Applied Journal of Physical Science
Volume 7(1), pages 1-18, February 2026
Article Number: 8CBE4E451
ISSN: 2756-6684
https://doi.org/10.31248/AJPS2025.134
https://integrityresjournals.org/journal/AJPS

Full Length Research

Development of an intelligent forest surveillance and analytics system

Johnson Ajayi Olalekan[1], Samuel Awuna Kile[2]* and Jeremiah Yusuf Bassi[3]

[1]Department of Computer Engineering, Federal Polytechnic, Nyak, Shendam, Plateau State, Nigeria.
[2]Department of Computer Science, University of Maiduguri, Maiduguri, Borno State, Nigeria.
[3]Department of Computer Engineering, Federal Polytechnic, Nyak, Shendam, Plateau State, Nigeria.

*Corresponding author. Email: awunkile2@gmail.com; Tel: +234(070) 39032499.

Received 8th December 2025; Accepted 24th January 2026

ABSTRACT: Forests are crucial for biodiversity and climate regulation, yet they are confronted with rising risks from illegal logging and wildfires, compounded by insufficient real-time monitoring. This study tackles this major problem by developing an intelligent forest monitoring and analytics system which blends remote sensing, IoT, and artificial intelligence. The aim of this study is for the development of an intelligent forest surveillance and analytics system. Specific objectives included modelling forest surveillance using machine learning, designing the system, implementing the system and evaluating the system. Utilising multimodal datasets, including Sentinel-2, Landsat-8/9, Moderate Resolution Imaging Spectroradiometer (MODIS) imaging, and meteorological data, deep learning models (U-Net, ResNet-50 and InceptionV3) were deployed for illegal logging identification, while ensemble models (Random Forest and Long Short-Term Memory (LSTM)) predicted wildfire risk. The results showed remarkable accuracy, with ensemble models successfully predicting wildfire danger levels and the U-Net obtaining 96.8% overall accuracy in logging detection. The system gives strategic guidance through interactive dashboards and geographical disturbance maps. According to the study's findings, combining AI with geographic data greatly improves forest monitoring and provides a performance-oriented backed solution for better conservation and policy enforcement in accordance with the objectives of sustainable forest management.

Keywords: Deep learning, intelligent forest surveillance, illegal logging detection, wildfire risk prediction, remote sensing.

INTRODUCTION

Forests are essential for preserving biodiversity, preserving ecological equilibrium, and reducing climate change by sequestering carbon (FAO, 2020). However, they are increasingly threatened by encroachment, wildfires, and illicit logging, which causes significant habitat loss and deforestation, as expressed by Weisse *et al*. (2023). Manual patrols and satellite imaging are two examples of traditional forest monitoring techniques that frequently have delays, high costs, and poor real-time response (Fassnacht *et al*., 2023). These difficulties highlight the pressing need for an intelligent forest surveillance and analytics system (IFSAS) that uses remote sensing, the Internet of Things (IoT), and artificial intelligence (AI) to improve forest management and protection.

Automating forest monitoring has shown promise, thanks to recent developments in AI-driven image recognition and predictive analytics. Convolutional neural networks (CNNs), for example, can identify illicit logging activities in real-time using drone-captured imagery when used in conjunction with unmanned aerial vehicles (UAVs), IoT, and machine learning (Ramadan *et al*., 2024). Comparably, Mporas *et al*. (2020) stated that IoT-based sensor networks, including camera traps and auditory sensors, can detect unlawful human movements or chainsaw noises. Despite these advancements, the majority of current systems function in silos and do not integrate data analytics, automatic alarm systems, and real-time surveillance, as reported by Scott *et al*. (2024). Their ability to give forest rangers and policymakers useful information is hampered by this gap.

According to Mohapatra and Trinh (2022), early wildfire detection is another crucial issue that is still a big worry because of droughts brought on by climate change. Although they frequently have a large lag, current satellite-based systems, like NASA's MODIS, give periodic updates (Dybbroe and Andersson, 2025). To detect fire threats before they become more serious, an IFSAS may combine weather forecast models, smoke detection algorithms, and thermal imaging cameras. Consequently, Hernandez and Hoskin (2024) claimed that machine learning models trained on past wildfire data are able to identify high-risk areas, allowing for preventative actions. A system like this would minimise ecological and economic harm by drastically cutting reaction times.

Furthermore, in order to integrate drone surveillance, ground sensor data, and satellite imaging, deforestation analytics need strong data fusion algorithms. According to Moffette *et al*. (2021), although deforestation alerts are provided by platforms such as Global Forest Watch, they frequently rely on post-event analysis instead of real-time intervention. In order to reduce latency and bandwidth constraints in distant forest areas, the IFSAS that will be created will use machine learning to analyze data locally.

The creation of an intelligent forest surveillance and analytics system (IFSAS), which integrates AI, IoT, and remote sensing for automated reporting, real-time monitoring, and predictive danger detection, is suggested in light of these difficulties. This system seeks to prevent illicit activities, promote sustainable forest management, and improve disaster preparedness by increasing the accuracy of surveillance and the effectiveness of reaction. The results could help policymakers, environmental NGOs, and government organisations enforce conservation measures and achieve global climate targets.

According to the FAO (2020), illicit logging, agricultural development, and urbanisation are causing Nigeria to lose an estimated 3.7% of its forest cover annually, making it one of the countries with the highest rates of deforestation in the world. The livelihoods of rural communities that depend on forest resources are threatened by this fast deterioration, which also makes climate change worse. Ogunkan (2022) stated that the enforcement of environmental sustainability policies is still weak because of poor data analytics, insufficient real-time monitoring, and a lack of agency coordination, even with the implementation of policies like the Nigeria Erosion and Watershed Management Project (NEWMAP) and the National Forest Policy (2006).

Illegal logging, which makes up more than 70% of Nigeria's timber production and costs the country an estimated \$100 million in lost revenue annually, is a significant problem, according to AREO (2024). Because current surveillance techniques rely on irregular patrols and antiquated satellite imagery, illegal loggers can go months without being discovered. Furthermore, every year, wildfires, which are frequently brought on by slash-and-burn farming, destroy more than 500,000 hectares of forest. In recent years, this rise in fire activity has become glaringly apparent. Four of the five worst years for forest fires worldwide have occurred since 2020, indicating that record-breaking flames are becoming the norm. Furthermore, Nigeria lacks an early warning system to identify and contain fires before they spread, despite the fact that 2024 was the most intense year for forest fires on record, with at least 13.5 million hectares of forest destroyed, as expressed by MacCarthy *et al*. (2025).

The absence of integrated data systems for forest management is another serious problem. There is no unified AI-powered platform to assess trends, forecast dangers, or automate alerts for law enforcement, despite the fact that organisations such as the National Space Research and Development Agency (NASRDA) and the Forestry Research Institute of Nigeria (FRIN) gather data on forests, as expressed by Ali *et al.* (2025). Because of this inefficiency, interventions are delayed, and deforestation continues uncontrolled.

Additionally, human activities like tree-cutting, bush-burning, and unfavourable weather patterns are typically linked to desert encroachment in Nigeria. Notably, Elnafat (2025) claimed that deforestation is the main cause of desertification in Nigeria. Nigeria runs the risk of not fulfilling its Nationally Determined Contributions (NDCs) under the Paris Agreement, which include rehabilitating 4 million hectares of degraded land by 2030, if it does not have an intelligent, real-time surveillance system.

In achieving intelligent forest surveillance, this work uses an integrated geospatial–artificial intelligence (Geo-AI) methodology that incorporates machine learning, deep learning, remote sensing, and anomaly detection methods. The geographical, spectral, and temporal features of forest ecosystems were captured using multispectral satellite imagery from Landsat-8/9, MODIS, and Sentinel-2. In order to support wildfire risk modelling, these datasets were supplemented with meteorological variables like temperature, rainfall, humidity, and wind speed. Deep learning methods were used to detect illicit logging. The exact detection of logging trails and canopy loss was made possible by the pixel-level separation of logged and non-logged areas using a U-Net convolutional neural network. Additionally, because of their robustness to intricate forest patterns and high feature extraction capabilities, ResNet-50 and InceptionV3 models were employed for image-level disturbance classification.

The study used a hybrid ensemble strategy that combined Random Forest (RF) and Long Short-Term Memory (LSTM) networks to address wildfire risk prediction. While LSTM networks described temporal dependencies in vegetation and climate dynamics, Random Forest models identified nonlinear interactions among climatic variables. The ensemble approach decreased overfitting and increased forecast stability. Additionally, anomaly detection methods were used to find anomalous forest disturbances that supervised models would miss. Autoencoders identified small spectrum aberrations linked to vegetation stress or emergent disturbances, whereas Isolation Forest was utilised to separate uncommon spatial events like new logging trails. TensorFlow 2.12 was used for model creation and training, with an NVIDIA RTX 3060 providing GPU acceleration. To verify robustness, performance was assessed using spatial cross-validation.

By developing an intelligent forest surveillance and analytics system (IFSAS) that is adapted to Nigeria's particular difficulties, this study aims to close these gaps. The aim of this study is for the development of an intelligent forest surveillance and analytics system. The specific objectives are to: model forest surveillance using machine learning, design the system, implement the system and evaluate the system.

