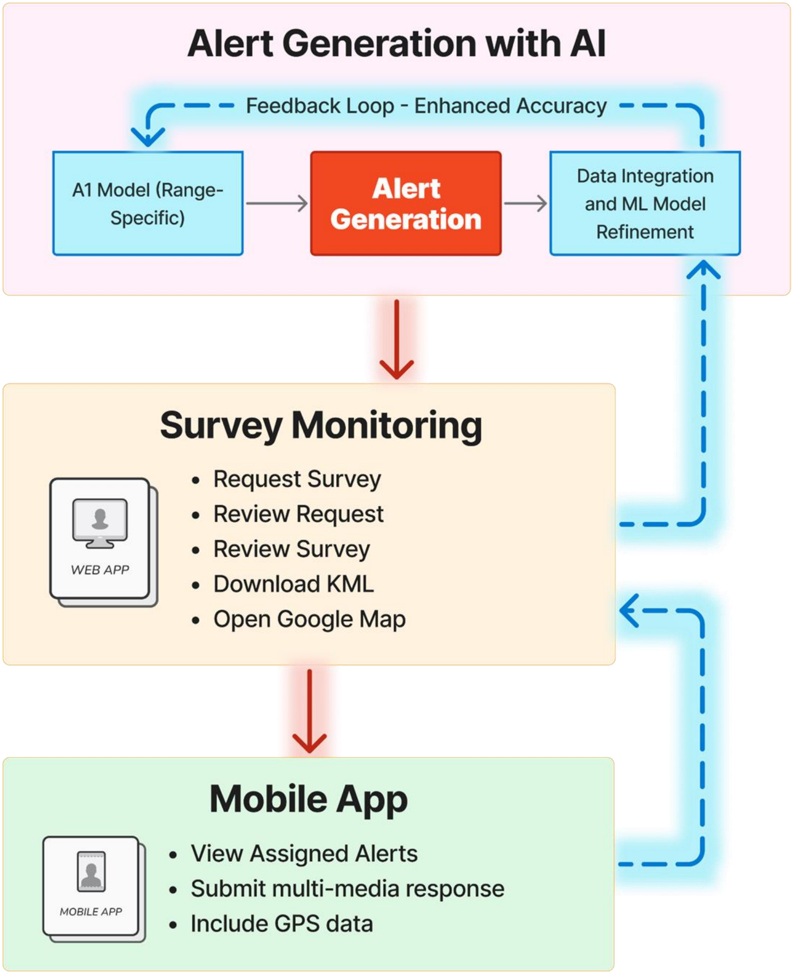
Satellite → Alert → Field Verification → Feedback → Model Retraining → Better Alerts

AI evolves based on how field officers classify alerts.

This is equivalent to giving model:
MP Forest Department experience
Ranger intuition
Beat-level knowledge

Real patrolling patterns

FIGURE 7: AI Feedback Loop Diagram



3. Results

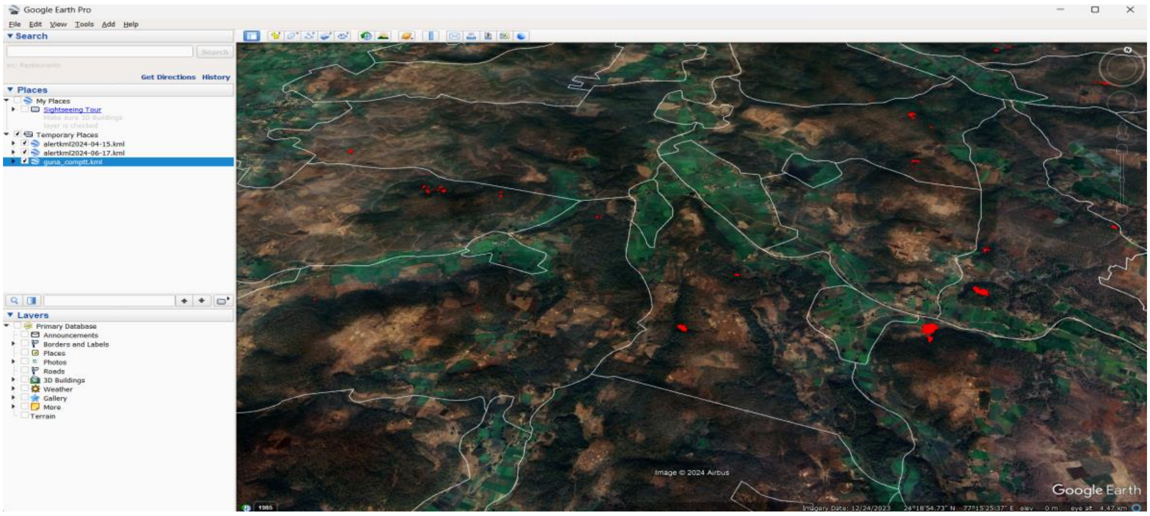
This section presents the outcomes of the near real-time change-detection workflow implemented across the Guna Forest Division. Results include spatial patterns of detected changes, typology of alert polygons, spectral and probability-based characteristics, field verification outcomes, and insights derived from enriched attribute analysis.

