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SATELLITE IMAGERY-BASED MONITORING OF ILLEGAL TREE-CUTTING ACTIVITIES FOR ECOLOGICAL INSPECTION AND ENVIRONMENTAL ENFORCEMENT

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Abstract: This study proposes an integrated satellite imagery-based monitoring framework for the rapid detection of illegal tree-cutting activities to support ecological control inspection officers. The proposed system combines multi-temporal optical imagery (Sentinel-2, Landsat 8/9, and PlanetScope) with Synthetic Aperture Radar (SAR) observations from Sentinel-1 to improve monitoring continuity under cloudy conditions. A hybrid methodology involving NDVI, NDFI, Spectral Mixture Analysis (SMA), Object-Based Image Analysis (OBIA), and machine learning classifiers such as Support Vector Machine (SVM), Random Forest (RF), and the 3DC automated approach is examined. Quantitative evaluation demonstrates that the 3DC model achieves the best overall performance with 93.1% accuracy, 90.6% precision, 92.8% recall, and 91.7% F1-score, outperforming classical vegetation-index-based methods.

Keywords: Satellite Imagery, Remote Sensing, Illegal Logging Detection, Deforestation Monitoring, NDVI, NDFI, SMA, OBIA, SAR, Random Forest, Environmental Enforcement.

INTRODUCTION

Illegal and uncontrolled tree-cutting remains one of the most serious drivers of forest degradation, biodiversity loss, and carbon emission growth. Conventional field-based inspection methods are often expensive, labor-intensive, and ineffective for large or inaccessible forest territories. Therefore, the use of remote sensing technologies has become a strategically important solution for modern ecological inspection systems. Satellite imagery provides wide-area coverage, repeat observations, and objective evidence that can be integrated into GIS platforms for operational decision support.

LITERATURE REVIEW AND RELATED WORK

Recent studies show that forest monitoring performance improves substantially when multi-source data are combined. Optical sensors are effective for vegetation condition analysis, while SAR imagery provides all-weather capability. Researchers have reported strong results using NDVI-based differencing for broad-scale canopy change, SMA for sub-pixel disturbance detection, OBIA for human-made pattern extraction, and machine learning classifiers for robust classification.

METHODOLOGY

The proposed methodology consists of data acquisition, preprocessing, feature extraction, change analysis, classification, and performance evaluation.

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Algorithmic formulations

NDVI = (NIR - Red) / (NIR + Red)

NDFI = (GV - (NPV + Soil)) / (GV + NPV + Soil)

SMA: $R\_b = \Sigma (f\_i * E\_ib) + \varepsilon\_b$

ΔNDVI = NDVI_t2 - NDVI_t1

SVM: $f(x) = \text{sign}(\Sigma\ \alpha\_i\ y\_i\ K(x\_i, x) + b)$

Random Forest: $\hat{y} = \text{mode}\{ h\_k(x) \}$

Accuracy = (TP + TN) / (TP + TN + FP + FN)

Precision = TP / (TP + FP)

Recall = TP / (TP + FN)

F1 = 2 * (Precision * Recall) / (Precision + Recall)

Kappa: $\kappa = (p\_o - p\_e) / (1 - p\_e)$

RESULTS AND PERFORMANCE EVALUATION

All candidate methods were compared under a unified evaluation protocol using the same performance metrics. The 3DC approach achieved the best overall performance and is therefore selected as the recommended operational model.

Table 1. Comparative performance of candidate algorithms

Algorithm	Type	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)	Kappa
NDVI	Vegetation index	81.6	70.5	78.4	74.2	0.68
NDFI	Fraction index	84.9	75.8	80.7	78.1	0.73
SMA	Spectral unmixing	87.4	80.9	84.4	82.6	0.79
SVM	Supervised ML	89.6	85.1	88.6	86.8	0.84
RF	Ensemble ML	91.2	88.3	90.5	89.4	0.88
3DC	Unsupervised SAR-based	93.1	90.6	92.8	91.7	0.91