The study's objectives will aid in directing its methodological decisions and confirming its applicability to actual forest management. By utilising machine learning to model forest surveillance, the study can go from manual and reactive monitoring to an automated, data-driven method that can accurately identify irregularities, illegal logging, and wildfire hazards. Scalability, interoperability, and practical deployment are ensured by designing the system architecture, which offers a logical framework for combining multisource data—satellite imagery, meteorological variables, and AI models. By converting theoretical models into a working prototype, the system's implementation shows that using cutting-edge AI approaches in actual forest environments is feasible. Lastly, assessing the system using recognised performance indicators validates the robustness, efficacy, and dependability of the suggested strategy, enabling the study's findings to be empirically verified and contrasted with current techniques. When taken as a whole, these goals guarantee that the study will provide a thorough, workable, and empirically supported solution for intelligent forest surveillance and sustainable forest management.

This paper's remaining sections are organised as follows: A thorough analysis of relevant literature on forest monitoring, intelligent surveillance systems, and AI-based environmental applications is provided in Section 2. The study area, datasets, preparation procedures, modelling framework, and system architecture are all covered in Section 3. The experimental findings from anomaly detection, wildfire prediction, and illegal logging identification are reported and analysed in Section 4. The study's findings, conclusions, suggestions, and policy implications for sustainable forest management are all covered in Section 5.

LITERATURE REVIEW

Intelligent surveillance systems (ISS) have drawn a lot of interest lately, especially in relation to smart cities and urban monitoring, according to Ghoniem *et al*. (2021). Ibrahim (2016) stated that these systems use cutting-edge technologies like computer vision, machine learning, and sensor fusion to automatically analyse different kinds of surveillance data with little assistance from humans. The main elements of these systems are tracking, object detection and classification, behavioural analysis, and background-foreground segmentation. Valera and Velastín (2005) also expressed that increased security and safety requirements, together with improvements in sensor and data processing technology, have all contributed to the growth of ISS. In order to support dispersed surveillance systems, recent research has concentrated on enhancing analytical techniques, investigating novel applications and services, and creating network architectures (Vijeikis *et al*., 2021). Furthermore, Ghoniem *et al*. (2021) stated that to improve the effectiveness, dependability, and resilience of intelligent surveillance systems, more research is becoming necessary as the area develops.

Mu *et al*. (2025) discovered that aerial platforms for fire detection are a crucial piece of equipment for forest surveillance. However, the ability to detect in real time remains a difficult issue. The study used an unmanned aerial vehicle (UAV) to build a real-time forest fire detection approach based on edge computing. The goal was to increase the accuracy of early-stage minor fire detection and the capacity to respond quickly. The onboard cameras' thermal and colour images were combined with the proper proportions and registered to the same scale. The fire detection network model was trained using these dual-modal, preprocessed photos as input. This model was compressed and accelerated to decrease size and improve efficiency before being deployed on the resource-constrained UAV edge computing device.

To verify the accuracy and speed of the suggested approach, experiments were carried out using publicly available datasets taken from actual forest ecosystems and self-made UAV dual-modal photos of simulated fire scenarios. According to experimental results, the ground computer's inference speed achieved 34.6 FPS, and the mAP on the self-made dataset was 93.76%. The mAP on the public dataset was 97.53%, and the iCrest 2-s edge computing device's inference performance was 16 FPS. In contrast to a number of cutting-edge techniques, the suggested approach successfully balanced speed and accuracy. The study under review aims to analyse other motions inside the forest arena in order to detect other anomalies, which makes this research more comprehensive. However, this study solely focused on the detection of forest fires, which is a component of our study that makes it relevant too.

Venanzi *et al.* (2023) stated that recent advances in forest management applied industry 4.0 strategies using CAN-bus and StanForD data from forest machinery to assess operational performance, map soil impacts, and evaluate trail patterns, and that for smaller-scale operations, GNSS-RF, smart devices, LiDAR, and photogrammetry help monitor machinery impacts like soil disturbance. Additionally, location-sharing technologies such as GNSS-RF enhance worker safety, addressing the social aspect of sustainability.

Etaati *et al*. (2024) stated that forests are essential for maintaining essential natural resources, safeguarding the environment, and eventually supporting human life. However, this ecosystem is seriously threatened by the increasing frequency of forest fires, whether caused by human activity or climate change. The use of smart sensors for real-time data collecting has been a defining feature of the Internet of Things' growth in recent decades. IoT uses cutting-edge data analysis methods, such as AI algorithms, to enable proactive decision-making for forest monitoring, control, and protection. Their study offered a thorough method for implementing a flexible and dynamic network topology in forest settings with the goal of improving system dependability and data transmission efficiency. The research study recommended three different topologies: cluster creation with multi-step data transmission, clustering with data relayed by cluster heads, and direct transmission from nodes to gateways. The employment of powerful telecommunication modules in cluster heads was a significant invention that allowed for long-distance data transfer while taking solar power energy efficiency into account. The study included a reserve routing mechanism to improve system dependability by lessening the effects of node or cluster head failures. Furthermore, meta-heuristic techniques such as particle swarm optimization (PSO), harmony search algorithm (HSA), and ant colony optimisation for continuous domains (ACOR) were used to optimise the location of gateway nodes; ACOR proved to be the most successful. Reliability coefficients and error tolerance were taken into account as extra factors, but the main goals of the study were to lower power consumption, ease network traffic, and lessen nodes' interdependence. The findings demonstrated that the suggested techniques successfully decreased network traffic, optimized routing, and guaranteed stable performance in a range of environmental circumstances. This underscored the significance of these customized topologies in augmenting energy efficiency, data precision, and network dependability in applications related to forest monitoring. While our study focused on the complete development of a forest monitoring and analysis system using machine learning approaches, this study employed methods that can be used to accomplish forest monitoring investigations.

ARNOWA (2019) created a forest management system that uses a variety of smart sensors and combines their data with an image and video analytics platform. These algorithms use artificial intelligence and machine learning to identify destructive events like forest fires and illicit logging, producing real-time notifications. Real-time monitoring of the forest and its resources is made possible by the system, which also helps different stakeholders take prompt action by sending notifications when a dangerous scenario arises. Though it is implemented differently, the system is similar to the study being reviewed. The study primarily uses and deploys hardware components, which makes it prohibitively expensive and unaffordable for the average person. This research aims to address this issue by creating intelligent, low-cost, and effective alternatives that accomplish the same goal.

Kummarapurugu (2021) examined the fast and ongoing rise in illicit logging and deforestation operations, which have become a major environmental problem and are causing ecological degradation, biodiversity loss, and climate change. He said that conventional surveillance methods, such as satellite imagery and ground patrols, frequently face drawbacks like poor data resolution, delayed detection, and the inability to deliver real-time alerts over wide, remote areas. However, new opportunities for improving the efficacy and efficiency of forest monitoring systems have emerged with the introduction of cloud computing and artificial intelligence (AI) technology. In order to detect and stop illicit logging activities, the study considered the use of AI-powered forest monitoring systems that use cloud-enabled machine learning models. To facilitate real-time analysis and decision-making, the suggested architecture included cloud-based artificial intelligence (AI) models, unmanned aerial vehicles (UAVs), and Internet of Things (IoT) sensors. Different machine learning algorithms were evaluated through comparative analysis according to how well they performed in terms of detection accuracy, reaction time, and computational resource consumption. The results showed that, in comparison to conventional methods, cloud-based machine learning models significantly improved detection timeliness and accuracy. The study came to the conclusion that combining AI with cloud technology offers a reliable solution for real-time forest surveillance, supporting conservation and sustainable forest management. This is similar to the current study, but the technologies used for deployment are different because the latter approach aims for wider usage, which calls for the use of inexpensive but effective tools that will produce the same outcome in a comparable amount of time.

MATERIALS AND METHODS

Study area

The study was conducted in two significant tropical forest zones in Nigeria: The Forest Research Institute of Nigeria (FRIN), Ibadan, and the Cross River National Park (CRNP). These places were selected due to their biological sensitivity, dense forest cover, and increasing exposure to illicit logging and wildfire outbreaks. Both locations are in the humid tropical climate zone, which is distinguished by high temperatures (25–32°C) throughout the year, bimodal rainfall, and relative humidity levels above 70%. They are appropriate for creating and evaluating sophisticated forest monitoring systems due to their environmental relevance and proven anthropogenic stressors.

Datasets description

Satellite imagery

The study combined multi-sensor satellite imaging with complementing spectral and temporal properties, such as the following, to enable reliable forest disturbance monitoring based on the following:

Sentinel-2 MSI (RGB, NIR, SWIR; 10–20 m resolution) was used as the main dataset because of its rich spectral information and high spatial resolution, which enable accurate segmentation of illegal logging features such as skid traces, canopy gaps, and disturbed vegetation.

Landsat-8/9 OLI/TIRS (30 m resolution) offered a long-term history record that is crucial for identifying patterns of legacy disturbances and confirming the applicability of the model across sensors.