3.1 Volume and Distribution of Alerts

Across the pilot period, the system generated a consistent stream of alerts corresponding to meaningful land-cover transitions. Alerts were not evenly distributed; instead, they exhibited clear spatial clustering along forest–agriculture interfaces, village peripheries, and historically sensitive compartments.

These patterns align with field observations and past enforcement records, indicating the system's capacity to detect real pressure zones.

FIGURE: Spatial Distribution of Alerts



3.2 Typology of Detected Changes

Analysis of Dynamic World probabilities and spectral signatures revealed three dominant categories of change:

3.2.1 Tree-to-Crop Transitions

These represent clearings where canopy is thinned or removed, followed by land preparation or early-stage cultivation.

They exhibited:

- Sharp declines in Trees_before – Trees_after
- Strong increases in Crops_after

3.2.2 Tree-to-Bare Transitions

Detected where trees were felled but no cultivation followed during the observation window. Common reasons: illegal fuelwood removal, boundary marking, or preparation for future cropping.

3.2.3 Grass/Shrub Dynamics Misinterpreted as Change

Several alerts captured strong seasonal fluctuations in grass or shrub-level vegetation, especially after monsoon breakup or pre-summer drying. These initially appear as land-cover change but were corrected through verification.

3.3 Characteristics of Alert Polygons

Alert polygons varied in shape, size, and intensity of Δ-change values. Key observations:

3.3.1 Polygon Size

- Small polygons (10–30 pixels) were often edge thinning, firelines, or early-stage encroachments.

- Medium polygons (30–150 pixels) represented active clearing activity.
- Large polygons (>150 pixels) typically corresponded to complete patch removal or large-scale ploughing.

3.4 Δ-Value Analysis and Spectral Behavior

Each alert's Δ-values across DW classes and Sentinel-2 indices helped characterize change intensity:

3.4.1 ΔTrees

Consistently the strongest signal.

True positives showed ΔTrees values typically in the range 0.20–0.65, indicating substantial canopy probability loss.

3.4.2 ΔCrops

High ΔCrops values confirmed conversion into agriculture.

Cases with ΔCrops > 0.40 strongly correlated with verified encroachments.

3.4.3 ΔBare

Increased bare probability often preceded cultivation, revealing stages of ground preparation.

3.5 Field Verification Outcomes

Field staff verified a large sample of alerts using GPS-tagged photos.

3.5.1 Verification Accuracy

- True Positives: 50% depending on month
- False Positives: Mostly due to seasonal herbaceous vegetation shifts
- Natural Category: Fire- or rainfall-triggered temporary bare patches

3.5.2 Common Field Observations

Verified alerts fell into:

- Fresh ploughing
- Removal of tree saplings
- Boundary widening
- Cutting for fuelwood
- Early-stage cultivation

3.6 AI Feedback Insights

The binary dependent variable (1 = True, 0 = False) was paired with enriched attributes to evaluate model-learned patterns.

3.6.1 High-Weight Predictors Identified

Preliminary model evaluation showed strongest contributions from:

- ΔTrees
- ΔCrops
- NDVI drop
- Slope
- pixelCount

3.6.2 False Positive Reduction

Incorporating field feedback helped:

- Filter out grassland seasonality
- Reduce shrub-related false triggers
- Suppress monsoon-driven spectral confusion

The model began learning location-specific vegetation cycles, reducing noise.

3.8 Operational Impact

The system demonstrated significant governance improvements:

- Patrols were directed to specific polygons, not broad areas
- Subdivisional Officers, Range Officers, deputy range officer and beat guards received structured daily updates
- Patrol logs became digitally auditable
- DFO, SDO and RO gained visual clarity on exact disturbance sites
- Early detection prevented expansion of small encroachments

This created a data-driven feedback loop connecting remote sensing and field enforcement.

3.9 Example Case: Verification of a Crop Encroachment Alert (Compartment P270, Amrod Beat, Guna North Range)

This example demonstrates how a single alert generated by the system moves through the full pipeline — from satellite detection to dashboard assignment, ground verification, and final reporting.