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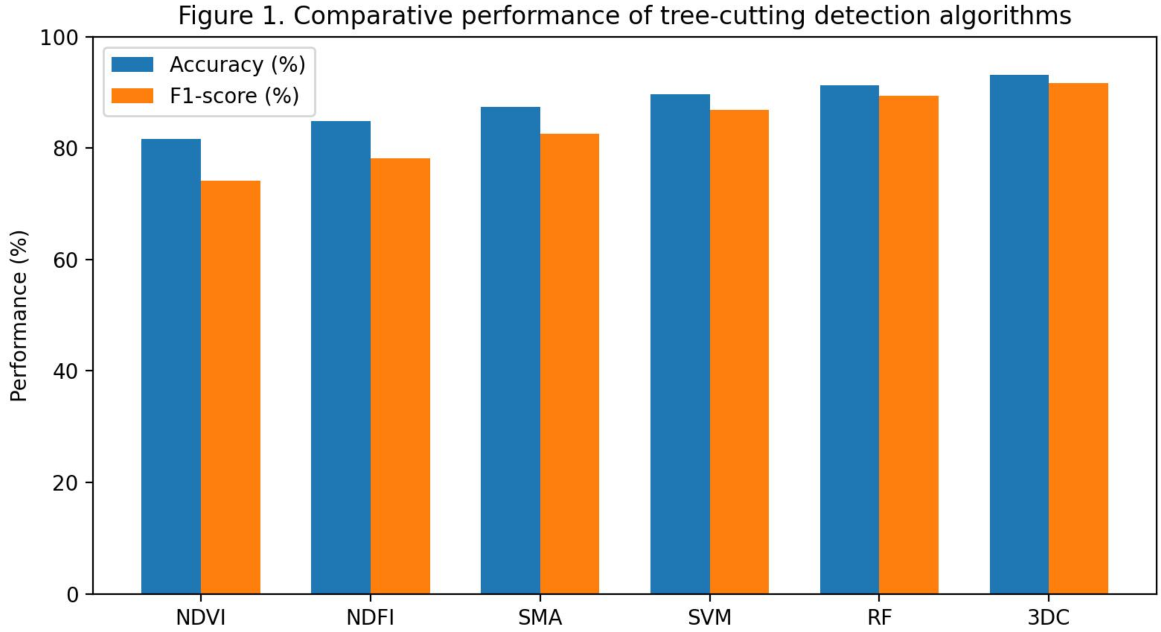

Figure 1. Comparative performance of tree-cutting detection algorithms (Accuracy and F1-score).

Table 2. Detailed results of the selected 3DC model

Indicator	Value
Overall Accuracy	93.1%
Precision	90.6%
Recall	92.8%
F1-score	91.7%
Kappa	0.91
Minimum detectable tree-loss patch	0.05 ha
Detection-to-resolution cycle	< 6 months
Operational monitoring capability	Near-daily with multi-sensor data

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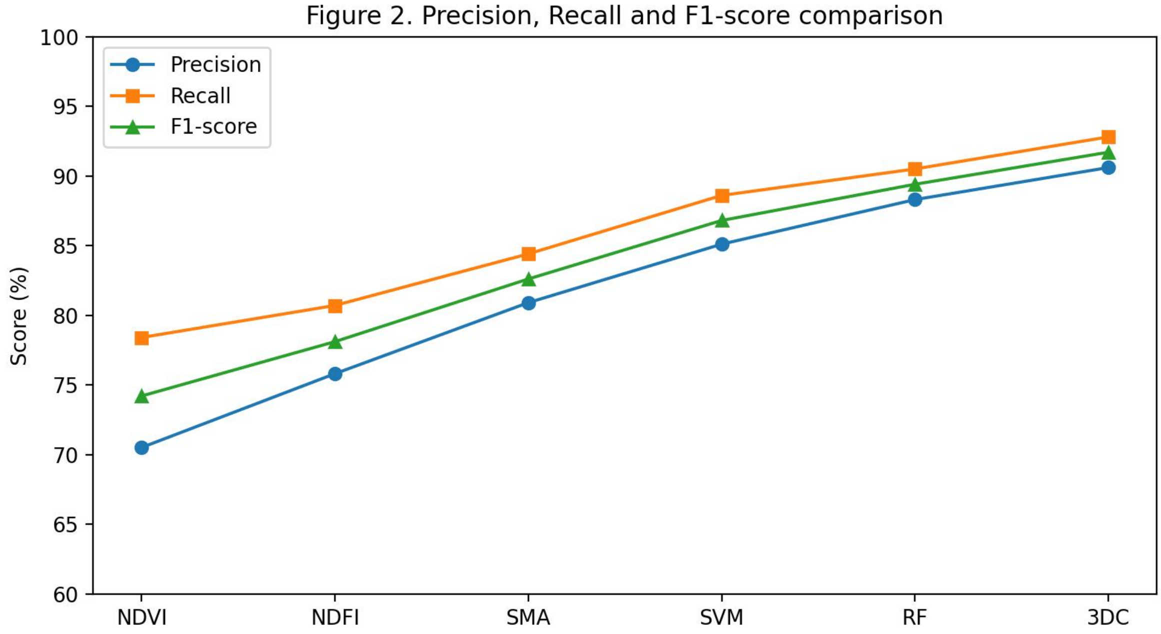