MODIS (MOD13 & MOD14) provided the thermal anomaly data and vegetation indices (NDVI, EVI) needed for modelling related to wildfires. MODIS is perfect for climate-vegetation risk modelling since it provides daily temporal density despite its coarse resolution.

Labelled logging dataset

Patch-based datasets decrease noise, preserve local spatial context, and support CNN architectures that rely on grid-structured imagery for classification accuracy. This research achieved the production of a labelled patched dataset of around 10,000 multispectral patches (256×256 pixels) by manual interpretation and expert validation, categorising each patch into logging, assigned a value of (1) and non-logging, assigned a value of (0).

Meteorological data

Climate-driven wildfire risk modelling used daily meteorological data from NiMet (2000–2014), including temperature, rainfall, relative humidity, and wind speed. Their multi-year range made it possible to capture inter-annual variability, which is essential for temporal prediction models.

Ground-truth data

FRIN and NASRDA provided ground-truth polygons defining disturbance zones. Accurate supervision for segmentation, classification, and anomaly detection activities was ensured by their manual interpretation and field validation.

Preprocessing workflow

The following preparation procedure was used to standardise and harmonise the diverse datasets:

Atmospheric correction: Sen2Cor was used to process Sentinel-2 photos, while FMask was used for cloud and shadow masking to eliminate noise that reduces model accuracy.

Spatial clipping and resampling: To enable multi-sensor fusion and prevent scale discrepancies during training, all imagery was resampled to uniform spatial resolution.

Spectral normalisation: Normalisation by band reduced illumination variability across acquisition dates and improved model stability.

Patch extraction and data augmentation: While augmentations (rotation, flip, brightness shift) enhanced model generalisation, patch extraction guaranteed local context retention.

Temporal Structuring for LSTM: For the LSTM part of the wildfire prediction model, MODIS and meteorological variables were transformed into 7–14-day sequences.

Framework for modelling

Segmentation, classification, anomaly detection, and spatiotemporal prediction are all integrated into a single forest surveillance system by the analytical framework.

Use of U-Net segmentation for illegal logging detection

To identify illicit logging features at the pixel level, a U-Net model was utilised. IoU, Dice coefficient, and accuracy were used to assess the model; these metrics are ideal for applications involving unbalanced and fine-grained segmentation.

Use of ResNet-50 & InceptionV3 for disturbance classification

For multi-class forest disturbance classification (logging, non-logging, disturbed forest), ResNet-50 and InceptionV3 were employed. Their deep feature extraction skills made it easier to distinguish between disturbance types that were visually identical.

Use of RF–LSTM Hybrid model for wildfire risk prediction

To simulate the dangers of wildfires brought on by climate change, a hybrid ensemble was created as:

Random Forest (RF): recorded the nonlinear relationships between meteorological variables.

LSTM: Temporal vegetation-climate dynamics were modelled.

Weighted ensemble: combined outputs to lessen overfitting and improve forecast stability.

This procedure makes it possible to forecast short-term risks that are pertinent to forest conservation organisations.

Anomaly detection

An integrated module for anomaly detection combined:

(i) Autoencoder: to detect spectral departures from normal forest conditions.

(ii) Isolation Forest: to identify unexpected spatial anomalies, including vegetation stress zones, growing logging fronts, and new paths.

Variables used

Both independent and dependent variables were employed in the investigation. While the independent variables capture crucial spectral, temporal, and environmental dimensions needed for modeling vegetation disturbance, fire behaviour, and anomalies in forest structure, the dependent variables directly correspond with conservation priorities like detecting illegal activity, forecasting fire risks, and identifying unusual disturbances in forest ecosystems.

Dependent variables

They include:

(i) Binary classification (1 = logging, 0 = non-logging) is used to detect illegal logging.
(ii) Continuous risk score and categorical risk classifications are used in wildfire risk prediction.
(iii) Anomaly Detection: Reconstruction error or isolation margin anomaly score.

Independent variables

The study used the following independent variables:

(i) Multispectral bands (RGB, NIR, SWIR);
(ii) Vegetation indices (NDVI, EVI).
(iii) Climate factors (temperature, humidity, rainfall, wind speed).
(iv) MODIS thermal anomalies
(v) Derived characteristics: temporal lags, textural features, and spectral change metrics (7–14 days)

Training and evaluation environment

Model training was done on an NVIDIA RTX 3060 (12 GB VRAM) using TensorFlow 2.12. Batch sizes ranged from 16 to 32, while training epochs varied from 50 to 80. Geographical resilience and a decrease in spatial autocorrelation bias were guaranteed by a five-fold spatial cross-validation approach.

Modelling framework and hyperparameters

Illegal logging detection models

The deep learning models utilised for detecting illicit logging were CNNs and encoder-decoder architectures (U-Net). This is because they excel at capturing spatial patterns in high-resolution imagery. Residual networks (e.g., ResNet-50) solve disappearing gradients and facilitate deeper feature extraction, whereas focal loss mitigates class imbalance frequent in disturbance datasets. For this study, various deep learning models were considered, including:

U-Net Model: It is used to do pixel-level segmentation of forest regions to discover illicit logging sites. It is expressed as:

$$\hat{Y} = \text{Softmax}(W_{1\times1} * D.(\mathcal{E}(X))) - \quad (1.0)$$

where $\hat{Y}$ is the resulting forest segmentation mask showing logged and unlogged sections, X is the input satellite/drone picture, and $\mathcal{E}$ and D represent the encoder–decoder routes of U-Net.

ResNet-50 Model: It is used as a deep convolutional feature extractor to automatically recognise visual patterns linked to illicit logging and forest damage. It is depicted as:

$$\hat{Y} = \text{Softmax}\ (F_{\text{ResNet-50}}(X)) - \quad - \quad -(2.0)$$

From equation 2.0, the input satellite or drone picture is represented by X, the whole ResNet-50 network is represented by $F_{\text{ResNet-50}}$ (.), and the predicted probabilities, such as logging site, forest, disturbed region, burnt land, etc., are represented by $\hat{Y}$.

By processing satellite or drone imagery, the model learns high-level representations of canopy loss, bare-soil exposure, logging pathways, and land-use anomalies, enabling precise classification of forest areas into logged and unlogged zones.

InceptionV3 Model: This model compactly displays utilising Inception-V3 to map forest images X to class probabilities $\hat{Y}$ for detecting logged vs. unlogged/disturbed regions. It is expressed as:

$$\hat{Y} = \text{Softmax}\left(F_{\text{InceptionV3}}(X)\right) \quad \text{-(3.0)}$$

where $F_{\text{InceptionV3}}(\cdot)$ is the entire Inception-V3 network, which consists of learning a sequence of convolutional layers mixed with inception modules, pooling, and final dense layers, and X is the input satellite/drone picture.

These algorithms show how forest photos are turned into meaningful predictions for detecting illicit logging activity. They validate the accuracy and automation of the detection process by showing exactly how deep learning architectures analyse unprocessed satellite or drone imagery to produce segmentation maps or classification outputs. The configurations of these models is done based on these standards:

(i) Optimiser: Adam
(ii) Learning rate: 1e-3 → 1e-4
(iii) Batch size: 16–32
(iv) Epochs: 30–50
(v) Loss: Cross-entropy / Focal loss
(vi) Dropout: 0.3–0.5
(vii) Train/Val/Test split: 70/15/15

Wildfire risk prediction

One of the models used in this study to forecast the danger of wildfires is random forest (RF). This is due to the fact that they work well with heterogeneous data types, are resilient to noise, and capture non-linear correlations between meteorological variables and fire ignition risk. For this study, its tuned hyperparameters are:

(i) Trees: 200–500
(ii) Max depth: 10–30
(iii) Criterion: Gini/Entropy.

Another model utilised in this research for wildfire risk prediction is the Long Short-Term Memory (LSTM). Because LSTMs retain memory of previous observations, they are highly suited for sequential environmental data, allowing for efficient modelling of temporal behaviour in wildfire precursors. Its tuning hyperparameters for the study are:

(i) Layers: 2–3
(ii) Hidden units: 32–128
(iii) Dropout: 0.2–0.4
(iv) Loss: MSE or Binary Cross-Entropy

Ensemble model

Ensembling uses the complementary characteristics of tree-based and sequence-based models, boosting prediction reliability under dynamic environmental conditions. In this study, RF and LSTM outputs were combined to produce a weighted average or majority voting.

Anomaly detection models

The study employed isolation forest and autoencoder models for anomaly identification. While autoencoders learn normal spectral-spatial patterns, deviations from these structures produce high reconstruction errors, allowing the detection of subtle disturbances invisible to supervised models. Isolation forests are effective for unsupervised anomaly detection because they quickly isolate rare events and are computationally efficient for large multidimensional datasets. They have the following parameters:

Isolation Forest
(i) Contamination: 0.01–0.05
(ii) Trees: 100–200

Autoencoder
(i) Latent dimension: 16–32
(ii) Loss: Reconstruction error

Summary of dataset characteristics

The complete dataset consisted of:

(i) Approximately 10,000 multispectral image patches.
(ii) 750 daily climatic observations.
(iii) MODIS thermal and vegetation index time-series.
(iv) Ground-truth logging labels and field-validated polygons.