Step 1: Satellite-Derived Alert Generation

Dynamic World before–after imagery detected a sharp **drop in tree probability** and a corresponding **rise in crop/bare probability** over a 0.036 ha patch inside Compartment P270. This pixel-level transition triggered an alert classified as: **“Crops – High Severity.”**

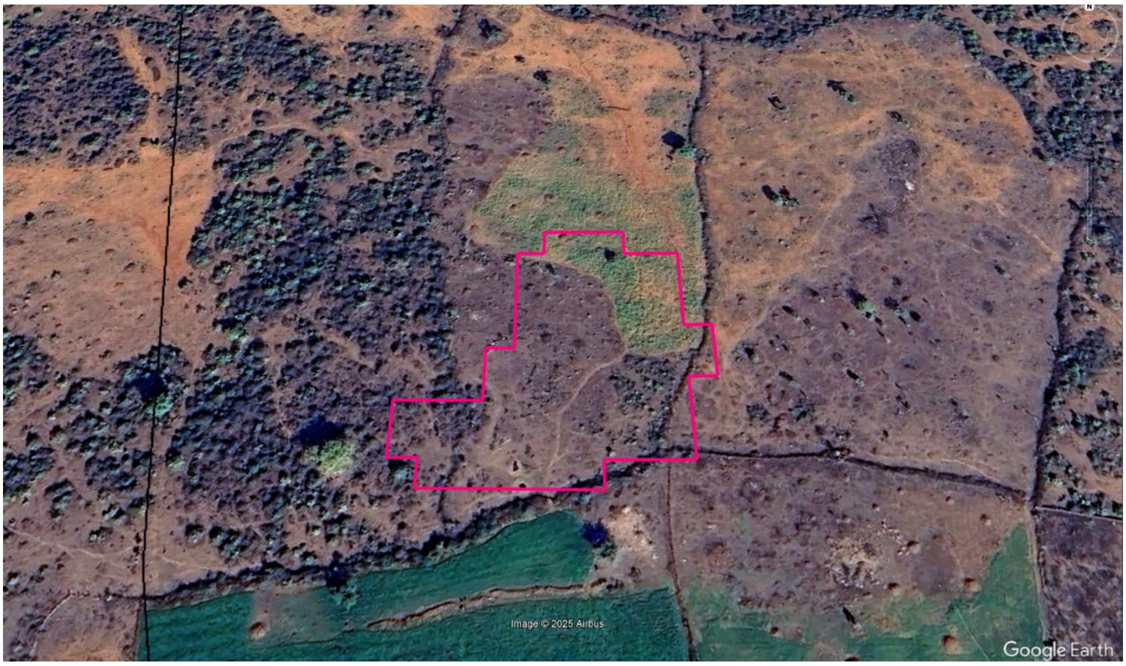


FIGURE: Example Alert Polygon (Zoomed)

Zoomed Google Earth visualization showing the detected polygon boundary (pink) over the change area.

Step 2: Alert Appears in Dashboard for Officer Review

The system generated the unique Alert ID **MPGUN091125AA43** and pushed it to the division dashboard. The alert record included:

- Range: Guna North
- Sub-range: Umari
- Beat: Amrod
- Compartment: P270
- Pixel Density: 69
- Detection Time: 08/11/2025, 01:42 AM
- Assigned Beat Guard: Rohit Raghuwanshi

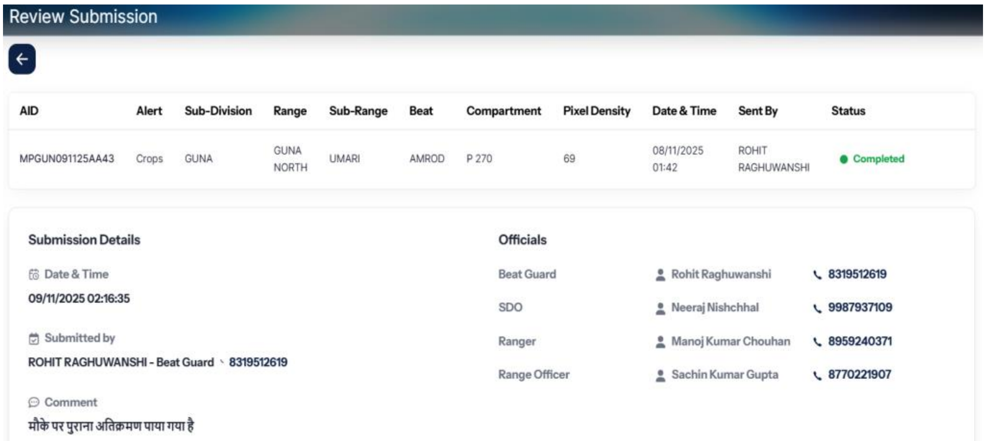


FIGURE: Alert Description in Dashboard

(Dashboard view displaying complete alert metadata, assignment chain, and operational hierarchy.