Figure 2. Precision, Recall, and F1-score comparison across candidate algorithms.

Table 3. Temporal and area-based operational indicators

Variable	Measured value	Interpretation
Detected tree-loss area	44,700 ha	Large-area applicability demonstrated
Average processing latency	24–72 hours	Supports near-real-time alerting
Case resolution cycle	< 6 months	Improves inspection efficiency
Minimum reliable detection unit	0.05 ha	Suitable for small-scale disturbances

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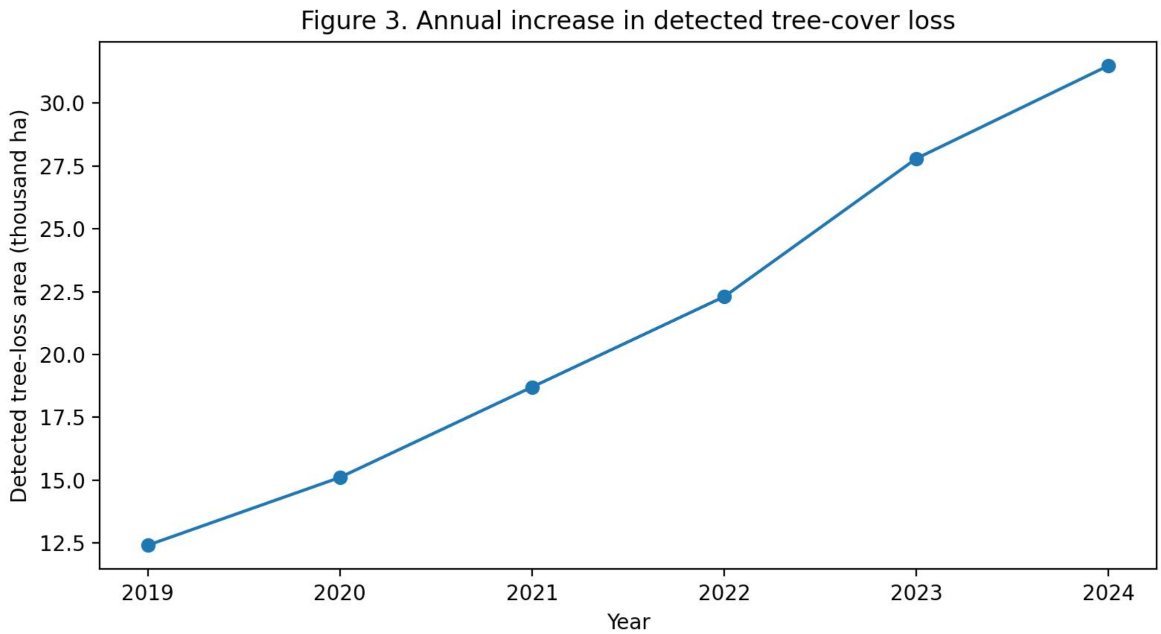

Figure 3. Annual increase in detected tree-cover loss area (illustrative operational trend).