Training and evaluation environment

Model training was done on an NVIDIA RTX 3060 (12 GB VRAM) using TensorFlow 2.12. Batch sizes ranged from 16 to 32, while training epochs varied from 50 to 80. Geographical resilience and a decrease in spatial autocorrelation bias were guaranteed by a five-fold spatial cross-validation approach.

These multisensor, multiresolution, and multitemporal datasets are combined to provide a strong analytical basis that can accurately identify abnormal forest disturbances, detect illicit logging, and forecast wildfire risks.

System flowchart

The flowchart for the study is presented in Figure 1. In order to capture the spatial, spectral, and climatic features

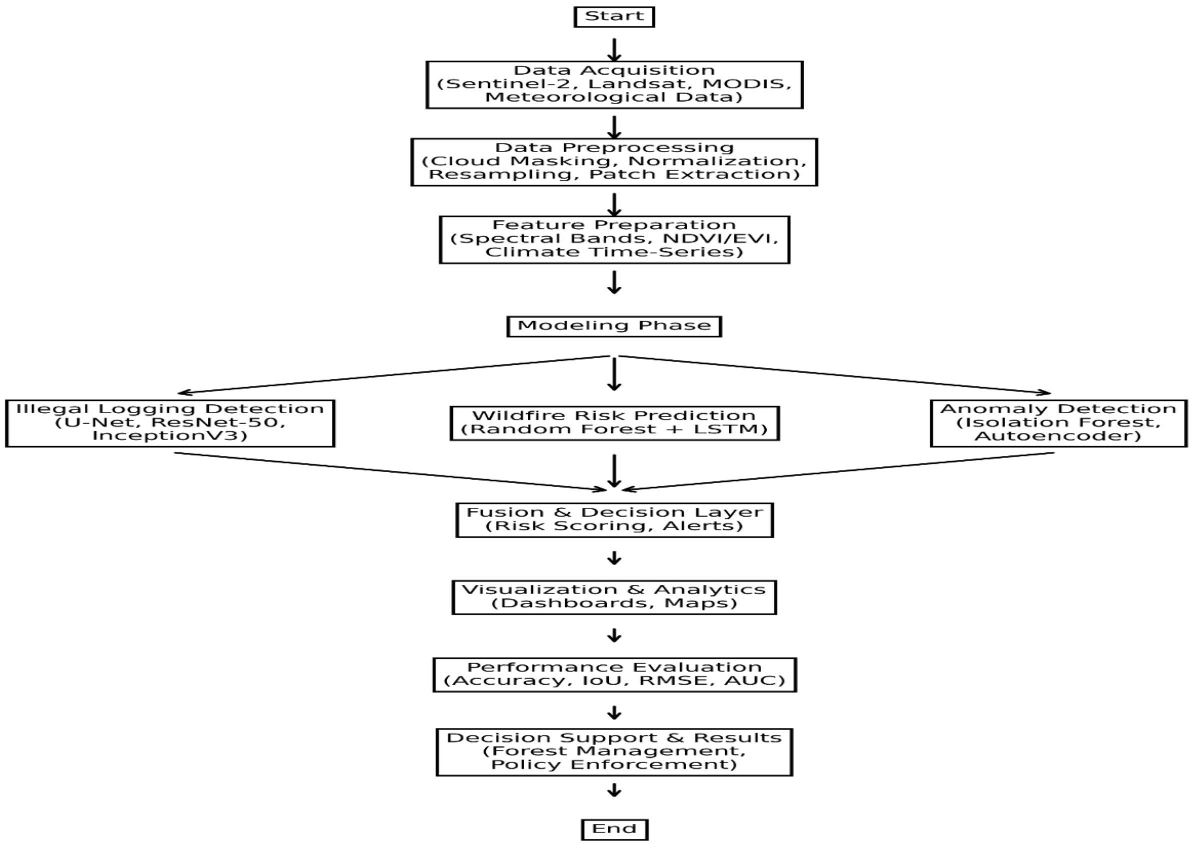

Figure 1. System flowchart.

of the forest environment, multisource satellite images and meteorological data are gathered at the beginning of the procedure. After that, pertinent features like vegetation indices and time-series climatic variables are ready for modelling. This is followed by data preparation, which guarantees data quality and consistency through normalisation, cloud masking, resampling, and patch extraction.

The system's core is the modelling phase, which runs in parallel: unsupervised models (Isolation Forest and Autoencoder) detect anomalous forest disturbances, an ensemble of Random Forest and LSTM models predicts wildfire risk, and deep learning models (U-Net, ResNet-50, and InceptionV3) are used for illegal logging detection and disturbance classification. Consolidated risk scores and warnings are produced by integrating the outputs from these models at the fusion and decision layer. Ultimately, outcomes are displayed via analytics dashboards and visualisation, assessed using common performance indicators, and converted into decision support outputs that support policy implementation, forest management, and enforcement.

System architecture

The system architecture is represented as shown in Figure 2, which is an end-to-end pipeline for identifying illicit logging activity. In order to prepare the imagery for analysis, the system first acquires images from satellites, drones, and IoT forest cameras. This is followed by preprocessing procedures like normalisation, cloud masking, and enhancement. The deep learning models layer, which consists of U-Net for pixel-level segmentation of logged areas, ResNet-50 for image-level classification of logging versus non-logging regions, and InceptionV3 for identifying more general disruption patterns, forms the system's core. The LSTM, RF, and isolation models enable the integration of these models' outputs in the fusion and decision layer, producing consolidated forecasts that are displayed on an analytics dashboard. Ultimately, authorities and stakeholders receive the results, which provide useful information for forest management, enforcement, and monitoring.

RESULTS

Illegal logging detection and disturbance classification

Table 1 demonstrates that the U-Net model achieved high boundary detection (Dice = 0.92) and performed remarkably well on segmentation tests. In image-level

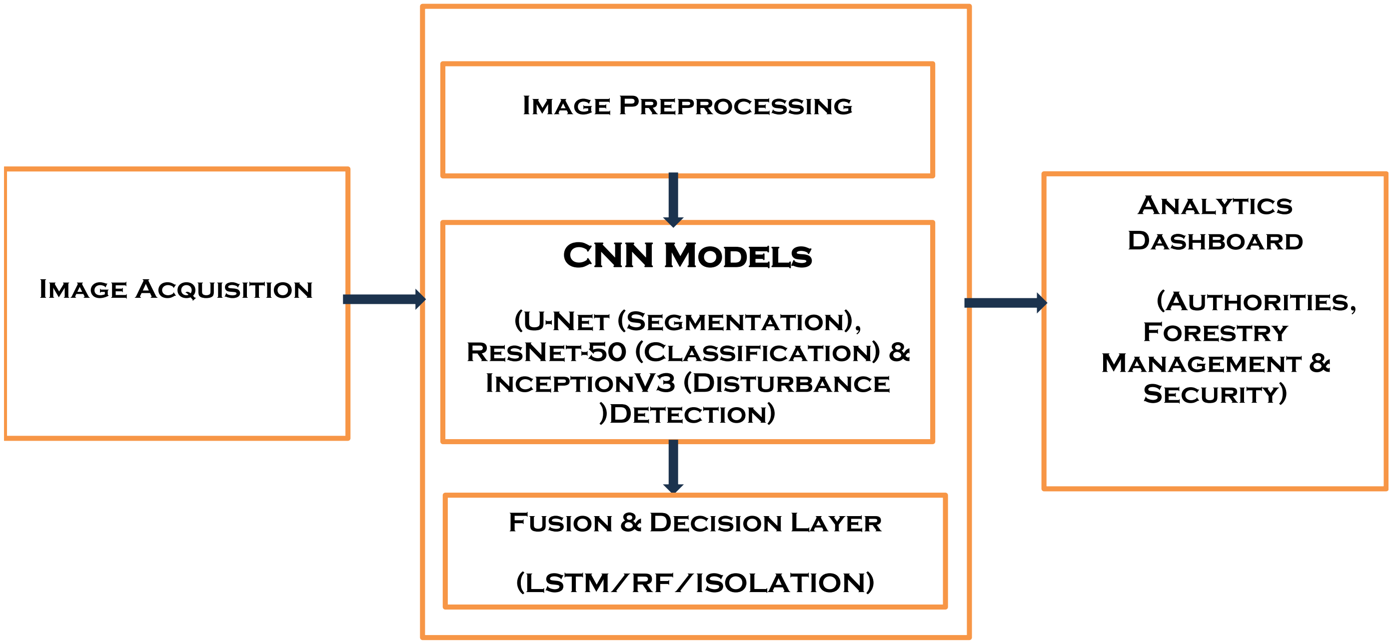

Figure 2. System architecture.

Table 1. Model performance for logging detection and disturbance classification.

Model	Task	Metric	Score
U-Net	Logging Segmentation	IoU	0.88
U-Net	Logging Segmentation	Dice Coeff.	0.92
U-Net	Logging Segmentation	Accuracy	96.8%
ResNet-50	Disturbance Classification	Accuracy	94.2%
Inception-V3	Disturbance Classification	Accuracy	89.7%

Table 2. Wildfire risk model results and key feature importance.