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Step 3: Field Verification by Beat Guard

The beat guard visited the site on **09/11/2025 at 02:16 AM**, captured multiple GPS-tagged photographs, and inspected the polygon area.

Observations:

- Land had been recently ploughed
- Old encroachment signs visible
- No standing trees or shrubs inside the boundary
- Field boundary pushed into forest land
- Comment submitted: **"मौके पर पुराना अतिक्रमण पाया गया है"**

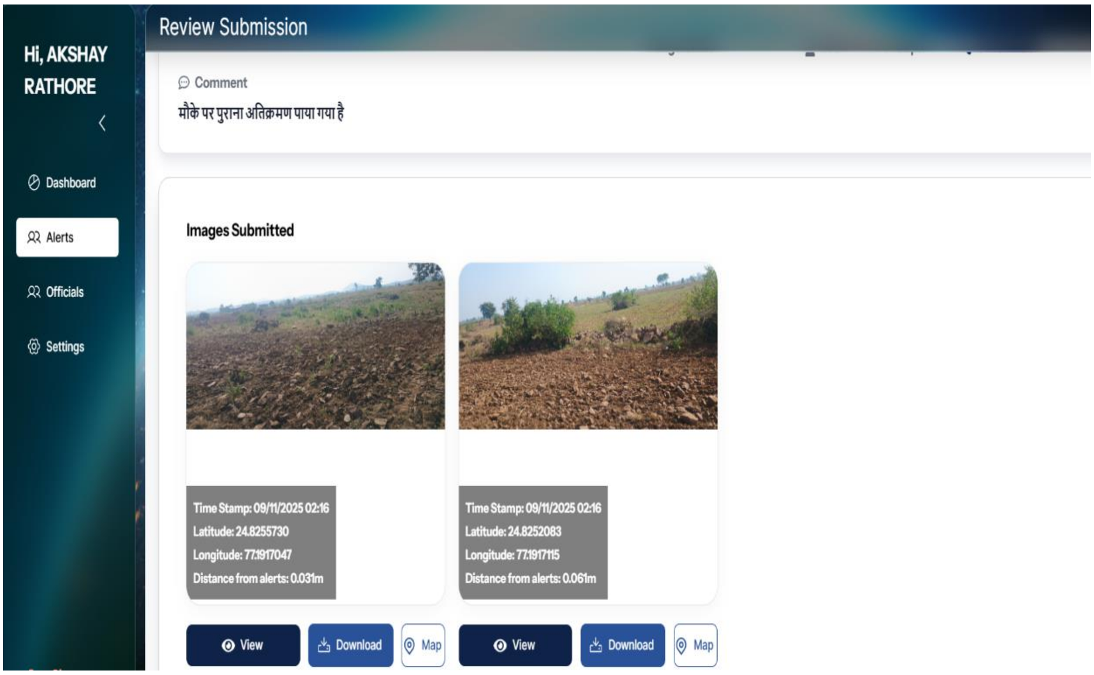

FIGURE 3: Field Verification Images Submitted by Staff
Ground-truth photos uploaded from the field showing ploughed land and expansion of agricultural boundary into forest area.

Step 4: DFO-Level Review and Final Decision

After reviewing both satellite-derived evidence and field photographs, the Divisional Forest Officer confirmed the alert as **accurate and valid**.

Status changed to: **Completed (True Positive)**

This feedback entered the AI system as:

Y = 1 (True Positive)