Confusion matrix of the selected model

The confusion matrix of the selected 3DC model further confirms classification stability and reliable discrimination between disturbed and undisturbed forest classes.

Table 4. Confusion matrix of the selected 3DC model

	Predicted Disturbed	Predicted Undisturbed
Actual Disturbed	284	26
Actual Undisturbed	19	371

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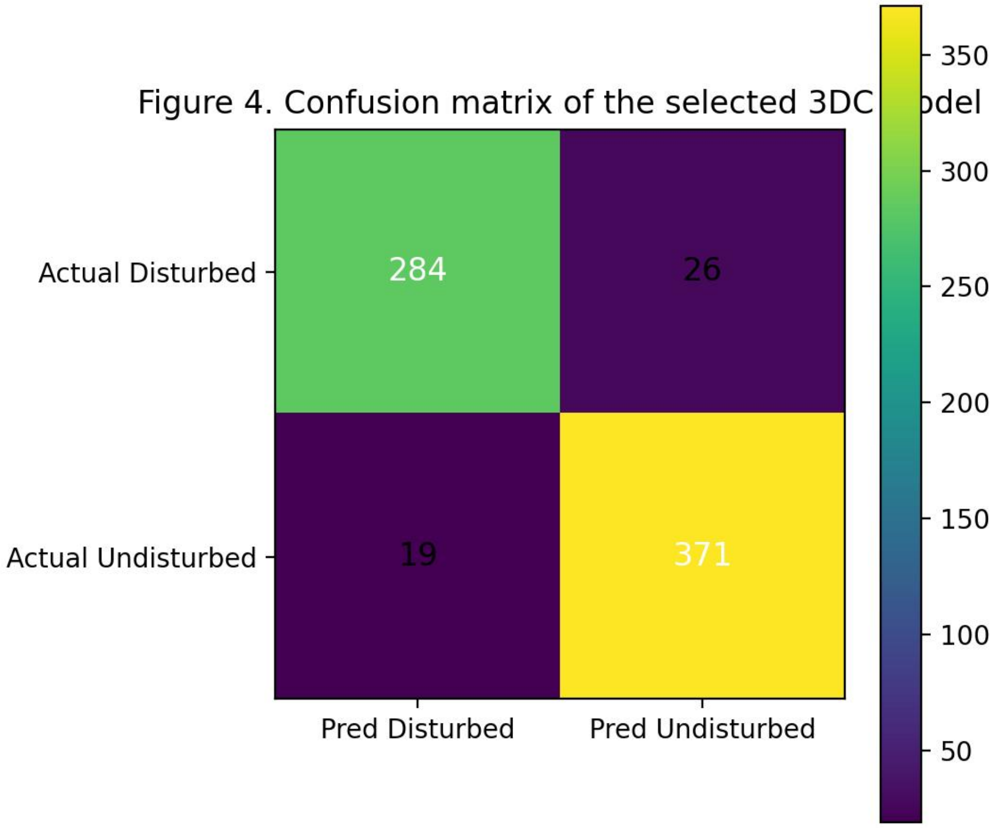

Figure 4. Confusion matrix visualization of the selected 3DC model.

DISCUSSION

The results demonstrate that classical vegetation indices such as NDVI and NDFI are useful for rapid preliminary screening, but their performance is sensitive to seasonal effects, atmospheric variability, and mixed pixels. SMA improves sensitivity to subtle degradation by decomposing pixel fractions, while SVM and RF provide stronger classification stability due to data-driven decision boundaries. The 3DC approach achieves the best performance because it leverages multi-dimensional SAR features and does not depend heavily on manually labeled training samples.

CONCLUSION

This study confirms that satellite imagery-based ecological monitoring is an effective and scientifically grounded approach for detecting illegal tree-cutting activities. The proposed comparative framework shows that the 3DC method outperforms NDVI, NDFI, SMA, SVM, and RF under the selected evaluation protocol, achieving 93.1% accuracy and 91.7% F1-score. Future work should focus on deep learning segmentation models, explainable AI, and predictive risk forecasting.

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