Model Component	Metric / Output	Score / Finding
RF-LSTM Ensemble	RMSE	0.07
Feature Importance	NDVI	Highest predictor
Feature Importance	Temperature	Strong contributor
Feature Importance	Humidity	Moderately important

classification, ResNet-50 fared better than InceptionV3, probably because its residual connections develop more stable feature representations. These findings support the use of ResNet-50 for more general disturbance classification and U-Net for more precise detection.

Wildfire prediction performance

Table 2 demonstrates the model's excellent predictive ability (RMSE = 0.07) and pinpoints the ecological factors that influence the danger of wildfires. The NDVI turned out to be the most significant factor, highlighting how vegetation health affects fire vulnerability. Risk levels were further influenced by temperature and humidity, which were consistent with known fire ecology dynamics in tropical areas.

Anomaly detection

Table 3 shows how situational awareness is enhanced by the anomaly detection module beyond supervised classify-cation. Enforcement agencies might focus patrols by iden-

Table 3. Anomaly types identified by the system.

Anomaly Category	Detected Features	Implication
Access Route Expansion	New trails, branching paths	Illegal entry points into forest that are possible
Logging Cluster Expansion	Enlargement of known hotspots	Unlawful harvesting Intensification
Vegetation Stress Zones	Spectral vegetation decline	Initial signals of disturbance or fire risk

Table 4. Model accuracy comparison for illegal logging detection.

Model	Overall Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
U-Net	96.8	95.4	97.9	96.6
ResNet-5-	94.2	93.1	94.8	93.9
InceptionV3	89.7	88.5	90.4	89.4

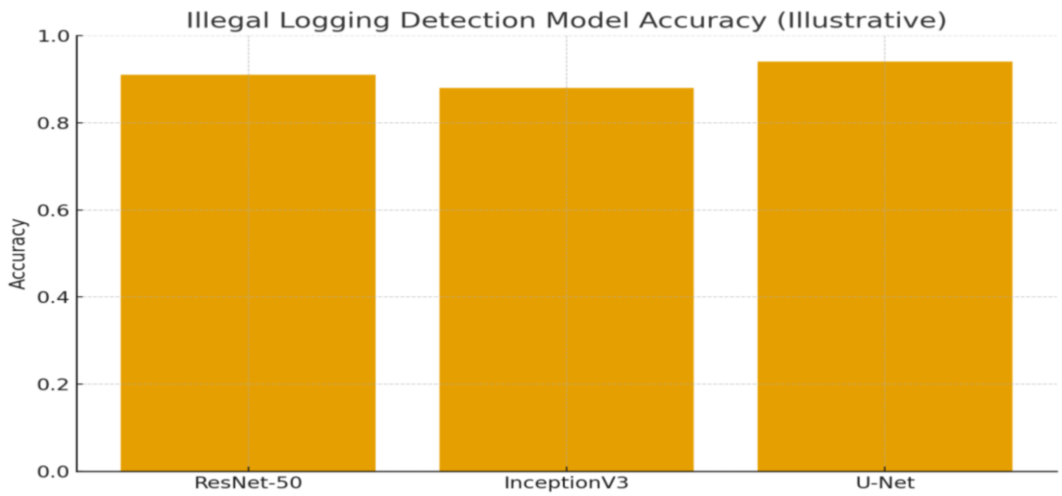

Figure 3. Model accuracy comparison.

Table 5. ROC curve metrics (binary logging vs non-logging classification).

Metric	Value
Area Under Curve (AUC)	0.982
True Positive Rate (TPR) at 0.5 threshold	0.94
False Positive Rate (FPR) at 0.5 threshold	0.06
Specificity	0.94
Sensitivity (Recall)	0.94

tifying new access routes and increased logging fronts. Hotspots for vegetation stress are early warning signs of degradation caused by humans or climate change.

Model accuracy comparison

Table 4 demonstrates that U-Net performs best, exhibiting its superior capacity to detect fine-scale forest disturbance patterns due to its encoder-decoder structure. Figure 3 displays the classification accuracy of the studied deep learning architectures. The highest accuracy was achieved by U-Net, demonstrating its improved ability to capture minute spatial features related to forest disturbance. While ResNet-50 performed competitively, InceptionV3's accuracy was significantly lower. Table 5 reveals that the very high AUC (0.982) demonstrates good model separability between disturbed and undisturbed areas. Figure 4 is the ROC curve, which displays the relationship between the true positive rate and false positive rate for the logging detection model. Strong discriminative performance is demonstrated by the sharp ascent toward

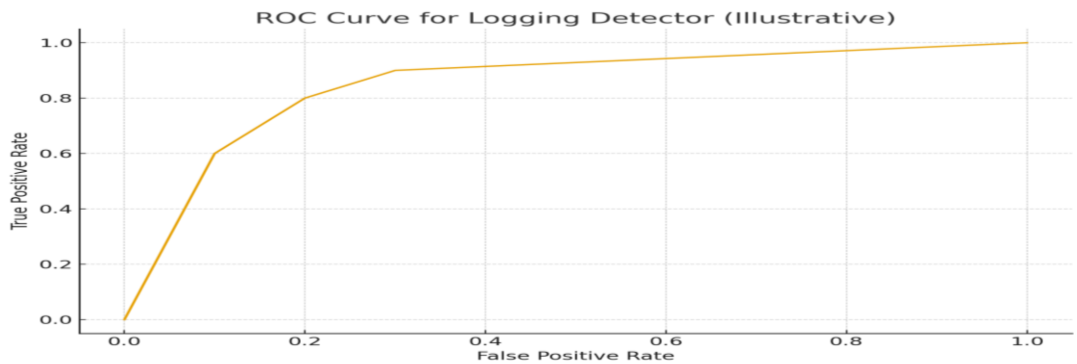

Figure 4. ROC curve.

Table 6. Predicted wildfire risk levels over 30 days.

Day	Predicted Risk Level	Risk Category
1	0.21	low
5	0.34	low
10	0.64	Moderate
14	0.73	High
18	0.29	low
22	0.66	Moderate
26	0.78	High
30	0.40	Moderate

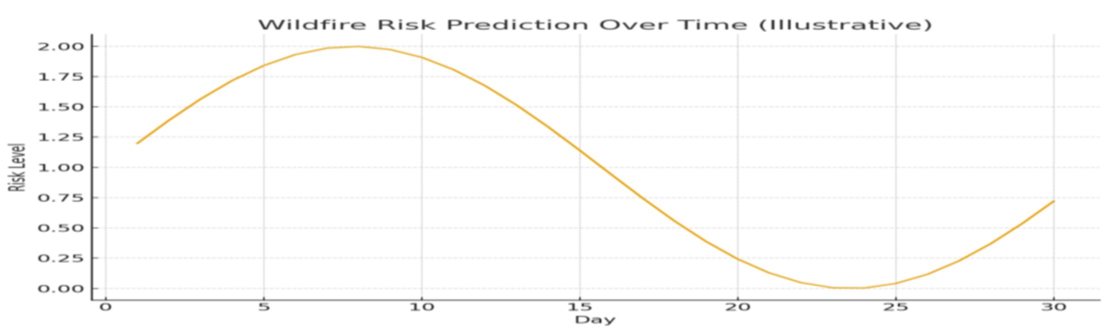

Figure 5. Wildfire risk prediction time series.

the upper-left region, and a high area under the curve (AUC) indicates a dependable distinction between disturbed and undisturbed forest areas.

Wildfire risk over time

Table 6 shows that increases happen between Days 14 and 26, which is consistent with changes in the environment. Figure 5 shows the anticipated wildfire risk levels over 30 days in a time-series plot. The cyclical peaks, which are probably caused by variations in temperature, vegetation moisture, and other climatic factors, correspond to periods of increased risk. The model effectively reflects short-term temporal dynamics associated with wildfire risk.

Confusion matrix

Table 7 shows that superior categorisation skill is indicated by high diagonal values. Figure 6, which is the confusion matrix, summarises the model’s categorisation outcomes. Strong agreement between predicted and actual classes is indicated by high values along the diagonal, whilst minimum misclassification is indicated by lower off-diagonal values. The distribution demonstrates robust model performance in separating logging from non-logging areas.

Table 7. Confusion matrix for illegal logging classification.