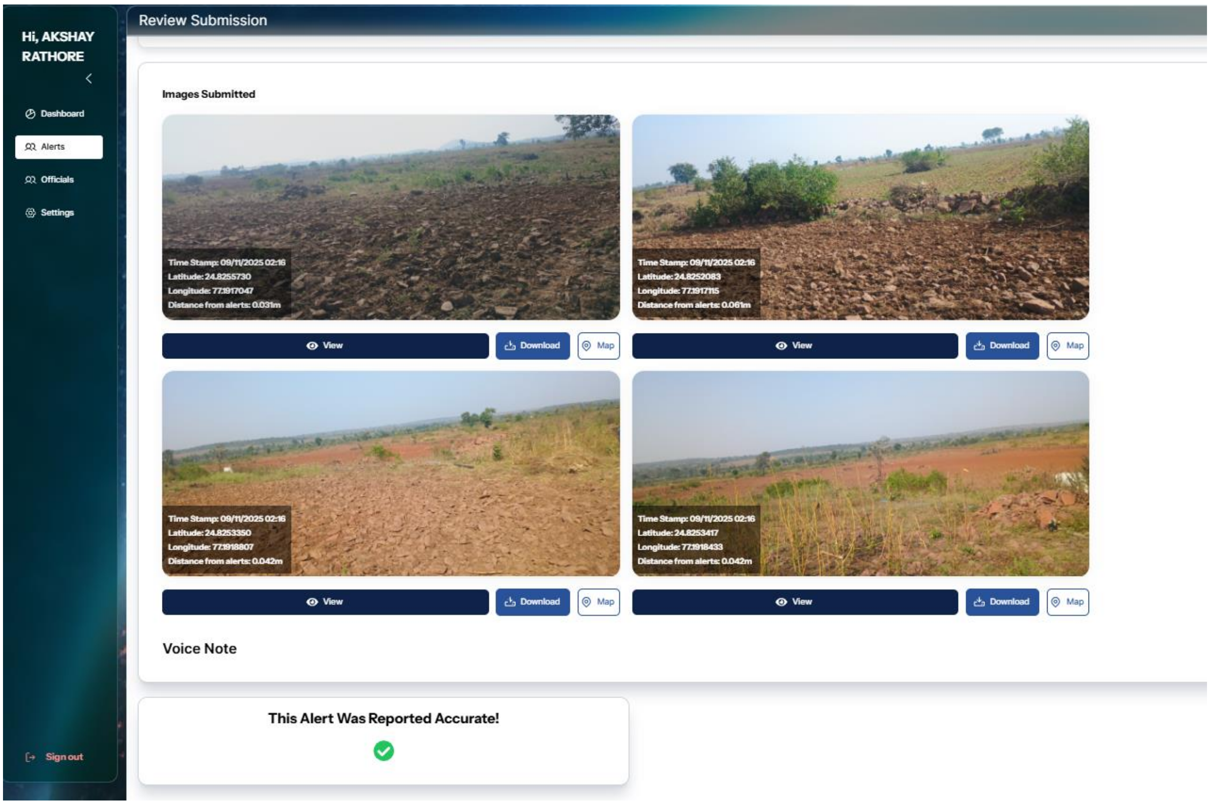

FIGURE: DFO Reporting Alert Accurate

DFO review page showing submitted evidence, officer comments, and final approval marking the alert as correct.

4. Discussion

- Improves early detection
- Links remote sensing with governance
- Reduces false positives with ML feedback
- Challenges: cloud cover, mixed pixels, small changes

5. Conclusion

The Pixels-to-Patrols workflow demonstrates that forest protection can be transformed when satellite intelligence, geospatial automation, and structured field verification operate as a single system. By integrating Google Earth Engine's continuous land-cover monitoring with Dynamic World's pixel-level probabilities, the method captures subtle yet meaningful forest disturbances that traditionally remain undetected until much later. The conversion of these spectral signals into compartment-wise alert polygons creates a direct operational bridge between cloud-based analytics and beat-level patrolling.

The example alert presented in this study illustrates the practical strength of the approach. A small clearing of only a few pixels—otherwise invisible in conventional field rounds—was automatically detected, routed to the appropriate beat guard, verified with geotagged photographs, and formally confirmed by the Divisional Forest Officer. This loop not only validates the detection but also provides high-quality ground truth that becomes the dependent variable for machine-learning refinement. Over time, this feedback enriches the system's intelligence, reducing false positives and improving prioritisation accuracy.

Beyond detection, the workflow strengthens accountability and transparency across the entire administrative chain. Every stakeholder—from beat guard to SDO to DFO—interacts with the same digital alert, creating a verifiable, timestamped operational trail. Terrain-based risk patterns, accessibility constraints, and seasonal vegetation cycles are progressively learned by the model, enabling proactive patrolling in high-pressure zones rather than reactive enforcement after significant damage has occurred.

The study thus positions Pixels-to-Patrols not merely as a monitoring tool but as a foundational step toward an adaptive, data-driven forest governance paradigm. As field feedback continues to expand and the AI layer matures, the system will evolve from early warning to predictive intelligence—anticipating where disturbances are most likely to occur. This capability has strong potential for replication across forest divisions and can form a core component of India's next-generation digital forest protection architecture

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