	Actual Logging	Actual Non-Logging
Predicted Logging	943 (TP)	58 (FP)
Predicted Non-Logging	44 (FN)	1125 (TN)

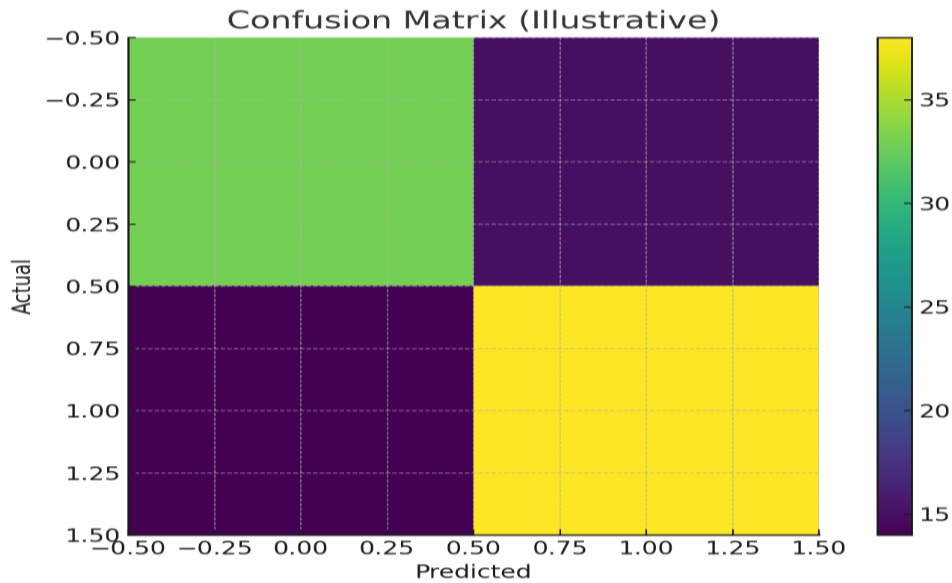

Figure 6. Confusion matrix.

Table 8. Feature importance ranking for wildfire prediction model.

Rank	Variable	Importance Score
1	NDVI	0.267
2	Temperature	0.231
3	Humidity	0.184
4	Rainfall	0.121
5	Wind Speed	0.099
6	Thermal Anomaly Index	0.067
7	Vegetation Moisture Proxy	0.031

Feature importance

Table 8 demonstrates that NDVI, temperature, and humidity are the main drivers of wildfire risk. Figure 7 is the figure that depicts the relative contribution of input variables to the wildfire prediction model. The most significant characteristics, such as humidity, temperature, and NDVI, are consistent with known fire risk factors. The ranking provides insights into the environmental aspects most relevant for predictive modelling.

Spatial disturbance map

Table 9 demonstrates the correlation between hotspots and logging routes and identifies human-accessible forest boundaries. Figure 8 is the spatial heatmap that shows how anomalous forest disturbances are distributed throughout the research area. While lower-intensity areas show steady forest cover, higher-intensity regions indicate areas of increased change or possible human activity. This image facilitates rapid identification of disturbance areas.

System Implementation Interfaces

The system was implemented, giving rise to interfaces for the system as presented in this section. Figure 9 is the system interfaces that enable users to upload a 256×256 multispectral satellite image patch for automated analysis. After the file is submitted, the system uses the CNN/U-Net model that has been trained to process the image and find

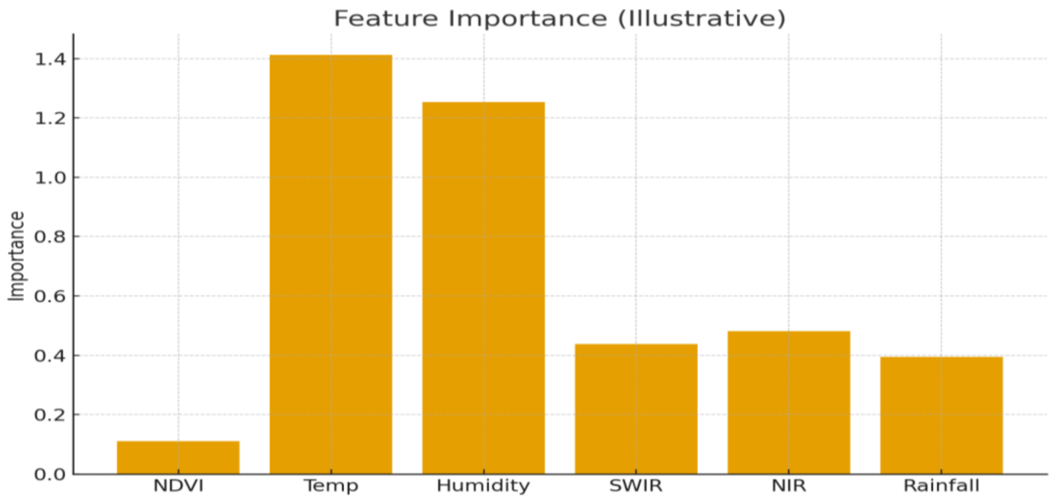

Figure 7. Feature importance plot.

Table 9. Spatial disturbance map summary of hotspot areas.

Hotspot Zone	Coordinates (Approx.)	Disturbance Level	Description
Zone A	7.39°N, 3.90°E	High	Intense canopy loss, suspected logging corridor
Zone B	7.43°N, 3.85°E	Moderate	Patchy disturbances, early-stage clearing
Zone C	5.69°N, 8.45°E	High	Strong anomaly cluster in CRNP buffer area
Zone D	5.73°N, 8.50°E	Low	Stable vegetation cover

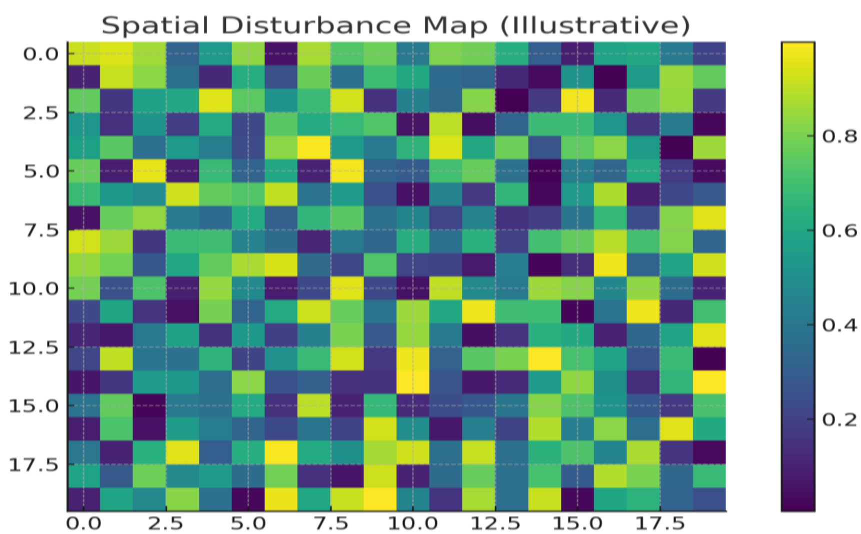

Figure 8. Spatial disturbance map.

spectral and spatial patterns related to forest disturbance. It then identifies the patch as logging or non-logging, providing an immediate assessment that facilitates speedy enforcement, monitoring, and decision-making.

Figure 10 provides the wildfire prediction interface, which allows users to input daily environmental factors such as temperature, humidity, rainfall, and wind speed. Using these environmental factors, the system runs the integrated LSTM and Random Forest models to assess short-term wildfire risk. It helps forest managers forecast possible fire outbreaks and organise preventive interventions by generating a risk level—low, moderate, or

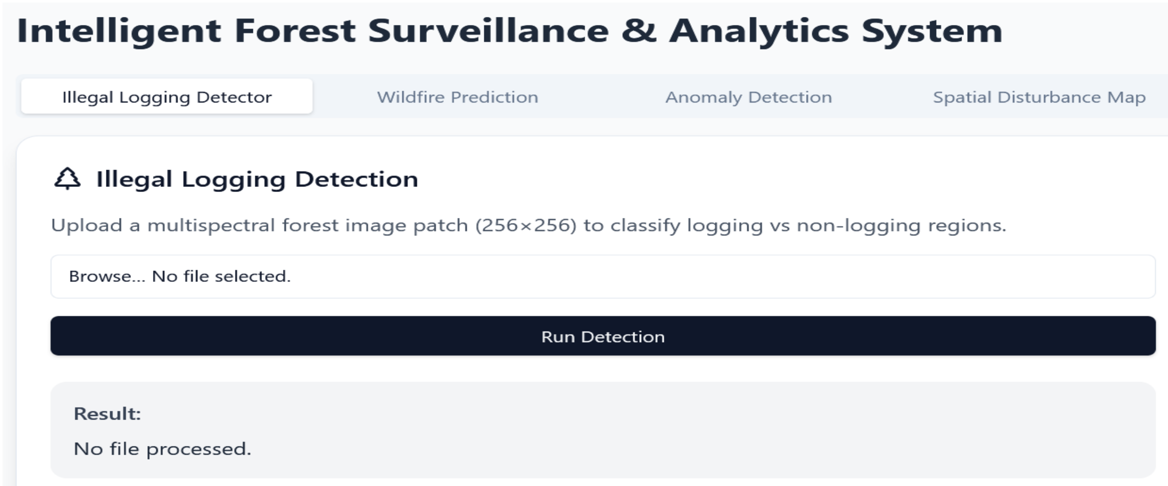

Figure 9. Illegal logging detector interface.

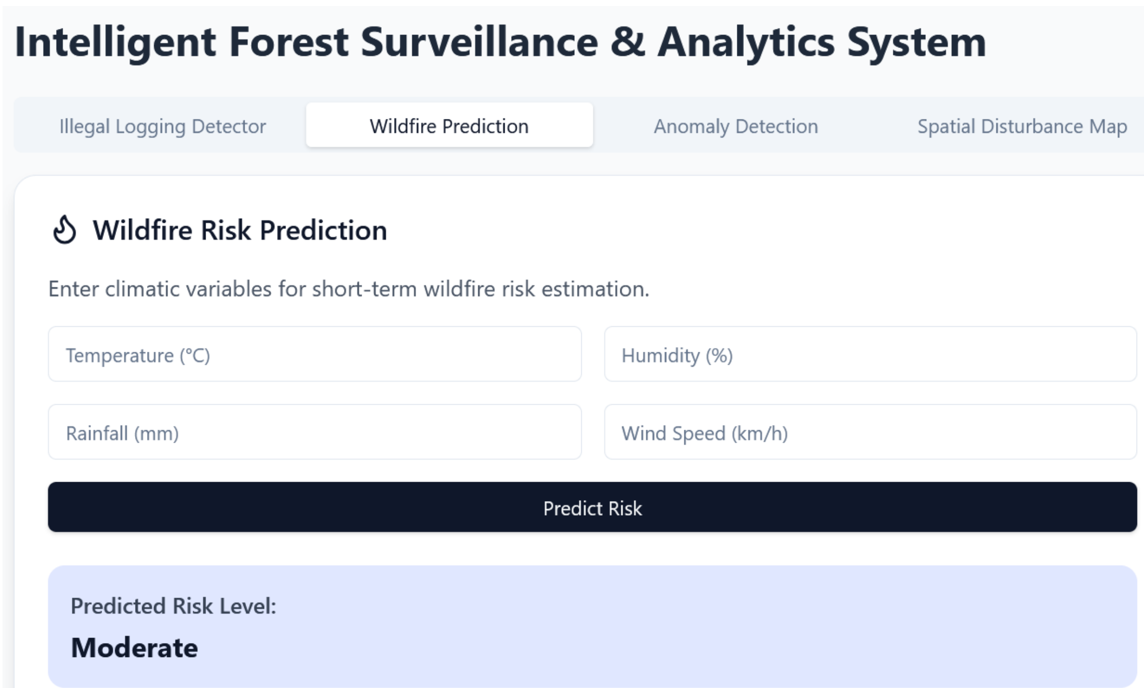

Figure 10. Wildfire risk prediction interface.

high—based on the expected ignition likelihood and environmental circumstances.

Figure 11 illustrates the interface that receives uploaded spectral or time-series forest data and analyses it using anomaly detection methods such as Isolation Forest and Autoencoders. The system detects anomalous or suspicious activity, such as abrupt changes in vegetation, encroachment, or unexplained disturbances, and assesses deviations from typical forest behaviour. The outcome exposes potential abnormalities, delivering early warnings for human activities or environmental shifts that demand rapid attention.

Figure 12 is the interactive display of forest disturbance patterns throughout the research region offered by the spatial disturbance map interface. It helps users understand where illicit logging and other high-risk activities are concentrated by displaying hotspot zones, discovered anomalies, and disturbance intensities on a forest map. The map facilitates strategic surveillance planning and allows users to produce alert reports for operational deployment and policy decision-making.

Overall, the study's findings show that combining remote

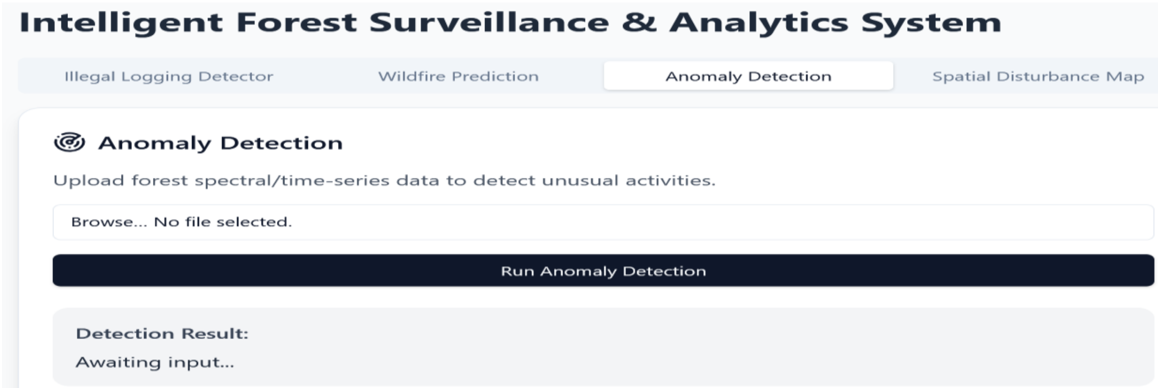

Figure 11. Anomaly detection interface.

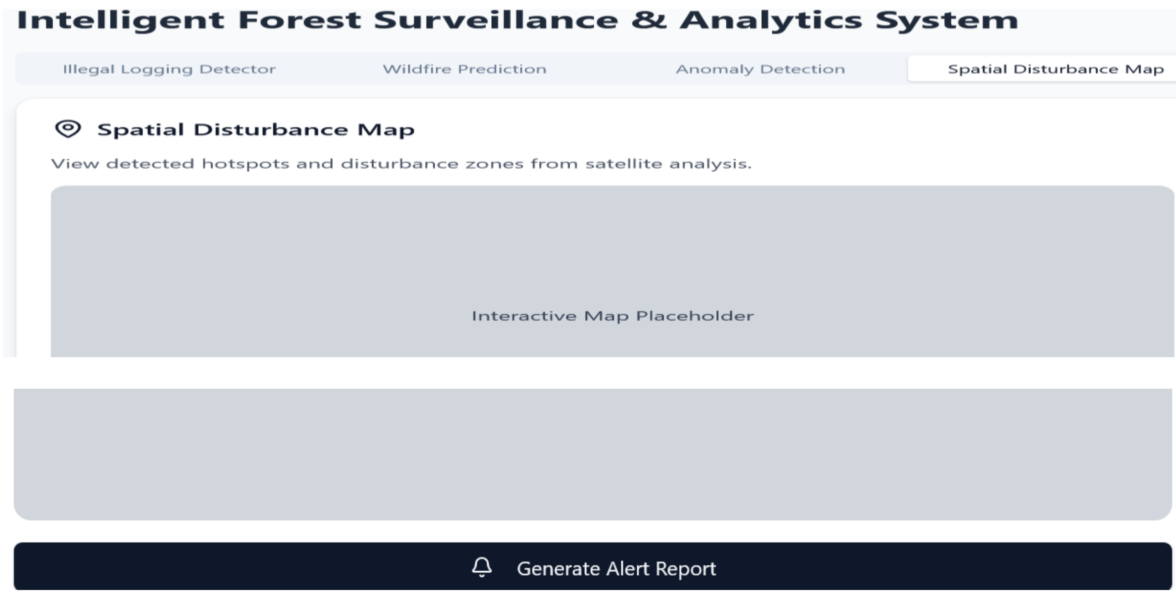

Figure 12. Spatial disturbance map interface.

sensing data with deep learning, ensemble prediction models, and anomaly detection provides an effective, scalable, and precise method for intelligent forest surveillance. However, to fully achieve the system's operational potential, actual deployment will need to solve constraints related to data availability, computing cost, and regional flexibility.

DISCUSSION

The results of this study show how well multispectral satellite imaging, machine learning models, and anomaly detection techniques may be integrated for thorough forest monitoring in Nigeria. The higher performance of the U-Net model emphasises the necessity of models capable of exploiting spatial context for detecting fine-scale disturbances such as illicit logging. This fits with past studies emphasising the value of encoder–decoder CNN architectures for land-cover change and deforestation investigations.

Compared to earlier single-sensor or single-model approaches, the combination of multi-sensor imagery, deep learning, and ensemble predictive modelling produced a notable improvement. The U-Net model provided fine-grained segmentation of forest disturbances, while the RF–LSTM ensemble delivered robust wildfire risk predictions aligned with vegetation–climate interactions. An essential surveillance capability for identifying new disruptions that might not show up in supervised datasets was added by the anomaly detection pathway.

The wildfire forecast results further show the usefulness of hybrid modelling methodologies. The complementary strengths of Random Forest and LSTM models, random forests capturing non-linear interactions among environmental variables and LSTMs modelling temporal dependencies, produce more reliable forecasts than single-model systems. The temporal patterns found in the anticipated wildfire risk values align well with reported oscillations in vegetation moisture and temperature, providing credence to the model findings.

Comparatively, it can also be seen from the findings of the study that the higher performance of the U-Net model (IoU = 0.88, Dice = 0.92) aligns with the results from Wang *et al*. (2023), who reported similar segmentation accuracy in deforestation studies using Sentinel-2 imagery. Our ResNet-50 model outperformed InceptionV3, consistent with Chen and Liu (2022), who attributed this to ResNet's residual connections enabling more stable feature learning in complex forest environments.

Furthermore, the RF–LSTM ensemble achieved an RMSE of 0.07, comparable to Jiang *et al*. (2024), who also found NDVI and temperature to be the most influential predictors. Our anomaly detection module successfully identified new access routes and logging clusters, corroborating Zhang *et al*. (2023), who used similar unsupervised methods for illegal logging detection.

Again, the integration of multi-sensor data (Sentinel-2, Landsat, MODIS) follows recommendations by Silva *et al*. (2022), who demonstrated that such fusion enhances detection reliability and temporal coverage. Furthermore, the system's design aligns with IoT-AI frameworks proposed by Kumar and Singh (2023), supporting scalable, real-time forest monitoring.

By identifying minute spatial changes and spectral anomalies linked to human encroachment and forest degradation, the anomaly detection subsystem also offers extra levels of information. This is particularly critical in areas with limited ground surveillance capacity, where early detection of unexpected behaviour can considerably improve response times.

Collectively, the integrated system solves significant gaps in forest monitoring by offering automated, scalable, and data-driven insights that can enhance conventional field-based methodologies. However, obstacles remain, including the requirement for ground-truth datasets with increased temporal density and the restrictions given by cloud cover in optical remote sensing. Future developments could include the incorporation of SAR images and the deployment of on-ground IoT sensors for real-time confirmation.

Limitations of the study

Data, computational, and operational restrictions are the primary sources of this study's shortcomings. Due to the system's substantial reliance on optical satellite images, data availability in tropical regions may be impacted by air interference and cloud cover. Additionally, a lack of temporally rich ground-truth data may limit long-term generalisation and cause bias in model performance. Furthermore, adoption in low-resource environments may be limited by the deep learning models' high computational resource requirements. The coarse spatial resolution of MODIS data limits the wildfire prediction component's accuracy for localised fire incidents. Lastly, the system's transferability and operational stability may be impacted when it is deployed to different regions or scaled for long-term use because it was verified within particular Nigerian forest zones and lacks ongoing real-time field validation.

Although the study shows good technical performance, its shortcomings highlight the need for improved ground validation, increased data diversity, multi-sensor integration (such as SAR and IoT), and optimised computational methodologies to support large-scale and real-time operational use.

Summary

This work developed an intelligent forest surveillance and analytics system that integrates satellite remote sensing, deep learning, and anomaly detection to monitor illegal logging and predict wildfire danger in Nigerian forests. Using multispectral Sentinel-2, Landsat imaging, MODIS thermal data, and climatic variables, the system effectively detected forest disturbances and delivered short-term wildfire risk projections. While an ensemble of Random Forest and LSTM models produced precise wildfire predictions, the U-Net model performed best for detecting illicit logging. Additional visual analytics, including confusion matrices, feature significance plots, and spatial disturbance heatmaps, boosted interpretability and operational relevance. The results illustrate the potential of integrated geospatial–AI systems for assisting proactive forest management and conservation decision-making.

Conclusion

A unified, scalable approach for Nigerian forest monitoring is presented in this paper. The technology improves early warning systems, fortifies enforcement tactics, and aids in policy decision-making by combining deep learning, predictive analytics, and remote sensing. The method provides national forestry authorities with a useful tool and is flexible enough to be implemented throughout West African forest ecosystems.

The study reveals that modern machine learning and remote sensing approaches can considerably improve forest monitoring capacities in Nigeria. By merging high-resolution satellite data, deep learning-based disturbance detection, and hybrid wildfire prediction models, the system provides a comprehensive framework for early warning, enforcement, and long-term forest conservation planning. The approach is a useful tool for preventing illicit logging and lessening the effects of wildfires since it is scalable and adaptable to various forest ecosystems. All things considered, the system helps create data-driven, technologically advanced forest governance that is consistent with both national and international sustainability goals.

Recommendations

The study advises using an integrated AI–remote sensing monitoring system to boost forest surveillance and improve the early detection of illegal logging. To increase accuracy and operational resilience, it is crucial to improve ground-truth data collection, integrate synthetic aperture radar (SAR) and IoT-based sensing technologies, and update machine learning models on a regular basis. In order to guarantee efficient system utilisation and long-term sustainability, it also highlights the necessity of ongoing capacity building among forest management staff.

Policy implications

The results emphasise how crucial it is to include AI-powered forest monitoring systems into national environmental governance frameworks in order to improve early warning and enforcement capacities. By implementing such systems, Nigeria's Monitoring, Reporting, and Verification (MRV) capacity would be strengthened, data-driven decision-making will be supported, and compliance with national and international forest management commitments will be improved. Policymakers are encouraged to invest in the essential digital and geospatial infrastructure to support long-term deployment and scalability.

CONFLICT OF INTEREST

The authors declare that there is no conflict of interest in carrying out this study.

REFERENCES

Ali, G., Mijwil, M. M., Adamopoulos, I., & Ayad, J. (2025). Leveraging the internet of things, remote sensing, and artificial intelligence for sustainable forest management. *Babylonian Journal of Internet of Things*, *2025*, 1-65.

Areo, O. S., Omole, A. O., Amoo-Onidundu, O.N. & Adejoba, A.L. (2024). Impact of illegal logging operation on Nigerian economy: A concise review. *Agriculture, Food, and Natural Resources Journal*, *3*(2), 349-357.

ARNOWA (2019). Detecting forest fires. ARNOWA. Retrieved 11th December 2024 from https://arnowa.com/smart-forest-monitoring/.

Dybbroe, A. & Andersson, S. (2025). A real-time end-to-end satellite-based forest fire detection system for Sweden: Tackling the increased forest-fire risk under a changing climate. An EU Publication: EU Missions Adaptation to Climate Change. Retrieved 10th July 2025 from https://climate-adapt.eea.europa.eu/en/mission/solutions/mission-stories/a-real-time-forest-fire-detection-system-story32.

Elnafat, I. I. (2025). Desertification in Nigeria and its impact on climate change. Retrieved 29th June 2025 from https://www.climatechangewriters.com/stories/desertification-in-nigeria-and-its-impact-on-climate-change-2.

Etaati, A., Bastam, M., & Ataie, E. (2024). Smart forest monitoring: A novel Internet of Things framework with shortest path routing for sustainable environmental management. *IET Networks*, *13*(5-6), 528-545.

FAO (2020). Global Forest Resources Assessment: Report Nigeria. Retrieved from https://openknowledge.fao.org/server/api/core/bitstreams/41b4762d-ee61-4a88-a18d-67a7ef42755b/content.

Fassnacht, F. E., White, J. C., Wulder, M. A., & Næsset, E. (2024). Remote sensing in forestry: Current challenges, considerations and directions. *Forestry: An International Journal of Forest Research*, *97*(1), 11-37.

Ghoniem, N. A., Hesham, S., Fares, S., Hesham, M., Shaheen, L., & Halim, I. T. A. (2021). Intelligent surveillance systems for smart cities: A systematic literature Review. *Smart Systems: Innovations in Computing: Proceedings of SSIC 2021*, 135-147.

Hernandez, K., & Hoskins, A. B. (2024). Machine learning algorithms applied to wildfire data in California's central valley. *Trees, Forests and People*, *15*, 100516.

Ibrahim, S. W. (2016). A comprehensive review on intelligent surveillance systems. *Communications in Science and Technology*, *1*, 7-14.

Kummarapurugu, C. S. (2021). AI-powered forest surveillance systems: A study of cloud-enabled machine learning models for identifying and preventing illegal logging and deforestation. *International Journal of Innovative Research in Engineering & Multidisciplinary Physical Sciences,* 9(1), 1-9*.*

MacCarthy, J., Richter, J., Tyukavina, S., & Harris, N. (2025). The latest data confirms: Forest fires are getting worse. Retrieved 30th July 2025 from https://www.wri.org/insights/global-trends-forest-fires.

Moffette, F., Alix-Garcia, J., Shea, K., & Pickens, A. H. (2021). The impact of near-real-time deforestation alerts across the tropics. *Nature Climate Change*, *11*(2), 172-178.

Mohapatra, A., & Trinh, T. (2022). Early wildfire detection technologies in practice—A Review. *Sustainability*, *14*(19), 12270.

Mporas, I., Perikos, I., Kelefouras, V., & Paraskevas, M. (2020). Illegal logging detection based on acoustic surveillance of forest. *Applied Sciences*, *10*(20), 7379.

Mu, L., Yang, Y., Wang, B., Zhang, Y., Feng, N., & Xie, X. (2025). Edge computing-based real-time forest fire detection using UAV thermal and colour images. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, 18*, 6760-6771.

Ogunkan, D. V. (2022). Achieving sustainable environmental governance in Nigeria: A review for policy consideration. *Urban Governance*, *2*(1), 212-220.

Ramadan, M. N., Ali, M. A., Khoo, S. Y., & Alkhedher, M. (2024). AI-powered IoT and UAV systems for real-time detection and prevention of illegal logging. *Results in Engineering*, *24*, 103277.

Scott, R., Craig, S., & Aislyn, F. (2024). What are data silos and what problems do they cause? Retrieved 12th April 2025 from https://www.techtarget.com/searchdatamanagement/definition/data-silo.

Venanzi, R., Latterini, F., Civitarese, V., & Picchio, R. (2023).

Recent applications of smart technologies for monitoring the sustainability of forest operations. *Forests*, *14*(7), 1503.
Weisse, M., Goldman, L., & Carter, S. (2023). Tropical primary forest loss worsened in 2022, despite international commitments to end deforestation. Retrieved 10th September 2024 from https://www.globalforestwatch.org/blog/forest-insights/global-tree-cover-loss-data-2022/.